SPADES 2021 - Cornell - Year-end Review

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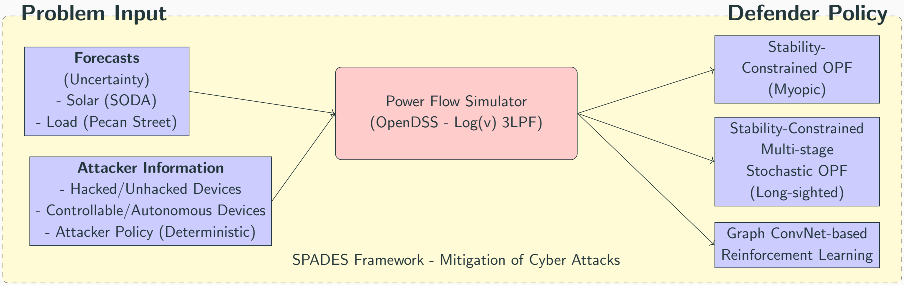
SPADES. Motivation/Context

- **Goal:** To learn defender policies that mitigate cyber attacks to distributed energy resources, e.g. solar inverters and energy storage.
- **Two different approaches:**
  - *Fundamental Approach.* Understanding behavior of controller devices in the network and finding guarantees of stability
  - *Learning Approach.* Leveraging low-dimensional representation of the voltage phasors to learn control policies through neural networks.
- **Tools needed:**
  - Forecasts (solar and load)[1]
  - Situational Awareness (compromised vs non-compromised devices)
  - Deterministic Attacker Policy.
  - Power Flow Simulator.

[1] In red are past contributions (published research)

Problem Framework



Past Work:

Log(v) 3LPF
A Linear Power Flow Solver for Unbalanced Three-Phase Distribution Systems

SoDa

Current Work:

Spatio-Temporal Graph ConvNet-based Reinforcement Learning for Distribution Network Voltage Control

Tong Wu, *Member, IEEE*, Ignacio Losada Carreño, *Member, IEEE*, Anna Scaglione, *Fellow, IEEE*, Daniel Arnold, *Member, IEEE*,

Voltage stability of three-phase unbalanced distribution power systems under uncertainty

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Log(v) 3LPF

Log(v) 3LPF is used as the power flow simulator

Log(v) 3LPF:

- Developed a linear power flow simulator derived from first principles.
- Agnostic to the structure of the network (mesh vs radial).
- Models all common network elements found in distribution systems.
- Efficiently solves the system of equations (i.e. it is fast)
- Convergence guarantees

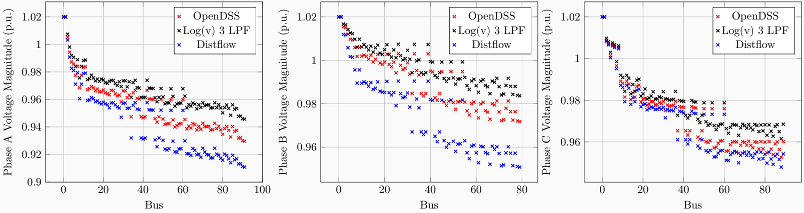


Figure 1: OpenDSS vs Log(v) 3LPF vs Linear DistFlow equations from Schweitzer et al., 2019. Voltage magnitude for all phases, IEEE-123 test case

Log(v) 3LPF solves very large test cases, e.g. the IEEE-8500

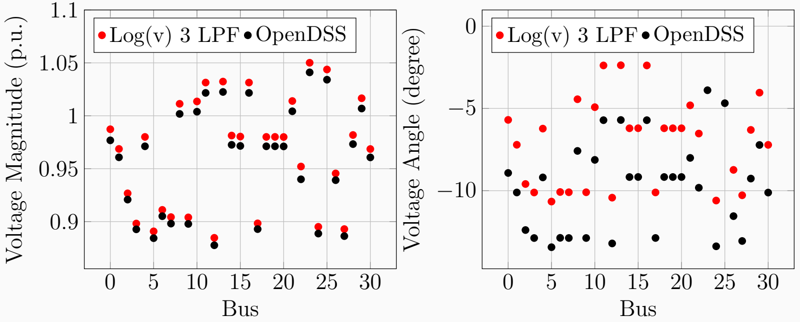


Figure 2: IEEE-8500, Voltage magnitude (left) and angle (right) results from phase 1. Figure shows 30 random buses

The Log(v) 3LPF yields results similar to the "exact" solution

Table 1: Accuracy of Log(v) 3LPF - OpenDSS

Case	**Voltage Magnitude**		**Voltage Angle**
	RMSE (p.u.)	MAPE (%)	RMSE (deg)
IEEE-13	0.01	1.06	1.58
IEEE-34	0.03	2.46	2.10
IEEE-37	0.03	2.97	0.38
IEEE-123	0.02	1.64	0.62
European LV	0.00	0.09	0.15
IEEE-8500	0.02	2.45	3.44

Log(v) 3LPF can be used in Reinforcement Learning

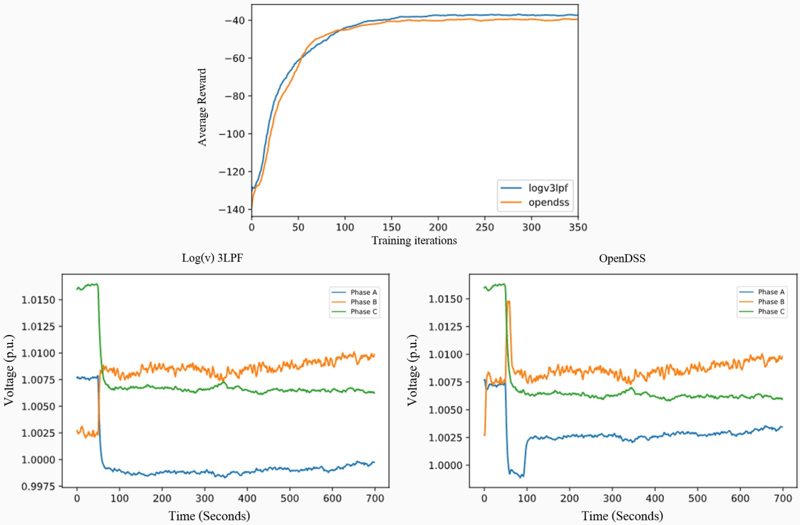


Figure 3: Average policy reward (top), OpenDSS vs Log(v) 3LPF. Policy evaluation (after training) with log(v) 3LPF (left) vs openDSS (right)

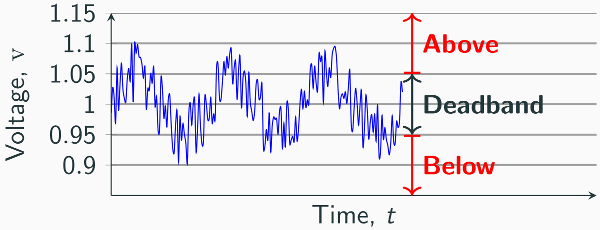
Voltage stability in distribution systems under uncertainty (a.k.a. fundamental approach)

Voltage stability in distribution power systems

Goal: Study the *voltage stability* of a distribution system and propose a method to dispatch generation (controls) to stabilize the system under a cyber attack.

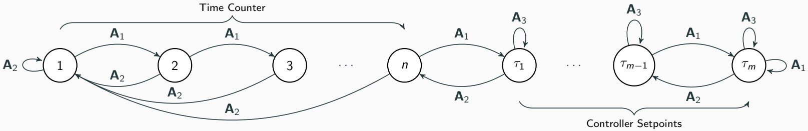
Voltage stability during a cyber attack:

- Destabilizing behavior created by controllers/generators.
- Controllers have 3 operating modes, above/below/within deadband
- Two categories:
    - Devices change power injection - *Continuous dynamics*
    - Devices change line admittance - *Discrete dynamics*



Discrete dynamics. Devices that change line admittance

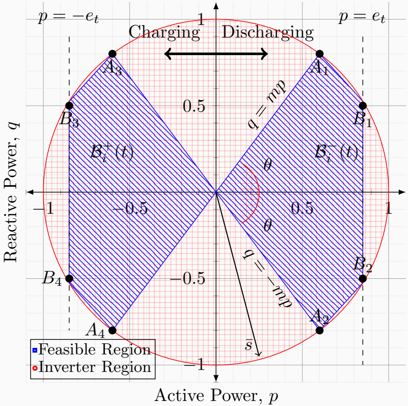
General Form: $\mathbf{x}_{t+1} = \mathbf{A}_{\sigma(\mathbf{x}_t; \boldsymbol{s}_t)} \mathbf{x}_t, \quad \mathbf{x}_t \in \{0,1\}^k, \sigma(\mathbf{x}_t; \boldsymbol{s}_t) \in \{1,2,3\}$



- Examples: Voltage regulator, cap banks, switches, relays.
- **Stability:**
  - System above is not stable under arbitrary switching
  - Provide a mathematical proof. *Intuition:* In figure above, I can always find a condition that moves the system to a new state.

Continuous dynamics. Devices that change power injection

$$\textbf{General Form:} \quad \mathbf{T}\dot{\mathbf{s}} = \mathbf{f}(\mathbf{s}_t, \mathbf{x}_t, \boldsymbol{\eta}_t, \mathbf{e}_t) - \mathbf{s}_t, \quad \boldsymbol{\eta}_t \in \{0,1\} \text{ (Charging)}$$
$$\dot{\mathbf{e}} = \mathbf{p}_t \quad \text{(only in batteries, } \mathbf{e}_t \text{ is power available)} \tag{1}$$

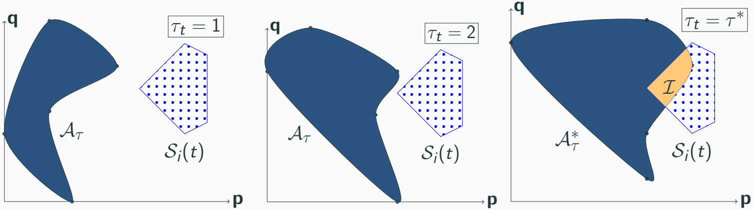


- Examples: Batteries and solar panels
- Feasible region is non-convex. Use binary to express as convex region.
- Stability proof found in *Reference Dan's paper

Discrete + Continuous dynamics. Hybrid automaton

What we know so far:

- Discrete dynamics are unstable under *arbitrary switching*
- We can find guarantees of stability of continuous dynamics
- Stability of both. How? By means of constrained switching



τ are the setpoints of the discrete controllers, $\mathcal{S}_i(t)$ is the feasible set of power injections that the inverters can produce, $\mathcal{A}_\tau$ are the set of power injections that induce a voltage within the deadband (stable), $\mathcal{I}$ is the "stable" regions.

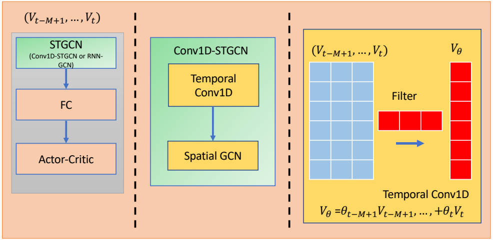
Graph ConvNet-based Reinforcement Learning

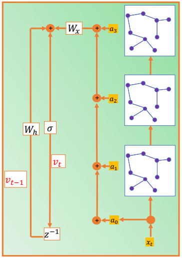
Graph ConvNet-based Reinforcement Learning

Goals: To design a model-free volt-VAR control (VVC) algorithm via spatio-temporal graph ConvNet-based RL framework to control power delivery elements in the unbalanced distribution systems.

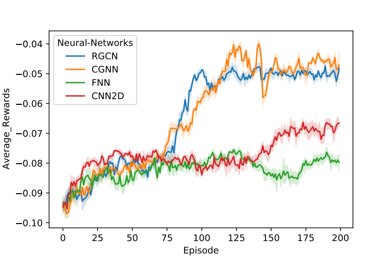
Contributions:

- To capture spatio-temporal correlation of voltage measurement:
  - We propose spatio-temporal Graph Convolutional Networks
- To consider sparse observation of voltage phasor measurement
- To consider distributed control by multi-agent RL
- Applications: cyber-attack mitigation





Reinforcement Learning for Voltage Regulation



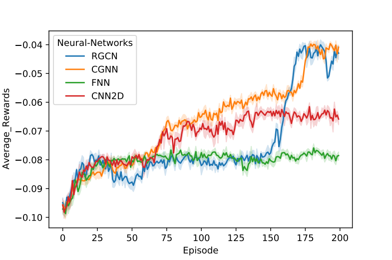


Figure 4: Based on the three-phase IEEE 13-bus feeder, two smart inverters are installed, and actions are taken by DRLs to change the power injections of smart inverters. The rewards are used to penalize voltage deviations , i.e., $rewards = -\sum_{i \in \mathcal{N}s} \left| V_i - V^{ref} \right|$. The two figures compare the performance of CGCN and RGCN with fully-connected NN, CNN within DRL, where the left one is based on full observations of graph signals, and the right one is based on sparse observations of graph signals (with 8 sensors installed in 41 buses).

Reinforcement Learning for Cyber-Attack Mitigation

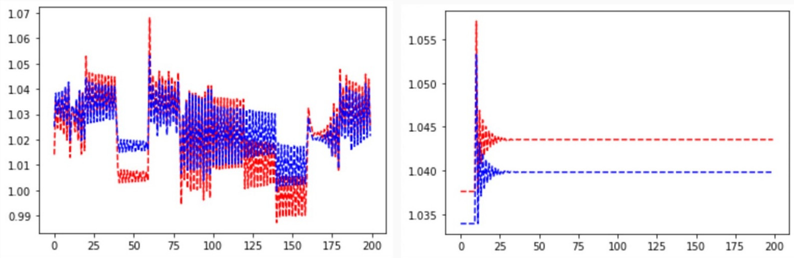


Figure 5: Voltage profiles with oscillations, including the left figure with the FC-based RL control and the right figure with the RGCN-based RL control.

Single-Agent and Multi-Agents

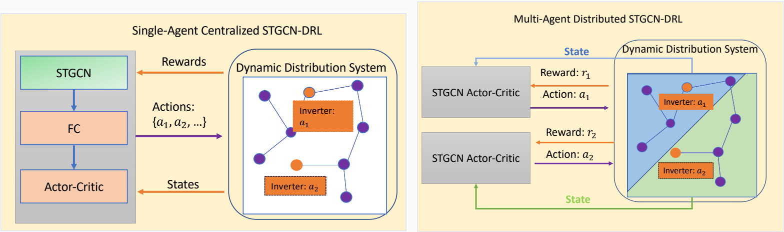


Figure 6: (Left) Singe-Agent DRL and (Right) Multi-Agent DRL.

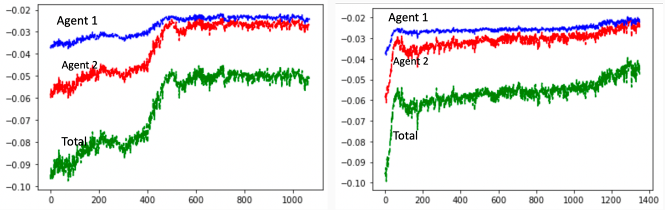


Figure 7: Reward Curves. (Left) Singe-Agent DRL and (Right) Multi-Agent DRL.

SPADES 2021 in a nutshell

Student/Staff:

- SINE Lab transferred to Cornell University
- Ignacio passed his Qualifying Exam
- Tong joined the lab as a Post-Doc in Summer

Research:

- SODA and Log(v) 3LPF are now open-source.
- Submitted "*Log(v) 3LPF: A Linear Power Flow Formulation for Unbalanced Three-Phase Distribution Systems*" to *IEEE Transactions on Power Systems*. 2nd round of revisions
- Working draft "*Voltage stability of three-phase unbalanced distribution power systems under uncertainty*"
- Working draft "*Spatio-Temporal Graph ConvNet-based Reinforcement Learning for Distribution Network Voltage Control*"

Future Work

Future Work (Tentative):

- Develop correlated load-solar time series
- Implement probabilistic attacker policy (modeling cyber layer).
- Develop GNN-based reinforcement learning open-source library for network control.