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Reinforced Learning Approach Based on Topology Reconfiguration to Enhance Operational Resilience against Hurricanes

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Outline

- *Introduction*
- *Spatiotemporal Characteristics of Extreme Weather Events*
- *Soft Actor-Critic Learning Approach*
- *Implementation*
- *Case Studies and Results*
- *Conclusion*

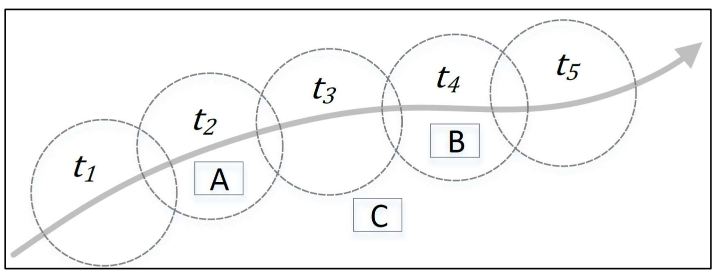
Introduction

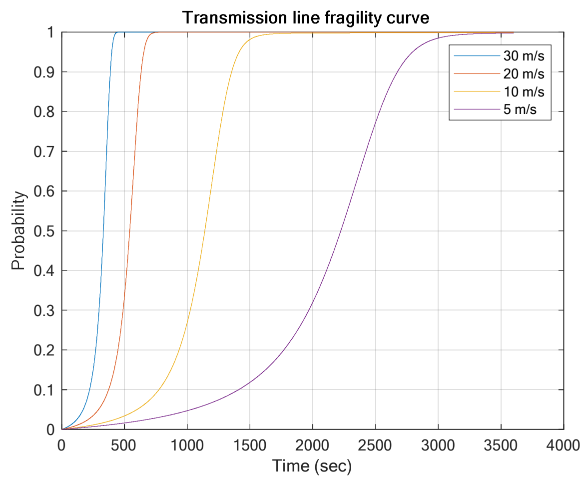
- *Definitions:*
  - Operational resilience enhancement strategy is to provide an immediate solution—a single action or a set of sequential actions—through utilization of available assets for improved performance during adverse events.
- *Motivations:*
  - Resilience enhancement strategies have been developed to reduce, mitigate, and prevent the catastrophic impacts of extreme events on power systems.
  - Resilience enhancement optimization is a mathematically involved problem accompanied with modeling challenges and computational burdens.
  - The importance of machine learning methods to provide a fast and effective control algorithm to improve resilience of power distribution systems is still under investigation.

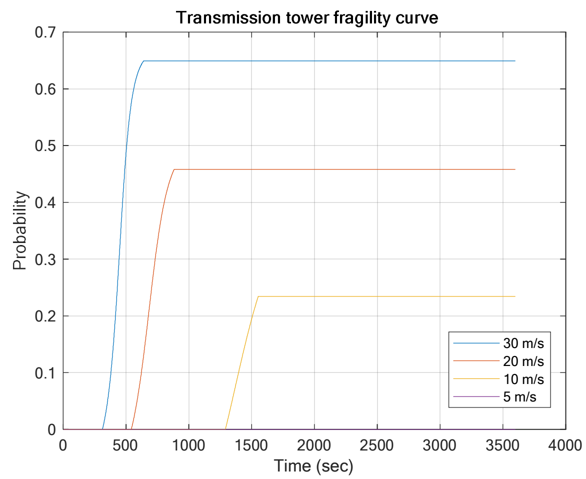
<u>Project Goal</u>: Implement a reinforced learning-based algorithm to enhance operational resilience of distribution systems considering realistic extreme weather models and system dynamic constraints.

Spatiotemporal Characteristics of Extreme Weather Events

- *Each extreme weather event has unique propagation properties and spatiotemporal characteristics.*
- *Various components can be impacted at sequential time intervals.*
- *Fragility models are usually used to identify potentially impacted components and their probability of failure.*

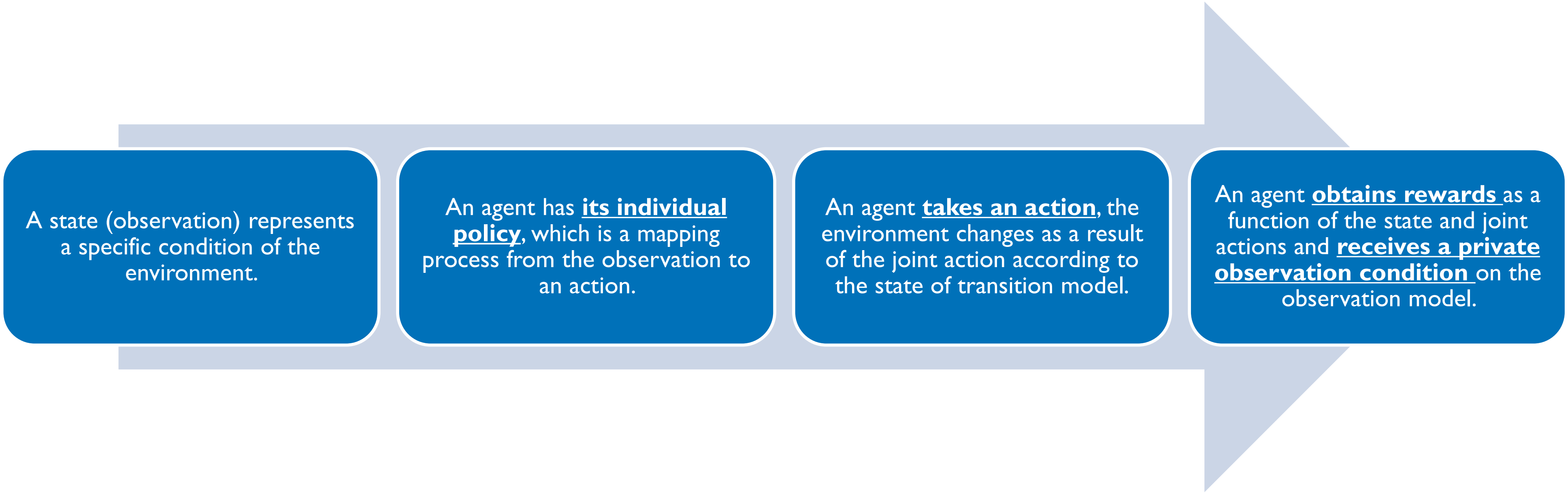






Soft Actor-Critic (SAC) Learning Approach

- *A single or multi-agent framework is utilized to formulate a Markov game, where it is required to maximize the discounted returns.*
  - Actor network: provides proper actions
  - Critic network: learns the optimal policy for the actor network to take decisions



Implementation

- *This paper utilizes SAC algorithm to control circuit switches of distribution feeder for operational resilience enhancement during hurricanes.*

Hurricane Impacts

- A hurricane propagates across power grid based on their spatiotemporal behavior.
- Various components can be impacted at sequential time intervals.
- A state represents a unique system topology.
- A power grid may reside in different states at each time instant.

Fragility Model

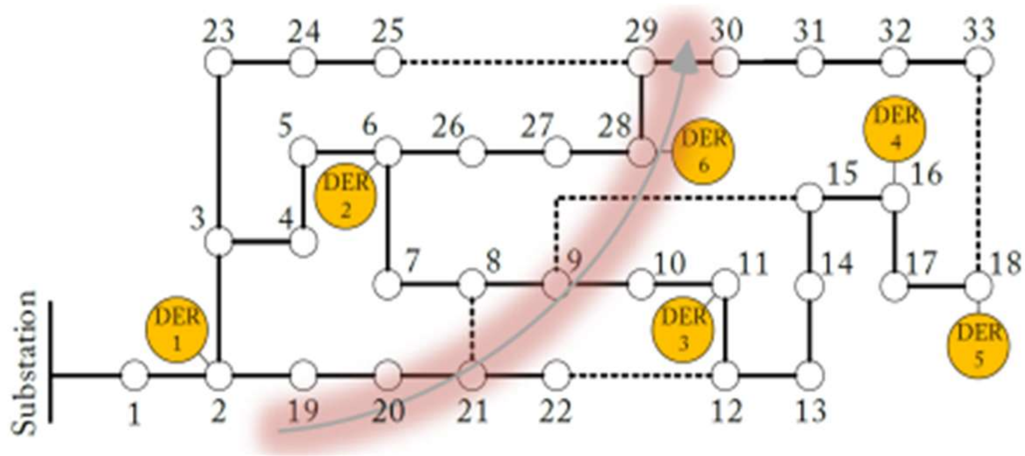
- Fragility model quantifies the failure probability of each component in terms of weather parameters from both temporal and spatial perspectives.
- The spatiotemporal characteristics of hurricanes are governed by key parameters that identify their uncertainties.
- The hurricane model is governed by wind speed, wind direction, central pressure, and translational speed.

SAC algorithm

- A single agent framework is utilized to train SAC networks for network reconfiguration in distribution system.
- For a specific state, operational constraints might not be fully satisfied such as the absence of a slack bus for each microgrid or lost connectivity to load spots.
- Even fulfilling all system constraints might lead to existence of load curtailments due to insufficient generation supply.

Case Study

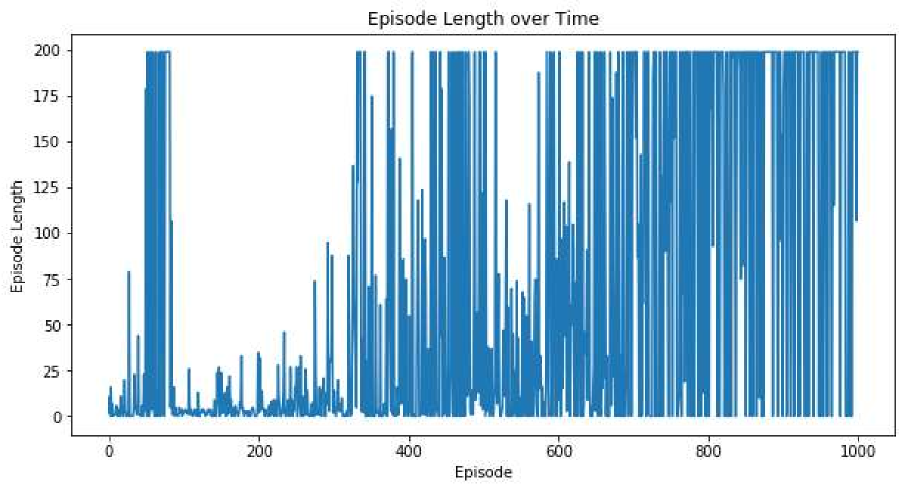
- *System under study:*
  - A modified IEEE 33-node distribution feeder.
  - 6 DERs with 1 MW maximum capacity each.
- *Hurricane scenario:*
  - Statistical parameters for hurricane model in Northeastern region of USA are obtained.
  - Fragility model is used to list of potential failure components.
- *Actor network:*
  - Single hidden layer (32 neurons)
  - ReLu activation function
  - Output layer has 44 outputs (switches)
- *Critic network:*
  - Single hidden layer (32 neurons)
  - Softmax activation function
  - Output layer has single output (Q-value)

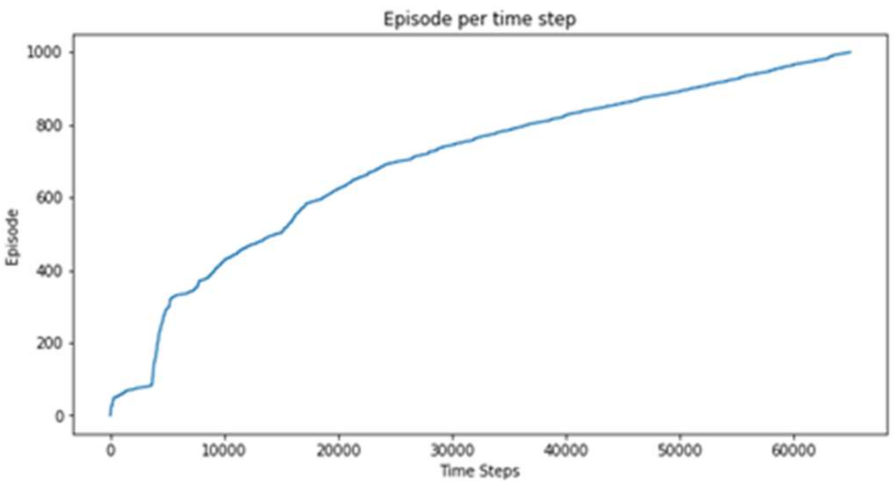


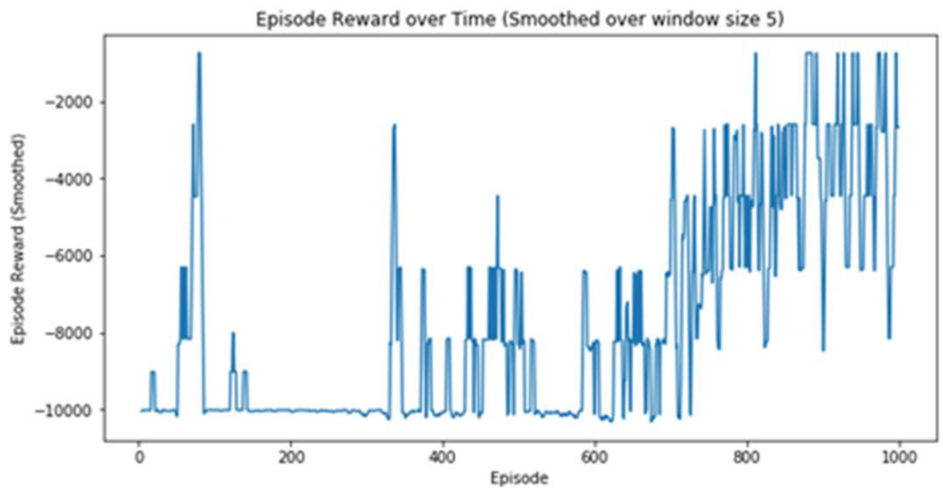
Key parameter	PDF type	Parameters
Wind speed	Lognormal	$\mu = 2.66\, m/s, \sigma = 0.5185$
Wind direction	Binormal	$\mu_1 = -73.3, \mu_2 = -7{,}2,$ $\sigma_1 = 22.6, \sigma_2 = 70.35, \alpha = 0.5$
Central pressure	Uniform	$H_0 \in [1.5, 3]\, hPa$
Translational speed	Uniform	$V_T \in [0{,}15]\, m/s$

Results

- *Case 1: 1000 episodes - 200 steps (decisions) per episode*
- *SAC learns to capture the features of the system states*
- *As SAC learns, it balances between exploratory and exploitation actions.*

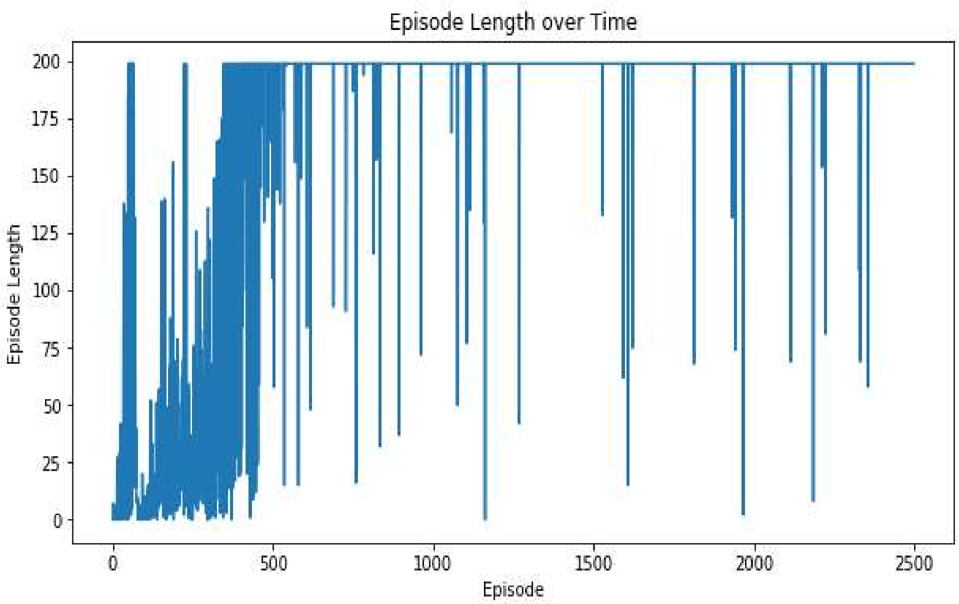


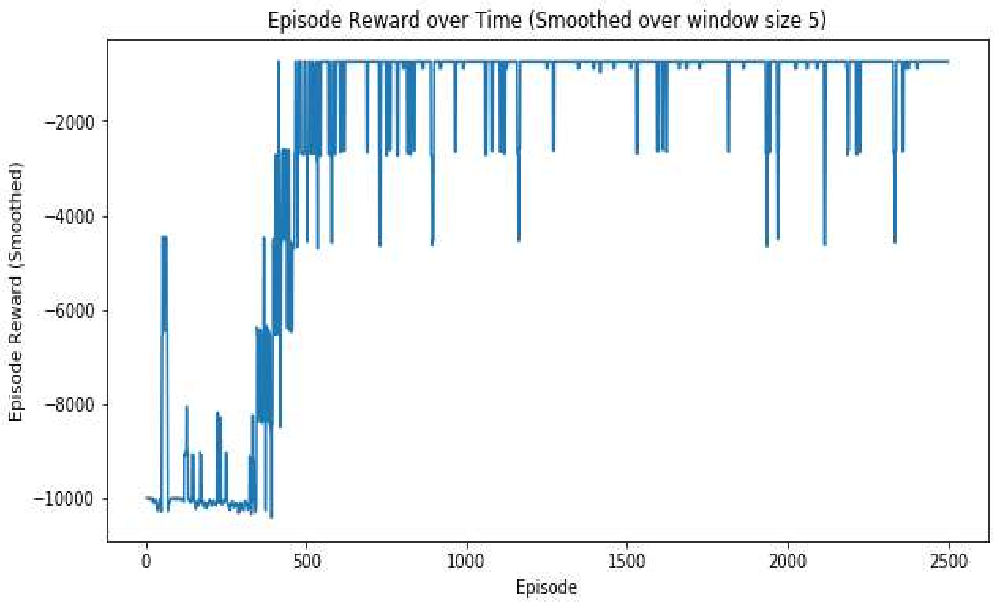




Results (Cont'd)

- *Case 2: 2500 episodes - 200 steps per episode*
- *As the larger number of episodes are simulated, the SAC algorithm attains better learning behavior.*
- *200 steps limit per episode are not properly sufficient to further improvements.*
- *SAC tuning parameters can be adjusted to achieve higher efficiency.*





Conclusion

- *This paper has proposed an RL-based resilience enhancement approach to improve the resilience of electric distribution systems against hurricanes.*
- *The proposed method trains a SAC algorithm to determine the best set of actions to reconfigure the network feeder into a new set of networks that maintain operational constraints and achieve minimal load curtailments.*
- *A hurricane fragility model is used to simulate numerous scenarios based on predefined weather parameters.*
- *The results showed the effectiveness of the SAC to learn from failure scenarios and to provide set of decisions for possible network configuration.*