

To the Graduate Council:

I am submitting herewith a dissertation written by Francisco Alexander Zelaya-Arrazabal entitled “Hybrid Model-Data Strategies to Improve Power System Control, Assessment, and Awareness.” I have examined the final paper copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Major.

Hector Pulgar, Major Professor

We have read this dissertation
and recommend its acceptance:

Fangxing Li

Amir Sadovnik

Jin Zhao

Accepted for the Council:

Dixie L. Thompson

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(Original signatures are on file with official student records.)

Hybrid Model-Data Strategies to Improve Power System Control, Assessment, and Awareness

A Dissertation Presented for the

Doctor of Philosophy

Degree

The University of Tennessee, Knoxville

Francisco Alexander Zelaya-Arrazabal

August 2025

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In memory of my mother.
Dedicated to my beloved father and grandmother.

Acknowledgements

I would like to start by thanking the person who, since the day we met, has been cheering me on and supporting me throughout this crazy journey. Since it all started, nine years ago, you have been there for me even in the days when we were miles apart with no idea we would end up building a life together. Thank you, Gaby. You have been my best friend, my confidant, and my backbone throughout this past decade. I love you so much and am proud of everything we have accomplished together.

I would also like to thank my family, especially my father and my grandmother, who gave me the tools I needed to be disciplined, hardworking, and passionate about everything I do. Your example has shaped the person I am today. Thank you to my siblings and my stepmom for encouraging me to keep going after my dreams, even after my father's accident. I truly admire you, love you, and will always be grateful for the way you took care of Dad during the hardest times. And to all of Gaby's family, thank you for being such a solid rock in this adventure.

I also want to thank my mentors. First, Dr. Pulgar. Thank you for giving me the opportunity to be part of your lab, for everything you taught me, and for the support you gave me. Working with you was definitely challenging, but also one of the most encouraging, constructive, and rewarding experiences I have had. You recognized my commitment and consistently pushed me to go further. Doing everything with passion and always giving your best is one of the most important lessons I will carry with me, thanks to you. Second, Dr. Paternina, my master's advisor. Doc, thank you for seeing something in me that even I did not see in myself. I never thought

of myself as a doctor, but you taught me to love doing research, to collaborate with others, and to say yes to difficult challenges even when we are not sure we are ready. I've learned a lot from our continued collaborations and truly value that connection. It was also a pleasure working with your team, and I'm thankful for the chance to contribute and grow alongside them.

Many thanks to the members of my committee. Dr. Li and Dr. Sadovnik, it was thanks to you that I became curious about applying deep learning to power systems. Your guidance, lectures, and conversations helped me deepen my understanding of AI and integrate it into my research. Dr. Zhao, you guided us through the first part of the damping controller coordination project, which marked my first experience combining deep learning and power systems. Working with you was a great experience. That project was a game changer, as it pushed me to learn so many new things. I truly value having you all as professors and as members of my committee.

I also thank Dr. Silva and my fellow Ph.D. student Jingzi for their collaboration on the damping controller coordination research. Dr. Silva not only laid the foundation for that work but also provided valuable suggestions that helped improve the quality of the final results.

How could I not thank my lab mates, Tim and Sebastian? Working with you both taught me so much. We learned so many things together, power systems, control, reinforcement learning, and more. It was great to share this journey with you. I especially want to thank Sebastian. My friend, I learned so much from you. Collaborating with you has been one of the greatest learning experiences of my entire life. I truly appreciate all our afternoons listening to Pink Floyd, Rush, RHCP, and more, and all the amazing concerts we went to. Thank you for all your support.

I would also like to thank all my friends who, even from far away, made me feel close to home. Geo, Javier, Zaca, Chamba, Karen, Felipe, Turcios, Gerardo, Taty, Sara, Charly, Pacheco, and many others. All your memes, messages, and visits made the hard times so much better. Finally, I want to thank life. My path has been hard since my early days, but I have learned that passion and dreams can take you

anywhere. I am truly grateful to God, to la virgencita de Guadalupe, and for all the good and bad things that have happened along the way. This journey has been amazing.

Abstract

This dissertation addresses the challenges introduced by the rapid transformation of modern power grids, driven by the growing penetration of inverter-based resources, declining system inertia, and emerging technologies. These shifts introduce increased variability and uncertainty into power system dynamics, complicating the task of maintaining stability. This work explores how combining model-based strategies with data-informed techniques can enhance system control, assessment, and awareness, providing scalable tools to improve grid reliability.

The first contribution focuses on improving the coordination of damping controllers for low-frequency electromechanical oscillations. Traditional controllers are typically tuned for fixed operating conditions and dominant modes, limiting their robustness under varying scenarios. To overcome this limitation, a data-informed coordination strategy is proposed. By leveraging wide-area measurements, it enables real-time optimization of damping control actions without relying on linearized models. This decentralized, non-intrusive framework enhances the damping of complex, multi-mode oscillations across the grid.

The second and central contribution presents a high-fidelity and computationally efficient method for estimating system frequency response (SFR) and frequency nadir—key indicators of system resilience following large disturbances. Traditional methods typically trade accuracy for speed or vice versa, limiting their practical use for fast assessment or precise planning. To overcome these limitations, a novel modal-based estimation approach is developed, which exploits the system’s modal structure

to predict the slow dynamic response that governs nadir behavior. This method accurately reconstructs the frequency trajectory from system modes and disturbance characteristics, enabling precise prediction of both nadir magnitude and timing. The approach is validated on standard IEEE test systems and the Salvadoran power grid, demonstrating significant accuracy improvements over legacy tools.

The final contribution introduces a hybrid model-AI framework for online estimation of SFR and frequency nadir. This approach integrates modal-based analysis with deep learning, enabling fast, predictive evaluation of major contingencies based on pre-contingency conditions and system-level features. The framework supports the identification of critical events and real-time forecasting of worst-case frequency deviations, enhancing operational awareness and decision-making.

Together, these contributions offer practical, hybrid model-data solutions for modern power system stability, addressing both current and future operational challenges.

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Chapter 1

Introduction

1.1 Background and motivation

Over the past decade, the power grid has undergone rapid and profound transformation. Key drivers include the increasing penetration of renewable energy sources, declining system inertia, and the widespread adoption of new technologies such as battery energy storage systems, distributed energy resources, electric vehicles, and, more recently, large-scale data centers [1–3]. This evolution has shifted the grid from one dominated by synchronous machines to a more complex system with significant participation of inverter-based resources (IBRs) and diverse dynamic elements.

One of the defining characteristics of the modern power grid is its increasing variability. Traditional systems, dominated by synchronous generators (SGs) and largely static loads, were designed to be controlled and analyzed under fixed, well-defined operating conditions [4]. In such settings, conventional methods were sufficient, as nonlinear behaviors typically became significant only during rare, large-scale contingencies. However, today’s grid operates under far more uncertain and dynamic conditions, necessitating new and more efficient analytical and control techniques that can adapt to evolving system dynamics [5, 6].

Two persistent challenges in power system stability are electromechanical oscillations and frequency deviations [7, 8]. Oscillations are typically addressed using linearized models, while frequency dynamics are assessed via nonlinear simulations or average frequency approximations. Yet, the growing complexity of system behavior under variable conditions calls for novel methods of assessment and mitigation.

Recent events have highlighted the urgency of this need. The Iberian blackout of April 28, 2025, drew global attention from engineers and researchers [9]. Although the causes remain under investigation, preliminary findings suggest that oscillatory behavior preceded the event. While it is unclear whether these oscillations directly triggered the generator outages that cascaded into system-wide failure, the incident underscores the critical role of both phenomena in grid stability. It has reignited discussions on current grid operation practices and highlighted the limitations of traditional control approaches in the face of increasing variability and declining system inertia.

This dissertation addresses both electromechanical oscillations and frequency stability. These issues are first examined through the lens of system dynamics and physical modeling. Building on this foundation, deep learning techniques are then leveraged to develop new approaches for the coordination of oscillation damping and the monitoring of frequency stability.

1.1.1 Damping controls in power systems

The sustained increase in renewable generation over the past decade has introduced greater variability and uncertainty in grid operation, compromising stability and leading to sub-optimal controller performance. For instance, damping controllers (DC) for low-frequency electromechanical oscillations (LFEO) are typically designed to target a dominant mode, assuming a typical operating condition required for linearization [10, 11]. As a result, the performance of DC depends on how closely the real-time operating point matches the one assumed during the design stage [12].

Additionally, the targeted mode must be excited by a disturbance; if it is not, the DC may fail to restrain oscillations and could even compromise system stability. Addressing these challenges requires damping control architectures—both local and wide-area damping control (WADC)—to adapt to varying operating conditions and disturbances, ultimately enhancing overall system stability [13].

Numerous adaptable approaches have been proposed [12–21], falling into two main categories: model-based and data-driven methods. Despite their promising results, each faces unique challenges. Model-based techniques depend on accurate and up-to-date data for effective controller parameterization but are hindered by legacy equipment and proprietary actuator models [22]. Data-driven approaches focus on real-time controller adjustments but may be restricted by utility companies due to security concerns, such as potential forced oscillations and resonance with natural modes caused by variable tuning parameters [23]. Additionally, as emphasized in [24], there is a significant demand for novel adaptable solutions that utilize more distributed resources while minimizing computational complexity and execution time. These challenges contribute to the limited presence of operational WADC solutions in current power grids [25–27]. For example, in the United States, the Pacific DC Intertie (PDCI) is the sole functioning wide-area damping control system within the entire US grid. Operating within a high-voltage DC transmission line, the PDCI uses a filter-based approach to dampen the North-South B mode of the Western Interconnection. As detailed in previous research [28, 29], one of the main challenges was accurately tuning compensation for the NS-B mode, requiring the involvement of multiple entities in the design, validation, and deployment phases [30]. Furthermore, the implementation process becomes more complex when considering multiple modes, highlighting that real-time adjustment of several tuning parameters may be restricted by independent system operators and utilities to prevent adverse effects on system stability.

An adaptable alternative was proposed by the authors, offering a solution for adaptively optimizing damping actions in the grid [31]. This approach focuses on the

coordination of DCs, efficiently managing numerous decentralized local or wide-area DCs across the grid without the need for real-time adjustment of tuning parameters. Notably, the coordination emphasizes IBRs, allowing these resources to act as DCs only when beneficial for improving grid damping. By avoiding changes to controller parameters, this approach proves to be non-intrusive and effective in reducing grid oscillations.

The model-based approach relies on sensitivities to determine the optimal controller status for the complexity of the coordination problem [31]. However, this necessitates either pre-computation or real-time calculation of a linearized model and sensitivities, increasing complexity and potentially impacting execution time.

1.1.2 System frequency response and nadir prediction

Frequency stability is a cornerstone of power system reliability and is becoming increasingly critical as the grid evolves with the growing integration of Distributed Energy Resources (DERs), IBRs, and large-scale unconventional loads such as data centers. These elements introduce fast and significant power imbalances that challenge traditional approaches to system analysis, protection, and control [32]. In this context, accurately estimating the system frequency response (SFR) and the frequency nadir—the lowest frequency reached after a disturbance—is vital for grid stability. These estimates guide key operational and planning decisions, including frequency relay coordination, under-frequency load shedding, spinning reserve allocation, and renewable integration [33–36].

Conventional approaches to frequency nadir prediction typically rely on detailed nonlinear simulations [34, 37], which, while accurate, are impractical for large-scale planning or real-time applications that require many simulations. To improve computational efficiency, simplified analytical methods based on the Average System Frequency (ASF) model have been widely used [38–47]. These models treat the grid as an aggregated system with linear responses to power imbalances, improving efficiency

but overlooking key dynamics—such as heterogeneous governor/turbine models, frequency-dependent loads, IBR controls, and high-order control loops [41, 44, 45]. Moreover, as the grid continues to evolve, these simplified models require frequent heuristic adjustments and structural redesigns to accommodate new technologies and emerging dynamics [42, 43, 46].

1.1.3 Frequency stability in dynamic security assessment

Growing system variability, driven by increasing renewable integration, has elevated the importance of Dynamic Security Assessment (DSA) in modern power grids. DSA evaluates a power system’s ability to withstand a defined set of contingencies and transition to an acceptable steady-state condition [48]. Depending on its timing and application, DSA is typically classified into offline and online approaches.

Offline DSA commonly relies on time-domain simulations or analytical methods applied across many operating scenarios to determine secure operating limits used by operators in real-time decision-making [49]. In contrast, online DSA leverages artificial intelligence or statistical techniques to rapidly assess system security following a disturbance, providing binary stability classification, stability indices, or margins [50–52]. The vast majority of recent research has focused on online DSA, which is inherently reactive—meaning that a contingency must occur before any assessment can be performed. This is often justified as a means to enhance situational awareness [53–61]. However, from an operator’s perspective, this is not entirely satisfactory, as reactive indices typically offer only a few seconds for control action, which limits their practical value in critical decision-making.

Traditionally, DSA has concentrated on rotor angle and voltage stability [48]. However, with the increasing penetration of inverter-based resources and the associated decline in system inertia, frequency stability has emerged as a critical concern. In recent years, various studies have explored frequency stability within the DSA framework, focusing on the estimation of the system frequency response

(SFR) following a disturbance [53–55], or key parameters such as the frequency nadir, nadir timing, post-disturbance steady-state frequency, and the rate of change of frequency (RoCoF) [56–58]. A growing trend in these studies is the application of artificial intelligence (AI) techniques to estimate these parameters and support real-time operational decisions [59].

However, this AI-driven trend presents several challenges. Purely data-driven models often require large volumes of historical data and diverse operating conditions to generalize well across unseen scenarios [59]. Alternatively, these models must be capable of retraining online to adapt to evolving system conditions, which is computationally expensive and often impractical. To manage variability in topology, demand, and renewable penetration, graph-based and structure-aware models have been proposed to better capture system dynamics [55, 56, 60]. While conceptually appealing, such approaches typically rely on high-dimensional input features derived from widespread real-time monitoring. Although technically feasible, deploying phasor measurement units (PMUs) at all nodes to support these models requires substantial infrastructure investment, making it economically unrealistic for most systems [62]. Furthermore, PMU-based methods face additional challenges, including data loss, noise, communication delays, and burdensome preprocessing [63]—issues that become more pronounced when models require a vast number of measurements.

Therefore, there is a clear need for models that can adapt to changing grid conditions without relying on extensive PMU deployment. These models should strike a balance between offline and online DSA: offering real-time evaluations without requiring a purely reactive approach. Instead, a predictive framework that leverages steady-state operating conditions to anticipate system behavior can enhance situational awareness and provide operators with more actionable insights and lead time for control. Importantly, such models are not intended to replace existing online DSA tools but rather to complement them by enriching the system’s understanding of its dynamic security margins ahead of a disturbance, thereby enabling more informed and proactive decision-making.

1.2 Dissertation outline and main contribution

The core findings of this research are presented across three main chapters, followed by the conclusions.

Chapter 2 presents the data-informed coordination (DIC) of DCs, which directly estimates the optimal on/off status of DCs without relying on a linearized model. This approach utilizes key wide-area measured variables within a hierarchical control structure to estimate the Total Action (TA), capturing all system nonlinearities, specific disturbances, and operating conditions. Notably, no proprietary models are necessary, and IBRs are utilized as DCs only when required.

Four main contributions are highlighted: a) Adaptive Data-Informed Coordination: Providing real-time switching on/off conditions based on wide-area measurements. b) Coordination Structure Based on TA Function Approximation: A structure comprising three main parts aims to gather accurate data and commission IBR-DCs. c) Overcoming Model-Based Coordination Drawbacks: Eliminating dependency on the linearized model and its corresponding sensitivities. d) Improving System Damping Against Multi-Mode Events: Enhancing system damping even when various modes are excited. Specifically, the DIC addresses both local and inter-area modes—the former in the range of 1 to 3 Hz and the latter at frequencies below 1 Hz [11].

Chapter 3 presents a novel method to predict the SFR and frequency nadir using a modal-based approach that directly leverages the full nonlinear dynamic model of the power system, without adopting simplified or average system models. Unlike traditional approaches that rely on reduced turbine-governor models constructed from reheater-type conventional governors, this method captures the full interaction between generation technologies and control dynamics. By decomposing the system's response into its modal components and retaining only a small subset of dominant modes, the method enables a closed-form analytical estimation of both the frequency trajectory and its nadir.

A key advantage of the proposed method is its robustness under evolving grid conditions, including the growing presence of IBRs. The dominant modes used for estimation exhibit low sensitivity to parameter variations and remain valid across a broad range of operating scenarios. As such, the method does not require custom adjustments to incorporate non-synchronous generation. Instead, it inherently captures the system-wide dynamic effects introduced by these resources, offering a unified and accurate framework as the grid’s composition evolves.

The following main contributions are highlighted: a) A methodology for deriving a closed-form algebraic expression of the SFR using modal decomposition. b) A practical framework for accurately predicting frequency nadir without relying on simplified aggregate models. c) A comprehensive comparative evaluation using standard test systems and the Salvadoran transmission planning network. d) A detailed sensitivity analysis of dominant modes that govern SFR. e) An analysis of the influence of IBRs in the estimation, offering a system-wide perspective without additional modeling complexity.

Chapter 4 presents a hybrid model–AI framework for improving real-time dynamic security assessment of frequency stability in power systems. Building on the modal-based system frequency response (SFR) and nadir prediction approach introduced in Chapter 3, this framework leverages a Deep Sets-inspired neural network to estimate key modal coefficients. These estimates enable fast and accurate prediction of frequency nadir and its timing across a wide range of operating conditions and disturbances.

By replacing repeated analytical computations with a data-driven estimation of complex modal weights, the proposed method significantly accelerates the assessment process while preserving the physical interpretability of the underlying dynamics. Designed to adapt to changing system conditions, the framework automatically identifies relevant contingencies based on the current unit commitment and generation dispatch. This allows the approach to strike a practical balance between offline and online DSA, offering predictive insight into system behavior without requiring

a disturbance-triggered response. The framework is validated using the IEEE 10-machine 39-bus and 118-bus systems, demonstrating its scalability and effectiveness.

The main contributions of this chapter are: a) the development of a real-time dynamic assessment framework to enhance situational awareness of frequency stability; b) the design of a Deep Sets-inspired neural model that captures the permutation-equivariant nature of grid states and modal information; and c) a lightweight, predictive solution that operates from steady-state data without the need for widespread deployment of wide-area measurement systems.

Chapter 5 presents the conclusions and future works.

Chapter 2

Data-Informed Coordination of Damping Controllers

This chapter presents an adaptive, data-informed coordination framework for damping controllers. It reduces Total Action by selecting optimal on/off controller combinations. A multivariate function approximator captures the nonlinear relationship between wide-area measurements, controller status, and disturbance conditions to estimate Total Action in real time. Validated on the Western North American Power System (wNAPS), the method outperforms model-based coordination, offering greater adaptability and significantly reducing low-frequency oscillations across varying operating conditions, fault locations, and time delays.

2.1 Background on controllers coordination

The controllers' coordination concept is possible due to the use of the TA metric, which is a performance index derived from the system oscillation energy. Assume a system with p synchronous generators (SGs). Then, the oscillation energy (E) is given by,

$$E(t) = \sum_{j=1}^p H_j \omega_s \Delta \omega_j^2(t) \quad (2.1)$$

where the subscript j represents the j -th SG, $w_s = 120\pi$ is the synchronous speed in rad/s, H_j is the inertia constant in s, and $\Delta w_j = w_j - w_{COI}$ the speed deviation in p.u.—the speed of the center of inertia (COI) is used, which is defined as $\omega_{COI}(t) = \sum_{j=1}^p H_j \omega_j(t) / \sum_{j=1}^p H_j$. The multivariate function $E(t)$ can exhibit an oscillatory pattern over time if some oscillatory modes are excited and converge to zero when the system is asymptotically stable. This is illustrated in Fig. 2.1, where a comparison of the oscillation energy for the same case, with and without DCs, is shown. The black curve demonstrates that the proper participation of DCs reduces grid oscillations.

The time integral of $E(t)$ over a horizon τ is known as the action $S(\tau) = \int_{t_0}^{t_0+\tau} E(t) dt$. The time t_0 can be the time of disturbance, or any other after this e.g. the time when the first measured data is available. In a stable system, the TA is defined as,

$$S_\infty = \lim_{\tau \rightarrow \infty} S(\tau) = \lim_{\tau \rightarrow \infty} \int_{t_0}^{t_0+\tau} E(t) dt \quad (2.2)$$

This equation considers the entire action of the system after a disturbance. A large value of this metric reflects large and sustained oscillations [31, 64]. In other terms, increased system damping would imply a low TA. Thus, this work prioritizes the minimization of the TA and oscillation energy, to reduce oscillations in the grid. These physical concepts avoid the use of arbitrary objective functions regarding oscillation damping and serve as a mechanism to weigh the importance of relevant modes without having to target the most critical ones in advance. By understanding TA metric for a given disturbance, the on/off status of the DCs can be determined base on those that

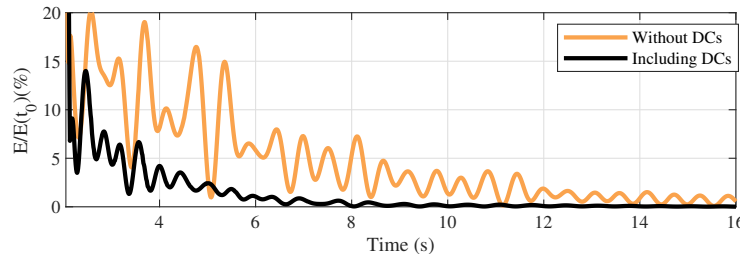


Figure 2.1: Oscillation energy comparison with and without DCs.

lead to its minimum value. A model-based approach, relying on a linearized model, has been proposed to solve the coordination problem [31]. A brief description follows.

2.1.1 Model-based coordination based on Total Action sensitivities

If A_q is the system matrix of the linearized model, a similarity transformation is used to convert the TA into an explicit expression in terms of the system eigenvalues and initial condition after a disturbance. With $\Lambda_q = M_q^{-1}A_qM_q = \text{diag}\{\lambda_{qi}\}$, where λ_{qi} is the i -th eigenvalue and M_q is the matrix of right eigenvectors, the TA can be estimated by,

$$S_\infty \approx -\frac{1}{2} \sum_{j=1}^n \sum_{i=1}^n \frac{z_{0i}z_{0j}g_{ij}}{\lambda_{qi} + \lambda_{qj}} \quad (2.3)$$

Here, g_{ij} is the (i,j)-term of the transformed inertia matrix, and z_{0i} and z_{0j} are the i -th and j -th terms of $z_0 = M_q^{-1}x_0$, with x_0 being the vector of state variables at time t_0 —initial condition of the transformed and original state variables. The subscript q indicates the dependency on the on/off switching status of the controllers.

Assume there are m DCs, and define $q_k \in \{0, 1\} \forall k \in \{1, 2, \dots, m\}$ as the on/off switching status of the k -th DC, i.e., $q_k=1$ if the m -th DC is activated, and $q_k = 0$ otherwise. The coordination aims at increasing the system damping by specifying $q_k \forall k \in \{1, 2, \dots, m\}$ based on the current operating condition and disturbance. The optimal on/off status of the DCs, q_k^* , is obtained by solving the binary integer problem that minimizes S_∞ . Due to the problem complexity, a sub-optimal solution can be achieved through linear sensitivities of the TA. By relaxing the switching variables q_k and varying them in the range $[0, 1] \in \mathbb{R}$, a first order Taylor expansion of S_∞ around an initial switching condition q_{k0} is obtained:

$$\Delta S_\infty \approx \frac{\partial S_\infty}{\partial \hat{q}_1} \Delta \hat{q}_1 + \frac{\partial S_\infty}{\partial \hat{q}_2} \Delta \hat{q}_2 + \dots + \frac{\partial S_\infty}{\partial \hat{q}_m} \Delta \hat{q}_m \quad (2.4)$$

The partial derivatives are called total action sensitivities (TAS) and are explicitly estimated by the linearized model and its modal information [64]. For a given operating condition and disturbance, while a gain increment of the k -th DC would worsen the dynamic performance if its TAS is positive, an enhanced performance would be achieved if its TAS is negative. The sub-optimal solution is obtained by applying the following on/off switching logic for all $k \in \{1, 2, \dots, m\}$: **Switch on** $\{q_k : 0 \rightarrow 1 \iff \frac{\partial S_\infty}{\partial q_k}|_{\hat{q}_k} < 0\}$ and **Switch off** $\{q_k : 1 \rightarrow 0 \iff \frac{\partial S_\infty}{\partial q_k}|_{\hat{q}_k} > 0\}$.

Implementing this coordination logic requires offline and online stages. In the offline stage, for each predefined operating condition and disturbance scenario, the TAS for all DCs are computed and stored in a data collection $\mathcal{G}_k$ within the superset $\mathcal{G}$. During the online stage, a closely matched operating condition is selected from $\mathcal{G}$, and the corresponding on/off condition is relayed by a centralized controller to each DC. If nothing close is found, a fast estimation of the TAS is required. Despite the approach's adaptability to disturbances and operating conditions, its implementation can be cumbersome due to the need for large data storage and fast computational capabilities to match the current operating scenario or calculate the TAS. However, the proposed data-informed coordination in this paper streamlines real-time implementation by directly estimating the optimal on/off status of DCs, thereby enhancing effectiveness through prompt control actions.

2.2 Data-informed coordination (DIC)

The model-based approach validates the use of the Total Action (TA) as a unique function capturing the electro-mechanical dynamics spectrum and reflecting control actions' impact. However, its accuracy is limited to predefined conditions. To enhance effectiveness, more scenarios for operating conditions and disturbances would be needed, increasing the superset $\mathcal{G}$'s cardinality. Therefore, a data-informed approach is an ideal solution.

This section presents the DIC, a coordination scheme that operates on top of a set of DCs across the entire power grid. Each DC provides a continuous control action in a decentralized manner, but it is activated right after a disturbance by a centralized controller that determines whether each DC should be turned on or not. The main goal of the DIC is to optimize the use of the decentralized DCs, which can be enabled in any device with damping capabilities—PSS, FACTS, or, as in this work, IBRs.

In this study, a nonlinear function approximator is used to provide complex nonlinear estimations involving Total Action (TA) dynamics. Finally, the optimal on/off status of the DCs is determined by minimizing the TA function. This section details the selected function approximator, the structure of data-informed coordination, and its functionality.

2.2.1 Total action function approximator

In this work, a Deep Neural Network (DNN) is employed to provide the nonlinear approximation of the total action function. Note that any data-driven algorithm with the capability to approximate complex nonlinear functions and scalability to large networks can suffice. According to the universal approximation theorem [65], despite nonlinearity and intrinsic complexities, a DNN capable of capturing the relationship between the TA and key features must exist. This constitutes a regression problem, where the TA estimation $\hat{S}_\infty = f(\mathbf{r})$ is given by the DNN function approximator, $f(x)$, based on the vector of features, $\mathbf{r}$. The approximator is a nested function, comprising layers with artificial neurons. Let l_n denote the number of layers with vector functions $\mathbf{f}_1, \mathbf{f}_2, \dots, \mathbf{f}_{l_n}$. the function approximator is given by,

$$\hat{S}_\infty = \mathbf{f}_{l_n} \circ \dots \circ \mathbf{f}_2 \circ \mathbf{f}_1(\mathbf{r}) \quad (2.5)$$

Each of the vector functions has the form $\mathbf{f}_l = \mathbf{g}_l(\mathbf{W}_l \mathbf{r} + \mathbf{b}_l)$ where l is the layer index, $\mathbf{W}_l$ is the matrix of weights, $\mathbf{b}_l$ is the vector of biases, and $\mathbf{g}_l$ is the activation function—in charge of providing the nonlinear behavior of the DNN. Note that $\mathbf{f}_l$ is

a function vector. Each one of its entries is an artificial neuron defined as $a_{l,u} = g_l(\mathbf{w}_{l,u}\mathbf{r} + b_{l,u})$, where u is the index of the neuron and $\mathbf{w}_{l,u}$ is the corresponding row vector from $\mathbf{W}_l$. In the particular case of the output layer, there is just one neuron, $u = 1$. Thus, the function provides a scalar value.

For an accurate estimation, the DNN must be trained to approximate the values from the training data set through the calculation of the optimal parameters for each layer, i.e., $\mathbf{W}_l, \mathbf{b}_l \forall l$. Let L_{DNN} be the loss function defined as,

$$L_{DNN} = \frac{1}{N} \sum_{i=1}^N ((\hat{S}_\infty)_i - (S_\infty)_i)^2 \quad (2.6)$$

where N is the number of samples in the training set. Note that the loss function is the mean square error of the difference between the estimated and actual TA. To minimize the loss function and to achieve an accurate estimation, stochastic gradient descent with backpropagation can be used to find the best DNN hyperparameters.

The features, r , can have an operational or control nature. To be precise, the vector r is decomposed as $r = [y_0, \gamma_k]^T$. The vector y_0 has features relevant to the dynamic response such as the speed deviation from each SG. The subscript zero indicates that these features are captured at time t_0 . On the other hand, the vector γ_k has a control nature and contains the on/off switching status of each DC. Assume n_c DCs. Then, $\gamma_k = [q_1, \dots, q_\ell, \dots, q_{n_c}]$, where $q_\ell \in \{0, 1\}$ is the on/off switching status of the ℓ -th DC. The subscript k is the combination index. There are 2^{n_c} possible on/off switching combinations, thus, $k \in \{1, \dots, 2^{n_c}\}$.

2.2.2 Switching combination selection

The approximator $\hat{S}_\infty$ generates the estimated TA using y_0 and γ_k as inputs. If oscillation modes are excited, the vector y_0 is formed using online measurements at time t_0 . Note that the specific operating condition and disturbance responsible for exciting the oscillation modes are inherently captured within the vector y_0 . Given

y_0 , the optimal vector γ^* must be found such that the estimated TA is minimized. In other words, when y_0 is known, the search for the optimal on/off switching combination is confined to a subspace relevant to the current state of the system. Formally, this problem is formulated as,

$$\gamma^* = \arg \min_{\gamma_k \forall k \in \{1, \dots, 2^{n_c}\}} \hat{S}_\infty(\mathbf{y}_0, \gamma_k) \quad (2.7)$$

This is a binary optimization problem and its complexity depends on n_c . For a small n_c , minimum seeking can be achieved by sequentially determining the on or off status for each DC that leads to a smaller TA. This is done by directly evaluating the approximator with a fixed y_0 and fixed γ_k . The optimal solution can be also obtained by exhaustive evaluation of all possible combinations. If n_c is large, integer optimization solvers are required.

2.2.3 Coordination framework

Figure 2.2 shows the coordination framework. First, the PMU data is filtered by a supervisory system for abnormal data correction. Then, the PMU data is sent to the centralized controller a few milliseconds after a disturbance. The centralized controller processes the data to derive the optimal switching combination (γ^*), which is then communicated to each IBR-DC to indicate whether they participate in the

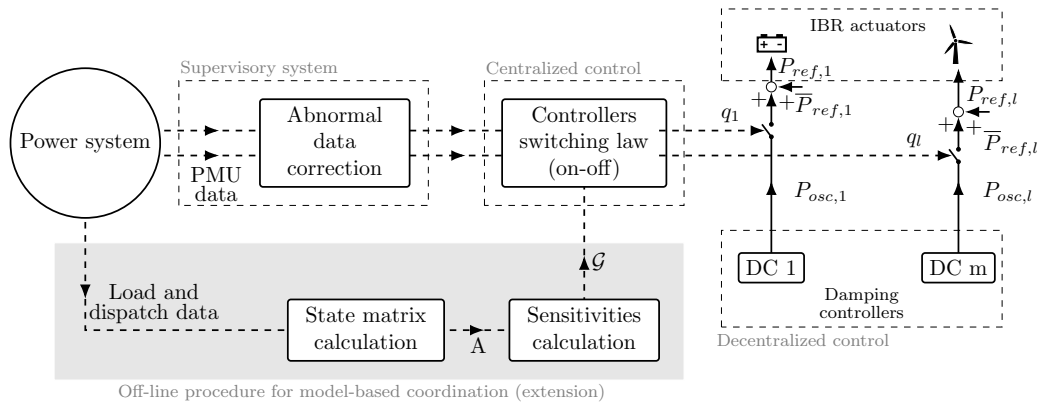


Figure 2.2: DCs coordination framework

damping actions. Note that DIC does not use the gray section; this is an additional offline section required by the MBC. Each sub-task is described below.

Supervisory System

The supervisory system is designed to handle abnormal data conditions, such as data loss, PMU failures, and inconsistencies in data arrival due to time delays or PMU asynchronism. Input correction and data alignment are performed asynchronously with the coordination process, meaning the supervisory mechanism continuously filters the incoming data before it is fed into the coordination system. When abnormal signals are detected, the system applies a defective data correction method that preprocesses the measurements using both historical and online data. Three methods to enhance the supervisory system were used:

- **Statistical-Value-Based Method:** Corrects defective features by replacing them with the mean or median of the corresponding historical data.
- **Minimal-Error-Based Method:** Selects a value that minimizes prediction error by generating random values within a historical range and evaluating them with a machine learning model.
- **DNN-Based Adaptive Method:** Uses deep neural networks (DNNs) trained on historical data to estimate defective feature values based on recent inputs.

In the worst-case scenario of PMU loss, these methods were validated through statistical analysis, showing that the mean error rate (MRE) could be improved to similar values to those of non-defective inputs (MRE = 1.74%). This validation and further details can be found in [63].

Centralized control

Once a fault has been cleared, a protection signal is transmitted to the centralized control at timestamp t_0 such that $\mathbf{y}_0$ is formed from the PMU measurements. The

DNN is used to derive the optimal switching combination, γ^* , for this particular fault and operating condition. Subsequently, each switching signal, $q_\ell \in \{0, 1\}$ (see Fig. 2.3), is transmitted by the centralized control to each DC, activating only those that are needed. If any of the IBRs participating in the coordination is out of service, the centralized control provides the best switching combination without taking into consideration the out-of-service IBR.

Decentralized control

DCs are assumed to be implemented in IBRs, modeled as controlled voltage sources [31]. Assume that IBRs follow a quasi-stationary power reference, $\bar{P}_{ref}$, related to mid-term energy goals i.e. economic dispatch or load shifting. To provide damping control, the power output is modulated around this reference targeting a specific oscillation mode through the supplementary reference signal P_{osc} , (see Fig. 2.3). For the ℓ -th IBR, the total power reference is given by $P_{ref,\ell} = P_{osc,\ell} \cdot q_\ell + \bar{P}_{ref,\ell}$. If q_ℓ is set to zero, the DC is switched off, leaving the IBR to follow $\bar{P}_{ref,\ell}$ only. Otherwise, the DC is turned on to provide damping control.

The P_{osc} signal is generated by the corresponding damping control loop of each specific IBR-DC, which was previously designed to damp specific modes. For instance, consider a specific mode with oscillation frequency ω_c and associated residue R_c . To damp this oscillation mode, it is necessary to compensate for the phase shift between the controlled output and its input measurement. The phase to be compensated is determined as $\phi = 180^\circ - \angle R_c$. Then, θ_k is a gain constant selected to achieve the desired damping response, T_w is the time constant of the washout filter, typically

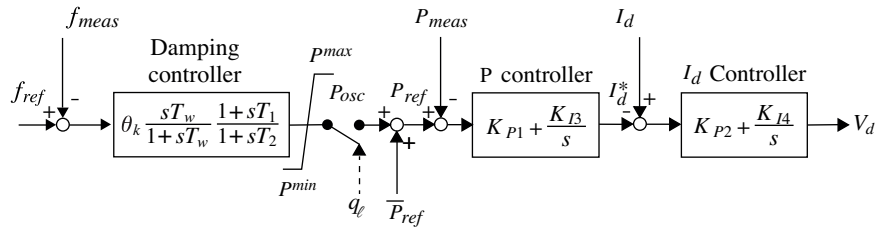


Figure 2.3: Active power control loop of ℓ -th IBR.

chosen between 5 to 10 seconds, so that a zero output can be provided in steady state, and the time constants T_1 and T_2 are selected using the following relations,

$$T_1 = aT_2, \quad T_2 = \frac{1}{\omega_c \sqrt{a}}, \quad a = \frac{1 + \sin(\phi)}{1 - \sin(\phi)} \quad (2.8)$$

for more details of this process please see references [66, 67]. The input signal is selected based on control objectives and the type of modes, whether local for local modes or remote for inter-area modes.

2.3 Setup and application

2.3.1 Test system

The Western North American Power System (wNAPS) with 179 buses, 30 machines, and 7 IBR-DCs—modeled as Battery Energy Storage Systems—is considered (see Fig. 2.4). 11 equivalent DFIG-based wind turbines are assumed to be installed throughout the system. The total instantaneous wind power generation ranges from 0-30% of the total generation for different operating scenarios. Although not resembling all actual conditions, the system model exhibits the five well-known inter-area modes of the wNAPS: “NS mode A”, “NS mode B”, “BC mode”, “EW A” and “Montana mode”. More details can be found in references [31] and [28].

2.3.2 Feature vector

The feature vector is the input vector that contains information associated with operating conditions and disturbances. In what follows, the sub-indices i and j are used to describe operating conditions and disturbances, respectively. To target each of these, the vector is further decomposed in two components as $\mathbf{y}_0 = [\mathbf{y}_{01}, \mathbf{y}_{02}]^T$.

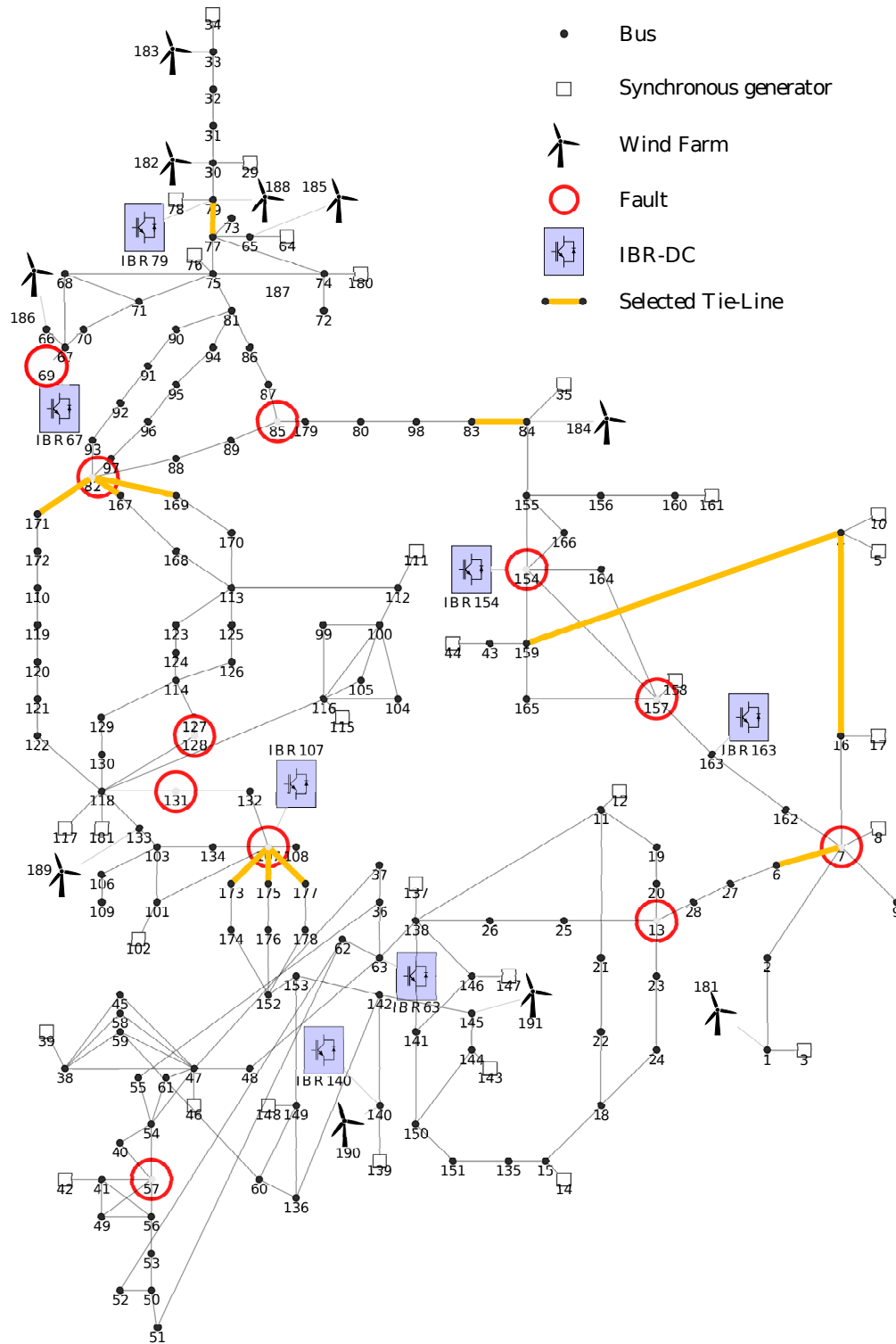


Figure 2.4: 179-bus, 30-machine, 7-DC test system.

Thus, the TA approximator becomes,

$$\hat{S}_{\infty,i,j,k} = f_{DNN}(\mathbf{y}_0, \gamma_k) = f_{DNN}(\mathbf{y}_{01,i}, \mathbf{y}_{02,j}, \gamma_k) \quad (2.9)$$

The first sub-vector, $\mathbf{y}_{01}$, contains information regarding the operating condition. To address LFEO, the ideal variables must reflect the dynamics across different electrical areas. A sensitivity analysis is used to identify links sensitive to system changes, Power Transfer Distribution Factors (PTDF) or Generator Shift Factors (GSF) can be used for this. For the wNAPS system, after identifying the most sensitive links and considering their relation to power transfer among the main three electrical areas and the Canada-USA corridor, transmission lines shown as thick solid lines in Fig. 2.4 are chosen. The power flows in these lines are selected as features, denoted as $\mathbf{p}_{tl}$, and stored in $\mathbf{y}_{01}$.

The second sub-vector, $\mathbf{y}_{02}$, holds information regarding the location of grid disturbances. For this, frequency deviation at SG buses with respect to a reference bus is employed as a feature, denoted as $\Delta\omega_{sg}$, and stored in $\mathbf{y}_{02}$. The rationale behind this choice is that frequency can capture the pattern of energetic modes with low damping and frequency, resulting in significantly higher TA while simultaneously capturing less energetic modes with high damping and frequency, resulting in lower TA. However, given that grid frequency is influenced by the balance of demand and generation, utilizing absolute frequency for pattern recognition across scenarios is challenging. Therefore, the frequency deviation will capture the change in magnitude contrary to an absolute value. This has proven to be appropriate, even with different pre-fault steady-state frequency values.

2.3.3 Data extraction

Dynamic simulations for all considered scenarios were conducted using DIgSILENT PowerFactory. Its Python API was used to run the time-domain simulations in the wNAPS under the set of specified operating conditions and disturbances, as

well as for the TA calculation and data collection. Algorithm 1 provides a specific pseudocode for data collection. Considering a total of n_o operating conditions, and n_d disturbances, define t_{cl} as the fault clearing time, t_a as coordination activation time, and t_e as the simulation end time. The collected data is stored in the super set $\Phi = \{\phi_1, \dots, \phi_s, \dots, \phi_{n_s}\}$, where $n_s = n_o \times n_d \times 2^{n_c}$, and $\phi_s = \{S_{\infty,i,j,k}, \mathbf{y}_{01,i}, \mathbf{y}_{02,j}, \gamma_k\} \forall s \in \{1, \dots, n_s\}$. Data collection occurs in three batches. The first batch, $\mathbf{y}_{01,i}$, captures power flow through selected transmission lines in steady-state to provide information on the operating condition. This ensures data consistency, as capturing it post-disturbance would not reflect the same operating condition. By keeping the element of the first set, a particular element of the second set $\mathbf{y}_{02,j}$ is formed. The

Algorithm 1 Data collection

```

1: Define  $\mu_i \forall i \in \{1, \dots, n_o\}$  ▷ Op. conditions
2: Define  $v_j \forall j \in \{1, \dots, n_d\}$  ▷ Disturbances
3: Define  $\gamma_k \forall k \in \{1, \dots, 2^{n_c}\}$  ▷ Switching comb.
4: for each  $\mu_i$  do
5:   Run power flow
6:    $\mathbf{y}_{01,i} = [\mathbf{p}_{tl}]$ 
7:   for each  $v_j$  do
8:     for each  $\gamma_k$  do
9:       Run time-domain simulation
10:      if  $t = t_{cl}$  then
11:         $\mathbf{y}_{02,j} = [\Delta\omega_{sg}]$ 
12:      if  $t = t_a$  then
13:        Activate coordination  $\gamma_k$ 
14:      if  $t = t_e$  then
15:        Calculate total action  $S_{\infty,i,j,k}$ 
16:        Store in  $\Phi$  the subset  $\phi_s = \{S_{\infty,i,j,k}, \mathbf{y}_{01,i}, \mathbf{y}_{02,j}, \gamma_k\}$ 

```

time-domain simulation is invoked and temporarily paused at time t_d to collect the frequency deviations. At t_a , the simulation is paused again to activate the switching combination of the DCs. At the end of the simulation, the subset ϕ_s , including the TA calculation, is stored in the super set Φ .

2.3.4 Training process

After data extraction, features $\mathbf{y}_{01}$ and $\mathbf{y}_{02}$ are standardized using a standard normal distribution (zero mean and unity standard deviation) to facilitate efficient and accurate learning. To optimize performance and reduce biases, cross-validation determines optimal hyperparameters for the DNN, including network structure, learning rate, number of epochs, and batch size. The best parameter set is then chosen to train the DNN, mitigating selection bias and overfitting. Training employs stochastic gradient descent and the backpropagation algorithm implemented with TensorFlow library in Python. Further details of the training process, the control implementation within PowerFactory, and the initial results of this research can be found in [68].

2.4 Case study

The base case of the wNAPS considers no IBR-DCs and includes only conventional PSS at buses 10, 29, 64, 69, 78, and 139. Alternatively, a fixed coordination (FC) is also considered, activating IBR-DCs at buses 63, 79, 107, and 140. This selection was chosen using traditional damping control theory to improve the most excited modes in the base case [31]. Then, the DIC is tested against both previous cases and the model-based coordination. Next, the coordination is enhanced to include adaptability to operating conditions. Finally, the time performance and time delay evaluation are presented.

2.4.1 Coordination performance for different disturbances

The DNN is trained considering 11 faults and 128 switching combinations ($n_c = 7$ and $2^{n_c} = 128$) meaning that the dynamic response of the grid was observed for the same disturbance in 128 simulations, leading to a total of 1,408 simulations. For more details, see Table 2.1. Each nonlinear simulation considers a 3-phase fault to

Table 2.1: DNNs considerations

DIC Adaptability	No. of Disturbances	No. of Operating Conditions	Total No. of Simulations	Inputs Measurements	DNN Structure
Disturbances	11	1	1,408	$\Delta\omega_{sg}$	[37, 5000, 5000, 5000, 5000, 1]
Operating Conditions and Disturbances	11	13	18,304	$\Delta\omega_{sg}$ and $\mathbf{p}_{tl}$	[48, 3000, 3000, 3000, 5000, 5000, 5000, 1]

ground at $t=2$ s, which is cleared after 3 cycles. The fault locations were strategically distributed across the grid so that the dynamics of all major oscillatory modes were excited at some point. It is not necessary to consider all possible disturbances for the training process; this will be discussed later. These locations are depicted in Fig. 2.4 using red circles. For simplicity, the DIC is activated at time $t_a = 2.55$ s, which is 0.5 s after the fault is cleared. In practice, the DIC should be activated as soon as the optimal switching combination is obtained—no more than a few centiseconds with current computational capabilities. For this initial case, the DIC activates all DC’s but DC 140. Fig. 2.5 shows the frequency at buses 117, 161, and 69, for a fault on bus 57 with different control scenarios: No DCs activated (NC), orange curve; fixed IBR-DCs coordination (FC), maroon dashed curve; and the proposed DIC, black curve. Both DIC and FC improve the system damping, however, the former produces the best oscillation damping. The TA for these cases are $S_{\infty,DIC} = 0.1619$ and, $S_{\infty,FC} = 0.207$, which correspond to a 38.70% and 21.60% of TA reduction, respectively, compared to the base case.

As previously mentioned, the training process for this coordination does not need to consider a fault at every location within the grid. To illustrate this, the corridor between buses 13 and 7 is studied. When evaluating the dynamic response of the corridor, faults at buses 28, 27, and 6 exhibit similar behavior to those at the vertices. Fig. 2.6a shows the Fourier spectrum of the system’s response for the entire corridor. The excited modes are the same for faults from bus 28 to 7, while at bus 13, the same modes remain excited, with an additional mode appearing around 0.70 Hz. This is important because, in the training process, only faults at buses 13 and 7 were considered.

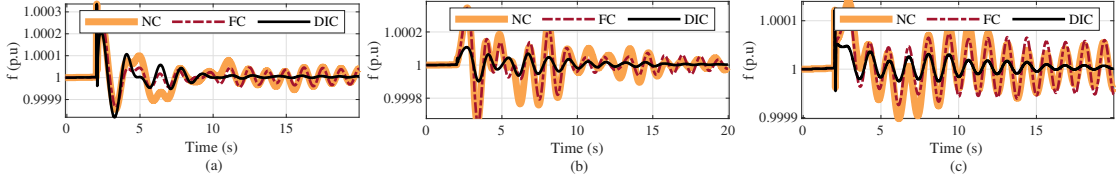


Figure 2.5: Frequency comparison for different control scenarios. Frequency at bus: (a) 117, (b) 161, and (c) 69.

When evaluating the total action, this behavior persists and can also be captured by the total action function approximator. This is shown in Fig. 2.6b, where the normalized actual TA is compared with the estimated one—blue curve vs. red curve, respectively. Each subplot corresponds to the evaluation of the total action for all controller combinations for a specific fault. The x-axis represents the controller combination, while the y-axis represents the normalized TA value. It is evident that the closer the faulted bus is to those considered in the training set, the more accurate the TA estimation will be. However, even with a fault at bus 27, which is in the middle of the entire corridor, the pattern of the TA for the different controller combinations remains consistent. This means that although the function approximation reduces its accuracy, the pattern in the data remains. This pattern is important as it reflects the ranking of the controller combinations and, consequently, the combination that should be activated.

The results are further validated through the mean Spearman rank correlation coefficient, which, in this case, is 95.7%. This index serves as a nonparametric measure of the strength and direction of the monotonic association between two ranked variables: the actual and estimated TA. The findings demonstrate that, in certain locations, the grid exhibits similar dynamic behavior in response to different faults. Consequently, strategic disturbances can be used to generalize to new ones, providing accurate estimations at fault locations not included in the training set.

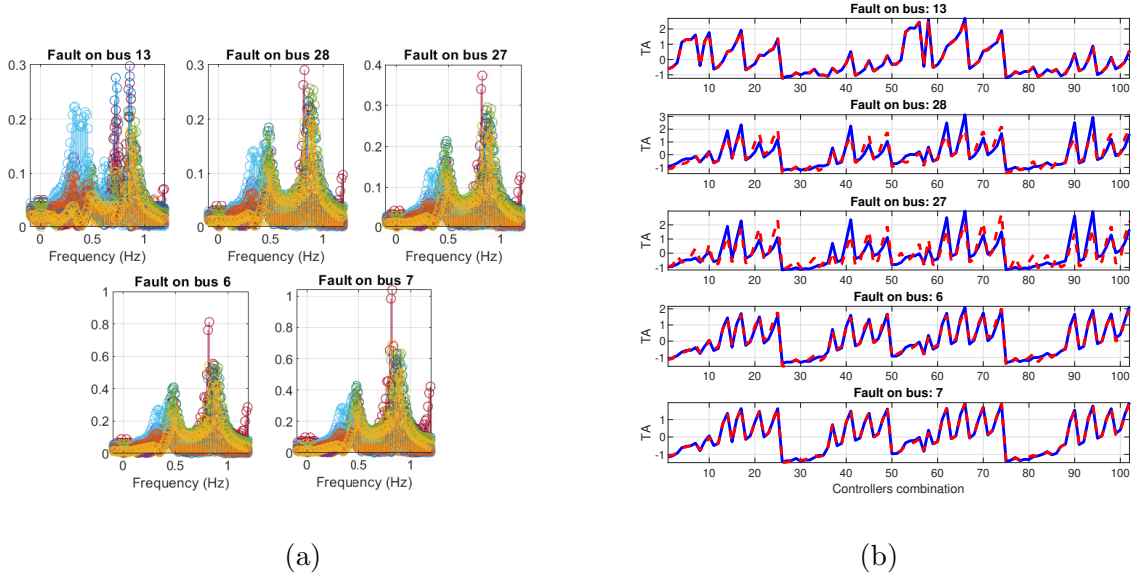


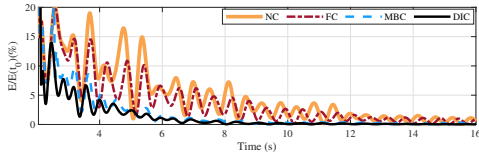
Figure 2.6: Analysis of the corridor between buses 13-7: (a) Fourier spectrum, and (b) Total Action - actual vs. estimated (blue vs. red).

2.4.2 Model-based vs data-informed adaptive coordination

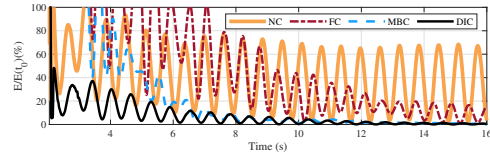
The proposed DIC has been compared with the adaptive MBC [31]. Two short circuits are considered: one at bus 157 and another at bus 69. Table 2.2 shows the coordinated DCs for both schemes. For the fault at bus 157, DIC activates one more DC than the MBC, while for the fault at bus 69, DIC only requires three damping controllers, whereas MBC requires six. Fig. 2.7 displays the oscillation energy for both cases, normalized with respect to the oscillation energy at time $t_0 = 2.05$ s. For both disturbances, the MBC and DIC significantly increase damping in the grid, as corroborated in Table 2.3, which compares the TA reduction. However, DIC achieves the highest oscillation energy reduction, with a 73.53% and 64.87% for faults at buses 157 and 69, respectively. This behavior holds for other disturbances in the grid and demonstrates that the new coordination approach not only eliminates the need for the system's modal information—including operating condition knowledge and TAS calculation—but also enhances damping capabilities.

Table 2.2: Comparison of Activated DCs

Faulted Bus	Coordination Scheme												
	DIC						MBC						
Bus 157	107	140	154	163	63	67	79	107	140	154	163	63	79
Bus 69	107 154 67						107 140 154 63 67 79						



(a)



(b)

Figure 2.7: MBC and DIC comparison for short-circuit at bus: (a) 157, and (b) 69.

Table 2.3: TA reduction per control scheme

Coordination	Short-circuit at bus 157		Short-circuit at bus 69	
	Total Action	Reduction (%)	Total Action	Reduction (%)
No DC	1.241	-	0.840	-
FC	0.998	19.60	0.998	-18.79
DIC	0.328	73.53	0.295	64.87
MBC	0.500	59.72	0.473	43.65

2.4.3 Performance under different disturbances and operating conditions

Various demand levels, conventional generation, and wind power generation have been considered, leading to 13 distinct operating conditions. In this case, the DNN is trained for 11 faults, 13 operating conditions, and 128 DC combinations. This results in 143 different study cases (11 faults * 13 operating conditions), with the dynamic response of the grid observed in a simulation for each of the 128 DC combinations. This totals 18,304 unique simulations. For more details, see Table 2.1. The conditions for each individual simulation are the same as those used in the preceding section. For the evaluation of controller performance, three cases are presented: Case-1 considers a fault at bus 107 and operating condition 2—the base scenario; Case-2 involves a fault at bus 154 and operating condition 10, which includes a reduction of 10% in demand, 9.6% in thermal power generation, and 31% in wind power generation compared to the base case; and Case-3 with a fault at bus 85 and operating condition 6, which shows reductions of 30% in demand, 54% in thermal generation, and no wind power generation at all.

Table 2.4 shows the activated damping controllers in each study case, all three scenarios present different combinations. The proposed DIC performs best for all cases (see Fig. 2.8). Even in Case 2, where the FC fails in its damping actions, DIC completely annihilates the system oscillations. The controller adapts to disturbances and operating conditions while keeping the DCs functionalities from the IBR off in the initial state (pre-fault state). As indicated before, the DIC only engages the DCs when required. Fig. 2.9 illustrates the activated coordination among all possible combinations. Each case presents 128 possible DC combinations (x-axis) producing different TA values (y-axis), normalized for comparison. The red circle in each scatter

Table 2.4: Activated DCs

Faulted BUS	107	154	85
Activated DC	107 154 163 63 67 79	107 140 154 163 63 67 79	154 163 67 79

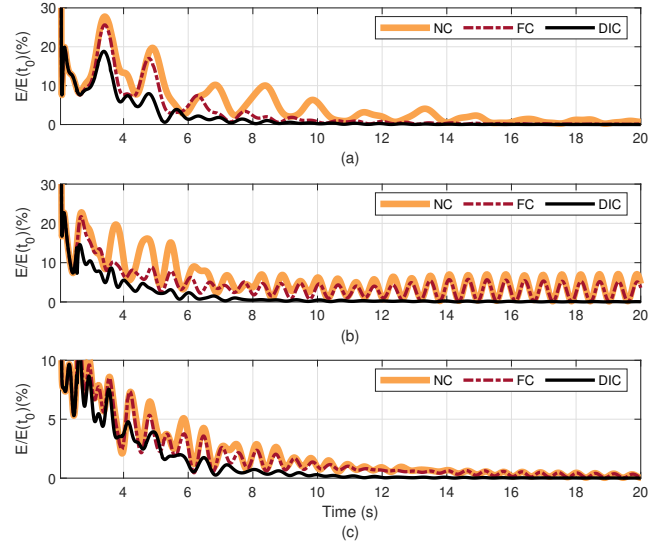


Figure 2.8: Oscillation energy comparison: a) Case-1, b) Case-2, and c) Case-3.

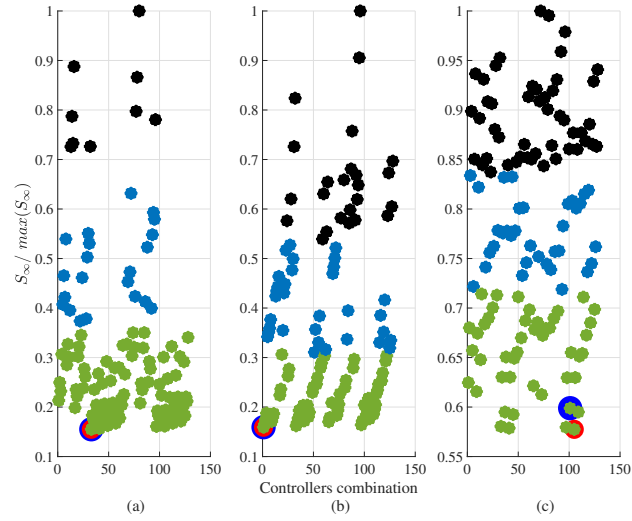


Figure 2.9: Controllers combination: a) Case-1, b) Case-2, and c) Case-3.

plot corresponds to the coordination that provides the highest TA reduction, while the blue circle is the actual activated DC coordination. In Case-1 and Case-2, the DIC matches the best coordination, while in Case-3, the combination activated is different from the best coordination but remains one of the switching combinations that leads to lower TA.

To ensure effective coordination, it is crucial to generalize across diverse operating conditions and maintain a low estimation error in the TA magnitude, even for scenarios not covered during training. Following the law of large numbers, accuracy should naturally improve with an increasing number of operating conditions. This was evaluated by observing the mean absolute percentage error (MAPE) as the range of operating conditions was expanded in the training set. As shown in Figure 2.10, the MAPE demonstrates noticeable improvement when incorporating more than six operating conditions, with a tendency to continue improving. This highlights the model's robustness in improving and adapting to other scenarios when a sufficient amount of operating conditions are considered.

Due to the evolving nature of the grid, concerns about the DIC's adaptability to drastic changes might arise. For instance, an increase in renewable energy or the integration of other IBRs may alter the grid's oscillatory modes. However, DIC can still capture these new dynamics, as it uses the optimal combination of DCs to minimize the TA, which, as shown in Equation 2, is a metric composed of the oscillation energy from all excited modes. Therefore, regardless of whether or not modes are changing, disappearing, or new ones emerging, the TA will reflect these

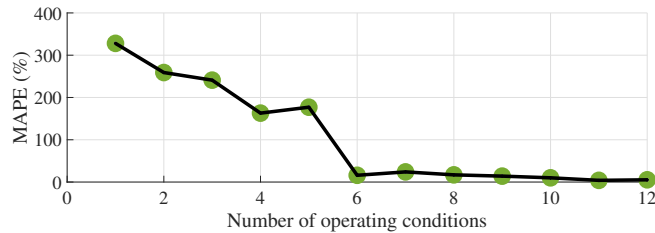


Figure 2.10: MAPE comparisson

changes, and DIC will continue to focus on reducing it. If grid changes are substantial, the function approximation may need to be updated to accurately capture these changes.

The DIC’s performance under noisy conditions was also evaluated. To do this, a large set of noisy data was tested, involving 110 scenarios, each representing a combination of disturbances and different operating conditions. For each of these 110 scenarios, 1,500 noisy datasets were prepared, resulting in a total of 165,000 evaluations. Each dataset was contaminated with white Gaussian noise at a 30 dB signal-to-noise ratio (SNR) to simulate challenging noise conditions that exceed the typical 45 dB SNR reported in real-world PMU cases [69]. The performance of the DIC in providing one of the top coordination configurations for each scenario was then tested, resulting in a mean ranking of the 4th-best coordination with a standard deviation of 6 for each scenario. This indicates that the DIC’s selections consistently remain within the top configurations across all scenarios.

2.4.4 Time performance assessment

A personal computer with intel(R) core(TM) i7-9750H CPU, NVIDIA GeForce GTX 1650 GPU, and 16 GB RAM has been used. The DNN was constructed using TensorFlow 2.11.0 and Numpy 1.21.5, implemented on Python 3.9. Once trained, TensorFlow enables the prediction of a batch of inputs, comprising the vector of input states $\mathbf{y}_0$ and the 128 controller combinations. Subsequently, 128 predictions are generated, and the combination with the smallest TA is selected. On average, this process takes 78 ms per 1,000 tests. Unlike the MBC, the DIC doesn’t need prior knowledge of the current operating condition or matching system conditions with stored state matrices, eigenvectors, and their derivatives.

2.4.5 Time delay assessment

The DIC is responsible for optimizing the commission of all DCs, this is distinct from the supplementary reference signal P_{osc} used for each DC to provide damping actions. Recall that each IBR-DC has a feedback loop previously designed (see section 2.2.3). Due to this, the time delay evaluation is performed on the activation signals for each DC (q_l on Fig. 2.3). In this study, the parameter τ_b represents the combined effect of computation and communication delays. For an optimistic scenario, τ_{b1} is set to 149 ms, considering the time performance of the DIC and reported delays associated with PMU communication and command handling, as documented in the Pacific DC Intertie WADC [29]. Conversely, the pessimistic case is arbitrarily set to $\tau_{b2} = 2$ s. Fig. 2.11a illustrates the oscillation energy for Case-3 discussed earlier, comparing the time delay scenarios. While the optimistic delay scenario yields the most significant reduction in TA, achieving a 41.4% decrease compared to the FC, it's noteworthy that even the pessimistic case results in an improved dynamic response, with a TA reduction of 23.8%.

Figure 2.11b evaluates the impact of time delays, showing TA reduction as a function of delays ranging from 149 ms to 4 seconds, with a decrease from 41.4% to 13.17%. Although DIC effectiveness declines with increased delays, it still achieves positive TA reduction. While this may vary with disturbances and systems, the DIC remains robust even in worst-case scenarios.

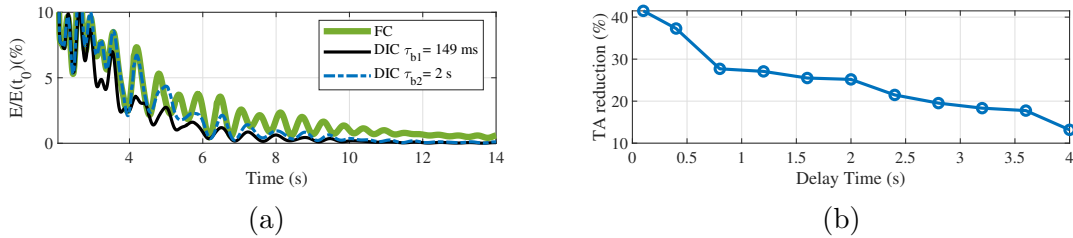


Figure 2.11: Time delay analysis: a) Oscillation Energy for different scenarios, b) TA reduction vs time delay

2.5 Final remarks

The proposed data-informed coordination differs significantly from the traditional approaches, where WADCs are designed to provide adaptable, continuous actuation in real-time [20]. Although theoretically sound, implementing the conventional approaches has some shortcomings, for instance, in the case of adaptability, there is a need to automatically adjust tuning parameters which can lead to undesired phenomena such as forced oscillations or resonance [23]. In addition, these approaches require modifying reference signals for actuators in a centralized fashion, which may belong to different entities, complicating communication and increasing vulnerability to communication hazards due to continuous modulation and parameter adjustment as oscillations evolve. The proposed coordination offers a practical alternative where each DC control operates independently of others after its initial commissioning, maximizing its combined effect in real-time. In this setup, activation is centralized, but actuation is decentralized. Some concerns regarding this application are discussed below:

2.5.1 Data concerns

While the DICs strongly depends on the data used in the training process, it is not necessary to consider all possible disturbances or operating conditions to provide a good TA estimation and effective coordination. As shown in Sections 2.4.1 and 2.4.3, this is handled using strategic disturbances and operating conditions. In practice, these can be the set of N-1 contingencies and different loading conditions used by ISOs for operation and planning—daily, seasonal, and special day variations. Similarly, the current input features were selected to reflect the system’s state for coordination, which has been proven effective. In the case of larger systems, a representative input space must be adopted without excessively increasing the number of features; otherwise, the coordination framework can become complex with a large number of inputs/measurements. Alternatively, features can be extracted beforehand using an

appropriate feature extraction algorithm. In this sense, the function approximator block will have two stages: strategic feature extraction and nonlinear regression.

2.5.2 Scalability and feasibility

The scalability and feasibility of DIC are determined by the system’s measurement capabilities, communication network infrastructure, and wide-area measurement and protection technologies. This approach has been designed to take advantage of the existing wide-area measurement infrastructure to monitor and control the grid, which has already been tested and validated in real implementations [25, 26, 70, 71]. Scalability also depends on the computational demand and information exchange. The results of this work demonstrate accurate coordination within short time periods (an average of 78 ms to provide coordination); however, these values and requirements may change depending on the particular system under study. Future work will investigate the increase in computational complexity and performance time as grid size increases.

2.5.3 Generalization

An important aspect to consider when implementing DIC’s approach is the potential for effective generalization of the function approximator, as this plays a crucial role in ensuring successful coordination. This work presents two specific analyses of this challenge. First, the TA was evaluated for a branch in the WECC system. Results showed that although accuracy in magnitude decreases, the accuracy in the activation pattern remains stable (see Sec. 5.1). This is because, in large power grids, the dynamics are tightly coupled due to their robustness, especially in relation to LFEO. This is a positive outcome, as it supports the results of the second analysis, where the MAPE was evaluated as the number of operating conditions increased (See Sec. 5.3). In this specific case, beyond six operating conditions, the accuracy improves considerably. This suggests that the pattern associated with the best

controller combinations and TA reduction has already been captured by the function approximator. Both cases address generalizability from the perspective of data quality and the diversity of system dynamics. However, generalizability must also be considered from the perspective of system observability. Larger systems might require more data, with numerous input measurements to determine these patterns. This is a topic currently being studied by other research groups, where large datasets with thousands of input measurements are considered in their applications [72–74]. Future research will focus on exploring the generalizability of more complex AI algorithms in larger systems using real-time environments.

2.6 Summary

This chapter has introduced the data-informed coordination of damping controllers based on the total action index. The coordination framework operates on top of traditional damping control and uses wide-area measurements to adaptively determine the on/off status of several damping controllers enabled in IBRs. The decision-making process employs a nonlinear function approximation, enabling the selection of the controller combination that minimizes the total action to optimally increase system damping. The results demonstrate efficiency across various disturbances, operating conditions, and time delay considerations. In contrast to model-based coordination, this new approach achieves precise results without the need for stored information or knowledge of the current operating condition. Consequently, this approach enhances speed, accuracy, and adaptability. Moreover, it facilitates a more appropriate use of IBRs by activating damping control actions only when necessary, thereby preventing energy curtailment or wastage. Its data-driven nature makes it ideal for constant adaptation to operating conditions and disturbances. From an operator’s standpoint, this is a practical, non-intrusive control scheme, as it does not require adjusting the tuning parameters of each damping controller in real-time. By exclusively managing the on/off status of the damping control loop of IBRs, the

coordination promptly responds to system disturbances, mitigates electromechanical oscillations, and enhances the dynamic system response.

Chapter 3

Modal-Based Prediction of Power System Frequency Response and Frequency Nadir

This chapter presents a modal-based approach for predicting system frequency response (SFR) and frequency nadir using a closed-form expression derived through modal decomposition and dominant modes. Unlike traditional ASF-based methods, it captures full system dynamics and remains accurate across operating conditions due to the low sensitivity of dominant modes. The approach is validated on the IEEE 9-bus, the IEEE 39-bus New England system, and the Salvadoran transmission network, demonstrating scalability, precision, and adaptability.

3.1 System frequency response models and nadir prediction

3.1.1 Average system frequency (ASF) model

This dynamic equivalent model captures the collective response of all generators to load-generation imbalances. It consists of a set of linear differential equations representing N synchronous generators through N swing equations from the classical model, along with their corresponding turbine-governor systems. Fig. 3.1 illustrates the model's structure.

The model was first introduced in [38] and assumes that all generators in the system are equipped with reheat steam turbine-governor models, as commonly studied in power system modeling literature [66, 75]. The swing equation of each k -th generator is given by $2H_k \frac{d\omega_k}{dt} = P_{m,k} - P_{e,k}$, where ω_k is the generator frequency in p.u., H_k is its inertia constant in seconds, $P_{m,k}$ is the mechanical power given by the generator turbine-governor dynamic model, and $P_{e,k}$ is the electrical power output of the generator, both in p.u. The system frequency response is governed by

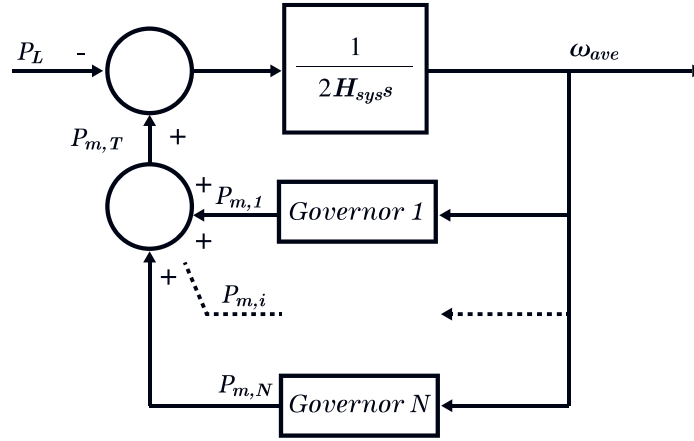


Figure 3.1: ASF equivalent model in laplace.

the following equations,

$$2H_{sys} \frac{d\omega_{ave}}{dt} = P_{m,T} - P_L, \quad \omega_{ave} = \frac{\sum_{k=1}^N H_k \omega_k}{H_{sys}} \quad (3.1)$$

were $H_{sys} = \sum_{k=1}^N H_k$, $P_{m,T} = \sum_{k=1}^N P_{m,k}$, and $P_L = \sum_{k=1}^N P_{e,k}$ are the system's total inertia, compound mechanical power, and total electrical load (power output of generators), respectively. The model considers the following assumptions: a) generation is dominated by reheat systems, b) static loads are assumed—no voltage or frequency dependence; c) electromechanical oscillations are ignored; d) the effect of SGs' damper windings is neglected; e) all generators remain in synchronism during transients. The model provides a good approximation of the SFR against disturbances, but requires solving the entire system to obtain the frequency trajectory and to extract the nadir.

This model was revised in [39] to reduce turbine-governor dynamics and propose its aggregation into a single closed-loop system. This simplified low-order ASF model is depicted in Fig. 3.2. Additionally, the damping factor D_ω is now considered; however, its computation or definition remains an empirical, experimental process. The set of parameters $\Psi = [F_H, R, T_R]$ is assumed to be the same for each machine, while K_m depends on the regulation capabilities of the system. To this day, this model remains valid and is widely used for comparison purposes and when a simple frequency representation is needed for complex tasks [58, 76].

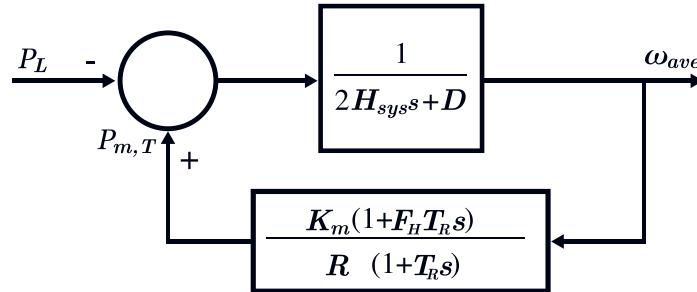


Figure 3.2: Low order SFR model.

3.1.2 Multi-machine ASF model

The traditional ASF model assumes all generator prime movers are reheat-type steam turbines. However, this simplification does not reflect actual power systems. To address this, a multi-machine SFR model (MM-SFR) was proposed [40], which extends the assumption by allowing any turbine-governor model to be treated as reheat-type through the identification of an equivalent parameter set Ψ . Non-reheat machines are grouped by original type (e.g., gas, hydro) and represented as dominant aggregated reheat-type models with their own Ψ . One limitation of this method is the absence of a systematic way to derive the equivalent reheat-type, making Ψ estimation heuristic.

Assuming Ψ is known, two aggregation approaches are described. The first method utilizes a partial fraction expansion in the Laplace domain to decompose the MM-SFR model. Each dominant turbine-governor model contributes a unique dynamic component to the overall frequency response [40]. The second method introduces a normalized gain for each dominant model, derived from its rated power and droop. These gains are used for parameter aggregation via weighted averaging, resulting in a reduced-order equivalent system. The frequency response of this system is then determined from the aggregated parameters [44].

Finally, the frequency nadir is obtained by finding the time at which the frequency deviation derivative is zero and evaluating the system response at that instant. It is important to note that these results rely on multiple assumptions, particularly the generalization of all turbine-governor types as reheat steam models, without a defined process for handling non-reheat types.

3.1.3 Numerical-analytical models

These models are specifically designed to provide an explicit expression for the frequency nadir. To achieve this, they primarily assume the SFR behavior during the initial seconds following a disturbance. Unlike the MM-SFR, which approximates

any generation technology as an equivalent reheat system, these methods represent any technology using a reduced low-order model, such as a first-order transfer function or a low-order polynomial approximation.

For example, building on the ASF model (Fig. 3.1), the SFR dynamics are approximated as a quasi-linear frequency decay within the first 1–2 seconds after a disturbance. To account for this, the governor input is modeled as a constant ramp, breaking the closed-loop control and resulting in the model shown in Fig. 3.3.

Each turbine-governor (TG) model is approximated using a first-order transfer function, derived via step-response fitting or real generator tests using a minimum-square-error technique, valid within 4–25 seconds. Though analytical expressions can be derived, computing the nadir involves solving $N + 1$ nonlinear equations, necessitating numerical methods [41, 43]. A refinement introduces parabolic frequency deviations and polynomial governor responses, requiring iterative fitting over 5–20 seconds [45]. While flexible, numerical methods may introduce errors due to modeling assumptions. This is evident in load variation tests on the IEEE 3-generator, 9-bus system [77], where different TG models (TGOV1, GAST, IEESGO) yield discrepancies (Fig. 3.4).

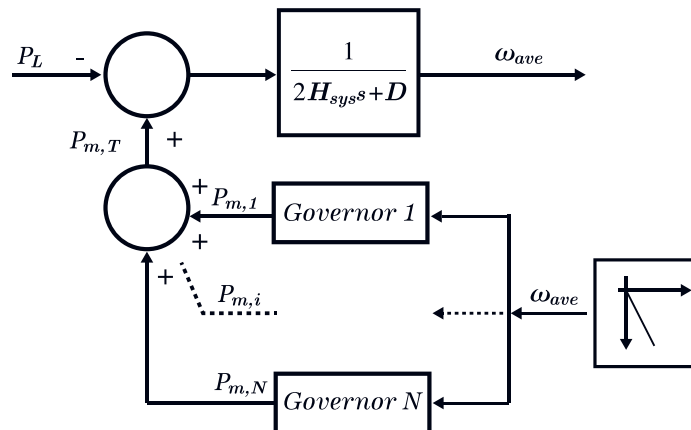


Figure 3.3: ASF model with open loop.

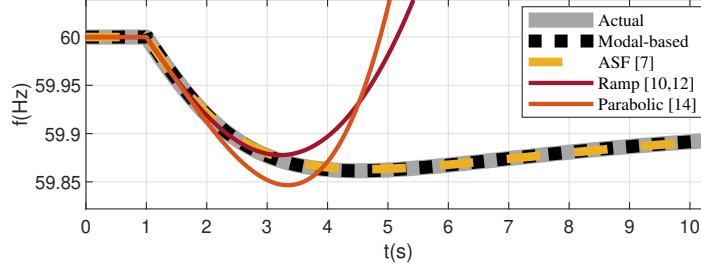


Figure 3.4: Frequency response comparison.

Ramp-based [41, 43] and parabolic-based [45] approximations with curve fitting can derive analytical nadir estimates but introduce timing and magnitude errors (orange/red curves in Fig. 4). The ASF model [38] offers better dynamic approximation (yellow curve), but lacks a closed-form nadir expression. Its revision [39] addresses this, yet applies only to reheater-type TGs. The MM-SFR method similarly requires reheater-type approximations and lacks implementation clarity [40, 44].

Unlike these methods, the modal-based approach—black curve—provides a general framework capable of deriving analytical expressions for the SFR, as well as the frequency nadir magnitude and timing, for any type of generation technology without relying on oversimplification. This will be shown in the following sections.

3.2 Frequency response estimation

The modal-based SFR and nadir prediction approach focuses on capturing the intrinsic dynamic behavior of the power system without requiring a reduced-order model. It leverages the fundamental principle that system responses can be characterized by the dominant dynamic modes that govern the evolution of state variables. By isolating and analyzing the most influential dynamic components, the method provides an efficient representation of system behavior while disregarding dynamics with negligible impact.

3.2.1 Modal characterization of grid frequency response

Consider a power system modeled through a set of differential-algebraic equations [11] such as $\dot{x} = f(x, y)$ and $0 = g(x, y)$. Here, $x \in \mathbb{R}^n$, and $y \in \mathbb{R}^l$ are the vectors of state variables and algebraic variables, respectively. Assume the system is in steady-state at x_0 when a power imbalance occurs. This creates a frequency excursion and the system stabilizes at a new equilibrium point x_e . When linearized around x_e , the model becomes $\Delta\dot{x} = J_1\Delta x + J_2\Delta y$ and $0 = J_3\Delta x + J_4\Delta y$. By eliminating algebraic equations through Kron reduction, the following simplified model is obtained,

$$\Delta\dot{x} = [J_1 - J_2J_4^{-1}J_3]\Delta x = A_s\Delta x \quad (3.2)$$

with initial condition $\Delta x(0) = \Delta x_0 = x_0 - x_e$, which is the difference between the pre- and post-fault states. To obtain the solution, the following similarity transformation is used: $V^{-1}A_sV = W^TA_sV = \Lambda$, where $V = \{v_i\} \in \mathbb{C}^{n \times n}$ is the right eigenvectors matrix of A_s , $W = \{w_i\} \in \mathbb{C}^{n \times n}$ is the left eigenvectors matrix of A_s , $\Lambda = \text{diag}\{\lambda_i\} \in \mathbb{C}^{n \times n}$ is a diagonal matrix containing the eigenvalues of A_s , and the index $i \in \mathcal{I} = \{1, 2, \dots, n\}$. Note that the set of right and left eigenvectors are considered to be orthonormal, i.e., $\langle w_i, v_k \rangle = w_i^T v_k = \delta_{ik} \forall i, k \in \mathcal{I}$, thus, $W^T = V^{-1}$. For an explicit solution of $\Delta\dot{x} = A_s\Delta x$, the transformed vector of state variables is defined as $q = V^{-1}\Delta x$ to obtain:

$$\Delta\dot{x} = A_s\Delta x, \quad \Delta x(t_0) = \Delta x_0 \quad (3.3)$$

$$\Rightarrow V^{-1}\Delta\dot{x} = V^{-1}A_sVq, \quad V^{-1}\Delta x(t_0) = V^{-1}\Delta x_0 \quad (3.4)$$

$$\Rightarrow \dot{q} = \Lambda q, \quad q(t_0) = W^T\Delta x_0 = q_0 \quad (3.5)$$

The explicit solution of Eq. (3.5) is given by $q(t) = e^{\Lambda t}q_0$, where $q_0 = W^T\Delta x_0 = [w_1, \dots, w_n]^T\Delta x_0 = [\langle w_1, \Delta x_0 \rangle, \dots, \langle w_n, \Delta x_0 \rangle]^T$. As $e^{\Lambda t}$ is a diagonal matrix, the

solution of Eq. (3.5) can be rewritten as,

$$q(t) = \begin{bmatrix} e^{\lambda_1 t} \langle w_1, \Delta x_0 \rangle \\ \vdots \\ e^{\lambda_n t} \langle w_n, \Delta x_0 \rangle \end{bmatrix}, \quad \forall t \geq t_0 \quad (3.6)$$

As a result, the solution for each transformed state variable i becomes $q_i(t) = e^{\lambda_i t} \langle w_i, \Delta x_0 \rangle$, $\forall i \in \mathcal{I}$. Given that $\Delta x = Vq = \sum_{i \in \mathcal{I}} v_i q_i$, the vector of state variables can be explicitly defined as $\Delta x(t) = \sum_{i \in \mathcal{I}} e^{\lambda_i t} \langle w_i, \Delta x_0 \rangle v_i$. Note that on the right hand side of this equation, all terms are scalars except for $v_i \in \mathbb{C}^n$. Finally, the explicit solution for a single state variable k corresponds to:

$$\Delta x_k(t) = \sum_{i \in \mathcal{I}} e^{\lambda_i t} \langle w_i, \Delta x_0 \rangle v_{i,k}, \quad \forall t \geq 0 \quad (3.7)$$

where $v_{i,k}$ is the k^{th} term of the i^{th} right eigenvector.

Let $\mathcal{Z} \subset \mathcal{I}$ be the index set related to the speed of the generators. Let H_z be the inertia of the generator whose speed index is $z \in \mathcal{Z}$. The total inertia is $H_t = \sum_{z \in \mathcal{Z}} H_z$, and the frequency of the center of inertia (COI) becomes,

$$\Delta \omega_{coi} = \sum_{z \in \mathcal{Z}} C_z \Delta x_z = \sum_{z \in \mathcal{Z}} C_z \sum_{i \in \mathcal{I}} e^{\lambda_i t} \langle w_i, \Delta x_0 \rangle v_{i,z} \quad (3.8)$$

where $C_z = H_z/H_t$. This is an explicit and general expression for the frequency response of the system under any initial condition.

3.2.2 Participation factor-guided mode selection

As we are interested in the frequency excursion after a power imbalance, note that only those modes associated with the slow dynamic response of the rotating masses and governors are required for an accurate approximation. Let $\mathcal{M} \subset \mathcal{I}$ be the index set of the most significant modes related to the frequency excursion. From now on,

these will be referred to as frequency control modes. Thus, the frequency of the COI can be approximated as,

$$\Delta\omega_{coi} \approx \sum_{z \in \mathcal{Z}} \sum_{m \in \mathcal{M}} C_z e^{\lambda_m t} \langle w_m, \Delta x_0 \rangle v_{m,z} \quad (3.9)$$

The subset $\mathcal{M}$ is obtained as follows:

- The participation factor matrix $P \in \mathbb{R}^{n \times n}$ is obtained as the element-wise multiplication of the left and right eigenvector matrices $P = V \circ W$.
- Let $\mathcal{S} \subset \mathcal{I}$ be the subset of the indices of state variables corresponding to rotor speed and governor variables. Define $P_{\mathcal{S}} \in \mathbb{R}^{s \times n}$, $s = \dim(\mathcal{S})$, as the matrix containing the participation factors for the $\mathcal{S}$ -indexed state variables.
- Define $\epsilon \in \mathbb{R}$ as a threshold, specific to each system, and determined through experimentation or optimization during the initial run.
- The subset $\mathcal{M} \subset \mathcal{I}$ is then defined as the set of indices corresponding to those columns of $P_{\mathcal{S}}$ where all entries in the column are below the threshold ϵ , i.e., $\mathcal{M} = \{j \in \mathcal{I} \mid \forall i \in \mathcal{S}, |P_{S_{ij}}| < \epsilon\}$

In brief, $\mathcal{M}$ contains the indices of the frequency control modes, in which all speed and governor variables have significant participation.

3.2.3 Initial condition computation

Eq. 3.9 provides the system's frequency response in terms of the initial condition $\Delta x_0 = x_0 - x_e$, where x_e must be estimated based on the power imbalance caused by the disturbance. Based on modal analysis and the use of participation factors, we argue that estimating only a few variables in Δx_0 is sufficient to accurately determine $\Delta\omega_{coi}$. These variables include the new steady-state frequency and the governor-related variables. To determine this, the post-disturbance steady-state frequency is

first obtained, as described in [75],

$$\Delta\omega = -\Delta P / \sum_{z \in \mathcal{Z}} \frac{1}{R_{D,z}} \quad (3.10)$$

where $1/R_{D,z}$ is the speed regulation of machine z , ΔP is the disturbance in p.u., and $\omega_e = \Delta\omega + \omega_0$. Consider the system of equations $\dot{x}_S = f_S(x_S, y)$, where $x_S \in \mathbb{R}^s$ represents the subset of state variables associated with rotor speed and governor dynamics. In the post-disturbance steady-state, this reduces to $0 = f_S(x_{S,e}, y_e)$, which can be solved for $x_{S,e}$. For instance, using the IEESGO model for turbines and governors [37], and assuming n_g generators, the post-disturbance governor-related variables are estimated as:

$$y_{1,i} = y_{3,i} = -\omega_e / R_{D,i} \quad \forall i \in \{1, 2, \dots, n_g\} \quad (3.11)$$

$$T_{m,i} = P_{C,i} - \omega_e / R_{D,i} \quad \forall i \in \{1, 2, \dots, n_g\} \quad (3.12)$$

Finally, x_0 is the known initial condition, and x_e is the vector composed of $x_{S,e}$ and the remaining variables, with the entries of the latter set to zero.

3.3 Frequency nadir prediction

The frequency nadir can be found through a numerical procedure that minimizes $\Delta\omega_{coi}$ given by Eq. (3.9). However, an analytical approach can simplify and expedite this prediction. For instance, consider that only three modes are involved in the frequency excursion dynamics: a complex conjugate pair of eigenvalues, $\lambda_{c1} = \lambda_{c2}^* \in \mathbb{C}$, and a real eigenvalue, $\lambda_r \in \mathbb{R}$. Thus, the frequency response estimation becomes:

$$\Delta\omega_{coi} \approx e^{\lambda_{c1}t} \gamma_{c1} + e^{\lambda_{c2}t} \gamma_{c2} + e^{\lambda_r t} \gamma_r \quad (3.13)$$

where $\gamma_m = \sum_{z \in \mathcal{Z}} C_z \langle w_m, \Delta x_0 \rangle v_{m,z}$, $\forall m \in \mathcal{M} = \{c1, c2, r\}$. Given the conjugated nature of the first two terms on the right-hand side, these can be compactly expressed in terms of the cosine function $2e^{\alpha t} r_c \cos(\beta t + \theta)$, where $\lambda_{c1} = \alpha + j\beta$, $\gamma_{c1} = E + jF$, $j = \sqrt{-1}$, $r_c = \sqrt{E^2 + F^2}$, and $\theta = \arctan(F/E)$. Thus, $\Delta\omega_{coi}$ and its derivative become,

$$\Delta\omega_{coi} \approx 2e^{\alpha t} r_c \cos(\beta t + \theta) + e^{\lambda_r t} \gamma_r \quad (3.14)$$

$$\frac{d\Delta\omega_{coi}}{dt} = Re^{\alpha t} \cos(\beta t + \theta + \phi) + \lambda_r e^{\lambda_r t} \gamma_r \quad (3.15)$$

with $R = 2r_c \sqrt{\alpha^2 + \beta^2}$ and $\phi = \arctan(\beta/\alpha)$. The time occurrence of the frequency nadir corresponds to the time when Eq. (3.15) vanishes. Note that this equation involves two transcendental functions, making it challenging to solve it analytically. Thus, a second order Taylor expansion around an initial guess, τ , can be used to approximate the right-hand side of Eq. (3.15), resulting in the following expression,

$$\frac{d\Delta\omega_{coi}}{dt} = (a_1 t^2 + a_2 t + a_3) + (a_4 t^2 + a_5 t + a_6) = 0 \quad (3.16)$$

where,

$$\psi = \beta\tau + \theta + \phi, \quad K_1 = Re^{\alpha\tau}, \quad K_2 = \sqrt{\alpha^2 + \beta^2} \quad (3.17)$$

$$a_1 = K_1 \left(\frac{(\alpha^2 - \beta^2)}{2} \cos(\psi) - \alpha\beta \sin(\psi) \right) \quad (3.18)$$

$$a_2 = K_1 \left(K_2 \cos(\psi + \phi) - ((\alpha^2 - \beta^2) \cos(\psi) - 2\alpha\beta \sin(\psi)) \tau \right) \quad (3.19)$$

$$a_3 = K_1 \left(\cos(\psi) - K_2 \cos(\psi + \phi) \tau + \left(\frac{(\alpha^2 - \beta^2)}{2} \cos(\psi) - \alpha\beta \sin(\psi) \right) \tau^2 \right) \quad (3.20)$$

$$a_4 = \frac{\lambda_r^3 e^{\lambda_r t_0} \gamma_r}{2}, \quad a_5 = \lambda_r^2 e^{\lambda_r \tau} (1 - \lambda_r \tau) \gamma_r \quad (3.21)$$

$$a_6 = \lambda_r e^{\lambda_r \tau} \left(1 - \lambda_r \tau + \frac{\lambda_r^2 \tau^2}{2} \right) \gamma_r \quad (3.22)$$

Therefore, the estimated time occurrence of the frequency nadir time is,

$$t_{nadir} = \frac{-(a_2 + a_5) + \sqrt{(a_2 + a_5)^2 - 4(a_1 + a_4)(a_3 + a_6)}}{2(a_1 + a_4)} \quad (3.23)$$

and the per unit frequency nadir prediction can be obtained through direct evaluation as $f_{nadir} = f_e + \Delta\omega_{coi}(t_{nadir})$, where f_e is the post-disturbance steady-state frequency and can be extracted from Eq. 3.10. If additional modes are required, either complex conjugated or real, the number of terms in Eqs. (4.1)-(3.16) will be increased; still, the solution for t_{nadir} will be always the solution of a quadratic function. In Section 3.4, it will be shown that a small subset of modes is sufficient to accurately estimate the frequency response and its nadir.

Fig. 3.5 summarizes the steps to obtain the SFR and frequency nadir. Unlike other methods, the modal-based approach avoids model oversimplification and iterative solutions. This process leads to the algebraic representation of Eq. 3.9, which is derived directly from the full dynamic model. Moreover, t_{nadir} and f_{nadir} can be easily calculated using Eq. 3.23.

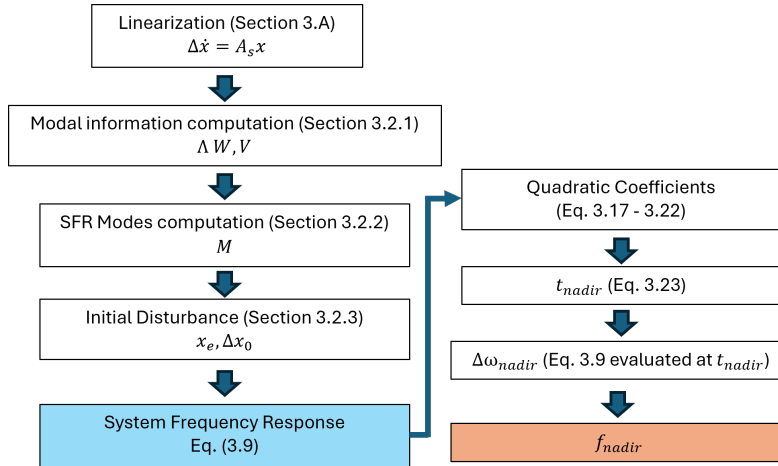


Figure 3.5: SFR and nadir prediction flow chart.

3.4 Case studies

The case studies thoroughly analyze different scenarios in three systems: the WSCC 9-bus system, the New England 39-bus system, and El Salvador’s transmission planning system. This section showcases the robustness of the modal-based approach, validated across these networks to demonstrate its scalability, precision, and adaptability.

3.4.1 WSCC 9-bus system

The system consists of three SGs modeled as two-axis machines with IEEE Type-1 exciters and three types of governors. G1 and G2 are steam units (TGOV1 and IEESGO), while G3 is a gas unit (GAST). The governor parameters are presented in Appendix A.1, and the system data is available in [77].

The initial evaluation considers three load steps—3%, 6%, and 10% of the total system load—occurring at $t = 1s$. Results are presented based on the frequency at the COI. Table 3.1 compares the nadir, timing estimates, and errors of the modal-based approach with those from [41] and [45], using time-domain simulation results as the benchmark.

Table 3.1:
Comparison of Nadir and Timing Across Different Methods

Case	3%		6%		10%	
	Nadir (Hz)	Timing (s)	Nadir (Hz)	Timing (s)	Nadir (Hz)	Timing (s)
Benchmark	59.888	4.496	59.778	4.491	59.626	4.487
Modal-based	59.888	4.536	59.779	4.531	59.626	4.515
[41]	59.911	3.431	59.823	3.431	59.702	3.431
[45]	58.310	14.300	56.660	14.300	54.370	14.300
Error Comparison						
Modal-based	-0.0002	-0.0395	-0.0003	-0.04	-0.0004	-0.0278
[41]	-0.0228	1.0648	-0.0451	1.0599	-0.0766	1.0559
[45]	1.5778	-9.804	3.1183	-9.8089	5.2555	-9.8129

The modal-based approach outperforms both methods in all scenarios. Method [41] provides a simple analytical expression for nadir with reasonable accuracy but fails to estimate nadir timing precisely. Method [45] struggles with both nadir magnitude and timing, likely due to its simplified form, where the governor response is approximated as a second-order polynomial and frequency response as a parabolic function. More accurate results would require an iterative process to determine the optimal fitting time and polynomial. Moreover, a common drawback across methods in the existing literature is the difficulty in achieving a low error for nadir timing. In contrast, the modal-based approach maintains a small error, demonstrating its superior performance. Fig. 3.6 compares the actual system frequency response with the modal-based response and the ASF, demonstrating accurate tracking of system dynamics in both cases.

The modal-based prediction is determined by four dynamics corresponding to the real eigenvalues $\Lambda_{\mathcal{M}} = [\lambda_{27}, \lambda_{32}, \lambda_{35}, \lambda_{36}] = [-1.679, -0.805, -0.213, -0.094]$. Notably, although the system comprises 38 state variables, only $\Lambda_{\mathcal{M}}$ is required for accurate estimation. Figure 3.7 illustrates these dynamics.

Finally, in terms of time performance, using a personal computer with an Intel(R) Core(TM) i7-9750H CPU and 16 GB of RAM—and assuming that the modal information has been previously computed—the average execution time for the nadir and timing estimation is 0.0115 seconds, whereas comparison methods report 0.076 seconds [41] and 0.021 seconds [45], respectively, for the same system.

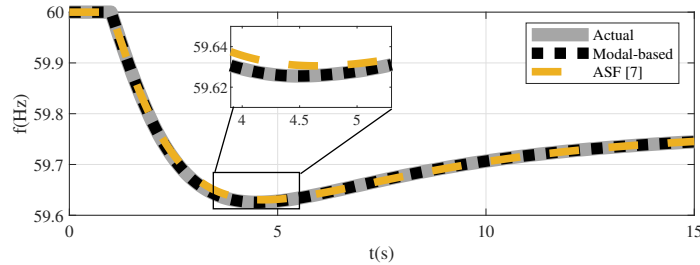


Figure 3.6: Frequency trajectory, 10% load step event.

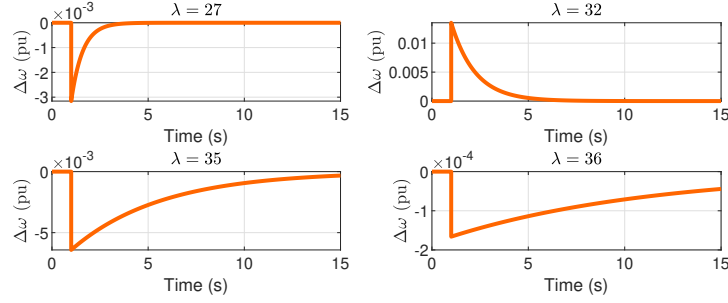


Figure 3.7: Dynamics from the System Frequency response

3.4.2 New england 39-bus system

The New England system includes 10 two-axis machines, IEEE Type-1 exciters, and three governor types: TGOV1, IEESGO, and GAST. System parameters are provided in [77], typical governor parameters were taken from [78] and are listed in Appendix A.1. To observe a larger nadir, the inertia was reduced by half. The system model has 136 state variables, and the SFR and frequency nadir are estimated using only 4 eigenvalues $\Lambda_{\mathcal{M}} = [\lambda_{97}, \lambda_{127}, \lambda_{128}, \lambda_{130}] = [-2.742, -0.191 + 0.111i, -0.191 - 0.111i, -0.093]$. These were selected using the participation factor-guided mode selection using a threshold of $\epsilon = 0.0001$.

Table 3.2 presents the evaluation of two generator trip events: (1) G1 outage, resulting in a loss of 4% of total system generation, and (2) G6 outage, resulting in a loss of 10.32%. The accuracy of the estimation is measured by the absolute percentage error (APE), defined as $APE = \left| \frac{\text{actual value} - \text{estimated value}}{\text{actual value}} \right| \times 100\%$. Results show a low estimation error, less than 10 mHz and 0.25 s. In terms of time performance, the average execution time for the predictions presented in this subsection is 0.01 seconds.

It is argued that linearizing the system for every operating condition is unnecessary. Instead, it is sufficient to derive the modal information from a representative base case and extend it to other scenarios. This approach is justified because the system's modal characteristics, as inferred from its frequency response, typically exhibit only minor variations across changes in loading levels, power flow patterns, and

Table 3.2:
Nadir and Timing Estimation for G1 and G6 Outage

Gen. Trip	G1		G6	
	Nadir (Hz)	Time (s)	Nadir (Hz)	Time (s)
Actual	59.489	9.6	58.961	9.4
Estimation	59.493	9.35	58.971	9.31
APE (%)	0.006	2.6	0.016	1.91

network topology. Even when the unit commitment changes, the modal information can often still reliably capture the system dynamics to a considerable extent. However, if the changes are substantial and significantly alter system behavior, it becomes necessary to recompute the modal information to maintain accuracy.

To investigate this, a sensitivity analysis is performed to evaluate how the frequency control modes ($\Lambda_{\mathcal{M}}$) vary under different operating scenarios. The analysis also evaluates how accurately the system response can be estimated when using only the base-case frequency control modes and their associated eigenvectors. As demonstrated earlier, a subset of four modes is sufficient for accurate estimation. Figures 3.8 and 3.9 illustrate how these modes evolve across various conditions.

To investigate this, a sensitivity analysis is performed to evaluate how the frequency control modes ($\Lambda_{\mathcal{M}}$) vary under different operating scenarios. The analysis also evaluates how accurately the system response can be estimated when relying solely on the base-case modes. As demonstrated earlier, for this test system, a subset of four is sufficient for accurate estimation. Figures 3.8 and 3.9 illustrate how these modes evolve across various conditions.

Different loading levels and power flows

Five loading levels were analyzed, with dispatch randomly varied to reflect different power flow scenarios. A total of 2,363 simulations were performed: 1,103 with a 10% load step at bus 15, and 1,260 with G1 outage. Fig. 3.8 shows the modes used in the estimation. Each cloud of points corresponds to one eigenvalue and its

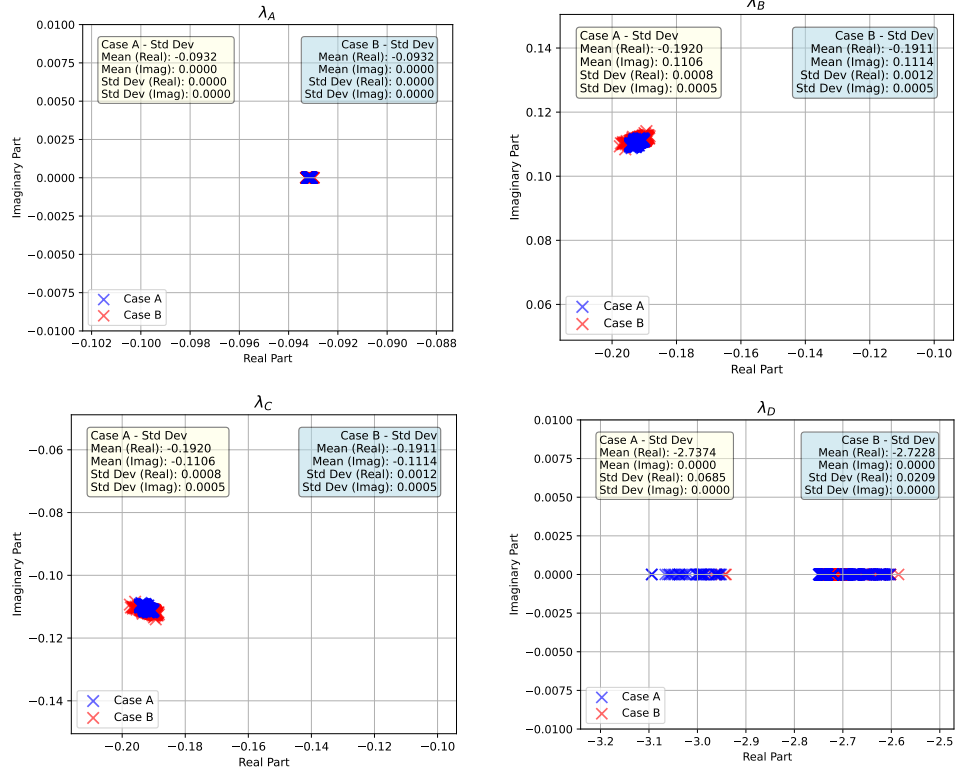


Figure 3.8: Sensitivity analysis results for different loading levels, load flow, and topology changes.

variation in the new steady state after the disturbance. The blue scatter plots (Case A) represent the full range of eigenvalues across scenarios, with the mean and standard deviation included. The standard deviation is on the order of 10^{-4} , indicating minimal variation under different conditions. Nadir values were estimated using the base case eigenvalues and modal information. The mean absolute percentage error (MAPE) in nadir magnitude and timing was $0.068 \times 10^{-3}\%$ and 0.913% for load step cases, and $0.068 \times 10^{-3}\%$ and 1.79% for generator trip cases. These results confirm that base case modal data allows accurate prediction across different loading levels and power flow conditions.

Different topologies and power flows

2,095 scenarios with $N-2$ and $N-3$ transmission line conditions were considered: 995 with a load step at bus 15, and 1,100 with G1 outage. Fig. 3.8 shows the modes used in the estimation. The red scatter plot (Case B) corresponds to the eigenvalues and their variation for this analysis. The standard deviation remains on the order of 10^{-3} , indicating minimal deviation from the mean. In this analysis, the MAPE in nadir and timing estimation for the load step scenarios is $0.036 \times 10^{-3}\%$ and 1.83% , respectively, and $0.075 \times 10^{-3}\%$ and 1.557% for the generator trip. The use of base case modal information remains effective, as the modes show low sensitivity to changes in network topology.

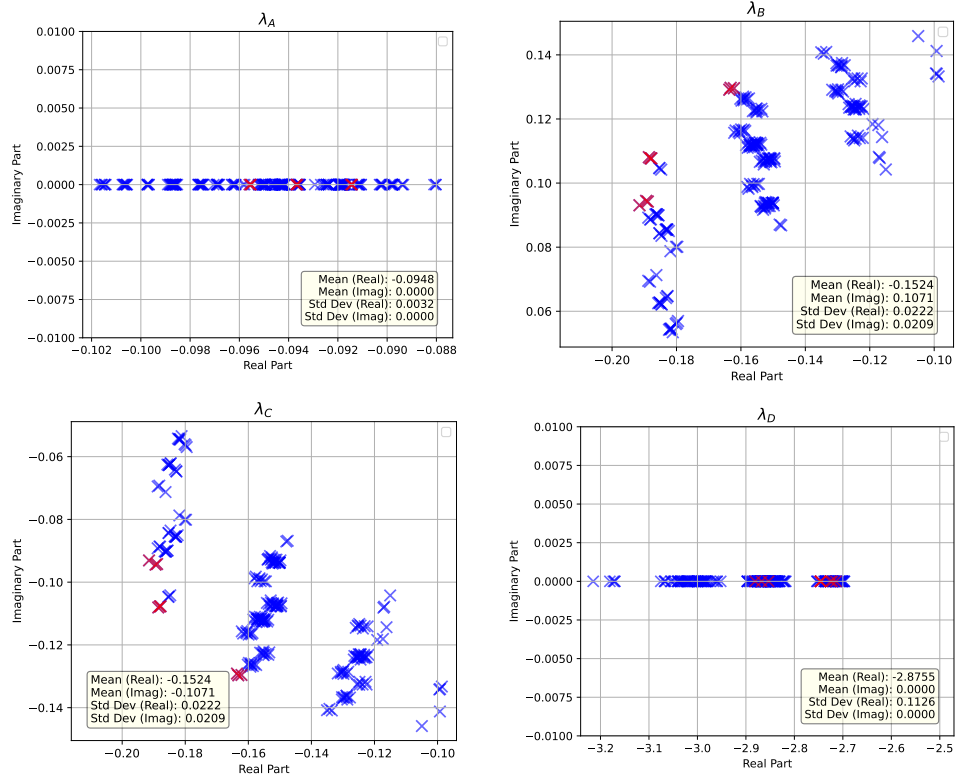


Figure 3.9: Sensitivity analysis results for different unit commitment.

Different unit commitment

This analysis evaluates the sensitivity of the modes used in the estimation to varying numbers and combinations of participating generators. A total of 354 stable simulations were selected: 261 with a load step (10% at bus 15) and 93 with G1 outage. The total demand was kept constant but supplied by different combinations of generators and dispatch.

The blue scatter plots in Fig. 3.9 show the frequency control eigenvalues and their variation. Unlike the previous two analyses, this one reveals greater variability, particularly for λ_A , λ_B , and λ_C , which now exhibit a larger standard deviation on the order of 10^{-2} —significantly affecting the period and damping of the modes. This outcome aligns with the fact that changes in generator participation affect system inertia and primary frequency support.

The MAPE in nadir and timing estimation for the load step cases were 0.0099% and 14.57%, respectively, and 0.13% and 13.598% for the generator trip cases. Although nadir errors remain within acceptable bounds for load steps, timing errors are significantly larger. In generator trip cases, the nadir error corresponds to approximately 0.07 Hz, which may be significant depending on the application. Fig. 3.9 illustrates by red samples the eigenvalue variation of the unit commitment changes by only one generator. For this scenario, the use of the base case modal information keeps valid results within an acceptable error. The MAPE in nadir and timing for the load step is reduced to 0.0017% and 4.11%, and to 0.03% and 6.11% for the generator trip.

In summary, the frequency control modes exhibit low sensitivity to variations in loading levels, power flows, and network topology. Additionally, its validity is maintained under small changes in unit commitment. These results indicate that linearizing the system at every possible operating condition is not required, which reduces computational effort while preserving estimation reliability. A complete summary of the results is presented in Table 3.3.

3.4.3 Transmission planning system from El Salvador

The method is validated on El Salvador’s transmission network, which includes 145 buses, 64 transmission lines, and 28 power plants (thermal, hydro, photovoltaic, and wind), operating at voltage levels from 23 kV to 230 kV. The system has an installed capacity of 2,322.6 MW and a peak demand of 1,131 MW. As part of the SIEPAC (Central American Electrical Interconnection System), it also features two 230 kV interconnections with Guatemala and Honduras. Further details and the full database are available on the national system operator’s website [79]. A key scenario occurs when these interconnections are lost, isolating the system from the rest of SIEPAC. Under such conditions, frequency deviations become more pronounced due to increased sensitivity.

The system is evaluated under two dry-season contingencies at minimum demand (631.45 MW) and isolated operation, using 20 generating units (steam, gas, and hydro), yielding a 259-state-variable model. The scenarios involve 15 MW and 50 MW load steps at Pedregal and Ateos—major load centers with high distributed PV penetration. Linearization and dynamic simulations are conducted in PowerFactory.

For estimation, 9 of the 259 eigenvalues are selected—3 real and 3 complex conjugate pairs. Figure 3.10 shows the predicted frequency responses compared to PowerFactory simulations, and Table 3.4 reports nadirs, timings, and errors.

The Ateos event proves most critical, with frequency dropping to 59.441 Hz—near the UFLS threshold—closely matched by the prediction. The method achieves high accuracy with a fast average execution time of 0.0205 seconds, even when the system has more state variables and the frequency trajectory is computed by a large set of dynamics.

These findings suggest that the approach can extend to more complex systems and may be compatible with commonly used software tools. Furthermore, results show that even when the number of state variables considerably increases, a small subset of dynamics is sufficient to accurately compute the predictions.

Table 3.3: Summary of Sensitivity Analyses and Estimation Errors

Scenario	Disturbance	Cases	Std. Order	MAPE Nadir (%)	MAPE Timing (%)
Loading levels	Load Step	1,103	10^{-4}	0.068×10^{-3}	0.913
	Generator Trip	1,260	10^{-4}	0.068×10^{-3}	1.79
Topologies	Load Step	995	10^{-3}	0.036×10^{-3}	1.83
	Generator Trip	1,100	10^{-3}	0.075×10^{-3}	1.557
Generator Participation	Load Step	261	10^{-2}	0.0099	14.57
	Generator Trip	93	10^{-2}	0.13	13.598
G. Part. (Removing 1 machine)	Load Step	9	10^{-3}	0.0017	4.11
	Generator Trip	9	10^{-3}	0.03	6.11

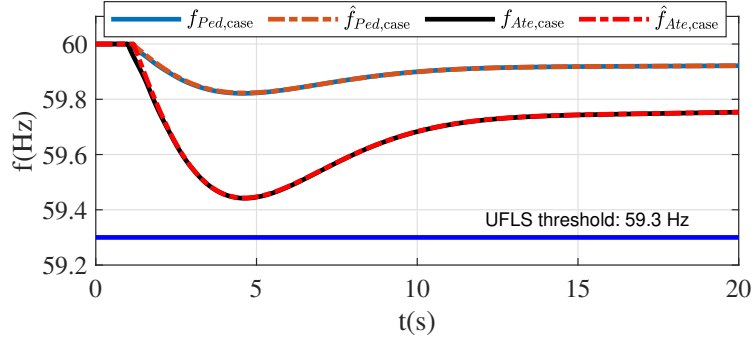


Figure 3.10: System frequency response comparison: actual vs estimated.

Table 3.4:
El Salvador's power grid results

Location	Pedregal		Ateos	
	Nadir (Hz)	Time (s)	Nadir (Hz)	Time (s)
Actual	59.821	4.60	59.441	4.64
Estimation	59.822	4.62	59.443	4.62
APE (%)	0.0025	0.43	0.002	0.43

3.5 Inverter-based resources considerations

To evaluate the impact of IBRs on SFR dynamics, frequency nadir, and their estimation, the Renewable Energy Generation Converter-B (REGC-B) model is used along with the controllers presented in [80]. This model, recommended by EPRI [81], is commonly implemented in commercial software to assess renewable energy integration on grid performance and reliability. Detailed information on the converter, controllers, and their DAE formulations is provided in [82], while parameter values are listed in Appendix A.2. The analysis is conducted using the New England 10-machine, 39-bus test system.

Two control modes are considered for IBRs: active/reactive power control (PQ-control) and frequency/voltage control (FV-control). To assess their impact on the proposed SFR and nadir estimation method, we analyze how each control mode influences estimation accuracy. Specifically, we examine the shifts of estimated modes in the complex plane and the participation of IBR state variables. Results indicate that, regardless of IBR participation or control mode, system dynamics remain dominated by SGs, with minimal modal variation. These findings support the method’s robustness across different control strategies and levels of IBR integration.

3.5.1 PQ-control operation

This operating mode regulates the current injected at the interconnection point to maintain the active and reactive power setpoints, regardless of system disturbances. Consequently, it does not participate in frequency support.

The New England system is evaluated under different scenarios of IBR penetration. The total system demand remains constant, with SGs progressively replaced by IBRs to increase the penetration level. Nadir estimation is assessed under the same disturbance across all scenarios—a 20% step increase in load at bus 7. Table 3.5 presents the IBR penetration percentages, system inertia values, and both actual and predicted nadir and nadir timing results for all scenarios. The results show an

Table 3.5:
Nadir and Timing Results under PQ and FV Operation Modes

Scen.	Systems data			PQ-control operation				FV-control operation			
	IBR Gen. (%)	SG Gen. (%)	System Inertia (s) (s)	Actual Nadir	Pred. Nadir	Actual Time (s)	Pred. Time (s)	Actual Nadir	Pred. Nadir	Actual Time (s)	Pred. Time (s)
1	0.00	100.00	313.08	59.861	59.863	9.096	9.037	59.861	59.863	9.096	9.037
2	3.96	96.03	296.28	59.850	59.853	9.355	9.446	59.863	59.866	9.075	8.978
3	14.29	85.70	281.96	59.820	59.824	10.167	10.194	59.854	59.857	9.074	9.124
4	22.35	77.64	271.56	59.805	59.809	10.758	10.767	59.858	59.861	9.246	9.057
5	31.12	68.87	257.64	59.754	59.759	11.900	11.880	59.849	59.852	8.944	9.185
6	44.60	55.39	243.84	59.672	59.677	13.469	13.487	59.839	59.842	9.440	9.361

increase in nadir deviation with higher IBR penetration and reduced system inertia. However, the estimation remains accurate across all scenarios.

To establish a clear reference point, the base case—corresponding to 0% IBR generation—is defined using the same operating conditions discussed in Section 3.4.2. The SFR and nadir under various IBR penetration levels are primarily governed by four dominant modes, which are identified through participation factor-guided mode selection. These modes, along with their evolution as IBR contribution increases, are illustrated in Fig. 3.11. Notably, despite the growing share of IBRs in the generation mix, the dominant dynamic behavior of the SFR remains largely unchanged, exhibiting only minor variations. Furthermore, all participation factors corresponding to these dominant eigenvalues and associated with IBR state variables consistently remain below the threshold $\epsilon = 10^{-4}$, indicating their negligible direct influence on the key dynamic modes used for the estimation.

3.5.2 FV-control operation

In this case, the IBR regulates the voltage at its interconnection point and provides frequency support to the grid through droop control. This enables it to participate in grid support by responding to disturbances.

Since IBRs participate in frequency regulation, their droop characteristics must be considered in the initial condition computation described in Section 3.2.3. In particular, the droop behavior of FV-control IBRs must be included in Eq. 3.10 by accounting for their speed regulation, such that $\Delta\omega = -\Delta P / \left(\sum_{z \in \mathcal{Z}} \frac{1}{R_{D,z}} + \sum_{u \in \mathcal{U}} \frac{1}{R_{p,u}} \right)$, where

$\mathcal{Z}$ and $\mathcal{U}$ denote the sets of synchronous generators and IBRs, respectively. This modification affects the computation of the post-disturbance steady-state frequency.

The SFR and nadir in this case are again determined by the same four dominant eigenvalues and their associated modal structures, as illustrated in Fig. 3.12. Although the total number of state variables and eigenvalues changes across different IBR penetration, no additional modes are required. The key eigenvalues governing the SFR show only minor variations, confirming the persistence of the dominant dynamics identified previously. As shown in Table 3.5, increased IBR participation in

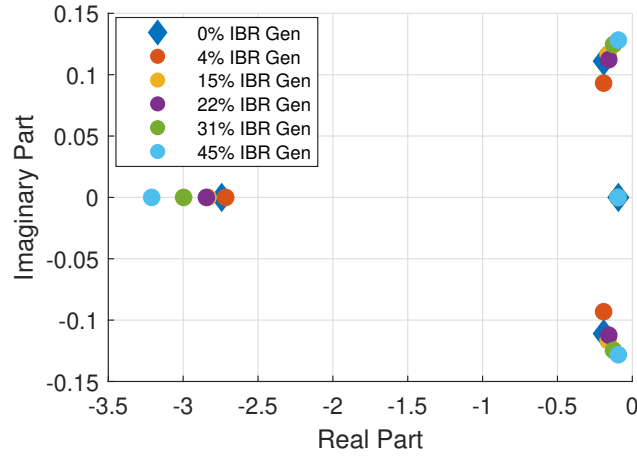


Figure 3.11: Estimation eigenvalues for PQ-control analysis

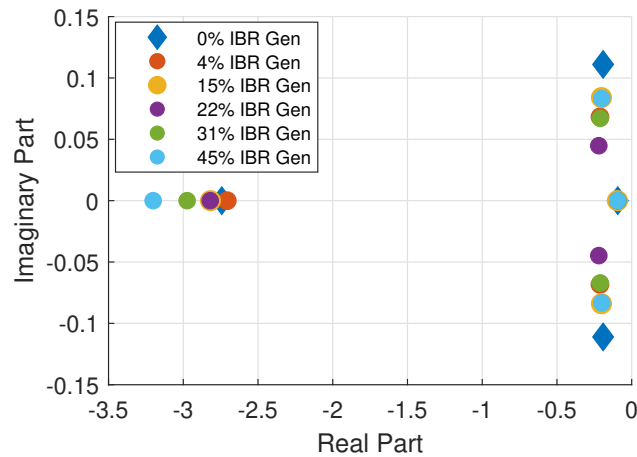


Figure 3.12: Estimation eigenvalues for FV-control analysis

FV-control mode leads to reduced frequency deviation, while the proposed prediction method continues to yield accurate results even under these altered conditions, reinforcing its effectiveness across diverse operational scenarios.

In the participation factor analysis, IBRs state associated with droop control exceeds the threshold ϵ in one of the four modes, but remains below it in the others. This observation suggests that, even when IBRs actively contribute to frequency regulation, the system’s frequency response is still predominantly governed by the dynamics and frequency control of SGs. Given the consistency observed across these experiments, it is reasonable to expect that modifications to the controllers or models of the converters would influence the existing modes or give rise to new ones. However, the system response can be reliably reconstructed by focusing on the subset of frequency control modes, as demonstrated by the method proposed in this work.

3.6 Summary

This chapter introduces a modal-based analytical methodology for predicting system frequency response and estimating the frequency nadir, grounded in the system’s eigenstructure. By performing modal decomposition and identifying the frequency control modes—those with the largest participation in the system frequency response—a closed-form expression of the frequency trajectory is derived, enabling accurate and computationally efficient assessments. The results show that these dominant modes exhibit low sensitivity to parameter variations, ensuring robust performance across a wide range of operating conditions, including those with high penetration of inverter-based resources. Validation on two benchmark systems and the Salvadoran transmission network confirms the method’s accuracy, scalability, and practical applicability. This shift from average-based representations to a mode-driven analysis underscores the value of leveraging system eigenstructure to capture

essential dynamics. Future work will focus on integrating this framework into real-time dynamic security assessment and improving planning efficiency.

Chapter 4

Hybrid Data–Model Framework for Dynamic Security Assessment of Frequency Stability

This chapter presents a hybrid model-AI framework for real-time dynamic assessment of frequency stability in power systems. The core idea is to enable fast and accurate estimation of frequency nadir and its timing under a variety of operating conditions and disturbances. The proposed method builds on the modal-based SFR and nadir prediction approach introduced in Chapter 3, and enhances its applicability in real-time settings by estimating key modal parameters using a Deep Sets-inspired neural model. This learning component replaces the need for repeated model-based computations of complex modal weights, significantly accelerating the assessment process. The framework dynamically adapts the set of major contingencies to the current unit commitment and dispatch. Results demonstrate high accuracy and fast computation across all scenarios, validated on both the IEEE 10-machine 39-bus system and the IEEE 118-bus system.

4.1 System frequency response and key parameters

The system frequency response (SFR) can be approximated by a sum of complex-weighted exponential terms given by the frequency control eigenvalues $\Lambda_{\mathcal{M}}$, leading to:

$$\Delta\omega_{\text{coi}}(t) \approx \sum_{i=1}^n e^{\lambda_i t} \gamma_i \approx e^{\lambda_1 t} \gamma_1 + e^{\lambda_2 t} \gamma_2 + \dots + e^{\lambda_n t} \gamma_n \quad (4.1)$$

where $\lambda_i \in \Lambda_{\mathcal{M}}$ and $\gamma_i \in \Gamma_{\mathcal{M}}$ for all $i = 1, 2, \dots, n$. The set $\Lambda_{\mathcal{M}}$ is determined using the participation factor-guided mode selection method introduced in Chapter 3. The subscript $\mathcal{M}$ denotes the subset of mode indices corresponding to those modes that contribute most significantly to SFR dynamics.

While $\Lambda_{\mathcal{M}}$ depends primarily on the system operating condition, $\Gamma_{\mathcal{M}}$ also reflects the disturbance characteristics and unit commitment. This formulation enables not only fast estimation of the full SFR response but also accurate calculation of the frequency nadir.

Sensitivity studies have shown that $\Lambda_{\mathcal{M}}$ is relatively insensitive to changes in topology, loading, and power flow. Therefore, it can be reused across scenarios with the same unit commitment. In contrast, $\Gamma_{\mathcal{M}}$ must be recomputed for each disturbance to capture differences in system response.

Let the system consist of n_g generators, and consider k disturbances, each producing a unique power imbalance $\Delta P_L^{(j)}$. The corresponding set of complex modal coefficients can be grouped into the following collection,

$$\Gamma = \left\{ \Gamma_{\mathcal{M}}^{(j)} = \Gamma_{\mathcal{M}}(\text{modal structure}, \Delta x_0^{(j)}(\Delta P_L^{(j)}), \text{dist}^{(j)}, \mathbf{u}_{\text{on}}) \right. \\ \left. \left| j = 1, 2, \dots, k \right. \right\} \quad (4.2)$$

where $\mathbf{u}_{\text{on}} \in \{0, 1\}^{n_g}$ is the binary unit commitment vector indicating the status (on/off) of each generator. The term $\Delta x_0^{(j)}$ represents the initial state deviation

induced by disturbance j , and $\mathbf{dist}^{(j)}$ contains information about the disturbance type (e.g., generator outage or load imbalance). The modal structure comprises the frequency control eigenvalues and the associated left and right eigenvectors $W_{\mathcal{M}}$ and $V_{\mathcal{M}}$, derived from the linearized system.

As detailed in Chapter 3, each set $\Gamma_{\mathcal{M}}^{(j)}$ can be efficiently obtained by computing the disturbance-induced initial condition (see Section 3.III) and applying Eq. (14) to calculate the modal coefficients γ_i .

Given $\Lambda_{\mathcal{M}}$ for a given operating condition, Equation 4.1 can be applied repeatedly by updating only the set of complex modal coefficients $\Gamma_{\mathcal{M}}$ for each disturbance. As defined in Equation 4.2, the full collection of these coefficients can be generated for a variety of scenarios using precomputed modal information and scenario-specific inputs. This modular structure makes the modal-based formulation particularly suitable for evaluating a large number of disturbances efficiently, as the same eigenbasis is reused while only $\Gamma_{\mathcal{M}}$ varies.

This workflow is particularly effective for offline analysis, where multiple contingencies must be assessed. Reusing precomputed eigenstructure and evaluating only the disturbance-dependent terms allows for fast, accurate estimation of both the SFR and frequency nadir.

4.2 System frequency response dynamic assessment

The modal-based approach can be adapted for real-time dynamic assessment, where contingencies must be evaluated rapidly to estimate frequency nadir and timing. Achieving this requires fast computation of both $\Lambda_{\mathcal{M}}$ and $\Gamma_{\mathcal{M}}$ for each disturbance. Here, the framework for fast dynamic assessment is introduced based upon the contributions and conclusions from Chapter 3.

4.2.1 General Framework

The core idea behind SFR dynamic assessment is to take the current system conditions and, based on them, evaluate a set Γ corresponding to a range of potential disturbances. The disturbance list is adapted according to the system operating state and unit commitment. The final output of this framework is the frequency nadir and timing associated with each defined contingency. Figure 4.1 illustrates the overall architecture. This framework is composed of the following four subprocesses:

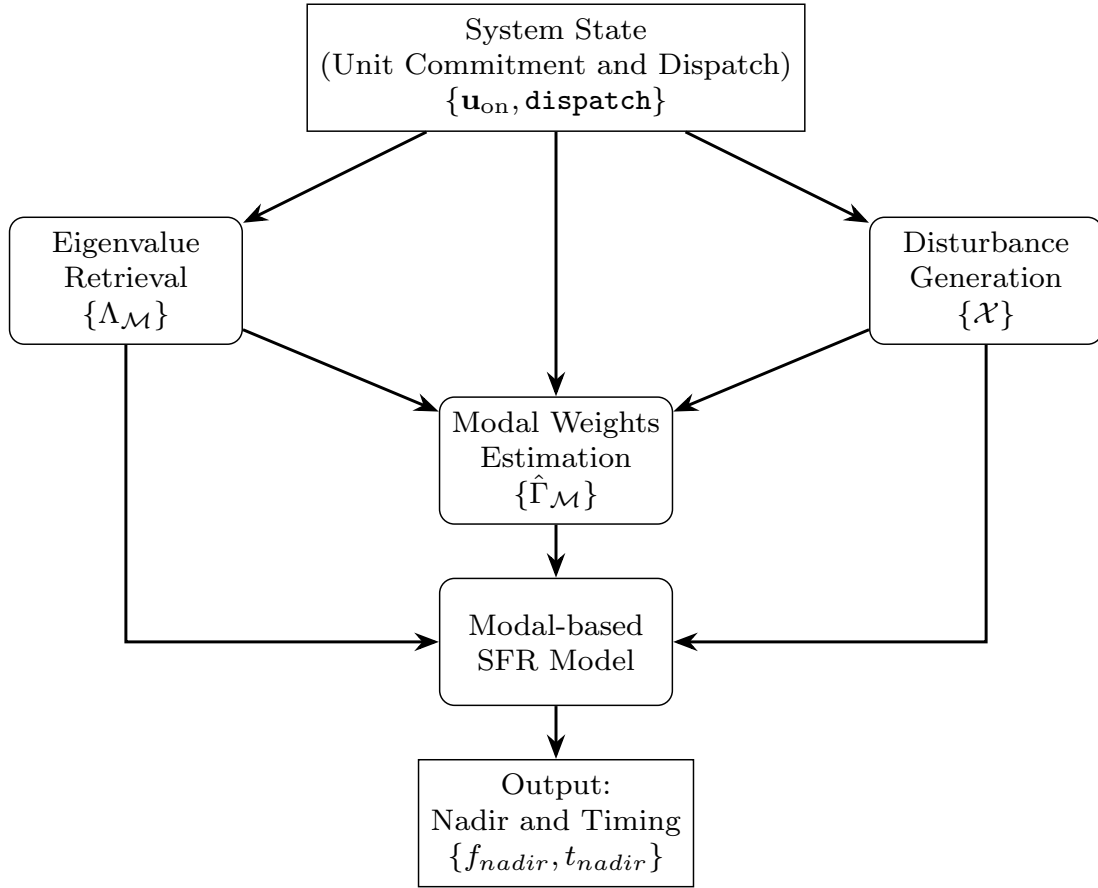


Figure 4.1: SFR dynamic assessment framework

4.2.2 Eigenvalue retrieval

Because frequency control eigenvalues are primarily influenced by the unit commitment, the $\Lambda_{\mathcal{M}}$ set can be reused for all scenarios sharing the same commitment configuration. A bank of precomputed $\Lambda_{\mathcal{M}}$ sets can be generated offline and stored. In real-time, the appropriate set is retrieved by matching the current unit commitment vector $\mathbf{u}_{\text{on}} \in \{0,1\}^{n_g}$ with one in the database. This bank can be updated daily based on the unit commitment schedule determined by the day-ahead market, or alternatively, constructed from historical data that reflects typical operating conditions.

4.2.3 Disturbance generation

Based on the current system state, the framework automatically generates a set of possible disturbances that may lead to critical frequency deviations. Each disturbance is represented by a vector $x_j = [\Delta P_L^{(j)}, \text{type}, \text{index}]$, where $\Delta P_L^{(j)}$ denotes the magnitude of the power imbalance in megawatts, **type** is a binary indicator specifying the disturbance type (0 for generator trip, 1 for load disturbance), and **index** identifies the affected system element, such as a generator or load bus. For example, $x_1 = [55, 0, 4]$ corresponds to a 55 MW trip at generator 4, while $x_2 = [40, 1, 7]$ represents a 40 MW load disturbance at bus 7.

The complete set of candidate disturbances is defined as:

$$\mathcal{X} = \left\{ x_j = [\Delta P_L^{(j)}, \text{type}, \text{index}] \mid j = 1, 2, \dots, k \right\} \quad (4.3)$$

The set $\mathcal{X}$ is automatically generated within the framework based on real-time system conditions, including unit commitment, dispatch levels, and the identification of critical loads. Since the framework is intended to run periodically for situational awareness, $\mathcal{X}$ is dynamically updated to reflect the current operating state.

This ensures adaptability: the list of possible disturbances reflects the current power injection from all generators when modeling generator trips, as well as critical load centers considered for load imbalance disturbances.

4.2.4 Complex modal weights

This subprocess receives the inputs $\mathbf{u}_{\text{on}} \in \{0, 1\}^g$, $\Lambda_{\mathcal{M}}$, and the disturbance set $\mathcal{X}$, and performs a fast batch estimation of the corresponding modal weights. Instead of computing the true collection $\Gamma = \{\Gamma_{\mathcal{M}}^{(j)}\}$ based on the disturbance-induced initial condition Δx_0 , this stage estimates an alternative collection denoted as $\hat{\Gamma} = \{\hat{\Gamma}_{\mathcal{M}}^{(j)}\}$, where each set $\hat{\Gamma}_{\mathcal{M}}^{(j)}$ corresponds to a disturbance $x_j \in \mathcal{X}$.

The estimation is carried out using a deep learning model designed for a permutation-equivariant setting. In this model, the input—an unordered and variable-size set of modal information—is mapped directly to the estimated modal coefficient vectors $\hat{\Gamma}_{\mathcal{M}}^{(j)}$. This learning-based approach significantly reduces computational burden by bypassing the need for computing disturbance-specific initial conditions. The full model architecture and training methodology are detailed in the following section.

4.2.5 Hybrid data-model based assessment

Once the set of estimated modal coefficients $\hat{\Gamma}$ has been obtained for all disturbances in $\mathcal{X}$, the modal-based formulation introduced in Section 3 can be applied to compute the nadir magnitude and timing. Given $\mathbf{u}_{\text{on}}$, x_j , and $\hat{\Gamma}_{\mathcal{M}}^{(j)}$, a set of coefficients $\mathcal{A} = [a_1, a_2, \dots, a_n] \in \mathbb{R}^z$ is computed, where $z = 3 \times m$, and m is the number of frequency control modes (including both real modes and complex-conjugate pairs). Each mode contributes three scalar coefficients used in the time-domain reconstruction.

These coefficients form a second-order Taylor approximation of the complex-exponential modal response. The resulting expression is differentiated and set to zero to obtain a quadratic equation, whose solution yields the estimated nadir timing.

The nadir magnitude is then computed by evaluating the analytical center-of-inertia frequency deviation at that specific time (see Sec. 3.3). Alternatively, the nadir value and its timing can be extracted directly from the reconstructed SFR response by evaluating Eq. 4.1 over a defined time horizon. Once $\Delta\omega_{coi}^{(j)}(t)$ is obtained for each disturbance $x_j \in \mathcal{X}$, the nadir magnitude and its corresponding time are defined as:

$$\Delta f_{\text{nadir}}^{(j)} = \min_{t \in [0, T]} \Delta\omega_{coi}^{(j)}(t), \quad t_{\text{nadir}}^{(j)} = \arg \min_{t \in [0, T]} \Delta\omega_{coi}^{(j)}(t) \quad (4.4)$$

where $\Delta f_{\text{nadir}}^{(j)}$ represents the frequency nadir as a deviation from the post-disturbance steady-state condition x_e . The actual nadir value $f_{\text{nadir}}^{(j)}$ is then computed as $f_{\text{nadir}} = f_e + \Delta\omega_{coi}(t_{\text{nadir}})$, where f_e is the post-disturbance steady-state frequency, which can be calculated as explained in Section 3.2.3. The complete output of the dynamic assessment framework is thus given by,

$$\mathcal{Y} = \left\{ \left(f_{\text{nadir}}^{(j)}, t_{\text{nadir}}^{(j)} \right) \mid j = 1, 2, \dots, k \right\} \quad (4.5)$$

This structure supports the rapid evaluation of multiple contingencies using a modular and efficient pipeline. Since eigenvalue retrieval and modal coefficient estimation are performed upfront, SFR predictions for each disturbance can be computed and analyzed in near real-time. As a result, the framework enables timely identification of critical events and enhances situational awareness without the need for full nonlinear simulations.

4.3 Complex modal weights estimation

This section presents the estimation of the complex-weight scalars collection $\hat{\Gamma} = \left\{ \hat{\Gamma}_{\mathcal{M}}^{(j)} \right\}$, where each set $\hat{\Gamma}_{\mathcal{M}}^{(j)}$ corresponds to a disturbance $x_j \in \mathcal{X}$. The estimation is performed in batch, using a deep learning model to approximate the relationship defined in Eq. 4.2.

The estimated mapping is given by:

$$\widehat{\Gamma}_{\mathcal{M}}^{(j)} = f(\Lambda_{\mathcal{M}}, \mathbf{u}_{\text{on}}, x_j) \quad (4.6)$$

where $\Lambda_{\mathcal{M}}$ is the vector of frequency control eigenvalues, $\mathbf{u}_{\text{on}} \in \{0, 1\}^{n_g}$ the unit commitment, and $x_j \in \mathcal{X}$ the encoded disturbance providing contextual information for each specific contingency.

A key modeling challenge is that $\Lambda_{\mathcal{M}}$ is a set of eigenvalues whose order varies with unit commitment. This means the model must operate on sets of eigenvalues, rather than fixed-order features vectors, where the input's order should accordingly alter the output mapping. Formally, a function f is permutation invariant if it satisfies $f(X) = f(\pi(X))$ for any permutation π of the set X , meaning the output is unchanged regardless of the input ordering. In contrast, a function is permutation equivariant if $f(\pi(X)) = \pi(f(X))$ which implies that the output changes in a consistent way with the input permutation. This property is essential in our case, where each i -th eigenvalue contributes a specific modal component to the output $\widehat{\Gamma}_{\mathcal{M}}$, and the model must preserve the correspondence between input eigenvalues and output weights, regardless of their order.

Therefore, the estimation the set $\widehat{\Gamma}_{\mathcal{M}}^{(j)}$ requires an architecture that respects permutation equivariance over the set $\Lambda_{\mathcal{M}}$, while simultaneously be conditioned by $\mathbf{u}_{\text{on}}$ and x_j .

4.3.1 Deep Sets

The Deep Sets framework provides a principled approach for learning functions over sets. As shown in [83], any permutation-invariant function $\mathcal{F}$ defined over a set $\mathcal{S} = \{\mathbf{s}_1, \mathbf{s}_2, \dots, \mathbf{s}_n\}$ can be expressed as:

$$\mathcal{F}(\mathcal{S}) = \Psi \left(\sum_{i=1}^n \Phi(\mathbf{s}_i) \right) \quad (4.7)$$

where Φ is a learned function (e.g., an MLP) applied independently to each element $\mathbf{s}_i \in \mathcal{S}$, the summation (or an alternative permutation-invariant operator such as mean or max) aggregates the transformed elements, and Ψ is another learned function that maps the aggregated result to the final output. This framework serves as a universal approximator for functions over sets and forms the theoretical basis of the Deep Sets architecture.

In this work, the Deep Sets framework is adapted to estimate the modal weights $\hat{\Gamma}_{\mathcal{M}}$ from the frequency control eigenvalue set $\Lambda_{\mathcal{M}}$. Since the task is permutation equivariant, the architecture is extended accordingly, as described in the next section.

4.3.2 Deep Sets-Inspired Model

The model is designed to be permutation equivariant with respect to the frequency control eigenvalues set $\Lambda_{\mathcal{M}}$, while conditioning on system-level features ($\mathbf{u}_{\text{on}}$ and x_j). The complete model architecture is illustrated in Fig. 4.2.

Input representation

The input is divided into two components: eigenvalue-based features and flat features. Each eigenvalue is converted to its polar form $[|\lambda|, \angle\lambda]$ and stacked into a tensor of shape $[N, M, 2]$, where N is the batch size and M is the number of eigenvalues. The flat inputs $\mathbf{u}_{\text{on}}$ and x_j are standardized to ensure consistent scaling.

DeepSet Block (Permutation-Invariant Branch)

The eigenvalue set $\Lambda_{\mathcal{M}}$ is processed by applying a shared dense transformation $\Phi(\cdot)$ independently to each element, mapping each eigenvalue into a d -dimensional latent space. In this work, $\Phi(\cdot)$ is implemented using a *TimeDistributed Dense* (TDD) layer from TensorFlow/Keras, which applies the same weights and biases across all modes. A dropout layer follows for regularization. This operation corresponds to the element-wise transformation term $\Phi(\mathbf{s}_i)$ in the Deep Sets formulation presented

in Eq. 4.7. The resulting latent representations are then aggregated using average pooling, producing a single d -dimensional vector that combines contributions from all modes equally—mirroring the summation $\sum_{i=1}^n \Phi(\mathbf{s}_i)$.

Flat feature conditioning

In parallel, the flat inputs $\mathbf{u}_{\text{on}}$ and x_j are passed through a Dense layer with output dimension d , projecting them into a similar dimension latent space. The pooled output from the Deep Sets branch and the flat input projection are concatenated into a single vector of size $2d$, referred to as the global context vector. This vector is then passed through an additional Dense layer, corresponding to the function $\Psi(\cdot)$ in Eq. 4.7.

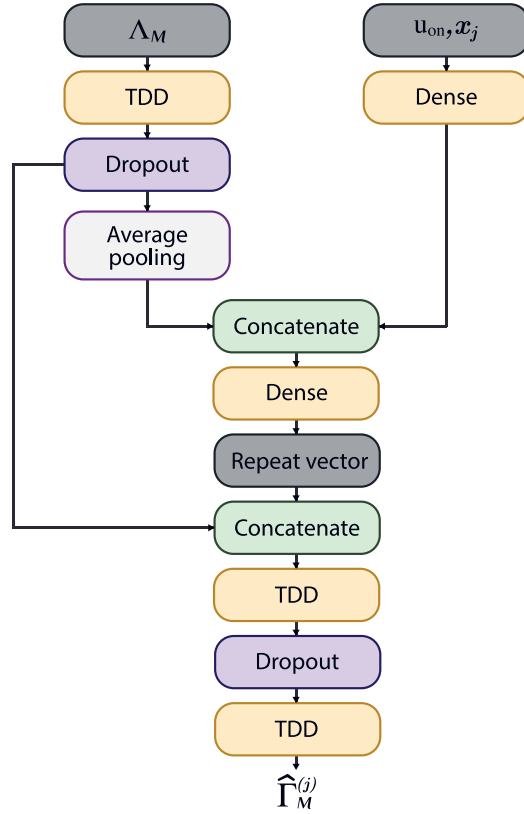


Figure 4.2: DeepSet-inspired network

Equivariant extension and output

To preserve permutation equivariance, the global context vector is repeated n times—where n is the number of eigenvalues in $\Lambda_{\mathcal{M}}$ —and concatenated with the original d -dimensional representation of each eigenvalue. This step ensures that each mode is enhanced with global context while maintaining input order. The resulting tensor is passed through another block of TDD and dropout layers, fusing the context with each mode, followed by a final TDD layer that produces the predicted set of complex modal weights $\widehat{\Gamma}_{\mathcal{M}}^{(j)}$.

Each predicted i -th entry is represented as a subvector $[|\gamma_i|, \sin(\angle\gamma_i), \cos(\angle\gamma_i)]$. The motivation for this representation is discussed in the next subsection, where the loss function is introduced. Finally, each modal coefficient γ_i is reconstructed from its polar representation by computing the angle as $\angle\gamma_i = \arctan 2(\sin(\angle\gamma_i), \cos(\angle\gamma_i))$ and recovering the complex form using $\gamma_i = |\gamma_i| \cdot e^{j\angle\gamma_i}$.

The number of TDD + dropout layers, Dense layers, and the hidden dimension d are tunable hyperparameters that can be adjusted to control model depth and capacity.

4.3.3 Loss function

To improve numerical stability and learning performance, each complex modal coefficient $\gamma_i \in \widehat{\Gamma}_{\mathcal{M}}^{(j)}$ is transformed into polar form, represented as the tuple $(|\gamma_i|, \angle\gamma_i)$. This transformation addresses issues with small magnitudes and angular discontinuities near the origin, which were found to hinder direct learning from raw complex values. By standardizing $|\gamma_i|$ and encoding $\angle\gamma_i$ as $[\sin(\angle\gamma_i), \cos(\angle\gamma_i)]$, discontinuities at $\pm\pi$ are avoided, providing smooth and bounded inputs.

The total loss is defined as a weighted sum of the magnitude and angular components,

$$\mathcal{L}_{\text{polar}} = \alpha \cdot \mathcal{L}_r + \beta \cdot \mathcal{L}_\theta \quad (4.8)$$

where α and β are weighting coefficients that control the relative contribution of each term.

The magnitude loss $\mathcal{L}_r$ is computed as the mean squared error between the predicted and true magnitudes:

$$\mathcal{L}_r = \frac{1}{n} \sum_{i=1}^n (|\gamma_i|^{\text{true}} - |\gamma_i|^{\text{pred}})^2 \quad (4.9)$$

The angular loss $\mathcal{L}_\theta$ is calculated using the vector difference between the predicted and true direction vectors,

$$\mathcal{L}_\theta = \frac{1}{n} \sum_{i=1}^n \left[\cos^{-1} \left(\frac{\mathbf{v}_i^{\text{true}} \cdot \mathbf{v}_i^{\text{pred}}}{\|\mathbf{v}_i^{\text{true}}\| \cdot \|\mathbf{v}_i^{\text{pred}}\|} \right) \right]^2 \quad (4.10)$$

where n is the number of modes per sample, and $\mathbf{v}_i = [\sin(\angle \gamma_i), \cos(\angle \gamma_i)]$ represents the angular direction vector of the predicted or true value. The argument of the inverse cosine is the normalized dot product between $\mathbf{v}_i^{\text{true}}$ and $\mathbf{v}_i^{\text{pred}}$, which computes the cosine of the angular difference between them.

4.3.4 Data preparation

The modal-based SFR framework requires far less training data than traditional ML approaches for dynamic stability assessment. As shown in Chapter 3, frequency control modes are largely insensitive to changes in load flow, topology, and dispatch, while the complex modal weights depend mainly on unit commitment, modal structure, and disturbance characteristics. Thus, the model can be effectively trained by varying only unit commitment and disturbance, without needing data from multiple operating conditions. Algorithm 2 summarizes the data generation process for generator trip scenarios.

Algorithm 2 Data Collection

```
1: Input: Set of unit commitments  $\mathcal{U}$ , scaling factors  $\alpha$ 
2: Output: Dataset  $\mathcal{D} = \left\{ \left( \Lambda_{\mathcal{M}}, \mathbf{u}_{\text{on}}, i, \Delta P_L^{(i)}, \Gamma_{\mathcal{M}}^{(i)} \right) \right\}$ 
3: for all unit commitment  $\mathbf{u}_{\text{on}} \in \mathcal{U}$  do
4:   Linearize the system and compute modal set  $\Lambda_{\mathcal{M}}$ 
5:   for all generator  $i \in \mathbf{u}_{\text{on}}$  do
6:     for all scaling factor  $\alpha_i \in \alpha$  do
7:       Scale the power output of generator  $i$  by  $\alpha_i$ 
8:       Trip generator  $i$ 
9:       Compute power imbalance  $\Delta P_L^{(i)}$ 
10:      Compute the set of modal weights  $\Gamma_{\mathcal{M}}^{(i)}$ 
11:       $\mathcal{D} \leftarrow \mathcal{D} \cup \left\{ \left( \Lambda_{\mathcal{M}}, \mathbf{u}_{\text{on}}, i, \Delta P_L^{(i)}, \Gamma_{\mathcal{M}}^{(i)} \right) \right\}$ 
```

For each predefined unit commitment $\mathbf{u}_{\text{on}} \in \mathcal{U}$, the system is linearized and the frequency control eigenvalue set $\Lambda_{\mathcal{M}}$ is computed. Two types of disturbances are considered: generator trips and load disturbances.

Focusing on generator trips, each online generator is subjected to multiple scenarios in which it is tripped at different output levels. For each online generator in the current unit commitment, its output is scaled using a set of predefined factors α , and each scaled case simulates a generator trip. The scaling factors can be selected based on the generator's operational limits, such that the resulting power levels span a representative range between $P_{\min}$ and $P_{\max}$. For each case, the resulting active power imbalance $\Delta P_L^{(i)}$ is recorded, and the complex modal weights Γ_i are computed using the formulation presented in Chapter 3. While the modal structure $\Lambda_{\mathcal{M}}$ remains constant for a given unit commitment, the weights Γ_i vary with the disturbance magnitude.

The resulting dataset $\mathcal{D}$ consists of tuples $(\Lambda_{\mathcal{M}}, \mathbf{u}_{\text{on}}, i, \Delta P_L^{(i)}, \Gamma_i)$, capturing the relationship between the system's modal structure, the generator trip event, the resulting power imbalance, and the modal response.

Load disturbances follow a similar data collection process but do not necessarily imply element tripping. Since the framework is based on the aggregate SFR, the specific location of the load step is not relevant to the modal dynamics. Instead, the disturbance is fully characterized by the active power imbalance ΔP_L . A separate dataset of load step events can be generated using various values of ΔP_L and concatenated with the generator trip dataset. Because the range of meaningful load step disturbances is narrower than that of generator trips, traditional data augmentation techniques can be used to enrich the load disturbance dataset and improve training robustness.

4.4 Case study

This section evaluates the performance of the proposed hybrid model-AI framework using two benchmark test systems: the IEEE 10-machine 39-bus system and the IEEE 118-bus system. The proposed method is also compared against XGBoost and a feedforward neural network (FNN).

In both test cases, generators are modeled using two-axis machine representations, IEEE Type-1 exciters, and three types of turbine governors: TGOV1, IEESGO, and GAST. System parameters for the IEEE 39-bus system are based on [77], and those for the 118-bus system are based on [84]. Governor settings are adopted from [78] and are listed in Appendix A.1. All relevant data is available in [82].

4.4.1 IEEE 10-Machine 39-Bus system

Following the procedure described in Section 4.3.4, a total of 9,700 stable samples were generated using 155 unique unit commitment configurations. Generator trip events were simulated by scaling the power output of each generator using factors in steps of $\alpha \in [0.35 : 0.05 : 0.95]$. For simplicity, only generator trips were considered in this study; however, load steps could also be incorporated into the training process. The

dataset was split 70/30 for training and validation. The DeepSets-inspired model and framework were implemented in Python 3.10.15 using TensorFlow/Keras and Scikit-learn.

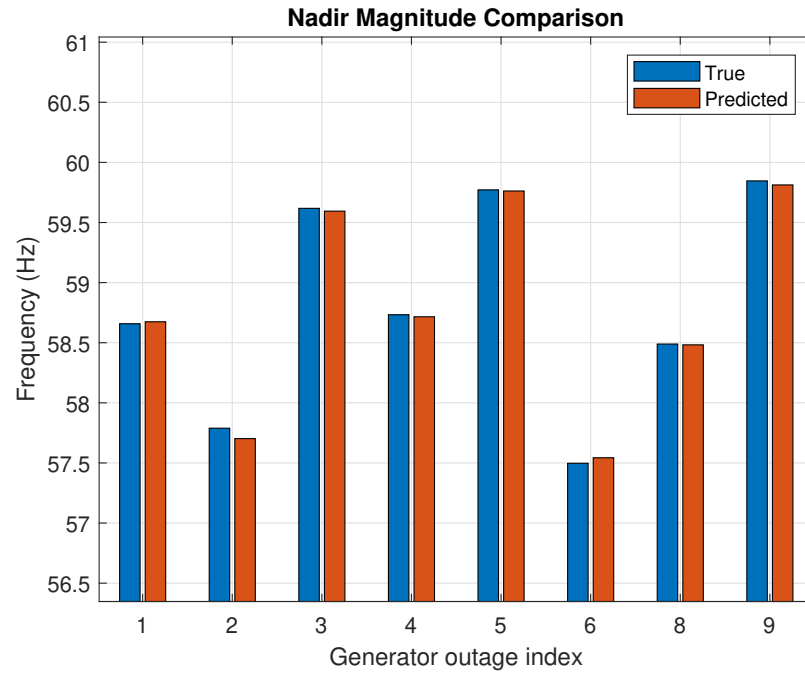
To evaluate the final framework, a set of dispatch scenarios—along with their associated unit commitments—was generated by solving a simple economic dispatch problem. Quadratic cost functions were assigned to each generator, with coefficients randomly varied within a small range around their nominal values. Table 4.1 presents five representative test scenarios used to evaluate generalization performance.

The goal of the proposed framework is to enhance situational awareness by rapidly predicting the frequency nadir and its timing for potential contingencies, using only dispatch and unit commitment information. Designed as a predictive tool, the framework can be executed periodically or on demand, supporting real-time or near-real-time operational decision-making.

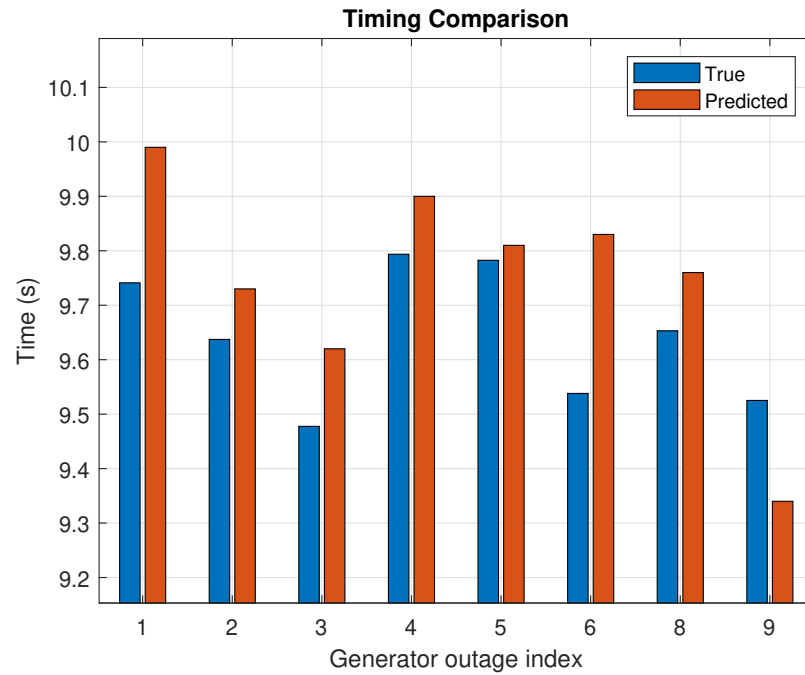
Figure 4.3 illustrates the prediction results for Scenario 1 (S1). The framework processes all eight possible generator trips in 0.65 s, achieving a Mean Absolute Error (MAE) of 0.02 Hz for nadir magnitude and 0.15 s for timing. The corresponding Mean Absolute Percentage Errors (MAPE) are 0.05% and 1.56%, respectively. Although the timing error is slightly higher, it remains well within acceptable bounds—especially when compared with reported MAPE values in the literature, which range from 7.69% to 19.97% [41, 45].

Table 4.1:
Test Scenarios: Generator Dispatch (MW)

Gen	S1	S2	S3	S4	S5
G1	400.77	174.48	239.51	70.75	253.72
G2	646.00	406.81	415.23	646.00	323.59
G3	118.95	0	229.59	187.60	0
G4	386.01	652.00	323.17	652.00	219.19
G5	84.79	0	0	0	67.58
G6	687.00	687.00	687.00	687.00	687.00
G7	0	78.40	0	0	160.12
G8	450.82	200.59	347.93	0	0
G9	59.77	211.72	677.71	575.33	665.88
G10	865.89	788.99	679.87	781.32	722.92



(a)



(b)

Figure 4.3: Comparison of actual vs. predicted results for 39 bus system: (a) Nadir Magnitude, (b) Nadir Timing

Table 4.2 summarizes the performance metrics across all five test scenarios. The average computation time per case is 0.678 s, demonstrating one of the core advantages of the proposed framework: the ability to deliver fast and accurate predictions without the need for full system simulation. Moreover, the low average magnitude and timing errors confirm the model’s generalization capability across unseen dispatch conditions. Further comparison with alternative machine learning frameworks is provided later in this section.

4.4.2 IEEE 118-Bus system

The system was modeled using 19 synchronous generators with a mix of TGOV1, IEEEESGO, and GAST governors. Following the procedure in Section 4.3.4, and considering 40 unit commitment configurations, $\alpha \in [0.35 : 0.05 : 0.95]$, and only generator trip disturbances, a total of 8,600 stable samples were generated. As before, the dataset was split 70/30 for training and validation. The framework was tested using the generator dispatch shown in Table 4.3.

Figure 4.4 compares predicted and actual nadir values. A total of 14 generator trips were evaluated in 1.15 s. Trips at G2, G15, G16, and G19 resulted in unstable conditions and non-convergent time-domain simulations. These scenarios are excluded from the error analysis, as the framework has not yet been trained to identify or handle potentially unstable conditions.

Future work could extend the current approach to include the classification or prediction of instability, which may arise from voltage collapse, severe oscillatory behavior, or topology-induced divergence. For the present study, only stable scenarios

Table 4.2:
Performance Metrics per Scenario

	S1	S2	S3	S4	S5	Avg.
Nadir MAE (Hz)	0.029	0.015	0.015	0.038	0.016	0.023
Timing MAE (s)	0.155	0.200	0.133	0.680	0.107	0.255
Time per batch (s)	0.69	0.65	0.72	0.66	0.67	0.678

Table 4.3:
Generator Dispatch (MW)

G1	G2	G3	G4	G5	G6	G7	G8	G9	G10
550	185	320	414	7	19	296	48	255	203
G11	G12	G13	G14	G15	G16	G17	G18	G19	
188	332	0	4	363	136	40	36	805	

are considered to ensure the validity of the predicted nadir and timing against well-defined ground truth values.

For the remaining stable cases, the model achieved a MAE of 0.026 Hz and 0.58 s, with MAPE of 0.044% and 14.49% for magnitude and timing, respectively. The higher timing error is primarily due to two outlier cases (6 and 14), which significantly deviated from the true timing values. Excluding these, the framework consistently delivers accurate and fast predictions.

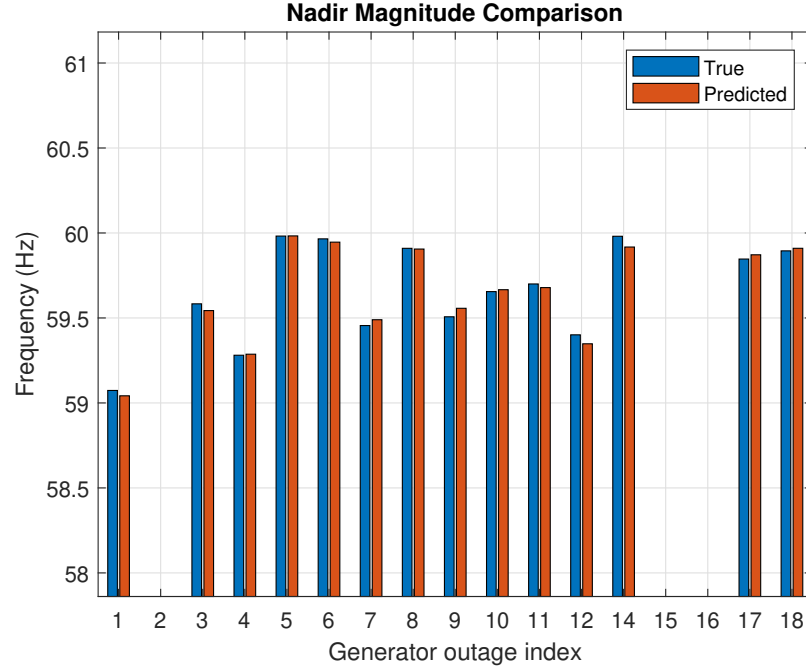
4.4.3 Comparison with alternative ML frameworks

To benchmark against conventional machine learning methods, the proposed framework is adapted to operate without model-based components. Instead, it uses direct grid measurements—assumed to be available from PMUs—to predict f_{nadir} and t_{nadir} through purely data-driven regression. Although the disturbance list is generated similarly to the proposed approach, this variant bypasses modal-based computation entirely.

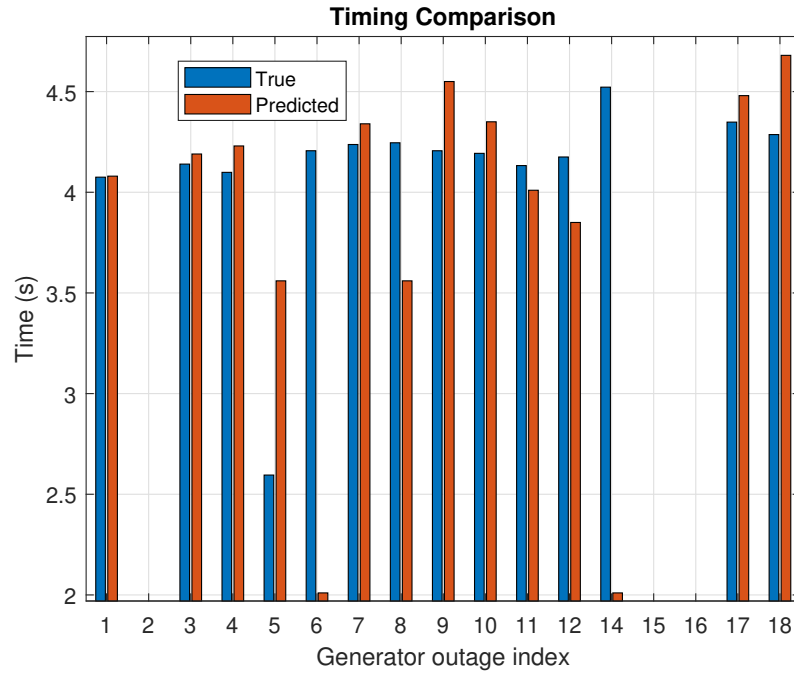
The input vector for this formulation is:

$$\mathbf{x} = [\mathbf{V}, \boldsymbol{\theta}, \text{Dispatch}, \Delta P_L, \mathbf{u}_{\text{on}}, i_{\text{trip}}] \quad (4.11)$$

where $\mathbf{V} \in \mathbb{R}^{n_b}$ and $\boldsymbol{\theta} \in \mathbb{R}^{n_b}$ are the bus voltage magnitudes and voltage angles, respectively; $\text{Dispatch} \in \mathbb{R}^{n_g}$ denotes the generator real power outputs; $\Delta P_L \in \mathbb{R}$ is the disturbance magnitude; $\mathbf{u}_{\text{on}} \in \{0, 1\}^{n_g}$ is the binary unit commitment vector



(a)



(b)

Figure 4.4: Comparison of actual vs. predicted results for the IEEE 118-bus system: (a) Nadir Magnitude, (b) Nadir Timing

indicating the on/off status of each generator; and i_{trip} is the index of the tripped generator.

XGBoost [85, 86] and FNN [65] are trained using the same training cases as the DeepSets-inspired model, with input features adjusted accordingly—100 for the IEEE 39-bus and 276 for the IEEE 118-bus system.

Table 4.4 compares training and evaluation performance. While FNN and XGBoost perform well on the training data, their evaluation errors increase significantly—particularly in nadir magnitude—reaching up to 0.27 Hz and 0.35 Hz, respectively. Such deviations can mislead protection schemes like under-frequency load shedding. In contrast, the DeepSets-inspired model exhibits lower and more consistent evaluation errors across both systems. The training error is not included in the comparison for the DeepSets-inspired model, as it estimates the set $\Gamma_{\mathcal{M}}^{(j)}$ rather than directly predicting frequency nadir and timing.

Regarding time performance, all analyses were conducted on a personal computer equipped with an Intel(R) Core(TM) i7-9750H CPU, NVIDIA GeForce GTX 1650 GPU, and 16 GB of RAM. XGBoost was the fastest, requiring only 0.07 s to evaluate all trip cases, followed by FFNN at 1.13 s. The DeepSets-inspired model required 1.76 s due to additional modal-based processing but achieved higher accuracy, stronger generalization, and required fewer measurement inputs.

Table 4.4:
Error comparison for the 39-bus and 118-bus systems

Metric	Unit	39-Bus System						118-Bus System					
		FFNN		XGBoost		DeepSet		FFNN		XGBoost		DeepSet	
		Train	Eval	Train	Eval	Eval		Train	Eval	Train	Eval	Eval	
Nadir MAE	(Hz)	0.048	0.27	0.024	0.32	0.023		0.015	0.35	0.007	0.11	0.026	
Timing MAE	(s)	0.081	0.80	0.098	2.32	0.25		0.048	0.78	0.060	0.55	0.58	

4.4.4 Summary

This chapter introduced a hybrid data-model framework for real-time dynamic security assessment of frequency stability in power systems. Building on the modal-based SFR and nadir prediction approach presented in Chapter 3, the proposed method leverages a DeepSets-inspired neural network to estimate complex modal coefficients that characterize the system’s response to disturbances. By replacing repeated model-based computations with a trained estimator, the framework enables fast and accurate predictions of frequency nadir and its timing under varying operating conditions.

The framework is validated on the IEEE 39-bus and 118-bus systems. Results demonstrate strong generalization and low prediction error compared to conventional machine learning models such as XGBoost and feedforward neural networks, which rely on complete system measurements. While the DeepSets-inspired model requires slightly more computation time due to modal reconstruction, it significantly outperforms these baselines in accuracy and robustness, all while requiring fewer input measurements—making it suitable for real-time or on-demand operator use.

Overall, this chapter demonstrates that hybrid approaches, which combine physical insights (modal-based SFR prediction) with learning-based parameter estimation, offer a scalable and effective solution for enhancing situational awareness in modern power systems.

Chapter 5

Conclusion

This dissertation presented a set of complementary methods to enhance power system control, assessment, and situational awareness by integrating model-based analysis with data-driven techniques. The proposed approaches target electromechanical oscillations and system frequency response, two critical aspects of the power grid stability.

First, a Data-Informed Coordination framework was introduced to optimize the ON/OFF activation of damping controllers based on real-time operating conditions and system disturbances. Deep learning models were used as nonlinear function approximators of key dynamic parameters, enabling adaptive and efficient coordination of damping controls. The framework demonstrated improved damping performance in the WECC test system by coordinating IBRs with traditional lead-lag compensators. This approach is particularly effective in modern grids, as it allows IBRs to contribute to system damping only when necessary, enhancing both control responsiveness and operational efficiency.

Second, the dissertation investigated system frequency response from a system dynamics perspective. A modal-based prediction method was developed by applying modal decomposition to the full nonlinear dynamic model of the grid, resulting in a closed-form expression for the SFR. This formulation enables fast and accurate

estimation of frequency nadir and its timing. The method was validated on three systems—the WSSC 9-bus test system, the IEEE 39-bus New England system, and the Salvadoran national grid—demonstrating its scalability and applicability across different network sizes. Sensitivity analyses revealed that the frequency control modes—those with the largest participation in the system frequency response—influencing the SFR are more dependent on the unit commitment than on network topology, operating condition, or loading levels. This insight supports the reuse of modal information across varying scenarios and remains valid even in systems with high IBR penetration. This last affirmation was validated using standard IBR dynamic models and escalating its penetration in the New England test system.

Finally, a hybrid data–model framework was developed for real-time dynamic security assessment of frequency stability. This framework combines the closed-form SFR model with a DeepSets-inspired neural network that estimates the complex modal coefficients governing system behavior. Validated on the IEEE 39-bus and 118-bus systems, the hybrid approach significantly outperforms conventional machine learning models such as XGBoost and feedforward neural networks. It offers enhanced generalization capabilities, reduced dependency on measurement data, and faster computation times, making it suitable for real-time or operator-on-demand applications.

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Appendix A

Selected Parameters for Benchmark Models

A.1 Governor parameters

Table A.1:
WSCC 9-bus System

Bus	T_1	T_2	T_3	T_4	K_1	A_t	K_t	D_t
1	0.25	2.50	9.00	0.00	20.00	0	0.0	0.2
2	0.30	5.00	12.00	0.10	30.00	0	0.0	0.0
3	0.25	0.25	2.50	0.00	25.00	1	2.5	0.2

Note: IEEESGO parameters for generator at bus 2: $K_2 = K_3 = 0$.

Table A.2: NE 39-bus System

Bus	Type	T_1	T_2	T_3	T_4	K_1	D_t	A_t	K_t
1	1	0.25	2.50	9.00	0.00	27.00	0.25	0.00	0.00
2	2	0.30	5.00	12.00	0.10	23.00	0.00	0.00	0.00
3	3	0.25	0.25	2.50	0.00	33.00	0.25	8.00	2.50
4	1	0.25	2.50	9.00	0.00	27.00	0.25	0.00	0.00
5	2	0.30	5.00	12.00	0.10	23.00	0.00	0.00	0.00
6	3	0.25	0.25	2.50	0.00	33.00	0.25	7.00	2.50
7	1	0.25	2.50	9.00	0.00	27.00	0.25	0.00	0.00
8	2	0.30	5.00	12.00	0.10	23.00	0.00	0.00	0.00
9	3	0.25	0.25	2.50	0.00	33.00	0.25	9.00	2.50
10	1	0.30	5.00	12.00	0.10	25.00	0.00	0.00	0.00

Note: Type 1 corresponds to TGOV1, Type 2 corresponds to IEESGO, and Type 3 corresponds to GAST.

A.2 IBR parameters

Table A.3: REGC-B dynamic parameters

T_Q	T_D	R_f	X_f	T_{eq}	T_{ed}
0.01	0.01	0.0040	0.05	0.01	0.01

IBR control parameters

K_{iq}	T_{Gqv}	K_{ip}	T_{Gpv}	T_r	R_q	K_i	K_p	T_{frq}	R_p
5	0.01	5	0.01	0.02	0.00	20.0	4.00	0.01	0.05

Note: For PQ-control operation T_r , K_i , K_p , T_{frq} , R_p parameters are set to 0.00.

Appendix B

Power System Modeling

B.1 PSSim: Power System Simulator

PSSim is a MATLAB package developed in the SPEED Lab as an educational tool for power system analysis. Its functionalities include power flow, RMS transient simulations, and small-signal analysis. The package, along with its documentation, models, and data, is available in [82]. The simulations in Chapter 3 and Chapter 4 were conducted using this software and the PowerFactory commercial software.

The tool is not intended to compete with established packages like PST [87] or PSAT [88], but to serve as an educational resource. It offers a clear, descriptive structure with well-documented models and code focused on readability rather than optimization. Equations and their interactions are explicitly detailed to help students and researchers understand and modify simulations easily. The framework includes block diagrams, DAE models, editable .mat files, and supports integration of custom models.

[DOI 10.5281/zenodo.15225910](#)


GitHub

PSSim: Power System Simulator

PSSim is a MATLAB-based power system dynamic simulator designed for research on power system dynamics and control ⚡👤.

Includes:

- ✓ Power flow analysis
- ✓ Time-domain RMS simulation
- ✓ Small-signal stability analysis.

PSSim is an educational tool for power system analysis, showcasing fundamental simulator structures, models, and practices from open-source and commercial software. It supports developing and testing new control and analysis solutions but is not meant to replace other simulators. Instead, it provides a simple, effective resource for students and educators to learn and teach key concepts.

Created by SPEED lab at The University of Tennessee, Knoxville. SPEED lab is under the direction of Dr. Hector Pulgar.



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Figure B.1: PSSim: Power System Simulator

B.2 REGC_B model

The Renewable Energy Generator/Converter (REGC) type B processes the real (I_{Pcmd}) and reactive (I_{Qcmd}) current commands from the control model and controls the output of real (ip) and reactive (iq) current injection to the grid. This model and its control are based on [80], [89], and block diagrams and equations for the converter and its controllers are shown below. The block diagram is shown in Fig. B.2.

B.2.1 Converter system equations

The model consists of 4 differential equations, plus 4 algebraic equations (Internal equations and equivalent circuits). The list of equations is shown below:

Differential equations

$$\frac{di_{iq}}{dt} = \frac{-1}{T_Q} (I_{Qcmd} + i_{iq}) \quad (\text{B.1})$$

$$\frac{di_{id}}{dt} = \frac{1}{T_D} (I_{Pcmd} - i_{id}) \quad (\text{B.2})$$

$$\frac{dE_x}{dt} = \frac{1}{T_{ed}} (E_d - E_x) \quad (\text{B.3})$$

$$\frac{dE_y}{dt} = \frac{1}{T_{eq}} (E_q - E_y) \quad (\text{B.4})$$

Algebraic equations

Internal block Eqn. (1),

$$E_d = v_d + i_{id}R_f - i_{iq}X_f \quad (\text{B.5})$$

$$E_q = v_q + i_{iq}R_f + i_{id}X_f \quad (\text{B.6})$$

equivalent circuit,

$$E_x = v_d + i_dR_f - i_qX_f \quad (\text{B.7})$$

$$E_y = v_q + i_qR_f + i_dX_f \quad (\text{B.8})$$

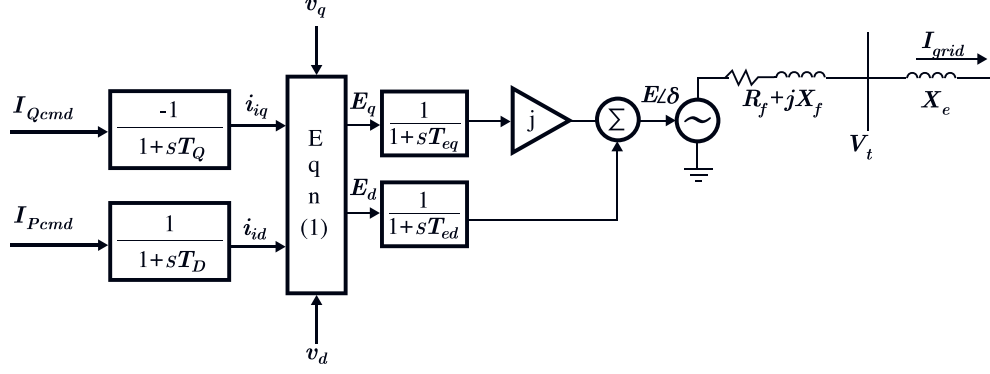


Figure B.2: REGC_B converter diagram

Note: v_d and v_q are the terminal voltages in the d-q axis. This model assumes that the d-axis is aligned with the terminal voltage, such that $v_q = 0$ and a PLL is not necessary to track the grid voltage.

Typical Data

A list of typical parameters is shown below:

$$\begin{aligned}
 T_Q &= 0.01 \\
 T_D &= 0.01 \\
 T_{eq} &= 0.01 \\
 T_{ed} &= 0.01 \\
 R_f &= 0.004 \\
 X_f &= 0.05
 \end{aligned}
 \tag{B.9}$$

B.2.2 PQ control

This control maintains P and Q references at the converters' point of interconnection. The model consists of 4 differential equations, plus 2 algebraic equations. Figure B.3 shows the block diagram of this control.

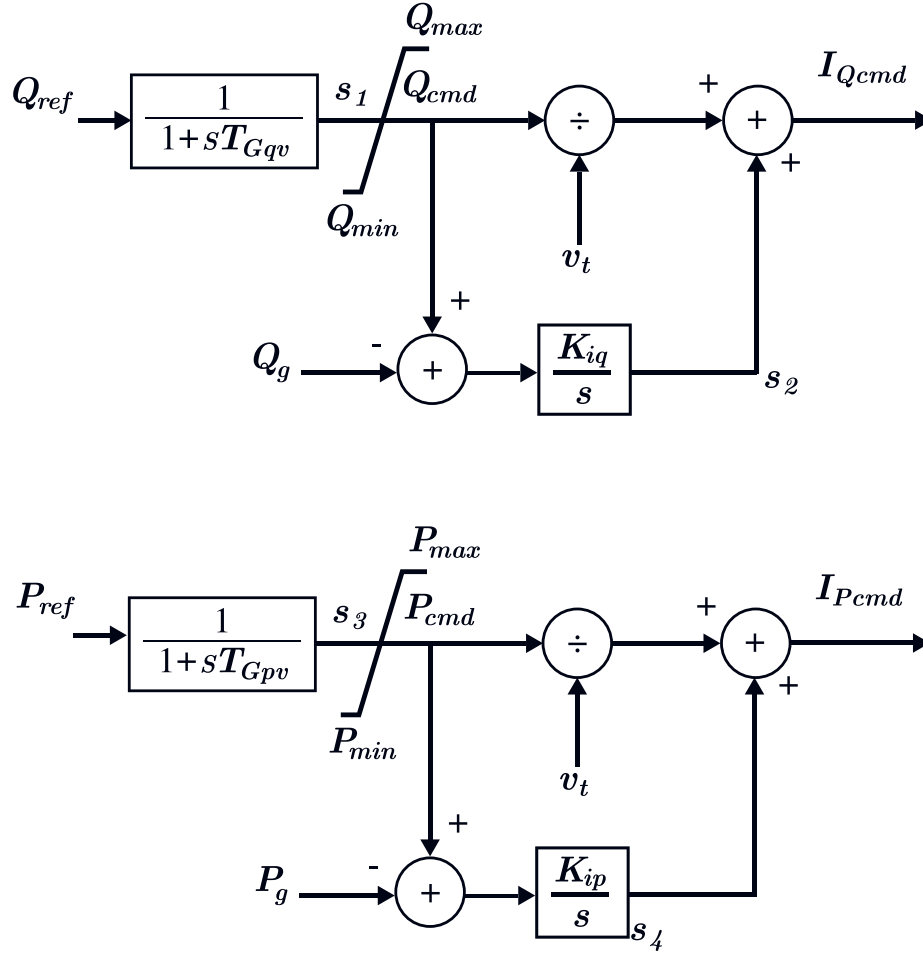


Figure B.3: PQ Control

Differential equations

$$\frac{ds_1}{dt} = \frac{1}{T_{Gqv}} (Q_{ref} - s_1) \quad (\text{B.10})$$

$$\frac{ds_2}{dt} = K_{iq} (Q_{cmd} - Q_g) \quad (\text{B.11})$$

$$\frac{ds_3}{dt} = \frac{1}{T_{Gpv}} (P_{ref} - s_3) \quad (\text{B.12})$$

$$\frac{ds_4}{dt} = K_{ip} (P_{cmd} - P_g) \quad (\text{B.13})$$

Algebraic equations

$$I_{Qcmd} = s_2 + \frac{Q_{cmd}}{|v_t|} \quad (\text{B.14})$$

$$I_{Pcmd} = s_4 + \frac{P_{cmd}}{|v_t|} \quad (\text{B.15})$$

$$Q_{cmd} = \begin{cases} s_1, & Q_{\min} \leq s_1 \leq Q_{\max} \\ Q_{\min}, & s_1 < Q_{\min} \\ Q_{\max}, & Q_{\max} < s_1 \end{cases} \quad (\text{B.16})$$

$$P_{cmd} = \begin{cases} s_3, & P_{\min} \leq s_3 \leq P_{\max} \\ P_{\min}, & s_3 < P_{\min} \\ P_{\max}, & P_{\max} < s_3 \end{cases} \quad (\text{B.17})$$

Typical Data

A list of typical parameters is shown below:

$$\begin{aligned}K_{iq} &= 5.00 \\T_{Gqv} &= 0.01 \\K_{ip} &= 5.00 \\T_{Gpv} &= 0.01 \\Q_{\min} &= -1.00 \\Q_{\max} &= 1.00 \\P_{\min} &= 0.00 \\P_{\max} &= 1.00\end{aligned}\tag{B.18}$$

B.2.3 FV control

The main intention of this control is to maintain f and v references at the converters' point of interconnection. The model consists of 7 differential equations, plus 2 algebraic equations. Figure B.4 shows the block diagram of this control.

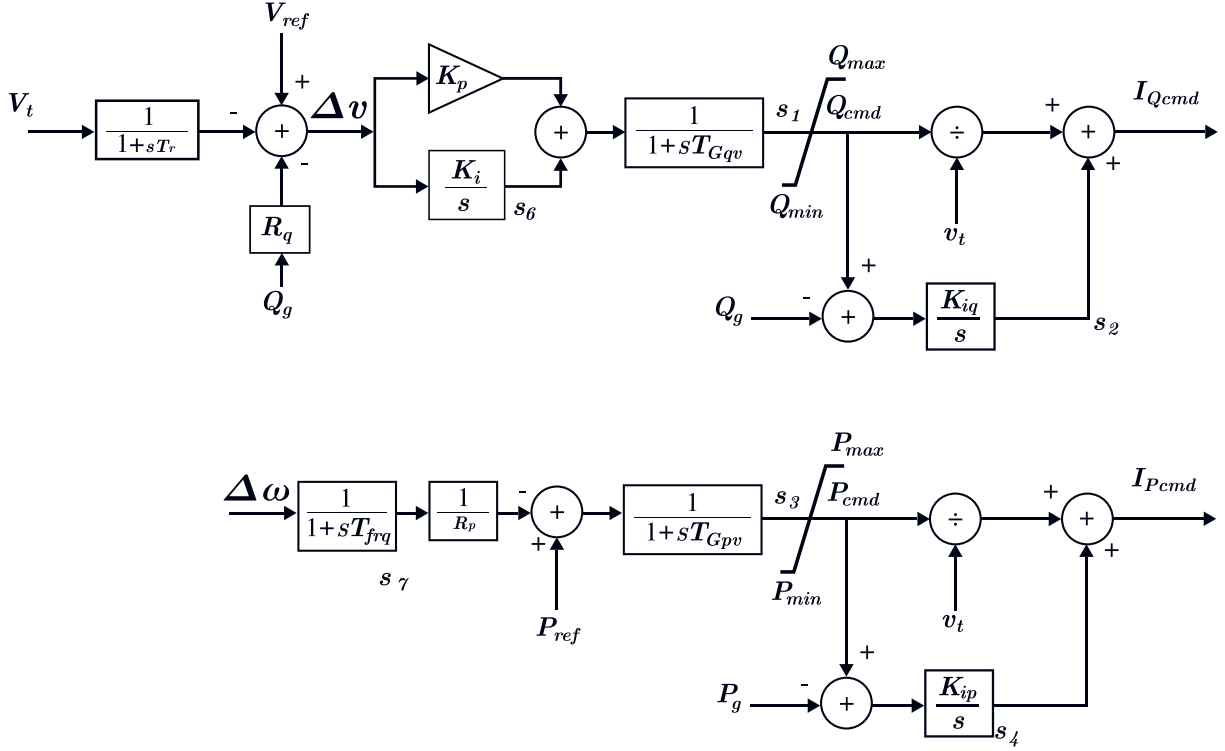


Figure B.4: FV Control

Differential equations

$$\frac{ds_1}{dt} = \frac{1}{T_{Gqv}} (s_6 + K_p(V_{ref} - s_5 - R_q Q_g) - s_1) \quad (\text{B.19})$$

$$\frac{ds_2}{dt} = K_{iq} (Q_{cmd} - Q_g) \quad (\text{B.20})$$

$$\frac{ds_3}{dt} = \frac{1}{T_{Gpv}} \left(P_{ref} - \frac{s_7}{R_p} - s_3 \right) \quad (\text{B.21})$$

$$\frac{ds_4}{dt} = K_{ip} (P_{cmd} - P_g) \quad (\text{B.22})$$

$$\frac{ds_5}{dt} = \frac{1}{T_r} (v_t - s_5) \quad (\text{B.23})$$

$$\frac{ds_6}{dt} = K_i (V_{ref} - s_5 - R_q Q_g) \quad (\text{B.24})$$

$$\frac{ds_7}{dt} = \frac{1}{T_{frq}} (\omega_{est} - 1 - s_7) \quad (\text{B.25})$$

Algebraic equations

$$I_{Qcmd} = s_2 + \frac{Q_{cmd}}{|v_t|} \quad (\text{B.26})$$

$$I_{Pcmd} = s_4 + \frac{P_{cmd}}{|v_t|} \quad (\text{B.27})$$

$$Q_{cmd} = \begin{cases} s_1, & Q_{\min} \leq s_1 \leq Q_{\max} \\ Q_{\min}, & s_1 < Q_{\min} \\ Q_{\max}, & Q_{\max} < s_1 \end{cases} \quad (\text{B.28})$$

$$P_{cmd} = \begin{cases} s_3, & P_{\min} \leq s_3 \leq P_{\max} \\ P_{\min}, & s_3 < P_{\min} \\ P_{\max}, & P_{\max} < s_3 \end{cases} \quad (\text{B.29})$$

Typical Data

A list of typical parameters is shown below:

$$\begin{aligned}K_{iq} &= 5.00 \\T_{Gqv} &= 0.01 \\K_{ip} &= 5.00 \\T_{Gpv} &= 0.01 \\Q_{\min} &= -1.00 \\Q_{\max} &= 1.00 \\P_{\min} &= 0.00 \\P_{\max} &= 1.00 \\T_r &= 0.02 \\R_q &= 0.00 \\K_i &= 20.0 \\K_p &= 4.00 \\T_{frq} &= 0.01 \\R_p &= 0.05\end{aligned}\tag{B.30}$$

Vita

Francisco Zelaya-Arrazabal was born in Santa Tecla, El Salvador. He received his B.Sc. and M.Eng. degrees from *Universidad Centroamericana José Simeón Cañas* in El Salvador and the *Universidad Nacional Autónoma de México* in México, in 2014 and 2019, respectively. His research areas include power system dynamics, stability and control, wide-area damping controllers, and the application of machine learning to power systems.