

A Neural Lyapunov Approach to Transient Stability Assessment in Interconnected Microgrids

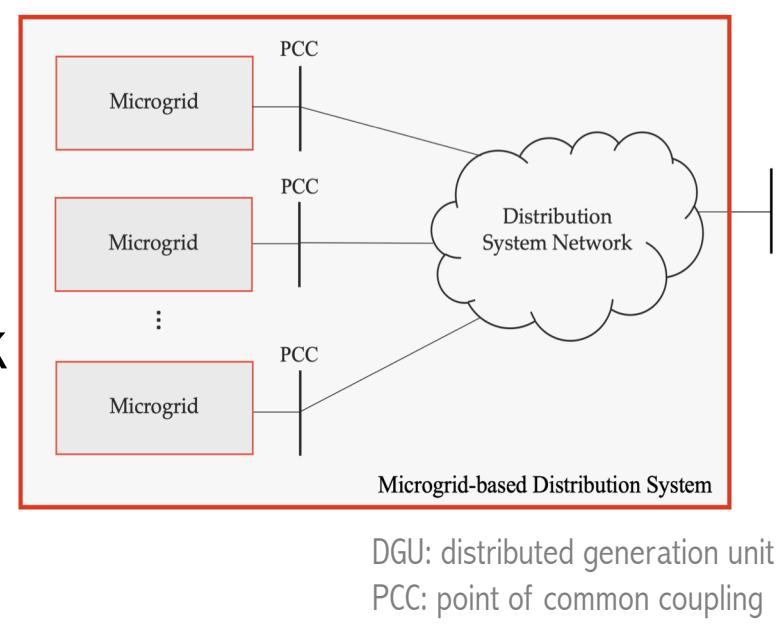
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Key Innovations

- We develop a novel transient stability assessment tool for networked microgrids using a machine learning-based Neural Lyapunov method.
- The tool can address the networked microgrids with lossy lines.
- The tool can provide a less conservative characterization of the security region, compared with conventional methods based on quadratic Lyapunov functions.

Background & Motivation

- Future distribution system: networked microgrids
- Disturbances: operation modes; network
- Transient stability assessment is critical for both planners & operators.



Interface Dynamics

- PCC: power-electronic interface for simplifying the control tasks of DSO and achieving power sharing
- Interface dynamics depend on control strategies.
- Frequency/angle droop control

Microgrid Interface Dynamics

$$\begin{aligned} T_{ai}\dot{\delta}_i + \delta_i - \delta_i^* &= D_{ai}(P_i^* - P_i) \\ T_{Vi}\dot{V}_i + V_i - V_i^* &= D_{Vi}(Q_i^* - Q_i), \end{aligned}$$

Network Constraints

$$P_i = V_i^2 G_{ii} + \sum_{k \neq i} V_i V_k Y_{ik} \sin(\delta_i - \delta_k - \theta_{ik} + \pi/2),$$

$$Q_i = -V_i^2 B_{ii} + \sum_{k \neq i} V_i V_k Y_{ik} \sin(\delta_i - \delta_k - \theta_{ik}), \forall i,$$

$$\dot{x} = f(x)$$

Is the system stable? How large are the disturbances that the system can tolerate?

Security Region Estimation

- Stable certification: Lyapunov function (LF)
- Security region estimation with Lyapunov function

Definition 1 If, in a ball $D_R := \{\mathbf{x} \mid \|\mathbf{x}\|_2^2 \leq R^2\}$, there exists a continuous differentiable scalar function V such that

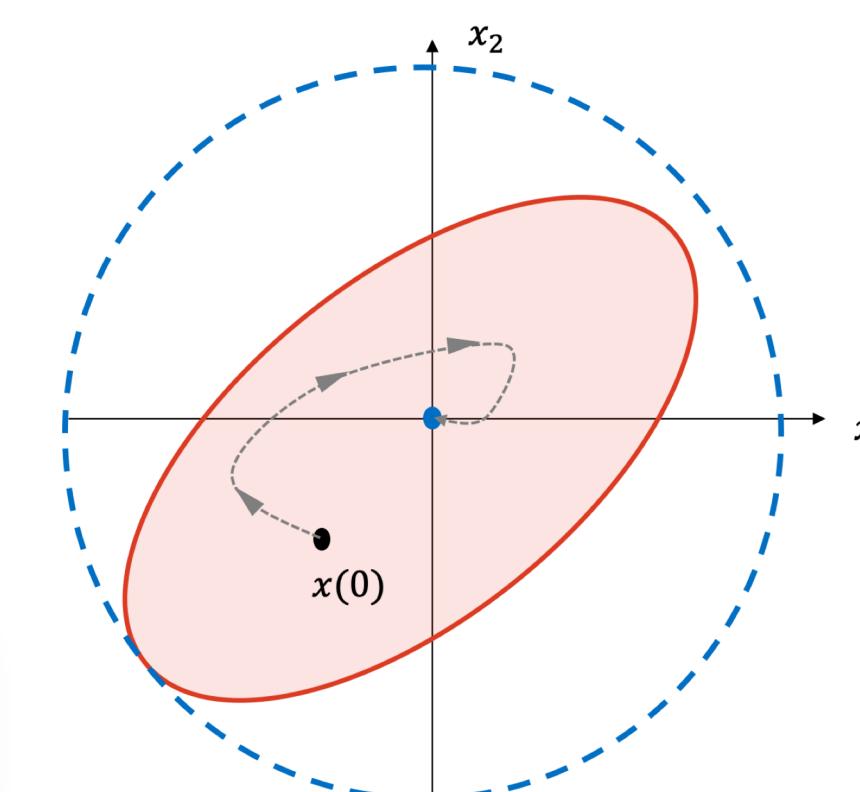
- V is positive definite in D_R ,
- \dot{V} is negative definite in D_R

then the equilibrium point \mathbf{o}' is asymptotically stable, and the function V is called a Lyapunov function.

Definition 2 A region $\mathcal{R} \subseteq \mathbb{R}^{m'}$ is a security region if

$$\mathbf{x}(0) \in \mathcal{R} \implies \mathbf{x}(\infty) = \mathbf{0}_{m'} \wedge \forall t > 0 (\mathbf{x}(t) \in \mathcal{R}).$$

How to find a Lyapunov Function? Can we learn it?



Neural Lyapunov Approach

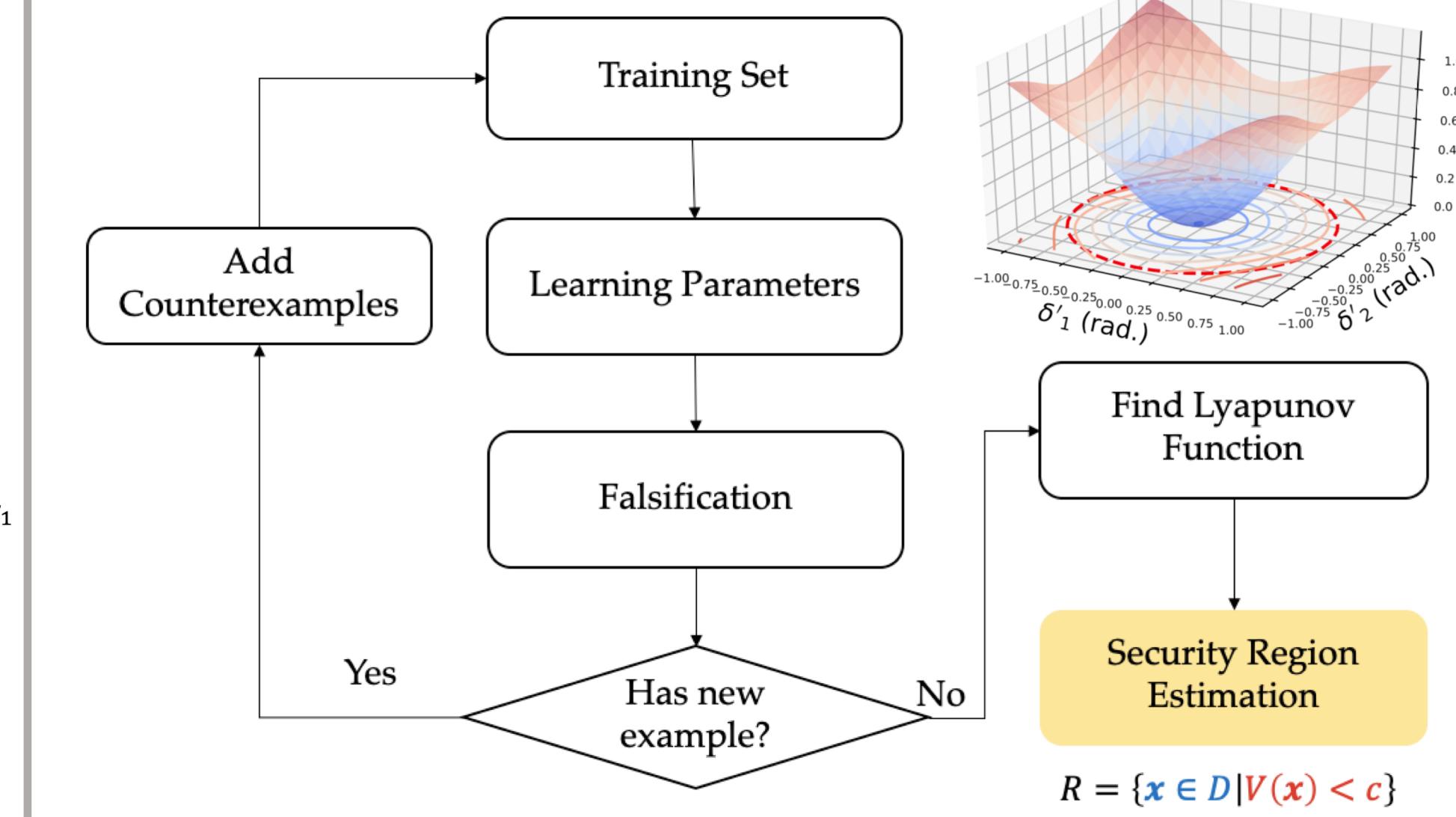
- The LF is assumed to be neural network-structured
- A neural network is a function
- Inputs: state variables x ; output: $V(x)$; hidden layer(s) and output layer
- How to tune the weights and bias of the NN such that the NN behaves like a Lyapunov function?
- Minimizing the following cost function via gradient decent algorithm

$$L_{N,\rho}(\theta) = \frac{1}{N} \sum_{i=1}^N \left(\max(-V_\theta(x_i), 0) + \max(\nabla_f V_\theta(x), 0) \right)$$

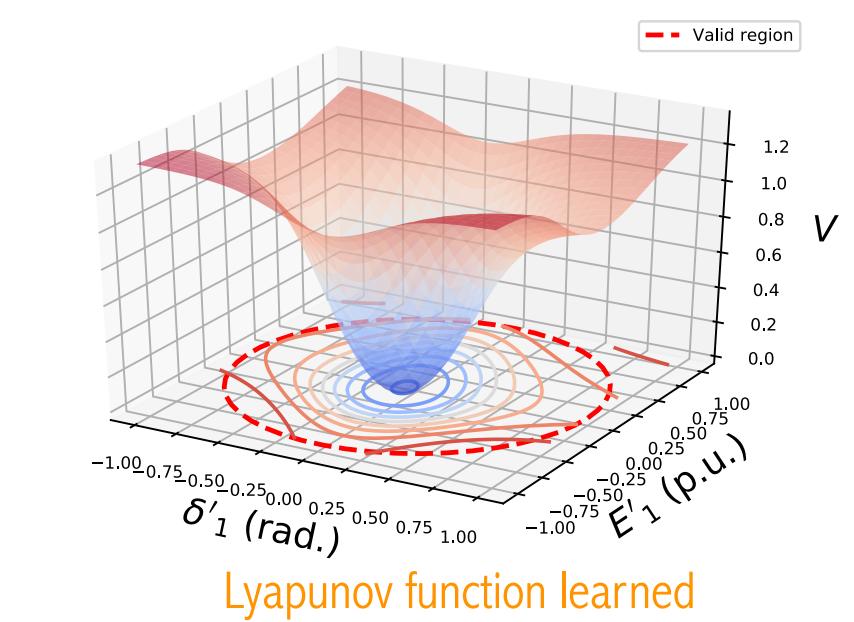
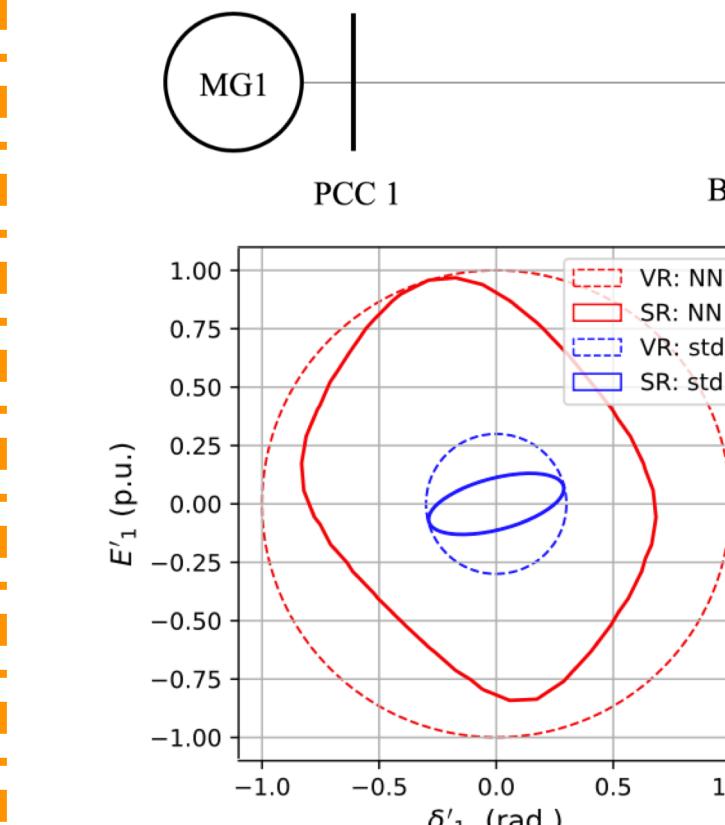
Penalty arises when $V(x) < 0$ or time derivative > 0

- For all $\mathbf{x} \in \mathcal{D}$, check if
$$V_\theta(\mathbf{x}) \geq 0 \text{ and } \nabla_f V_\theta(\mathbf{x}) < 0$$
- How to check satisfiability: Satisfiability Modulo Theories (SMT) solver

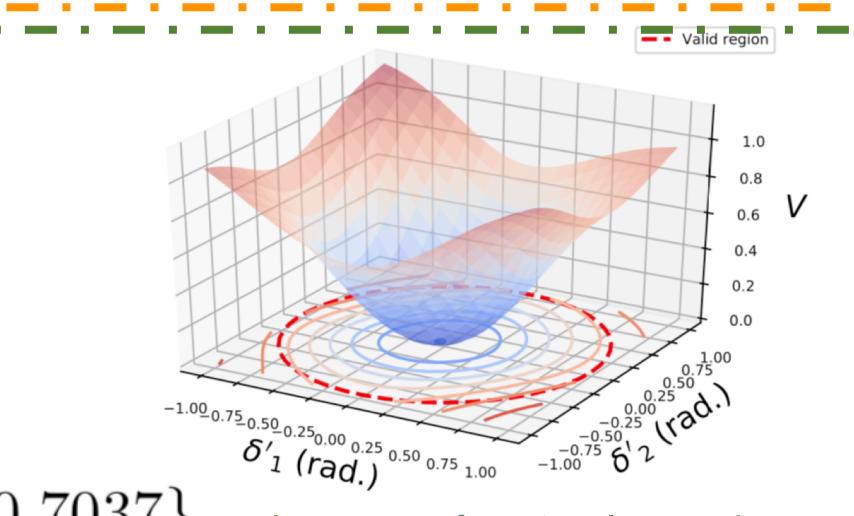
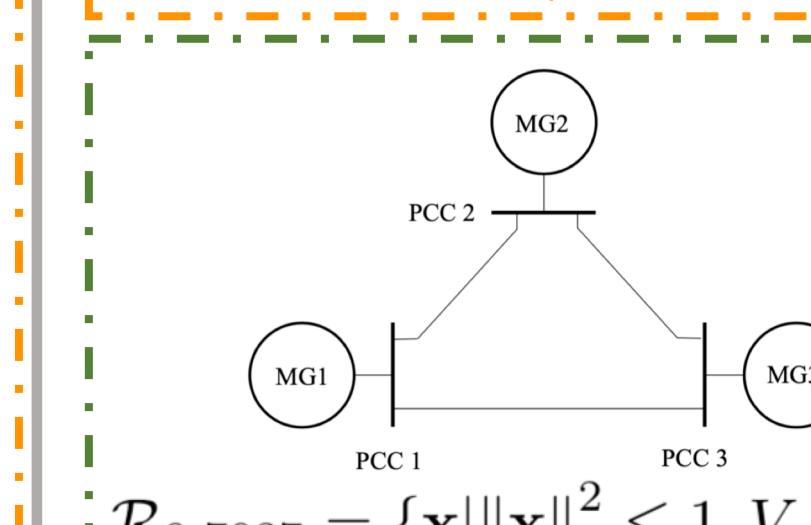
Implementation Scheme



Case Studies



The proposed method is less conservative than a conventional method.



$$\mathcal{R}_{0.7037} = \{x \mid \|x\|_2^2 \leq 1, V_{\alpha^*}(x) < 0.7037\}$$

Lyapunov function learned

Conclusion

- A neural Lyapunov approach to transient stability assessment
- The proposed method is less conservative than a conventional approach
- Future work will test the algorithm in systems with various dynamics