Enhancing Microgrid Flexibility and Dynamic Performance with Inverter-based Resources (IBRs)

Presenter: Fangxing (Fran) Li, Buxin She

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The University of Tennessee Knoxville

Contents

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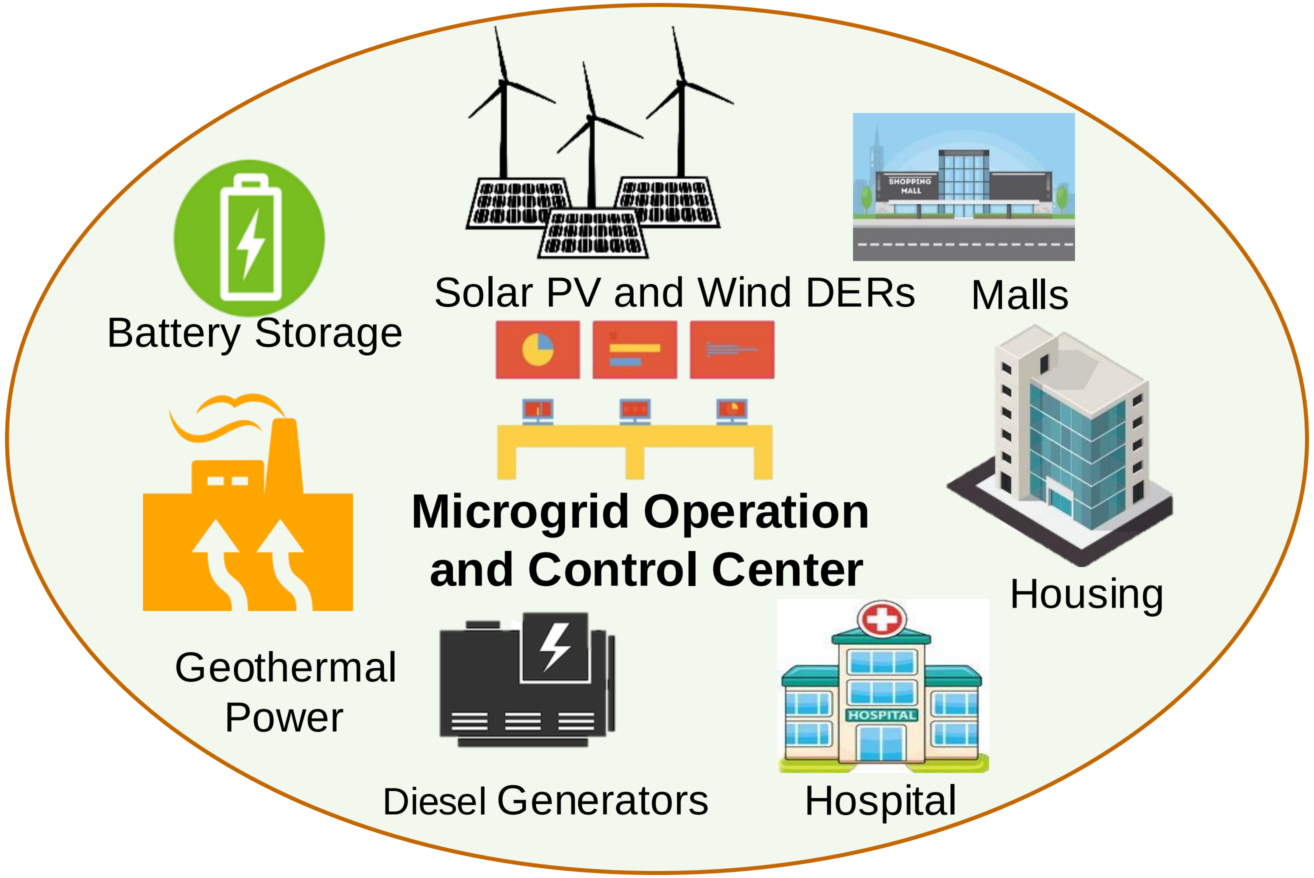
Microgrid definition



A typical microgrid

Definition

- ❑ An integrated energy system composed of multiple **distributed energy resources (DERs), energy storage systems, and local loads**, which can operate in either grid-connected mode or islanded mode.

Characteristic

- ❑ Small system size
- ❑ High penetration of **inverter-based resources (IBRs)**
- ❑ Low system inertia
- ❑ High R/X ratio of the feeders
- ❑ Strong voltage and frequency (V-f) coupling

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Challenges and Opportunities

- **Challenges**
- Higher uncertainty
- Elements that are difficult to model
  - Customer behavior
  - Extreme weather
- Model and parameter accessibility/Privacy
- Faster dynamics of IBRs
- Requirement for improved resilience

- **Opportunities**
- Renewable Energy
- Flexibility and Controllability of IBRs
  - Address uncertainty
  - Provide grid dynamic support
  - Supply critical load
- Cutting-edge techniques
  - Deep learning
  - Reinforcement learning

Challenges and opportunities coexist in microgrids, and the key point is how we effectively manage the challenges and utilizing the existing resources.

High-level research map of microgrid control

① Operation mode

② Function grouping

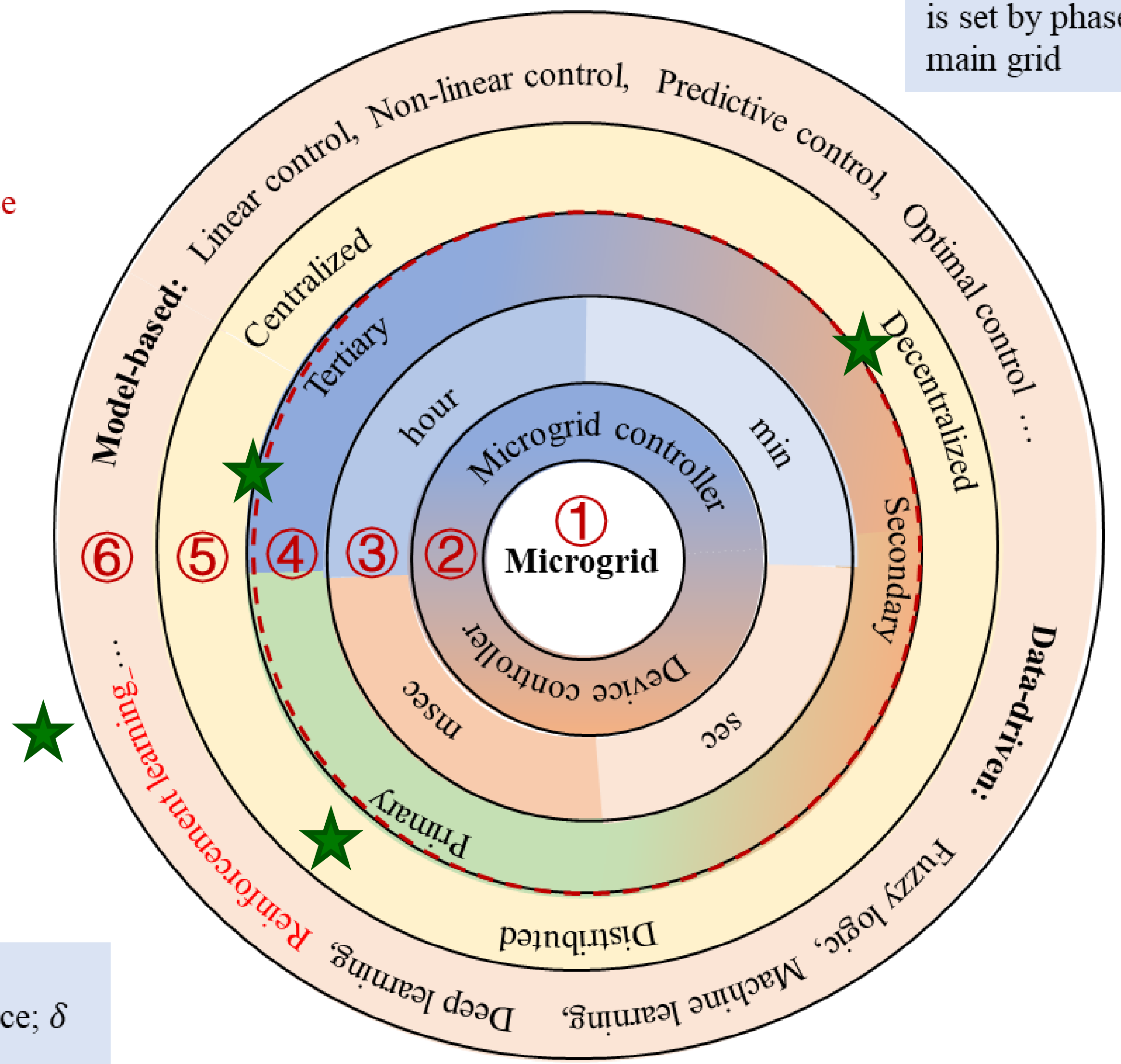
③ Timescale

④ Hierarchical structure

⑤ Communication interface

⑥ Control techniques

- **Grid-connected mode**
Controlled as current source; δ is set by phase-locking to the main grid

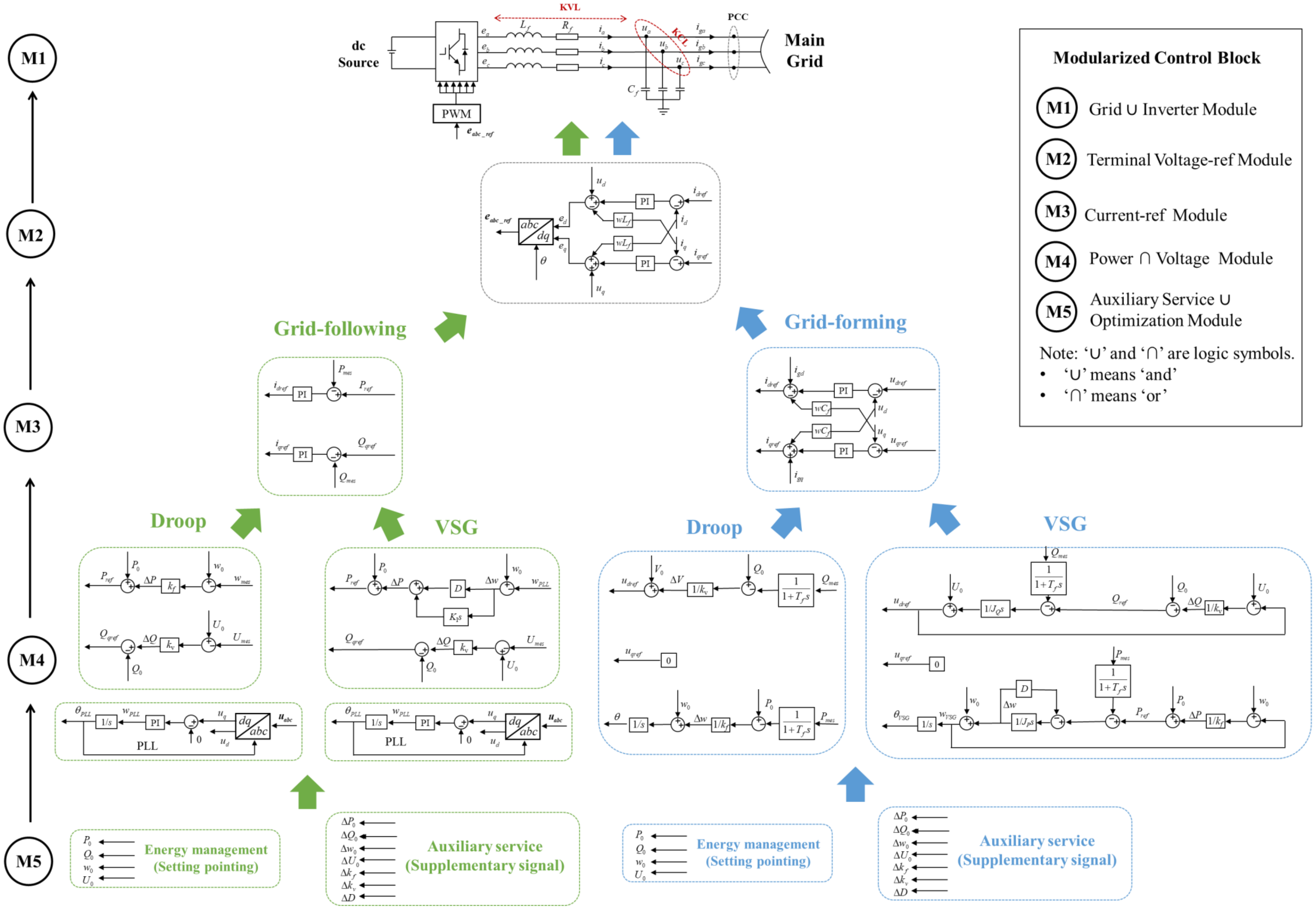


- **Islanded mode**
Controlled as a voltage source; δ is self-generated

★ Marks the presentation focus

B. She, F. Li, H. Cui, J. Zhang, and R. Bo, “Fusion of Microgrid Control with Model-Free Reinforcement Learning: Review and Vision,” *IEEE Transactions on Smart Grid*, vol. 14, no. 4, pp. 3232-3245, July 2023.

Modularized control blocks for IBRs



Improve microgrid:

- Flexibility
- Dynamic performance

Presentation Outline

Inverter-based Microgrids

Topic		Physical Model	Technique	Toolbox
Device-level control	Inverter P-Q control with trajectory tracking capability	IBR transfer function	Model-free reinforcement learning	Simulink, TensorFlow
Grid-level control	V-f control considering DER inadequacy and demand control	IBR transfer function, IBR-integrated power flow	Control theory	Simulink, Script power flow
Combined device- and grid-level economic operation	Virtual inertia scheduling (VIS) with guaranteed dynamic performance	Grid transfer function, Economic dispatch model	Deep learning, Mixed integer linear optimization	Andes, AMS Gurobi, Pytorch

Contents

Objective: Guaranteed Trajectory

➢ Objective

Assume a step input, the PQ output of **grid-following** IBRs can be controlled smoothly and accurately

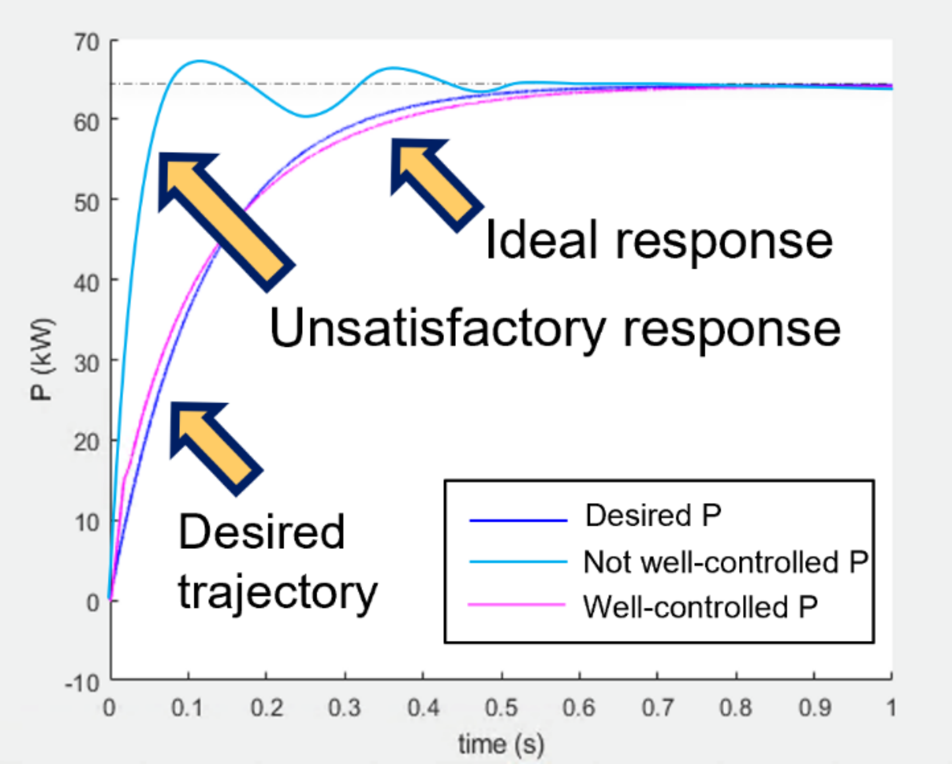
$$y(t) = 1 - e^{-t/\tau}$$

Where τ is response time constant that can be freely assigned.

➢ Benefits

Improve the **controllability** and **flexibility** of IBRs

- Intentional power injection → large time constant
- Emergency support → small time constant



Key Idea: the actual response following the desired trajectory

H. Li, F. Li, Y. Xu, D. T. Rizy, and J. D. Kueck, "Adaptive Voltage Control with Distributed Energy Resources: Algorithm, Theoretical Analysis, Simulation and Field Test Verification," *IEEE Transactions on Power Systems*, vol. 25, no. 3, pp. 1638-1647, August 2010.

Methodology: Adaptive gains

➢ Methodology

- Use **adaptive** PI controller with time-varying gains to ensure the actual response following the desired trajectory

$$\begin{cases} k_p = f(t) \\ k_i = g(t) \end{cases}$$

- Implement the adaptive controller in the outer **PQ regulation loop**, because it has lower bandwidth and its output determines the inverter PQ response
- Do model-based analysis to **inform** the reinforcement learning based implementation

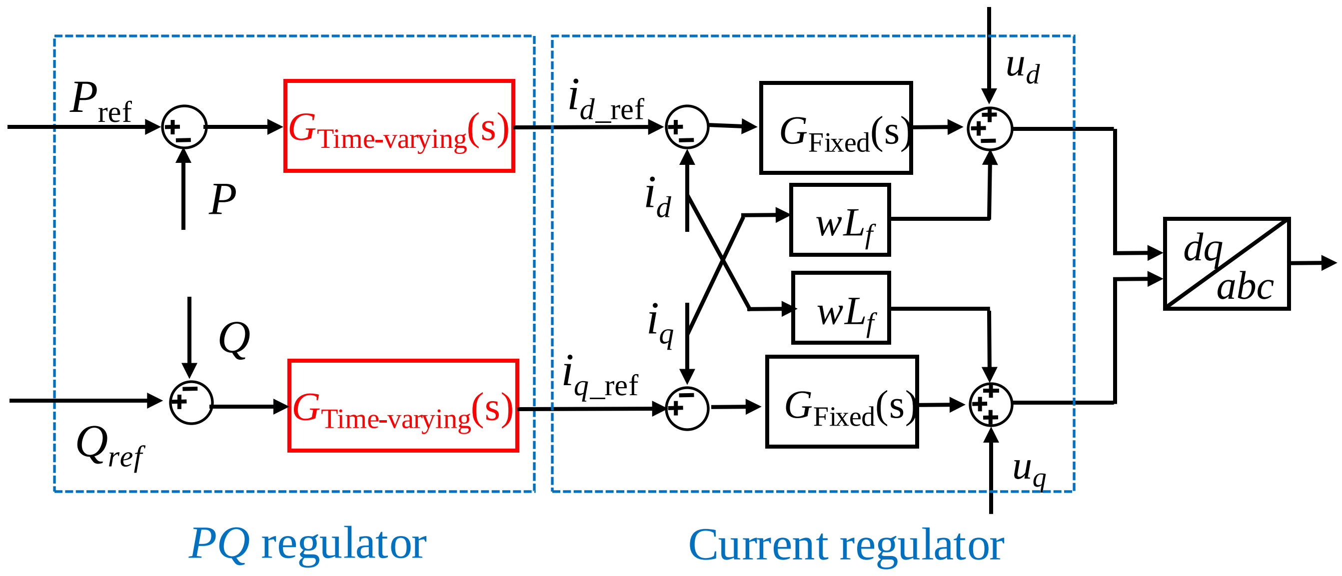
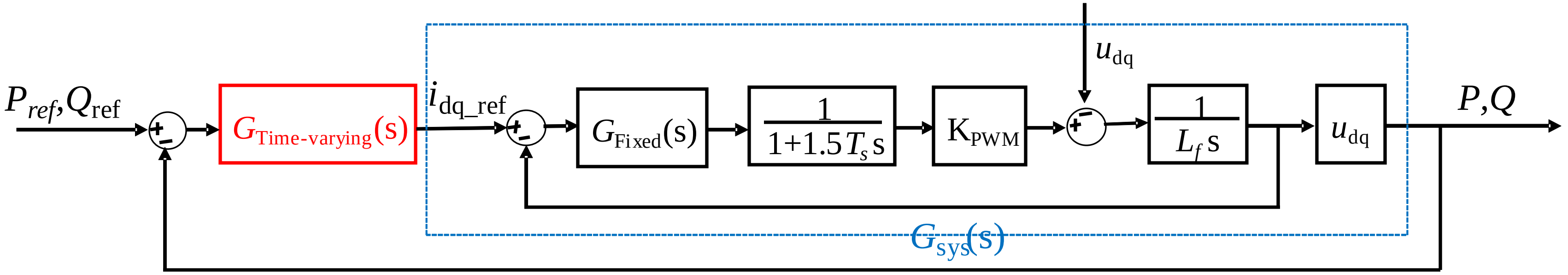


Diagram of the Proposed Adaptive Inverter PQ Controller

Model-based Analysis



Inverter-based P-Q control diagram

$$G(s)=\frac{K_{PWM}(k_{p2}s+k_{i2})}{s(R+wL_f s)(1+1.5T_s s)+K_{PWM}(k_{p2}s+k_{i2})}=\frac{n(s)}{m(s)}$$

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

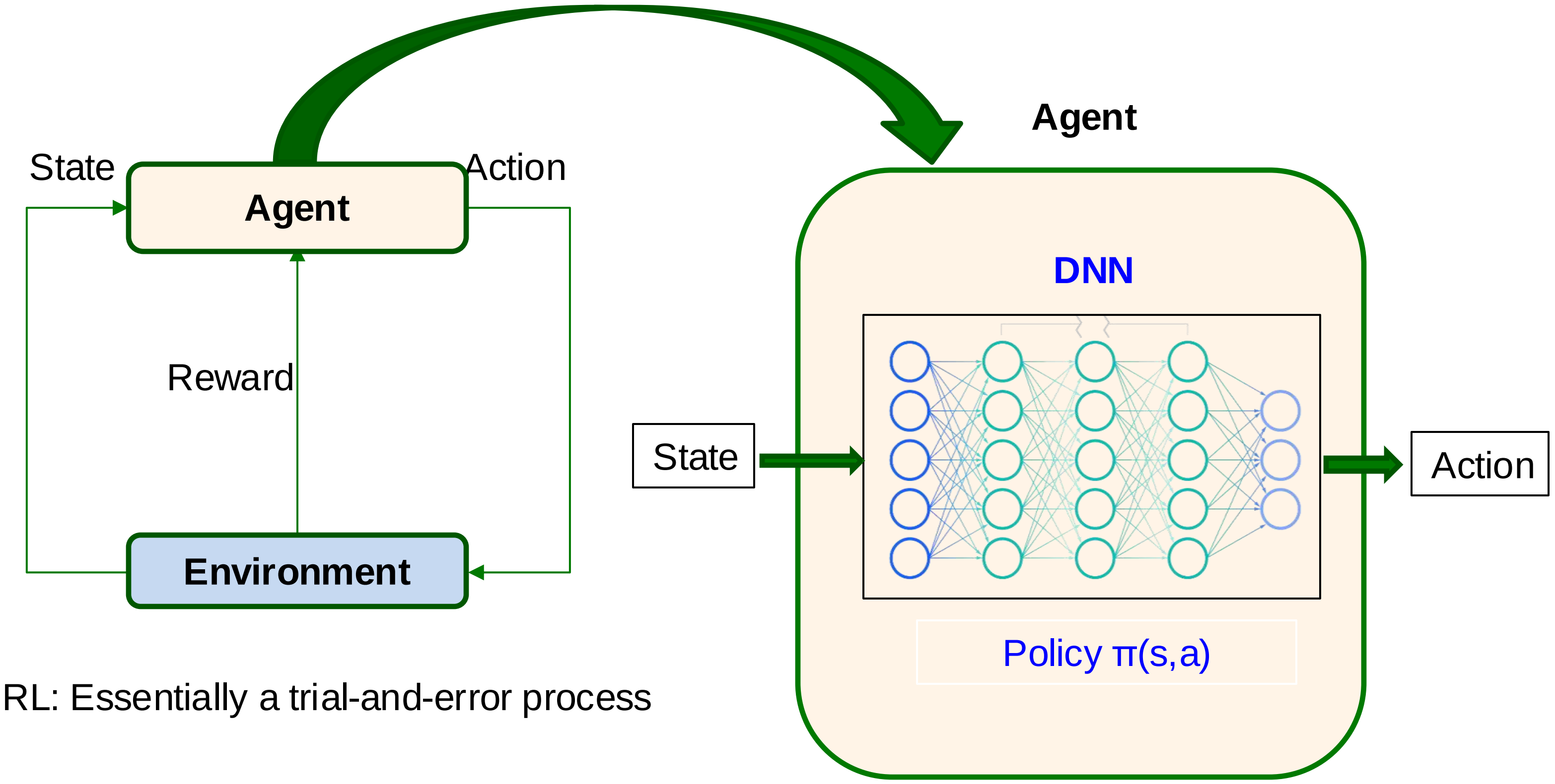
where

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

Question: What if $G_{sys}(s)$ is unavailable or inaccurate ?

B. She, F. Li, H. Cui, H. Shuai, O. Oboreh-Snapps, R. Bo, N. Praisuwanna, J. Wang, L. M. Tolbert, “Inverter PQ Control with Trajectory Tracking Capability for Microgrids Based on Physics-informed Reinforcement Learning,” *IEEE Transactions on Smart Grid*, In-Press, 2023.

Data-driven Implementation: DRL



RL: Essentially a trial-and-error process

Reinforcement learning :

- RL is a basic machine paradigm formulated as a Markov Decision Processes.

Deep reinforcement learning:

- Use **deep neural network** to map:
  State, action → value (Q-value);
  State → action

Training Target:

- *a well-trained RL agent chooses optimal actions for maximum accumulated reward (best performance)*

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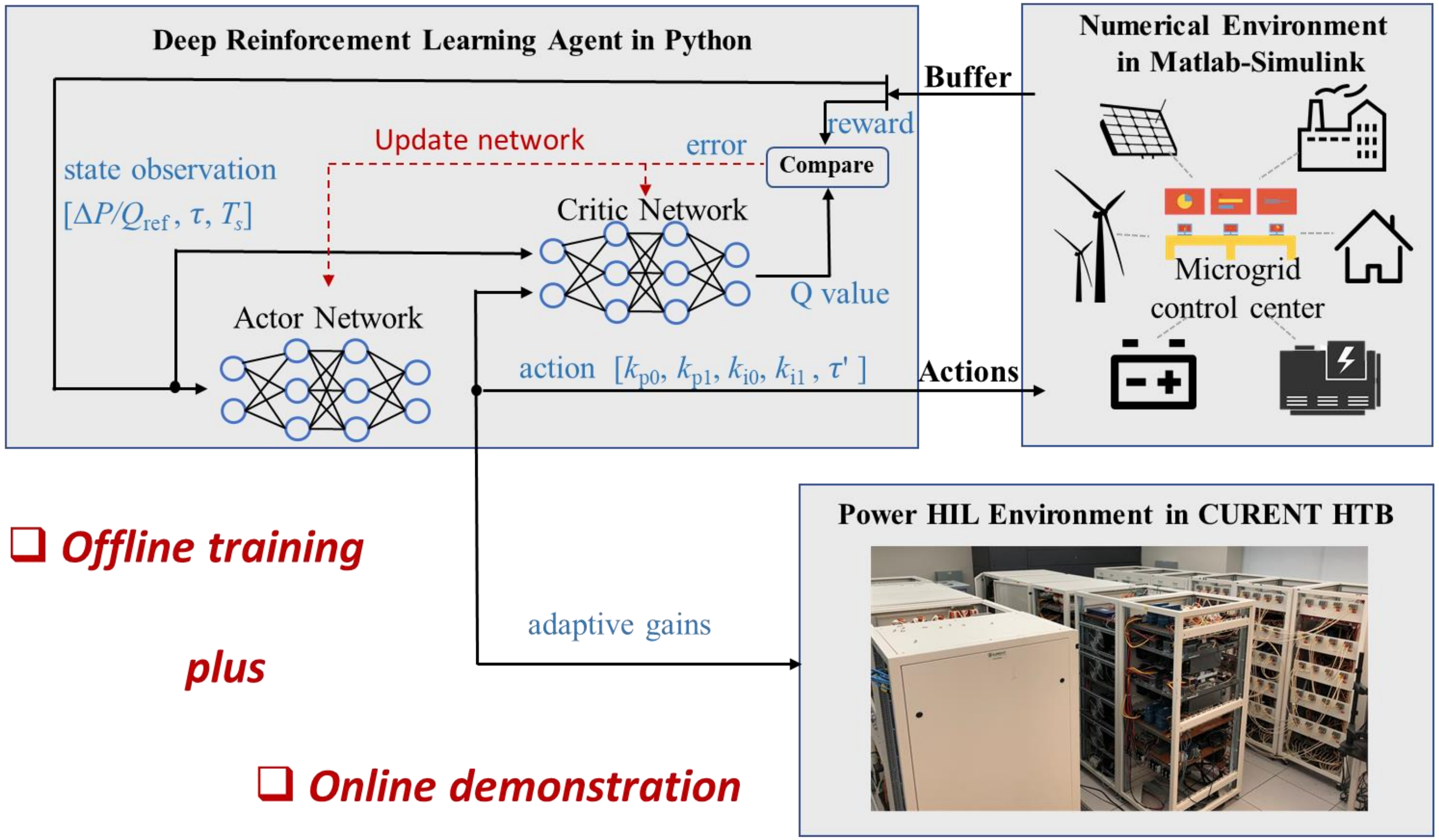
Physics-informed DRL and HIL Test



- ❑ ***Offline training***

plus

- ❑ ***Online demonstration***

Diagram of Physics-informed Reinforcement Learning (RL) in the Numerical Simulator and Power HIL demonstration in HTB

- ❑ Model-based analysis reduce learning space from **function space** to **real space**

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

$$k_p(t), k_i(t) \in \boldsymbol{f}(t)$$

$$k_{p0}, k_{p1}, k_{i0}, k_{i1} \in \boldsymbol{R}$$

Test Microgrid and Training Results

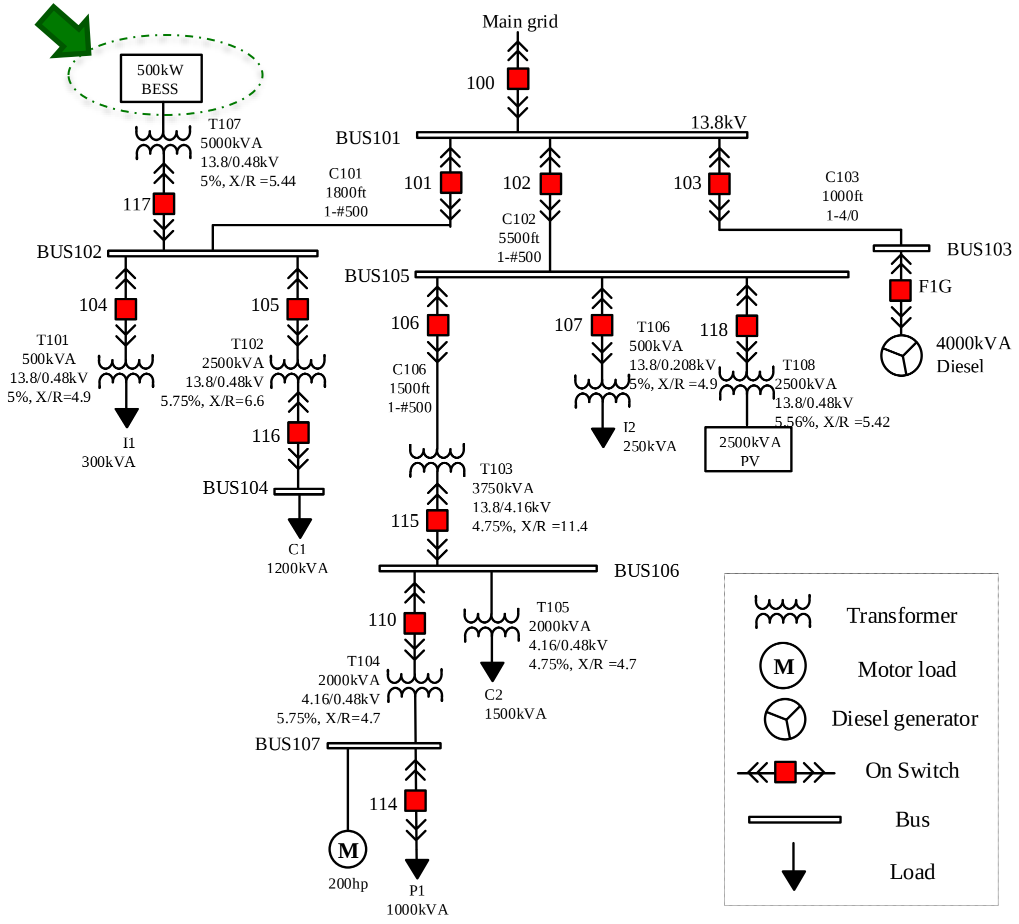
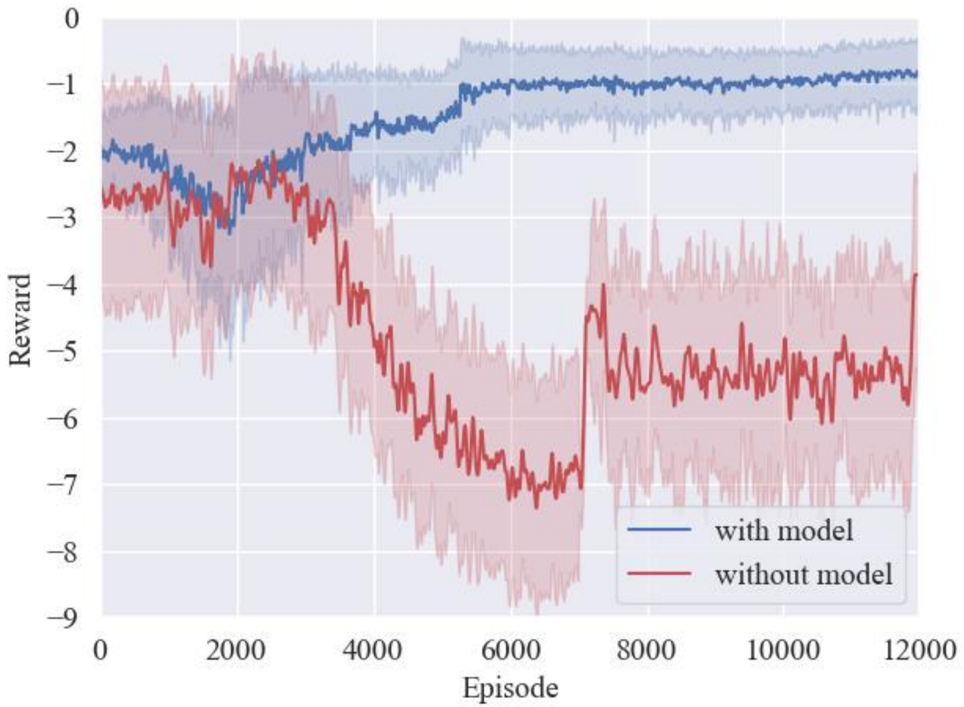


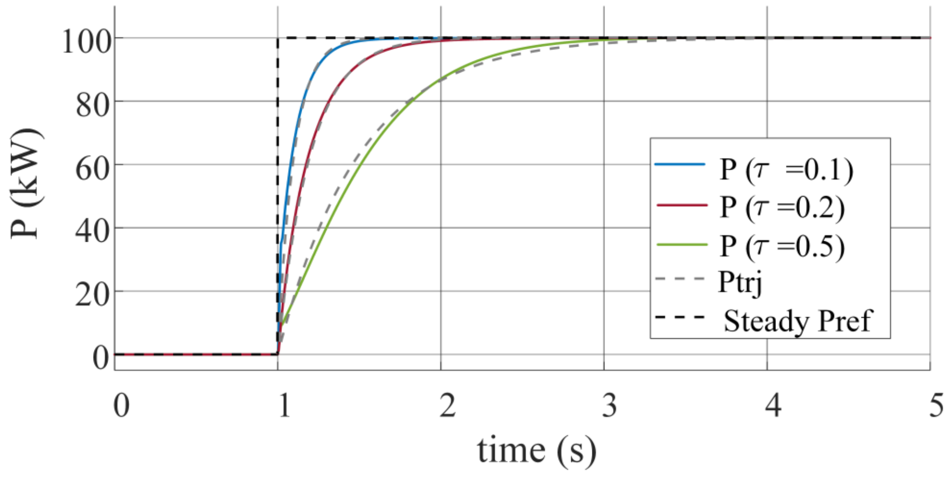
Diagram of modified Banshee microgrid



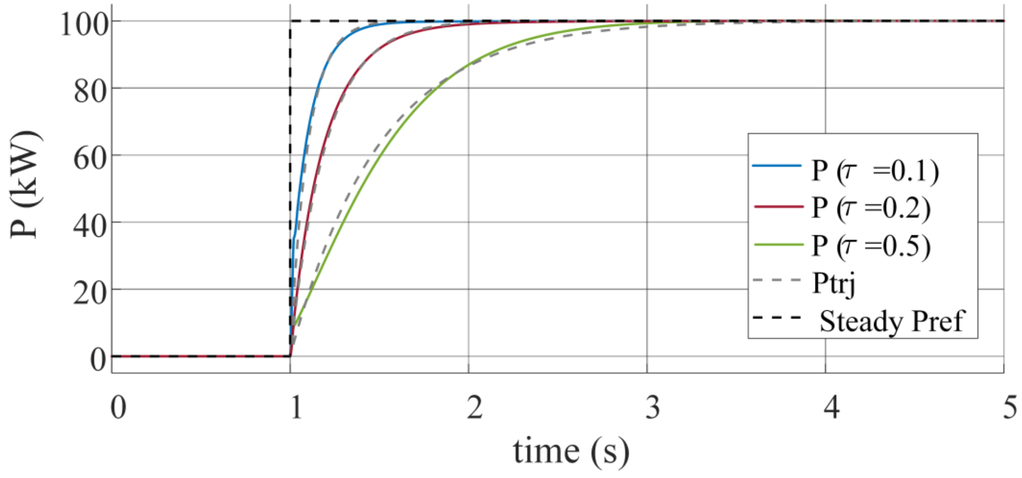
Reward curve with and without model-based analysis

Validation in MATLAB-Simulink

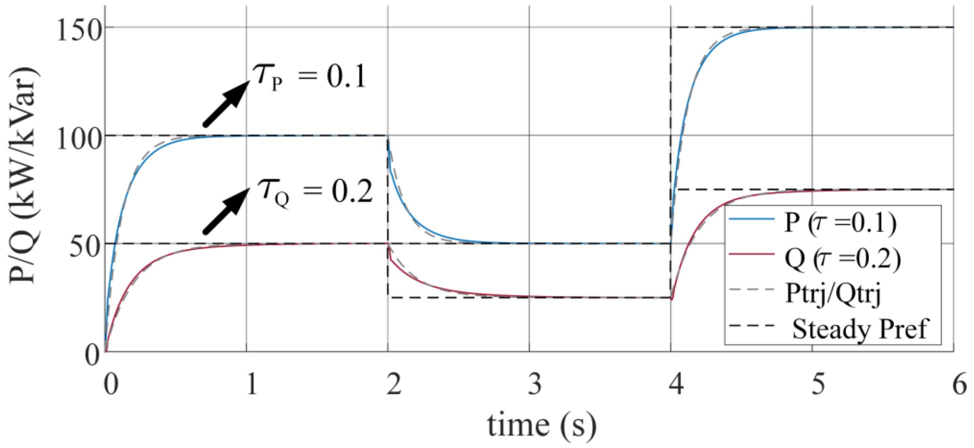
➢ **Scenario 1-1**: Scheduling P_{ref} change



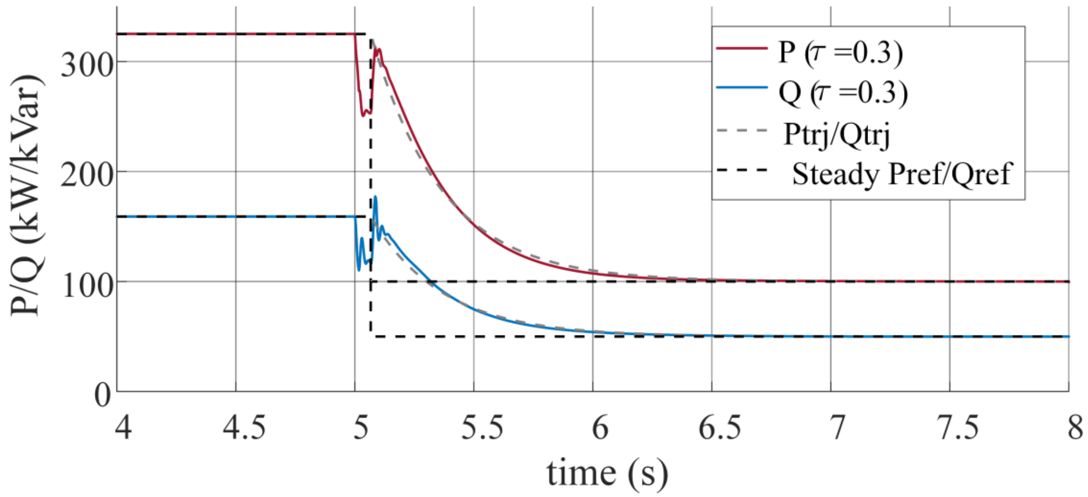
➢ **Scenario 2**: Generation loss and Power Support



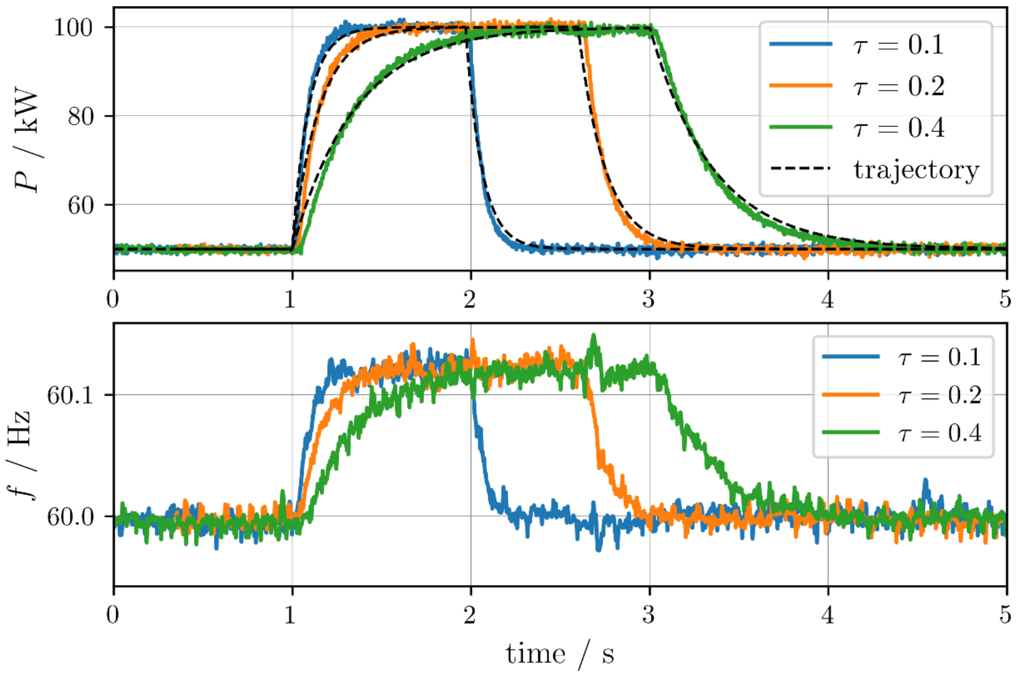
➢ **Scenario 1-2**: Scheduling P_{ref} and Q_{ref} change



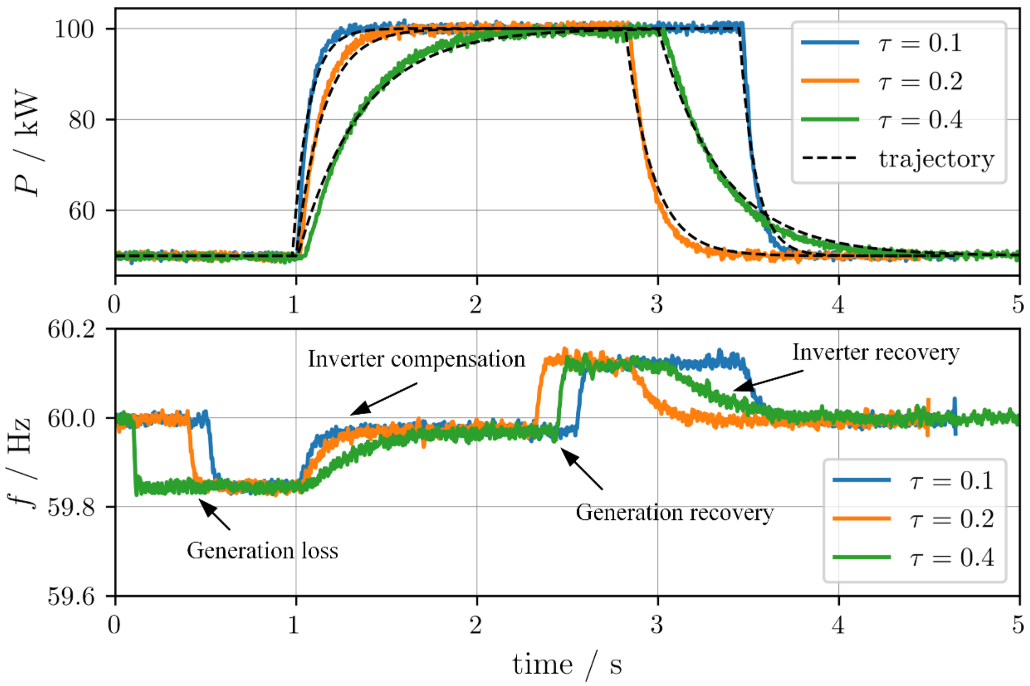
➢ **Scenario 3**: Grounded fault



Validation in CURENT HTB



Scheduling reference change



Generation reduction & recovery

- ❑ Inverters can be freely assigned **any time constant** and respond either slow or fast to changing commands.
- ❑ The proposed control algorithm is valid under the **power hardware-in-the-loop demonstration**.

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Summary

- There exists a time-varying-gain adaptive PI controller that can track a **predefined exponential trajectory** for microgrid inverter-based PQ control.

- The proposed controller outperforms the conventional fixed-gain and adaptive PI controllers. **Without manual re-tuning**, it can accurately track the predefined trajectory with any assigned time constant.

- 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.

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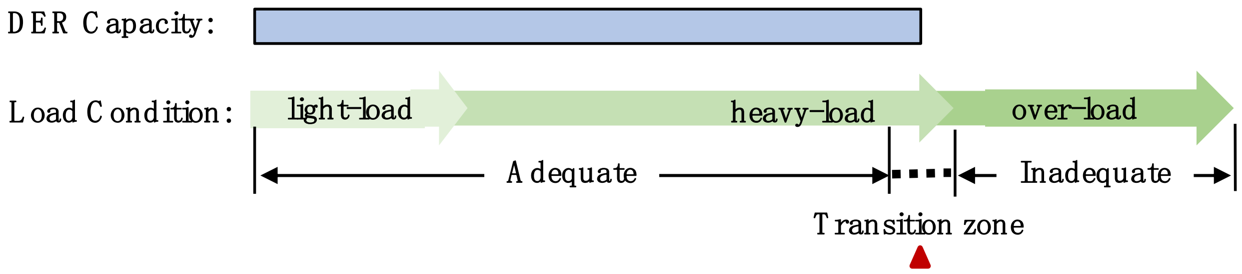
Background and Motivation

➢ Background

An islanded microgrid forms a self-sufficient system with **grid-forming IBRs** supplied by distributed energy resources (DERs).



DER inadequacy under various load level

➢ Challenges

Conflict between fluctuating DC side DERs capacity and automatic load sharing based on fixed droop gains.

- ○ **IBR saturation** caused by overloads
- ○ Large frequency and voltage **deviation**
- ○ Unexpected DC voltage dip and **IBR trip**

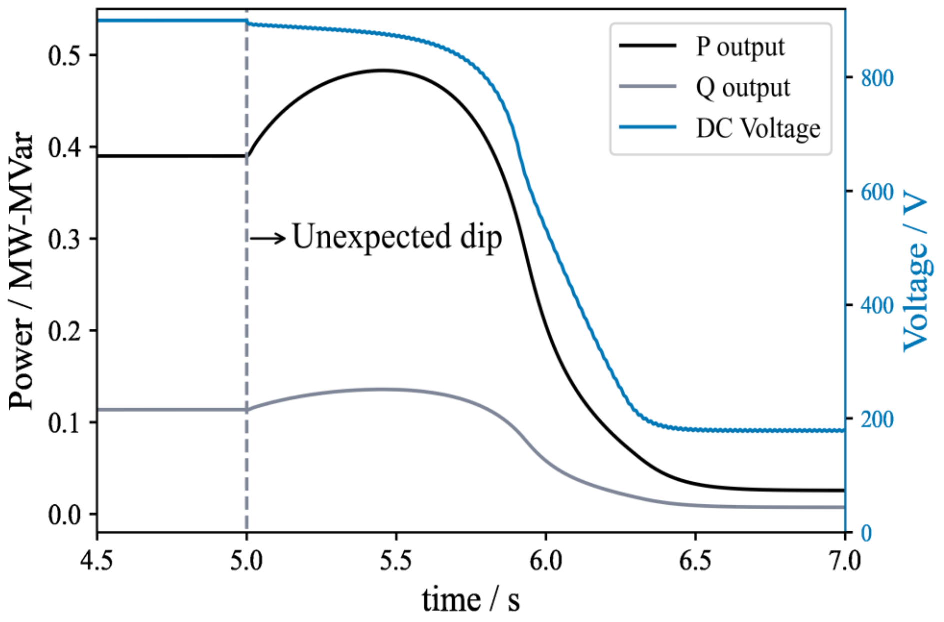


Diagram of DC voltage dip and IBR trip caused by DER inadequacy

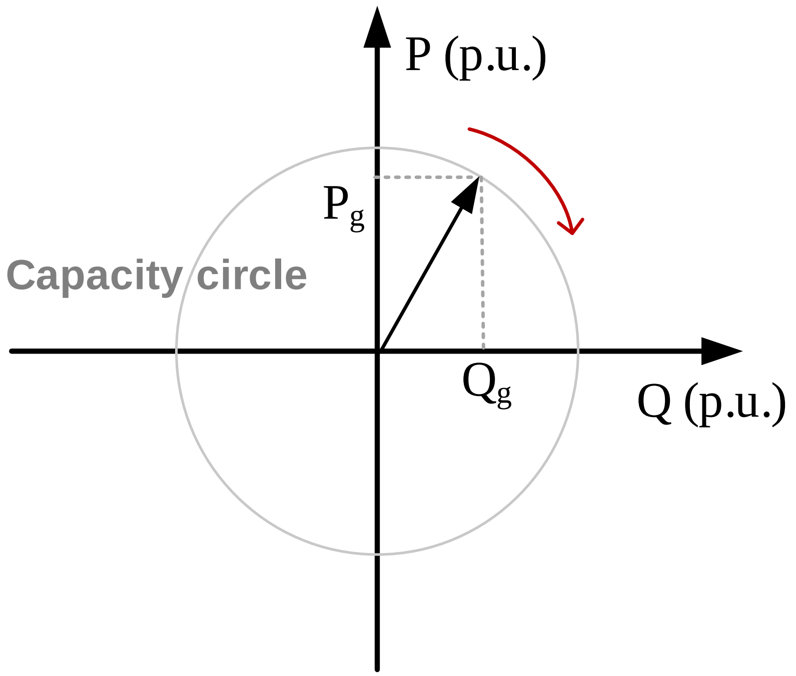
Objective

➢ Objective

- Accurately control the **output of GFM inverters** when DER is insufficient;
- **Improve load sharing** results based on real-time DER capacity;
- **Coordinate** voltage and frequency (V-f) regulation under the condition of constrained DER capacity;

➢ Benefits

- Improve the **controllability** and **stability** of IBRs
- Make the best use of limited DER capacity
- Reduce V-f deviation
- Reduce involuntary load shedding



Constrained operation of IBRs

Methodology (1)

- **Key idea**
  - Generate **supplementary signal** based on real-time DER capacity and feed it to **primary regulator**
  - Consider the impact of load sensitivity to voltage and frequency

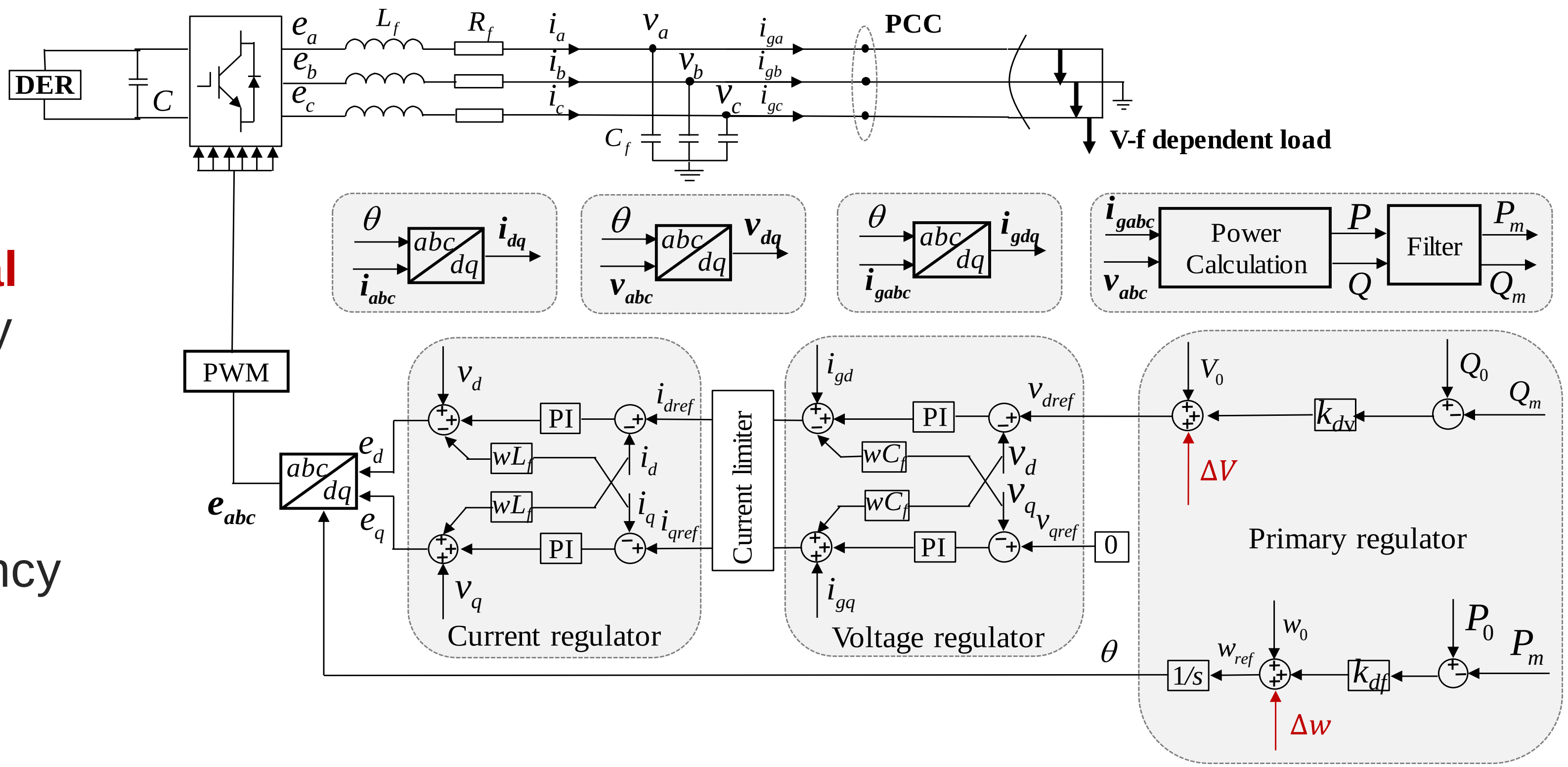


Diagram of a droop-controlled GFM inverter supplying V-f dependent load

Methodology (2)

➢ Proposed Control framework

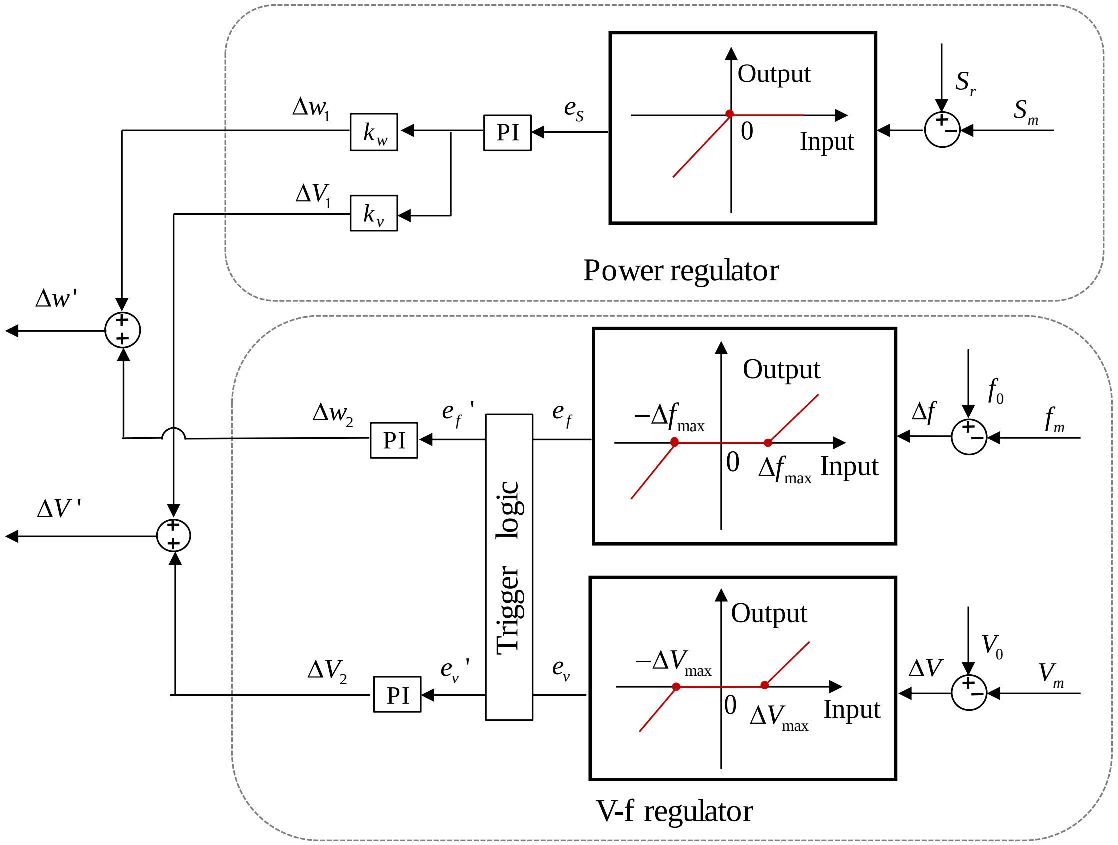


Diagram of the proposed decentralized and coordinated control framework

- ❑ Power regulator and V-f regulator generate **supplementary signals** for the primary regulator
- ❑ **Power regulator** generates control signals based on the error between inverter output and DER capacity, which help limit the output of grid-forming inverters
- ❑ **V-f regulator** generates control signals based on voltage and frequency deviations, which reallocates limited generation for acceptable V-f deviations

Proposed Approach (1)

➢ IBR integrated power flow

A general islanded microgrid formed by ***N* inverters**, each inverter is connected to an independent bus with a local V-f dependent load

$$\begin{cases} f = f_{0,i} + k_{df}(P_{inv,i} - P_{inv0,i}) \\ V_i = V_{0,i} + k_{dv}(Q_{inv,i} - Q_{inv0,l}) \end{cases} \quad \forall i = 1, 2, \cdots, N$$

2*N* Droop equation

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

2*N* V-f dependent load

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

2*N* Network power flow

6*N* decision variables:

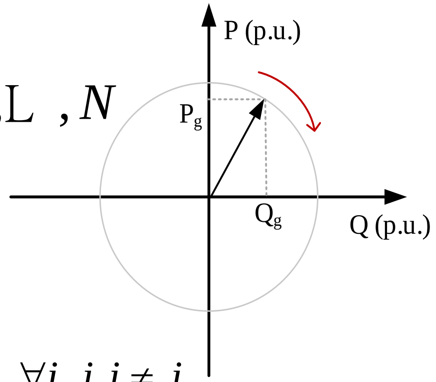
1 global frequency, *N* voltage, *N*-1 power angle, *N* active inverter output, *N* active load, *N* active inverter output, and *N* reactive inverter output.

Proposed Approach (2)

IBR integrated power flow considering the proposed framework

- Primary regulator become invalid due to DER inadequacy
- *2N* Droop equations are changed to *N* capacity constraints

$$
\begin{cases}
\text{Load}: \begin{cases} P_{l0,i}' = P_0 + \Delta P \\ Q_{l0,l}' = Q_0 + \Delta Q \end{cases} & \forall i = 1,2,\ldots,N \\
\text{Generation}: \boxed{P_{inv,i}'^2 + Q_{inv,i}'^2 = S_i^2}
\end{cases}
$$



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

New equilibrium

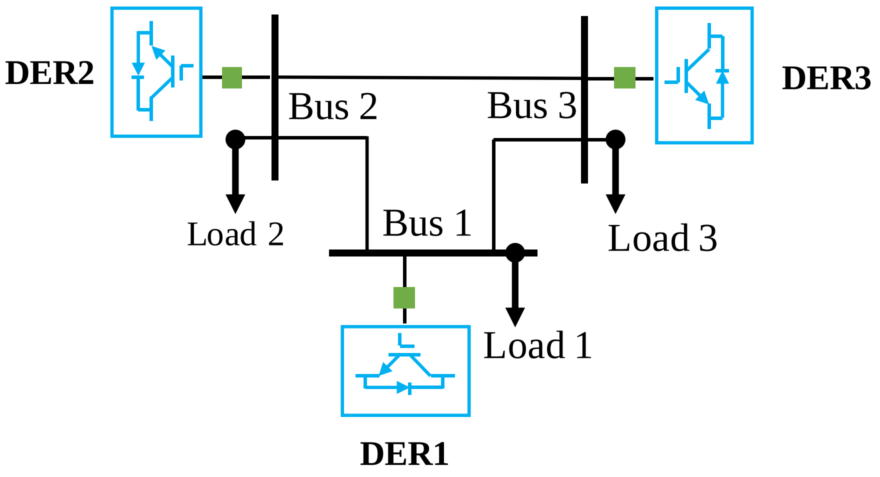
- Given ($P_{inv,i}'$, $Q_{inv,i}'$) on the capacity circle, there are ***4N*** state variables and ***4N*** equations left.
- Then for each ($P_{inv,i}'$, $Q_{inv,i}'$), the corresponding new equilibrium V-f is solvable.

Show the existence of new **equilibrium** when integrating the proposed control framework

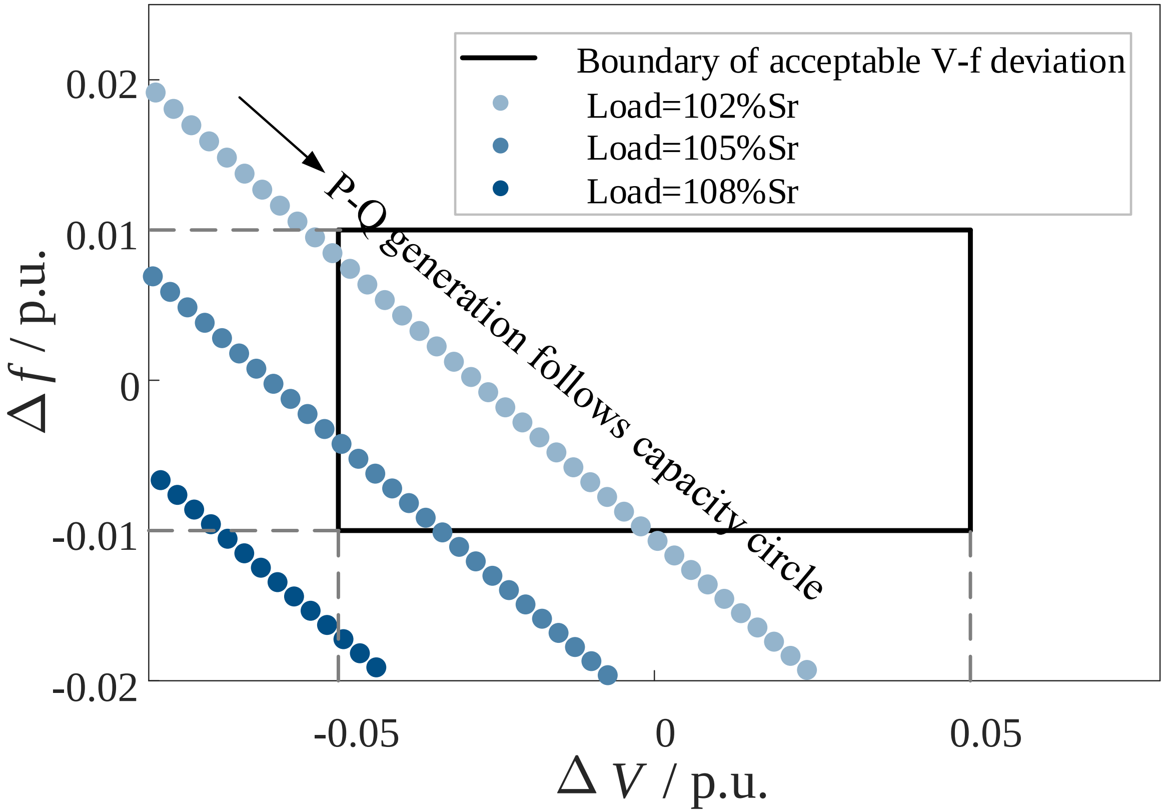
B. She, F. Li, H. Cui, J. Wang, L. Min, O. Oboreh-Snapps, R. Bo, "Decentralized and Coordinated V-f Control for Islanded Microgrids Considering DER Inadequacy and Demand Control," *IEEE Transactions on Energy Conversion*, vol. 38, no. 3, pp. 1868-1880, Sept. 2023.

Case Study in An Ideal System

- **IBR-based 3-bus system**



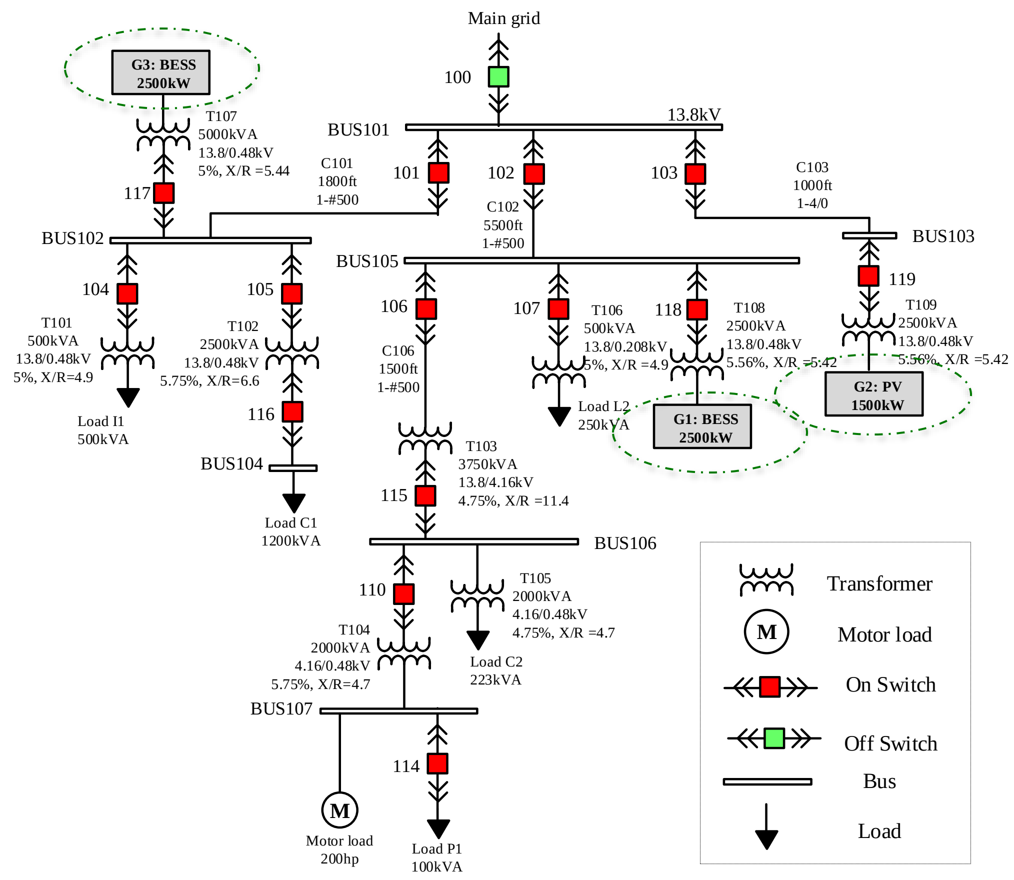
- Assume the total load is close to but small than the total DER capacity
- An intentional load increase at the initial operating point (P_0, Q_0) and the total load **exceed** the DER capacity.
- Predict the **new equilibrium**



V-f deviation under bounded generation constraints

Case study in a Real Microgrid (1)

➢ Modified Banshee Microgrid



Single-line diagram of modified Banshee microgrid

Table. 1 Control parameters of grid-forming inverters

Parameter		G1	G2	G3
Filter	L_F /H	5×10^{-5}	2.5×10^{-5}	5×10^{-5}
	C_F /F	1×10^{-5}	1×10^{-5}	1×10^{-5}
Current regulator gains / $[k_P, k_I]$		[0.5, 2]	[0.5, 2]	[0.5, 2]
Voltage regulator gains / $[k_P, k_I]$		[0.1, 1]	[0.1, 1]	[0.1, 1]
Droop gains / $[k_{dF}, k_{dV}]$		[0.01, 0.05]	[0.005, 0.025]	[0.01, 0.05]
Power regulator gains / $[k_{ps}, k_{is}, k_w, k_v]$		[0.5, 10, 0.04, 0.5]	[0.25, 5, 0.02, 0.25]	[0.5, 10, 0.04, 0.5]
V-f regulator gains / $[k_{pf}, k_{if}, k_{pv}, k_{iv}]$		[0.5, 10, 0.5, 10]	[0.5, 10, 0.5, 10]	[0.5, 10, 0.5, 10]

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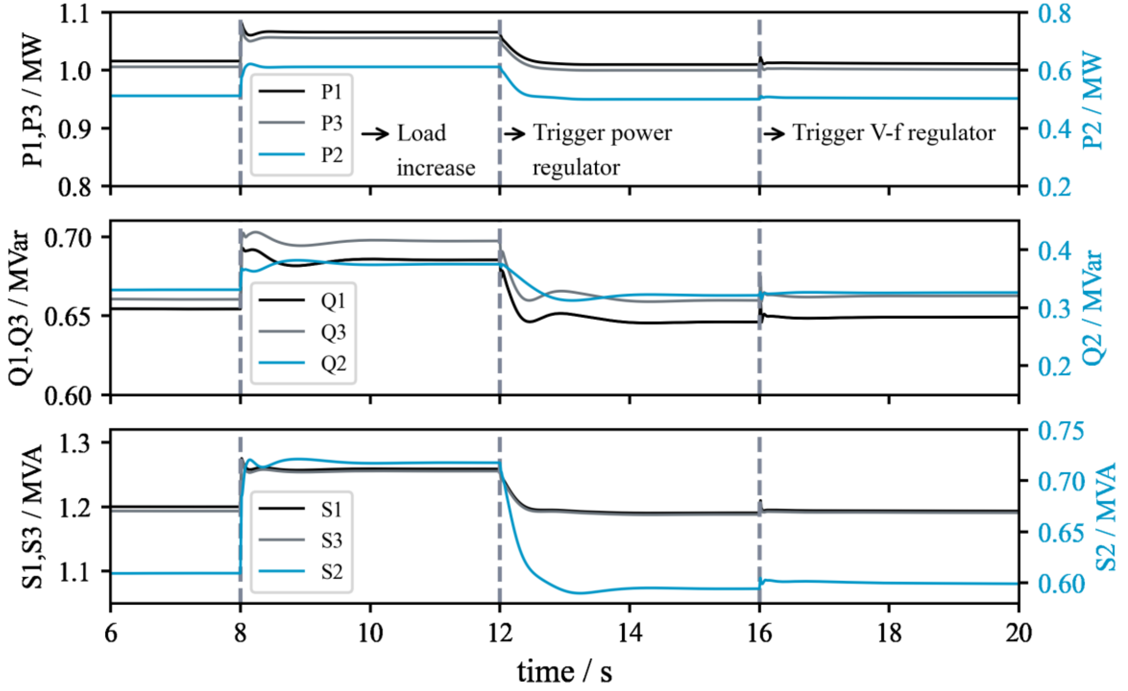
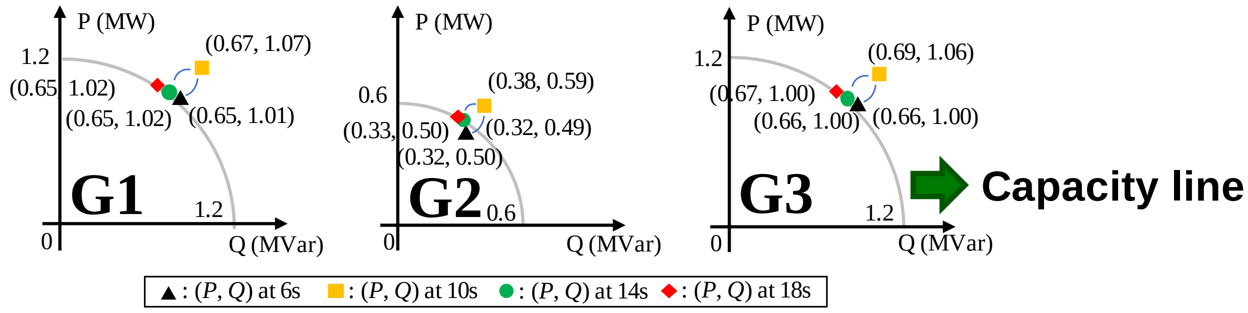
Case study in a Real Microgrid (3)

Scenario 1: P-Q regulator + V-f regulator

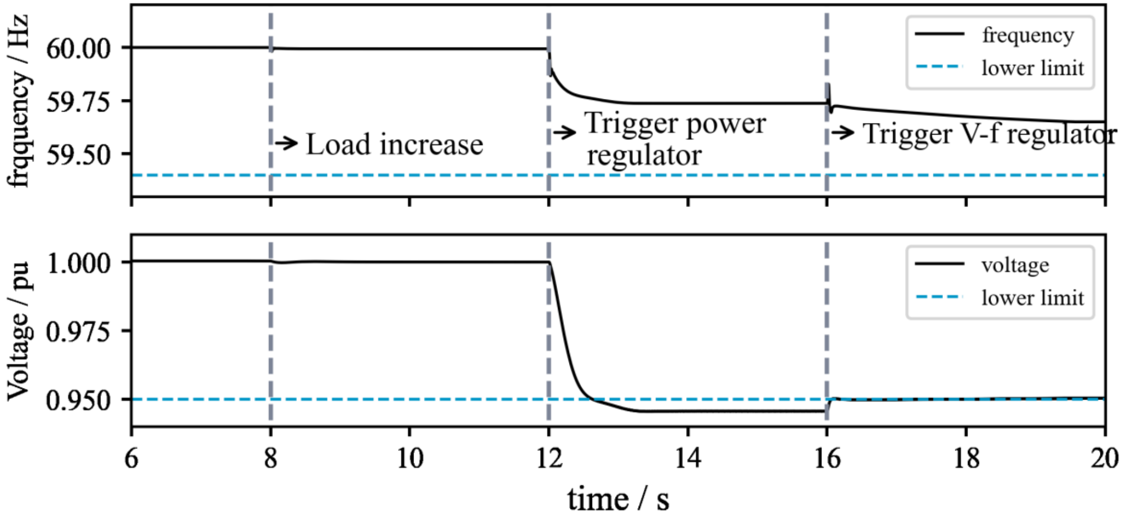
- Voltage over dip and recovery



Dynamic inverter output



Static operation point

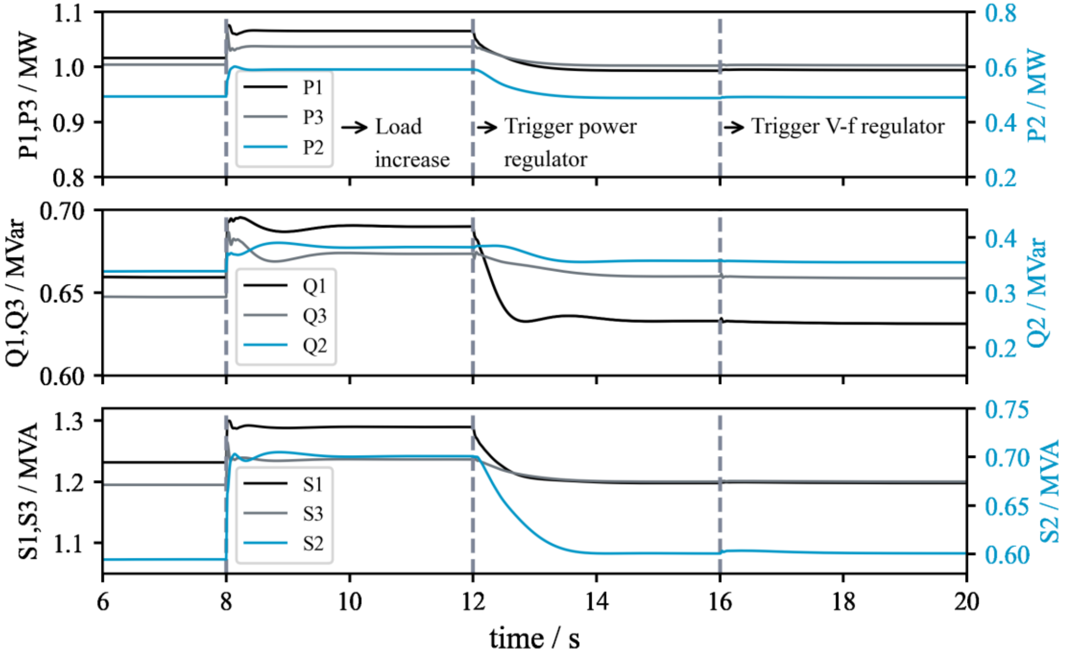


V-f response: increase Q, decrease P

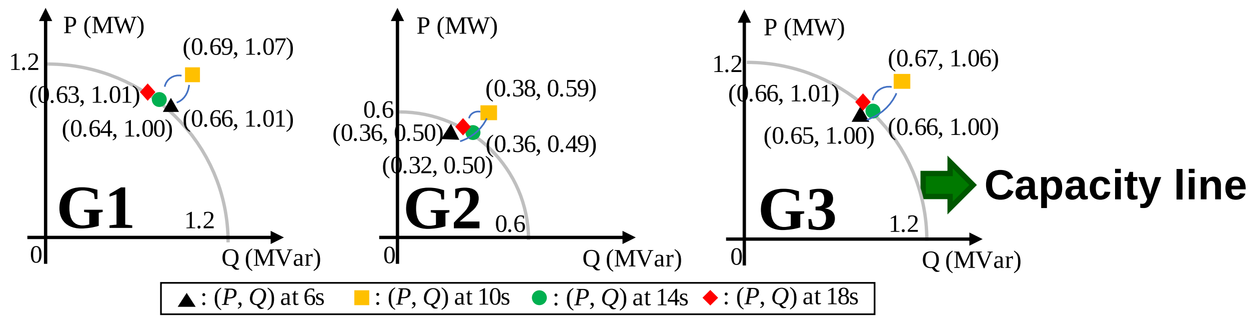
Case study in a Real Microgrid (4)

Scenario 2: P-Q regulator + V-f regulator

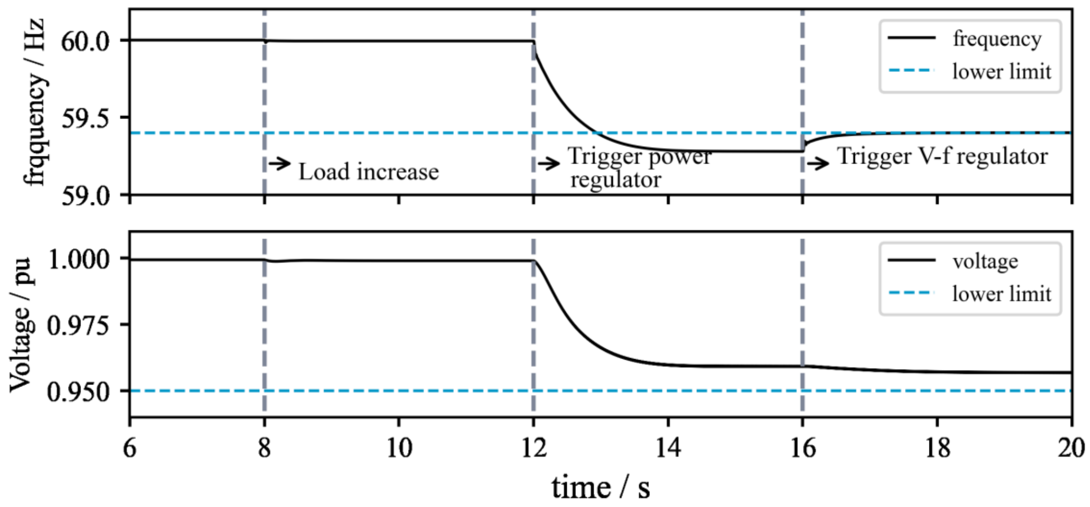
- Frequency over dip and recovery



Dynamic inverter output



Static operation point



V-f response: increase P, decrease Q

Summary

- **DER inadequacy** poses challenges to the operation of grid-forming inverters in islanded microgrids.

- **Power regulator** limits the output of grid-forming inverters by generating supplementary control signals based on the error between inverter output and DER capacity.

- **V-f regulator** generates control signals based on voltage and frequency deviations, which reallocates limited generation for acceptable V-f deviations.

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Motivation and Objective

➢ Background

The penetration of **IBRs** decrease the **inertia** of microgrids. Existing research address low inertia problems by

- **Device-level Control**: Design new control algorithm to improve the inertia support capability of IBRs
- **Grid-level Dispatch**: integrate dynamic frequency constraints into the economic operation framework

Decoupled in the conventional synchronous generator (SG) dominant system because

- Distinct time scales
- Physical inertia of SGs is fixed

IBRs make a difference !

➢ Objective

Develop a **unified inertia management framework** that combines the device-level control and grid-level economic operation and leverages the inertia support capability of grid component.

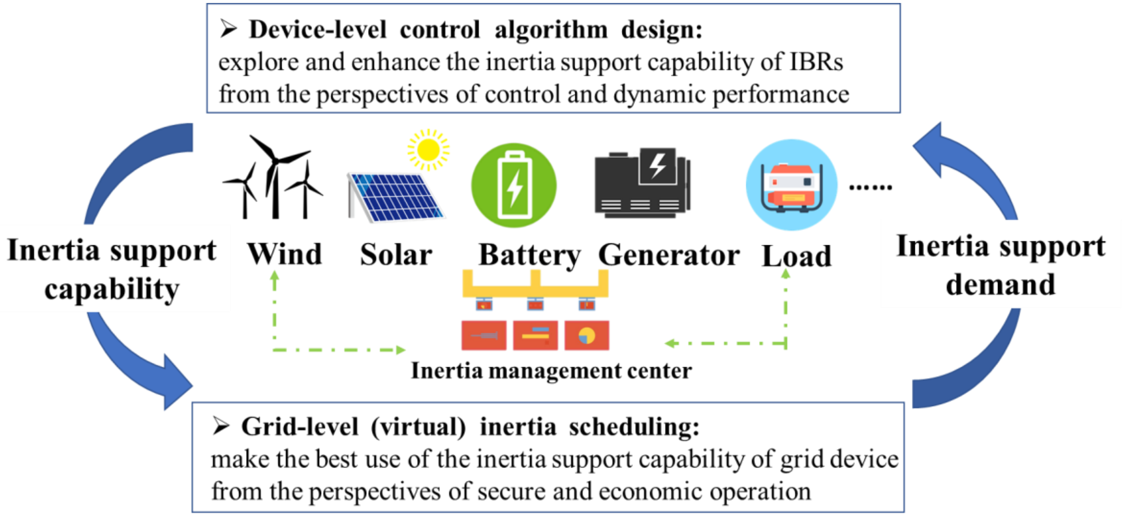


Diagram of virtual inertia scheduling for future low inertia microgrids

Virtual Inertia Scheduling (VIS)

➢ Concept of VIS

- **VIS**: an inertia management framework that targets **security-constrained** and **economy-oriented** inertia scheduling and generation dispatch of microgrids with a large scale of IBRs.

- **VIS** schedules the power setting points, as well as the **control modes** and **control parameters** of IBRs to provide secure and cost-effective inertia support.

VIS can be integrated into the existing economic operation framework, i.e., UC, RTED, and AGC.

B. She, F. Li, H. Cui, J. Wang, Q. Zhang, R. Bo, "Virtual Inertia Scheduling for Real-time Economic Dispatch of IBR-penetrated Power Systems," *IEEE Transactions on Sustainable Energy*, In-Press, 2023.

➢ General Formulation of VIS

$$\min_{P,M,D} \underbrace{C_{gen}(P)}_{\text{Generation cost}} + \overbrace{C_{aux}(P,M,D)}^{\text{Inertia support cost}}$$

s.t. 1) Standard dispatch constraints

$$2)\ \begin{cases} M_i^{\min,ibr} \le M_i^{ibr} \le M_i^{\max,ibr}, \forall i \in \{1,\cdots,N_{ibr}\} \\ D_i^{\min,ibr} \le D_i^{ibr} \le D_i^{\max,ibr}, \forall i \in \{1,\cdots,N_{ibr}\} \end{cases}$$

$$3)\ \begin{cases} -RoCof_{\lim} \le f_0 \dfrac{\Delta P_{e,t}}{M_t} \le RoCof_{\lim},\ \forall t \in \{1,\text{L}\ ,T\} \\ f_{\min} \le f_0 + \Delta f_{nadir,t} \le f_{\max},\ \forall t \in \{1,\text{L}\ ,T\} \end{cases}$$

4) Stability constraints

- *Hourly* dispatch or *minutes* dispatch
- *Single* stage or *multiple* stage
- *Normal* load change or given *contingency* set

VIS for Real-time Economic Dispatch

➢ VIS for Real-time Economic Dispatch (VIS-RTED)

- RTED: a multi-interval optimization problem with the objective of minimizing the total generation cost

- Specified VIS-RTED
  1) One-hour dispatch with 12 intervals
  2) Quadratic generation cost
  3) Opportunity cost caused by inertia support
  4) Additional decision variables of virtual inertia and damping
  5) Additional dynamic constraints of frequency nadir and RoCof

Question

*" How to **quantify** and then **linearize** dynamic power of IBR (ΔP_{peak}^{ibr}) and frequency nadir (Δf_{nadir})?"*

objective: Minimize quadratic generation cost

$$\min_{P,M,D} \sum_{t\in T} [\underbrace{\sum_{i=1}^{N_{sg}} (a_{i,t}^{sg} P_{i,t}^{sg\,2} + b_{i,t}^{sg} P_{i,t}^{sg} + c_{i,t}^{sg} + b_{r,i,t}^{sg} P_{i,r,t}^{sg})}_{SG}$$

$$+ \underbrace{\sum_{i=1}^{N_{ibr}} (a_{i,t}^{ibr} P_{i,t}^{ibr\,2} + b_{i,t}^{ibr} P_{i,t}^{ibr} + c_{i,t}^{ibr} + \boxed{b_{r,i,t}^{ibr} \Delta P_{i,r,t}^{ibr}})}_{IBR}]$$

Opportunity cost caused by inertia support

s.t. 1) Power balance + line limit constraints

2) $$\begin{cases} P_{s,i,t}^{ibr} + P_{i,ru,t}^{ibr} + \boxed{\Delta P_{i,peak,t}^{ibr}} \le P_{i,t}^{\max,ibr} & \forall t \in \{1,\cdots,T\} \\ P_{s,i,t}^{ibr} - P_{i,rd,t}^{ibr} - \boxed{\Delta P_{i,peak,t}^{ibr}} \ge P_{i,t}^{\min,ibr} & \forall t \in \{1,\cdots,T\} \end{cases}$$

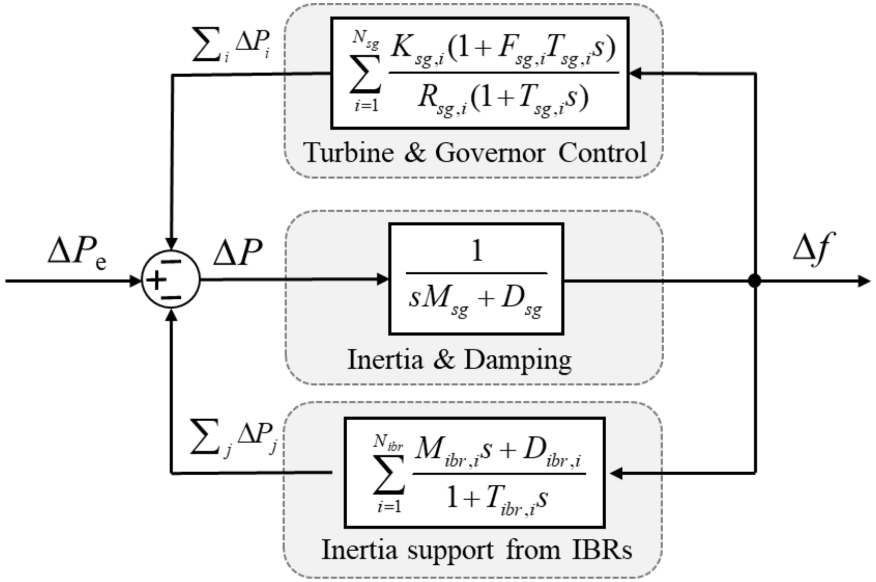
3) $$\begin{cases} M_i^{\min,ibr} \le M_i^{ibr} \le M_i^{\max,ibr}, \forall i \in \{1,\cdots,N_{ibr}\} \\ D_i^{\min,ibr} \le D_i^{ibr} \le D_i^{\max,ibr}, \forall i \in \{1,\cdots,N_{ibr}\} \end{cases}$$

4) $$\begin{cases} -RoCof_{\lim} \le f_0 \dfrac{\Delta P_{e,t}}{M_t} \le RoCof_{\lim}, & \forall t \in \{1,\cdots,T\} \\ f_{\min} \le f_0 + \boxed{\Delta f_{nadir,t}} \le f_{\max}, & \forall t \in \{1,\cdots,T\} \end{cases}$$

CURENT

VIS for Real-time Economic Dispatch

➢ Dynamic estimation



Uniform frequency dynamics model of IBR-penetrated grids

Dynamic index:

$$\begin{cases} \Delta f_{nadir} = \dfrac{\Delta P_e}{MTw_n^2}\left[1-\sqrt{1-\zeta^2}\eta e^{-\zeta w_n t_m}\right] \\ \Delta P_{\max}^{ibr} = \dfrac{\Delta P_e D_{ibr}}{MTw_n^2}\left[-1+\alpha\eta' e^{-\zeta w_n t_m'}\sin(w_d t+\phi')\right] \end{cases}$$

➢ Deep learning assisted linearization

$$\begin{cases} \Delta f_{nadir} = NN_1(\Delta P_e, M, D, R, F, T) \\ \Delta P_{\max}^{ibr} = NN_2(\Delta P_e, M, D, R, F, T) \end{cases}$$

- m^{th} hidden layer of neural network (NN) with ReLU activation function:

$$\begin{cases} \hat{z}_m = W_m z_{m-1} + b_m \\ z_m = \max(\hat{z}_m, 0) \end{cases}$$

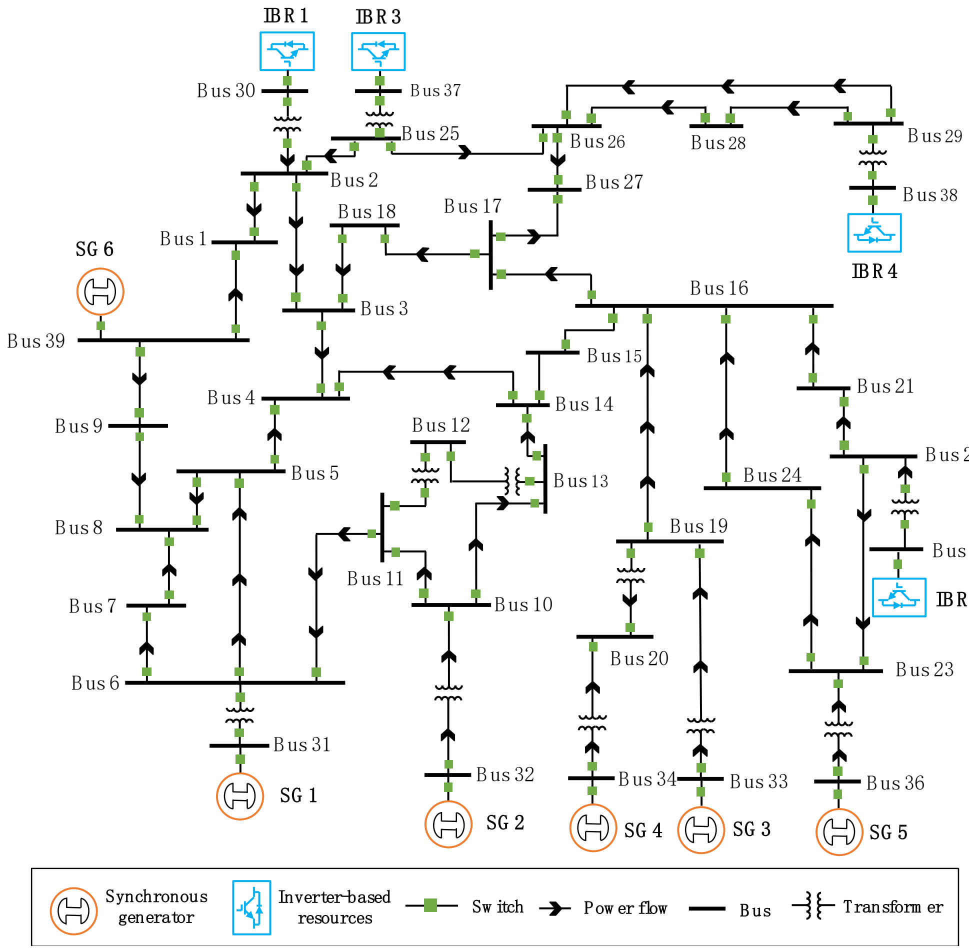
- ***Linearization*** *by introduction binary variables* a_m [1]:

$$\begin{cases} z_m \le \hat{z}_m - \underline{h} \cdot (1-a_m) \\ z_m \ge \hat{z}_m \\ z_m \le \overline{h} \cdot a_m \\ z_m \ge 0 \end{cases}$$

[1] Y. Zhang et al., "Encoding Frequency Constraints in Preventive Unit Commitment Using Deep Learning With Region-of-Interest Active Sampling," *IEEE Trans. Power Syst.*, vol. 37, no. 3, pp. 1942–1955, 2022, doi: 10.1109/TPWRS.2021.3110881.

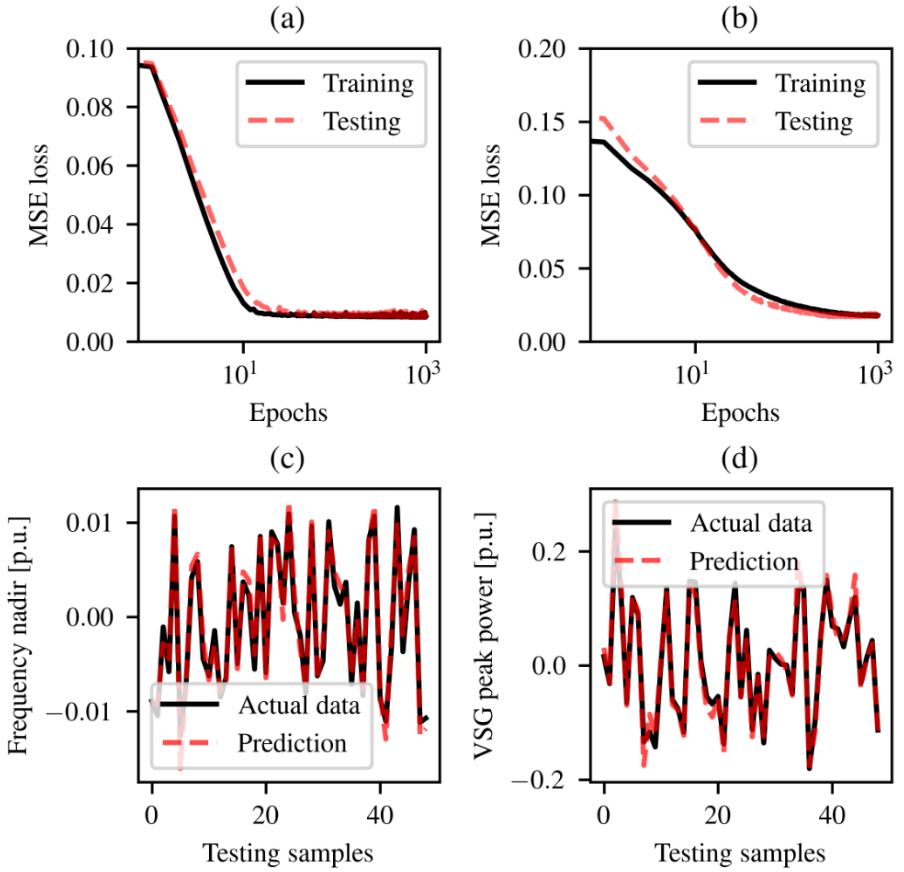
VIS for Real-time Economic Dispatch

➢ Test System



Single-line diagram of modified IEEE-39bus system

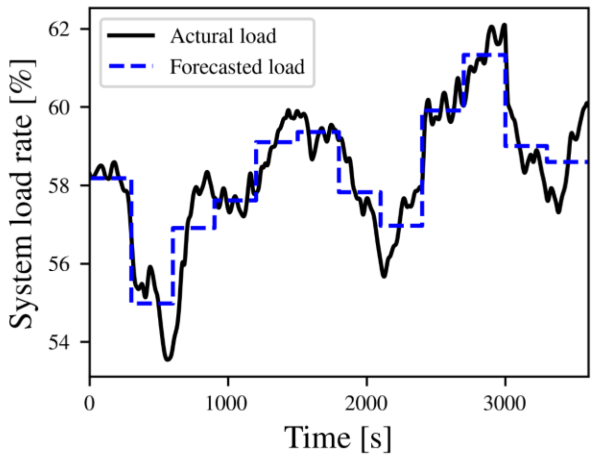
➢ Deep learning training results



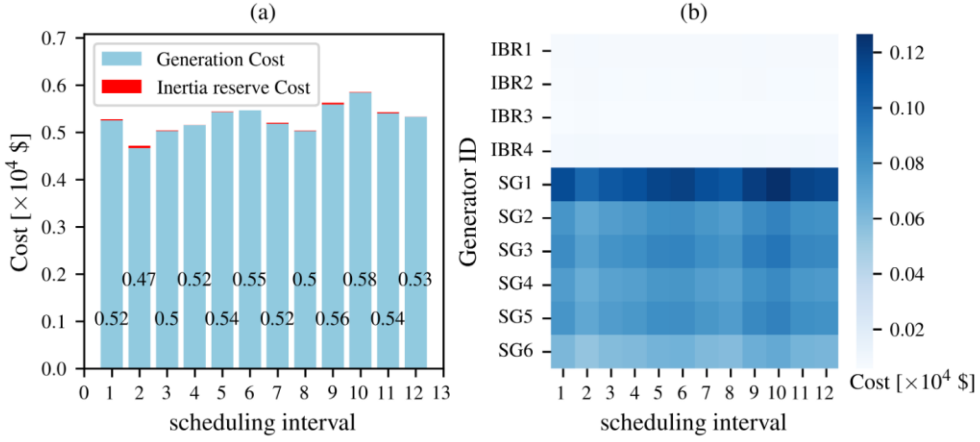
(a) Training loss of frequency nadir prediction;
(b) Training loss of IBR peak power prediction;
(c) Testing of frequency nadir prediction;
(d) Testing of IBR peak power prediction.

VIS for Real-time Economic Dispatch

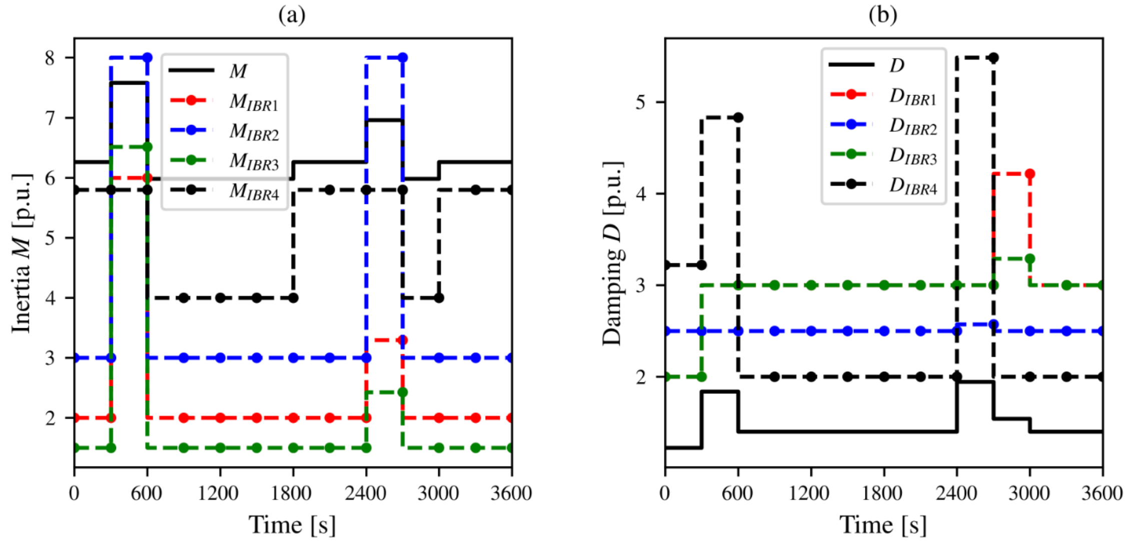
- **One-hour load profile**



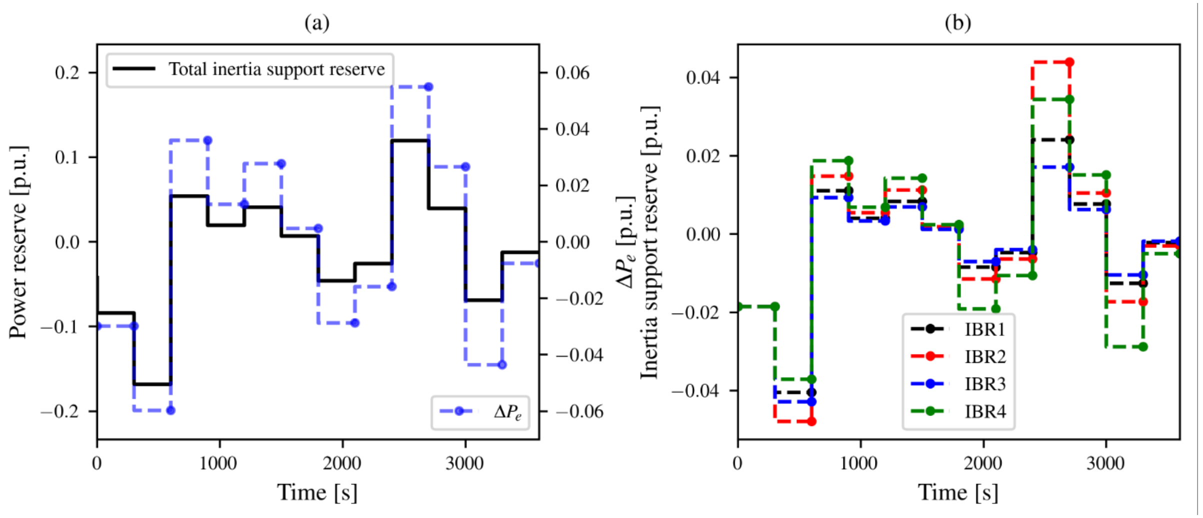
- **Scheduling results**



Cost scheduling results



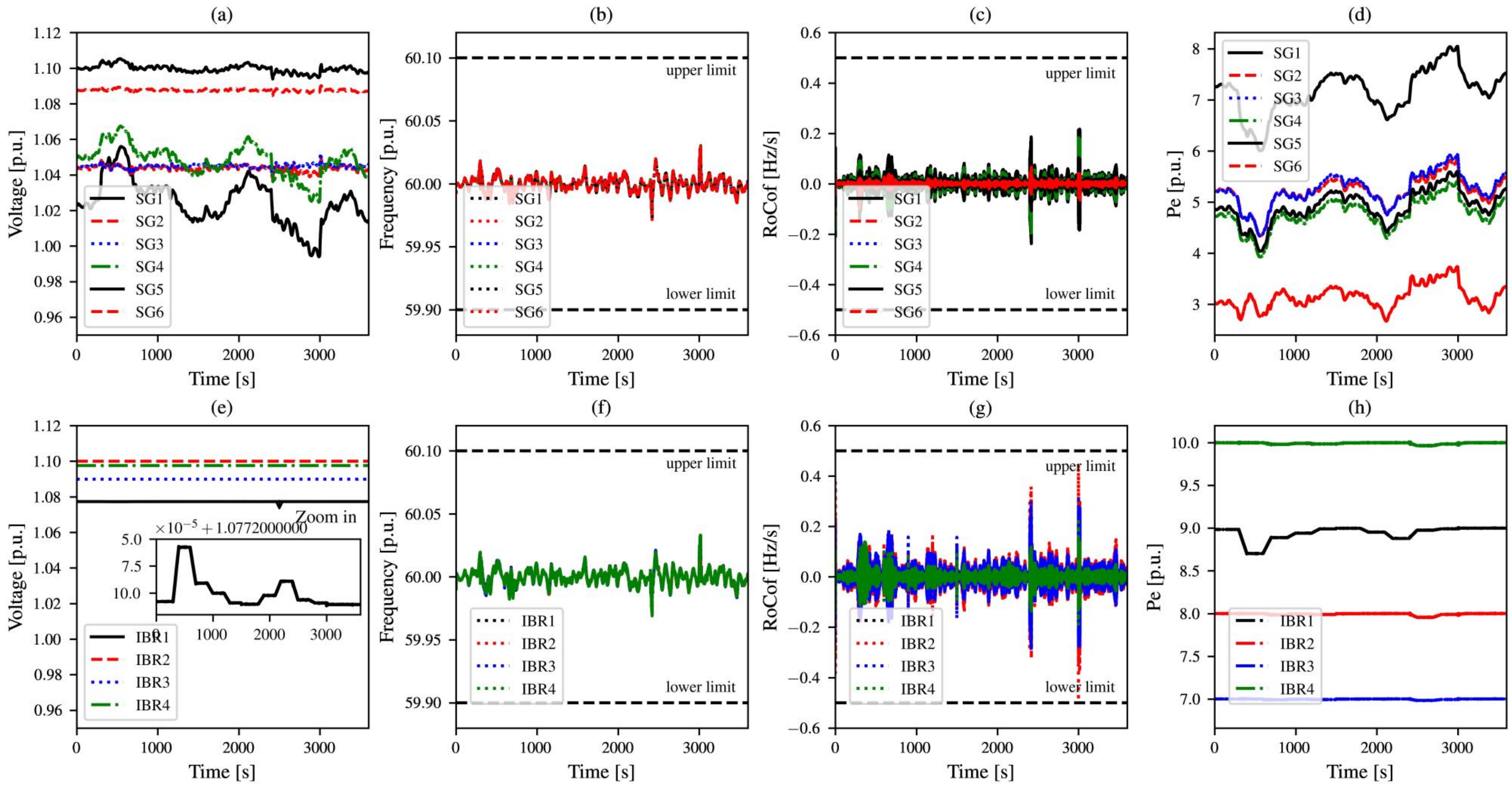
Virtual inertia and damping scheduling results



Reservation scheduling results

VIS for Real-time Economic Dispatch

➢ **Dynamic Validation Through One-hour Time-domain Simulation**



Dynamics results through full-order time-domain simulation

Microgrid Virtual inertia Scheduling

➢ Microgrid VIS

- *Challenge 1*: **Stability guarantee**

As device-level control parameters, virtual inertia and damping play a critical role in microgrid stability.

- *Challenge 2*: **Resilient operation**

Addressing security constraints, both static and dynamic, during extreme events remains a significant and challenging task.

✓ ***Model-based? -> Scalability***

✓ ***Data-driven? -> Reliable Data; Performance Guarantee***

✓ ***Hybrid Method?***

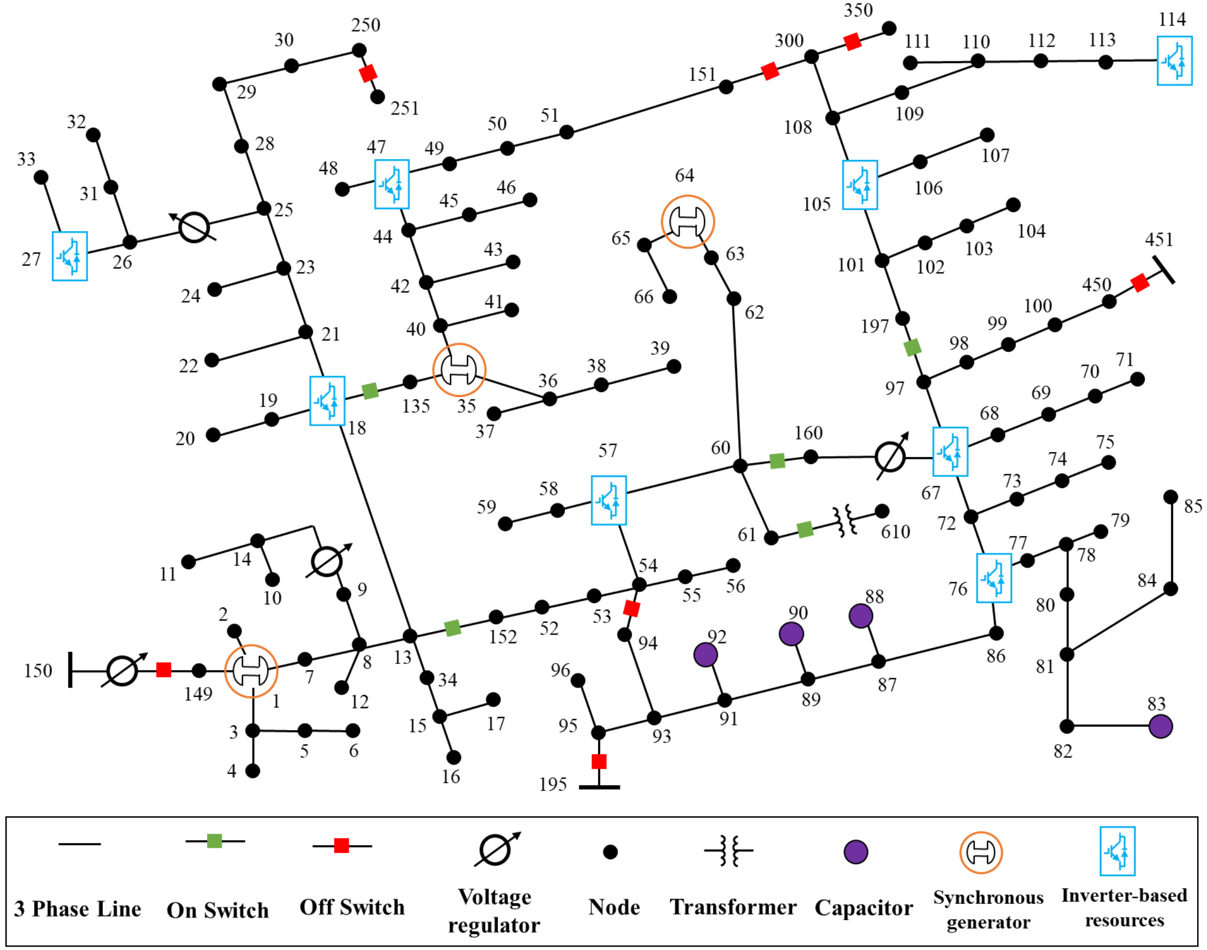


Diagram of islanded microgrid modified from IEEE 123-Bus system

Summary

- Although IBRs present **low inertia** characteristics, their **controllability** and **flexibility** allow for the design of an advanced inertia management framework for future low-inertia power grids.
- **Virtual inertia scheduling (VIS)** is an inertia management concept that targets **security-constrained** and **economy-oriented** inertia scheduling and generation dispatch of microgrids with a large scale of IBRs.
- The formulation of VIS is quite **flexible** and can be integrated into the conventional economic dispatch framework, but with **customized** decision variables and objective functions, operational conditions, and critical dynamic constraints.

Take-aways

- **Core contribution: improve microgrid flexibility and dynamic performance with IBRs**

  - The proposed **P-Q controller** can track the predefined power trajectory with any time constant. It enables the customized response speed of IBRs and thus improved microgrids **flexibility**.
  - The proposed **V-f control framework** can accurately regulation the output of droop-controlled GMF inverters and improve V-f deviation with limited DER capacities. It enables the coordination of P-Q generation, V-f regulation, and demands control, and thus improved microgrids **flexibility** and **stability**.
  - The proposed **virtual inertia scheduling (VIS)** can effectively management the inertia of IBR-penetrated microgrids, and thus improves microgrid **security**, **stability**, and **economy**.
  - Relevant publications:

    - Buxin She, Fangxing Li, Hantao Cui, Jingqiu Zhang, and Rui Bo, “Fusion of Microgrid Control with Model-Free Reinforcement Learning: Review and Vision,” *IEEE Transactions on Smart Grid*, vol. 14, no. 4, pp. 3232-3245, July 2023.
    - 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*, In-Press, 2023.
    - 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 Inadequacy and Demand Control,” IEEE Transactions on Energy Conversion, vol. 38, no. 3, pp. 1868-1880, Sept. 2023.
    - Buxin She, Fangxing Li, Hantao Cui, Jinning Wang, Qiwei Zhang, and Rui Bo, “Virtual Inertia Scheduling for Real-time Economic Dispatch of IBR-penetrated Power Systems,” IEEE Transactions on Sustainable Energy, In-Press, 2023.

Acknowledgements

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Other Contributors: Hantao Cui, Jinning Wang, Hang Shuai,
Oroghene Oboreh-Snapps, Rui Bo,
Nattapat Praisuwanna, Jingxin Wang, Leon M. Tolbert

Backup Slides

Model-based Analysis (1)

- Derive $k_p(t)$ and $k_i(t)$ that can ensure the exponential PQ trajectory with specific time constant

➢ Step 1:

General PI controller

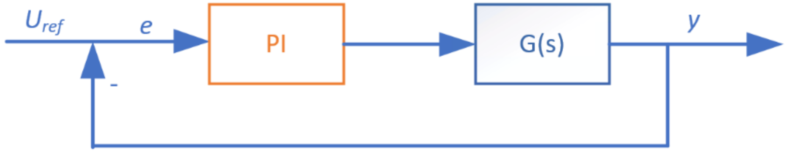
multiply

- Fixed gains: $$Y(s) = k_p \cdot U(s) + k_i \cdot \frac{U(s)}{s} \Rightarrow \frac{Y(s)}{U(s)} = k_p + \frac{k_i}{s}$$

- Adaptive gains: $$Y(s) = k_p * U(s) + k_i * \frac{U(s)}{s} \Rightarrow \frac{Y(s)}{U(s)} = \frac{1}{U(s)}[K_p(s) * U(s) + K_i(s) * \frac{U(s)}{s}]$$

convolution

➢ Step 2:



Adaptive gain PI controller in a general system

- Step input signal: $$u_{ref} = \begin{cases} 1 & t \ge 0 \\ 0 & t < 0 \end{cases} \Rightarrow U_{ref} = \frac{k_i}{s}$$

- Exponential error: $$e(t) = e^{-t/\tau} \Rightarrow E(s) = \frac{1}{s + 1/\tau}$$

- Ideal response: $$y(t) = 1 - e^{-t/\tau} \Rightarrow Y(s) = \frac{1}{s} - \frac{1}{s + 1/\tau}$$

Plug in

$$Y(s) = E(s)G_{PI}(s)G(s)$$

Model-based Analysis (2)

- Derive $k_p(t)$ and $k_i(t)$ that can ensure the exponential PQ trajectory with specific time constant

➢ Step 3:

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

- For the left side:

$$\mathcal{L}^{-1}[\frac{Y(s)}{G(s)}] = \mathcal{L}^{-1}[\frac{1}{\tau s(s+1/\tau)} \cdot G(s)]$$

- For the right side:

$$\mathcal{L}^{-1}[K_p(s) * \frac{1}{s+1/\tau} + K_i(s) * \frac{1}{s(s+1/\tau)}]$$

$$= [k_p(t) - \tau k_i(t)]e^{-\frac{t}{\tau}} + \tau k_i(t)$$

System transfer function G(s) determines whether 'left side = right side' has a solution in time domain.

Conclusion:

$$\text{Assume } G(s) = \frac{n(s)}{m(s)}$$

✓**Condition 1:** $D[n(s)] = 0$ (D means degree)

$$\begin{cases} k_p(t) = l_1 + l_2 \\ k_i(t) = \dfrac{l_2}{\tau} \end{cases}$$

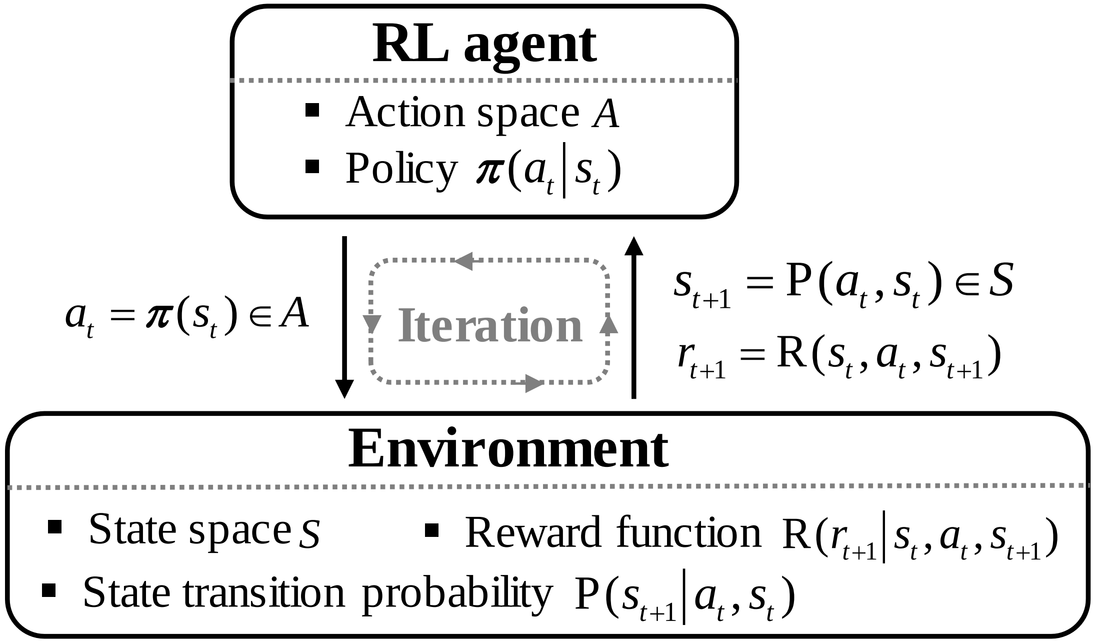
✓**Condition 2:** $D[n(s)] \neq 0, D[n(s)] - D[m(s)] \leq 2$

$$\begin{cases} k_p(t) = l_1 + \mathcal{L}^{-1}[\dfrac{l_2(s)}{s \cdot n(s)}] \\ k_i(t) = \dfrac{\mathcal{L}^{-1}[\dfrac{l_2(s)}{s \cdot n(s)}]}{\tau} \end{cases}$$

✓**Condition 3:** $D[n(s)] - D[m(s)] > 2$

$k_p(t)$ and $k_i(t)$ don't exist

Data-driven Implementation: DRL



Reinforcement learning :

- RL is a basic machine paradigm formulated as a Markov Decision Processes.

Deep reinforcement learning:

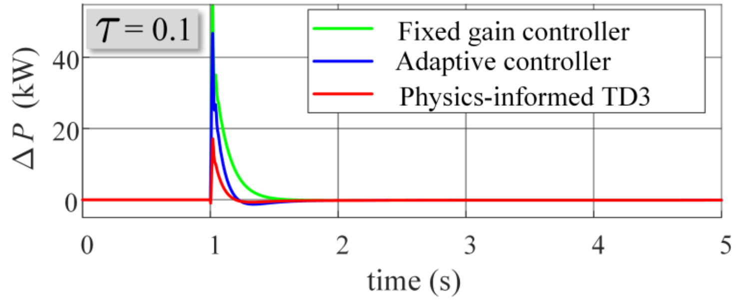
- Use **deep neural network** to map:
  State, action → value (Q-value);
  State → action

Training Target:

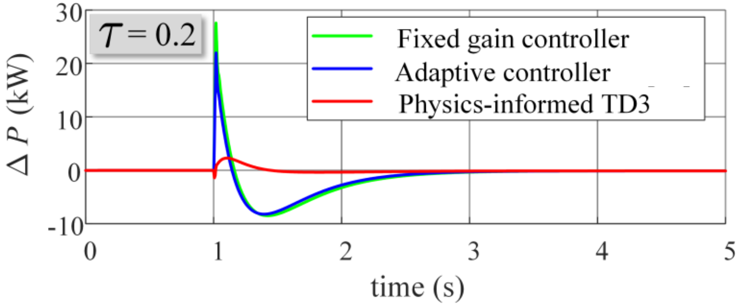
- *a well-trained RL agent chooses optimal actions for maximum accumulated reward (best performance)*

Comparison(1)

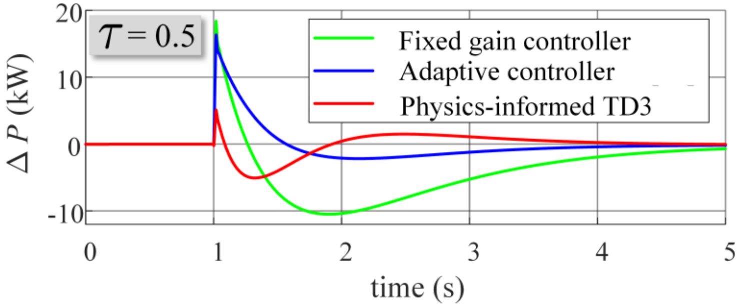
- **Scenario 1-1**: Scheduling P_{ref} change



(a)

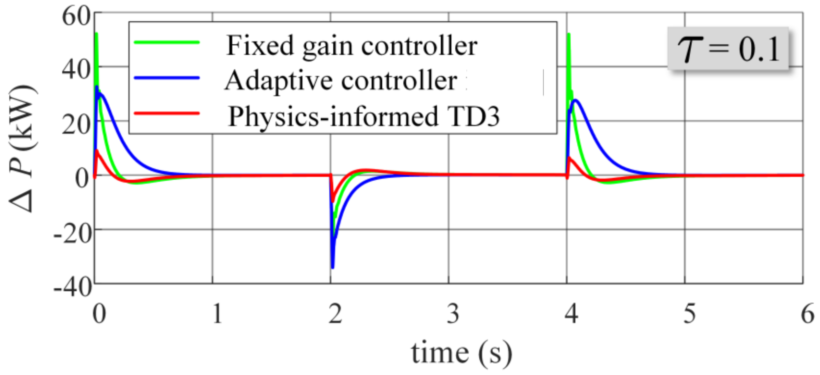


(b)

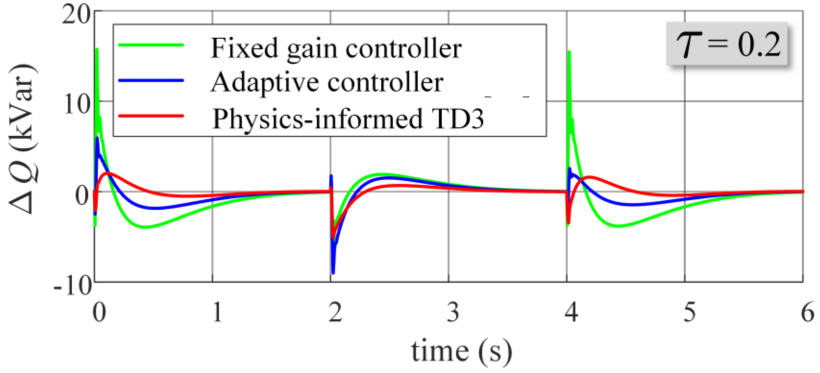


(c)

- **Scenario 1-2**: Scheduling P_{ref} and Q_{ref} change



(a)

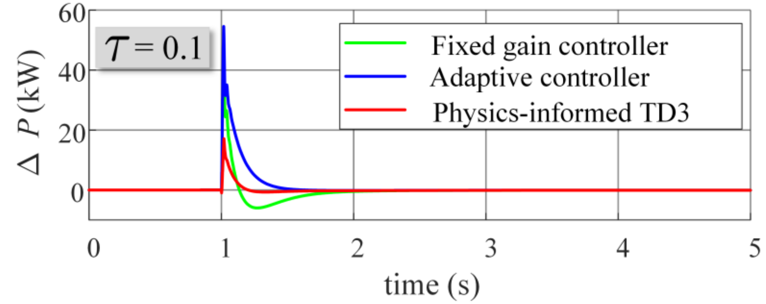


(b)

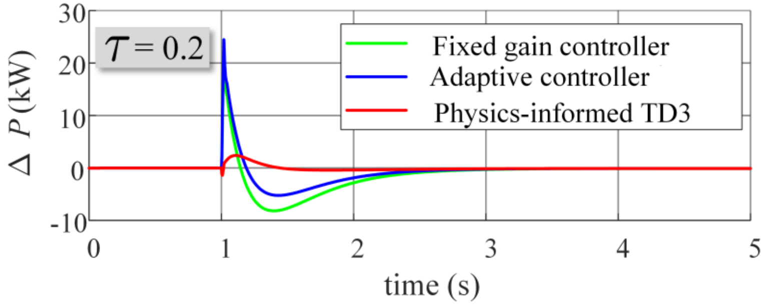
Where $\Delta P = P_{inv} - P_{trj}$ is real-time trajectory tracking error.

Comparison(2)

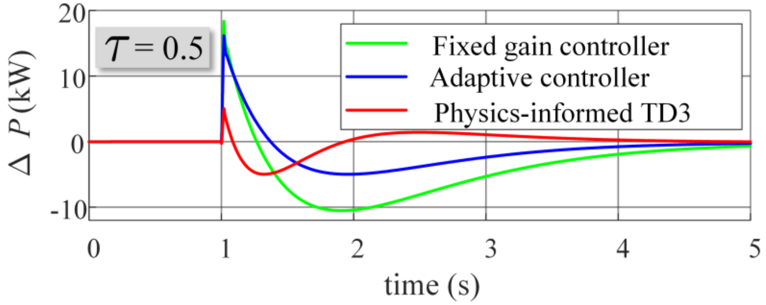
- **Scenario 2**: Generation loss and Power Support



(a)

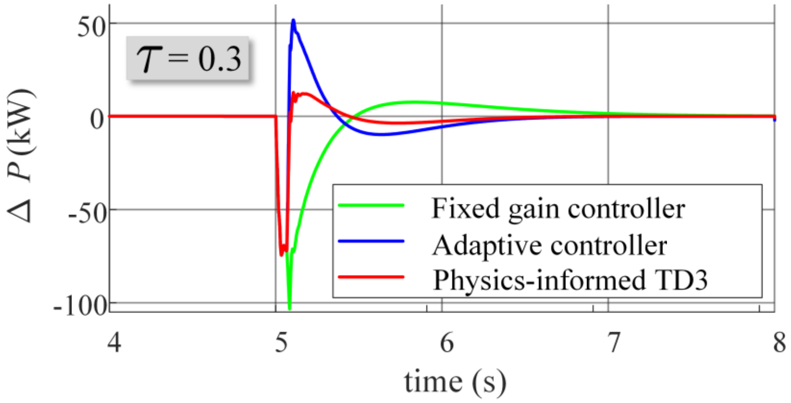


(b)

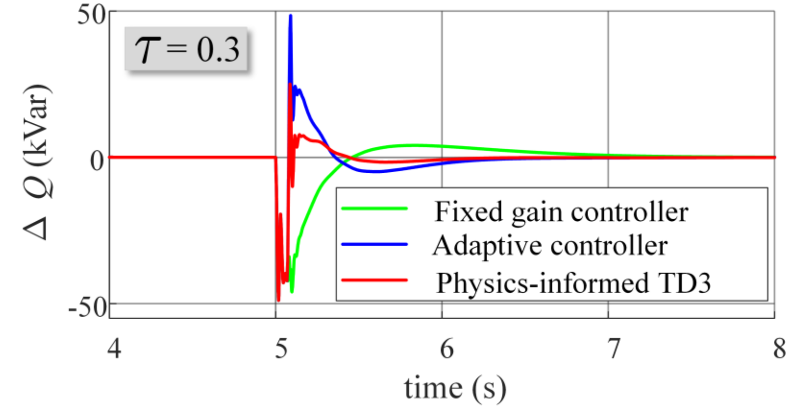


(c)

- **Scenario 3**: Grounded fault



(a)



(b)

Where $\Delta P = P_{inv} - P_{trj}$ is real-time trajectory tracking error.

Summary

- 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.

- The microgrid inverter-based PQ 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 proposed controller outperforms the conventional fixed-gain and adaptive PI controllers. **Without manual re-tuning**, it can accurately track the predefined trajectory with any assigned time constant.

- 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.