Automatic Control Laboratory

ETH Zurich, D-ITET

Project Title: Enhancing Stability of Large-Scale Power Systems via Learning Dissipativity
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Abstract

Modern power systems are nonlinear, complex, and interconnected with numerous heterogeneous components, causing significant challenges to system stability. Control theory techniques that provide stability guarantees typically rely on a simplified model and do not capture the nonlinear behavior of the dynamics, motivating a deep-learning-based approach. However, naive deep-learning-based approaches generally suffer from the scale of dimensionality, especially in the context of large-scale power systems. Therefore, this project aims to develop a deep learning-based controller in a decentralized fashion based on dissipativity theory, in order to ensure the global stability of the system in a scalable fashion.

Figure 1: Modern power systems.

Background

Modern power systems are undergoing a rapid and profound transformation driven by the increasing integration of renewable energy sources, the proliferation of distributed generation, and the deployment of advanced control and communication technologies. As a result, today's large-scale power systems are no longer simple, hierarchically structured networks dominated by synchronous machines, but **complex, interconnected, and interconnected with numerous heterogeneous components**—ranging from conventional generators and inverter-based resources to responsive loads and energy storage units.

While these advances enhance efficiency and sustainability, they also pose **significant challenges to system stability**. Maintaining stability, in particular under disturbances, operating point shifts, and switching between multiple operating modes remains a cornerstone requirement for secure power system operation. Historical events such as the 2003 North American blackout, the 2012 India blackout, the 2025 Spain blackout and several regional grid collapses in recent years have demonstrated the devastating economic and societal consequences of losing system-wide stability. These incidents often arise from cascading failures initiated by local instabilities that propagate through the network, exacerbated by nonlinear interactions and mode switching behaviors within the system.

In large-scale power systems, **the stability problem is compounded by high dimensionality, nonlinearity, and interconnection complexity**. Traditional analytical techniques such as small-signal stability analysis, Lyapunov-based methods, or modal decomposition often rely on simplified linear models or localized assumptions, which can fail to capture the global nonlinear dynamics and coupling effects across the network. Furthermore, with the increasing prevalence of power electronic interfaces and data-driven control strategies, the system's behavior may evolve rapidly, making model-based stability analysis less tractable and less adaptive to changing operating conditions. Finally, as the system grows in size and complexity, centralized stability assessment becomes increasingly difficult.

Aim of the project

The aim of this project is **to develop a deep-learning-based approach for enhancing the stability of large-scale power systems in a decentralized manner**. To achieve this, the project will leverage the concept of **dissipativity**, an energy-oriented framework that can be used to verify the stability of interconnected systems. Using measurements or simulated trajectories, a neural network is trained to approximate a storage function that captures how the subsystem stores and dissipates energy in response to its inputs and outputs. Once the local dissipativity properties have been identified, the overall network can be regarded as an interconnection of locally dissipative components whose supply rates determine the global behavior of the system. The project will explore how the learned local properties can be composed to verify and improve the stability of the entire network, based on the principles from dissipativity theory and interconnection analysis. Furthermore, the project will explore how the global stability condition can be decomposed and leveraged for the scalable training of neural networks.

Tasks

The tasks of the project are as follows:

1. Study and understand the basic concepts of dissipativity and stability of interconnected systems [1, 2];
2. Understand the methods proposed in [3, 4];
3. Propose a decentralized deep-learning-based algorithm for enhancing stability;
4. Analyze the proposed algorithm and validate it on simulation and real power systems;
5. Write a report and prepare a presentation.

Publications: If the final results are promising they can be turned into a publication (a previous semester project on a similar topic has also resulted in an academic paper).

Prerequisites

The prerequisites for the project are as follows:

- The student must be a master student at ETH Zürich;
- The student should have experience in deep learning, especially proficiency in frameworks such as Pytorch;
- The student should have basic knowledge in power system;
- Background in control theory is a plus.

How to Apply

Please send your resume/CV (including lists of relevant publications/projects) and transcript of records in PDF format via email to Dr. Han Wang (hanwang@control.ee.ethz.ch) and Taiki Nakano (nakanot@control.ee.ethz.ch).

References

[1] M. Arcak, C. Meissen, and A. Packard, *Networks of dissipative systems: compositional certification of stability, performance, and safety*. Springer, 2016.

[2] F. Bullo, J. Cortés, F. Dörfler, and S. Martínez, *Lectures on network systems*, vol. 1. CreateSpace PlatformScotts Valley, 2018.

[3] T. Nakano, A. Aboudonia, J. Eising, A. Martinelli, F. Dörfler, and J. Lygeros, "Dissipativity-based data-driven decentralized control of interconnected systems," *arXiv preprint arXiv:2509.14047*, 2025.

[4] H. Wang, K. Miao, D. Madeira, and A. Papachristodoulou, "Learning neural controllers with optimality and stability guarantees using input-output dissipativity," *arXiv preprint arXiv:2506.06564*, 2025.