

# AI-Assisted Stability Certification for Net-Zero Power Systems

*Symbolic Transformer Approach to Lyapunov Function Discovery*

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**N8 CIR Winter Internship 2025/26**

March 2026

# The Stability Challenge

*Why automated Lyapunov function discovery matters for the energy transition?*

## The Problem

A Lyapunov function  $V(x)$  is a mathematical stability certificate. Despite 130+ years of effort, no general method exists to find one for complex, non-polynomial power systems.

## The Approach

Alfarano et al. (NeurIPS 2024) showed a symbolic transformer can predict Lyapunov functions from system descriptions.

Trained on 1M synthetic systems with known solutions using backward construction.

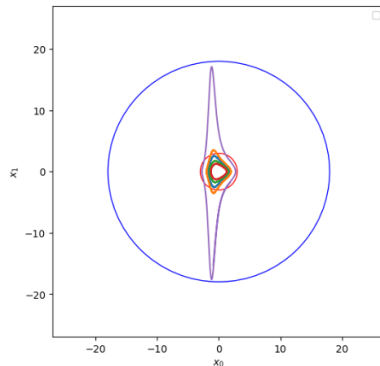
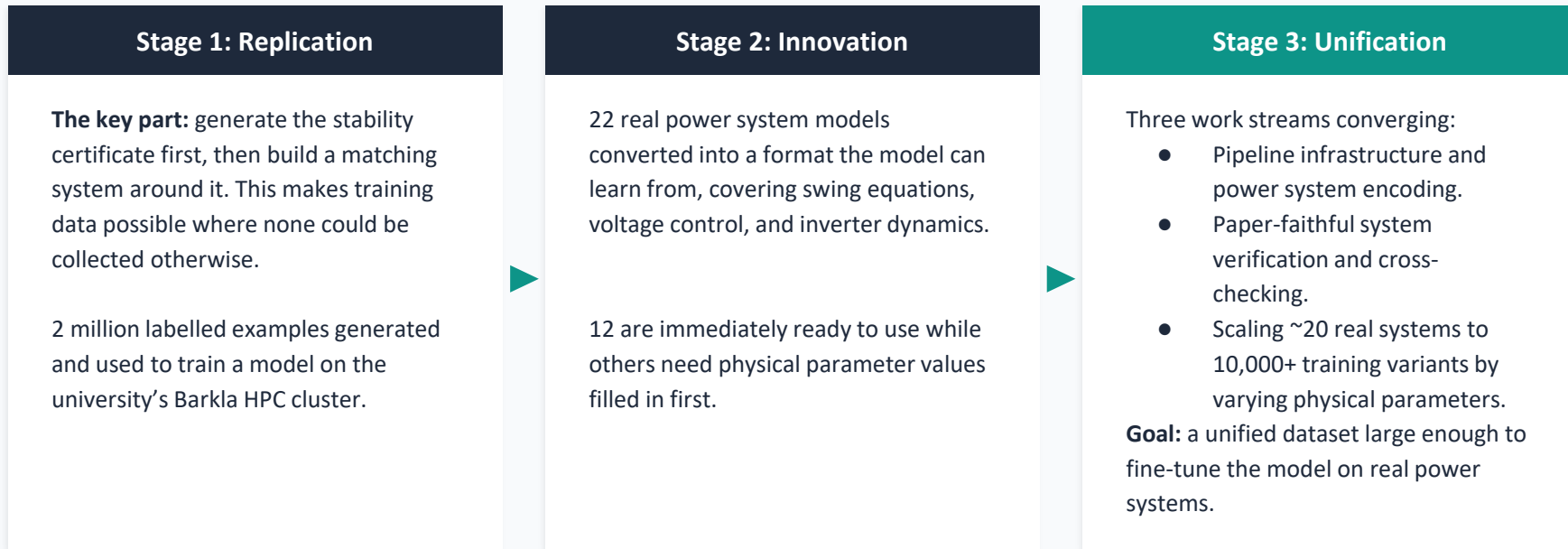
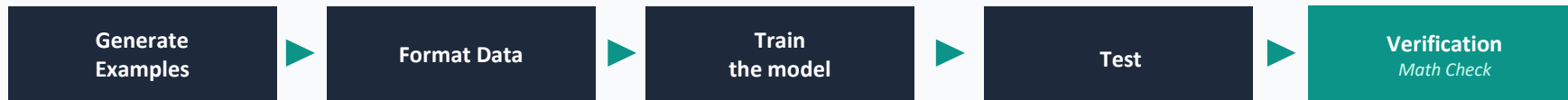


Figure 1: Dynamic of a stable system: trajectories may be complicated but as long as they start in the red ball they remain in the blue ball.

# End-to-End Pipeline



*Key idea: generating the answer first, then building the question around it, is what makes training data possible at all.*

# HPC Infrastructure and Engineering

*Barkla cluster, University of Liverpool Research IT*

## Computing Infrastructure

Barkla cluster provided the GPU hardware needed to train large-scale models on H100 GPU nodes.

## Reproducible Pipeline

The entire pipeline of data generation, model training, evaluation, and environment setup is automated end-to-end.

## Adapting to the Paper's Codebase

The paper's verification step runs many parallel workers, each of which spawns multiple sub-processes. Running the default configuration on shared cluster hardware caused the total number of active processes to multiply far beyond what the node could handle.

### Before



Each worker spawns its own sub-threads on a 168-core node, this multiplied to 5,000+ active threads.



### After



Each worker limited to one thread for more predictable resource use, no overload.

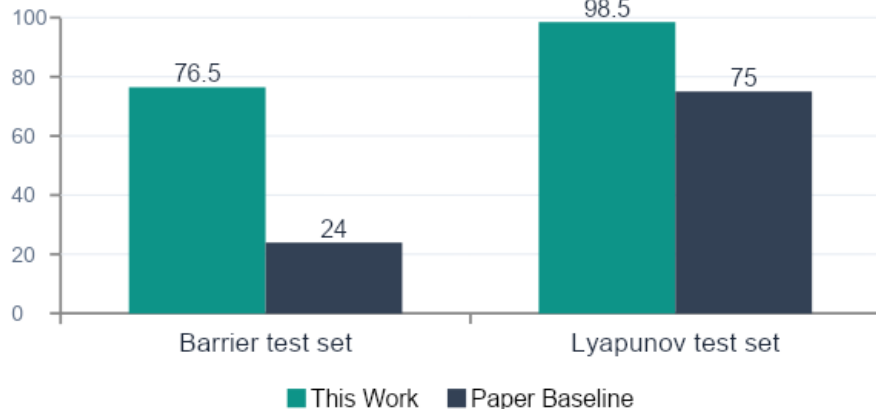
# Results: Benchmark Performance

BNonPoly model | Replication of Alfarano et al. | Best checkpoint: epoch 36

Training Loss Convergence



Beam Accuracy (%)



**92%**

Accuracy on test cases from the same distribution as training data

**~100%**

All candidate functions produced were mathematically valid

**0**

The model always returned an answer within the time limit

*Note: direct comparison with the paper's published numbers is approximate. The paper uses different training data, hardware configuration, and evaluation methods. These results confirm the model learns correctly; they are not a claim of exceeding the original paper.*

# Encoding Real Power Systems for the Model

## A Real Power System, Encoded

*Category I, System 03: 3-Machine Swing Equations*

A 3-machine power network with 4 interacting state variables:

$$\dot{x}_1 = x_2$$

$$\dot{x}_2 = -\sin(x_1) - 0.5\sin(x_1 - x_3) - 0.4x_2$$

$$\dot{x}_3 = x_4$$

$$\dot{x}_4 = -0.5\sin(x_3) - 0.5\sin(x_3 - x_1) - 0.5x_4 + 0.05$$

Known Lyapunov function  $V(x)$  provided  
(SOS-derived polynomial, 30+ terms)

Written in symbolic form using Python, then  
converted into a format the model can process.

## Ready Now vs. Needs Setup

**Ready:** fixed physical values, directly usable as training data.

**Needs setup:** real installations vary in line resistance, inertia, and load. These need actual values substituted before use.

## What Was Built

**What:** 22 real power system models across 3 categories.

**Why:** Real grids contain many different equipment types.

**How:** Written in Python, automatically converted for the AI. New systems can be added by the team independently.

Power system equations → Automatically converted → Model training data

# Discussion

## What Was Achieved

- End-to-end training pipeline running on Barkla HPC, fully automated and reproducible.
- Model trained to convergence, with strong benchmark accuracy on the Lyapunov and barrier test sets.
- Real power system models encoded and ready for the research team to build on.
- Delivered a fully documented and reproducible prototype.

## Next Steps

- Expand the training dataset by systematically varying physical parameters across the systems. Each system becomes hundreds of variants, directly addressing the gap between real and synthetic data.
- Fine-tune the model on real power system data, then verify outputs using formal methods (SOS, SMT, LMI) where LMI in particular is well-suited to the structured dynamics of power systems.

*Core challenge: ~20 real power systems versus 1,000,000 synthetic training examples. Closing that gap through parameter perturbation and LMI-based sampling is the critical next step.*

## Acknowledgements

Supervisors: Dr. Lin Jiang, Dr. Manhui Wang.

This work made use of the Barkla HPC facilities at the University of Liverpool.

Funded by the N8 Research Partnership.