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# Safe Learning for Voltage Control

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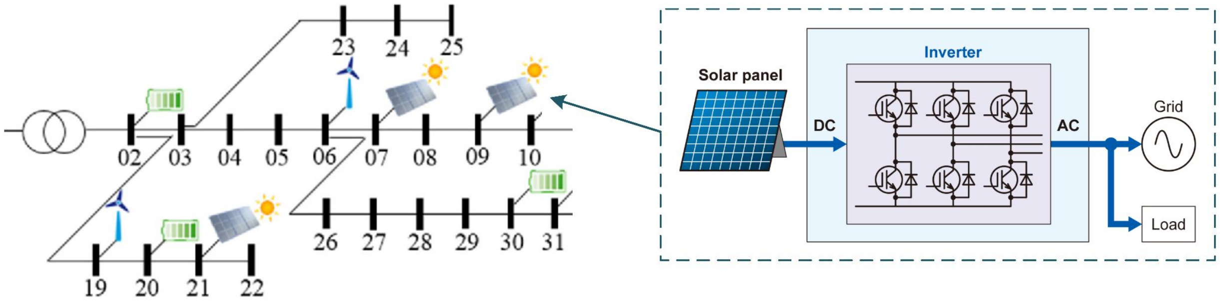
# Background

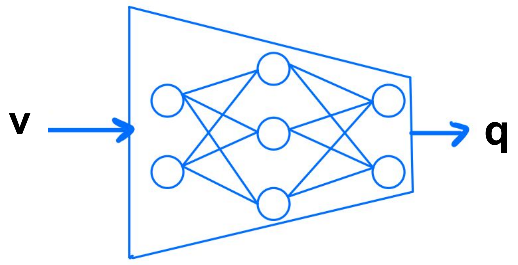
- High variability of distributed energy resources (DERs)
- No real-time communication infrastructure
- Controllability of reactive power



# Our approach: RL for voltage control

Goal: voltage close to nominal value with small control effort

- RL trains a neural network-based controller mapping from voltage to reactive power




- We provide the right structure constraints on the neural network

# Model

Objective Function: $C(\boldsymbol{u}) = \sum_{t=1}^{T} \left(||\boldsymbol{v}_t||_1 + \gamma||\boldsymbol{u}_t||_1\right)$

The voltage of the system follows the LinDistFlow model:

voltage

active power

reactive power

$$\boldsymbol{v} = \mathbf{R}\boldsymbol{p} + \mathbf{X}\boldsymbol{q} + \mathbb{1}$$

network matrices

We update q and v iteratively as:

$$\boldsymbol{q}_{t+1} = \boldsymbol{q}_t - u_t$$

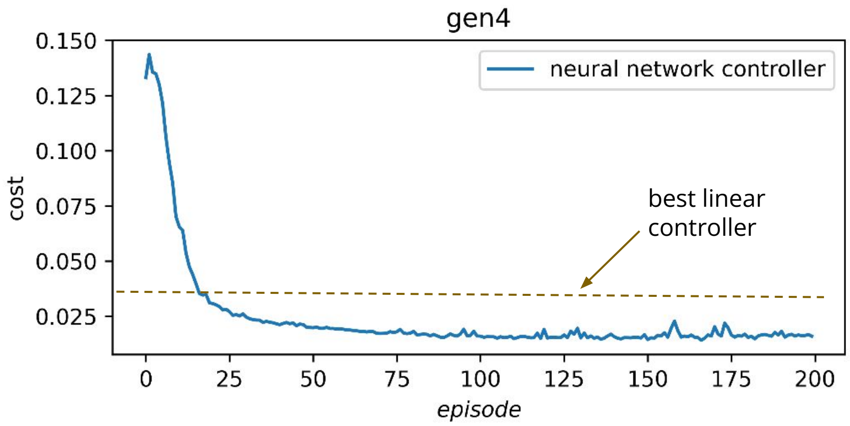
control law at time t:
mapping from v to q

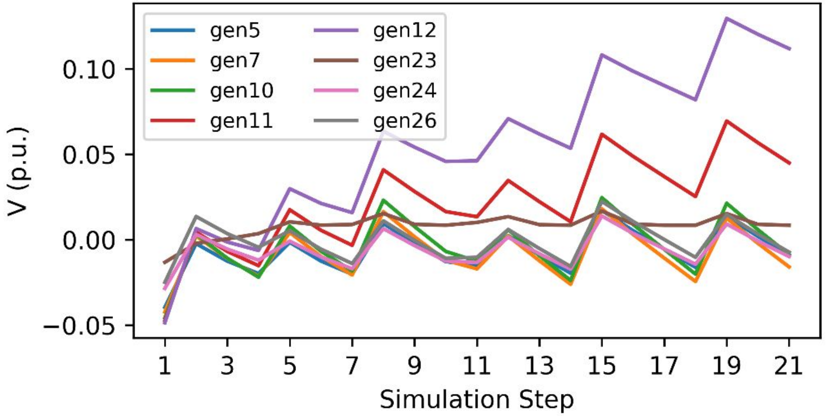
$$\boldsymbol{v}_{t+1} = \boldsymbol{R}\boldsymbol{p} + \boldsymbol{X}\left(\boldsymbol{q}_t - \boldsymbol{u}_t\right) + \mathbb{1}$$

# Hard Constraint on Stability

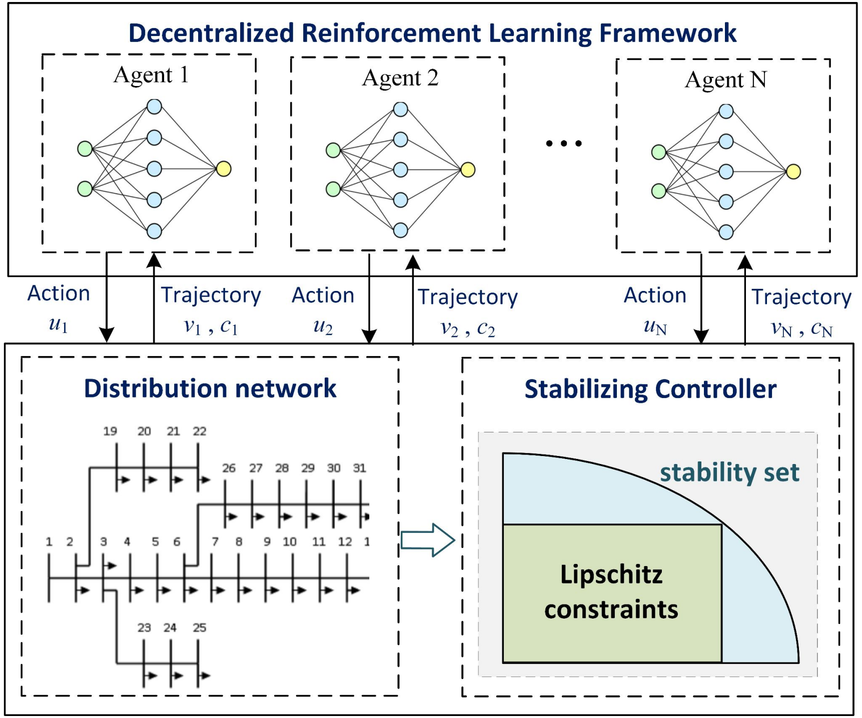
Necessity to consider Stability

- neural network controller performs better compared to traditional linear controller
- doesn’t stabilize the system

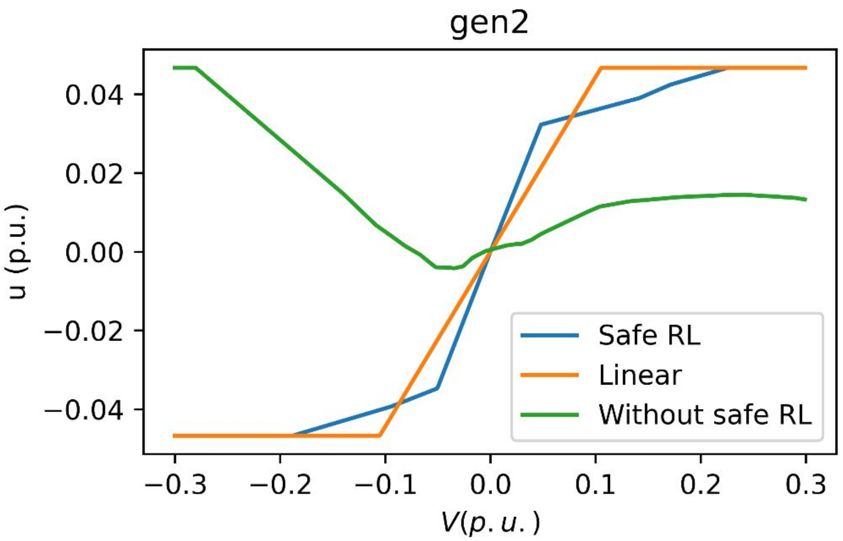


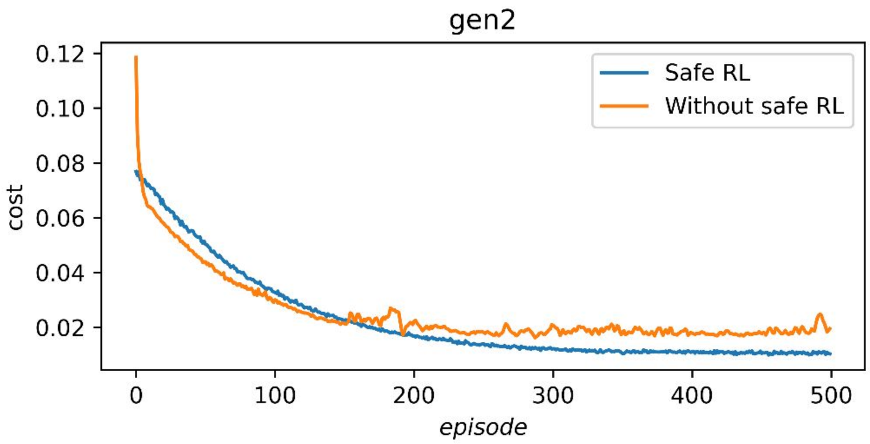
# Decentralized RL framework



# Case study




Control Action *u* obtained by different approaches




- Learning trajectories converge very well in the decentralized model-free setting.
- Safe RL guarantees system stability and achieves lower cost

Please refer to our arXiv submission for more details: http://arxiv.org/abs/2110.01126

# Thank you!