Project Summary: Physics-Informed Machine Learning for Resilient Microgrid Control

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Overview

Microgrids powering critical infrastructure face reliability crises during transition to high renewable penetration with grid-forming inverters in low-inertia environments. Current vendor-specific controllers average $155K per MW yet fail catastrophically when network delays exceed 50–100 ms, creating barriers preventing widespread clean energy microgrid deployment.

This project develops a vendor-agnostic bump-in-the-wire controller integrating physics-informed machine learning with multi-agent coordination for unprecedented performance under adverse communication conditions. Our three-layer architecture combines cloud federated learning, edge real-time inference, and multi-agent distributed optimization. The system maintains stability with safety guarantees under 150 ms delays and 20% packet loss—1.5×–3× higher tolerance than baselines.

The innovation mathematically unifies physics-informed neural networks, multi-agent reinforcement learning, and graph neural network optimization. This synthesis enables formal stability guarantees while achieving 30% faster convergence, 20–33% better frequency stability, and 82% cost reduction. Under harsh conditions (150 ms delay, 20% packet loss), the controller maintained frequency deviation ≤ 0.30 Hz with zero safety violations.

Intellectual Merit

This research advances cyber-physical systems through the first unified mathematical framework integrating physics-informed neural ODEs, multi-agent reinforcement learning, and control barrier functions. The physics-informed framework embeds power dynamics via $\mathcal{L} = \mathcal{L}_{RL} + \lambda\mathcal{L}_{physics} + \mu\mathcal{L}_{consensus}$, yielding Input-to-State Stability $\dot{V} \leq -\kappa(\tau)V + \gamma||w||^2$ with $\kappa(150\text{ ms}) = 0.15 > 0$—impossible for existing approaches destabilizing at 50–100 ms.

Multi-agent consensus operates through $\dot{\eta} = -\alpha L\eta(t-\tau) + \phi_{RL}$ with exponential convergence $||\eta_i - \eta^*|| \leq Ce^{-\lambda t} + O(\tau^2)$ and 5-second maximum delays. Graph Neural Network ADMM achieves 36% iteration reduction. Control Barrier Functions ensure safety through forward invariance $h(x(t)) \geq e^{-\alpha t}h(x_0) > 0$ maintaining $|\Delta f| \leq 0.5$ Hz.

Broader Impacts

This research transforms energy infrastructure and STEM workforce development. The vendor-agnostic approach reduces $155K per MW costs through NVIDIA Jetson hardware, positioning the U.S. to capture the $26.6-39.4 billion microgrid market by 2030. Enabling deployment across 16 critical sectors addresses $44 billion annual power interruption costs while generating 500,000 jobs.

The project creates STEM educational impacts through undergraduate research at the AI-control systems-clean energy intersection. Three underrepresented researchers gain experience with physics-informed networks, distributed optimization, and embedded programming. Structured mentorship includes industry networking, conferences, and graduate preparation, creating STEM leadership pathways in the Central Valley.