ICML Workshop

Reinforcement Learning for Optimal Frequency Control: A Lyapunov Approach

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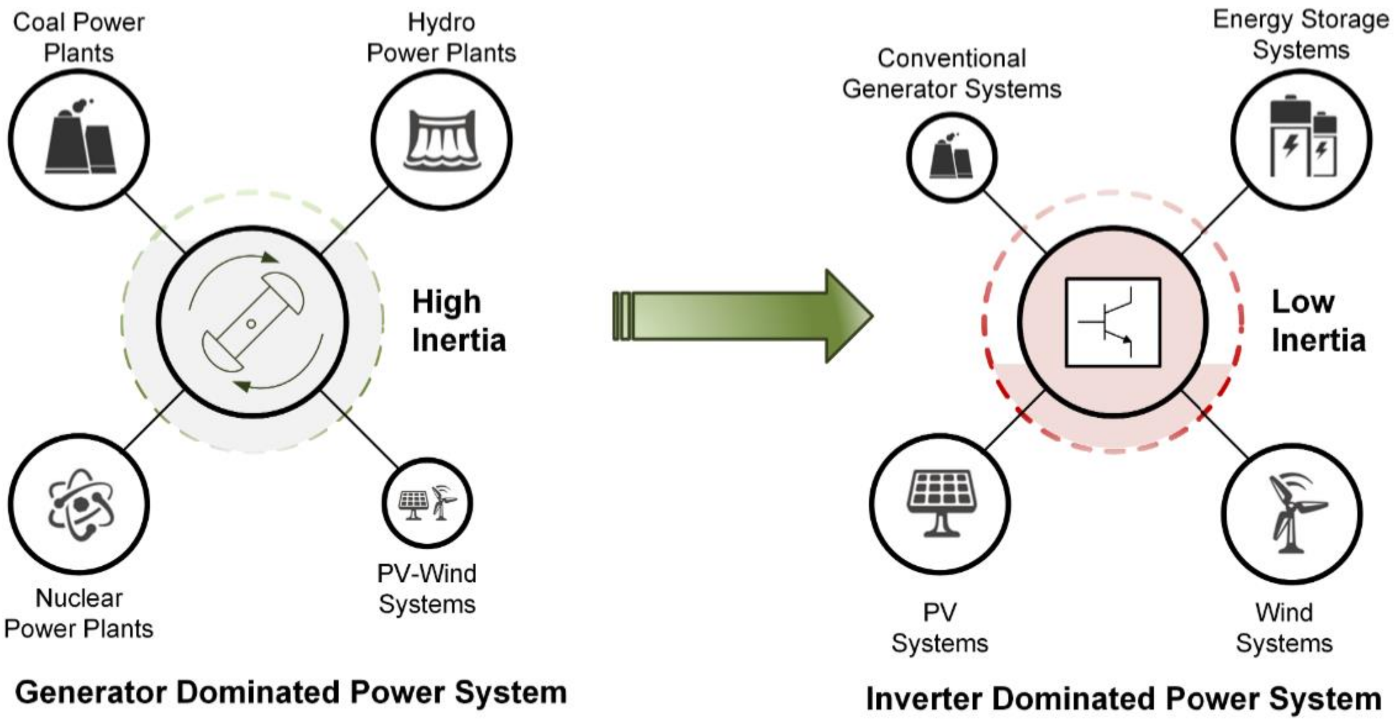
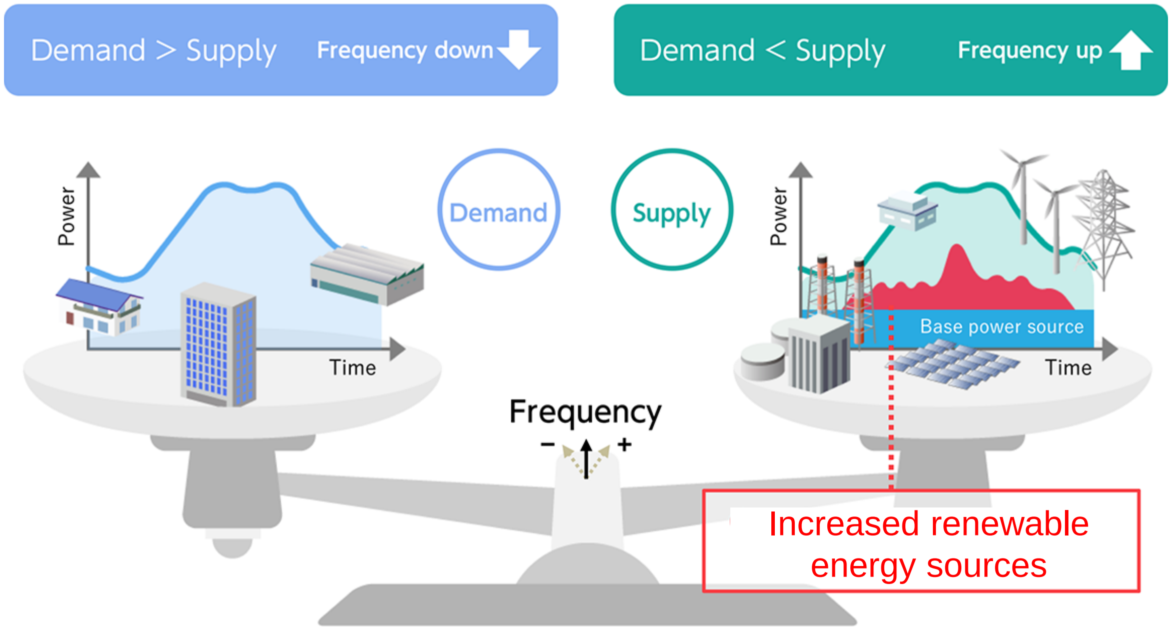
1. Background



[1] Tamrakar, Ujjwol, et al. "Virtual inertia: Current trends and future directions." *Applied Sciences* 7.7 (2017): 654.

1. Background

- Frequency deviation reflects the demand – supply mismatch
- In frequency control problem, we adjust the active power from generators to reduce the frequency deviation.

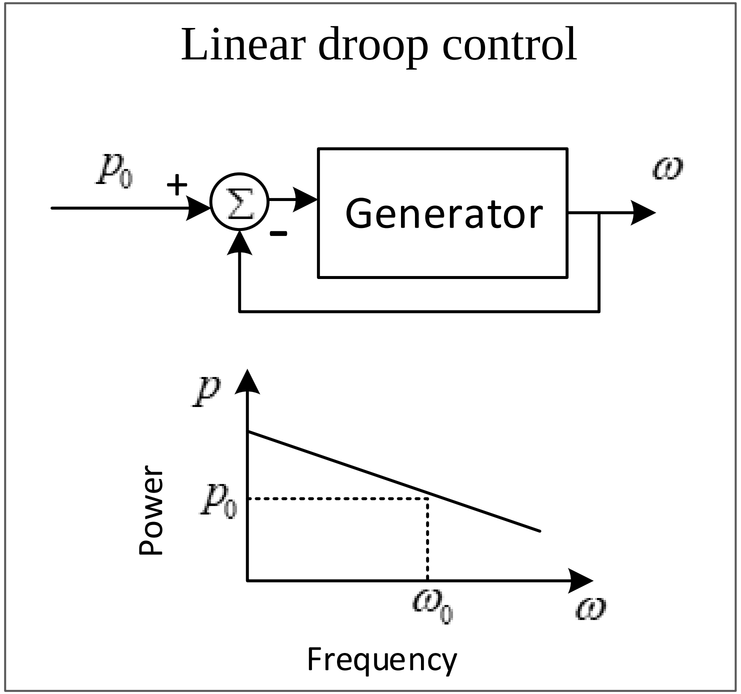


[2] https://www.mitsubishielectric.com/eig/energysystems/ictpowersystem/solutions/Large-capacityStorageBattery.html

1. Background

Synchronous generators follow negative linear feedback from frequency deviation

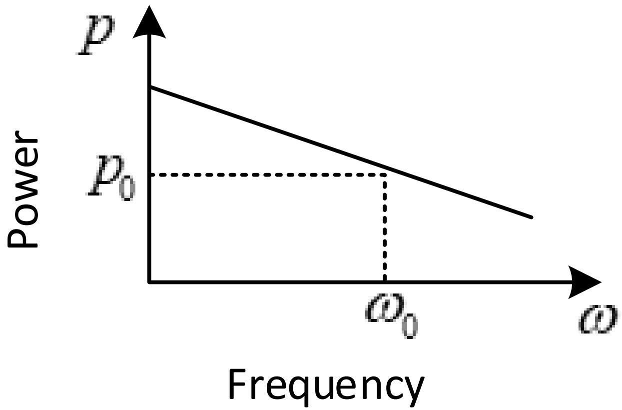
a) Frequency drops and governor opens valve, increasing power [3]



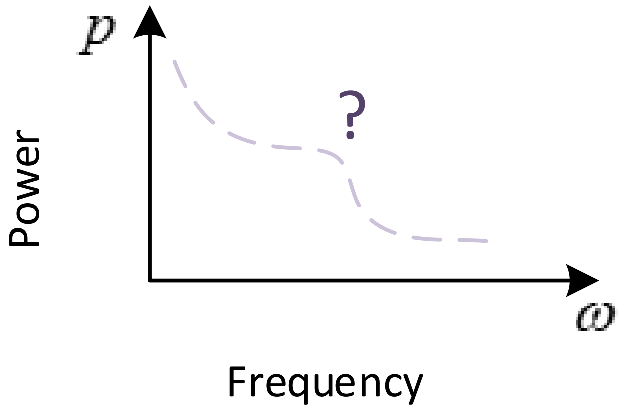
[3] Denholm, Paul, et al. *Inertia and the power grid: A guide without the spin*. National Renewable Energy Laboratory, 2020.

1. Background - Challenge

Inverter-based resources can implement almost arbitrary control law



Linear control may not be optimal

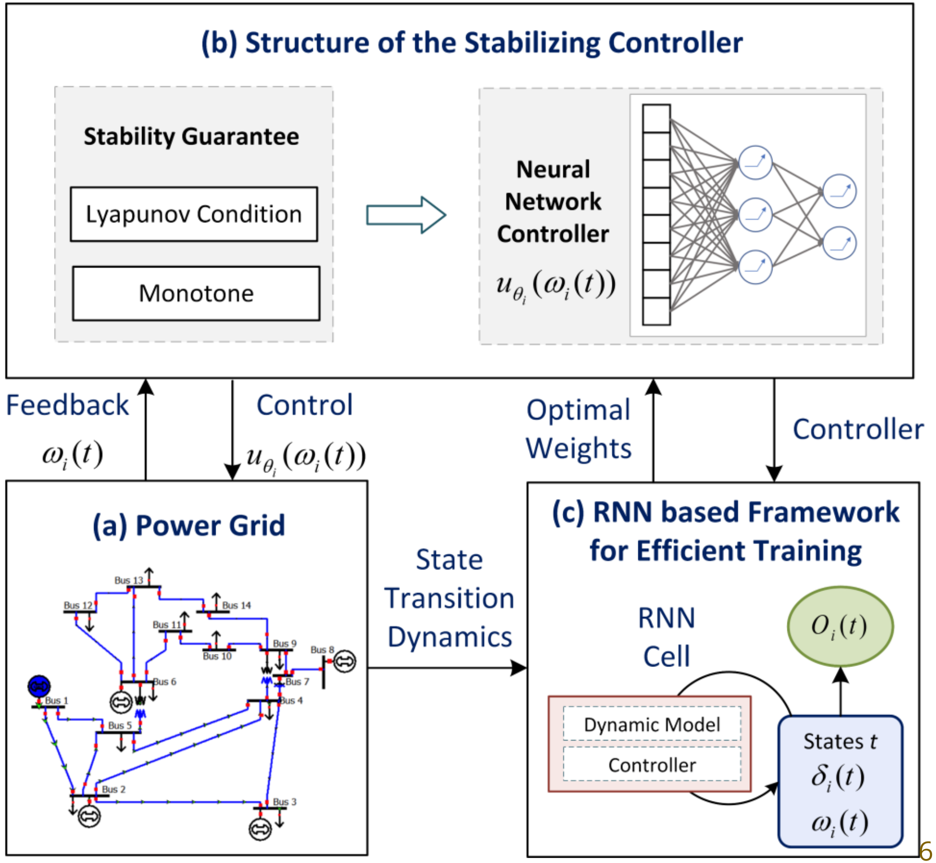


- ✓ Stabilizing
- ✓ Frequency deviation
- ✓ Control cost

1. Background – Our approach

Reinforcement learning (RL) for optimal frequency control

- Parameterize the controllers with neural network and RL is used to train them
- Obtain structure property of stabilizing controller using Lyapunov function
- RNN-based framework for efficient training



2. Problem Formulation - Model

The dynamics of the power system are represented by the swing equation

Angle

Frequency

State Variables

Static controller that change active power for primary frequency regulation

$$\dot{\delta}_i = \omega_i, \forall i \in \mathcal{B} \quad (1a)$$

$$M_i \dot{\omega}_i = P_i - D_i \omega_i - u_i(\omega_i) - \sum_{j=1}^{N} B_{ij} \sin(\delta_i - \delta_j), \forall i \in \mathcal{B} \quad (1b)$$

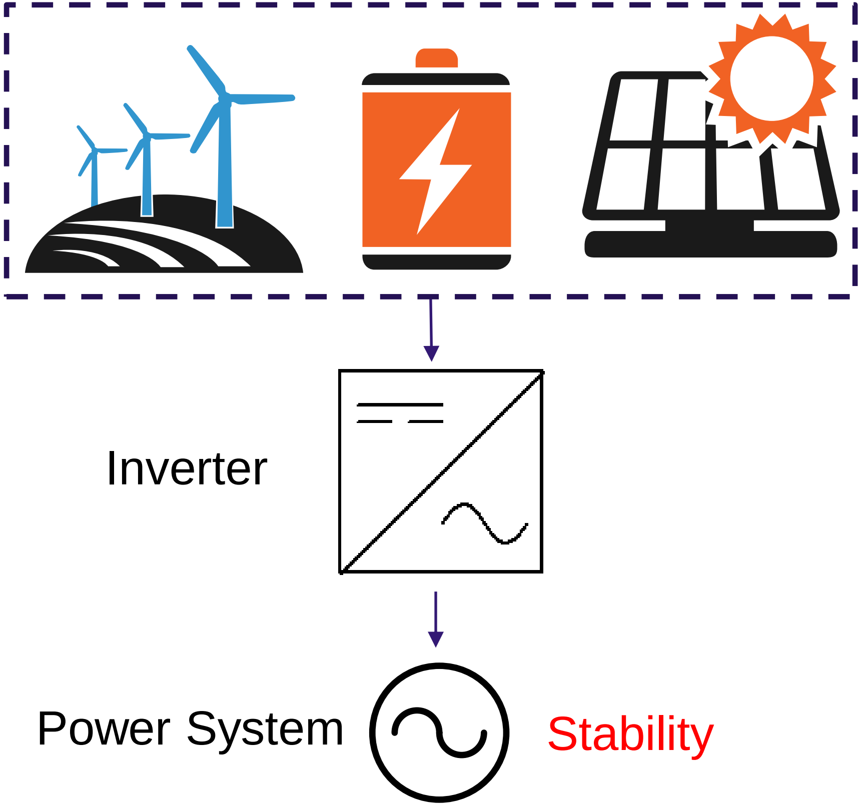
Inertia constant

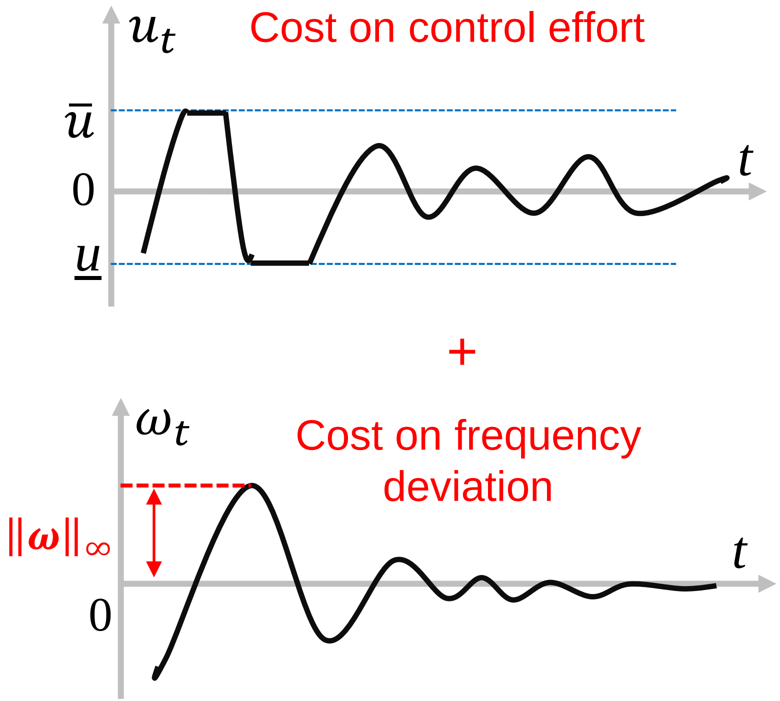
Net power injection

Damping coefficient

The susceptance of the line (i, j)

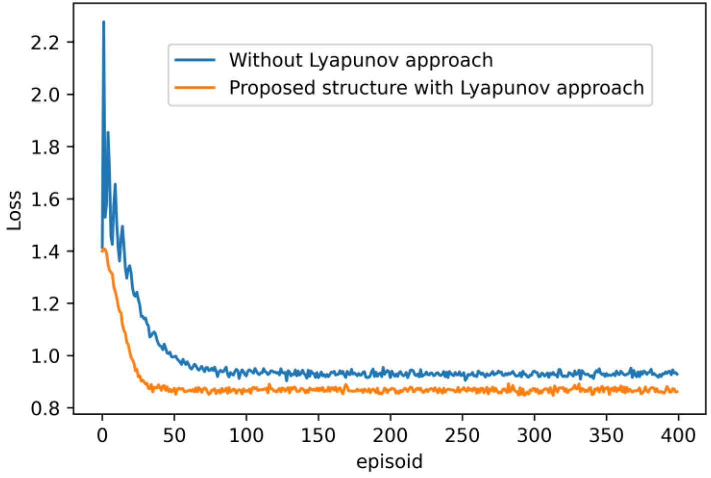
2. Problem Formulation – Optimization Objective



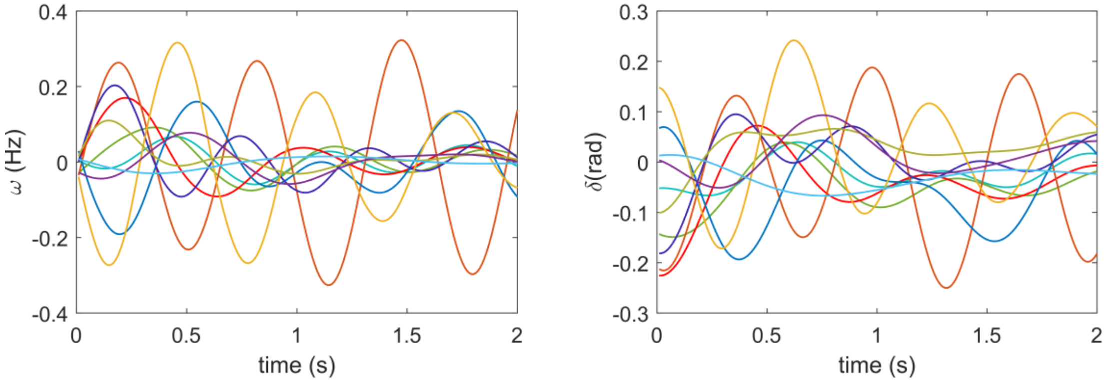


2. Problem Formulation – Hard Constraint on Stability

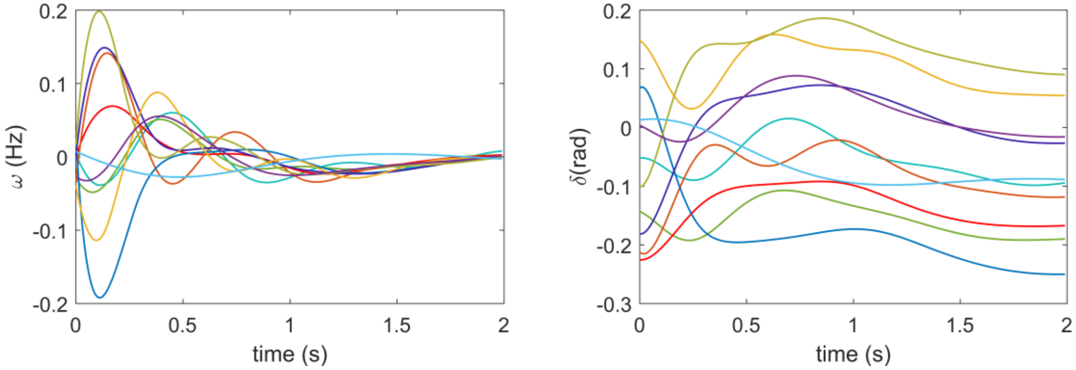
- Necessity to consider Stability



(a) Average batch loss along episodes



(b) Dynamics of ω(left) and δ (right) for RNN-Wo-Lyapunov



(c) Dynamics of ω(left) and δ (right) for RNN-Lyapunov

3. Lyapunov Approach for a Stabilizing Controller

A local Lyapunov function $V(\delta, \omega)$ for the dynamic system is

$$V(\delta,\omega) = \frac{1}{2}\sum_{i=1}^{N} M_i\omega_i^2 - \sum_{i=1}^{N} P_i\delta_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} B_{ij}\cos(\delta_i - \delta_j)$$

The total derivative of the Lyapunov function with respect to t is

$$\dot{V}(\delta,\omega) = \sum_{i=1}^{N}\left(\frac{\partial V(\delta,\omega)}{\partial \delta_i}\dot{\delta}_i + \frac{\partial V(\delta,\omega)}{\partial \omega_i}\dot{\omega}_i\right) = \sum_{i=1}^{N}\left(-\omega_i u_i(\omega_i) - D_i\omega_i^2\right)$$

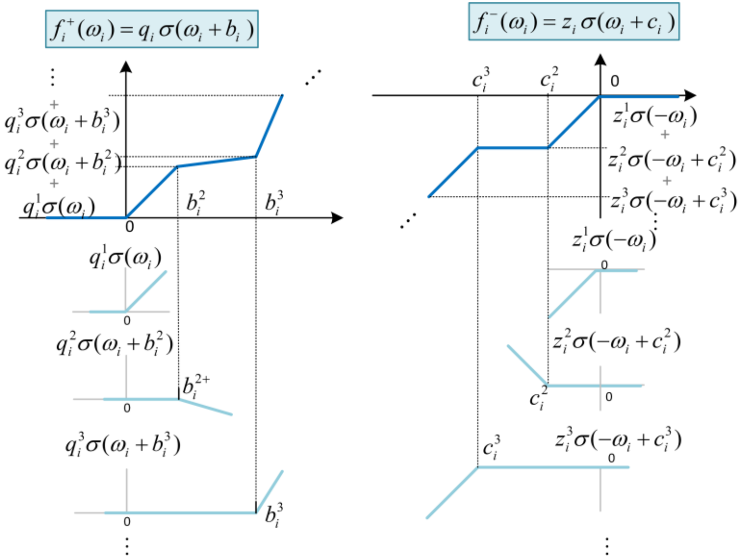
3. Lyapunov Approach for a Stabilizing Controller

According to Lyapunov stability theory, we design the neural networks to have the following structures such that the controller will be locally exponentially stabilizing

1) $u_{\theta_i}(\omega_i)$ has the same sign as ω_i

2) $u_{\theta_i}(\omega_i)$ is monotonically increasing

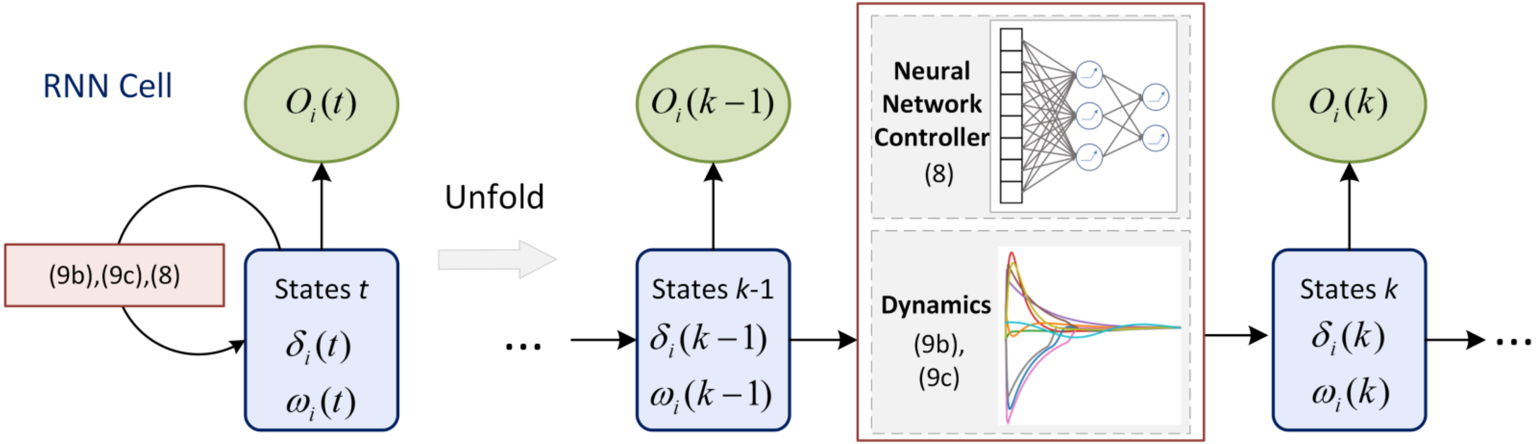
3) $\underline{u}_i \leq u_{\theta_i}(\omega_i) \leq \overline{u}_i$



4. RNN for Efficient Training

Integrate state transition dynamics in recurrent neural network (RNN)

- Define the cell states to be δ_i and ω_i
- Operation of cell unit follows the swing equation

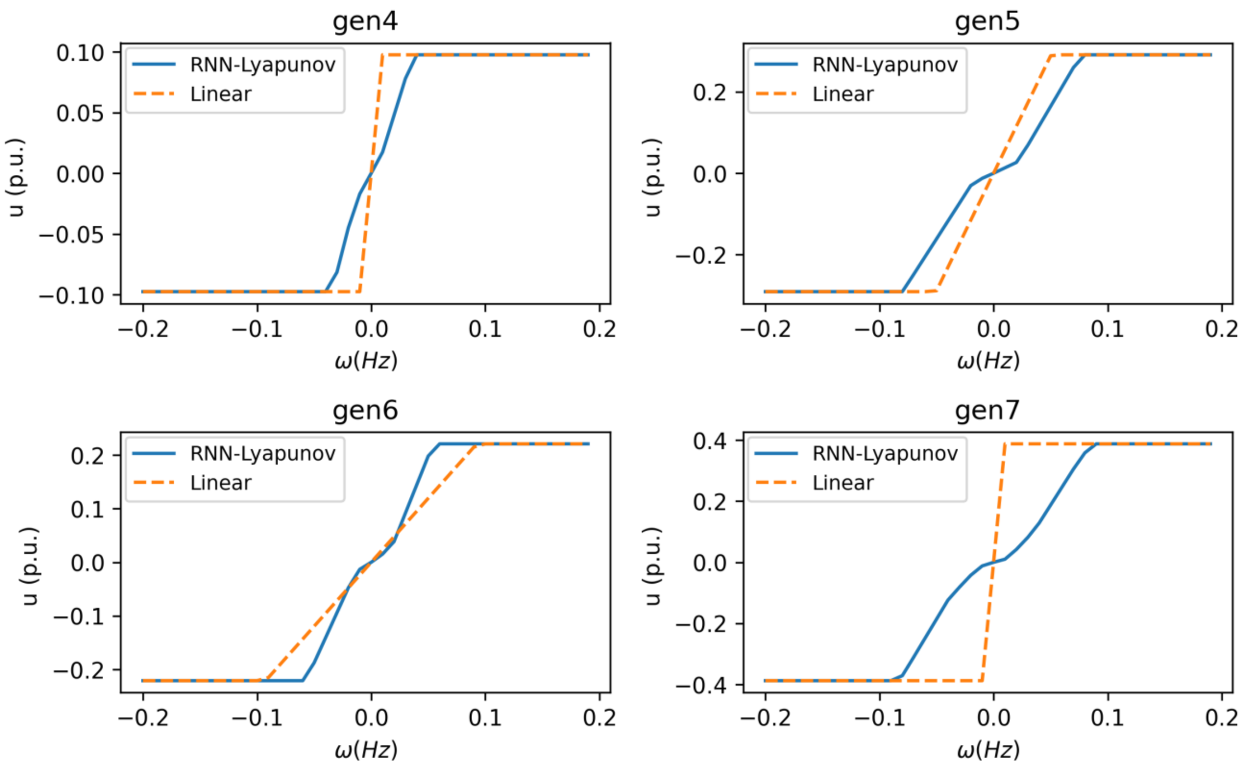


Compared with the general reinforcement learning structure, the proposed RNN based structure reduces computational time by approximate 74.32%

5. Case study

Case studies are conducted on the IEEE New England 10-machine 39-bus (NE39) power network

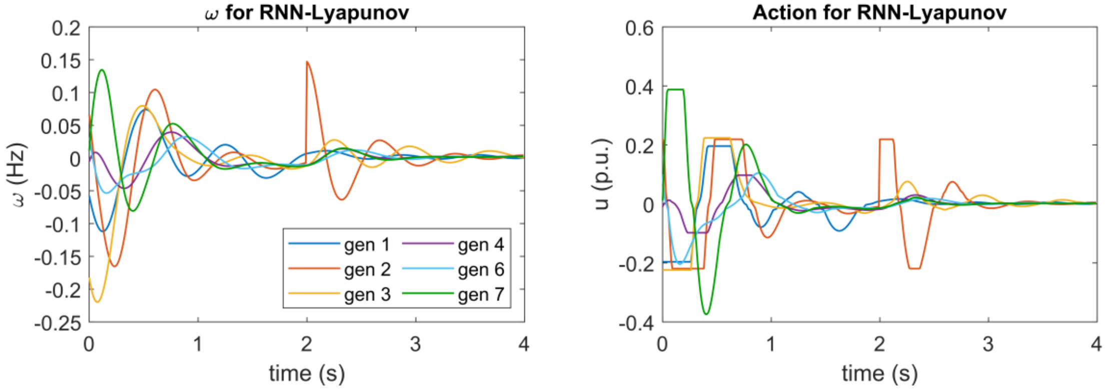
- Benchmark: Linear droop control with optimal linear coefficient
- The proposed approach learns a non-linear control law



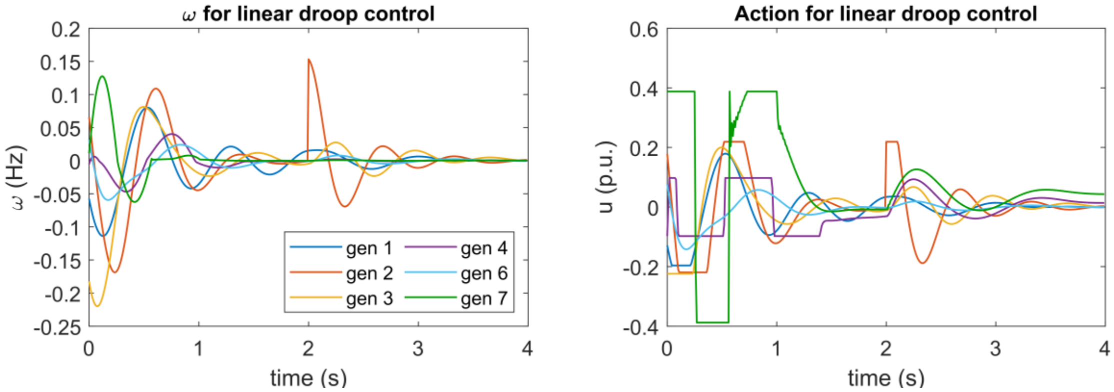
Control Action *u* obtained by different approaches

5. Case study

- Start from the same initial states at t=0, loss of load at bus 2 at t=2s
- Compared with the linear droop control, RNN-Lyapunov achieve similar frequency deviation with much smaller control effort.



(a) Dynamics of ω(left) and u (right) for RNN-Lyapunov



(b) Dynamics of ω(left) and u (right) for linear droop control

Thank you!