

Hybrid Decision and Control Methods for Multi-Scale Grid Resilience and Oscillation Damping

September 2026

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Executive Summary

This report presents multiple new results related to the development of multi-scale analytics and control designs for grid oscillations and stability in presence of large-scale power electronics based resource integration. This work investigates two main oscillation types. In the initial part of the report, we consider wide-area inter-area oscillations under high grid-forming inverter (GFM) penetration. Our findings show that significant integration of GFMs replacing conventional generation alter the conventional coherency structure of the grid, necessitating modifications to wide-area control. We propose a distributed, risk-constrained reinforcement learning based wide-area control design that accounts for this perturbed coherency. Additionally, we study how GFM droop, inverter capacity, and active power headroom affect natural low-frequency modes in heavily GFM-integrated grids, highlighting the importance of droop tuning. A zeroth-order gradient-based algorithm is proposed to optimize such settings and ensure adequate stability margins. Subsequently, we focus on sub- and super-synchronous control interactions (SSCIs). We extend the Dissipative Energy Flow (DEF) method to detect oscillation paths at faster frequencies, validated through PSCAD EMT cases with superimposed sub and super synchronous oscillations. Using an extended MiniWECC EMT case, we show oscillation propagation through MTDC links between cluster of IBRs and grid-side resources. To this end, we develop an EMT-in-the-loop learning framework for adaptive SSCI mitigation. Finally, we propose a physics-informed neural learning framework to emulate proprietary inverter dynamics, addressing challenges posed with proprietary inverter models. Our Physics-Informed Latent Neural ODE Model (PI-LNM) integrates physics with learning layers to capture black-box inverter dynamics, improving accuracy in grid simulations and control studies.

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1.0 Introduction

The rapid integration of power electronic resources at a large scale brings forth new dynamical challenges to grid behavior. Changes in the synchronous-dominant grid behavior due to power electronic interfaced renewables have the potential to inject unwanted and previously unseen oscillation patterns and changes in the stability and oscillation behaviors of bulk power systems [1]. The modified dynamics needs to be thoroughly understood to predict the grid dynamics, and subsequently, perform controls. Recent research efforts are looking into utilizing utility-scale grid forming inverter (GFM)-based resources [2, 3] where the GFM can act as a voltage source that can provide voltage and frequency support. For large, interconnected grids, poorly damped power oscillations in the tie-lines connecting utility regions can, therefore, result in catastrophic failures. Recently operators have seen unexplained trips of generation resources due to complex interactions of the inverter-based resource (IBR) controls, for example, in the Texas grid unexpected concurrent loss of synchronous and a group of inverters posed a significant risk to the bulk power system reliability [4]. Another recent example is the widespread blackout across the Iberian Peninsula [5], which disrupted power across mainland Portugal and peninsular Spain for nearly ten hours. Therefore, it is of high importance to characterize the dynamic grid behavior with high penetration of IBRs and design necessary controls that can enhance the damping performance of the grid oscillations and ensure safe and stable grid operations. Moreover, with the co-existence of low-inertia IBRs and high-inertia synchronous generators, there are complex, multi-timescales interactions between dynamics and controls that complicate the design and operation of such grids. As such, there is a need for advanced decision support framework and methods that can support multi-scales design and coordination via efficient exchange of critical information (e.g., safety and stability objectives and constraints) in a scalable and distributed fashion.

In this work, we have investigated two specific oscillation types. Chapters 2.0, 3.0, and 4.0 will delve into analysis and controls related to wide-area inter-area oscillations in presence of high integration of grid-forming inverters (GFMs). Our research shows that high GFM penetration could alter the conventional coherency structure of the power grid, which will require modifications in the wide-area control design. We proposed a distributed risk-constrained reinforcement learning based wide-area control design that are aware of the perturbed coherency structure due to high GFM integrations. In another work on wide-area stability, we show how variations in grid-forming inverter (GFM) droop, inverter capacity, and active power headroom influence natural low-frequency oscillation modes for heavily GFM-integrated grids. We highlight the need for careful droop tuning and propose a zeroth-order gradient-based algorithm to identify optimal settings that ensure sufficient small-signal stability margins across a wide range of parameter variations. Subsequently, in chapters 5.0, 6.0, we presented advanced analytics for sub-synchronous and super-synchronous control interactions (SSCIs). First, we extend the Dissipative Energy Flow (DEF) based method, originally developed for low-frequency electromechanical oscillations, to identify oscillation paths involving much faster sub- and super-synchronous oscillations, with tests performed on PSCAD-based EMT cases. The methodology can distinguish frequency-dependent source and sink roles, including cases where the same resource acts as a source at one frequency and a sink at another. Subsequently, we experimented with an extended MiniWECC EMT test-case where oscillations are propagated through the MTDC links from one side of IBR generations to the grid

side resources. Subsequently, in Chapter 7.0, we have developed an EMT-in-the-loop learning framework to adaptively tune the control gains to mitigate SSCIs. Finally, we propose a novel physics-informed neural ordinary differential equations-based framework in Chapter 8.0 to emulate the proprietary dynamics of the inverters – essential for improved accuracy in grid dynamic simulations. In current industry practice, the original equipment manufacturers (OEMs) often do not disclose the exact internal controls and parameters of the inverters, posing significant challenges in performing accurate dynamic simulations and other relevant studies, such as gain tunings for stability analysis and controls. To address this, we propose a Physics-Informed Latent Neural ODE Model (PI-LNM) that integrates system physics with neural learning layers to capture the unmodeled behaviors of proprietary units.

2.0 Structural Impact of Grid-Forming Inverters on Power System Coherency

Increased presence of inverter-interfaced resources within contemporary power grids has lead to many modeling and control challenges. Presently, the forefront of inverter technology mainly consists of two control methodologies: grid-following (GFL) and grid-forming (GFM) as outlined in [7, 8]. GFLs function as current sources, managing the AC-side current injected into the grid while synchronizing with the grid voltage phase angle through a phase-locked loop (PLL). In contrast, advanced grid-forming (GFM) inverters [2, 3] replicates the fundamental behaviors of synchronous generators (SGs) enabling the regulation of system voltages and frequencies. GFM technology effectively supports grid stability by autonomously controlling voltage and frequency at the points of interconnection with the transmission system. Among different design approaches for GFMs, the droop control stands out as a well-established solution [9]. This method involves adhering to the active power-frequency ($P - f$) and reactive power-voltage ($Q - V$) droop curves and guides the power-sharing during steady-states as well as transients. The synchronous generator-esque characteristics have been motivating operators for large deployment of GFM-interfaced renewable resources in future grid [3].

From the system theoretic viewpoint, the integration of low-inertia GFM-based resources inherently impacts the dynamics and eigenstructure of the underlying power systems. In small signal stability of power system dynamics, slow coherency is a fundamental characteristic, which results from the time-scale separation of synchronous generator's dynamics [10–12]. Generators with strong coupling tend to oscillate in unison, synchronizing rapidly to form slow coherent groups or clusters. Conversely, these groups sway against each other and synchronize over a slower time scale due to weaker coupling. Coherency has been used in operations for transmission planning for dynamic equivalencing, controlled islanding, oscillation damping control, etc [13–15]. Few articles have explored the impact of wind generation on coherency [16, 17], yet the foundational theory regarding the influence of grid-forming resources on coherency remains unresolved. Keeping the view of futuristic large integration of grid-forming technology [18], it is pertinent to fill the gap in theorizing how these resources may impact the coupled-oscillation structures of the grid in the low-frequency ranges (less than 2 Hz). The implications of this study are multi-fold. The coherent structures in presence of grid forming inverters will help the operator identify the power transfer paths that are influenced by the inter-area modes which many times are poorly damped. Therefore, the operator would be well-guided to design damping control infrastructures with the modified coherent structure information as prescribed by our studies in this work [18]. Moreover, the dynamic equivalents can also be effectively computed once the structural impact of these inverter dynamics has been captured in the coherent couplings.

This chapter presents the mathematical system description for a power system with droop-based GFMs replacing a fraction of the conventional synchronous generators. Thereafter, the chapter provides a detailed analytical treatment of how such a heterogeneous resource mix manifests in the small-signal oscillation behavior of the system. We show that the dynamics of

The work in this chapter is taken from this published article [6]: Mukherjee, S., Hossain, R.R., Chatterjee, K., Kundu, S., Kwon, K.B., Nekkalapu, S. and Elizondo, M.A., 2024, November. Structural impact of grid-forming inverters on power system coherency. In IECON 2024-50th Annual Conference of the IEEE Industrial Electronics Society (pp. 1-7). IEEE.

the GFMs help to preserve the weighted Laplacian-like structural behavior for the integrated system; however, the effective coupling between generation resources can lead to considerable perturbations in the slow eigenspace. This, in turn, alters the coherent oscillatory responses, leading to shifting of the cluster boundaries. We confirm our propositions with numerical simulations validated on the modified IEEE 68-bus system with GFMs added at selected locations.

2.1 System Model: GFM Integration Replacing Synchronous Resources

Consider a power grid composed of N buses. Let N_r be the number of resource buses with either SG or GFM-based resources. The behavior of synchronous generator i within bus i is described by the following swing equations [19]:

$$\dot{\delta}_i = \omega_i - \omega_0, \quad (1a)$$

$$\dot{\omega}_i = \frac{1}{M_i} [D_i(\omega_0 - \omega_i) + P_i - P_{ei}], \quad (1b)$$

Here, δ_i , ω_i , P_i , and P_{ei} denote the angle, frequency, input mechanical, and generated electrical powers of synchronous generator i . Parameters $\{M_i, D_i\}$ represent the inertia and damping coefficients, respectively. The swing equations represent the dynamics of a SG [19] and can be compactly written as, $\dot{x}_s = f_{\text{sync}}(x_s, V)$, where $f_{\text{sync}}(\cdot)$ denotes the functional form of the dynamics with $V = [V_{1_{Re}}, \dots, V_{N_{Re}}, V_{1_{Im}}, \dots, V_{N_{Im}}]$, and x_s denotes the SG states. Initially, we consider all the resources to be SGs; thereafter, we replace p SGs with GFMs having equal ratings. Consequently, after this modification, the number of SGs in the system is reduced to $N_r - p$ indexed in the set $\mathcal{G}$, with p newly added GFMs with indices in the set $\mathcal{F}$. For each GFM $j \in \mathcal{F}$, we consider the following dynamics that are also depicted in Fig. 1 and Fig. 2 [9,20,21]:

$$\dot{\delta}_j = \omega_j - \omega_0, \quad (2a)$$

$$\dot{\omega}_j = \frac{1}{\tau_j} [\omega_0 - \omega_j + \lambda_j^p (P_j^s - P_j^n)], \quad (2b)$$

$$\dot{V}_j^e = \frac{1}{\tau_j} [V_j^s - V_j^e - V_j + \lambda_j^q (Q_j^s - Q_j^n)], \quad (2c)$$

$$\dot{E}_j = k_j^{pv} \dot{V}_j^e + k_j^{iv} V_j^e, \quad (2d)$$

where $\lambda_j^p, \lambda_j^q, \tau_j$ are the active and reactive power droops and droop time constant, k_j^{pv} and k_j^{iv} are respectively the proportional and integral gains in the Q-V droop loop, τ_j is the time-constant associated with measurement filter, V^s , P^s , and Q^s are the set-points for voltage, active power and reactive power, respectively. The state vector for each GFM j becomes $x_j := [\delta_j, \omega_j, V_j^e, E_j]$. We stack these states together and denote the state-vector as $x_f := [\{x_j\}_j]$. Their dynamics can then be written as $\dot{x}_f = f_{\text{gfm}}(x_f, V)$.

Next, the active and reactive power flow balance at any bus j , $j = 1, \dots, m$ can be written

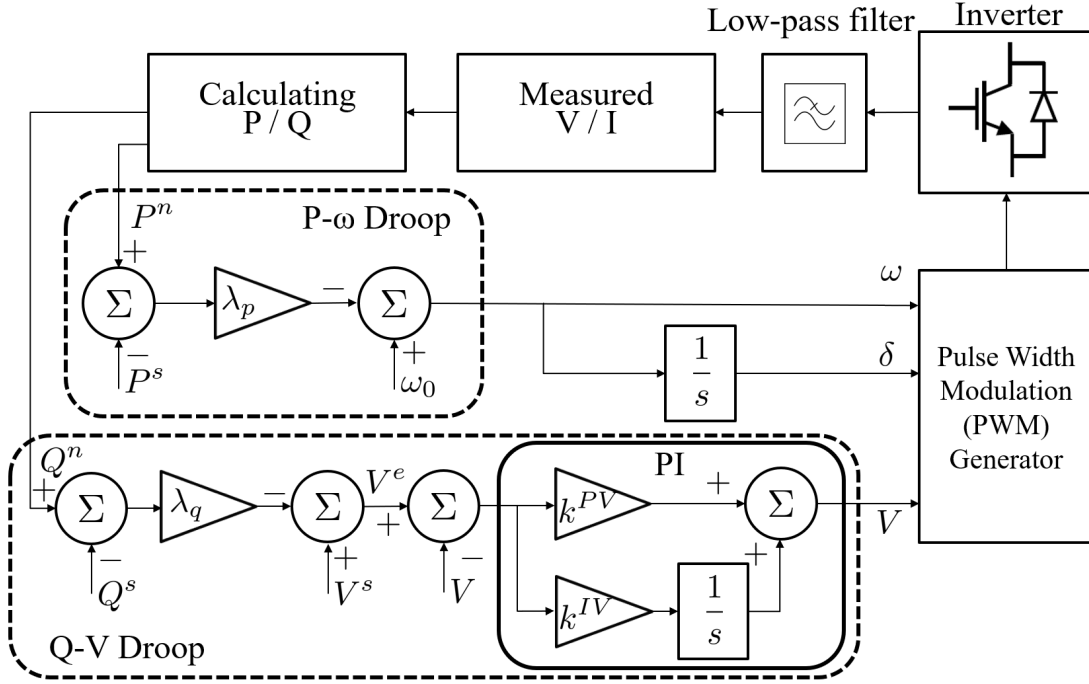


Figure 1: GFM dynamics based on droop controls [6].

as,

$$0 = P_{ej} - \operatorname{Re} \left\{ \sum_{k=1, k \neq j}^N V_j (V_{jk} B_{jk})^* \right\} - V_j^2 G_j, \quad (3a)$$

$$0 = Q_{ej} - \operatorname{Im} \left\{ \sum_{k=1, k \neq j}^N V_j (V_{jk} B_{jk})^* \right\} - V_j^2 B_j, \quad (3b)$$

where G_j and B_j represent the conductance and susceptance, respectively, of the shunt load at bus j when considering line charging. In the case of lossless transmission lines, B_{jk} indicates the susceptance of the tie-line linking bus j to bus k . The powerflow equations can be expressed with the functional form captured by $g(\cdot) : 0 = g(x_s, x_f, V)$.

Next, we will investigate the integrated small-signal frequency dynamics, aiding in the characterization of perturbations within the Laplacian dynamics, ultimately influencing the slow coherency.

2.2 Main Results: Impacts of GFMs on System Laplacian and Slow Coherency

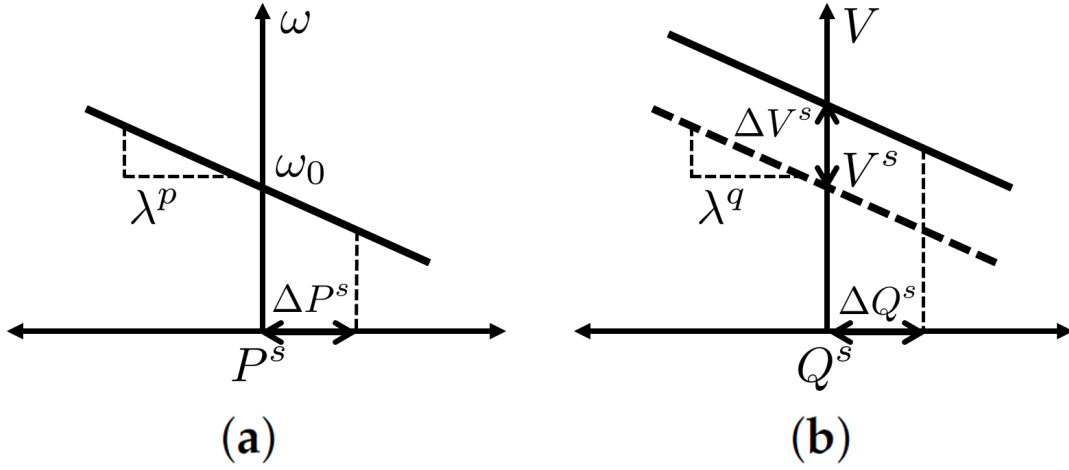


Figure 2: (a) $P - \omega$ and (b) $Q - V$ droop characteristics [6].

2.2.1 Structure-preserving Laplacian Sub-Matrix

To extract the Laplacian sub-matrix of the state dynamics, we examine the frequency dynamics influenced by the angles associated with the resources. Consider a vector that concatenates all angles for SGs denoted as δ_s and for GFMs as δ_f . Similarly, vectors for frequencies are denoted as ω_s for SGs and ω_f for GFMs. We can then express the frequency dynamics concisely for SGs as follows: $M\dot{\omega}_s = \bar{f}_{\text{sync}}(\delta_s, V)$, where $\bar{f}_{\text{sync}}(\cdot)$ represents the part of the complete functional form corresponding to the frequency dynamics. The SG angles influence the dynamics, as the electrical active power from SG i is defined by

$$P_{si} = \frac{E_i}{x'_{di}} (V_{iRe} \sin \delta_i - V_{iIm} \cos \delta_i).$$

Now, for the GFMs, we can similarly express this in a concise form as, $M_f \dot{\omega}_f = \bar{f}_{\text{gfm}}(\delta_f, E_f, V)$, where $\bar{f}_{\text{gfm}}(\cdot)$ represents a segment of the overall dynamics related to the frequency evolution, and E_f denotes the stacked internal voltage states for inverters. The equivalent inertia, M_f , offered by the grid-forming inverter unit depends on the GFM droop control parameters: $M_f = \text{blkdiag}(\{\frac{\tau_j}{\lambda_j^p}\}_j)$. Also, the powerflow equations in the functional form can be slightly expanded to include the additional state variables, such that $0 = g(\delta_s, \delta_f, E_f, V)$. At a stable operating point, linearizing the differential equations from SG and GFM dynamics, and the algebraic equations from powerflow, we have

$$M\Delta\dot{\omega}_s = A_{11}\Delta\delta_s + A_{12}\Delta V, \quad (4)$$

$$M_f\Delta\dot{\omega}_f = A_{21}\Delta\delta_f + A_{22}\Delta V + A_{23}\Delta E_f, \quad (5)$$

$$0 = A_{31}\Delta\delta_s + A_{32}\Delta\delta_f + A_{33}\Delta V + A_{34}\Delta E_f, \quad (6)$$

where the matrices A_{ij} denote the Jacobians corresponding to the argument variables. Further, we define, $A_1 = \text{blkdiag}(A_{11}, A_{21})$, $A_2 = [A_{12}; A_{22}]$, $M_e = \text{blkdiag}(M, M_f)$, $A_3 = [A_{31} A_{32}]$, $A_4 = [\mathbf{0}; A_{34}]$. Following which we may write,

$$\Delta V = -A_{33}^{-1}A_3 \begin{bmatrix} \delta_s \\ \delta_f \end{bmatrix} - A_{33}^{-1}A_{34}\Delta E_f. \quad (7)$$

Using this expression in (4), and (5), we will have,

$$M_e \begin{bmatrix} \Delta \dot{w}_s \\ \Delta \dot{w}_f \end{bmatrix} = (A_1 - A_2A_{33}^{-1}A_3) \begin{bmatrix} \delta_s \\ \delta_f \end{bmatrix} + (A_4 - A_2A_{33}^{-1}A_{34})\Delta E_f. \quad (8)$$

Therefore, the Laplacian matrix, L , for this Kron-reduced coupled SG-GFM interaction network is captured by

$$L = (A_1 - A_2A_{33}^{-1}A_3), \quad (9)$$

and the sub-matrix weighted by inertia that captures the impact of angles on the frequency dynamics is expressed as $M_e^{-1}L$. The eigenstructure of this weighted Laplacian matrix compared to that of the all-synchronous generator case determines the extent to which the addition of GFMs alters the dynamic coupling between the generating resources.

Lemma 1. *Droop-based GFMs preserve the Laplacian structure of the integrated sub-matrix L , ensuring that $L \cdot \mathbf{1} = \mathbf{0}$.*

Proof: The frequency dynamics of GFMs (GFMs) induce behavior resembling synchronous behavior, incorporating modifications to the inertia parameters. The equivalent inertia is determined by the parameter $\frac{T_j}{\lambda_j^p}$ for inverter j . Consequently, after the admittance matrices are Kron-reduced to capture the all-to-all coupling among generation resources, including SGs (SGs) and GFMs, the active power generated by the i^{th} GFM unit towards another GFM or SG (let's denote it as the j^{th} unit) is equivalently given by $E_i E_j B_{ij} \sin(\delta_i - \delta_j)$, where B_{ij} represents the equivalent Kron-reduced admittance between SG/GFM resources. Therefore, the components of the matrix L will result in:

$$L(i, j) = E_i E_j B_{ij} \cos(\delta_{i0} - \delta_{j0}) \text{ if } i \sim j, \quad (10)$$

$$= 0, \text{ if disconnected.} \quad (11)$$

Because of the active power-balance structure between the SG/GFMs to supply the loads, we will have,

$$L(i, i) = - \sum_{j \in \mathcal{N}_i} L(i, j). \quad (12)$$

Therefore, we will have $\mathbf{1}$ as one of its eigenvectors with zero eigenvalue resulting in the condition: $L \cdot \mathbf{1} = \mathbf{0}$. $\square$

Future research will investigate other control strategies for grid-forming resources, and how they impacts the Laplacian structures.

2.2.2 Perturbation in Coherent Boundaries

Despite replacing the active power generation from SGs (SGs) with GFM-based resources, operational constraints may limit the operator's ability to connect GFM resources only to nearby

buses. As a result, the integration of GFMs in place of SGs perturbs the operating points. However, it can be assumed, without loss of generality, that the error introduced to power flow Jacobians due to slight shifts in operating conditions is sufficiently small for practical purposes. If the operator can substitute SG generation with an equal capacity GFM, this would also justify the small perturbation. When considering only conventional synchronous machines integrated into the grid, the linearized model can be expressed as follows:

$$M\Delta\dot{\omega}_s = A_{11}\Delta\delta_s + A_{12}\Delta V, 0 = A_{31}\Delta\delta_s + A_{33}\Delta V, \quad (13)$$

and the Kron-reduced frequency dynamics would lead to,

$$M\Delta\dot{\omega}_s = (A_{11} - A_{12}A_{33}^{-1}A_{31})\Delta\delta_s. \quad (14)$$

Hence, the inertia-weighted Laplacian for the grid with only SGs is defined as $M^{-1}\bar{L}$, where,

$$\bar{L} = (A_{11} - A_{12}A_{33}^{-1}A_{31}). \quad (15)$$

As a result, the perturbation induced by significant GFM integration, resulting in $M_e^{-1}L$, would capture the inherent clustering behavior. Consequently, we present the following proposition regarding the modified coherency behavior.

Proposition 1. *Considerable GFM-based replacement can lead to shifts in coherent area partitions through perturbations in the slow eigen-space.*

Proof: We consider r coherent areas, taking into account the slow coherent behaviors as discussed in [11]. We examine matrices W_r and $\bar{W}_r$, whose columns are the eigenvectors corresponding to the zero eigenvalue and the $(r - 1)$ slow eigenvalues of the weighted Laplacians $M_e^{-1}L$ and $M^{-1}\bar{L}$, respectively. In [10], a Gaussian elimination-based procedure is used to construct permuted versions of W_r and $\bar{W}_r$ denoted as $\mathcal{W}_r$ and $\bar{\mathcal{W}}_r$ by first identifying reference machines for each group.

The canonical angles between these two sub-spaces are defined as $\theta_i = \cos^{-1} \sigma_i, i = 1, \dots, r$, where $\sigma_i, i = 1, \dots, r$ are the r smallest singular values of $\bar{\mathcal{W}}_r^T \mathcal{W}_r$. Let e_i and $\bar{e}_i$ be the i^{th} eigenvalues of $M_e^{-1}L$ and $M^{-1}\bar{L}$, respectively. If there is a gap $|e_r - \bar{e}_{r+1}| > \beta, \beta > 0$, then the perturbation in the sub-spaces can be captured by

$$\|\sin(\Theta)\|_F \leq \frac{1}{\beta} \|M^{-1}\bar{L}\mathcal{W}_r - \mathcal{W}_r\Sigma_r\|_F, \quad (16)$$

where $\Theta = \text{diag}(\theta_1, \dots, \theta_r)$, and $\Sigma_r = \text{diag}(e_1, \dots, e_r)$ [22, 23]. Due to this perturbation, the row vectors of the permuted GFM-integrated slow-subspaces (α_i 's) would be perturbed from the all-synchronous case ($\bar{\alpha}_i$'s) as follows [23]:

$$\|\alpha_i - \bar{\alpha}_i Q\|_F \leq \frac{1 + \sqrt{2}}{\beta} \|M_e^{-1}L - M^{-1}\bar{L}\|_F, \quad (17)$$

Here, Q is an orthogonal matrix that minimizes $\|\mathcal{W}_r - \bar{\mathcal{W}}_r Q\|_F$. However, as discussed in [11], these row vectors are constrained by the hyperplane

$$\sum_{j=1:r} \alpha_{ij} = 1, i = 1, \dots, n. \quad (18)$$

Subsequently, following Lemma 1, they will undergo a rotational shift, leading to the formation of a new clustering structure with a substantial change in $\|M_e^{-1}L - M^{-1}\bar{L}\|_F$. This captures the impact of GFM integration, introducing a perturbation in the slow eigenspace that propagates through the row vectors of the slow subspace, ultimately altering the clustering. $\square$

Remark 1 (*time-scale separation*). As the connections among resources within the same coherent areas being more rigid compared to those between different areas, we can still decompose, $L = L^I + \epsilon L^E$, where L^I , and L^E are the internal and external coupling matrices, and ϵ captures the worst-case ratio of tie-line reactances, considering both internal and external connections within the coherent areas. With GFM integrated dynamics the slow variable would be given as

$$\frac{\sum_{i \in \mathcal{G}} M_i \Delta \delta_{s_i} + \sum_{i \in \mathcal{F}} M_{f_i} \Delta \delta_{f_i}}{\sum_{i \in \mathcal{G}} M_i + \sum_{i \in \mathcal{F}} M_{f_i}}$$

for a particular modified coherent cluster, and the angle differences from a reference would be the fast variable.

Discussion 1 (*Implications from Operators Perspective*). The findings of this work inform a system planner of the potential changes in the inter-area oscillations following the interconnection of grid-forming inverter-based resources. From a system planners point of view, it is important to assess the risks of poorly-damped oscillations as the system evolves with increasing renewable penetration. An application where understanding the shifts in coherent boundary may be useful is the design of wide-area damping controllers to stabilize critical inter-area modes. Typically, in the design of damping controllers, the frequency difference between two areas oscillating against each other is used as the feedback signal for modulating the generator set-points. The knowledge of inter-area boundaries and their shifts helps the system engineer to select the feedback signals appropriately.

2.3 Case Studies and Numerical Validations

This section presents results from numerical studies on an IEEE test system to validate the claims and propositions made in the chapter. The positive-sequence fundamental frequency phasor model of the IEEE 68-bus New York – New England test system is considered. The network and model data for the test system is obtained from [24]. The base case of the IEEE 68-bus test system has 16 SGs in 5 coherent areas as shown in Fig. 3. The generators are connected to buses numbered between 53 and 68. We focus on the generators in Areas 1 and 2 (see the base case in Table 1), with their inter-area or coherent boundary shown with *red dotted line* in Fig. 3.

In this study, we investigate the impact of replacing SGs with GFMs on the coherent groups and their inter-area boundary. To this end, we study the following two scenarios.

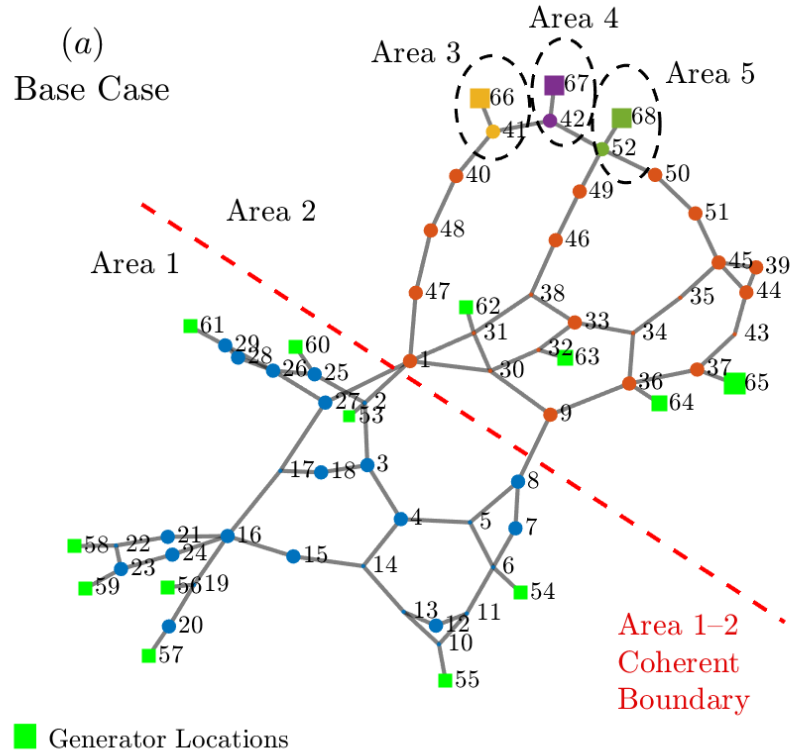


Figure 3: Coherent inter-area boundary between areas 1 and 2 for the base case [6].

Table 1: Summary of the Test Case Scenarios and their Coherent Groups [6]

Scenarios	Generators Replaced	Generators in Area 1	Generators in Area 2
(a) Base Case	—	Bus: 53, 54, 55, 56, 57, 58, 59, 60, 61	Bus: 62, 63, 64, 65
(b) Scenario 1	Bus: 65	Bus: 56, 57, 58, 59, 61	Bus: 53, 54, 55, 60 , 62, 63, 64
(c) Scenario 2	Bus: 63, 64, 65	Bus: 56, 57, 58, 59	Bus: 53, 54, 55, 60, 61 , 62

1. *Scenario 1*: The generator at bus 65 is retired and replaced with a GFM at the adjoining bus 37.
2. *Scenario 2*: The generators at buses 63, 64, and 65 are retired and replaced with GFMs at their adjoining buses 33, 36, and 37 respectively.

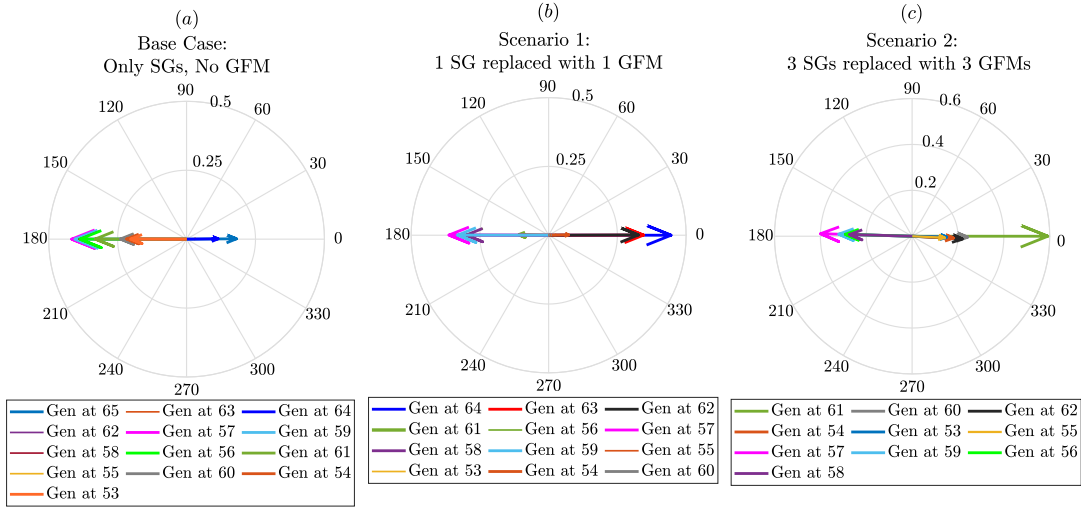


Figure 4: Generator modeshapes of the dominant inter-area mode for different test scenarios: (a) Base case, (b) Scenario 1, and (c) Scenario 2 [6].

The steady-state power injection set-points for the GFMs are the same as those of the retiring SGs. In Scenario 1, the synchronous generator at bus 65 is retired and replaced with a grid-forming IBR of the same capacity at bus 37. Retiring generator at bus 65 had an output of 3591 MW in the system data. Therefore, in Table 2, it is described that the total GFM output in Scenario 1 is 3591 MW. Similarly, in Scenario 2, three generators with a total power output of 5941 MW are retired and replaced by GFMs of same capacity. Therefore, in Table 2, the total GFM power is 5941 MW. The total real power injection from the GFMs in each scenario, both in absolute values and as a percentage of the system load (18408 MW), is shown in Table 2 (20% and 33% of total generation for Scenario 1 and 2, respectively), whereas the total generation is slightly greater than 18408 MW accounting for the network losses. The system model for each case is linearized about the steady-state equilibrium and the inter-area modes obtained from eigen-analysis are shown in Table. 4.

Table 2: Real Power Injections from the GFMs in Different Scenarios [6]

Scenarios	Total Real Power from GFMs	% of Total Load
1	3591 MW	20%
2	5941 MW	33%

First, we provided numerical validation of **Lemma 1**. Please note that $L \cdot \mathbf{1}$ is a vector. Table 3 shows that the statistical dispersion of the elements of the $L \cdot \mathbf{1}$ vector expressed in terms of their (a) mean and standard deviations (Std.), and (b) maximum value, are numerically 0 as expected. This confirms our proposition that $L \cdot \mathbf{1} = \mathbf{0}$ holds for both Scenarios 1 and 2. Please note that instead of tabulating each elements of the vector, we summarize using the

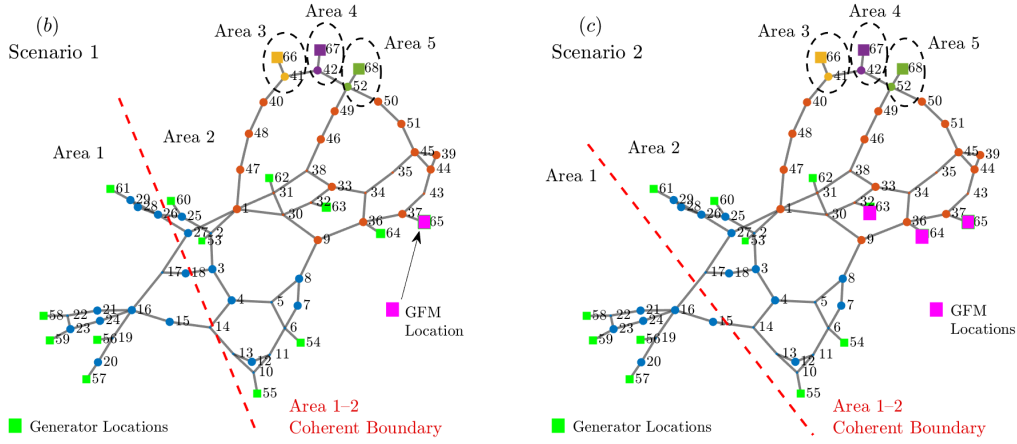


Figure 5: Coherent inter-area boundary between Areas 1 and 2 for Scenarios 1 and 2 [6].

Table 3: Numerical Validation of **Lemma 1** [6]

Mean $\pm$ Std. value for elements in $L \cdot 1$	
Scenario 1	Scenario 2
$(0.67 \pm 2.66) \times 10^{-15}$	$(0.94 \pm 2.56) \times 10^{-14}$

Maximum value for elements in $L \cdot 1$	
Scenario 1	Scenario 2
1.07×10^{-14}	9.95×10^{-14}

representative statistics.

From Table 4, observe that the inter-area modal frequencies 0.4 Hz, 0.57 Hz, and 0.85 Hz remained unchanged from the system modifications. However, the 0.75 Hz mode in the base case changed significantly in Scenarios 1 and 2 from the SG retirement and GFM addition. The relative participation of the retired generators in the inter-area modes can explain this selectivity in modal behavior. The retirement of a large ($\approx 20\%$ of total capacity) generator in Scenario 1 reduces the system inertia, which increases the modal frequency¹.

The system changes in Scenarios 1 and 2 also cause a shift in the inter-area or coherent area boundaries in the system. This is verified by the mode shapes obtained from eigenvector analysis. In Fig. 4, we plot the modeshapes of the generator speeds corresponding to the GFM-sensitive 0.75 Hz inter-area mode for the base case and scenarios 1 and 2 respectively. Observe that, transitioning from the base case to Scenario 1, the SGs connected to buses 53, 54, 55, and 60 flipped from Area 1 (coherent with SGs at buses 56 – 61) to Area 2 (coherent with SGs

¹For the relationship between single machine-equivalent inertia and modal frequency, please see [19, Eqn. (12.81)].

Table 4: Inter-Area Modes for Different Scenarios [6]

	Base Case	Scenario 1	Scenario 2
Inter-area Modes (Modal Frequencies)	0.41 Hz	0.47 Hz	0.49 Hz
	0.57 Hz	0.56 Hz	0.56 Hz
	0.75 Hz	1.14 Hz	1.36 Hz
	0.85 Hz	0.85 Hz	0.85 Hz

at buses 62 – 64). Further, with more SGs replaced in Scenario 2, the change in the slow-coherent oscillation pattern is more pronounced, as shown in Fig. 4(c). In this case, in addition to the SGs at buses 53, 54, 55, and 60 from Scenario 1, the SG at bus 61 also flipped from Area 1 to 2. The summary of the cases and the generators in the coherent groups are shown in Table 1. Figure 5 shows the transition of coherent area boundary (*red dotted line*) from the base case to Scenario 1, and finally to Scenario 2.

Table 5: Coherent Groups with *Slow-Coherency Grouping Algorithm* [10]

Scenarios	Generators in Area 1	Generators in Area 2
Scenario 1	Bus: 53, 55, 56, 57, 58, 59, 60, 61	Bus: 54 , 62, 63, 64
Scenario 2	Bus: 56, 57, 58, 59	Bus: 53, 54, 55, 60, 61, 62

To validate our findings on the coherency groups, we compared our results with those obtained from *Slow-Coherency Grouping Algorithm* [10, Chapter 3.4]. The algorithm outcomes for Scenario 1 and 2 are listed in Table 5. Now, comparing Table 1 and Table 5, we found that the coherent grouping obtained by the algorithm identically matches with our observation for Scenario 2, where 3 SGs (SGs at buses 63, 64, and 65) are replaced, while there is slight disagreement in Scenario 1, where only SG at bus 65 is replaced. We further observed that the mismatches are related to SGs at buses 53, 54, and 60, which have relatively less contribution in interarea mode (see Fig. 4(b)). Additionally, from Fig. 5 (b) it is evident that these 3 SGs are located close to the interarea boundary; therefore intuitively the grouping algorithm appears less sensitive for those low contributing SGs, causing the mismatch.

The results of this study provide system planners with insights into potential changes in inter-area oscillations following the integration of grid-forming inverter-based resources. For system planners, the study helps to evaluate the risks of poorly damped oscillations as the system evolves with increasing renewable energy penetration.

2.4 Conclusions

This chapter focuses on the the impact of replacing SGs with GFM-based resources on the inter-area oscillation patterns in transmission networks. Theoretical analysis and numerical

observations based on small-signal models of inverters and SGs have shown that such impacts can be significant in changing the long-perceived coherency structures of the system. Insights drawn from the study can aid in system planning and can avert the potential risks originating from poorly-damped low-frequency oscillations.

3.0 Coherency-Aware Learning Control of IBR-Dominated Grids: A Distributed Risk-Constrained Approach

In the last chapter we show how the significant penetration of GFM-interfaced utility-scale distributed energy resources (DERs) affects the intrinsic dynamic behavior of power systems. Designing wide-area controls would benefit from understanding the grid's underlying clustering structure with GFM-based renewable resources. We address this gap by first capturing the modified coherency structure of the grid due to GFM integration, then designing oscillation control using this coherency information.

Over the last few decades, Reinforcement Learning (RL) has effectively tackled intricate nonlinear dynamic tasks within the context of a Markov Decision Process (MDP) [26], and control-theoretic state-spaces [27, 28]. In power systems, RL is used for short-term transient voltage control [29, 30], energy storage control in microgrids [31], and wide-area damping control [32]. However, RL's model-free approach results in high sample complexity for training [33]. To address this, we use a hybrid approach: employing the nominal dynamic model of the grid with additional process noise to account for uncertainties from load and renewable fluctuations. We then use a zero-order gradient optimization approach within a risk-constrained linear-quadratic regulator (LQR) setting. In addition to the recent work [21], the control design incorporates a distributed architecture to account for infusing the perturbed coherency information, which improves the oscillation performance.

Contributions. The contribution of the work is multi-fold. First, we present the formulation of wide-area oscillation control when large-scale GFM integration replaces some of the conventional synchronous generation. Due to the consideration of the load and renewable fluctuations, the mean-variance risk constraints are enforced within the control framework. Next, we present the theoretical analysis of how large-scale grid-forming penetration can structurally impact grid clustering behavior. Subsequently, the chapter presents the design of a distributed output feedback reinforcement learning controller that leverages the domain-aware coherency information, demonstrating improved performance compared to coherency-agnostic control designs. Lastly, numerical experiments conducted on the IEEE 68-bus system validate the efficacy of the proposed approach.

3.1 GFM Integration for SG Replacement: Grid Control Problem

3.1.1 Control Formulation

The system operator would like to minimize oscillatory power grid behavior following faults and other disturbances. The operator can create a linearized grid model by linearizing around a stable operating point (Kron reduction [19]) in normal operations. Let us concatenate all the generator states such that $x_s = [\delta_1, \dots, \delta_{N_r-p}, \omega_1, \dots, \omega_{N_r-p}]$, and the state vector per GFM j are denoted as $x_f = \{x_j\}$, $x_j := [\delta_j, \omega_j, V_j^e, E_j]$. Thereafter, the stacked state-vector $x = [x_s, x_f]^T$ would result in an integrated discrete small-signal dynamics by considering the

The work in this chapter is published in this article [25]: Kwon, K.B., Hossain, R.R., Mukherjee, S., Chatterjee, K., Kundu, S., Nekkhalapu, S. and Elizondo, M., 2024. Coherency-aware learning control of inverter-dominated grids: A distributed risk-constrained approach. IEEE Control Systems Letters, 8, pp.2120-2125.

GFM control time Δt as:

$$x_{t+1} = Ax_t + Bu_t + \xi_t, t = 0, 1, \dots, \quad (19)$$

where $u := [\Delta V^{ref}, \Delta P^{ref}, \Delta Q^{ref}]^\top \in \mathbb{R}^{3N_f}$ with $V^{ref} = \{V_j^{ref}\}_j$, $P^{ref} = \{P_j^{ref}\}_j$, $Q^{ref} = \{Q_j^{ref}\}_j$. Here, we add process noise ξ_t to account for the variability in the grid due to load and renewable perturbations to formulate a robust design.

Utilizing the system dynamics given in equation (19), we determine an optimal control strategy by solving a linear quadratic regulator (LQR). This objective aims to minimize the overall cost associated with both state and control variables:

$$\min_K R_0(K) = \lim_{T \rightarrow \infty} \frac{1}{T} \mathbb{E} \sum_{t=0}^{T-1} [x_t^\top Q x_t + u_t^\top R u_t], \quad (20)$$

with Q and R being positive semi-definite and positive definite weight matrices for each state and control variables, respectively. Our objective is to find the distributed static controller gain matrix K for $u_t = -K y_t$. Here, y_t are the outputs Cx_t with output matrix C indicating the list of observable states, which enforces the distributed nature of the wide-area control. Along with (20), we implement a mean-variance risk constraint to improve the worst-case performance:

$$\begin{aligned} \min_K R_0(K) &= \lim_{T \rightarrow \infty} \frac{1}{T} \mathbb{E} \sum_{t=0}^{T-1} [x_t^\top Q x_t + u_t^\top R u_t] \\ \text{s.t. } R_c(K) &= \lim_{T \rightarrow \infty} \frac{1}{T} \mathbb{E} \sum_{t=0}^{T-1} (x_t^\top Q x_t - \mathbb{E}[x_t^\top Q x_t | \mathcal{H}_t])^2 \leq c \end{aligned} \quad (21)$$

where $\mathcal{H}_t = [x_0, u_0, \dots, x_{t-1}, u_{t-1}]$ being a state and control trajectory up to t and c being a risk tolerance parameter. The mean-variance risk measure indicates deviations between the expected and realized state costs. Incorporating the risk constraint helps address challenges from system variability due to external load disturbances, renewable fluctuations, and imperfect modeling, thus enhancing the controller's worst-case performance. Here, we introduce the distributed consideration in the design.

Coherent-structure-aware Control: From a system-level perspective, integrating GFM-dominated resources inherently influences the dynamic behavior of power systems. Slow coherency, a key characteristic, arises from the time-scale separation in the dynamics of synchronous machines. Strongly coupled machines oscillate together, forming slow, coherent groups, while these groups oscillate against each other over a slower time scale due to weaker coupling. The goal of distributed control is to leverage this slow coherency structure for better oscillation damping control. Understanding the inherent clustering pattern, especially with significant GFM-based renewable energy, enhances wide-area control performance. Thus, we first identify the altered coherency structure from GFM integration and then design distributed control accordingly.

3.2 Distributed Risk-Constrained Learning Control Solution

The pre-tuning is designed to select appropriate feedback variables based on the modified clustering structure. Here, the main steps are as follows:

- *Step-1: Compute* small-signal model for the grid with GFM penetration.
- *Step-2: Examine* eigen-vectors corresponding to slow eigenvalues (inter-area oscillations) and compute mode-shapes (an example will be given in numerical experiments).
- *Step-3: Compute* the all-new coherent groupings encompassing SGs and GFMs based on the mode-shapes.
- *Step-4: Construct* angular differences along the new partitions, which are used as distributed feedback. This step signifies capturing tie-line active power flows as they are dependent upon angular differences of the boundary resources.

Therefore, feedback are taken from the generating resources assuming they are equipped with decentralized estimators near the coherent boundaries within the nearest possible hops of the form $\Delta\delta_i - \Delta\delta_j$ (signifying P_{ij}) where i^{th} and j^{th} resources belong to neighboring areas. Next, we describe the algorithm to compute $u_t = -Ky_t$. Zeroth-order RL Problem (21) poses difficulty due to the risk-aware constraints, and static output feedback, therefore, we utilize the policy gradient based reinforcement learning framework. To solve (21), we first reformulate the constraint to a quadratic form while removing the conditional expectation with respect to $\mathcal{H}_t$ [34]. Specifically, with an assumption that the noise ξ_t has a finite fourth-order moment, the constraint is reformulated as

$$R_c(K) = \lim_{T \rightarrow \infty} \frac{1}{T} \mathbb{E} \sum_{t=0}^{T-1} \left(4x_t^\top Q W Q x_t + 4x_t^\top Q M_3 \right) \leq \bar{c} \quad (22)$$

where $\bar{c} := c - m_4 + 4\text{tr}\{(WQ)^2\}$, $\bar{\xi} := \mathbb{E}[\xi_t]$, $W := \mathbb{E}[(\xi_t - \bar{\xi})(\xi_t - \bar{\xi})^\top]$, $M_3 := \mathbb{E}[(\xi_t - \bar{\xi})(\xi_t - \bar{\xi})^\top Q(\xi_t - \bar{\xi})]$, and $m_4 := \mathbb{E}[(\xi_t - \bar{\xi})^\top Q(\xi_t - \bar{\xi}) - \text{tr}(WQ)]^2$. Here, we consider random noise samples for ξ to represent worst-case variability in actual real-world load and generation variations. Hence, the required moment values are computed by gathering samples of ξ , which are used in offline trajectory generation. Once learning is complete, the learned K is utilized to generate control actions during online implementation. In practice, designers can adopt more systematic methods to generate ξ using historical measurements gathered by utilities. From these datasets, measures of the noise statistics can be obtained.

Next, we implement a stochastic gradient-descent method with a max-oracle (SGDmax), which can consider both the risk constraint and structured feedback using dual approach [35]. First, we formulate the Lagrangian function with the multiplier $\mu \geq 0$, as given by,

$$\mathcal{L}(K, \mu) := R_0(K) + \mu[R_c(K) - \bar{c}]. \quad (23)$$

Note that the Lagrangian retains the same quadratic structure as the original LQR objective. This characteristic allows us to apply a gradient-based approach, which is widely used for solving the unconstrained LQR problem [34]. Specifically, we employ the policy gradient method with the Lagrangian function considered as a value function. We directly update our policy K by computing the estimated gradient of the value function, which, in our case, is represented by the Lagrangian function [26]. With (23), the dual problem is formulated as the maximin problem:

$$\max_{\mu \in \mathcal{Y}} \min_K \mathcal{L}(K, \mu), \quad (24)$$

where $\mathcal{Y} := [0, \bar{\mu}]$ is a bounded set for μ by assuming that (21) is feasible and thus μ is finite. Here, we consider minimax counterpart of (24) instead, i.e.

$$\min_K \Phi(K), \text{ where } \Phi(K) := \max_{\mu \in \mathcal{Y}} \mathcal{L}(K, \mu), \quad (25)$$

which enables us to find the stationary point of (24) since the KKT stationary condition is the same in both problems. Note that we can directly find optimal μ by choosing $\mu = 0$ if the constraint is satisfied and $\mu = \bar{\mu}$ otherwise as $\mathcal{L}(K, \mu)$ is a linear function of μ . In order to further minimize $\Phi(K)$, we can implement the gradient descent (GD) method with the zero-order policy gradient (ZOPG) [35]. Specifically, we can estimate the ZOPG by utilizing the expression:

$$\hat{\nabla}_K \mathcal{L}(K; U) = \frac{n_K}{r} \mathcal{L}(K + rU, \mu') U, \quad (26)$$

where U represents a random perturbation following the same structure as K , with $\|U\| = 1$, while r and n_K indicates the smoothing radius and the number of non-zero entries and $\mu' = \arg \max_{\mu \in \mathcal{Y}} \mathcal{L}(K + rU, \mu)$. Note that incorporating ZOPG eliminates the necessity of computing the first-order gradient $\nabla_K \mathcal{L}(K, \mu)$ as ZOPG can directly utilize the function value $\mathcal{L}(K, \mu)$ to estimate the gradient.

By utilizing the ZOPG, we implement the stochastic gradient-descent with max-oracle (SGDmax) algorithm as indicated in Algorithm 2. From the initial policy K_0 , we perform iterative gradient descent updates on K . To mitigate estimation variance, we leverage $\hat{G}(K)$, which denotes the average of N_i estimates obtained through ZOPG. It is noteworthy that by selecting appropriate values for the smoothing radius r , step-size η , and the number of iterations M along with the Lipschitz and smoothness constants of $\Phi(K)$, we can achieve a high convergence probability to the stationary point, as stated in Lemma 1. The detailed proof with selection of parameters can be found in [35, Appendix B].

Lemma 1. [35] *By appropriately selecting parameters r, η , and M in accordance with the local Lipschitz and smoothness properties of $\Phi(K)$, and initializing a feasible K_0 , Algorithm 2 is demonstrated to converge to the stationary point of (25) with a high probability of approximately 90%.*

Remark 1. *The proposed method can be practically implemented utilizing GPS-synchronized pre-deployment compensators mitigating total communication delay. Robust statistical regression approaches can effectively address measurement noise issues. However, a limitation of the study lies in the unavailability of linearized dynamic models for very large-scale grids. Nevertheless, many independent system operators (ISOs) possess nearly accurate dynamic models in standard softwares with periodic updates based on the field up-gradations, facilitating coherency studies for newly connected inverter resources. Moreover, the use of coherency structure in the algorithm helps make the design scalable to larger networks.*

3.3 Numerical Experiments

We conducted numerical tests using the standard IEEE 68-bus system. As described in Section 3.1, we replaced $p = 3$ SGs out of a total of 16 SGs with GFMs, positioned at nodes

Algorithm 1: Coherency-aware Stochastic gradient-descent with max-oracle (SGDmax)

- 1 **Inputs:** A feasible and stable policy K_0 , upper bound $\bar{\mu}$ for μ , step-size η , the number of ZOPG samples N_i and the number of iterations M .
 - 2 Run steps 1-4 as of pre-tuning to select the modified coherency structure and distributed feedback.
 - 3 **for** $m = 0, 1, \dots, M - 1$ **do**
 - 4 **for** $s = 1, \dots, N_i$ **do**
 - 5 Sample the random U_s where $\|U_s\| = 1$.
 - 6 Use (26) to return $\hat{\nabla}_K \mathcal{L}(K_m; U_s)$.
 - 7 **end**
 - 8 Compute the averaged stochastic gradient $\hat{G}(K_m) = \frac{1}{N_i} \sum_{s=1}^N \hat{\nabla}_K \mathcal{L}(K_m; U_s)$.
 - 9 Update $K_{m+1} \leftarrow K_m - \eta \hat{G}(K_m)$.
 - 10 **end**
 - 11 **Return:** the final iterate K_m .
-

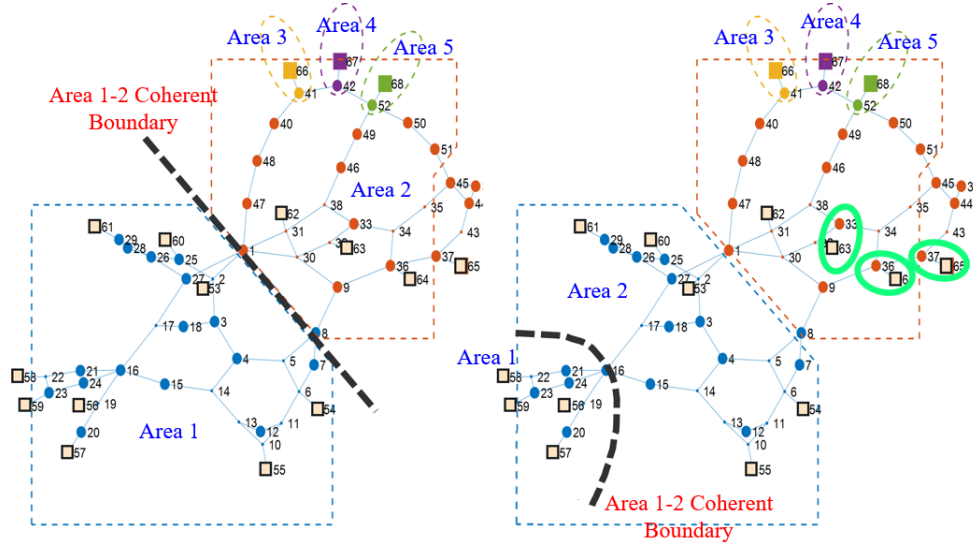


Figure 6: Transition in Coherent Area Partitioning [25]

63, 64, and 65. The parameters for the GFMs were configured as follows: $\tau = 0.01$, $k^{pv} = 1.00$, $k^{iv} = 5.86$, $\lambda^p = 0.05$, $\lambda^q = 0.05$. For the distributed feedback, we considered that only angle differences $\Delta\delta_{ij}$ could be observed between SGs and GFMs in different areas, within nearest-possible hops from the area boundary, and set the output matrix C accordingly. This captures the tie-line active power flows as they are dependent upon angular differences. Fig. 6 shows how the GFM integration impacts the coherent area boundaries where SGs at buses 53, 54, 55, 60, and 61 are transitioned from the nominal area grouping to form an all-new area partitioning. Fig. 7 shows how the mode-shapes (eigenvector elements corresponding to

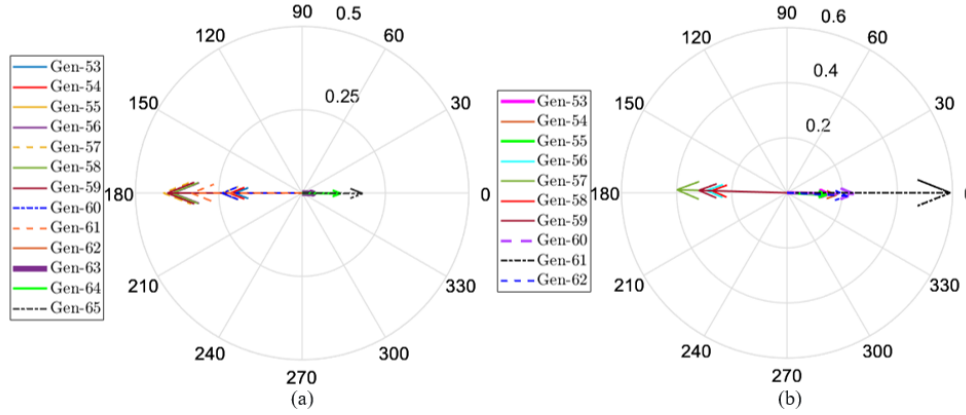


Figure 7: Mode shape plots for (a) Nominal (Base) and, (b) Modified GFM integrated power system model [25]

the low-frequency(slow) modes) of the resources signify this shift in area boundaries. More details on such changes can be found in the pre-print [36].

We compared two scenarios with different area partitioning strategies aimed at enhancing oscillation control, as illustrated in Fig. 6. In scenario 1 (*coherency-agnostic*), default areas were utilized as in the left figure of Fig. 6, while scenario 2 (*coherency-aware*) implemented a coherency-aware distributed design for area partitioning by following the right one. Consequently, scenario 1 involved buses $\{53, 54, 60, 61\}$ in Area 1 and $\{62, 63, 64\}$ in Area 2, whereas scenario 2 considered $\{56, 57, 58, 59\}$ in Area 1 and $\{53, 55, 60, 61\}$ in Area 2. Both scenarios underwent training using the SGDmax algorithm outlined in Algorithm 2, with the following parameters: $r = 0.01$, $M = 10$, and $\eta = 10^{-8}$. The control time step was set to $\Delta t = 0.01s$, with observations conducted from 0 – 100s. At $t = 0$, we generate the impulse

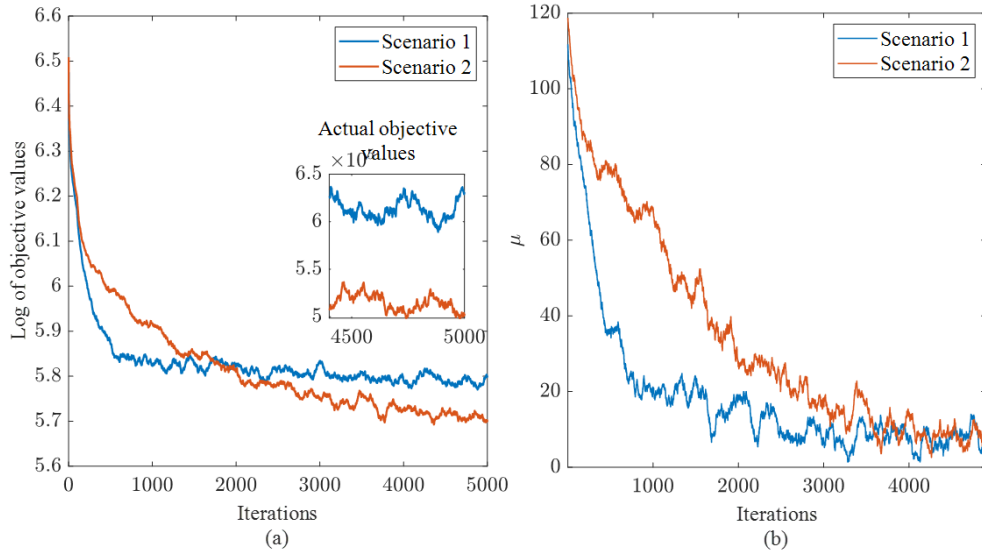


Figure 8: (a) Training performance and (b) Average μ for Scenario 1 and Scenario 2 [25]

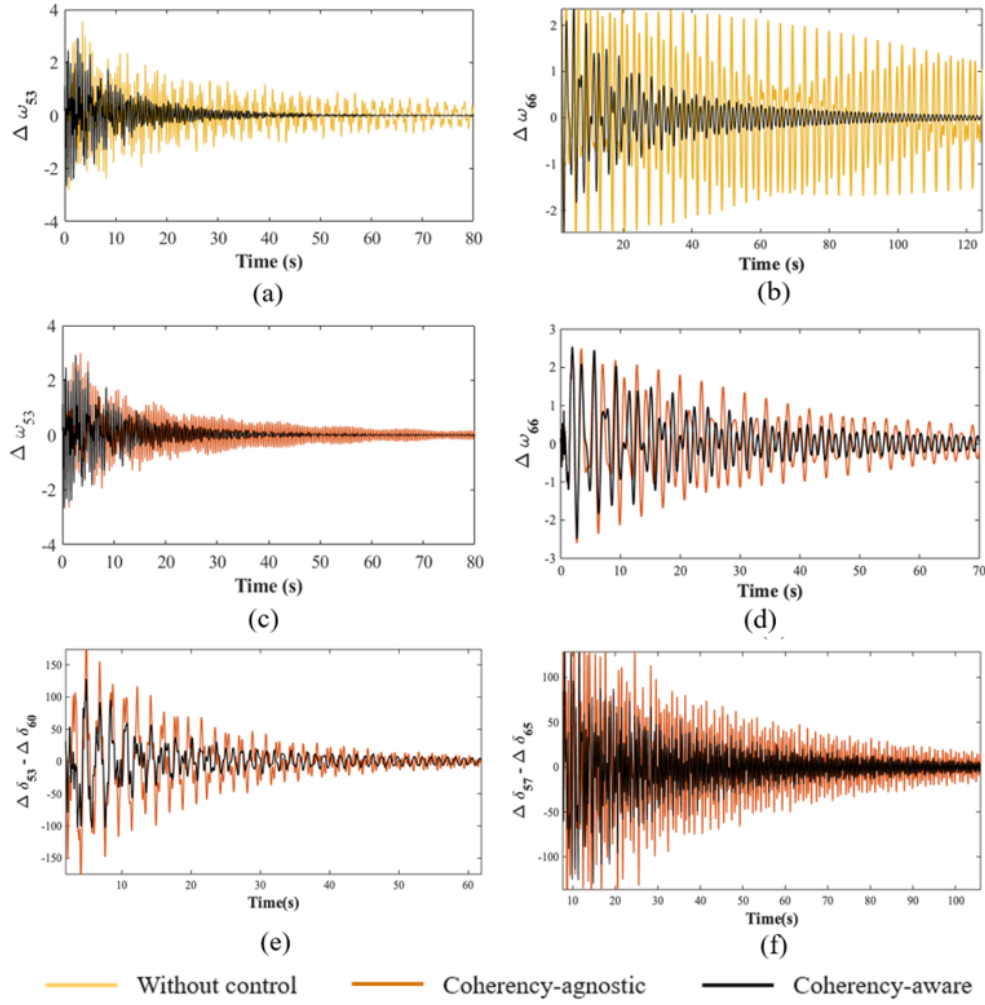


Figure 9: Plots for *without control* vs *coherency-aware* (a) frequency at SG-53, (b) frequency at SG-66; plots for *coherency-agnostic* vs *coherency-aware* (c) frequency at SG-53, (d) frequency at SG-66, (e) angle difference between SG-53 and SG-60, and (f) angle difference between SG-57 and GFM-65 [25].

inputs to each SG and GFM, while ξ_t follows the Gaussian distribution.

We first present training results to verify the convergence of Algorithm 2 and check the solution satisfies the constraint. Fig. 32(a) depicts the evolution of the objective values over time. Along with convergence, notably, the coherency-aware design consistently yields smaller objective values compared to the coherency-agnostic approach, achieving approximately a 30% enhancement. In addition, during the convergence phase, after the initial transients settle around 2000 iterations, the cost objectives of the coherency-aware design consistently remain lower bounds compared to those of the coherency-agnostic design. This observation suggests that integrating perturbed area-partitioning information into the distributed feedback significantly enhances the learning process for wide-area control. Next, Fig. 32(b) illustrates the

trajectory of average μ from N_i ZOPG samples during training. It is evident that starting near $\bar{\mu}$, the average μ gradually converges towards 0. This outcome suggests that as the iterations continue, we approach the optimal solution that satisfies the constraint as $\mu = 0$ when the constraint is satisfied, whereas $\mu = \bar{\mu}$ otherwise.

Using the converged policies in both scenarios, we conduct tests between scenarios 1, 2, and the one without control. Fig. 9 illustrates $\Delta\omega_i$ and $\Delta\delta_i - \Delta\delta_j$ for some typical scenarios. Specifically, Fig. 9(a) and Fig. 9(b) compare $\Delta\omega_{53}$ and $\Delta\omega_{66}$ between the one without control (yellow) and scenario 2 (black), respectively. Clearly, the control policy of scenario 2 outperforms the one without control. More specifically, the damping of a couple of slow modes 0.49 and 0.56 Hz have been improved from 1.2%, 1.8% to 13.4% and 4.5%, respectively. Similarly, Fig. 9(c) and Fig. 9(d) depict the comparison of $\Delta\omega_{53}$ and $\Delta\omega_{66}$ between scenario 1 (orange) and scenario 2 (black). Still, scenario 2 exhibits better performance than scenario 1, indicating that coherent area partitioning enhances damping performance. This is further demonstrated in Fig. 9(e) and Fig. 9(f), which illustrate $\Delta\delta_{53} - \Delta\delta_{60}$ and $\Delta\delta_{57} - \Delta\delta_{65}$, respectively. Similar to $\Delta\omega$, scenario 2 displays superior performance in reducing deviations in both cases. Since these angle differences are closely related to tie-line power flow, the result highlights the effectiveness of the proposed method in mitigating the power flow deviations across the coherent areas.

3.4 Conclusions

This chapter explores the significance of incorporating coherency-aware control design for mitigating persistent oscillations in large-scale power grids with substantial presence of inverter-based resources. Our proposed coherency-aware design employing distributed output feedback-based reinforcement learning has demonstrated superior training and oscillation performance compared to coherency-agnostic control designs. Future research will include high-fidelity transmission-scale models, different types of power electronics interfaced resources causing coherent clustering behavior of the bulk power grids. Additionally, robust data-driven control designs in presence of net-load uncertainties and incorporation of other risk measures, such as conditional value at risk (CVaR) will be investigated.

4.0 Stability Assessment and Guided Droop Design for Grid-Forming Inverter Resources in Bulk Grid

The growing penetration of grid-forming (GFM) inverter-based resources (IBRs) in bulk grids necessitates in-depth analysis and characterization of critical network behaviors such as those concerning system stability. Of particular interest are the small-signal studies on the risks of poorly-damped natural modes and their evolution with system conditions and design choices. Thus motivated, this chapter presents model-based eigenanalysis to evaluate the impacts of parameter variation and derive stability-informed design insights. The study considers an IBR-dominated bulk power grid with a resource mix that constitutes droop-controlled GFM inverters and traditional synchronous generators. The work analyzes the impacts of (a) varying GFM droop for a fixed inverter capacity and fixed active power headroom, (b) varying the inverter capacity for a fixed GFM droop setting, and (c) varying the active power headroom for a fixed GFM droop and inverter capacity. The findings highlight that, in certain cases, fine-tuning the droop parameter is crucial to maintaining the desired stability margin. To address this, the chapter subsequently proposes a zeroth-order gradient-based algorithm for identifying the optimal droop settings that guarantee small-signal stability with a specified margin over a wide range of parameter variations. Numerical simulations for guiding the design choice and validation of the proposed algorithm are presented for an IEEE benchmark test system interfaced with multiple GFM IBRs.

The droop parameters governing the inverter's P - ω and Q - V characteristics influence the system's transient dynamics and play an important role in determining stability [38–41]. Prior research in this area has shown that tuning the droop impacts the system's eigenvalues and, by extension, its oscillation modes [38]. In this context, one may refer to the real-world events from Hawaii's Kaua'i Island, which have shown that aggressive P - ω droop in the inverters can induce sustained low-frequency oscillations in the system [41]. These oscillations, if unchecked, may pose serious reliability risks. Besides droop, other operating parameters like the inverter capacity, dispatch, available headroom on real and reactive powers, as well as network conditions such as the grid strength at the POI, also influence the stability [38, 42]. Deployments, therefore, have to consider both optimal design and operating regimes to ensure that interconnecting resources do not negatively impact the system's dynamic behavior.

In this context, research works such as [43] and [44] report findings specific to microgrids and do not address the challenges critical to bulk power systems with heterogeneous resource mix. For large systems, theoretical studies assessing stability with detailed models of inverters are complex and often analytically intractable. Therefore, practical approaches to obtaining stability-informed design settings, in most cases, rely on numerical simulations [39, 45]. These, for small-signal stability assessment, study the loci of the critical eigenvalues over a wide range of design choices and parameters. In multivariable co-design problems, it might so happen that the loci for the eigenmodes do not follow a uniform trend. In other words, tuning a parameter might shift one eigenvalue to the left while another to the right, imposing contradictory requirements for stability. To address design challenges of this nature, the chapter presents a zeroth-order gradient-based search algorithm [46] followed by a bisection method for identi-

The work in this chapter is published in this article [37] : Hossain, R.R., Chatterjee, K., Kwon, K.B., Mukherjee, S., Kundu, S., Elizondo, M. and Adetola, V., Stability Assessment and Guided Droop Design for Grid-Forming Inverter Resources in Bulk Grid. IEEE PES General Meeting 2025.

fying the optimal GFM droop settings that are cognizant of these stability constraints while ensuring that sufficient margins are guaranteed for all critical oscillation modes in the system. The numerical simulations are performed on a MATLAB-based positive-sequence phasor model of an IEEE test system modified with a GFM inverter network.

The following are the main contributions. First, eigenvalue sensitivity studies are performed on the small-signal model of the system to study the impacts of (a) droop parameter variation, (b) inverter capacity variation, and (c) active power headroom variation on small-signal stability. Next, inferences derived from the parameter sensitivity studies are used to design a two-stage method including a zeroth-order gradient-based algorithm and a bisection search for optimal droop selection. The algorithm ensures that for a given IBR penetration scenario with a specified capacity and real power headroom, an optimal setting for GFM droop is obtained that respects operator-desired stability margins for all critical eigenmodes. The performance of the proposed algorithm is verified through numerical simulations on the mentioned IEEE test system.

4.1 Grid Forming Inverter Dynamics

This study considers an N -bus transmission system comprising m synchronous generators (SGs) and n GFM-based inverters. The GFMs are represented as P - ω and Q - V droop-controlled resources following the WECC-approved positive sequence REGFM_A1 model [47] developed at PNNL. The dynamics of GFMs are described as follows [47]:

$$\dot{\delta}_j = \omega_j - \omega_0, \quad (27a)$$

$$\dot{\omega}_j = \frac{1}{\tau_j} [\omega_0 - \omega_j + m_{p_j}(P_j^{set} - P_j)], \quad (27b)$$

$$\dot{V}_j^e = \frac{1}{\tau_j} [V_j^{set} - V_j - V_j^e + m_{q_j}(Q_j^{set} - Q_j)], \quad (27c)$$

$$\dot{E}_j = k_j^{pv} \dot{V}_j^e + k_j^{iv} V_j^e \quad (27d)$$

where $\delta_j, \omega_j, V_j, E_j$ are voltage angle, frequency, and external and internal voltage magnitudes, respectively. P_j^{set}, Q_j^{set} , and V_j^{set} are the active power, reactive power, and voltage set-points. P_j and Q_j denote the active and reactive power injections at the bus where GFM j is connected. V_j^e represents voltage error. m_{p_j}, m_{q_j} are the P - ω and Q - V droop gains, respectively. τ_j is the time constant of the low-pass measurement filter and is set to 0.01 s. k_j^{pv} and k_j^{iv} are, respectively, the proportional and integral gains in the Q - V droop control. The P - ω and Q - V droop coefficients, $m_{p,j}$ and $m_{q,j}$, are normalized by the inverter capacity S_j (in MVA), such that $m_{p,j} = \frac{\hat{m}_{p,j}}{S_j}$, and $m_{q,j} = \frac{\hat{m}_{q,j}}{S_j}$, where $\hat{m}_{p,j}$ and $\hat{m}_{q,j}$ represent the droop settings in %. The active and reactive power injections at bus j follow the ac-power flow equations [19].

4.2 Small-signal Analysis: Objectives, Numerical Case Studies, and Assessments

The system follows a set of differential-algebraic equations (DAEs), where the dynamics of SGs are represented by second-order swing equations [19], the dynamics of the GFMs are

modeled using droop-controlled equations in (27), and the transmission lines represented by lumped Pi-models with ac-power flow equations forming the algebraic constraints. Next, these DAEs governing the grid dynamics for N -bus transmission network are linearized around the stable operating point to obtain the small-signal model of the system. The generic representation of the linearized model is as follows:

$$\dot{\mathbf{x}} = \mathbf{A}(\rho) \mathbf{x} \quad (28)$$

where, $\mathbf{x}$ presents the concatenation of all state variables:

$\mathbf{x} = [\delta_i]_{i \in \mathcal{N}_G}^\top, [\omega_i]_{i \in \mathcal{N}_G}^\top, [\delta_j]_{j \in \mathcal{N}_I}^\top, [\omega_j]_{j \in \mathcal{N}_I}^\top, [V_j^e]_{j \in \mathcal{N}_I}^\top, [E_j]_{j \in \mathcal{N}_I}^\top]$. $\mathbf{A}(\rho)$ provides a parametric representation of the state matrix with parameters $\rho = [\hat{m}_{p,j}, \hat{n}_{p,j}, P_j^g, S_j]_{j \in \mathcal{N}_I}$. $\mathcal{N}_G$ and $\mathcal{N}_I$ denote the set of SG and GFM buses, respectively. Please note that $P_j = P_j^g - P_j^l$, where P_j^g is the inverter's active power output and P_j^l is the load at the bus where it is connected.

For given parameter values, the eigenvalues of $\mathbf{A}(\cdot)$ matrix characterize the natural modes of oscillation in the system. The eigen analysis of $\mathbf{A}(\cdot)$ offers valuable insights into the stability of the networked dynamics, particularly with respect to oscillatory behaviors. As the parameters in the set ρ change, the eigenvalues of the matrix $\mathbf{A}(\cdot)$, denoted by λ , are altered. The eigen-sensitivity to the parameters is reflected in their respective root loci plots. The sensitivity studies offer crucial insights into the margins of small-signal stability of the related oscillatory modes, as will be illustrated in this chapter.

In this work we study the eigen-sensitivities for a broad spectrum of parametric variations in ρ . We formulate the problem in a numerical setting considering the positive-sequence model of the IEEE 16-machine, 68-bus test system. The generator and network parameters are obtained from the standard data set. The test system is modified to include GFM IBRs on select buses. There are a total of 35 such inverters each at a load bus — note that, the inverter buses are represented by the set $\mathcal{N}_I$ as mentioned earlier. The outputs of the generators and inverters are appropriately adjusted to match the total load and generation of the network. Here, we define inverter penetration and headroom (in terms of active power) as follows:

$$x\% \text{ IBR penetration} : \sum_{j \in \mathcal{N}_I} P_j^g = \frac{x \times \sum_{j \in \mathcal{N}_I} P_i^l}{100}, \quad (29a)$$

$$y\% \text{ IBR headroom} : y = \left(1 - \frac{\sum_{j \in \mathcal{N}_I} P_j^g}{\sum_{j \in \mathcal{N}_I} P_j^{cap}}\right) \times 100 \quad (29b)$$

In (29), P_j^g represents the active power output from the GFM at bus j , and P_j^l is the active power load at bus i , implying $\sum_{j \in \mathcal{N}_I} P_i^l$ as the total load of the system. P_j^{cap} defines MW capacity of the GFM j with $S_j = P_j^{cap} + jQ_j^{cap}$ as its MVA capacity. When total inverter capacity is the same as the total inverter output $\implies \sum_{j \in \mathcal{N}_I} P_j^{cap} = \sum_{j \in \mathcal{N}_I} P_j^g$, the percentage headroom y is zero.

The small-signal model and corresponding state matrix $\mathbf{A}(\cdot)$ are computed at multiple operating conditions and for different parametric settings, for the GFM-integrated modified IEEE 68-bus test system. In this, we focus on the eigenvalues λ corresponding to low-frequency oscillations in the range $0.1 < f(\lambda) < 1$ Hz, that represent inter-area modes in a power system. Typically, these are eigenmodes for which a group of generators in one area oscillates against

groups of generators from other areas in the system. Note that, the base case of the 68-bus test system without the GFM IBRs has four dominant inter-area oscillation modes with modal frequencies 0.40 Hz, 0.50 Hz, 0.65 Hz, and 0.78 Hz. Next with the GFMs added, we perform model linearization and eigenvalue sensitivity studies to evaluate the impacts of (a) droop parameter variation, (b) inverter capacity variation, and (c) active power headroom variation on the small-signal stability. Without loss of generality, in our analysis, we consider the same droop gains for all GFMs, i.e., $\hat{m}_{p,j} = \hat{m}_{p,k} = \hat{m}_p$ and $\hat{m}_{q,j} = \hat{m}_{q,k} = \hat{m}_q$, $\forall j, k \in \mathcal{N}_I$.

4.2.1 Eigenvalue Sensitivity to GFM Droop Parameter Variation

First, we study the sensitivity of the inter-area eigenvalues to variation in the droop gain, for a fixed IBR penetration level with zero headroom (implying IBR penetration equals the IBR capacity). Here, the droop parameter $\hat{m}_p$ is varied over a feasible range of 1 – 5%. The state matrix A is computed for each case; the corresponding dominant eigenvalues are plotted and shown in Fig. 10. Note that the real and imaginary parts of the eigenvalue λ are represented by $\Re(\lambda)$ and $\Im(\lambda)$, respectively. It is observed that with a decrease in $\hat{m}_p$, the eigenvalues of interest (related to the inter-area modes) move progressively to the left, far from the $j\omega$ -axis on the complex plane. Hence, reducing the values of $\hat{m}_p$ enhances the margin of stability for the system.

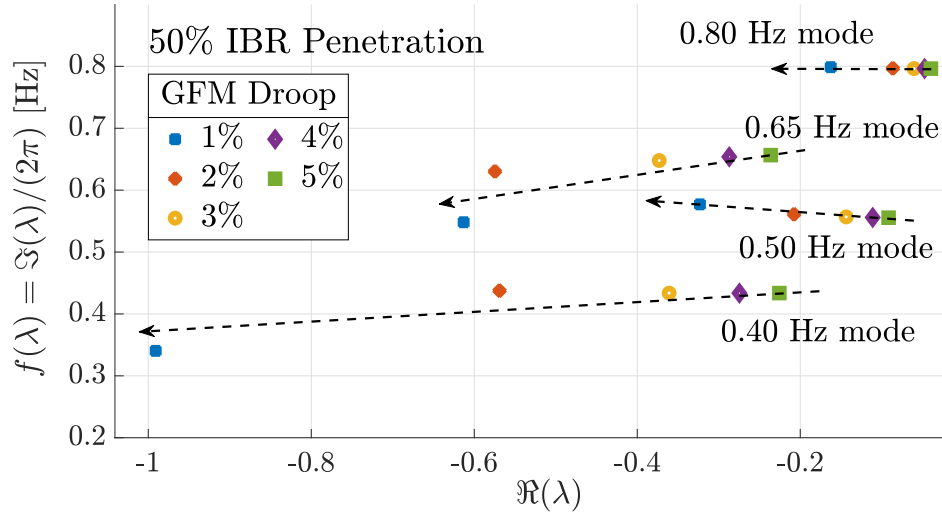


Figure 10: Loci of the four dominant inter-area eigenvalues for variation in the droop gain $\hat{m}_p$ at fixed penetration level [37].

4.2.2 Eigenvalue Sensitivity to IBR Capacity Variation

Next, we study the impact of varying IBR capacity for fixed droop gain ($\hat{m}_p = 3\%$) while ensuring IBRs are dispatching at their maximum level. In other words, at each penetration level, the inverter dispatch equals its capacity with zero available headroom. The 0% penetration scenario represents the case where the total load is supported by the SGs only. In the simulation,

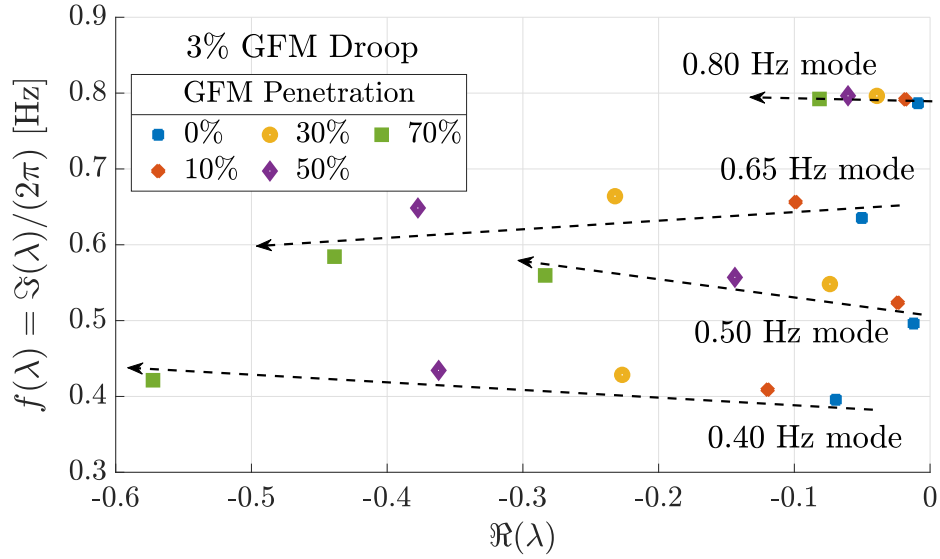


Figure 11: Loci of the four dominant inter-area eigenvalues for variation of IBR capacity at the fixed droop gain $\hat{m}_p$ [37].

the combined capacity of the IBRs is progressively increased from 0% to 70%. The findings show that with an increase in GFM penetration, the eigenvalues for all four inter-area modes move to the left on the complex plane (see Fig. 11) highlighting improvement in stability.

4.2.3 Eigenvalue Sensitivity to IBR Headroom Variation

In this case, we fix the total GFM IBR capacity at the 50% of the total active power load. Now, keeping the IBR capacity and droop gain $\hat{m}_p$ constant (at 3%), we vary the IBR penetration (or inverter dispatch) from 0 to 80% of IBR capacity. Please note that varying inverter dispatch or penetration for a fixed capacity implies variation in available headroom. For instance, 0% dispatch implies 100% headroom, and similarly, 80% penetration implies 20% headroom. For each headroom level, the inter-area eigenvalues obtained from the linearization of $A(\cdot)$ are plotted (see Fig. 12). The movement of the eigenvalues for this scenario gives a conflicting trend. With a reduction in the available headroom, the eigenvalues corresponding to the 0.50 Hz mode moved left, whereas the same for the 0.65 Hz mode moved right. On the other hand, the eigenvalues of 0.80 and 0.40 Hz modes remained largely insensitive to headroom variation. This lets us conclude that, unlike droop or penetration, headroom variation does not result in a uniform trend on the loci of eigenvalues. The conflicting behavior of two different eigenvalues sets the premise for a co-design framework for enhancing the overall stability margin.

In summary, the eigenvalues of low-frequency oscillations are sensitive to changes in the parameters of GFM IBRs. It is crucial to maintain a certain level of resilience and stable system operation against such oscillatory behavior. This requires ensuring small-signal stability with a defined margin across a wide range of parameter variations. Specifically, Figs. 10 and 11 illustrate that adjustments to the droop parameters are necessary to prevent violations of the specified stability margin as IBR penetration changes. To address this issue, the next section presents a two-stage algorithm for tuning the droop in response to variations in the parameter

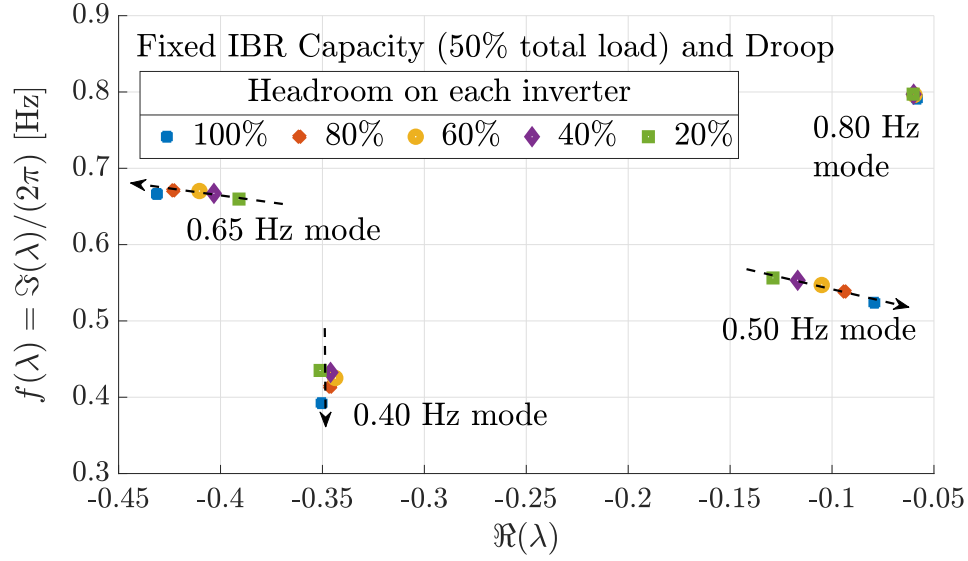


Figure 12: Loci of the four dominant eigenvalues for variation in IBR headroom at the fixed droop gain $\hat{m}_p$ and fixed IBR capacity [37].

space.

Although this chapter considers only three types of parameter variations, a comprehensive multi-factor assessment of additional parameter variations would be necessary in practice to accurately capture the small-signal stability boundary.

4.3 Stability-Guided Droop Design: Methods and Case Studies

This section focuses on the algorithmic framework development facilitating the adjustment of droop gains for certain parametric variations of IBRs. In general, droop parameter values are selected following generic guidance, for instance, $1 - 5\%$ for $\hat{m}_p$. There are conflicting advantages and disadvantages of setting $\hat{m}_p$ at the higher or lower side of the above range based on different grid services offered by GFMs. As indicated in Section 4.2, for fixed IBR penetration, lower $\hat{m}_p$ value offers better stability for inter-area oscillation modes [38]. However, higher $\hat{m}_p$ provides faster power-sharing in the networked operation of GFMs during contingencies [39]. Besides, for various factors, the IBR penetration and capacity can change and influence small-signal stability without adequate attention to the droop parameter value $\hat{m}_p$.

For a change in ρ , $A(\rho)$ perturbs, shifting the location of low-frequency eigenvalues (the modes of interest) in the complex frequency plane. Here, we define the stability margin (SM) with respect to the closest among the four dominant eigenvalues from $j\omega$ axis of complex frequency plane. The set of the eigenvalues of interest Λ_{int} are defined as follows:

$$\Lambda_{int} := \left\{ \lambda : 0.1 \leq f(\lambda) = \frac{\Im(\lambda)}{2\pi} \text{ (in Hz)} \leq 1 \right\} \quad (30)$$

where, $\lambda = \Re(\lambda) + j\Im(\lambda)$. To ensure a pre-specified $SM \rightarrow \alpha$, we define the following

Algorithm 2: ZOGS for Droop Adjustment

```

1 Inputs: Base value of droop parameter  $\hat{m}_{p,0}$ , lower and upper limit of droop gain
    $\{\underline{m}_p, \overline{m}_p\}$ , stability margin  $\alpha$ , step-size  $\zeta$ , the number of perturbation samples  $\eta$  and
   the number of iterations  $M$ .
2 For the given % IBR penetration and capacity, compute the parameterized small-signal
   model  $A(\rho)$ .
3 for  $K = 1, \dots, M$  do
4   for  $s = 1, \dots, \eta$  do
5     | Sample in a small sphere around  $\hat{m}_{p,K}$ .
6     | Use (31) to compute  $\Phi^i(\hat{m}_{p,K,s})$ .
7   end
8   Compute the averaged gradient using (32)
9   Compute  $\hat{m}_{p,K} = \hat{m}_{p,K-1} + \zeta \nabla \Phi(\hat{m}_{p,K-1})$ .
10  if  $\Phi(\hat{m}_p) \geq 0$  then
11    | break
12  end
13  if  $\hat{m}_{p,K} = \underline{m}_p$  then
14    | break
15  end
16 end
17 Return:  $\hat{m}_p^{gs,1} = \hat{m}_{p,K}$ , and  $\hat{m}_p^{gs,2} = \hat{m}_{p,K-1}$ 

```

objective function in terms of $\hat{m}_p$ and associated criteria for satisfying the SM.

$$\begin{aligned}
\Phi(\hat{m}_p) &:= \min_{\lambda \in \Lambda_{int}} |\Re(\lambda)| - \alpha, \\
\Phi(\hat{m}_p) \geq 0 &\implies \text{SM is satisfied,} \\
\Phi(\hat{m}_p) < 0 &\implies \text{SM is not satisfied.}
\end{aligned} \tag{31}$$

Therefore, in the presence of variation in IBR penetration with zero headroom, the droop gain $\hat{m}_p$ needs to be designed in such a way that SM criteria is satisfied. It is important to note that $\Phi(\cdot)$ is an implicit function of $\hat{m}_p$, plus, it is non-smooth and complex. To this end, we propose to utilize two-stage zeroth-order gradient search followed by a bisection method to optimally select the $\hat{m}_p$ for which $\Phi(\hat{m}_p) \geq 0$ can be achieved when IBR penetration changes. Next, we discuss the zeroth-order gradient search method for the underlying problem.

4.3.1 Zeroth-order Gradient Search (ZOGS)

For a given IBR penetration, if $\Phi(\hat{m}_p) < 0$, we need to adjust $\hat{m}_p$ to make $\Phi(\hat{m}_p) \geq 0$ which implies an increase in the value of $\Phi(\hat{m}_p)$ is required. To achieve this, we sample η such $\hat{m}_{p,k}$, $k = 1, \dots, \eta$ in a small sphere (with radius $\epsilon \rightarrow 0$) around the current value of $\hat{m}_p$, and compute the respective objective values $\Phi(\hat{m}_{p,k})$, $k = 1, \dots, \eta$. Now, the zeroth-order gradient

estimation can be obtained as follows,

$$\nabla\Phi(\hat{m}_p) = \frac{1}{\eta} \sum_{k=1}^{\eta} \frac{\Phi(\hat{m}_{p,k}) - \Phi(\hat{m}_p)}{\hat{m}_{p,k} - \hat{m}_p} \quad (32)$$

With this obtained gradient value, we use the gradient ascent method to select new $\hat{m}_p$ increasing $\Phi(\hat{m}_p)$. The successive steps of this method are detailed in Algorithm 2.

Algorithm 3: Bisection Method for Droop Fine-tuning

```

1 Inputs:  $\hat{n}^{gs,1}, \hat{n}^{gs,2}, \underline{m}_p, \overline{m}_p$ , and  $\alpha$ .
2 Set  $\hat{m}_{p,low} = \hat{n}_p^{gs,1}$  and  $\hat{m}_{p,high} = \hat{n}_p^{gs,2}$ .
3 while  $\Phi(\hat{m}_p) < 0$  do
4   Compute  $\hat{m}_{p,mid} = \frac{1}{2}(\hat{m}_{p,low} + \hat{m}_{p,high})$ .
5   Compute  $\Phi(\hat{m}_{p,mid})$ .
6   if  $\Phi(\hat{m}_{p,mid}) \geq 0$  then
7      $\hat{m}_p \leftarrow \hat{m}_{p,mid}$ 
8     break
9   end
10  else
11    if  $\Phi(\hat{m}_{p,mid}) < 0$  then
12       $\hat{m}_{p,high} \leftarrow \hat{m}_{p,mid}$ 
13    end
14  end
15  if  $\hat{m}_p = \underline{m}_p$  then
16    break
17  end
18 end
19 Return:  $\hat{m}_p$ .

```

4.3.2 Bisection Method for Fine-tuning the Droop Design

Algorithm 2 provides primary correction of the $\hat{m}_p$ for any IBR penetration level where $\Phi(\hat{m}_p) < 0$; now to ensure optimality (or best value) in choosing $\hat{m}_p$ for which $\Phi(\hat{m}_p) \geq 0$, we pass the output of Algorithm 2 through the standard bisection search given in Algorithm 3. Finally, Algorithm 3 gives the adjusted $\hat{m}_p$ for the given IBR penetration.

4.3.3 Numerical Case Studies

The proposed algorithms are tested for the developed GFM-integrated IEEE 68-bus test system. For this study, assuming the requirement of faster power sharing, we have selected the

base value of $\hat{m}_{p,0}$ as 5% (upper limit). Here, we selected $\alpha = 0.025$. The numerical tests conducted with different penetration levels (with zero headroom) have shown that $\Phi(\hat{m}_p) \geq 0$ is predominantly maintained at higher penetration levels, while at low penetration, the stability margin is violated if $\hat{m}_p$ is set at the upper limit value, implying $\Phi(\hat{m}_p) < 0$ — necessitating the correction in droop parameter to achieve the desired margin. Now, for varying IBR pene-

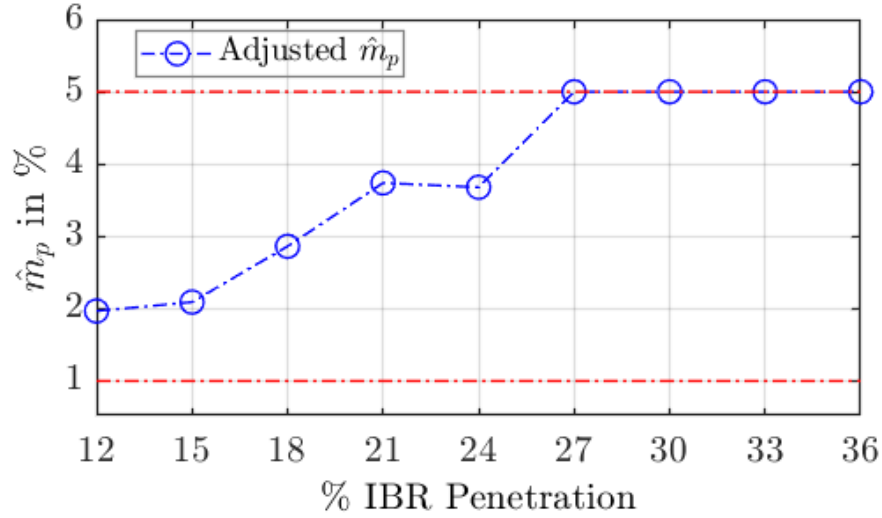


Figure 13: Adjusted $\hat{m}_p$ for varying IBR penetration level [37].

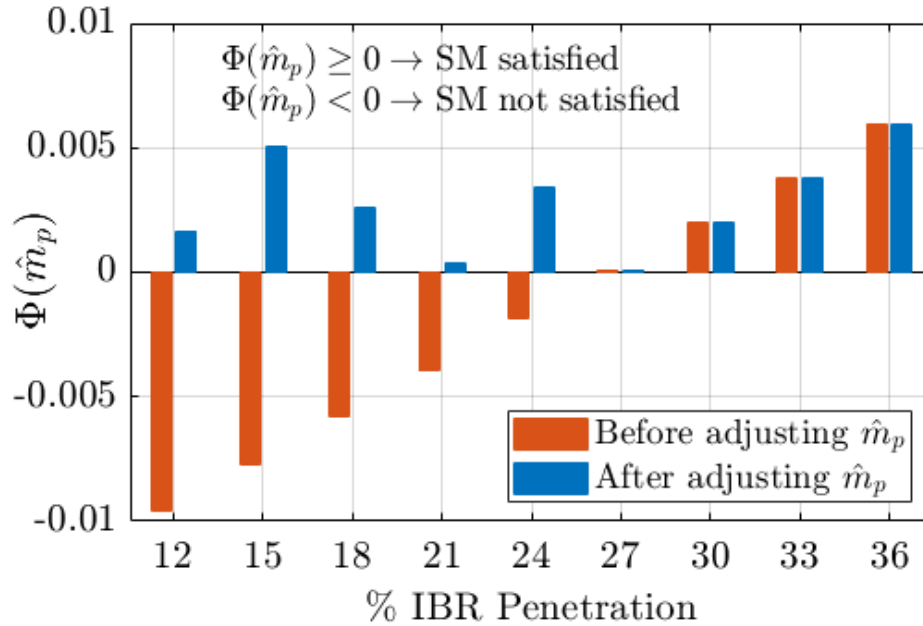


Figure 14: $\Phi(\hat{m}_p)$ values before and after adjusting $\hat{m}_p$ [37].

tration levels, we utilize the proposed two-stage method: Algorithm 2 and 3 adjust droop gain value $\hat{m}_p$ for violations in stability margin i.e. $\Phi(\hat{m}_p) < 0$. Fig. 13 shows the adjusted $\hat{m}_p$ values to maintain $\Phi(\hat{m}_p) \geq 0$ at respective IBR penetration level, while Fig. 14 depicts the $\Phi(\hat{m}_p)$ values before and after $\hat{m}_p$ adjustment at different penetration level. This validates the efficacy of the proposed two-stage algorithm for stability-guided droop adjustment.

4.4 Conclusions

This study highlights the critical role of parametric settings of GFM IBRs in maintaining the stability of bulk power grids. Using eigenanalysis of the modified IEEE 68-bus test system, this chapter demonstrates that variations in GFM droop, inverter capacity, and active power headroom significantly influence the natural oscillation modes of GFM-integrated power systems. The insights obtained from these studies highlight the need for fine-tuning GFM droop parameters to ensure desired stability margins under certain operating and parametric conditions. To this end, the chapter proposes a two-stage method combining zeroth order gradient search and bisection method to adjust droop parameters for variations in IBR penetration and capacity. The proposed algorithm is finally validated with numerical simulations of the modified IEEE 68-bus test system.

5.0 Identification of Sub/Super-Synchronous Control Interaction Paths Using Dissipative Energy Flow

Sub- and super-synchronous control interactions (SSCIs) are sustained oscillations caused by adverse interactions between the fast control loops of inverter-based resources (IBRs) and the network at frequencies below or above the nominal synchronous frequency [49,50]. They form a subset of sub- and super-synchronous oscillations (SSOs) that are purely control-driven and do not involve mechanical resonance [49]. While historically associated with wind farms connected through series-compensated transmission lines, SSCIs have also been observed in uncompensated and weak grids [50], such as 4 Hz voltage-control oscillations in ERCOT's Texas grid [51] and 3.5 Hz real- and reactive-power oscillations in Hydro One [52]. These interactions can accelerate equipment degradation, trigger protection misoperations, and compromise stability, motivating mitigation through converter retuning, supplemental damping controls, and coordinated system design.

Tracing the paths of oscillatory energy exchange between components can provide valuable insight into how targeted control adjustments may mitigate SSCIs. However, identifying the source and propagation routes of SSCIs is challenging due to the complex nature of the interactions. Unlike forced oscillations (FOs), where a single component can often be uniquely identified as the dominant contributor, SSCIs may involve multiple components sometimes at more than one frequency exchanging energy through several interconnected pathways. To address the source localization problem, several analytical methods have been proposed, among which the Dissipative Energy Flow (DEF) method [53,54] stands out for its intuitive, physics-based foundation and straightforward implementation. Originally developed for identifying the sources of low-frequency electromechanical oscillations in synchronous generator-dominated grids, the DEF framework can be extended to higher-frequency phenomena and adapted for networks with high IBR penetration [55]. Prior studies have examined the theoretical extension of DEF to inverter-based generation resources, as well as inverter-based transmission assets such as STATCOMs and VSC-HVDC systems [56,57]. However, these works have primarily focused on low-frequency oscillations and have not addressed the unique challenges associated with SSCIs.

A recent study [58] applied an enhanced formulation of DEF, referred to as complex-DEF (CDEF) [59], to address the SSO source localization problem in an IEEE test system. While CDEF demonstrates improved localization accuracy, it requires careful tuning of a hyperparameter K that can vary with network conditions and oscillation frequency, making it less practical for real-time or wide-scale deployment.

In this chapter, we propose an alternate approach that builds on the original DEF formulation, computing the energy functions for the SSO components from dynamic phasors in the dq frame, derived from three-phase voltage and current measurements at the point of interconnection of the resource. The proposed method preserves the simplicity and parameter-free nature of the original DEF, improving robustness and suitability for online implementation. Furthermore, this work extends the application of DEF to multi-frequency SSOs, demonstrating cases where the same resource acts as a source at one frequency and a sink at another scenario not

The work in this chapter is published in this article [48]: Chatterjee, K., Nekkalapu, S., Mukherjee, S., Hosain, R.R. and Elizondo, M., Identification of Sub/Super-Synchronous Control Interaction Paths Using Dissipative Energy Flow. IEEE PES General Meeting 2026, available on arXiv preprint arXiv:2508.11561.

studied in the CDEF-SSO chapter [58]. The proposed method is demonstrated on an electromagnetic transients model of a meshed test network with synchronous and DFIG-based wind generation under varying series-compensation levels, illustrating accurate source-path localization without case-specific calibration.

5.1 Sub/Super-Synchronous Control Interactions

The IEEE PES IBR SSO Task Force categorizes SSCIs into two types [50]: (1) series-compensator SSCI, caused by interactions between IBR control dynamics and the resonant modes of series-compensated lines, and (2) weak-grid SSCI, driven by control-grid impedance interactions under low short-circuit strength. The former is resonance-driven, typically when the series-capacitor resonant frequency lies within the IBR control bandwidth; the latter is control-instability-driven and can occur without series compensation. Both have been observed in practice [60], producing sustained or growing oscillations that propagate across network paths.

In series-compensator SSCI, instability occurs when the resonant frequency of the compensated network aligns with the bandwidth of the inverters outer loops (active/reactive power or voltage regulators). High PI gains and PLL interactions can introduce negative damping, allowing transient energy to circulate between the converter controls, inner current loop, PLL, and the series-compensated network [50]. This adverse coupling between control loops (outer, inner, and PLL) and network impedance enables oscillatory energy exchange across sub- or super-synchronous frequencies. A simulation study of a real-world series compensator SSCI event is presented next to illustrate the mechanisms and interaction paths.

Simulation Study of a Real-World Event

In 2009, the southern Texas grid experienced a sub-synchronous control interaction event involving a large wind farm equipped with doubly-fed induction generators (DFIGs) [51], [61]. Following the tripping of a 345 kV line to clear a fault, the plant became radially connected through a 50% series-compensated line. The interaction between the DFIG control loops and the series-capacitor resonance excited sub-synchronous oscillations, causing significant concerns in the system.

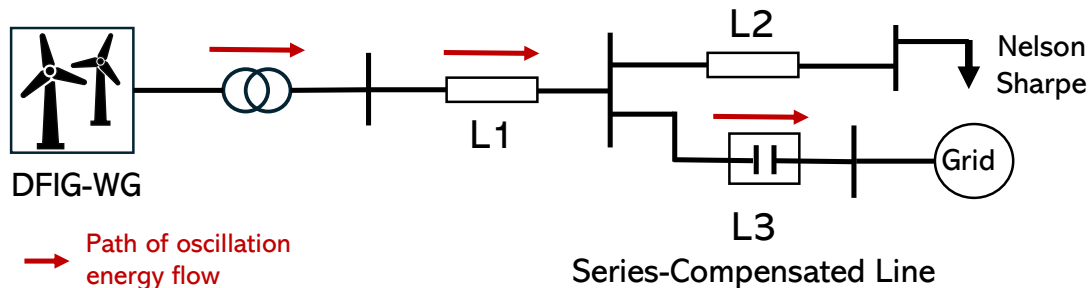


Figure 15: Single-line diagram of the test system, used to replicate the SSCI event from Texas, showing the path of oscillation energy flow or control interaction [48].

This work replicates the operating condition, in the electromagnetic transients simulation

platform PSCAD, using the network shown in Fig. 31. In this, around 200 MW of generation is being produced by the DFIG wind source. The load at the Nelson Sharpe bus has been considered to be negligible to mimic the tripping of the 345 kV line. Series compensation is set to 400 μ F, selected from sensitivity studies as the minimum value that remains stable under nominal conditions but becomes unstable with small changes to control gains in the DFIG. A parallel breaker provides soft capacitor switching to mitigate overvoltage. Transmission lines L1, L2, and L3, between Zorillo-Ajio, Ajio-Nelson Sharpe, and Ajio-Rio Hondo locations, are modeled using lumped 60 Hz PI-coupled parameters. In the simulated event (Figs. 16), the proportional gain K_p of the two inner loop and the two outer-loop rotor side controls of the DFIG is increased from 2 to 4 at $t = 15$ s. The gain adjustment excites two sideband oscillatory components at 12 Hz and 108 Hz in the instantaneous phase currents, along with their harmonics, arising from the DFIGseries capacitor interaction. These components also appear in the dq -frame as a shifted frequency of $60 - 12 = 48$ Hz (equivalently $108 - 60 = 48$ Hz), as shown in Fig. 17. In this scenario, the source of instability is the DFIGs outer-loop control interacting with the network resonance path formed by the series-compensated line, with oscillatory energy circulating between the converter controls, the inner current loop, and the resonant network branch via lines L1 and L3 (Fig. 31). The corresponding figures illustrate how this energy propagates along the interaction path involving the DFIG and the compensated line, sustaining the observed oscillations.

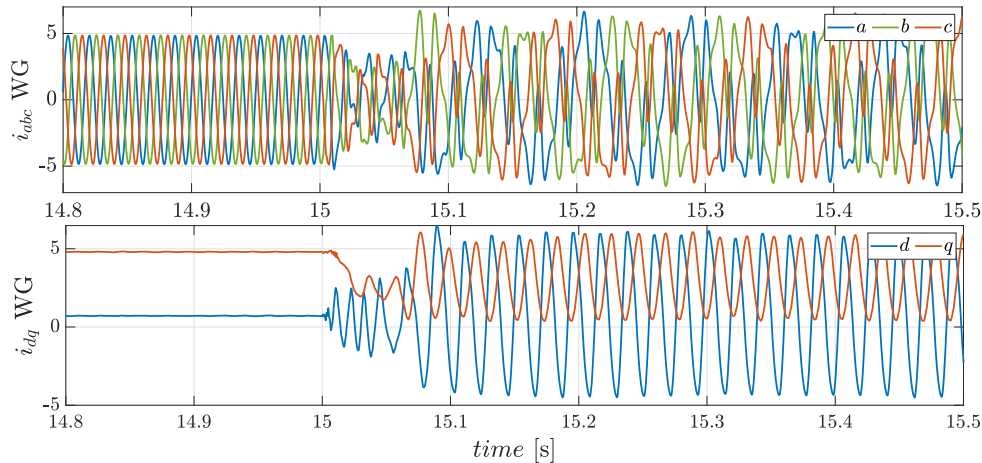


Figure 16: abc phase waveforms and dq components of the current injected by the WG in the Texas system [48].

This example demonstrates how SSCI can be traced to a specific source—the DFIG outer-loop controls—and a well-defined interaction path through the network impedance. Such events underscore the need for systematic methods to localize instability sources and map energy propagation routes. The following subsection introduces the DEF framework, a physics-based, automation-friendly approach for identifying SSCI sources and interaction paths from measurement data.

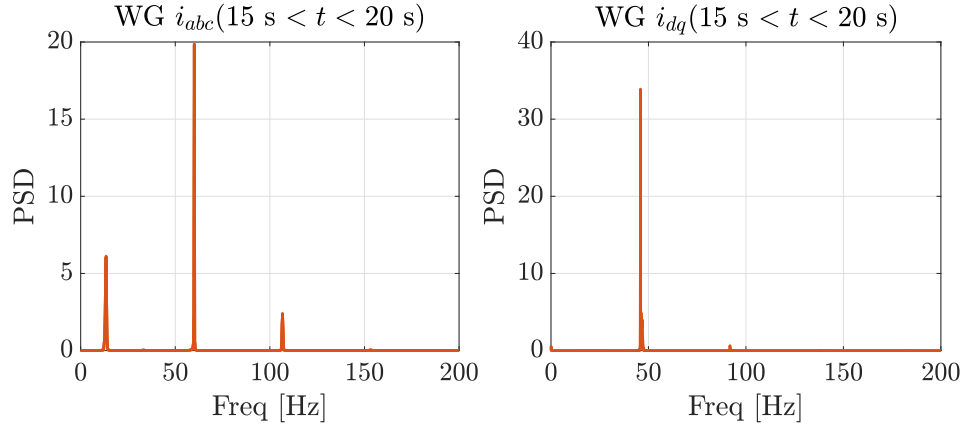


Figure 17: Frequency spectrum of the currents injected by the WG computed for (a) instantaneous three-phase components and (b) dq components [48].

5.2 Determination of Interaction Path Using Dissipative Energy Flow

Dissipative Energy Flow (DEF) formulations proposed in the literature for source localization of low-frequency oscillations have predominantly utilized positive-sequence phasor representations, as outlined below.

$$W = \int \Im\{\vec{I}^* d\vec{V}\} = \int P d\theta + \frac{Q}{V} dV \quad (33)$$

In (7.2), the quantity W denotes the transient oscillation energy injected into the power network from a node with voltage $\vec{V}$ and current injection $\vec{I}$. The terms P and Q are, respectively, the real and reactive powers injected from that node. The time-derivative of W averaged over a cycle τ – referred to as the slope of DEF and denoted by $\dot{W}$, determines the rate of dissipation of transient energy emanating from the node. If the slope of the DEF from a node $\dot{W} > 0$, the shunt element connected to that node is characterized as an *oscillation source*. Alternatively, if $\dot{W} < 0$, the shunt element is characterized as an *oscillation sink*.

5.2.1 DEF Formulation in the dq Frame

While fundamental-frequency phasor representations are adequate for analyzing low-frequency electromechanical oscillations, they are insufficient for studying higher-frequency transients such as those associated with sub-synchronous oscillations (SSOs). To overcome this limitation, we adopt a dynamic phasor framework for DEF, employing dq -sequence components derived from abc quantities via the Park transformation, as follows:

$$\begin{aligned} W &= \int \Im\{\vec{I}^* d\vec{V}\} = \int \Im\{(i_d - j i_q)(dv_d + j dv_q)\} \\ &= \int i_d dv_q - i_q dv_d \end{aligned} \quad (34)$$

In this approach, three-phase (abc) voltage and current data, obtained either from field-deployed point-on-wave (POW) recorders or from electromagnetic transient (EMT) simulations, are transformed into their corresponding d and q components. In the original three-phase waveform data, transient oscillations appear as sidebands around the fundamental frequency component. When transformed into the dq frame, these sideband oscillations manifest as oscillations at the difference frequency the frequency difference between the fundamental and the sidebands. For example, sideband components at $f_0 \pm \Delta f$ in the abc frame translate into oscillations at a frequency of Δf in the dq components.

Algorithm 4: DEF-Based SSCI Path Determination

```

1 Inputs:  $v_{abc}(t), i_{abc}(t)$ ; sampling  $f_s$ ; slope thresholds  $\epsilon, \epsilon_n$ .
2 Compute  $(v_d, v_q, i_d, i_q) \leftarrow \text{ParkTransform}(v_{abc}, i_{abc})$ .
3 Extract SSO frequencies  $\{f_m\} \leftarrow \text{WindowedSpectralID}(v_d, v_q, i_d, i_q)$ .
4 foreach  $\Delta f_m \in \{f_m\}$  do
5   Filter signals:  $(\Delta v_d, \Delta v_q, \Delta i_d, \Delta i_q) \leftarrow \text{Bandpass}_{f_m}(\dots)$ .
6   Initialize  $\mathcal{G}_m = (\mathcal{N}, \emptyset)$ .
7   foreach edge  $e \in \mathcal{E}$  do
8     Compute  $W_e[k]$  iteratively:
          
$$W_e[k+1] = \text{UpdateWork}(W_e[k], \Delta v, \Delta i)$$

          Calculate  $\dot{W}_e \leftarrow \text{Slope}(W_e, T_{\text{win}})$ .
9     Add edge  $(i \rightarrow j), (j \rightarrow i)$ , or None based on  $\dot{W}_e$  and  $\epsilon$ .
10  end
11  Classify each node  $n \in \mathcal{N}$ :
          
$$\mathcal{C}_{m,n} \leftarrow \begin{cases} \text{Source,} & \text{if } \sum \dot{W}_e > \epsilon_n, \\ \text{Sink,} & \text{if } \sum \dot{W}_e < -\epsilon_n, \\ \text{Neutral,} & \text{otherwise.} \end{cases}$$

12 end
13 Return: Directed graphs  $\{\mathcal{G}_m\}$  and node classifications  $\mathcal{C}_{m,n}$ .

```

In the first step of SSO characterization and analysis, a windowed Fourier-based spectral identification algorithm is applied to the dq components to identify the dominant frequencies present in the signal. Subsequently, bandpass filtering is performed on the dq voltage and current components to isolate the oscillations of interest. The resulting filtered signals are then used in the DEF computation defined in (35).

$$\begin{aligned}
 W[k+1] = & W[k] + \Delta i_d[k] (\Delta v_q[k+1] - \Delta v_q[k]) \\
 & - \Delta i_q[k] (\Delta v_d[k+1] - \Delta v_d[k])
 \end{aligned} \tag{35}$$

The equation in (35) is a discretized representation of (34), where $\Delta i_d, \Delta i_q, \Delta v_d$ and Δv_q

are the detrended bandpass-filtered dq components of the injected current and node voltage, and k indexes the time instant.

5.2.2 Determination of Interaction Path

To determine the direction of oscillation energy flow, the dissipative energy term W is computed at each node in the system for each connected line, specifically in the direction of outward current flow. For example, at a node i connected to a set of lines $\mathcal{L}_i = \{\ell_j | j \in 1, 2, \dots, N_i\}$, the DEF W_i^j is calculated for each line ℓ_j using the current I_j flowing out of the node i and the corresponding node voltage V_i . If the slope of W_i^j is positive ($\dot{W}_i^j > 0$), the oscillation energy is flowing outward from the node i along line j . Conversely, a negative slope ($\dot{W}_i^j < 0$), indicates energy flow toward the node i from that line. An algorithmic summary of the DEF-based procedure for determining SSO interaction paths is provided in Algorithm 1. Next, we demonstrate the effectiveness of the proposed approach using a test system adapted from [62].

5.3 Illustrative Case Study

The test system from [62] consists of a meshed network with a synchronous generator (SG) and a type-3 DFIG-based wind generator (WG), interconnected to a larger grid via both series-compensated and uncompensated long transmission lines, as shown in Fig.18. Under nominal operating conditions, the SG and WG supply 600MW and 200MW, respectively. The systems dynamic behavior is studied, in PSCAD, for varying series-compensation levels, and it is observed that a capacitance of $25\mu\text{F}$ produces sustained oscillations.

The system is analyzed in two operating regimes: (1) *Window-A* ($t = 0\text{--}15$ s), where it operates with the selected compensation level and nominal SG and WG control parameters; and (2) *Window-B* ($t = 15\text{--}30$ s), where the proportional–integral (PI) gain in the DFIG-WG’s outer real power control loop is detuned. The objective is to examine the control oscillations in each window and determine their corresponding interaction paths.

The d - and q -axis current components injected by the WG and SG are shown in Fig. 19. The corresponding frequency spectra, computed using the power spectral density (PSD), are shown in Fig. 20. In Window-A, a single 25Hz sub-synchronous component is present with contributions from both SG and WG. Following the PI-gain detuning, in Window-B, two oscillatory components: a sub-synchronous at 25Hz and another super-synchronous at 105Hz are observed, superimposed in the dq -domain currents (Fig. 19). The Dissipative Energy Flow (DEF) method is applied to identify oscillation energy sources, sinks, and interaction paths for each frequency component in its respective time window. Bandpass filtering is first applied to isolate the dq -axis currents at the target frequencies, after which DEF is computed as described in Algorithm 1.

For Window-A, Fig. 21 shows the DEF at 25Hz injected by the SG, WG, and the series-compensated line into buses 1, 2, and 1, respectively. The average DEF slope $\dot{W}$ for each component, shown in Fig. 22, indicates that both the SG and WG act as energy sources for this SSCI, with the series-compensated line acting as the primary sink.

In Window-B, DEF is computed separately for the 25 Hz and 105 Hz components (Fig. 23). Before detuning, the WG and SG exhibit comparable DEF injections at 25 Hz, indicating similar source behavior. After detuning, the WGs 25 Hz injection decreases, while a new 105

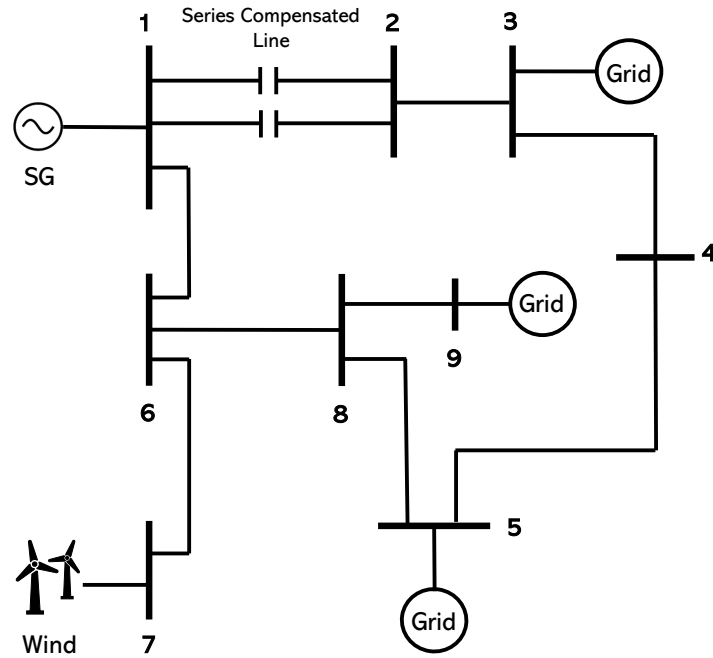


Figure 18: Test system with DFIG WG and SG interconnected to the grid [48].

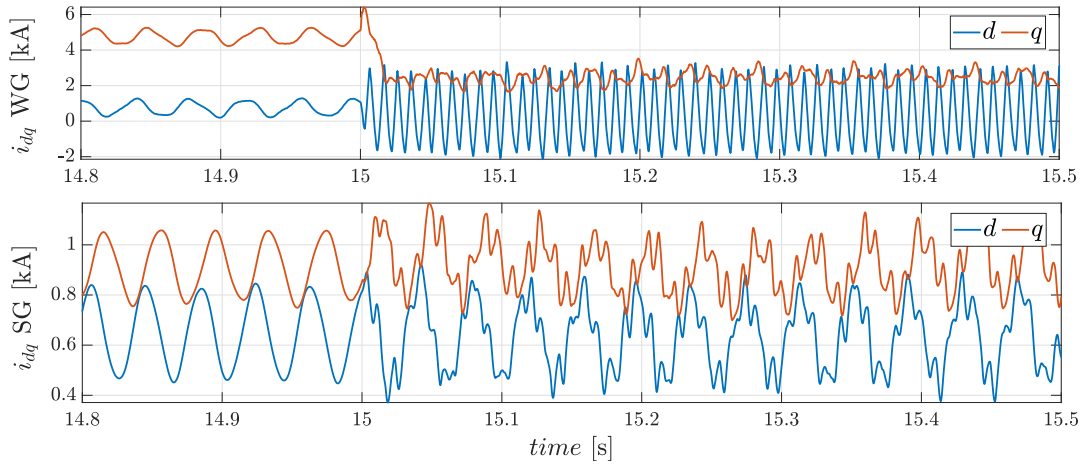


Figure 19: d - and q -axis components of the currents injected by the WG and SG derived from the three-phase quantities [48].

Hz component emerges. Notably, the SG, which is a source at 25 Hz, becomes a sink at 105 Hz. The 105 Hz oscillation is characterized by the WG as the sole source, with both the SG and the series-compensated line acting as sinks (see Fig. 23 and Fig. 24).

Fig. 25 summarizes the identified interaction paths determined from the values in Fig. 24. At 25 Hz, oscillation energy propagates between the WG and SG, with dissipation through the series-compensated line. At 105 Hz, the WG acts as the sole source, injecting oscillatory energy into both the SG and the compensated line. Notably, the SG serves as a source for the

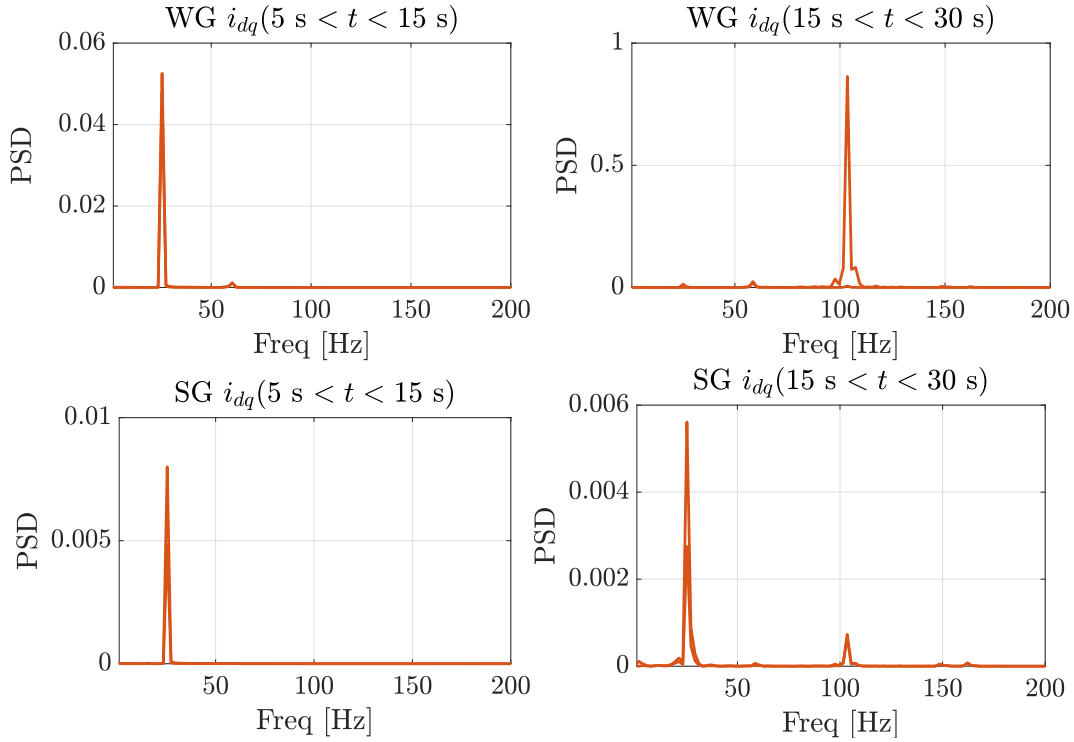


Figure 20: Frequency spectra (as PSD) of dq -axis currents injected by WG and SG in Windows A and B [48].

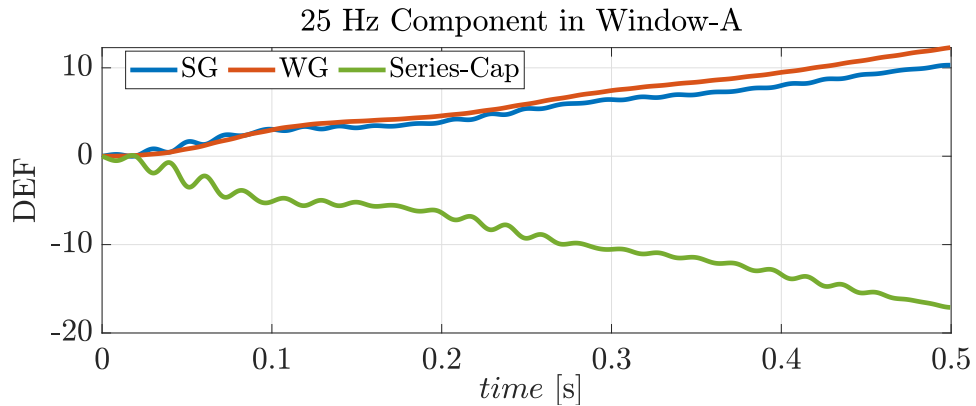


Figure 21: DEF from the grid elements into the grid computed from the data in Window-A between 14.5–15 s for the 25 Hz component [48].

25 Hz mode but as a sink for the 105 Hz mode, illustrating how a components role in oscillation energy exchange can vary with frequency. This case study demonstrates the capability of DEF to not only locate oscillation sources but also map the corresponding propagation paths across multiple frequencies in a multi-machine network.

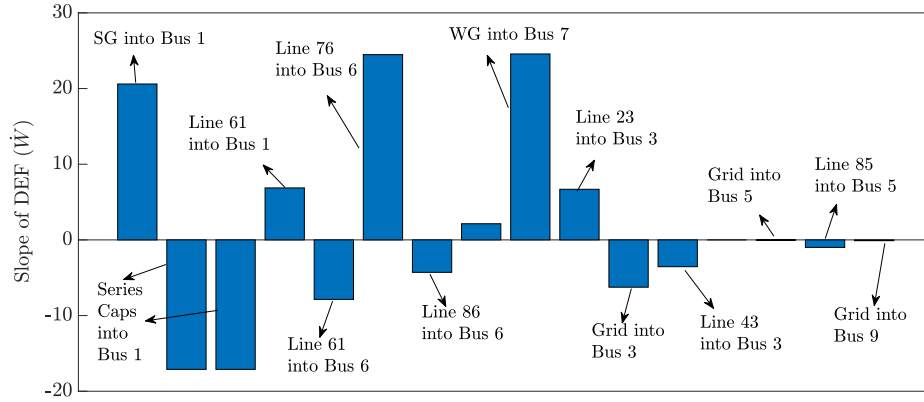


Figure 22: Average slope of DEF from different grid elements calculated for the 25 Hz in Window-A [48].

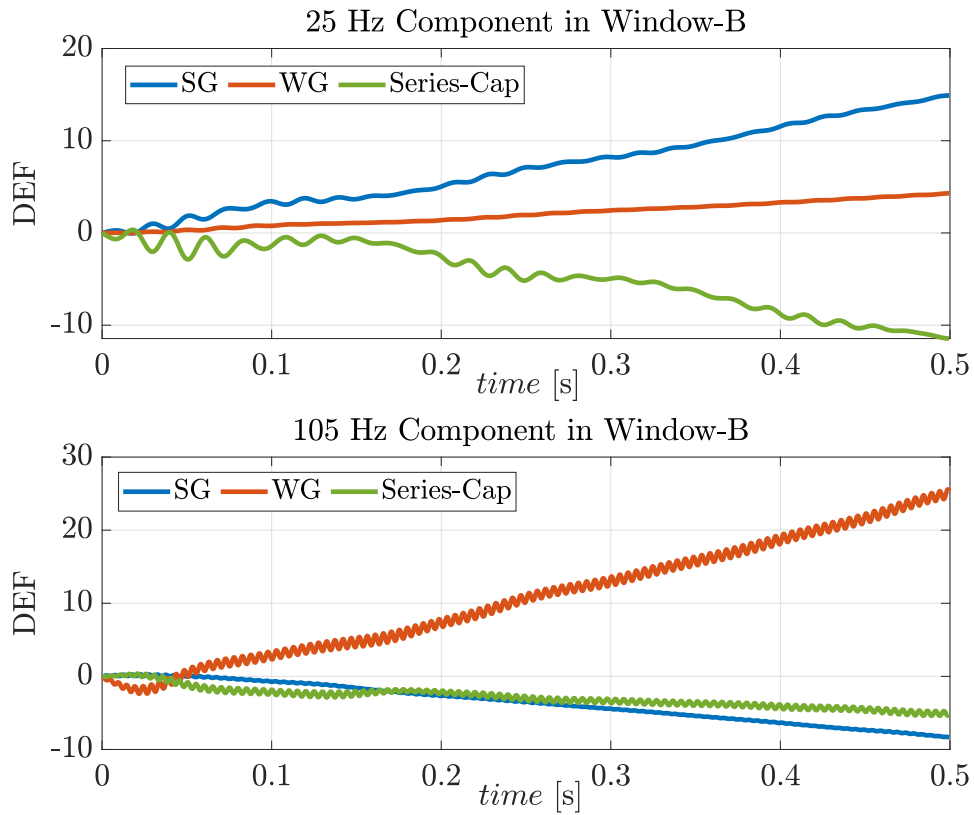


Figure 23: DEF from the grid elements into the grid computed from the data in Window-B between 15–15.5 s for the (a) 25 Hz and (b) 105 Hz components [48].

5.4 Conclusions

This chapter extends the Dissipative Energy Flow (DEF) framework to identify sources and interaction paths of sub- and super-synchronous control interactions (SSCIs) in inverter-based Identification of Sub/Super-Synchronous Control Interaction Paths Using Dissipative Energy Flow

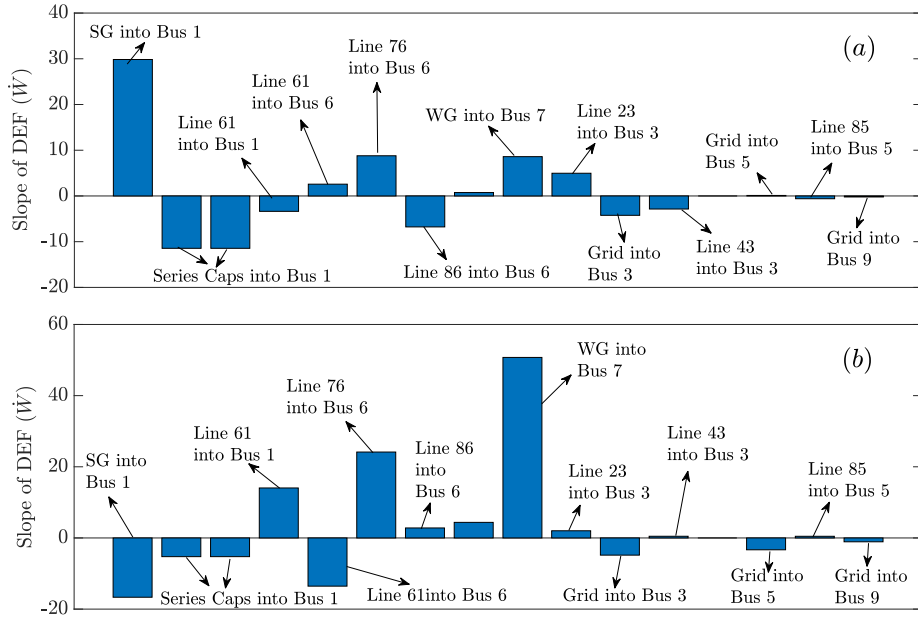


Figure 24: Average slope of DEF from different grid elements calculated for the (a) 25 Hz and (b) 105 Hz components in Window-B [48].

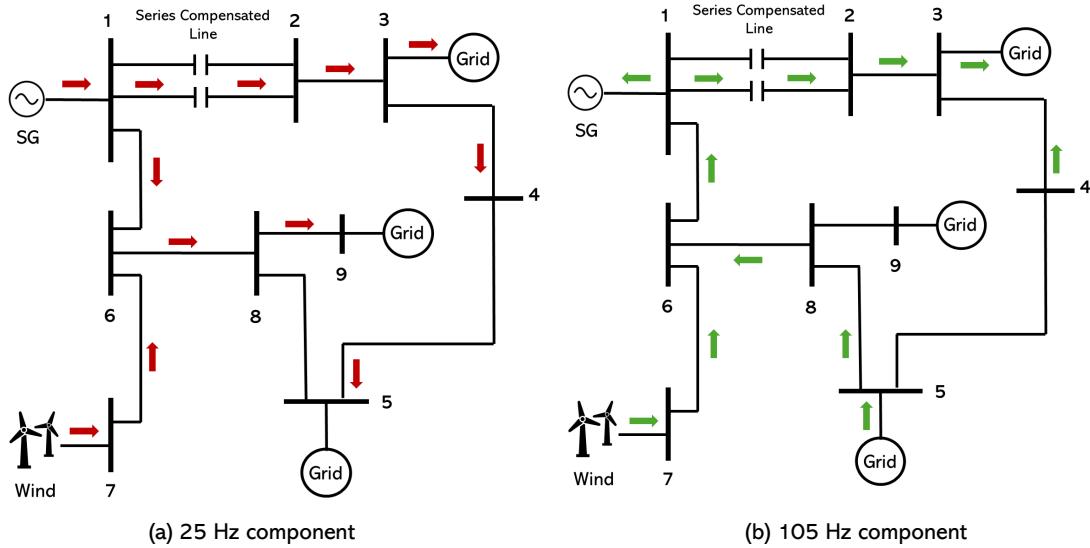


Figure 25: Identified SSCI path and oscillation energy flow for the (a) 25Hz and (b) 105Hz components in Window-B [48].

resource (IBR)-rich grids. The proposed approach operates in the dq domain using dynamic phasors derived from three-phase voltage and current measurements, enabling mode-specific DEF computation for oscillations well above the fundamental frequency. Applied to an EMT test system with synchronous and DFIG-based generation, it successfully localized sources and sinks, mapped propagation paths across multiple frequencies, and captured cases where

the same resource acted as a source at one frequency and a sink at another. The approach is easy to implement and interpret, providing actionable insights for targeted control retuning and system reconfiguration.

Acknowledgment

The authors would like to thank Dr. Kaustav Dey at the University of Manitoba, CA, for comments and discussions.

6.0 Sub-synchronous Oscillation Analysis with MTDC-MiniWECC Test System

E-COMP work [63] presents the development of a detailed electromagnetic transient (EMT) model of the Western Electricity Coordinating Council (WECC) grid to better study the impacts of integrating large wind farms. With the rapid growth of inverter-based resources in Northern California and Southern Oregon, traditional phasor-based simulations fall short in capturing their fast dynamic behaviors. To address this, [63] convert an existing 240-bus miniWECC model from PSS/e [64] into PSCAD using E-Tran, creating a robust foundation for high-fidelity EMT studies. The model has been extended by incorporating Type-4 wind turbine units with detailed control systems, including maximum power point tracking, pitch angle control, and rotor/grid-side converters. Simulation studies are then conducted under varying wind speed conditions and during fault events to test the systems dynamic response. Fig. 26 shows the diagram of integrating wind farms through MTDC network with the MiniWECC grid.

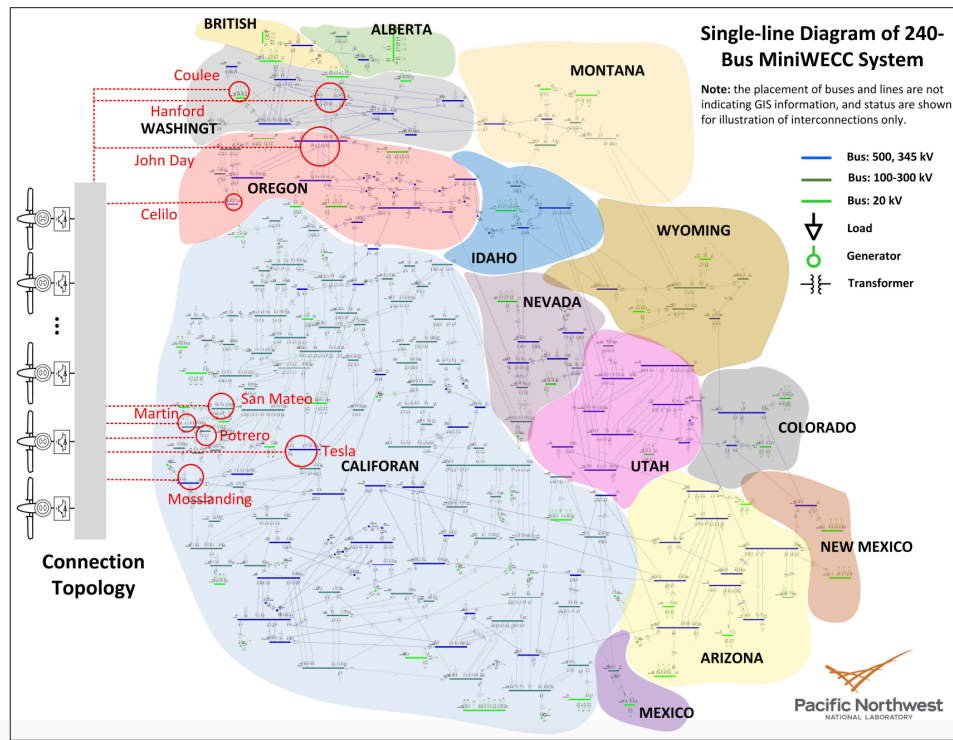


Figure 26: Overview of 240-bus miniWECC system with integrated Wind Farms (from [63])

As this large-scale EMT model is computationally very expensive to use for multiple set of simulations in investigating SSCIs, we have generated two reduced order equivalent models as shown in Fig. 27. For the first step, The miniWECC system has been substituted with equivalent representations that include five points of interconnection while maintaining identical steady-state power injections. Subsequently, the miniWECC system has been substituted

with a portion of the actual grid, while the remaining sections are represented by equivalents that preserve the same steady-state power injections. We have kept parts of WA and OR where there are a cluster of IBRs and synchronous generators to capture the impacts of SSCIs on such resources propagating through MTDC.

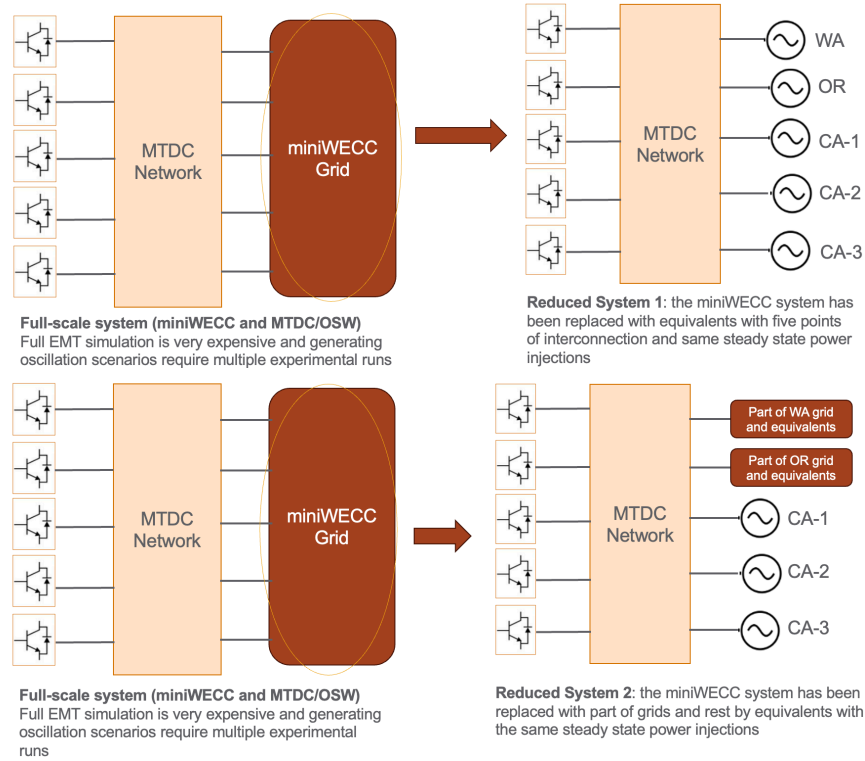


Figure 27: Reduced order modeling for faster experimentation

Fig. 28 illustrates a scenario in which the active power control loop proportional gain of a wind farm IBR (IBR 1, located at the topmost connection point to the MTDC) is modified at $t = 17$ seconds. This perturbation induces oscillations of approximately 426 MW (peak-to-peak) at the IBRs point of coupling with the MTDC. The oscillations occur at a sub-synchronous frequency of 47 Hz, as confirmed by the power spectral density plot. The MTDC network mitigates these oscillations, since the WECC-side MTDC converter exhibits only minimal response, as shown in Fig. 29. At $t = 25$ seconds, the gain of the WECC-side MTDC converter is perturbed, leading to additional oscillations of about 15 MW (peak-to-peak) at the MiniWECC grid side. This newly introduced oscillatory mode occurs at a super-synchronous frequency of 118 Hz. The bottom panel of Fig. 29 further highlights the interaction among the MTDC converters on the WECC side, showing the superimposed SSCIs with varying degrees of amplitudes.

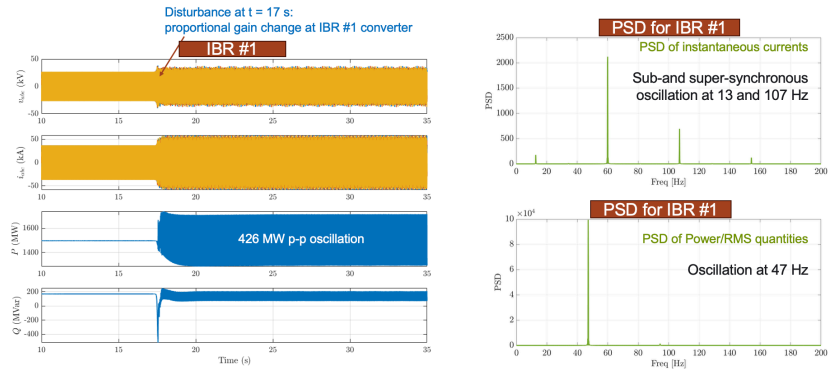


Figure 28: Occurrence of 47 Hz Sub-synchronous Oscillations caused by the WF IBR

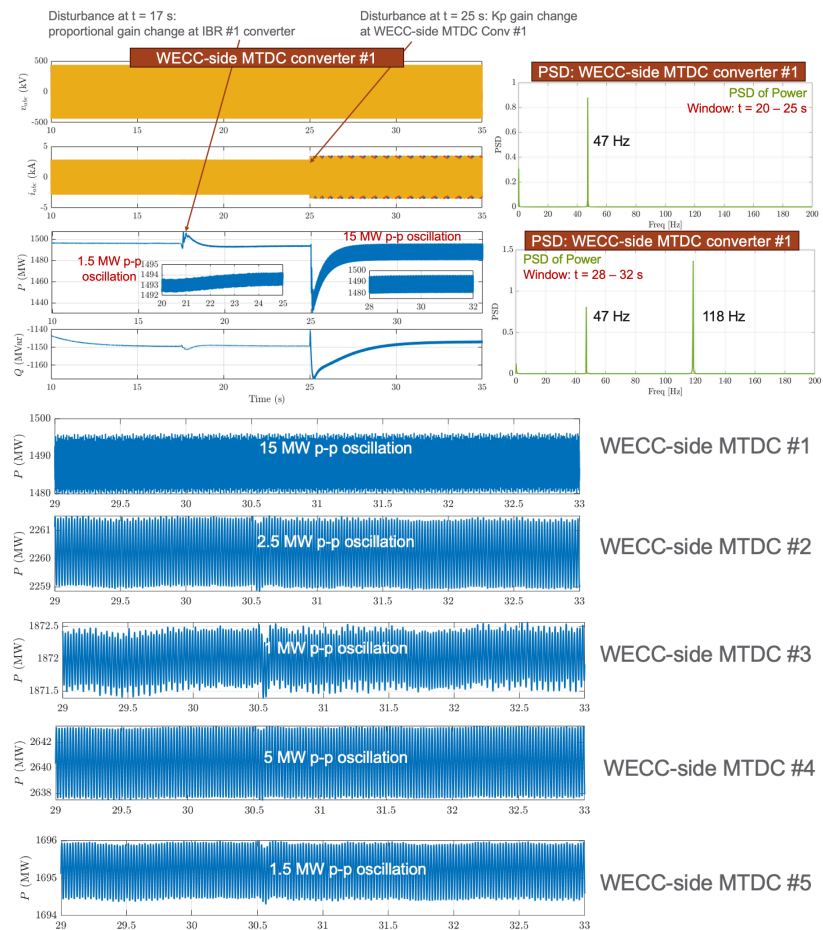


Figure 29: Occurrence of additional 118 Hz Super-synchronous Oscillations caused by the MTDC inverter

Acknowledgment

The authors would like to thank Dr. Hisham Mahmood at PNNL for providing the MTDC-MiniWECC test system and helpful discussions.

7.0 Policy Gradient-based EMT-in-the-loop Learning Capability to Mitigate Sub-synchronous Oscillations

As we described the emergence of SSIs in the previous chapters, consequently, increasing research efforts have focused on developing control solutions to mitigate SSIs/SSCIs in inverter-rich grids. Prior work has proposed damping strategies for doubly-fed induction generators (DFIGs) and series-compensated transmission systems [66, 67], as well as robust coordinated schemes for suppressing sub-synchronous oscillations [68]. Adaptive multi-modal damping controllers tailored for weak grids have also been reported [69]. More recent contributions explore hybrid line-commutated converter (LCC) HVDC approaches to oscillation suppression [70], while data-driven and machine learning-based methods for SSI mitigation are presented in [71].

This chapter delves into developing tunable control gains using EMT-in-the-loop simulators in order to mitigate critical oscillations. The methodology integrates PSCAD with an outer-loop Python API framework to invoke the simulator and dynamically adjust gain parameters. A data extraction script is formulated to perform down-sampling and bandpass filtering, thereby curating the required observation windows. The control policy is represented by a multi-layer perceptron (MLP)-based neural network. The reward function is defined in terms of the computed oscillation energy associated with the active power generated by the inverter. During each training epoch, batches of reward samples are collected and used to backpropagate errors and iteratively update the neural network policy.

7.1 Approach

This research investigates learning tunable gains with EMT-in-the-loop simulators to mitigate critical oscillations. As described in the previous chapter, we consider the Texas grid example, and consider a SSCI event, where the gains of the wind farm controller needs to be properly tuned in order to mitigate any adverse oscillations. Fig. 34 shows the overall architecture for the AI-based closed-loop control design to mitigate SSIs. For the development of this framework, we consider the following design considerations.

1. *EMT-in-the-loop Training Setup:* We first created the computational framework that integrates PSCAD, an EMT simulator, with an external python-based interface that can send commands to the simulator, and can also read the measurements. We have utilized the PSCAD's built-in API to integrate the external training module that can communicate with the simulator to parse data and send remedial control commands, such as tunable gains.
2. *Data extraction module:* The data extraction script performs required down-sampling when needed, and band-pass filtering to remove any offsets that may be present in the raw measurements. These essential processing scripts help curate the desired observation

The work in this chapter is accepted in this article [65]: Mukherjee, S., Hossain, R.R., Chatterjee, K., Nekkalapu, S. and Elizondo, M., 2025. Policy Gradient-Based EMT-in-the-Loop Learning to Mitigate Sub-Synchronous Control Interactions. IEEE PES General Meeting 2026. Available on arXiv preprint arXiv:2511.0

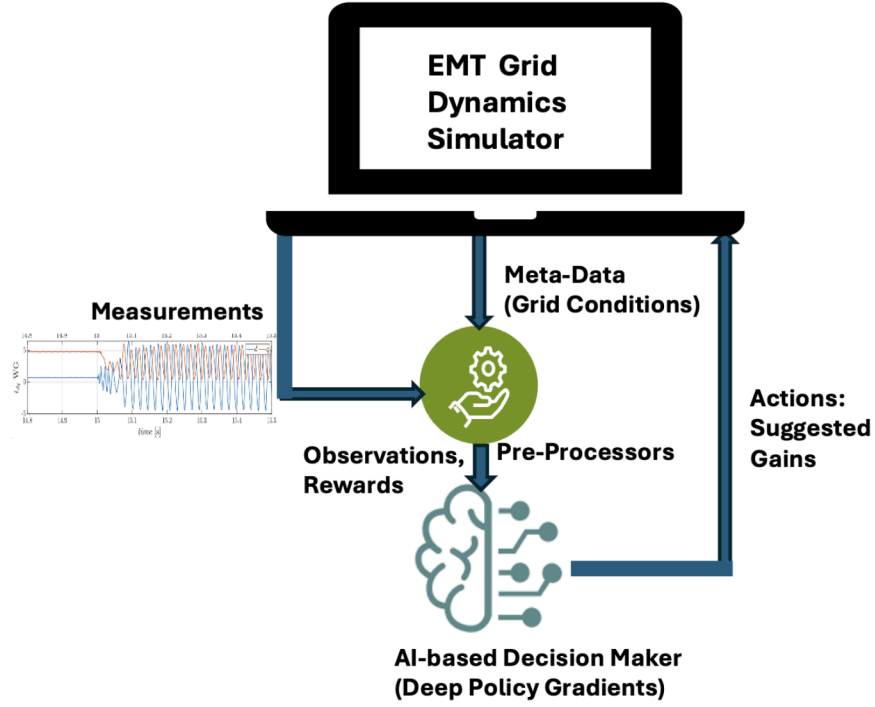


Figure 30: Schematic of the AI-based Mitigation of SSCI with EMT-in-th-loop Training

windows, that will be passed to the AI-based decision maker to perform reward computation and utilized as feedback measurements.

3. *Reward Design:* Reward (R) is defined using the computed oscillation energy under the active power generated by the WF-IBR such as:

$$E_{\text{osc}} = \int_0^T (P(t) - P_{\text{nom}})^2 dt, R = -E_{\text{osc}}, \quad (36)$$

for the observation window captured by final time T . When a band-pass filtered active power output signal is utilized we will have, $P_{\text{nom}} = 0$, and the signal itself will contain all the effect caused due to the oscillations.

4. *Policy:* We parameterize the policy as a Gaussian distribution

$$\pi_{\theta}(a | s) = \mathcal{N}(\mu_{\theta}(s), \sigma_{\theta}^2(s)), \quad (37)$$

where $s \in \mathbb{R}^{d_{\text{obs}}}$ is the observation and the mean and variance are obtained from a neural network:

$$h_1 = \text{ReLU}(W_1 \text{LN}(s)), \quad (38)$$

$$h_2 = \text{ReLU}(W_2 h_1), \quad (39)$$

$$\mu_{\theta}(s) = W_3 h_2, \quad (40)$$

$$\sigma_{\theta}^2(s) = \text{Softplus}(W_3' h_2). \quad (41)$$

Algorithm 5: Policy Gradient Training with PSCAD-in-the-Loop

```

1 Inputs: Number of epochs  $n_{\text{epoch}}$ , iterations per epoch  $n_{\text{iter}}$ , policy  $\pi_\theta$ , optimizer.
2 Initialize best loss:  $L^* \leftarrow \infty$ .
3 for  $e = 1$  to  $n_{\text{epoch}}$  do
4   Initialize storage for log-probabilities, actions, and losses.
5   for  $n = 1$  to  $n_{\text{iter}}$  do
6     Run PSCAD without control, extract trajectory  $(X_{\text{in}}, T_{\text{in}})$ .
7     Preprocess trajectory into state  $s$ .
8     Sample action from policy:
        
$$a \sim \pi_\theta(\cdot | s), \quad \ell = \log \pi_\theta(a | s)$$

        Send  $a$  to PSCAD and obtain controlled trajectory  $(X_{\text{out}}, T_{\text{out}})$ .
9     Compute oscillation energy loss:
        
$$\mathcal{L} = \sum_t \|x_{\text{out}}(t)\|^2 \Delta t$$

10    Store  $\ell$  and  $\mathcal{L}$ .
11  end
12  Compute policy gradient objective:
        
$$J(\theta) = \frac{1}{n_{\text{iter}}} \sum_{j=1}^{n_{\text{iter}}} \ell_j \mathcal{L}_j$$

        Update policy parameters:
        
$$\theta \leftarrow \theta - \alpha \nabla_\theta J(\theta)$$

13  Save average epoch loss and update best model if improved.
14 end
15 Return: Optimized policy parameters  $\theta^*$ .

```

The controller samples actions using the reparameterization trick:

$$a = \mu_\theta(s) + \sigma_\theta(s) \odot \epsilon, \quad \epsilon \sim \mathcal{N}(0, I). \quad (42)$$

The log-probability of the sampled action is

$$\log \pi_\theta(a | s) = -\frac{1}{2} \left[\frac{(a - \mu_\theta(s))^2}{\sigma_\theta^2(s)} + \log(2\pi\sigma_\theta^2(s)) \right], \quad (43)$$

and the entropy of the policy is

$$\mathcal{H}[\pi_\theta(\cdot | s)] = \frac{1}{2} \log(2\pi e \sigma_\theta^2(s)). \quad (44)$$

5. *Training Framework:* We train the policy using an episodic policy gradient method with PSCAD-in-the-loop simulation as described in Algorithm 5. To decrease the EMT computational burden, we employ a restricted training strategy where if the suggested gains from the AI agent are within a preset range we just use a representative PSCAD simulation run to evaluate its dynamic performance, and restrict the action space.

7.2 Results

We consider the southern Texas grid model that experienced a sub-synchronous control interaction event in 2009 involving a large wind farm equipped with doubly-fed induction generators (DFIGs) [51], [61]. Following the tripping of a 345 kV line to clear a fault, the plant became radially connected through a 50% series-compensated line. The interaction between the DFIG control loops and the series-capacitor resonance excited sub-synchronous oscillations, causing significant concerns in the system.

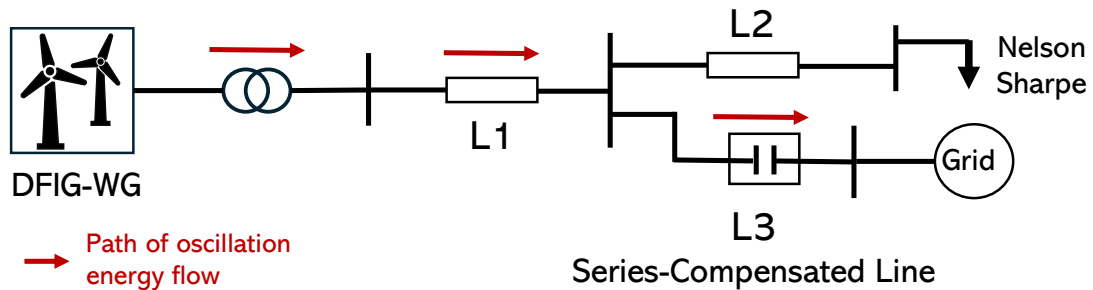


Figure 31: Single-line diagram of the test system, used to replicate the SSCI event from Texas, showing the path of oscillation energy flow or control interaction.

We replicated the operating conditions in the electromagnetic transients simulation platform PSCAD using the network illustrated in Fig.31. In this setup, approximately 200MW of power is generated by the DFIG-based wind source. The load at the Nelson Sharpe bus is assumed negligible in order to emulate the tripping of the 345kV line. Series compensation is set to 400 μ F, determined through sensitivity studies as the minimum value that ensures stability under nominal conditions but becomes unstable with small perturbations in the DFIG control gains. A parallel breaker is included to enable soft capacitor switching and thereby mitigate overvoltage conditions. Transmission lines L1, L2, and L3, connecting ZorilloAjo, AjoNelson Sharpe, and AjoRio Hondo, are modeled using lumped 60Hz PI-coupled parameters. In the simulated event (Fig.16), the proportional gain K_p of both the inner-loop and outer-loop rotor-side controls of the DFIG has been modified to inject SSCI. Fig. 33 shows that 1 second onward, system experiences unwanted and dangerous oscillations as reported in Chapter with sub-synchronous frequency of 48 Hz. We then conducted the RL policy training as depicted in Algorithm 5 with the training performance shown in Fig. 32. This shows that the oscillation energy has been decreased over the training episodes with optimal SSCI mitigation policy has been learned. Subsequently, we test the performance of such policy by activating the learned control at 5 seconds in Fig. 33. Both the active and reactive power oscillations are greatly minimized when the learned optimal controller is actuated in the system. As the policy network's

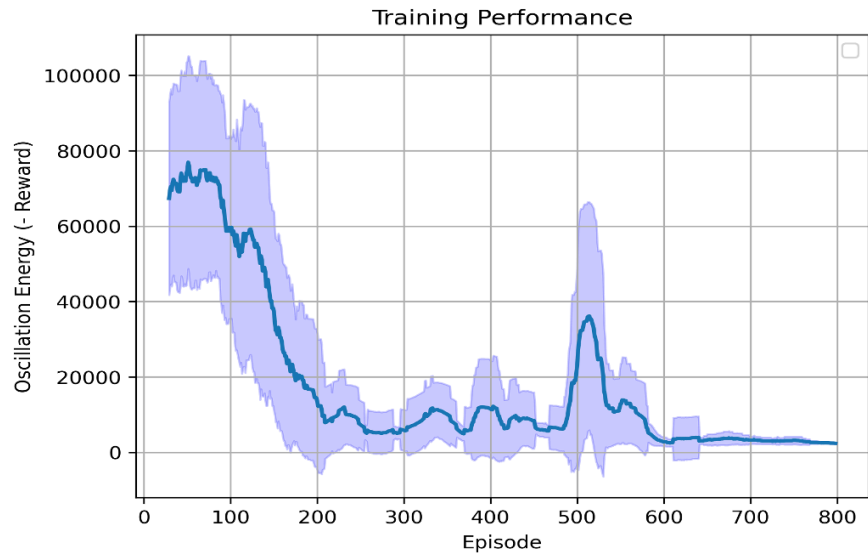


Figure 32: Policy gradient training progress

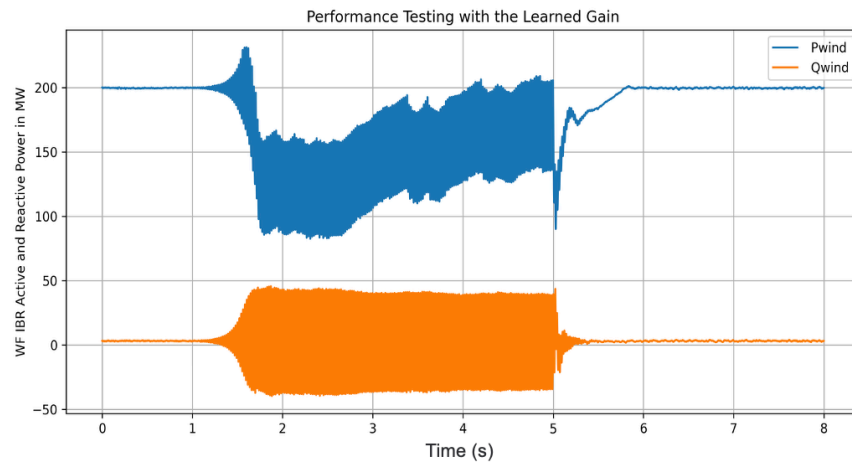


Figure 33: Onset of oscillations due to control gain mistuning at 1 second, and the learned policy helps to mitigate the oscillation with optimal control gain at 5 seconds

input is the active power measurements from the grid, the gain is adaptively updated based on the grid's operating conditions. In presence of heavy SSCI-based oscillations the policy has been trained to compute an optimal gain for the tunable active power loop of the WF IBR.

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8.0 Physics-Informed Learning of Proprietary Inverter Models for Grid Dynamic Studies

Power systems dynamical analysis and studies depend heavily on the precision and accuracy of the simulation models utilized to represent various grid assets and components. With the increasing penetration of inverter-based resources (IBRs), replicating the inverter dynamics has become essential to represent grid behaviors observed in practice. Traditionally, power system simulators incorporate well-validated detailed representations of conventional generation assets, e.g., synchronous generators (SGs). There are recent efforts to develop generic models of inverters. However, the internal control architectures and parameters of these inverters are often unknown or inaccessible to operators as OEMs often restrict the proprietary information related to those models [72]. This poses significant challenges to develop high-precision dynamic models needed for system-level studies. Recent advances in AI and deep learning have demonstrated the potential of learning-based latent dynamical systems capturing complex nonlinear interactions in physical systems [73]. These approaches can be further enhanced by integrating nominal physics knowledge in the learning process, as explored in prior works [74].

To this end, we propose a *physics-informed neural latent ordinary differential equation modeling framework* to infer and emulate the dynamic behavior of proprietary inverter models where nominal inverter dynamics are explicitly embedded along with additional neural learning layers to mimic the original dynamics. The main contribution of this chapter is summarized as follows: The proposed architecture leverages a baseline representative inverter control structure to inject partial physical priors into the learning process, resulting in a hybrid model that combines neural network components with physics-informed dynamics. We introduce a physics-informed latent neural ordinary differential equation-based model (PI-LNM) framework that blends data-driven learning with structural knowledge from inverter dynamics to replicate the behavior of black-box proprietary models.

8.1 Proposed Methodology

Let us consider the power grid composed of M buses, with M_m being the number of resource buses with either SGs or GFM-based resources. The dynamics of the SGs are well-established [75] and can be compactly represented as, $\dot{x}_s = f_{\text{sync}}(x_s, V)$, where $f_{\text{sync}}(\cdot)$ presents the functional form of the dynamics with $V = [V_{1_{Re}}, \dots, V_{M_{Re}}, V_{1_{Im}}, \dots, V_{M_{Im}}]$, and x_s denotes the SG states. Without loss of generality, in this chapter, we study proprietary dynamic models of the GFMs — compactly denoted as: $\dot{x}_f = f_{\text{gfm}}(x_f, V)$, where GFM state vectors are stacked together as x_f . Here, we assume that system operators have some knowledge of the generic GFM models, for instance, the dynamic representation of the WECC-approved REGFM_A1 model [76] with P - ω and Q - V droop. However, the exact model provided by the OEM is unknown. Therefore, our objective is to approximate the dynamics of the actual GFM model with a data-driven learning-based neural model infusing the generic physics

The preliminary work in this chapter is available as preprint (arXiv preprint arXiv:2507.15259), and an extended journal version with subsequent E-COMP support in FY26 is accepted at: Kwon, K.B., Mukherjee, S., Hossain, R.R. and Elizondo, M., Physics-Informed Learning of Proprietary Inverter Models for Grid Dynamic Studies. Electric Power Systems Research, vol. 265, 2027.

knowledge, represented in (45).

$$\dot{x}_f = N_\theta(\hat{f}_{\text{gfm}}(x_f, V)). \quad (45)$$

where $N_\theta(\cdot)$ represents a learnable neural function, $\hat{f}_{\text{gfm}}(\cdot)$ considers generic physics of GFM model, e.g. the dynamics described in [76]. This chapter specifically investigates the physics-informed latent ODE framework to replicate the behavior of proprietary GFM models. First, we briefly introduce the neural latent ODE (NODE) models. Next, the learning framework utilized for GFM models will be discussed.

8.1.1 Physics-informed Latent Neural ODE

Our approach combines NODE models that capture unknown characteristics from real-world field data with physical information derived from known mathematical dynamics [77]. The process of a latent ODE model can be formalized as follows [78]. The initial latent state z_0 is sampled from a prior distribution $p(\cdot)$: $z_0 \sim p(z_0)$. In the standard approach, the latent trajectory is computed by solving an ODE parameterized by a neural network function f_θ over the observation times $t_0, \dots, t_N$:

$$z_0, z_1, \dots, z_N = \text{ODESolve}(f_\theta, z_0, (t_0, t_1, \dots, t_N)). \quad (46)$$

The function f_θ models the time derivative of the latent state as $\frac{dz}{dt} = f_\theta(z, t)$, where θ represents trainable parameters. We propose a PI-LNM where some representative dynamic equations are considered (e.g., $\hat{f}_{\text{gfm}}(\cdot)$) along with additional neural ODEs:

$$\frac{d}{dt} \begin{bmatrix} z \\ z_r \end{bmatrix} = \begin{bmatrix} f_\theta(z, z_r, t) \\ \hat{f}_{\text{gfm}}(z, z_r, t) \end{bmatrix} \quad (47)$$

where the dynamics of z_r uses a representative model:

$$\frac{dz_r}{dt} = \hat{f}_{\text{gfm}}(z_r, z, t), \quad (48)$$

The decoder function, a trainable neural network, maps the latent states back to the observation space $x_i \sim p(x_i|z_i)$, $i = 0, \dots, N$. In standard designs, this can be a multi-layer perceptron (MLP) based neural network.

To estimate the posterior distribution over latent trajectories, an ODE-RNN was proposed as an encoder [79]. This approach entails encoding the sequence of observations $\{x_i, t_i\}_{i=0}^N$ using an encoder neural ODE and an RNN to produce a hidden state representation at the final time step, denoted as h_T . A neural network g maps this hidden state to the parameters of the approximate posterior distribution:

$$q_\phi(z_0|\{x_i, t_i\}_{i=0}^N) = \mathcal{N}(\mu_{z_0}, \sigma_{z_0}) \text{ where } (\mu_{z_0}, \sigma_{z_0}) = g(h_T).$$

Training a latent ODE model involves jointly optimizing the parameters of the encoder (ODE-RNN) and the decoder, and the latent ODE's neural functions f_θ by maximizing the evidence lower bound (ELBO):

$$\mathcal{L}_{ELBO} = \mathbb{E}_{q_\phi(z_0|\{x_i, t_i\})} \left[\sum_{i=0}^N \log p(x_i|z_i) \right] - D_{KL}(q_\phi(z_0|\{x_i, t_i\}) \parallel p(z_0)) \quad (49)$$

Remark 2. Since latent ODEs are a generative model in which ODEs govern the dynamics of latent variables [78], our approach merges the generative representation power of latent models with the infusion of physical information. As such, latent ODEs differ from traditional autoregressive models such as RNNs and their variants (e.g., GRU and LSTM).

8.1.2 Learning Framework for GFM models

To implement the physics-informed latent ODE model that mimics the GFM dynamics, we consider the following steps, also depicted in Fig. 34:

Step 1: In a controlled experimental environment, the operator first interconnects the proprietary actual GFM unit to a source (replicating an infinite bus), along with a load connected at the POI. If the experimental setup is not feasible, the black-box proprietary software models can be connected in similar fashion to a grid simulator.

Step 2: Generate different events by changing the active power consumed by the load in a certain large range, and store T number of time-steps. We store the trajectories of the state tuple x for K number of trajectories.

Step 3: Process the observation data in batches through the encoder network to estimate an initial condition and perform roll-out forward in time using the physics-informed Neural ODE function (47).

Step 4: Using the optimization framework as described in equation (49), we compute ELBO losses and perform back-prop to learn the latent ODE model where $|z| \gg |x|$ ($|\cdot|$ denotes cardinality).

Step 5: Once the neural GFM dynamics is learned, we utilize this as our equivalent model with physics-enabled prior embedded for simulations. To this end, we connect the learned dynamical block to the target grid simulation platform with other grid components and perform dynamic simulations.

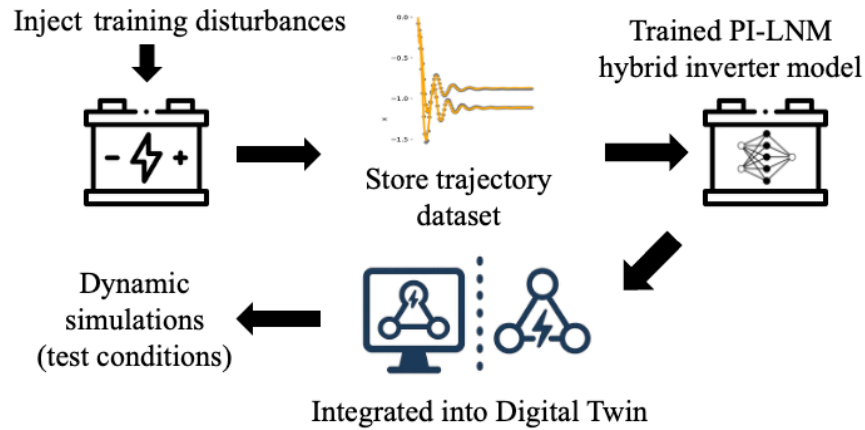


Figure 34: Schematic overview of the learning framework

Remark 3. As shown in Fig. 34, our proposed model can be directly incorporated into the digital twin framework because it learns a compact, physics-informed representation of GFM dy-

namics from field data. This enables seamless coupling with existing grid simulators, offering a real-time, data-driven surrogate that preserves underlying physical laws while significantly reducing computational complexity.

8.2 Simulation Results

To mimic an actual power grid setup, we use an emulator model with an assumed proprietary restricted GFM unit and a test system to generate data and test the performance of the learned PI-LNM model. To generate the training data, at $t = 0$, we introduce a change in the load between 0.5 p.u. and 5 p.u. and record a trajectory of the observations $\mathbf{x} := [\theta_j, \omega_j, V_j^e, V_j, P_j^n, Q_j^n]$, which includes both the GFM states (angles, frequencies, voltage control errors, and the internal voltage magnitude) and the active, reactive power delivered through the network. The time interval is set to $\Delta t = 0.01$ seconds, and we observe for 10 seconds. We generate 2000 samples, each consisting of six trajectories of state variables. Using this data, we apply latent ODE to learn the GFM dynamics. A total of 24 latent variables are set, out of which the first four variables correspond to $[\theta_j, \omega_j, V_j^e, V_j]$. Here, we assume that the exact values of the GFM parameters $\hat{f}_{GFM}$ are unknown, and introduce a $\pm 20\%$ error from the approximated GFM droop and gain parameters $\{m_p, m_q, k_{pv}, k_{iv}\}$. We utilize these approximated parameters in $\hat{f}_{GFM}$, whereas the training data is generated with the actual dynamics. The batch size is set to 200 out of the 2000 samples, with an initial learning rate of 0.02. The number of iterations is set at 2000. To show the effectiveness of our latent-ODE-based model, we compare three cases: *Actual GFM dynamics*, *RNN-based without physics information*, and *PI-LNM*. The training results of *LNM* are shown in Fig. 35, illustrating the results at iterations 600, and 2000, respectively. As seen in the figure, with each iteration, the latent ODE agent progressively estimates the time-series trajectory with increasing accuracy. In addition, the training trajectory of *RNN*-based model is depicted in Fig. 36, showing at iteration 2000, and compared to *LNM*, *RNN* cannot converge to the target due to a lack of physics guidance.

With the trained model, we conduct tests on an experimental test system, as shown in Fig. 37. Similar to the training setup, the load is connected at bus 1, where the GFM is located, and sudden, randomly chosen changes in load occur at $t = 0$. We observe the trajectory for 5 seconds. With an initial power flow solution, the trajectory is accumulated using estimates of the next steps through the trained NODE agent, based on the previous observations. Fig. 38 shows the trajectory comparison where the proposed model could effectively mimic the dynamics of the actual GFM with respect to a standard RNN-based model.

Table 6: Comparison of RMSE values for Prediction

Metric (RMSE)	RNN	PI-LNM	Improvement (%)
Voltage (pu)	6.0×10^{-3}	4.0×10^{-3}	33.3%
Frequency (Hz)	5.8×10^{-3}	2.2×10^{-3}	62.1%

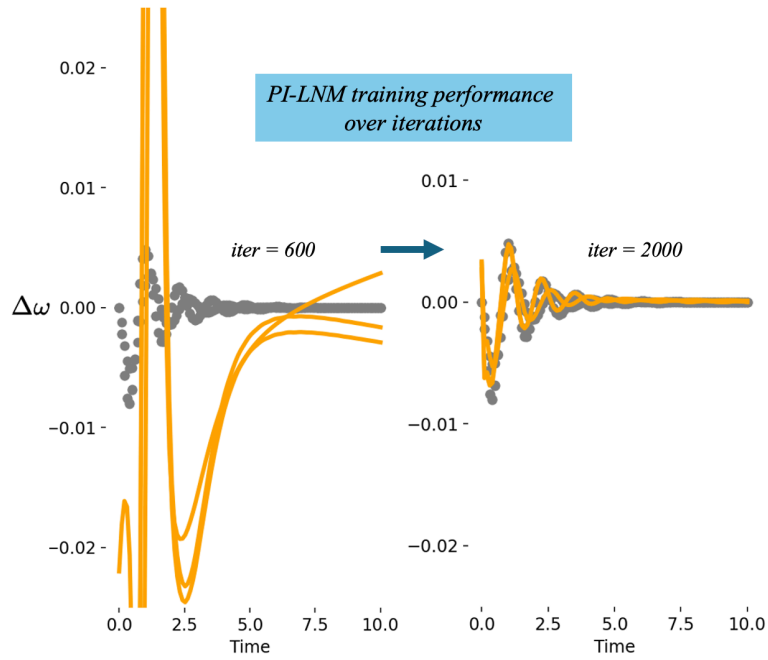


Figure 35: PI-LNM training performance

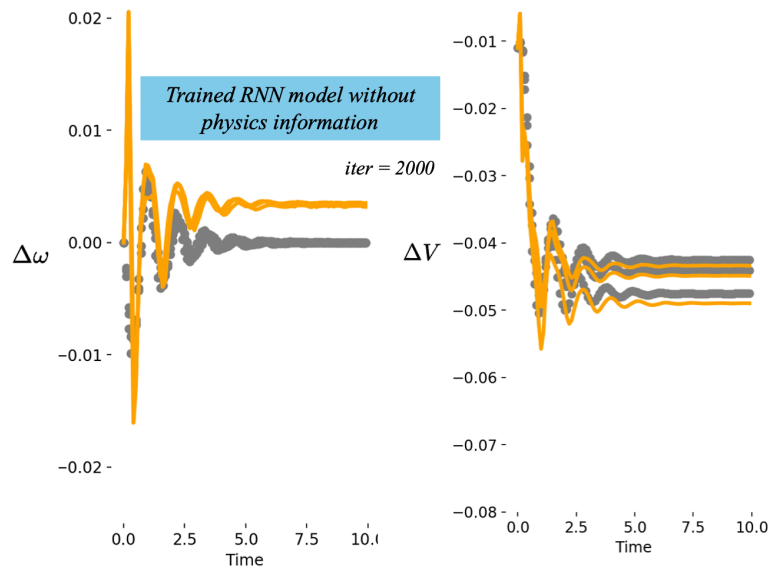


Figure 36: Insufficient training performance of RNN-based (not physics-informed) modeling framework

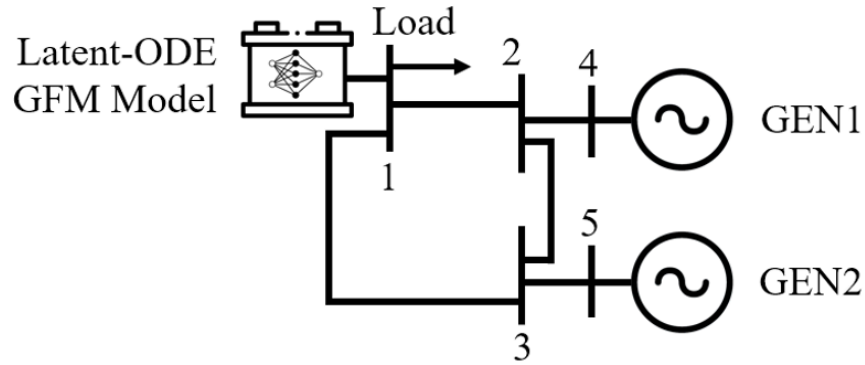


Figure 37: Trained PI-LNM GFM model integrated to simulation

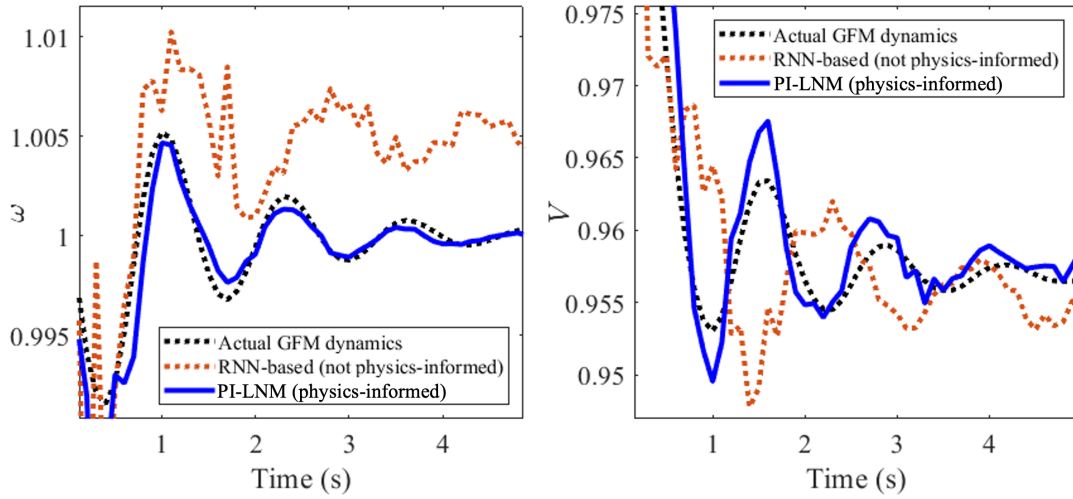


Figure 38: Test-time performance evaluation

8.3 Conclusion

In this chapter, we developed a PILNM framework to emulate proprietary GFM dynamics by embedding nominal droopcontrol priors into a neuralODE architecture. The proposed PILNM combines an ODERNN encoder with a physicsaugmented latent ODE decoder to learn both known and unmodeled behaviors from timeseries data. Numerical experiments show that PILNM outperforms an RNN baseline, reducing RMSE in voltage and frequency trajectories by over 30% and 60%, respectively. This approach demonstrates that incorporating physics enhances learning efficiency and generalization, offering a practical pathway for emulation of blackbox inverter models in power system analysis.

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