

Forced Oscillation Analysis and Model Reduction Techniques in Power Systems

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Doctor of Philosophy

Degree

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DEDICATION

This dissertation is dedicated to all my family and friends for their love and support along
the journey

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ABSTRACT

The presence of forced oscillations and poorly damped low-frequency oscillations poses significant challenges to the operation of modern interconnected power systems. These phenomena can lead to severe consequences, including damage to critical equipment, reduced efficiency in power transfer, and compromised overall stability of the grid. Forced oscillations, often triggered by periodic disturbances, propagate through networks, amplifying stress on system components. Similarly, low-frequency oscillations, arising from weak system damping, can persist and undermine operational reliability. Addressing these challenges is critical to maintaining the safety and resilience of power systems amid increasing complexity and demand.

The first part of this dissertation investigates how different exciter and governor model parameters influence the magnitude of forced oscillations. Chapter 2 examines these parameter impacts, providing insights for power system planners and operators to optimize settings and enhance stability. Chapter 3 explores the forced oscillation frequency impact under resonance conditions. Chapter 4 categorizes oscillation sources, identifying exciters, governors, or renewable energy plants as potential origins. Mitigation strategies using inverter-based resource (IBR) actuators are explored in Chapter 5.

The second part addresses the growing complexity of modern power grids, intensified by the integration of intermittent renewable energy sources. Simulating large-scale systems using traditional model-based approaches has become computationally demanding. To overcome this, a measurement-based model reduction approach utilizing

long short-term memory (LSTM) and gated recurrent unit (GRU) neural networks is proposed. This technique enables efficient and accurate analysis of power system dynamics, offering a scalable solution for managing the challenges posed by renewable integration.

This comprehensive dissertation provides a multi-faceted approach to improving power system stability and resilience, offering practical solutions for managing forced oscillations, leveraging advanced machine learning techniques for system analysis.

TABLE OF CONTENTS

Chapter 1 Introduction	1
1.1 Background and Motivation	2
1.2 Contribution	4
1.3 Dissertation Outline	4
Chapter 2 IMPACT OF EXCITER MODEL PARAMTERS ON FORCED OSCILLATIONS	6
Abstract	7
2.1 Introduction	8
2.2 Methodology	14
2.3 Exciter Models	16
2.3.1 SCRX Exciter	17
2.3.2 ESST1A Exciter	20
2.3.3 AC7B Exciter	22
2.4 Parameters Testing of Governor Models	25
2.4.1 GAST Governor	26
2.4.2 HYGOV Governor	28
2.4.3 GGOV1 Governor	28
2.5 Results and Discussion	32
2.5.1 SCRX Exciter	32
2.5.2 ESST1A Exciter	36
2.5.3 AC7B Exciter	39

2.5.4 GAST Governor	42
2.5.5 HYGOV Governor	44
2.5.6 GGOV1 Governor.....	46
2.6 Conclusion	52
Chapter 3 FORCED OSCILLATION FREQUENCY IMPACT ANALYSIS DURING RESONANCE.....	54
Abstract.....	55
3.1 Introduction.....	55
3.2 Methodology	57
3.3 Case studies.....	58
3.3.1 Kundur system	58
3.3.2 ERCOT system	59
3.3.3 EI system.....	61
3.4 Case study Results & Discussion.....	61
3.4.1 Kundur System Results.....	61
3.4.2 ERCOT System Results.....	63
3.4.3 EI System Results	65
3.4.4 Comparision of Generator and Load Induced FOs	67
3.5 Conclusion	69
Chapter 4 FORCED OSCILLATION SOURCE LOCATION AND SOURCE TYPE CLASSIFICATION	71
Abstract.....	72

4.1 Introduction.....	72
4.2 Methodology for Designing Simulation Cases.....	79
4.3 FO Source Location and Type Identification Algorithm.....	79
4.4 Results and Discussion	84
4.4.1 Inter-area Mode Analysis.....	84
4.4.2 Local Mode Analysis	84
4.4.3 Source Type Classification	89
4.4.4 Summary of Case Studies	89
4.5 Conclusion	92
Chapter 5 ANALYSIS OF EFFECTIVE IBR ACTUATORS FOR FORCED OSCILLATION MITIGATION	93
Abstract.....	94
5.1 Introduction.....	94
5.2 Methodology	96
5.2.1 Theoretical Background.....	97
5.2.2 Mesh Modeling & IBRs Selection Analysis	99
5.3 Structure of FODC Through IBR	101
5.4 Case Study Results.....	103
5.5 Effect of Transmission line distance/Impedance	107
5.6 Conclusion	109
Chapter 6 MEASUREMENT-BASED DYNAMIC EQUIVALENCING OF LARGE- SCALE POWER SYSTEMS USING RECURRENT NEURAL NETWORKS	111

Abstarct	112
6.1 Introduction.....	112
6.2 Problem Formulation	118
6.2.1 Dynamic Equivalence Representation	118
6.2.2 LSTM, and GRU Model Based Equivalent Load Modeling	120
6.3 LSTM, and GRU Models Architecture.....	121
6.3.1 LSTM Cell Structure.....	122
6.3.2 GRU Cell Structure.....	125
6.4 Methodology	127
6.4.1 Dataset Preparation, Pre-processing and Training.....	129
6.5 Case Studies and Discussion.....	132
6.5.1 Introduction of Study Cases.....	132
6.5.2 Reduction of the NPCC Model	136
6.5.3 Reduction of the EI System-FRCC Area.....	141
6.5.4 Response to a Generator Trip Event Under EI Model Operating Dispatch Conditions Change	143
6.5.5 Reduction of an EI-TVA area	145
6.6 Conclusion	152
Chapter 7 CONCLUSION AND FUTURE WORK.....	155
References.....	159
Vita.....	179

LIST OF TABLES

Table 2-1. Default models of kundur's system.....	15
Table 2-2. Parameters of SCRX exciter model.....	19
Table 2-3. Parameters of ESST1A exciter model.....	20
Table 2-4. Parameters of AC7B exciter model.....	24
Table 2-5. Parameters of GAST governor model.....	27
Table 2-6. Parameters of HYGOV governor model	29
Table 2-7. Parameters of GGOV1 governor model.....	31
Table 2-8. Sensitive parameters of SCRX exciter with respect to reactive power change	33
Table 2-9. Sensitive parameters of ESST1A exciter with respect to reactive power change.	37
Table 2-10. AC7B exciter sensitive parameters and their associated ranks	40
Table 2-11. GAST governor sensitive paramters and their associated ranks.	43
Table 2-12. HYGOV governor model sensitive parameters and their associated ranks...	47
Table 2-13. GGOV1 governor sensitive parameters and their associated ranks.....	50
Table 3-1. Small signal stability results of the kundur's system	60
Table 3-2. Small signal stability results of the for machine U1 at Bus 150111 in ERCOT system	60
Table 4-1. Simulated test cases of the synthetic ERCOT system	78
Table 4-2. Case studies result of the spectral energy flow method.....	90
Table 5-1. Small signal stability results of the mesh system	100

Table 5-2. Participating generator location for Mode 1 & 2	104
Table 5-3. Damping performance comparison	106
Table 5-4. Peak-to-peak frequency deviation versus distance.....	110
Table 6-1. Summary of training and validation sets of NPCC system	133
Table 6-2. Summary of training and validation sets of EI-FRCCsystem	135
Table 6-3. Summary of trained epochs versus computation time.....	137
Table 6-4. Performance metric analysis of the NPCC system.....	140
Table 6-5. Performance metric analysis of the EI system.....	144
Table 6-6. Summary of generator dispatch changes	144

LIST OF FIGURES

Figure 2-1. Block diagram of dynamic models in the physical power system structure	9
Figure 2-2. Schematic diagram of Kundur's two-area system	15
Figure 2-3. Block diagram of SCRX exciter model	19
Figure 2-4. Block diagram of ESST1A exciter model.....	20
Figure 2-5. Block diagram of AC7B exciter model.....	23
Figure 2-6. Block diagram of GAST governor model.....	27
Figure 2-7. Block diagram of HYGOV governor model.....	29
Figure 2-8. Block diagram of GGOV1 governor model.....	30
Figure 2-9. Response of SCRX exciter gain (K) changed from 10 to 1000 value in steps of 100	33
Figure 2-10. Response of gain reduction ratio (T_A/T_B) changing from 0.1 to 1.0 in steps of 0.1	35
Figure 2-11. FFT response of the SCRX parameters.....	35
Figure 2-12. FFT response of the ESST1A model: K_A parameter change	38
Figure 2-13. FFT response of the ESST1A model parameters.....	38
Figure 2-14. Response of voltage regulator proportional gain (K_{PA}) changing from 0.0 to 50.0.....	41
Figure 2-15. FFT response of AC7B model parameters.....	41
Figure 2-16. Response of speed droop (R) changing from 0.0 to 1.0 in steps of 0.1	45
Figure 2-17. FFT response of GAST model parameters change	45
Figure 2-18. Response of turbine gain (A_T) changing from -1.0 to 4.0 in steps of 0.5 ...	47

Figure 2-19. Response of temporary droop (r) changing from 0.0 to 2.0 in steps of 0.2 .	48
Figure 2-20. FFT response of HYGOV model parameters change	48
Figure 2-21. Time domain and FFT response of turbine gain (K_{turb})	51
Figure 2-22. FFT response of R and T_{act} parameters change.....	51
Figure 3-1. Part of the ERCOT system.....	60
Figure 3-2. Response of the kundur's system with respective to FO frequency	62
Figure 3-3. Response of the ERCOT system with respect to FO frequency	64
Figure 3-4. Response of the EI system with respect to FO frequency.....	66
Figure 3-5. Comparision between the governor and load injection methods	68
Figure 4-1. Synthetic Texas power grid model area map	77
Figure 4-2. Flowchart of the FO source location and classification algorithm.....	83
Figure 4-3. Maximum peak-to-peak deviation of frequency and voltage channes for the cases 1A-D	85
Figure 4-4. Energy flow results for governor, and IBR-current loop (P-type) oscillation cases of 1A and 1B	86
Figure 4-5. Energy flow results for exciter, and IBR-voltage loop (Q-type) oscillation cases of 1C and 1D	86
Figure 4-6. Maximum peak-to-peak deviation of frequency and voltage channes for the cases 6A-D	87
Figure 4-7. Energy flow results for governor, and IBR-current loop (P-type) oscillation cases of 6A and 6B	88

Figure 4-8. Energy flow results for exciter, and IBR-voltage loop (Q-type) oscillation cases of 6C and 6D	88
Figure 5-1. 121-Bus mesh grid with two dominant oscillation model.....	100
Figure 5-2. Flowchart for IBR selection and tuning process.....	102
Figure 5-3. The block diagram of FODC controller	102
Figure 5-4. Frequency Response with 8 IBRs control at the highly participating and non-participating generators.....	106
Figure 5-5. Frequency response in case of FO Event at non-participating generator.....	108
Figure 5-6. Frequency response with no control and 8 IBRs control for FO Event at generator – 83	108
Figure 6-1. Representation of original and reduced model.....	119
Figure 6-2. Single LSTM and GRU structures	123
Figure 6-3. Flowchart of open-loop training and closed-loop testing procedure.....	128
Figure 6-4. LSTM/GRU-based RNN model structure for NPCC & EI-FRCC systems	131
Figure 6-5. LSTM/GRU-based RNN model structure for EI-TVA system.....	131
Figure 6-6. Single line diagram of NPCC original and reduced system.....	133
Figure 6-7. Single line diagram of US Interconnection map	135
Figure 6-8. Generator trip and bus fault event response of NPCC system	139
Figure 6-9. Load trip and successive load trip event response of NPCC system	139
Figure 6-10. Generator trip and bus fault event response of FRCC area.....	142
Figure 6-11. Load trip and successive load trip event response of FRCC area	142

Figure 6-12. Generator trip event response of FRCC area at bus – 401260.....	146
Figure 6-13. Generator trip event response for tie-lines between the TVA and PJM area	147
Figure 6-14. Generator trip event response for tie-lines between the TVA and MISO_IN area.....	147
Figure 6-15. Generator trip event response for tie-lines between the TVA and MISO_MO_IL	148
Figure 6-16. Generator trip event response for tie-lines between the TVA and VACAR area.....	148
Figure 6-17. Generator trip event response for tie-lines between the TVA and SOCO area	149
Figure 6-18. Generator trip event response for tie-lines between the TVA and Enenergy area.....	150
Figure 6-19. Generator trip event response for tie-lines between the TVA and RTO MIDW area	151
Figure 6-20. Model prediction error comparison for EI-TVA study area	153

CHAPTER 1
INTRODUCTION

1.1 Background and Motivation

The stability and reliability of modern power grids are increasingly challenged by oscillatory behaviors resulting from the continuous transfer of energy among system components. These oscillations, characterized by frequency, damping, amplitude, and phase, can manifest as forced oscillations (FOs) when driven by external periodic inputs [1]. Over the last two decades, FOs have posed significant operational challenges, increasingly threatening grid stability. These oscillations can stem from various sources, including faulty equipment, control system malfunctions, improperly tuned power system stabilizers (PSS), incorrect generator settings, and cyclic loads [2], [3], [4]. Additionally, mechanical factors, such as irregularities in combustion or steam valve issues in turbines, can induce FOs [5]. With the growing integration of renewable energy technologies, such as wind and hydro turbines, the grid is increasingly susceptible to oscillations caused by wind turbine vibrations and hydro ramping events [6]. As renewable penetration continues to rise, the likelihood of FO events increases, making effective FO detection, localization, and mitigation more complex and essential for maintaining system security.

FOs can impact both local systems and wide-area networks, depending on their frequency. According to NERC guidelines [7], local oscillations typically occur above 1 Hz, while inter-area oscillations, often below 1 Hz, can resonate with natural grid modes, posing a risk to grid-wide stability. For wide-area resonant FOs to occur, three conditions must be met: the FO frequency is close to a system mode, the mode has significant participation near the source, and damping is insufficient [6].

Simulation studies reveal that weakly damped modes interacting with FOs can

lead to large-scale disturbances, resonant oscillations, and potential equipment damage, including generator trips and mechanical fatigue. Depending on their frequency and amplitude, these oscillations can degrade power quality. As FO occurrences increase and the grid becomes more complex, research on robust mitigation strategies becomes vital to preserving system stability.

Despite their prevalence in Bulk Power Systems (BPS), FOs remain challenging to analyze due to their irregular occurrence and weak correlation with system eigenvalues. Unlike natural oscillations, FOs result from external cyclic forces and can appear across various frequencies. FOs may also exhibit harmonics, though these are not always detectable, making conventional modal analysis inadequate for their identification.

Motivated by these challenges, this dissertation aims to advance the understanding of how key power system control components, such as exciters, governors, and renewable generation systems, influence the severity and propagation of FOs. The research systematically investigates the sensitivity of forced oscillation magnitudes to selected exciter and governor model parameters and examines how oscillation frequency affects resonance conditions. To improve FO mitigation, the study proposes optimal selection of inverter-based resource (IBR) actuators to enhance damping.

Furthermore, this dissertation addresses the challenge of analyzing large-scale power systems by developing a measurement-based model reduction strategy using recurrent neural networks (RNNs), enabling efficient dynamic analysis. Through theoretical analysis, simulation studies, and proposed mitigation techniques, this work

contributes to strengthening the stability and security of evolving power systems.

1.2 Contribution

This dissertation makes the following key contributions:

- Demonstrating the impact of selected exciter and governor models parameters on the forced oscillation magnitude.
- Investigating the FO frequency impact during the resonance condition.
- Identifying the FO source location, distinguishing source type at the sub-control level representing the FO originating from exciters or IBR-voltage loop as Q-type, and governor or the IBR-current loop as the P-type potential source.
- Proposing optimal IBR actuators selection for FO mitigation.
- Development of measurement-based large scale power system model reduction strategy using RNN models.

1.3 Dissertation Outline

This section presents an outline of each chapter covered in this dissertation.

Chapter 2 examines exciter and governor models, analyzing the impact of parameter variations on FO magnitudes. Parameters are ranked based on sensitivity.

Chapter 3 explores FO resonance effects by comparing dynamic responses in different power system models when FO frequencies approach resonance frequencies.

Chapter 4 presents a methodology to identify FO source location, categorizing exciters, governors, IBR-current and voltage loops as the oscillation source at the sub-control level.

Chapter 5 focuses on optimal IBR actuator selection for mitigating FO events occurring

at highly participating and non-participating generator location for an inter-area resonance mode, the case study results are demonstrated on a 121-bus ideal mesh system.

Chapter 6 introduces a measurement-based model reduction technique using long short-term memory (LSTM) and gated recurrent unit (GRU) neural networks. This framework is evaluated on case studies of 140 bus Northeast Power Coordinating Council (NPCC) system and a 70,000-bus synthetic Eastern Interconnection (EI) models using PSSE/Python integration.

Chapter 7 summarizes conclusions and recommendations for future work.

CHAPTER 2

IMPACT OF EXCITER MODEL PARAMETERS ON FORCED OSCILLATIONS

ABSTRACT

In recent years, the frequency of FO events due to control system malfunctions or improper parameter settings has increased. Tuning the parameters of exciters and governor models is crucial for maintaining power system stability. Traditional simulation studies typically involve small transient disturbances or step changes to find optimal parameter sets, but existing optimization algorithms often fall short in fine-tuning for FOs. Identifying the sensitive parameters within these control models is essential for ensuring stability during large, sustained disturbances. This study focuses on identifying these critical exciter and governor model parameters by analyzing their influence on sustained FOs. Using Kundur's two-area system, we analyze common exciter models such as SCR_X, ESST1A, and AC7B, along with governor models like GAST, HYGOV, and GGOV1, utilizing PSS[®]E software version 34. Sustained FOs are injected at generator-1 of area-1, with individual parameter changes dynamically simulated. By considering a local oscillation frequency of 1.4 Hz and an inter-area oscillation mode of 0.25 Hz, we analyze the impact of each parameter change on the magnitude and frequency of FOs as well as on active and reactive power outputs. This novel approach highlights the most influential parameters of each tested model-such as exciter, governor, and turbine gains, as well as time constant parameters-on the impact of FOs. Based on our findings, the sensitive parameters of each tested model are ranked. These would provide valuable insights for industry operators to fine-tune control settings during oscillation events, ultimately enhancing system stability.

2.1 INTRODUCTION

The physical power system is divided into mechanical and electrical subsystems, as shown in **Figure 2-1** [8]. The mechanical subsystem includes handling the fuel source, furnace, boiler, and turbine to generate and control steam flow. Using the fuel source, the furnace and boiler produce high-pressure steam, which the turbine converts into mechanical energy to drive the synchronous generator. The generator then converts this energy into electrical power. The governor control system regulates the generator's speed using droop speed control, adjusting the fuel supply based on grid frequency. An exciter, a type of DC generator, controls the field voltage (E_{fd}) and current (I_{fd}) by supplying DC current to the generator's field winding to maintain a constant system voltage [9].

Exciters typically include an excitation power unit, excitation regulator, automatic voltage regulator (AVR), and power system stabilizer (PSS). The excitation power unit provides current to the generator rotor, while the excitation regulator adjusts the output. The AVR and PSS enhance system stability during disturbances [9].

For a generator exciter, certain parameters like limits, exciter time constant, voltage sensing time constant, and saturation value are fixed by the manufacturer. However, voltage regulator gains, time constants, reactive compensation, and limit level values are tunable by the operator. Similarly, in the governor control system, parameters like water starting time, no-load gate, full load gate, turbine power fractions, maximum power, dead band, and turbine damping are fixed in the design, while droop, time constant, gains, and rate limits are tunable by the plant operator [10].

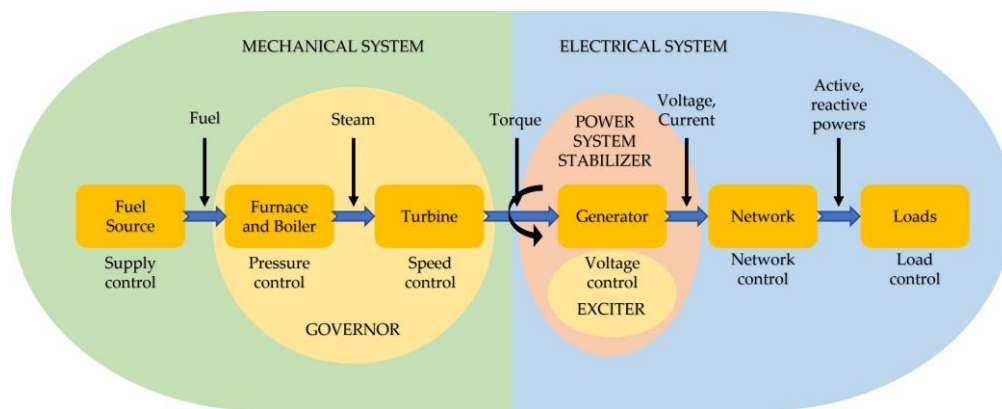


Figure 2-1. Block diagram of dynamic models in the physical power system structure [11]

Before commissioning a new unit into the grid, power system planning and operational studies analyze the grid's stability and reliability with the changes. These studies use detailed models of synchronous machines and their control systems to simulate real-world performance [10]. Sometimes, hardware-in-the-loop simulations are used to model and pre-tune synchronous generator controls [12]. During commissioning, extensive testing, including off-line, open-circuit, and online tests, tunes the governor and exciter parameters to ensure optimal performance and stability. Once set, these parameters maintain stable operation under various conditions, minimizing the need for frequent adjustments. Real-time manual adjustments to governor or exciter parameters are rare, typically occurring only in response to system disturbances or significant operational changes, with re-tuning performed during scheduled maintenance. However, specific oscillation events like low frequency FOs in nuclear or steam power plants require immediate attention for modal analysis and parameter fine-tuning.

FOs in power systems are typically triggered by external periodic disturbances from cyclic loads, equipment malfunctions, inadequate control design or parameter settings, mechanical oscillations of a generator under unusual conditions, or adverse interactions within the power system [13], [14]. Growing FOs within the low-frequency oscillations (LFO) or ultra-low-frequency oscillations (ULFO) range are increasingly serious and can damage equipment, restrict the ability to transfer power, and degrade the power quality. Additionally, resonance of forced oscillation with weakly damped local or inter-area system modes can also result in high-magnitude oscillations [15]. There have been numerous forced oscillation events that lasted for minutes to hours that have

occurred around the world [16]. On 11 January 2019, the U.S. Eastern Interconnection experienced a forced oscillation event as a result of a defective input to a generator's steam turbine controller. The forced oscillation occurred for 18 min at a frequency of 0.25 Hz [17]. Bonneville Power Administration (BPA) reports several sustained oscillations due to interactions between the PSS and under-excitation limiter (UEL) of a hydropower plant. Also in 2016, active power erratic behavior was noticed due to problems with the interaction between a plant controller and the governor of a generating unit [18]. Several oscillation events across the U.S. summarizing generator equipment failures and the improper setting of system components like the governor, PSS, exciter, etc. rather than inaccurate modeling are discussed in [19], [20]. Detecting and identifying the source of FOs within the sub-control level of a generator remains an unsolved problem. However, analyzing oscillation trends and adjusting sub-control system parameters are crucial to restoring system stability in a short timeframe.

In the literature, several studies focus on tuning the AVR and PSS of the excitation system, using online tuning algorithms to adjust gain and time constant parameters to maintain system stability in real time [21], [22], [23], [24], [25], [26], [27], [28]. However, the obtained parameters are acceptable for steady-state and small transient disturbance events and sometimes require an engineer's judgement for a few cases such as the wrong value of AVR gain, incorrect values of the PSS, bad turbine-governor data, wrong generator inertia and time constants, etc. [29]. These optimization algorithms are not suitable for tuning parameters during sustained forced oscillation events. Also, the level of accuracy of the algorithms depends on the field measurement transducers, which

might not be available in all locations or may have inaccuracies. The authors of [30] studied the influence of excitation system PID control parameters of the power system using 5% step response dynamic characteristics. This study's results showed the parameters' impact on the transient response of the power system. In [31], the fault analysis was performed to find the root causes of the rectifier bridge filter and the excitation system's 24 V power supply failure causing two downtime accidents. These failures require a deep investigation of component analysis. But few oscillation events, which appear due to dynamic control model parameter inconsistencies in nuclear or steam plants, need immediate oscillation event re-creation and model parameters' re-tuning. However, in the literature, less attention was drawn towards the exciter parameters' tuning during large, forced oscillation events.

Similarly, most studies focus on tuning the PID parameters of a few governor models. Recent works [32], [33], [34], [35], [36] summarize the latest optimal algorithms for PID controllers for a hydro-turbine-based governor control. The importance of hydro power plant controller settings for suppressing frequency oscillations in the Turkish power system is highlighted in [37]. In [38], the authors discuss optimal techniques for tuning diesel governor parameters in hybrid renewable power systems using an exhaustive search approach. However, the tuning governor parameters described in [37], [38] are for islanded mode operations. In [39], low-frequency oscillation events related to governor control are presented, including a special case scenario that analyzes how governor control parameters influence the damping characteristics of inter-area oscillations and introduce a special ultra-low-frequency model into the power system. A

few case studies in [40], [41], [42] examined the impact of hydro-turbine and governor parameters on power systems with low- and ultra-low- frequency oscillations, focusing on isolated grid and single machine infinite bus system analyses. The work in [43] discusses the impact of governor and hydraulic model parameters on grid stability through eigenvalue analysis but does not address the influence of model parameters during fault and low-frequency oscillation scenarios.

The literature shows a scarcity of research on the impact of exciter and governor parameters on persistent FOs. Few historical low-frequency oscillation events related to governor control have been studied, but there is limited focus on exciter parameters and their relation to oscillations. Moreover, the literature focuses on optimizing a few parameters of the control system all at a time for a new steady-state and/or small transient disturbance. The novelty of this paper lies in bridging this gap by analyzing how changes in tuning for each single governor and exciter parameter will affect the persisting FOs on the system. The findings will equip power plant operators and planning engineers with the knowledge to adjust control system parameters effectively.

The major contributions of this chapter are summarized as follows. It (1) considers the influence of tuning each excitor and governor model parameter one at a time on the FOs for an oscillation frequency in the 0.25 Hz and 1.4 Hz modes using a PSS/E dynamic simulation, (2) identifies and ranks the most sensitive model parameters of the SCRX, ESST1A, and AC7B exciters models, (3) obtains and ranks the sensitive parameters of HYGOV, GAST, and GGOV1 models, and (4) examines the time domain and frequency domain analysis of the model parameters.

The rest of the chapter is organized as follows: the process of forced oscillation injection and oscillation frequency modes are specified in Section 2.2; chosen exciter models, their standard parameters, and their tested range are described in Section 2.3; selected governor models and their parameters are specified in Section 2.4; the simulation results of sensitive excitor and governor model parameters are discussed in Section 2.5; and the conclusions of the study are drawn in Section 2.6.

2.2 Methodology

This study was conducted on Kundur's two-area multi-machine system using PSS/E dynamic simulation tools. The system's schematic diagram and default synchronous machine models are shown in **Figure 2-2** and **Table 2-1**, respectively. The literature indicates that forced oscillation events associated with the governor control system typically occur at frequencies ranging from 0.1 to 0.38 Hz, with most at 0.25 Hz involving inter-area oscillations. Forced oscillation events caused by the exciter, AVR, and PSS generally range between 1 to 1.8 Hz, with most at 1.4 Hz involving local oscillations. To address both inter-area and local oscillation frequencies, this study selected oscillation frequencies of 0.25 Hz and 1.4 Hz. In this study, the FOs were injected at the Gen-1 of Kundur's system using a sinusoidal signal with a fixed frequency introduced to the governor model's reference setpoint (G_{REF}) or the exciter model's voltage reference setpoint (V_{REF})[9] as defined by:

$$\Delta P(t) = A * \sin(2\pi ft) \quad (1)$$

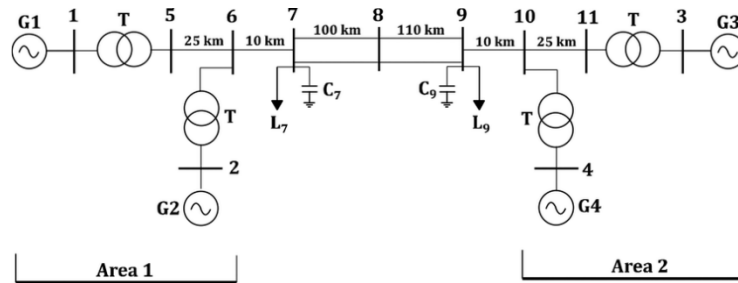


Figure 2-2. Schematic diagram of Kundur's two-area system. Reprinted from [9]

Table 2-1. Default models of Kundur's system

Generator No.	Machine	Exciter	Governor	PSS
Gen-1, Gen-2, Gen-3, Gen-4	GENROE	ESST1A	TGOV1	IEEEST

where ‘ f ’ is the selected frequency of the forced oscillation (0.25 Hz or 1.4 Hz), ‘ A ’ is the sinusoidal wave amplitude, and ‘ $P(t)$ ’ is the active power added to the governor reference setpoint. There were 10 MW peak-to-peak active power oscillations injected into the governor models and 10 MVAR peak-to-peak reactive power oscillations injected into the exciter models starting from 2 seconds. The forced oscillation disturbance magnitude and frequency are maintained constant. At 2 seconds, each tunable exciter or governor parameter was individually changed in the dynamic simulation to study its impact on FOs. The impact on the frequency, voltage response, exciter/governor output, and active/reactive power output responses of Gen-1 were recorded as outputs.

For the exciter models, analyses on the frequency, voltage, and reactive power changes were performed to study the influence of exciter parameter change. Similarly, for the governor model, frequency and active power responses were analyzed to study the influence of governor parameters. The sensitive parameters of the tested models were identified and ranked accordingly. In this study, fast Fourier transform (FFT) was used to analyze and to identify the parameter change influence on the dominant frequency as well as the magnitude. The frequency data were sampled at a frequency of 120 Hz. For both the oscillation modes, the changes in the oscillation magnitude were plotted with respect to the parameter changes. The key parameter values that changed the oscillation frequency were specified.

2.3 Exciter Models

Traditionally, low-frequency oscillations in power systems are thought to be primarily connected to the high gain and quick reactions of excitation systems [42]. The

use of the appropriate excitation system model and parameters in the power system stability calculation has a significant impact on the calculation results. Excitation system parameters including the excitation time constant, the excitation system static gain, the PID time constant, the open circuit time constant of the generator excitation windings, and so on may affect the output during disturbance simulations of a generator [30]. As a result, it is critical to the plant operator to investigate the influence of important excitation system parameters on generator transient characteristics. To provide a foundation for the identification, verification, and optimization of generator excitation parameters in real time, each of the model's selected exciter parameters were tested in this study.

A simple excitation control system called SCR_X, a modified IEEE ST1A static excitation system, and an AC7B exciter model were selected to study their impact on the FOs. The selected model block diagram, its associated parameters, and their tested parameters are specified in the following subsections. The ESST1A exciter of generator Gen-1 was replaced with the selected exciter model with the parameters specified in the respective tables. To study the parameters' impact, FOs of magnitude 10 MVAR peak to peak with a frequency of 0.25 Hz and 1.4 Hz were injected into the V_{REF} of a selected exciter model. At 2 seconds, each of the individual exciter model parameters varied within the specified range of the respective model.

2.3.1. SCR_X Exciter

The SCR_X is a basic excitation system model that represents the generic properties of many different excitation systems. The block diagram of the SCR_X

excitation system and its parameters are given in **Figure 2-3** and **Table 2-2**, respectively [44]. The voltage regulator reference voltage setpoint is denoted by V_{REF} . The input voltage (V_s) to the SCR_X is obtained by adding three signals: the PSS signal (i.e., V_{OTHSG} signal), the under-excitation input limit (V_{UEL}), and the V_{OEL} signal (which is the difference between the reference voltage setpoint and the generator terminal voltage). E_C is the compensated terminal voltage. The tunable parameters in the SCR_X exciter include the lead-lag block parameters T_A and T_B , exciter gain K , and time constant T_E parameters. The E_{FDMIN} and E_{FDMAX} parameters represent the minimum and maximum field voltage outputs. These parameters are tuned based on the steady-state and transient characteristics of the power system, which were studied in this model. C_{SWITCH} parameter distinguishes between systems (bus fed) in which the ac supply is proportional to the generator terminal bus voltage and systems (solid fed) in which the supply is independent of the generator terminal voltage. More details of the SCR_X excitation system can be found in [45].

2.3.2. ESST1A Exciter

The ESST1A exciter is a modified IEEE ST1A static excitation system without an over-excitation limiter (V_{OEL}) and under-excitation limiter (V_{UEL}). The block diagram of ESST1A is shown below in **Figure 2-4**. The standard values of the model and the parameters' tested range are given in **Table 2-3**. Model ESST1A, a potential source-controlled rectifier-excitation system, is meant to simulate systems in which excitation power is provided from the generator terminals (or the unit's auxiliary bus) via a transformer and is regulated by a controlled rectifier.

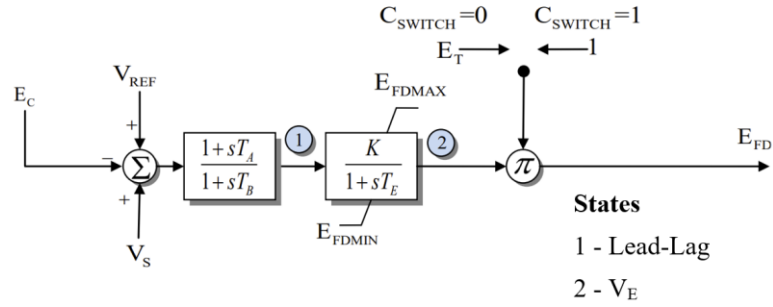


Figure 2-3. Block diagram of SCR exciter model [44]

Table 2-2. Parameters of SCR exciter model [44]

Name	Description	Parameters of Gen-1 SCR Exciter	Parameter Range Tested
T_A/T_B	Gain reduction ratio	0.1	$0.05 < T_A/T_B < 1.0$
T_B	Time constant (s)	10.01	$1 < T_B < 50$
K	Exciter gain	100	$10 < K < 1000$
T_E	Time constant (s)	0.01	$0 \leq T_E < 1$
E_{MAX}	Maximum field voltage output (pu)	5	$2 < E_{\text{MAX}} < 10$
E_{MIN}	Minimum field voltage output (pu)	-4	$-5 < E_{\text{MIN}} \leq 0$
C_{SWITCH}	Voltage source switch Bus fed = 0, Solid fed = 1	0	$C_{\text{SWITCH}} = 0 \text{ or } 1$
rc/rfd	Ratio of the crowbar resistance to the field winding resistance	0	$0 \leq \text{rc/rfd} \leq 10$
V_{REF}	Voltage regulator reference voltage (pu)	-	$0 < V_{\text{REF}} < 2.0$
V_S	Output voltage of a PSS (pu)	-	Off and ON
V_{UEL}	Under-excitation limiter		
V_{OEL}	Over-excitation limiter		
I_{FD}	Synchronous machine field current (pu)		

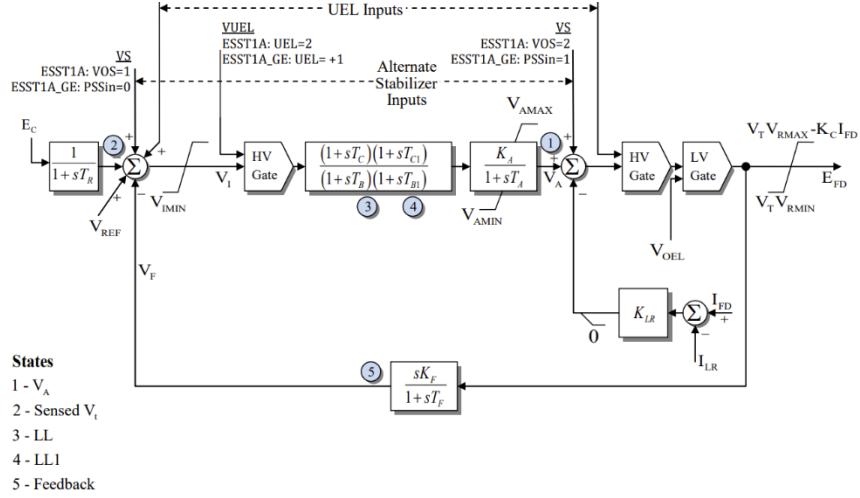


Figure 2-4. Block diagram of ESST1A exciter model [36]

Table 2-3. Parameters of ESST1A exciter model [44]

Name	Description	Parameters of Gen-1 Exciter	Parameter Range Tested
T_R	Filter time constant (s)	0.0167	$0 < T_R < 1$
V_{IMAX}	Maximum voltage regulator input limit	0.092	$0 < V_{IMAX} < 2$
V_{IMIN}	Minimum voltage regulator input limit	-0.083	$-1 < V_{IMIN} < 1$
T_C	Voltage regulator time constant (s)	1.2	$0 < T_C < 10$
T_B	Voltage regulator time constant (s)	2.5	$0 < T_B < 20$
T_{C1}	Voltage regulator time constant (s)	0	$0 < T_{C1} < 10$
T_{B1}	Voltage regulator time constant (s)	0	$0 < T_{B1} < 20$
K_A	Voltage regulator gain	600	$10 < K_A \leq 1000$
T_A	Voltage regulator time constant (s)	0	$0 \leq T_A < 1$
V_{AMAX}	Maximum voltage regulator output limit	4.14	$0 < V_{AMAX} < 10$
V_{AMIN}	Minimum voltage regulator output limit	-3.71	$-10 < V_{AMIN} < 0$
V_{RMAX}	Maximum voltage regulator output limit	4.14	$0 < V_{RMAX} < 10$
V_{RMIN}	Minimum voltage regulator output limit	-3.71	$-10 < V_{RMIN} < 0$
K_C	Rectifier loading factor proportional to commutating reactance (pu)	0.041	$0 < K_C < 0.6$
K_F	Excitation control system stabilizer gains (pu)	0	$0 < K_F < 1$
T_F	Excitation control system stabilizer time constant ($T_F > 0$) (s)	1	$0.1 < T_F < 2.1$
K_{LR}	Exciter output current limiter gain (pu)	18	$0 < K_{LR} < 50$
I_{LR}	Exciter output current limiter reference (pu)	3.953	$0 < I_{LR} < 10$

The maximum exciter voltage available from such systems is proportional to the voltage at the generator terminals [37]. Most of the ESST1A models employ fully controlled bridges. The inherent exciter time constants in this sort of system are quite modest; hence, exciter stabilization is typically not necessary. On the other hand, it may be beneficial to lower the transient gain of such devices for various reasons. The model given is adaptable enough to reflect transient gain reduction applied either in the forward path via time constants, T_B and T_C (in which case K_F would generally be set to zero), or in the feedback path via an appropriate choice of rate feedback parameters, K_F and T_F [43]. The second lead-lag block's time constants, T_{C1} and T_{B1} , indicate a representation of transient gain increase, in which case T_{C1} would be larger than T_{B1} . K_A and T_A reflect the voltage regulator gain and exciter time constants [45].

The internal limiter following the summing junction can be ignored in many cases, but the field voltage limits, which are functions of both terminal voltage (except when the exciter is supplied from an auxiliary bus, which is not supplied from the generator terminals) and generator field current, must be modeled.

It is feasible to describe the field voltage limitations as linear functions of the generator field current. Furthermore, for most transformer-fed systems, K_C is fairly small, allowing the term to be ignored in many studies. The ESST1A model simulates a field current limiter to safeguard the generator rotor and exciter from damage that might occasionally occur because of these systems' extremely high forcing capabilities. K_{LR} and an I_{LR} start setting serve as the limit's gain indicators [46].

2.3.3. AC7B Exciter

The AC7B exciter is applied to ac/dc rotating exciters. To create the required dc fields, this excitation system combines a stationary or rotating rectifier with an ac alternator. The AC7B model is the result of advancements to previous ac excitation systems, which simply replaced the controls while preserving the ac alternator and diode rectifier bridge. Some of the characteristics of this excitation system are a quick exciter current limit (V_{FEMAX}) to protect the ac alternator's field, a high bandwidth inner loop regulating generator field voltage or exciter current (V_A , K_{F1} , K_{F2}), and the PID generator voltage regulator (V_R). If the V_R lacks a derivative term, a separate rate feedback loop (K_{F3} , T_F) is used to stabilize it [46]. The block diagram and the parameters of the AC7B excitation system are shown in **Figure 2-5** [44]. The notations, standard values, and the tested range of the AC7B model parameters are given in **Table 2-4**.

As shown in **Figure 2-5**, E_C is the compensated generator terminal voltage filtered through a filter block with a filter time constant denoted as T_R . The AC7B exciter consists of a regulator designed with PID control with proportional (K_{PR}), integral (K_{IR}), and derivative (K_{DR}) gains. The voltage regulator has proportional and integral gains represented as K_{PA} , K_{IA} , respectively. The brushless exciter is represented by T_E , K_E , S_E , K_C , and K_D parameters. The limits of V_E are used to represent the effects of a feedback limiter operation. This excitation system model includes the power source for the controlled rectifier. The user can set the logic switch to determine if the rectifier's power source is from terminal voltage (position "A") or independent of it (position "B"). More details about this model can be found in [46]

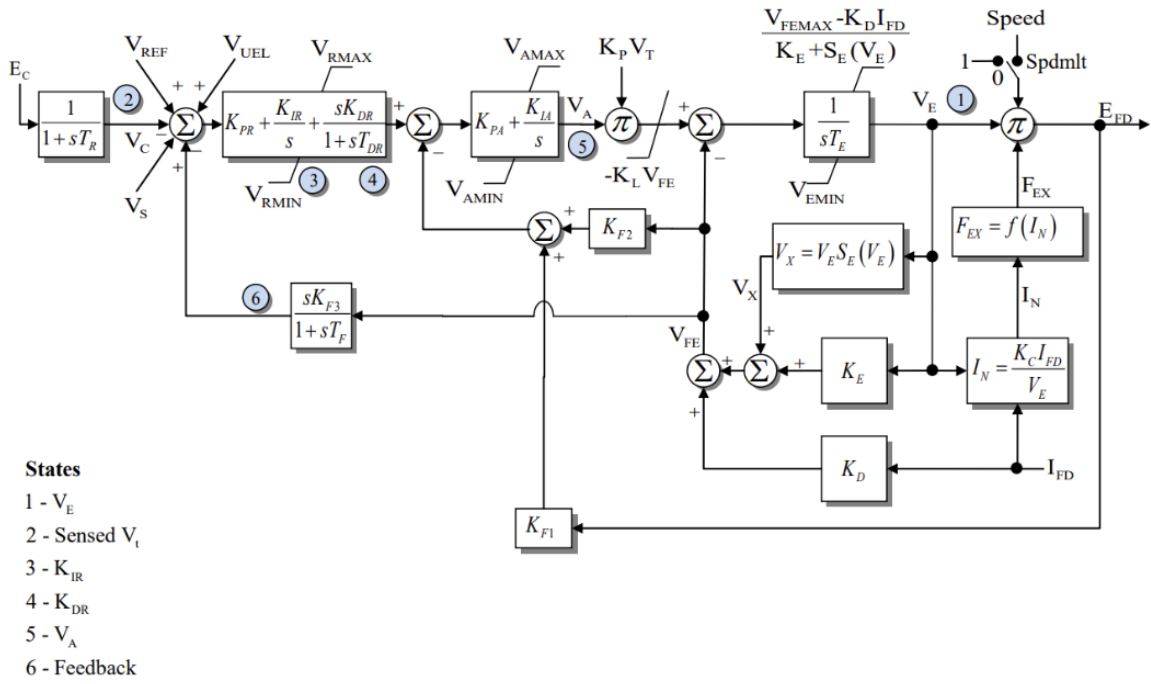


Figure 2-5. Block diagram of AC7B exciter model [44]

Table 2-4. Parameters of AC7B exciter model [44]

Name	Description	Parameters of Gen-1 AC7B Exciter	Parameter Range Tested
T_R	Regulator input filter time constant (s)	0.0167	$0.0 < T_R < 1$
K_{PR}	Regulator proportional gain (pu)	22.5	$0 < K_{PR} < 50$
K_{IR}	Regulator integral gain (pu)	22.5	$0 < K_{IR} < 50$
K_{DR}	Regulator derivative gain (pu)	0	$0 < K_{DR} < 40$
T_{DR}	Regulator derivative block lag time constant (s)	0	$0 < T_{DR} < 1$
V_{RMAX}	Regulator output maximum limit (pu)	4.52	$0 < V_{RMAX} < 10$
V_{RMIN}	Regulator output minimum limit (pu)	0	$-5 < V_{RMIN} < 5$
K_{PA}	Voltage regulator proportional gain (pu)	25	$0 < K_{PA} \leq 50$
K_{IA}	Voltage regulator integral gain (pu)	50	$0 < K_{IA} \leq 100$
V_{AMAX}	Regulator output maximum limit (pu)	31	$0 < V_{AMAX} < 50$
V_{AMIN}	Regulator output minimum limit (pu)	-31	$-10 < V_{AMIN} < 40$
K_P	Potential circuit gain coefficient (multiplier) (pu)	0	$0 < K_P < 50$
K_L	Exciter field voltage lower limit parameter (multiplier) (pu)	999	$0 < K_L < 20$
K_{F1}	Excitation control system stabilizer gain (pu)	0	$0 \leq K_{F1} < 5$
K_{F2}	Excitation control system stabilizer gain (pu)	1	$0 < K_{F2} \leq 5$
K_{F3}	Excitation control system stabilizer gain (pu)	0	$0 < K_{F3} \leq 5$
T_{F3}	Excitation control system stabilizer time constant (>0) (s)	1	$0.1 < T_{F3} \leq 2.1$
K_C	Rectifier loading factor proportional to commutating reactance (pu)	0	$0 < K_C \leq 1$
K_D	Demagnetizing factor, a function of AC exciter reactances (pu)	0.5	$0 < K_D \leq 2$
K_E	Exciter constant related to self-excited field (pu)	0.5	$0 < K_E \leq 2$
T_E	Exciter time constant (>0) integration rate associated with exciter control (s)	0.33	$0.1 < T_E \leq 2.1$
V_{FEMAX}	Exciter field current limit reference (>0) (pu)	999	$0 < V_{FEMAX} < 10$
V_{EMIN}	Minimum exciter voltage output (pu)	0	$-5 < V_{EMIN} < 5$
E_1	Exciter alternator output voltages back of commutating reactance at which saturation is defined (pu)	3.51	$0 < E_1 \leq 10$
$S(E_1)$	Exciter saturation function value at the corresponding exciter voltage, E_1 , back of commutating reactance (pu)	0.01	$0 < S(E_1) \leq 2$
E_2	Exciter alternator output voltages back of commutating reactance at which saturation is defined (pu)	4.68	$0 < E_2 \leq 10$
$S(E_2)$	Exciter saturation function value at the corresponding exciter voltage, E_2 , back of commutating reactance (pu)	0.05	$0 < S(E_2) \leq 2$

2.4 Parameters Testing of Governor Models

The turbine-governor modeling is critical for transient rotor angle stability, frequency control, and, to a lesser extent, small-signal stability. A crucial component of the turbine-governor dynamics is fast-valving, which is the governor's quick response in the first couple of seconds after a grid disturbance. This control is distinguished by the quick closing of the intercept valves on a steam turbine in response to a nearby fault to reduce mechanical power on the generator shaft and, hence, limit shaft acceleration and the risk of rotor angle instability. Any such controls that will abruptly influence the mechanical output of the turbine as a result of a nearby grid fault must be modeled for transient stability studies [47]. An example is the installation of acceleration controls on gas turbines, which may be activated in some situations during a nearby catastrophic grid failure. However, acceleration controls are not available on all gas turbines. Also, where droop is implemented via electrical power feedback and the use of a proportional integral (PI) or proportional integral derivative (PID) controller in the turbine-governor controls can influence transient stability and should be modeled accordingly [47]. In the frequency range of electromechanical modes of rotor oscillation, the turbine governor may have a little negative dampening impact for small-signal stability concerns.

In this work, a simple gas turbine-governor model called GAST, a hydro-turbine-based HYGOV governor model, and a most used GGOV1 governor model were selected to study their influence on FOs. Each model block diagram, its associated parameters, and their tested parameters range are provided in the following subsections. The TGOV1 model of generator Gen-1 was replaced with the selected governor model with standard

parameters. There were 10 MW peak-to-peak active power oscillations injected at the P_{REF} of the selected governor models. Each governor model parameters were changed one at a time to test their impact on the FOs after 2 seconds. The parameters' change and their influence on the FOs are discussed in the results section. The parameters of the tested HYGOV, GAST, and GGOV1 governor models, their standard values according to the NERC, PowerWorld, and PSSE documentation, and their tested parameter ranges for these models are specified in this section.

2.4.1. GAST Governor

This is the simplest basic illustration of a gas turbine. It assumes a simple droop control, a constant load limit (turbine rating), and three-time constants, one for the fuel valve response (T_1), one for the turbine response (T_2), and one for the load limit response (T_3). This model entirely disregards all aspects of a heavy-duty gas turbine's mechanics [17]. **Figure 2-6** depicts the GAST gas turbine block diagram referred from [38].

In the GAST model, the permanent droop is denoted by R . A_T denotes the ambient temperature load limit, and V_{MIN} and V_{MAX} are the minimum and maximum turbine power set limits. D_{turb} denotes the turbine damping factor. During commissioning of the unit, the speed governor parameters are obtained from gas injection setpoint change tests and load rejection tests, with damping factors and time constants tuned from load rejection; operational limits and permanent droop parameters are usually defined from steady-state tests [39]. In this work, the tunable parameters such as R , T_1 , T_2 , T_3 , K_T , D_{turb} , V_{MAX} , and V_{MIN} parameters were examined within the tested range specified in

Table 2-5.

2.4.2. HYGOV Governor

HYGOV is a basic non-linear hydroelectric-plant governor with a simple hydraulic representation of the penstock, unconstrained head, and tail race and no surge tank. **Figure 2-7** shows the block diagram of the HYGOV governor model. The notations of the model parameters, standard values, and the tested parameter range of the HYGOV model are given in **Table 2-6**. The speed deviation from nominal to actual speed (Δf) and the gate position (GV) in per unit are the inputs to the model, and P_{mech} is the output parameter. R and r are called the permanent and temporary droop parameters specified in per unit. The time constants of filter time constant (T_f), governor time constant (T_r), servo time constant (T_g), and water starting time constant (T_w) are the important parameters [48]. V_{elm} is the velocity limit, which is reciprocal to the time taken for the wicket gates to move from fully open to fully closed. H represents the per unit head. The q_{NL} represents the no-load power flow rate required to maintain the rated speed while off-line. A_T and D_{turb} is the turbine gain and damping factor. These are the tunable parameters that can influence the performance of the HYGOV during transient studies. Each of the individual parameters were tested to find the influence on the FOs.

2.4.3. GGOV1 Governor

The GGOV1 model can be used to depict a wide range of prime movers that are controlled by PID governors and are often used in conjunction with a combustion turbine. **Figure 2-8** shows the block diagram of the GGOV1 model. The notations of the model parameters, standard values, and the tested parameter range of the model are given in **Table 2-7**.

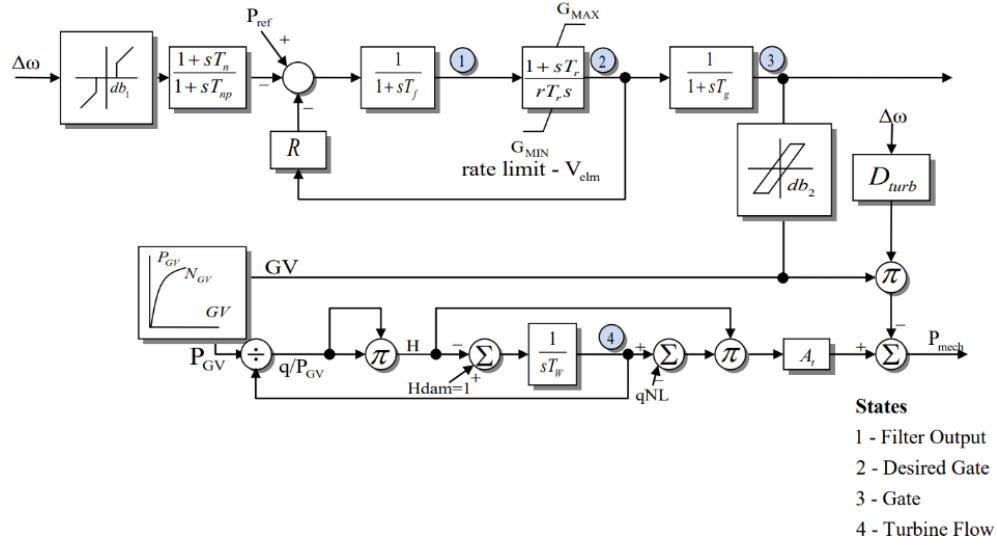


Figure 2-7. Block diagram of HYGOV governor model [47]

Table 2-6. Parameters of HYGOV governor model [47]

Name	Description	Parameters of Gen-1 HYGOV Governor	Parameter Range Tested
R	Permanent droop ($R < r$)	0.07	$0 < R \leq 1$
r	Temporary droop	0.56	$0 < r \leq 2$
$T_R (>0)$	Governor time constant (s)	9.0	$0 < T_R \leq 50$
$T_F (>0)$	Filter time constant (s)	0.4	$0 < T_F \leq 0.5$
$T_G (>0)$	Servo time constant (s)	0.33	$0.1 < T_G \leq 5$
$\pm V_{ELM}$	Gate velocity limit	0.07	$0 < V_{ELM} \leq 1$
G_{MAX}	Maximum gate limit ($G_{MIN} < G_{MAX}$)	1.0	$0 < G_{MAX} \leq 10$
G_{MIN}	Minimum gate limit	0.0	$-5 \leq G_{MIN} < 5$
$T_W (>0)$	Water time constant	1.0	$0 < T_W < 10$
A_T	Turbine gain	1.25	$-1 < A_T < 4$
D_{turb}	Turbine damping	1.0	$0 \leq D_{turb} < 10$
q_{NL}	No power flow	0.07	$0 \leq q_{NL} < 0.5$

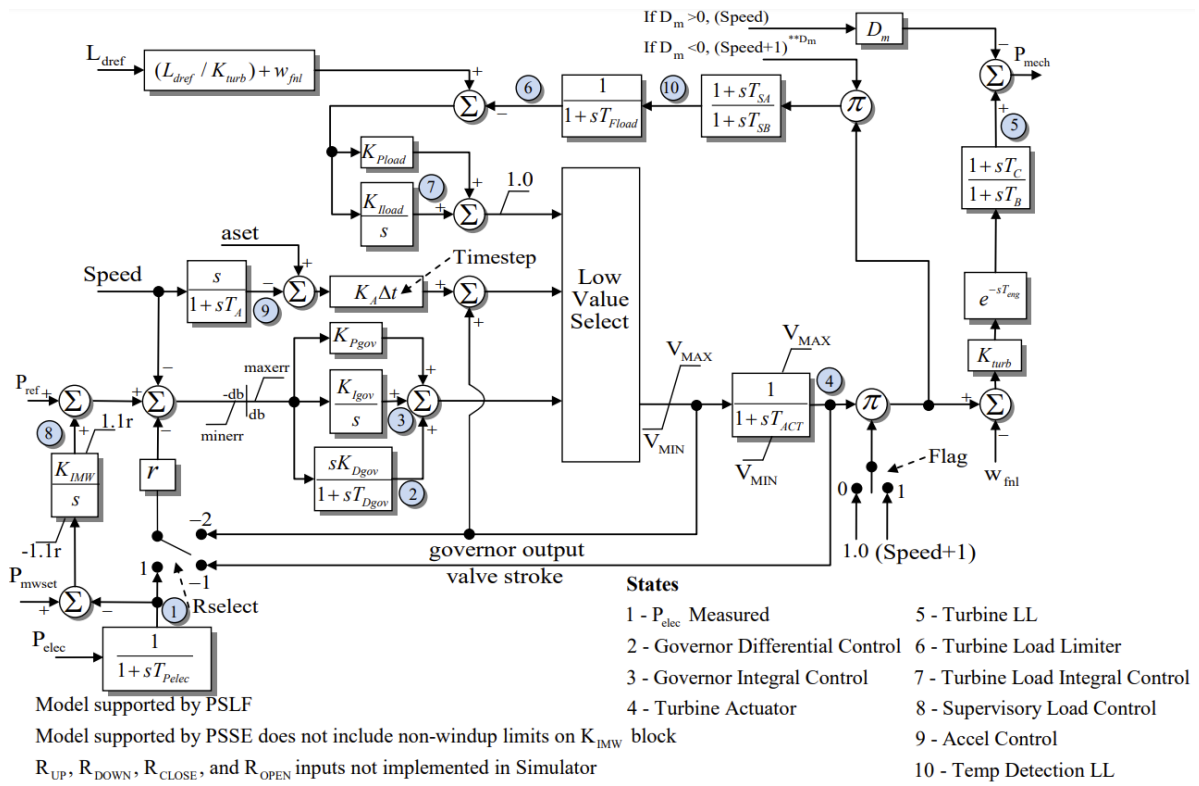


Figure 2-8. Block diagram of GGOV1 governor model [47]

Table 2-7. Parameters of GGOV1 governor model [47]

Name	Description	Parameters of Gen-1 GGOV1 Governor	Tested Parameter Range
R	Permanent droop (pu)	0.04	$0 < R \leq 1$
T _{pelec}	Electrical power transducer time constant (s)	1.0	$0 < T_{pelec} \leq 10$
MAXERR	Maximum value for a speed error signal	0.05	
MINERR	Minimum value for a speed error signal	-0.05	
K _{Pgov}	Governor proportional gain	10	$0 < K_{Pgov} \leq 40$
K _{Igov}	Governor integral gain	2	$0 < K_{Igov} \leq 10$
K _{Dgov}	Governor derivative gain	0	$0 < K_{Dgov} \leq 10$
T _{Dgov}	Governor derivative controller time constant (s)	1	$0 < T_{Dgov} \leq 5$
V _{MAX}	Maximum valve position limit	1	$0 < V_{MAX} \leq 10$
V _{MIN}	Minimum valve position limit	0.15	$-2 \leq V_{MIN} < 2$
T _{act}	Actuator time constant (s)	0.5	$0 < T_{act} \leq 5$
K _{turb}	Turbine gain	1.5	$0 < K_{turb} \leq 5$
W _{finl}	No-load fuel flow (pu)	0.2	$0 < W_{finl} \leq 1$
T _B	Turbine lag time constant (s)	0.1	$0.1 < T_B \leq 5$
T _C	Turbine lead time constant (s)	0	$0 < T_C \leq 2.5$
T _{eng}	Transport lag time constant for diesel engine (s)	0	$0 < T_{eng} \leq 5$
T _{load}	Load limiter time constant (s)	3	$0 < T_{load} \leq 10$
K _{pload}	Load limiter proportional gain for PI controller	2	$0 < K_{pload} \leq 10$
K _{lload}	Load limiter integral gain for PI controller	0.67	$0 < K_{lload} \leq 10$
L _{dref}	Load limiter reference value (pu)	1	$0 < L_{dref} \leq 10$
D _m	Mechanical damping coefficient (pu)	0	$0 < D_m \leq 10$
R _{open}	Maximum valve opening rate (pu/s)	0.1	
R _{close}	Maximum valve closing rate (pu/s)	-0.1	
K _{I_{mw}}	Power controller (reset) gain	0	$0 < K_{I_{mw}} \leq 10$
A _{SET}	Acceleration limiter setpoint (pu/s)	0.01	$0 < A_{SET} \leq 10$
K _A	Acceleration limiter gain	10	$0 < K_A \leq 50$
T _A	Acceleration limiter time constant (s)	0.1	$0 < T_A \leq 10$
T _{rate}	Turbine rating (MW)	800.0	
db	Speed governor deadband	0.0	$0 < db \leq 1$
T _{sa}	Temperature detection lead time constant (s)	4.0	$0 < T_{sa} \leq 10$
T _{sb}	Temperature detection lag time constant (s)	5.0	$0 < T_{sb} \leq 10$
R _{up}	Maximum rate of load limit increase	99	
R _{down}	Maximum rate of load limit decrease	-99	

Control blocks are also included in the model to simulate valve position and actuation, fuel system dynamics, a load limiter for exhaust temperature controls, a load controller for plant-level or outer loop controls, an acceleration limiter, and a governor deadband. More details about the modeling of the GGOV1 governor can be found in [49].

2.5 Results and Discussion

This section discusses the sensitive parameters of the selected exciter and governor models based on the influence of each parameter change on FOs. For both the local oscillation frequency of 1.4 Hz and inter-area frequency of 0.25 Hz, the deviation of the forced oscillation magnitude, frequency response, change in active/reactive power magnitude from the fixed frequency, and magnitude were used to rank the sensitive parameters. The analysis of individual parameter influence on the active power magnitude in governors and the reactive power characteristics in the exciter helped us to understand and find the dominant parameters to see how each of these can alter the sustained FOs. The specific results of each model are discussed in the respective subsections below.

2.5.1. SCRX Exciter

According to each parameter change, the impact on the FOs frequency, magnitude, reactive power output, the SCRX model parameters, and their respective ranks are shown in **Table 2-8** below. Among the exciter models, the exciter gain was the most important parameter. The SCRX exciter gain (K) was changed from 10 to 1000 value, and the corresponding frequency and voltage responses are shown in **Figure 2-9**. The very low value of $K = 10$ caused instability in the system response. The value of $K =$

Table 2-8. Sensitive parameters of SCR exciter with respect to reactive power change

SCRX Parameters	Tested Parameters' Range	Reactive Power Output (MVAR)		Rank
		0.25 Hz	1.4 Hz	
K—Exciter Gain	K—100	10.012	10.043	1
	K—1000	21.436	86.422	
T_A/T_B —Gain reduction ratio	T_A/T_B —0.1	10.044	10.051	2
	T_A/T_B —1.0	20.986	74.193	
T_E —Time constant	T_E —0.0	10.011	10.026	3
	T_E —1.0	0.601	0.859	
T_B —Time constant	T_B —1.0	15.697	9.962	4
	T_B —50.0	7.484	9.912	

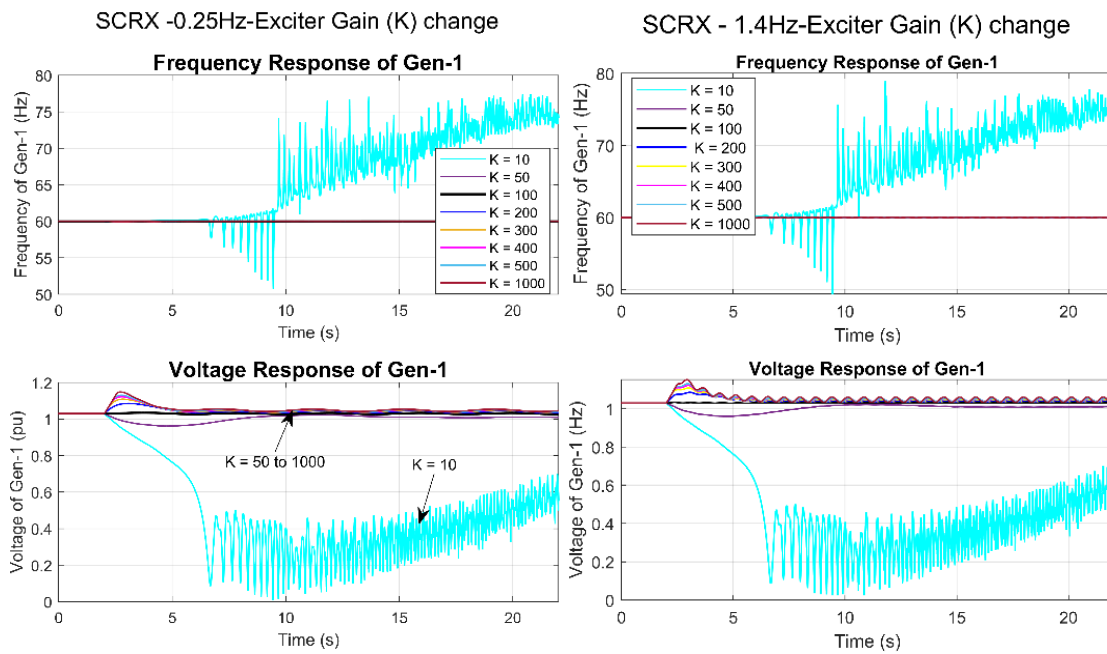


Figure 2-9. Response of SCR exciter gain (K) changed from 10 to 1000 value

100 had around 10 MVAR of forced oscillation magnitude. Increasing the K value from 100 to 1000 in steps of 100 increased the oscillation magnitude of 10 MVAR to 21.436 MVAR and 86.422 MVAR for the 0.25 Hz and 1.4 Hz modes, respectively. Similarly, the gain reduction ratio (T_A/T_B) changed from 0.05 to 1.0 in steps of 0.1. The frequency and voltage responses of Gen-1 for the T_A/T_B change are shown in **Figure 2-10**.

The increase in the T_A/T_B parameter value from 0.1 to 1.0 increased the oscillation magnitude to 20.986 MVAR and 74.193 MVAR for the 0.25 Hz and 1.4 Hz modes, respectively. In contrast, the time constants T_E and T_B values increased, reducing the oscillation magnitude for both oscillation modes, as shown in **Table 2-8**. The FFT analyses of the SCRX model parameters are shown in **Figure 2-11**. The increase in the K and T_A/T_B values increased the oscillation magnitude linearly for the 1.4 Hz local oscillation mode, and, for the low-frequency 0.25 Hz mode, a very small oscillation magnitude change was observed. The exciter time constant T_E significantly affected the system's dynamic response. At lower K values ($K = 10, 50$), the system's sensitivity to $T_E \geq 7$ was higher, resulting in a noticeable change in the oscillation frequency to 0.11719 Hz.

2.5.2. ESST1A Exciter

The ESST1A exciter model plays a critical role in maintaining the stability of power systems by regulating voltage. To understand how changes in the ESST1A parameters influence FOs, we conducted comprehensive analysis by varying key parameters and measuring the resulting reactive power output (MVAR) at oscillation

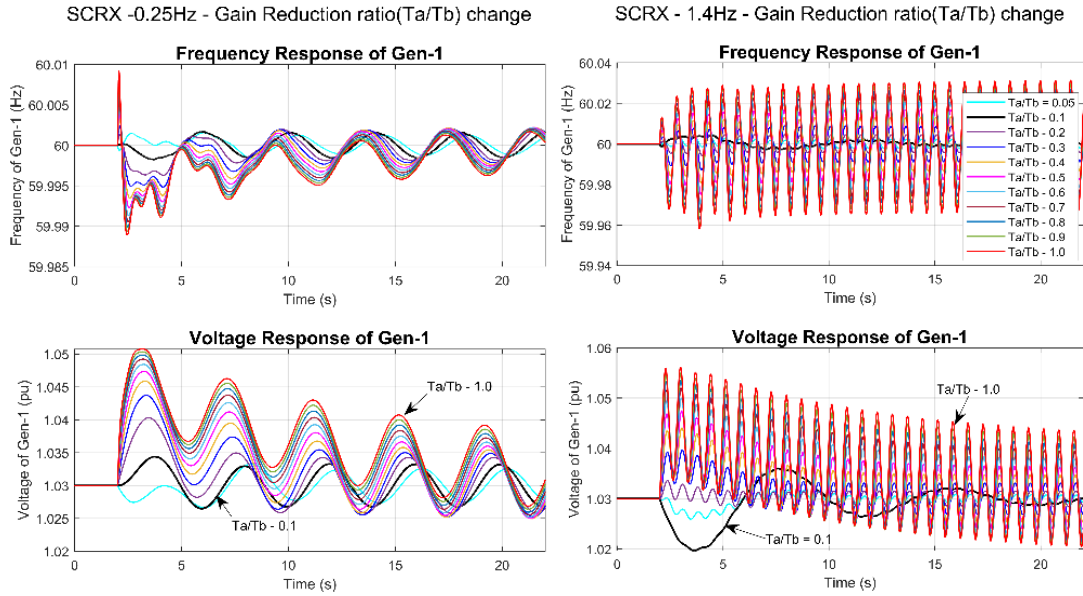


Figure 2-10. Response of gain reduction ratio (T_A/T_B) changing from 0.1 to 1.0 in steps of 0.1

FFT Response of SCRX Parameters

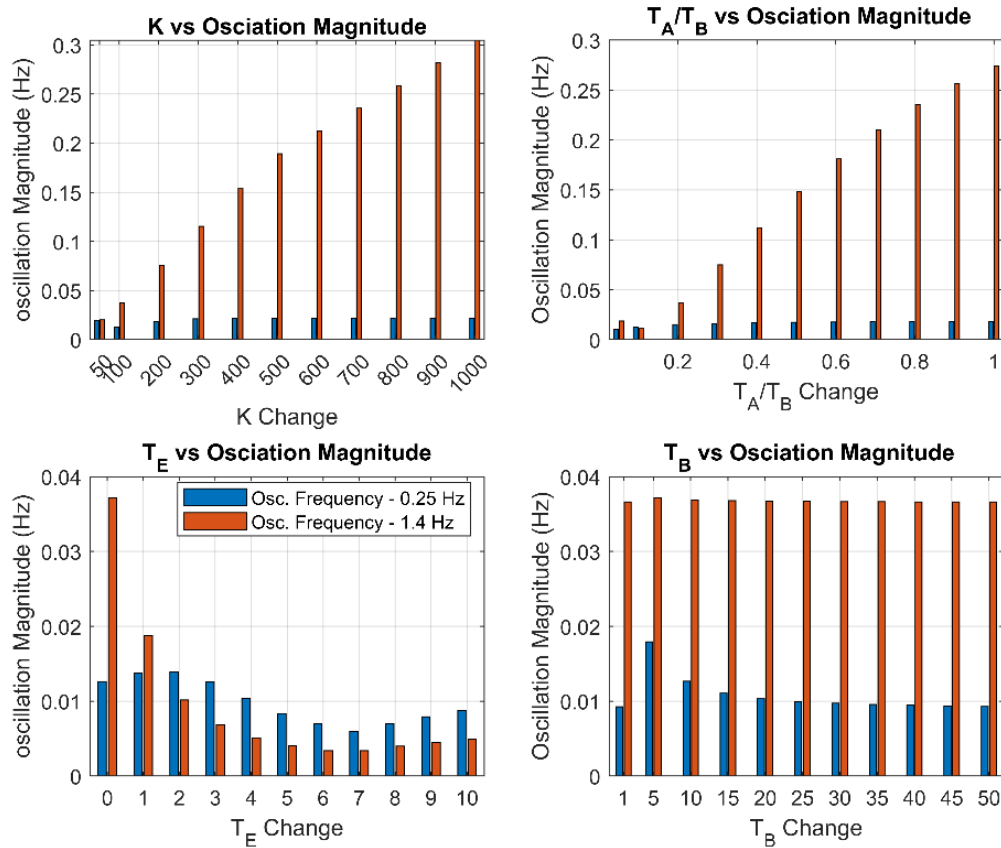


Figure 2-11. FFT response of the SCRX parameters

frequencies of 0.25 Hz and 1.4 Hz. This study focused on several parameters, including the voltage regulator gain (K_A), regulator time constant (T_A), voltage regulator time constant (T_C), filter time constant (T_R), and voltage regulator time constants (T_B and T_{B1}). The results, summarized in **Table 2-9**, indicate that changes in these parameters significantly impact the oscillation magnitudes and frequencies.

The voltage regulator gain (K_A) parameter was changed from 10 to 1000 in steps of 100. The low value of $K = 50$ had around a 0.5 MVAR forced oscillation magnitude. As shown in **Table 2-9**, increasing the exciter gain value from 50 to 1000 increased the oscillation magnitude to 20.012 MVAR and 117.101 MVAR for the 0.25 Hz and 1.4 Hz modes, respectively. The FFT response of K_A for the 1.4 Hz oscillation mode is shown in **Figure 2-12**. The low values of K_A from 50 to 400 showed a linear increase and, from 500 to 1000, the oscillation magnitude remained constant. Tuning extremely low values of $K_A \leq 50$ caused instability in the system. The regulator time constant (T_A) value was changed from 0 to 1 in step of 0.1. As shown in **Figure 2-13**, for T_A values below 0.3 and above 0.5, the system appeared more stable with lower oscillation magnitudes. The middle range of T_A (0.3 to 0.5) led to higher oscillation magnitudes specifically for the 1.4 Hz mode, indicating potential instability with an oscillation frequency of 1.298 Hz in both modes. Similarly, the rise in the voltage regulator time constant (T_C) parameter value increased the oscillation magnitude to 110.137 MVAR. For both oscillation modes, the increase in $T_C > 8$ caused the change in oscillation frequency to 13.33 Hz. Likewise, the filter time constant (T_R) increased the forced oscillation magnitude from 10 MVAR to 24 MVAR with a T_R value increase from 0 to 1.

Table 2-9. Sensitive parameters of ESST1A exciter with respect to reactive power change

ESST1A Parameters	Tested Parameters' Range	Reactive Power Output (MVAR)		Rank
		0.25 Hz	1.4 Hz	
K _A —Voltage regulator gain	K _A —50	0.32	0.5811	1
	K _A —1000	20.012	117.101	
T _A —Regulator time constant	T _A —0	10.022	10.041	2
	T _A —0.1 to 1	T _A ≥ 0.4 induced growing oscillations with a frequency of 1.298 Hz		
T _C —Voltage regulator time constant	T _C —0	19.99	29.104	3
	T _C —1 to 10	Changed oscillation frequency to 13.33 Hz if T _C > 6		
T _R —Filter time constant	T _R —0	10.027	10.071	4
	T _R —1	24.316	24.154	
T _{B1} —Voltage regulator time constant	T _{B1} —0	26.918	117.118	5
	T _B —20	19.96	2.791	
T _B —Voltage regulator time constant	T _B —0	19.98	115.796	6
	T _B —20	17.554	45.229	
I _{LR} —Current limiter reference	I _{LR} ≤ 2	System Unstable		
K _A —Voltage regulator gain	K _A ≤ 40	System Unstable		
K _F —Excitation control system stabilizer gain	K _F ≥ 0.1	System Unstable		
K _C —Rectifier loading factor	K _C ≥ 0.6	System Unstable		
V _{AMAX} —Maximum voltage regulator output limit	V _{AMAX} ≤ 2	System Unstable		
V _{AMIN} —Minimum voltage regulator output limit	V _{AMIN} ≥ 0.2	System Unstable		
V _{RMAX} —Maximum voltage regulator output limit	V _{RMAX} ≤ 2	System Unstable		
V _{RMIN} —Minimum voltage regulator output limit	V _{RMIN} ≥ 0.2	System Unstable		
V _{IMAX} —Maximum voltage regulator input limit	V _{IMAX} ≤ 0	System Unstable		
V _{IMIN} —Minimum voltage regulator input limit	V _{IMIN} ≥ 0.2	System Unstable		

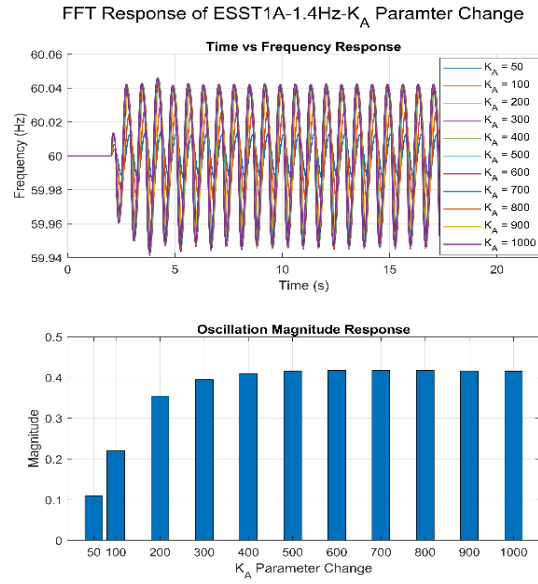


Figure 2-12. FFT response of the ESST1A model: K_A parameter change

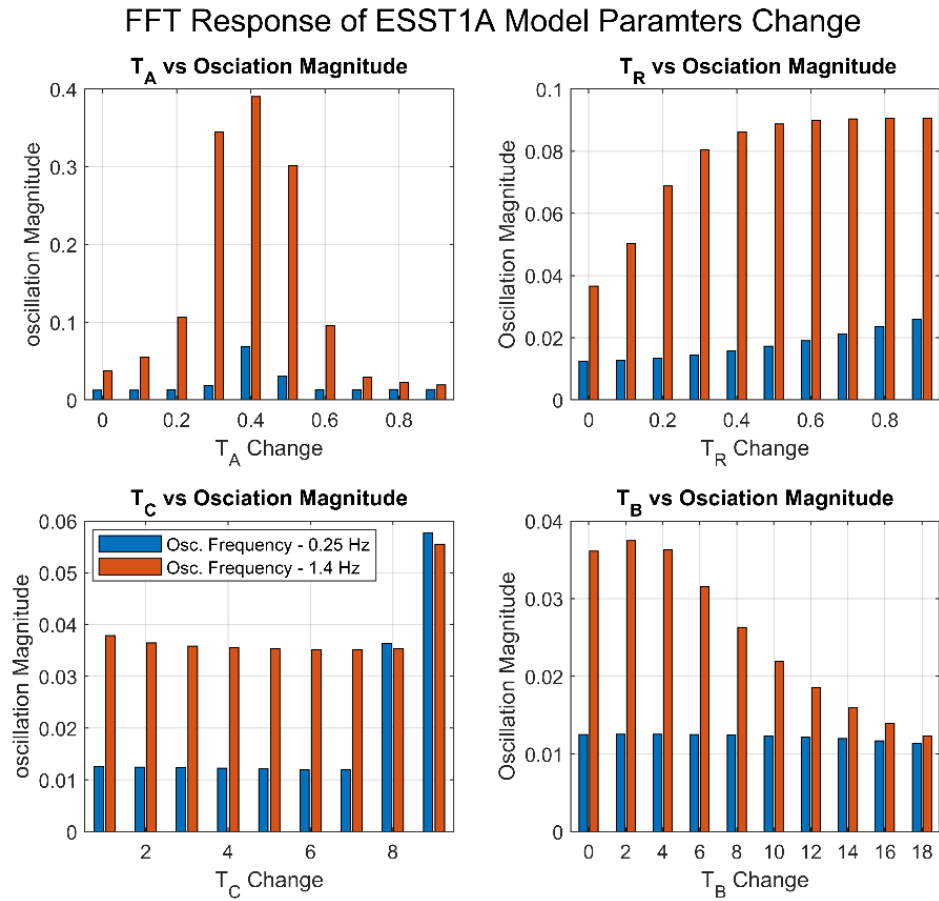


Figure 2-13. FFT response of the ESST1A model parameters

Similarly, the filter time constant (T_R) increased the forced oscillation magnitude from 10 MVAR to 24 MVAR with a T_R value increase from 0 to 1. In contrast, the increase in voltage regulator time constants T_B and T_{B1} values reduced the oscillation magnitude. As shown in **Figure 2-13**, the time constants T_A , T_C , T_R , T_B , T_{C1} , and T_{B1} had a large influence on the system stability for the 1.4 Hz mode. The ESST1A parameters K_{LR} , T_F , and T_{C1} showed no impact on FOs. The low values of the parameters $I_{LR} \leq 2$, $K_A \leq 40$, $V_{AMAX} \leq 2$, $V_{RMAX} \leq 2$, $V_{IMAX} \leq 0$, and $V_{REF} \leq 0.6$ can make the system become unstable. The higher values of these parameters $K_F \geq 0.1$, $K_C \geq 0.6$, $V_{AMIN} \geq 0.2$, $V_{RMIN} \geq 0.2$, and $V_{IMIN} \geq 0.2$ can also make the system become unstable. K_A , T_C , T_R , T_{B1} , and T_B were the sensitive parameters of the ESST1A exciter model.

2.5.3. AC7B Exciter

The sensitive parameters of the AC7B exciter model were identified and ranked based on the parameter change response on forced reactive power oscillations as shown in **Table 2-10**. The voltage regulator gain (K_{PA}) parameter was changed from 0 to 50 in steps of 5.0, as shown in **Figure 2-14**. The low values of K_{PA} of 0 to 5 had around a 174 MVAR magnitude, K_{PA} values from 10 to 50 maintained the magnitude around 10 MVAR for both modes. For both the oscillation modes, the oscillation magnitude of the K_{PA} , K_{PR} , K_E , and T_R parameters from the FFT analysis is shown in **Figure 2-15**. Similarly, the rise in the excitor constant (K_E) parameter value from 0 to 1.4 decreased the oscillation magnitude to 2.51 MVAR and 5.68 MVAR for the 0.25 Hz and 1.4 Hz modes, respectively, as shown in **Figure 2-15**.

Table 2-10. AC7B exciter sensitive parameters and their associated ranks

AC7B Parameters	Tested Parameters’ Range	Reactive Power Output (MVAR)		Rank
		0.25 Hz	1.4 Hz	
K _{PA} —Voltage regulator proportional gain	K _{PA} —0 to 5	174.382	172.583	1
	K _{PA} —10 to 50	10	10	
K _E —Exciter constant related to self-excited field	K _E —0 to 0.2	67.716	75.955	2
	K _E —0.4–1.4	2.51	5.68	
	K _E ≥ 1.6	System Unstable		
K _P —Potential circuit gain coefficient	K _P —0 to 5.0	10	10	3
	K _P —10 to 50	10	22.006	
K _{PR} —Regulator proportional gain	K _{PR} —0.0	28.671	0.992	4
	K _{PR} —50.0	10	18.709	
T _R —Regulator input filter time constant	T _R —0.0	10	10	5
	T _R —1.0	41.776	10	
V _{AMIN} —Regulator output minimum limit	V _{AMIN} ≤ −10.0	22.032	23.884	6
	V _{AMIN} —0 to 40	10	10	
K _{F1} —Excitation control system stabilizer gain	K _{F1} —0 to 0.5	10	10	7
	K _{F1} —1.0	6.181	3.721	
	K _{F1} ≥ 1.5	System Unstable		
K _{F2} —Excitation control system stabilizer gain	K _{F2} —0	10	10	8
	K _{F2} —0.5 to 1.0	10	5.072	
	K _{F2} ≥ 2.5	System Unstable		
K _{IR} —Regulator integral gain	K _{IR} —0 to 5.0	6.9658	8.0614	9
	K _{IR} —10 to 50	10	10	
K _{F3} —Excitation control system stabilizer gain	K _{F3} ≥ 1.5	System Unstable		
T _E —Exciter time constant (>0)	T _E ≤ 0.3	Distorted Oscillations		
V _{AMAX} -Maximum voltage regulator output limit	V _{AMAX} ≤ 0	System Unstable		
V _{RMAX} —Maximum voltage regulator output limit	V _{RMAX} ≤ 2	System Unstable		
V _{FEMAX} —Exciter field current limit reference	V _{FEMAX} ≤ 2	System Unstable		

AC7B-0.25Hz-Voltage regulator Proportional Gain(K_{PA}) Change AC7B-1.4Hz-Voltage regulator Proportional Gain(K_{PA}) Change

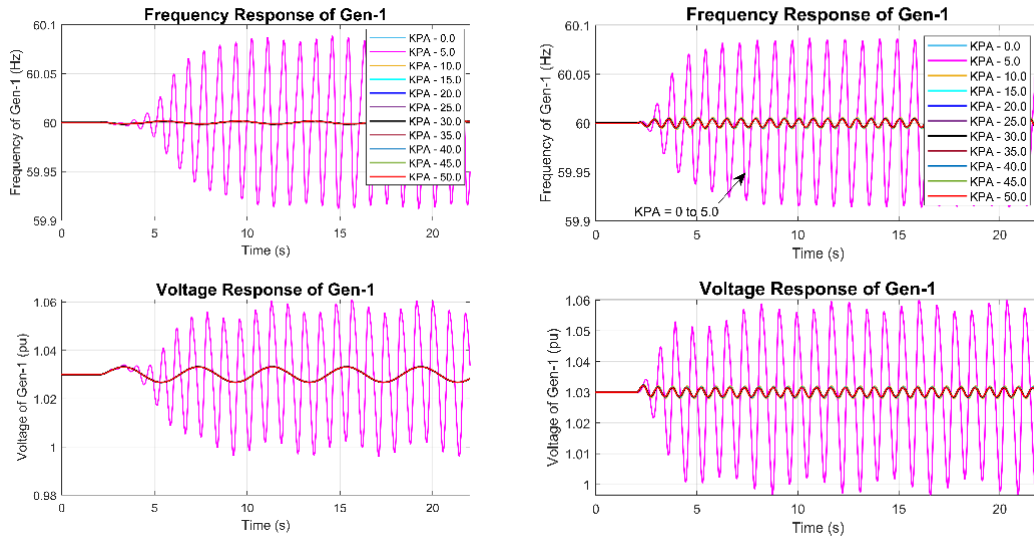


Figure 2-14. Response of voltage regulator proportional gain (K_{PA}) changing from 0.0 to 50.0

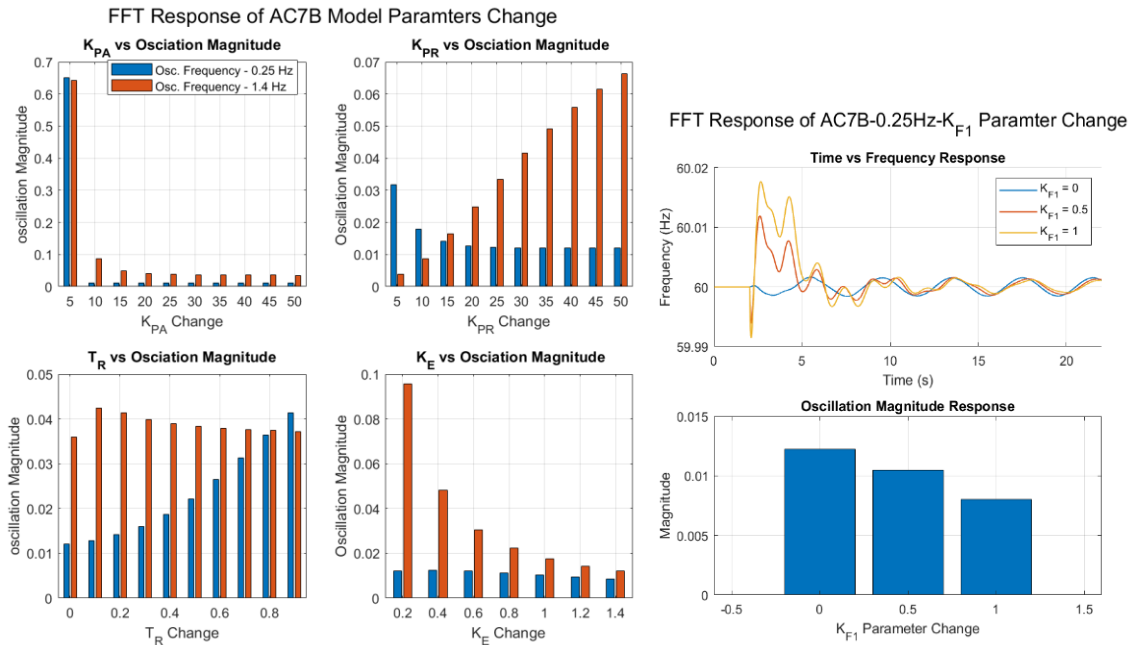


Figure 2-15. FFT response of AC7B model parameters

In contrast, the increased values of the potential circuit gain coefficient (K_P), regulator proportional gain (K_{PR}), and filter time constant (T_R) increased the forced oscillation magnitude, as shown in **Figure 2-15**. The excitation control stabilizer gain K_{F1} oscillation magnitude response from the FFT analysis is shown in **Figure 2-15**. The K_{F1} , K_{F2} , and K_{F3} values between 0.5 to 1.0 had a stable response. The higher values of the parameters $K_E \geq 1.6$, $K_{F1} \geq 1.5$, $K_{F2} \geq 2.5$, and $K_{F3} \geq 1.5$ can cause the system to become unstable. The lower values of $V_{AMAX} \leq 0$, $V_{RMAX} \leq 2$, and $V_{FEMAX} \leq 2$ can also make the system unstable. The AC7B exciter parameters K_C , K_{IR} , K_{DR} , K_{IA} , K_L , T_{DR} , T_{F3} , V_{EMIN} , V_{PSS} , E_1 , E_2 , $S(E_1)$, $S(E_2)$, V_R , and V_A did not show any influence on the FOs. The regulator gains K_{PA} , K_{PR} , K_{IR} , K_E , K_P , and T_R and the excitation control system stabilizer gains K_{F1} and K_{F2} were the sensitive parameters of the AC7B exciter model.

2.5.4. GAST Governor

The sensitivity of the GAST governor parameters was analyzed based on their influence on the forced oscillation magnitude, oscillation frequency, and active power oscillations of Gen-1. A forced oscillation magnitude of 10 MW peak to peak was applied at the GAST governor's P_{REF} input to assess these effects. The sensitive parameters of the GAST governor and their associated ranks are given in **Table 2-11**, as follows. The speed droop (R) parameter was changed from 0 to 1. The low value of $R = 0$ had distorted oscillations with an oscillation frequency of 2.695 Hz for both oscillation frequency modes. As shown in **Figure 2-16**, increasing the speed droop value from 0.1 to 1 produced an oscillation magnitude of around 13.33 MW and 10.08 MW for the 0.25 Hz and 1.4 Hz modes, respectively.

Table 2-11. GAST governor sensitive parameters and their associated ranks

GAST Parameters	Tested Parameters Range	Active Power Output (MW)		Rank
		0.25 Hz	1.4 Hz	
R—Speed droop	R—0.0	Distorted oscillations		1
	R—0.1–1.0	13.339	10.089	
T ₁ —Governor mechanism time constant	T ₁ —0.0	16.917	10.091	2
	T ₁ —0.2 to 2.0	15.427	9.063	
T ₂ —Turbine power time constant	T ₂ —0.1	16.934	11.12	3
	T ₂ —2.1	13.038	10.026	
V _{MAX} —Maximum turbine power	V _{MAX} —0.0	19.8871	22.8798	4
	V _{MAX} —1 to 5	34.511	Damped oscillations	
V _{MIN} —Minimum turbine power	V _{MIN} = -4 to 1	34.791	Damped oscillations	5
	V _{MIN} ≥ 2	Distorted oscillations	Distorted oscillations	

Likewise, the increase in time constant T_1 and T_2 values had a very small impact on the forced oscillation magnitude. However, the $T_2 = 0$ made the system become unstable. Its value should always be greater than 0, i.e., $T_2 \geq 0.1$. The minimum turbine power $V_{\text{MIN}} \geq 2$ made the system unstable. The graphs presented in **Figure 2-17** show the FFT response of the GAST model parameters R , T_1 , T_2 , and T_3 changes. Each graph depicts the oscillation magnitude for two different oscillation frequencies, 0.25 Hz and 1.4 Hz, as the respective parameters were varied. Notably, the 0.25 Hz oscillations tended to exhibit higher magnitudes compared to the 1.4 Hz oscillations across all parameter changes. The GAST parameters R , T_1 , T_2 , V_{MAX} , and V_{MIN} were the sensitive parameters of the model. The speed droop $R = 0$ and minimum turbine power $V_{\text{MIN}} \geq 2$ had distorted oscillations.

The turbine damping factor (D_{turb}), temperature limiter gain (K_T), and the exhaust temperature time constant (T_3) of the GAST governor model did not show any influence on the FOs.

2.5.5 HYGOV Governor

The sensitivity of the HYGOV governor parameters was analyzed based on their influence on the forced oscillation magnitude, oscillation frequency, and active power oscillations of Gen-1. The sensitive parameters of the HYGOV governor model were identified and ranked, as shown in **Table 2-12**, as follows. The turbine gain (A_T) was the most sensitive parameter of the HYGOV model. The A_T values, $A_T < 0$ and $A_T \geq 1.5$, made the system unstable and had around 390 MW oscillations. A_T values between 0 to 1 showed damped oscillations for both oscillation modes, as shown in **Figure 2-18**.

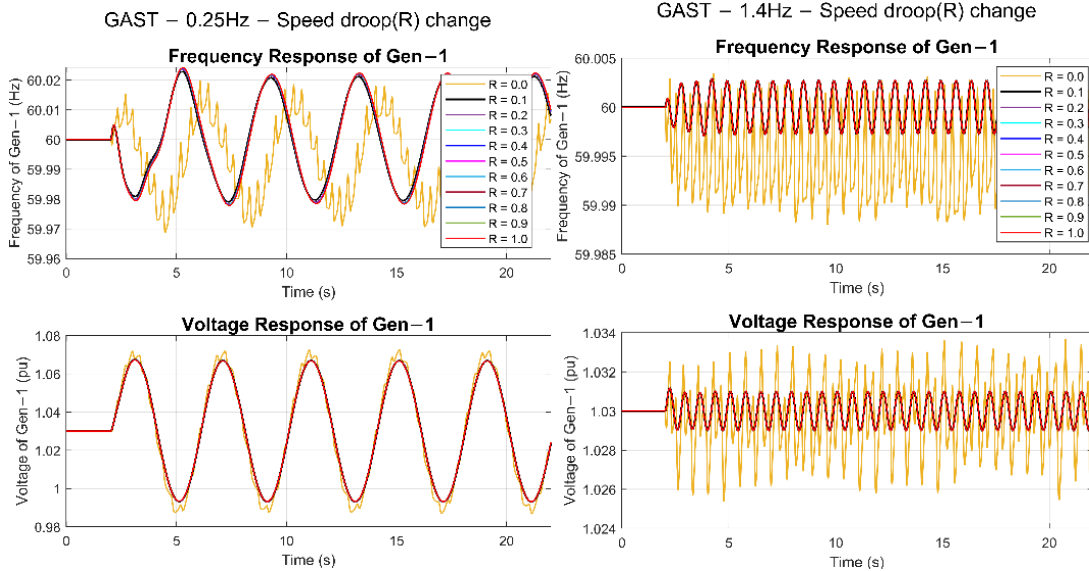


Figure 2-16. Response of speed droop (R) changing from 0.0 to 1.0 in steps of 0.1

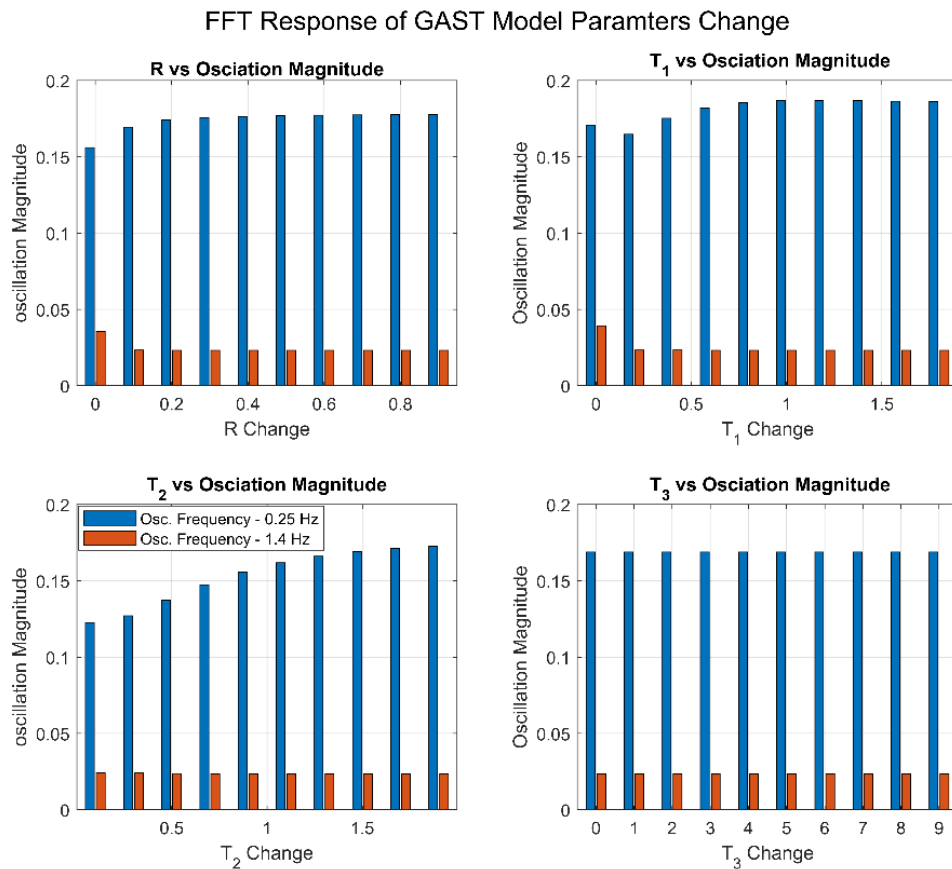


Figure 2-17. FFT response regarding GAST model parameters change

The temporary droop (r) parameter was changed from 0 to 2, and the corresponding frequency and voltage responses are shown in **Figure 2-19**. The low value of $r = 0$ had high 105 MW oscillations for both frequency modes. Increasing the temporary droop value from 0.2 to 2 reduced the oscillation magnitude to 2.9 MW and 5.709 MW for the 0.25 Hz and 1.4 Hz modes, respectively.

Figure 2-20 presents the effect of varying four different parameters of the HYGOV model on the oscillation magnitude for two different oscillation frequencies (0.25 Hz and 1.4 Hz). Each subplot illustrates the oscillation magnitude in response to changes in specific parameters: R , temporary droop (r), T_G , and T_w . The speed droop R and T_G showed a significant increase in the oscillation magnitude as their values increased. Conversely, the temporary droop (r) parameter significantly reduced the oscillation magnitude with increasing values. The water inertia time constant (T_w) had a comparatively minor effect on the oscillation magnitude.

The higher values of permanent droop and no power flow had damped oscillations. The minimum and maximum gate limit values, $G_{MIN} \geq 2$ and $G_{MAX} \leq 0$, made the system unstable. The turbine gain was the most sensitive parameter, and $A_T < 0$ and $A_T > 1.5$ can make the system unstable. The permanent droop (R), temporary droop (r), servo time constant (T_G), and water time constant (T_w) were the sensitive parameters of the HYGOV model and had a more pronounced effect on the 0.25 Hz oscillation mode.

2.5.6. GGOV1 Governor

The analysis focused on the sensitivity of various GGOV1 model parameters; specifically, their impacts on the reactive power output (MW) at two oscillation modes

Table 2-12. HYGOV governor model sensitive parameters and their associated ranks

HYGOV Parameters	Tested Parameters’ Range	Active Power Output (MW)		Rank
		0.25 Hz	1.4 Hz	
A _T —Turbine gain	A _T —1 to 0; ≥1.5	System unstable; 390.33		1
	A _T —0 to 1	Damped oscillations		
r—Temporary droop	r—0 .0	105.33	108.41	2
	r—0.2	25.47	9.8	
	r—2.0	2.9	5.709	
T _G —Servo time constant	T _G —0.1	11.188	21.832	3
	T _G —0.5	8.896	6.57	
	T _G —5.0	1.33	0.728	
T _W —Water time constant	T _W —0.0	8.046	5.674	4
	T _W —1.0	10.067	10.03	
	T _W —10.0	14.332	10.185	
T _R —Governor time constant	T _R —0	131.774	10.007	5
	T _R —5 to 50	10.097	10.012	
R—Permanent droop	R—0 to 0.2	10.05	10.13	6
	R—0.3 to 1.0	Damped oscillations	10.05	
Q _{NL} —No power flow	Q _{NL} —0 to 0.4	10.101	10.13	7
	Q _{NL} —0.45 to 0.5	10.066	Damped oscillations	
G _{MAX} —Maximum gate limit	G _{MAX} ≤ 0	System unstable		
G _{MIN} —Maximum gate limit	G _{MIN} ≥ 2	System unstable		

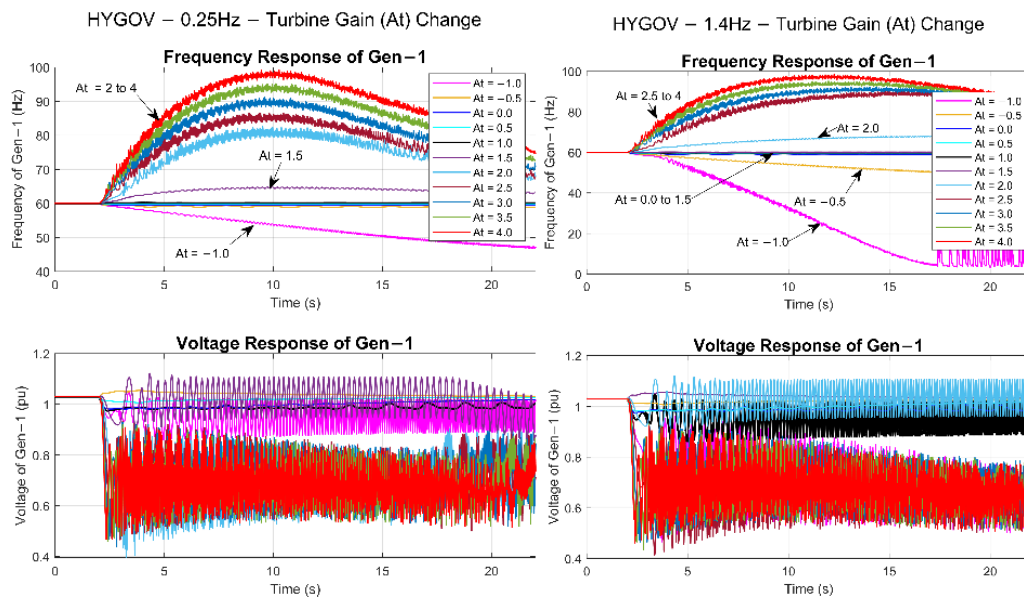


Figure 2-18. Response of turbine gain (A_T) changing from -1.0 to 4.0 in steps of 0.5

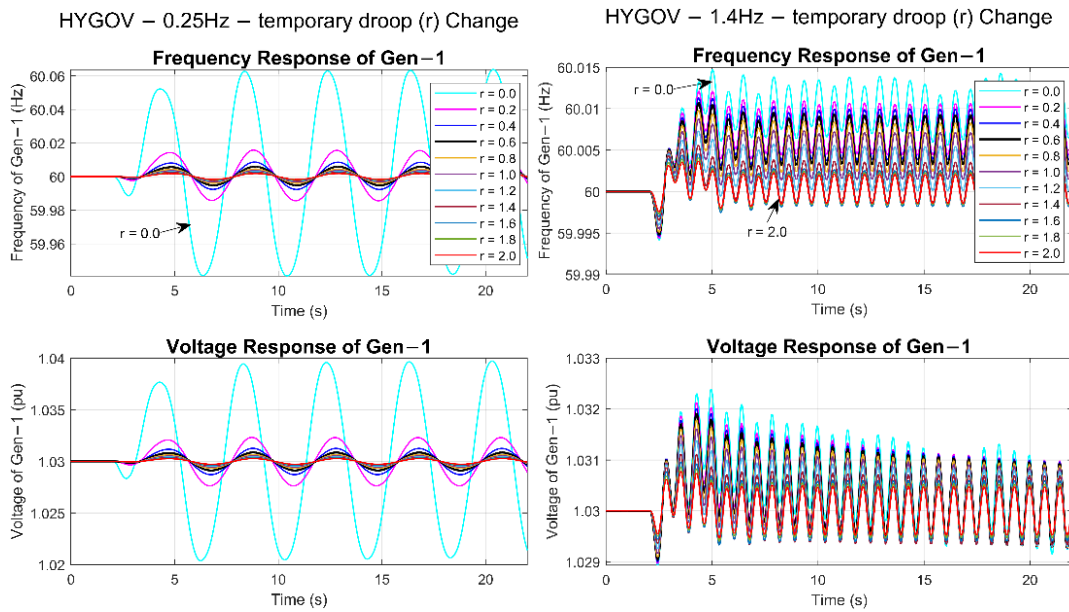


Figure 2-19. Response of temporary droop (r) changing from 0.0 to 2.0 in steps of 0.2

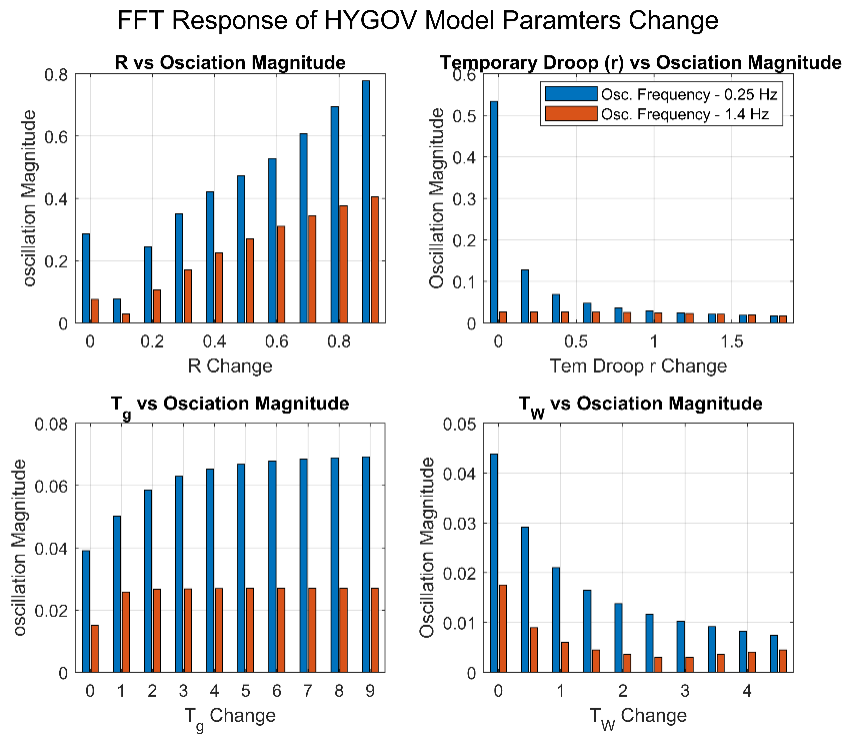


Figure 2-20. FFT response of HYGOV model parameters' change

are discussed in this section. The parameters were ranked based on their influence on the system stability and oscillation magnitude, as summarized in **Table 2-13**.

The turbine gain (K_{turb}) was the most sensitive parameter of the GGOV1 model. The K_{turb} change response from 0 to 4 in steps of 1 is shown in **Figure 2-21**. The $K_{\text{turb}} < 0$ and $K_{\text{turb}} \geq 4$ made the system unstable and had around 316 MW of oscillations. The K_{turb} values increasing from 1 to 3 increased the oscillation magnitude for both oscillation frequency modes. The permanent droop (R) parameter was changed from 0 to 1. The low value of $R = 0$ had damped oscillations for both frequency modes. Increasing the R value from 0.1 to 1 increased the oscillation magnitude to 116.04 MW and 157.059 MW for the 0.25 Hz and 1.4 Hz modes, respectively. The FFT response of R and actuator time constant (T_{ACT}) parameters are shown in **Figure 2-22**.

The high values of T_{ACT} and turbine lag time constant (T_{B}) parameters also impacted the forced oscillation magnitude. In contrast, the increase in the governor proportional gain (K_{Pgov}) value increased the oscillation magnitude. Likewise, the high values of the turbine lead time constant ($T_{\text{C}} \geq 1$) and no-load fuel flow ($W_{\text{FNL}} \geq 1$) can cause the system to become unstable. The higher values of the parameters $V_{\text{MIN}} \geq 1.2$, $K_{\text{turb}} \geq 4$, $W_{\text{FNL}} \geq 1.0$, and $T_{\text{C}} \geq 1$ made the system unstable. The permanent droop $R > 0.1$, K_{Igov} , T_{Dgov} , T_{pelec} , and $L_{\text{DREF}} = 0$ delayed the system's response. The turbine gain (K_{turb}), permanent droop (R), turbine lead and lag time constants (T_{C} and T_{B}), actuator time constant (T_{ACT}), and no-load fuel flow (W_{FNL}) were the sensitive parameters of the GGOV1 governor model.

Table 2-13. GGOV1 governor-sensitive parameters and their associated ranks

GGOV1 Parameters	Tested Parameters' Range	Reactive Power Output (MW)		Rank
		0.25 Hz	1.4 Hz	
K_{turb} —Turbine gain	$K_{\text{turb}}=0$	Distorted oscillations—316.572		1
	$K_{\text{turb}}=1$	6.923	9.523	
	$K_{\text{turb}}=2$	10.876	14.739	
	$K_{\text{turb}}=3$	158.147	127.572	
	$K_{\text{turb}} \geq 4$	System unstable		
R—Permanent droop	R=0	Oscillations damped		2
	R=0.1	11.104	9.333	
	R=0.2	12.704	14.837	
	R=0.3 to 1.0	116.042	157.059	
T_{C} —Turbine lead time constant	$T_{\text{C}}=0$	10	10	3
	$T_{\text{C}}=0.5$	18.539	45.086	
	$T_{\text{C}} \geq 1$	System unstable		
W_{FNL} —No-load fuel flow	$W_{\text{FNL}}=0.0$	12.56	11.762	4
	$W_{\text{FNL}}=0.4$	6.292	8.89	
	$W_{\text{FNL}}=0.6$ to 0.8	Oscillations damped		
	$W_{\text{FNL}}=1.0$	System unstable—316.819		
T_{ACT} —Actuator time constant	$T_{\text{ACT}}=0.0$	9.997	48.295	5
	$T_{\text{ACT}}=0.5$	10.11	10.08	
	$T_{\text{ACT}}=5.0$	1.607	0.88	
T_{B} —Turbine lag time constant	$T_{\text{B}}=0.1$	10.21	10.324	6
	$T_{\text{B}}=5.0$	1.363	0.384	
K_{Pgov} —Governor proportional gain	$K_{\text{Pgov}}=0$	1.171	0.321	7
	$K_{\text{Pgov}}=40.0$	25.448	12.572	
K_{Igov} —Governor integral gain	$K_{\text{Igov}}=0$	9.292	7.542	8
	$K_{\text{Igov}}=1$ to 10	10.098	10.195	
K_{A} —Acceleration limiter gain	$K_{\text{A}}=0$	10.183	10.253	9
	$K_{\text{A}}=20$ to 50	10.012	12.57	
K_{IMW} —Power controller (reset) gain	$K_{\text{IMW}}=1$ to 10	Distorted oscillations		
V_{MAX} —Maximum valve position limit	$V_{\text{MAX}} \leq 0$	System unstable		
V_{MIN} —Minimum valve position limit	$V_{\text{MIN}} \geq 1.2$	System unstable		

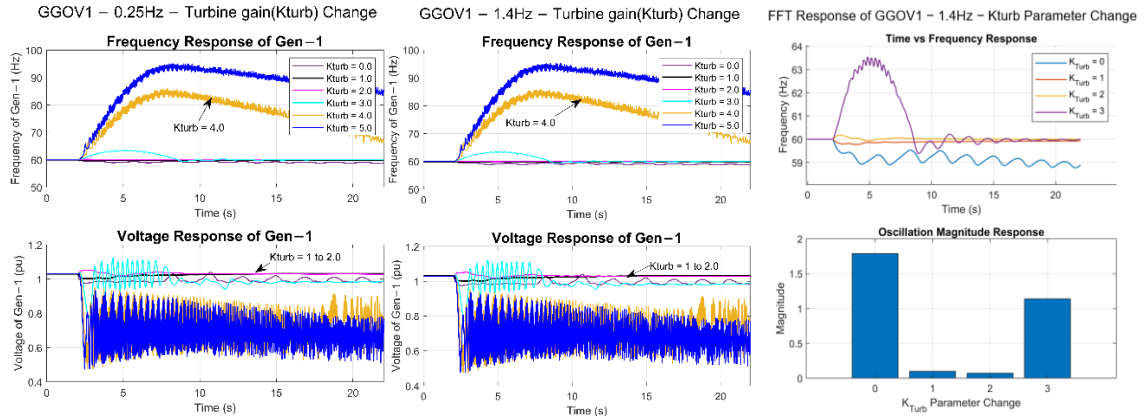


Figure 2-21. Time domain and FFT response of turbine gain (K_{turb})

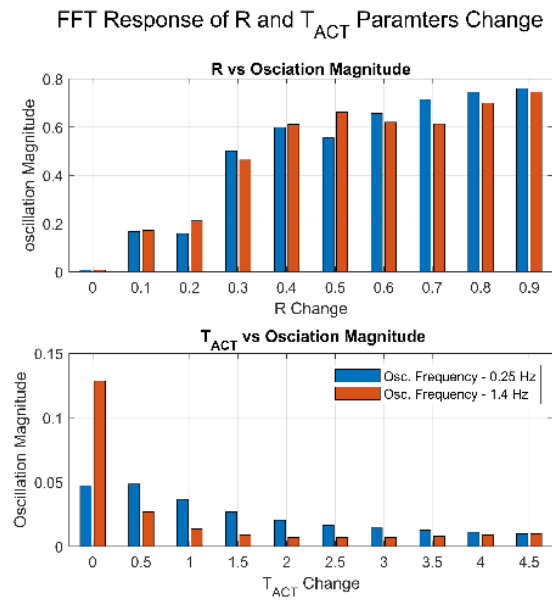


Figure 2-22. FFT response of R and T_{act} parameters' change

2.6 Conclusion

This study utilized Kundur's two-area system in PSS/E to investigate the impact of exciter and governor parameters on FOs, presenting a comprehensive analysis that highlights the novelty of our approach. By examining widely used exciter models such as SCR_X, ESST1A, and AC7B, alongside governor models like HYGOV, GAST, and GGOV1, by systematically injecting FOs and altering model parameters, their influence on frequency, voltage response, and oscillation magnitudes are assessed at 0.25 Hz and 1.4 Hz. This research offers practical insights for plant operators, enabling them to fine-tune control settings and improve system stability, thereby contributing to more resilient and reliable power system operations. The following key findings identify and rank the sensitive parameters of each model according to their impact on FOs:

- **SCR_X Model:** Parameters K , T_A/T_B , T_E , and T_B are the sensitive parameters of the SCR_X exciter model. The oscillation magnitude for the 1.4 Hz mode increases linearly with K and T_A/T_B values, while the 0.25 Hz mode remains largely unaffected. The exciter time constant T_E significantly influences the oscillation frequency at lower values.
- **ESST1A Model:** Parameters K_A , T_C , T_R , T_{B1} , and T_B are highly sensitive, crucial for dynamic response and system stability. These parameters help to control FOs. The parameters K_{LR} , T_F , and T_{C1} show no impact on the FOs.
- **AC7B Model:** Sensitive parameters of this model include regulator proportional gains K_{PA} , K_{PR} , K_{IR} , K_E , K_P , T_R , K_{F1} , and K_{F2} . Other parameters, such as K_C , K_{IR} , K_{DR} , K_{IA} , K_L , T_{DR} , T_{F3} , V_{EMIN} , E_1 , E_2 , $S(E_1)$, $S(E_2)$, V_R , and V_A , do not show any influence on the FOs stability.

- **GAST Model:** The speed droop parameter R significantly affects oscillation magnitudes and system stability. Parameters T_1 , T_2 , V_{MAX} , and V_{MIN} also influence oscillation characteristics.
- **HYGOV Model:** Sensitive parameters of this model include permanent droop R , temporary droop r , servo time constant T_G , and water time constant T_W , especially impacting the 0.25 Hz oscillation mode.
- **GGOV1 Model:** The most sensitive parameters are turbine gain K_{turb} , permanent droop R , turbine lead and lag time constants T_C and T_B , actuator time constant T_{ACT} , and no-load fuel flow W_{FNL} . The other parameters, $R > 0.1$, K_{Igov} , T_{Dgov} , and T_{pelec} , delayed the response of the system.

CHAPTER 3

**FORCED OSCILLATION FREQUENCY IMPACT ANALYSIS DURING
RESONANCE CONDITION**

Abstract

FOs in power systems can destabilize grids when their frequencies align with weakly damped natural modes, leading to resonance. As more inverter-based resources (IBRs) are integrated into power grids, the number of potential forcing sources increases, making it crucial to understand their impact on system stability. This study examines FO sensitivity using a frequency scanning approach across three different power systems: Kundur, ERCOT, and EI models. A key focus is determining how close the forced source frequency needs to be to the natural resonance frequency to excite significant FOs. The findings highlight the critical influence of FO frequency near resonance proximity on oscillation amplitudes and differentiate the effects of generator and load-induced FOs. These insights contribute to improved damping strategies and enhanced grid reliability.

3.1 Introduction

Power system oscillations naturally result from energy ex- changes among system components. However, with increasing renewable integration, dynamic load variations, and evolving grid infrastructure, maintaining stability has become more challenging. The rise in FOs events highlights the need to understand their impact on grid dynamics [7]. Unlike natural oscillations driven by electromechanical dynamics, FOs stem from diverse sources, including equipment failures, mistuned controllers, cyclic loads, and abnormal operating conditions [4], [5], [50], [51].

The shift from synchronous generators to inverter-based resources (IBRs) in the modern power grid has altered system dynamics, reducing inherent damping, modifying

power flow paths, and introducing new oscillation modes. The intermittency of renewables also causes frequent variations in existing modes, further complicating stability assessments. Globally, low-frequency oscillations are increasingly reported, threatening power transfer capability and system security [16], [20].

A critical challenge posed by high renewable penetration is the variability of grid operating conditions. Unlike conventional systems with relatively stable parameters, modern grids experience continuous shifts in oscillation modes. Traditional damping controllers, designed for specific operating points, may not effectively adapt to these variations, necessitating advanced stability strategies.

Resonance occurs when an external disturbance closely matches the system's natural oscillation frequency, amplifying oscillation amplitudes and degrading grid stability [6]. FO interactions with weakly damped modes are particularly concerning, especially in inter-area oscillations spanning large geographical regions [52]. The severity of these effects increases when FO sources are near generators with high modal participation, making FO frequency sensitivity analysis crucial for system stability.

With the growing integration of IBRs, the number of potential forced sources in the grid is expected to increase, making the risk of FOs more prevalent. This study examines FO-induced resonance by applying constant-magnitude disturbances at varying frequencies to assess their impact on oscillation amplitudes and damping [53]. A key focus is determining how close a forcing source frequency must be to the system's natural resonance frequency to trigger significant oscillations. The findings highlight the critical role of frequency proximity in amplifying instability,

offering insights for improving damping strategies and enhancing grid reliability. A deeper understanding of resonance behavior can help mitigate equipment stress, prevent cascading failures, and strengthen overall power system resilience.

This work contributes to the state of the art by offering a unified framework to evaluate FO sensitivity across a small Kundur system and large-scale ERCOT and EI planning simulation models. By systematically examining the proximity effect of FO frequencies to natural modes, it provides new insights into how even small frequency mismatches can lead to large amplitude oscillations, especially in systems with high IBR penetration. This detailed comparison across generator and load-induced FOs helps bridge the gap between academic analysis and practical grid operation needs, informing more effective FO source detection and mitigation strategies.

3.2 Methodology

To conduct the frequency scanning analysis, Small-signal Stability Analysis Techniques (SSAT) are first performed to identify the natural oscillation modes in the Kundur and ERCOT models. Due to the high volume of user-defined models within the EI grid model, SSAT cannot be applied. The natural oscillation mode of 1.4Hz is obtained from Prony analysis using ring-down data from previous research. A sinusoidal signal with a fixed amplitude of 30 MW or 30 MVAR is applied at the governor or exciter reference terminals of the generator serving as the FO source. Additionally, a new load is introduced at the same bus terminal where the generator is connected, the FOs can also be injected through the load.

The frequency scanning process involves systematically varying the FO frequency while keeping the source location constant. For all three power systems, the frequency is incremented by a 0.05 Hz step size from 0.1 Hz to 2 Hz. To evaluate the system's response, the frequency, voltage, active power, and reactive power are analyzed at the bus located after the transformer, where the forced oscillation source is connected, for each applied FO frequency. For each case, the simulation data is obtained for 40 seconds with a forced signal injected from 2 seconds. The peak-to-peak deviations of the measurements are calculated based on the last 10 oscillation cycles. Dynamic simulations are conducted using PSSE 35 for all three systems to monitor system responses.

The frequency scanning results, including inter-area and local mode resonance frequencies, were analyzed to assess frequency sensitivity at resonance and the impact of frequency proximity to resonance on system behavior. Additionally, the differences in magnitude between generator-induced and load-induced FOs were examined, along with the influence of generator governor and exciter dynamics on load-induced FOs.

3.3 Case Studies

3.3.1 Kundur System

In this study, the Kundur two-area, four-machine system, depicted in **Figure 2-2**, is selected as the benchmark model to investigate the influence of FO frequency on system dynamics. For this analysis, the generator control models of the Kundur system, as presented in **Table 2-1**, are utilized. To isolate the effects of FOs, power system stabilizers (PSSs) are deactivated on all generators. Natural oscillation modes of the Kundur system are identified using SSAT analysis, with key mode frequencies

summarized in **Table 3-1**. The dominant area 1 in both the inter-area mode with a frequency of 0.66 Hz and a local mode of 1.161 Hz are considered for this analysis.

3.3.2 ERCOT System

A comprehensive analysis has been conducted on an industry-grade ERCOT system model comprising 10,938 buses under summer peak conditions. SSAT is utilized to identify dominant modes within the system. **Figure 3-1** depicts a part of the study system. For the generator unit with a capacity of 1,205 MW located at bus 150111, two dominant modes are identified: 0.7084 Hz (inter-area) and 1.433 Hz (local mode).

Table 3-2 presents the SSAT results, highlighting the participation factors of different nearby generators. The local mode exhibited a higher magnitude compared to the inter- area mode, indicating its significance in the system's dynamic behavior.

Among the generators whose participation factors in the local mode have been displayed, U1 and U2's points of interconnection (POI) are bus 1900, and C1 and C0's POI is 1868, while C2's POI is 11879. So, these buses frequency, voltage, active power, and reactive power have been observed. A range of forced frequencies, spanning from 0.45 Hz to 2 Hz with increments of 0.05 Hz, is applied at machine U1, ensuring a consistent 30 MW peak-to-peak oscillation magnitude for all cases. Multiple methods were employed to inject FOs, including modulation of the generator governor reference, adjustment of the exciter voltage reference, and injection through active and reactive loads.

Table 3-1. Small signal stability analysis results of the kundur's system

Modes	Real part	Imaginary part	Frequency	Damping	Gen participation factor
Mode1	-0.1082	4.1516i	0.6607 Hz	2.61%	G1 = 1.0; G2 = 0.71 G3 = -0.81; G4 = -0.78
Mode2	-0.6467	7.2963i	1.1613 Hz	8.83%	G1 = -0.95; G2 = 1.00 G3 = -0.20; G4 = 0.11
Mode3	-0.6351	7.4685i	1.189 Hz	8.47%	G1 = 0.28; G2 = -0.33 G3 = -0.98; G4 = 1.00

Table 3-2. Small signal stability analysis results for machine U1 at Bus 150111 in ERCOT system

Modes	Frequency	Damping	Gen Participation Factor
Mode 1	0.7084 Hz	7.56%	U1(150111) = 1.0 U2 (150112) = 0.96 C4(110754) = 0.79 C1(110751) = 0.78 etc.
Mode 2	1.4333 Hz	8.74%	U1(150111) = 1.0 U2 (150112) = 0.4 C1(1150171) = 0.49 C0(150173) = 0.08 C2(150172) = 0.97 etc.

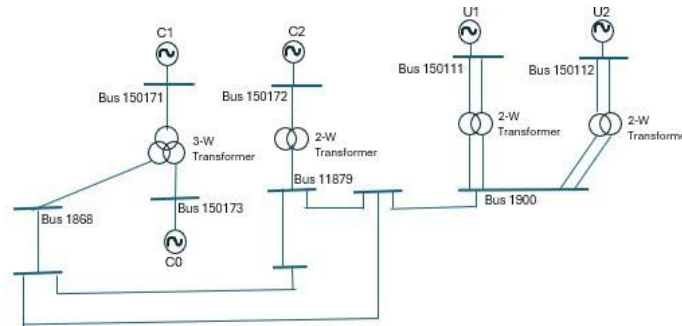


Figure 3-1. Part of the ERCOT system

3.3.3. EI System

The Multi-Regional Modeling Working Group (MMWG) 2019 series, specifically the 2024 summer peak load planning model, is utilized in this study for its robustness and ability to represent current EI grid conditions. Given the vast number of regions within the EI grid, a comprehensive analysis of all regions was not feasible. Thus, the Tennessee Valley Authority (TVA) area was selected for this forced oscillation frequency sensitivity study. A 490 MW traditional generator at the center of the TVA area was chosen as the forcing source based on comprehensive participation study results. Unlike the Kundur and ERCOT systems, the MMWG models incorporate numerous user-defined machine and load models, rendering SSAT inapplicable. Prior research has identified a 1.4 Hz local oscillation mode within this system.

3.4 Case Study Results & Discussion

The section introduces the frequency scanning results for all the case studies.

3.4.1 Kundur System Results

The simulation results demonstrate the notable influence of FO frequencies on system dynamics. **Figure 3-2** illustrates the peak-to-peak amplitude variations for oscillations introduced at generator G1 through the exciter and governor reference points, as well as at the nearby load.

In the Kundur system, the inter-area mode exhibits greater amplitude deviations than the local mode due to its lower damping. The trend in active power FOs induced at generator G1 and the connected load remains consistent across **Figure 3-2(a)** and **(b)**. However, as shown in **Figure 3-2(c)** and **(d)**, the exciter injection results in an

Injecting Forced Oscillations at the Generator Versus at the Load

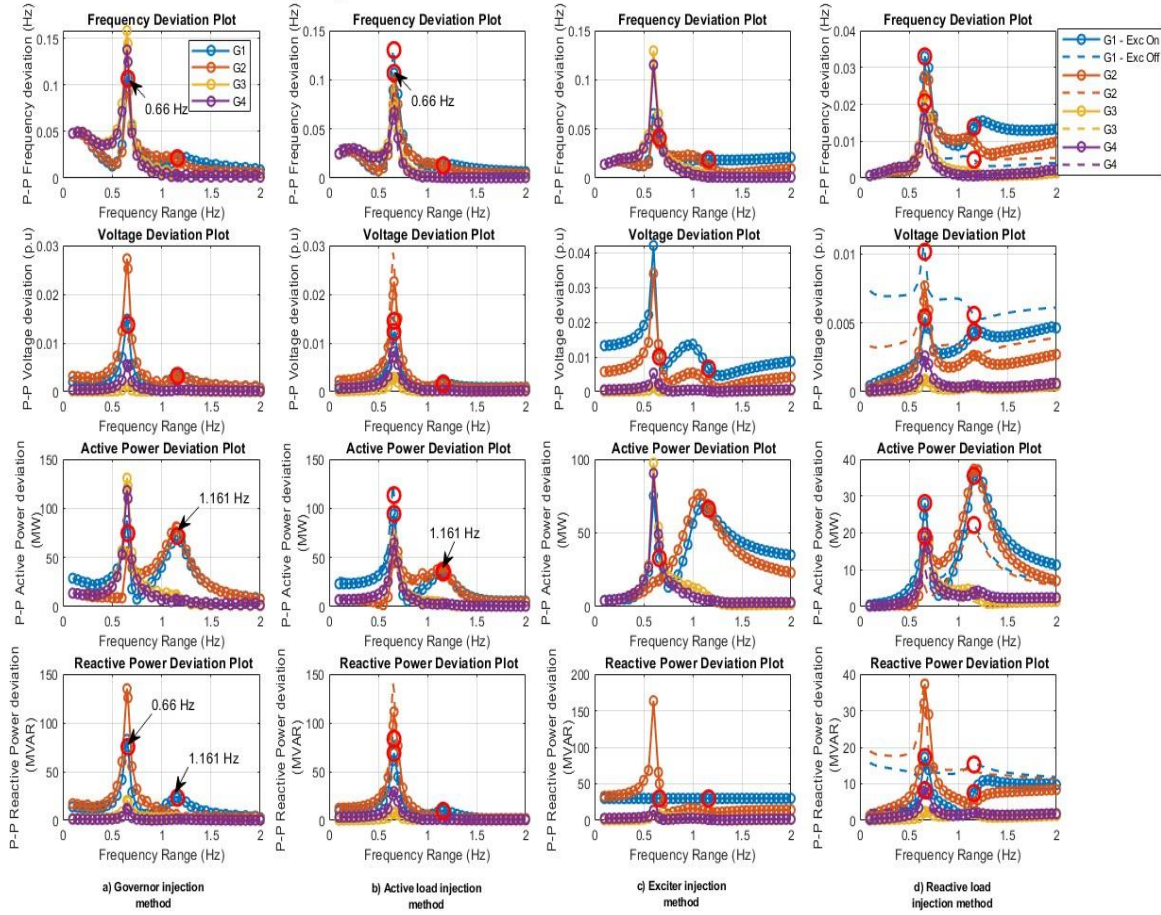


Figure 3-2. Response of the Kundur's system with respect to FO frequency

amplitude twice as large as that observed with reactive load power injection. To isolate the effects of load injections, the governor and exciter of generator G1 were disabled during active and reactive load injections, respectively. The dashed line in **Figure 3 - 2(b)** and **(d)** represents the corresponding results for all generators. Disabling the governor during active power load injection has a negligible effect on load-induced FOs, whereas turning off the exciter during reactive power load injection leads to a voltage deviation twice as large as when the exciter is active.

For the 0.66 Hz inter-area mode, a Gaussian distribution with increasing amplitude has been observed within the frequency range of 0.5 to 0.8 Hz. Similarly, for the 1.161 Hz local mode, the peak-to-peak deviations exhibit a rising amplitude trend from 0.9 to 1.5 Hz. A comparative analysis further highlights how resonance amplifies oscillatory energy within the system, increasing mechanical stress on equipment and reducing stability margins. These results underscore the importance of accurately identifying and mitigating FO sources, particularly in inter-area modes, to prevent resonance conditions that could compromise power system reliability and operational security.

3.4.2 ERCOT System Results

Figure 3-3(a) illustrates the peak-to-peak frequency deviation curves in nearby buses under the governor injection method, while **Figure 3-3(b)** shows the same for active load injection. Similarly, **Figure 3-3(c)** represents the results for the exciter injection method, and **Figure 3-3(d)** for reactive load injection. For the 0.7084 Hz interarea mode, a Gaussian distribution with increasing amplitude has been observed

Injecting Forced Oscillations at the Generator Versus at the Load

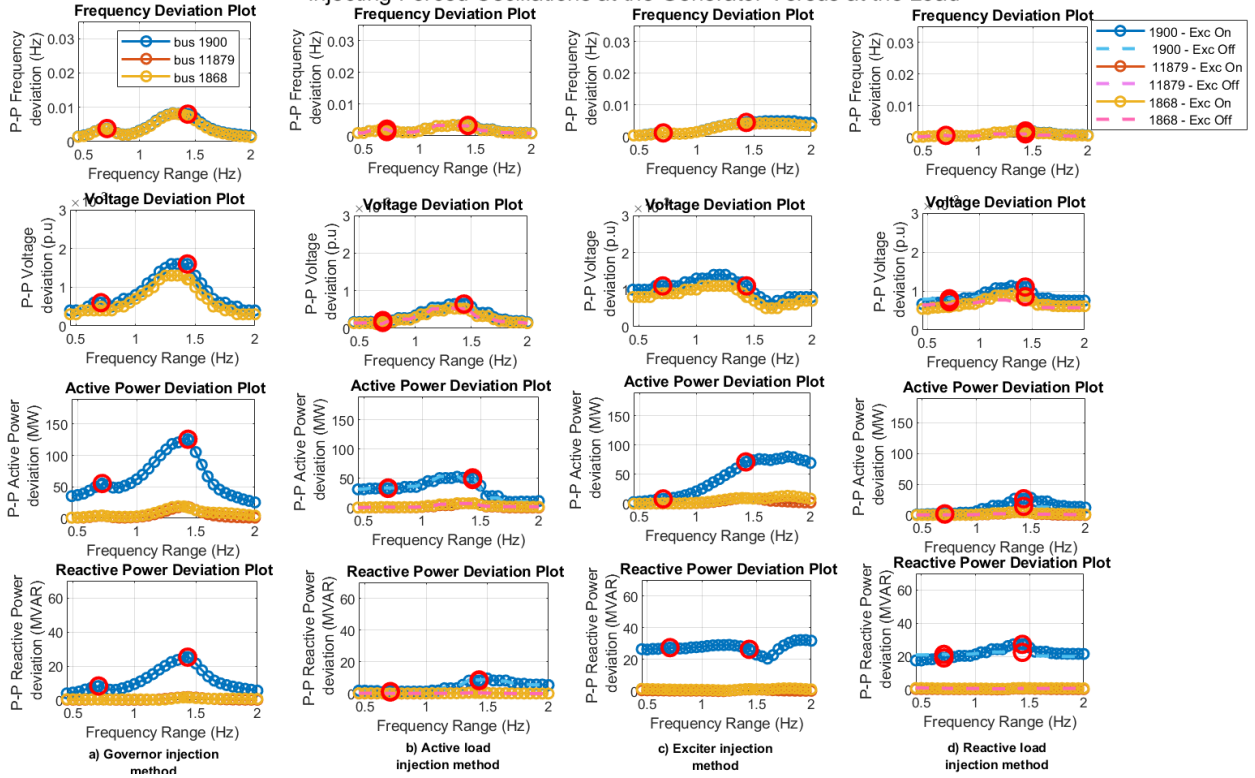


Figure 3-3. Response of the ERCOT system with respect to FO frequency

within the frequency range of 0.5 to 0.8 Hz. Similarly, for the 1.433 Hz local mode, the peak-to-peak deviations exhibit a rising amplitude trend from 1.0 to 1.7 Hz. However, the active load injection method exhibited lower response magnitudes than the governor injection method, and the reactive load injection method exhibited lower response magnitudes than the exciter method. These differences are likely to be due to how energy is exchanged or dissipated in the system under these injection techniques.

3.4.3 EI System Results

Figure 3-4 illustrates the peak-to-peak frequency, voltage, active power, and reactive power deviations analyzed at the bus located after the transformer that is connected to the forcing source. Similar to the other two systems, the active load injection method exhibited lower response magnitudes than the governor injection method, and the reactive load injection method exhibited lower response magnitudes than the exciter method. To be more specific, the upper left subplot of **Figure 3-4** illustrates the peak-to-peak frequency deviation curves induced by the four different methods. For the 1.4 Hz local mode, the peak-to-peak frequency deviations exhibit a rising amplitude trend from 1.0 to 1.7 Hz for the generator methods and from 1.2 to 1.7 Hz for the load methods. The frequency deviation induced by the generator methods is much larger than the frequency deviation induced by the load methods. This is because the active power flow from the generator methods is greater than the load methods, as shown in the lower left subplot. The upper right subplot of **Figure 3-4** illustrates the peak-to-peak voltage deviation curves induced by the four different methods. For the 1.4 Hz local mode, the peak-to-peak voltage deviations exhibit a rising amplitude trend

Injecting Forced Oscillations at the Generator and Load in TVA Area

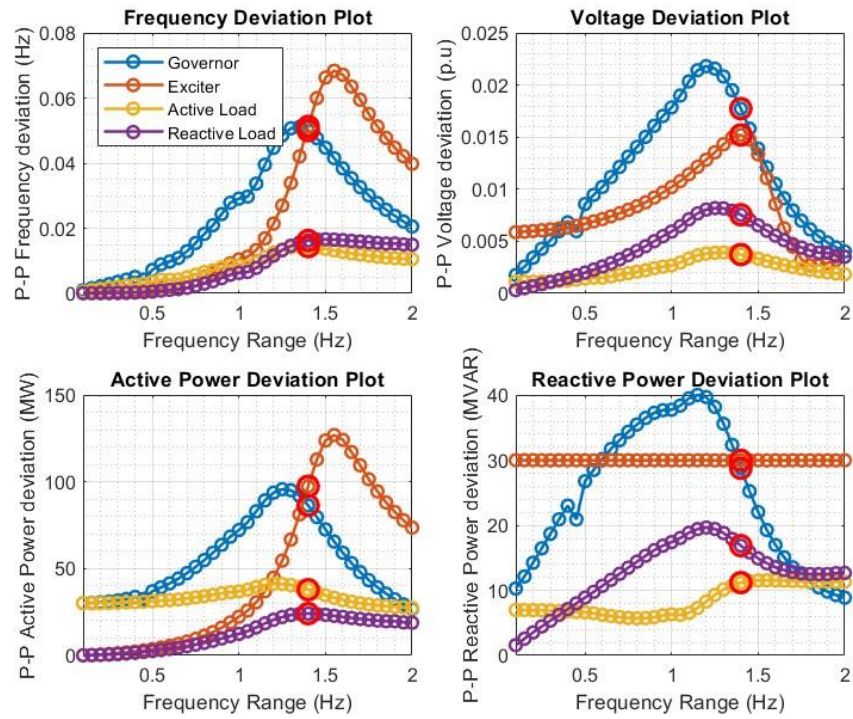


Figure 3-4. Response of the EI system with respect to forced oscillation frequency

from 1 to 1.5 Hz for all four methods. In conclusion, the deviation curves also exhibit Gaussian nature, with peaks occurring at or near the dominant modes.

3.4.4 Comparison of Generator and Load Induced FOs

To evaluate the impact of different disturbance injection methods, a test is performed on the ERCOT system. Unlike mechanical power injections, introducing an oscillating load consumes power, reducing the net power flow from the source to the point of interconnection (POI) at bus 1900. To demonstrate this effect, two scenarios are simulated. First, the power flow to bus 1900 is recorded under the governor injection method. Then, the load disturbance magnitude is carefully tuned to match the same power flow to bus 1900.

Figure 3-5 demonstrates the comparison between the two methods. The resulting frequency and voltage deviation plots from both methods exhibit closely matching amplitudes, indicating that proper tuning of load injections can replicate the dynamic response of governor-based injections. Minor discrepancies are likely due to variations in power flow contributions from nearby generators at their respective POI buses 11879 and 1868. So, when the output power at a high-voltage bus is held constant, both generator-based and load-based injections can trigger similar high-magnitude oscillations in the system. However, the load injection method tends to be more sensitive: even small load perturbations can induce noticeable oscillations throughout the network. While the quantitative results are specific to the Kundur, ERCOT, and EI test systems, the underlying observations and trends are expected to generalize to other power systems with comparable modal characteristics.

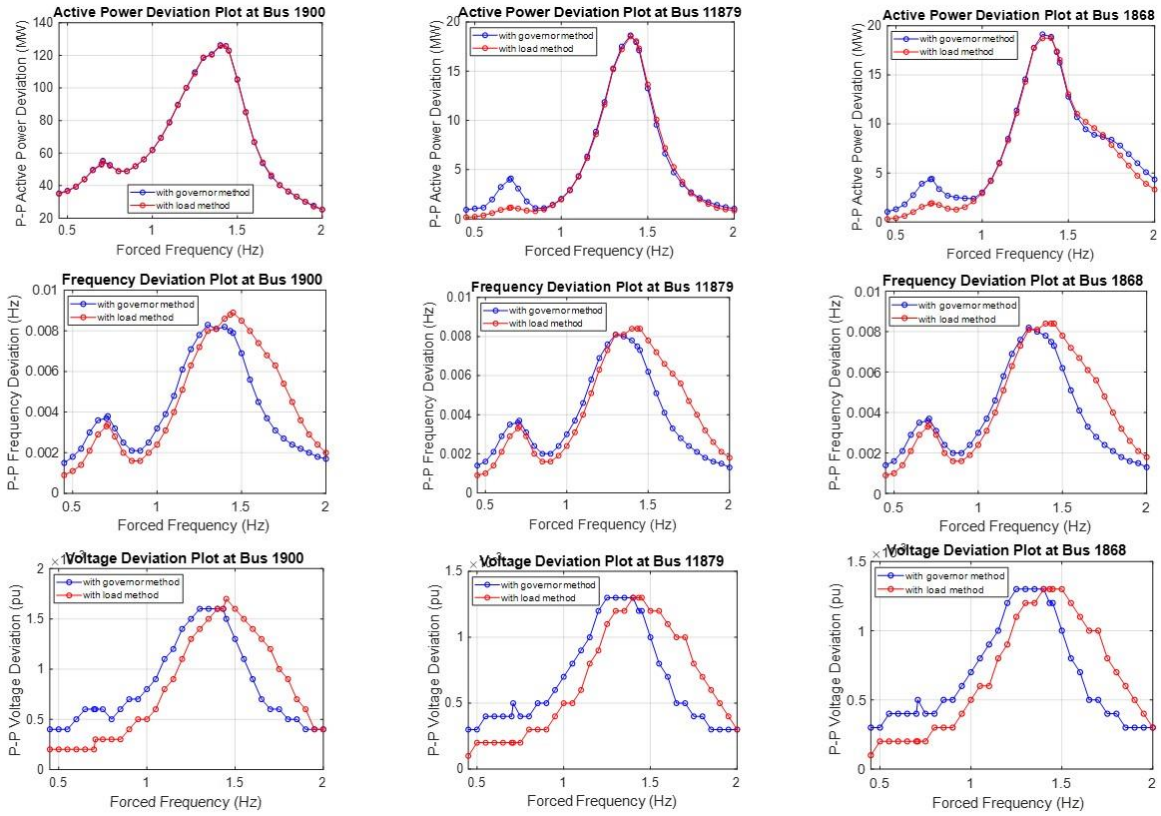


Figure 3-5. Comparison between the governor and load injection methods

Across all three systems, a consistent pattern emerges: (i) load-based injection methods produce similar but slightly lower frequency and voltage deviations compared to generator-based methods, (ii) inter- area modes with lower damping are more susceptible to resonance effects, and (iii) oscillation amplitudes tend to follow a Gaussian-like distribution centered around the system's natural modes. Notably, the dominant frequency ranges are observed, typically between $\pm 0.2\text{Hz}$ Hz for inter-area mode, and approximately from $\pm 0.4\text{ Hz}$ near the natural oscillation frequency, and they remain similar across all test systems. This consistency suggests that the mechanisms of forced oscillation propagation and modal resonance are not unique to any one system but rather stem from fundamental dynamic interactions that are broadly applicable. Therefore, the insights gained from this study provide valuable guidance for analyzing and mitigating FOs in other real-world systems.

3.5 Conclusion

This study investigated the impact of FO frequency variation on power system dynamics, focusing on their interaction with natural system modes. The results demonstrated that when the FO frequency aligns with an inherent system mode, resonance occurs, leading to significant amplitude magnification. Additionally, a comparative analysis of different FO injection points revealed that generator-based injections induce stronger oscillations compared to active and reactive load injections. Notably, the forced source frequency response around the local mode exhibits a broader Gaussian-like distribution in amplitude, indicating greater sensitivity over a wider frequency band compared to the inter-area mode.

Furthermore, turning off the governor during active power load injections had a minimal influence on the FO response, whereas turning off the exciter during reactive load injections resulted in a twofold increase in voltage deviations. This indicates that FOs occurring at or near the local mode can significantly increase mechanical stress on nearby components, highlighting the need for damping and mitigation strategies to enhance power system resilience.

Importantly, these findings were consistently observed across three different systems- Kundur, ERCOT, and EI despite their differences in topology and scale. The similarity in frequency response trends and dominant FO frequency ranges suggests that the results can be generalized to other power systems with similar modal characteristics.

CHAPTER 4
FORCED OSCILLATION SOURCE LOCATION AND SOURCE TYPE
CLASSIFICATION

Abstract

FOs pose significant challenges to power system stability, particularly when their frequencies align with natural system modes, leading to resonance and wide-area impacts. Identifying the precise source location and control-loop origin of such oscillations is critical for timely mitigation. This paper presents a robust spectral energy-flow algorithm for FO source localization and type classification at the equipment sub-controller level. The proposed method utilizes a cycle-based sliding window approach to compute cross-spectral energy terms between active/reactive power and frequency/voltage signals, including $S_{P\omega}$, S_{PV} , $S_{Q\omega}$, and S_{QV} . A composite index is formulated to identify the FO source location, while relative energy dominance among the spectral terms is used to classify the FO as either P-type (active power driven) or Q-type (reactive power driven). The algorithm is evaluated on a synthetic 2000-bus ERCOT test system under various local and inter-area resonance conditions. Results demonstrate accurate localization and reliable source type identification across all test scenarios, including challenging resonance cases. The proposed method offers a practical and computationally efficient solution for real-time oscillation monitoring and diagnosis in large-scale power systems.

4.1 Introduction

Locating the source of FOs in power systems remains a significant challenge, especially under limited PMU coverage or when the oscillation spans wide-area modes. Traditional approaches can be broadly classified as model-based or measurement-based. However, model-based techniques often become unreliable in the presence of FOs,

particularly when resonance with system modes occurs [54]. Consequently, measurement-driven methods have gained prominence for FO detection and localization. Several strategies have been proposed for FO source identification, including hybrid simulations, mode shape estimation, damping torque analysis, and various energy-based methods [55]. While hybrid simulations offer accuracy, they are typically suited for post-event diagnostics. Mode shape and damping torque methods, though applicable in real-time, may yield ambiguous results particularly under complex multi-machine interactions or resonance conditions.

Among energy-based methods, the Dissipating Energy Flow (DEF) approach has demonstrated strong potential and has been adopted by utilities such as ISO-NE [56], [57]. However, its effectiveness depends on the full observability of the system, requiring detailed network topology and comprehensive measurements constraints that limit its deployment in practical environments. Additionally, DEF-based techniques lack the ability to distinguish which internal control subsystem (e.g., governor vs. exciter) is responsible for the FO, which is critical for implementing corrective action within a generator or IBR.

More recently, advanced spectral and data-driven methods, such as Fast Fourier Domain Decomposition (FFDD), Fast Stochastic Subspace Identification (FSSI), and machine learning-based analytics, have been employed to detect FOs and identify the potential source location from PMU data [58], [59]. While effective for identifying FO presence and system modes, these methods do not offer detailed insight into the internal mechanism particularly the controller-level source behind the oscillation. Moreover, it is

important to acknowledge that the availability of good quality labeled field data for these types of events to train machine learning models is significantly limited.

One of the most critical challenges in FO source localization arises when the oscillation frequency aligns closely with an inter-area mode of the system, a condition referred to as resonance or near-resonance. Under such circumstances, the oscillation energy can become widely distributed across the system, often leading to misleading indicators in measurement-based localization methods. Existing techniques, including mode shape analysis, DEF-based methods, and even data-driven spectral estimators, tend to mis-identify the source or attribute high energy to non-source regions due to widespread mode participation. In practical power systems, this can result in false positives or an inability to distinguish between a true source and a passive resonator. The difficulty is further exacerbated when PMU coverage is sparse or when the system topology is highly meshed, which is typical in real-world grids. Therefore, developing robust algorithms capable of accurately identifying FO sources under resonance conditions remains a significant gap in current literature and practice particularly for inter-area oscillations that span large geographic or control areas.

As many FOs events stem from malfunctioning generator control loops or inverter-based resources at or near resonance conditions, there is a growing need for algorithms that not only identify the source location but also determine the type of FO (P-type or Q-type) based on its origin in the generator's mechanical or electrical subsystems. Understanding whether an FO is driven by a governor, exciter, or inverter control is essential for operators to respond effectively and maintain system stability.

To address these limitations, this chapter presents a spectral energy-flow-based algorithm for FO source location and source-type classification, applied at the sub-controller level. The method is implemented and evaluated on a high-fidelity dynamic simulation of the synthetic 2000-bus ERCOT system, enabling assessment under both local and inter-area FO conditions. The remainder of the chapter is structured as follows: Section 4.2 details the FO case creation methodology using generator and IBR models; Section 4.3 outlines the proposed source location and classification algorithm; Section 4.4 discusses the case study results; and Section 4.5 concludes with key findings and directions for future work.

4.2 Methodology for Designing Simulation Cases

In this study, a synthetic 2000-bus Texas power system model, developed by Texas A&M university using publicly accessible data, is utilized to investigate system dynamics under forced oscillation conditions. This model, compatible with the PSS®E simulation environment, comprises 432 active generators with an aggregate generation capacity of 84.1 GW, supplying a total load of 67.1 GW. Among these, 81 units represent renewable energy sources, collectively capable of generating up to 11.83 GW, with an operational output of approximately 8.9 GW. The transmission network encompasses 2,345 lines operating at four primary voltage levels: 500 KV, 230 KV, 161 KV, and 115 KV. Each synchronous generator is equipped with a governor, an excitation system, and a power system stabilizer. Renewable generation is modeled using generic dynamic models recommended by the western electricity coordinating council (WECC), which includes both converter and electrical control components.

As depicted in **Figure 4-1**, the system architecture consists of eight areas subdivided into 28 zones. Area 5, located in the north-central region, serves as the primary load center, while significant power transfers occur from area 7 (coastal) and area 8 (eastern) toward area 5, as indicated by directional flow arrows. Renewable energy resources are primarily distributed across areas 1 through 5, resulting in a renewable penetration level of approximately 13.92% based on the system's total generation capacity.

Small-signal stability assessment is carried out using the small signal analysis tool (SSAT) from DSA tools, which identifies system modes exhibiting damping ratios below 10%. Based on these results, forced oscillation scenarios are constructed by injecting sinusoidal signals at frequencies coinciding with, or slightly offset from, the identified natural modes. For these scenarios, disturbances are introduced at selected bus locations by adding either a classical generator model (GENCLS) with a SCRX exciter and TGOV1 governor, or a utility-scale inverter-based renewable generator modeled using the REGCAU2 converter and REECCU1 electrical control system. In p-type oscillation cases, a 50 MW sinusoidal signal is injected at the TGOV1 model's " P_{ref} " input or the REGCAU2 model's " P_{aux} " input. For Q-type cases, a 50 MVAR sinusoidal signal is applied to the SCRX model's " V_{ref} " or the IBR model's " P_{faref} " input, in accordance with the methodology in [3]. All simulation scenarios are developed in PSS®E version 34 and the algorithm. A summary of the simulated forced oscillation cases is presented in **Table 4-1**.



Figure 4-1. Synthetic Texas power grid model area map [3]

Table 4-1. Simulated test cases of the synthetic ERCOT system

Case No	Natural Frequency	Damping	FO Frequency	Source location bus	Source Type	Description
1[A-D]	0.667	5.1%	0.667	4085	Governor, IBR-Current loop, Exciter, IBR voltage loop	Resonance case with inter-area 0.667 Hz mode
2[A-D]	0.595	6.31%	0.63	7208	Governor, IBR-Current loop, Exciter, IBR voltage loop	Case with FO injection close to inter-area 0.595 Hz mode
3[A-D]	1.154	7.51%	1.154	4061	Governor, IBR-Current loop, Exciter, IBR voltage loop	Resonance case with local 1.1544 Hz mode
4[A-D]	1.154&1.415	7.51&9.16%	1.25	4061	Governor, IBR-Current loop, Exciter, IBR voltage loop	FO Frequency above the local 1.1544 Hz mode
5[A-D]	0.884	5.59%	0.884	1051	Governor, IBR-Current loop, Exciter, IBR voltage loop	FO Frequency equal to the local 0.884 Hz mode
6[A-D]	0.884 & 1.106	5.59 & 6.84%	1	1051	Governor, IBR-Current loop, Exciter, IBR voltage loop	FO Frequency in between the two local modes
7[A-D]	1.2326&1.2852	5.24 & 7.72 %	1.25	7098	Governor, IBR-Current loop, Exciter, IBR voltage loop	FO frequency in between the two local modes.
8[A-D]	1.324	9.62%	1.35	7353	Governor, IBR-Current loop, Exciter, IBR voltage loop	FO Frequency slightly above the 1.324 Hz local mode
9[A-D]	0.960	6.39%	1	6147	Governor, IBR-Current loop, Exciter, IBR voltage loop	FO Frequency slightly above the 0.96 Hz local mode
10[A-D]	1.520	8.48%	1.4	2117	Governor, IBR-Current loop, Exciter, IBR voltage loop	FO Frequency below the 1.520 Hz local mode

4.3 FO Source Location and Type Identification Algorithm

From the literature [60], the dissipating transient energy (E_{mn}) from branch m to n is represented as

$$E_{mn}(t) = \int \Delta P_{mn}(t) \Delta \omega_m(t) dt + \Delta Q_{mn}(t) d(\Delta \ln(V_m(t))) \quad (2)$$

where $\Delta \omega_m$ is the frequency deviation of bus m, V_m is the voltage magnitude at bus m, ΔP_{mn} and ΔQ_{mn} is the electrical real and reactive power deviation on branch mn, and t is the time. This formulation quantifies the directional energy exchange associated with system oscillations. This concept was reformulated in the frequency domain using Parseval's theorem, as presented in [61]. The resulting energy-flow spectra at a specific frequency f is defined by:

$$\hat{E}_{mn}(f) = 2Re\{S_{\Delta P_{mn}\Delta \omega_m}(f) + S_{\Delta Q_{mn}\Delta V_m}(f)\} \quad (3)$$

Here, $\hat{E}_{mn}(f)$ is referred as the energy-flow spectra with a frequency component f , $S_{\Delta P_{mn}\Delta \omega_m}(f)$ represents the cross spectral density of the active power and frequency deviation signals, and $S_{\Delta Q_{mn}\Delta V_m}(f)$ represents the cross spectral density of the reactive power and voltage deviation signals.

This spectral formulation is particularly useful for locating forced oscillation (FO) sources. If an FO is known to occur at a particular frequency f , a positive value of $\hat{E}_{mn}(f)$ indicates that energy is propagating away from bus m, implying it is likely the

origin of the oscillation. Conversely, a negative value suggests that energy flowing into bus m , ruling it out as the source.

However, prior studies [59] primarily applied this method using only the active power and frequency component ($S_{\Delta Q_{mn}\Delta V_m}(f)$) in contour-based regional groupings. While this can be effective under certain conditions, it may fail to reliably identify the source in inter-area scenarios involving near-resonance conditions, where the FO frequency closely aligns with a natural mode of the system.

To enhance the robustness of the energy-flow approach and adapt it for real-time dynamic simulation environments, several improvements are introduced in the oscillation source location algorithm. These enhancements support both accurate identification of the oscillation source location and classification of its underlying type (active or reactive power driven).

Once a forced oscillation is detected and its dominant frequency (f_0) is estimated, typically via Fast Fourier Transform (FFT), a full cycle-based sliding window technique is employed to capture transient spectral behavior while preserving frequency resolution. The windowing parameters are defined as:

$$T_w = \frac{1}{f_0}, T_{step} = T_w \times (1 - \alpha) \quad (4)$$

where T_w is the duration of one oscillation cycle, and $\alpha \in (0,1)$ denotes the overlap fraction (commonly set to 0.5 for 50% overlap). This configuration allows for temporally localized spectral analysis, facilitating tracking of oscillatory energy across the grid as it evolves.

Using the sliding window approach, the following four cross-spectral components as shown in equation 5 are computed for each signal pair over each time window using the FFT.

$$\begin{aligned} S_{P\omega}(f_0) &= S_{\Delta P_{mn}\Delta\omega_m}(f_0), & S_{QV}(f_0) &= S_{\Delta Q_{mn}\Delta V_m}(f_0), \\ S_{Q\omega}(f_0) &= S_{\Delta Q_{mn}\Delta\omega_m}(f_0), & S_{PV}(f_0) &= S_{\Delta P_{mn}\Delta V_m}(f_0) \end{aligned} \quad (5)$$

These spectral terms capture energy transfer effects between power (real and reactive) and both frequency and voltage dynamics. Integrating these components yields an extended energy-flow formulation:

$$E_{mn}^{total}(f_0) = 2Re\{S_{P\omega}(f_0) + S_{QV}(f_0) + S_{Q\omega}(f_0) + S_{PV}(f_0)\} \quad (6)$$

This equation provides a more comprehensive and physically meaningful measure of oscillatory energy propagation through system branches. Its application proceeds in three main stages:

- (i) Potential source area/region localization: Once the presence of an FO is identified, branches exhibiting the largest peak-to-peak deviations in power, voltage, or frequency are shortlisted as candidate source regions or buses.
- (ii) Spectral Computation: The dominant FO frequency f_0 is estimated using FFT. Then, Equation (6) is evaluated for each monitored branch using the sliding window approach.
- (iii) If the branches that have maximum energy of $|S_{QV}|$, $|S_{PV}|$, $|S_{Q\omega}|$, $|S_{P\omega}|$, are observed at four different locations, the branch X that has $\max(\max(|S_{QV}|,$

$\max|S_{PV}|, \max|S_{Q\omega}|, \max|S_{P\omega}|$) is selected and the $|S_{Q\omega}|, |S_{P\omega}|$ are compared. If $|S_{P\omega}| > |S_{Q\omega}|$, it is considered as P-type oscillation originating from branch location X.

- (iv) If $|S_{PV}|$, & $|S_{P\omega}|$ are at the same location X, similarly $|S_{Q\omega}|$ & $|S_{QV}|$ are also at the same location of X, the source location is finalized, and the magnitudes are compared to identify the source type.
- (v) Ranking and Classification: A composite energy index is computed to rank branch contributions:

$$E_{mn} = |S_{P\omega}| + |S_{QV}| + |S_{Q\omega}| + |S_{PV}| \quad (7)$$

This scalar metric aggregates the absolute contributions of all four signal components and highlights the branches with highest E_{mn} values as most likely to be the origin of oscillation. To identify the specific source type as P-type or Q-type, the absolute maximum energy of that particular FO source branch is compared. If $|S_{P\omega}| > |S_{Q\omega}|$, and $|S_{PV}| > |S_{QV}|$, the FO is classified as P-type. If $|S_{QV}| > |S_{PV}|$, and $|S_{Q\omega}| > |S_{P\omega}|$, the FO is classified as Q-type FO. This classification scheme provides insight into whether the source is likely a malfunctioning generator governor (P-type) or voltage control device such as an inverter or exciter (Q-type). The complete workflow is outlined in the flowchart presented in **Figure 4-2**.

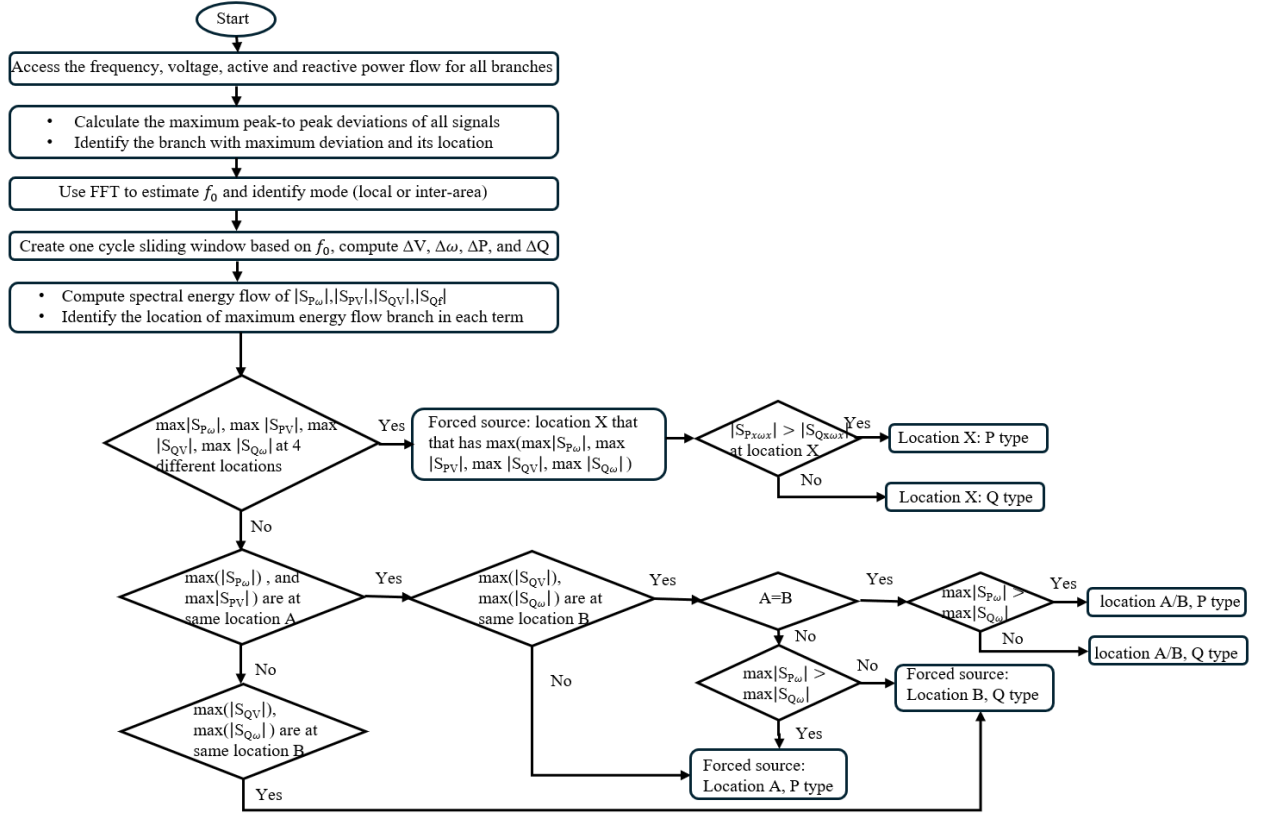


Figure 4-2. Flowchart of the FO source location and classification algorithm

4.4 Results and Discussion

4.4.1 Inter-area Mode Analysis

For inter-area oscillation modes, the energy flow spectra result for Case 1 are illustrated in **Figures 4-3 to 4-5**. In this case, the dominant oscillation frequency corresponds to an inter-area resonance, with the highest peak-to-peak deviations in both frequency and voltage observed in Area 4, as shown in **Figure 4-3**. A system-wide evaluation was conducted, and the energy flow spectral components $S_{P\omega}$, S_{PV} , S_{QV} , $S_{Q\omega}$, along with the total energy flow E_{mn} were computed across all branches for each sub-case (1A to 1D), as presented in **Figures 4-4 and 4-5**. For the exciter, inverter-based resource (IBR) voltage control, and IBR current loop injection cases, the maximum energy in all four spectral components was consistently located at the same branch. This confirmed the source location through strong agreement across $S_{P\omega}$, S_{PV} , S_{QV} , $S_{Q\omega}$, and E_{mn} components. In contrast, for the governor-injected FO case, the maxima in $S_{P\omega}$, S_{PV} , $S_{Q\omega}$, and E_{mn} were all aligned at one branch (location A), whereas the maximum S_{QV} occurred at a different branch (location B). In such cases, location A was correctly selected as the FO source, consistent with the method's robustness in handling partial spectral divergence.

4.4.2 Local Mode Analysis

For local mode excitation (Case 6), the maximum frequency and voltage deviations were directly observed at the true source bus (Bus 1051), as depicted in **Figure 4-6**. The proposed energy-flow spectra method accurately identified Bus 1051 as the source location in all spectral windows, as shown in **Figures 4-7 and 4-8**.

Maximum Peak to Peak Frequency and Voltage Deviation Across the Texas Region
Case 1: 4085 Source Bus Location

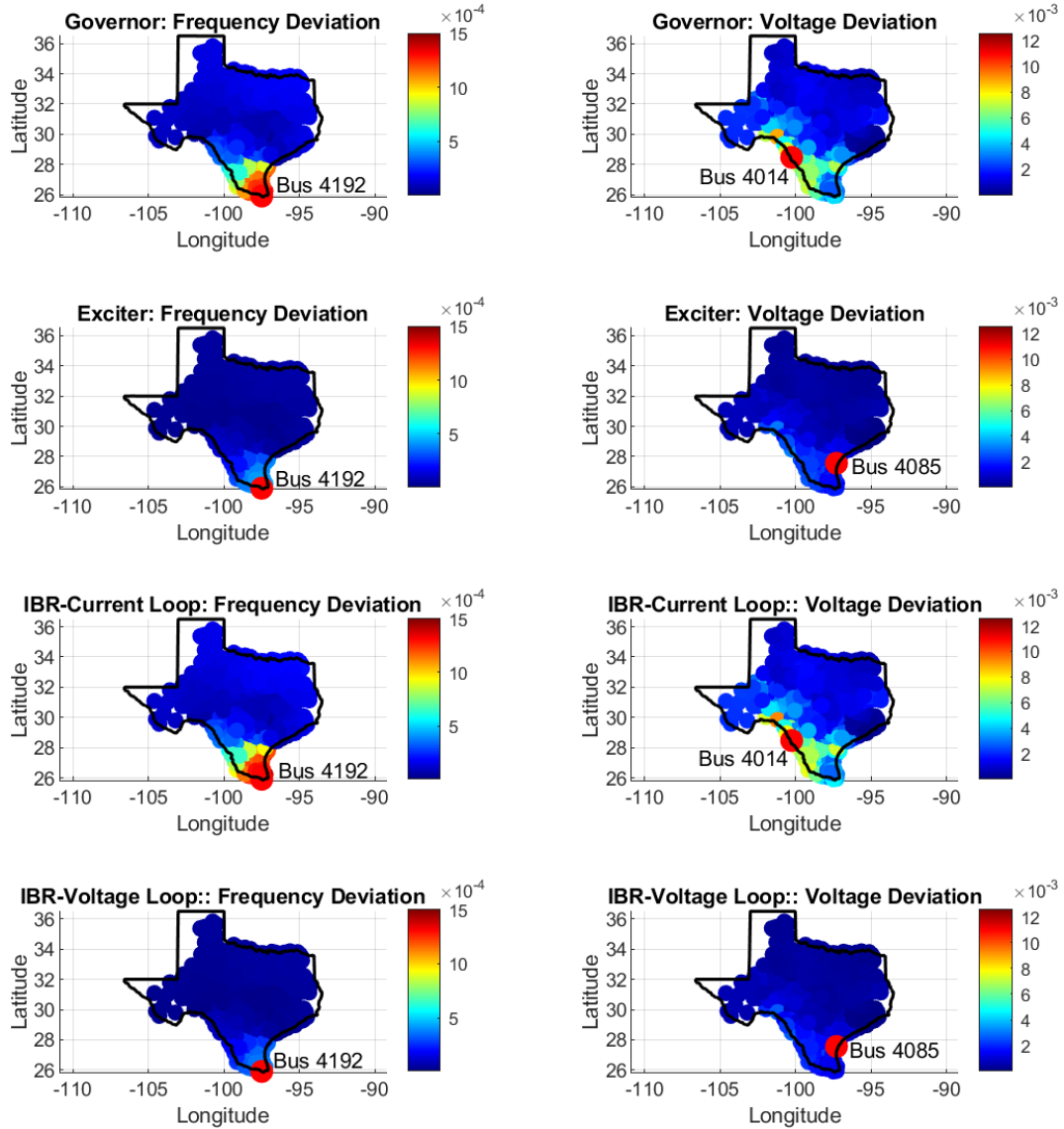
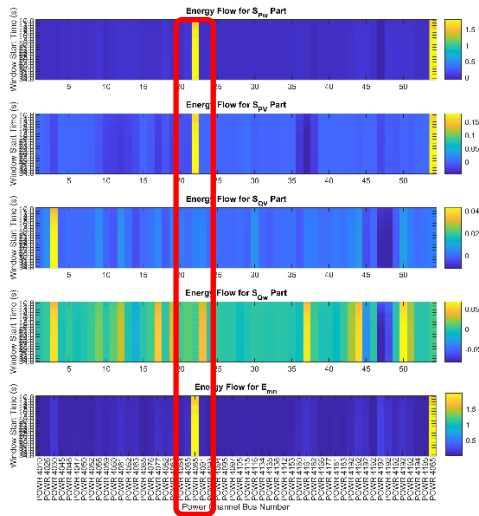


Figure 4-3. Maximum peak-to-peak deviation of frequency and voltage channels for the cases 1A-D

Energy Flow Method Results - 4085 Source - Governor Induced Forced Oscillations



Energy Flow Method Results - 4085 Source - IBR-Current Loop Induced Forced Oscillations

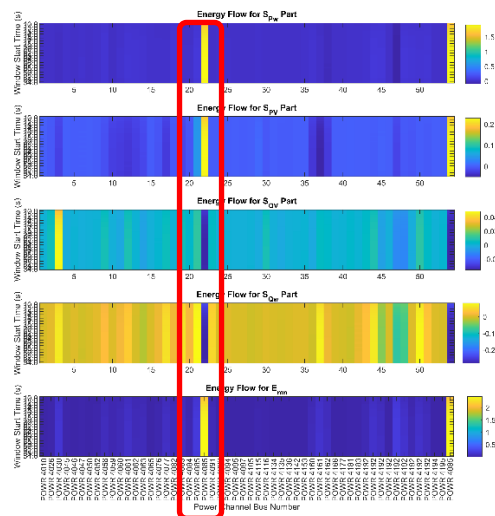
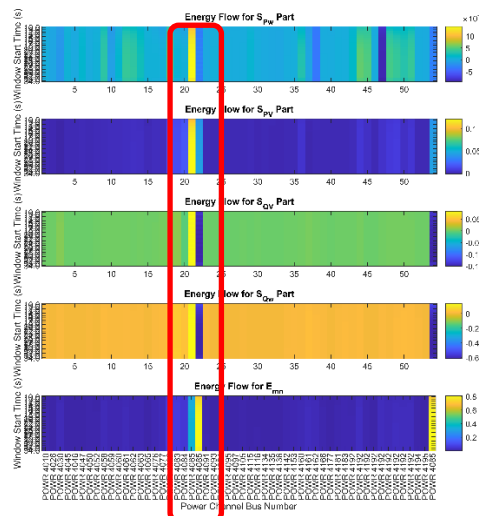


Figure 4-4. Energy flow results for governor, and IBR-current loop (P-type) oscillation cases of 1A and 1B

Energy Flow Method Results - 4085 Source - Exciter Induced Forced Oscillations



Energy Flow Method Results - 4085 Source - IBR-Voltage Loop Induced Forced Oscillations

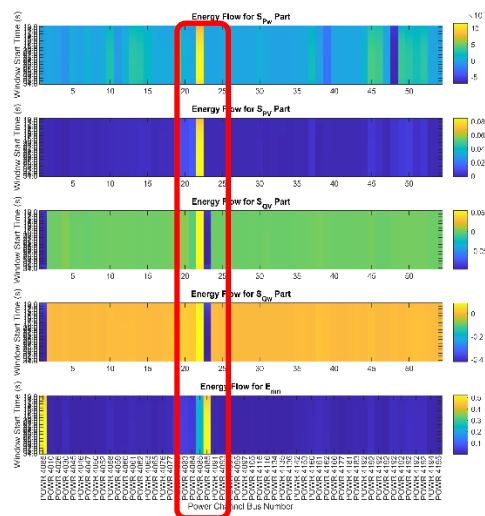


Figure 4-5. Energy flow results for exciter and IBR-voltage loop (Q-type) oscillation cases of 1C and 1D

Maximum Peak to Peak Frequency and Voltage Deviation Across the Texas Region
Case 6: 1051 Source Bus Location

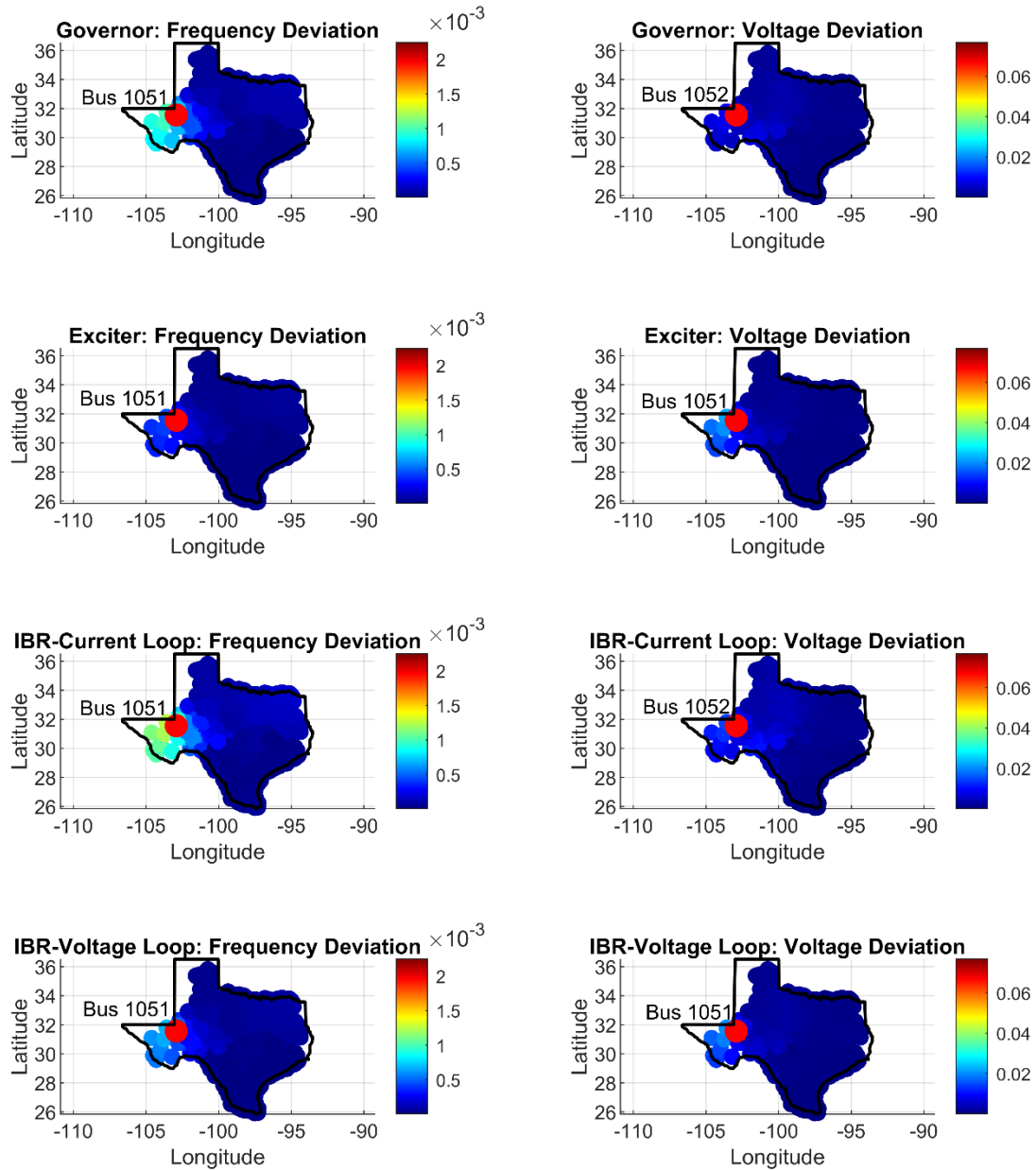
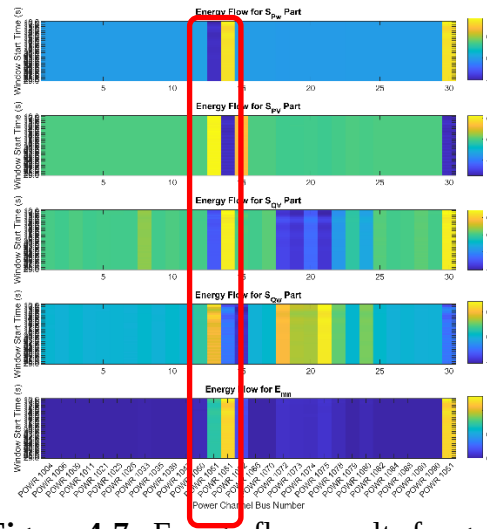


Figure 4-6. Maximum peak-to-peak deviation of frequency and voltage channels for the cases 6A-D

Energy Flow Method Results - 1051 Source - Governor Induced Forced Oscillations



Energy Flow Method Results - 1051 Source - IBR-Current Loop Induced Forced Oscillations

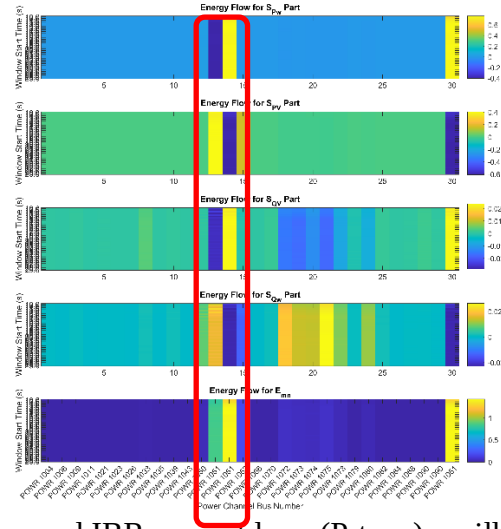
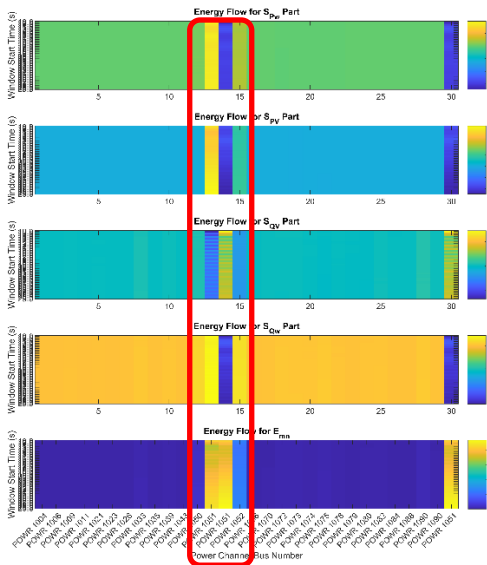


Figure 4-7. Energy flow results for governor, and IBR-current loop (P-type) oscillation cases of 6A and 6B

Energy Flow Method Results - 1051 Source - Exciter Induced Forced Oscillations



Energy Flow Method Results - 1051 Source - IBR-Voltage Loop Induced Forced Oscillations

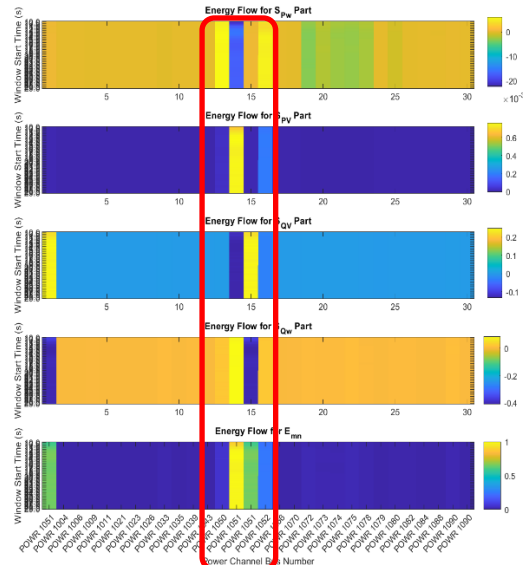


Figure 4-8. Energy flow results for exciter and IBR-voltage loop (Q-type) oscillation cases of 6C and 6D

This confirms the method's precision even for local oscillation modes, where the signal strength is highly concentrated around the origin.

4.4.3 Source Type Classification

In all tested cases, the spectral energy patterns enabled clear FO type classification. Specifically:

- For P-type sources (e.g., governor or active power injection), the magnitudes of $|S_{P\omega}|$ and $|S_{PV}|$ were consistently greater than $|S_{Q\omega}|$ and $|S_{QV}|$, respectively.
- For Q-type sources (e.g., exciter or IBR voltage control), the spectral energy of $|S_{Q\omega}|$ and $|S_{QV}|$, dominated over the active power-related terms.

These trends were consistent across all test cases, validating the effectiveness of the classification logic outlined in the methodology.

4.4.4 Summary of Case Studies

A summary of all simulated forced oscillation cases, including source location accuracy and FO type classification, is provided in **Table 4-2**. The proposed algorithm reliably identified the FO source branches and correctly classified their types for both local and inter-area resonance scenarios. Even in challenging near-resonance conditions, the method demonstrated high robustness. It was observed that in some cases, the identified source was either the true source bus or an adjacent, electrically connected bus, an acceptable margin of error given the spatial spread of oscillation signatures.

Table 4-2. Case studies result of the spectral energy flow method

Case No	FO Freq	Source bus	Source Type	Identified Branch	$ S_{\Delta P^* \Delta f} $	$ S_{\Delta P^* \Delta V} $	$ S_{\Delta Q^* \Delta V} $	$ S_{\Delta Q^* \Delta f} $	Comparison	Source Type
1A	0.667	4085	Governor	POWR 4085	1.7696	0.17611	0.003569	0.0095574	$ S_{\Delta P^* \Delta f} > S_{\Delta Q^* \Delta f} $, $ S_{\Delta P^* \Delta V} > S_{\Delta Q^* \Delta V} $	P-type
1B			IBR-Current loop	POWR 4085	1.878	0.22434	0.034947	0.2733920		
1C			Exciter	VARs 4085	0.0035	0.04281	0.14491	0.60148	$ S_{\Delta Q^* \Delta V} > S_{\Delta P^* \Delta V} $, $ S_{\Delta Q^* \Delta f} > S_{\Delta P^* \Delta f} $	Q-type
1D			IBR-Voltage loop	VARs 4085	3.00E-05	1.65E-04	0.0905	0.41416		
2A	0.63	7208	Governor	POWR 7208	0.15399	0.00544	3.16E-05	0.00127	$ S_{\Delta P^* \Delta f} > S_{\Delta Q^* \Delta f} $, $ S_{\Delta P^* \Delta V} > S_{\Delta Q^* \Delta V} $	P-type
2B			IBR-Current loop	POWR 7208	0.16264	0.006207	6.59E-06	0.00023		
2C			Exciter	VARs 7208	2.43E-05	1.49E-03	0.03124	0.06262	$ S_{\Delta Q^* \Delta V} > S_{\Delta P^* \Delta V} $, $ S_{\Delta Q^* \Delta f} > S_{\Delta P^* \Delta f} $	Q-type
2D			IBR-Voltage loop	VARs 7208	2.20E-07	2.95E-05	0.02307	0.04432		
3A	1.154	4061	Governor	POWR 4061	0.39367	0.040192	0.00074	0.00716	$ S_{\Delta P^* \Delta f} > S_{\Delta Q^* \Delta f} $, $ S_{\Delta P^* \Delta V} > S_{\Delta Q^* \Delta V} $	P-type
3B			IBR-Current loop	POWR 4061	0.39628	0.06063	4.12E-04	0.000823		
3C			Exciter	VARs 4061	0.00283	0.0194	0.06258	0.04968	$ S_{\Delta Q^* \Delta V} > S_{\Delta P^* \Delta V} $, $ S_{\Delta Q^* \Delta f} > S_{\Delta P^* \Delta f} $	Q-type
3D			IBR-Voltage loop	VARs 4061	1.02E-04	0.000865	4.05E-02	6.34E-02		
4A	1.25	4061	Governor	POWR 4061	0.26752	0.0364	0.000429	0.00205	$ S_{\Delta P^* \Delta f} > S_{\Delta Q^* \Delta f} $, $ S_{\Delta P^* \Delta V} > S_{\Delta Q^* \Delta V} $	P-type
4B			IBR-Current loop	POWR 4061	0.27366	0.05492	0.00020	0.00013		
4C			Exciter	VARs 4061	0.00119	0.02905	0.0303	0.0616	$ S_{\Delta Q^* \Delta V} > S_{\Delta P^* \Delta V} $, $ S_{\Delta Q^* \Delta f} > S_{\Delta P^* \Delta f} $	Q-type
4D			IBR-Voltage loop	VARs 4061	4.86E-05	8.29E-04	0.0087	0.0546		
5A	0.884	1051	Governor	POWR 1051	3.3022	0.68993	0.05767	0.16015	$ S_{\Delta P^* \Delta f} > S_{\Delta Q^* \Delta f} $, $ S_{\Delta P^* \Delta V} > S_{\Delta Q^* \Delta V} $	P-type
5B			IBR-Current loop	POWR 1051	3.61074	1.5887	0.08293	0.03928		
5C			Exciter	VARs 1051	0.09479	0.077055	0.16593	0.48518	$ S_{\Delta Q^* \Delta V} > S_{\Delta P^* \Delta V} $, $ S_{\Delta Q^* \Delta f} > S_{\Delta P^* \Delta f} $	Q-type
5D			IBR-Voltage loop	VARs 1051	0.003924	0.010692	0.71188	1.4144		
6A	1	1051	Governor	POWR 1051	0.82641	0.32931	0.01296	0.00898		P-type

Table 4-2 Continued

6B			IBR-Current loop	POWR 1051	0.754657	0.60554	0.02340	0.02231	$ S_{\Delta P^* \Delta f} > S_{\Delta Q^* \Delta f} $, $ S_{\Delta P^* \Delta V} > S_{\Delta Q^* \Delta V} $	
6C			Exciter	VARs 1051	0.0148301	0.037468	0.492421	0.253676	$ S_{\Delta Q^* \Delta V} > S_{\Delta P^* \Delta V} $, $ S_{\Delta Q^* \Delta f} > S_{\Delta P^* \Delta f} $	Q-type
6D			IBR-Voltage loop	VARs 1051	0.000441	0.005603	0.24094	0.401350		
7A	1.25	7098	Governor	POWR 7098	0.80387	0.596289	0.048972	0.065097	$ S_{\Delta P^* \Delta f} > S_{\Delta Q^* \Delta f} $, $ S_{\Delta P^* \Delta V} > S_{\Delta Q^* \Delta V} $	P-type
7B			IBR-Current loop	POWR 7098	0.913570	0.839044	0.272619	0.29619		
7C			Exciter	VARs 7098	0.009097	0.028132	0.155851	0.199594	$ S_{\Delta Q^* \Delta V} > S_{\Delta P^* \Delta V} $, $ S_{\Delta Q^* \Delta f} > S_{\Delta P^* \Delta f} $	Q-type
7D			IBR-Voltage loop	VARs 7098	1.10E-04	2.23E-04	0.169645	0.180647		Q-type
8A	1.35	7353	Governor	POWR 7353	0.064835	0.001949	1.24E-05	1.07E-03	$ S_{\Delta P^* \Delta f} > S_{\Delta Q^* \Delta f} $, $ S_{\Delta P^* \Delta V} > S_{\Delta Q^* \Delta V} $	P-type
8B			IBR-Current loop	POWR 7353	0.066167	0.002515	1.93E-05	1.56E-04		
8C			Exciter	VARs 7353	8.69E-06	3.77E-04	1.84E-03	5.28E-03	$ S_{\Delta Q^* \Delta V} > S_{\Delta P^* \Delta V} $, $ S_{\Delta Q^* \Delta f} > S_{\Delta P^* \Delta f} $	Q-type
8D			IBR-Voltage loop	VARs 7353	1.16E-06	3.54E-05	0.002421	4.06E-03		
9A	1	6147	Governor	POWR 6147	0.137533	0.030004	1.40E-04	0.001723	$ S_{\Delta P^* \Delta f} > S_{\Delta Q^* \Delta f} $, $ S_{\Delta P^* \Delta V} > S_{\Delta Q^* \Delta V} $	P-type
9B			IBR-Current loop	POWR 6147	0.132178	0.035467	0.005572	0.021995		
9C			Exciter	VARs 6147	0.000952	2.30E-04	0.015602	0.019345	$ S_{\Delta Q^* \Delta V} > S_{\Delta P^* \Delta V} $, $ S_{\Delta Q^* \Delta f} > S_{\Delta P^* \Delta f} $	Q-type
9D			IBR-Voltage loop	VARs 6147	6.40E-07	1.97E-05	0.01215	0.018129		
10A	1.4	2117	Governor	POWR 2117	0.226212	0.080291	0.001501	0.00023	$ S_{\Delta P^* \Delta f} > S_{\Delta Q^* \Delta f} $, $ S_{\Delta P^* \Delta V} > S_{\Delta Q^* \Delta V} $	P-type
10B			IBR-Current loop	POWR 2117	0.240735	0.116382	0.00107	0.001177		
10C			Exciter	VARs 2117	7.39E-04	1.09E-02	0.00334	0.053177	$ S_{\Delta Q^* \Delta V} > S_{\Delta P^* \Delta V} $, $ S_{\Delta Q^* \Delta f} > S_{\Delta P^* \Delta f} $	Q-type
10D			IBR-Voltage loop	VARs 2117	7.32E-05	6.83E-04	0.010644	0.045617		

4.5 Conclusion

This paper presents an enhanced energy-flow spectral analysis method for accurately locating FO sources and classifying their types in large-scale power systems. By incorporating a full set of cross-spectral components, linking active and reactive power flows with both frequency and voltage dynamics, and employing a cycle-based sliding window strategy, the proposed approach improves temporal resolution and robustness under resonance and near-resonance conditions. Simulation results on a synthetic Texas power system demonstrate the method's effectiveness in identifying both local and inter-area FO sources, with consistent source type classification across various injection scenarios.

Future work will focus on extending this framework to accommodate real-world PMU data with missing or asynchronous measurements. Additionally, integration with real-time grid monitoring systems and exploration of machine learning techniques for automated FO source location and classification present promising directions to further enhance situational awareness in modern power grids.

CHAPTER 5

ANALYSIS OF EFFECTIVE IBR ACTUATORS FOR FORCED OSCILLATION

MITIGATION

Abstract

FOs occurring at frequencies close to a system's natural oscillation mode can induce resonance and widespread of high-amplitude oscillations. Different from mitigation approaches for natural oscillations, addressing FO mitigation requires special attention due to uncertainties of the FO source localization. Currently, the accurate identification of FO source at the component level is time-consuming and unreliable. Supplementary FO damping control (FODC) through Inverter-Based Resources (IBR) is one state-of-the-art FO mitigation method. Selecting effective IBRs for FO mitigation is a critical step to guarantee the FO damping performance. This study explores how to select the most effective IBRs for damping FO resonant event with an inter-area natural oscillation. The study results in the 121-bus mesh system show that the FODC through the IBRs near the FO source and close to the generators with high participation factor of natural oscillations can effectively mitigate FO events than other locations.

5.1 Introduction

The occurrence of FOs presents a substantial threat to the secure and reliable operation of power grids. It is one of the prominent challenges confronted by the electric power industry in real-time as it reduces the power quality, limits the power transfer capability, and potentially damages the equipment. Several forced oscillation cases that occur across the US are summarized in [16], [20], [50] . Unlike natural oscillations that occur due to electromechanical dynamics governing the system, FOs may originate from diverse root causes, encompassing malfunctioning equipment, mechanical valve failures, control systems with faulty designs or incorrect settings, mistuned power system

stabilizer (PSS) and governor control settings, inaccurate DC converter station settings, abnormal generator operating conditions, and cyclic load [13], [50].

The occurrence of FO aligning with undamped or inadequately damped natural oscillation modes in the system can lead to resonance, resulting in the widespread propagation of FO with amplified magnitude [6]. Inter-area natural modes, given their widely distributed geographical nature, are particularly prone to resonance when FO's frequency is close to a weakly damped natural inter-area mode [6]. Additionally, the resonance between FOs and inter-area natural oscillations becomes more serious when the FO sources are close to the generators with high participation of natural oscillation mode. Hence, it is crucial to mitigate these FOs promptly and efficiently in order to preserve the stability of the power system, avoid cascading failures, and make the most use of Inverter based resources (IBRs).

The disconnection or correcting of the source that creates the FO is the straightforward path for FO elimination. Additionally, theoretical measures to mitigate FO include shifting the disturbance frequency far from the system's natural frequency mode, reducing the amplitude of forced disturbances, and enhancing the damping ratio of the system mode [62]. Several oscillation source detection algorithms have been proposed to identify the FO source at a specific region level [15], [62], [63], [64]. However, locating the source accurately within the specific control level of the substation and/or the generator can be a time-consuming process at the present moment. Therefore, suppressing the FO energy to be within the safe level is the feasible measure before identifying the source.

Traditionally, large-scale power systems frequently employ power system stabilizers (PSSs) at conventional synchronous generators to control the local or inter-area natural oscillations. However, the decommissioning of conventional synchronous generators and the growing integration of IBRs, changing the grid characteristics by reducing inertia and the damping of the inter-area natural modes. Concurrently, the increase in IBR penetration can also be used for fast oscillation-damping of FO and natural oscillations by tuning the active and reactive power of IBRs. However, it is extremely important to accurately design and tune the damping control of IBRs as they can also trigger other stability problems.

In literature, several forced oscillation damping controllers (FODCs) have been proposed to effectively dampen the natural and FOs. Using the wide-area phasor measurement units (PMUs) and with the help of remote feedback signals, several FODC methods have been proposed for synchronous generators, IBRs, HVDCs, and battery energy storage systems (BESSs) [65], [66], [67], [68]. The fidelity of the grid simulation model is still crucial to several FODC designing techniques using IBRs and requires remote feedback signals. The power grid's dynamic features are subject to large fluctuations due to the variability of renewable energy sources and load demand, making accurate real-time modeling challenging.

The control strategy demonstrated in [69] and [14], discusses the effective way to mitigate the FO by tuning the active power of IBR through a supplementary controller close to the FO source. However, identification of the FO location is a time-consuming process as this strategy works to mitigate the FO amplitude before removing the FO.

Moreover, the details on the selection of feedback signal, and the selection of IBRs are not discussed. While some FODC techniques depend on choosing a feedback signal from buses with the highest magnitude during the FO event [13], it is noteworthy that these high-magnitude generators are typically those exhibiting significant participation in the natural oscillation rather than those directly linked to the forced source. Consequently, relying solely on a remote feedback signal proves impractical, potentially leading to inaccuracies in representing the magnitude of the FO.

In this study, the local bus feedback signals are used to study the optimal selection of IBRs for damping resonant FO events. Different locations of IBRs are selected to analyze their impact on damping FOs. The power system topology impact, such as transmission line distance, is also studied. The rest of the chapter is organized as follows. Section 5.2 provides the theoretical background of the FO external disturbance; mesh modeling and the effective IBR selection method for FODCs. Section 5.3 describes the structure of the FODC controller. Section 5.4 discusses the case study results. Finally, Section 5.5 summarizes the study.

5.2 METHODOLOGY

5.2.1. Theoretical Background

During the FO event occurrence, the total response of the power system consists of forced response as well as natural (Modal) response. In [5], considering the power system dynamics with external FO disturbance (u_f) ($u_f = P_f \sin(\omega_f)$) at bus n , the explicit expression of transient response ($\Delta y(t)$) is given as:

$$\Delta \mathbf{y}(t) = \sum_{i=1}^n \sum_{r=1}^m Z [e^{-i\zeta_{nr}\omega_{nr}t} \sin(\omega_{nr}t + \varphi_n) - \beta \sin(\omega_f t + \varphi_f)] \quad (5)$$

where ω_f is the external FO source oscillation frequency, ω_{nr} is the natural mode (λ_r) oscillation frequency with damping ratio ζ_{nr} .

The FO magnitude (Z) is defined as:

$$Z = c_i |\phi_{ir}| |\psi_{ri}| P_f * \frac{2\omega_f}{\sqrt{(\omega_{nr}^2 - \omega_f^2)^2 + 4\zeta_r^2 \omega_{nr}^2 \omega_f^2}} \quad (6)$$

$$\varphi = \tan^{-1} \left(\frac{\omega_{nr}^2 - \omega_f^2}{2\zeta_r \omega_{nr}^2} \right) \quad (7)$$

where P_f is the amplitude of the FO source, φ is the phase shift between the FO ($\Delta y(t)$) and the forced disturbance u_f . For the natural mode λ_r , the Φ_{ir} and Ψ_{ri} are the corresponding right and left eigenvector matrices.

As shown in equations (1) and (2), the location of FO, which is defined by the high participation factor $|\phi_{ir}| |\psi_{ri}|$ of the natural oscillation mode (λ_r), and the amplitude P_f of the forced source, both have a direct impact on the severity of FO events. Additionally, the severity increases when FO frequency (ω_f) approaches the natural oscillation frequency (ω_{nr}) with a low damping ratio (ζ_{nr}), as the magnitude (Z) increases [5]. Acknowledging the time-consuming process of FO source location, and the uncontrollable nature of FO frequency and location, this study aims to study the ways to reduce the severity of FO by improving the damping ratio (ζ_{nr}) of the natural oscillation

mode and reducing FO energy (P_f) through the implementation of FODC control at multiple IBRs. This study results could be useful for effective selection of IBR actuators at highly participating generators to improve the oscillation damping and reduce the severity of FO.

5.2.2. Mesh Modeling & IBRs Selection Analysis

A uniform 121-bus mesh power grid is designed for this study in PSS/E Version 34. The mesh system is balanced by connecting a generator, a load at each bus, and an IBR device with 0 MW output. The synchronous generator generates an active power (P_{gen}) of 100 MW, and reactive power (Q_{gen}) of 10 MVAR. The maximum and minimum active and reactive power capacity of each generator is 300 MW, 50 MVAR, and -50 MW, -50 MVAR respectively. A load of 100 MW and 10 MVAR is connected to each bus. Each bus is spaced equally in both horizontal and vertical directions considering a transmission line length of 50 Km with a corresponding transmission line reactance of $0.0367j \Omega$. The four corner buses 1,11,111, and 121 of the mesh are defined as swing buses. The classical generator model “GENCLS” is used for each synchronous generator and the exciters and/or governors are not defined in the mesh system. The small signal stability analysis is conducted using SSAT tool to obtain the natural inter-area oscillation modes of the mesh system as given in **Table 5-1**. The structure of the 121-bus system with two dominant inter-area oscillation modes with highly participating generator locations are shown in **Figure 5-1**.

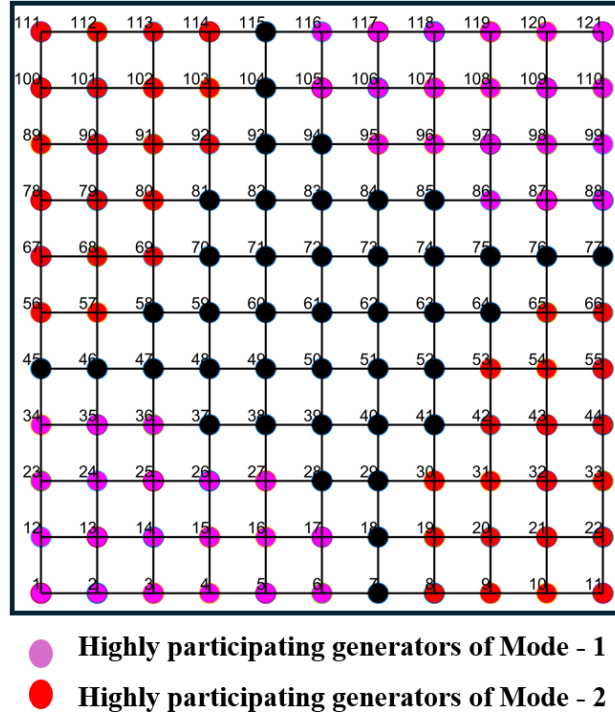


Figure 5-1. 121-Bus mesh grid with two dominant oscillation modes

Table 5-1. Small signal stability results of the mesh system

Modes	Eigen Values	Frequency	Damping
Mode 1	$-0.20+4.0695i$	0.647 Hz	4.91%
Mode 2	$-0.20+4.0696i$	0.647 Hz	4.91%

To mimic the FO in the mesh system, a simple turbine- governor (TGOV1) model is attached to the specific generator in each case and a sinusoidal signal with an inter-area oscillation frequency of 0.647 Hz, 200 MW is injected at the reference point of the governor active power set point (P_{ref}) as specified in [13]. Considering the small signal stability analysis results, and the control strategy specified in the following section, multiple IBR actuators are chosen according to the participation factor of the generators in the inter area mode to study the impact of IBR damping. The flowchart for selecting and tuning IBRs control is given in **Figure 5-2**.

5.3 STRUCTURE OF FODC THROUGH IBR

The design of the FODC for IBR's active power modulation is presented in this section. A utility-scale inverter-based wind/solar model or battery energy storage system (BESS) can be used to implement the proposed controller. Dynamic models such as the converter model (REGCAU2), the electrical control model (REECCU1), and the plant controller model (REPCA1) with default parameters specified in [70] are used to model the IBRs in this work. The performance of auxiliary FODC injection at the inverter-level control and plant-level control are studied respectively. The frequency deviation (Δf) of the local IBR bus from the nominal frequency (i.e., 60 Hz) is used as the feedback signal of the FODC. The structure of the FODC through IBR is shown in **Figure 5-3**. The FODC consists of a lead-lag structure that includes a limiter, a washout (τ_w), a filter (K_f), phase correction blocks (T_1, T_2, T_3, T_4), and a gain (K). The washout time constant is $\tau_w = 10$ seconds, T_1, T_2, T_3 , and T_4 are the lead and lag time constants of the phase compensation block. P_{FODC_max} and P_{FODC_min} are upper and lower limits of the FODC

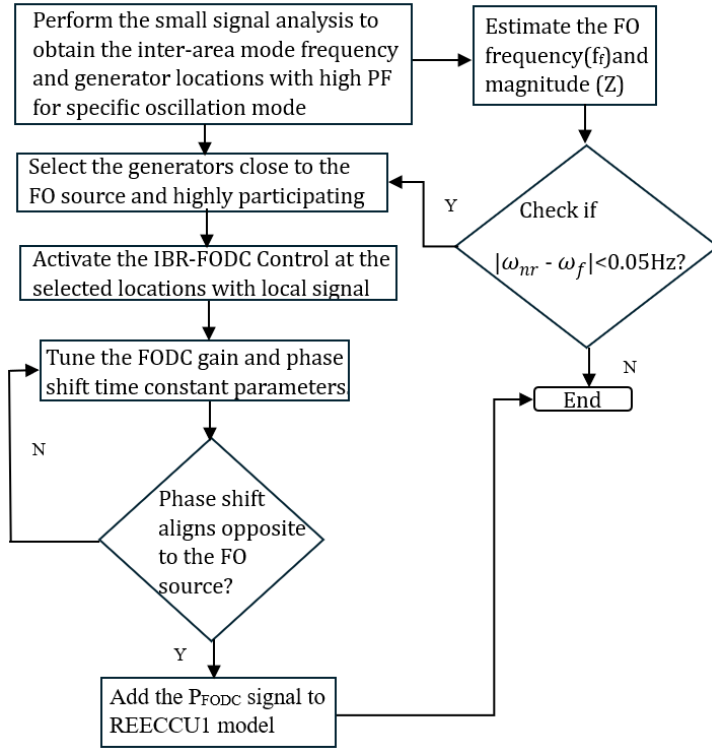


Figure 5-2. Flowchart for IBR selection and tuning process

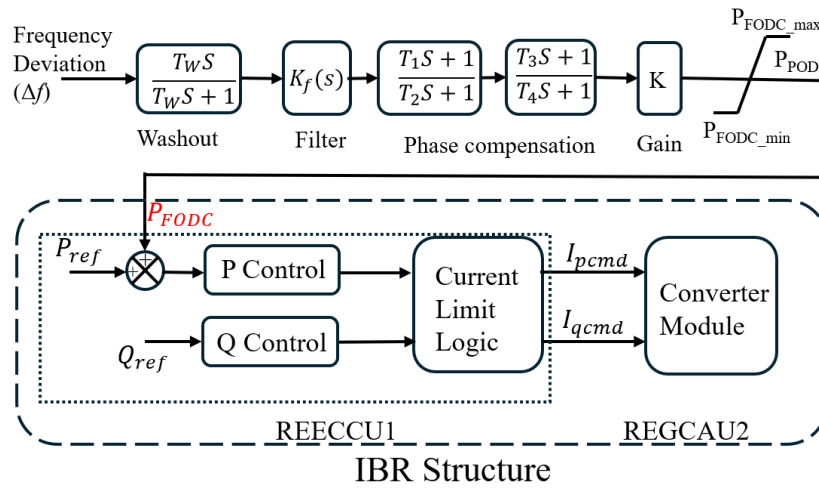


Figure 5-3. The block diagram of FODC controller [70]

output. The gain and phase compensation of a controller are the key factors that dictate the controller's performance; thus, they must be carefully considered during design. For the specific oscillation mode and the control gain, the phase compensation can be computed using the specified method in [70]. The controller's output (P_{FODC}) can be added either to the ' P_{aux} ' signal of the REECUI model or at the 'Plant_ref' of the REPCA1 model to adjust the active power of each IBR as shown in **Figure 5-3**.

5. 4. CASE STUDY RESULTS

In this section, the case study results of FOs mitigation with multiple IBRs selection are discussed. The necessity of multiple IBRs selection and activation, parameters influencing the FO damping, and the optimal selection of IBR locations are discussed. The participation factors of generators higher than 0.65 for the two inter-area modes are summarized in **Table 5-2**. The two buses in each row of **Table 5-2** are opposite to each other with the same participation factor as shown in **Figure 5-1**.

Case – 1: FO Event and IBR Control at generator locations with High Participation factors in Natural Oscillation.

Generators that strongly relate to a weakly damped inter-area mode in a practical power system always have large participation factors. If an FO event with sustained nature of large magnitudes occurs at these generators, severe FO will emerge and be widespread across the system [5]. The occurrence of FO events on these generators can cause resonance if the FO frequency is close to the natural mode. To simulate the resonance case, 200 MW FOs are injected with an inter-area frequency of 0.647 Hz at highly participating generator 119.

Table 5-2. Participating generator location for Mode 1 & 2

Mode-1 participating Generators		Mode-2 Participating Generators	
<i>Gen. No</i>	<i>PF</i>	<i>Gen. No</i>	<i>PF</i>
121, 1	1.0	111, 11	1.0
110, 12	0.96	112, 10	0.96
120, 2	0.96	100, 22	0.95
109, 13	0.92	101, 21	0.92
99, 23	0.89	113, 9	0.90
119, 3	0.88	89, 33	0.87
98, 24	0.84	102, 20	0.85
108, 14	0.84	90, 32	0.83
88, 34	0.78	114, 8	0.80
97, 25	0.76	91, 31	0.76
118, 4	0.76	103, 19	0.75
87, 35	0.74	78, 44	0.75
107, 15	0.72	79, 43	0.71
86, 36	0.66	115, 7	0.68
77, 45	0.66	92, 30	0.67

In the event of FO at generator 119, the activation of 8 IBRs control at the highly participating generators is compared with the 8 IBRs control at the non-participating generators, as illustrated in **Figure 5-4**. The left column of **Figure 5-4** displays the locations of the FO source and the IBRs. The middle column shows the frequency response of all 121 buses when the FODC signal is injected at the inverter-level control. The right column presents the frequency response when the FODC signal injected at plant control model. To improve the damping, 8 IBRs control at the highly participating generators are tuned. When the FODC signal is injected at the inverter level, each IBR generates 20 MW, totaling 161.11 MW. As shown in the plot of **Figure 5-4(b)**, the maximum peak-to-peak frequency deviation is reduced from 0.1680 Hz to 0.0393 Hz, mitigating the FO magnitude by 72.5%. In comparison, the activation of 8 IBRs control at the non-participating generators in the center reduced the frequency deviation of the FO source only by 19.76% from 0.1680 Hz to 0.1348 Hz. As shown in the middle and the right-side plots of **Figure 5-4**, the implementation of the auxiliary FODC control at the inverter-level control as well as the plant control level will guarantee a similar damping performance. The comparison of damping performance in case of injecting FODC signal at the inverter-level and the plant-level control is summarized in **Table 5-3**.

Case –2: FO Event at Non-Participating Generator and IBR Control Selection

The effectiveness of the multiple IBR control, in the case of injecting FO at the non-participating bus, is studied. The 200MW, 0.647Hz FO is injected at the generator connected to bus 83. The IBR control strategy is implemented at 4 closest generators to the FO source, 4 highly participating generators, as well as the 8 IBRs comprising 4

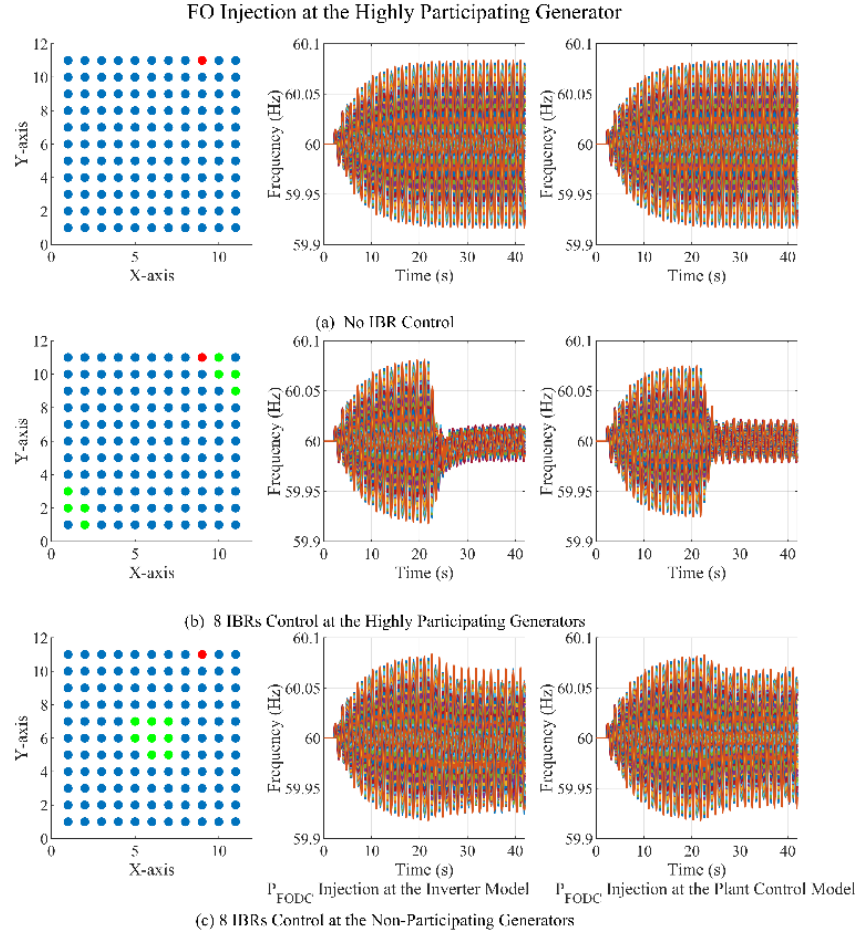


Figure 5-4. Frequency Response with 8 IBRs control at the highly participating and non-participating generators.

Table 5-3. Damping performance comparison

Cases	Mode	Inverter-level Control	Plant-level Control
Case - 1	No control	0.1680 Hz	0.1680 Hz
	8 IBRs at High-PF Generators	0.0393 Hz	0.0417 Hz
	8 IBRs at Non-PF Generators	0.1348 Hz	0.1310 Hz
Case - 2	No control	0.0517 Hz	0.0517 Hz
	4 IBRs close to the FO source	0.0286 Hz	0.0220 Hz
	4 IBRs close to the FO source	0.0280 Hz	0.0214 Hz
	8 IBRs at High-PF Generators	0.0219 Hz	0.0210 Hz

closest generators and 4 IBRs at the highly participating generators of the mesh are activated. The frequency response of this case is shown in **Figure 5-5**. The frequency response of this case is shown in **Figure 5-5**. The maximum peak-to-peak frequency deviation under no control is 0.0517 Hz as shown in **Figure 5-5(a)**. In **Figure 5-5(b)** and **5-5(c)**, 4 IBRs control at generators close to the FO source, and 4 IBRs at the corner highly participating generators are compared. When the auxiliary control was injected from the inverter-level at the closest 4 IBRs, the FO source maximum peak-to-peak frequency deviation reduced to 0.0286 Hz. Similarly, activation of 4 IBRS at the corner highly participating generators can reduce the maximum peak-to-peak frequency deviation to 0.0280Hz. In **Figure 5-5 (d)**, activation of 8 IBRs reduced the maximum peak-to-peak frequency deviation of FO source by 57.64% from 0.0517 Hz to 0.0219 Hz. Similarly, FODC implemented at plant-level control and inverter-level control can get similar damping performance as shown in **Table 5-3**. The peak-to-peak frequency deviation of the system with no control, and with 8 IBRs control is shown in **Figure 5-6**. The activation of multiple IBRs at the highly participating generators and close to the FO source with significantly reduced the severity of the FO source and can achieve the best damping performance [71].

5.5 Effect of Transmission line distance/ Impedance

Transmission line distance/impedance plays an inverse relationship in the damping of oscillations. Proximity of IBR activation to the FO source increases damping, while the damping capacity decreases with an increase in transmission line distance/reactance.

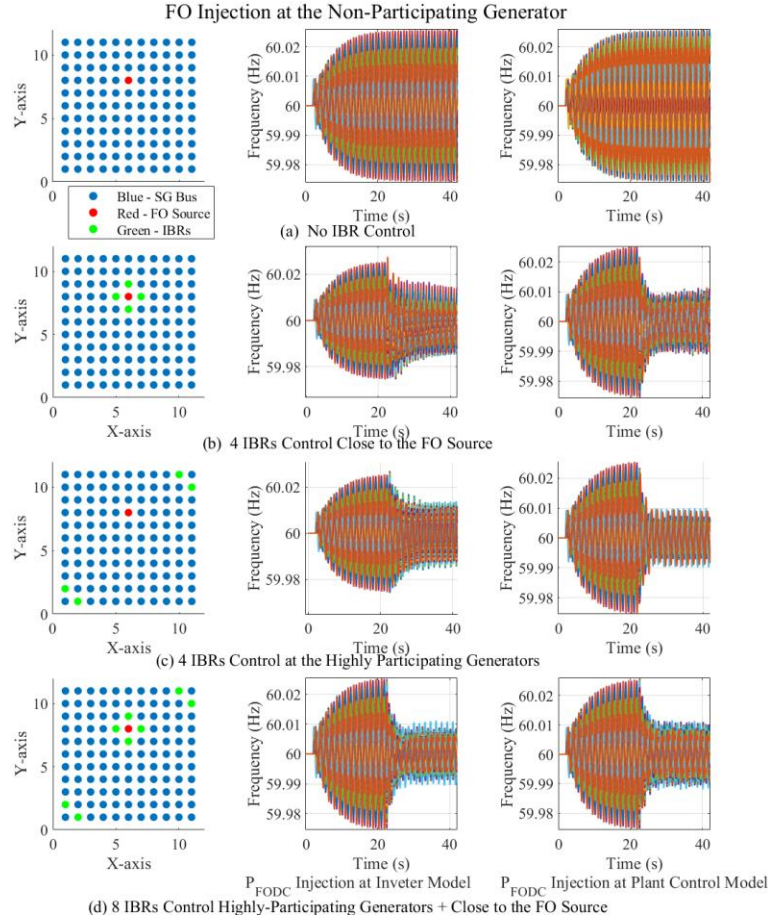


Figure 5-5. Frequency response in case of FO Event at non-participating generator

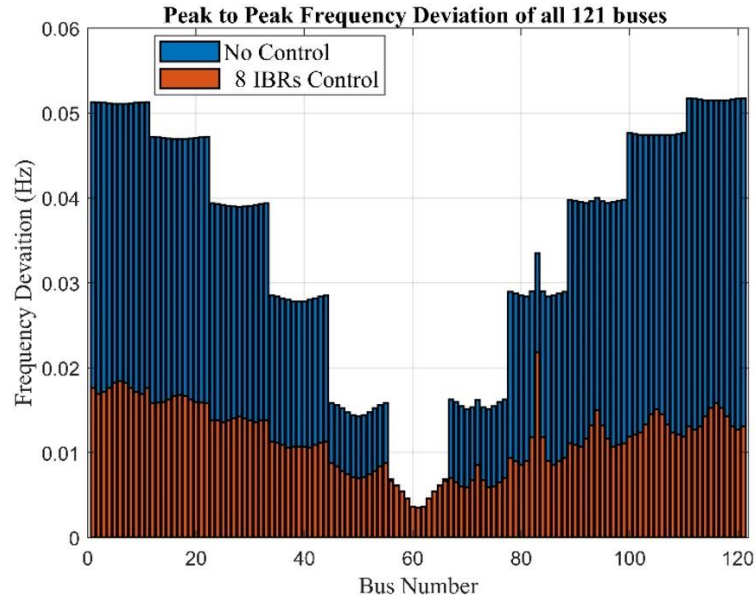


Figure 5-6. Frequency response with no control and 8 IBRs control for FO Event at generator – 83.

To study the impact of transmission line distance/Impedance on FO damping, the 200 MW FO is injected at bus 119, and a single IBR at the closest generator is activated with a gain of -1000. The transmission line reactance is increased according to the transmission line length of 10, 50, and 100 KM. As shown in **Table 5-4**, under no control, the maximum peak-to-peak frequency deviation is 0.1542 Hz. Activation of an IBR in 10 Km reduced the frequency deviation to 0.096 Hz. While the frequency deviation is increased to 0.1119 Hz, increasing the distance to 100 KM.

5.6 CONCLUSION

The FO frequency mode close to the inter-area natural oscillation mode of the system can cause increased amplitude and wide propagation of oscillations. By implementing FODCs at the effective location of IBRs with local feedback signals can reduce the FO impact significantly. Case studies demonstrate the effectiveness of activating IBR control near the FO source and close to the generator locations with high PF of inter-area natural oscillation mode, thereby increasing the damping performance and reducing the overall impact of FO on the bulk power system. Transmission line impedance/reactance is identified as a crucial factor, with an increase in distance/impedance potentially reducing IBR damping effectiveness. Overall, this research contributes valuable insights in mitigating FO impact and informs IBR selection strategies for enhancing system stability. Future work will involve the implementation of FODC control for local FO mitigation and analyzing the influence of grid forming IBRs on FO damping.

Table 5-4. Peak-to-peak frequency deviation versus distance

Mode	Transmission Line Distance		
	<i>10 KM</i>	<i>50 KM</i>	<i>100 KM</i>
No control	0.156 Hz		
Single IBR Control	0.096 Hz	0.0108 Hz	0.1119 Hz

CHAPTER 6

**MEASUREMENT-BASED DYNAMIC EQUIVALENCING OF LARGE-SCALE
POWER SYSTEMS USING RECURRENT NEURAL NETWORKS**

Abstract

The growing complexity of interconnected power systems increases the dynamic simulation time of full-order systems, creating computational challenges for dynamic security assessment. Researchers explore model reduction strategies to improve efficiency, focusing on a study area while approximating external regions. Measurement-based techniques use online measurement or historical data to derive and update the dynamic equivalents in response to the changing system operating conditions. Recurrent Neural Networks (RNNs), such as long short-term memory (LSTM), and gated recurrent unit (GRU), excel at predicting non-linear power system behavior. In this study, a dynamic equivalencing approach is proposed, where equivalent loads at the boundary tie-lines represent external areas. These equivalent loads are updated through predictions from an LSTM/GRU-based model, with boundary voltage and frequency measurements as inputs. The case study analysis is performed on the Northeast Power Coordinating Council (NPCC) 140-bus system and the Eastern Interconnection constituting 70,000 bus systems. The dynamic response of power system events such as generator trip, load trip, bus fault, and successive load trip events are predicted. The results confirm the LSTM/GRU model's high accuracy in predicting power system behavior during tested events and adapting to changes in operating conditions, highlighting their potential for dynamic equivalencing in large-scale power systems.

6.1 Introduction

Power system planners and operators use dynamic simulations to evaluate the system's behavior under various disturbances, ensuring reliable grid operation. However,

modern power systems, with their intermittent renewable energy sources, present challenges due to the increased complexity and size of the grid. These factors demand more computational resources for dynamic simulation. The integration of smart grid technologies plays a crucial role in addressing these challenges by enabling better management and coordination of renewable energy sources. However, the significant variations in power generation from renewables still necessitate the use of real-time dynamic model reduction to optimize simulation processes and ensure grid stability. Normally, individual utilities are primarily interested in the dynamics within their service territory. To address this, the power industry aims to minimize the size and simulation time of large-scale power systems while maintaining dynamic behavior within the service region. One effective strategy to achieve this is model reduction, which involves partitioning the large power system into two groups: the study area and the external area [72]. The study area, which is the primary focus, retains all model details, while the external area, representing the overall behavior, is truncated. The tie-lines between these areas maintain the reduced system's integrity. This approach aims to predict the power system's dynamic trajectory faster than real-time simulation, enhancing operational efficiency.

Many of the model reduction strategies require access to a detailed dynamic model of large-scale systems. The complexity of these interconnections complicates dynamic analysis due to nonlinear responses during disturbances, with each electrical component governed by algebraic and differential equations. Simulating vast power systems is time-consuming, given the limited processing capabilities of current software,

making real-time solutions of differential-algebraic equations (DAEs) increasingly difficult. Additionally, because detailed dynamic models are not frequently updated, the accuracy of the simulations can degrade over time, further complicating the reduction process and affecting the reliability of system responses. The challenge of dynamically reducing large-scale power systems while preserving essential dynamics, minimizing errors, and using fewer computational resources remains unsolved.

In literature, various dynamic equivalencing techniques have been developed over the past few decades. Based on the level of knowledge required to represent the external system for power system analysis, the dynamic equivalencing methods are categorized into two types as Model-based and Measurement-based methods. As a preliminary step towards reducing the models via model-based techniques, principal component analysis is used to linearize the original model[73]. Subsequently, linear model-based reduction techniques, including the Krylov subspace [74], [75] , dominating pole [76], low-rank Choleski factor [77], and balanced truncation methods have been proposed [78]. These techniques have demonstrated accurate performance in projecting the relationship between the study area and the external area, especially under small disturbances. However, for large power grid disturbances, these methods can produce inaccurate results due to large error values [79]. Additionally, linearly reduced models can be computationally complex. To address this, nonlinear model reduction strategies have been proposed [80], [81], [82]. The adaptive nonlinear model reduction approach involves determining an appropriate threshold for simulated state variables, such as rotor angle deviations. This threshold must be determined by experience or approximation

from adequate offline research, as it is frequently system specific. Another methodology using participation factors of state variables on system modes for more adaptable model reduction has been proposed in [79].

While the aforementioned linear and nonlinear reduction techniques are integral to model-based methods, another key subset of model-based approaches includes coherency-based methods, linear model equivalencing methods, synchrony, and system identification approaches [83]. These require a detailed full model of the external system and are primarily used in offline studies. Among all, the coherency-based method is one of the most promising and widely used techniques. It involves identifying coherent generators through specific perturbations, grouping them into equivalent generators, and performing network reduction to eliminate load buses [72], [84], [85], [86], [87], [88], [89], [90], [91]. A commercial software tool called 'DYNRED', developed by EPRI, is based on this approach [92]. However, coherency-based methods face several challenges. Coherent groups depend on system operating conditions, which continuously change in real-time operations, requiring substantial computational effort to update, making it impractical for online applications. Additionally, the accuracy of these methods depends on the fidelity of the detailed model, and in real-time applications, accurate modeling of the external system may be difficult or unavailable to a single entity. Furthermore, aggregating generators can introduce errors due to the omission of detailed controller representations [93].

In contrast to model-based methods, measurement-based reduction techniques have been extensively reviewed over the past few years [94], [95], [96], [97]. This class

of methods doesn't depend on the detailed model of the entire system. Measurement-based methods utilize real-time measurements from phasor measurement units (PMUs) and frequency disturbance recorders (FDRs) devices to update the dynamic equivalents of the external system through system identification techniques [98], [99]. These approaches consider linear boundary conditions between the study and external areas and do not require specific details about the external system to derive the dynamic equivalents. As system operating conditions change, the dynamic equivalents are frequently updated based on boundary measurements. Notable approaches include linear transfer function-based method [100], [101], data-driven dynamic equivalents approach using weighted least square nonlinear optimization [102], the Artificial Neuro-Fuzzy Inference System (ANFIS) [103], and transfer function-based auto-regressive model (ARX) dynamic equivalence methods [104]. However, these methods may not yield accurate responses under contingencies beyond their training events if the training cases do not cover all possible disturbance types and dispatch values.

In recent years, deep learning has gained significant attraction and revolutionized numerous research domains, including dynamic state estimation, fault diagnosis, short-term load forecasting, energy management, and attack detection within power systems [105], [106]. Recent literature proposes a physics-informed neural networks-based ordinary differential equations solver for a linear classical synchronous generator model [107] and a power converter models [108]. The regression and artificial neural network schemes for dynamic model reduction of power systems are discussed in [106], [109], [110], [111]. The dynamic equivalents are derived by modeling the power system

components as black-box systems using RNN models, where the inputs and outputs are represented using simplified second-order differential equations, assuming constant voltage and lossless transmission system. Similarly, researchers have proposed using long short-term memory (LSTM) and gated recurrent unit (GRU) based neural networks for dynamic equivalence in microgrids and Active distribution networks [105], [108], [112], [113], [114]. The use of a recurrent neural network (RNN) structure to represent the dynamic equivalent for transmission networks based on a series-parallel model is presented in [115]. However, the literature covers the basis of RNN models for the physical representation of power system components using very simple power systems with constant system parameters and steady operating conditions with small training datasets. The complex behavior of the power grid with a variety of generation resources under transient conditions is not considered.

RNN-based models offer a novel solution for dynamically equivalencing external areas of large power systems using real-time PMU data. Unlike traditional linear transfer function methods [93], [100], [101], RNNs capture complex, non-linear dynamics and long-term temporal dependencies, making them ideal for power system modeling. They excel in processing real-time data, handling high-dimensional inputs, and updating predictions dynamically. Continuous RNN training with real-time event data simplifies external system modeling, aiding in stability assessment under various contingencies. LSTM is preferred for capturing long-term dependencies, while GRU offers computational efficiency, providing robust alternatives for dynamic system response prediction. Since power system behavior is nonlinear during disturbances, our evaluation

encompasses LSTM and GRU models to assess their performance in modeling power system dynamic responses.

The remainder of this paper is structured as follows: Section II briefly details the problem statement and the details about LSTM, and GRU model-based equivalent load modeling. Section III introduces the detailed LSTM and GRU cell architectures. Section IV introduces the study cases, methodology of the dynamic equivalence approach as well as the data preparation and pre-processing steps. Section V presents the case study results obtained from validating these models, and Section VI encapsulates the conclusion.

6.2 Problem Formulation

6.2.1. Dynamic Equivalence Representation

The primary objective of dynamic equivalencing is to preserve dynamics within the study area of a typical large-scale power system. The system can be divided into two regions: the study area, which is the main focus, and the external area, defined based on the area of interest, as depicted in **Figure 6-1(a)** [116]. These two areas are interconnected through tie-lines (red lines). As illustrated in **Figure 6-1 (b)**, in this paper, the external area is depicted with equivalent dynamic load models (L_{eq1} , L_{eq2}, L_{eqn}) for each tie-line. An effective dynamic equivalent of the external system could accurately predict the power of these equivalent loads such that they match the dynamic responses of the tie line power of the full-order system. The proposed LSTM/GRU structure will predict the power of the equivalent loads using voltage (V) and frequency (f) at the boundary mapping the inputs to the corresponding outputs for sequential time-series data.

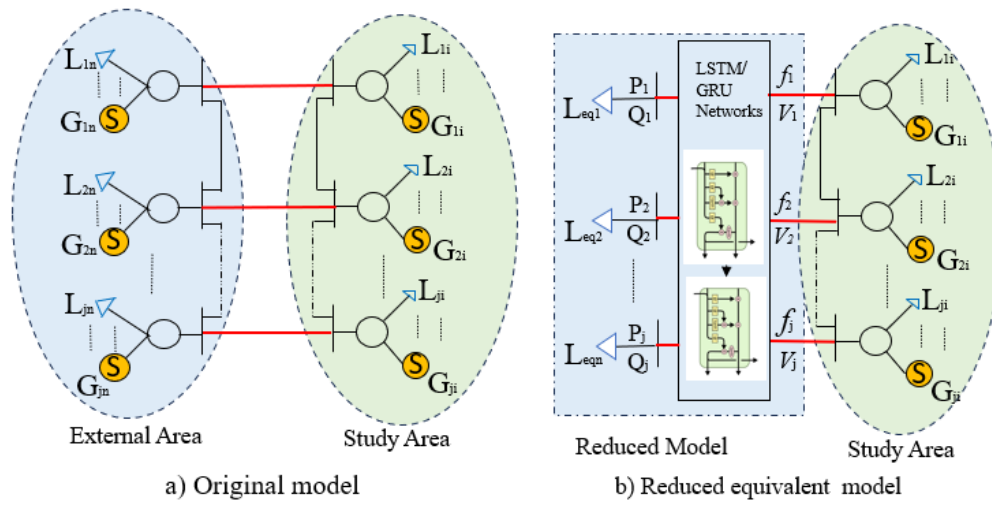


Figure 6-1. Representation of original and reduced model

6.2.2 LSTM, and GRU Model Based Equivalent Load Modeling

This paper analyzes the study area dynamics by considering the external area with balanced loads observed from boundary tie-lines. Considering the similarities between the LSTM and GRU model cell structures and the differential equations of equivalent loads, this section describes the method of representing the external area using dynamic equivalent loads. Specifically, the dynamic properties of high-order power system loads in the state space are characterized by the following differential and algebraic equations (DEs and AEs)[105]:

$$\dot{x} = f(x, i, p) \quad (8)$$

$$y = g(x, i, p) \quad (9)$$

where $\dot{x}$ denotes the state vector, i the input vector, y the output vector, and p the parameter variable. The discrete version of equation \ref{eq:1} can be written as follows:

$$x(t) = f'(x(t-1), i(t), p) \quad (10)$$

Where, f' represents the discrete-time approximation of the continuous function f , used to model system dynamics at specific time steps.

Load modeling maps bus voltage and frequency to active and reactive power [9]. RNN models, including LSTM and GRU networks, effectively represent non-linear dynamic systems by handling sequential data. Derived from [105], the construction and calculation flows of an LSTM/GRU structure, with LSTM/GRU units in the hidden layer followed by a fully connected layer, can represent the relationship between inputs and

outputs similar to DAEs. The DEs and AEs in equations (8) - (10) are represented by the LSTM structure as follows:

$$h_t = F(h_{t-1}, i_t, W_l, b_l) \quad (11)$$

$$O_t = G(h_t, i_t, W_f, b_f) \quad (12)$$

Here, O_t is the output vector at time step t , h_t is the state vector of LSTM hidden layers, and i_t is the input vector for the LSTM/GRU cell. W_l and b_l are the LSTM hidden layer weight matrix and bias vector, respectively, while W_f and b_f are the fully connected layer weight matrix and bias vector. The dynamic equivalent load modeling approach leverages the RNN model's ability to preserve study area dynamics through LSTM/GRU models. Considering the similarities between the discrete version of DAEs and mathematical formulations of the proposed RNN model structures, the dynamic equivalent load modeling approach is proposed by drawing the capabilities of preserving the study area dynamics through the LSTM/GRU models.

6.3 LSTM, and GRU Models Architecture

RNNs are designed to model dynamic power systems and excel in tasks involving sequential inputs by recognizing and handling patterns in sequences. They demonstrate outstanding performance in applications like machine translation and speech recognition. RNNs store information from previous time steps in an internal state, updating their hidden state at each timestep based on the previous hidden state and the current input, thus capturing temporal dependencies. However, basic RNN models suffer from vanishing and exploding gradient problems, which can lead to instability during training.

To address these limitations, advanced architectures like LSTM and GRU models are developed. These models mitigate the difficulties of vanishing gradients, gradient explosion, and long-term memory inadequacy in conventional RNNs, enabling the neural network to effectively employ long-distance temporal information. LSTM and GRU-based RNNs build a mapping link between input and output through the training process, capturing the dynamic properties of power systems without requiring detailed system knowledge. **Figure 6-2** shows the structure of an LSTM and GRU cell [117].

6.3.1. LSTM Cell Structure

LSTM cells are more complex, consisting of a memory cell and three gates (input, output, and forget gates) to regulate the flow of information. This allows LSTMs to remember long-term patterns and dependencies. In the LSTM cell, the cell state C_t carries information across different time steps, and the hidden state h_t is the output at each time step. The input gate i_t controls the addition of new information, the forget gate f_t controls the retention of past information, and the output gate O_t controls the output as the hidden state. The LSTM cell updates at each time step t is represented using the following equations[118]:

1) Forget Gate (f_t):

The forget gate decides what information to discard from the cell state. It uses the current input x_t and the previous hidden state h_{t-1} .

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (13)$$

Here, W_f and b_f are the weight matrix and the bias of the forget gate. The sigmoid function

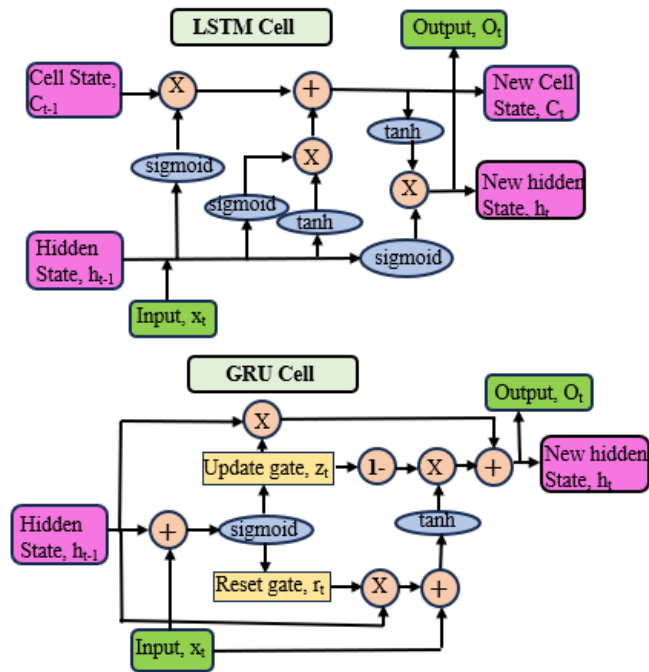


Figure 6-2. Single LSTM and GRU structures

σ outputs a value between 0 and 1, indicating how much of the previous cell state C_{t-1} should be kept. If f_t is close to 1, most of the previous cell state is retained. If f_t is close to 0, most of the previous cell state is discarded.

2) Input Gate (i_t):

The input gate decides what new information is needed to store in the cell state.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (14)$$

where W_i and b_i are the weight matrix and the bias associated with the input gate.

The sigmoid function σ outputs a value between 0 and 1, indicating how much of the new candidate cell state C_t should be added to the cell state.

3) Candidate Cell Gate ($\tilde{C}_t$):

The candidate cell state ($\tilde{C}_t$) is a potential value that could be added to the cell state.

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (15)$$

where W_c and b_c are the weight matrix and the bias of the candidate cell gate. The hyperbolic tangent function $\tanh$ outputs a value between -1 and 1, providing the ($\tilde{C}_t$) that could be added to the cell state.

4) Update Cell Gate (C_t):

The cell state is updated by combining the old cell state $\tilde{C}_{t-1}$ and the candidate cell state $\tilde{C}_t$, modulated by the forget and input gates. This allows the cell to retain important information over long sequences.

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (16)$$

5) Output Gate (O_t):

The output gate decides what part of the cell state to output as the hidden state.

$$O_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (17)$$

where W_o and b_o are the weight matrix and the bias associated with the output gate. The sigmoid function σ outputs a value between 0 and 1, indicating how much of the cell state should be output as the hidden state.

6) Hidden State (h_t):

The hidden state is the product of the output gate and the hyperbolic tangent of the cell state, providing the output of the LSTM unit.

$$h_t = O_t * \tanh(C_t) \quad (18)$$

Compared to the GRU cell, the LSTM architecture has a complex design for long-term information storage and gates control information flow to enable task-specific adaptation. However, the application of LSTMs on Large-scale systems may be limited because of the additional gates and cell states in LSTMs, which demand more memory and computing power. If the training dataset is small or improperly regularized, LSTMs may overfit the data due to its intricacy.

6.3.2. GRU Cell Structure

The Gated Recurrent Unit (GRU) is a simplified version of the LSTM network, designed with fewer parameters. This simpler architecture allows GRUs to be trained more quickly and with less processing power, making them an ideal choice for real-time

processing applications and large-scale systems. Despite their simplicity, GRUs often outperform LSTMs on various tasks, including time-series prediction, due to their computational efficiency.

Both GRUs and LSTMs handle long-term dependencies in sequential data, crucial for time-series forecasting. GRUs combine the cell state and hidden state into a single unit and integrate the forget and input gates into an "update gate." This design results in fewer parameters and improves computational efficiency. The GRU cell updates at each time step t are represented using the following equations [119]:

1) Update Gate (z_t):

The update gate controls how much of the previous hidden state h_{t-1} needs to be passed to the current hidden state h_t . It determines the degree to which the previous state is preserved versus how much of the candidate hidden state ($\tilde{h}_t$) is added.

$$z_t = \sigma (W_z \cdot [h_{t-1}, x_t] + b_z) \quad (19)$$

where, σ is the sigmoid activation function, W_z and b_z are the weight matrix and bias vector of the update gate.

2) Reset Gate (r_t):

The reset gate decides how much of the past information should be forgotten. It determines how much of the previous hidden state h_{t-1} is considered when calculating the new candidate hidden state ($\tilde{h}_t$). The reset gate equation is defined as follows:

$$r_t = \sigma (W_r \cdot [h_{t-1}, x_t] + b_r) \quad (20)$$

where, σ is the sigmoid activation function, W_r and b_r are the weight matrix and bias vector of the reset gate.

3) Candidate Hidden State ($\tilde{h}_t$)

The candidate's hidden state represents the new memory content. It is calculated based on the current input x_t and the previous hidden state $\tilde{h}_t$, modulated by the reset gate r_t . The candidate hidden state equation is defined as follows:

$$\tilde{h}_t = \tanh(W \cdot [r_t * h_{t-1}, x_t] + b) \quad (21)$$

where $\tanh$ is the hyperbolic tangent activation function, W is the weight matrix, and b is the bias vector. The r_t determines how much of the previous hidden state is used.

4) Final Hidden State (h_t):

The final hidden state h_t is a Linear interpolation between the previous hidden state h_{t-1} and the candidate hidden state $\tilde{h}_t$ based on the update gate z_t . Here, the update gate z_t decides the extent to which the candidate hidden state $\tilde{h}_t$ contributes to the final hidden state h_t . The final hidden state equation is defined as follows:

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t \quad (22)$$

The simplified design of GRUs, with fewer parameters and gates, allows for faster training and lower computational costs compared to LSTMs, making them suitable for real-time processing and large-scale applications. In this work, the time series forecasting power system events using LSTM and GRU models are analyzed.

6.4. Methodology

This section outlines the methodology for training, testing, and validating the LSTM/GRU models. The process is illustrated in the flowchart in **Figure 6-3**. To create the training dataset, the full power system model is loaded into PSSE, where various

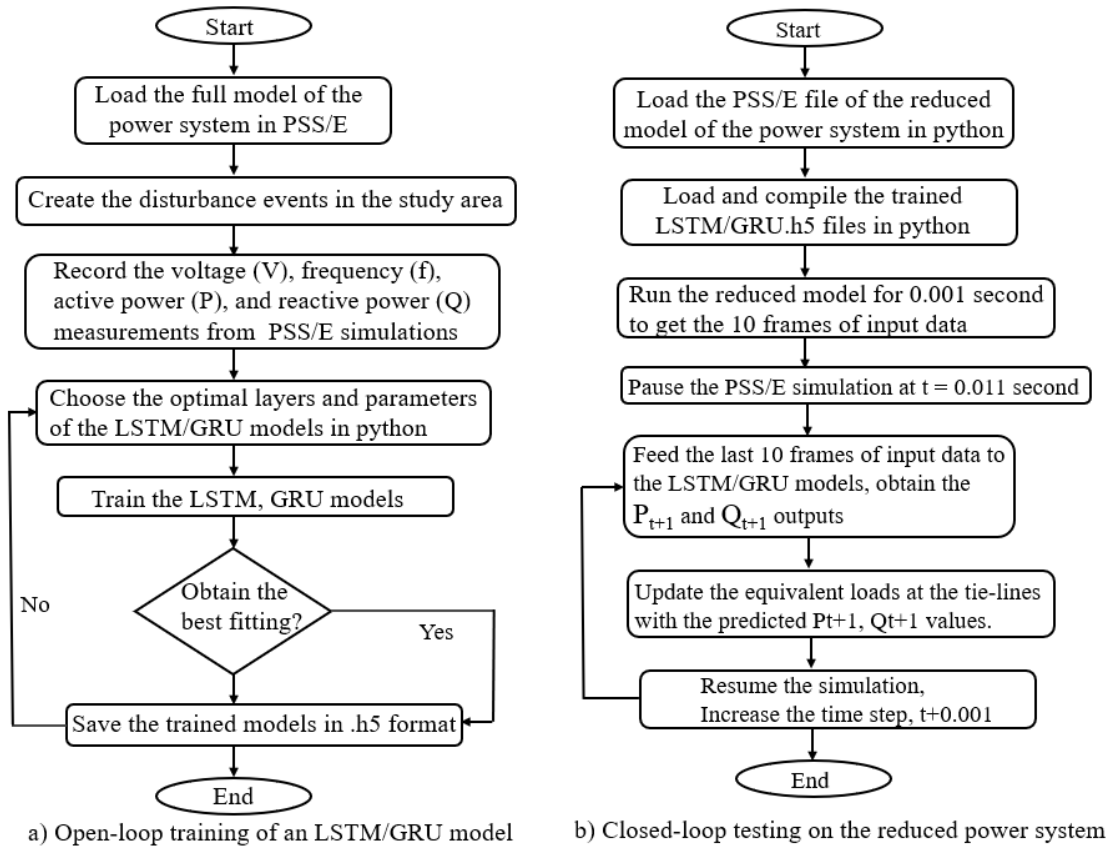


Figure 6-3. Flowchart of open-loop training and closed-loop testing procedure

disturbances are simulated in the study area. Key measurements such as voltage, frequency, and tie-line power flows of active and reactive power are recorded. After preprocessing, the LSTM/GRU models are configured with optimal layers and trained until the best accuracy is achieved, with early stopping employed to prevent overfitting. The trained models are then saved in .h5 format.

The effectiveness of the trained LSTM/GRU models is tested through closed-loop simulations with PSS/E, integrated with Python. This involves forecasting time series events under various contingencies, following the steps in **Figure 6-3(b)**. The reduced power system and trained models are loaded into Python, and a dynamic simulation is initiated in PSSE. At each millisecond, the simulation is paused to feed the last 10 voltage and frequency data time frames into the models. The predicted outputs update the system loads and the simulation resumes. This process continues until the dynamic simulation concludes, using real-time voltage and frequency inputs to update the dynamic equivalents. Simulations, training, and closed loop testing are performed using PSSE Version-35.6 with Python-3.9.13 on a computer with a 13th Gen Intel(R) Core (TM) i9-13900K CPU @ 3.00 GHz and 16.0 GB RAM capacity.

6.4.1 Dataset Preparation, Pre-processing and Training

To train, test, and validate the LSTM/GRU models for each case study, dynamic disturbance scenarios such as single-generator trips, double-generator trips, and load trips were simulated using the full system model in PSSE. For each case, frequency (f) and voltage (V) from tie-lines were used as input features, while active (P) and reactive (Q) power served as target outputs. The time-series data from these simulations was

processed into a supervised learning format using a 'series to supervised' transformation function [120], which frames each sample as a sequence of 10 past time steps to predict outputs at the next timestep. Normalization was applied using either MinMax scaling or StandardScaler, depending on the case study. The processed data was then split into training and testing sets, typically using an 80/20 ratio.

For the NPCC and EI-FRCC systems, the LSTM/GRU architecture shown in **Figure 6-4**, following the procedure in **Figure 6-3(a)**, was used. Each tie-line was modeled independently using a dedicated network to forecast either active or reactive power at the next timestep. The Adam optimizer was employed with its default learning rate for training.

For the EI-TVA region, which involved 59 boundary tie-lines, the model structure illustrated in **Figure 6-5** was adopted. All tie-lines were trained together in a multi-output setting, using .xlsx event files containing f , V , P , and Q measurements for each line. The files were read and processed into overlapping input-output windows and then used to train a deep LSTM/GRU model composed of two recurrent layers, dense layers, and dropout regularization. The output layer consisted of 118 nodes ($59 \text{ lines} \times 2 \text{ outputs for } P \text{ and } Q$). After training, the outputs were inverse transformed to their original scale using the stored scalers. A total of 30 generator trip events were used in the training.

The model performance was evaluated by comparing predictions against both traditional Dynred results and the original full-model simulation responses. Metrics such as Root Mean Square Error (RMSE) and the coefficient of determination (R^2) were used for quantitative evaluation, calculated using equations (23) and (24):

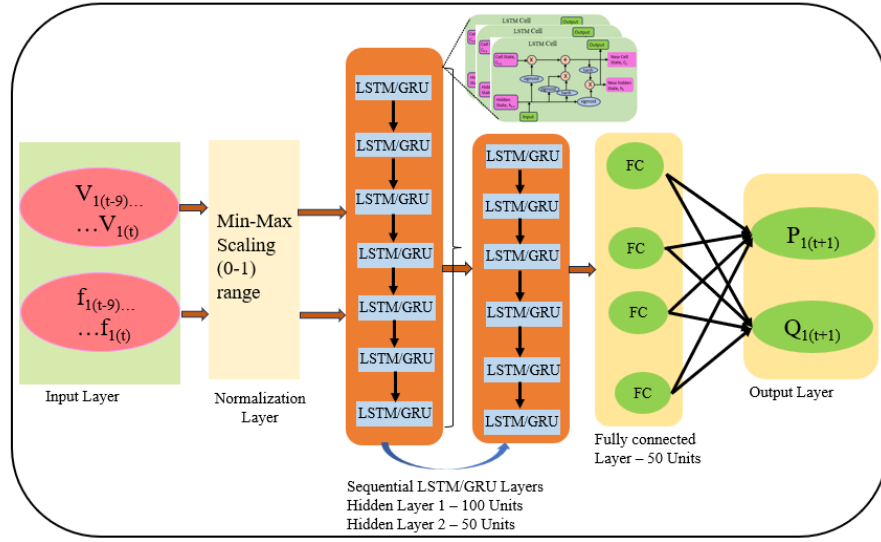


Figure 6-4. LSTM/GRU-based RNN model structure for NPCC & EI-FRCC systems

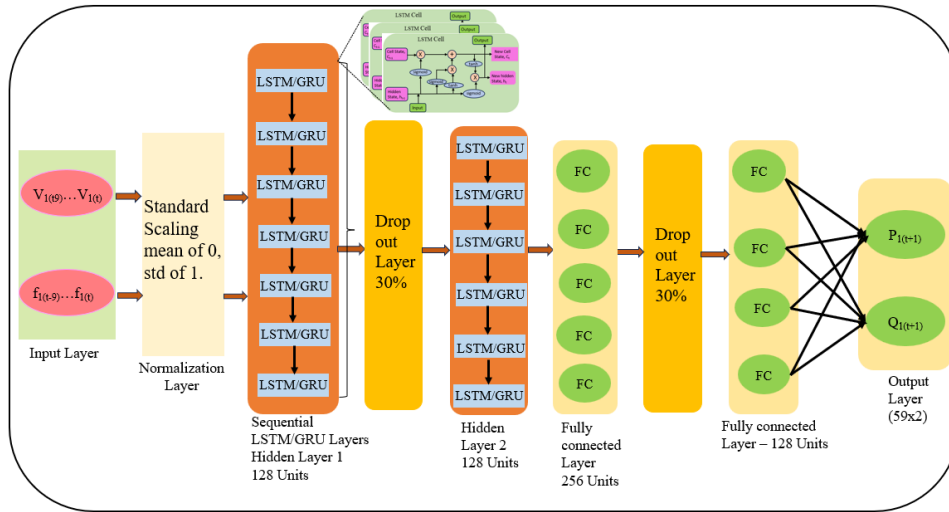


Figure 6-5. LSTM/GRU-based RNN model structure for EI-TVA system

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (23)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (24)$$

where, n is the number of observations, y_i is the actual value at time i , $\hat{y}_i$ is the predicted value at time i , $\bar{y}$ is the mean of the actual values.

6.5 Case Studies and Discussion

In this section, the case study systems are introduced, and the training and closed loop testing results are discussed. The performance of LSTM and GRU models is evaluated against the responses of the full model and the coherency-based DYNRED model under various disturbance events.

6.5.1 Introduction of Study Cases

In this paper, the Northeast Power Coordinating Council (NPCC) regional system is used as one of the case studies. The NPCC system baseline model consists of 140 buses and 48 machines with a generation capacity of 28 GW. **Figure 6-6(a)** shows the single-line diagram of the original NPCC model. Zone-1, the study area (green box), is preserved with all its dynamics, while the other five zones (blue box) are reduced using RNN-based LSTM/GRU models. The study and external areas are connected by two tie-lines (red solid lines) between Bus-35 to Bus-73 and Bus-29 to Bus-37. **Figure 6-6(b)** illustrates the reduced NPCC model with an LSTM block and two equivalent loads at the tie-lines. The disturbance event dataset of the NPCC system is summarized in **Table 6-1**.

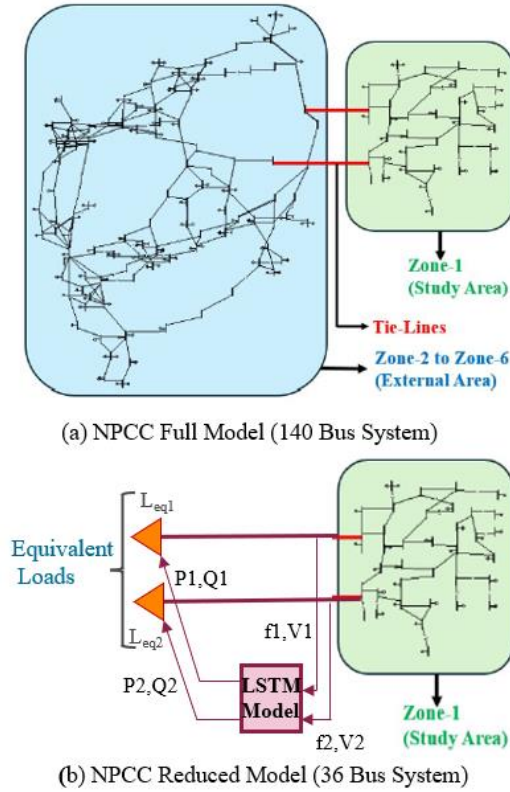


Figure 6-6. Single line diagram of NPCC original and reduced system

Table 6-1. Summary of training and validation sets of NPCC system

Event Type	Training Sets	Validation Sets
Single generator trip	7	2
Single load trip	10	6
Successive loads trip	6	1
Bus fault	7	1
Branch fault	6	1

Voltage (V_1 , V_2) and frequency (f_1 , f_2) measurements at the boundaries are inputs to the LSTM/GRU models, while active power (P_1 , P_2) and reactive power (Q_1 , Q_2) are the outputs for prediction. The dataset includes 30 disturbance events for training and testing, with a train/test split of 0.2, and 10 new disturbance events for validation, which were not used in model training. The generation trip training events are conducted at the following generators: generator 21 - 650 MW, 23(1) - 276.65 MW, 23(2) - 226.35 MW, 24 - 700 MW, 25 - 560 MW, 26 - 800.0566 MW, 27 - 540 MW, and generator 36 - 554 MW. The load trip events are selected in increments of 50 MW.

To assess the performance of the tested models on a bulk power system, a case study is conducted on the Eastern Interconnection (EI) system. This system's detailed dynamic model includes 70,000 buses and 9,000 machines with a total generating capacity of approximately 590 GW [83]. The Florida Reliability Coordinating Council (FRCC) area, shown in **Figure 6-7** within the EI system, is the primary focus, connected to the SERC Reliability Corporation via two tie lines. The remainder of the EI system, comprising 66,000 buses and 8,300 machines, is reduced using LSTM/GRU-based equivalent models. The FRCC area itself contains 3,170 buses with voltages up to 500 kV, 495 generators with a maximum output of 2,095.275 MW and a reactive power capacity of 393 MVAR, as well as 2,157 loads consuming up to 295.024 MW and 59.907 MVAR. **Table 6-2** summarizes the training, and validation sets for the EI system, where generation and load trip events were selected in 100 MW increments to ensure comprehensive coverage. Two new disturbance sets were used for each event type to evaluate model performance.

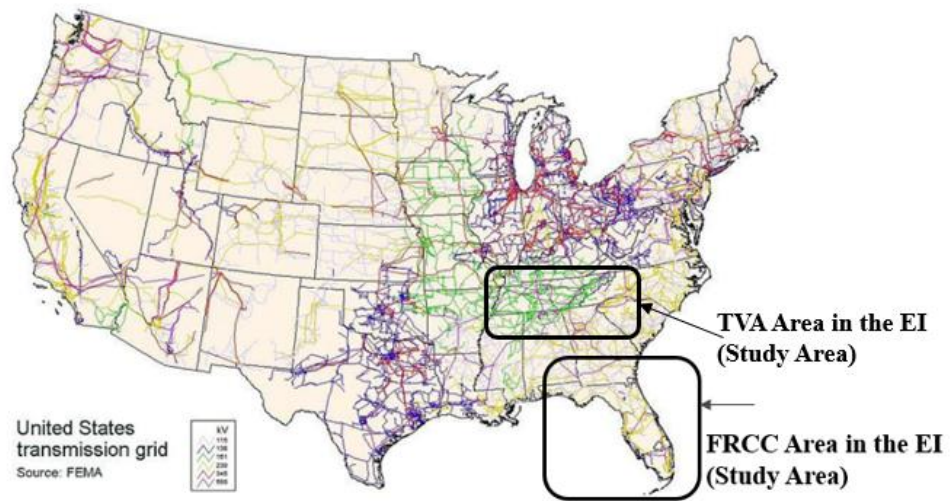


Figure 6-7. Single line diagram of US Interconnection map

Table 6-2. Summary of training and validation sets of EI-FRCC system

Event Type	Training Sets	Validation Sets
Single generator trip	27	2
Single load trip	34	2
Successive loads trip	24	2
Bus fault	20	2

During the training step, the computational time taken for the model's training versus the number of epochs trained is summarized in **Table 6-3** below. To validate the effectiveness of the proposed approach, the TVA region within the EI system is selected as the third case study. As shown in **Figure 6-7**, the TVA area is interconnected with several neighboring regions via a total of 59 boundary tie-lines: 13 with the SOCO area, 4 with the MISO_MO_IL area, 6 with the MISO_IN area, 11 with the Entergy area, 3 with the VACAR area, 6 with the PJM_RTO area, and 16 with the RTO_MIDW area. The TVA area itself contains 1,836 buses and 227 generators with a maximum output of 29.15GW and a reactive power capacity of 7730.8 MVAR. **Table 6-3** summarizes the training, and validation sets for the EI-TVA system. For the generation trip events training and prediction, a total number of 30 generator trip events were selected by covering the minimum generation range of 1.3741 MW, 1.4 MVAR to a maximum range of 3424.361 MW, 1305.6 MW to ensure comprehensive coverage. Two new disturbance events were used for each event to evaluate model performance.

6.5.2. Reduction of the NPCC Model

In the NPCC system, Zone-1 retains detailed nonlinear models for generation units, while external areas are represented by two equivalent load models at tie-lines. The LSTM/GRU models update these equivalent load values every 0.001 seconds using boundary voltage and frequency inputs to predict active and reactive power outputs. These models trained on the NPCC system's training data set, comprising seven events, were evaluated against a new generator trip event which involves 632 MW and 110 MVAR trip at bus 22 within the study area.

Table 6-3. Summary of trained epochs versus computation time

System	Tie-line number	LSTM		GRU	
		<i>Epochs</i>	<i>Time (min)</i>	<i>Epochs</i>	<i>Time (min)</i>
NPCC	Tie line 1	58	49.94	43	33.00
NPCC	Tie line 2	49	44.87	39	30.79
EI	Tie line 1	49	97.72	53	36.63
EI	Tie line 2	62	67.95	48	31.96

Since the fault scenarios are different than the generator/load trip scenarios, the three-phase bus fault events are included in the training sets as specified in **Table 6-1**.

Figure 6-8 shows the performance of the LSTM/GRU models for an untrained generator trip event at bus 22 (on the left) and a bus fault event (on the right) at bus 30 triggered at 1 second and cleared at 1.03 seconds. As illustrated in **Figure 6-8**, even with a limited number of training events covering a wide generation dispatch range, the LSTM/GRU models mimic the active and reactive power dynamic response outputs similar to the full model response and outperformed with high R^2 value close to 1 compared to the DYNRED results.

To further assess the model's performance, it was evaluated on both an untrained single load trip event and successive load trip events, depicted in **Figure 6-9**. In the single load trip event, a load of 281 MW and 76 MVAR at bus 18 was tripped. Similarly, for a successive load trip event, a load of 309 MW and -92 MVAR at bus 15 was tripped at 1 second, followed by a load of 224 MW and 47 MVAR at bus 16 tripped at 5 seconds.

As shown in **Figure 6-9**, the LSTM/GRU models successfully capture and preserve the dynamics of these successive events with minimal training events for each event class. Compared to the DYNRED model results, the RNN models outperform in terms of preserving the dynamic characteristics of the reduced system with high R^2 value and low RMSE. The quantitative metric results for the NPCC system under the considered disturbances are presented in **Table 6-4**. From **Table 6-4**, it can be concluded that both the LSTM and GRU outperformed DYNRED across all the event types with low RMSE and high R^2 coefficient.

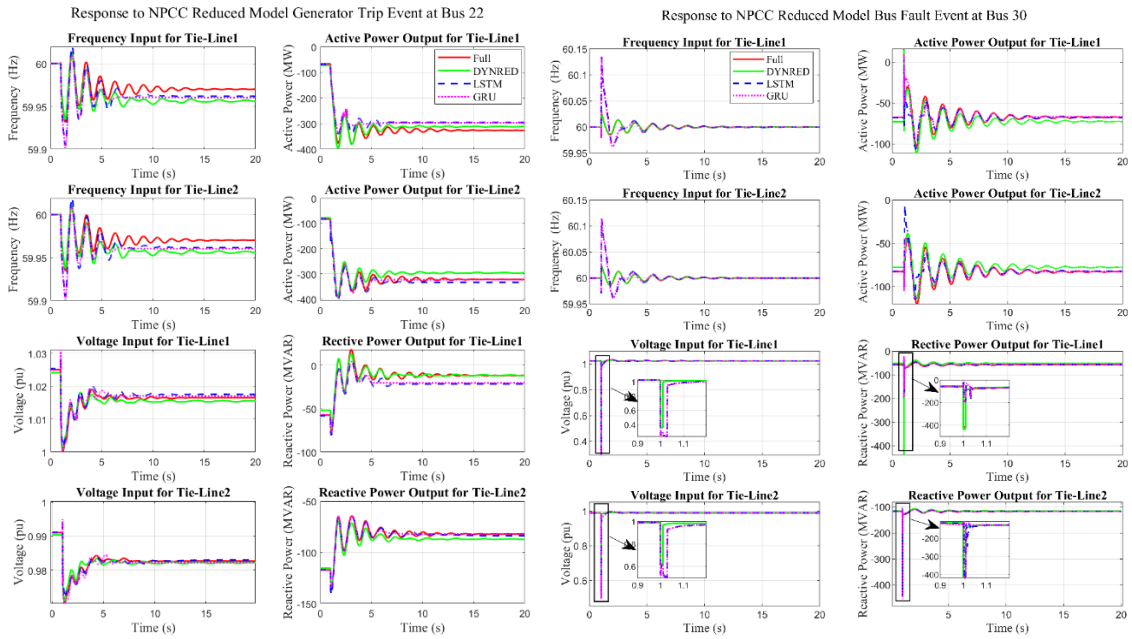


Figure 6-8. Generator trip and bus fault event response in the NPCC system

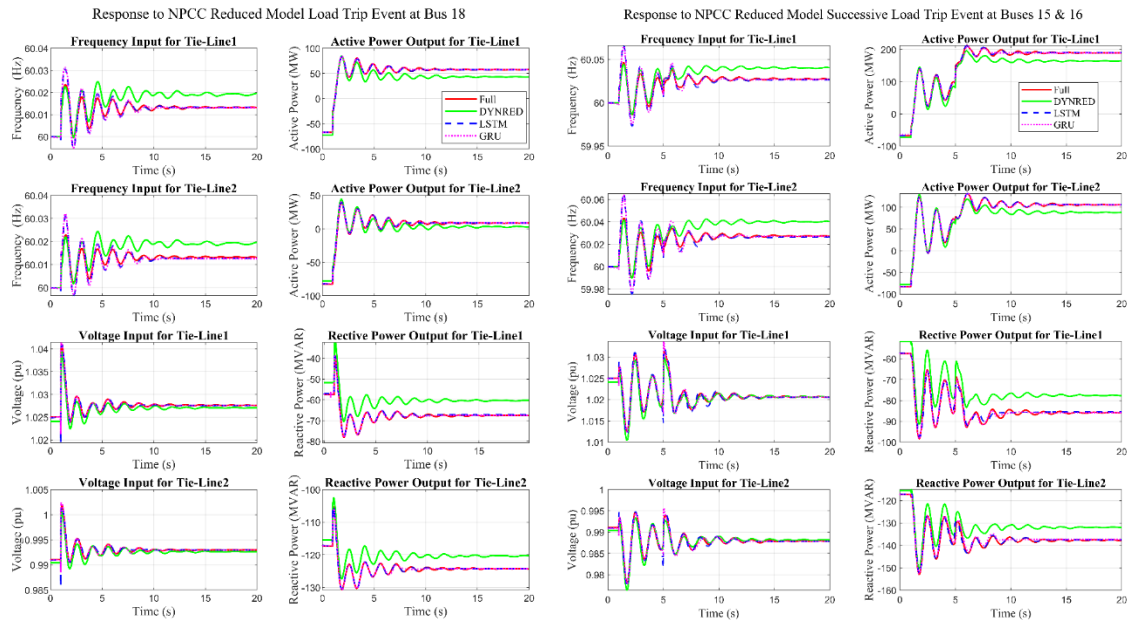


Figure 6-9. Load trip and successive load trip event response of NPCC system

Table 6-4. Performance metric analysis of the NPCC system

Event Type	Metrics	DYNRED				LSTM				GRU			
		<i>P1</i>	<i>P2</i>	<i>Q1</i>	<i>Q2</i>	<i>P1</i>	<i>P2</i>	<i>Q1</i>	<i>Q2</i>	<i>P1</i>	<i>P2</i>	<i>Q1</i>	<i>Q2</i>
Generator Trip	RMSE	13.3008	23.443	2.1436	4.9178	17.527	12.353	6.4732	1.474	17.146	6.3675	5.6096	1.3046
	R ²	0.95322	0.8347	0.97659	0.7972	0.9224	0.9541	0.8228	0.9817	0.9256	0.9878	0.8423	0.9857
Single Load Trip	RMSE	13.1756	5.3018	7.3214	3.9085	1.4134	1.425	0.4677	0.3106	1.2521	0.8348	0.4521	0.2816
	R ²	0.79553	0.9432	-1.5297	-0.613	0.9976	0.9959	0.9896	0.9898	0.9981	0.9985	0.9903	0.9916
Successive Load Trip	RMSE	21.194	14.366	8.3072	5.4505	3.7171	1.7826	1.1963	0.8329	2.6896	1.0714	0.6258	0.7713
	R ²	0.91107	0.9138	-0.007672	0.1866	0.9972	0.9986	0.9791	0.9810	0.9985	0.9995	0.9942	0.9837
Bus Fault	RMSE	5.3504	5.232	5.7867	2.0104	2.5446	3.2025	2.7119	2.6666	2.3148	1.9992	2.4768	2.3527
	R ²	0.68267	0.7098	0.59009	0.7287	0.9768	0.9322	0.9264	0.9429	0.9810	0.9396	0.9300	0.9518

While both the LSTM and GRU models have shown similar performance, the GRU is faster and computationally efficient than LSTM due to its short-term dependencies.

6.5.3 Reduction of the EI System-FRCC Area

Similar to the NPCC system, the LSTM/GRU models for the EI system-FRCC area are trained using a minimal number of disturbance events that cover a wide range of generation and load dispatch scenarios. To assess the accuracy of the reduced EI-FRCC model in capturing the dynamic characteristics of the original bulk power system, various disturbance event predictions are evaluated through closed-loop simulations. The performance of the LSTM/GRU models is compared against the full model response, as they show superior performance in the previous case study. An untrained generator trip event at bus 401260, involving 155.9930 MW and 157.0 MVAR, and a bus fault event at bus 400019 are tested in the EI-FRCC reduced model. As shown in **Figure 6-10**, the responses of the trained RNN models to these disturbances indicate that the LSTM and GRU models closely match the full system's response during the transient state. A single load trip event is initiated by tripping a load of 107.220 MW and 21.772 MVAR at bus 404845. Additionally, a successive load trip event is triggered at buses 400024 and 400025, with one load tripping at 1 second and another at 5 seconds. The performance of the LSTM/GRU models for these events is illustrated in **Figure 6-11**. The predictions of the single load trip event and successive load trip events in **Figure 6-11** follow a similar trend to the full model response.

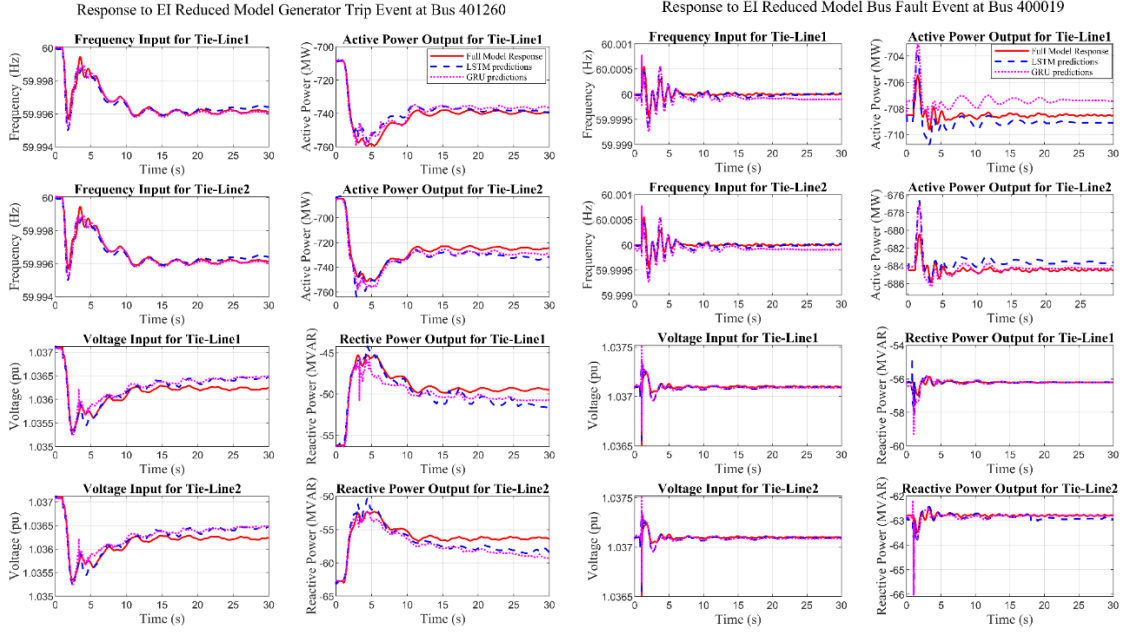


Figure 6-10. Generator trip and bus fault event response of FRCC area

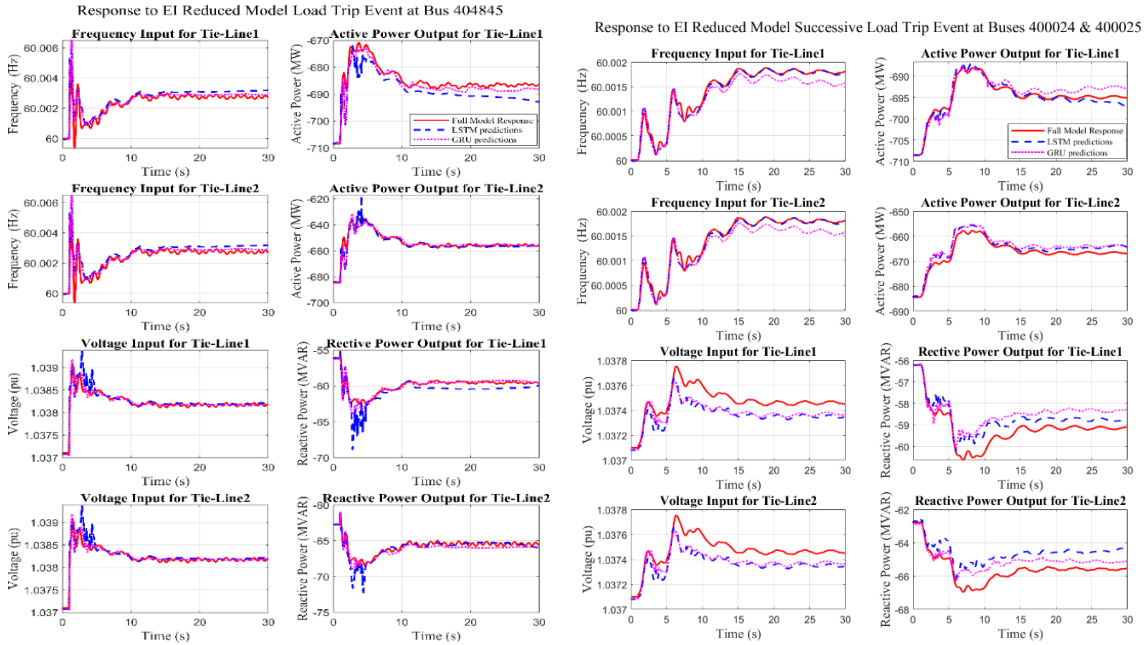


Figure 6-11. Load trip and successive load trip event response of FRCC area

As shown in **Table 6-5**, for all the event types, the LSTM and GRU models accurately capture the transient dynamics with low RMSE values and high $R^2 > 0.85$ values. Both the models performed well for event prediction tasks, but their relative performance depends on the specific event datasets. Because of their more intricate gating mechanism, the LSTM can capture long-term dependencies for the generator trip and subsequent load trip events with great precision. On the other hand, the GRU model, which has a smaller cell structure, can function just as well in situations where the dataset doesn't call for an LSTM's depth, such as bus faults and single-load trip events. With smaller datasets, the more straightforward GRU structure reduced overfitting and facilitated faster training.

6.5.4 Response to a generator trip event under EI-FRCC Model operating dispatch conditions change

To assess the performance of the trained model under different operating conditions, the dispatch of several generators is adjusted. Specifically, we increased the MW/MVAR of one generator while decreasing the MW/MVAR of one or more other generators that are closely connected. For this case, the dispatch changes summarized in **Table 6-6** are applied with a total dispatch change of 300 MW to generators that are connected in the first and second boundary of bus 401260 in the FRCC study area. With these power flow modifications, we then evaluated the performance of the previously trained models by simulating a generator trip at bus 401260. The previously trained models were evaluated for a generator trip at bus 401260 with these power flow adjustments.

Table 6-5. Performance metric analysis of the EI system

Event Type	Metric s	LSTM				GRU			
		<i>P1</i>	<i>P2</i>	<i>Q1</i>	<i>Q2</i>	<i>P1</i>	<i>P2</i>	<i>Q1</i>	<i>Q2</i>
Generator Trip	RMSE	3.0935	2.2072	1.1521	1.2537	3.086	2.1312	1.1006	1.1452
	R ²	0.98897	0.96977	0.88465	0.86175	0.98847	0.96785	0.8713	0.85941
Single Load Trip	RMSE	4.33	2.577	1.1008	0.68232	2.2365	2.2916	0.43816	0.50377
	R ²	0.8723	0.98829	0.90429	0.92128	0.90056	0.99578	0.96124	0.97865
Successive Load Trip	RMSE	0.84753	0.8958	1.52269	1.0573	0.79508	0.85592	1.49508	1.10335
	R ²	0.98044	0.96349	0.76556	0.75732	0.98213	0.96408	0.72615	0.75592
Bus Fault	RMSE	1.046	0.67084	0.14327	0.16672	1.15	0.59253	0.18759	0.14348
	R ²	0.80533	0.83564	0.97040	0.95689	0.76237	0.88396	0.95549	0.97202

Table 6-6. Summary of generator dispatch changes

Bus Number	Voltage (KV)	Original Dispatch (MW)	Changed Dispatch (MW)
401260	18	155.993	155.993
401261	18	155. 993	55.993
401262	18	127.183	27.183
410132	22	1078.26	978.26
400131	22	0	150
400132(1)	22	0	150

Figure 6-12 displays the response of the LSTM/GRU models to this generator trip under altered system dispatch conditions. As depicted in **Figure 6-12**, the trained RNN models accurately predict disturbance responses, maintaining an accuracy similar to the full model response. This is true as long as the operating condition changes are relatively minor and not drastically different from the original training dispatch. Significant changes in system dispatch, which could involve large shifts in generator loading or network configuration, would require new training events to ensure accurate predictions.

6.5.5 Reduction of an EI-TVA Area

Similar to the EI-FRCC case, single LSTM and GRU models were trained using data from generator trip events involving 59 tie-lines connecting the TVA area to neighboring regions. A large generator at bus 364001, producing 1281.42 MW and 1305.60 MVAR, was used as an unseen test event to evaluate the models' predictive capabilities. The model predictions were compared against the full model simulation results, with visual comparisons shown in **Figures 6-13** through **6-19**. The predicted active and reactive power flows for each tie-line show strong agreement with the full model outputs, particularly in capturing the timing and magnitude of the initial transients. Among the 59 tie-lines, for 44 tie-lines LSTM outperformed GRU by 50%, and for 15 tie-lines GRU outperformed LSTM by 25%. Overall, the LSTM provided marginally better accuracy in capturing reactive power variations during fast-changing dynamics.

Among the 59 tie-lines, the most significant prediction errors were observed on lines with low power flow magnitude, suggesting that model accuracy is influenced by

Response to EI Reduced Model Generator Trip Event at Bus 401260 During Dispatch Change

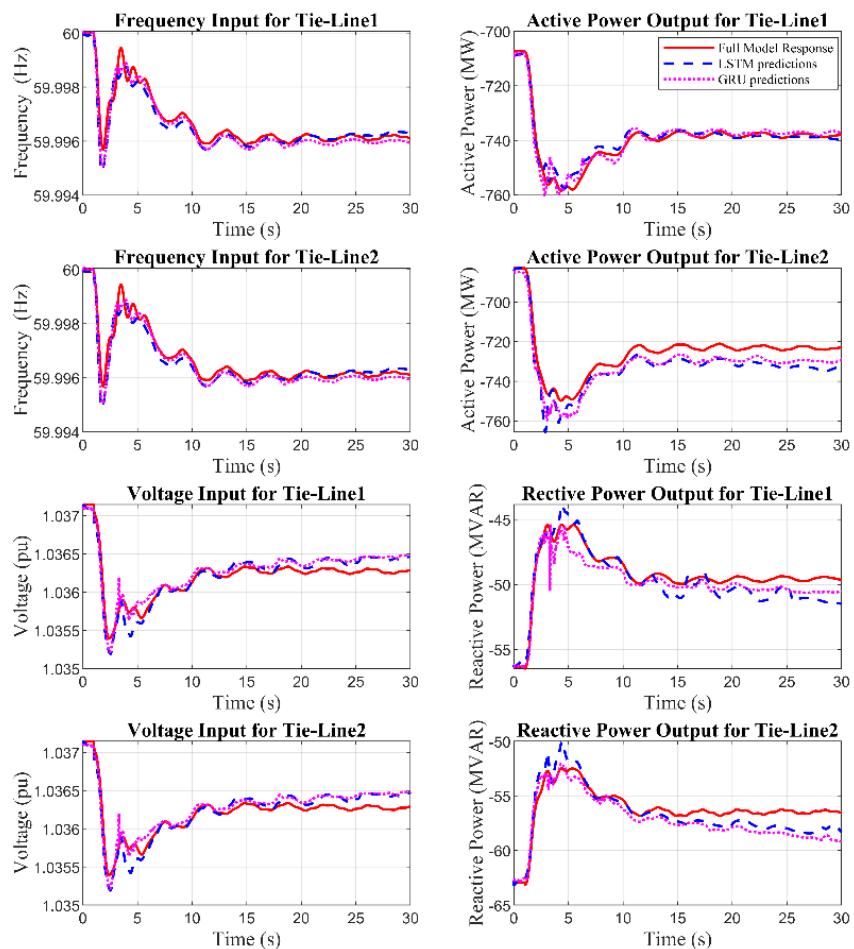


Figure 6-12. Generator trip event of FRCC area at bus-401260

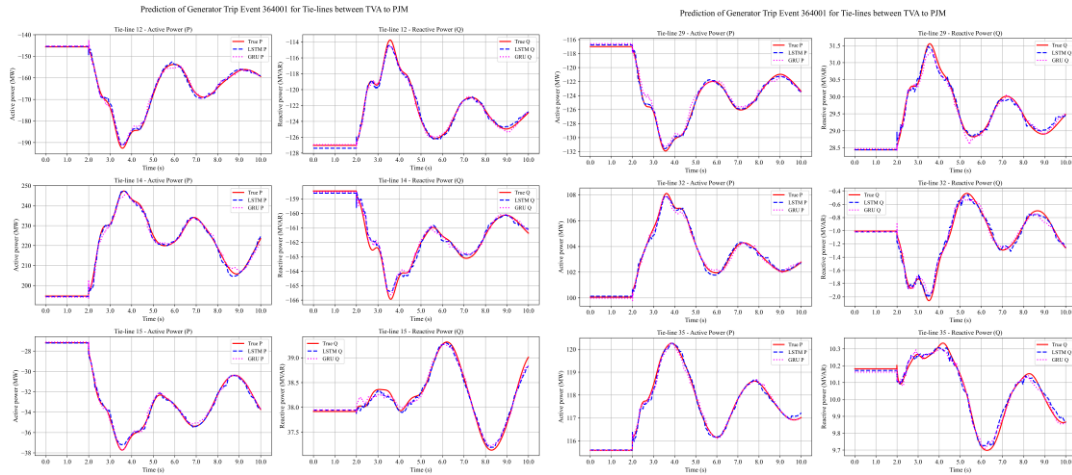


Figure 6-13. Generator trip event response for tie-lines between the TVA and PJM area

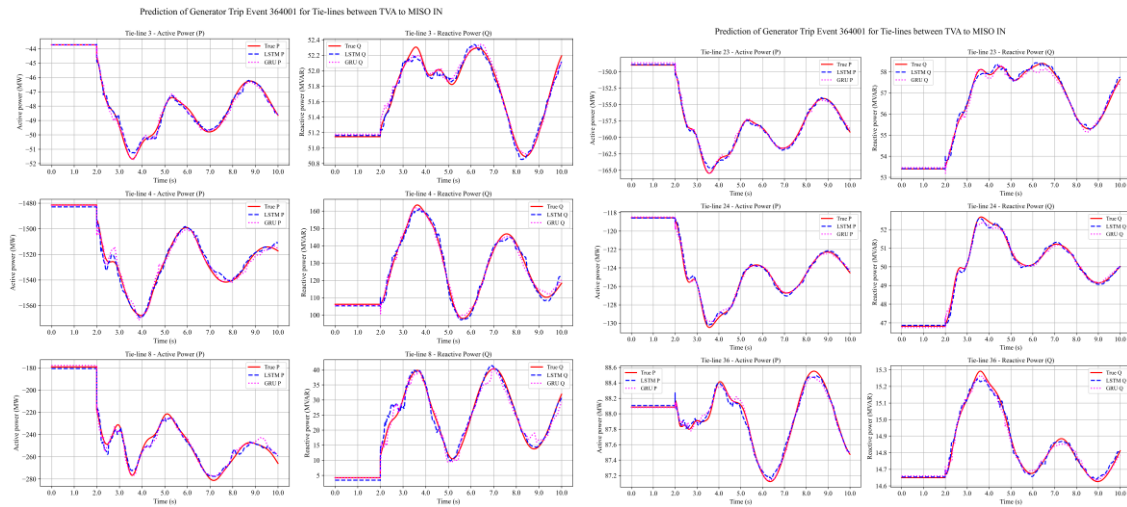


Figure 6-14. Generator trip response for tie-lines between the TVA and MISO_IN area

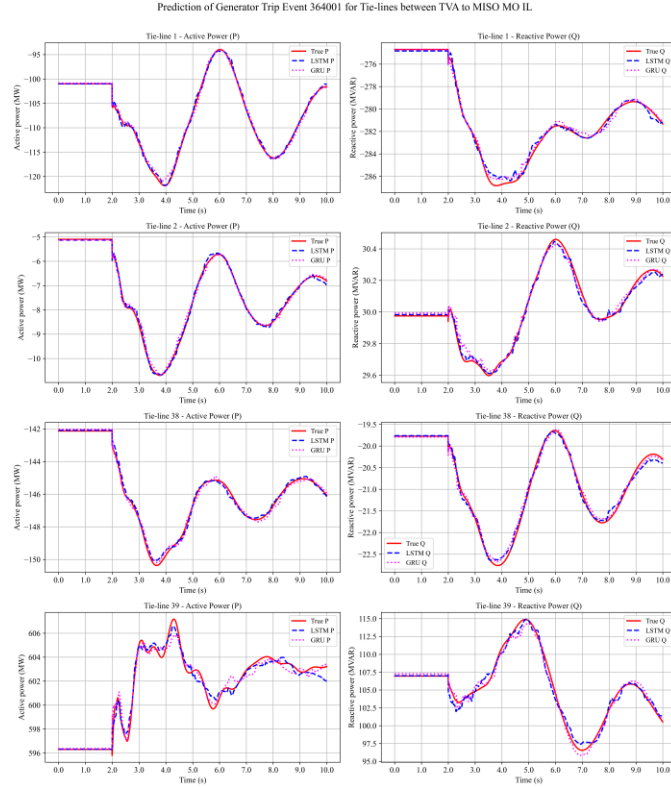


Figure 6-15. Generator trip response for tie-lines between the TVA and MISO_MO area

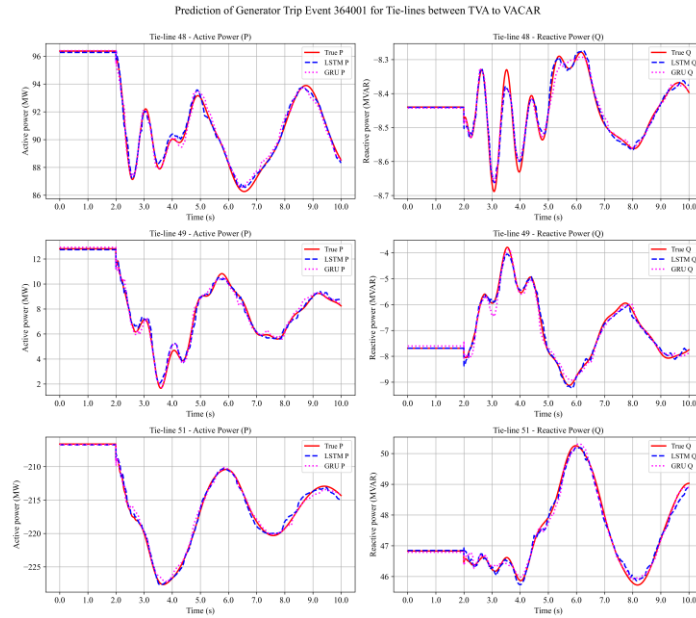


Figure 6-16. Generator trip response for tie-lines between the TVA and VACAR area

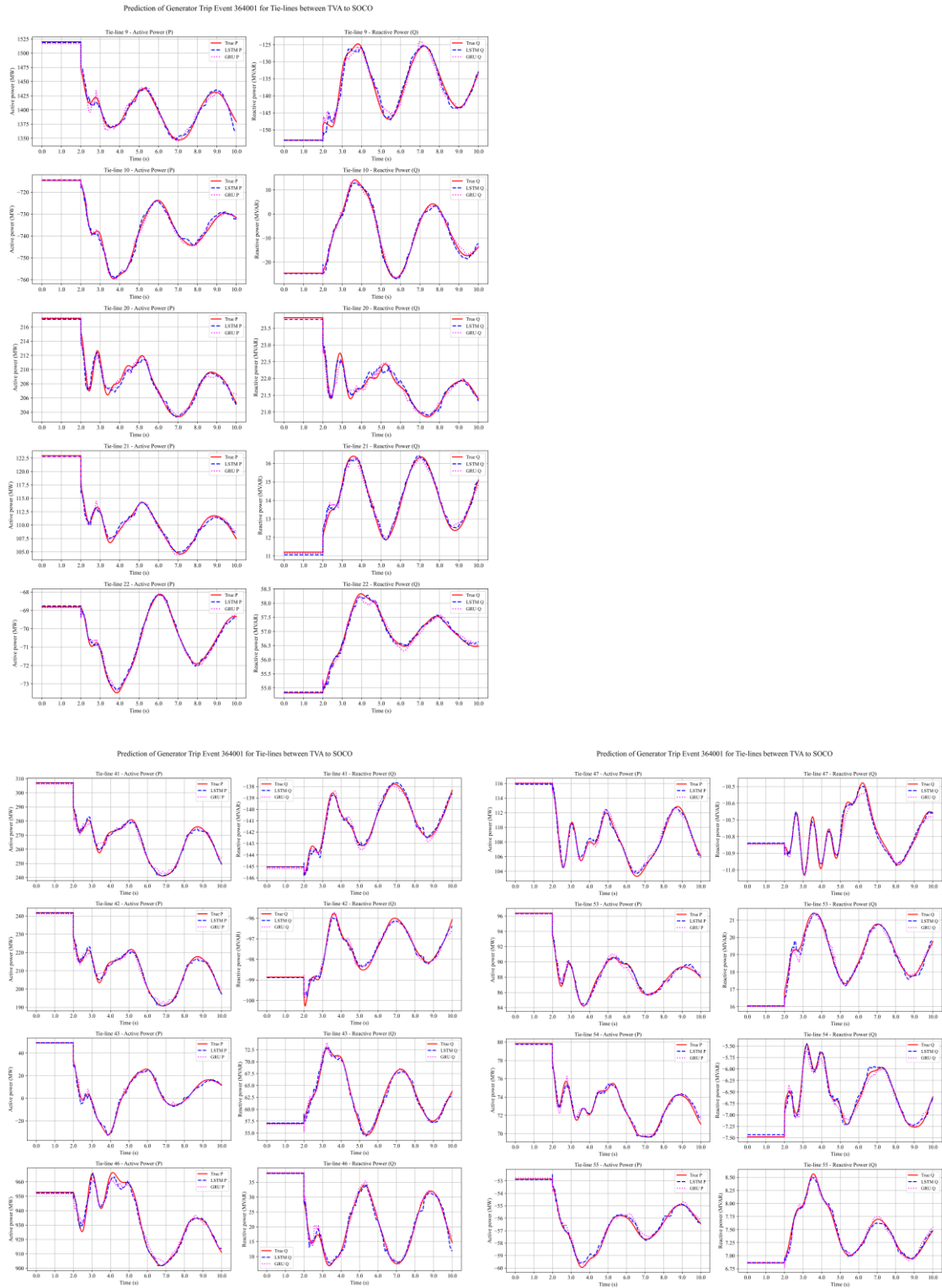


Figure 6-17. Generator trip response for tie-lines between the TVA and SOCO area

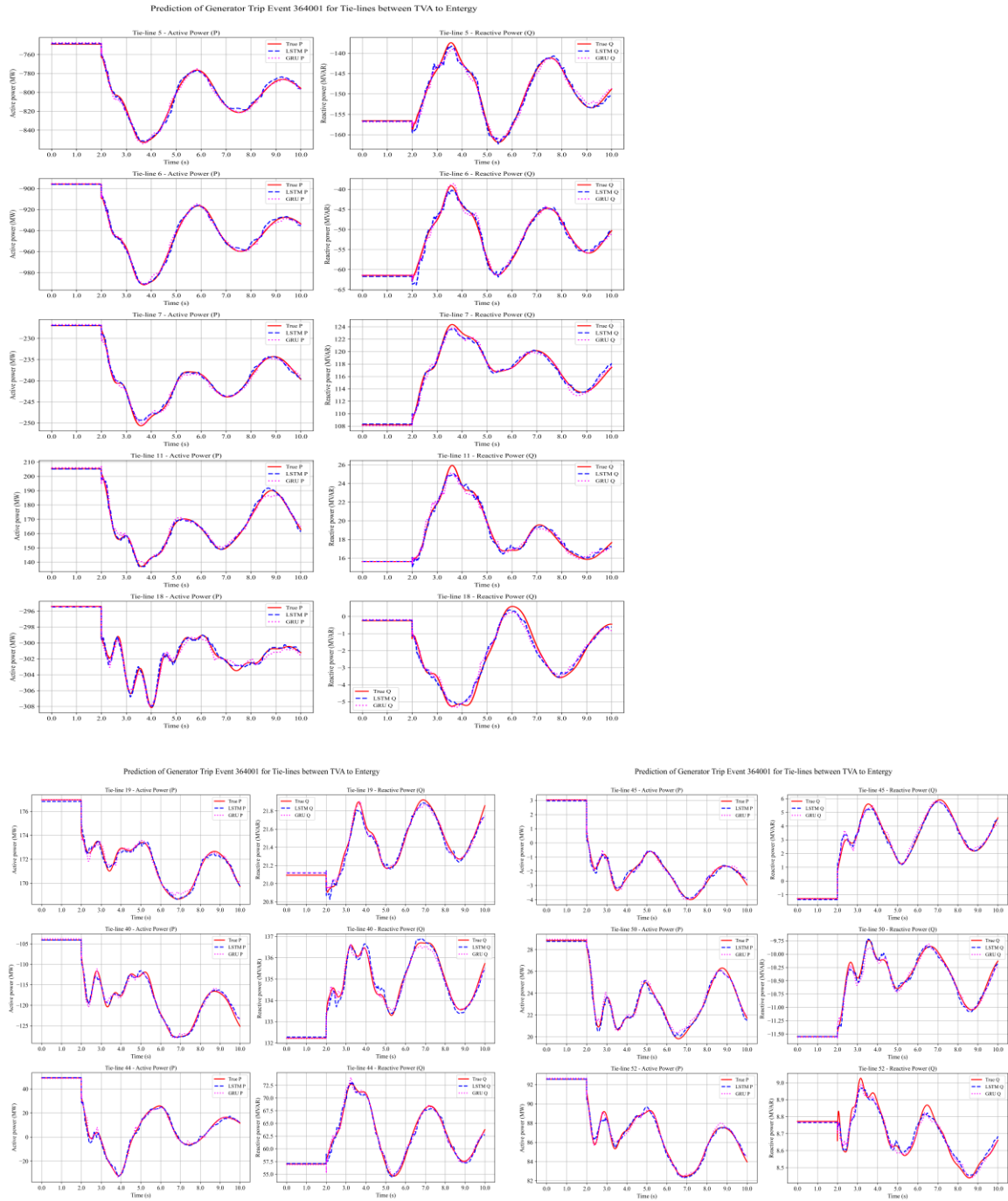


Figure 6-18. Generator trip response for tie-lines between the TVA and Entergy area



Figure 6-19. Generator trip response for tie-lines between the TVA and RTO MIDW area

large variation in the training data. Nonetheless, the overall trend and oscillatory behavior were well-represented across all tie-lines, demonstrating the generalization ability of the trained models. The RMSE and R^2 metrics results for the EI-TVA system are shown in **Figure 6-20**.

These results confirm that the LSTM/GRU-based reduced model for the EI-TVA region is capable of accurately replicating the response of the full model under unseen large disturbance conditions, supporting its use in real-time simulations.

6.6 Conclusion

This study introduces a novel approach for implementing a closed-loop dynamic equivalent of large-scale power systems using RNN-based LSTM and GRU models. The proposed method involves open-loop training of the models using full-system dynamic responses under typical events, with a reduced model created by representing external areas as equivalent loads at the tie-lines. By integrating the PSS/E system with Python, the trained models are evaluated in closed-loop simulations on the reduced system, using boundary measurements as inputs. Load values are updated every 0.001 seconds with the predicted power values, and the method is tested under various events, including three-phase faults, generator trips, load trips, and generation dispatch changes. Results indicate that the models possess strong predictive capabilities, closely matching the full system responses. Both LSTM and GRU models successfully preserve system dynamics while reducing external complexity, however, GRU models demonstrate superior computational efficiency and performance compared to the LSTM model.

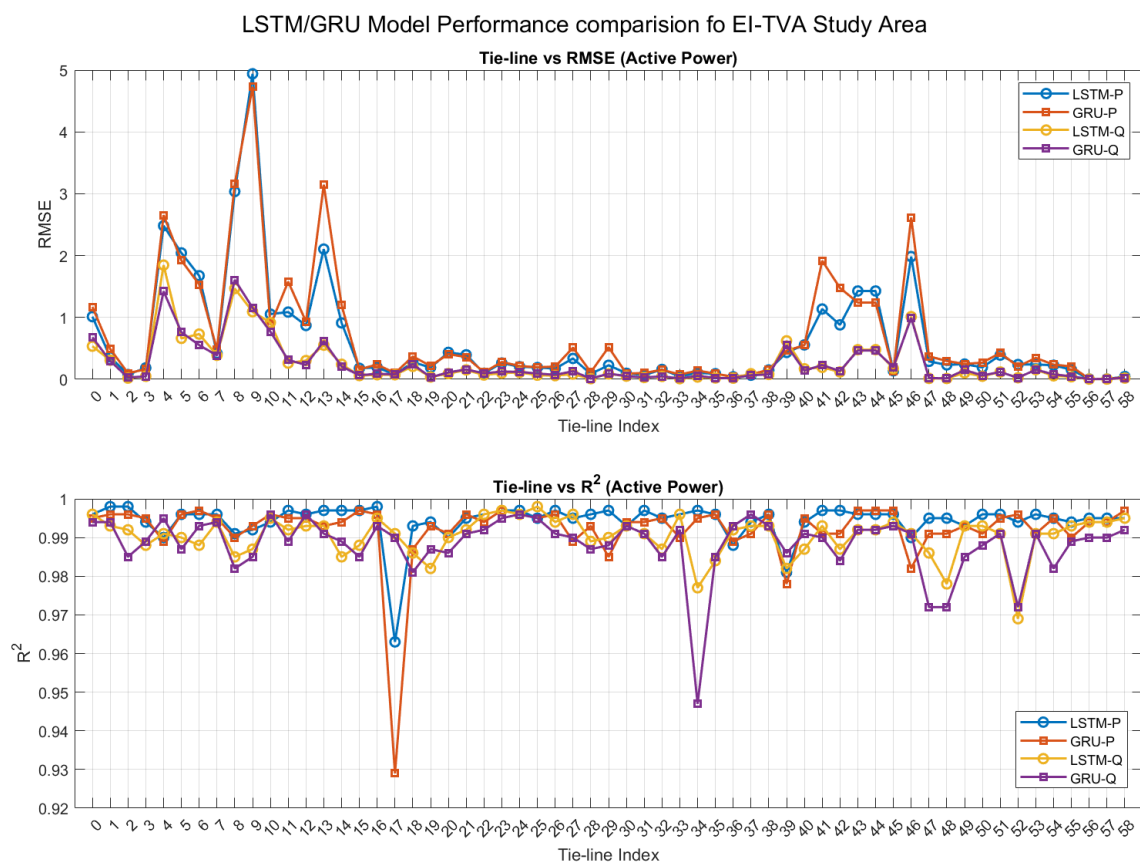


Figure 6-20. Model Prediction Error comparison for EI-TVA study area

Future research will focus on extending this approach to online applications by continuously updating the training sets and fine-tuning the models to reflect current operating conditions. Additionally, alternative models such as transformer networks and reinforcement learning techniques will be explored to achieve dynamic equivalence, particularly under contingencies involving high levels of renewable energy penetration.

CHAPTER 7
CONCLUSION AND FUTURE WORK

This dissertation presents a comprehensive investigation into FO analysis and model reduction techniques for power systems, emphasizing the influence of generator sub-controller parameters, resonance impacts, FO source identification, and interarea oscillation mitigation strategies. Additionally, a measurement-based dynamic equivalencing method using recurrent neural networks is introduced for large-scale power system reduction. The key contributions and findings of this research are summarized below:

- 1) The tuning of exciter and governor models significantly affects power system stability, particularly under FOs. A systematic analysis was performed by injecting 100 MW/MVAR FOs at both the governor and exciter control points. Among the tested exciter models, parameters such as exciter gain, voltage regulator gain, and voltage regulator time constants were identified as highly sensitive. Similarly, for the tested governor models, turbine gain, droop settings, and turbine control time constants proved critical. These insights offer practical guidance for plant operators and planning engineers to optimize controller settings during oscillatory conditions.
- 2) This research examined how FO frequencies affect power system behavior, with a focus on resonance conditions where external forcing frequency matches natural oscillation modes. Results from the kundur's system, ERCOT, EI systems demonstrated a Gaussian-distribution response at both interarea and local modes spanning approximately 0.3 Hz and 0.6 Hz near the natural frequency, respectively. As the FO frequency diverges from resonance, its

impact on dynamic system behavior diminishes. When the output power flows at high voltage bus maintained constant, the small magnitude FO originating from load can cause a similar response of the generator, making load induced FO events more sensitive.

- 3) Identifying the source of FOs occurring near natural modes remains challenging.

This study proposes using a synthetic Texas power system model to develop a comprehensive test case library by injecting FOs at varying magnitudes into exciters, governors, and renewable resources. The one-cycle sliding window based spectral energy-flow method was applied for source localization, and to pinpoint sub-controller components as potential sources. This approach aims to enhance the speed and accuracy of FO source location, classification, facilitating timely mitigation.

- 4) When interarea resonance-induced oscillations occur, wide-area system oscillations necessitate mitigation at multiple points. This dissertation explores optimal IBR placement strategies to suppress FOs effectively. Simulation results from the 121-bus mesh system indicate that damping control (FODC) through IBRs near the oscillation source and generators with high natural mode participation factors significantly reduce oscillation amplitudes.

- 5) A novel large-scale model reduction technique leveraging long short-term memory (LSTM) and gated recurrent unit (GRU) networks was developed. Testing on NPCC and EI systems showed that using equivalent loads updated at tie-lines preserved system dynamics while significantly reducing computational

complexity. The high predictive accuracy of these models provides a scalable solution for dynamic simulations, closely approximating full model responses with reduced computational requirements.

Future research can extend to test the spectral energy-flow method on real-time captured FO events. Lastly, the dynamic equivalencing approach can be implemented on a utility-scale large power system to showcase real-time dynamic response on a reduced power system model using AI and deep learning method.

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VITA

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