

Grid Mind

-Data-driven Autonomous Grid Dispatch and Control Based on AI

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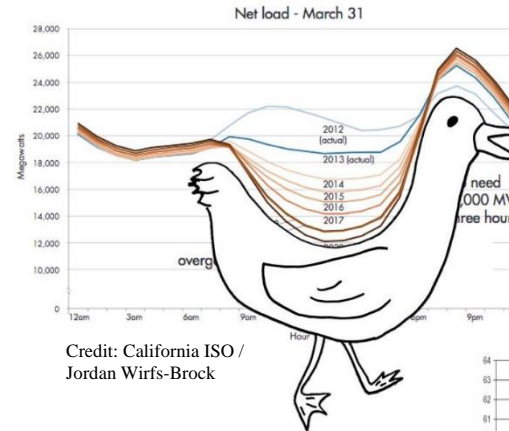
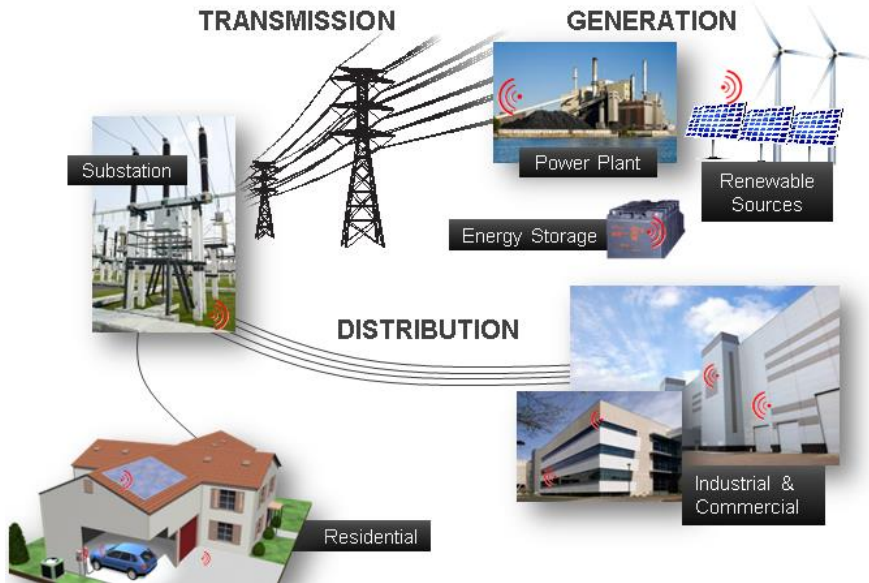
GEIRI North America (GEIRINA)
San Jose, CA 95134

June 27, 2019

Outline

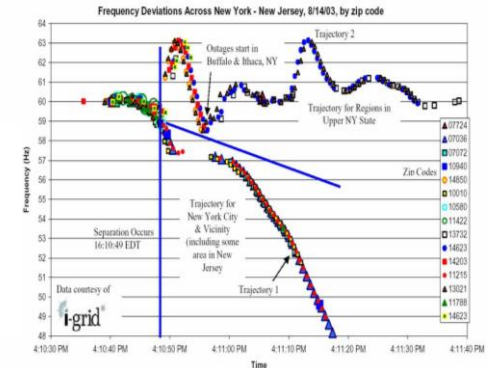
- Background and motivation
- Autonomous grid dispatch and control based on PMU measurements
 - Deep Reinforcement Learning
 - Autonomous voltage control
 - Demo
- How to architect/tune an effective self-learning agent?
- Discussion/other applications

Challenges



Credit: California ISO / Jordan Wirfs-Brock

System fast dynamic responses under extreme events – the August 2003 North American Blackout



Grand challenges: the increasing dynamics and stochastics in the modern power grid, making it difficult to design and implement optimal control actions in real time

- Increased penetration of renewable energy
- Demand response
- New market behavior
- Energy storage
- Experience/model based control suggestions using limited studied cases are either conservative or risky for operation



Need for accurate and fast wide-area monitoring system to detect potential issues

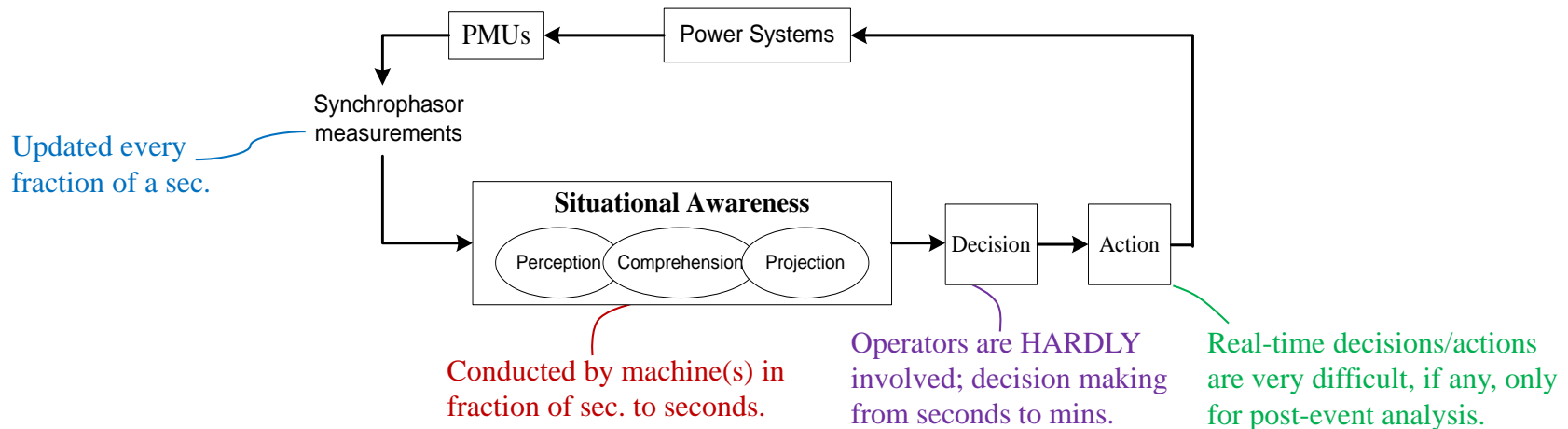
- PMU coverage is increasing, but still limited
- Known data quality issues affect apps
- Lack of preventive measures to mitigate operational risks

Need for effective optimal control suggestions in real time to support operators

- Most operational rules are offline determined
- Either by experiences or projected simulations

The Gap

- Past efforts were mostly focused on enhancing/increasing grid situational awareness using advanced modeling, various data analysis approaches, machine learning, etc.
- Very few WAMS apps can instruct operators what to do in real time due to the lack of effective approaches that can transform massive amount of measurements directly into actionable decisions in real time.



- ❑ Potential apps of WAMS are limited, and GEIRINA wish to bridge this gap.
- ❑ On Sept. 25 2018, DOE announced investments to improve resilience and reliability of the nation's energy infrastructure using PMU measurements and big data, AI, machine learning technologies.
 - ✓ "...to inform and shape development and application of **fast grid analytics** and **sub-second automatic control** actions that preclude costly cascading grid outages"
 - ✓ "...**PMU-based automated controls**, better grid asset management, and real time monitoring for modeling..."

FINANCIAL ASSISTANCE
FUNDING OPPORTUNITY ANNOUNCEMENT



Department of Energy (DOE)
Office of Electricity (OE)

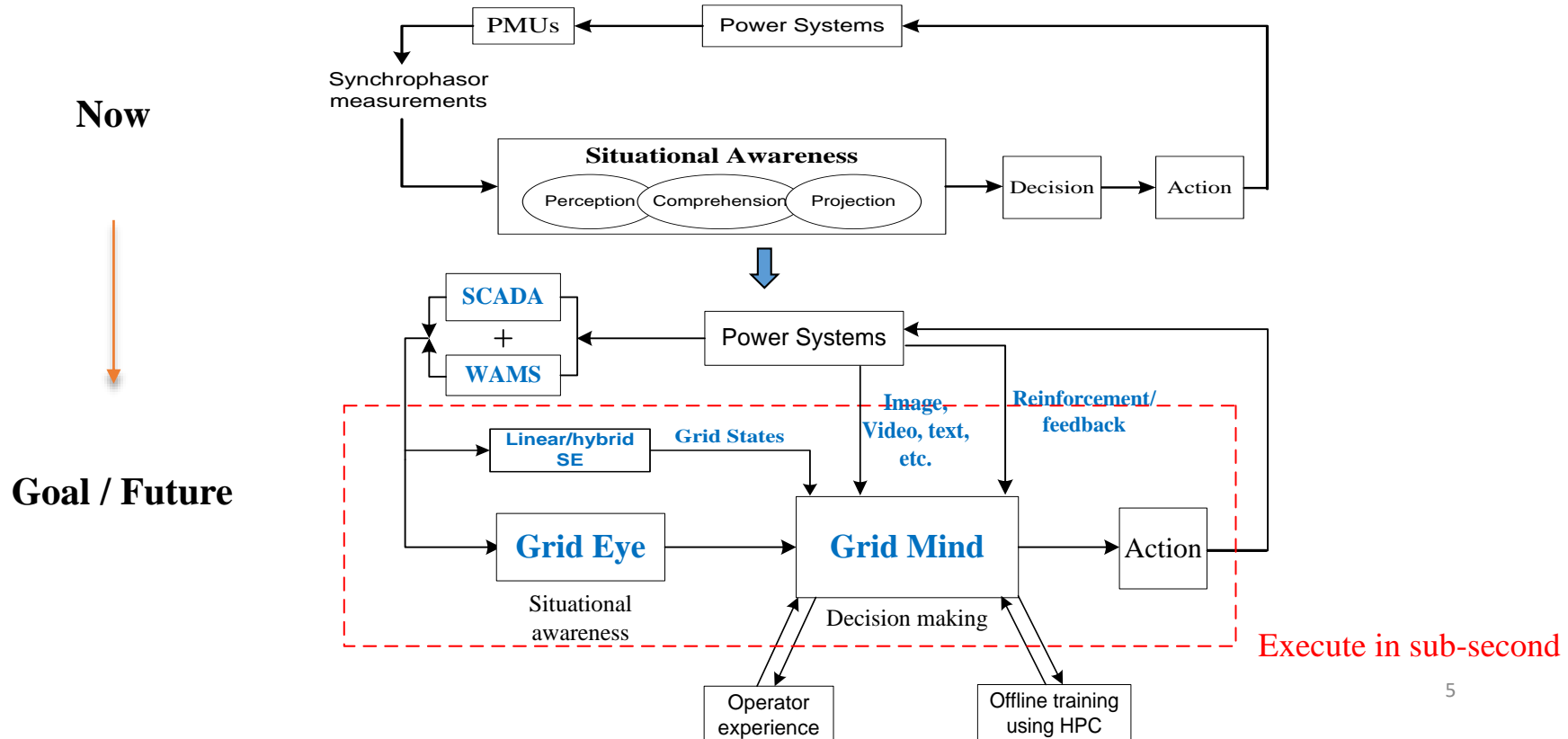
BIG DATA ANALYSIS OF SYNCHROPHASOR DATA
Funding Opportunity Announcement (FOA) Number: DE-FOA-0001861
FOA Type: Initial
CFDA Number: 81.122, Electricity Delivery and Energy Reliability, Research, Development and Analysis

FOA Issue Date:	September 25, 2018
Submission Deadline for Full Applications:	November 9, 2018/8:00 PM ET
Expected Date for Selection Notifications:	January 2019
Expected Date for Award:	March 2019

The Grid Mind Vision

- **Grid Mind: A measurement-driven, grid-interactive, self-evolving, and open platform for power system autonomous dispatch and control.**
- ❑ In the short term, we want to create an example of AlphaGo Zero in power systems.
- ❑ In the mid-term, Grid Mind serves as an assistant to grid operators.
- ❑ In the long term, Grid Mind will be the core of power system operation ROBOT.

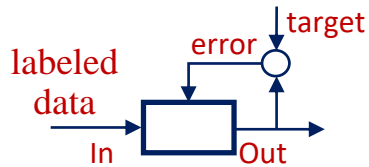
Goal: To develop a tool that can transform massive amount of measurements into actionable decisions in real time.



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Supervised Learning



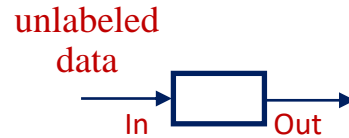
Application

- ✓ Classification
- ✓ Predict a target numeric value

Common Algorithms

- *k*-Nearest Neighbors
- Linear Regression
- Decision Trees
- Naïve Bayes
- SVM
- Neural Networks

Unsupervised Learning



Application

- ✓ Clustering
- ✓ Visualization
- ✓ Dimensionality reduction
- ✓ Anomaly detection

Common Algorithms

- *k*-Means
- Hierarchical Cluster Analysis
- Principal Component Analysis

Semi-supervised Learning



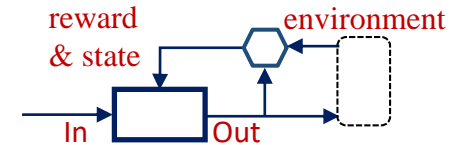
Application

- ✓ Google Photos
- ✓ Webpage classification

Common Algorithms

- Combination of unsupervised and supervised learning

Reinforcement Learning



Application

- ✓ DeepMind's AlphaGo
- ✓ Fire-extinguish robots
- ✓ **Grid Mind**

Common Algorithms

- Dynamic programming
- Monte Carlo
- Temporal Difference (TD)
 - ✓ Q-Learning
 - ✓ SARSA

Reinforcement Learning (RL)

❑ Learn what to do and how to map situation to action.

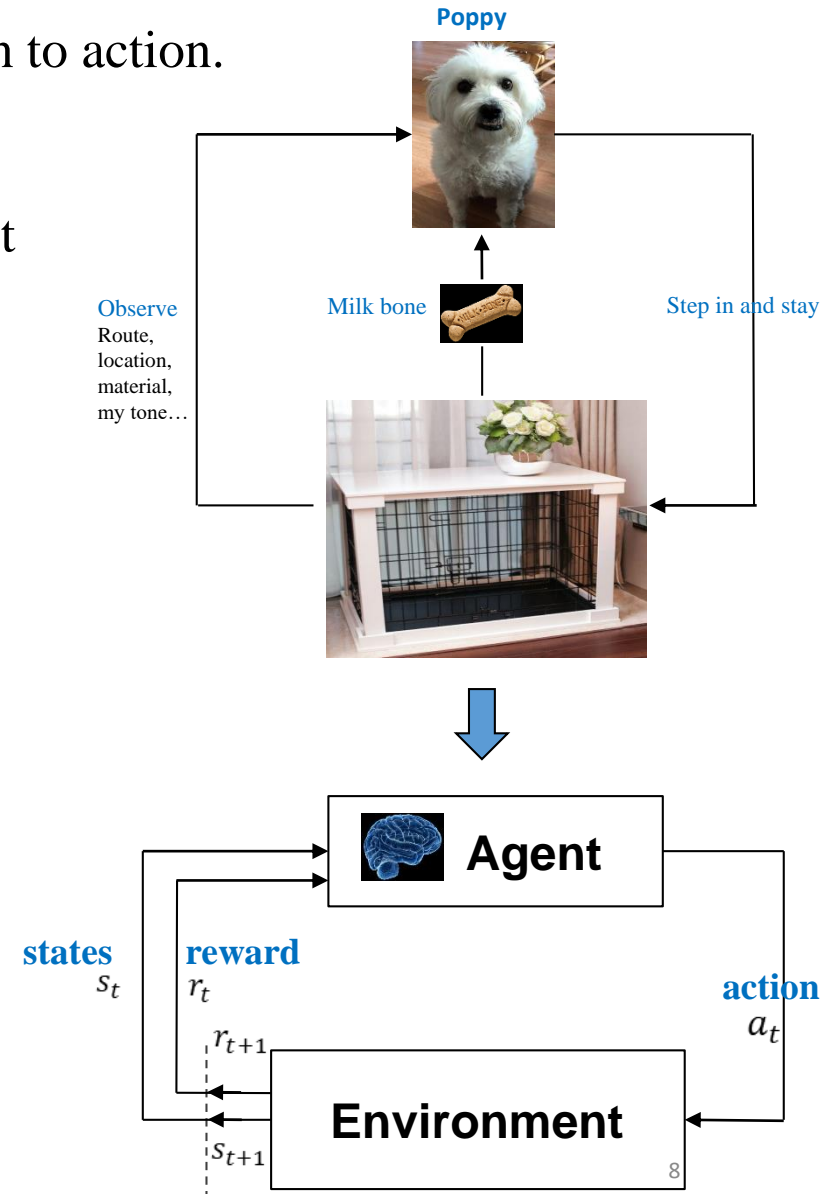
❑ Poppy's example.

❑ The RL system: agent and environment. At each time step t :

- The agent
 - ✓1) executes action a_t
 - ✓2) observes states s_t
 - ✓3) receives a scalar reward r_t
- The environment
 - ✓1) receives action a_t
 - ✓2) emits states s_{t+1}
 - ✓3) issues a reward r_{t+1}

❑ Reinforcement function

- Trial-and-error interactions
- Mapping states/action pair to reinforcement
- Maximization of the sum of reward/value



RL Agent

❑ An RL agent may include one or more of the following components:

- **Policy:** agent's behavior function
 - ✓ A map from state to action
 - Deterministic policy $a = \pi(s)$
 - Stochastic policy $\pi(a|s) = P(a|s)$
- **Value function:** prediction of future reward
 - ✓ How much reward can be obtained if I perform action a in state s
- **Model:** agent's representation of the environment

❑ Q-value function gives expected total reward

- ✓ from state s and action a
- ✓ under policy π
- ✓ with discount factor γ

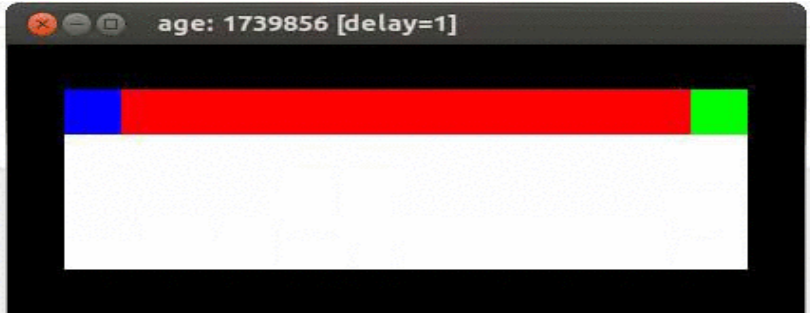
$$Q^\pi(s, a) = \mathbb{E}(r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \dots | s, a)$$

❑ An optimal value function is the maximum achievable value

$$Q^*(s, a) = \max_{\pi} Q^\pi(s, a) = Q^{\pi^*}(s, a)$$

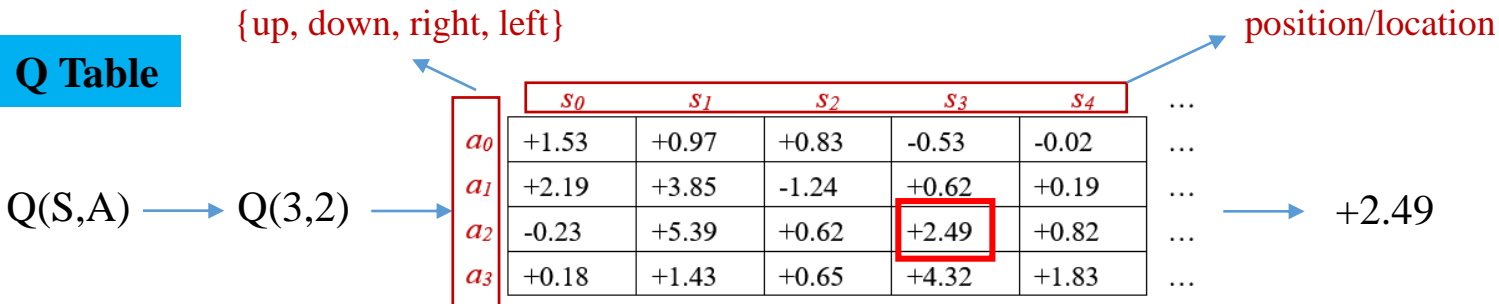
Q-Learning

Example: Mouse vs Cliff¹

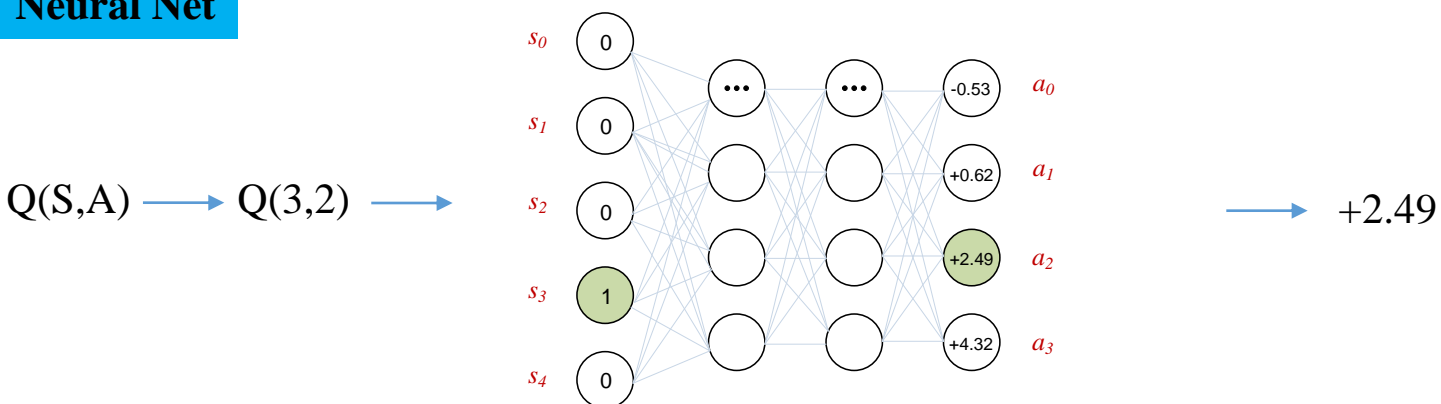


Blue-mouse
Red-cliff
Green-cheese

Q Table



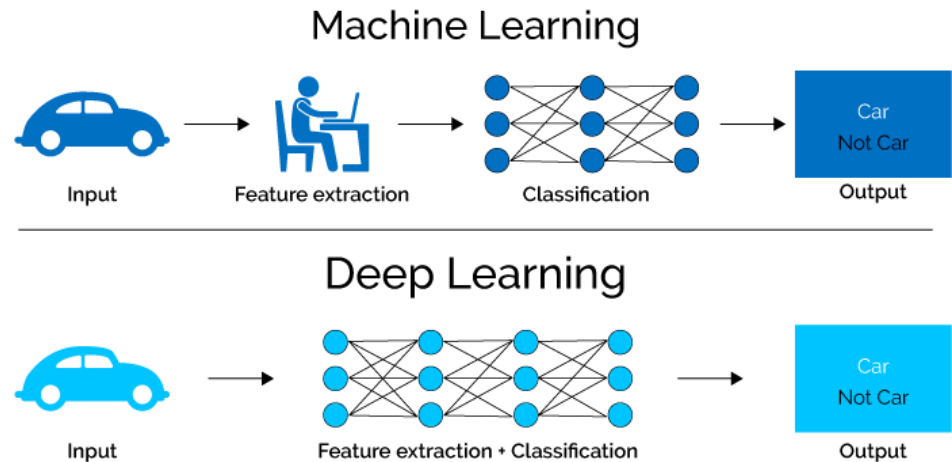
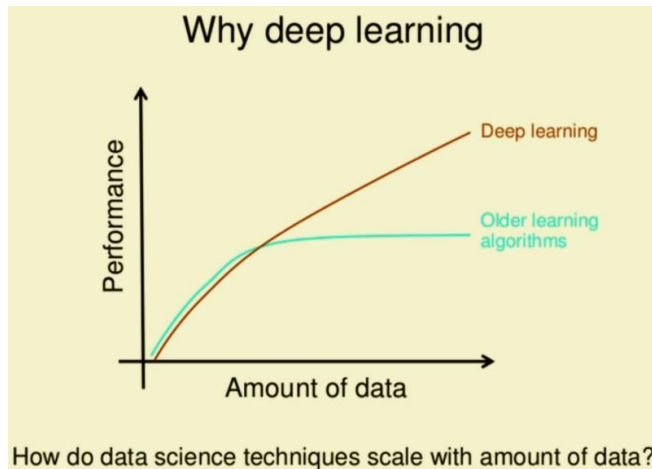
Neural Net



¹<https://studywolf.wordpress.com/2013/07/01/reinforcement-learning-sarsa-vs-q-learning/>

Deep Learning in a Nutshell

- Deep learning is a general-purpose framework for representation learning
 - Given an **objective**
 - Learn **representation** that is required to achieve objective
 - Directly from **raw inputs**
 - Using **minimal domain knowledge**
 - Represent the world using **nested hierarchy of concepts** (each using simpler ones)



Source: <https://towardsdatascience.com>

Deep Reinforcement Learning (DRL)

- ❑ DRL=DL+RL
- ❑ DL is a general-purpose framework for representation learning
- ❑ RL is a general-purpose framework for decision-making in a dynamic environment
- ❑ We seek a single agent that can solve a human-level task
 - RL defines the objective
 - DL gives the mechanism
 - RL+DL → general intelligence
- ❑ Use deep neural networks to represent
 - Value function
 - Policy
 - Model

Outline

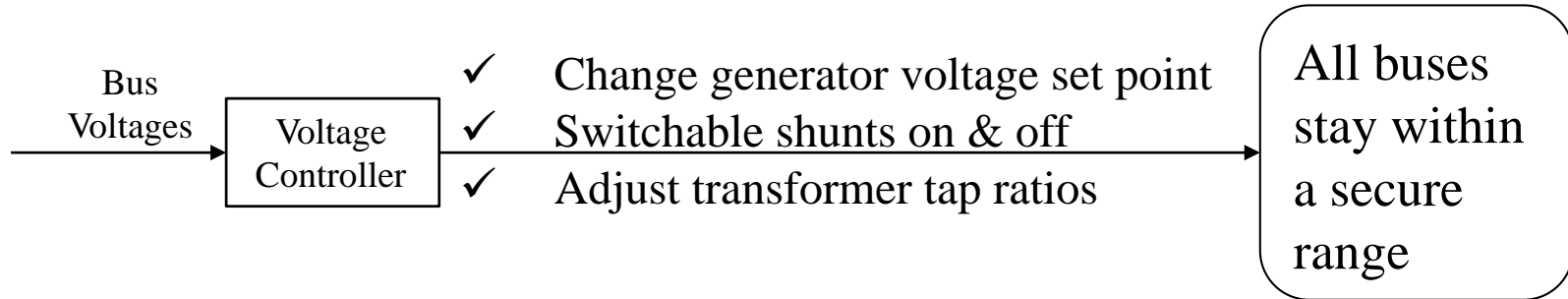
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Autonomous Voltage Control (AVC)

(Considering load variation, renewable intermittency and contingency conditions)

Objective:

Maintain steady-state voltages at all buses within the range of 0.95-1.05pu after disturbance(s) or contingencies from any given initial operating point.

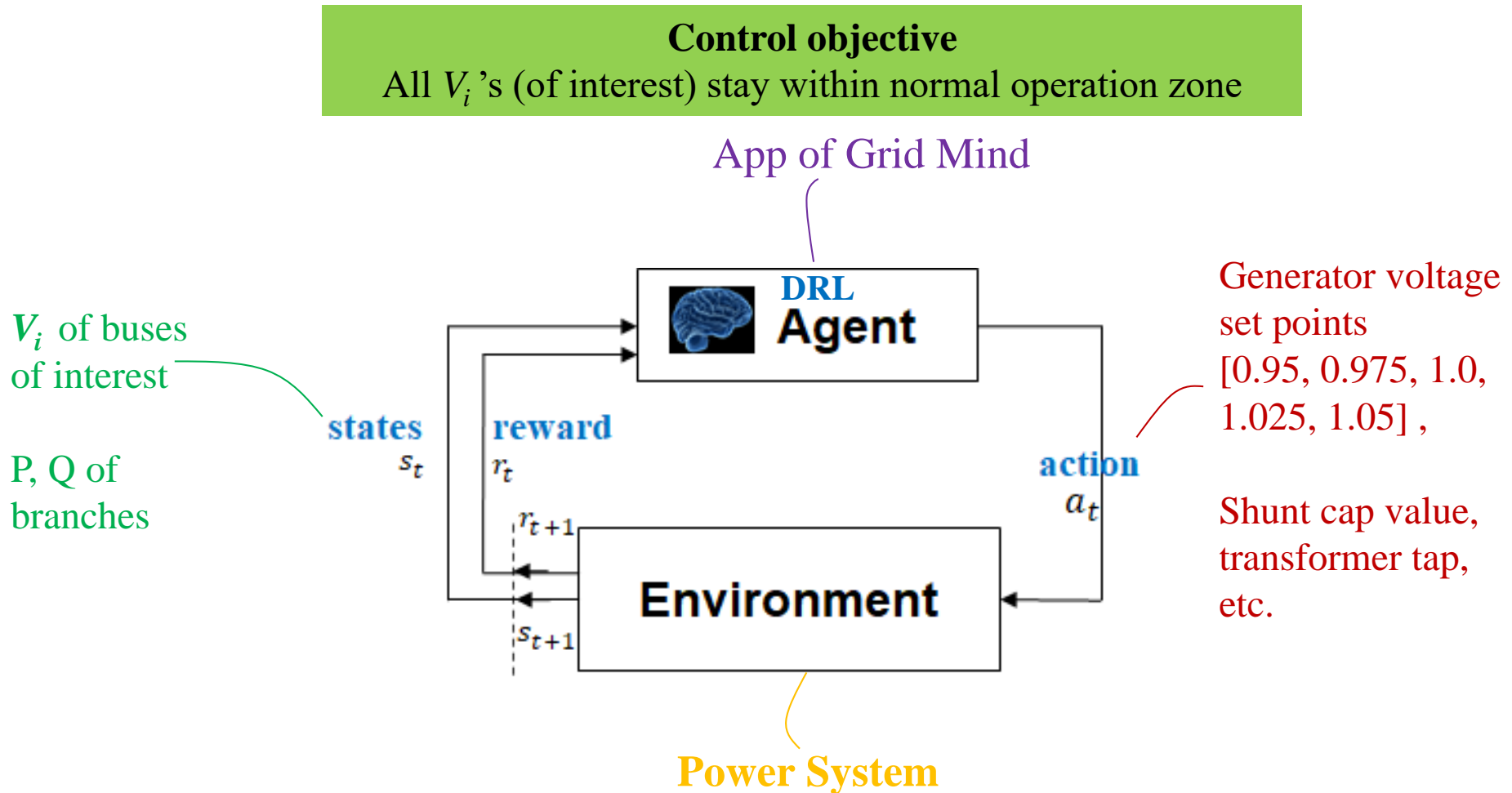


Challenges for conventional technologies

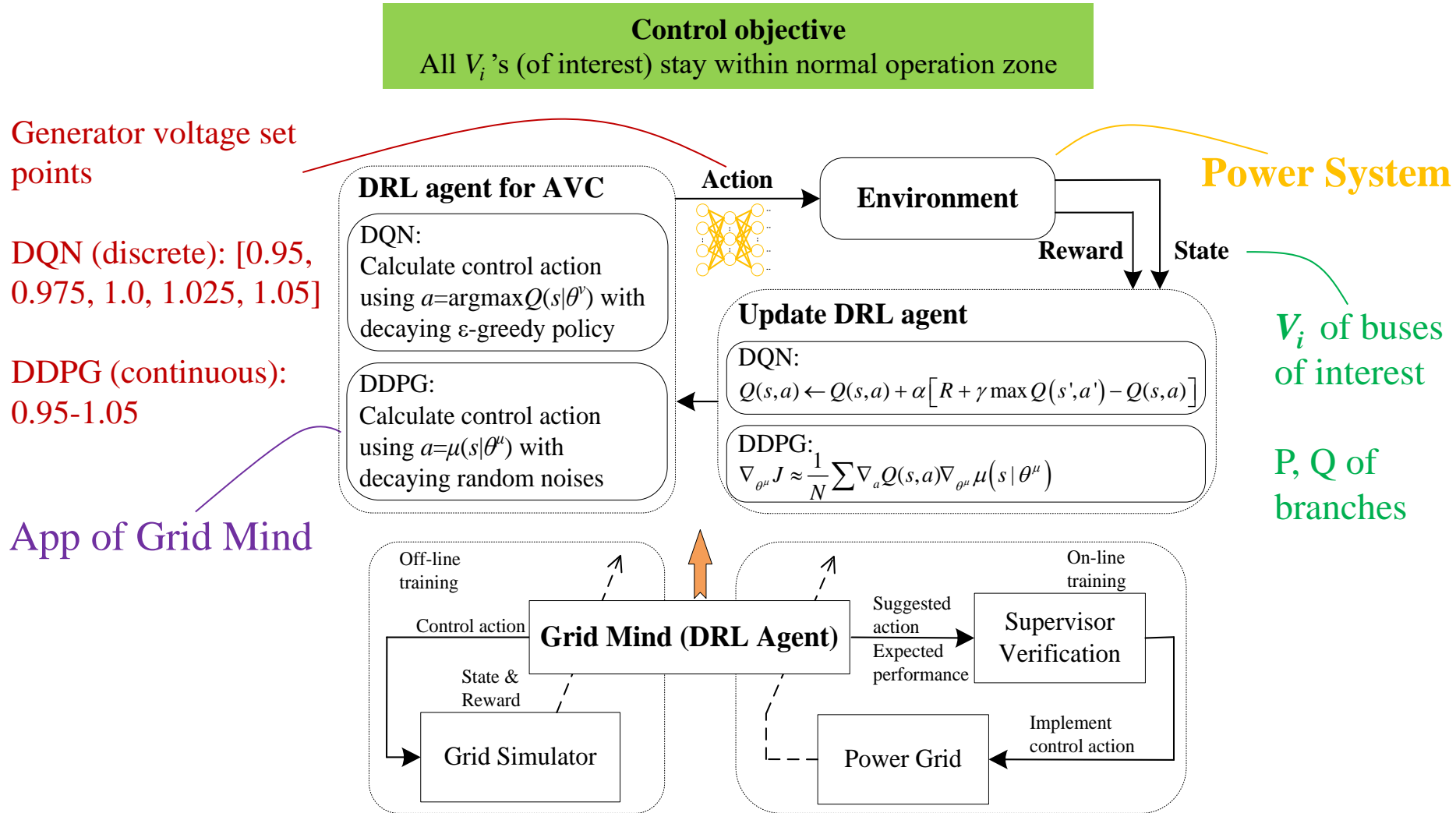
- Increasing complexity, e.g., renewable energies
- Increasing scale, e.g., wide-area power systems
- High nonlinearity, e.g., nonlinear loads
- Fast response speed, e.g., power electronics

DRL Formulation for AVC

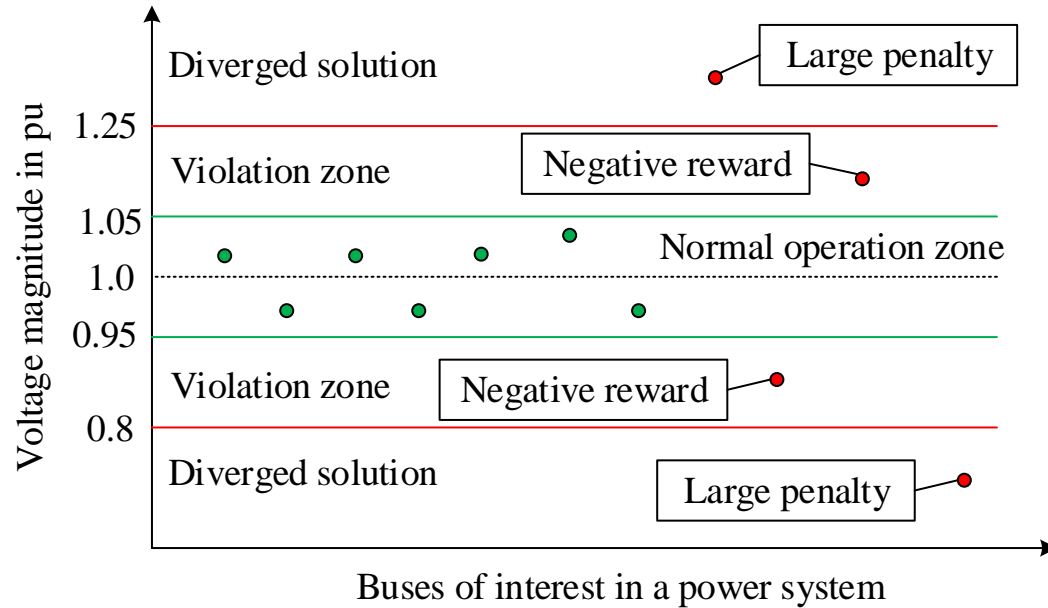
Firstly, let's define V_i as the voltage phasor of bus i (including both magnitude and phase angle).



AVC Training Algorithm



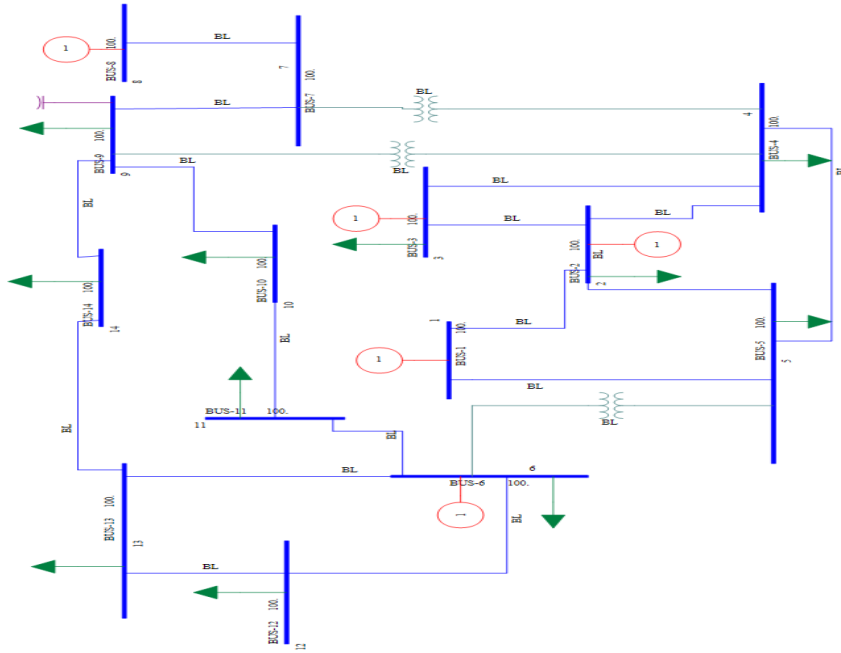
DRL Formulation for Voltage Control-Reward



$$\mathbf{Reward} \text{ at one iteration} = \begin{cases} \text{Large reward } (+R_p), & \forall V_i \in \text{normal operation zone} \\ \text{Large penalty } (-P_e), & \exists V_i \in \text{diverged solution} \\ \text{Negative Reward } (-R_N), & \exists V_i \in \text{violation zone} \end{cases}$$

$$\mathbf{Final Reward} = \text{Sum}(\mathbf{Reward}) / \text{number of iterations}$$

Case Study



Testing system: IEEE 14-Bus system

System Info.

- 14 buses
- 5 generators
- 11 loads
- 17 lines
- 3 transformers
- Active load: 259 MW
- Reactive load: 73.5 MVar

Testing Condition

- IEEE 14-bus System
- 10k episodes (created randomly)
- 60%~120% random load change
- A single-NN DQN agent
- 2 layers with 20 neurons/layer
- Without using regularization
- 120 action space (permutation of 5 choices)

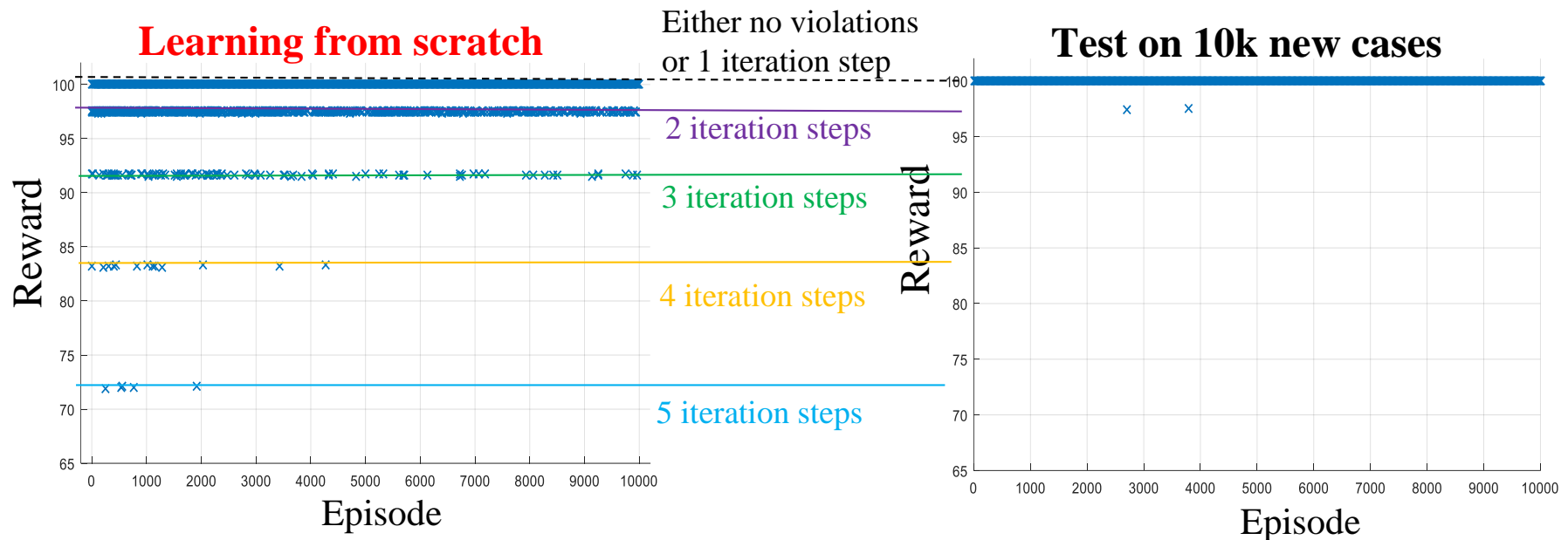
Note: Grid Mind does not know the model of the system or its electrical parameters.

So it learns from the scratch

1. Initializing the probability of using random control actions to be $p_r(0)=1$
2. for Episode i
3. $p_r(i+1)=0.95p_r(i)$

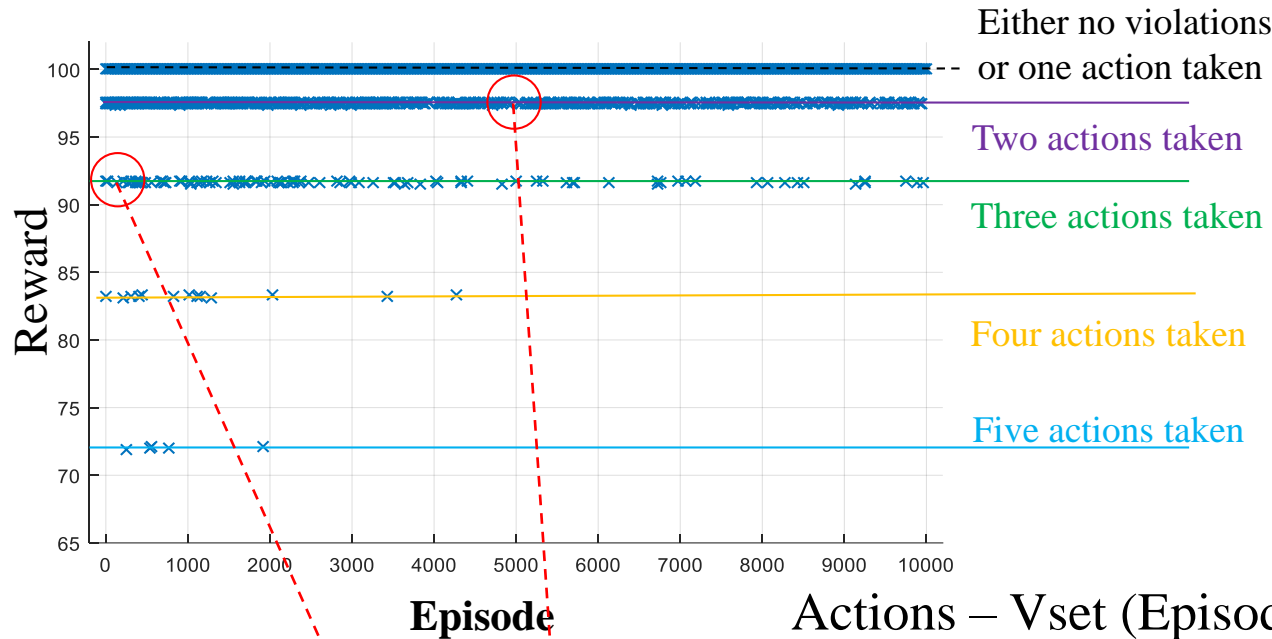
DQN Agent for IEEE 14-bus System

60%-120% random load changes are applied to each episode



After 10,000 episodes' learning, the designed DQN agent starts to master the voltage control problem by making decisions autonomously.

A Closer Look at the Results



60%-120% random
system load changes

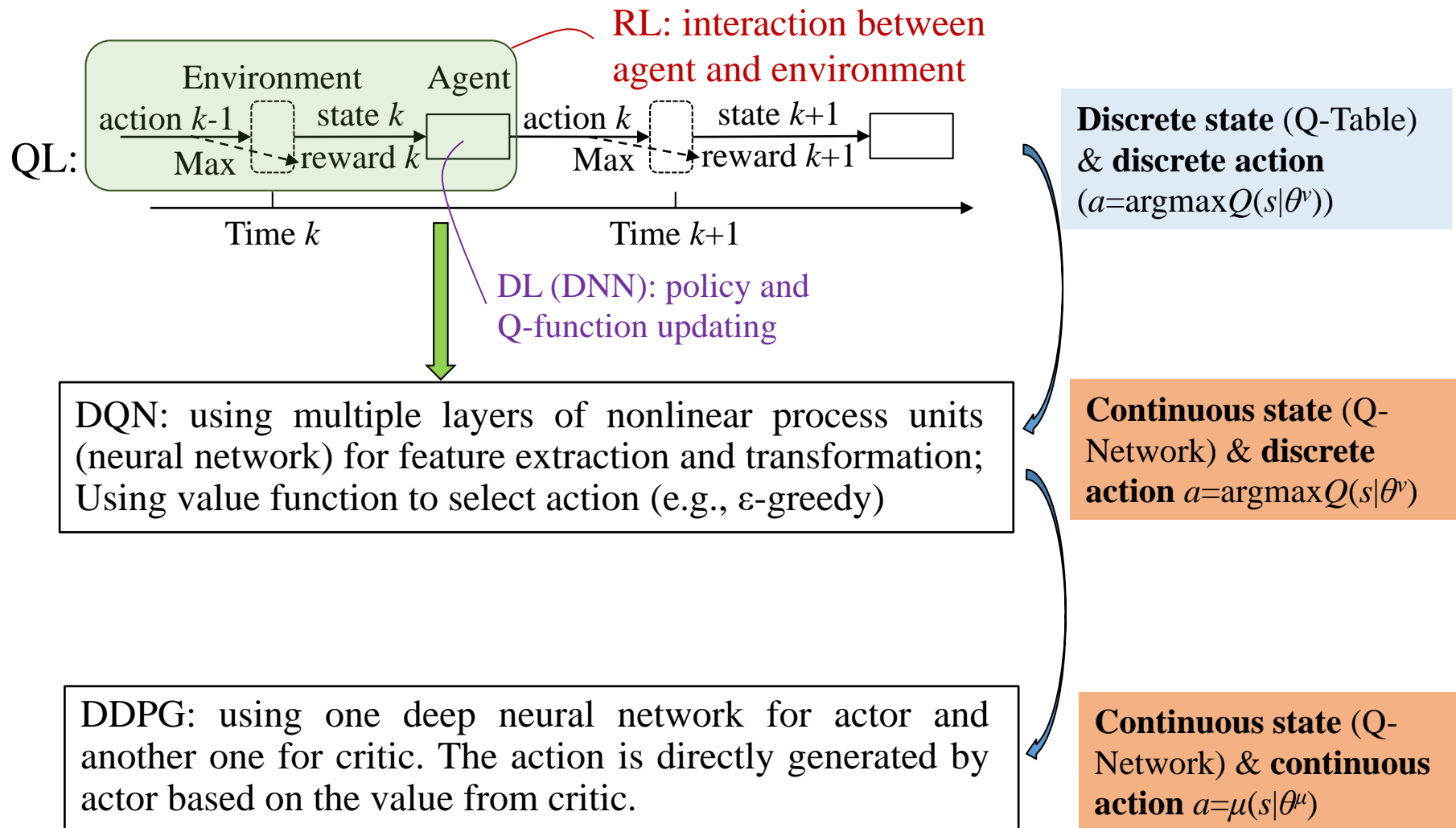
Actions – Vset (Episode 8 and 5000)

gen1_vset	gen2_vset	gen3_vset	gen6_vset	gen8_vset	episode
1.05	1.025	1	0.95	0.975	8
1.025	0.975	0.95	1	1.05	8
0.975	1	0.95	1.025	1.05	5000

States – Bus Voltage (Episode 8 and 5000)

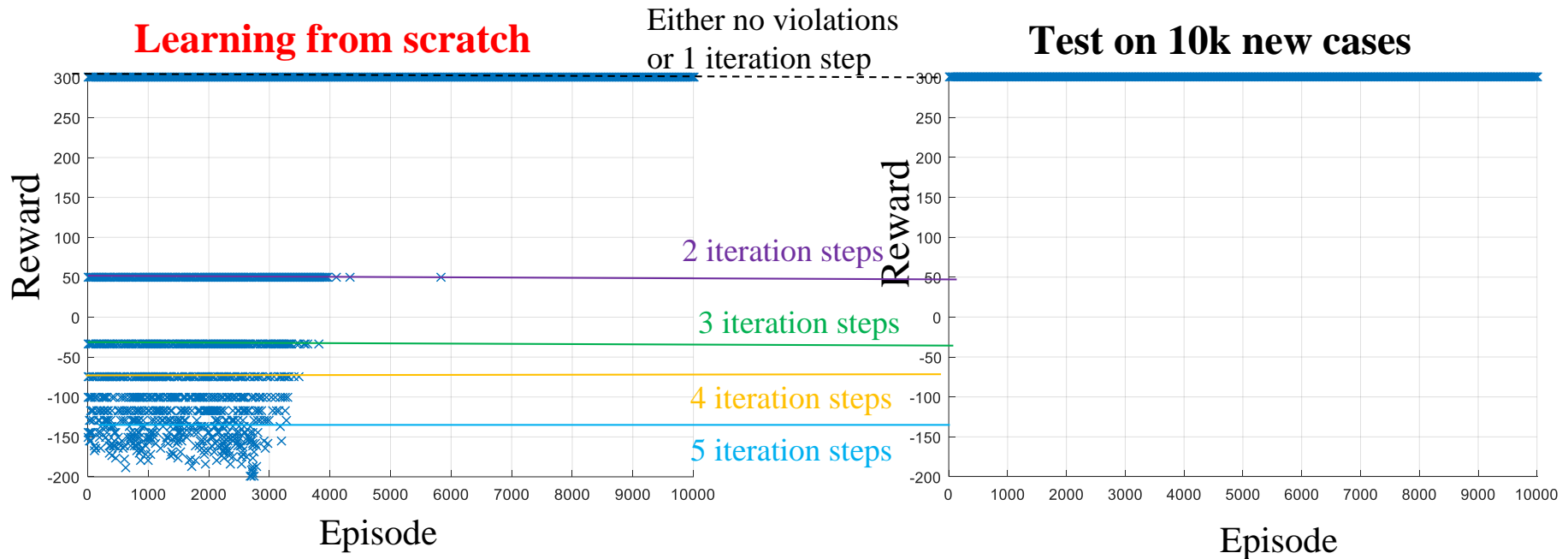
bus1	bus2	bus3	bus4	bus5	bus6	bus7	bus8	bus9	bus10	bus11	bus12	bus13	bus14	episode
1.06	1.045	1.01	1.01797	1.02025	1.07	1.06204	1.09	1.05682	1.05137	1.05756	1.05568	1.05237	1.03698	8
1.05	1.025	1	0.97375	0.9756	0.95	0.974	0.975	0.96352	0.95255	0.94802	0.93591	0.9342	0.93076	8
1.025	0.975	0.95	0.95572	0.95909	1	1.00554	1.05	0.99402	0.98678	0.99011	0.98523	0.98225	0.96972	8
1.06	1.045	1.01	1.01699	1.01936	1.07	1.06047	1.09	1.05409	1.04913	1.05583	1.05456	1.05036	1.03339	5000
0.975	1	0.95	0.9627	0.96341	1.025	1.01158	1.05	1.00331	0.99898	1.00803	1.00845	1.00369	0.98341	5000

Discrete vs Continuous Action Space



DDPG Agent for IEEE 14-bus System

60%-120% random load changes are applied to each episode

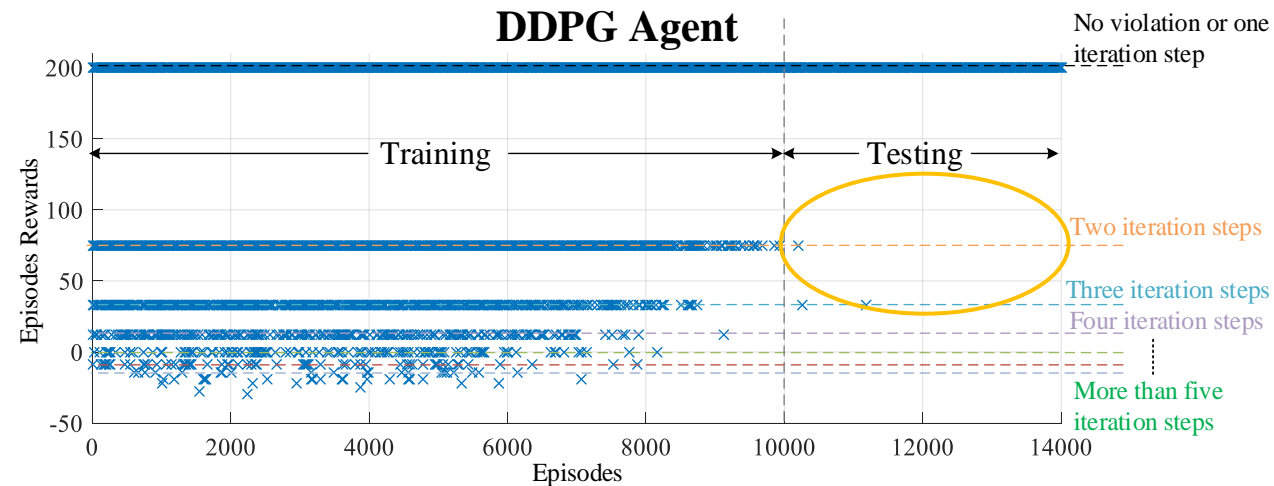
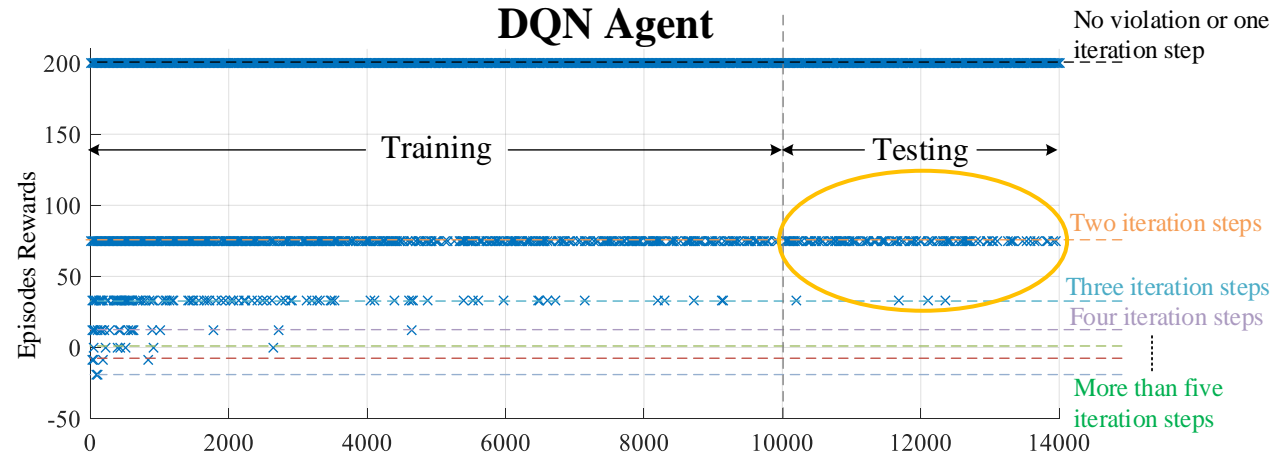
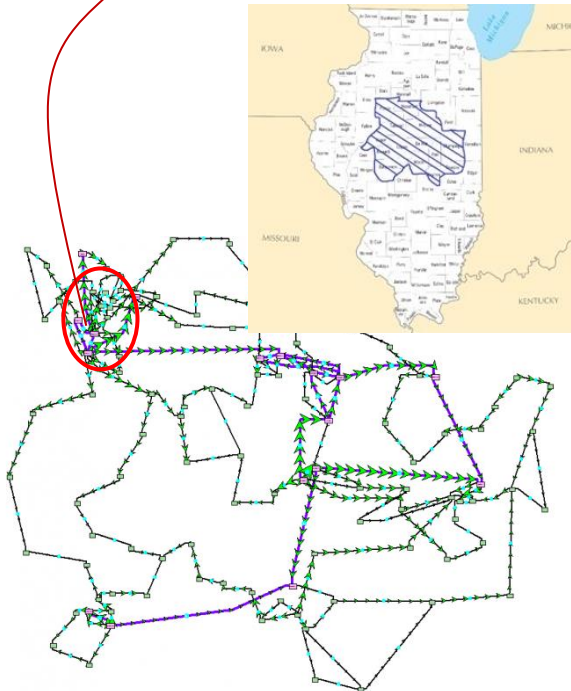


After 6,000 episodes' learning, the designed DDPG agent starts to master the voltage control problem by making decisions autonomously.

DQN and DDPG Agents for 200-bus System

60%-120% random load changes are applied to each episode

Regional voltage control is considered for DQN agent:
5 adjacent generators with 30 interconnected buses in the neighborhood subsystem



After 10,000 episodes' learning, the designed DRL agents start to master the voltage control problem in the 200-bus system by making decisions autonomously.

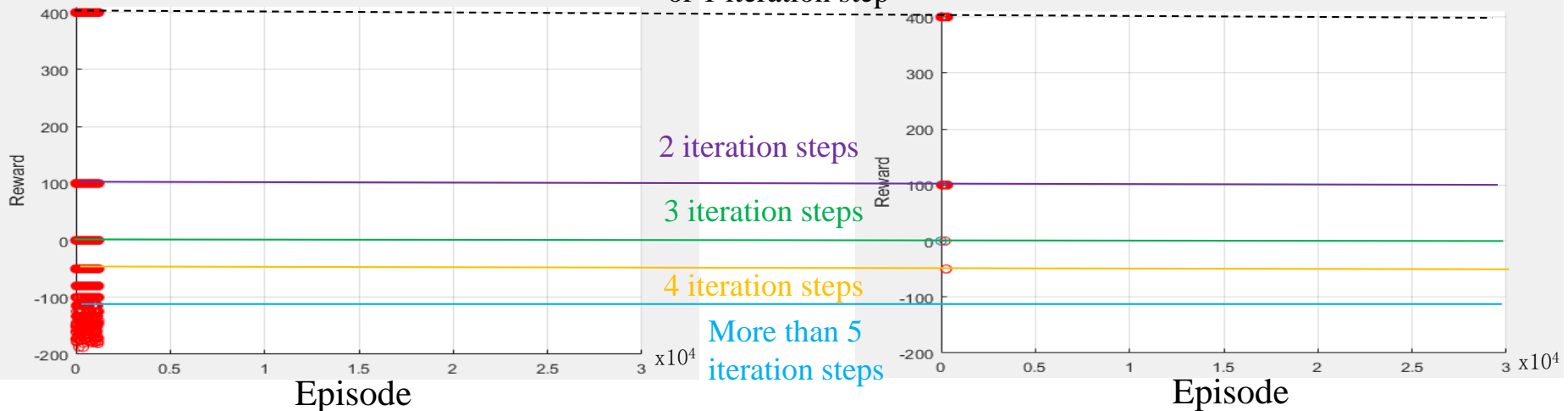
Further Testing Results-200 Bus System

- Test the DRL agent under different loading conditions: heavily loaded, fully loaded, and lightly loaded.
- **Consider different topological changes. For example, random line tripping contingency or N-1 conditions.**

DDPG; 60%-140%; Enforcing Q limit

Either no violation
or 1 iteration step

DQN; 60%-140%; Enforcing Q limit



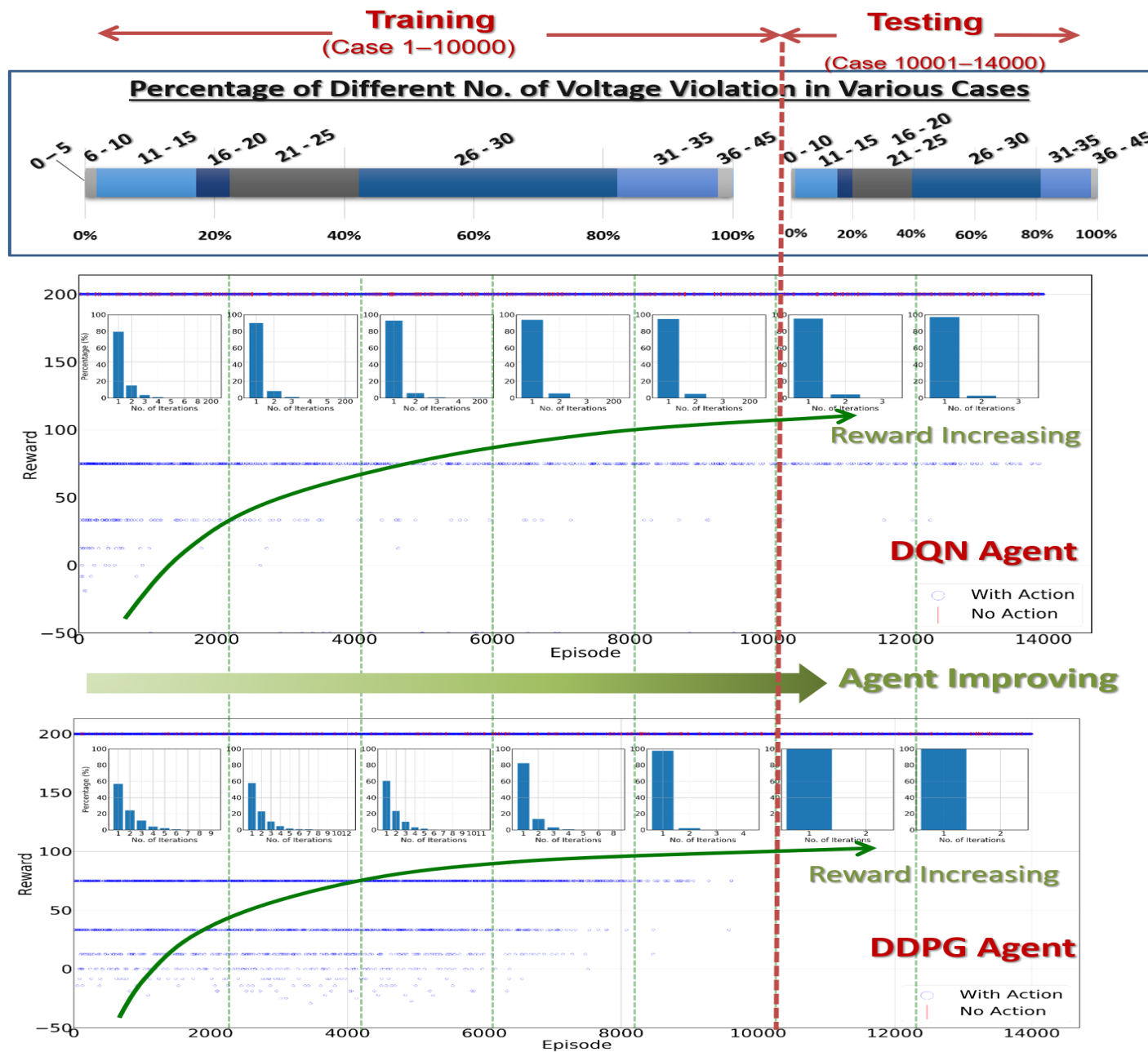
Observations:

1. The designed agents work very well under all testing conditions.
2. The results comply with basic power system principles and engineering judgement very well.
3. The proposed framework is promising for power system autonomous operation and control.

GEIRINA
GEIRI NORTH AMERICA



Summary of Results: Illinois 200-bus System



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Demo of Grid Mind: Autonomous Voltage Control

Go to Step1: Perturb Grid System

Grid Mind Flowchart



Maintain the bus voltage
within 0.95 – 1.05

Illinois 200 Bus System



Step 1

Perturb the Grid System

Change the operating condition through:

- 1) **Modifying** the load
- 2) **Switching** off a line

Step 2

Check Voltage Violation

Run **Power Flow Simulation** to see whether any voltage violation exists

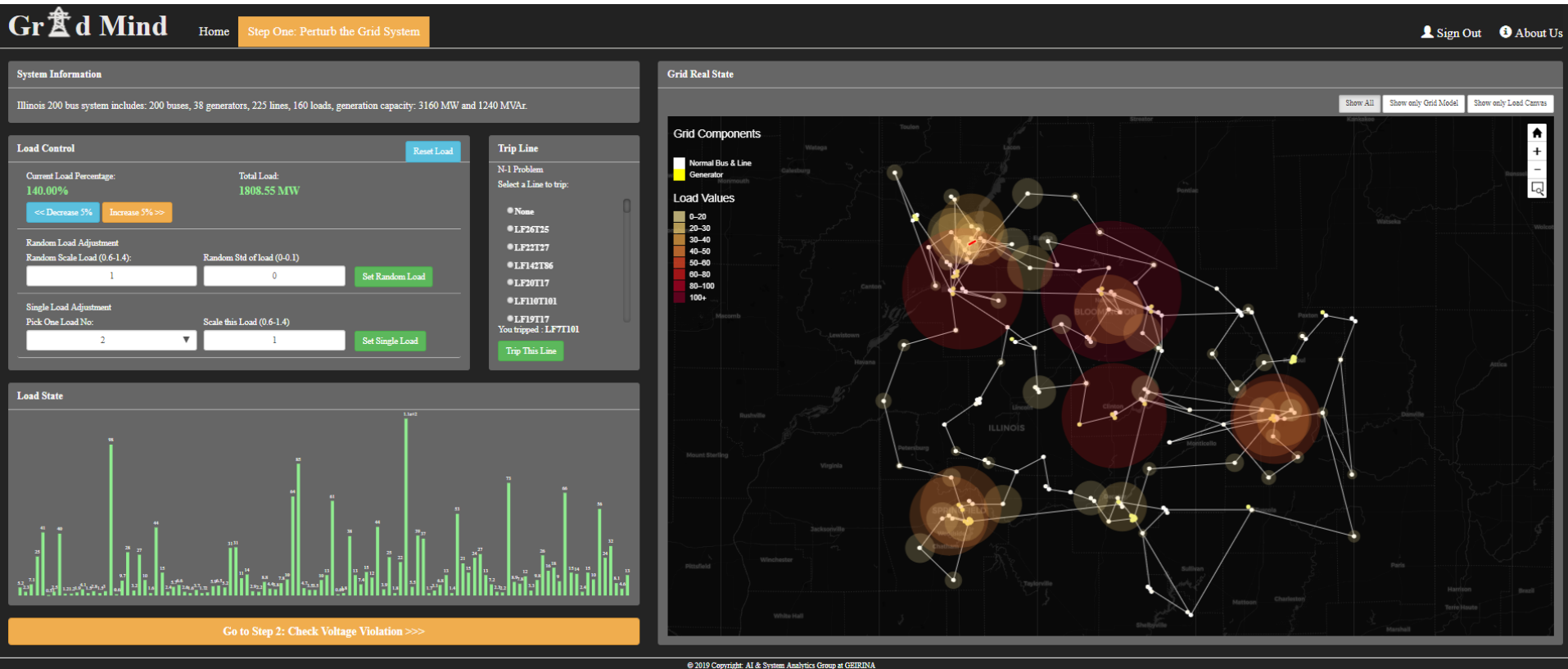
Normal range of the voltage: 0.95 – 1.05

Step 3

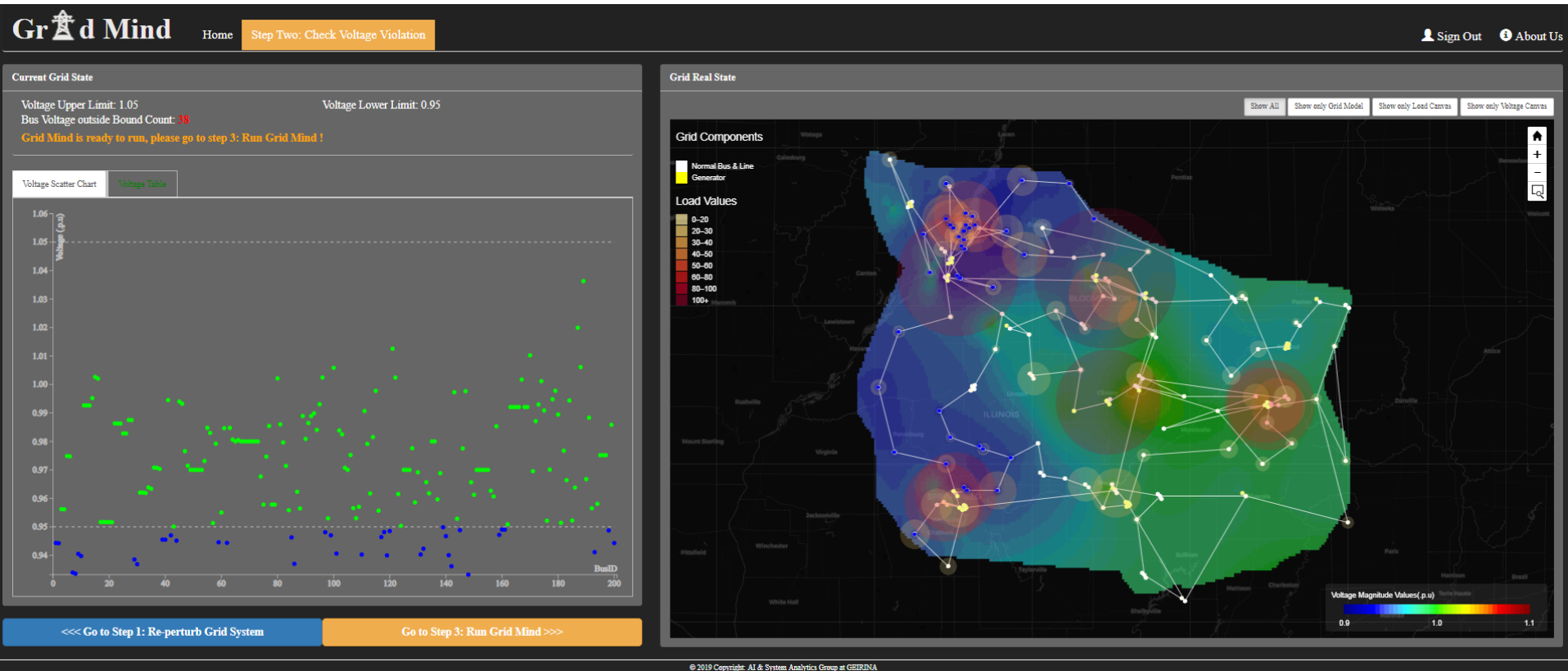
Run Grid Mind

Run **Grid Mind** to **Eliminate the voltage violation** by controlling the voltage on the generator buses

Step 1: Perturb the System



Step 2: Check for Voltage Violations



Step 3: Grid Mind Suggests Actions and Performance



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How to Design/Train an Effective DRL Agent

➤ Considerations

There are tons of parameters, settings, and different formulations that need to be designed and specified. And subtle difference in them may generate very different results.

➤ Testing Roadmap

1. Consider different sizes of action space
2. Consider different neural network structures
 - Number of neural networks
 - Number of layers
 - Number of neurons
3. Consider different regularization methods
 - Batch normalization
 - Layer dropout
4. Consider different DRL formulations
 - Deep-Q-Network (DQN)
 - Deep-Deterministic-Policy-Gradient (DDPG)
5. Consider dynamic adjustment process

Lessons Learned, After Hundreds of Thousands of Numerical Experiments

Summary of Tuning Results

DQN Agent		
Objective	Measures	Conclusion
Evaluate influence of different sizes of action space	Change action space from 5^4 to 5^5	Performance deteriorates when action space size grows
Evaluate the influence of two different types of DQN structure	Single-DQN and double-DQN are tested	A double-DQN has a better performance over a single-DQN
Evaluate the influence of layers and neuron numbers	Test with 2/3 layers with 20/40 neurons	Subtle performance degradation is observed when increasing lay. or neu.
Evaluate the influence of regularization methods	Using batch normalization and layer dropout	Applying regularization methods significantly improves performance
DDPG Agent		
Objective	Measures	Conclusion
Evaluate the influence of regularization methods	Using batch normalization and layer dropout	Applying regularization methods significantly improves performance
Evaluate a different formulation way to control voltage	Dynamically increase or decrease the voltage setting point for a small step in each iteration	The agent is able to solve the voltage problem using minimum iterations after well trained.

Conclusion and Future work

- The proposed DRL framework demonstrates very promising results for power system autonomous dispatch and control, using measurements from advanced sensors, PMU as an example.
 - When reactive resources are sufficient and/or distributed unevenly, Grid Mind can find very fast and effective solutions for fixing voltage issues.
 - Research team will train and enhance AI agents to find optimal solutions for scenarios with limited reactive resources.
- Thorough testing has been carried out to study the influence of various factors, which sheds light on the design of an effective agent/robot.
- Therefore, we have duplicated an example of Alpha Zero, Grid Mind, for power systems.
- With extensive offline calculation and online learning, in the mid-term, Grid Mind serves as an assistant to grid operators; in the long term, Grid Mind will be the core of power system operation ROBOT.
- With proper modifications, the proposed framework can be applied to many other applications.

Related Publications

- R. Diao, Z. Wang, D. Shi, Q. Chang, J. Duan, and X. Zhang, “Autonomous Voltage Control for Grid Operation Using Deep Reinforcement Learning,” IEEE PES General Meeting, Atlanta, GA, USA, 2019. **[Best Paper]**
- J. Duan, Z. Yi, D. Shi, and Z. Wang, "Reinforcement-Learning-Based Optimal Control for Hybrid Energy Storage Systems in Hybrid AC/DC Microgrids", IEEE Transactions on Industrial Informatics, 2019.
- J. Duan, D. Shi, R. Diao, B. Zhang, Z. Wang, etc., “Deep-Reinforcement-Learning-Based Autonomous Control for Power Grid Operations,” IEEE PES Letters, under 2nd-round review.
- D. Bian, Z. Yu, D. Shi, R. Diao, Z. Wang, "A Real-time Robust Low-Frequency Oscillation Detection and Analysis (LFODA) System with Innovative Ensemble Filtering," CSEE Journal of Power and Energy Systems, 2019.
- L. Mang, D. Shi, Z. Yu, Z. Yi, Z. Wang, and Y. Xiang, “An ADMM Based Approach for Phasor Measurement Unit Data Recovery,” IEEE Transactions on Smart Grid, 2018.
- H. Banna, Z. Yu, D. Shi, Z. Wang, D. Su, C. Xu, S. Solanki, and J. Solanki, “Online Coherence Identification Using Dynamic Time Warping for Controlled Islanding,” Journal of Modern Power System and Clean Energy, vol. 7, no. 1, pp. 38-54, Jan. 2019.
- Z. Yu, D. Shi, Z. Wang, Q. Zhang, J. Huang, and S. Pan, “Distributed Estimation of Oscillations in Power Systems: an Extended Kalman Filtering Approach,” CSEE Journal of Power and Energy Systems, 2018.
- X. Lu, D. Shi, B. Zhu, Z. Wang, J. Luo, D. Su, and C. Xu, “PMU Assisted Power System Parameter Calibration at Jiangsu Electric Power Company,” IEEE PES General Meeting, Chicago, IL, USA, 2017. **[Best Paper]**
- F. Hu, K. Sun, D. Shi, and Z. Wang, “Measurement-based Voltage Stability Assessment for Load Areas Addressing n-1 Contingencies,” IET Generation, Transmission & Distribution, vol. 11, no. 15, pp. 3731-3738, 2017.

Thank you!

Please refer to the following sites for more information:

<https://www.geirina.net/assets/pdf/gridmindppt.pdf>

https://www.geirina.net/assets/pdf/GridMindDemo_JD4.mp4