# A Set-Theoretic Approach to Safe Reinforcement Learning in Power Systems

*Daniel Tabas and Baosen Zhang*
*Department of Electrical and Computer Engineering*
*University of Washington, Seattle*

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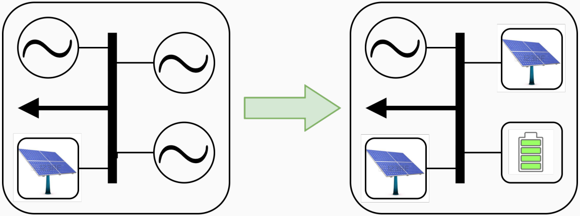
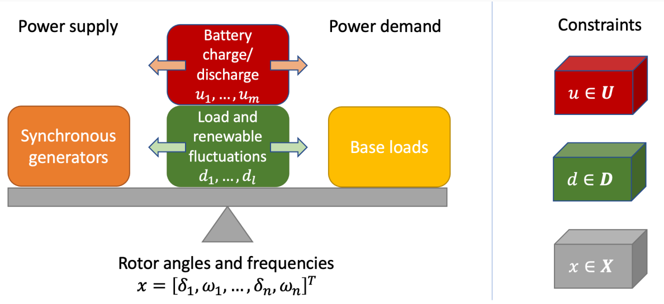
# Introduction



Power systems are transitioning from synchronous generator-based to inverter-based.

- More flexibility, less inherent stability
- Enables and necessitates new control techniques
- Increasing complexity → difficult to find good policy
- New control policies must be **safe**

# Model



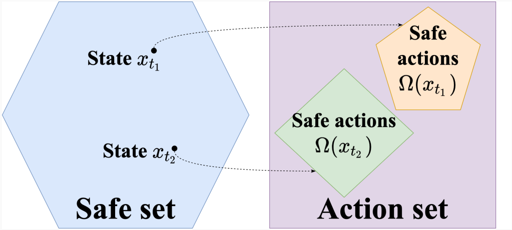

Power system stability requires balancing power supply with power demand.

- Loads and renewables fluctuate, but energy storage can be used to balance the fluctuations
- System operates under constraints: capacity limits $(U, D)$ and safety constraints $(X)$

# Previous work

- Lyapunov stability [1, 3, 7] and robust control guarantees [4, 5]
  - Guarantee stability but not hard constraint satisfaction
- Optimization-based safety filters [2, 8]
  - Calling an optimization solver in real time may not be practical
- Geometric approaches [9]
  - Can lead the system into states that are safe but have no safe action

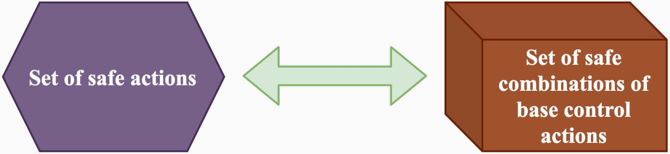
# Policy network architecture




The current set of safe actions is a moving target for a policy network.

- Changing geometry
- Difficult to parameterize
- Difficult to enforce as action constraints without solving projection (LP) at best

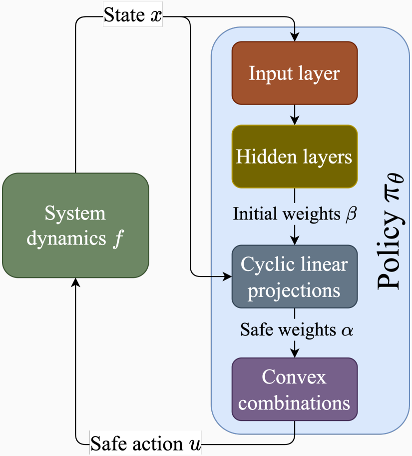
# Output feature map




The set of **safe combinations** of base control actions has simpler geometry than the set of safe actions. We can reach the set of safe combos through a small number of iterative linear projections.

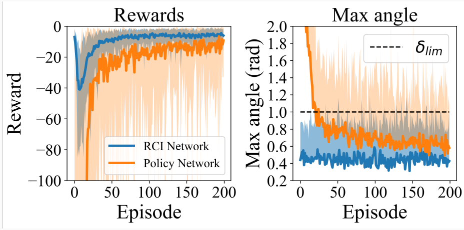
- **Base control actions:** safe actions associated with each vertex of the safe set
- **Safe combos:** any convex weights that generate the current state when applied to the vertices of the safe set

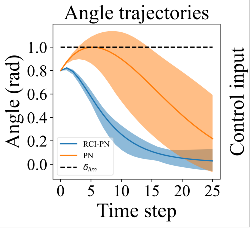
# Policy network architecture




- Policy parameterized by a neural network and trained using RL (DDPG algorithm [6])

# Simulations




Compared performance of our method (blue) to a policy network trained with a soft penalty on constraint violations (orange). Our proposed method demonstrated:

- Better rewards
- Far fewer constraint violations throughout training
- Better constraint satisfaction during testing

# Conclusions and future work

Conclusions:

- Proposed computationally efficient safe RL paradigm for power systems

Future work:

- Devise an output layer that has a closed-form solution
- Investigate robustness of learned policies to topology changes

# References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