Stony Brook University The Graduate School

Doctoral Defense Announcement

Abstract

AI-enabled grid discovery and analytics

By

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Ensuring the stability of large-scale power grids requires accurate grid discovery and analytics, yet challenges persist due to nonlinear dynamics, complex coherency, and incomplete models. This research proposes machine learning-based approaches for power system modeling, analysis, and control. For unknown subsystems, we introduce Neural Dynamic Equivalence (NeuDyE), a physics-aware, data-driven method that integrates ODE-Net to capture continuous-time system behavior. To enhance adaptability with limited boundary knowledge, we propose Driving-Port NeuDyE, improving grid model accuracy and closed-loop performance. For systems with known physics models, we leverage Physics-Informed Neural Networks (PINNs) to enhance generalization and minimize data dependence. PINNs are deployed in Physics-Informed Neuro-Models (PIM) for transient analysis. A data-physics hybrid, multi-neural learning structure is introduced to adapt PIM to varying data availability, while a balanced-adaptive PIM optimizes the learning process automatically. Beyond modeling, we enhance grid stability by designing Grid-Forming Hamiltonian control, which enforces strict passivity through machine learning while leveraging the port-Hamiltonian framework. A candidate Lyapunov function is derived from the learned model to facilitate stability analysis. Expanding on this, we develop a composite controller that combines the steady-state convergence of PI control with the robustness of neural-based passivity enforcement. This compositional approach enables distributed learning, improving efficiency and allowing large-scale plug-and-play deployment. These advancements provide a transformative framework for power system discovery and control, bridging data-driven learning with physics-based modeling to enhance grid reliability.

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