Fusion of Microgrid Control with Reinforcement Learning: From Direct Application to Physics Priors

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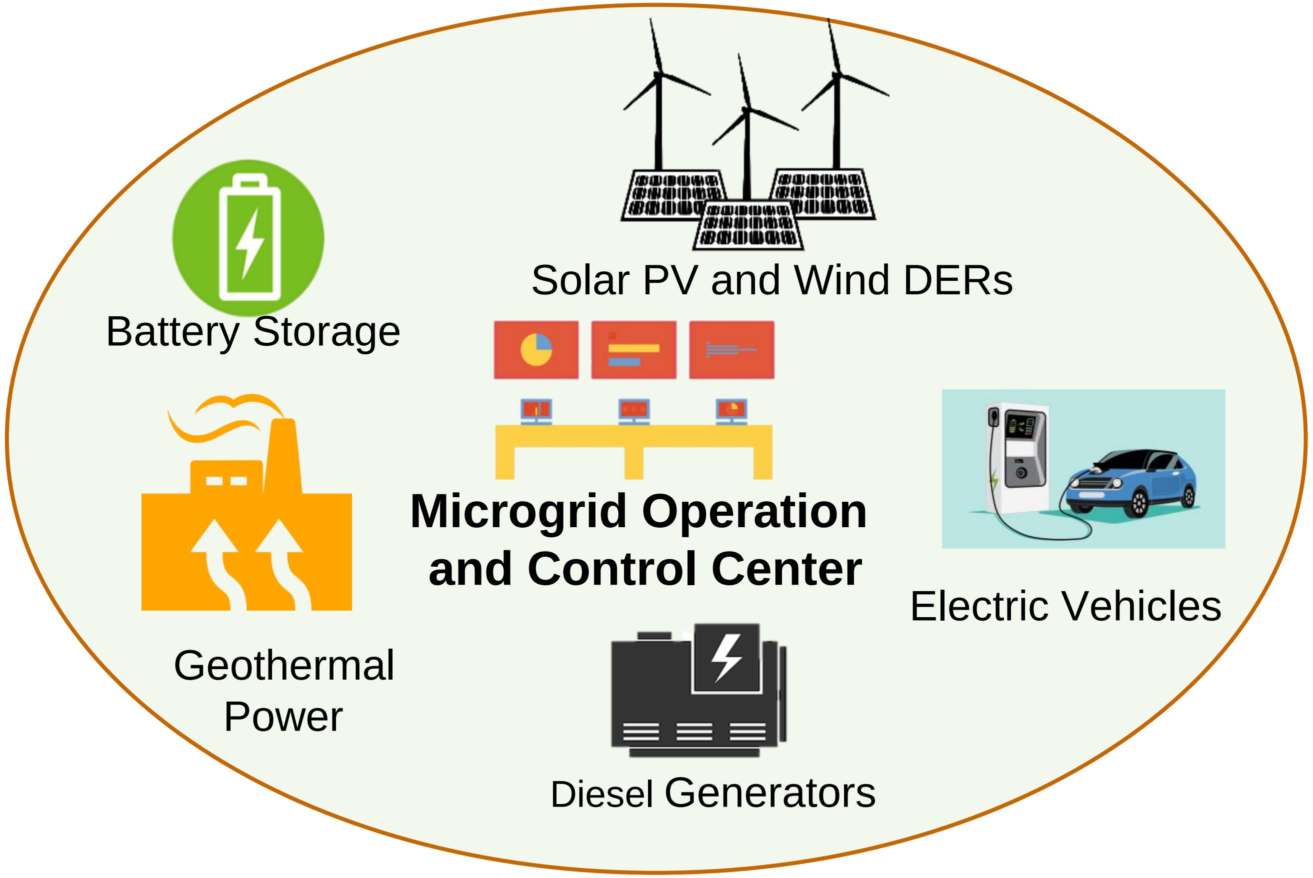
Microgrid Control Framework

Overview

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

High-level Research Map of Microgrid Control

① Operation mode

② Function grouping

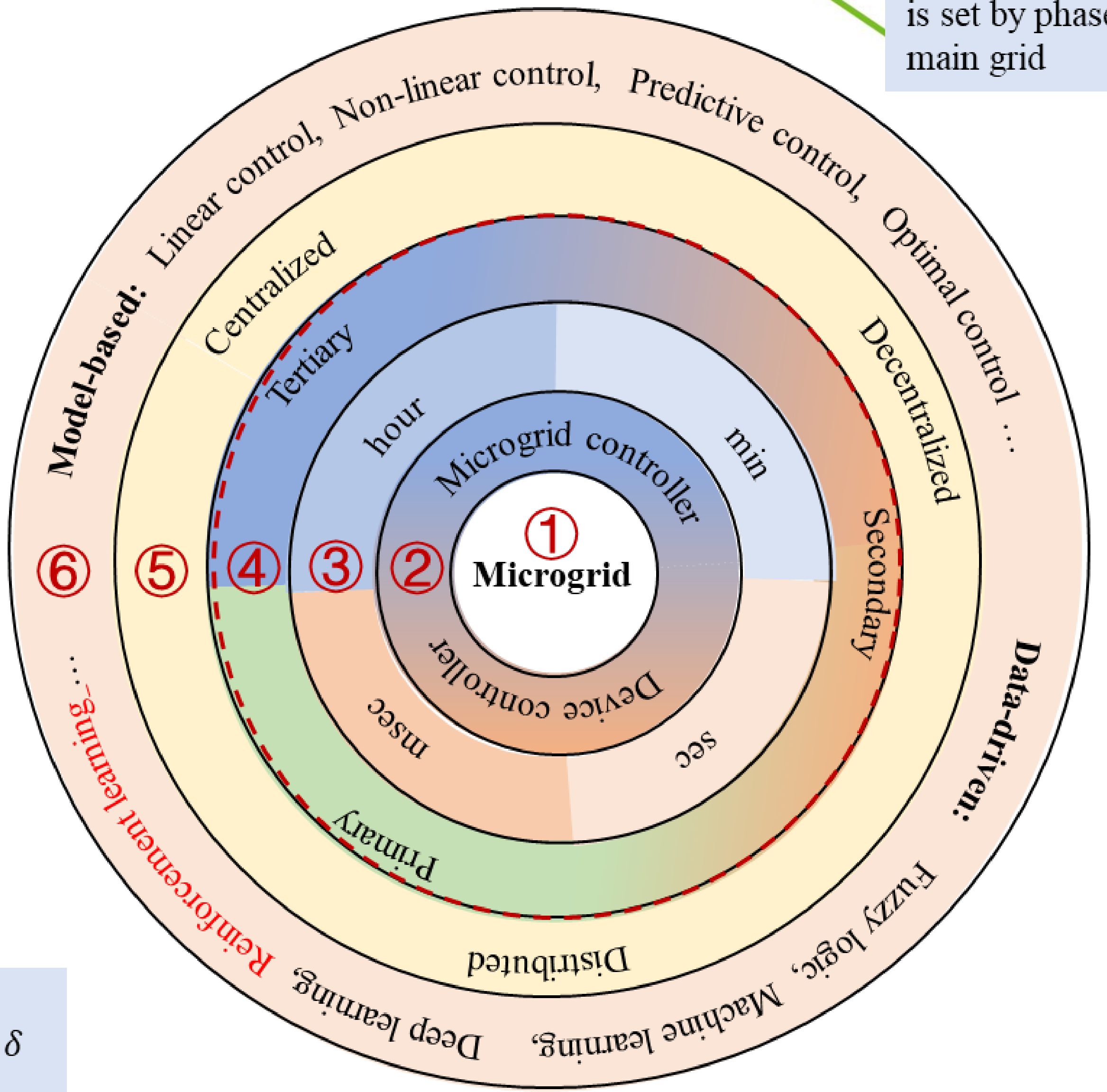
③ Timescale

④ Hierarchical structure

⑤ Communication interface

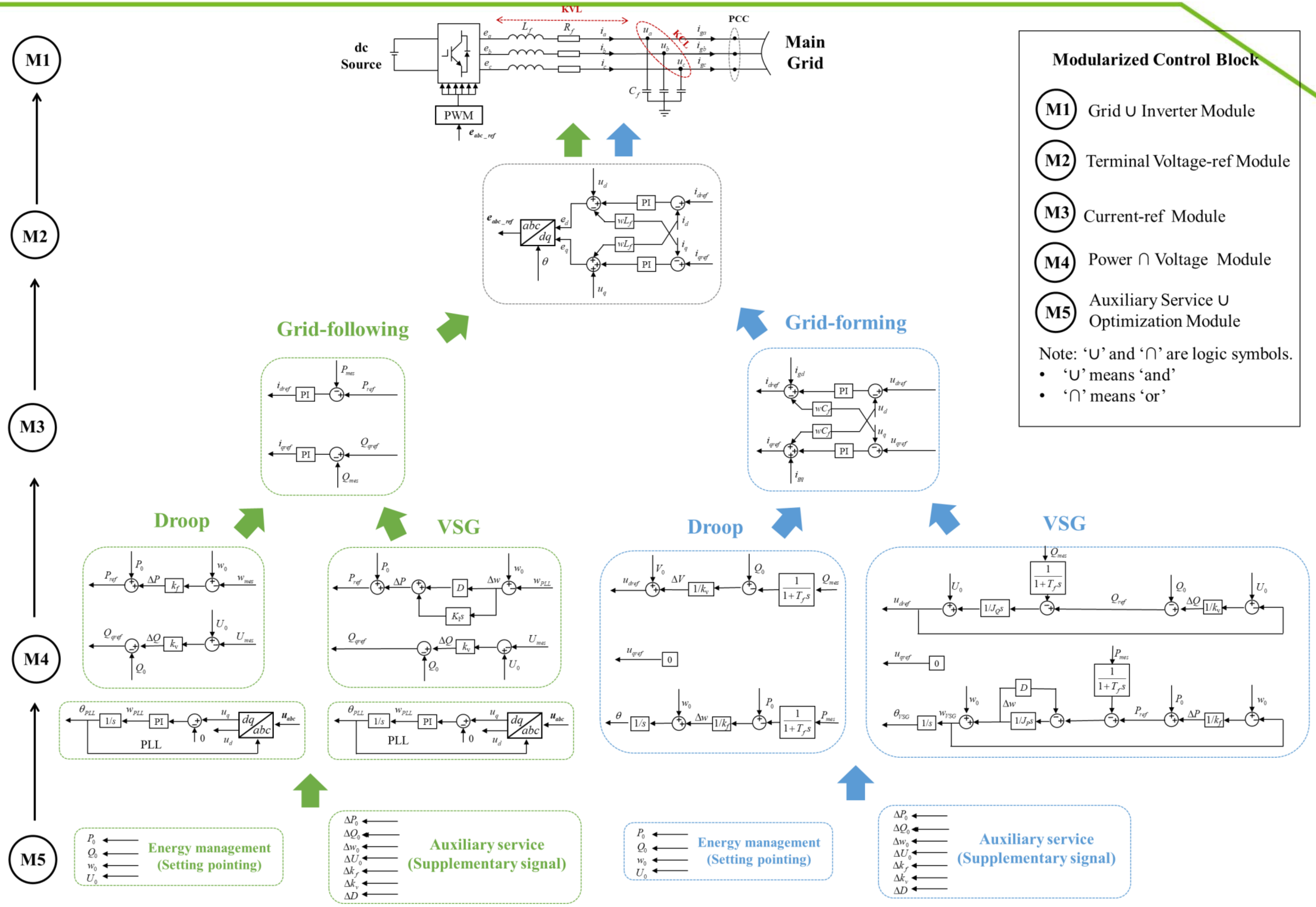
⑥ Control techniques

- **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

Modularized control blocks for IBRs



Improve microgrid:

- Flexibility
- Stability
- Economy

Fusion of Microgrid Control with RL

Application and Challenges

Reinforcement Learning

Concept

RL agent

- Action space $\mathcal{A}$
- Policy $\pi(a_t|s_t)$

$a_t = \pi(s_t) \in \mathcal{A}$

Iteration

$s_{t+1} = \mathbb{P}(a_t, s_t) \in \mathcal{S}$

$r_{t+1} = \mathbb{R}(s_t, a_t, s_{t+1})$

Environment

- State space $\mathcal{S}$
- Reward function $\mathbb{R}(r_{t+1}|s_t, a_t, s_{t+1})$
- State transition probability $\mathbb{P}(s_{t+1}|a_t, s_t)$

Reinforcement learning :

- RL is a basic machine paradigm formulated as a Markov Decision Processes (MDP)

Model-free Reinforcement Learning:

- Does not assume knowledge or an exact mathematical model of the environment

Deep Reinforcement Learning (DRL):

- Use **deep neural network** to map state and action to reward/value and actions
- Can be extended to multi-agent DRL

***Target:** a well-trained RL agent to choose optimal actions for maximum accumulated reward (best performance)*

RL in Microgrid Control

Application Area and The Way of Fusion

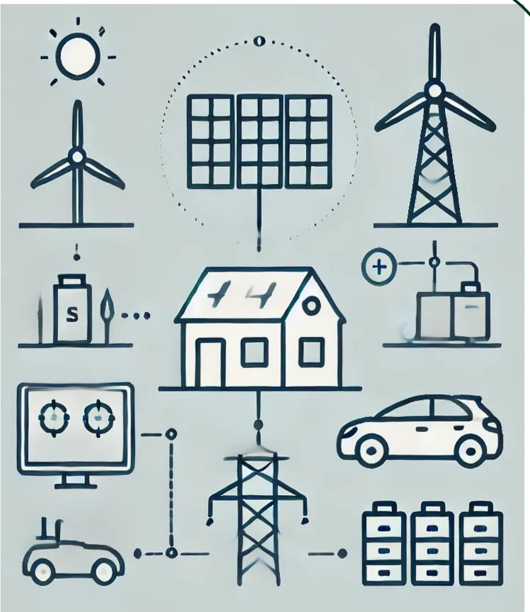
➢ RL can handle either **control** or **optimization** tasks in microgrids.

1) System Planning

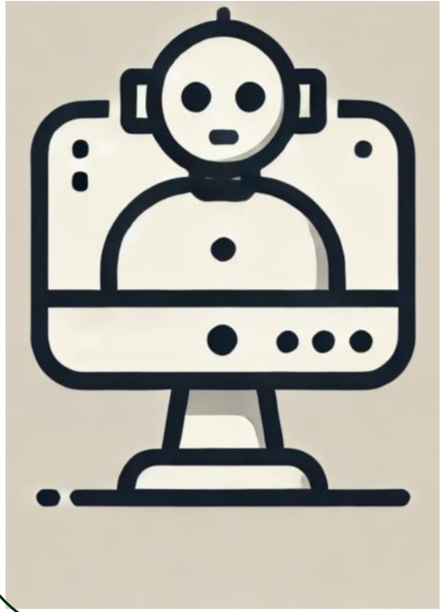
2) Economic Operation

3) Voltage regulation

4) Frequency regulation



Microgrid Environment and Tasks



1) Model identification and parameter tuning

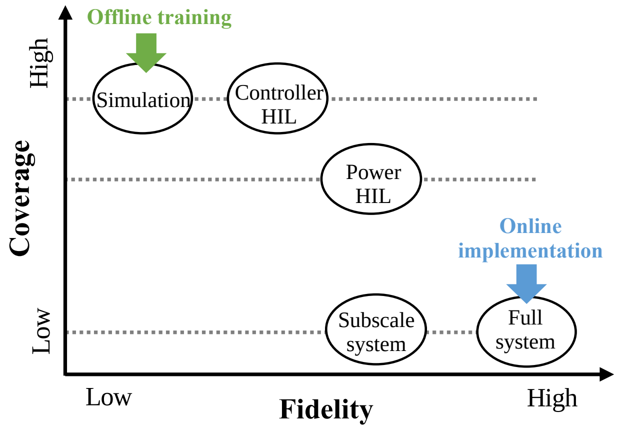
2) Supplementary signal generation

3) Controller substitution

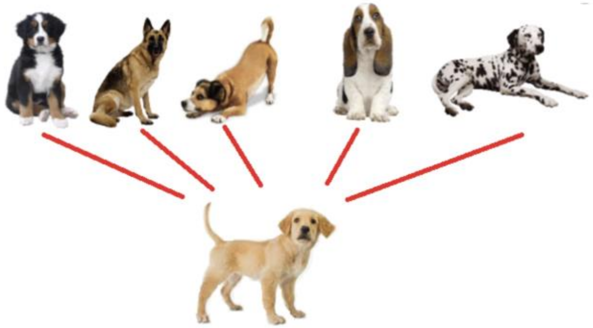
The Role of RL Agents in Microgrids

RL in Microgrid Control

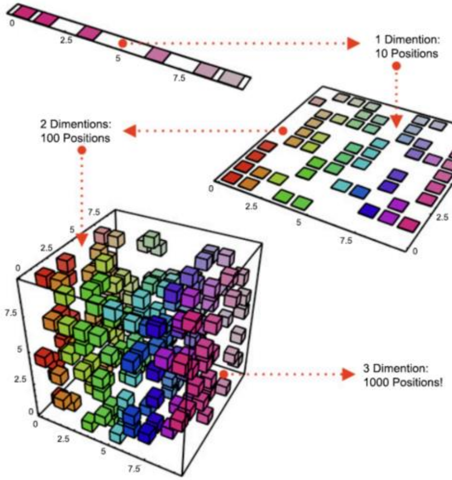
Challenges and Gaps



1) Environment



2) Generalization



3) Scalability

4) Security

Physics-informed Reinforcement Learning

From Direct Application to Physics Priors

Overview

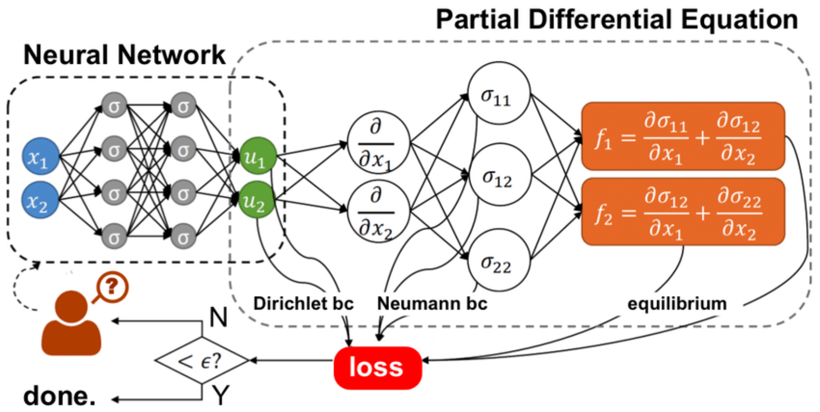
Physics-informed RL in Microgrid

Physics Priors in machine learning [1]

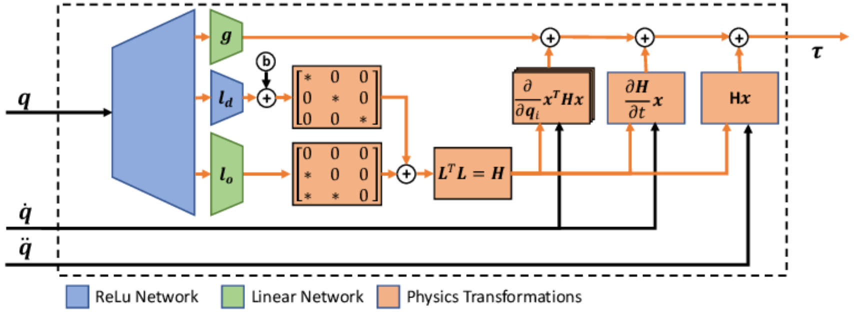
1) Observational bias: This approach uses multi-modal data that reflects the physical principles governing their generation.

2) Learning bias: Reinforce prior knowledge of physics through soft penalty constraints, i.e., PINN.

3) Inductive biases: Custom neural network-induced ’hard’ constraints can incorporate prior knowledge into models, i.e., DLN.



Physics informed neural network (PINN) [2]



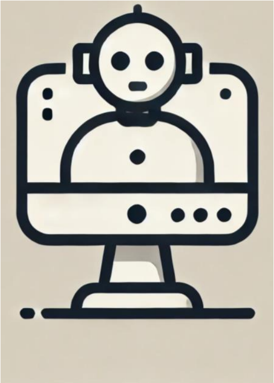
Deep Lagrangian networks (DLN) [3]

[1] Banerjee, Chayan, et al. "A survey on physics informed reinforcement learning: Review and open problems." *arXiv preprint arXiv:2309.01909* (2023).
[2] Peng, Grace CY, et al. "Multiscale modeling meets machine learning: What can we learn?." *Archives of Computational Methods in Engineering* 28 (2021): 1017-1037.
[3] Lutter, Michael, Christian Ritter, and Jan Peters. "Deep lagrangian networks: Using physics as model prior for deep learning." *arXiv preprint arXiv:1907.04490* (2019).

Physics-informed RL in Microgrid

Physics-informed Reinforcement Learning (PIRL)

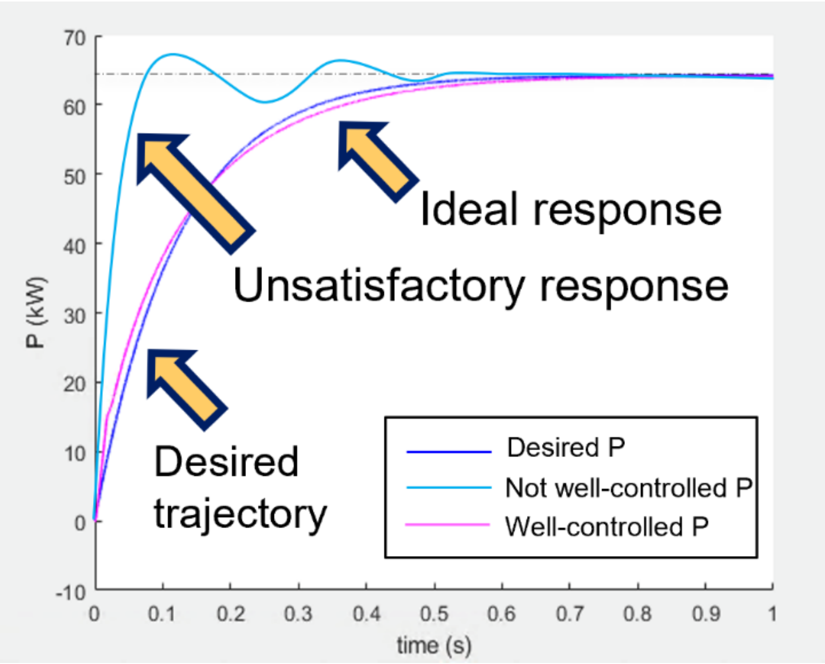
Physics-informed RL involves incorporating physics structures, priors, and real-world physical variables into the policy learning or optimization process.



	Physics priors for task simplification	Physics priors for performance guarantee	Physics priors for additional regulation
Value Network	• action/state space reduction • efficient reward design	\	• data augmentation
Policy Network	• action/state space reduction	• physics embedding for ensuring static security • physics embedding for ensuring dynamic stability	• data augmentation • additional learning bias • additional law integration • safe exploration

Example 1

Inverter P-Q control with Trajectory Tracking Capability [1]



Physics Priors reduce learning space from **function space** to **real space**

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

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

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

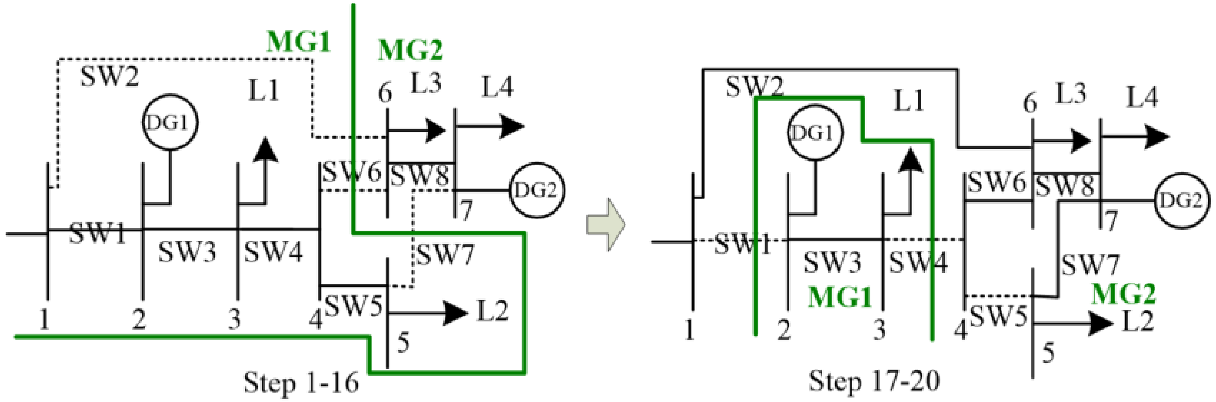
$$k_{p0}, k_{p1}, k_{i0}, k_{i1} \in \boldsymbol{R}$$

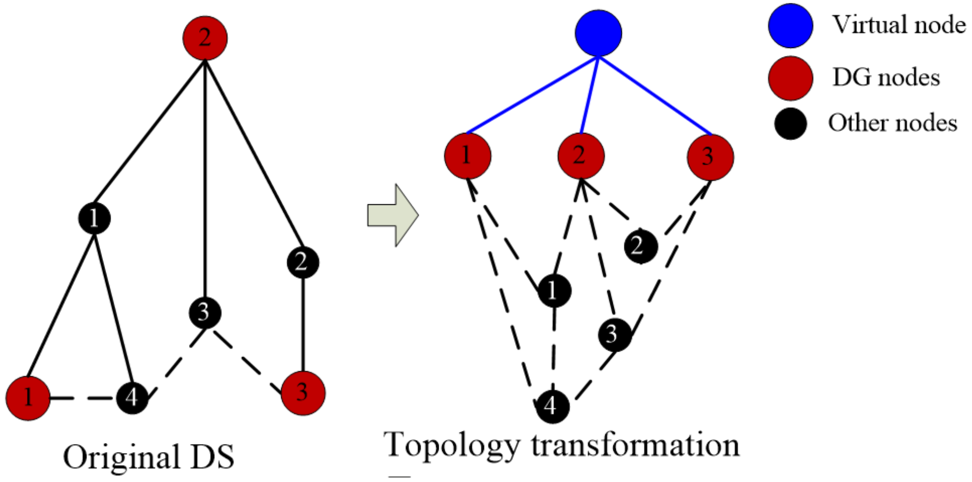
Objective: the actual response of IBR following the desired trajectory

[1] B She, F Li, H Cui, H Shuai, et al. "Inverter PQ control with trajectory tracking capability for microgrids based on physics-informed reinforcement learning." *IEEE Transactions on Smart Grid* 15.1 (2023): 99-112.

Example 2

Dynamic Multi-Microgrid Formation for Enhanced Resilience [1]





- Topology transformation
  - Transfer a splitting problem to a reconfiguration problem
  - Reduce action space from an exponential form 2^w to a polynomial form C (w, n-n_g).

[1] J. Zhao, F. Li, S. Mukherjee, C. Sticht, "Deep Reinforcement Learning based Model-free On-line Dynamic Multi-Microgrid Formation to Enhance Resilience," *IEEE Transactions on Smart Grid*, vol. 13, no. 4, pp. 2557-2567, July 2022.

Example 3

Stability Guaranteed RL for Frequency Regulation [1]

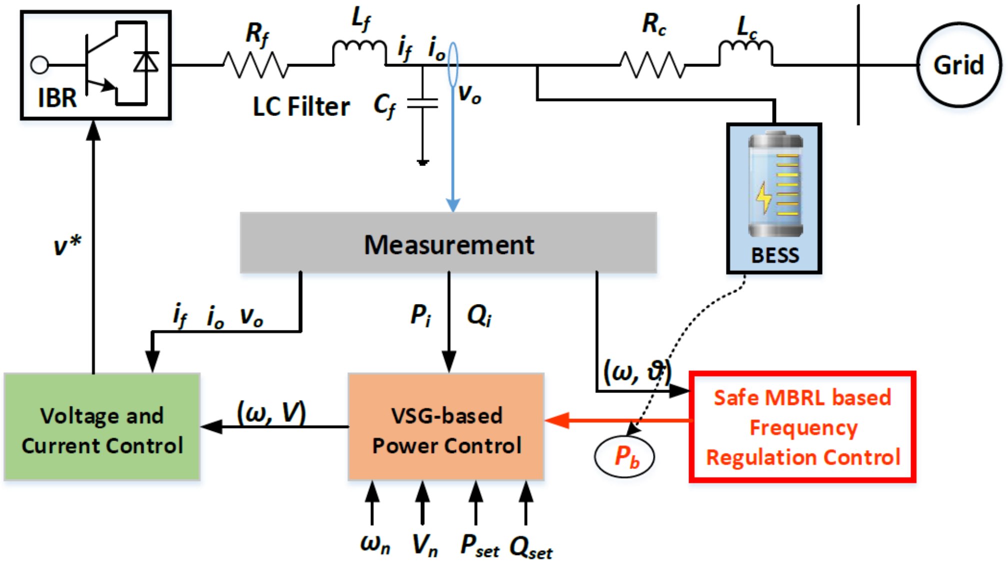


Figure 1. Diagram of frequency GFM inverter based primary frequency control

Lyapunov function V

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

Designing the Lyapunov function as the value function of the Bellman's equation to guarantee stability.

$$V = J(x) = r\left(x, \pi_W(x)\right) + \gamma J\left[u_{n-1}\left(x, \pi_W(x)\right)\right]$$

[1] H. Shuai, B. She, J. Wang and F. Li, "Safe Reinforcement Learning for Grid-Forming Inverter Based Frequency Regulation with Stability Guarantee," in *Journal of Modern Power Systems and Clean Energy*, doi: 10.35833/MPCE.2023.000882.

Take Aways

Take Aways

- RL can handle either **control** or **optimization** tasks in microgrids, but there are remaining gaps in the perspective of environment, generalization, scalability, and security.

- PIRL can be leveraged to streamline training processes, ensure security and stability, and enhance generalization and scalability.

Thank you!

Q&A