

Enhancing Microgrid Flexibility, Stability, and Economy with Inverter-based Resources

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Acknowledgments

Upon penning the final lines of my dissertation, a montage of the last four years unfolded in my mind. I vividly recall the moment when I hoisted my baggage, commencing my first national flight from Beijing. Immense gratitude within me for everyone who has been a part of my life and lent their helping hand, guidance, and support throughout my Ph.D. journey.

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Abstract

Microgrids face both challenges and opportunities due to the wide integration of inverter-based resources (IBRs) and advanced control techniques. On the one hand, IBRs enable the optimal use of renewable energies, which are environmentally friendly; On the other hand, IBRs introduce fast dynamics and high non-linearities to microgrids, degrading their stability and complicating the design of effective controllers. It remains an open question of how to maximize the benefits of IBRs for microgrids while overcoming the limitations. Hence, this dissertation addresses these issues by proposing new device-level control algorithms for IBRs, deriving analytical stability criteria, and integrating device-level controller design into the grid-level economic operation of microgrids.

Firstly, an adaptive PQ control method with trajectory tracking capability is developed to improve the controllability and flexibility of the IBRs in microgrids, combining model-based analysis, physics-informed reinforcement learning, and power hardware-in-the-loop experiment. Exponential response time constants can be freely assigned to IBRs to follow any predefined trajectory without complicated gain tuning.

Secondly, a decentralized and coordinated voltage and frequency (V-f) control framework is proposed for islanded microgrids, with full consideration of the limited capacity of distributed energy resources (DERs) and V-f dependent load. The control framework is composed of a power regulator and a V-f regulator, which generate the supplementary signals for the primary controller.

Thirdly, a systematic controller design approach that ensures stability and domain of attraction (DOA) is developed for islanded microgrids. The stability conditions, i.e., certified stability, certified DOA, and their combination, are derived to rigorously guarantee whether

a designated range is a subset of DOA. A systematic method for identifying the candidate control parameter set is further developed by integrating the analytical stability conditions.

Lastly, the concept of virtual inertia scheduling (VIS) is proposed to efficiently handle the high penetration of IBRs. VIS is an inertia management framework targeting security-constrained and economy-oriented inertia scheduling and generation dispatch of microgrids with a large scale of DERs. It schedules the power setting points of synchronous generators and IBRs, as well as the control modes and control parameters of IBRs, to provide secure and cost-effective inertia support.

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Chapter 1

Introduction

1.1 Overview

Microgrids are gaining popularity due to their capability to accommodate distributed energy resources (DERs) and form a self-sufficient system [124]. Microgrids not only contribute to the development of a zero-carbon city but also work as a fundamental component of the ‘source, network, and load’ integrated energy systems. A microgrid may incorporate various types of energy sources and act as an energy router [54], making it possible for the grid to survive severe events while also making the country more energy-resilient and secure [107].

A typical microgrid is composed of various DERs, energy storage systems, and loads that are connected locally as a united controlled entity [29]. In comparison to a traditional synchronous generator-dominated bulk power system, microgrids have a larger penetration of DERs [99, 169], a smaller system size [83, 79], a greater degree of uncertainty [133], lower system inertia [121], [139], and a stronger coupling of voltage and frequency (V-f). All these features pose challenges to the design of a microgrid control system. A complete microgrid control system is comprised of software and hardware that can both perform microgrid functionalities and guarantee stability at the same time [17]. The software is also referred to as microgrid controllers, which is the focus of this dissertation.

Existing microgrid controllers are usually designed under a hierarchal framework that includes the primary, secondary, and tertiary controllers [168], which covers the device-level control and grid-level economic operation. Reference [1] conducted a thorough review of the hierarchal control of microgrids. There are also some articles providing an overview from the different perspectives of communication interfaces [62], operation modes [7], and control techniques [3]. All these reviews provided an excellent summary and future directions for microgrid control research. As a result, this dissertation synthesizes these valuable viewpoints and develops a high-level research map of microgrids based on existing work, as detailed in Section 1.2.

1.2 High-level Research Map of Microgrids

Figure 1.1 shows the high-level research map of microgrid control from the perspectives of 1) operation mode, 2) function grouping, 3) timescale, 4) hierarchical structure, 5) communication interface, and 6) control techniques. The foundation of each perspective is illustrated as follows.

1) Operation mode

A microgrid can operate in either grid-connected (GC) mode or islanded (IS) mode depending on its connectivity to the main grid [6], [66]. In GC mode, the microgrid keeps tracking the phase of the main grid through the phase-locking loop (PLL), and exchanges the mismatched power at the point of common coupling (PCC). In IS mode, the microgrid forms a self-sufficient system based on the local generations. Reference [45] summarized the strategies for the seamless transition between GC and IS modes.

2) Function grouping

To meet the objectives of the microgrid operation, the 2nd viewpoint is associated with function grouping, which specifically includes the microgrid controller and device controller [76]. Grid-level controllers focus on supervisory control functions and grid interactive control functions, and they are more likely to be software-based and applied to the hardware; while device controllers focus on device-level control functions and local-area control functions, and they are more likely to be applied directly on the hardware (devices and assets).

3) Timescale

The time scale of microgrid control is tightly related to the control structure. So, it will be discussed in detail in the next discussion about hierarchical structure.

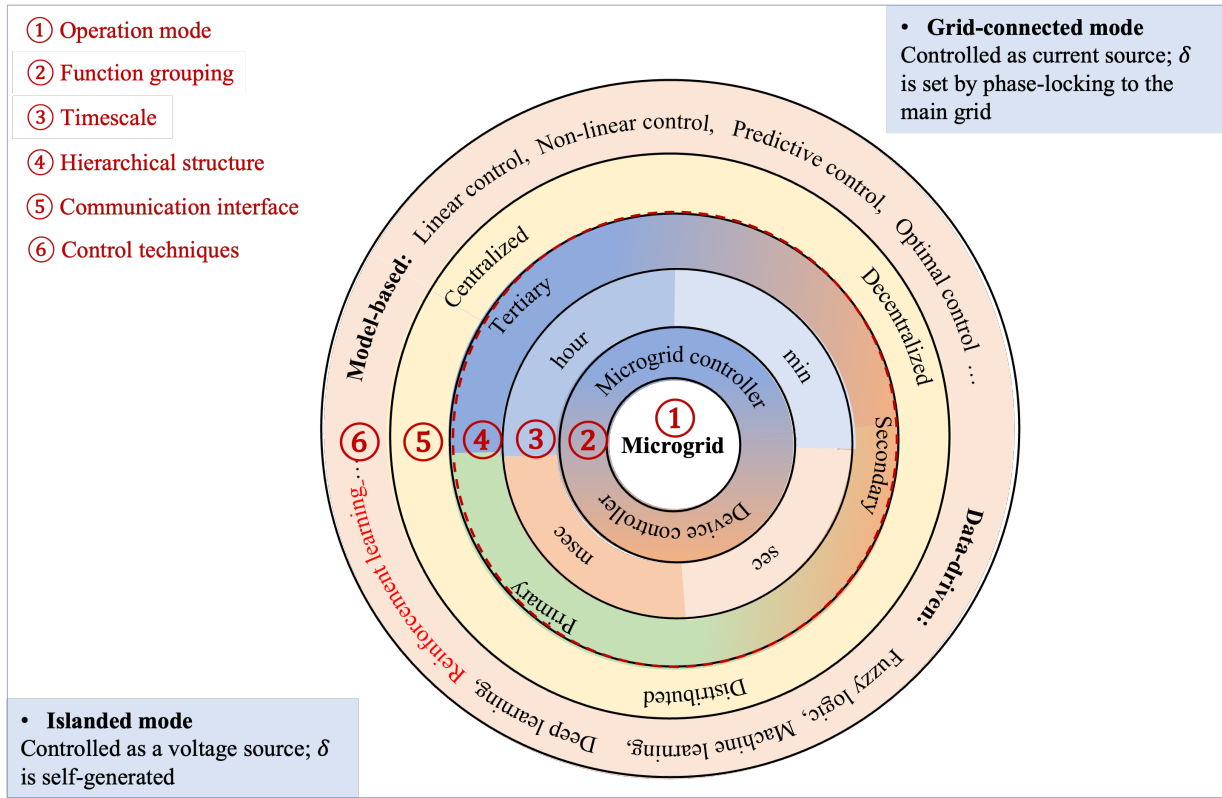


Figure 1.1: High-level research map of microgrids.

4) Hierarchical structure

The hierarchical control structure is another specific function grouping perspective that clearly sets up the control targets for all the controllers, with which each level controller can work independently within the distinct timescales [17].

The primary controller is responsible for voltage and current control of inverters and automatic power sharing among generations while maintaining V-f stability on a timescale of seconds. The indirect current control is used in the early stages [46], [100], and is later replaced by the direct current control due to its fast response and accurate current control capability [134]. More details can be found in the review paper [135]. Because the primary controller pertains to fast control actions, it predominantly determines the stability of microgrids [54]. Reference [91] gave an overview of the primary control of microgrids. The secondary controller mitigates the V-f deviation unsolved by the primary controller in the timescale of seconds to minutes. It improves the power quality by generating supplementary signals based on the errors between the measurements and reference values. Reference [151] and [170] performed a review on the secondary control of ac microgrids. The tertiary controller mainly focuses on economic and resilient operations in the timescale of minutes to hours. It adjusts the setting points of the primary and secondary controllers by solving optimal power flow and considering the load-side demand response. Some reviews can be found in [4], [88].

5) Communication interface

Depending on the communication interface, the control structure of the microgrid can also be categorized into centralized control, decentralized control, and distributed control [52].

In centralized control, the microgrid control center coordinates the load and generation and responds to all disturbances. It collects and processes all the local information before sending the control signals to each device. The centralized control has the advantage of accurate power-sharing and good transient performance but suffers from the high cost of the communication device and single-point failure. In distributed control, each node

communicates only with its adjunct nodes. Average-based, consensus-based, and event-triggered distributed algorithms are employed in microgrid control [152]. Distributed control algorithms require the connected communication graph of microgrids. They also have a reduced convergence speed as the network grows [136]. In decentralized control, the control signals are generated based on local measurements. It has the advantage of plug-and-play capability and is free of communication channel time delay, but it suffers from inaccurate power-sharing and large V-f deviation after disturbances. Reference [13] conducted a review from the perspective of communication interfaces and summarized some tricks to address their flaws.

6) Control techniques

Both model-based and data-driven control techniques have been utilized in microgrid control. Beginning with the classical linear control theory, advanced model-based control approaches such as non-linear control, optimum control, and model-predictive control (MPC) are then extensively used in microgrids. Reference [116] summarized the advances and opportunities of employing MPC in microgrids, and [118] reviewed the robust control strategies in microgrids. To address the problems of model uncertainty and unavailability, a variety of data-driven methodologies such as cutting-edge machine learning and deep learning are also employed in microgrid control. Reference [11] reviewed the application of big data in microgrids, and [46] conducted a survey on deep learning for microgrid load and DERs forecasting.

1.3 Bottom-level Modulization of IBRs

Grid-following (GFL) and grid-forming (GFM) inverters are no doubt one of the most important units in microgrids [181]. This subsection develops the modularized control blocks to present the bottom-level control details of GFL and GFM inverters. Figure 1.2 shows the diagram of the modularized control blocks, with which a GFL or GFM inverter can be configured easily by connecting the modules in series.

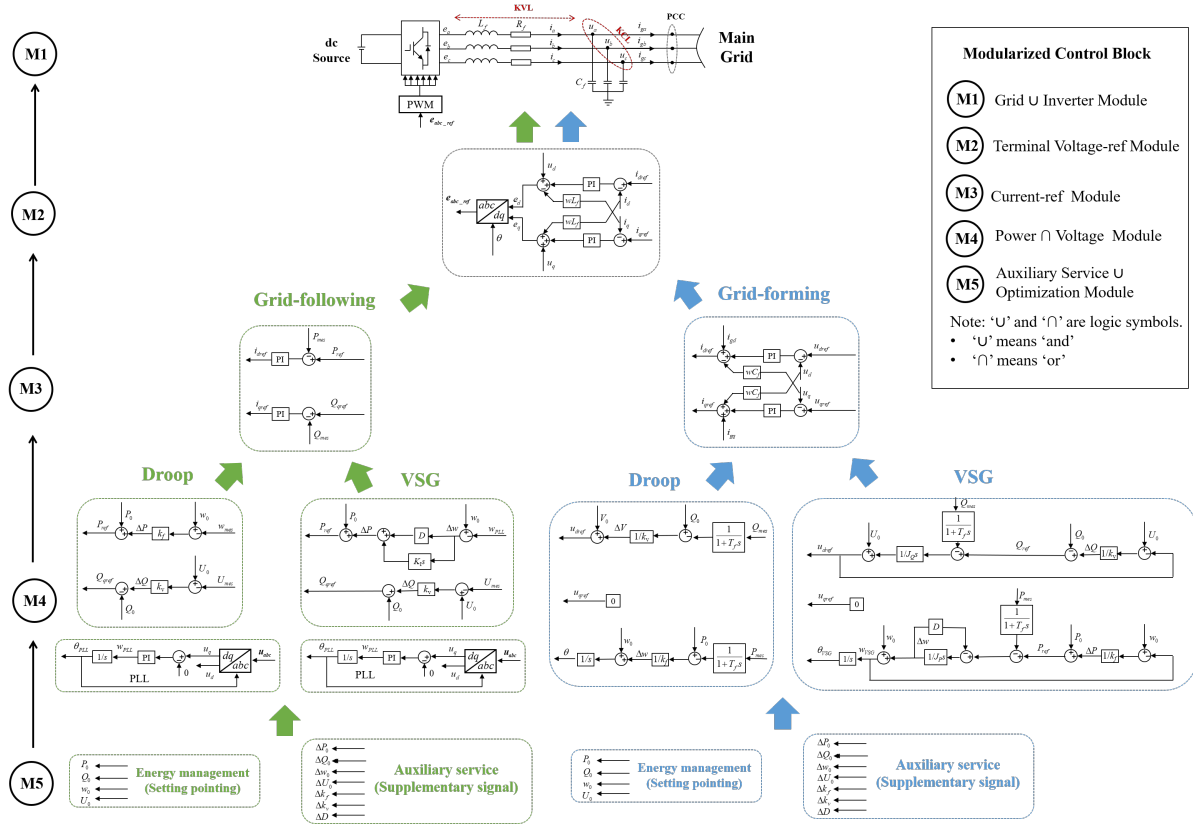


Figure 1.2: Modularized control blocks of GFL and GFM inverters.

1) M1: Grid $\cup$ inverter module

The 1st module (M1) is named the ‘Grid $\cup$ Inverter Module’ because it illustrates the connection of an inverter to the main grid. As shown in Figure 1.2, the dc source, dc-ac inverter, and RLC filter are linked in series, which are then connected to the main grid through the point of coupling (PCC). Here, an average model of an inverter that neglects the switching of pulse-width modulation (PWM) is often employed for the control system design. All the high-level controllers work together to generate the reference terminal voltage $e_{abc-ref}$ for PWM.

2) M2: Terminal Voltage-ref module

The 2nd module (M2) is named the ‘Terminal Voltage-ref Module’ since it directly generates the reference terminal voltage. The control model is formulated using Kirchhoff’s current law (KCL) from e_{abc} to u_{abc} and conducting Park transformation. Then, after implementing proportional-integral (PI) controllers, the physical model and control transfer function in dq framework are shown in (1.1) and (1.2), respectively.

$$L_f \begin{bmatrix} \frac{di_d}{dt} \\ \frac{di_q}{dt} \end{bmatrix} + wL_f \begin{bmatrix} -i_q \\ i_d \end{bmatrix} = \begin{bmatrix} e_d \\ e_q \end{bmatrix} - \begin{bmatrix} u_d \\ u_q \end{bmatrix} \quad (1.1)$$

$$\begin{bmatrix} e_d \\ e_q \end{bmatrix} = \begin{bmatrix} u_d \\ u_q \end{bmatrix} + wL_f \begin{bmatrix} -i_q \\ i_d \end{bmatrix} + \begin{bmatrix} k_{pid} + \frac{k_{iid}}{s} & 0 \\ 0 & k_{piq} + \frac{k_{iiq}}{s} \end{bmatrix} \left(\begin{bmatrix} i_{dref} \\ i_{qref} \end{bmatrix} - \begin{bmatrix} i_d \\ i_q \end{bmatrix} \right) \quad (1.2)$$

3) M3: Current-ref module

The 3rd module (M3) is named the ‘Current-ref Module’ since it generates the reference current $[i_{dref}, i_{qref}]$ for M2. For a GFL inverter, $[i_{dref}, i_{qref}]$ are regulated based on the error between the actual output and the reference value. Equations. (1.3)-(1.4) show the transfer function of M3 using PI controllers, where two low-pass filters are used to filter measured

power output.

$$\begin{bmatrix} i_{dref} \\ i_{qref} \end{bmatrix} = \begin{bmatrix} k_{pP} + \frac{k_{iP}}{s} & 0 \\ 0 & k_{pQ} + \frac{k_{iQ}}{s} \end{bmatrix} \begin{bmatrix} P - P_{ref} \\ Q - Q_{ref} \end{bmatrix} \quad (1.3)$$

$$\begin{bmatrix} P \\ Q \end{bmatrix} = \begin{bmatrix} \frac{1}{T_{fP}s+1} & 0 \\ 0 & \frac{1}{T_{fQ}s+1} \end{bmatrix} \begin{bmatrix} P_{mes} \\ Q_{mes} \end{bmatrix} \quad (1.4)$$

For a GFM inverter, its physical model is formulated using Kirchhoff's voltage law (KVL) at point u_{abc} . After Park transformation and PI controller integration, the algebraic equation and control transfer function in dq framework are shown in (1.5) and (1.6), respectively.

$$C_f \begin{bmatrix} \frac{du_d}{dt} \\ \frac{du_q}{dt} \end{bmatrix} + wC_f \begin{bmatrix} -u_q \\ u_d \end{bmatrix} = \begin{bmatrix} i_d \\ i_q \end{bmatrix} - \begin{bmatrix} i_{gd} \\ i_{gq} \end{bmatrix} \quad (1.5)$$

$$\begin{bmatrix} i_{dref} \\ i_{qref} \end{bmatrix} = \begin{bmatrix} i_{gd} \\ i_{gq} \end{bmatrix} + wC_f \begin{bmatrix} -u_q \\ u_d \end{bmatrix} + \begin{bmatrix} k_{pud} + \frac{k_{iud}}{s} & 0 \\ 0 & k_{puq} + \frac{k_{iuq}}{s} \end{bmatrix} \left(\begin{bmatrix} u_{dref} \\ u_{qref} \end{bmatrix} - \begin{bmatrix} u_d \\ u_q \end{bmatrix} \right) \quad (1.6)$$

4) M4: Power $\cap$ Voltage module

The 4th module (M4) is named the 'Power $\cap$ Voltage Module' which indicates the fundamental difference between GFL and GFM inverters. A GFL inverter is controlled as a current source and requires a power reference as an input, while a GFM inverter is controlled as a voltage source and needs a voltage reference as an input [135]. Another big difference is that a GFL inverter needs a PLL to track the phase of the main grid while a GFM inverter is self-synchronized [44]. Droop control is the most widely used control method in microgrids. It takes advantage of the coupling between power generation and the grid V-f [131]. Typically, an inductive microgrid employs the $P-f$ and $Q-V$ droop curves, while resistive microgrids use the reverse $P-V$ and $Q-f$ droop curves. The M4 plotted in Figure 1.2 shows the control blocks for an inductive microgrid, and their control models are shown below.

- Droop-controlled GFL inverter

$$\begin{bmatrix} P_{ref} \\ Q_{ref} \end{bmatrix} = \begin{bmatrix} k_f & 0 \\ 0 & k_v \end{bmatrix} \left(\begin{bmatrix} w_0 \\ U_0 \end{bmatrix} - \begin{bmatrix} w_{mes} \\ U_{mes} \end{bmatrix} \right) + \begin{bmatrix} P_0 \\ Q_0 \end{bmatrix} \quad (1.7)$$

- Droop-controlled GFM inverter

$$\begin{bmatrix} w_{ref} \\ u_{dref} \end{bmatrix} = \begin{bmatrix} \frac{1}{k_f} & 0 \\ 0 & \frac{1}{k_v} \end{bmatrix} \left(\begin{bmatrix} P_0 \\ Q_0 \end{bmatrix} - \begin{bmatrix} P_{mes} \\ Q_{mes} \end{bmatrix} \right) + \begin{bmatrix} w_0 \\ V_0 \end{bmatrix} \quad (1.8)$$

To provide more inertia support to microgrids leveraging DERs, the virtual synchronous generator (VSG) control method is proposed to emulate the behavior of synchronous generators [69]. Mathematically speaking, the VSG belongs to proportional-differential control. Below is the transfer function of the GFL and GFM inverters implementing the VSG.

- VSG-controlled GFL inverter

$$\begin{bmatrix} P_{ref} \\ Q_{ref} \end{bmatrix} = \begin{bmatrix} D + Ks & 0 \\ 0 & k_v \end{bmatrix} \times \left(\begin{bmatrix} w_0 \\ U_0 \end{bmatrix} - \begin{bmatrix} w_{mes} \\ U_{mes} \end{bmatrix} \right) + \begin{bmatrix} P_0 \\ Q_0 \end{bmatrix} \quad (1.9)$$

- VSG-controlled GFM inverter

$$\begin{bmatrix} w_{ref} \\ u_{dref} \end{bmatrix} = \begin{bmatrix} \frac{1}{J_P s} & 0 \\ 0 & \frac{1}{J_Q s} \end{bmatrix} \left\{ \left(\begin{bmatrix} P_{ref} \\ Q_{ref} \end{bmatrix} - \begin{bmatrix} P \\ Q \end{bmatrix} \right) - \begin{bmatrix} D\Delta w \\ 0 \end{bmatrix} \right\} + \begin{bmatrix} w_0 \\ U_0 \end{bmatrix} \quad (1.10)$$

Readers are encouraged to check [73] and [183] for some modified VSG and droop control techniques that provide more effective inertia support to microgrids.

5) M5: Auxiliary service $\cup$ Optimization module

Microgrids exploiting M1-M4 can withstand normal disturbances such as load changes and plug-and-play generations. Then, M5 participates in grid optimization and provides auxiliary services, i.e., optimized active and reactive power sharing, demand-side management, and V-f support [96]. In order for more economic energy management, M5 also calculates the steady-state setting points such as (P_0, Q_0) by solving optimal power flow [166]. On the other hand, it generates the supplementary signals for controller parameters and outputs [40] according to the targets of auxiliary service. Review papers regarding M5 can be seen in [18], [58].

1.4 Challenges in the IBRs-based Microgrids

The high-level research map and modularized control blocks clearly show how existing microgrids work. However, the evolution of microgrids brings more challenges to the existing control and operation framework. The general challenges are as six-fold:

i). The increasing penetration of DERs brings higher and higher uncertainties to microgrids. ii). Microgrid dynamics are becoming faster because more and more IBRs are participating in grid services by adaptively changing their control modes and control parameters. iii). It is difficult to model each element of microgrids in detail, i.e., customer behavior. The information that is difficult to model is critical for energy management. iv). The main grids are facing resilience issues and expect microgrids to provide islanding support, distributed generation, redundancy, advanced control, and rapid deployment. v). Smart grids call for autonomous microgrids, with which engineers and grid operators are free from parameter tuning for modules in Figure 1.2. vi). Cybersecurity measures must also be implemented to protect against cyber-attacks and data breaches that could compromise the safety and reliability of the microgrid.

In addition to the general challenges summarized above, there are several specific challenges that need to be addressed, and they are closely related to microgrid flexibility, stability, and the economy. All of these specific challenges are associated with the control and optimization of IBRs in microgrids.

- The existing inverter active power and reactive power (P-Q) controller is not flexible enough because the P-Q output of the inverter cannot accurately track the predefined trajectories, making it hard to respond to the customized grid-side demand.
- GFM inverters are controlled as voltage sources, and their output is mostly determined by the grid side performance, thus degrading the flexibility of microgrids. This is critical when the total generation capacity is insufficient, which may further result in some stability issues.
- IBRs are expected to be more actively involved in grid service, i.e., switching between GFL and GFM modes and providing auxiliary service by adaptively changing control parameters [141]. This necessitates a more rigorous guarantee of stability. A systematic approach to certifying transient stability is yet to be developed.
- The device-level control and grid-level economic operation have always been decoupled in the existing microgrid control framework. IBRs' controllability and flexibility open the possibility of a more advanced scheduling framework by changing the control modes and parameters of IBRs. Such a control framework guarantees the dynamic stability and performance of microgrids while also accounting for economic operation.

1.5 Dissertation Outline

This dissertation improves microgrid flexibility, stability, and economy by addressing the specific challenges summarized in Section 1.4. They lay the foundations for addressing those emerging general challenges in microgrids.

Chapter 2 proposes an adaptive P-Q control method with trajectory tracking capability, combining model-based analysis, physics-informed reinforcement learning (RL), and power hardware-in-the-loop (HIL) experiments. With the physics-informed learning method, exponential response time constants can be freely assigned to GFL IBRs, and they can follow any predefined trajectory and respond to customized grid-level commands without complicated gain tuning.

Chapter 3 proposes a decentralized and coordinated V-f control framework is proposed for islanded microgrids, with full consideration of the limited DER capacity DERs and

V-f dependent load. The control framework can regulate the output of each GFM inverter accurately and quickly. It also improves V-f deviation and reduces involuntary load shedding without depending on knowledge and measurements from adjacent nodes.

Chapter 4 presents a systematic controller design approach that ensures stability and domain of attraction (DOA) for islanded microgrids. It identifies the candidate control parameter set that makes sure a designated range is a subset of DOA. The designated range is customized and flexible enough to cover the normal or emergency operational ranges of microgrids, such as low- and high-voltage ride-through (L/HVRT) conditions.

Chapter 5 proposes the concept of virtual inertia scheduling (VIS), which is an inertia management framework that targets security-constrained and economy-oriented inertia scheduling and generation dispatch of microgrids with a large scale of DERs. VIS integrates the device-level control into grid-level economic operation, which guarantees static and dynamic security while also accounting for economic operation.

Chapter 2

Inverter P-Q Control with Trajectory Tracking Capability Based on Physics-informed Reinforcement Learning

This chapter introduces an inverter P-Q controller with trajectory tracking capability to improve the flexibility of microgrids, combining model-based analysis, physics-informed reinforcement learning, and power HIL experiments.

2.1 Literature Review

Whether a microgrid operates in grid-connected or islanded mode, active and reactive power control is a basic control mode for IBRs [182]. The controllers at the secondary and tertiary levels generate P-Q reference values and supplementary signals for the primary controllers [175]. In P-Q control, the inverter is controlled as a current source [32] and the three-phase rotating voltage and current are converted to direct and quadrature DC variables through Park transformation. Then, these DC quantities can be regulated by PI controllers in the outer P-Q regulation loop and the inner current regulation loop [50]. This double loop structure with PI controllers has been used extensively in industry and academia [119].

To improve the flexibility and controllability of inverters so as to provide better ancillary services to microgrids, the existing literature developed several gain tuning methods for microgrid P-Q controllers, including the trial-and-error method, model-based method, heuristic method, and artificial intelligence (AI) based method [103]. The straightforward trial-and-error approach has typically been used in the field of industry. However, such case-by-case tuning was a time-consuming job for utility engineers. Hence, [34] implemented differential evolution metaheuristic algorithms to update P-Q controller gains automatically. Reference [80] obtained the optimal fixed gains based on the controller bandwidth and the phase margin of the single-phase inverter-based system. Although [34] and [80] found a fixed gain, the P-Q output of the inverter cannot be customized after different disturbances.

To make the IBRs more controllable, some adaptive strategies have been proposed to update P-Q controller gains in real time. Reference [8] proposed a robust load frequency control strategy using a fuzzy logic-based adaptive PI controller. In [190], a fuzzy-adaptive strategy was adopted to compensate for the dead time in the three-phase grid-connected inverter. Although the fuzzy logic controller has good performance in real-time gain scheduling, its membership function still needs an elaborate case-by-case design based on a

system model. Then, [12] developed a novel control strategy for grid-connected PV systems based on adaptive controllers. The controller gains are continuously updated based on the gradient of tracking error. Reference [92] designed an adaption law for inverter control based on the Lyapunov function. In [117], an adaptive controller was designed for a three-phase constant voltage constant frequency inverter with an output filter, using adaptive gain scheduling control and feedback control. References [99] and [176] discretized the control time window and scheduled gains according to real-time error. The above adaptive control theory-based methods have two disadvantages: 1) the shape of the inverter response cannot be freely designed and accurately controlled, which degrades the inverter’s flexibility and controllability; 2) some adaptive parameters still require case by case detailed design, which is not only time-consuming but is vulnerable to parameter or model uncertainties.

Existing adaptive microgrid P-Q controllers are not truly controllable because the P-Q output of the inverter cannot accurately track the predefined trajectories, and thus cannot respond to the customized grid-side demand. Therefore, this paper proposes an adaptive microgrid P-Q controller with trajectory tracking capability. To design such a P-Q controller, the first question to answer is ‘*whether there exists a P-Q controller or not that can track a predefined exponential response trajectory?*’. If it exists, then how can we find the controller gains without performing time-consuming gain tuning, and the controller itself can accommodate parameter or model uncertainties? The trajectory tracking concept was first proposed for voltage control [99, 100], and we extended it to P-Q control using an upgraded inverter model. Specifically, we developed an adaptive P-Q controller with time-varying gains to track the predefined trajectory, using a hybrid model-based and physics-informed RL approach.

The integration of physics knowledge is an effective way to ensure efficient and safe learning of RL [143]. For example, [186] proposed a physical-aware, safe multi-agent RL method for the power management of distributed generators and energy storage systems in microgrids, where the gradient information is applied for constraint satisfaction during the training process. Reference [138] narrowed down the learning space and avoided baseline violations of network physical constraints. Hence, we first perform model-based analysis to prove the existence of an adaptive PI controller with time-varying gains to guarantee the

predefined trajectory. The time-varying-gain is a function of time with a constant factor and an exponentially decaying factor. Then, a model-free deep RL algorithm known as the twin delayed deeper deterministic (TD3) policy gradient [82] is implemented to determine the time-varying PI gains, which is suitable for continuous control and proven to be more efficient than Deep Deterministic Policy Gradient (DDPG) algorithm by AI research [39] and engineering control research [49, 194]. With the guidelines provided by the model-based derivation, the RL agent just needs to find the real constant coefficients instead of the time-domain gain function. Hence, the learning space is narrowed down from a function space to a real space. This function reduction provides a new perspective on integrating physics knowledge into RL. It is more effective than value reduction and thus reduces the training complexity more significantly. This hybrid method can be applied to other systems that employ PI controllers and wish to have the desired system response.

2.2 Model-based Theory and Analysis

This section first derives the adaptive PI controller with time-varying gains that can track an exponential response trajectory with a specific time constant in a general feedback system, and then applies it in inverter P-Q control.

2.2.1 Adaptive PI controller

1) Transfer function

The conventional PI controller uses fixed gains, and its transfer function is obtained in (2.1).

$$G_{\text{Fixed}}(s) = \frac{Y(s)}{E(s)} = k_p + \frac{k_i}{s} \quad (2.1)$$

As shown in Figures 2.1(a)-(b), the diagram of the PI controller changes if time-varying gains are used. Because the multiplication operation in the time domain corresponds to the convolution operation in the frequency domain, the transfer function of the time-varying PI controller is derived as follows.

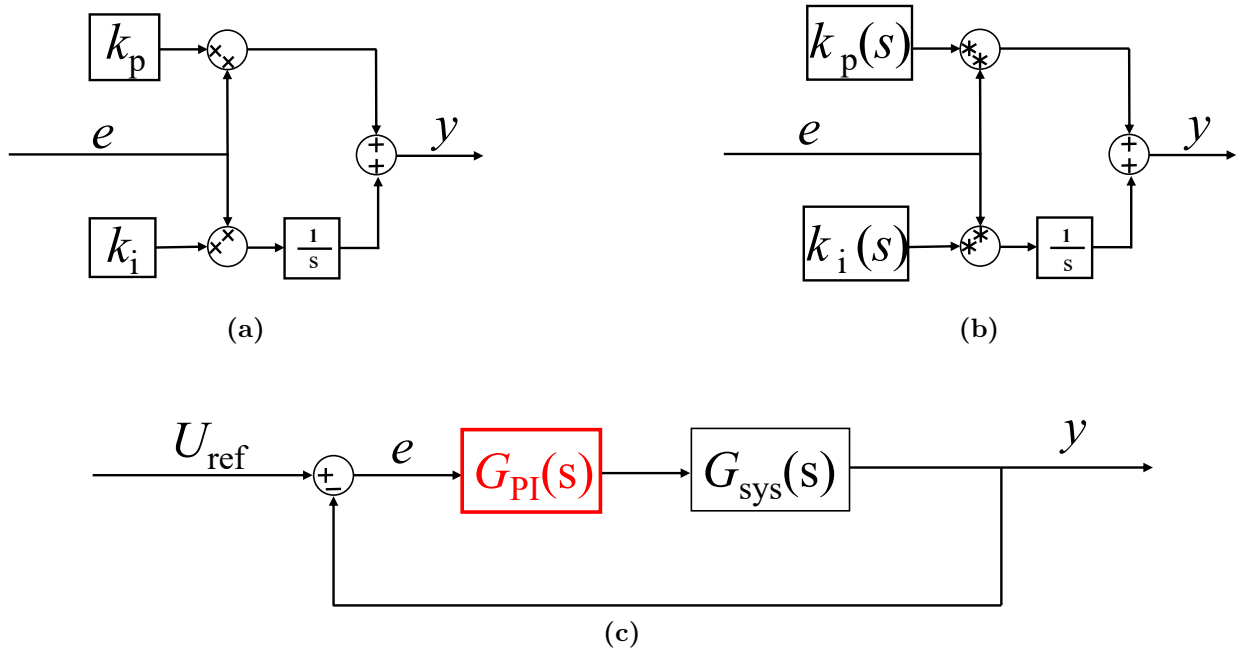


Figure 2.1: (a) Diagram of the fixed-gain PI controller; (b) Diagram of the adaptive PI controller with time-varying gains; (c) PI controller in a feedback system.

$$Y(s) = K_p(s) * E(s) + \frac{K_i(s) * E(s)}{s} \quad (2.2)$$

$$G_{\text{Varying}}(s) = \frac{1}{E(s)} \left[K_p(s) * E(s) + \frac{K_i(s) * E(s)}{s} \right] \quad (2.3)$$

where ‘*’ is the convolution operator.

In fact, if $K_p(s)$ and $K_i(s)$ in (2.3) are constant, (2.3) is identical to (2.1), which means the time-varying gain PI controller is simplified to the conventional fixed-gain PI controller.

2) Adaptive PI controller in a feedback system

When a general PI controller is implemented in a feedback system, such as the one shown in Figure 2.1(c), its transfer function is represented by the input error $E(s)$, system transfer function $G_{\text{sys}}(s)$, and system output $Y(s)$.

$$G_{\text{PI}}(s) = \frac{Y(s)}{E(s)} G_{\text{sys}}(s) \quad (2.4)$$

Combining (2.3) and (2.4), one obtains (2.5). Then, it is possible to derive $k_p(t)$ and $k_i(t)$ in the time domain when $G_{\text{sys}}(s)$ and $Y(s)$ are known or predefined.

$$K_p(s) * E(s) + K_i(s) * \frac{E(s)}{s} = \frac{Y(s)}{G_{\text{sys}}(s)} \quad (2.5)$$

2.2.2 Analytical formulation of adaptive gains

1) Design of ideal smooth trajectory

Assume the controller input U_{ref} is a step signal and the error e is a decaying exponential signal with a time constant τ in the control diagram shown in Figure 2.1(b), then the output y is an ideal smooth trajectory. Their expressions in the time domain and frequency domain are shown in (2.6) and (2.7), respectively.

$$u_{ref} = \begin{cases} 1 & t \geq 0 \\ 0 & t < 0 \end{cases} \quad e(t) = e^{-t/\tau}, \quad y(t) = 1 - e^{-t/\tau} \quad (2.6)$$

$$U_{ref} = \frac{1}{s}, \quad E(s) = \frac{1}{s + 1/\tau}, \quad Y(s) = \frac{1}{s} - \frac{1}{s + 1/\tau} \quad (2.7)$$

2) Derivation of adaptive gains

Assume $G_{sys}(s) = n(s)/m(s)$ and plug (2.6)-(2.7) in (2.5). Then,

$$K_p(s) * \frac{1}{s + 1/\tau} + K_i(s) * \frac{1}{s(s + 1/\tau)} = \frac{1}{\tau s(s + 1/\tau)} \cdot \frac{m(s)}{n(s)} \quad (2.8)$$

Next, perform an inverse Laplace transformation for both the left and right sides of (2.8). The left side is

$$\mathcal{L}^{-1}[\text{left side}] = \tau k_i(t) + [k_p(t) - \tau k_i(t)] e^{-t/\tau} \quad (2.9)$$

The system transfer function $G_{sys}(s)$ is found on the right side and determines whether or not the ‘left side = right side’ has a time domain solution. Let D represent the degree of a polynomial. $G_{sys}(s)$ can be categorized into three types based on the numerator and denominator degrees, which results in three different solutions.

Condition 1: $D[n(s)] = 0$ and $D[m(s)] \leq 2$. The system transfer function does not have zero points and thus will not bring a new pole to the right side. Then,

$$\begin{aligned} \mathcal{L}^{-1}[\text{right side}] &= \mathcal{L}^{-1} \left[\frac{1}{\tau s(s + 1/\tau)} \cdot \frac{m(s)}{n(s)} \right] \\ &= \mathcal{L}^{-1} \left[\frac{l_1}{s + 1/\tau} + \frac{l_2}{s} \right] \\ &= l_1 \cdot e^{-t/\tau} + l_2 \\ &= \mathcal{L}^{-1}[\text{left side}] \end{aligned} \quad (2.10)$$

$$k_p(t) = l_1 + l_2, \quad k_i(t) = l_2/\tau \quad (2.11)$$

where l_1 and l_2 are constants. In *Condition 1*, the adaptive PI controller changes to a conventional PI controller with fixed-gains.

Condition 2: $D[n(s)] \neq 0$ and $D[m(s)] - D[n(s)] \leq 2$.

$$\begin{aligned}
\mathcal{L}^{-1}[\text{right side}] &= \mathcal{L}^{-1} \left[\frac{1}{\tau s(s + 1/\tau)} \cdot \frac{m(s)}{n(s)} \right] \\
&= \mathcal{L}^{-1} \left[\frac{l_1}{s + 1/\tau} + \frac{l_2(s)}{s \cdot n(s)} \right] \\
&= l_1 \cdot e^{-t/\tau} + \mathcal{L}^{-1} \left[\frac{l_2(s)}{s \cdot n(s)} \right] \\
&= \mathcal{L}^{-1}[\text{left side}]
\end{aligned} \tag{2.12}$$

$$\begin{cases} k_p(t) = l_1 + \mathcal{L}^{-1} \left[\frac{l_2(s)}{s \cdot n(s)} \right] \\ k_i(t) = \mathcal{L}^{-1} \left[\frac{l_2(s)}{s \cdot n(s)} \right] / \tau \end{cases} \tag{2.13}$$

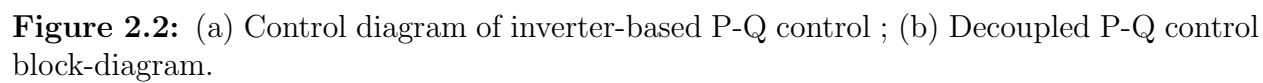
where l_1 is constant and $l_2(s)$ is an s function obtained through fractional decomposition. In *condition 2*, $k_p(t)$ and $k_i(t)$ are time-varying gains.

Condition 3: $D[m(s)] - D[n(s)] \geq 3$. The right side is irreversible because the numerator has a higher degree than the denominator. In *condition 3*, there is no solution for $k_p(t)$ and $k_i(t)$ in the time domain.

2.2.3 Inverter P-Q control with trajectory tracking capability

Figure 2.2(a) shows the complete diagram of this inverter-based P-Q control. The decoupled control diagram is shown in Figure 2.2(b) using the feedforward decoupling method. Here, the adaptive PI controller is only implemented in the P-Q regulator because the bandwidth of the inner current regulator is wider than that of the power regulator, and the output of the power regulator determines the shape of the final P-Q response. Furthermore, this paper assumes PLL is tuned properly and has wider bandwidths than the P-Q regulation loop [114, 191]. Note, although the model-based derivation does not encompass the dynamics of the PLL, it is modeled in great detail in both the numerical simulator and HIL experiment. Implementing a data-driven approach in Section III could eliminate the modeling errors.

Based on Figure 2.2, $G_{sys}(s)$ is written in (2.14).



$$G_{\text{sys}}(s) = \frac{K_{pwm}(k_{p2}s + k_{i2})}{wL_f s^2 (1 + 1.5T_s s) + K_{pwm}(k_{p2}s + k_{i2})} \quad (2.14)$$

where k_{p2} and k_{i2} are fixed-gains of the current regulator in Figure 2.2(a). Assume $G_{\text{sys}}(s) = n(s)/m(s)$, then $D[n(s)] = 1$, $D[m(s)] = 3$, and $D[m(s)] - D[n(s)] = 2$, satisfying *Condition 2*. Through fractional decomposition, the $k_p(t)$ and $k_i(t)$ of the power regulator are shown in (2.15).

$$\begin{cases} k_p(t) = k_{p0} + k_{p1}e^{-t/\tau'} \\ k_i(t) = k_{i0} + k_{i1}e^{-t/\tau'} \end{cases} \quad (2.15)$$

where

$$\begin{cases} k_{p0} = \frac{L_f(1-1.5T_s/\tau)}{\tau K_{pwm}(k_{i2}/k_{p2}-1/\tau)} \\ k_{p1} = \frac{L_f}{\tau K_{pwm}} \left(1.5T_s + \frac{1.5T_s/\tau-1}{k_{i2}/k_{p2}-1/\tau} \right) \\ k_{i0} = 0, k_{i1} = k_{p1}/\tau \\ \tau' = k_{p2}/k_{i2} \end{cases} \quad (2.16)$$

The adaptive gains that can help track a predefined P-Q trajectory consist of a constant factor and an exponentially decaying factor. The four constant coefficients k_{p0} , k_{p1} , k_{i0} , and k_{i1} as well as the decaying time constant τ' are determined by PWM gain K_{pwm} , sampling delay T_s , filter reactance L_f , trajectory time constant τ , and fixed current regulator PI gains k_{p2} and k_{i2} .

2.2.4 Importance and challenges of analytical formulation

The analytical formulation in the previous subsections illustrates that there exists an adaptive controller that can perfectly track a predefined trajectory following an exponential decay. The derivations, on the other hand, give a theoretical foundation for controller design, while the previous works [100] only determined how to track a given trajectory. Although this model-based mathematical proof is rigorous, it may not be suitable for direct implementation in a real-world system for the following reasons:

- It is difficult to model each component of the inverter in detail.

- The microgrid parameters are not always accessible; even if accessible, they are not necessarily accurate.
- Model-based suggestions also require further manual adjustments in the real application. The more simplified model needs more tuning effort.

With these challenges as our motivations, a data-driven approach is proposed to implement the adaptive P-Q control in the next section.

2.3 Physics-informed Learning and Power HIL Demonstration

This section implements the adaptive P-Q controller in a physics-informed data-driven way and demonstrates it through power HIL experiments.

2.3.1 Motivation for deep reinforcement learning

To address the application challenges discussed in the above subsection, a deep RL approach is implemented with the following considerations.

- RL is goal-oriented and can output sequences of actions. Also, it does not require a large number of labeled datasets like supervised learning.
- RL is adaptable because the uncertainties of the model and parameters are offset by the interactive training between the agent and environment.
- Since RL is an intelligent algorithm, it releases microgrid operators from time-consuming manual tuning.

Although the RL agent can directly replace the PI controller and output control signals, its training complexity will increase exponentially as the discretized control interval decreases. Also, the output of PI controller is somehow unpredictable, making it difficult to set a safe range for power electronics control. To address this issue, we further narrow down the learning space based on physical knowledge. Because the derived coefficient has a typical range based on engineering practice, this physics-informed implementation can improve the safety of the data-driven method and avoid damaging the hardware device.

2.3.2 Physics-informed reinforcement learning

1). Overview of the proposed framework

Figure 2.3 shows the general framework of the proposed method, where the offline training is performed in numerical simulators (Matlab-Simulink and Python) and training results are further validated through online power HIL experiments. Python receives the buffer data generated by Simulink to update the parameters of the actor and critic networks. In reverse, Simulink receives the actions in Python to regenerate the buffer data. This process repeats until the rewards converge. Then, the well-trained parameterized policy is implemented online in the CURENT HTB for further demonstration.

2) Physics-informed TD3 implementation

This subsection exemplifies the physics-informed design of a single inverter. Note that the proposed method is scalable because the inverter P-Q control is local and independent of the knowledge of other generators.

(i). Control Agent: Each inverter holds two control agents for the active power (P) loop and the reactive power (Q) loop, each with an actor and a critic parameterized by fully connected neural networks (NNs). The actor outputs control gains and the critic estimates the Q -value of state-action pair. In TD3, actor and critic are further extended into twin NNs to prevent the overestimation of the Q -value.

(ii). State Set: The P loop state vector is defined as $\mathbf{S}^P = [\Delta P_{ref}, P_t, \tau, T_s]$, while that for Q loop agent is $\mathbf{S}^Q = [\Delta Q_{ref}, Q_t, \tau, T_s]$.

(iii). Action Set: The action vector is defined as $\mathbf{a} = [k_{p0}, k_{p1}, k_{i0}, k_{i1}, \tau']$, which means the agent outputs four coefficients and a time constant. Then, real-time k_p and k_i can be further calculated based on the model-based derivation in (2.15). The decaying exploration noise was added and implemented in the TD3 training. Without the model-based conclusion, the agent must output real-time gains following the simulation step size throughout the whole episode in Simulink, which may result in millions of distinct actions in each episode.

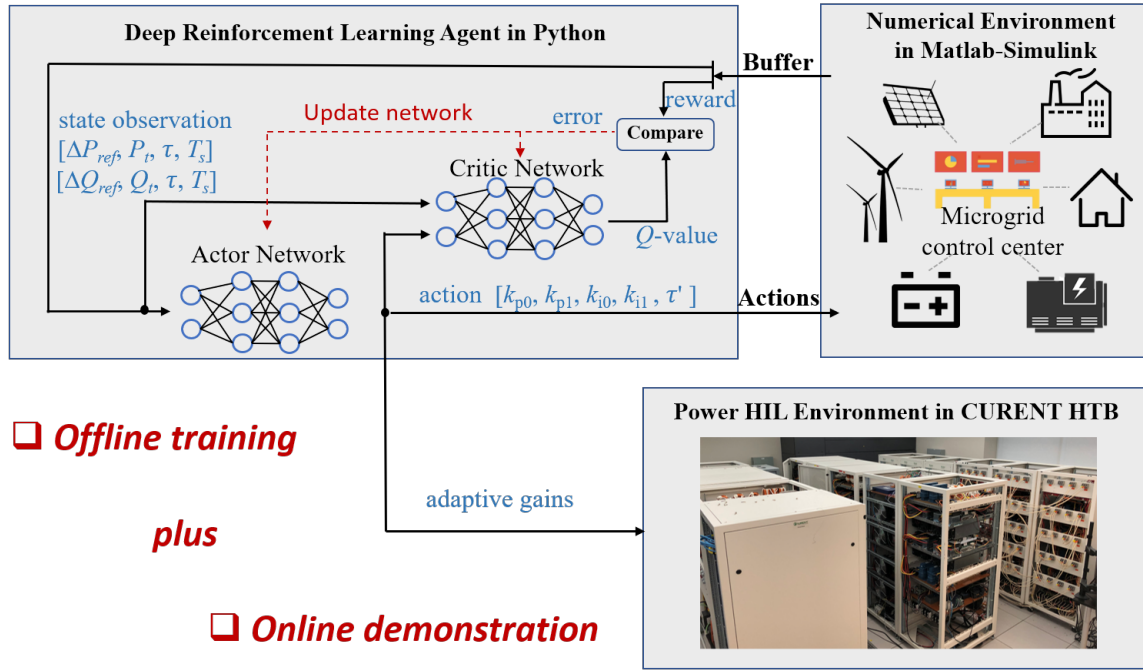


Figure 2.3: Diagram of physics-informed learning in the numerical simulator and power HIL demonstration in HTB.

(iv). Control Policy: The control policy is denoted as π_θ , a deterministic function with parameter θ . It is actually the parameterized actor outputting the deterministic actions $\mathbf{a} = \pi_\theta(\mathbf{S})$.

(v). Design of reward function: The training reward is designed as an integral part of the error between the real-time P-Q output and the designed trajectory. To better differentiate the features of the real-time trajectory, e.g., initial oscillation, overshooting, and steady-state errors, the reward function has a punishment factor γ . The final reward function for active power and reactive power regulation is shown in (2.17).

$$r = \frac{1}{2} (r_P + r_Q) \quad (2.17)$$

where

$$\begin{aligned} r_P &= - \int \gamma(t) \cdot [P_{trj}(t) - P(t)] dt \\ r_Q &= - \int \gamma(t) \cdot [Q_{trj}(t) - Q(t)] dt \end{aligned} \quad (2.18)$$

(vi). Policy update: After defining the required set, the agent keeps interacting with the environments and updating the policy through temporal-difference learning. The complete training process is detailed in *Algorithm 1*. Physics-informed TD3 implements three training techniques to prevent the overestimation of the Q -value in DDPG [105]-[93] and use physics information to reduce training complexity.

- Twin critic networks: two critic networks estimate the state-action value at the same time, and the smaller one is chosen as the estimated Q -value, as shown in line 12, *Algorithm 1*.

- Delayed update of target and policy: the updated frequency of the critic network is higher than that of the actor network, as shown in line 13, *Algorithm 1*.

- Target policy smoothing: random noise is added to $\pi_{\theta_a}(\mathbf{S})$ when the actor network outputs the future actions, as shown in line 10, *Algorithm 1*.

- Physics-informed action mapping: The output of the actor network was transformed to real-time gains based on (2.15), as shown in line 7, *Algorithm 1*. This physics integration also induced an additional chain-rule-based gradient ∇f_a , as illustrated in line 14, *Algorithm 1*.

Algorithm 1 Physics-informed TD3 Training

- 1: Select $T, N, \mathbf{b}, \boldsymbol{\sigma}, \boldsymbol{\eta}, \boldsymbol{\alpha}$
 - 2: Initialize $\boldsymbol{\theta}_a$ and $\boldsymbol{\theta}_c$; Initialize physics function f based on (2.15)
 - 3: Initialize replay buffer $\mathbf{B}$
 - 4: for $t \leftarrow$ to T do
 - 5: $\mathbf{S} \leftarrow \mathbf{S}'$ [Update state]
 - 6: $\mathbf{a} = \pi_{\boldsymbol{\theta}}(\mathbf{S}) + \mathcal{E}$, where $\varepsilon \sim N(0, \boldsymbol{\sigma})$ [Select action]
 - 7: $k_p, k_i \leftarrow f(\mathbf{a})$ [Physics-informed action mapping]
 - 8: $\mathbf{B} \leftarrow$ Append $(\mathbf{S}, \mathbf{a}, r, \mathbf{S}')$ [Store transition tuple]
 - 9: $\mathbf{B}_M \leftarrow \mathbf{B}'_M$ [Sample mini-batch tuples]
 - 10: $\mathbf{a}' = \pi_{\boldsymbol{\theta}_a}(\mathbf{S}) + \mathcal{E}'$, where $\mathcal{E}' = \text{clip}(\mathcal{E}, -\mathbf{b}, \mathbf{b})$
 - 11: $y \leftarrow r + \alpha \min(Q_{\boldsymbol{\theta}_{c1}}(\mathbf{S}', \tilde{\mathbf{a}}), Q_{\boldsymbol{\theta}_{c2}}(\mathbf{S}', \tilde{\mathbf{a}}))$
 - 12: $\boldsymbol{\theta}_c \leftarrow \text{argmin}_{\boldsymbol{\theta}_c} \mathbf{E} \sum [y - Q_{\boldsymbol{\theta}}(S, a)]^2$ [Update critics]
 - 13: **if** $t \bmod d$ **then**
 - 14: $\nabla J(\boldsymbol{\theta}) = E \nabla_a Q_{\pi_{\boldsymbol{\theta}}}(s, a)|_{a=\pi_{\boldsymbol{\theta}}(s)} \nabla_{\boldsymbol{\theta}} \pi_{\boldsymbol{\theta}}(s) \nabla f_a$ [deterministic policy gradient]
 - 15: $\boldsymbol{\theta}_a \leftarrow \boldsymbol{\eta} \boldsymbol{\theta}_a + (1 - \boldsymbol{\eta}) \boldsymbol{\theta}'_a$ [Soft update for target actor networks]
 - 16: $\boldsymbol{\theta}_c \leftarrow \boldsymbol{\eta} \boldsymbol{\theta}_c + (1 - \boldsymbol{\eta}) \boldsymbol{\theta}'_c$ [Soft update for target critic networks]
 - 17: **end if**
 - 18: **end for**
 - 19: Output well-trained parameterized policy $\pi(\boldsymbol{\theta}_a)$
-

2.3.3 Power HIL demonstration

1) Power HIL environment

As shown in Figure 2.3, a power HIL experiment is involved to further demonstrate the proposed control method. The HIL environment will be emulated through CURENT HTB, which uses identical commercial-grade power electronics inverters to emulate real microgrids. Each inverter in the HTB is programmed digitally with built-in digital signal processors (DSPs) to behave as various devices, including sources, loads, energy storage, and solar PV [187, 159]. HTB has various interfaces with a real-time simulator, so the trained policy will be programmed through RSCAD® to control the hardware devices. The detailed configuration of a test microgrid will be illustrated in Subsection 2.4.4.

2) Safe HIL demonstration

Because the RL agent may output bad actions and damage the hardware devices during the exploration, the offline learning results are demonstrated in the power HIL environment after the reward curve converges in the numerical simulator. The converged reward curve means the policy is well-parameterized. Further, the HIL environment is equipped with some protection devices and built-in protection algorithms to guarantee safe data-driven implementation. Once a voltage or current exceeds the predefined threshold, switches will be turned off to isolate the endangered device or shut down the whole system.

2.4 Case Studies

2.4.1 Test system: modified Banshee microgrid

Figure 2.4 shows the single-line diagram of the test microgrid to demonstrate the proposed adaptive P-Q controller. The test microgrid is modified from the Banshee distribution system [137, 140] by keeping feeder 1 and adding renewable energy and energy storage devices. A 500 kW BESS on Bus 102 and a 2,500 kW PV device on Bus 105 diversify the power sources. The BESS supplements the diesel generator for power output. When combined with the

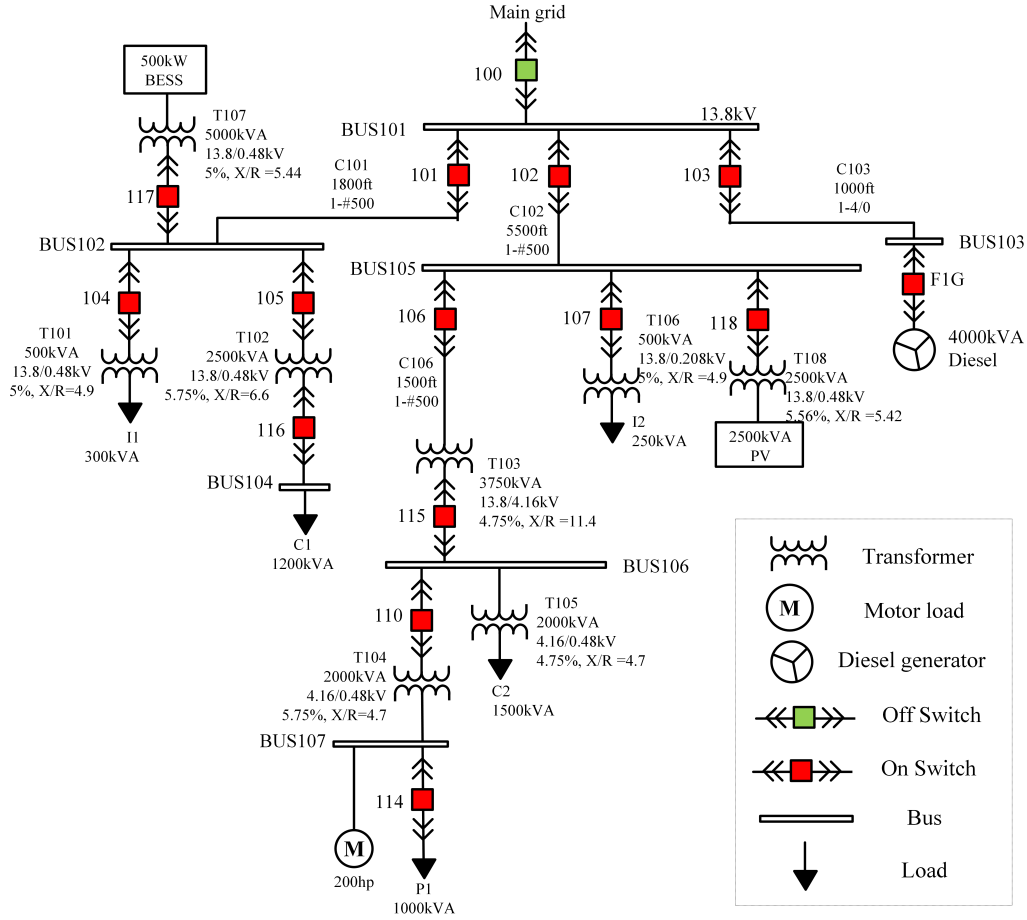


Figure 2.4: Single-line diagram of modified Banshee microgrid.

BESS and diesel generator, the PV device can achieve all-day self-sustaining operation in grid-forming modes.

2.4.2 Training in numerical simulators

1) Basic settings

The proposed adaptive PI controller is implemented in the BESS connected to Bus 102. Through normalization, the active (P) and reactive (Q) loops can share one PI controller in the training process. After training, two PI controllers are then applied in the P and Q loops separately to enable asynchronous control of active and reactive power.

2) Distinct settings with and without the physics information

To show the advantages of the physics-informed learning approach, the RL agent is trained with and without model derivations. The key training parameters are listed in Tables 2.1 and 2.2. The main difference between the methods with and without physics information lies in the state and action sets, which further result in differences in the design of actor network and critic network, and the final search space.

With the physics information, the state vector is defined as $\mathbf{S}_t^P = [\Delta P_{ref}, P_t, \tau, T_s]$ and the action vector as $\mathbf{a} = [k_{p0}, k_{p1}, k_{i0}, k_{i1}, \tau']$. Hence, the critic network has $[\mathbf{S}_t^P, \mathbf{a}]$ (4+5 elements) as input and Q -value (1 element) as output, and the actor network has $\mathbf{S}_t^P$ (4 elements) as input and $\mathbf{a}$ (5 elements) as output. The actor network outputs four constant coefficients and a time constant that are independent of the time at the beginning of each episode, which is then transformed to real-time k_p and k_t based on the model-based derivation in (2.15).

Without the physics information, the RL agent shares the same state vector but has a different actor vector as $\mathbf{a} = [k_p, k_i]$. Hence, the actor network has $\mathbf{S}_t^P$ (4 elements) as input and $\mathbf{a}$ (2 elements) as output. Note that $\mathbf{a}$ is dependent on time without knowing (2.15). Then, the actor network must output real-time gains following the simulation step size throughout the whole episode in Simulink, which may result in millions of distinct actions in a single episode.

Table 2.1: Key parameters of TD3 training with model-based derivation

Item	Parameters
Punishment factor	$\gamma(t) = 20t + 1$
Actor network structure	$[4] \times [256] \times [256] \times [5]$
Critic network structure	$\begin{bmatrix} 4 \\ 5 \end{bmatrix} \times \begin{bmatrix} 32 \\ 32 \end{bmatrix} \times [256] \times [256] \times [1]$
Actor network update frequency	20
Actor network learning rate	0.0005
Critic network learning rate	0.001
Optimizer	Adam
Simulation step size in Simulink	5×10^{-5}

Table 2.2: Key parameters of TD3 training without model-based derivation

Item	Parameters without model-based derivation
Punishment factor	$\gamma(t) = 20t + 1$
Actor network structure	$[4] \times [256] \times [256] \times [2]$
Critic network structure	$\begin{bmatrix} 4 \\ 2 \end{bmatrix} \times \begin{bmatrix} 32 \\ 32 \end{bmatrix} \times [256] \times [256] \times [1]$
Actor network update frequency	20
Actor network learning rate	0.0005
Critic network learning rate	0.001
Optimizer	Adam
Simulation step size in Simulink	5×10^{-5}

3) Training results

All simulations have been performed in MATLAB® version R2020a, Python version 3.7, and Tensor flow version 2.1 with a PC Intel® Core i7-8665U CPU at 2.10 GHz and 16 GB RAM. Figure 2.5 shows the TD3 training results. The training time with and without physics guidelines for a single episode is around 5.45s and 10.67s, respectively. In Figure 2.5, the average reward curve based on model analysis converges after training for 6,000 episodes, while the reward curve without model analysis cannot converge. The physics guidelines provided by model-based derivation greatly reduce the training complexity and, therefore, facilitate convergence and reduces training time.

2.4.3 Validation in numerical simulators

This subsection verifies the model-based derivation and physics-informed TD3 training results in a numerical simulator. Because the modified Banshee microgrid is more vulnerable to disturbances in islanded mode (switch 100 is off in Figure 2.4), this subsection mainly shows the islanded test results. Three scenarios, i.e., scheduling reference change, generation loss, and grounded faults, are demonstrated with distinct assigned time constants. The conventional fixed-gain PI controller and the adaptive controller in [92] work as the benchmark to show the superior performance of the physics-informed RL approach. Considering that one group of fixed gains can only track a specific predefined trajectory, we manually update these gains when assigned a new trajectory time constant to improve the performance of fixed-gain controllers and make a fair comparison.

1) Scenario 1: Scheduling reference change

In Scenario 1, the reference values of the P-loop and Q-loop are scheduled to change, which includes two sub-conditions as follows.

(i). *Scheduling single-loop single-step reference change*: P_{ref} changes from 0 to 100 kW at 1 s. Figure 2.6 depicts the active power of the inverter under scheduling single-loop single-step changes when applying the proposed method. The gray and black dashed lines represent the predefined trajectories and steady-state reference, respectively.

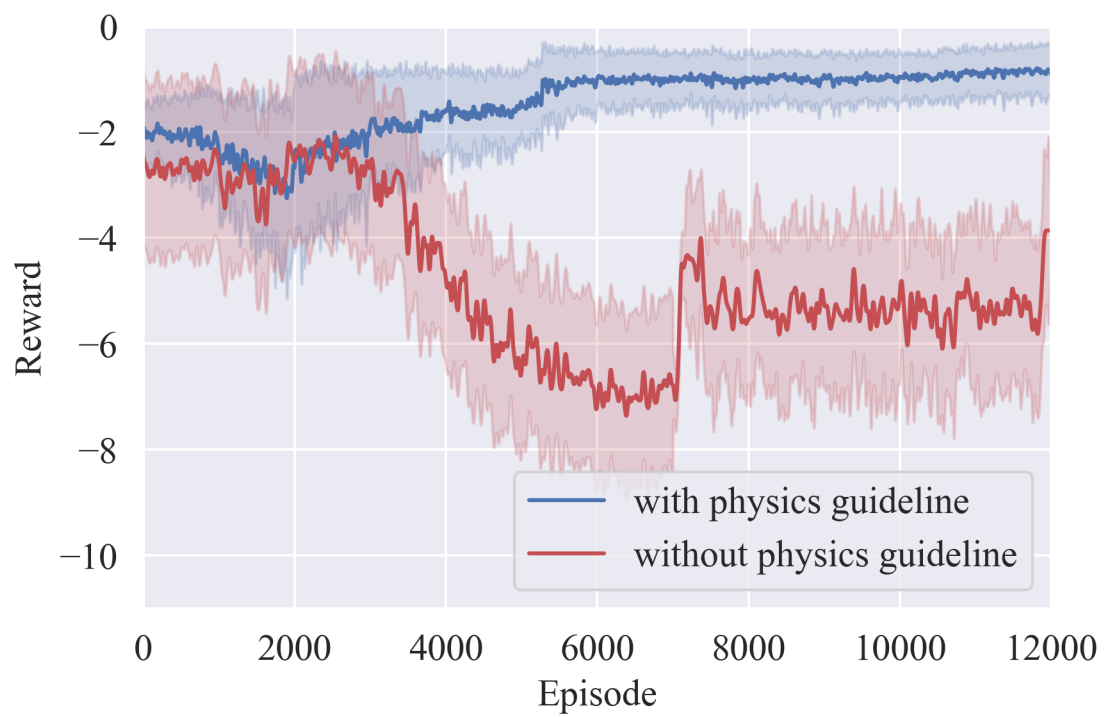


Figure 2.5: Reward curve with and without physics guideline.

In Figure 2.6, the active power response almost coincides with the trajectories when the RL agent adaptively tunes the PI controllers. This verifies the effectiveness of the model-based derivation in Section II and the training results in Subsection IV-B.

Figure 2.7 further shows the trajectory tracking errors when applying different controllers. In Figures 2.7(a)-(c), the physics-informed approach has minimum tracking error for any trajectory time constant. Particularly, the fixed-gain controller and the adaptive controller in [92] have obvious tracking errors with $\tau = 0.5$, as detailed in Figure 2.7(c). This demonstrates the superiority of the proposed physics-inform data-driven approach.

(ii) *Scheduling double-loop cascaded-step reference change:* P_{ref} and Q_{ref} continuously change at 0 s, 2 s, and 4 s. To verify the robustness of the offline training, P-loop and Q-loop trajectories are assigned distinct time constants of 0.1 and 0.2, respectively. Figure 2.8 shows the inverter response with the proposed method under the scheduling of a double-loop cascaded-step reference change.

In Figure 2.8, the actual P-Q response follows the predefined trajectories exactly, which means that the active power and reactive power can be controlled separately and simultaneously with the proposed method. As visualized in Figure 2.9, the trajectory tracking errors are close to zero with the physics-informed TD3 controller, whereas for the fixed gain controller and the adaptive control in [92], there are noticeable trajectory errors, especially at the beginning of the reference change.

2) Scenario 2: Generation loss

The uncertainty of renewable energy resources may result in the loss of generation from time to time. In Scenario 2, it is assumed that the PV panel loses 100 kW of generation at 1 s. The P_{ref} of the BESS increases from 0 to 100 kW to compensate for the generation loss. Similar to Scenario 1, three different time constants are assigned to the active power trajectory.

Figure 2.10 shows that the inverter output can closely follow the predefined trajectories when using the proposed controller, as demonstrated by the active power response. In addition, Figure 2.11 illustrates the trajectory tracking errors for three different controllers, where the fixed-gain controller and the adaptive method in [92] have large tracking errors.

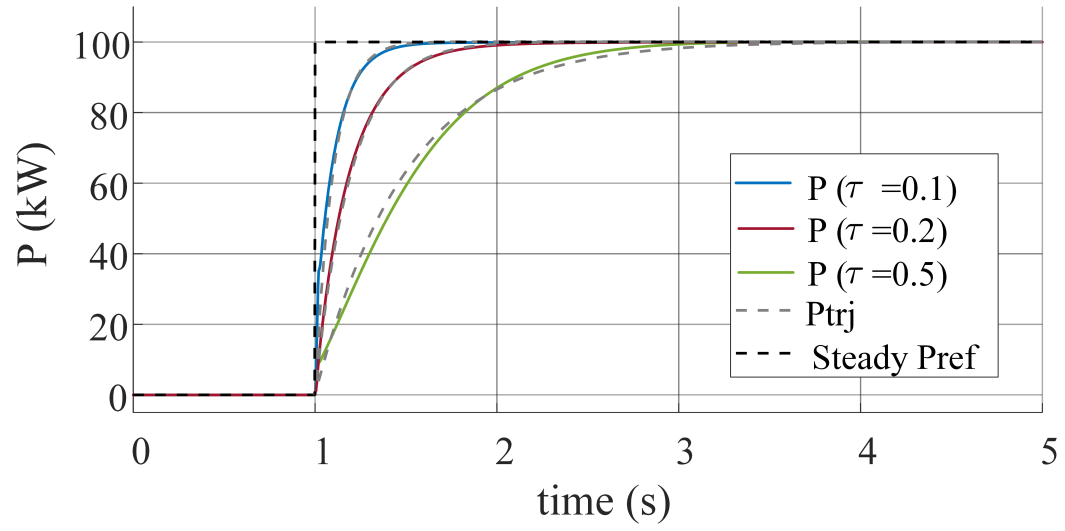
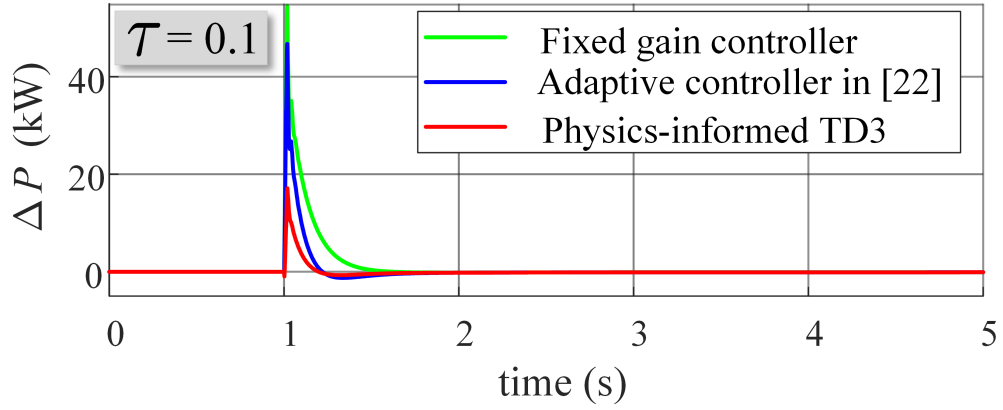
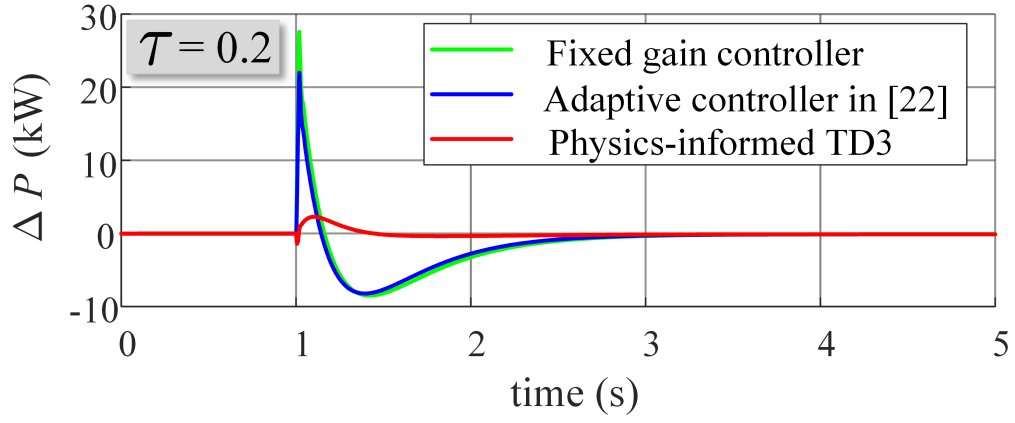


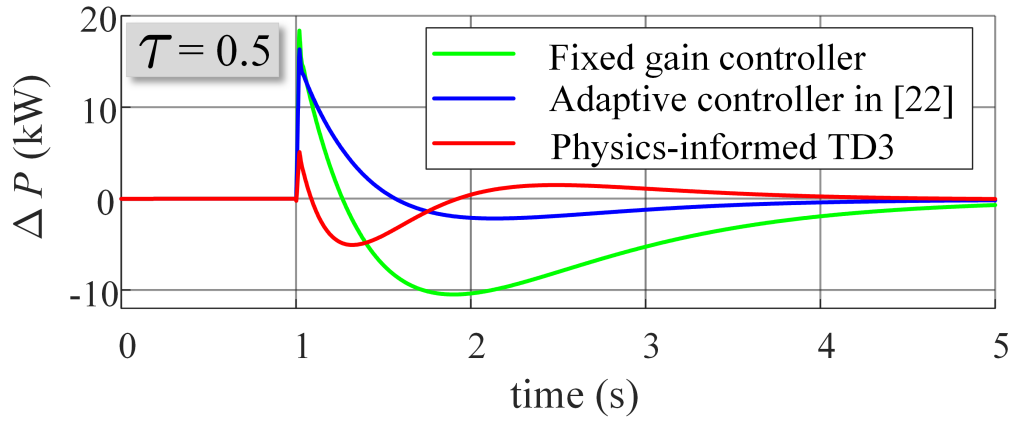
Figure 2.6: Inverter response with the proposed method under scheduling single-loop single-step reference change.



(a)



(b)



(c)

Figure 2.7: Comparison of trajectory tracking errors with different controllers for single-loop single-step reference change: (a) $\tau = 0.1$; (b) $\tau = 0.2$; (c) $\tau = 0.5$.

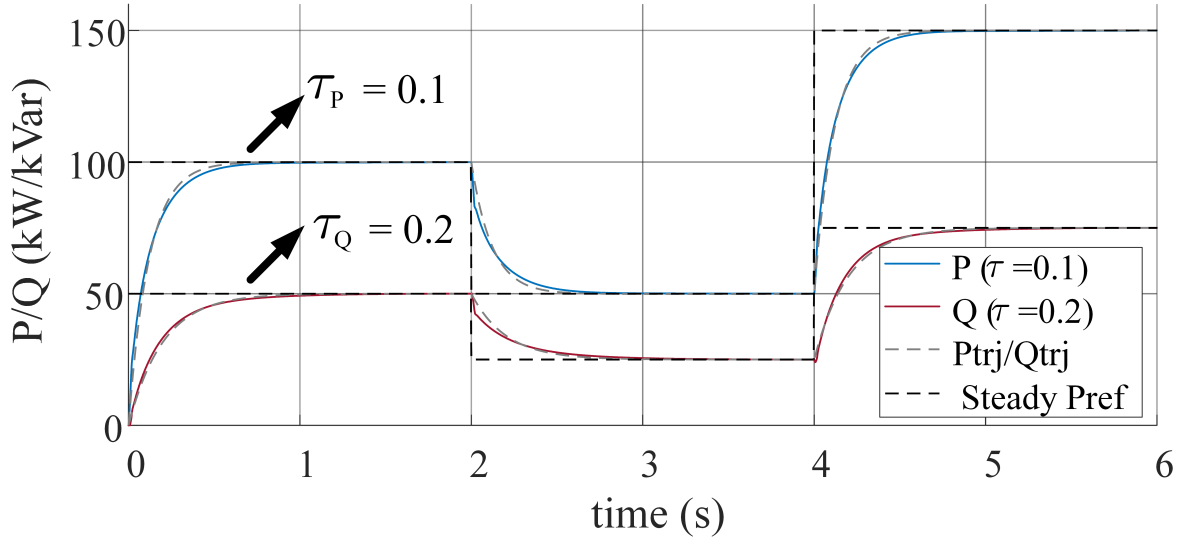
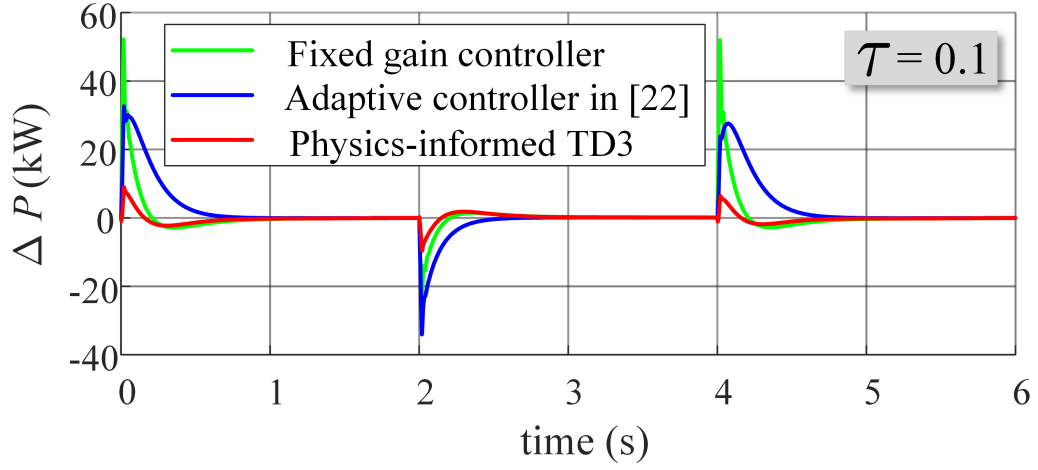
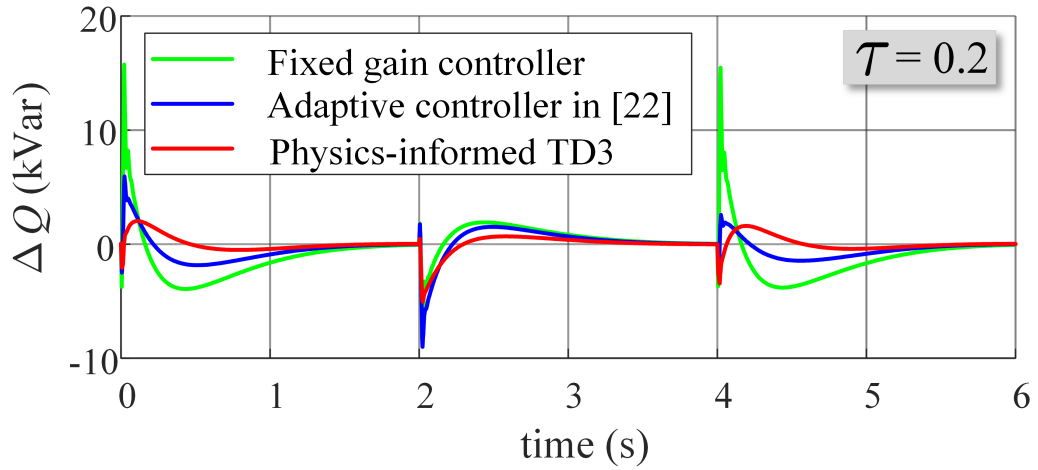


Figure 2.8: Inverter response the proposed method under scheduling double-loop cascaded-step reference change.



(a)



(b)

Figure 2.9: Comparison of trajectory tracking errors with different controllers for double-loop cascaded-step reference change: (a) $\tau = 0.1$; (b) $\tau = 0.2$; (c) $\tau = 0.5$.

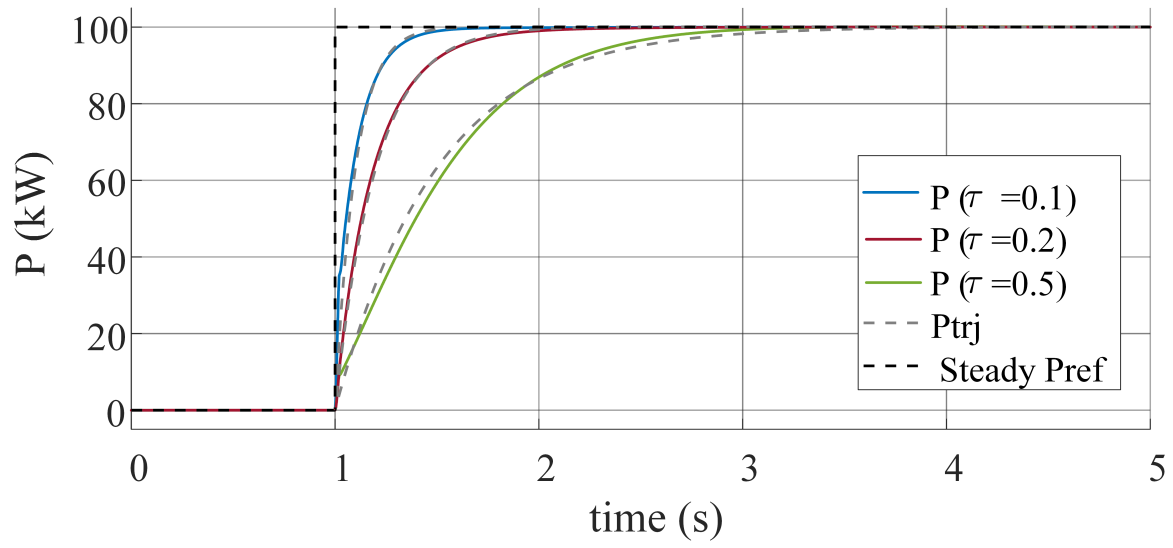
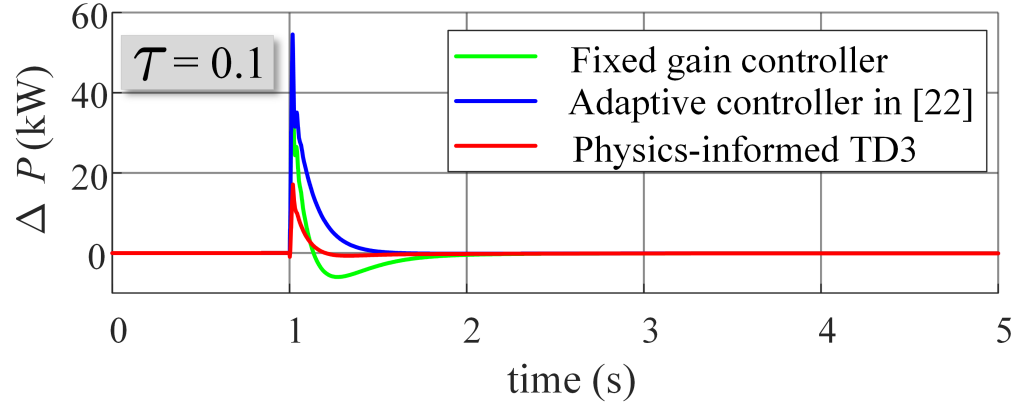
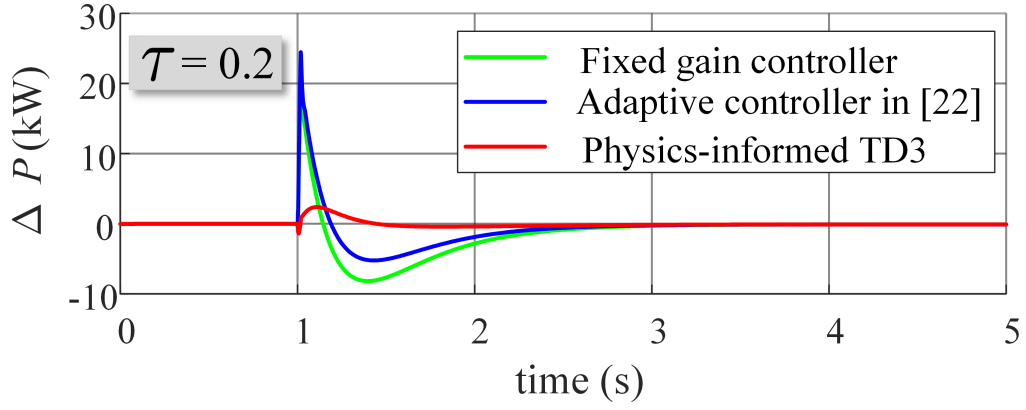


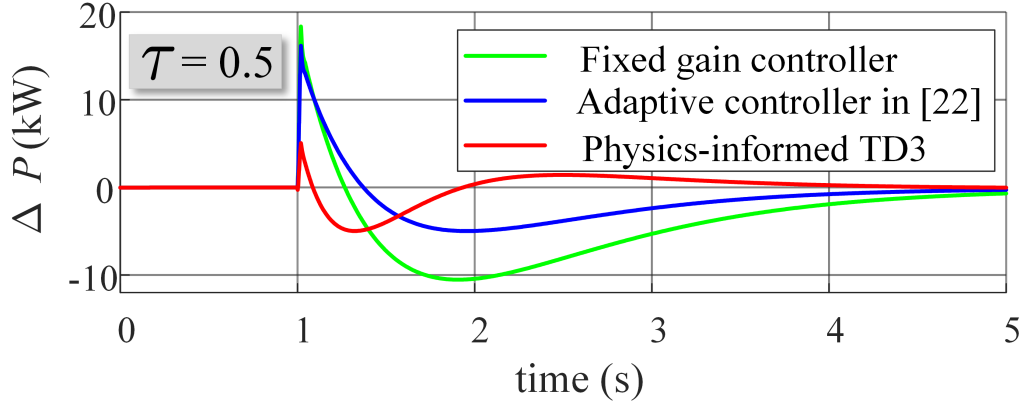
Figure 2.10: Inverter response with the proposed method under generation loss.



(a)



(b)



(c)

Figure 2.11: Comparison of trajectory tracking errors with different controllers for generation loss: (a) active power; (b) reactive power.

Despite continuously updating k_p and k_i online based on the pre-configured adaptation law in [92], the tracking errors are still larger than those of the proposed approach.

3) Scenario 3: Grounded Fault

Assume a three-phase grounded fault occurs in transformer T106 at 5 s. Then, switch 107 is turned off to isolate the faults after 4 cycles (0.067 s). Instantly after the fault clearance, the BESS adjusts its output to follow the load change and thus mitigates the voltage and frequency deviations dynamically. Originally, $P_{ref} = 325$ kW and $Q_{ref} = 159$ kVar. P_{ref} and Q_{ref} are then changed to 100 kW and 50 kVar at 5.067 s to offset the 250 kVA shed load connected to T106.

Figure 2.12 shows the inverter response, where the inverter output has obvious dips during the fault. With the proposed method, the active and reactive power can simultaneously track the predefined trajectories right after the fault clearance. Figure 2.13 further shows the trajectory tracking errors with different controllers. During the fault, all three controllers have evident tracking errors. Applying the proposed physics-informed approach quickly mitigates the tracking error instantly after the fault clearance. However, the fixed-gain controller has a considerable tracking delay (large negative tracking error), whereas the adaptive controller in [92] shows a significant overshoot (large positive tracking error) right after the fault clearance. These results confirm the superiority of the proposed physics-informed data-driven approach.

In general, the proposed P-Q controller can accurately follow any predefined trajectory after a disturbance. It has smaller trajectory tracking errors and better adaptability than the existing methods. The numerical simulation demonstrates that the model-based derivation is valid, the TD3 agent is well-trained, and the exponentially decaying time constant can be freely assigned to the P-Q response trajectory.

2.4.4 Validation in CURENT HTB

To further validate the proposed adaptive P-Q controller, a power HIL experiment is performed in CURENT HTB [159] to validate the well-trained parameterized policy $\pi(\theta_a)$.

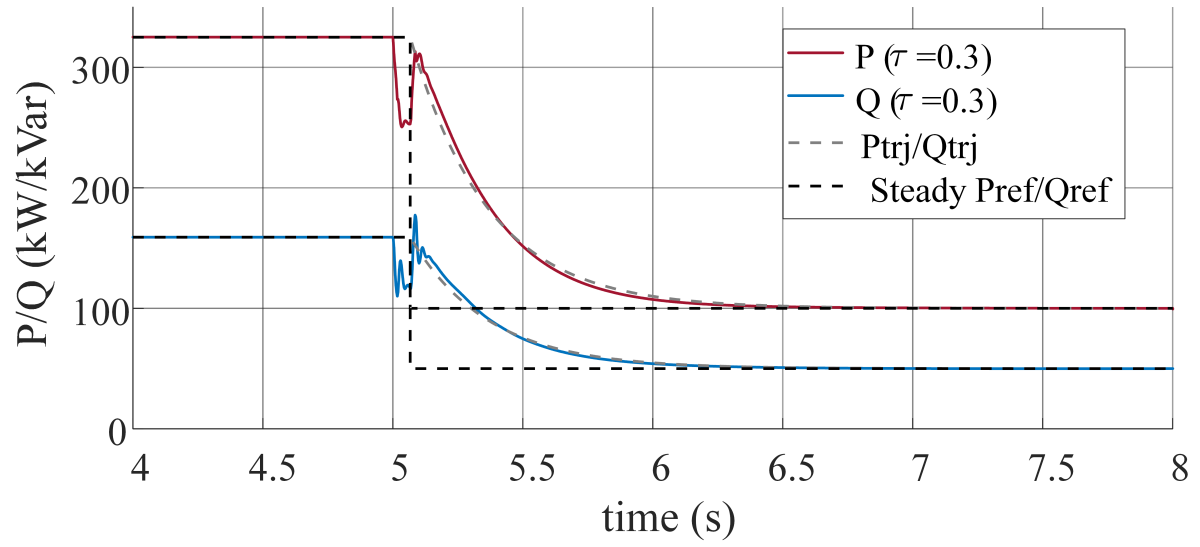
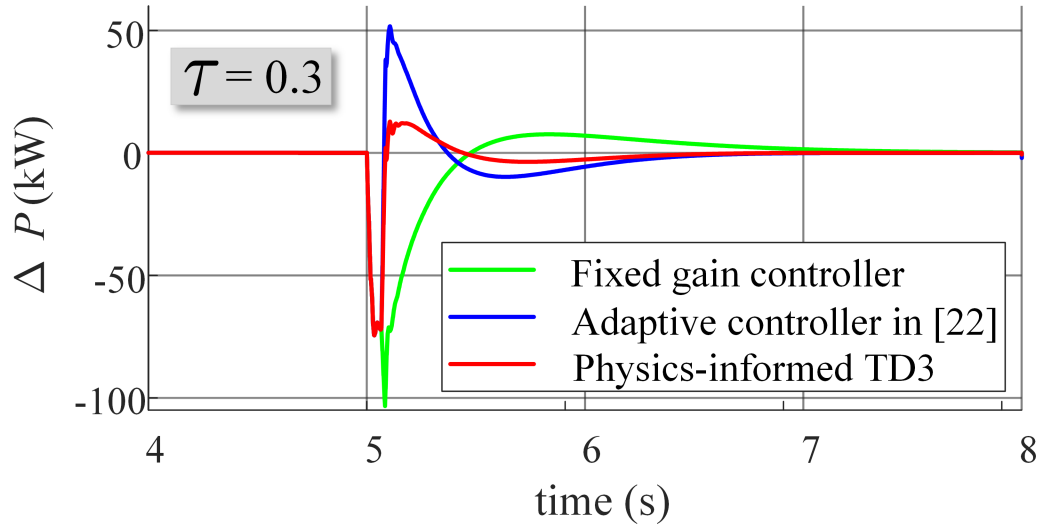
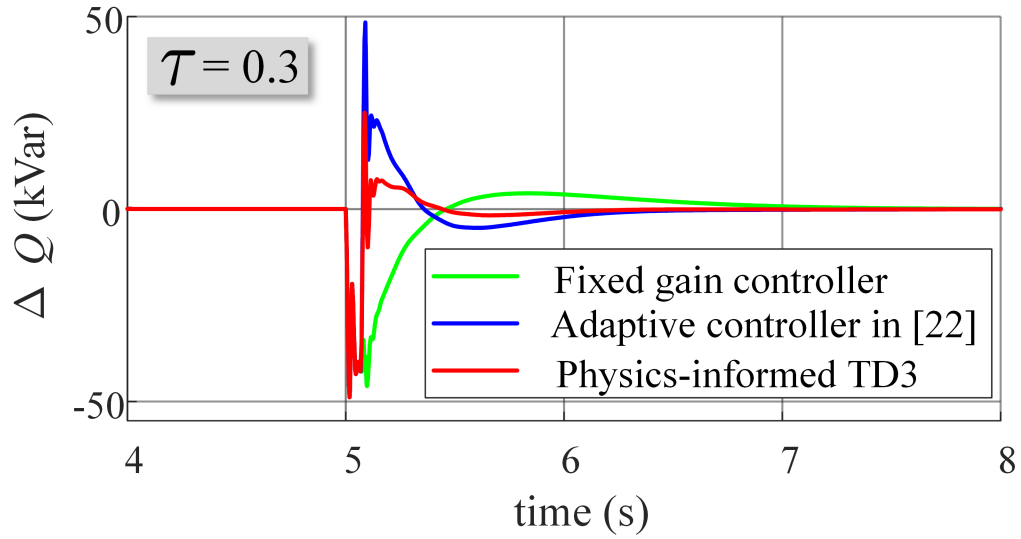


Figure 2.12: Inverter response with the proposed method under grounded fault.



(a)



(b)

Figure 2.13: Comparison of trajectory tracking errors with different controllers for grounded fault: (a) active power; (b) reactive power.

1) Configuration of a modified Banshee microgrid in CURENT HTB

There are generally six types of grid elements in the modified Banshee microgrid, i.e., the connection line, transformer, impedance-type load, motor load, inverter-based generation, and diesel generation. The impedance of the transformer is integrated into the connection line, which is emulated by real inductance. Except for the connection line and grid-following inverter, the rest of the elements are emulated by voltage-controlled current source inverters.

Four cabinets are involved in the configuration of the modified Banshee microgrid. The first cabinet contains the inductors and switches to fix the grid topology; the second cabinet contains several inverters to emulate the constant impedance loads; the third cabinet contains four inverters, two of which are to emulate synchronous generator and motor loads; and the last cabinet contains two inverters and the interface with RTDS. Figure 2.14 shows how HTB is controlled, where Figure 2.14(a) is the diagram of the communication structure and 2.14(b) is the control panel when testing the adaptive PI controller. The video on the CURENT YouTube channel shows the detailed configuration [144]. A more detailed introduction to measurement, control, and communication architecture can be found in Section III of [187].

2) Controller validation

Scheduling power reference change and generation loss are validated through the HTB. To test the generalization of the proposed method, a new time constant of $\tau = 0.4$ is assigned to the trained RL agent to output the adaptive gains for inverters in addition to the time constants of $\tau = 0.1$ and $\tau = 0.2$ used in numerical validation. Further, the initial P_{ref} is modified from 0 to 50 kW.

The secondary controller was not implemented in HTB to better observe the impacts of assigned time constants on system dynamics. Hence, the steady state frequency may deviate from the nominal value after intentional power injection and generation loss.

The response of inverters employing the adaptive P-Q controller to track the predefined trajectory is shown in Figure 2.15. As shown in Figure 2.15(a) and 2.15(b), the actual P-Q response follows the predefined trajectories exactly, demonstrating the model-based analysis and the physics-informed learning.

The frequency curves further indicate how the proposed method could help the grid work better. Specifically, faster power injection is beneficial to the microgrid when it needs support; while in normal conditions, the inverters are expected to have slower intentional power injection because the injected power breaks down the load-generation balance.

In the scenario of generation loss shown in Figure 2.15(b), the blue curve RL agent was assigned a smaller time constant ($\tau = 0.1$), so it has faster active power injection after generation loss around 1 s. Then, the blue curve frequency recovers faster than the other two curves. In the scenario of the intentional reference change shown in Figure 2.15(a), the power reference was changed from 50 kW to 100 kW. Then, the green curve frequency ($\tau = 0.4$) deviates slower from the nominal value, which brings milder dynamic disturbances. This shows the potential capability of the proposed method to support the main grids by customizing the trajectory time constant. The specific utilization of the proposed method for improved grid performance needs additional design, which is not covered in this dissertation.

2.5 Discussion About Fusion of Microgrid Control with Model-free Reinforcement Learning

Model-free reinforcement learning (MFRL) is proven to be an effective technique for addressing the arising challenges in microgrids, which is an advanced decision-making technique with goal-oriented, data-driven, and model-free characteristics [149]. With the help of MFRL, the uncertainties of the model and parameters may be mitigated through repeated interaction between the environment and the RL agent. It is also beneficial to the autonomous operation of microgrids because the RL agent can actively update its policy based on the microgrid dynamics.

2.5.1 Application guideline

1) Problem formulation

Microgrid control is intrinsic to an infinite MDP that MFRL can solve. Reference [30] answered the question of ‘How’, that is, ‘How to formulate a control problem that can be

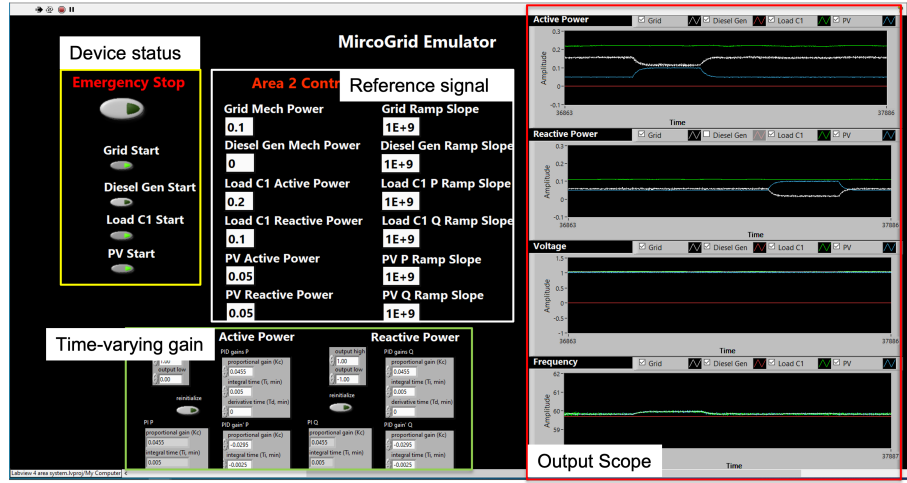
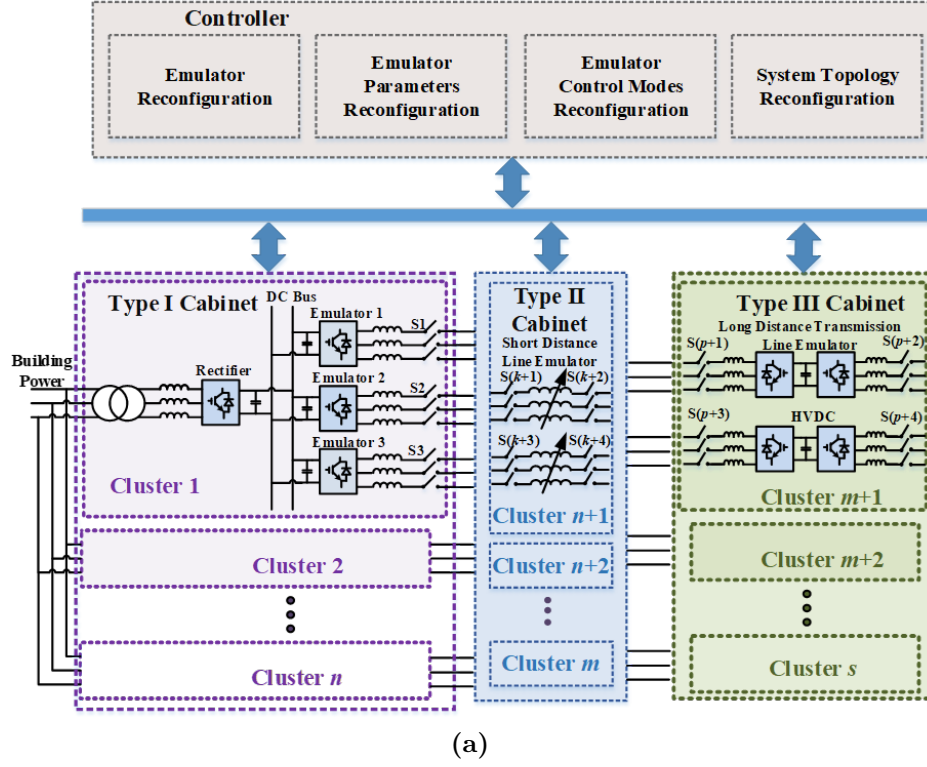
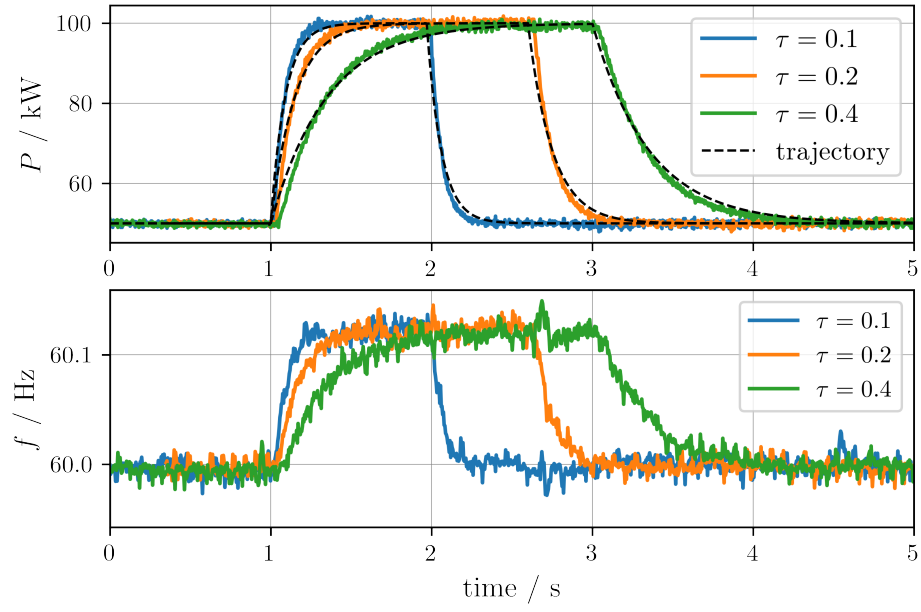
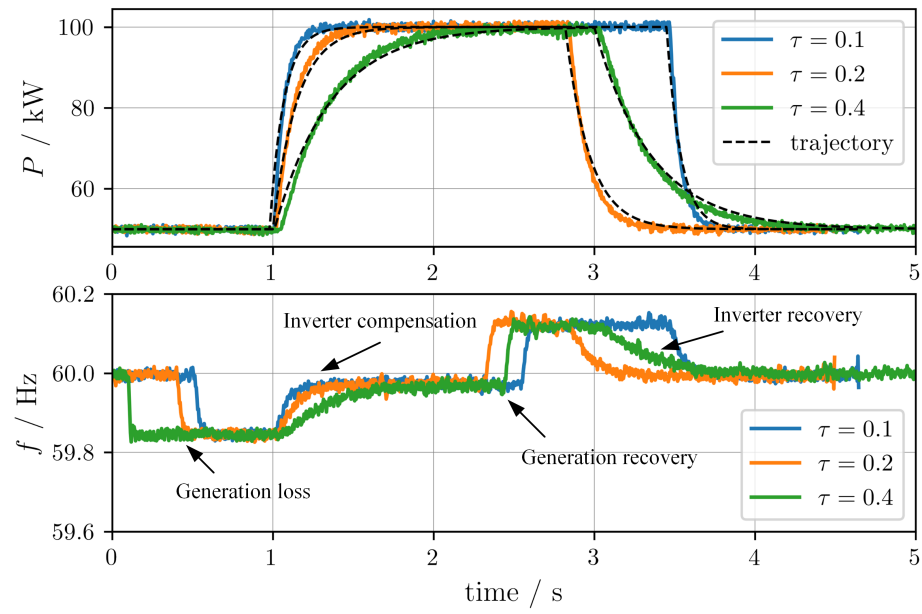


Figure 2.14: Diagram of HTB: (a) communication structure; (b) control panel.



(a)



(b)

Figure 2.15: Power HIL test results: (a) reference change; (b) generation loss.

solved by MFRL?', which includes four steps: i). Determine the environment, state space $\mathcal{S}$, and action space $\mathcal{A}$; ii) Design reward function $\mathcal{R}$ according to control targets; iii). Select the proper learning algorithm; iv). Train agents and validate the learned policy. The four steps are exemplified below based on two specific application scenarios, frequency regulation and voltage regulation.

i) Formulation of frequency regulation: Eqs. (2.19)-(2.21) shows the general configuration of an MFRL agent for frequency regulation in microgrids. The agent has unique action space when fusing with different modules in Figure 1.2.

$$\mathcal{S}_f := \left[(w_i)_{i \in \mathcal{N}}, (P_{ij}, Q_{ij})_{ij \in \mathcal{E}} \right] \quad (2.19)$$

$$\mathcal{A}_f = \begin{cases} \text{M2} : [(e_{abc,i})_{i \in \mathcal{I}}] \\ \text{M3} : [(i_{d,i}, i_{q,i})_{i \in \mathcal{I}}] \\ \text{M4} : [(P_{ref,i}, Q_{ref,i})_{i \in \mathcal{I}_{GFL}}, (w_{ref,i}, u_{dref,i})_{i \in \mathcal{I}_{GFM}}] \\ \text{M5} : [(P_{0,i}, Q_{0,i}, \Delta x_i)_{i \in \mathcal{I}}] \end{cases} \quad (2.20)$$

$$\mathcal{R}_f(t) = - \sum_{i \in \mathcal{N}} [w_i(t) - w_0]^2 \quad (2.21)$$

Where w_i is the frequency at each bus i ; (P_{ij}, Q_{ij}) is the power flow over the line from bus i to bus j ; M2-M5 are the modules summarized in Figure 2; $\mathcal{I}$ is the inverter set; $\mathcal{I}_{GFL}$ and $\mathcal{I}_{GFM}$ are the set of GFL inverters and GFM inverters, respectively. Since the control target is to maintain frequency, the deviation of frequency is designed as reward function.

ii) Formulation of voltage regulation: Eqs. (2.22)-(2.24) show the general configuration of an MFRL agent for frequency regulation in microgrids.

$$\mathcal{S}_v := \left[(v_i)_{i \in \mathcal{N}}, (P_{ij}, Q_{ij})_{ij \in \mathcal{E}}, (\tau_i)_{i \in \mathcal{T}} \right] \quad (2.22)$$

$$\mathcal{A}_v = \begin{cases} \text{M}_2 : [(e_{abc,i})_{i \in \mathcal{I}}] \\ \text{M}_3 : [(i_{d,i}, i_{q,i})_{i \in \mathcal{I}}] \\ \text{M}_4 : [(P_{ref,i}, Q_{ref,i})_{i \in \mathcal{I}_{GFL}}, (w_{ref,i}, u_{dref,i})_{i \in \mathcal{I}_{GFM}}] \\ \text{M}_5 : [(P_{0,i}, Q_{0,i}, \Delta x_i)_{i \in \mathcal{I}}, (\tau_i)_{i \in \mathcal{T}}] \end{cases} \quad (2.23)$$

$$\mathcal{R}_v(t) = - \sum_{i \in \mathcal{N}} [v_i(t) - v_0]^2 \quad (2.24)$$

Where v_i is the voltage magnitude of bus i , and τ_i is the tap positions of the on-load tap changers (OLTPs) of transformers. Compared with frequency regulation, the agent has distinct action of OLTPs for voltage regulation.

After selecting $\mathcal{S}$, $\mathcal{A}$, and $\mathcal{R}$, the mainstream MFRL algorithms are selected to update the policy of the agent. Note that the selected algorithms should be applicable to the application scenarios. For example, the discrete algorithm is better for discrete control actions like OLTPs. In addition, the above formulations give a general form of configuring an MFRL agent for microgrid control, and they can be modified according to customized control tasks.

In addition to problem formulation, there are another two fundamental questions regarding ‘What’ that remain to be answered. They are

- *Q1: What kinds of tasks is MFRL suitable for?*
- *Q2: How can MFRL be fused with the existing microgrid control framework?*

The following two subsections try to answer these two questions based on the state-of-the-art of MFRL. The answers can serve as the application guideline for adopting MFRL in microgrids.

2) What kinds of tasks is MFRL suitable for?

In general, MFRL is suitable for tasks with the following four features:

i) Relatively unchanged environment. Policy learned by RL agents reflects the physical law in the training environments, which fundamentally determines the state transition probability. The environment generates rewards based on $\mathbb{P}(s_{t+1} | s_t, a_t) : \mathcal{S} \times \mathcal{A} \rightarrow \Delta(\mathcal{S})$ and feed the rewards to RL agent for policy updating. A new environment has a distinct state transition probability function, which may have conflicts with the buffer data and trained policy. Thus, the working environment should not differ too much from the training environment.

ii) Clear control target. Clear control targets facilitate the design of reward functions. The objective function in the optimization problem, optimal control, and MPC can be directly transformed into a reward function. The specific control targets can be briefly categorized into frequency regulation, voltage regulation equation, and economic benefits. Then, the voltage deviation [26], frequency deviation [60] and energy management cost or revenue [138, 148] are transformed into reward functions in (2.21) and (2.24). Crucially, a well-designed reward function gives the MFRL agent the best guide to learning the optimal policy.

iii) Available data. Environmental data must be accessible if the agent interacts with a real system. Also, the real environment should tolerate improper actions for exploration. If the environment is a simulator, the simulation should run quickly to allow for thousands of repetitions. For example, a fast simulator and a real Tokamak vessel were developed for training and validation in [41].

iv) Acceptable control complexity. ‘Acceptable’ means the control complexity should be neither too low nor too high. For each perspective summarized in the high-level research map, there is no research trying to replace all the controllers. Most of the research just focused on a specific task that a model-based controller cannot handle but MFRL can because there is no need to replace a simple model-based controller that has good performance and it is unrealistic to let AI directly control the whole microgrid for now.

3) How can MFRL be fused with the existing microgrid control framework?

MFRL is essentially a useful tool that serves microgrid control. It follows microgrid control targets when fused with the existing control framework. In general, there are three ways of fusing as follows.

i). Model identification and parameter tuning. MFRL assists in identifying the uncertain models of the grid components accurately. Also, it can address the uncertainty and unavailability of model parameters and release the grid operators from complex and time-consuming parameter tuning, especially tuning a large model with many parameters.

ii). Supplementary signal generation. MFRL can generate supplementary control signals for model-based controllers, with which the current controllers can be made more robust and deal with complicated control tasks.

iii). Controller substitution. MFRL can completely replace the existing model-based controllers if they are no longer effective. It needs fewer inputs but has better performance than model-based controllers owing to the ANN's strong fitting capability.

In general, the application guide is summarized based on the existing microgrid control research that employs MFRL. The challenges and corresponding insights will be introduced in the next subsection.

2.5.2 Challenges and insights

Although many researchers have been investigating the applications of MFRL in microgrid control, there is still a clear gap between theory (simulation) and practice (real microgrid operation). The main concerns are the aspects of the environment, scalability, generalization, security, and stability. This subsection summarizes these challenges and gives some insights on how to tackle them.

1) Environment

- Challenges: As shown in Figure 2.16, the conventional model-based microgrid controllers have several types of tests before implementation, i.e., simulation, controller HIL test, power HIL test, subscale system test, and full system test. They are the options for the MFRL environment. Existing literature suggests offline training in the numerical simulator and online implementation in real systems [48] because the RL agent requires sufficient exploration during training which is unrealistic in HIL or real systems. That's why early RL was mainly used in video games, where the simulator could perfectly emulate the working environments [65]. Among the current power testbed types, simulation has the highest coverage of test scenarios but the least fidelity, which is the major concern of employing MFRL. Even if the agent learned a good policy in a numerical simulator, it may not function effectively in a real microgrid.

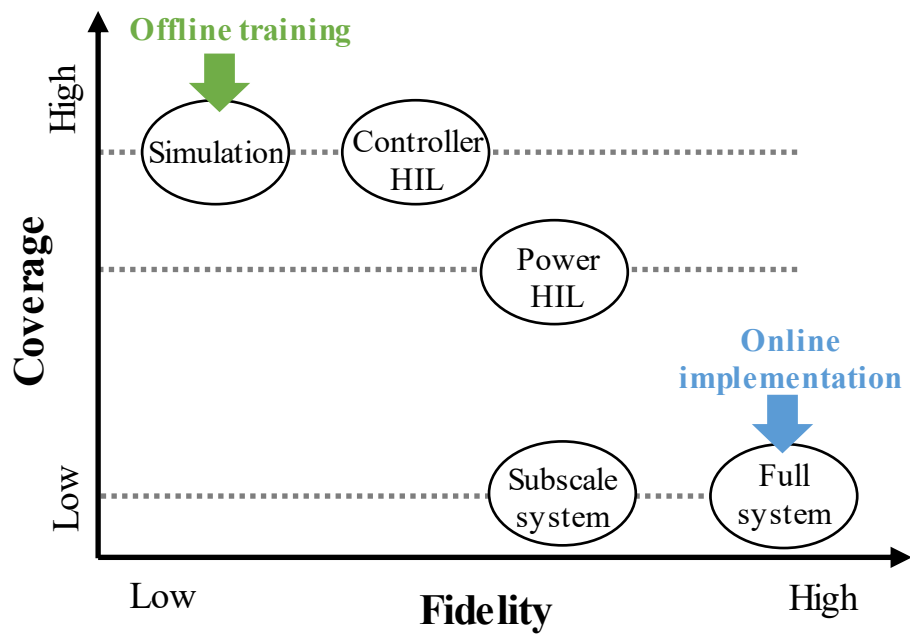


Figure 2.16: Microgrid testbeds [76] and MFRL environment.

- Insights: As for numerical simulators, they are on the way to developing a more accurate and faster toolbox capable of serving as a high-fidelity MFRL environment. Improved power system modeling [68] and more efficient numerical simulation techniques, such as the hybrid symbolic-numeric framework [147], are currently being developed. Further, it would be better to develop a standardized and customized training environment that assists in setting up the interface with power simulators such as PSSE, PSCAD, EMTP, and MATLAB-Simulink, just like “Gym” in the field of deep RL [35]. The standardized environment can also serve as a baseline for algorithm tests and comparisons. On the other hand, it is a good way to design a HIL test system that is equipped with specialized protection and can tolerate random exploration to some degree. In this way, the HIL test system may work as an environment that closely resembles an actual microgrid. Moreover, MFRL agents can learn from historical data. To improve learning efficiency and address the problem of real-data insufficiency, some advanced techniques have been developed. For example, i) long-tail learning [108] can learn effectively on biased data set; ii). Deep active learning [189] can also be used to more efficiently label disturbance data.

2) Scalability

- Challenges: MFRL suffers from the curse of dimensionality like some model-based controllers. The expansion of state space and action space will result in an exponential increase in control complexity, thereby increasing the difficulty of exploration and training. Existing MFRL research on microgrid control mainly focuses on some small-scale problems [154] and utilizes ANN with a few layers. To promote the application of MFRL in microgrid control, it is necessary to improve its scalability.

- Insights: On the one hand, it is an effective way to reduce control complexity by integrating domain knowledge into problem formulation. For example, [24] narrowed down the learning space and avoided baseline violations based on the generation constraints. On the other hand, it would be better to increase the capability of existing MFRL models by: i). increasing the exploration efficiency by designing guided exploration strategies like evolutionary RL [90]; ii). increasing the fitting capability of ANN through the modern design of network structures, i.e., sequential-to-sequential networks and transformers [162];

iii). increasing the training efficiency through distributed techniques like federated learning [102] and edge computing [23]. All of these methods can help relieve the pressure on training and make MFRL more scalable for microgrid control.

3) Generalization

- Challenges: Similar to DL, MFRL was accused of “inability of generalization” because a well-trained agent does not function effectively in a changing environment [2]. Even in an unchanged environment, the diversity of disturbances may also distort the agent. In microgrid control, it is difficult to cover all the disturbances during the training, which is critical on the condition that RL agents replace the existing controllers.

- Insights: Firstly, rich training scenarios benefit the generalization of MFRL. For example, [106] addressed the uncertainty of Volt-Var control in active distribution systems by generating a bunch of offline training scenarios. It is also a good way to employ robust RL that can tolerate the uncertainty of the environment [127]. Further, transfer learning can also improve the MFRL’s generalization capability, which has proven to be effective in the field of deep learning.

4) Security

- Challenges: Security is referred to as static security in this paper, meaning that the system state should respect the static physical constraints to avoid damaging the device. In microgrids, these constraints can be thermal limit constraints and control signal constraints decided by the physical capability of microgrid components. They are usually explicit and known according to microgrid device manufacture, and there are IEEE Standards setting the secure operational range of voltage and frequency. However, due to the non-interpretability of ANN, the learned policy cannot always guarantee each variable respects the constraints. Furthermore, it is also a problem to guarantee secure exploration in a HIL or real system. In the future, MFRL agents may be trained in a HIL microgrid to overcome the shortcomings of numerical simulators, where the exploration cannot violate the physical constraints of the HIL or real system for sure.

- Insights: Through constrained RL [22, 84] and safe RL [104, 16], the actions of RL agents can be projected to a safety region and thus always respect the physical operational constraints. In addition, physics-constrained and physics-informed deep learning [72] is also under development and can be integrated into MFRL to address security concerns. In physics-constrained deep learning, a “safety layer” is often leveraged to maintain constraint satisfaction under different physics knowledge, while physics-informed learning embeds the knowledge of physical laws that are governed by partial differential equations into training.

5) Stability

- Challenges: Stability is referred to as dynamic stability under a disturbance. According to the definition in [67], stability is the ability of an electric power system, for a given initial operating condition, to regain a state of operating equilibrium after being subjected to a physical disturbance, with most system variables bounded so that practically the entire system remains intact. Model-based microgrid controllers must pass the stability test through eigenvalue analysis or the Lyapunov function validation before implementation. However, the employment of MFRL challenges the model-based criteria because the uninterpretable RL agents dramatically change the closed-loop dynamics of microgrids.

- Insights: Integrating domain knowledge is the best way to guarantee microgrid stability for now. As for the first two fusing approaches, i) model identification and parameter tuning and ii) supplementary signal generation, model-based stability criteria can still be used to verify the system stability because the MFRL agent doesn’t break down closed-loop systems. MFRL complements the model-based approaches and improves them in a data-driven way. The supplementary signals generated by the MFRL agent can be viewed as hyper-parameters. Through techniques like semi-definite programming (SDP), linear matrix inequality (LMI), and sum-of-square programming [109], the security range of these hyper-parameters can be obtained to guarantee dynamic stability [191]. As for the third way of fusion, the complete controller substitution, MFRL agents dramatically change the closed-loop dynamics and make the system difficult to model. To address the stability issues in this condition, this paper gives three potential solutions. i). enrich the training data and training scenarios. The

learned policies basically reflect the state transition of the environment. If the training data set has covered sufficient instability scenarios, the corresponding punishment reward can help RL agents avoid unstable actions. ii). use a physics-informed approach by integrating model-based stability criteria into MFRL training. For example, the Lyapunov function [33] and the Gaussian process estimation [16] can be used to generate stability criteria for MFRL training, and [37] proposed a Lyapunov-regularized RL for transmission system transient stability. iii).perform policy stability validation through time-domain simulation (TDS). TDS has been widely used in power systems to validate the stability of nonlinear components or modules. It can also help validate the stability of the inexplicable RL policy.

2.6 Summary

Model-based controllers are still the foundation of existing microgrid control systems. However, the emerging challenges caused by the uncertainty of DERs and extreme weather call for advanced control techniques. As a model-free and data-driven approach, MFRL opens the possibility of non-linear, high-dimensional, and high-complex microgrid control. It may contribute to a huge upgrade of the existing control framework.

This chapter proposes an adaptive microgrid P-Q control method with guaranteed trajectory, combining model-based analytical proof, physics-informed learning, and power HIL experiments. The model-based analysis shows the existence of an adaptive controller that can perfectly track a predefined trajectory with exponential decay. This provides critical guidance to the RL implementation that is highly necessary, since direct controller substitution may bring about exponentially increased training complexity.

The proposed P-Q inverter control is essentially an optimized local control based on a PI controller. Using the PI controller as the basic implementation, an inverter-based P-Q controller trained in a numerical simulator can ensure a good initial performance for plug-and-play use in microgrids. When it is applied in a new environment like a new distribution feeder or microgrid, incremental training using operational data can further optimize the performance to achieve the plug-and-play capability.

The physics-informed training results are verified through power HIL hardware experiments, which is beneficial for the implementation of the advanced model-free technique in real microgrids. The conclusions are summarized as follows.

1) The system transfer functions are categorized into three conditions, determining whether there exists a time-varying-gain adaptive PI controller that can track an exponentially traceable curve. In *Condition 1*, fixed-gains work; in *Condition 2*, time-varying gains are required; in *Condition 3*, no adaptive PI controller works.

2) The proposed controller outperforms the conventional fixed-gain and adaptive PI controllers. It can accurately track the predefined trajectory with any assigned time constant.

3) The microgrid inverter-based P-Q control system meets Condition 2. After implementing the proposed adaptive PI controller, the active and reactive power output of inverters can track a predefined exponential trajectory. The trajectory time constant that benefits microgrid frequency and voltage could be customized in the application.

4) The model-based analysis provides guidelines for deep RL training, which relieves the training pressure and saves training time. In turn, the implementation of physics-informed deep RL solves the problem of unavailability and uncertainty in the model-based method.

5) The proposed control method allows inverter active and reactive outputs to follow a predefined exponential trajectory without the need for manual gain-tuning. The interaction between the RL agent and the training environment compensates for the uncertainties caused by model simplification, parameter distortion, and state variation.

Chapter 3

Decentralized and Coordinated V-f Control Considering DER Inadequacy and Demand Control

This chapter proposes a decentralized and coordinated V-f control framework for islanded microgrids, with full consideration of the limited capacity of DERs and V-f dependent load.

3.1 Literature Review

An islanded microgrid has many inverter-based generations. As a result of the high penetration of renewable energy, a major cause of grid instability and large V-f deviation pertains to the inadequacy of DERs [70]. DER inadequacy indicates that the capacity of inverter-based generations is insufficient to supply a microgrid's total load. The impacts of limited DER capacity can be seen at both the inverter level and the grid level. For a single inverter, the DC side voltage maintained by the buck-boost converter tends to ripple first and then droop across the linked capacitor when DERs cannot supply enough power [163]. For the whole microgrid, insufficient P-Q may result in over frequency and voltage dip [56, 172]. The negative impacts of insufficient DERs necessitate more efficient use of existing generation capacity, which makes the power regulation of inverter-based generations critical in islanded microgrids. The output of GFL inverters can be controlled easily by changing the P_{ref} and Q_{ref} . GFM inverters, on the other hand, make it hard to control power accurately and quickly. GFM inverters are controlled as voltage sources, and their output is mostly determined by the grid-side performance. Some research has been focused on limiting the output of GFM inverters. References [61] and [180] designed a current limiter and put it between the current and voltage regulator. The threshold of the current limiter is usually set at 2 p.u. to 3 p.u. because it is designed to prevent high currents in abnormal conditions, e.g., the high currents in low voltage ride through after grounded faults [20]. Apart from the current limiter, [163] and [28] added a virtual impedance to the voltage control loop to limit the terminal voltage of the inverter. However, the current limiter and virtual impedance are mainly designed to protect the hardware device and cannot accurately control the output of inverters in normal conditions. Moreover, the saturation caused by the current limiter and virtual impedance may result in the instability of the microgrids [46]. In fact, the output of GFM inverters in islanded microgrids is determined by the load-sharing results. Their output can be regulated by changing the power-sharing parameters, such as nominal P_{ref} , Q_{ref} , and

droop gains. The droop gains are tuned proportionally to DER capacities, allowing each DER to take on new loads according to its capacity [19]. Considering that a DER's capacity may fluctuate from time to time due to its intermittent nature, [43, 71] and [25] developed some adaptive droop strategies, but each with different control targets. [43] and [64] aimed at better reactive power-sharing. [129] focused on better transient performance. [59] presented a method for suppressing circulating current between inverters. [25] addressed inverter-based load control. Although the adaptive control algorithms improve the load sharing results, they are no longer effective if the overall DER capacity is insufficient. This is caused by the saturation of various control modules. Thus, a new GFM inverter power regulator considering DER inadequacy has yet to be developed. Further, since P-Q generation shares the same apparent capacity, it is critical to enable the coordination between P-Q generation while regulating the output of inverters [161].

Based on the above discussions, this chapter developed a decentralized and coordinated V-f control framework to address DER inadequacy in islanded microgrids. With the proposed control methods, each GFM inverter can output any power according to real-time capacity constraints without communicating with adjacent inverters. In addition, demand control [78, 94] is incorporated into this control framework to reduce load-generation mismatch when DER capacity is insufficient. Demand control leverages load sensitivity to V-f and minimizes involuntary load shedding. Mathematical analysis and simulation results show that demand control collaborates well with inverter output regulator within the decentralized and coordinated framework.

3.2 DER Inadequacy in Islanded Micorgrids

This section presents the challenges related to DER inadequacy in islanded microgrids and introduces the foundation of the control framework to address these challenges.

3.2.1 Configuration of islanded microgrids

1) Grid-forming inverter

A droop-controlled GFM inverter is the basic unit of islanded microgrids. Figure 3.1 shows the diagram of a GFM inverter supplying static V-f dependent load. The GFM inverter is controlled as a voltage source, and the control framework consists of a current regulator, a voltage regulator, and a primary regulator, as shown in (3.1)-(3.3). As a negative feedback controller, the purpose of the primary regulator below is to emulate the droop characteristics of conventional synchronous generators and automatically share the load among microgrid inverters.

$$\begin{bmatrix} e_d \\ e_q \end{bmatrix} = \begin{bmatrix} v_d \\ v_q \end{bmatrix} + wL_f \begin{bmatrix} -i_q \\ i_d \end{bmatrix} + \begin{bmatrix} k_{pid} + \frac{k_{iid}}{s} & 0 \\ 0 & k_{piq} + \frac{k_{iiq}}{s} \end{bmatrix} \left(\begin{bmatrix} i_{dref} \\ i_{qref} \end{bmatrix} - \begin{bmatrix} i_d \\ i_q \end{bmatrix} \right) \quad (3.1)$$

$$\begin{bmatrix} i_{dref} \\ i_{qref} \end{bmatrix} = \begin{bmatrix} i_{gd} \\ i_{gq} \end{bmatrix} + wC_f \begin{bmatrix} -v_q \\ v_d \end{bmatrix} + \begin{bmatrix} k_{pud} + \frac{k_{iud}}{s} & 0 \\ 0 & k_{puq} + \frac{k_{iuq}}{s} \end{bmatrix} \left(\begin{bmatrix} v_{dref} \\ v_{qref} \end{bmatrix} - \begin{bmatrix} v_d \\ v_q \end{bmatrix} \right) \quad (3.2)$$

$$\begin{bmatrix} w_{ref} \\ V_{ref} \end{bmatrix} = \begin{bmatrix} k_{df} & 0 \\ 0 & k_{dv} \end{bmatrix} \left(\begin{bmatrix} P_0 \\ Q_0 \end{bmatrix} - \begin{bmatrix} P_m \\ Q_m \end{bmatrix} \right) + \begin{bmatrix} w_0 \\ V_0 \end{bmatrix} \quad (3.3)$$

where P_0 and Q_0 are initial power setting points; P_m and Q_m are measured output; k_{df} and k_{dv} are frequency and voltage droop gains, respectively.

2) V-f dependent load

As shown in (3.4), V-f dependent ZIP loads are modeled in this paper [36].

$$\begin{cases} P_l = P_0 (p_1 V_l^2 + p_2 V_l + p_3) [1 + K_{pf} (f - f_0)] \\ Q_l = Q_0 (q_1 V_l^2 + q_2 V_l + q_3) [1 + K_{qf} (f - f_0)] \end{cases} \quad (3.4)$$

where V_l is the load side voltage; $p_1 + p_2 + p_3 = 1$ and $q_1 + q_2 + q_3 = 1$; K_{pf} is the sensitivity of P_l to f ; K_{qf} is the sensitivity of Q_l to f .

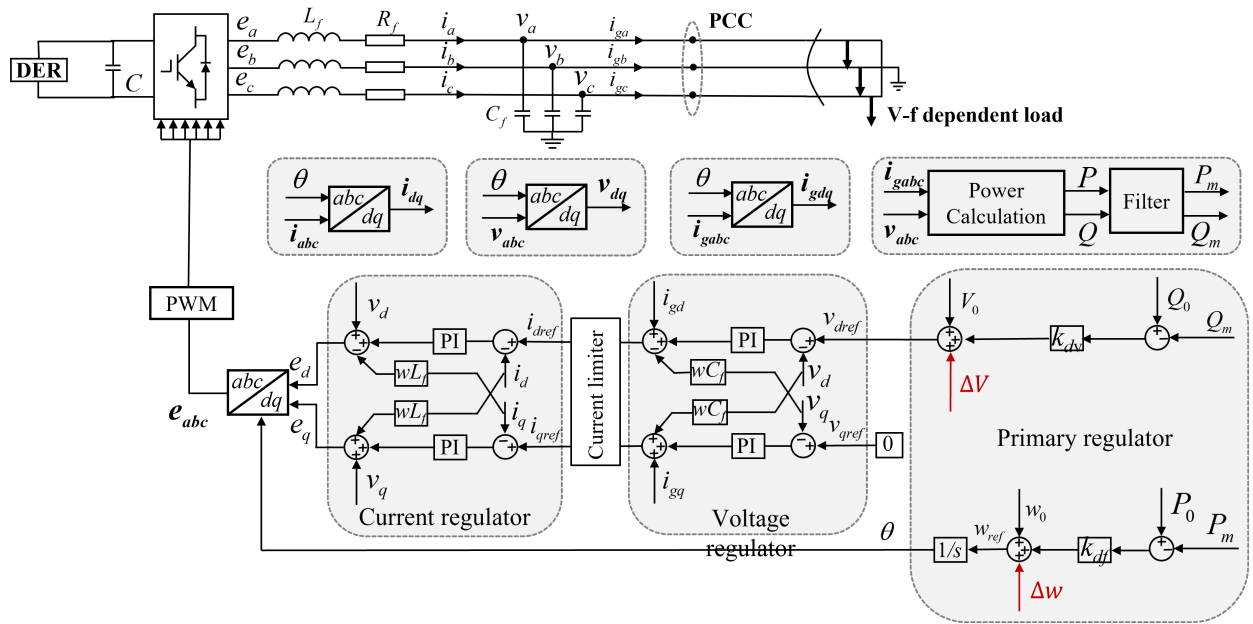


Figure 3.1: Diagram of a droop-controlled GFM inverter supplying V-f dependent load.

The coefficients in (3.4) represent the compositions of ZIP loads. They change with the time of day and week, seasons, and weather [164], but can be assumed as constant in the timescale of primary control. Because microgrids are usually small in scale, the change in inverter terminal voltage is quickly reflected at the load side, which in turn changes the system demand that depends on the load sensitivity to V-f [54]. As a result, demand control can participate in V-f regulation in islanded microgrids.

3.2.2 DER inadequacy and its challenges

1) Load condition and DER inadequacy

Figure 3.2 shows a diagram of DER inadequacy under different load levels. With the DER capacity as the baseline, there are generally three load conditions, i.e., light-load, heavy-load, and over-load. 1) In the light-load condition, the total load is much smaller than the DER capacity. Thus, grid V-f may not significantly deviate from the nominal value after normal load change. 2) In the heavy-load condition, the total load is close to, but slightly under, the DER capacity. The output of some GFM inverters may exactly equal the capacity of the DC side source. 3) In the over-load condition, the total load is larger than the DER capacity, such that the power balance cannot be guaranteed unless conducting load shedding.

In Figure 3.2, if the total load is significantly lower than the generation capacity, the DER is adequate; if the total load is much larger than the generation capacity, the DER is inadequate. The load-generation balance in the critical transition area between the adequate and inadequate zones merits more attention. This dissertation investigates this critical transition area for its potential to improve stability and reduce V-f deviation, which is critical in the background of high penetration of intermittent renewable generation and extreme weather conditions.

2) Challenges

There are three main challenges in islanding microgrids when it comes to DER inadequacy, including improper load sharing, DC side instability, and large V-f deviation.

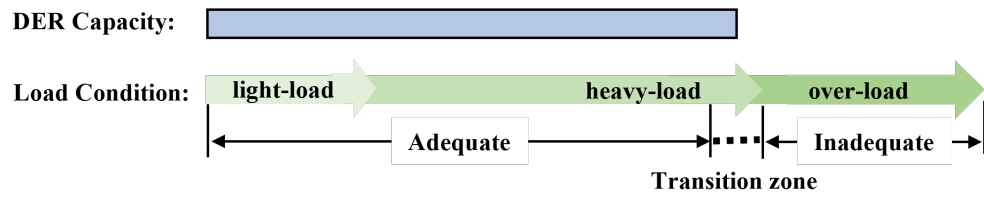


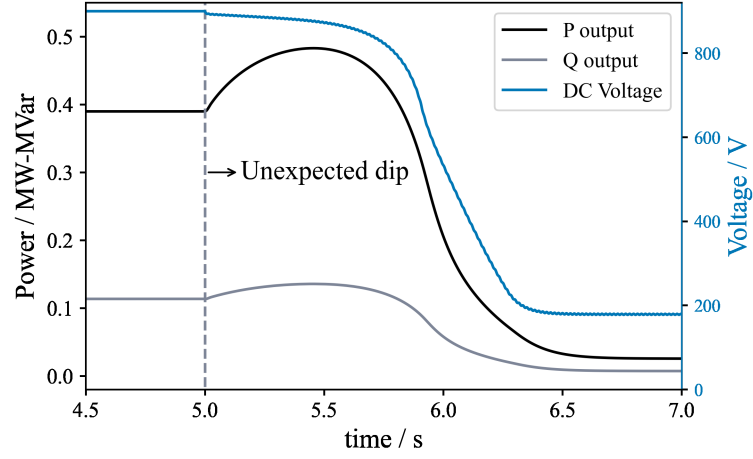
Figure 3.2: DER inadequacy under various load levels

The first challenge is related to load sharing. In the conventional droop control, the load sharing results are determined by the initial setting point $[P_0, Q_0]$ and droop gains $[k_{dp}, k_{dv}]$. The load change at an equilibrium point is shared proportionally with the droop gains and among the microgrid inverters, which are tuned based on the DER capacity. However, due to the intermittency of DERs, their capacities may fluctuate from time to time. The GFM inverter has a stability issue if load sharing cannot adapt to the real-time DER capacity. The challenge is more critical in the transition zone shown in 3.2 because most GFM inverters work in critical states with little reserved capacity.

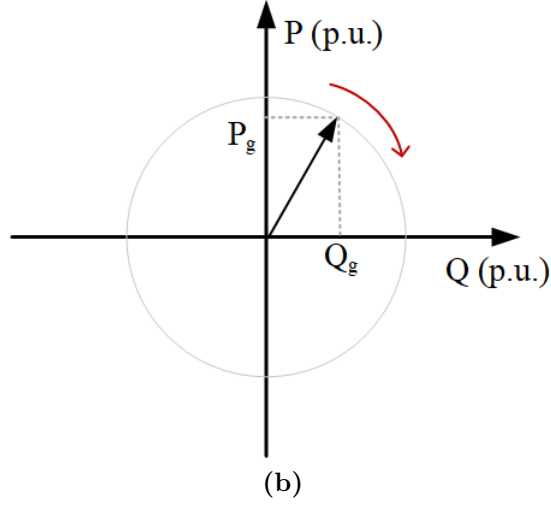
The second challenge stems from improper load sharing among DERs and is related to DC side voltage. When the shared loads exceed the capacity of the DC side DERs, there is insufficient energy to support the capacitor voltage, which may result in a voltage dip first and then distort PWM. Furthermore, the inverter-based generation will trip and compound the DER inadequacy. Figure 3.3a shows an unexpected DC voltage dip and generation loss when the shared loads exceed the DER capacity at 5s.

The third challenge relates to large V-f deviation. The first two challenges often impact single or several inverters, while the third challenge, which is about allocating limited generation capacity to the V-f regulation loop, impacts the whole grid. Figure 3.3b shows the bounded generation constraint. Following the same capacity constraint, V-f regulation results are quite different when implementing distinct P-Q generation strategies. Under bounded generation constraints, a large k_{df} means more active power decrease and more frequency dip, while a large k_{dv} means more reactive power decrease and more voltage dip. Figure 3.3c shows the unexpected V-f regulation with distinct droop gains. Usually, the deviation of frequency should be less than 0.01 p.u. and the deviation of voltage should be less than 0.05 p.u.. In Figure 3.3c, the requirements for V-f deviation cannot be met at the same time. V-f deviation can be improved according to the supplementary signals generated by the conventional secondary controller. However, due to saturation caused by the capacity constraints in Figure 3.3b, the inverter may fail to respond to these signals, resulting in an unexpected DC voltage dip.

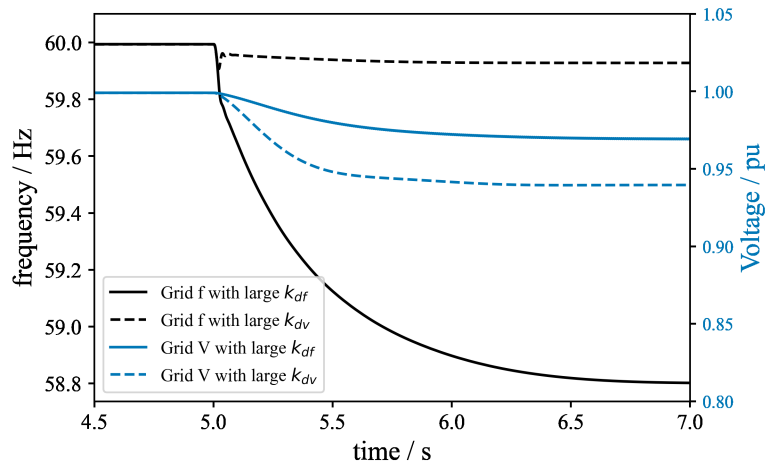
Considering the challenges discussed above, it is urgent to develop a V-f control framework that can: 1) regulate the output of GFM inverters and improve load sharing results based on



(a)



(b)



(c)

Figure 3.3: Challenges related to DER inadequacy: (a) DC side voltage dip; (b) Constrained generation capacity for V-f regulation; (c) Unexpected V-f regulation with distinct droop gains.

real-time DER capacity; 2) adjust P-Q generation under the condition of constrained DER capacity for both acceptable voltage and frequency deviation.

3.2.3 Foundation of the decentralized and coordinated V-f control framework

In 3.1, the primary control signals w_{ref} and v_{dref} determine the load sharing results and V-f deviation. The foundation of the proposed control method is to design a power regulator and a V-f regulator, which generate the supplementary signals for w_{ref} and v_{dref} based on real-time measurements. Specifically, the supplementary signal of the power regulator is generated according to the error between real-time reference capacity S_r and measured output S_m , which automatically re-shares the exceeding output among the other inverters. The supplementary signal of the power regulator guarantees the constrained generation shown in Figure 3.3b. Then, like the conventional secondary control, the V-f regulator can further adjust P-Q generation along the boundary and perform load power control through V-f regulation. Finally, the proposed control framework can regulate inverter output and improve V-f deviation at the same time.

As in the conventional droop control, all the supplementary signals are generated depending on local measurements. The proposed control method further enables cooperation between

- Generation and load: Generation and load power are regulated simultaneously till reaching a new equilibrium.
- V regulation and f regulation: Requirements for V-f deviation are considered at the same time. A tradeoff is made while allocating limited DER capacity for V-f regulation.
- P generation and Q generation: Limited DER capacity is allocated to P-loop and Q-loop properly.

As a result, the proposed method is decentralized and coordinated. Section III dives into the control framework.

3.3 Decentralized and Coordinated Control Framework

This section introduces the proposed decentralized and coordinated V-f control framework. As shown in Figure 3.4a, the control framework consists of a power regulator and a V-f regulator. They are implemented locally, generating supplementary signals $\Delta w'$ and $\Delta V'$ for the primary controller of each GFM inverter.

3.3.1 Power regulator

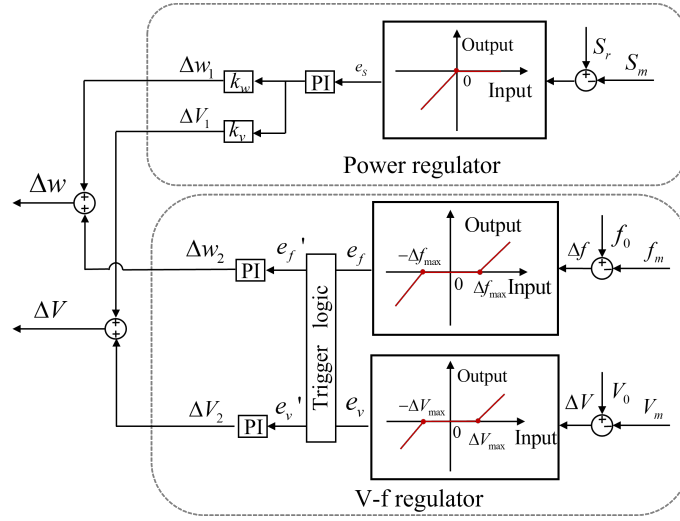
The transfer function of the power regulator is shown in (3.5)-(3.6).

$$\begin{bmatrix} \Delta w_1 \\ \Delta V_1 \end{bmatrix} = \left(k_{pc} + \frac{k_i}{s} \right) e_s \begin{bmatrix} k_w \\ k_v \end{bmatrix} \quad (3.5)$$

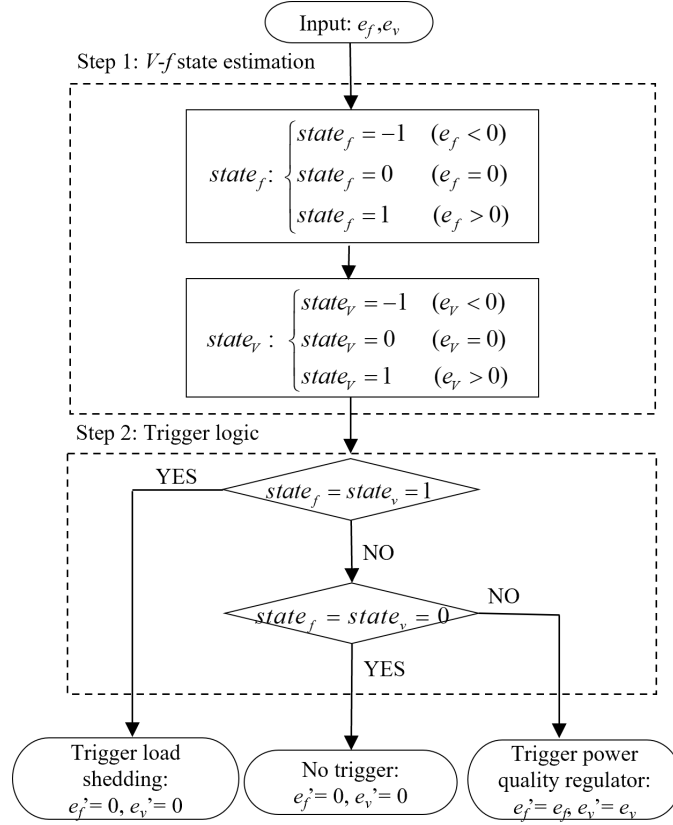
$$e_s = \begin{cases} 0, & \text{if } S_r > S_m \\ S_r - S_m, & \text{if } S_r \leq S_m \end{cases} \quad (3.6)$$

The errors between S_r and S_m are fed to a PI controller, which is then allocated to the frequency and voltage regulation loop according to regulation gains k_w and k_v , respectively. Typically, if the inverter outputs more power than S_r , e_s is negative, and the inverter will decrease its output by decreasing the terminal voltage and angle frequency. The final decrease was determined by e_s proportionally allocated to the active power loop and the reactive power loop, specifically, the proportion between k_w and k_v . Given load sensitivity and disturbance, a larger k_w means more sharing in the active power loop and more frequency dip, while a larger k_v means more sharing in the active power loop and more voltage dip.

It is worth noting that e_s allocation by the power regulator was not always optimized due to the uncertainties from both the generation and load sides. There are no single-value, fixed k_w and k_v that can handle all the disturbance scenarios at the same time. Hence, this chapter proposed the V-f regulator to generate additional supplementary signals and further adjust the active power and reactive power sharing results. In practice, it is suggested to



(a)



Note: “ $state=1$ ” means more generation is required; “ $state=0$ ” means state is acceptable; “ $state=-1$ ” means less generation is required.

(b)

Figure 3.4: Diagram of decentralized and coordinated control: (a) control framework (b) trigger logic of V-f regulator.

set k_w and k_v based on load power factor (PF), so as to match the load-side disturbance as much as possible. Specifically, if $\text{PF} = \cos \theta$, then set $k_w/k_v = \tan \theta$.

3.3.2 V-f regulator

The transfer function of the V-f regulator is shown in (3.7)-(3.9).

$$\begin{bmatrix} \Delta w_2 \\ \Delta V_2 \end{bmatrix} = \begin{bmatrix} k_{pf} + \frac{k_{if}}{s} & 0 \\ 0 & k_{pv} + \frac{k_{iv}}{s} \end{bmatrix} \mathbf{Tr} \left(\begin{bmatrix} e_f \\ e_v \end{bmatrix} \right) \quad (3.7)$$

$$e_f = \begin{cases} \Delta f + \Delta f_{\max}, & \text{if } \Delta f < -\Delta f_{\max} \\ 0, & \text{if } -\Delta f_{\max} \leq \Delta f \leq \Delta f_{\max} \\ \Delta f - \Delta f_{\max}, & \text{if } \Delta f > \Delta f_{\max} \end{cases} \quad (3.8)$$

$$e_v = \begin{cases} \Delta V + \Delta V_{\max}, & \text{if } \Delta V < -\Delta V_{\max} \\ 0, & \text{if } -\Delta V_{\max} \leq \Delta V \leq \Delta V_{\max} \\ \Delta V - \Delta V_{\max}, & \text{if } \Delta V > \Delta V_{\max} \end{cases} \quad (3.9)$$

where $\Delta f = f_0 - f_m$, $\Delta V = V_0 - V_m$, and $\mathbf{Tr}$ is the trigger logic shown in Figure 3.4. The diagram of the trigger logic is shown in Figure 3.4b, which considers the relationship between V-f regulation and load-generation balance. Step 1 estimates the state of V-f and determines the required capacity for V-f regulation. For example, if $e_w > 0$ ($state_f = 1$), more reactive power is required for frequency regulation, and frequency regulation will take up more generation capacity; in reverse, $e_w < 0$ means less need for active power and frequency regulation could give up some generation capacity. This logic is also applicable to the reactive power loop (V regulation loop). Then in step 2, the trigger logic judges whether the existing DER capacity is adequate or not to meet the V-f deviation requirements, which are categorized into the following three conditions.

- “ $state_f = state_v = 1$ ” means V-f droop too much at the same time, and both V-f regulation loops need more generation capacity. The existing DER capacity is not sufficient to regulate V-f, thus load shedding is needed.

- “ $state_f = state_V = 0$ ” means V-f deviations are within the acceptable region and no additional regulation signal is needed.

- The remaining combinations of $state_f$ and $state_v$ mean that one regulation (V or f) loop needs more generation capacity and the other could give up some generation capacity. Then, grid V-f could be maintained without the need for load shedding.

Note that the power regulator has priority over the V-f regulator because it guarantees the capacity constraints that are closely related to DC voltage stability. Hence, a power regulator usually has larger controller gains and higher bandwidth than a V-f regulator.

3.4 Static Feasibility and Small Signal Stability

This section proves the static fixability and small signal stability of the proposed control framework through algebraic formulation and eigenvalue analysis.

3.4.1 Static feasibility

The proposed microgrid control framework has two main functionalities: 1) regulate the output of GFM inverters through load re-sharing; 2) improve V-f deviation by reallocating generation capability along the constrained boundary in 3.3b. The mechanism of load re-sharing is similar to that of the adaptive droop gain method, which has been clearly illustrated in [97]. Hence, this subsection mainly verifies the second functionality through algebraic formulation.

The V-f regulator is identical to the conventional secondary controller when DER capacity is adequate, which improves V-f deviation by adjusting the output of inverter-based generations. It changes to a constrained secondary controller in the transition zone when the load is close to the total generation. In the following discussion, the static equilibrium is derived when the total generation is insufficient, based on which the state change in the transition zone is further derived.

1) Static equilibrium

With the focus on a general islanded microgrid formed by N inverters, each inverter is connected to an independent bus with a local V-f dependent load. Under droop control and the proposed framework, there are $6N$ independent equations, including $2N$ droop equations in (3.10), $2N$ load equations in (3.11), and $2N$ power flow equations in (3.12).

$$\begin{cases} f = f_{0,i} + k_{df} (P_{inv,i} - P_{inv0,i}) \\ V_i = V_{0,i} + k_{dv} (Q_{inv,i} - Q_{inv0,i}) \end{cases} \quad (3.10)$$

$$\begin{cases} P_{l,i} = P_{l0,i} (p_1 V_i^2 + p_2 V_i + p_3) [1 + K_{pf} (f - f_0)] \\ Q_{l,i} = Q_{l0,i} (q_1 V_i^2 + q_2 V_i + q_3) [1 + K_{pf} (f - f_0)] \end{cases} \quad (3.11)$$

$$\begin{cases} P_i = P_{inv,i} + P_{l,i} = G_{ij} V_i^2 - G_{ij} \sum_{i \neq j} V_i V_j \cos \theta_{ij} - B_{ij} \sum_{i \neq j} V_i V_j \sin \theta_{ij} \\ Q_i = Q_{inv,i} + Q_{l,i} = G_{ij} V_i^2 - G_{ij} \sum_{i \neq j} V_i V_j \sin \theta_{ij} - B_{ij} \sum_{i \neq j} V_i V_j \cos \theta_{ij} \end{cases} \quad (3.12)$$

where f is the global steady state frequency; and $f_{0,i}$ and $V_{0,i}$ are the nominal frequency and voltage of the i th inverter, respectively. Assume the reference inverter has a power angle $\theta = 0$, and then there are $6N$ decision variables in (3.10)-(3.14), including 1 global frequency, N voltage, $N - 1$ power angle, N active inverter output, N active load, N active inverter output, and N reactive inverter output. The number of decision variables equals the total number of equations. Thus, the new equilibrium after a given disturbance can be calculated, allowing further estimation of the proposed method to reduce load shedding.

2) State transition under constrained DER capacity

In initial equilibrium, $P_{inv,i} = P_{inv0,i}$ and $Q_{inv,i} = Q_{inv0,i}$. Then, assume a step increase in the base load and capacity constraints on the inverters.

$$\begin{cases} \text{Load: } \begin{cases} P_{l0,i}' = P_0 + \Delta P \\ Q_{l0,i}' = Q_0 + \Delta Q \quad \forall i = 1, 2, \dots, N \end{cases} \\ \text{Generation: } P_{inv,i}'^2 + Q_{inv,i}'^2 = S_i^2 \end{cases} \quad (3.13)$$

The original equilibrium will transition to a new equilibrium while also meeting the network power flow and power balance constraints as follows.

$$\left\{ \begin{array}{l} P_i' = P_{inv,i}' + P_{l,i}' \\ \quad = G_{ij}V_i'^2 - G_{ij} \sum_{i \neq j} V_i'V_j' \cos \theta_{ij}' - B_{ij} \sum_{i \neq j} V_i'V_j' \cos \theta_{ij}' \quad \forall i, j, i \neq j \\ Q_i' = Q_{inv,i}' + Q_{l,i}' \\ \quad = G_{ij}V_i'^2 - G_{ij} \sum_{i \neq j} V_i'V_j' \cos \theta_{ij}' - B_{ij} \sum_{i \neq j} V_i'V_j' \cos \theta_{ij}' \quad \forall i, j, i \neq j \end{array} \right. \quad (3.14)$$

where the prime symbols mark the new state variables.

During the transition, the conventional droop control is rendered ineffective, and the $2N$ droop equations are replaced by N bounded capacity constraints. This gives us the freedom to design the new generation output. Given that $P_{inv,i}'$ and $Q_{inv,i}'$ meet the capacity constraints in (3.13), there are $4N$ state variables and $4N$ equations left. Then, for each $(P_{inv,i}', Q_{inv,i}')$ point on the capacity circle, the corresponding new equilibrium V-f deviation is solvable, as the number of equations and decision variables is identical.

3.4.2 Small signal stability

The power system model is composed of some differential equations and algebraic equations. The proposed power regulator and V-f regulator are incorporated into the conventional droop control controller in 3.1. Then, the complete dynamic model of microgrids is expressed as a set of differential-algebraic equations (DAEs) as follows.

$$\left\{ \begin{array}{l} \dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{y}) \\ \mathbf{0} = \mathbf{g}(\mathbf{x}, \mathbf{y}) \end{array} \right. \quad (3.15)$$

where $\mathbf{x}$ is the vector of state variables and $\mathbf{x} = [\varphi_{vs}, \varphi_{fs}, \varphi_v, \varphi_f, \varphi_{ud}, \varphi_{uq}, \varphi_{id}, \varphi_{iq}, \varphi_p, v_d, v_q, i_d, i_q, P_m, Q_m, i_{gd}, i_{gq}]$; and $\mathbf{y}$ is the vector of algebraic variables and $\mathbf{y} = [v_{dref}, v_{qref}, i_{dref}, i_{qref}, e_d, e_q, P, Q]$.

After linearizing the DAEs in (3.15), the small-signal model is obtained in (3.16). Then, the state matrix $\mathbf{A}$ is calculated by eliminating the algebraic variables. Due to the fact that

the V-f regulator consists of piecewise functions, each linear part can be analyzed according to initial operating points.

$$\begin{bmatrix} \Delta \dot{x} \\ 0 \end{bmatrix} = \begin{bmatrix} f_x & f_y \\ g_x & g_y \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} \quad (3.16)$$

$$A = f_x - f_y g_y^{-1} g_x \quad (3.17)$$

Note that small signal stability can only guarantee the stability of the system around a specific equilibrium. As (3.8) and (3.9) are nonlinear functions with dead bands, time-domain simulation (TDS) was required to validate the stable transition between equilibriums, as detailed in subsection 3.6.

3.5 Exemplification in an Ideal System

This section verifies the static equilibrium and small signal in an ideal system in Figure 3.5.

3.5.1 Static feasibility

Assume an intentional load increase at the initial operating point (P_0, Q_0) . Then, (3.13) and (3.14) predict the new equilibrium after an intentional load change under the condition that the conventional primary controller becomes invalid. Figure 3.6 shows the new equilibriums when implementing different generation strategies under various load increases. To facilitate observation, the high-dimensional state space is projected into 2-dimensional ΔV_1 - Δf space, where ΔV_1 is Bus 1 voltage deviation. Based on Figure 3.5, the observations are three-fold:

a) For Load=102% S_r and Load=105% S_r , although the total load is larger than the generation capacity, load-generation balance can still be achieved without performing load shedding because there are some new equilibriums inside the black security rectangle that meet the V-f deviation requirements.

b) If the current operating point is located outside the black security rectangle where the V-f regulator may be triggered, the P-Q generation can be adjusted along the bounded generation circle until the operating point comes back to the acceptable region.

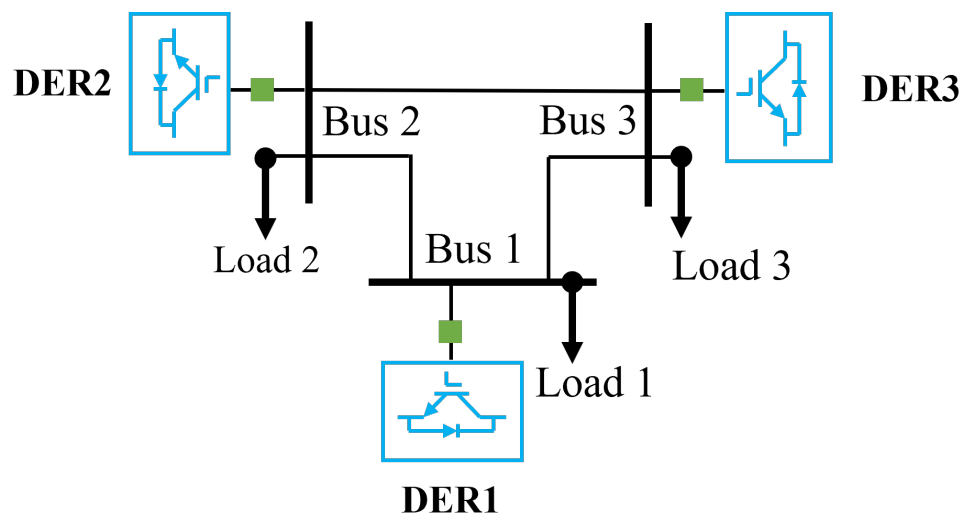


Figure 3.5: Single-line diagram of the ideal three-inverter system.

c) If the total load is too large, e.g., $\text{Load}=108\%S_r$, load shedding is required since there is no operating point inside the security rectangle. However, the shed load could be less than conventional strategies to reduce unnecessary involuntary load shedding. For example, 3% to 5% is enough to improve V-f deviation using demand control.

3.5.2 Small signal stability

Choose an operating point outside the black security rectangle in Figure 3.6 and calculate the eigenvalues of $\mathbf{A}$. To verify the robustness of the proposed method, the eigenvalues are plotted by sweeping control parameters in three different ways.

- Condition 1: sweep droop gain $[k_{df}, k_{dv}]$ without the integration of the proposed control framework.
- Condition 2: sweep droop gain $[k_{df}, k_{dv}]$ with the integration of the proposed control framework.
- Condition 3: sweep power regulator gain $[k_w, k_v]$ with the integration of the proposed control framework.

The eigenvalue trajectories under Conditions 1, 2, and 3 are shown in Figures 3.7a, 3.7b, and 3.7c, respectively, where the critical gains that force the eigenvalue to cross the y axis are also marked in the title. Based on Figure 3.7, the following observations are two-fold:

a) In Conditions 1 and 2, all the eigenvalues are on the left half-plane before and after the integration of the proposed method. Then, increasing the droop gains could result in instability, which shows that the system maintains a specific stability margin if tuned properly.

b) Condition 2 has smaller crossing gains than Condition 1. The integration of the proposed framework method could decrease the stability margin of the original system, but it still preserves a specific yet sufficient margin for increasing the power regulator gains, as shown in Condition 3.

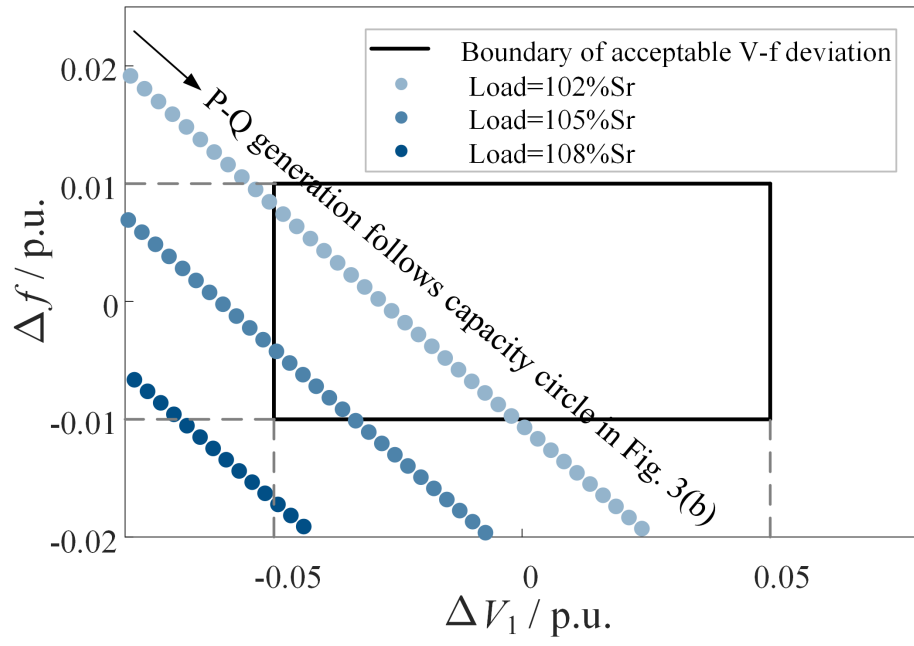


Figure 3.6: V-f deviation under bounded generation constraints.

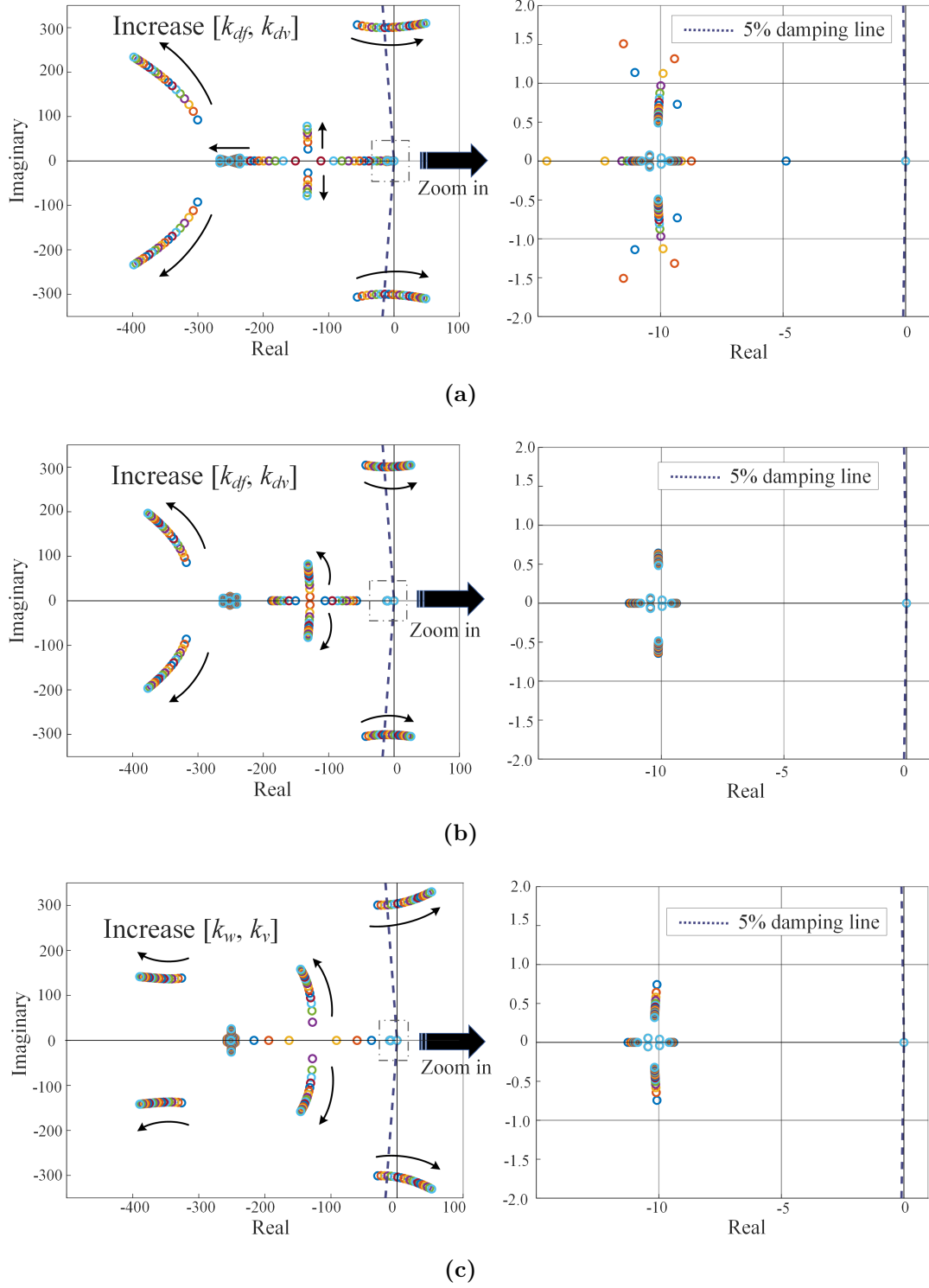


Figure 3.7: Eigenvalue trajectories when sweeping control parameters (a) Condition 1: crossing droop gain $[k_{df}, k_{dv}] = [0.025, 0.125]$; (b) Condition 2: crossing droop gain $[k_{df}, k_{dv}] = [0.0165, 0.0825]$; (c) Condition 3: crossing power regulator gain $[k_w, k_v] = [0.0825, 0.0619]$.

3.6 Case Study in a Modified Banshee Microgrid

This section verifies the functionalities of the proposed method in a modified real microgrid and further demonstrates its transient performance between different equilibriums.

3.6.1 Case overview

The microgrid shown in Figure 3.8 operates in islanded mode with switch 100 off. It is modified from the Banshee distribution system by replacing the diesel generator on BUS 103 with a battery energy storage system (BESS) and connecting a PV and a BESS to BUS 102 and 105, respectively [137]. The three GFM inverters are named G1, G2, and G3 in Figure 3.8. The microgrid also supplies the static V-f dependent ZIP load and motor load [137]. The load parameters are listed in Table 3.1. All the simulations were run in MATLAB® version R2020a, with a PC Intel® Core i7-8665U CPU at 2.10 GHz and 16 GB RAM.

Two test scenarios are designed to validate the key functionalities of the proposed control framework. Scenario 1 focuses on inverter power regulation, while Scenario 2 focuses on the cooperation of the power regulator and V-f regulator, which leverages the limited DER capacity and demand control to improve V-f deviation and reduce involuntary load shedding. In addition, the current limiter is chosen as a baseline to show the advantages of the proposed method.

3.6.2 Scenario 1: inverter power regulation

Following the timeline, the basic settings of Scenario 1 are three-fold:

- a) Before 8 s, G1-G3 are controlled with the conventional droop method represented in 3.1.
- b) At 8s, the inverter power regulators of G1-G3 are implemented and triggered immediately. Meanwhile, the real-time reference capacities of G1-G3 are set as 1.2 MVA, 0.6 MVA, and 2.0 MVA, respectively.
- c) At 12s, load C2 connected to Bus 106 increases by 200kW, 100kVar.

Table 3.1: ZIP load parameters

Load	$\mathbf{P}$ composition/ [P_1, P_2, P_3]	$\mathbf{Q}$ composition/ [q_1, q_2, q_3]	$\mathbf{V} - \mathbf{f}$ sensitivity/ [$k_{\text{pf}}, \mathbf{k}_{\text{qf}}$]
L1	0.1, 0.3, 0.6	0.5, 0.3, 0.2	2, -0.1
L2	0.6, 0.2, 0.2	0.6, 0.2, 0.2	2.5, -2
C1	0.5, 0.3, 0.2	0.2, 0.3, 0.5	3, -0.1
C2	0.4, 0.3, 0.3	0.4, 0.3, 0.3	1, -0.5
P2	0.5, 0.3, 0.2	0.5, 0.3, 0.2	3, -1

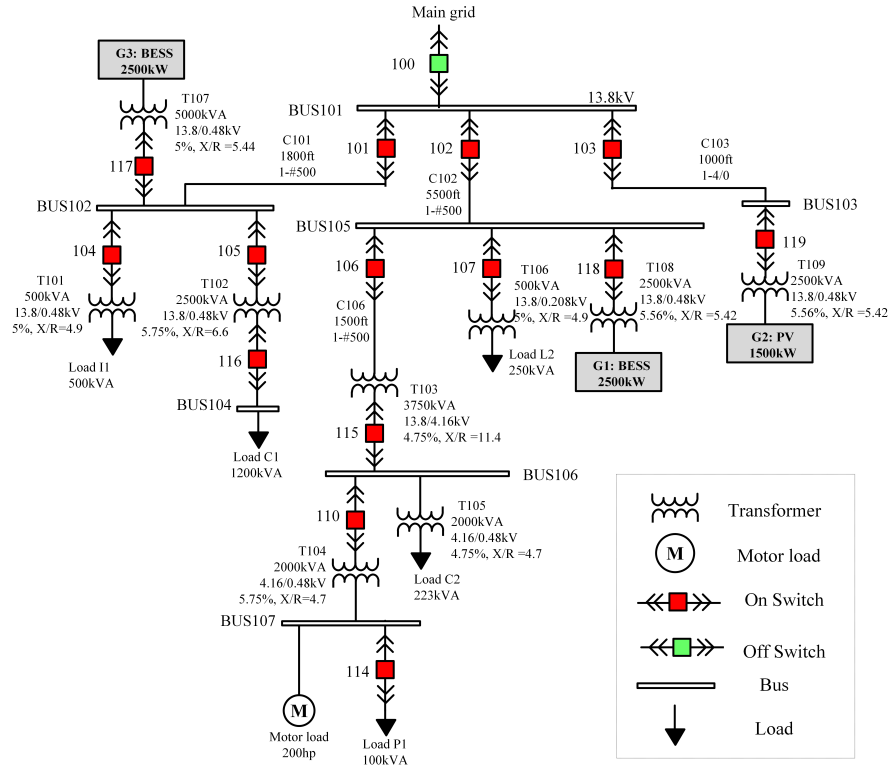


Figure 3.8: Single line diagram of the islanded microgrid [137].

1) Performance of power regulator

Figure 3.9 shows the microgrid performance in Scenario 1, where Figure 3.9a is the dynamic output of G1-G3, Figure 3.9b is the static output, and Figure 3.9c is the dynamic voltage and frequency.

In Figure 3.9a, the output of G1 and G3 follows the left axis, while the output of G2 follows the right axis, based on which the following observations are three-fold:

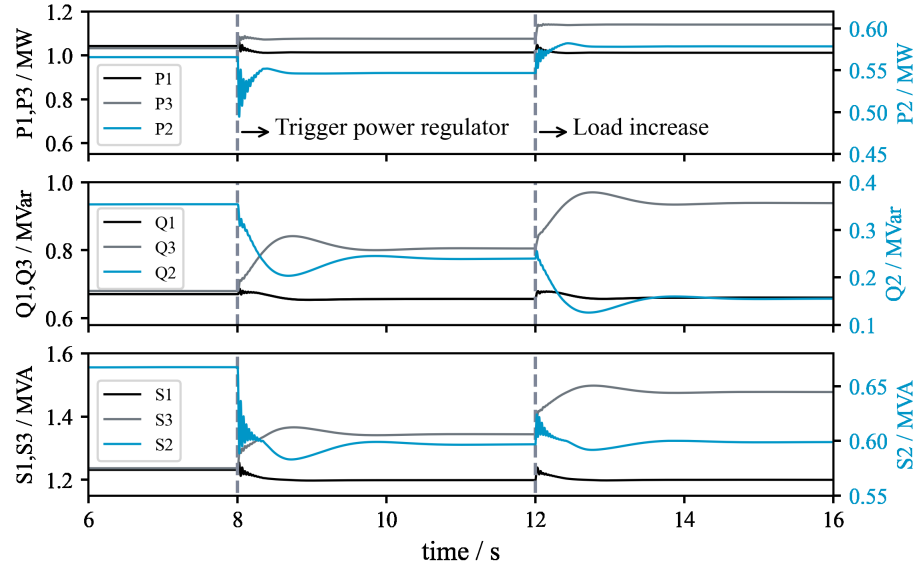
- According to the initial setting point (P_0, Q_0) and droop gains (k_{df}, k_{dv}) before 8 s, all the load is automatically shared among G1, G2, and G3 as 1.24 MVA, 0.67 MVA, and 1.24 MVA, respectively.
- At 8s, S1 and S2 violate the real-time capacity constraints, and the power regulator starts working. Then, P1, Q1, P2, and Q2 decrease until S1 and S2 are regulated to the reference value.
- Even though there is a sudden load increase at 12 s, S1 and S2 still converge to the reference value. Meanwhile, P3, Q3, and S3 increase at 8 s and 12 s to compensate for the decreased generation and the increased load.

Figure 3.9b further presents three static operating points at 6s, 10s, and 14s. In Figure 3.9b, the circle and square operating points of G1 and G2 lie exactly on the capacity boundary after triggering the power regulator.

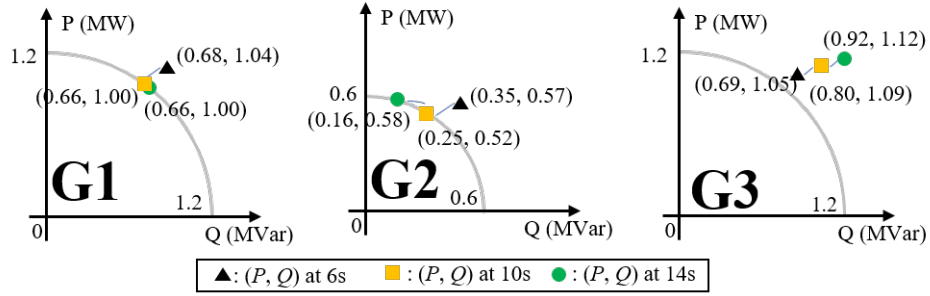
In Figure 3.9c, the voltage and frequency are measured at the terminal of G3, and they hardly change after the power regulator starts working. This indicates that the power regulator is able to regulate the output of GMF inverters without significantly affecting the grid's voltage and frequency.

2) Comparison with the current limiter

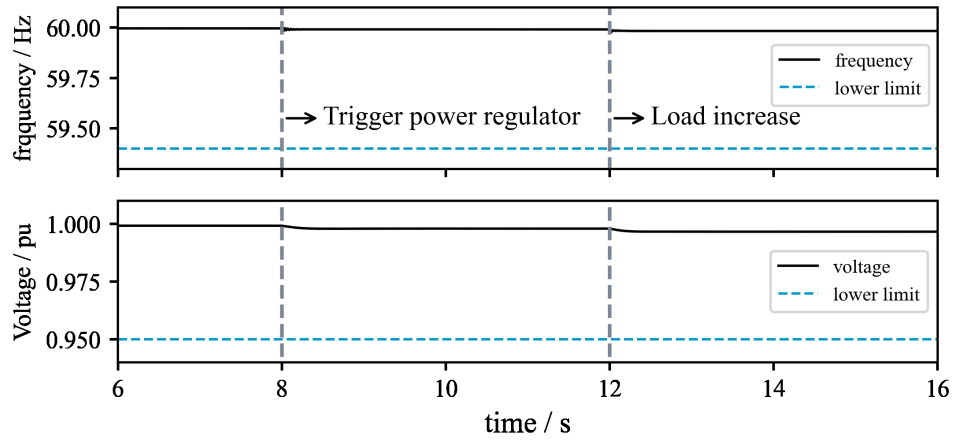
The existing current limiter is mainly designed for protecting devices in abnormal conditions [61], [180], and the threshold is usually set at 2 p.u. to 3 p.u.. To make it more comparable with our proposed method, assume that the threshold is adaptively updated according to the real-time DER capacity. In addition, the DER capacity is preferentially allocated to the frequency regulation loop. Then, the performance of the current limiter is shown in Figure



(a)



(b)



(c)

Figure 3.9: Performance of power regulator in Scenario 1: (a) dynamic inverter output; (b) static inverter output; (c) dynamic frequency and voltage.

10. After triggering the current limiter, the output of G1 and G2 is limited to their real-time generation capacities. However, the sudden limit results in larger voltage and frequency deviations around 8 s, as detailed in Figure 3.10c.

3.6.3 Scenario 2: cooperation of power regulator and V-f regulator

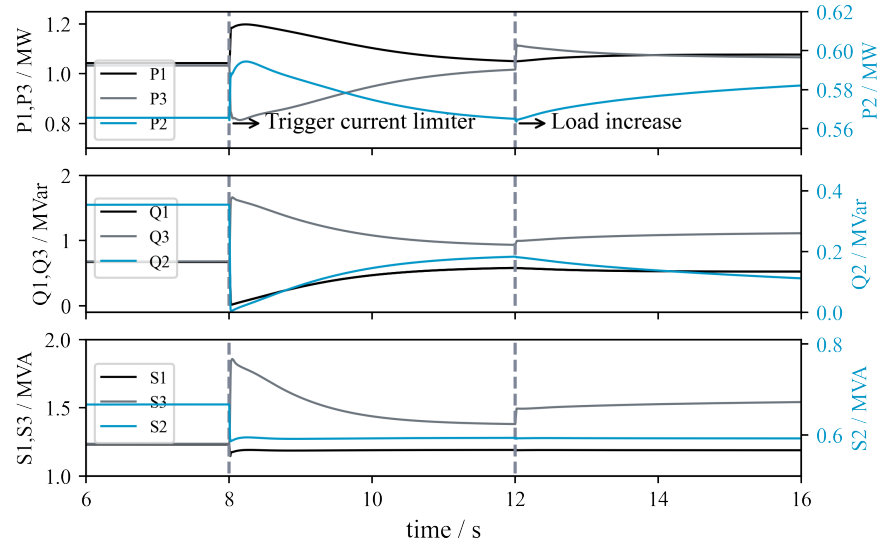
In the transition zone shown in Figure 3.2, the conventional primary and secondary controllers become invalid due to the saturation caused by insufficient DER capacity. Then, the cooperation of the power regulator and V-f regulator becomes important. Scenario 2 is further divided into two parts, Scenario 2-1 and Scenario 2-2, to show their cooperation under various load changes. Specifically, load C2 increases by 100 kW, 200 kVar in Scenario 2-1 while by 200 kW, 100 kVar in Scenario 2-2. Following the timeline, Scenario 2-1 and Scenario 2-2 have the same settings as follows, and their grid performance is shown in Figures 3.11a and 3.12a.

- a) Before 8 s, G1-G3 are controlled with the conventional droop method represented in 3.1.
- b) At 8 s, load C2 increases.
- c) At 12 s, the reference capacities of G1-G3 are set as 1.2 MVA, 0.6 MVA, and 1.2 MVA, respectively. The total load is thus larger than the total generation capacity, and the power regulator starts working.
- d) At 16 s, the V-f regulator starts working.

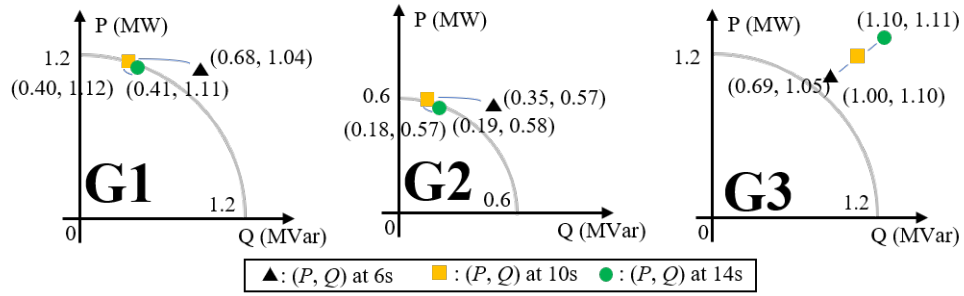
1) Performance of the proposed control framework

Figure 3.11 and Figure 3.12 show the performance of the proposed control method in Scenarios 2-1 and 2-2, respectively. They both demonstrate the cooperation of the power regulator and V-f regulator.

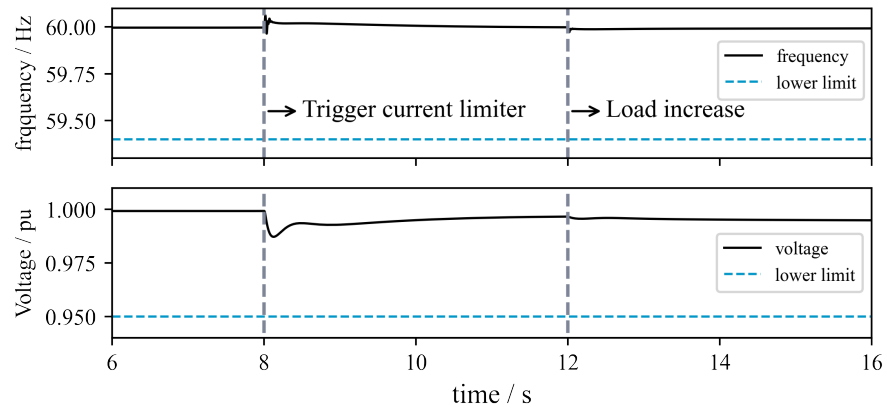
In Figures 3.11a and 3.12a, as a result of different load changes, Scenario 2-1 and Scenario 2-2 have distinct load sharing results after 8 s. At 12 s, the power regulator starts working. S1, S2, and S3 are regulated to 1.2 MVA, 0.6 MVA, and 1.2 MVA at around 12.5 s, which are exactly equal to the reference capacities. The reduced generation is compensated by



(a)



(b)



(c)

Figure 3.10: Performance of current limiter in Scenario 1: (a) dynamic inverter output; (b) static inverter output; (c) dynamic frequency and voltage.

the load response to V-f regulation (load power decreases as V-f decrease). S1-S3 remain unchanged after triggering the V-f regulator at 16s, indicating that the power regulator and the V-f regulator work well together.

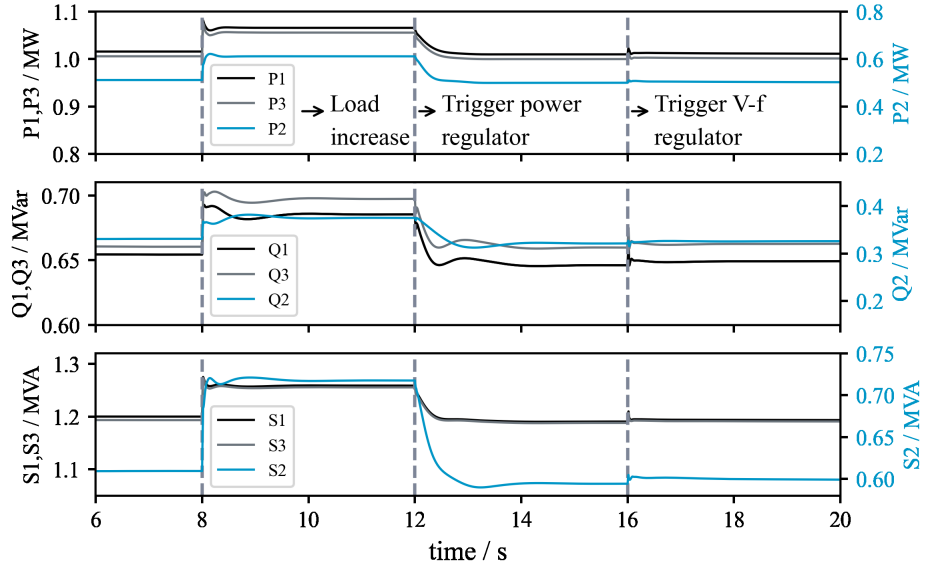
Figures 3.11b and 3.12b show the static operating points at 6 s, 10 s, 14 s, and 18 s. After the power regulator is turned on, the circle and square operations of G1-G3 all fall on the constrained boundary.

Figures 3.11c and 3.12c show the dynamic frequency and voltage measured at the terminal of G3. Both frequency and voltage have an obvious dip at 12 s because the total load is larger than the generation capacity. To achieve load-generation balance again, the load power decreases after the voltage and frequency dip. Scenario 2-1 and Scenario 2-2 have different V-f regulation results due to distinct load changes. Scenario 2-1 has a more reactive power increase and thus a larger voltage dip, while Scenario 2-2 has a more active power increase and thus a larger frequency dip. From 12 s to 16 s, the voltage in Scenario 2-1 and the frequency in Scenario 2-2 violate the requirements of V-f deviation. The violations are mitigated after the trigger of the V-f regulator at 16 s without performing any load shedding.

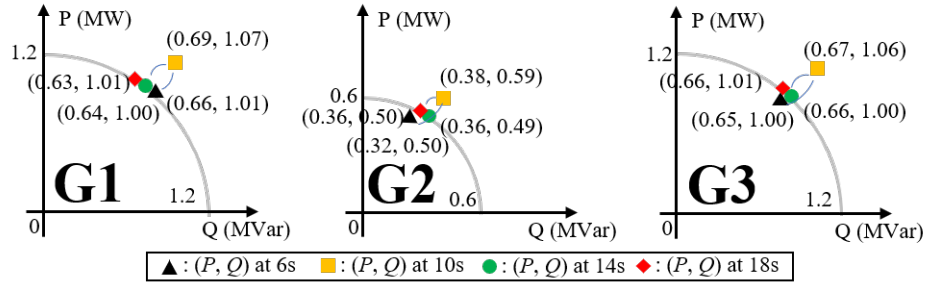
2) Comparison with the current limiter

Like the comparisons in Scenario 1, the threshold of the current limiter is adaptively updated according to the real-time DER capacity, and active power priority is implemented. It is discovered that triggering three current limiters simultaneously in Scenario 2 would result in instability. Hence, the current limiter of G3 is triggered 0.5 s later than those of G1 and G2. In addition, the threshold for G3 was gradually decreased. Then, the comparison results of Scenarios 2-1 and 2-2 are shown in Figures 3.13 and 3.14, respectively. Based on the comparisons, the following observations are three-fold:

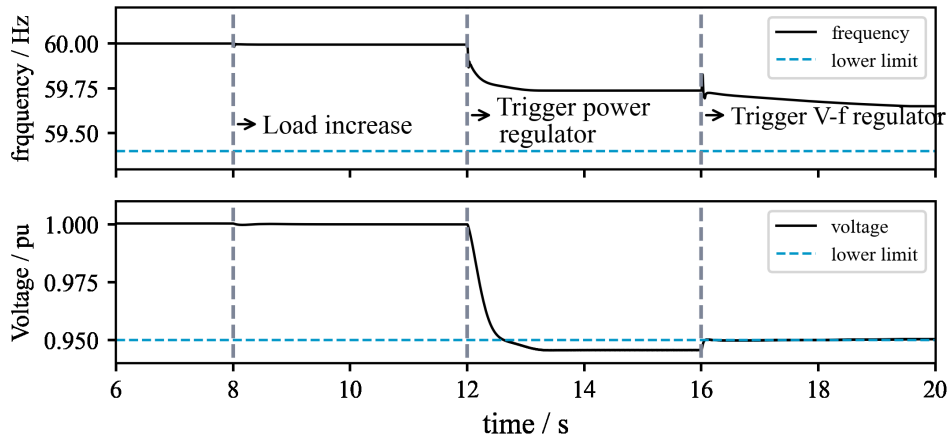
- The current limiter causes large P-Q and V-f deviations at 8 s, while our proposed method has a smoother state transition due to the implementation of a PI controller.
- The output regulation of the current limiter was not accurate due to the voltage deviation. Scenario 2-1 has a large voltage dip in Figure 3.13c, and the inverter generation was inside the capacity circle at 14 s, as shown in Figure 3.13b.



(a)

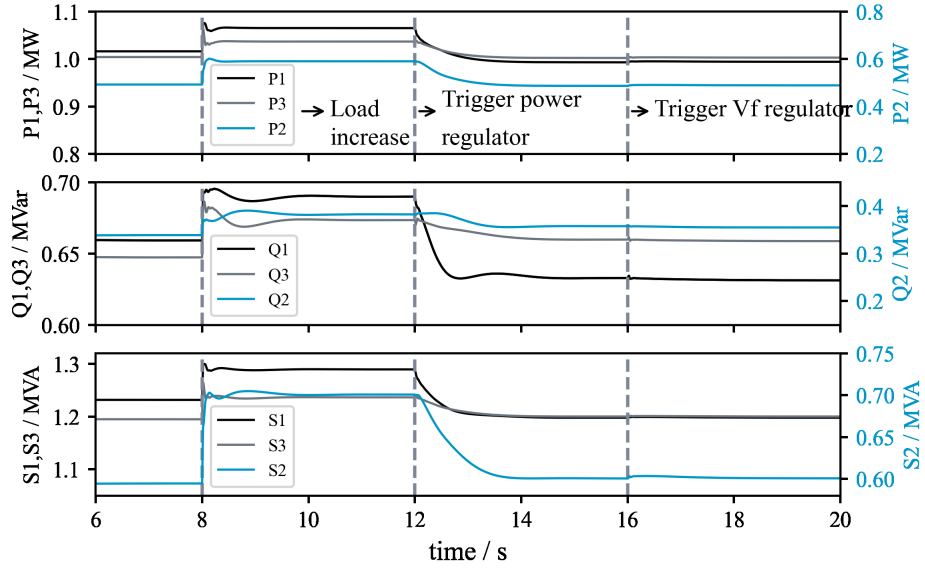


(b)

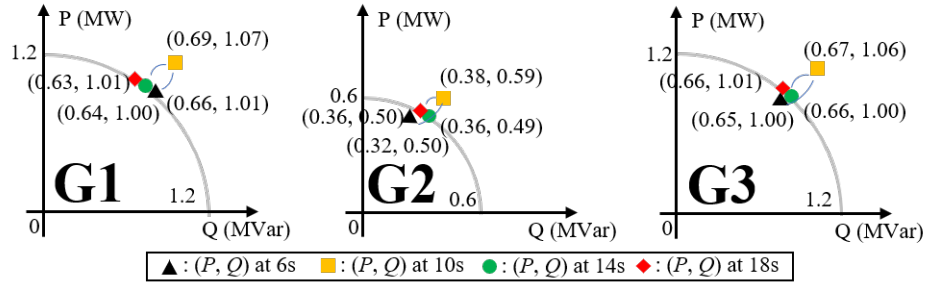


(c)

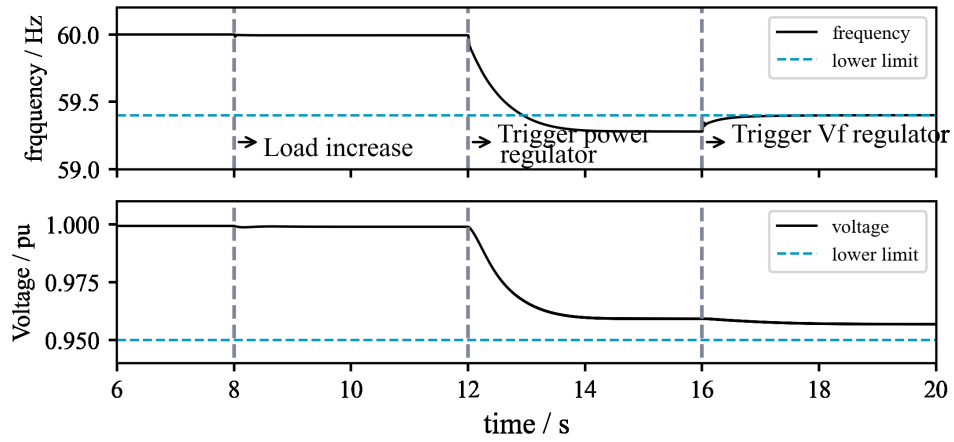
Figure 3.11: Performance of the proposed control framework in Scenario 2-1: (a) dynamic inverter output; (b) static inverter output; (c) dynamic frequency and voltage.



(a)

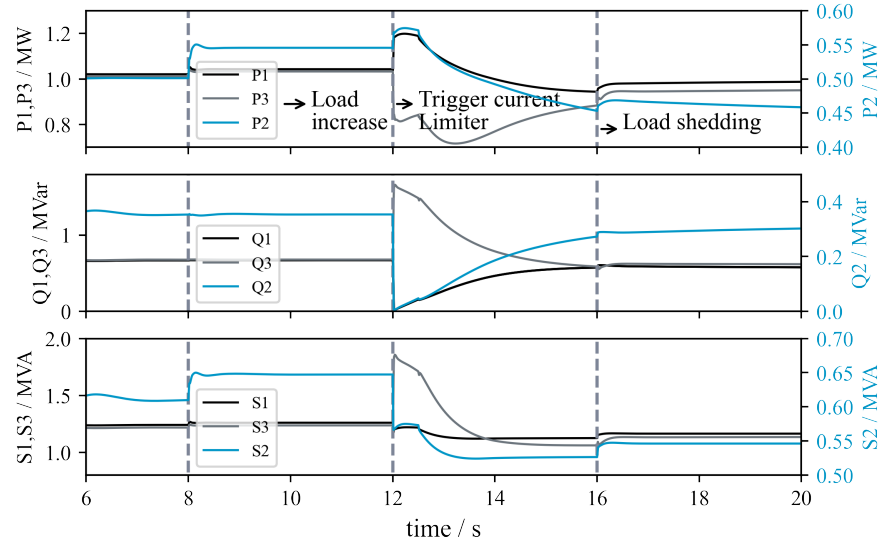


(b)

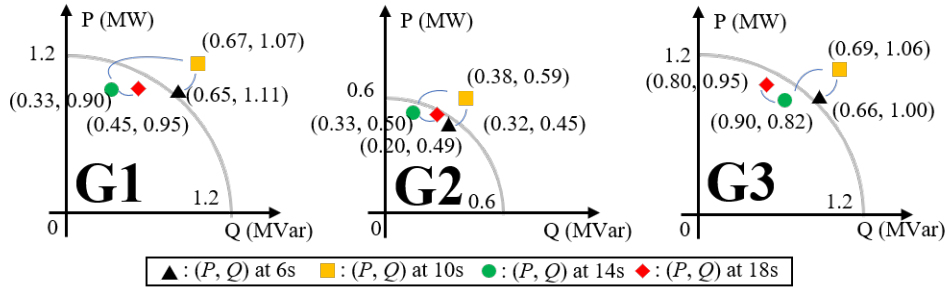


(c)

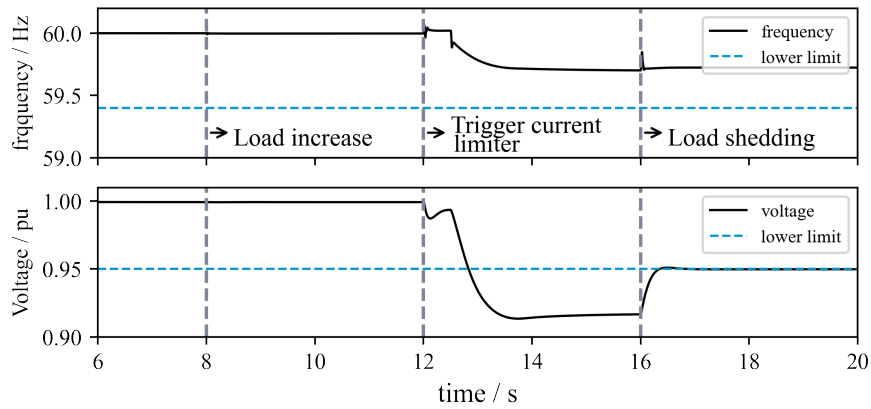
Figure 3.12: Performance of the proposed control framework in Scenario 2-2: (a) dynamic inverter output; (b) static inverter output; (c) dynamic frequency and voltage.



(a)

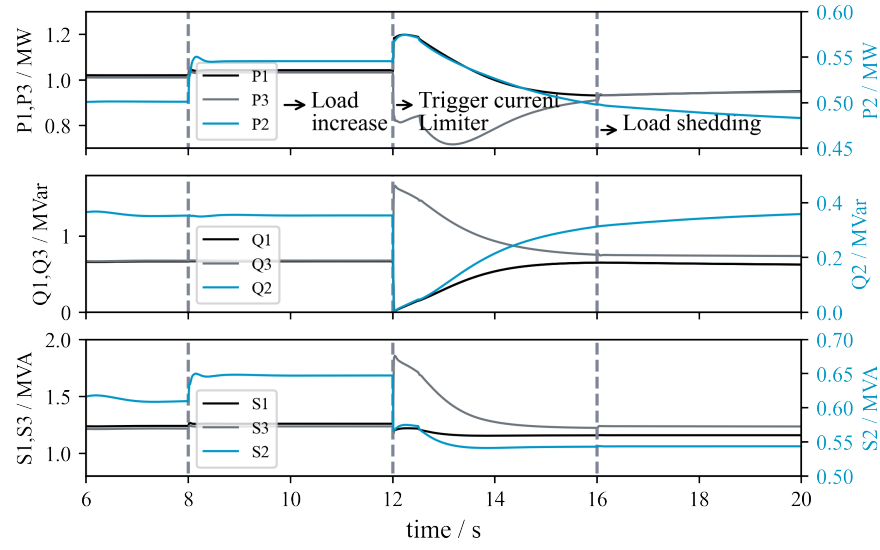


(b)

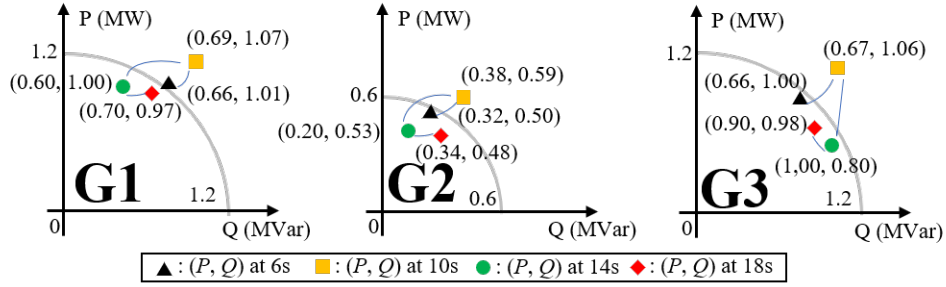


(c)

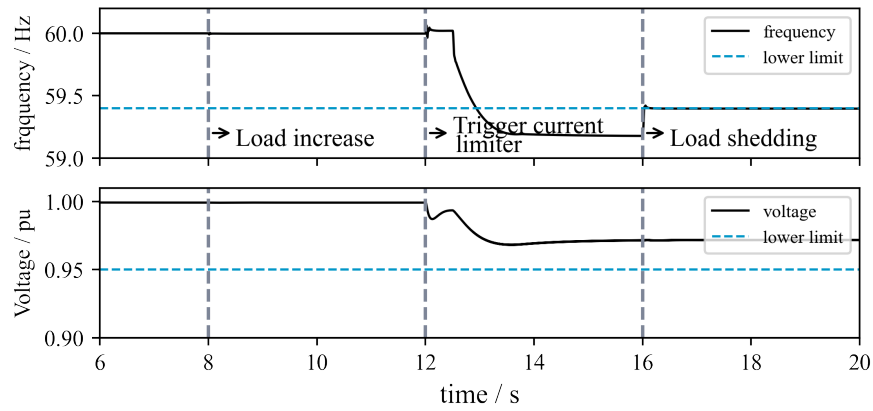
Figure 3.13: Performance of current limiter in Scenario 2-1: (a) dynamic inverter output; (b) static inverter output; (c) dynamic frequency and voltage.



(a)



(b)



(c)

Figure 3.14: Performance of current limiter in Scenario 2-2: (a) dynamic inverter output; (b) static inverter output; (c) dynamic frequency and voltage.

- The current limiter failed to reallocate the constrained generation capacity. Hence, to recover voltage and frequency, load shedding is required after 16 s.

In Scenario 2-1, an additional counterintuitive observation has been made: the output of the inverters increased following load shedding. After load shedding, the grid voltage increased, and since the current was constrained by the limiter, the actual output increased.

In general, Scenarios 2-1 and 2-2 verify the proposed decentralized and coordinated control framework. The framework enables output control of GFM inverters and V-f improvement under the condition of constrained DER capacity and outperforms the current limiter.

3.7 Summary

This chapter proposes a decentralized and coordinated V-f control framework to address the challenges brought by DER inadequacy in islanded microgrids. The control framework is composed of a power regulator and a V-f regulator. The power regulator can regulate the output of GFM inverters without violating real-time reference capacities, while the V-f regulator improves the V-f deviation by leveraging the load response to voltage and frequency. The control framework is developed based on droop control and is thus purely decentralized and not dependent on costly communication interfaces. In addition, it guarantees DC voltage stability and reduces involuntary load shedding. Within the proposed control framework, three-level coordination is achieved simultaneously when DERs are inadequate, including 1). Generation and load, 2). V regulation and f regulation, and 3). P generation and Q generation.

Chapter 4

Systematic Controller Design with Guaranteed Large-Signal Stability and Domain of Attraction

This chapter introduces a systematic controller design method for inverter-based microgrids to guarantee large-signal stability and designated DOA.

4.1 Literature Review

Stability is one of the essential factors to ensure whether optimizing microgrid operation or designing microgrid controllers. However, the high penetration of inverter-based resources (IBRs) can degrade the stability of microgrids and pose challenges to the existing operation and control framework. On the one hand, the dynamics of IBRs are much faster than those of synchronous generators [173], thereby posing greater threats to the stability of microgrids [165, 171]. On the other hand, IBRs are expected to be more actively involved in grid service, i.e., switching between GFL mode and GFM mode, and providing auxiliary service by adaptively changing control parameters [142]. This further necessitates a more rigorous guarantee of stability.

Research on the stability of ac microgrids is mainly categorized into local stability (small-signal stability) and transient stability (large-signal stability). Small-signal stability analysis focuses on a sufficiently small region around an equilibrium, which can be represented by various linearized models such as the state space model [95, 114], transfer function model [63], and impedance model [132]. The relevant analytical criteria, i.e., eigenvalue [51], root locus [63], Middlebrook's stability criterion [75], and Nyquist criteria [160], can be used for small-signal stability estimation and integrated into dynamic controller design [177] or economic operation [126].

A stable equilibrium induces a region where each trajectory starts and eventually converges to the equilibrium itself, referred to as DOA. Small-signal stability criteria, which typically rely on a linearized model, generally cannot explicitly characterize the geometry of the DOA. However, this information is critical in determining the stability condition of ac microgrids when they deviate significantly from equilibrium after a large disturbance [86]. Hence, the transient stability of ac microgrids has been the subject of research.

Like small-signal stability, several criteria have been developed for determining the transient stability of nonlinear ac microgrids, based on Lyapunov's direct method [87],

Popov’s absolute method [89], bifurcation theory [86], singular perturbation theory [5], and equal area method [158]. These criteria can be used for DOA estimation. For example, [87] estimated the DOA of islanded microgrids by enlarging the candidate state set until the Lyapunov stability condition is infeasible. Reference [85] estimated the DOA of a droop-controlled inverter connected to an infinite bus using Takagi-Sugeno multi-modeling. In [191], the converter is simplified as an ideal current source controlled by a PLL. Then, periodical DOA is obtained by transforming the certified Lyapunov stability condition into SDP and solving it with the sum-of-squares programming (SOS) method. Except for DOA estimation, these criteria have been applied in controller design to certify transient stability. Reference [5] derived the sufficient frequency stability conditions for controllers using a simplified system model that omits network topology and voltage dynamics. The maximum active power perturbation, the system damping, and the frequency are bounded to a specific range so that there exists a positive definite Lyapunov function that can guarantee stability. In [57], the large-signal stability boundaries are derived to guarantee the transient performance of GFL and GFM inverters. Reference [153] ensures the transient stability of droop-controlled inverter networks when subject to multiple operating constraints based on a physically meaningful Lyapunov-like function and derived mathematical and computational stability criteria. Reference [47] designed various topology change strategies for inverter-based microgrids while guaranteeing large-signal stability using Takagi-Sugeno fuzzy modeling.

Despite extensive research into the transient stability of ac microgrids, there are some limitations that must be addressed. Firstly, a more detailed electromagnetic transient (EMT) model is expected to be used due to the involvement of the fast dynamics of power electronic devices. A few studies use simplified inverter models without modeling voltage and current regulation loops [191], [153, 74, 9, 47] or reduced network models through Kron reduction [5, 47]. Secondly, the detailed modeling will be used to extend the transient analysis from a single-inverter or parallel-inverter system [158, 27] to general networked-inverter microgrids. Thirdly, although some research could estimate the DOA of nonlinear microgrids, they usually rely on the direct inspection of stability criteria without performance guarantees, i.e., guaranteeing stable operation in L/HVRT conditions. Fourth, existing research on ac

microgrids has derived conditions to certify a given DOA [9] but has not systematically designed the control modes or control parameters to actively modify the geometry of a DOA to contain a certain operational range. This is especially critical for being more actively involved in grid service, whether normal or emergency.

To bridge the gap in the existing literature, this chapter proposes a systematic controller design approach for inverter-based microgrids to certify stability and DOA. A nonlinear EMT model of droop-controlled islanded microgrids is formulated with detailed dynamic modeling of the device-level controller and network-side behavior. To facilitate the analytical stability analysis, this model is then transformed into a homogeneous-like system with nonlinear terms as superimposed parameter uncertainties. Based on the nonlinear model, the stability criteria certifying that a given set is contained in the system DOA is rigorously derived. Next, a systematic approach that integrates the analytical transient stability conditions is developed to identify the candidate parameter set, which can be integrated into the existing online adaptive methods [9] and inform the data-driven control [37]. The proposed approach is then exemplified in droop controller design so as to improve microgrid stability and resilience.

4.2 Electromagnetic Transient Model of Inverter-based Microgrids

This section builds up the EMT model of inverter-based microgrids in a rotating reference frame, which is then transformed into a homogeneous-like system to facilitate the analytical stability analysis.

4.2.1 Component modeling

Figure 4.1 shows the grid components of an inverter-based islanded microgrid, including GFM inverters, connection lines, buses, and loads [87]. These components can be written in a general form in (4.1).

$$\begin{cases} \dot{x}_c = A_c(x_c) x_c + B_c u_c \\ y_c = C(x_c) x_c \end{cases} \quad (4.1)$$

where x_c is the component state variable; y_c is the component output variable, and u_c is the component input variable. Each variable is further categorized based on the grid component it represents. For example, x_c could specifically be x_{inv} for the inverter, x_r for the load, x_l for the line, or x_b for the bus. Equation (4.1) is a nonlinear model with the state variable embedded in the state matrix A_c .

All the grid components are modeled under the rotating reference frame. Specifically, each inverter is regulated at the local rotating dq reference frame, and one of the local references serves as the global rotating DQ reference frame for the rest grid components. Then, the variables observed from the local dq reference frame are transferred to global DQ reference frame [47]:

$$\mathbf{x}_{cDQ} = \mathbf{T}_s \mathbf{x}_{cdq} = \begin{bmatrix} \cos \theta_i & -\sin \theta_i \\ \sin \theta_i & \cos \theta_i \end{bmatrix} \mathbf{x}_{cdq} \quad (4.2)$$

where $\mathbf{x}_{cDQ} = [x_{cD}(t), x_{cQ}(t)]$ and $\mathbf{x}_{cdq} = [x_{cd}(t), x_{cq}(t)]$ are the state vectors observed on the DQ/dq -axis from the global and local reference frame, respectively, and θ is the angle mismatch between the two references.

1) GMF inverter

Figure 4.1a shows the diagram of a GFM inverter, which consists of a current regulator, a voltage regulator, and a primary regulator, each with several parameters that need elaborate design. The mathematical modeling is detailed in (4.3)-(4.8).

- Power angle

$$\dot{\theta} = \omega_{ref} - \omega_{DQ} \quad (4.3)$$

- Droop equation

$$\begin{cases} v_{dref} = V_n + k_{dv} (Q_n - Q_m) \\ w_{ref} = w_n + k_{df} (P_n - P_m) \end{cases} \quad (4.4)$$

- Low pass filter

$$\begin{cases} P_m = \frac{G_P}{1+sT_P} P \\ Q_m = \frac{G_Q}{1+sT_Q} Q \end{cases} \quad (4.5)$$

- Power stage loop

$$\begin{cases} P = v_d i_{bd} + v_q i_{bq} \\ Q = v_d i_{bq} - v_q i_{bd} \end{cases} \quad (4.6)$$

- Current regulation loop

$$\begin{cases} i_{dref} = \left(k_{pid} + \frac{k_{iid}}{s}\right) (v_{dref} - v_d) - w_n C_f v_q + i_{bd} \\ i_{qref} = \left(k_{piq} + \frac{k_{iiq}}{s}\right) (v_{qref} - v_q) + w_n C_f v_d + i_{bq} \end{cases} \quad (4.7)$$

- Voltage regulation loop

$$\begin{cases} e_d = \left(k_{pvd} + \frac{k_{ivd}}{s}\right) (i_{dref} - i_d) - w_n L_f i_q + v_d \\ e_q = \left(k_{pvq} + \frac{k_{ivq}}{s}\right) (i_{qref} - i_q) + w_n L_f i_d + v_q \end{cases} \quad (4.8)$$

Then, a full-scaled 13th order state space model is obtained by introducing some internal variables in (4.9). The nonlinear state space model has $x_{inv} = [\theta, \varphi_{vd}, \varphi_{vq}, \varphi_{id}, \varphi_{iq}, v_d, v_q, i_d, i_q, P_m, Q_m, i_{bd}, i_{bq}]^T$ as state variables, bus voltage $u_{inv} = [v_{bD}, v_{bQ}]^T$ as input variables, and filter current $y_{inv} = [i_{bD}, i_{bQ}]^T$ as output variables.

$$\begin{cases} \varphi_{id} = \frac{k_{iid}}{s} (i_{dref} - i_d) \\ \varphi_{iq} = \frac{k_{iiq}}{s} (i_{qref} - i_q) \\ \varphi_{vd} = \frac{k_{ivd}}{s} (v_{dref} - v_d) \\ \varphi_{vq} = \frac{k_{ivq}}{s} (v_{qref} - v_q) \end{cases} \quad (4.9)$$

Utilization of the full-scaled inverter model for analytical stability analysis can avoid the conservativeness resulting from model-reduction [85, 47]. It has a group of control parameters that fundamentally determine the stability of microgrids. These parameters include droop gains, proportional integral gains, filter inductance, and so on, all requiring elaborate design. By grouping these parameters into a vector K , this paper focuses on designing K to ensure both stability and DOA certification.

2) Network component

The network components operate in the global rotating DQ reference frame. Figures 4.1b-d show the diagram of a constant RL load, a π connection line, and a general bus. Considering that each line is connected to two independent buses, its capacitors are integrated into the connected bus to reduce the number of state variables and thus simplify the modeling. By implementing Kirchhoffs Circuit Law and performing Park Transformation, network components have distinct state variables, input variables, and output variables as follows:

- (i). Load: $x_r = [i_{rD}, i_{rQ}]^T$, $u_r = [v_{bD}, v_{bQ}]^T$, and $y_r = [i_{rD}, i_{rQ}]^T$;
- (ii). Line: $x_l = [i_{lD}, i_{lQ}]^T$, $u_l = [v_{bD1}, v_{bQ1}, v_{bD2}, v_{bQ2}]^T$, and $y_l = [i_{lD}, i_{lQ}]^T$;
- (iii). Bus: $x_b = [v_{bD}, v_{bQ}]^T$, $u_b = [i_{bD1}, i_{bQ1}, i_{bD2}, i_{bQ2} \cdots]^T$, and $y_b = [v_{bD}, v_{bQ}]^T$.

The detailed expressions of each model can be seen in [87] and [47]. They lay the foundation for developing a unified microgrid that accounts for the nonlinearities of each component and the coupling between grid components.

4.2.2 Unified microgrid modeling

Assuming a reference inverter that provides the global rotating DQ reference frame for all the microgrid components, the remaining inverters are referred to as the following inverters in this paper. As visualized in Figure 4.2, the unified microgrid model is formulated through the coupling of grid components. By plugging the output of grid components into the state space model of the corresponding coupling components, the unified model is obtained in (4.10).

$$\dot{x} = Ax = \begin{bmatrix} A_{inv} & 0 & 0 & A_{inv-b} \\ A_{r-inv} & A_r & 0 & A_{r-b} \\ A_{l-inv} & 0 & A_l & A_{l-b} \\ A_{b-inv} & A_{b-r} & A_{b-l} & A_b \end{bmatrix} x \quad (4.10)$$

Where A is the state matrix of the unified model, and A_{inv} , A_r , A_l , and A_b are the united state matrix of inverters, load, lines, and bus, respectively. The off-diagonal matrices represent the coupling between grid components, which matches the data flow shown in Figure 4.2. The diagonal elements do not have any inner coupling, except for A_{inv} . Denote the state

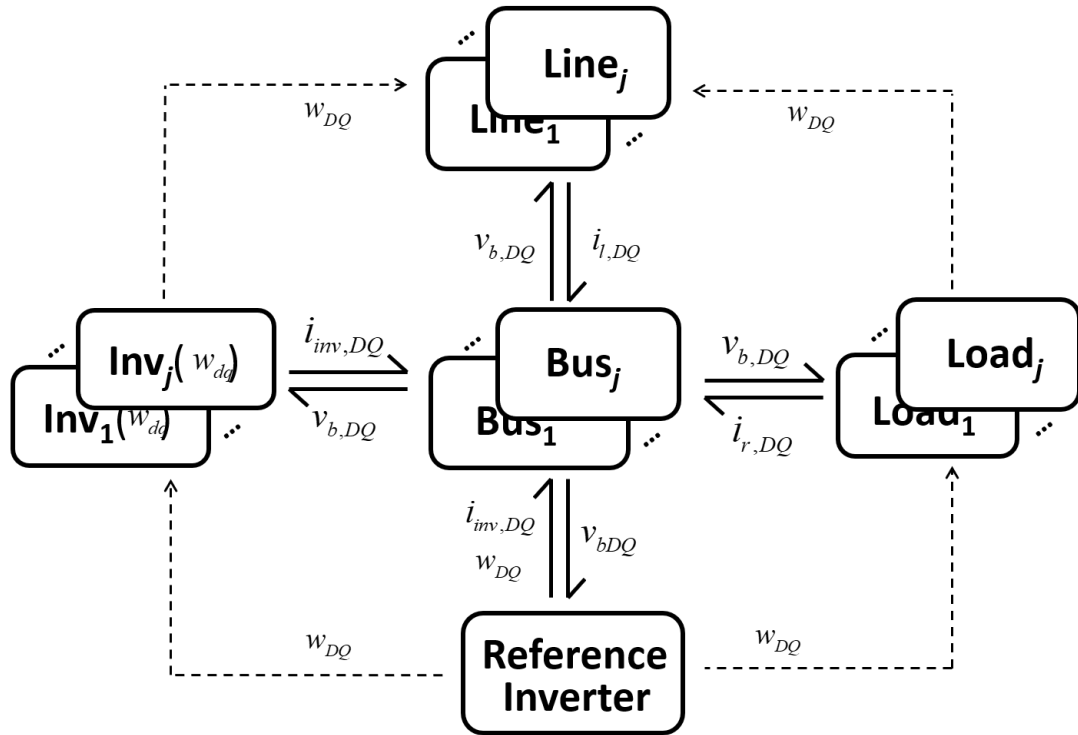


Figure 4.2: Unification of microgrid components.

matrix of the reference inverter as $A_{inv,ref}$, and the following inverters are numbered from 1 to j . Then, (4.11) details A_{inv} .

$$A_{inv} = \begin{bmatrix} A_{inv,ref} & 0 & 0 & 0 \\ A_{inv,ref-1} & A_{inv,1} & 0 & 0 \\ \vdots & 0 & \ddots & 0 \\ A_{inv,ref-j} & 0 & 0 & A_{inv,j} \end{bmatrix} \quad (4.11)$$

Where $A_{inv,j}$ is the state matrix of the j th following inverter and $A_{inv,ref-j}$ is the coupling between the reference inverter and the j th following inverter. The reference inverter couples with the following inverters via w_{DQ} , as visualized in Figure 4.2.

In summary, component unification eliminates the input and output variables of each component and makes the microgrid a unified system. Then, matrix A embedding K can be used for analytical stability analysis.

4.2.3 Homogeneous-like system

To better track the nonlinear dynamics of (4.2), it is changed into a homogeneous-like system through a coordinate transformation [167]. Assume the state derivation from equilibrium is $\Delta x \triangleq x - x_e$. Plug Δx and x_e into (4.2), then (4.2) is transformed into a homogeneous-like form while preserving the nonlinearities. The stability of the transformed system is the same as the original system, but it is more suitable for analytical stability analysis.

$$\Delta \dot{x} = \hat{A}(\Delta x, K, x_e) \Delta x = \hat{A}(h) \Delta x \quad (4.12)$$

where $h = h(\Delta x, K, x_e)$ is the nonlinear terms in $\hat{A}$. Then, (4.12) represents a homogeneous linear parameter varying (LPV) system with h as a superimposed parameter uncertainty. The stability of an LPV system could be guaranteed by bounding h to a specific range, which is fundamental to the systematic controller design in the next section.

4.3 Systematic Control Design with Certified Stability and Domain of Attraction

This section derives the analytical criteria that can certify stability and DOA and integrates them into microgrid controller design.

4.3.1 Foundation of the systematic design

1) Concept of certified stability and DOA

DOA is defined based on a stable equilibrium. It determines a set where each trajectory starts and eventually converges to the equilibrium itself [158].

A microgrid is stable for sure if the system state is initialized within its DOA whether in normal or emergency conditions. IEEE standard [112] and some institution guidelines define a few important operational requirements for microgrids, i.e., the 1% frequency deviation limit and 7% voltage deviation limit after normal disturbances, and L/HVRT capability when there is 60% voltage deviation under emergency conditions [192]. These requirements define a critical set for microgrids, which is desired to be a subset of the DOA and can be referred to as the designated DOA [146, 109]. This concept is shown in *Definition 1* and equation (4.13).

Definition 1. *A microgrid governed by (4.12) is called stable with a guaranteed DOA if $\Delta\mathcal{X}^o$ is a subset of the system DOA.*

$$\begin{cases} \Delta\mathcal{X}^o \triangleq \{\Delta x \in \mathbb{R}^n : \Delta x \in [\Delta\bar{x}_-, \Delta\bar{x}]\} \\ \Delta\mathcal{X}^o \subset DOA \end{cases} \quad (4.13)$$

where $\Delta\bar{x}_-$ and $\Delta\bar{x}_+$ are the upper and lower bound of state variable deviation, which is customized and defined according to IEEE standards or institution requirements.

2) Scope of the systematic controller design

Matrix $\hat{A}$ is composed of x_e , Δx , and K , all together fundamentally determining whether or not a microgrid meets (4.13). If the designated DOA contains any operation point outside the actual DOA, microgrids may encounter unexpected stability issues [109]. Hence, this paper aims to systematically design $\mathcal{K}$, the candidate set of K , that makes (4.13) feasible for a given designated DOA.

4.3.2 Analytical certified stability and DOA

This subsection derives the analytical conditions that certify stability, DOA, and their combination, with the assumption that K remains constant throughout.

1) Certified stability

Given the homogeneous-like system (4.12), there is a quadratic Lyapunov function $V(\Delta x(t)) \triangleq \Delta x(t)^\top P \Delta x(t)$ that can certify stability, where $P \succ 0$ is a positive definite matrix.

Since $\hat{A}$ is bounded internally by h , define $\mathcal{H}$ as the complete set of h that can guarantee the homogeneous-like system (4.12) stable. $\mathcal{H}$ is a convex hull according to [15]. Although $\mathcal{H}$ is difficult to represent explicitly, it is possible to find a subset $\mathcal{H}'$ by introducing a base vector and a scaling factor. Denote the subset as $\mathcal{H}' \triangleq \{h : h \in [\beta h_-^o, \beta h_+^o]\} \subseteq \mathcal{H}$, where h_-^o and h_+^o are guessed base vectors of the convex hull. Then, the stability condition is formulated in (4.14) by maximizing the scaling factor while also satisfying the Lyapunov stability criteria.

$$\begin{aligned} \text{Certified stability: } & \max_{P \succ 0, \beta > 0} \beta \\ \text{s.t. } & \hat{A}^\top P + P \hat{A} \leq -I, P \succ I \end{aligned} \tag{4.14}$$

Equation (4.14) induces *Lemma 1*, which is then integrated into the controller design process. It determines a subset of $\mathcal{H}$ and a common quadratic Lyapunov function that renders the nonlinear system (4.12) Hurwitz stable.

Lemma 1. For given $h_-^o \leq 0$ and $h_+^o > 0$, if β and P are the solution of semi-definite programming (4.14), $V(\Delta x) = \Delta x^\top P \Delta x$ is a common quadratic Lyapunov function for (4.12) with $\dot{V}(\Delta x) < 0$ for $h \in [\beta h_-^o, \beta h_+^o]$.

2) Certified DOA

This condition aims to find a minimum sub-level set of DOA that covers $\Delta\mathcal{X}^o$. Assume an open set $D \subset \mathbb{R}^n$ contains the equilibrium point x_e and a continuous, differentiable Lyapunov function $V : D \rightarrow \mathbb{R}$, then (4.15) certified a subset of DOA and (4.16) further describes a positive invariant domain in a DOA [191].

$$\begin{cases} V(0) = 0 \\ V(\Delta x) > 0, \forall \Delta x \in D \setminus \{0\} \\ \dot{V}(\Delta x) = \nabla V \Delta x \leq 0, \forall \Delta x \in D \setminus \{0\} \end{cases} \quad (4.15)$$

$$\mathcal{S} = \{\Delta x \in \mathbb{R}^n \mid V(\Delta x) \leq \alpha\} \quad \text{with} \quad \mathcal{S} \subset DOA \quad (4.16)$$

Since $P \succ 0$ and quadratic V have been obtained in (4.14), it is trivial to find the invariant sub-domain defined by (4.16): $\mathcal{S}(P, \alpha) = \{\Delta x : \Delta x^\top P \Delta x \leq \alpha\}$. Then, multi-linear matrix LMIs are formulated in (4.17) to certify $\Delta\mathcal{X}^o \subset \mathcal{S}(P, \alpha)$, which finally ensures $\Delta\mathcal{X}^o \subset \mathcal{S}(P, \alpha) \subset DOA$ and induces Lemma 2.

$$\begin{aligned} \textbf{Certified DOA:} \quad & \min_{\alpha > 0} \alpha \\ \text{s.t.} \quad & (\Delta\mathcal{X}_k^o)^\top P \Delta\mathcal{X}_k^o \leq \alpha, k = 1, \dots, m \end{aligned} \quad (4.17)$$

where $\Delta\mathcal{X}_k^o$ is the k_{th} vertex of $\Delta\mathcal{X}^o$ and m is the number of vertices.

Through the minimization of α , (4.17) identifies the minimum sub-level set of DOA that covers $\Delta\mathcal{X}^o$. While this process typically involves multiple LMIs, the symmetrical property of $\Delta\mathcal{X}^o$ can be leveraged to transform into a single LMI to reduce the computational burden. In (4.17), each P will certify an ellipse sub-level set of DOA, which needs to cover the expected range $\Delta\mathcal{X}^o$. To achieve this, a minimum-volume symmetric ellipsoid covering $\Delta\mathcal{X}^o$ can first be found, followed by the identification of a sub-level set that contains the symmetric

ellipsoid. Remarkably, each of these steps requires only a single LMI [21], resulting in a significant improvement in computational efficiency.

Lemma 2. *For given $\beta > 0$ and $P \succ 0$ as the solution of (4.14) and α as the solution of (4.17), $\mathcal{S}(P, \alpha) = \{\Delta x : \Delta x^\top P \Delta x \leq \alpha\}$ is the minimum ellipsoid set that covers $\Delta \mathcal{X}_k^\circ$.*

3) Combined stability and DOA

The stability condition in (4.14) and the certified DOA (4.17) could be combined as a unified condition in (4.18) with the following logic:

- Equation (4.18–1) guarantees $\Delta \mathcal{X}^\circ \subset \mathcal{S}(\gamma, 1)$, where $\mathcal{S}(\gamma, 1) \triangleq \{\Delta x : \Delta x^\top [\gamma] \Delta x \leq 1\}$;
- Equation (4.18–2) guarantees $\mathcal{S}(\gamma, 1) \subset \mathcal{S}(P, 1)$;
- Equation (4.18–3) combined with constraint $P \succ 0$ is like (4.14), rendering the nonlinear system (4.12) Hurwitz stable.

$$\begin{aligned} \text{Co-Stability-DOA: } & \max_{P \succ 0, \gamma > 0} \det \text{rootn}(P) \\ \text{s.t. } & \begin{cases} (\Delta \mathcal{X}_k^\circ)^\top [\gamma] \Delta \mathcal{X}_k^\circ \leq 1 & (4.18 - 1) \\ P \preceq [\gamma] & (4.18 - 2) \\ \hat{A}^\top P + P \hat{A} \prec 0 & (4.18 - 3) \end{cases} \end{aligned} \quad (4.18)$$

Then, (4.18) minimizes the volume of $\mathcal{S}(P, 1)$ and certifies stability and DOA as $\Delta \mathcal{X}^\circ \subset \mathcal{S}(\gamma, 1) \subset \mathcal{S}(P, 1) \subset DOA$. Figure 4.3 visualized the set-covering relationship, which further induces Lemma 3. Note that β is a decision variable in (4.18), which can be found through the grid-search method to make (4.18) and the set-covering feasible.

Lemma 3. *For given $\beta > 0$, $\gamma \succ 0$ and $P \succ 0$ as the solution of (4.18), $\mathcal{S}(\gamma, 1) = \{\Delta x : \Delta x^\top P \Delta x \leq \alpha\}$ is the minimum symmetric ellipsoid set that covers $\mathcal{X}_k^\circ$, which is also the subset of DOA.*

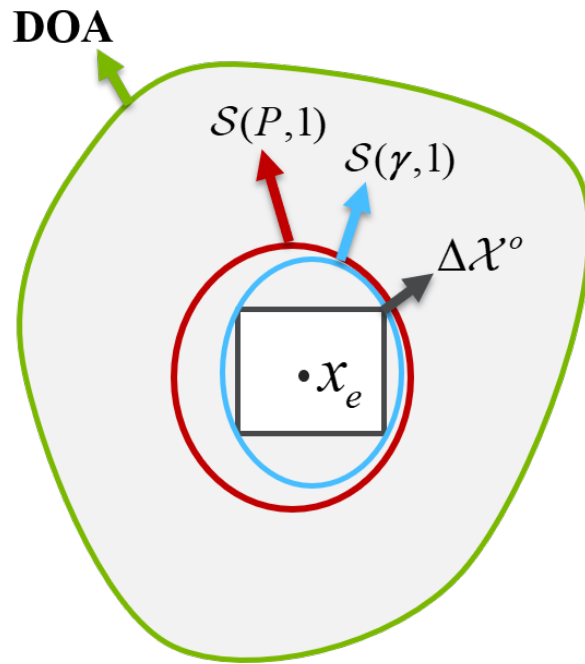


Figure 4.3: Visualized set-covering relationship.

4.3.3 Systematic controller design

1) Mathematical formulation

Sub-section 4.3.2 derived the analytical condition that makes (4.13) feasible, assuming K as constant parameters. The systematic design changes K to decision variables and embeds the derived stability condition, as formulated in (4.19).

$$\begin{aligned} & \textbf{Candidate-set: } \mathcal{K} \\ \text{s.t. } & \begin{cases} P \succ 0, \beta > 0, \alpha > 0, \gamma > 0 \\ (4.14), (4.17) \text{ or } (4.18) \end{cases} \end{aligned} \quad (4.19)$$

Where $\mathcal{K}$ is the set of K subject to the constraints in (4.19).

Either the separate stability conditions (4.14) and (4.17), or the combined stability (4.18), can be included in the systematic design. For the separate conditions, K first impacts the range of the superimposed parameter uncertainty h that makes (4.14) feasible, and then determines whether or not (4.17) is feasible to have an ellipsoid set covering $\mathcal{X}^\circ$. Meanwhile, for the combined condition, K directly impact P solved by (4.18) since K is included in $\hat{A}$, which further determines whether or not $\mathcal{S}(P, 1)$ (red ellipse in Figure 4.3) has a sub-set $\mathcal{S}(\gamma, 1)$ (blue ellipse in Figure 4.3) to cover $\mathcal{X}^\circ$. Hence, (4.19) groups the inner coupling between control parameter, equilibrium, and state deviations and defines a candidate parameter set that certifies stability and designated DOA, which further induces *Lemma 4*.

Lemma 4. *If $\mathcal{K}$ defined by (4.19) isn't an empty set, any $K \in \mathcal{K}$ ensures stability with a certified DOA for system (4.2).*

2) Practical design

Although (4.19) rigorously defines a candidate set that certified stability and DOA, it was difficult to find the exact set or derive the explicit expressions of $\mathcal{K}$. Hence, a practical design approach is further proposed to find a sub-set of $\mathcal{K}$.

Algorithm 2 Identify candidate parameter set to make system (4.10) stable with a guaranteed DOA

Input: state space matrices: $\hat{A}$; constraints set: $\mathcal{X}^e$; target parameter vector K , designated DOA: $\Delta\mathcal{X}^o$; initial guess: h_-^o , h_+^o , β , K_0 , and λ_0 ; and searching interval $\Delta\lambda$.

Output: Candidate control parameter set: $\mathcal{K}'$.

Step 1: Identify upper boundary of $\mathcal{K}'$.

Assume $K = (1 + k\Delta\lambda)K_0$; obtain subset $\mathcal{H}'$ and the minimum subset of DOA by solving (4.18); increase k to k_{up} until (4.18) is infeasible; then, $\lambda_+ = 1 + k_{up}\Delta\lambda$.

Step 2: Identify lower boundary of $\mathcal{K}'$.

Assume $K = (1 - k\Delta\lambda)K_0$; obtain subset $\mathcal{H}'$ and the minimum subset of DOA by solving (4.18); increase k to k_{down} until (4.18) is infeasible; then, $\lambda_- = 1 - k_{down}\Delta\lambda$.

Step 3: Obtain $\mathcal{K}'$.

$$\mathcal{K}' \leftarrow \{K \in \mathbb{R}^n \mid K = \lambda K_0, \lambda_- \leq \lambda \leq \lambda_+\}.$$

Assume a base vector K_0 and a scaling factor λ . Through a grid-search method, it is trivial to find a subset $\mathcal{K}' \triangleq \lambda K_0$ where $\lambda \in [\lambda_-, \lambda_+]$, and λ_- and λ_+ are the minimum and maximum λ making (4.19) feasible. The detailed progress is shown in *Algorithm 2*.

Note that it is not necessary to include all control parameters in $\mathcal{K}$, but rather to flexibly choose any combination of target parameters with less confidence. Furthermore, such a design is flexible since the designated DOA can be customized to include not only the normal operational range but the emergency operational range, such as L/HVRT requirements.

The practical design does not directly formulate the control law for microgrids. Instead, it takes a systematic approach to determine the subset of secure candidate control parameters. By utilizing the feasible candidate set obtained, it is convenient to incorporate it into any controller design, including adaptive control, optimal control, or data-driven control that involves online parameter updates. This method allows for the systematic design of microgrid controllers to ensure stability with a designated DOA, which is particularly crucial for power grids that are penetrated by IBRs or DERs and at risk of instability. In addition, simulation-based sensitivity analysis can be conducted by introducing uncertainties to critical parameters. This can determine robust design results under worst-case conditions. In the following, the practical design is exemplified by droop-controlled GFM inverters.

4.3.4 Exemplify in droop controller design

A droop controller for IBRs is designed to emulate the behavior of conventional synchronous generators and automatically share the load among generations. Due to its rapid response and crucial power-sharing functionality, the droop gain tuning results fundamentally determine the microgrid's transient stability as well as oscillation conditions [54].

Equation (4.20) represents a candidate set of droop gains for microgrid GFM inverters to ensure stability and DOA. Then, *Algorithm 2* can be utilized to obtain a subset $\mathcal{K}'$ bounded

by λ_+ and λ_- .

$$\begin{aligned} & \text{Candidate-droop-gain: } \mathcal{K} \\ & \text{s.t. } \begin{cases} P \succ 0, \beta > 0, \alpha > 0, \gamma > 0 \\ K = \lambda[k_{df,0}, k_{df,1}, \dots, k_{dv,i}, k_{dv,i}, \dots] \\ (4.14), (4.16) \text{ or } (4.18) \end{cases} \end{aligned} \quad (4.20)$$

where $k_{dv,i}$ and $k_{df,i}$ are the voltage droop gain and frequency droop gain of the i th inverter, respectively.

4.4 Case Studies

This section demonstrates the proposed method in a single inverter system and a modified real-world microgrid. The simulation environment is equipped with an Intel(R) Core i7-8665U CPU running at 2.10 GHz, 16 GB of memory, and a MATLAB R2020a simulation platform. *Algorithm 2* is executed using CVX and MOSEK, while the dynamic performance of microgrids with the systematic design is verified using the MATLAB ode45 solver.

4.4.1 Single-inverter system

1) Systematic droop controller design

Assume a single droop-controlled GFM inverter connected to an infinite bus, as shown in Figure 4.1, and find the candidate droop gain set that can certify stability and DOA under L/HVRT conditions with the proposed systematic approach. Table. 4.1 shows the key parameters of the single-inverter system.

According to IEEE 1547-2018 [77], IBRs must be able to ride through short-duration voltage disturbances. The required voltage for L/HVRT is not a fixed value and depends on the specific requirements of the power system and the technical capabilities of the IBRs. This paper chooses 40% voltage deviation (v_b droops as low as 0.6 p.u. and increases as high as 1.4 p.u.) as the L/HVRT operational boundary.

Table 4.1: Parameters of single-inverter system

Item	Value	Item	value	Item	Value
L_{f1} (p.u.)	5.25×10^{-6}	k_{dv0}	0.05	k_{df0}	0.01
C_f (p.u.)	1.9×10^{-4}	kp_{vd}	0.05	ki_{vd}	0.5
L_{f2} (p.u.)	5.25×10^{-4}	kp_{vq}	0.05	ki_{vq}	0.5
T_{fP}	0.004	kp_{id}	0.5	ki_{id}	5
T_{fQ}	0.004	kp_{iq}	0.5	ki_{iq}	5

Then, Figure (4.4) visualizes the systematic design results with the implementation of *Algorithm 2*, where λ_- and λ_+ are solved as 0.036 and 1.828, respectively. Then, the candidate droop gain set is obtained as $\mathcal{K}' = \{K \in \mathbb{R}^2 \mid K = \lambda[k_{dv0}, k_{df0}], 0.036 \leq \lambda \leq 1.828\}$. Based on *Lemma 4*, for $\forall[k_{dv}, k_{df}] \in \mathcal{K}'$, the single inverter system is stable with guaranteed DOA covering L/HVRT operational range.

2) Numerical Verification

To verify the correctness of the design results, several groups of droop gains are sampled randomly from the candidate set $\mathcal{K}'$. They are tested through time domain simulation in Matlab using an ode45 solver with a relative tolerance of 5×10^{-6} and an absolute tolerance of 5×10^{-5} . Results show that all state variables converge to equilibrium with randomly sampled droop gains in $\mathcal{K}'$. For instance, Figure 4.5a shows the transient trajectory of the single-inverter system when initialized from the L/HVRT boundary with $\lambda = 1 \in \mathcal{K}'$ and $[k_{dv}, k_{df}] = [0.0525, 0.015]$. The system stabilizes with all state variables converging to equilibrium at around 0.15 s. Conversely, if $\lambda = 2.5 \notin \mathcal{K}'$ and $[k_{dv}, k_{df}] = [0.125, 0.025]$, the system is demonstrated to diverge when initialized from the L/HVRT boundary, and the corresponding transient trajectory is displayed in Figure 4.5b.

3) Comparison

This chapter proposes a new controller design approach that utilizes a full-scaled homogeneous-like EMT model. It ensures stability and designated DOA flexibly. A comparison study was conducted to highlight the advantages of this approach. The comparison involved implementing the proposed systematic approach in controller design using a simplified IBR model [85]. The study also tried a DOA estimation method [191] for controller design but found the estimated DOA may fail to cover the L/HVRT range as desired.

Using a simplified IBR model and *Algorithm 2*, λ_- and λ_+ are solved as 0.50 and 1.78 in Fig. 4.6, respectively. Then, the candidate droop gain set yields $\mathcal{K}' = \{K \in \mathbb{R}^2 \mid K = \lambda[k_{dv0}, k_{df0}], 0.50 \leq \lambda \leq 1.78\}$, which is smaller than the set obtained based on full-scale model. Such conservativeness resulting from model reduction aligns with the observations in [85].

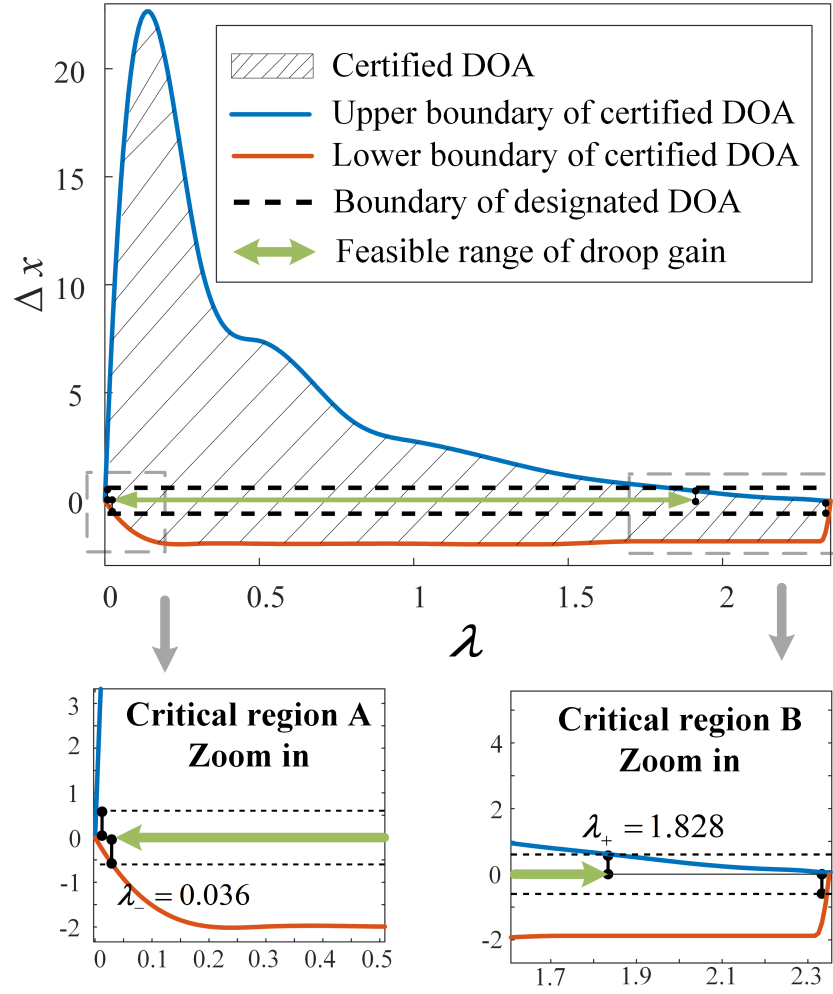


Figure 4.4: Visualized systematic droop controller design results for single inverter system.

If solely relying on the DOA estimation method [191] for stability analysis without systematic design, the estimated DOA is $\{\Delta x \in \mathbb{R}^{13} \mid -1.02x_e \leq \Delta x \leq 0.26x_e\}$ with a given $\lambda = 2$. The estimated DOA does not encompass the L/HVRT boundary, potentially jeopardizing system stability. Engineers may need to use additional methods like the sensitivity-based approach [193] to ensure stability. In contrast, the systematic design ensures a feasible range of λ for set-covering, alleviating the need for engineers to engage in extra parameter tuning for stability guarantee.

4) Discussion

Not all droop gains outside $\mathcal{K}'$ will lead to instability. This is because the quadratic Lyapunov function represents a sufficient condition for transient stability, and (4.15)-(4.16) only quantifies a subset of the actual DOA.

Furthermore, the proposed approach focuses on ensuring that the designated operational range is a subset of the actual DOA. The control objective does not include transient performance, which may vary as control parameters change within the feasible region obtained. However, transient performance could be a design objective, as discussed in [42, 110]. This systematic design can complement those methods to guarantee stability.

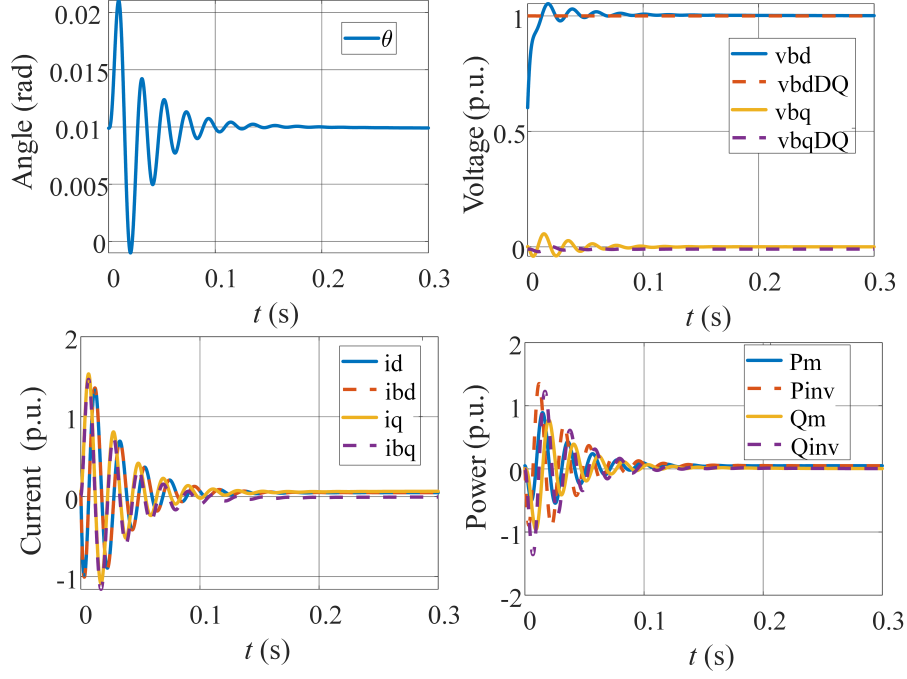
The proposed method can also include fault recovery capability design by incorporating the initial post-fault state in the designated DOA. The state can be determined by considering different types of faults and a defined time threshold for fault clearing. If the initial post-fault state falls within the designated DOA, the microgrid can recover from faults without any stability concerns when equipped with the designed controller.

4.4.2 Modified Banshee microgrid

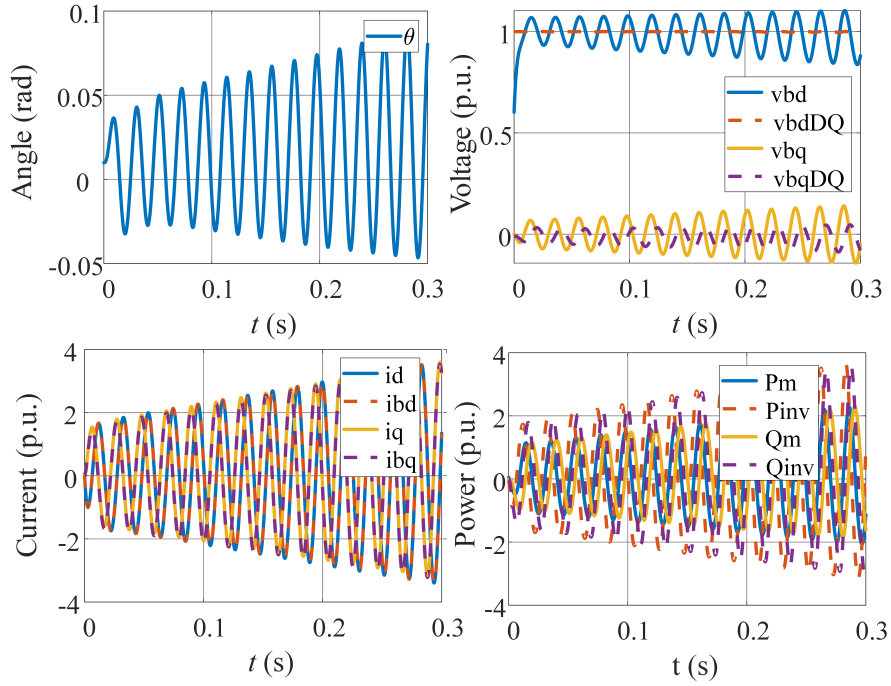
This subsection further verifies the proposed method in the modified Banshee microgrid.

1) System configuration

As shown in Figure 4.7, the microgrid used for testing is a modification of the Banshee distribution system [137, 140]. The modification involves keeping feeder 1 and integrating



(a)



(b)

Figure 4.5: Transient trajectories of single-inverter system: (a) $[k_{dv}, k_{df}] = [0.0525, 0.015]$, (b) $[k_{dv}, k_{df}] = [0.125, 0.025]$.

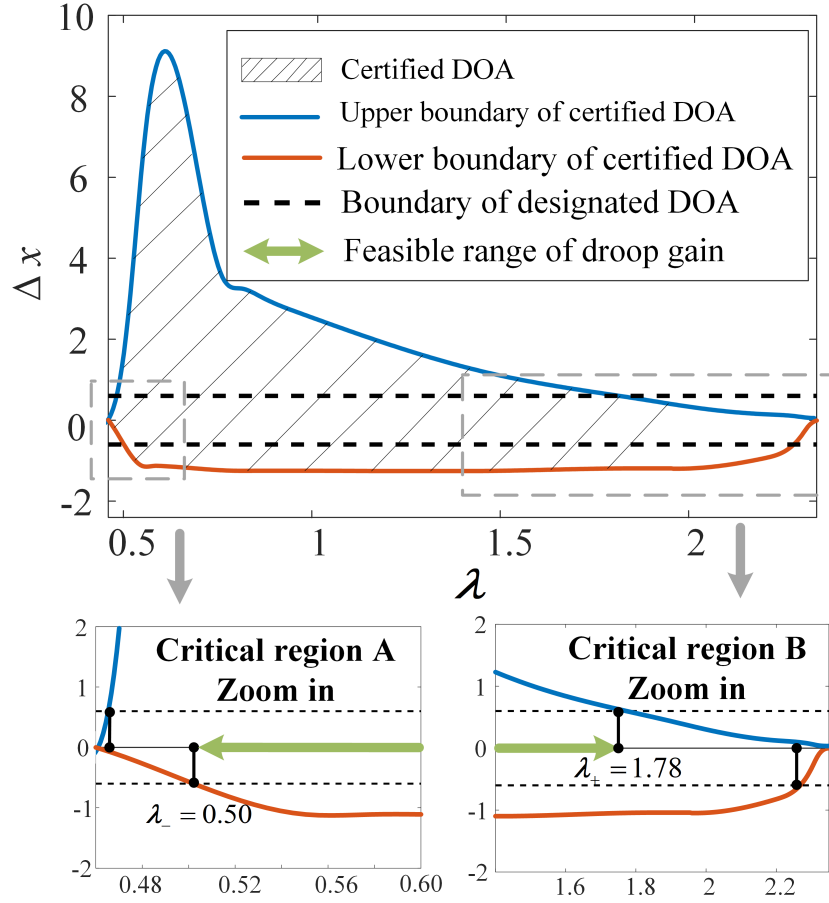


Figure 4.6: Visualized systematic droop controller design results for single inverter system based on simplified IBR model.

renewable energy and energy storage devices, resulting in a self-sufficient system that operates in islanded mode with switch 100 off. Three GFM inverters are connected to Bus 105, Bus 103, and Bus 102, respectively, each with distinct rated capacities of 1,500 kVA, 3,000 kVA, and 4,500 kVA. These rated capacities provide a reference for initializing the droop gain vector.

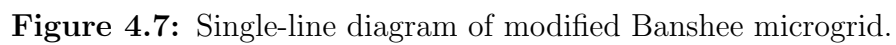
2) Systematic droop controller design

Similar to the design of the single-inverter system, the target is to find the candidate droop gain set that can certify stability and DOA under extreme L/HVRT conditions. Therefore, assume $K = [k_{dv,1}, k_{df,1}, k_{dv,2}, k_{df,2}, k_{dv,3}, k_{df,3}]$.

According to the engineering practice, droop gains of GFM inverters are typically tuned proportionally to their rated capacity to reasonably share microgrid loads. Specifically, $k_{dv,1} : k_{dv,2} : k_{dv,3} = k_{df,1} : k_{df,2} : k_{df,3} = S_1 : S_2 : S_3$. Assume $K_0 = [0.017, 0.0033, 0.035, 0.0067, 0.05, 0.01]$, then λ_+ and λ_- are solved as 0.028 and 1.513 based on *Algorithm 2*, and the candidate droop gain set is obtained as $\mathcal{K}' = \{K \in \mathbb{R}^6 \mid K = \lambda K_0, 0.028 \leq \lambda \leq 1.513\}$.

3) Numerical verification

The dynamic performance of inverters under the systematic design is verified by randomly sampling droop gain vectors from $\mathcal{K}'$. Results show that all state variables can converge to equilibrium. For instance, using $\lambda = 1$ and $K = [0.017, 0.0033, 0.035, 0.0067, 0.05, 0.01]$, the three-dimensional voltage trajectory of the three GFM inverters is shown in Figure 4.8 when initialized from the varying L/HVRT boundary. Figure 4.8 displays eight initial points starting from the cube's vertices, all of which converge to equilibrium eventually. The transient trajectories of some other key state variables are further shown in Figure 4.10 when initialized from $[v_{d1}, v_{d2}, v_{d3}] = [0.6, 0.6, 0.6]$. All state variables converge around 0.15 s, verifying the correct behavior of the proposed methodology. However, the state variable diverges if λ is set to 2, as depicted in Figure 4.9.



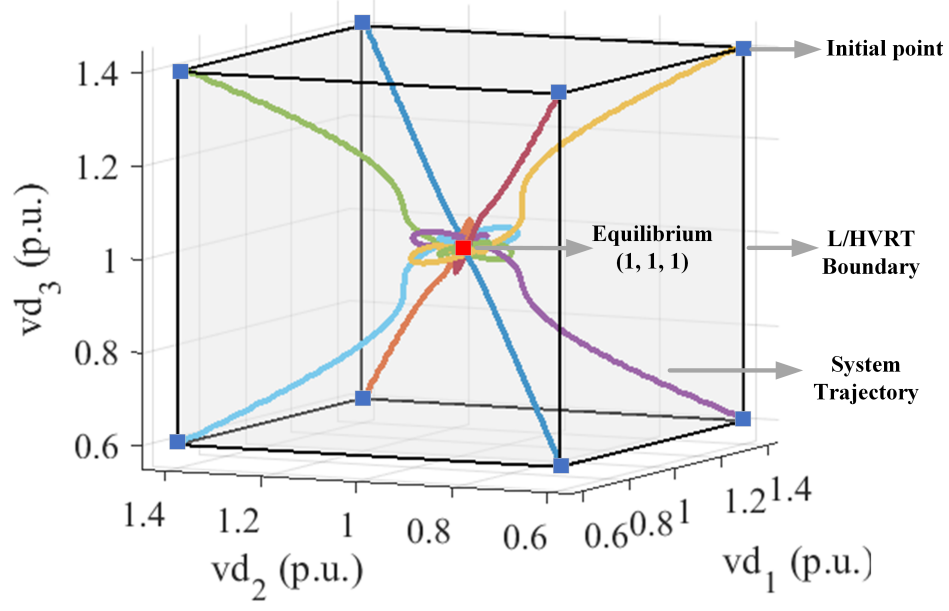
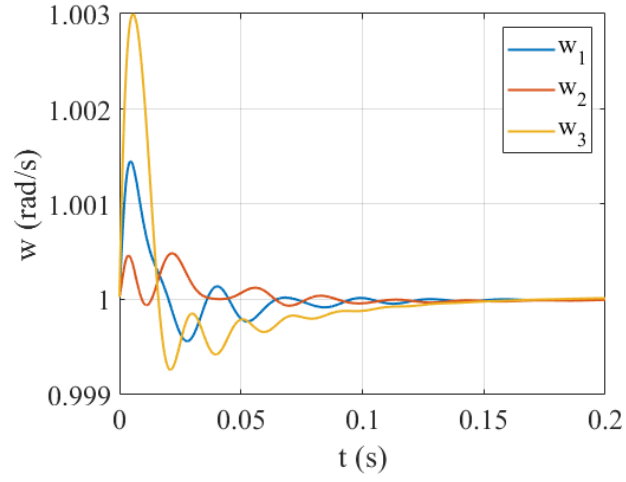
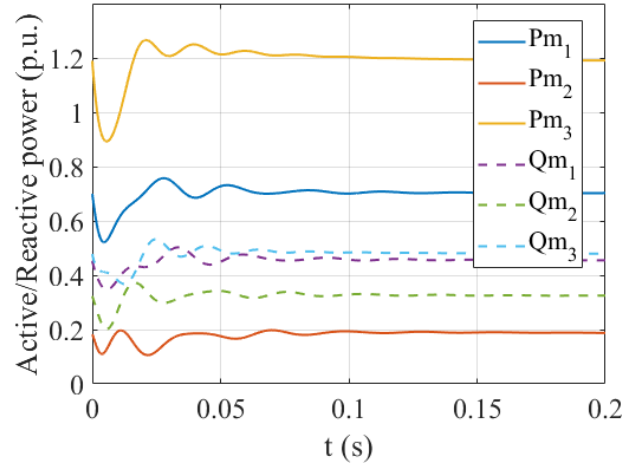


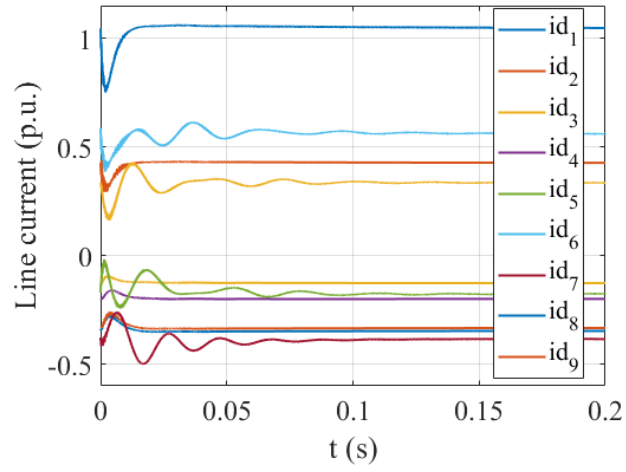
Figure 4.8: Three-dimensional Banshee microgrid trajectories with varying initial conditions.



(a)

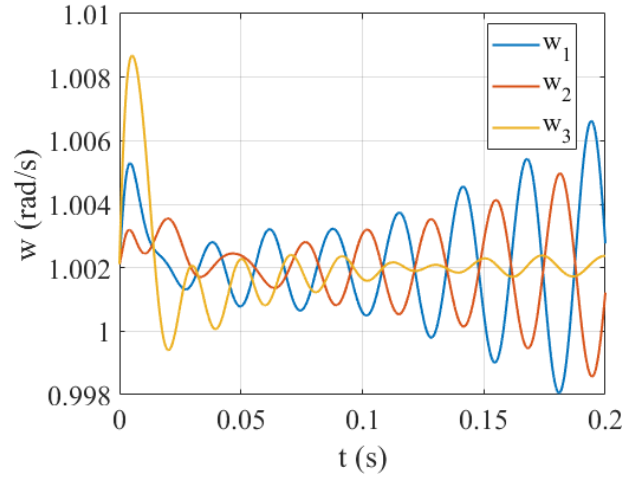


(b)

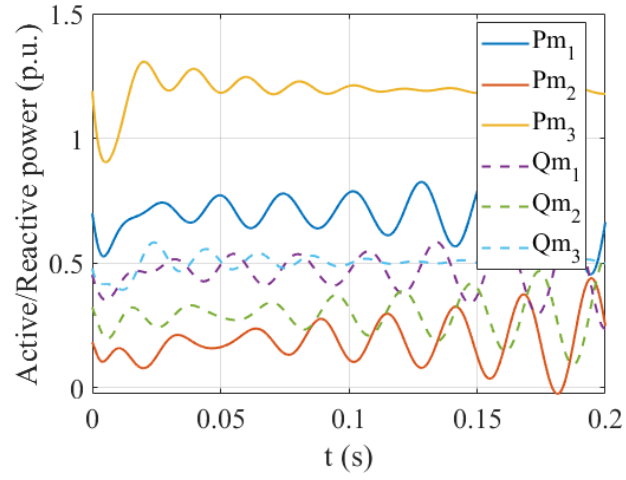


(c)

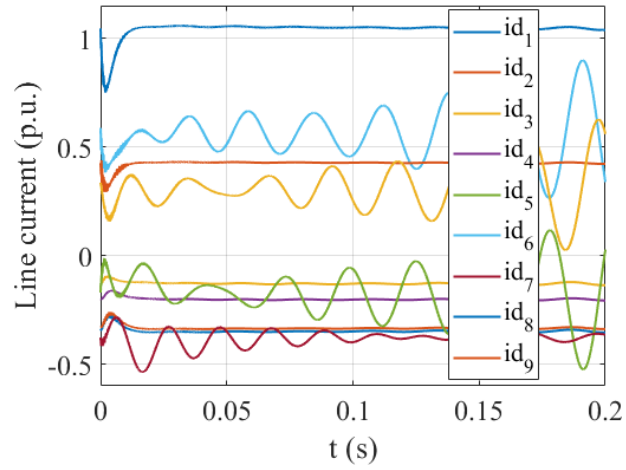
Figure 4.9: Transient trajectories of Banshee microgrid (partial) with $\lambda = 1$: (a) Angle frequency; (b) Power output of inverter; (c) Grid line current.



(a)



(b)



(c)

Figure 4.10: Transient trajectories of Banshee microgrid (partial) with $\lambda = 2$: (a) Angle frequency; (b) Power output of inverter; (c) Grid line current.

4) Comparison

Referring to the comparison conducted in the single inverter system, the candidate droop gain set of the modified Banshee microgrid is obtained as $\mathcal{K}' = \{K \in \mathbb{R}^6 \mid K = \lambda K_0, 0.48 \leq \lambda \leq 1.47\}$ using a simplified IBR model. The design results are more conservative than those obtained from the full-scale EMT model. If solely relying on the DOA estimation method for stability analysis without systematic design, the estimated DOA is $\{\Delta x \in \mathbb{R}^{71} \mid -0.98x_e \leq \Delta x \leq 0.12x_e\}$ given $\lambda = 1.4$. Such a design can potentially lead to operational risks because the estimated DOA fails to cover the L/HVRT range, necessitating extensive parameter tuning to ensure stability. These adjustments are known to be time-intensive, thus highlighting the superiority of the proposed method.

4.4.3 Power HIL verification for the modified Banshee microgrid controller design

The systematic controller design for the modified Banshee microgrid is further demonstrated through CURENT HTB. For a more comprehensive understanding of the measurement, control, and communication architecture, please refer to Section III in [187].

Referring to the numerical verification, droop gains are randomly sampled from the obtained candidate set and tested in HTB under LVRT conditions. Due to the capability constraints of HTB and its built-in protection schemes, it is difficult to emulate LVRT conditions for all three inverters at the same time. Therefore, only inverter 1 is subjected to LVRT conditions by injecting a large external inductive reactive power into BUS 106.

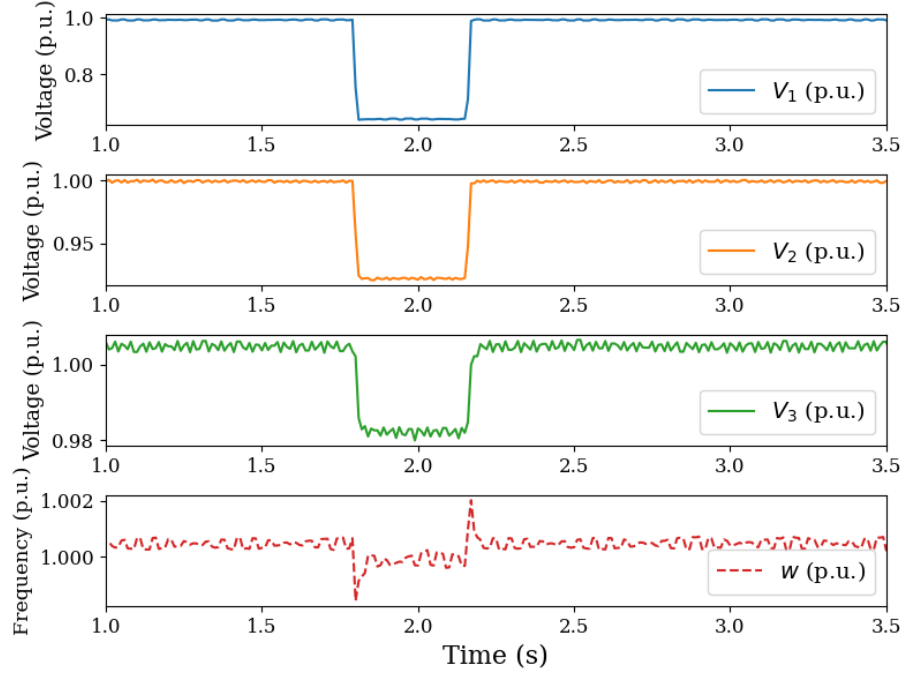
The power HIL test results are shown in Fig. 4.11. Fig. 4.11a depicts IBRs with droop gains assigned at $\lambda = \lambda_-$, where the terminal voltage of inverter 1 drops to the LVRT boundary around 1.7 s due to inductive reactive power injection. The voltage recovers to the nominal value after the disturbance is cleared around 2.2 s. During the disturbance, the system frequency experiences mild deviations. Similarly, Fig. 4.11a displays the system voltage and frequency when IBRs are assigned droop gains with $\lambda = \lambda_+$. Even with a voltage droop that reaches the LVRT boundary, inverter 1 can continue operating until the disturbance is resolved. Beyond the results displayed in Fig. 4.11, a few other gains are

randomly selected and tested. The system consistently returns to its original equilibrium point after disturbances, proving the effectiveness of the formulated homogeneous-like EMT model and the systematic controller design approach.

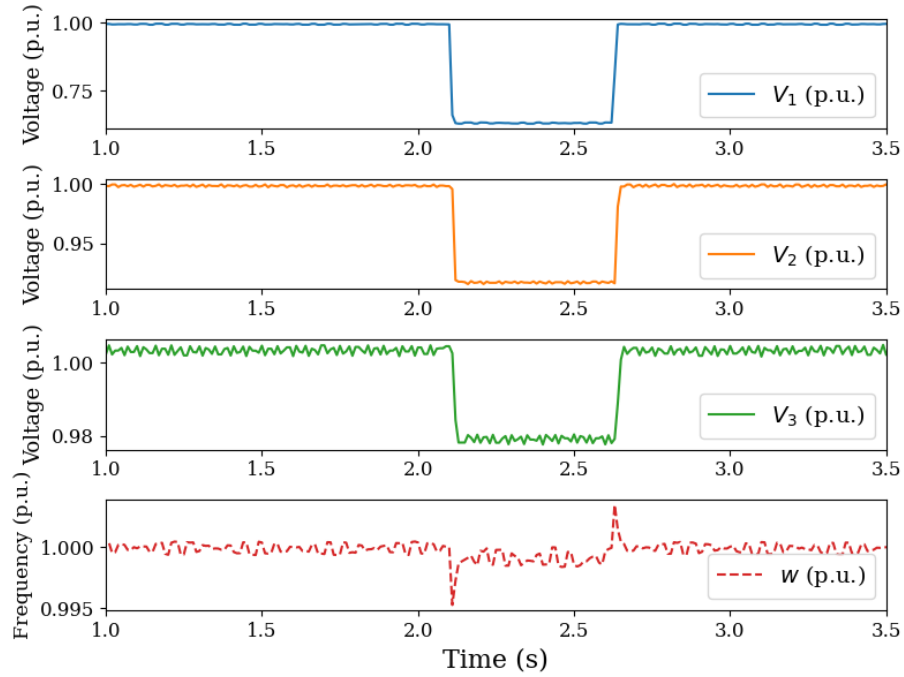
In summary, the proposed method can ensure the stability of the modified Banshee microgrid. Based on *Lemma 4*, $\mathcal{K}'$ can rigorously guarantee stability and DOA. With the design results in mind, some adaptive algorithms that update the droop gains online can work safely and reliably under L/HVRT conditions. This is particularly important because IBRs are expected to actively provide grid support and improve microgrid resilience in the face of natural and man-made hazards that may pose risks to the system.

4.5 Summary

This chapter proposes a systematic approach for inverter-based microgrids to certify large-signal stability and a designated DOA. A nonlinear EMT model is developed to accurately capture the fast dynamics of grid components, which is then transformed into a homogeneous-like system to facilitate the analytical stability derivation. The nonlinear terms are treated as superimposed parameter uncertainties and bounded within a specific range to derive the stability criteria. Using the stability criteria, a systematic controller design approach is further developed to identify the candidate control parameter set that ensures stability and DOA, whenever in normal or emergency conditions. The proposed methodology shows great flexibility and can be integrated into some adaptive approaches and physic-informed data-driven approaches for stability and performance guarantee.



(a)



(b)

Figure 4.11: Power HIL test results: (a) $\lambda = 0.028$, the lower boundary of $\mathcal{K}'$; (b) $\lambda = 1.153$, the upper boundary of $\mathcal{K}'$.

Chapter 5

Virtual Inertia Scheduling with Static and Dynamic Security Constraints

This chapter introduces VIS with static and dynamic security constraints to effectively manage the inertia of microgrids.

5.1 Literature Review

Positioned as an essential infrastructure component in future power systems, microgrids are gaining increased attention for their advantages [143], including various renewable energy accommodations [185], efficient energy management, and enhanced resilience [150]. Facilitated by the integration of variable renewable energies (VREs) interfaced with IBRs, microgrids exhibit the flexibility to operate either in grid-connected mode, providing grid support, or in islanded mode, forming a local and self-sufficient system [165].

Despite the benefits brought by IBRs, they pose certain challenges to the operation and control of microgrids. The fast dynamics inherent in IBRs impact the conventional static economic operation and degrade the stability of power electronic interfaced systems. Specifically, IBRs can change the nature of unstable modes and underlying dynamics, potentially challenging the optimal power flow (OPF) dispatch result [130]. Furthermore, in comparison to conventional synchronous generators (SGs), IBRs have lower overload capability and short circuit ratio, rendering them more vulnerable to disturbances. More importantly, they have insufficient physical inertia and thus reduce the overall inertia of the microgrid [155].

Low physical inertia increases the rate of change of frequency (RoCoF) to excessive levels and lowers the frequency nadir. It may energize the protection relays of load-shedding and potentially result in generation stuttering and successive outages [111]. Hence, there is a lot of work addressing the low-inertia issues of microgrids. They are categorized into three aspects as follows.

5.1.1 Emulating inertia through VSG control

The first group of work focuses on the device-level inertia emulation of IBRs. They draw inertia support from IBRs by developing advanced VSG control algorithms. VSG-controlled IBRs can provide virtual inertia support by rapidly increasing the active power injection

after a disturbance under the guidance of pre-configured control strategies. GFL IBRs are controlled as current sources, with power references updated based on microgrid frequency deviations. GFM IBRs, acting as voltage sources, are controlled based on the swing equation derived from SGs.

Basic VSG is enhanced through adaptive control, optimal control, and data-driven control to make IBRs more efficiently adapt to the change of microgrid inertia and frequency [55, 101, 174, 113, 125]. For example, [55] proposed an adaptive VSG control for microgrids based on constrained model-predictive control (MPC), aimed at minimizing frequency deviation and control efforts. Reference [101] proposes an adaptive VSG to address the conflict between the transient response of the active power and the angle frequency. Notably, the angular frequency stability needs a larger inertia, while the active power response leans towards a smaller inertia. Moreover, [174] proposed an improved VSG control algorithm to address the contradiction between steady-state deviation in active power and dynamic impact regulation. This was achieved by cascading a differential into the first-order virtual inertia forward channel. Additional approaches utilizing LQR or MPC for VSG control in frequency regulation are detailed in [113, 125].

Despite the sophistication of these advanced VSG control algorithms, they are typically implemented locally without system-level coordination. The absence of such coordination can lead to increased costs, as inertia support through VSG control is not free. Extra headroom is often offset from the maximum power point tracking (MPPT) [156], or ancillary battery energy storage systems (BESS) are required during inertia support [38].

5.1.2 Developing security-constrained OPF

The second group of work focuses on system-level security-constrained economic operation, integrating dynamic constraints—such as the transient performance quantified by frequency nadir, RoCoF, and settling time [122]—and stability constraints like small-signal stability criteria and transient stability constraints [109] into the conventional static OPF.

Reference [31] introduced a probabilistic transient stability-constrained OPF method, integrating the critical clearing time and instability mode. Reference [130] incorporated small-signal stability constraints into OPF using a Lyapunov stability equation. A

convex relaxation method combining semidefinite programming, parabolic relaxations, and sequential heuristic penalty function was developed to solve the problem. In [10], the frequency divider formula (discretized model) was employed to predict RoCoF and angle difference explicitly based on local variables, subsequently integrated into OPF to ensure transient stability. Additionally, [120] integrated the voltage stability constraints into microgrid OPF in the presence of plug-in electric vehicles. Reference [81] actively designed control parameters of IBRs, integrating the small signal stability constraints into OPF and solving it with particle swarm optimization (PSO). In [126], a bilinear matrix inequality method based on SDP was developed to ensure small signal stability for OPF problems. A vector-norm-based objective penalty function is also proposed for feasibility recovery while working over large and dense binary matrix variables.

While the second group of efforts addresses the dynamic challenges at the system level, IBRs are typically viewed as passive devices providing limited virtual inertia, without leveraging their flexibility and controllability. Furthermore, existing work usually focuses on a single type of dynamic constraint. A unified framework that integrates diverse dynamic constraints, particularly those arising after large disturbances, has yet to be developed.

5.1.3 Pioneering the inertia market

The third group work focuses on the development of an inertia market to incentivize both the generation and demand side owner to contribute to grid-level inertia support. Unlike the conventional ancillary market, the inertia market has not yet been well-established in America. Reference [128] proposes an inertia market mechanism for virtual inertia, where the system dynamics are approximated by a linearized state space model. A robust H_2 performance metric penalizes the worst-case primary control effort. As for industry efforts, initiatives such as the Enhanced Frequency Control Capability (EFCC) project and Future Power System Security Program project are established by the National Grid and Australia Energy Market Operator, respectively [53]. However, these market-related works are focused on inertia support from an economic perspective, overlooking the dynamic constraints and active control modes of IBRs.

Based on the above discussion, it is critical to develop an inertia management framework that considers both the static economic operation and dynamic control of microgrids. Accordingly, this chapter proposes the concept of VIS, a security-constrained and economy-oriented inertia management framework. The fundamental idea is to combine the device-level controller design and grid-level economic operation, leveraging the controllability and flexibility of IBRs for inertia management.

5.2 Concept and Generic Formulation of Virtual Inertia Scheduling

This section introduces the concept and generic formulation of VIS, which features the active management of virtual inertia of IBRs to address the low inertia issue of future power grids.

5.2.1 Concept of VIS

VIS is an inertia management framework designed to ensure the secure and economic operation of low-inertia power grids penetrated by VREs [142]. As shown in Figure 5.1, each component can provide inertia support under the background of reduced physical inertia caused by the retirement and replacement of SGs. The core concept behind VIS is to coordinate the device-level and grid-level operations, actively managing them to provide secure and economic inertia support.

Grid components can provide either passive inertia support or actively change their operation modes to provide active (virtual) inertial support. For example, motor loads contribute passive inertia support like SGs by releasing stored energy in rotating mass. IBRs, on the other hand, can emulate SGs through elaborate control algorithm design, actively providing virtual inertia support. Then, the device-level operation involves estimating and quantifying passive inertia, alongside the design of control algorithms for these active components, determining their maximum inertia support capability. This information is critical for grid-level inertia management.

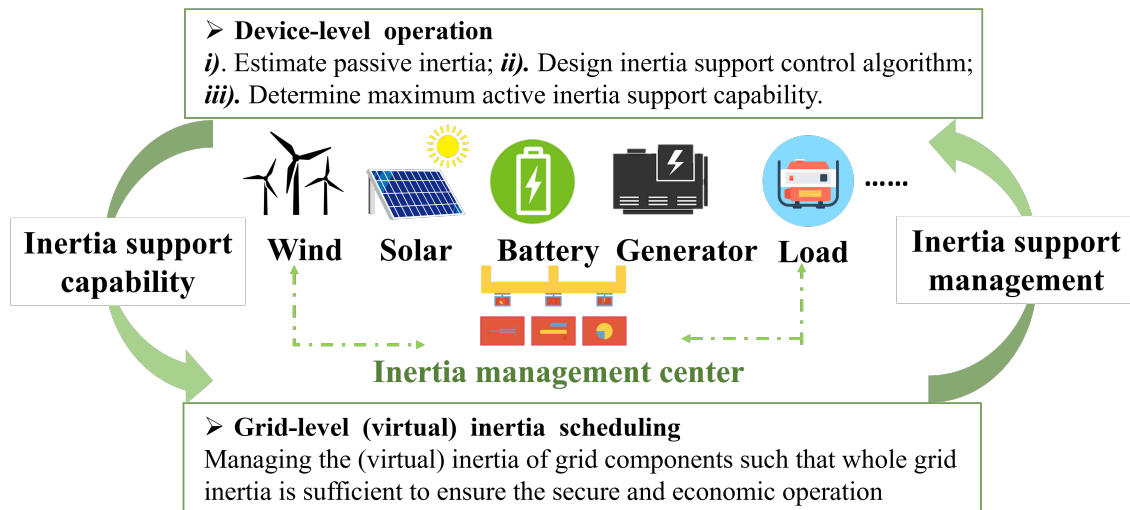


Figure 5.1: Diagram of virtual inertia scheduling.

The inertia management center implements the VIS concept at the grid level, tasked with managing the inertia of each component to ensure that the overall grid inertia is adequate for secure and cost-effective operation. To have a good dynamic performance, the straightforward approach is to have each grid component operate in its maximum inertia support mode. However, active inertia support is not free. For example, VSG-controlled IBRs provide inertia support by rapidly injecting a large amount of active power into the grid instantly after the disturbance. This energy usually comes from the extra headroom from PV or BESS [157], introducing additional opportunity costs or investments. Hence, it is essential to strike a balance between dynamic performance and economic considerations, thereby motivating the proposal of VIS.

5.2.2 Generic mathematical formulation of VIS

Extended from the conventional economic operation model, (5.1) shows the generic compact modeling of VIS. It is formulated as an optimization problem with an economic objective function while satisfying physical constraints.

$$\begin{aligned}
& \min_{\Theta} \sum_{t \in T} C_t^{gen} + C_t^{aux} \\
& \text{For } \forall t = 1, 2, \dots, T \text{ and } \boldsymbol{\psi}_t \in \boldsymbol{\Psi}, \\
& \text{s.t. } \left\{ \begin{array}{l} \text{i). economic dispatch constraints} \\ \text{ii). transient performance constraints} \\ \text{iii). stability constraints} \end{array} \right. \tag{5.1}
\end{aligned}$$

Compared with the conventional economic dispatch model, the generic mathematical formulation of VIS exhibits several distinct features.

- Incorporation of ancillary service cost in the objective function. The increasing penetration of VAEs interfaced by IBRs degrades the strength of power grids, consequently increasing the expenses associated with system maintenance. It's important to consider these costs, such as the virtual inertia and damping support cost [128], under the ongoing development of ancillary service markets.

- Formulate the device-level control parameters as decision variables for grid components to provide better active support. The decision variable set includes not only the conventional economic dispatch variables but also control variables that determine the dynamic support capability of grid components. Higher support capability typically involves increased control efforts or cost, necessitating detailed customized design and coordination.
- Integration of the transient performance constraints. Conventional economic operations usually consider static constraints, such as power flow constraints, generation constraints, line thermal limit constraints, and voltage constraints. However, transient performance, quantified by indices such as frequency nadir and RoCoF, is increasingly susceptible to disturbance in low inertia power grids. These indices are expected to be bounded to a specific range to avoid the activation of protection relays for load shedding and the initiation of generation stuttering [111].
- Integration of the stability constraints, covering small signal or transient stability constraints. As the control variables are actively designed in VIS and can fundamentally impact grid stability, it is necessary to incorporate these constraints for stability guarantee.
- Facilitation of flexible modeling for diverse application scenarios. It can either be a single-interval or multi-interval VIS by adjusting the scheduling interval T . Also, the decision variable set can be custom-designed, and the contingency set can include extreme events to enhance the resilience of power grids.

In a word, with the generic formulation in (5.1), VIS can be conducted with guaranteed static and dynamic security constraints.

5.3 Microgrid Virtual Inertia Scheduling with Static and Dynamic Security constraints

This section formulates microgrid-VIS for the inertia management of IBRs with guaranteed static and dynamic performance. Linearization approaches are introduced to facilitate the solution of the nonlinear model.

5.3.1 Formulation of microgrid-VIS

Equations (5.2)-(5.8) formulate microgrid-VIS by specifying the objective function, decision variables, scheduling interval, contingency set, and constraints in (5.1).

$$\min_{\Theta} \sum_{t \in T} C_t^{gen} + C_t^{anx} \quad (5.2)$$

$$\begin{aligned} C_t^{gen} = & \sum_{t \in T} \underbrace{\sum_{sg}^{N_{sg}=1} (a_{i,t}^{sg} P_{i,t}^{sg2} + b_{i,t}^{sg} P_{i,t}^{sg} + c_{i,t}^{sg})}_{SG} \\ & + \underbrace{\sum_{i=1}^{N_{ibr}} (a_{i,t}^{ibr} P_{i,t}^{ibr2} + b_{i,t}^{ibr} P_{i,t}^{ibr} + c_{i,t}^{ibr})}_{IBR} \end{aligned} \quad (5.3)$$

$$C_t^{anx} = \sum_{t \in T} \sum_{i=1}^{N_{ibr}} d_{i,t}^{ibr} M_{i,t}^{ibr} + e_{i,t}^{ibr} D_{i,t}^{ibr} \quad (5.4)$$

$$\Theta \triangleq [P_{ij}, Q_{ij}, v_i, p_i, q_i, M, D] \quad (5.5)$$

$$i). \left\{ \begin{aligned} & V_i - V_j = z_{ij} I_{ij}, \forall (i, j) \in \mathcal{B} \\ & S_{ij} = V_i I_{ij}^*, \forall (i, j) \in \mathcal{B} \\ & \sum_{k:j \rightarrow k} S_{jk} - \sum_{i:i \rightarrow j} (S_{ij} - z_{ij} |I_{ij}|^2) = s_j, \forall j \in \mathcal{N} \\ & \underline{V}_i \leq V_i \leq \overline{V}_i, \forall i \in \mathcal{N} \\ & \underline{s}_i^g \leq s_i^g \leq \overline{s}_i^g, \forall i \in \mathcal{N} \\ & \underline{I}_{ij} \leq I_{ij} \leq \overline{I}_{ij}, \forall (i, j) \in \mathcal{B} \end{aligned} \right. \quad (5.6)$$

$$ii). \cdot \begin{cases} \underline{M}_i^{ibr} \leq M_i^{ibr} \leq \overline{M}_i^{ibr}, \forall i \in \mathcal{R} \\ \underline{D}_i^{ibr} \leq D_i^{ibr} \leq \overline{D}_i^{ibr}, \forall i \in \mathcal{R} \\ \underline{RoCoF} \leq RoCoF \leq \overline{RoCoF} \\ \underline{\Delta f} \leq \Delta f \leq \overline{\Delta f} \end{cases} \quad (5.7)$$

$$iii). \begin{cases} \Theta \in \Theta^{ss} \\ \Theta \in \Theta^{ls} \end{cases} \quad (5.8)$$

Microgrid-VIS is formulated as an optimization problem with the objective of minimizing the quadratic generation cost in (5.3) and linear inertia and damping support cost in (5.4). Considering that IBRs are among the most controllable and flexible active components that can provide inertia support, the virtual inertia and damping of VSG-controlled IBRs are formulated as decision variables in (5.5). Equation (5.6) is nonlinear distribution power flow constraints, (5.7) is transient performance constraint, and (5.8) is stability constraints covering both small- and large-signal stability constraints. The contingency set includes both normal load change and unplanned generation trips.

5.3.2 Linearization of microgrid-VIS

While (5.2)-(5.8) formulate microgrid-VIS with static and dynamic security constraints following load change or generation trips, they are non-linear, non-convex, and implicit models. Hence, this subsection aims to make (5.7)-(5.8) explicit and linearize distribution power flow constraints.

1) Linearized distribution power flow

Referring to the assumptions in [14, 179], the nonlinear terms in (5.6) can be ignored since they are much smaller than the linear branch flow terms. In addition, assuming the bus voltage is close to the nominal value, then nonlinear distribution power flow can be simplified

as follows.

$$i) \cdot \begin{cases} p_j = \sum_{k:j \rightarrow k} P_{jk} - \sum_{i:i \rightarrow j} P_{ij}, \forall j \in \mathcal{N} \\ q_j = \sum_{k:j \rightarrow k} Q_{jk} - \sum_{i:i \rightarrow j} Q_{ij}, \forall j \in \mathcal{N} \\ v_j = v_i - (r_{ij}P_{ij} + x_{ij}Q_{ij}), \forall (i, j) \in \mathcal{B} \\ \underline{v}_i \leq |v_i| \leq \overline{v}_i, \forall i \in \mathcal{N} \\ \underline{p}_i^g \leq |p_i^g| \leq \overline{p}_i^g, \forall i \in \mathcal{N} \\ \underline{q}_i^g \leq |q_i^g| \leq \overline{q}_i^g, \forall i \in \mathcal{N} \end{cases} \quad (5.9)$$

2) Linearized stability constraints and transient performance index

There are generally two types of methods to make (5.7)-(5.8) explicit: model-based methods and data-driven methods. Model-based methods derive the transient performance index and stability criteria based on the system model [109]. However, most indexes are derived under normal operation conditions, and the corresponding criteria are for ensuring small signal-signal stability [130, 178]. Deriving a large-signal stability criterion is challenging. Furthermore, these derived indices and criteria may not be inherently convex and accurate after derivation, making it difficult to seamlessly integrate into microgrid-VIS.

The data-driven methods, on the other hand, are flexible and can be customized to cover various scenarios. Refs. [188] predict the frequency nadir and RoCoF with DNN, and then linearize the network, incorporating it into the unit commitment problem. This approach serves as inspiration for the work presented in this paper, aiming to predict both transient performance indices and stability using data-driven methods. As shown in (5.10), a DNN with the ReLU activation function maps the decision variables and contingencies to RoCoF, frequency nadir, and the stability condition. The stability condition s can either be a specific criterion like eigenvalue or stability condition through one hot encoding [123].

$$RoCoF, \Delta f_{\text{nadir}}, s = DNN(\Theta, \psi) \quad (5.10)$$

Then, by introducing binary variables, (5.10) can be linearized and incorporated into microgrid-VIS, transforming it into a mix-integer linear programming problem (MILP) [188]. Equations (5.11)-(5.12) show the expressions of the m th hidden layer before and

after linearization, respectively.

$$\begin{cases} \hat{\mathbf{z}}_m = \mathbf{W}_m \mathbf{z}_{m-1} + \mathbf{b}_m \\ \mathbf{z}_m = \max(\hat{\mathbf{z}}_m, \mathbf{0}) \end{cases} \quad (5.11)$$

$$\begin{cases} \mathbf{z}_m \leq \hat{\mathbf{z}}_m - \underline{\mathbf{h}} \odot (\mathbf{1} - \mathbf{a}_m) \\ \mathbf{z}_m \geq \hat{\mathbf{z}}_m \\ \mathbf{z}_m \leq \bar{\mathbf{h}} \odot \mathbf{a}_m \\ \mathbf{z}_m \geq \mathbf{0} \end{cases} \quad (5.12)$$

Note that DNN typically doesn't achieve 100% prediction accuracy, which could pose risks to microgrids. Hence, this paper develops a workflow that integrates full-order TDS to make the data-driven method applicable in power grids, as illustrated in Section 5.4.

5.4 Workflow for Solving Microgrid-VIS

This section presents an efficient workflow for solving microgrid-VIS. Several strategies are introduced to facilitate the seamless integration of DNN into microgrid-VIS.

5.4.1 General workflow

As shown in Figure 5.2, the workflow for solving microgrid-VIS has three key steps: i). initialization, ii). dynamic approximation and linearization, iii). solution and validation.

- Step 1 involves initializing VIS by specifying the target system and the generic model. In this paper, the generic model is specified as microgrid-VIS in Section 5.3. Additionally, a dynamic model for TDS is configured in ANDES [35], an open-source Python library for power system analysis and a foundation for the CURENT LTB [98]. ANDES is utilized for batch dynamic data generation and validating the VIS results to ensure stability and dynamic performance.
- Step 2 focuses on generating batch data for dynamic approximation using DNN, which is then employed to linearize the original VIS model. Such linear rules extracted from

simulation results, as demonstrated in [188] and [184], have been proven to be sufficient for encoding frequency dynamics. Further details on data generation, cleaning, and labeling will be introduced in Subsection 5.4.2.

- Step 3 involves solving the linearized VIS and validating the scheduling results through TDS performed in ANDES. If the scheduling results fail to satisfy the stability and transient performance constraints, additional corrections are necessary, as elaborated in Subsection 5.4.3.

5.4.2 Data generation, cleaning, and labeling

Given a predefined disturbance, power system TDS tools such as ANDES typically output transient trajectories of system states. These raw data must undergo cleaning and labeling before being utilized for DNN training.

1) Data generation

The raw training data, specifically referred to as TDS data, is generated based on predefined system parameters using Monto Carlo Simulation. Fixed system parameters include the system topology, dynamic models (governor and exciter) of SGs, and dynamic model (voltage and current regulator) of IBRs. Changing system parameters include load conditions, contingency, power output of SGs and IBRs, as well as virtual inertia and damping of IBRs.

Load conditions are extracted from historical data and clustered as a few representative scenarios to enhance computational efficiency. Generation output is determined based on the conventional economic dispatch model without considering dynamic constraints. To improve the efficiency of data generation, virtual inertia and damping are first sampled uniformly within the specific upper and lower boundaries. Then, region-of-interest active sampling [188] is employed to sample under marginal stability conditions.

Then, for each contingency, with fixed system parameters, and a set of changing system parameters, TDS is performed utilizing ANDES. Time-serious data for frequency and power angle, and system eigenvalues before and after each contingency are recorded for further processing.

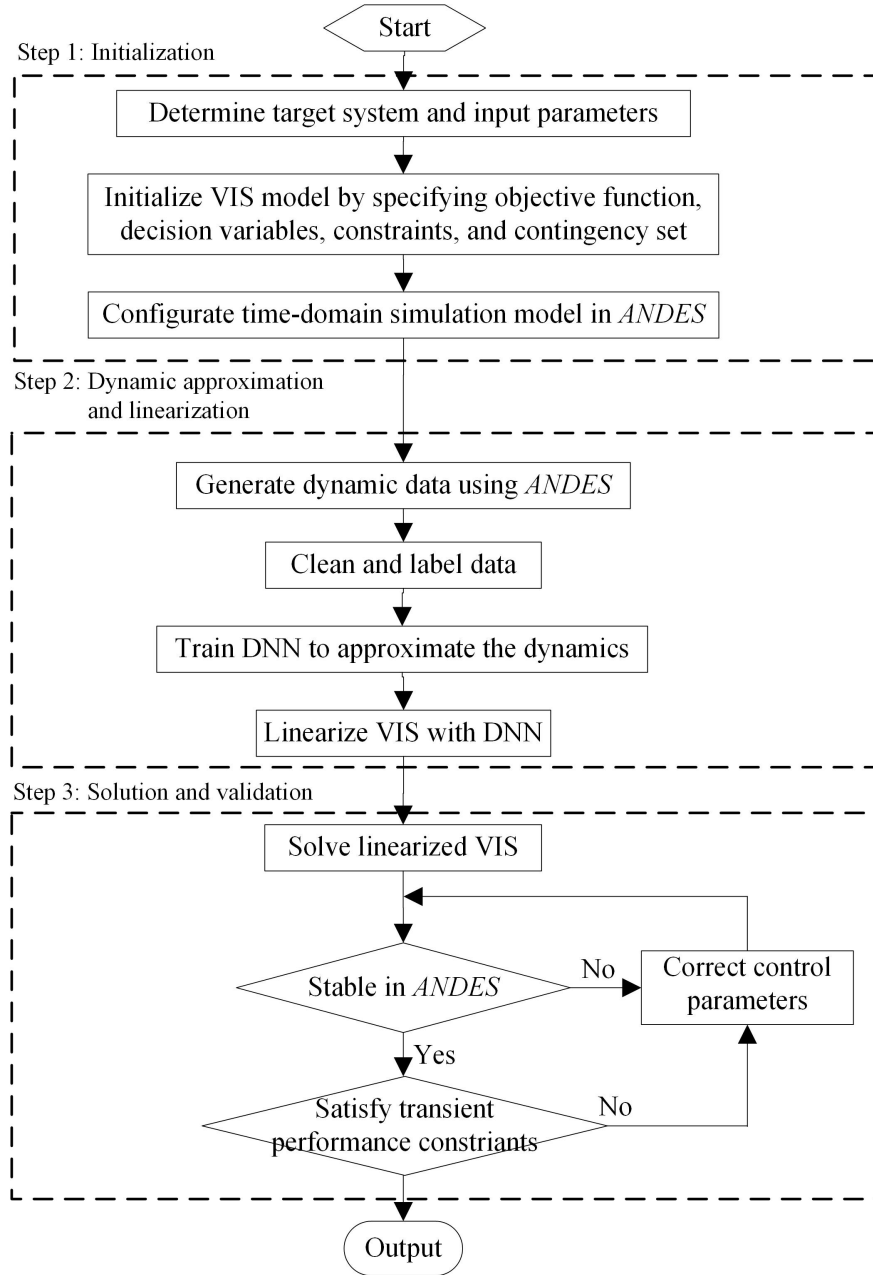


Figure 5.2: Diagram of workflow for solving microgrid-VIS.

2) Data cleaning and labeling

The raw transient trajectories are challenging to use directly for DNN training. They are cleaned and labeled in sequence through the following steps.

- Transform time-series data to dynamic indices: Maximum frequency nadir and maximum RoCoF are obtained from time-series frequency data, while the maximum power angle deviation is calculated from time-series power angle data using (5.13) [115, 195].

$$\Delta\delta_{\max} = \max(|\delta_j(t) - \delta_k(t)|), \forall j, k \in \Omega^G, t > 0 \quad (5.13)$$

- Clean unusual data: Due to the inclusion of large disturbances such as generation trips in the contingency set, some data may deviate several orders of magnitude beyond the normal range. This could lead to singularities and pose a significant burden on DNN training. To address this, unusual maximum RoCoF, maximum frequency deviation, and maximum angle difference are transformed to a reasonable value, as shown in (5.14)-(5.16). Additionally, for each scenario, recorded eigenvalues are transformed to a single real number by keeping the maximum real part of all the eigenvalues. Real numbers with large magnitudes are also transformed to reasonable values, as shown in (5.17)-(5.18).

$$RoCoF_{\max,i} = \begin{cases} -1 & RoCoF_i < -1 \\ RoCoF_{\max,i} & -1 \leq RoCoF_i \leq 1 \\ 1 & RoCoF_i > 1 \end{cases} \quad (5.14)$$

$$\Delta f_{\max,i} = \begin{cases} -1 & \Delta f_{\max,i} < -1 \\ \Delta f_{\max,i} & -1 \leq \Delta f_{\max,i} \leq 1 \\ 1 & \Delta f_{\max,i} > 1 \end{cases} \quad (5.15)$$

$$\Delta\delta_{\max,i} = \begin{cases} \Delta\delta_{\max,i} & \Delta\delta_{\max,i} \leq 2\pi \\ 2\pi & \Delta\delta_{\max,i} > 2\pi \end{cases} \quad (5.16)$$

$$eig_{\max,i}^{\text{real}} = \begin{cases} 1 & eig_{\max,i}^{\text{real}} > 1 \\ eig_{\max,i}^{\text{real}} & eig_{\max,i}^{\text{real}} \leq 1 \end{cases} \quad (5.17)$$

where

$$eig_{\max,i}^{\text{real}} = \max [\text{real}(eig_{\text{pre}}), \text{real}(eig_{\text{post}})] \quad (5.18)$$

Note that the transformation thresholds in (5.14)-(5.18) can be customized, as long as they remain in proximity to the normal values defined in IEEE standards.

- Label data: Using the cleaned data, the final training data are labeled as: $[RoCoF_{\max}, \Delta f_{\max}, eig_{\max}^{\text{real}}, \Delta \delta_{\max}]$, where $eig_{\max}^{\text{real}}$ quantifies the small-signal stability and $\Delta \delta_{\max}$ quantified the large-signal transient stability. These labels align the dynamic constraints formulated in (5.7)-(5.8).

Finally, a DNN can be trained to predict system dynamics accurately, thus making dynamic constraints explicit and VIS a MILP for the solution.

5.4.3 TDS-based validation and correction

It is acknowledged that a DNN hardly achieves 100% prediction accuracy, especially in new testing scenarios. Such slight mismatches are critical in power systems because a minor control error can lead to severe outcomes. Therefore, TDS validation and correction are integral parts of the solution workflow.

After solving the linearized VIS, check both transient performance and stability with the implementation of VIS results in ANDES. If constraints (5.7)-(5.8) are violated after running TDS, corrections are implemented, which are categorized into the following three conditions.

- RoCoF constraint violation: Increase the virtual inertia of IBRs that are below the upper boundary with a small step size, as shown in (5.19). Through a few rounds of iteration, it is trivial to find the minimum ΔM that makes TDS results satisfy RoCoF constraints.

$$M_i^{\text{ibr}'} = \begin{cases} M_i^{\text{ibr}} & M_i^{\text{ibr}} = \overline{M_i^{\text{ibr}}} \\ M_i^{\text{ibr}} + \Delta M & M_i^{\text{ibr}} < \overline{M_i^{\text{ibr}}} \end{cases} \quad (5.19)$$

- Frequency nadir constraints violation: Increase virtual damping using the line search method, similar to the approach used for addressing RoCoF violation, as expressed in (5.20).

$$D_i^{ibr'} = \begin{cases} D_i^{ibr} & D_i^{ibr} = \overline{D_i^{ibr}} \\ D_i^{ibr} + \Delta D & D_i^{ibr} < \overline{D_i^{ibr}} \end{cases} \quad (5.20)$$

- Stability constraint violation: Reset virtual inertia and damping to default conservative values because developing an efficient fine-tuning method for stability guarantee is challenging. The default values could be extracted from batch data generation.

These correction methods ensure that VIS results are validated to satisfy both static and dynamic security constraints. It is important to emphasize that VIS results are generally feasible in most conditions, implying that the control parameter corrections will not be triggered. They are just backup for performance guarantee under edge scenarios.

5.5 Case Studies

This section demonstrates microgrid-VIS in an islanded microgrid modified from the IEEE 123-bus system. Comparison studies are conducted to show the advantages of VIS with static and dynamic security constraints.

5.5.1 Case overview

1) Configuration of islanded microgrid

Figure 5.3 shows the diagram of the islanded microgrid modified from the IEEE 123-bus system. It is configured by connecting 4 SGs and 8 IBRs, such that forms a self-sufficient system when the switch nodes 149 and 150 are closed. Table 5.1 shows the cost data, including power generation cost, inertia cost, and damping cost. The contingency set includes $\pm 5\%$, $\pm 10\%$ load change, and unplanned single SG trip.

As for dynamic data, SGs are equipped with governors and exciters, and their capacities are assumed to be much larger than IBRs. IBRs are controlled in VSG mode [8] with

controllable virtual inertia and damping constrained by $[0.01, 6]$ p.u. and $[0.01, 4]$ p.u., respectively. The lower limit of virtual inertia and damping is set slightly larger than 0 to ensure the basic VSG control mode. Detailed dynamic models and parameters used in ANDES have been uploaded to the LTB website and made public to readers [145].

2) Scheduling schemes

Three scheduling schemes (Scheme I, II, and III) are designed as baselines for comparison to show the advantage of the proposed microgrid-VIS (Scheme IV):

- Scheme I involves the conventional economic dispatch, considering the static security constraints. Virtual inertia M and damping D of IBRs are not decision variables and are set at the upper boundary to ensure dynamic performance.
- Scheme II integrates the conventional economic dispatch, taking into account the cost of inertia and damping support, along with the static security securities. It formulates M and D as decision variables but ignores the dynamic security constraints.
- Scheme III implements VIS with static constraints, transient performance constraints, and small signal stability constraints. It doesn't address stability issues arising from large disturbances like an unplanned SG trip.
- Scheme IV employs the proposed microgrid-VIS with comprehensive static and dynamic security constraints outlined in (5.6)-(5.8).

5.5.2 Dynamic training and approximation

Dynamic training and approximation are conducted in an environment equipped with Intel(R) Core i7-12800HX running at 2.0 GHz, 64 GB of memory, and ANDES 1.8.8.

Following the guideline in subsection 5.4.2, ten thousand scenarios are randomly generated and simulated. Virtual inertia and damping are sampled uniformly using NumPy function '*random.uniform*' within their upper and lower limits. After data generation, cleaning, and labeling, a fully connected neural network with one hidden layer containing 128

Table 5.1: Cost data

Generator ID	Generation cost			Inertia cost	Damping cost
	a	b	c	d	e
	[\$/p.u. ²]	[\$/p.u.]	[\$]	[\$/p.u.]	[\$/p.u.]
SG1	0.014	10	100	/	/
SG2	0.015	20	150	/	/
SG3	0.02	30	200	/	/
IBR1	0	0	0	3	2
IBR2	0	0	0	4	3
IBR3	0	0	0	1	1
IBR4	0	0	0	1	1
IBR5	0	0	0	2	1.5
IBR6	0	0	0	1	1
IBR7	0	0	0	1	1
IBR8	0	0	0	1	1

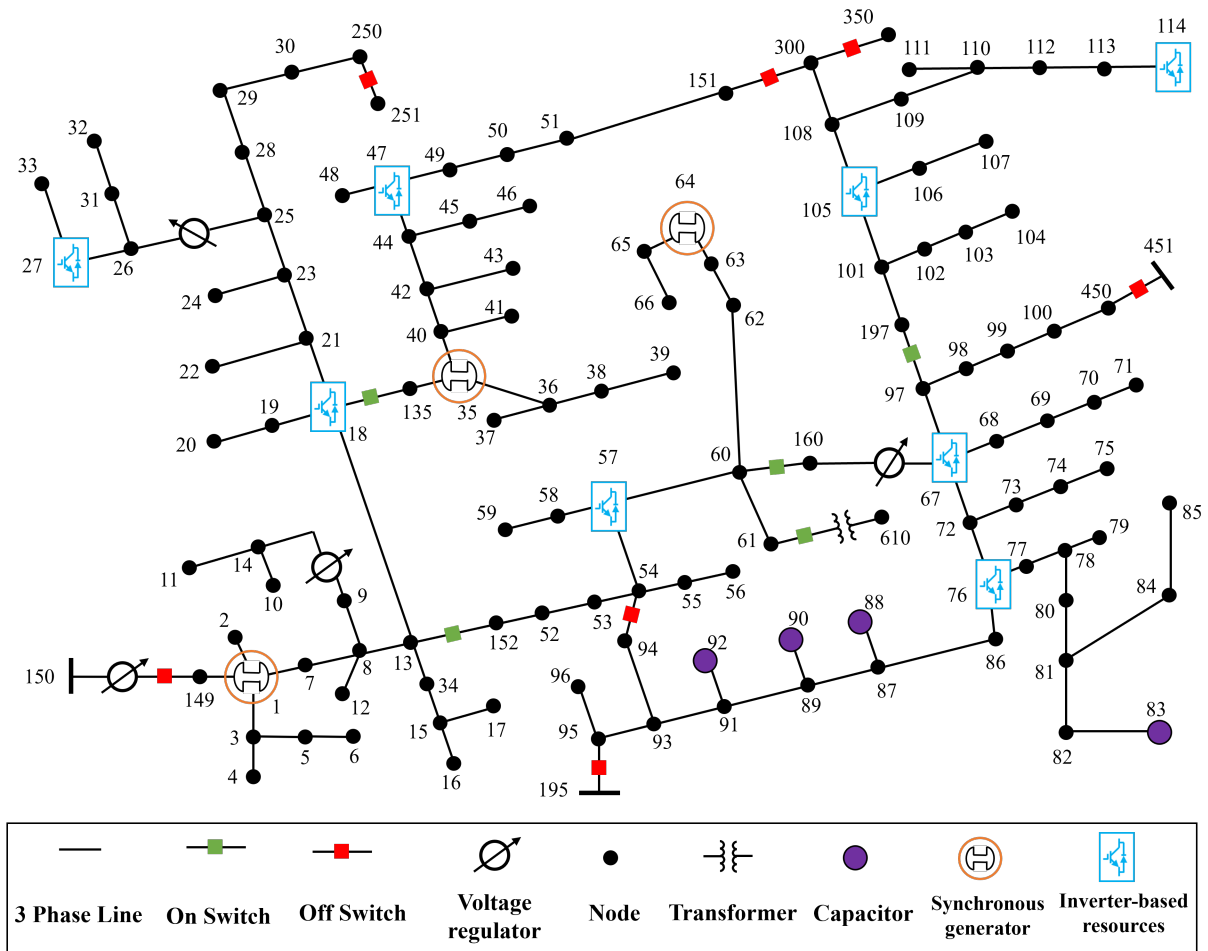


Figure 5.3: Diagram of islanded microgrid modified from IEEE-123 bus distribution system.

neutrons is built in PyTorch 2.0.1 and trained to approximate the dynamics of the islanded microgrid.

5.5.3 Solution and validation

Assuming a scheduling interval $T = 1$, the optimization model is formulated using AMS and solved with GUROBI 9.5.2. AMS is a power market simulation tool developed with Python, as an important part of CURRENT's LTB [98].

1) Scheduling results

Schemes I-IV yield identical scheduling results for active power generation: $[p_{SG1}, p_{SG2}, p_{SG3}] = [17.50, 31.50, 26.75]$ MW and $[p_{IBR1}, p_{IBR2}, p_{IBR3}, p_{IBR4}, p_{IBR5}, p_{IBR6}, p_{IBR7}, p_{IBR8}] = [7.00, 8.40, 4.90, 4.20, 6.30, 5.25, 5.60, 5.95]$ MW. However, they exhibit distinct scheduling results for virtual inertia and damping, as illustrated in Figure 5.4. This difference results in varied cost results and dynamic performance under disturbance, detailed in Table 5.2, where “✓” means satisfy the constraints, “×” means violate the constraints, and “|” separates the results for small disturbance and large disturbance. The observations are as follows.

- Scheme I sets M and D at the highest value conservatively to ensure dynamic performance. While it satisfies all the dynamic security constraints, it incurs the highest inertia and damping support cost.
- Scheme II has the smallest scheduling results for M and D with sole consideration of the economic aspect. This aggressive setting results in the lowest scheduling cost but violates all the dynamic security constraints.
- Scheme III exhibits M/D scheduling results slightly larger than those of Scheme II. It satisfies the transient performance constraints and small signal stability constraints but loses stability after an unplanned generation trip.
- The M/D scheduling results of microgrid-VIS lie between Schemes I and III. In Figure 5.4, M and D of IBR1, IBR2, and IBR3 are lower than other IBRs due to their high support cost. The scheduling results not only satisfy all the static and dynamic security

constraints like the conservative Scheme I but strike a good tradeoff between economy and dynamic performance.

2) TDS validation

The scheduling results are further validated in ANDES. Figures 5.5 and 5.6 present the TDS results of Schemes I-IV, visualizing the dynamic performance as summarized in Tab. 2. The transient curves include frequency, RoCoF, and bus voltage. In ANDES, RoCoF is calculated numerically and measured through a low pass filter, with this paper setting the filter time constant as $T_w = T_r = 0.3$.

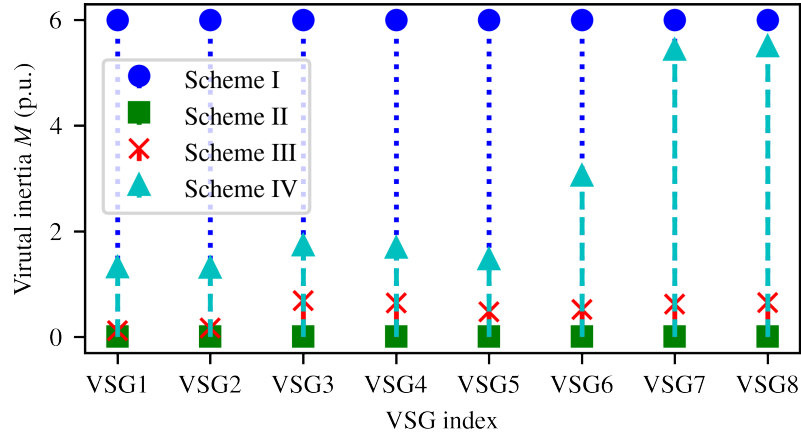
In Figures 5.5 and 5.6, two contingencies are simulated: a 10% load increase and an unplanned trip of SG2 occurring at 5 seconds, respectively. The observations are summarized as follows:

- Implementation of Scheme I results in a maximum frequency deviation and RoCoF are 0.1 Hz and 0.078 Hz/s after load change, and 0.32 Hz and 0.2 Hz/s after the SG2 trip. These values are comfortably below the threshold of 0.6 Hz and 0.5Hz/s, attributable to the conservative settings.
- Implementation of Scheme II leads to microgrid diverging after both a load change and the SG2 trip, thereby violating the dynamic security constraints.
- The dynamic performance of Scheme III is better than that of Scheme II. After a 10% load increase, the maximum frequency deviation and RoCoF are 0.25 Hz and 0.26 Hz/s, meeting small-signal stability constraints. However, the islanded microgrid collapses after the SG2 trip, violating the large-signal stability constraints.
- Scheme IV results in the microgrid converging to a new equilibrium after both a load change and the SG2 trip. In particular, the maximum RoCoF reaches the threshold, with the frequency nadir slightly below the threshold.

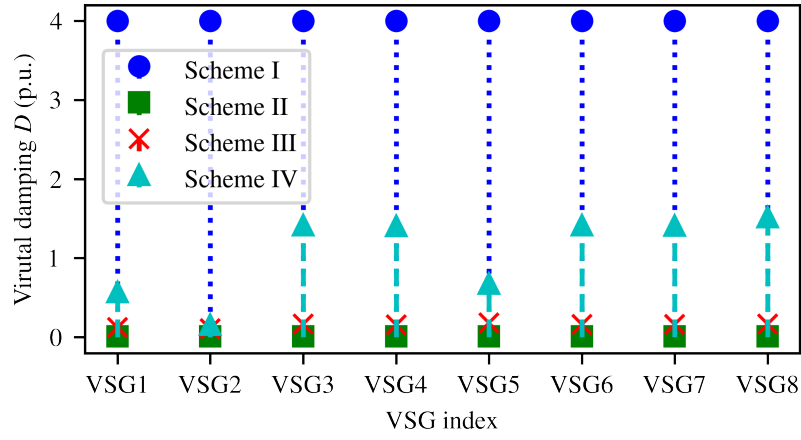
In summary, microgrid-VIS is demonstrated effective in managing the inertia and damping of the islanded microgrids. It outperforms other schemes in achieving a balance between economic benefits and dynamic performance. Following a load change or unplanned

Table 5.2: Scheduling results

Item	I	II	III	IV
Total scheduling cost/\$	759.17	629.42	635.91	668.56
Inertia support cost/\$	84.00	0.14	5.09	29.60
Damping support cost/\$	46.00	0.11	1.65	9.79
RoCoF constraints	✓ ✓	× ×	✓ ×	✓ ✓
Frequency nadir constraints	✓ ✓	× ×	✓ ×	✓ ✓
Small-signal stability	✓ ✓	× ×	✓ ×	✓ ✓
Large-signal stability	✓ ✓	× ×	× ×	✓ ✓



(a)



(b)

Figure 5.4: Virtual inertia and damping scheduling results: (a) M , (b) D .

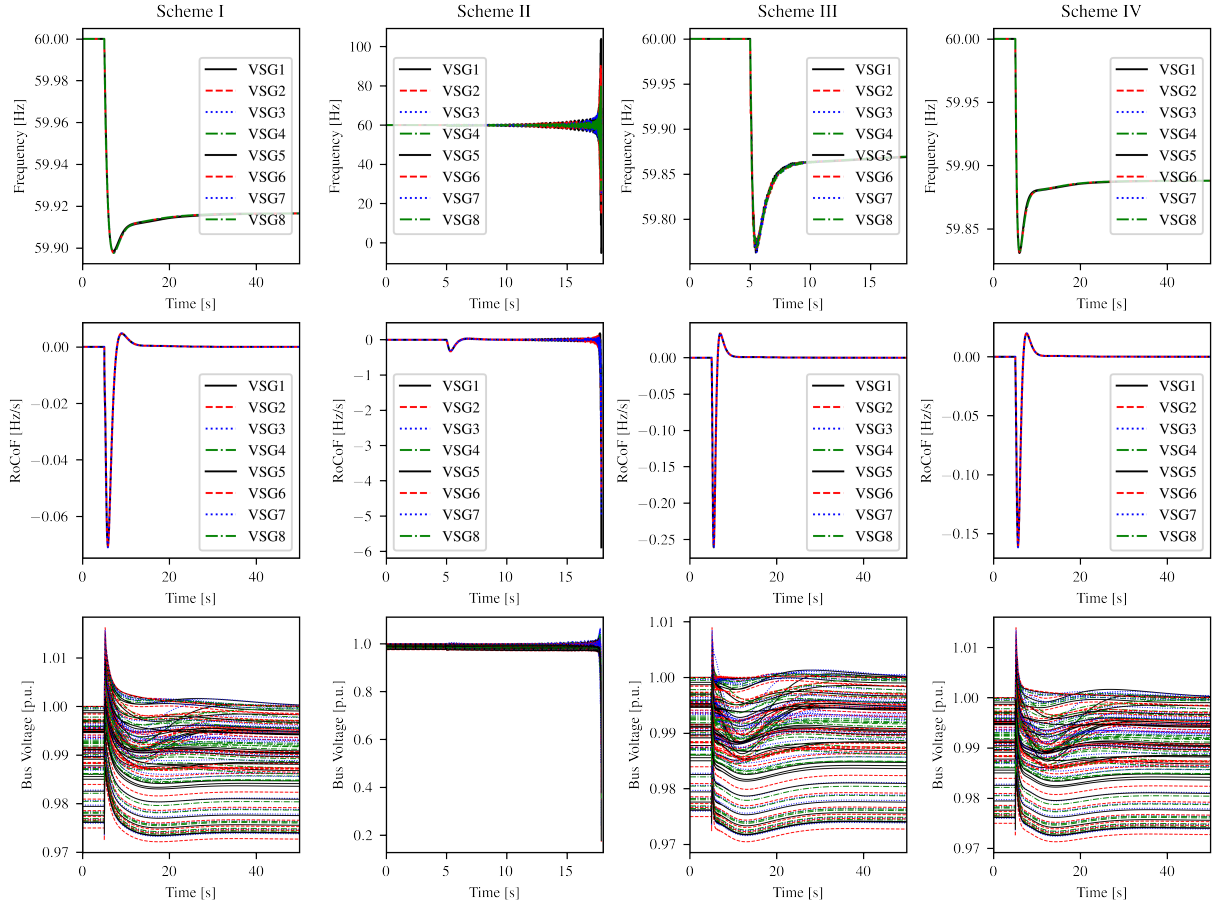


Figure 5.5: Microgrid transient performance under 10% load increase.

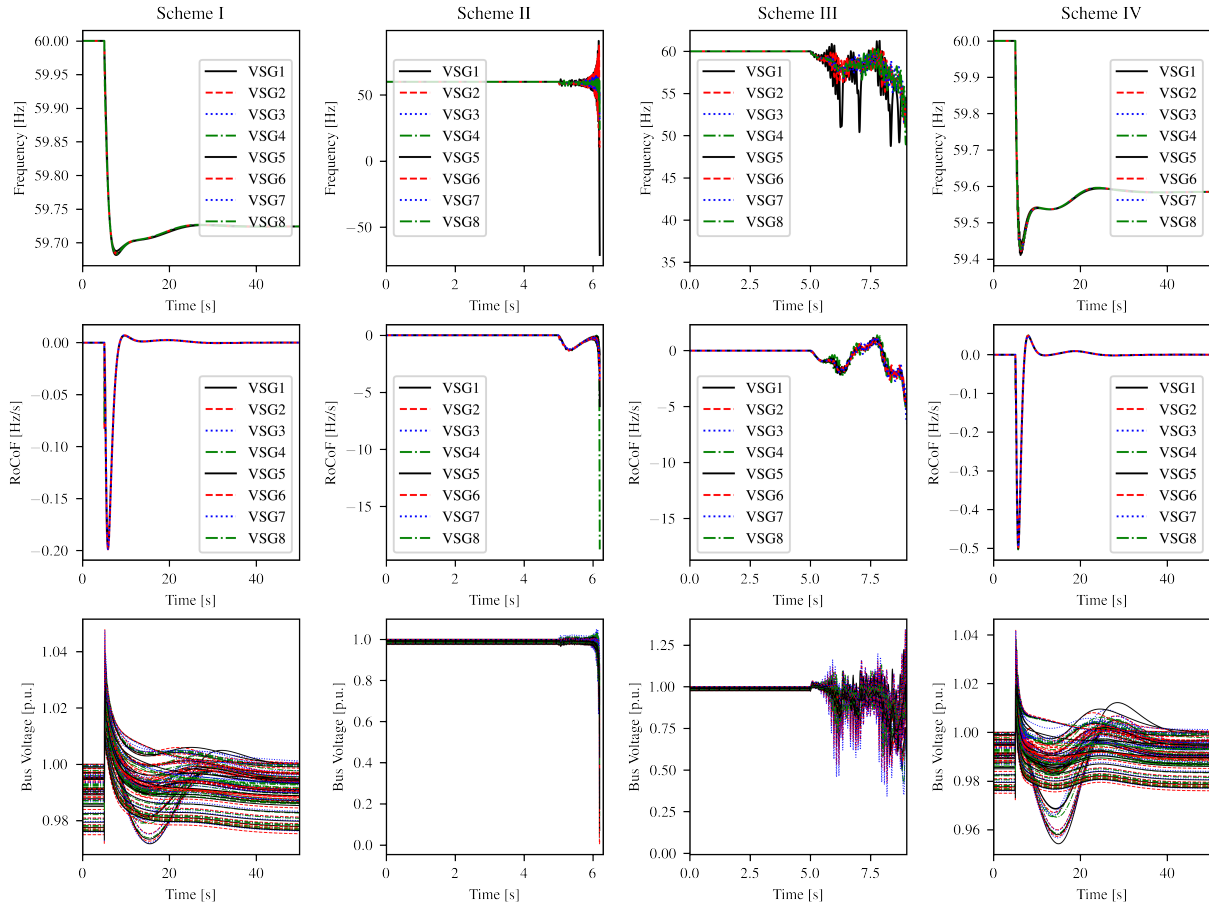


Figure 5.6: Microgrid transient performance under unplanned SG2 trip.

generation trip, microgrid-VIS ensures compliance with both static and dynamic security constraints, achieving the minimum cost for generation, inertia, and damping support.

5.6 Summary

This chapter proposes the concept of VIS, a security-constrained and economy-oriented inertia management framework. The fundamental idea is to combine the device-level controller design and grid-level economic operation, leveraging the controllability and flexibility of IBRs for inertia management. A generic mathematical formulation of VIS is established, which exhibits the flexibility to seamlessly integrate fundamental static economic operation constraints, dynamic stability considerations, and performance metrics. Additionally, VIS is implemented in microgrids, with a specific focus on incorporating dynamic constraints, such as transient performance and small- and large-signal stability constraints, within a contingency set that accounts for large disturbances. This approach makes a tradeoff between the economy and security, ensuring that the microgrid operates with guaranteed static and dynamic security constraints.

Chapter 6

Conclusions

6.1 Main contributions and conclusions

This dissertation consists of four main parts: 1) the design of an inverter P-Q controller with trajectory tracking capability to enable the customized response speed of microgrid IBRs; 2) the development of a decentralized and coordinated V-f control framework considering DER inadequacy and demand control; 3) the design of a systematic controller with certified stability and designated DOA; and 4). the proposition of VIS is to efficiently manage the virtual inertia of microgrids while also accounting for economic operation. All four parts are within the scope of enhancing microgrid flexibility, stability, and economy with IBRs.

Chapter 2 proposed an adaptive P-Q control method with trajectory tracking capability. Model-based analysis proves that there exists an adaptive PI controller with time-varying gains that can ensure any exponential P-Q output trajectory of IBRs. These gains consist of a constant factor and an exponentially decaying factor, based on which the learning space of the RL agent is narrowed down from a function space to a real space. The adaptive controller enables the GFL inverters to follow any predefined trajectory and respond to customized grid-level commands without complicated gain tuning, which eventually improves the microgrid flexibility.

Chapter 3 proposes a decentralized and coordinated V-f control framework to regulate the output of inverter-based generations and reallocate limited DER capacity for V-f control. The control framework is composed of a power regulator and a V-f regulator, which generates the supplementary signals for the primary controller. The power regulator can regulate the output of GFM inverters without violating real-time reference capacities, while the V-f regulator improves the V-f deviation by leveraging the load response to voltage and frequency. It improves DC voltage stability caused by DER inadequacy and reduces involuntary load shedding, which eventually improves microgrid flexibility and stability.

Chapter 4 proposes a systematic approach to identify the candidate parameters that ensure stability and designated DOA, based on nonlinear EMT modeling of IBR-based microgrids. The designated range is customized and flexible enough to cover the normal or emergency operational ranges of microgrids, such as L/HVRT conditions. The proposed

methodology is flexible and can be integrated into some adaptive approaches and physic-informed data-driven approaches for stability and performance guarantee. Which eventually improves microgrid flexibility and stability.

Chapter 5 proposes the concept and generic formulation of VIS to effectively manage the inertia of future power grids. By integrating the dynamic security constraints into the conventional economic operation and formulating virtual inertia and damping of IBRs as decision variables, VIS is flexible and customized to cover various operation scenarios for performance guarantee.

6.2 Future research directions

Continuation of the research proposed in this dissertation can be carried out in the following directions:

1. For the P-Q controller with trajectory tracking capability, there are higher-level controllers generating P-Q references. The specific coordination strategy between higher- and lower-level controllers needs an elaborate design to best use the controllability of the inverter. In addition, the impact of the PLL on the proposed method needs investigation.
2. The coordinated V-f control framework focuses on the primary level for the balanced microgrids. Future works may apply the fundamental idea to unbalanced systems and develop detailed energy management strategies that generate real-time constrained capacity.
3. The systematic design can identify the candidate parameter set that guarantees stability and designated DOA. Detailed integration strategies need to be investigated to harness the full potential of the proposed systematic approach.
4. The DNNs-assisted dynamic approximation and linearization yield conservative results, future work will dive into deriving model-based criteria to mitigate conserveness. Additionally, the extension of VIS to multi-components with active inertia support capability and multi-energy systems will be explored.

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Appendices

A Publications During Ph.D. Study

A.1 Journal papers

1. **Buxin She**, Fangxing Li, Hantao Cui, Jingqiu Zhang, and Rui Bo. “Fusion of Reinforcement Learning and Microgrid Control: Review and Vision”, *IEEE Transactions on Smart Grid*, 15 November 2022.
2. **Buxin She**, Fangxing Li, Hantao Cui, Hang Shuai, Oroghene Oboreh-Snapps, Rui Bo, Nattapat Praisuwanna, Jingxin Wang, and Leon M Tolbert. “Inverter PQ Control with Trajectory Tracking Capability for Microgrids Based on Physics-informed Reinforcement Learning”, *IEEE Transactions on Smart Grid*, 17 May 2023.
3. **Buxin She**, Fangxing Li, Hantao Cui, Jinning Wang, Liang Min, Oroghene Oboreh-Snapps, and Rui Bo. “Decentralized and Coordinated V-f Control for Islanded Microgrids Considering DER Adequacy and Demand Control”, *IEEE Transactions on Energy Conversion*, 21 March 2023.
4. **Buxin She**, Fangxing Li, Hantao Cui, Jinning Wang, Qiwei Zhang, and Rui Bo. “Virtual Inertia Scheduling (VIS) for Real-time Economic Dispatch of IBR-penetrated Power Systems”, *IEEE Transaction on Sustainable Energy*, 26 September 2023.
5. **Buxin She**, Jianzhe Liu, Feng Qiu, Hantao Cui, Nattapat Praisuwanna, Jingxin Wang, Leon M Tolbert, and Fangxing Li. “Systematic Controller Design for Inverter-based Microgrids with Certified Large-signal Stability and Domain of Attraction”, *IEEE Transactions on Smart Grid*, 28 November 2023.
6. **Buxin She**, Fangxing Li, Hantao Cui, Jinning Wang, Qiwei Zhang, and Rui Bo. “Virtual Inertia Scheduling (VIS) for Microgrids with Static and Dynamic Security Constraints”, *IEEE Transaction on Smart Grid*, To submit.
7. **Buxin She**, Yuqing Dong, and Yilu Liu. “Time Delay of Wide Area Damping Control in Urban Power Grid: Model-based Analysis and Data-driven Compensation”, *Frontiers in Energy Research*, 27 April 2022.

8. Qiwei Zhang, Fangxing Li, Jin Zhao, and **Buxin She**, “False Data Injection Attack and Corresponding Countermeasure in Multienergy Systems”. *IEEE Transaction on Power System*, 16 May 2023.
9. Jinning Wang, Fangxing Li, Xin Fang, Wenbo Wang, Hantao Cui, Qiwei Zhang, and **Buxin She**, “Electric Vehicles Charging Time Constrained Deliverable Secondary Frequency Regulation Provision”, *IEEE Transaction on Smart Grid*, Under R2 review.
10. Hang Shuai, Fangxing Li, **Buxin She**, Xiaofei Wang, and Jin Zhao, “Post-storm repair Crew Dispatch for Distribution Grid Restoration Using Stochastic Monte Carlo Tree Search and Deep Neural Networks”, *International Journal of Electrical Power & Energy Systems*, 1 January 2023.
11. Jingqiu Zhang, **Buxin She**, Jimmy Chih-Hsien Peng, Fangxing Li. “A distributed Consensus-based Optimal Energy Management Approach in DC Microgrids”, *International Journal of Electrical Power & Energy Systems*, 1 September 2022.
12. Oroghene Oboreh-Snapps, **Buxin She**, Shah Fahad, Haotian Chen, Jonathan Kimball, Fangxing Li, Hantao Cui, and Rui Bo. “Virtual Synchronous Generator Control Using Twin Delayed Deep Deterministic Policy Gradient Method”, *IEEE Transactions on Energy Conversion*, 30 August 2023.
13. Jun Xiao, Yuqing Qu, **Buxin She**, Chenhui Song, “Operational Boundary of Flow Network”, *Reliability Engineering & System Safety*, 1 March 2023.
14. Jun Xiao, Chuanqi Wang, **Buxin She**, Fangxing Li, et.al. “Total Supply and Accommodation Capability Curves for Active Distribution Networks: Concept and Model”, *International Journal of Electrical Power & Energy Systems*, 1 December 2021.
15. Jun Xiao, Zhongwei Cai, Ziyu Liang, **Buxin She**. “Mathematical Model and Mechanism of TSC curve for Distribution Networks”, *International Journal of Electrical Power & Energy Systems*, 1 May 2022.

16. Zhenglai Shen, Som Shrestha, Daniel Howard, Tianli Feng, Diana Hun, and **Buxin She**, “Machine Learning–assisted Prediction of Heat Fluxes Through Thermally Anisotropic Building Envelopes“, *Building and Environment*, 13 April 2023.

A.2 Conference papers

1. Oroghehene Oboreh-Snapps, Rui Bo, **Buxin She**, Fangxing Fran Li, and Hantao Cui, “Improving Virtual Synchronous Generator Control in Microgrids Using Fuzzy Logic Control”, *2022 IEEE/IAS Industrial and Commercial Power System Asia (I&CPS Asia)*.
2. Jun xiao, Yuqing Qu, Chenhui Song, Baoqiang Zhang, **Buxin She**, and Qisi Lin, “Security Region and Total Supply Capability under $N-0$ for Urban Distribution Network”, *2020 IEEE Power & Energy Society General Meeting (PESGM)*, page 2-6, December 2020.

Vita

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