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Convergence of AI, Physics, Computing, and Control for Intelligent Power System Control and Beyond

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Acknowledgement

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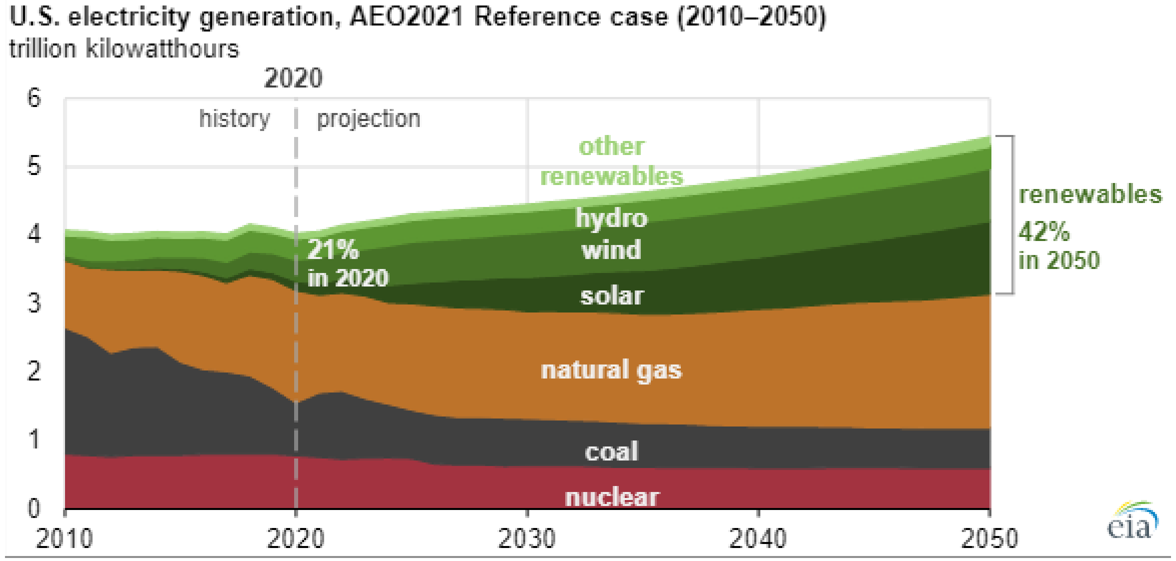
Outline

1. Convergence of AI, Physics, Computing, and Control for Intelligent Power System Control
2. An example from ARPA-E HADREC: AI-enhanced grid emergency control
3. Recent progress in AI for grid operation
4. Summary and perspectives

Grid Transformation: Increasing Renewables and Rapidly Changing Operation Conditions

EIA projects renewables share of U.S. electricity generation mix will double by 2050



Sources: EIA

California ISO net load "duck curve"

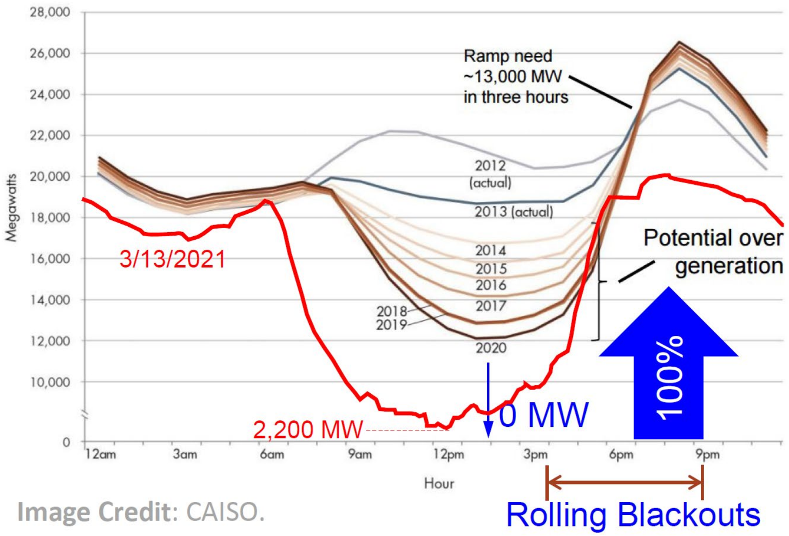
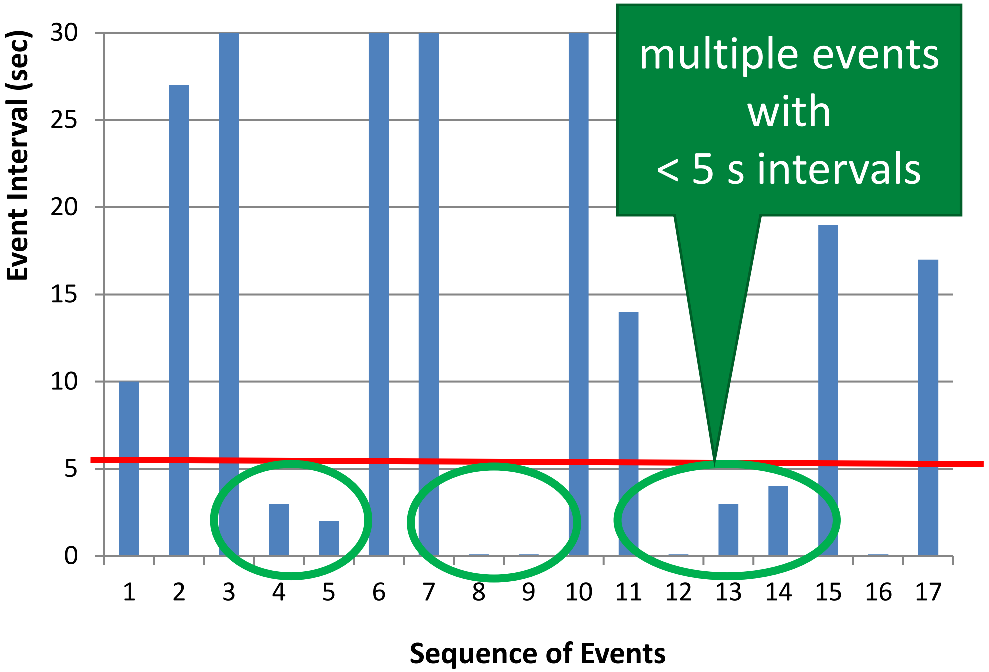


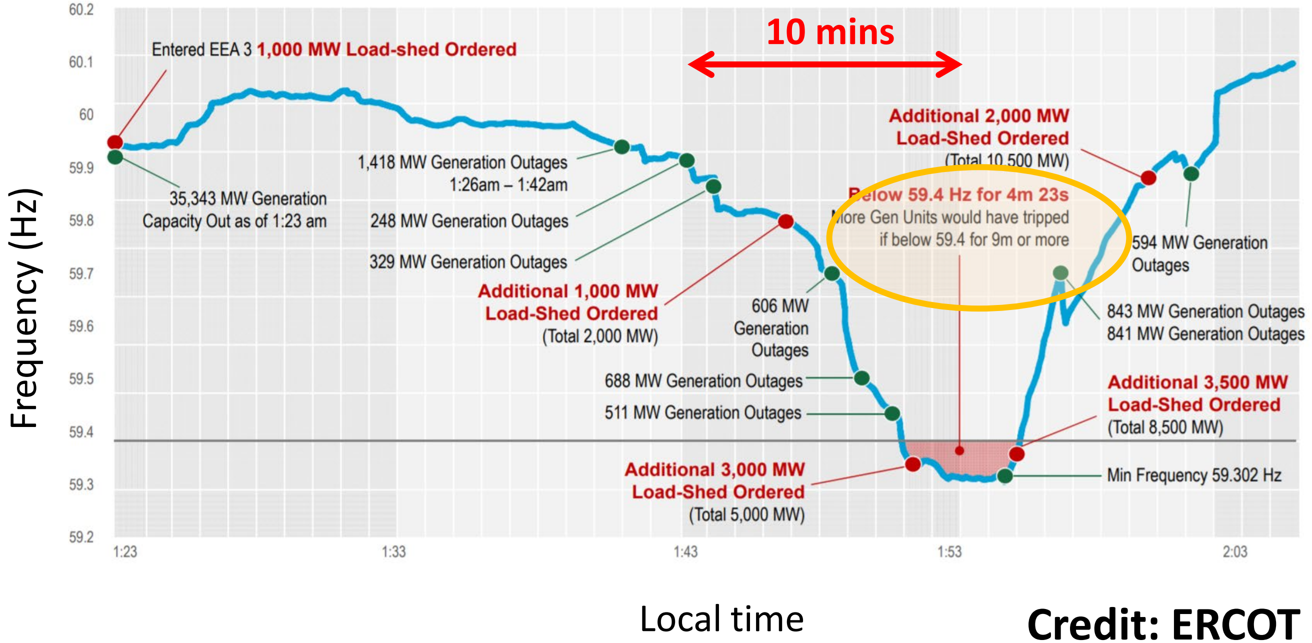
Image Credit: CAISO.

Big Challenges in Grid Operation and Control

September 8, 2011 Pacific Southwest Blackout in U.S.



Texas was "seconds and minutes" away from catastrophic monthslong blackouts[1]



Credit: ERCOT

[1] https://www.texastribune.org/2021/02/18/texas-power-outages-ercot/
[2] http://www.ercot.com/content/wcm/key_documents_lists/225373/Urgent_Board_of_Directors_Meeting_2-24-2021.pdf

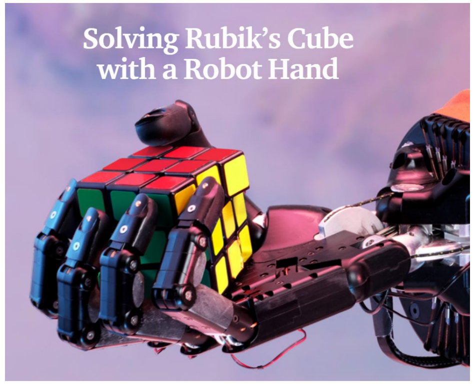
The Grand Challenge of Achieving Intelligent Emergency Control

- Power system post-event emergency control has **strong requirements:**
  - **Scalability:** >20,000 buses (with 1000s of control devices)
  - **Solution time:** < 5 seconds
  - **Security and adaptability** (to fast-changing conditions)

- Existing control methods and issues:
  - Rule-based control (not adaptive, time-consuming to develop and update them)
  - Model-predictive control (scalability and solution time issues)
  - Learning-based (or data-driven) control (scalability, security and adaptability issues)

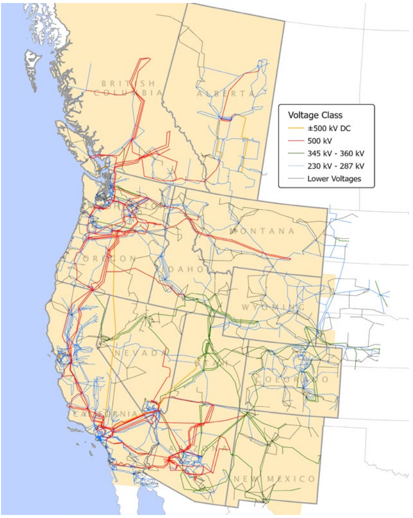
Can we bring successes in games to complex grid operation and control?

Credit: Nature



Credit: OpenAI

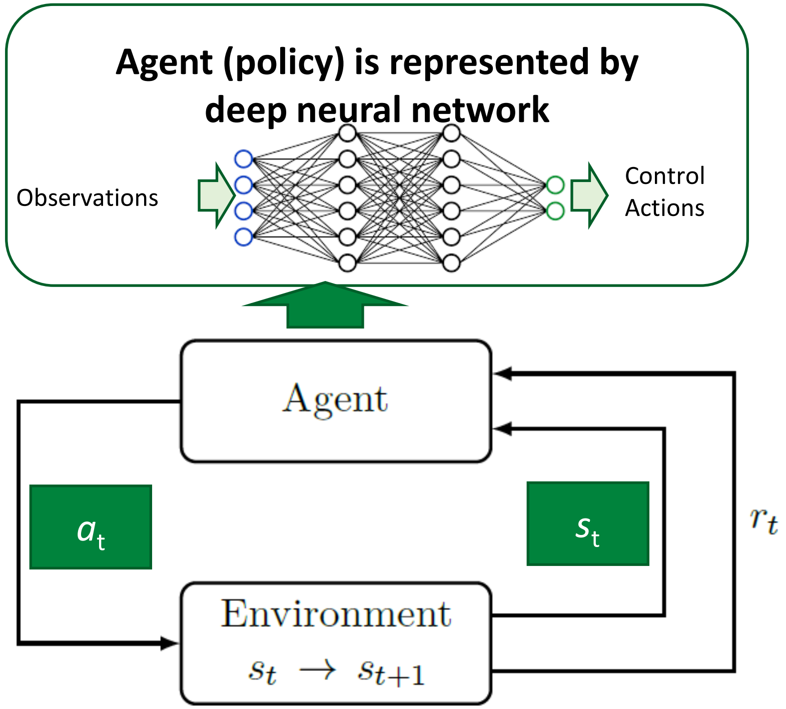
Credit: CAISO



https://www.wecc.org/epubs/StateOfTheInterconnection/Pages/Western-Interconnection.aspx

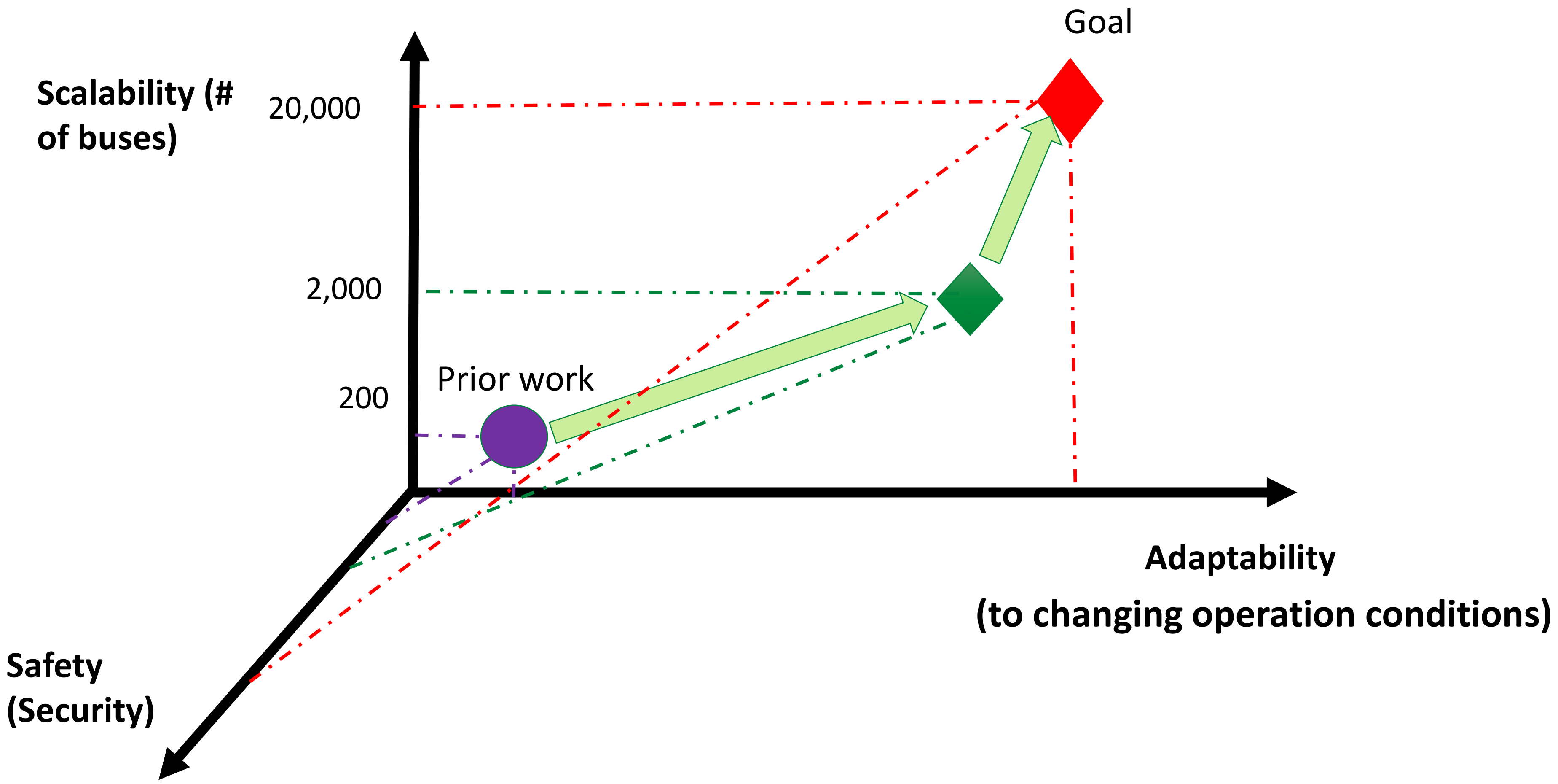
Deep Reinforcement Learning

- Reinforcement learning is designed for solving sequential decision-making problems
- The agent learns a control policy iteratively through interacting with the environment via trial-and-errors guided by the reward signal
- Deep Reinforcement Learning = Deep learning + Reinforcement Learning
- Previous work on RL-based power system operation and control showed promising results, but focused on small-scale studies, e.g., IEEE 39-bus test system.

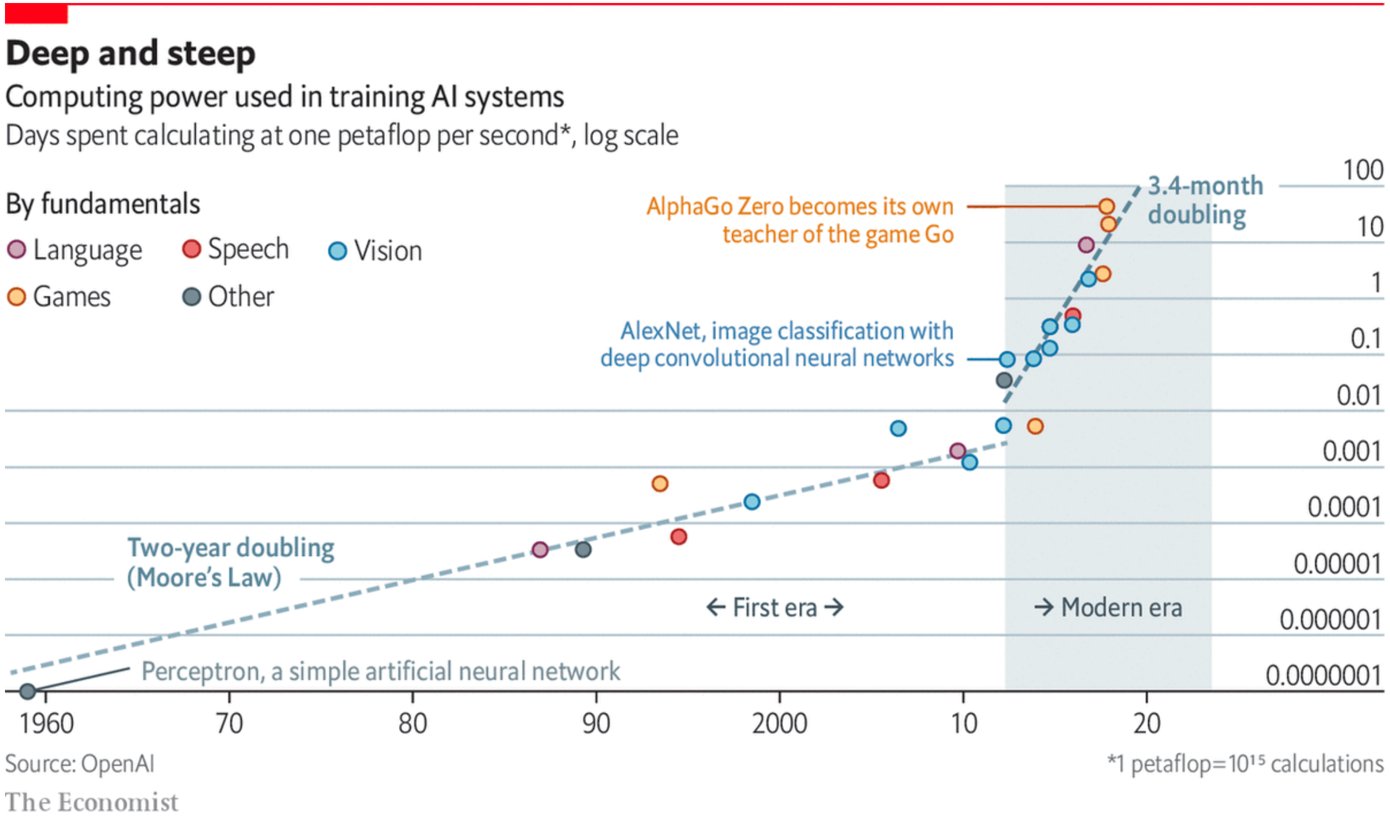


- Power Grid

Key Challenges in Deep Reinforcement Learning for Large-scale Grid Control



Advanced Computing Powers AI Breakthroughs



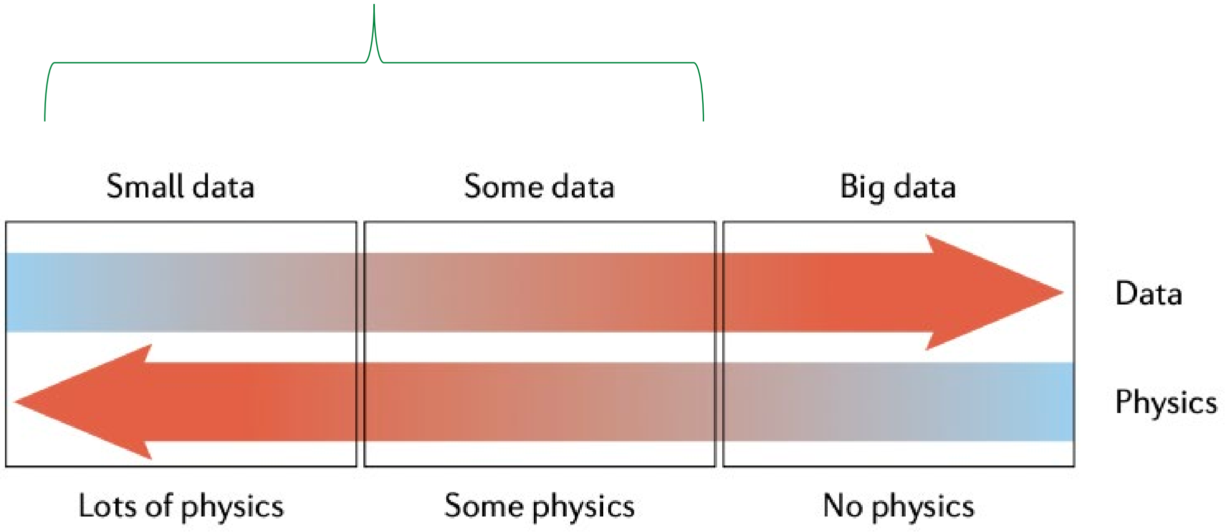
"The biggest lesson that can be read from 70 years of AI research is that general methods that leverage computation are ultimately the most effective, and by a large margin. "

-- Professor Rich Sutton

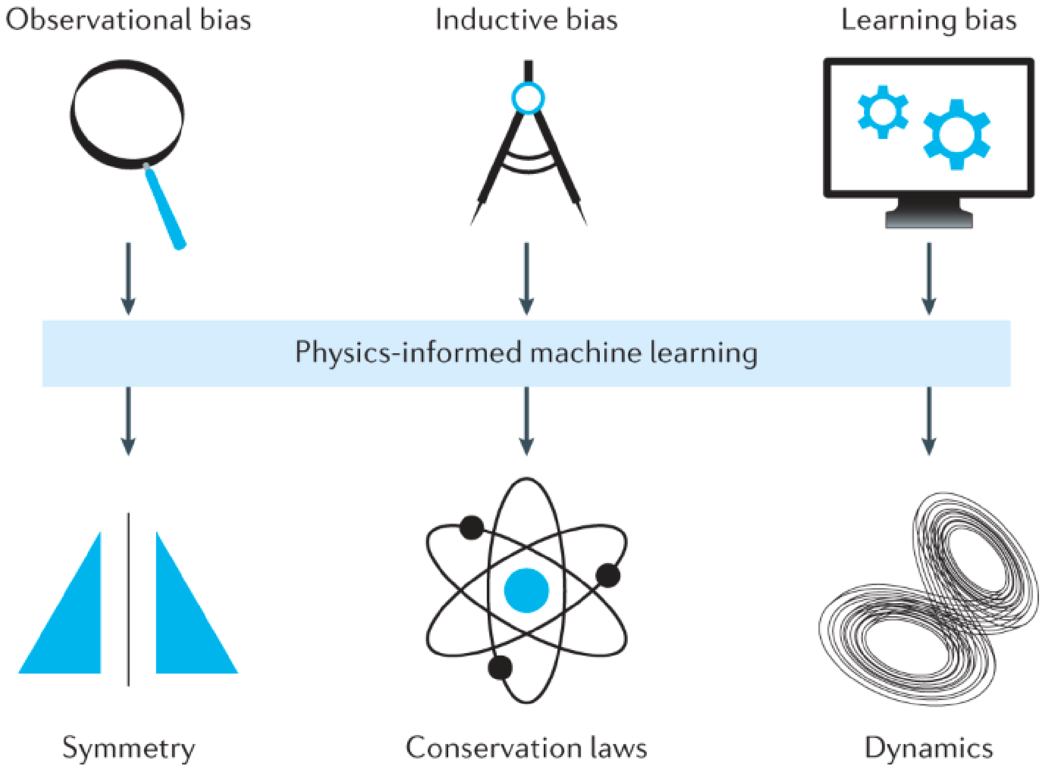
Source: http://www.incompleteideas.net/IncIdeas/BitterLesson.html

Physics Help Overcome Data Limitations and Enhance AI

Most AI applications in power systems



Availability of data and physics for AI. (Source: [1])

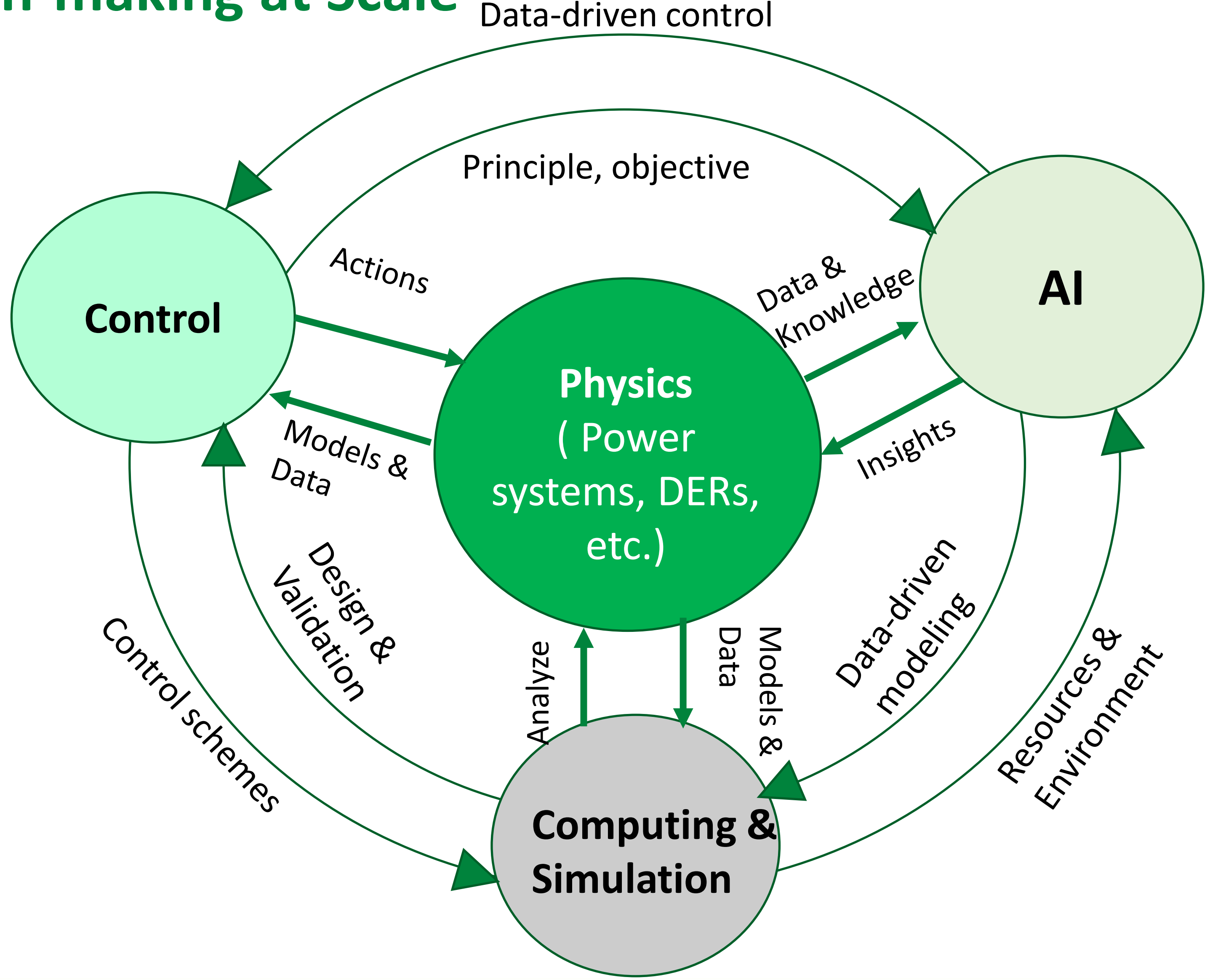


Methods for embedding physics into AI. (Source: [1])

[1] Karniadakis, G.E., Kevrekidis, I.G., Lu, L. *et al.* Physics-informed machine learning. *Nat Rev Phys* **3,** 422–440 (2021)

Convergence of Physics, AI, Computing, and Control for Decision-making at Scale

- **Strong connections among them**
- **Overcome some key challenges in each domain by leveraging advancements in others**
- **Many recent breakthroughs are due to similar convergences**
    - **AlphaGo**
    - **AlphaStar**
    - **AlphaFold**

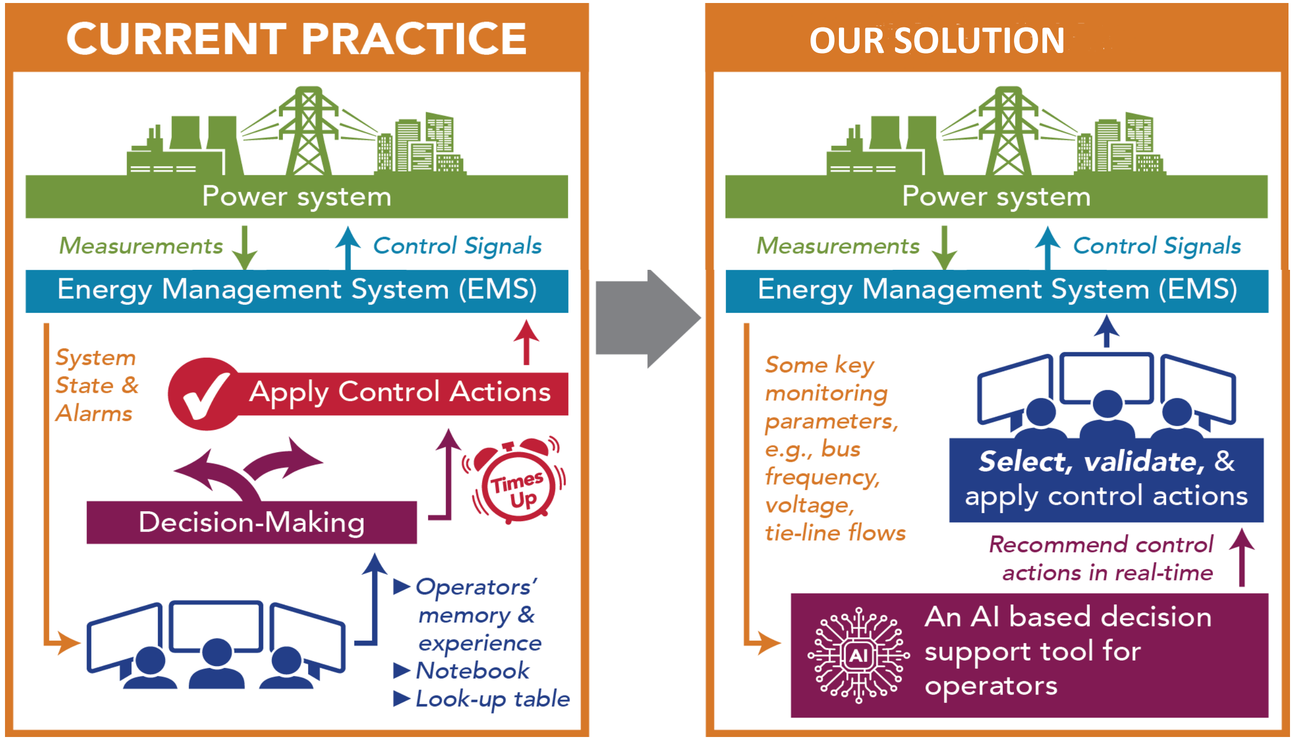


ARPA-E HADREC

AI-enhanced Real-time Grid Emergency Control

ARPA-E HADREC: High Performance Adaptive Deep Meta-Reinforcement Learning for Grid Emergency Control

Objective: to construct an intelligent, real-time emergency control decision-support tool to provide effective and fast control actions to system operators in response to large contingencies or extreme events.

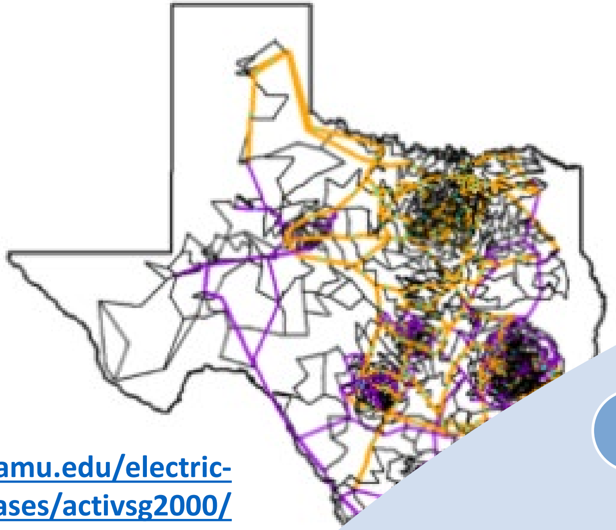


Project team:

- PNNL
- V&R Energy
- Google
- PacifiCorp

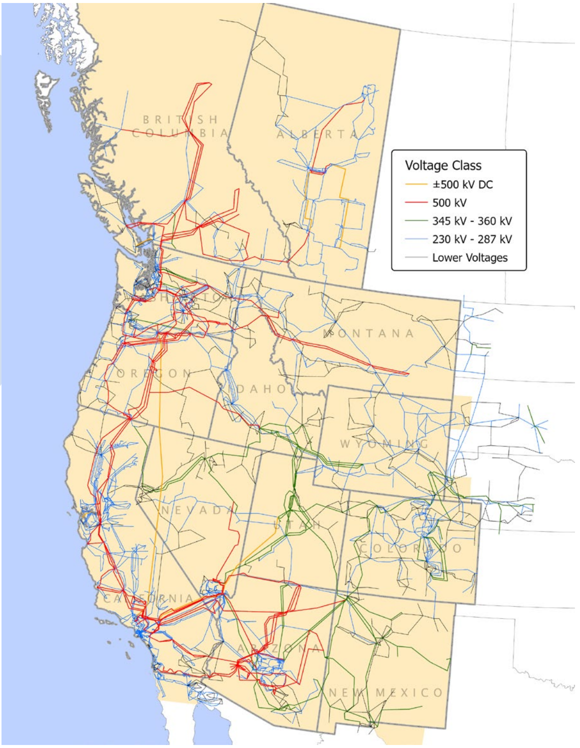
Project summary website: https://arpa-e.energy.gov/technologies/projects/high-performance-adaptive-deep-reinforcement-learning-based-real-time

Develop AI-enhanced Solutions for Large-scale Power Systems



https://electricgrids.engr.tamu.edu/electric-grid-test-cases/activsg2000/

- IEEE 300-bus
  - 2020
- A synthetic Texas System (2000-bus)
  - 2021
- A WECC-size system (~20K-bus)
  - 2022



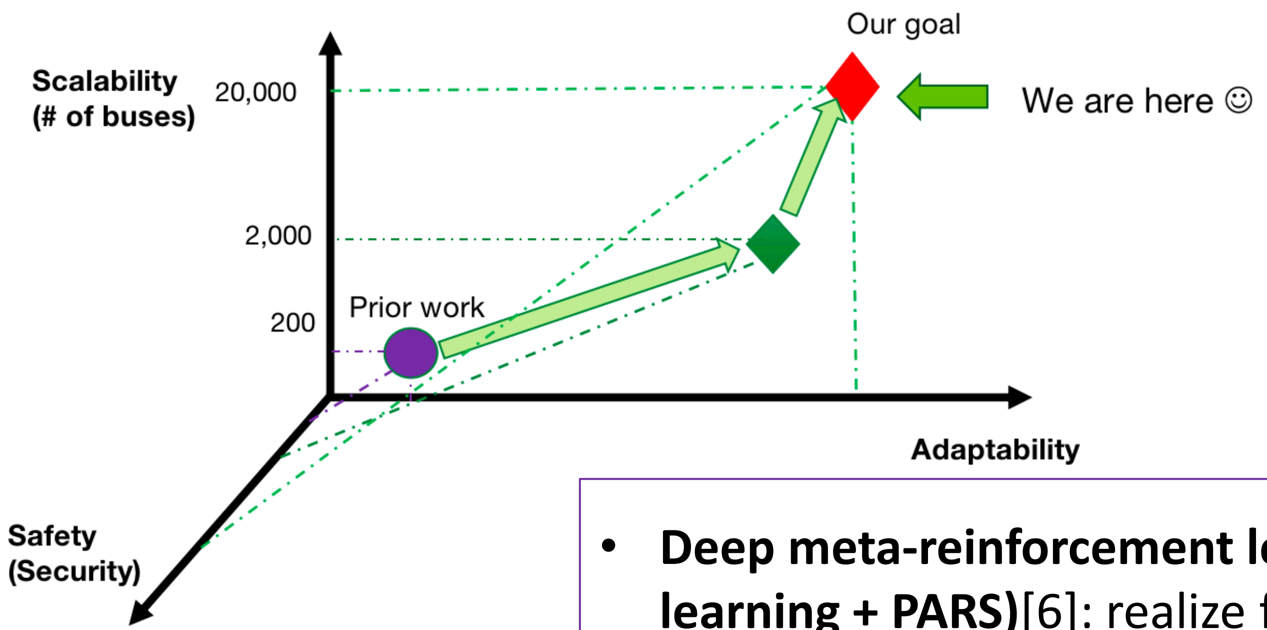
https://www.wecc.org/epubs/StateOfTheInterconnection/Pages/Western-Interconnection.aspx

Three dynamic emergency control schemes:

- Under voltage load shedding
- Generator tripping
- Controlled islanding

We Addressed the Challenges by Fusing AI, Physics, Advanced Computing, and Control

- **Parallel Augmented Random Search (PARS) algorithm**[1],
- High performance power system simulation platform **GridPACK [2]**
- **Smart sampling** for scenario reduction [3]



- **Physics-informed PARS** [4]: incorporate physics knowledge through a trainable action mask
- **Safe PARS** [5]: control barrier function + PARS

- **Deep meta-reinforcement learning (meta-learning + PARS)**[6]: realize fast adaptation (~5 mins) of control policies to changing grid conditions

[1] R. Huang, et al "Accelerated Derivative-free Deep Reinforcement Learning Based Load Shedding for Emergency Voltage Control," *IEEE Trans. on Power Systems*, 2021
[2] GridPACK, https://www.gridpack.org/
[3[X. Sun *et al*., "Smart Sampling for Reduced and Representative Power System Scenario Selection," in *IEEE Open Access Journal of Power and Energy*, vol. 8, pp. 293-302, 2021
[4] D. Yan, et al "Physics-informed Evolutionary Strategy based Control for Mitigating Delayed Voltage Recovery", *IEEE Trans. on Power Systems*, 2022
[5] T. Vu, et al. "Safe Reinforcement Learning for Emergency Load Shedding of Power Systems." In Proc of IEEE PES General Meeting 2021
[6] R. Huang, et al, "Learning and Fast Adaptation for Grid Emergency Control via Deep Meta Reinforcement Learning, *IEEE Trans. on Power Systems*, 2022

HPC-based Platform

- Scalable from laptop to HPC clusters/clouds by developing our solutions on top of the RAY platform.
- OpenAI Gym, a de facto toolkit for environment and interface definition.

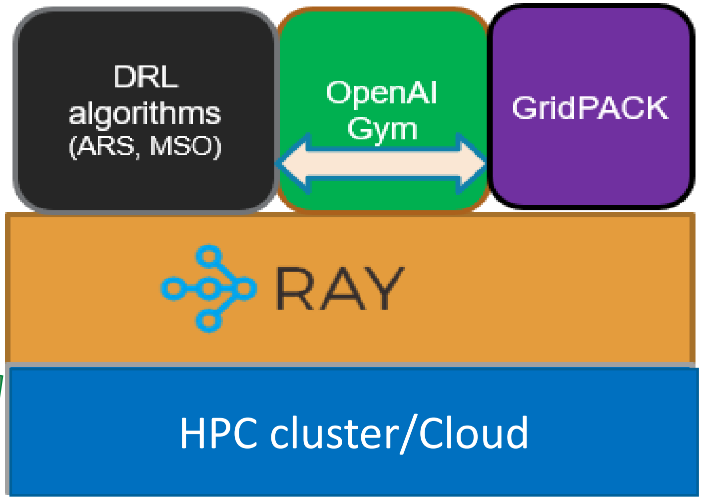


Figure 2 Architecture of the platform for training and testing

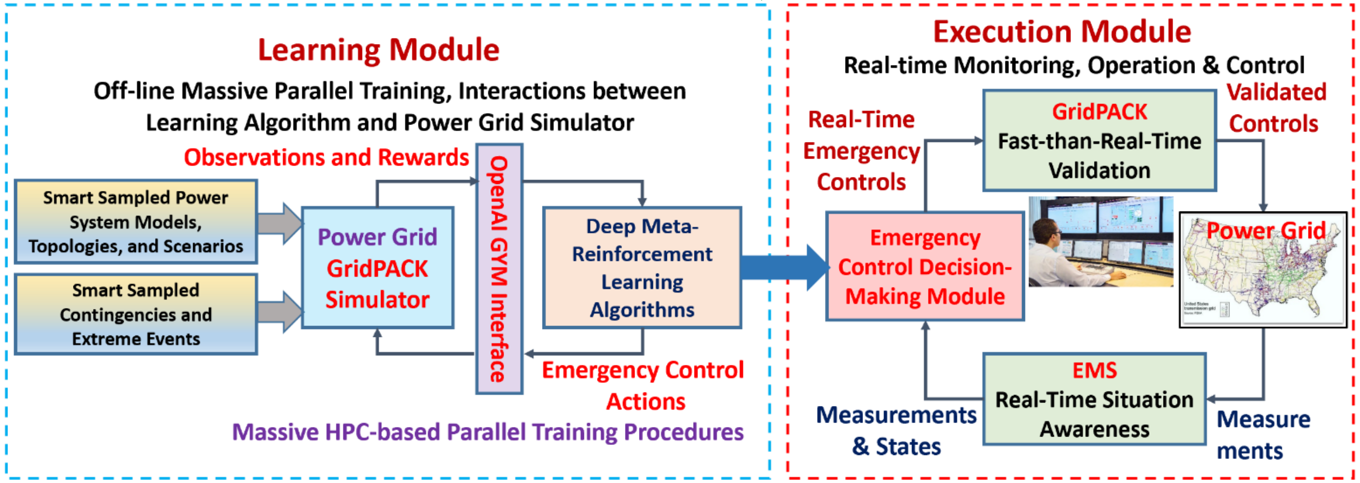
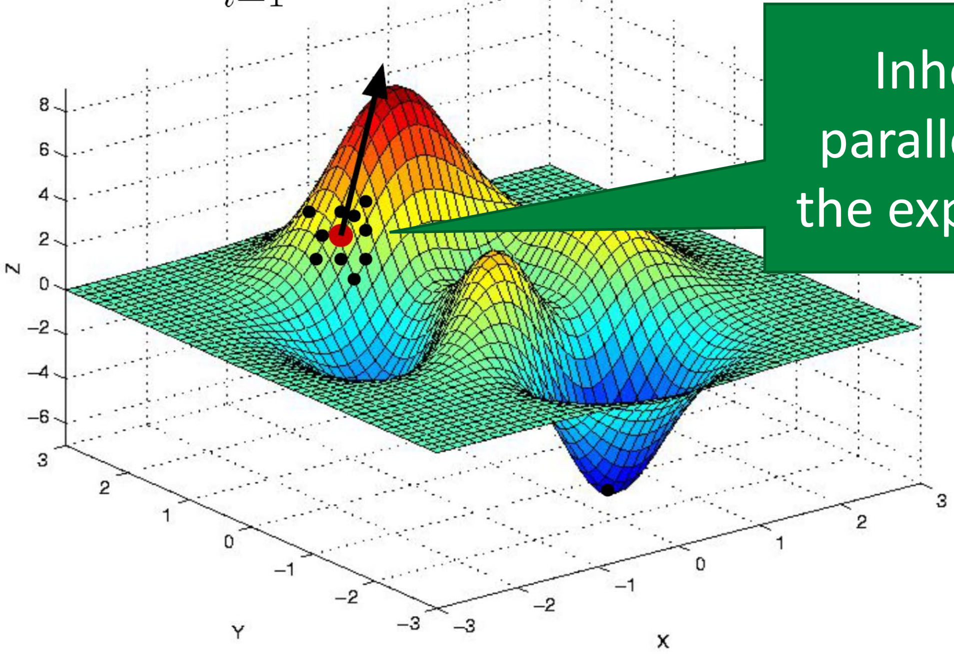


Figure 1 Illustration of the HADREC Methodology

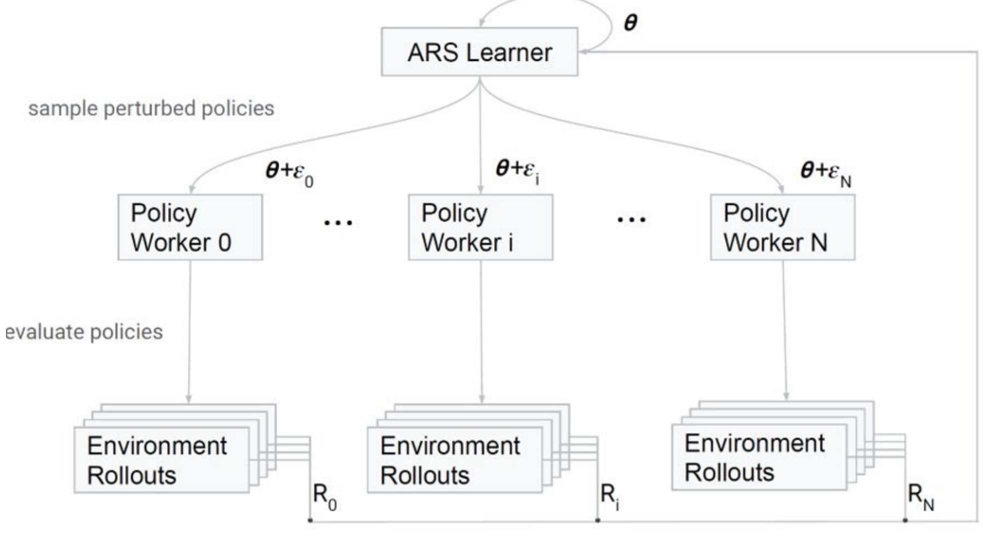
Parallel Augmented Random Search (ARS) Algorithm

Basic idea: Estimate the gradient using random search

$$\nabla F(\theta) \approx \frac{1}{n\sigma} \sum_{i=1}^{n} \{F(\theta + \sigma\epsilon)\epsilon\} \quad \text{where} \quad \epsilon \sim N(0, I)$$



Inherent parallelism in the exploration

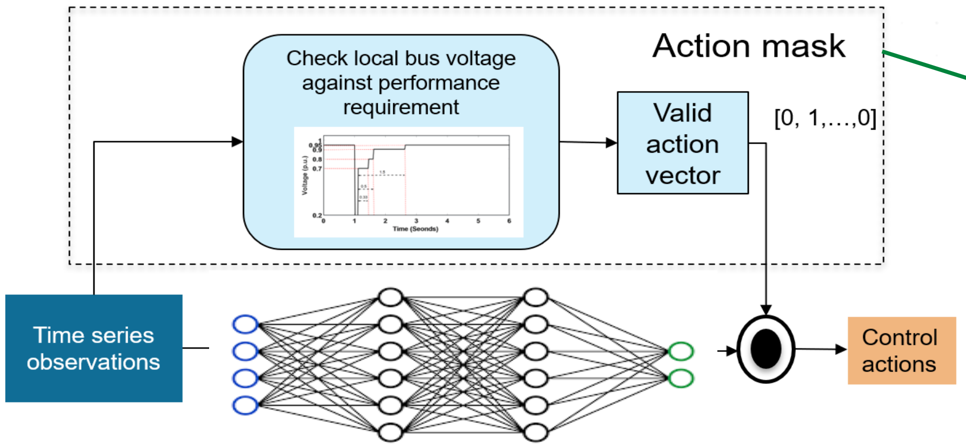


Two-level Parallelism of PARS

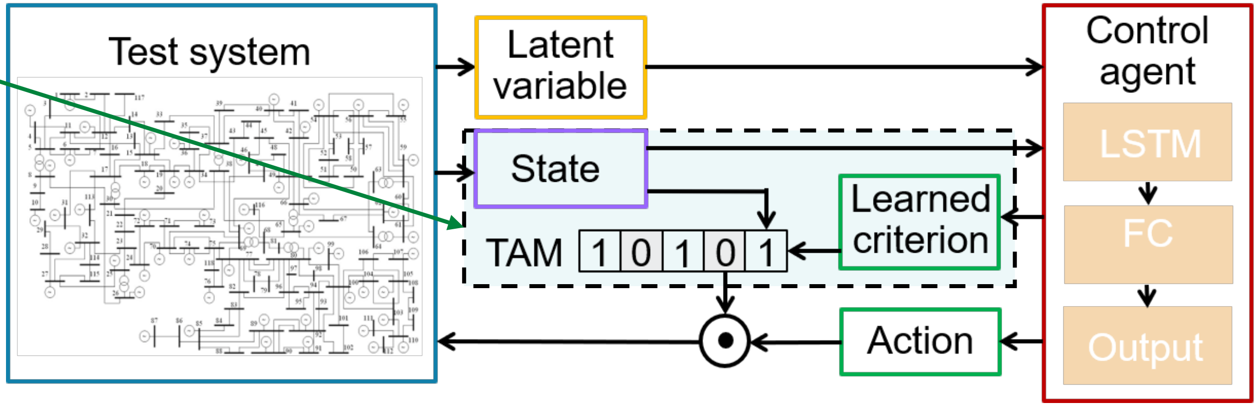
R. Huang, et al "Accelerated Derivative-free Deep Reinforcement Learning Based Load Shedding for Emergency Voltage Control," *IEEE Trans. on Power Systems*, 2021

Physics-informed DMRL Enhances Training Efficiency and Control Robustness

- Power system community have developed vast amount of domain knowledge in forms of physics laws, standards, rules, and performance requirements.
- Physics-informed Deep Meta-Reinforcement Learning (DMRL): we incorporated system performance requirements as a trainable action mask (TAM) into the agent and significantly improved its sampling efficiency and robustness[1].



Incorporate prior knowledge into the agent with a fixed action mask [1]

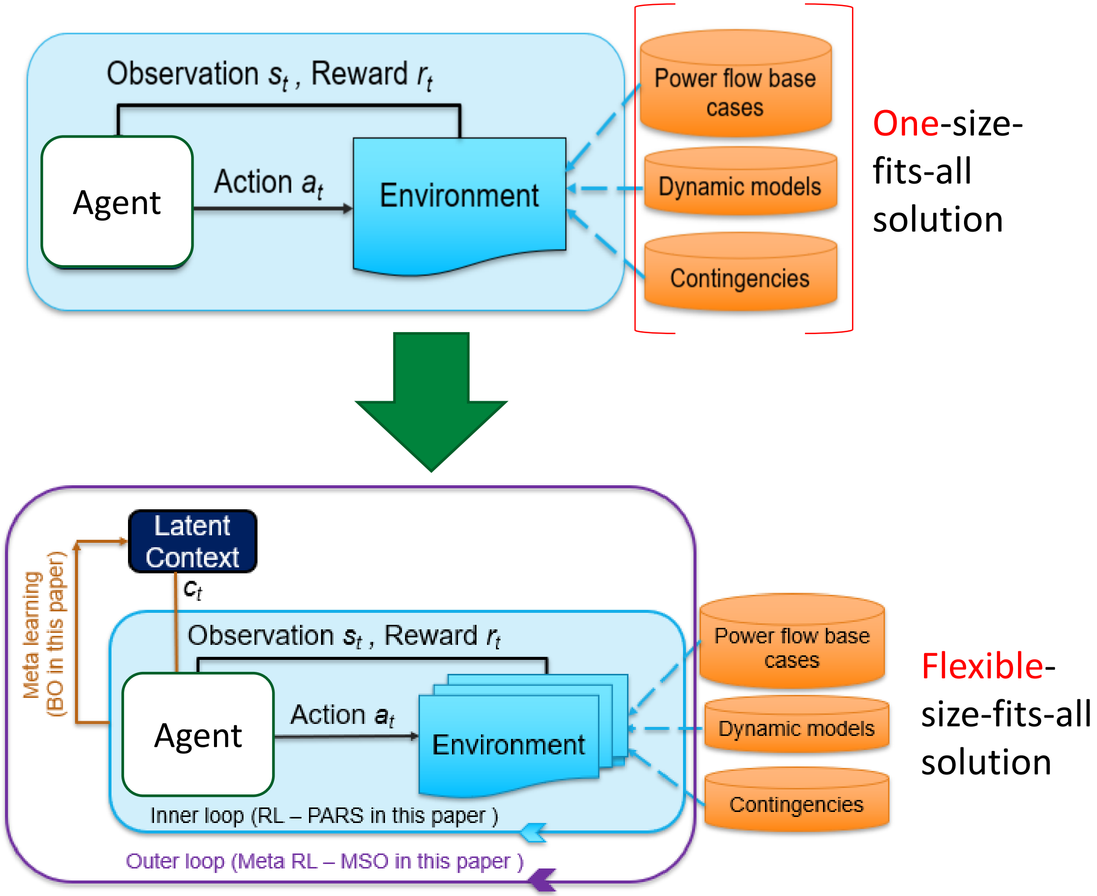


Incorporate prior knowledge with TAM [1]

[1] Y. Du, Q. Huang, R. Huang; T. Yin; J. Tan; W.Yu; X. Li, "Physics-informed Evolutionary Strategy based Control for Mitigating Delayed Voltage Recovery," in IEEE Transactions on Power Systems, doi: 10.1109/TPWRS.2021.3132328.

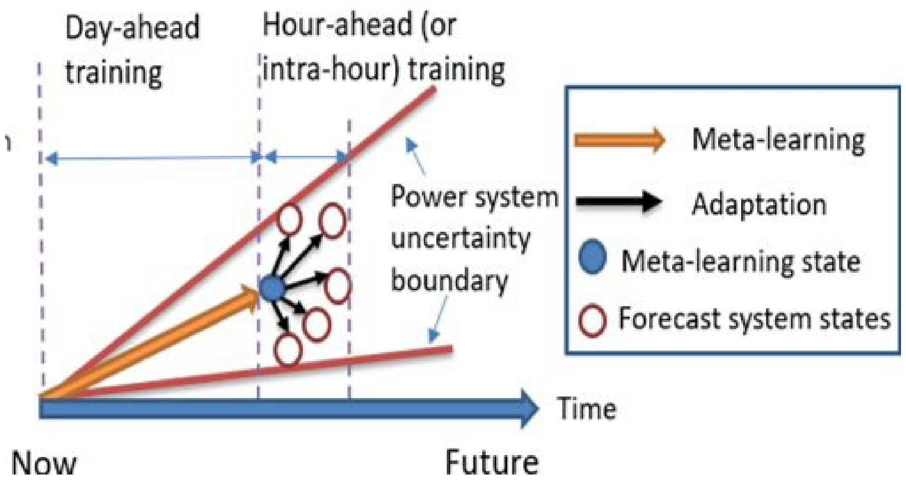
Deep Meta-Reinforcement Learning (DMRL) for Addressing the Adaptability Issue

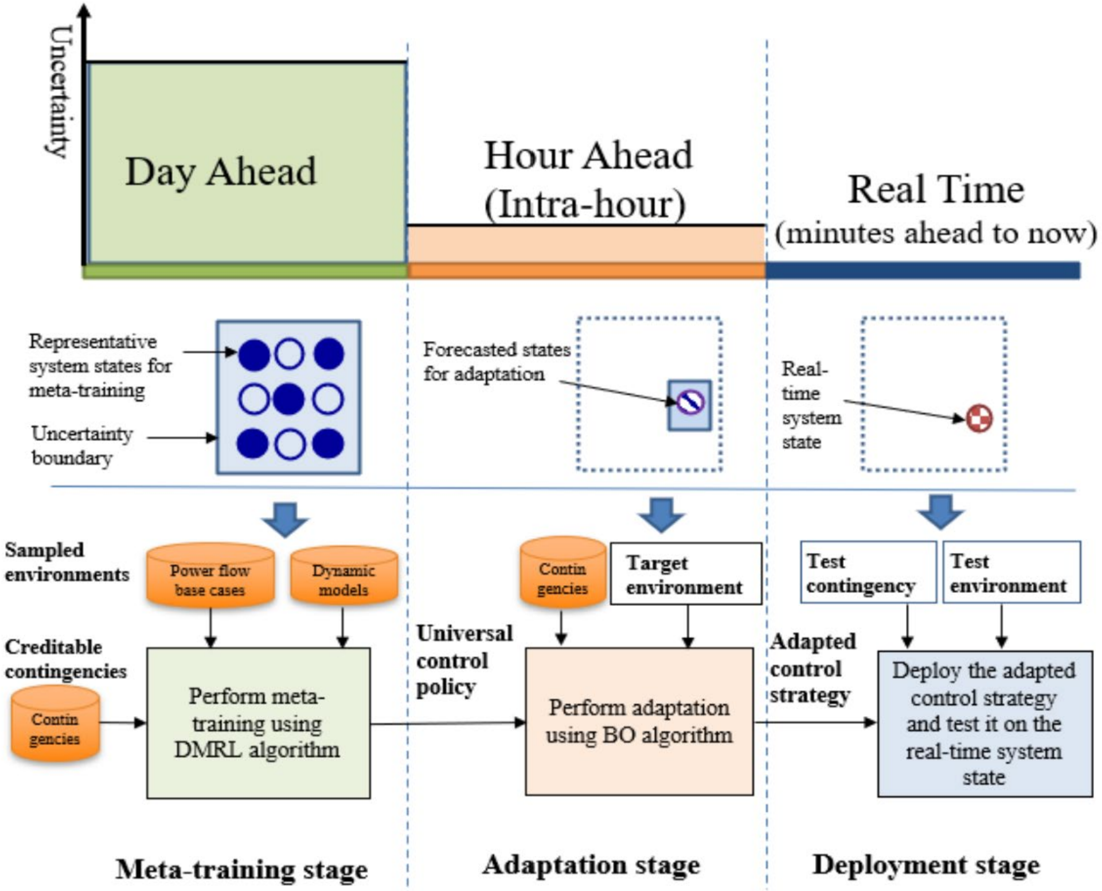
- Learning a universal control policy for very different grid conditions is challenging and not scalable.
  - A one-size-fits-all-solution
- Humans behave adaptively based on the context.
  - Q： How to help the agent learn the context and adapt the control strategies accordingly?
- DMRL (meta-learning + PARS): learn a latent context automatically through Bayesian optimization in the outer loop.
  - A flexible-size-fits-all-solution



R. Huang, Y. Chen, T. Yin, Q. Huang, J. Tan, W. Yu, X. Li, A. Li, Y. Du, “Learning and Fast Adaptation for Grid Emergency Control via Deep Meta Reinforcement Learning,” IEEE Trans. on Power Systems, 2021

Meta-training and Fast Adaptation to Changing Operation Condition





Learning and adaptation to overcome increasing uncertainties

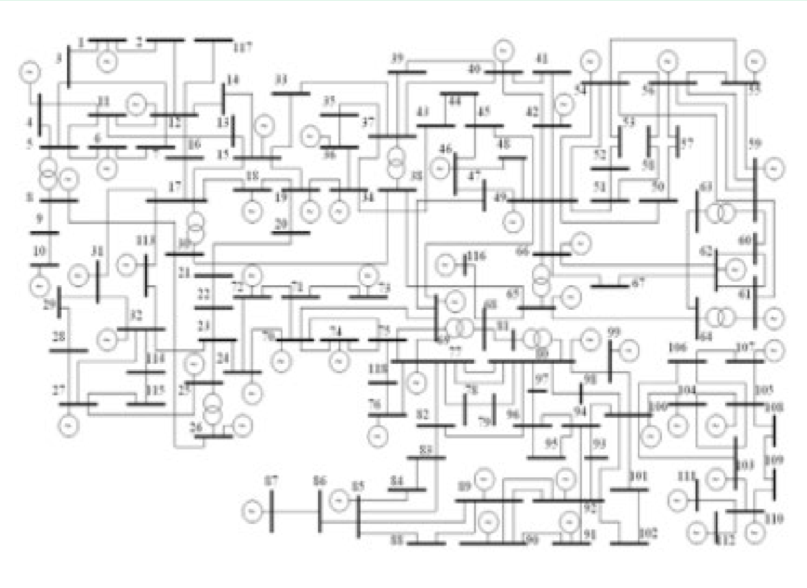
The procedure fits into existing operation time framework

R. Huang, Y. Chen, T. Yin, Q. Huang, J. Tan, W. Yu, X. Li, A. Li, Y. Du, "Learning and Fast Adaptation for Grid Emergency Control via Deep Meta Reinforcement Learning," IEEE Trans. on Power Systems, 2021

An Example: Load Shedding for Emergency Voltage Control

O_t: Observations

154 bus voltage magnitudes and 46 bus load levels

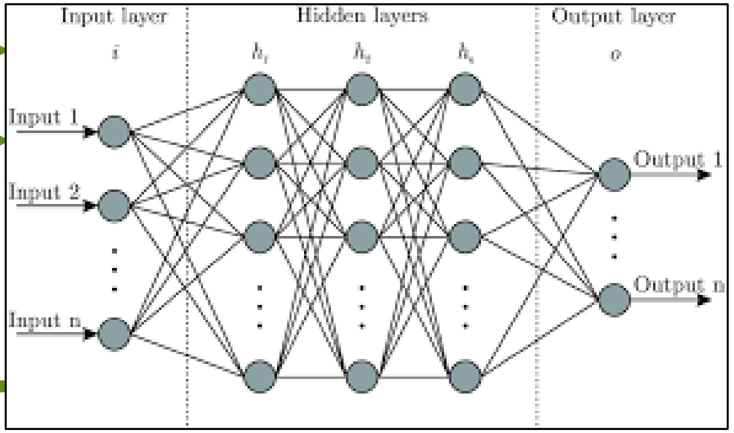


IEEE 300-bus system model

o_t

r_t (for training)

a_t



(for illustration only)

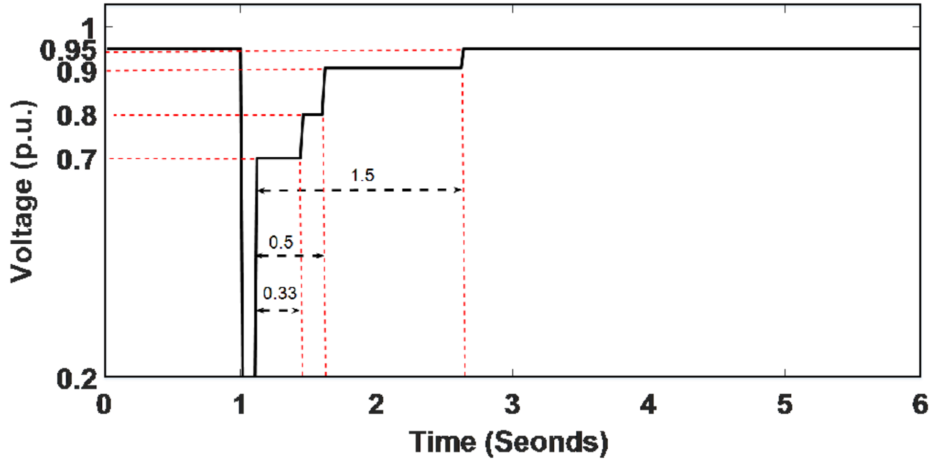
A Neural Network for representing agent's policy

a_t: Actions

- 46 load substations could shed load.
- Each area, for each training time step, the load could be shed between 0% and 20% .
- The action space is 46.

R. Huang, Y. Chen, T. Yin, Q. Huang, J. Tan, W. Yu, X. Li, A. Li, Y. Du, "Learning and Fast Adaptation for Grid Emergency Control via Deep Meta Reinforcement Learning," IEEE Transactions on Power Systems, accepted, 2022

Reward Function Design



Bus voltage performance requirement

Voltage criteria

Load shedding

Invalid actions

$$Reward = \begin{cases} c_1 \sum_i \Delta V_i - c_2 \sum_j \Delta P_j (p.u.) - c_3 u_{invalid} \\ -10000, \text{ if } V_i(t) < 0.95, \quad t > T_{pf} + 4 \end{cases}$$

Large-penalty for non-acceptable performance

$$\Delta V_i(t) = \begin{cases} \min\{V_i(t) - 0.7, 0\}, \text{ if } T_{post\_fault} < t < T_{post\_fault} + 0.33 \\ \min\{V_i(t) - 0.8, 0\}, \text{ if } T_{post\_fault} + 0.33 < t < T_{post\_fault} + 0.5 \\ \min\{V_i(t) - 0.9, 0\}, \text{ if } T_{post\_fault} + 0.5 < t < T_{post\_fault} + 1.5 \\ \min\{V_i(t) - 0.95, 0\}, \text{ if } T_{post\_fault} + 1.5 < t \end{cases}$$

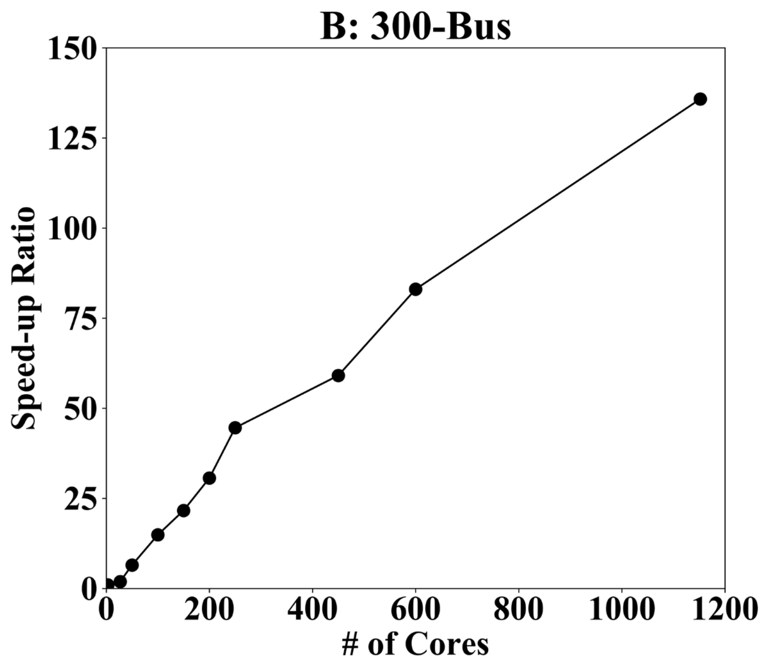
Meet the minimum performance requirement

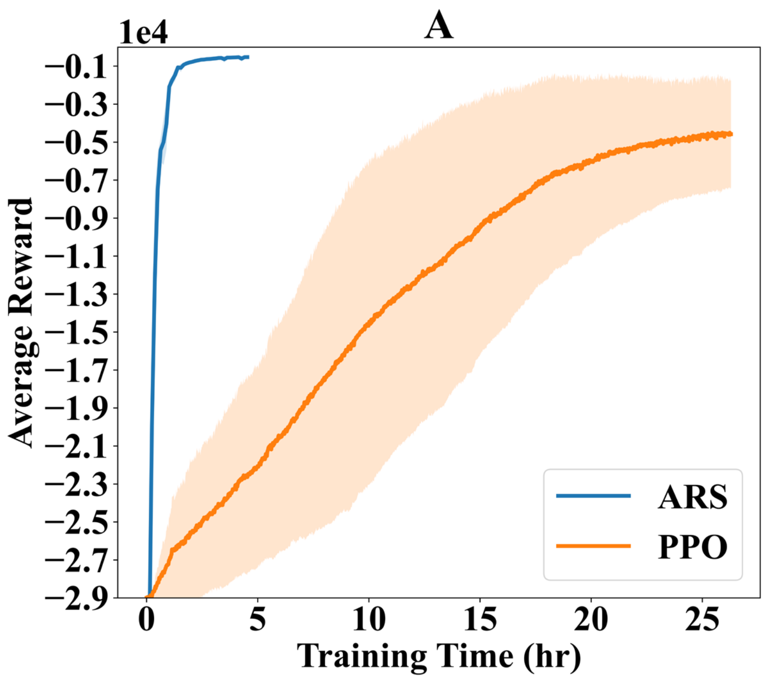
Reward Function

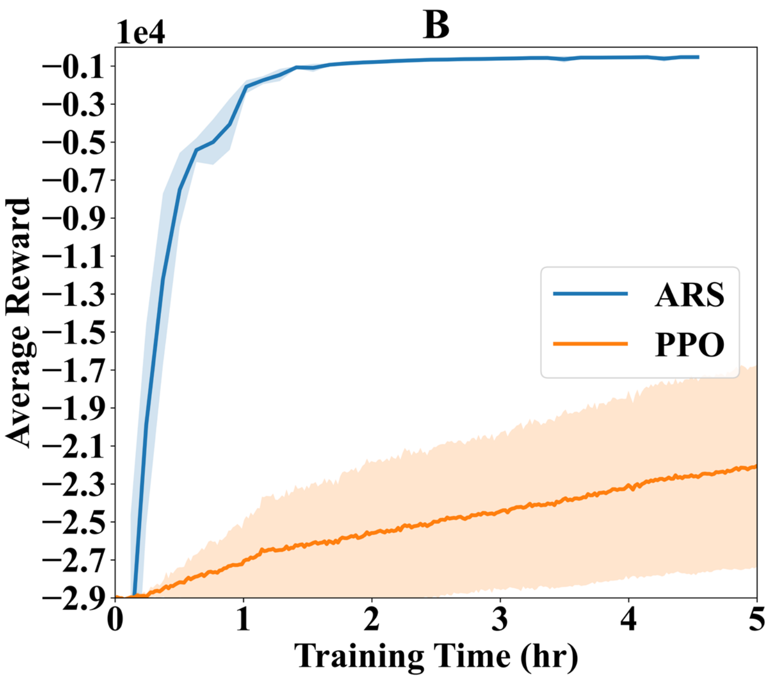
R. Huang, Y. Chen, T. Yin, Q. Huang, J. Tan, W. Yu, X. Li, A. Li, Y. Du, “Learning and Fast Adaptation for Grid Emergency Control via Deep Meta Reinforcement Learning,” IEEE Transactions on Power Systems, accepted, 2022

Parallel ARS Algorithm Test Results

- Emergency voltage control on the IEEE 300-bus system







PPO: Proximal Policy Optimization

High scalability of Parallel ARS

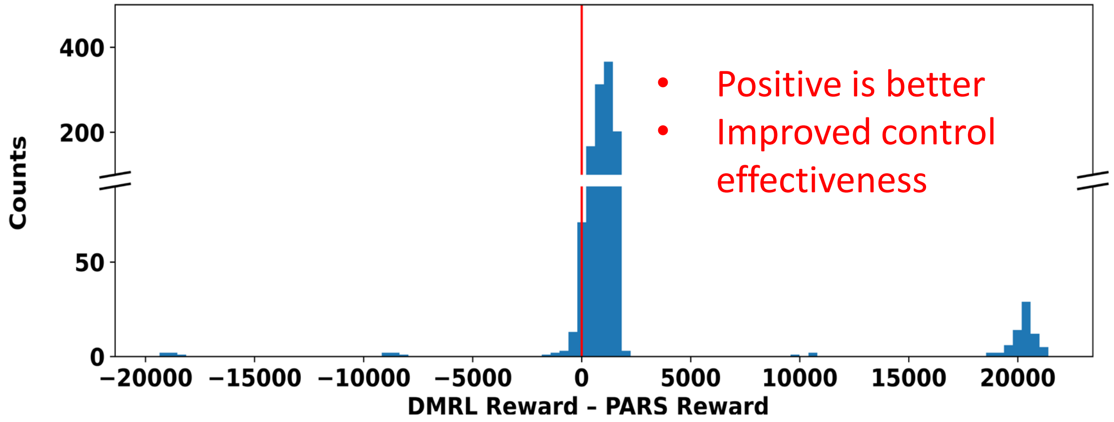
Much faster and more robust training with larger average rewards using Parallel ARS

R. Huang, Y. Chen, T. Yin, X. Li, A. Li, J. Tan, W. Yu, Y. Liu, Q. Huang. "Accelerated Derivative-Free Deep Reinforcement Learning Based Load Shedding for Emergency Voltage Control," in IEEE Transactions on Power Systems, vol. 37, no. 1, pp. 14-25, Jan. 2022, doi: 10.1109/TPWRS.2021.3095179.

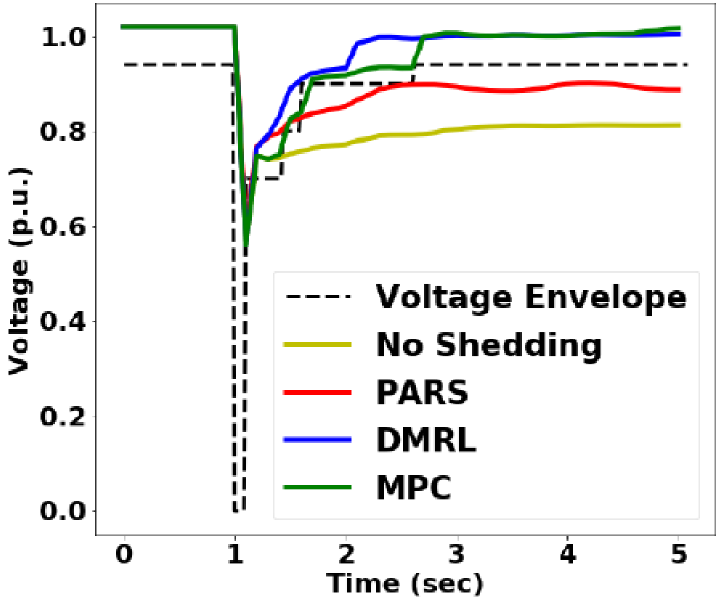
Deep Meta-Reinforcement Learning Test Results

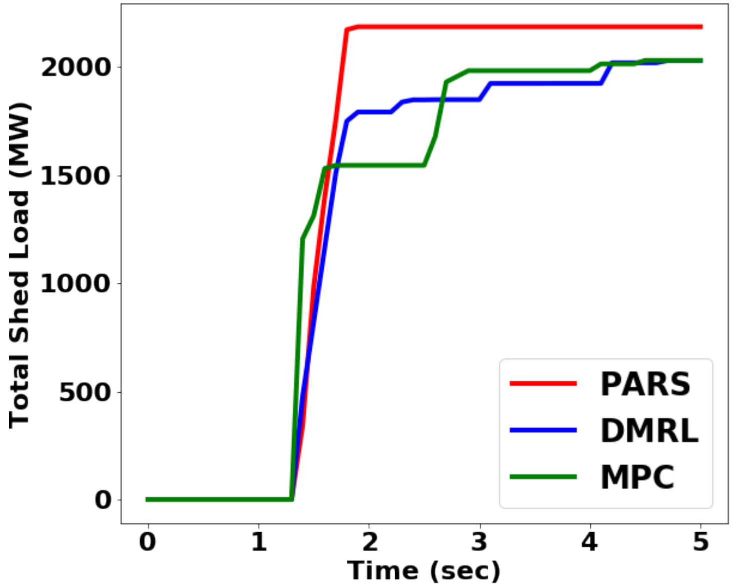
	DMRL	PARS	MPC*
Training	11.6 hours	9.5 hours	N/A
Adaptation	5.3 mins	N/A	N/A
Solution time	0.7 sec	0.7 sec	63.3 sec

*MPC: Model-predictive control



All test scenarios are unseen during training

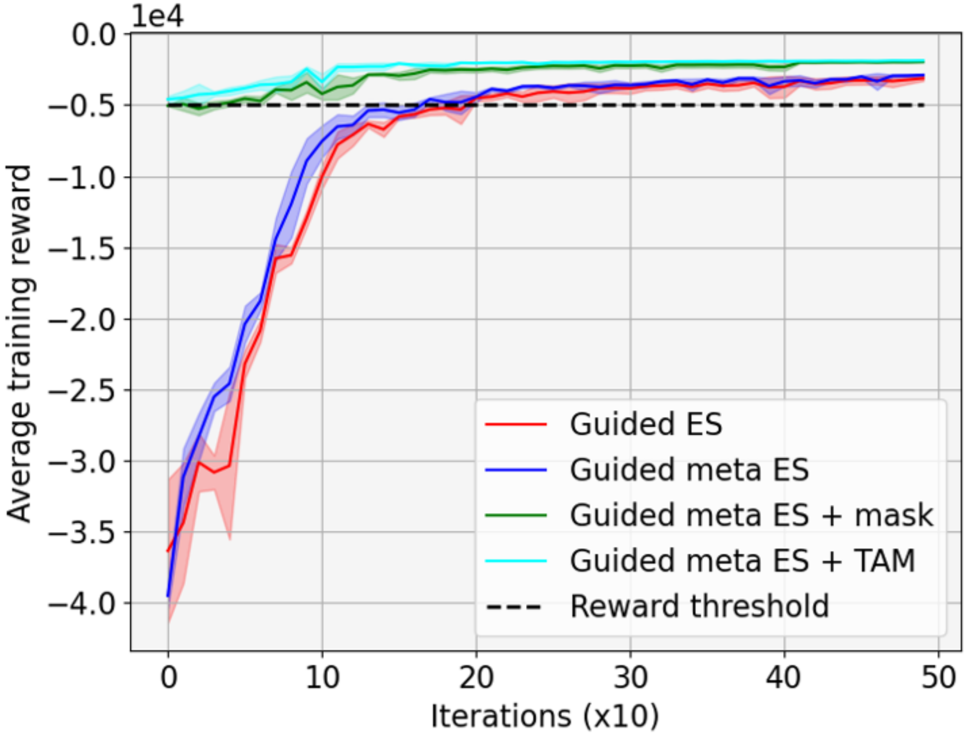




R. Huang, Y. Chen, T. Yin, Q. Huang, J. Tan, W. Yu, X. Li, A. Li, Y. Du, "Learning and Fast Adaptation for Grid Emergency Control via Deep Meta Reinforcement Learning," IEEE Transactions on Power Systems, accepted, 2022

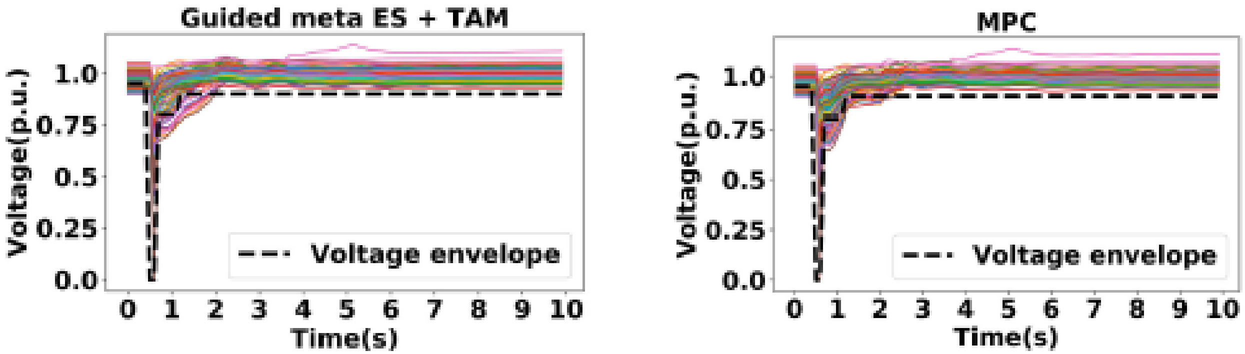
Physics-informed DMRL Test Results

Physics-informed DMRL enhances training efficiency by 3X and control robustness by 75%



Training results

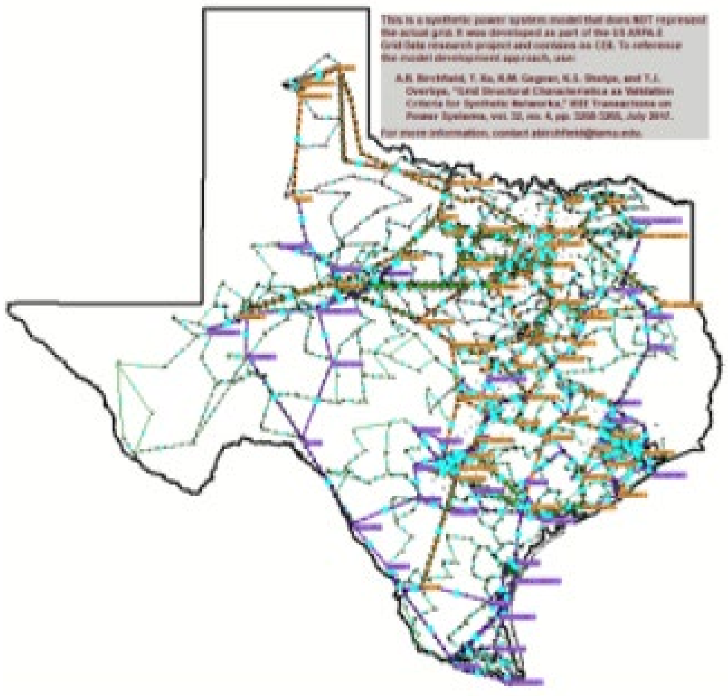
Method	Average test reward	No. of failed cases
ARS	-1.27×10^4	72
Guided ES	-5.6×10^3	17
Guided meta ES	-4.3×10^3	12
Guided meta ES + mask	-2.8×10^3	8
Guided meta ES + TAM	-1.89×10^3	3
MPC	-1.82×10^3	3



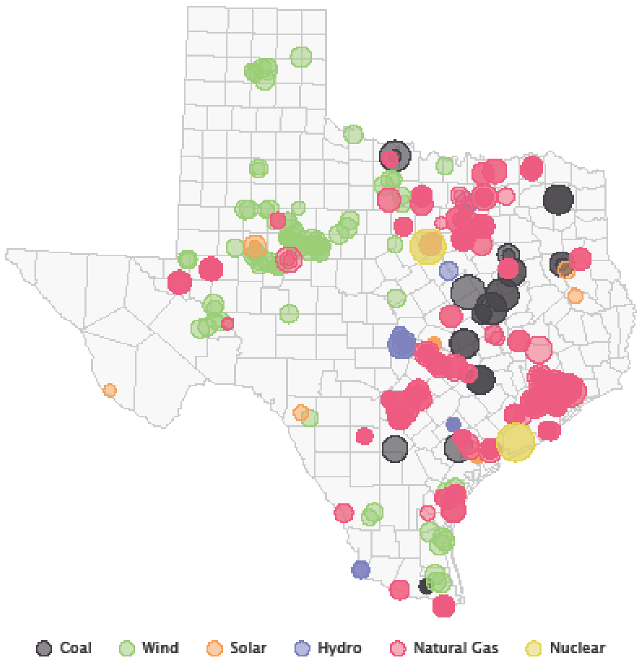
Test results based on 136 new scenarios

Y. Du, Q. Huang, R. Huang; T. Yin; J. Tan; W.Yu; X. Li, "Physics-informed Evolutionary Strategy based Control for Mitigating Delayed Voltage Recovery," in IEEE Transactions on Power Systems, 2022,doi: 10.1109/TPWRS.2021.3132328.

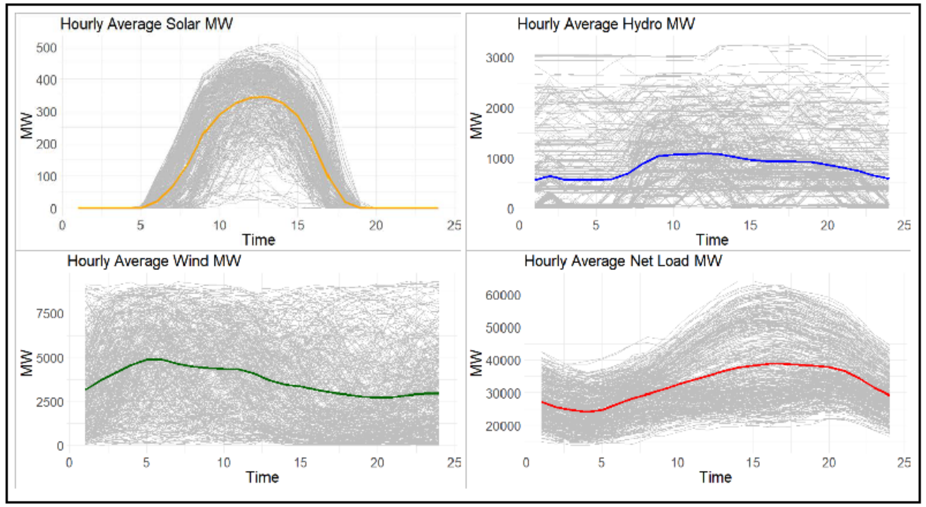
A 2000-bus Synthetic Texas System



Single-line diagram



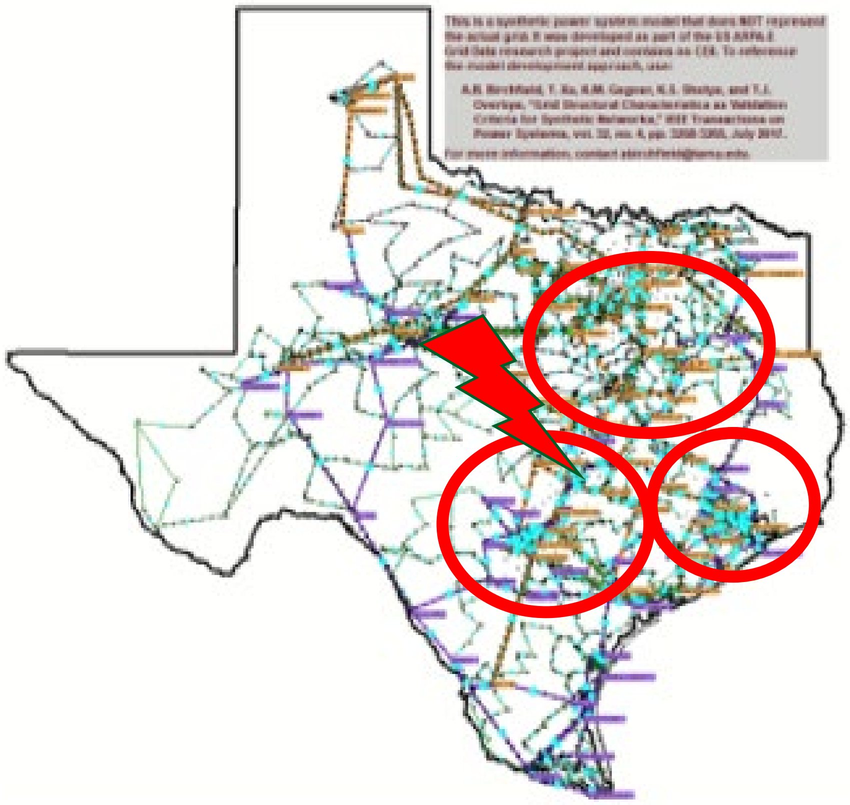
Generation mix based on EIA data



Hourly renewable outputs and net load demands

Source: https://electricgrids.engr.tamu.edu/electric-grid-test-cases/activsg2000/

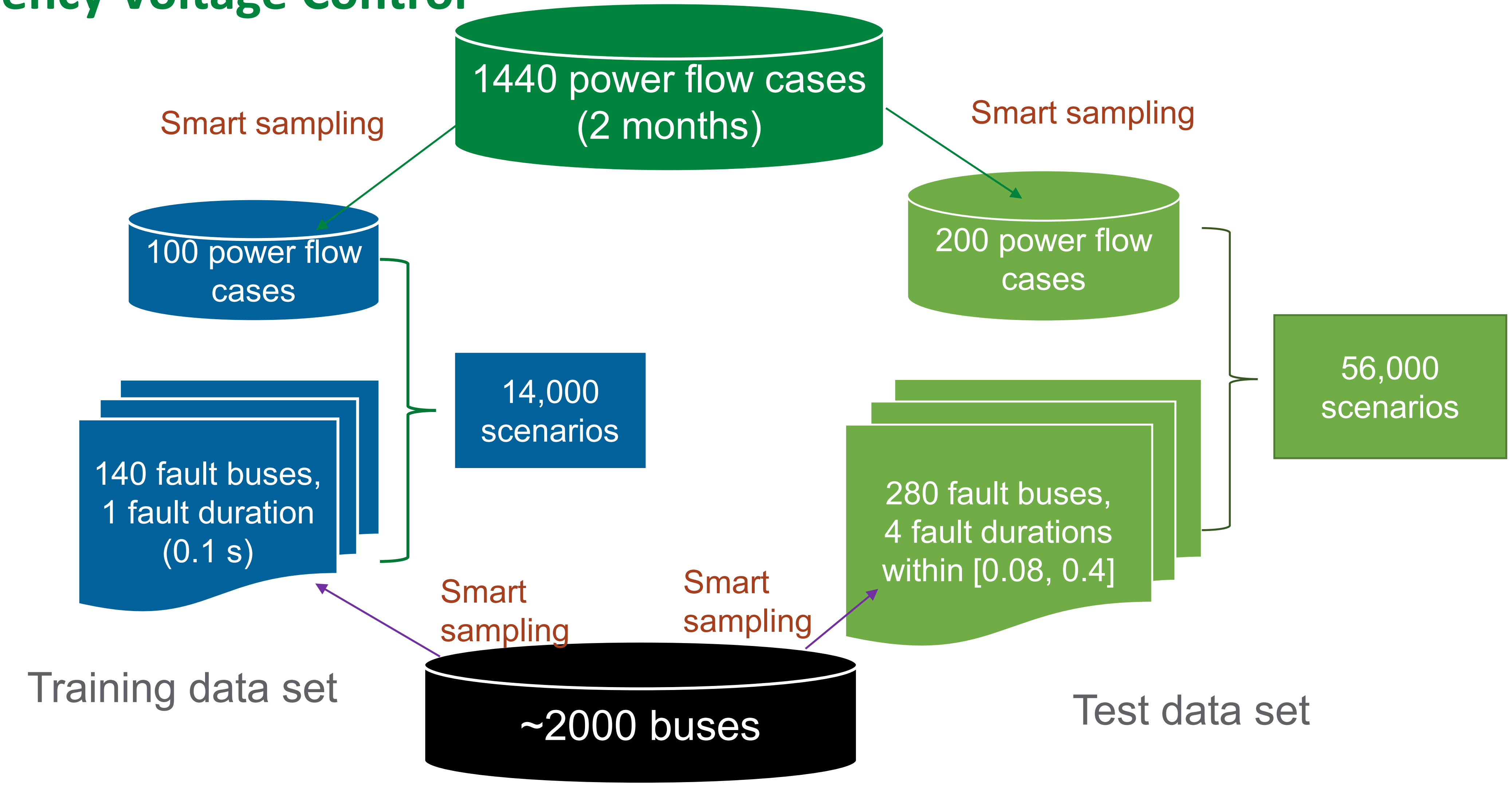
Physics-informed Training



Physics: the voltage stability problem in power systems are mostly local issues

1. Areas are loosely coupled for voltage problems
2. Yet, actions in two or three of the regions are required for faults near or at the boundary of the regions.
3. Solutions: divided training and then coordinative training

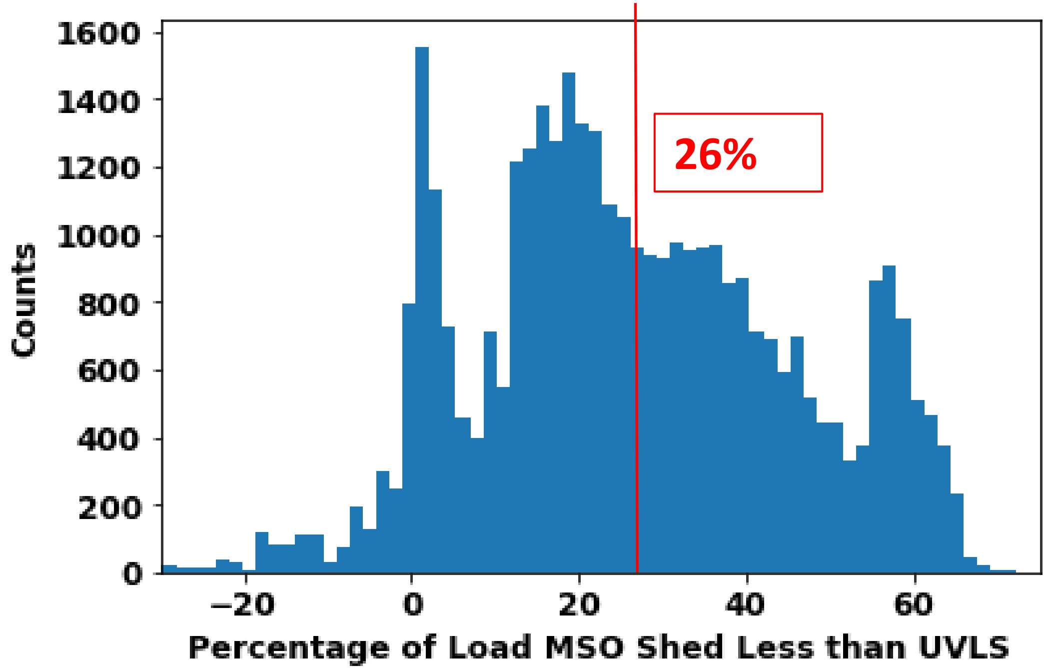
Datasets for Training and Testing of AI-based Emergency Voltage Control



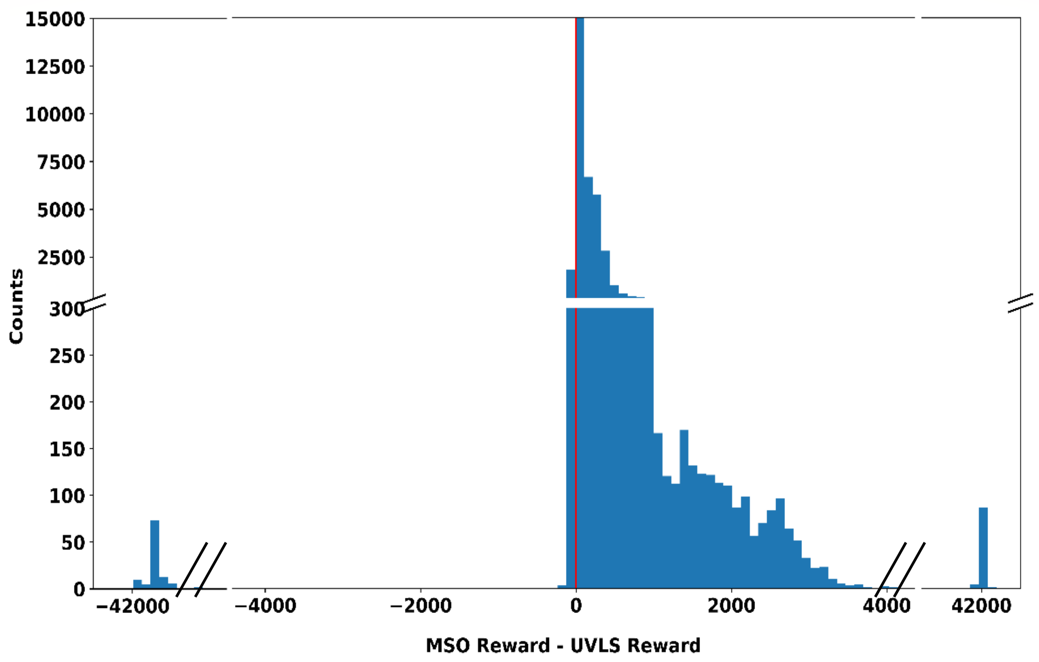
X. Sun *et al*., "Smart Sampling for Reduced and Representative Power System Scenario Selection," in *IEEE Open Access Journal of Power and Energy*, vol. 8, pp. 293-302, 2021,

Off-line Testing Results: Comparison with Rule-based Under-voltage Load Shedding (UVLS) Control

- Reduce load shedding by 26% on average while improving the control performance
    - More selective in load shedding locations, and more intelligent in the action time and amount
- Meet real-time control requirements: 0.7 second for determining solutions for 80 control intervals



Histogram of % reduced load shedding compared with the existing UVLS (positive is better)

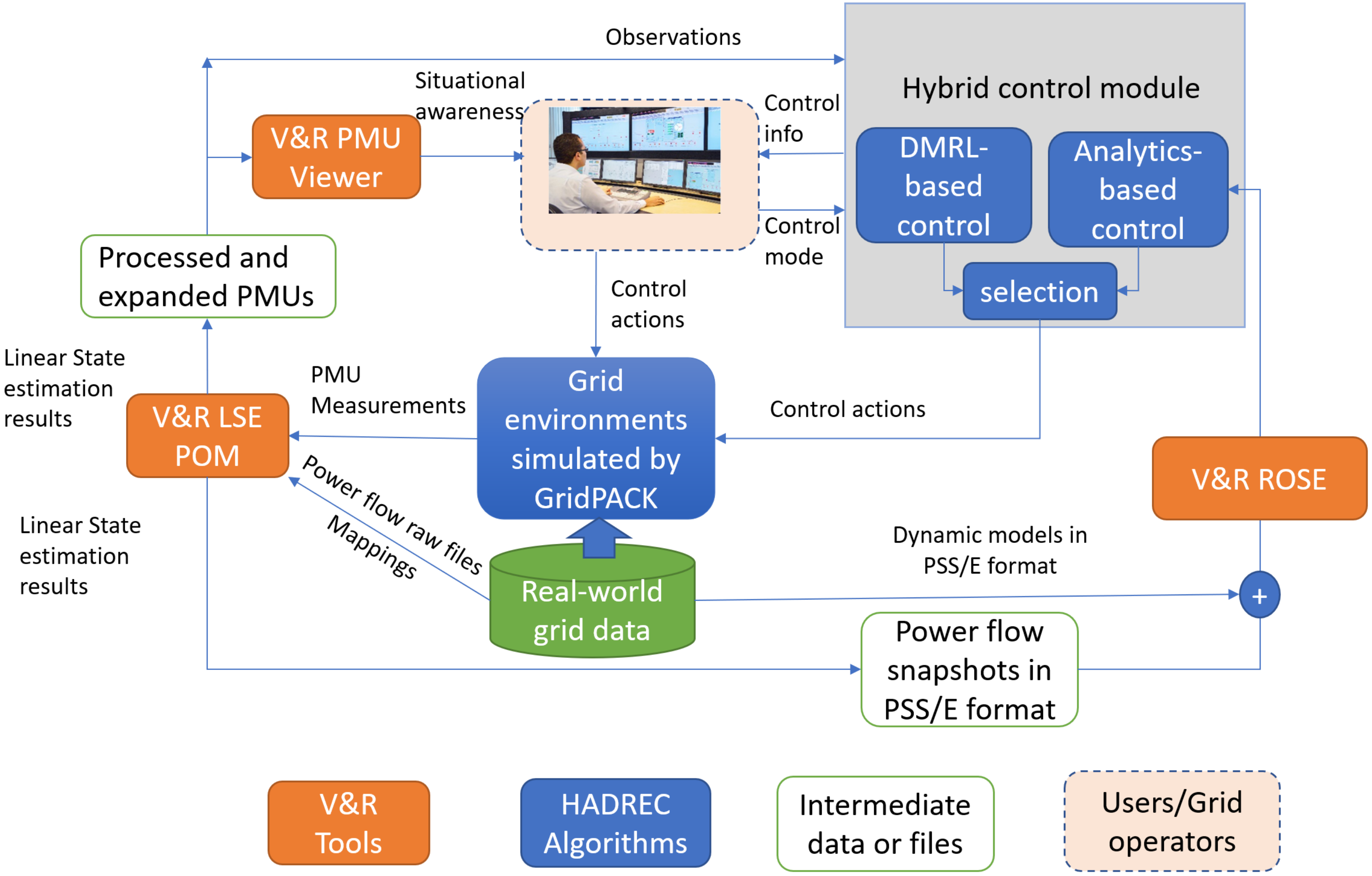


Objective value (total reward) differences (positive is better)

ARPA-E HADREC

Integration with V&R Energy's Tools and Demonstration

HADREC Demonstration Setup



Power System State Estimator

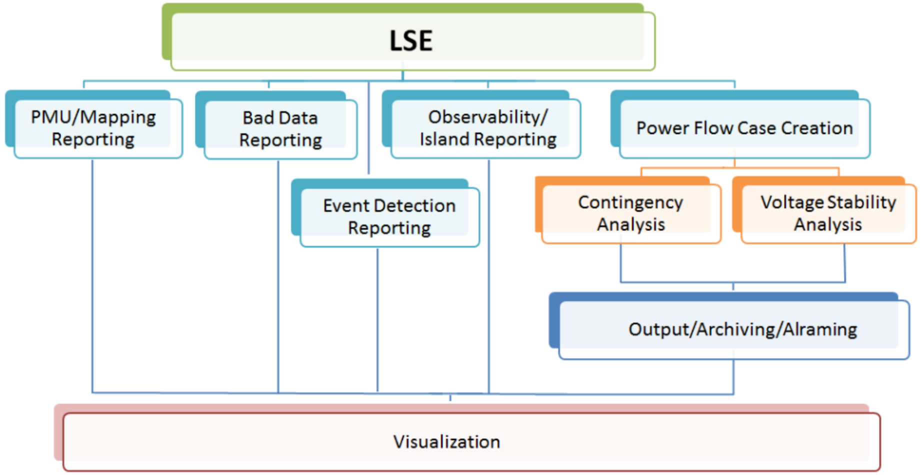
- Main tool to assess reliability and stability of a power system in real-time environment at a utility/ISO:
  - Basis for all advanced applications and market applications
- Designed to produce a system state based on the “best estimate” of the system voltages and phase angles:
  - Provided that there are errors in the measured quantities; and
  - That there is a redundancy in measurements
- Minimizes the sum of the squares of the differences between the measured and estimated values of variables:
  - Voltage magnitude
  - Current on the branches

Importance of Linear State Estimator

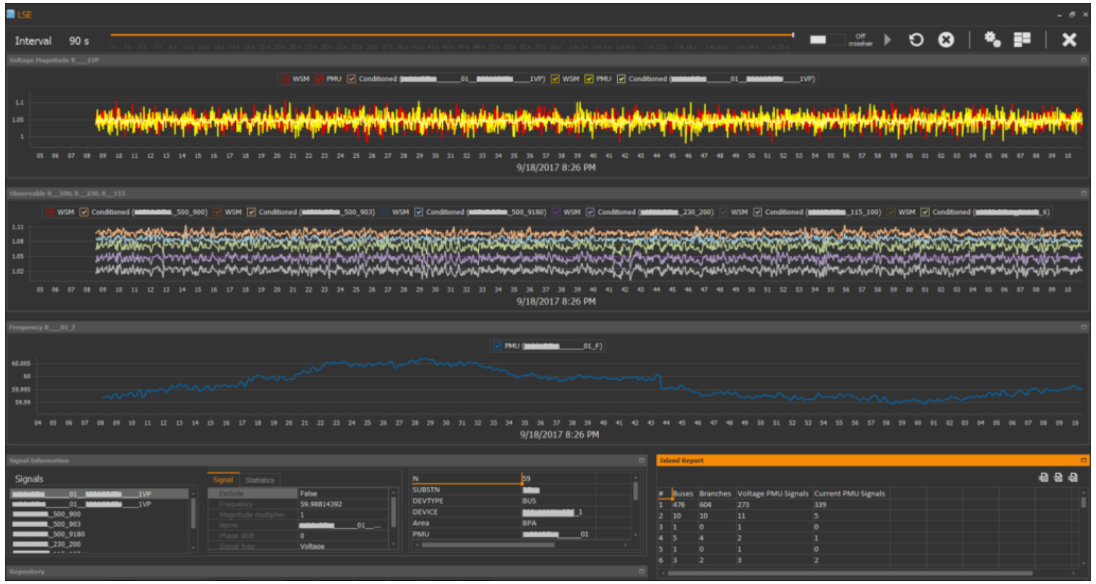
- Linear State Estimator (LSE) is based on PMU measurements of voltage and current:
  - Voltage and current vectors are considered as the state variable
- Advantages of LSE:
  - Improves real-time resilience:
    A backup to the conventional SE solution if it fails to solve or SCADA data is not available
  - Improves real-time reliability:
    A check/validation for the quality of conventional state estimator
  - High speed of state estimation due to using a direct non-iterative solution
    Solves at PMU sample rate (30 times/sec – transmission system or 60 times/sec – distribution system)

Introduction to V&R Energy's PMU ROSE

LSE POM Server



LSE PMU Viewer



- Bad data detection and conditioning
- Observability analysis
- Linear state estimation based on weighted least squares method
- Creation of conditioned and expanded PMU streams
- Visualization and data stream APIs
- Creation of PMU-based LSE cases
- Advanced applications based on LSE cases

Integration of PMU ROSE with GridPACK

Input:

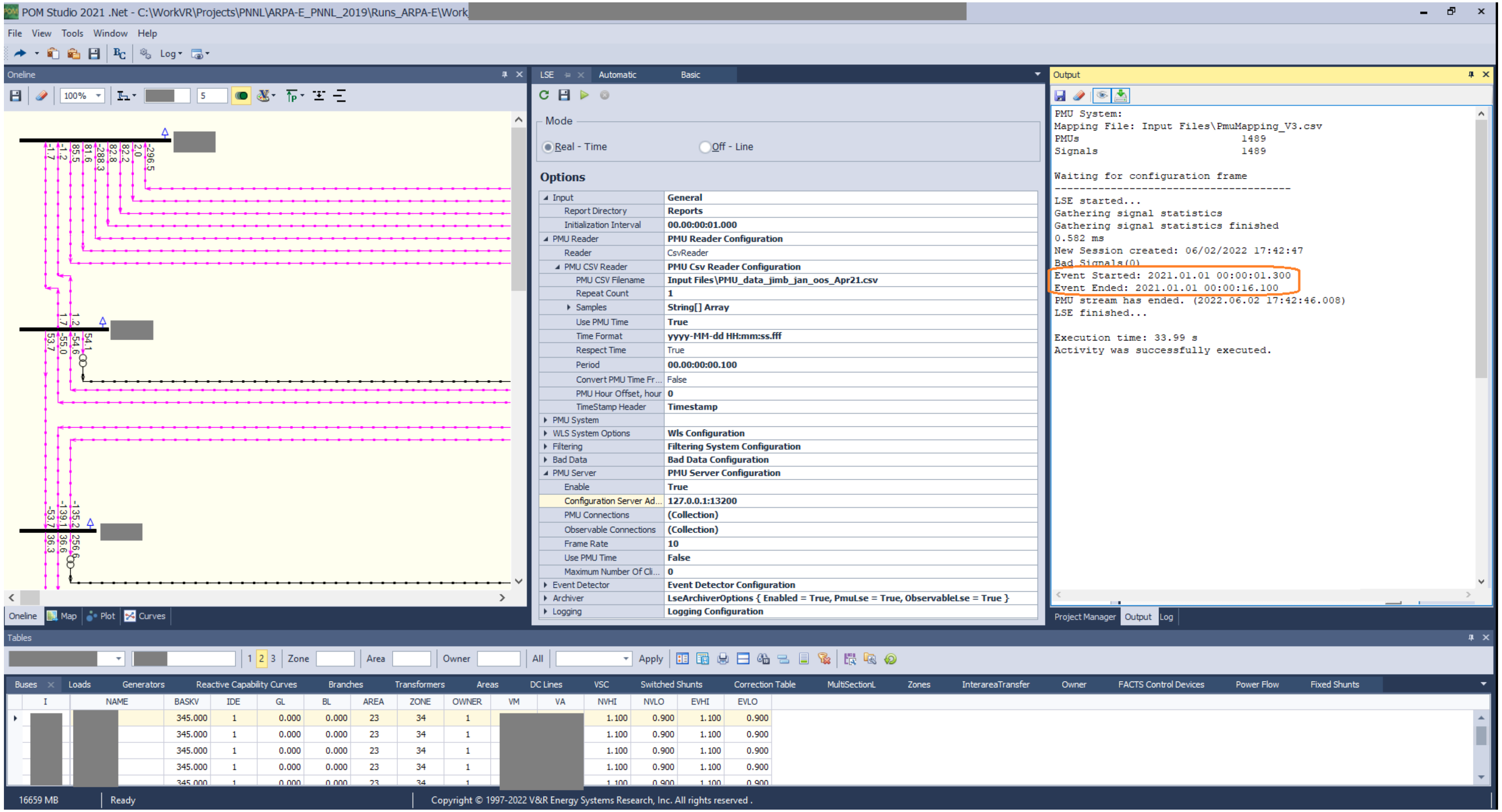
- State Estimator cases:
  - Network parameters, connectivity, initial topology
- PMU data in IEEE Standard C37.118
- State Estimator to PMU signal mapping
- Data for different scenarios/events was simulated

Output:

- Processed data after LSE for PMU locations and observable locations
  - Estimated data for locations where PMUs are installed
  - Additional “calculated PMUs” at locations identified through observability analysis
  - Includes voltage magnitude and phase angle, and current amplitude and phase angle
- Reports:
  - Bad data reports
  - Observability reports
- Alarms:
  - Event-related and PMU-related
- Archives, logs

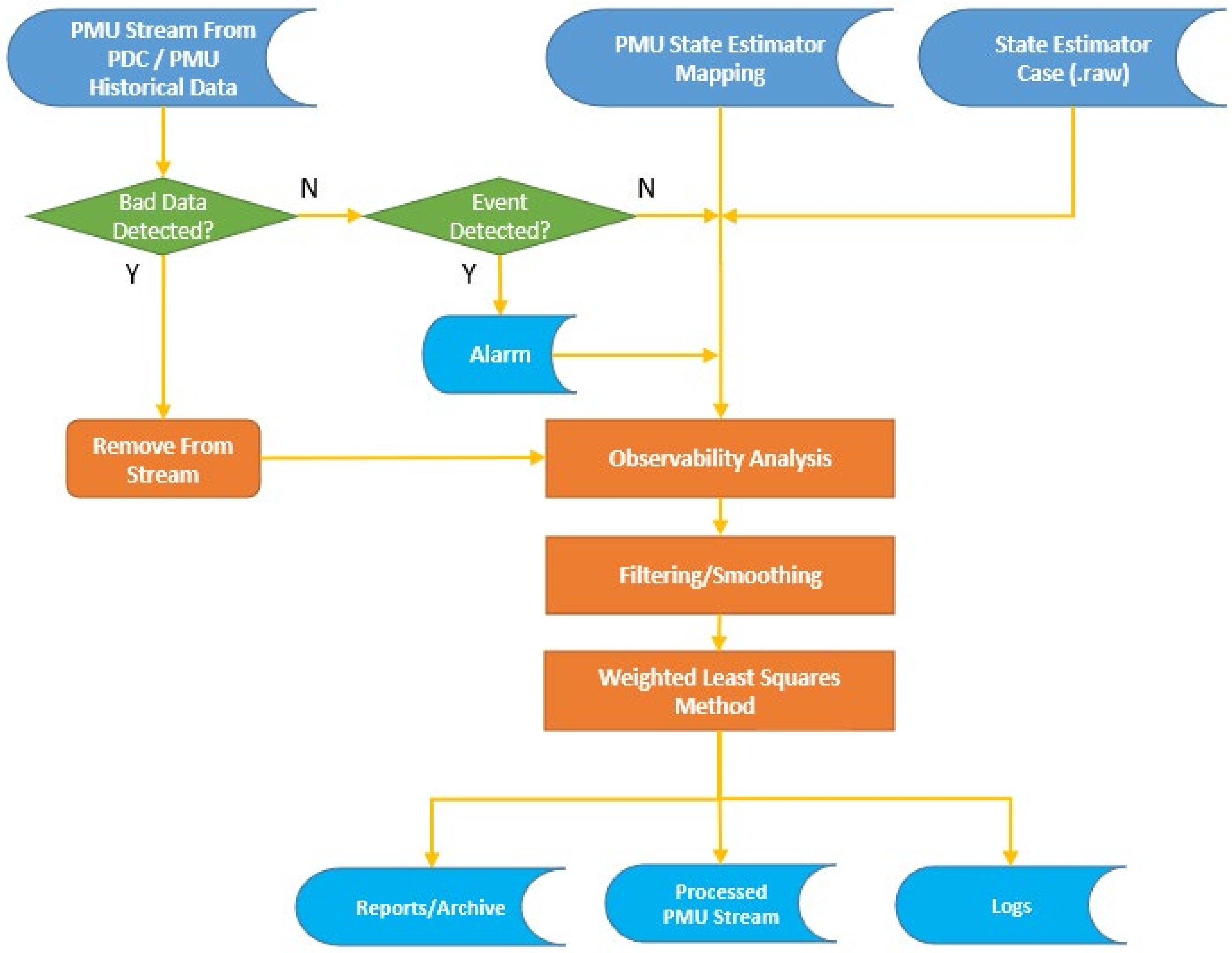
LSE POM Server for Demonstration – 1

- PMU data with realistic properties (e.g., noise, bad data) was generated by GridPACK
- Sent to LSE POM Server at the rate of 10 fps

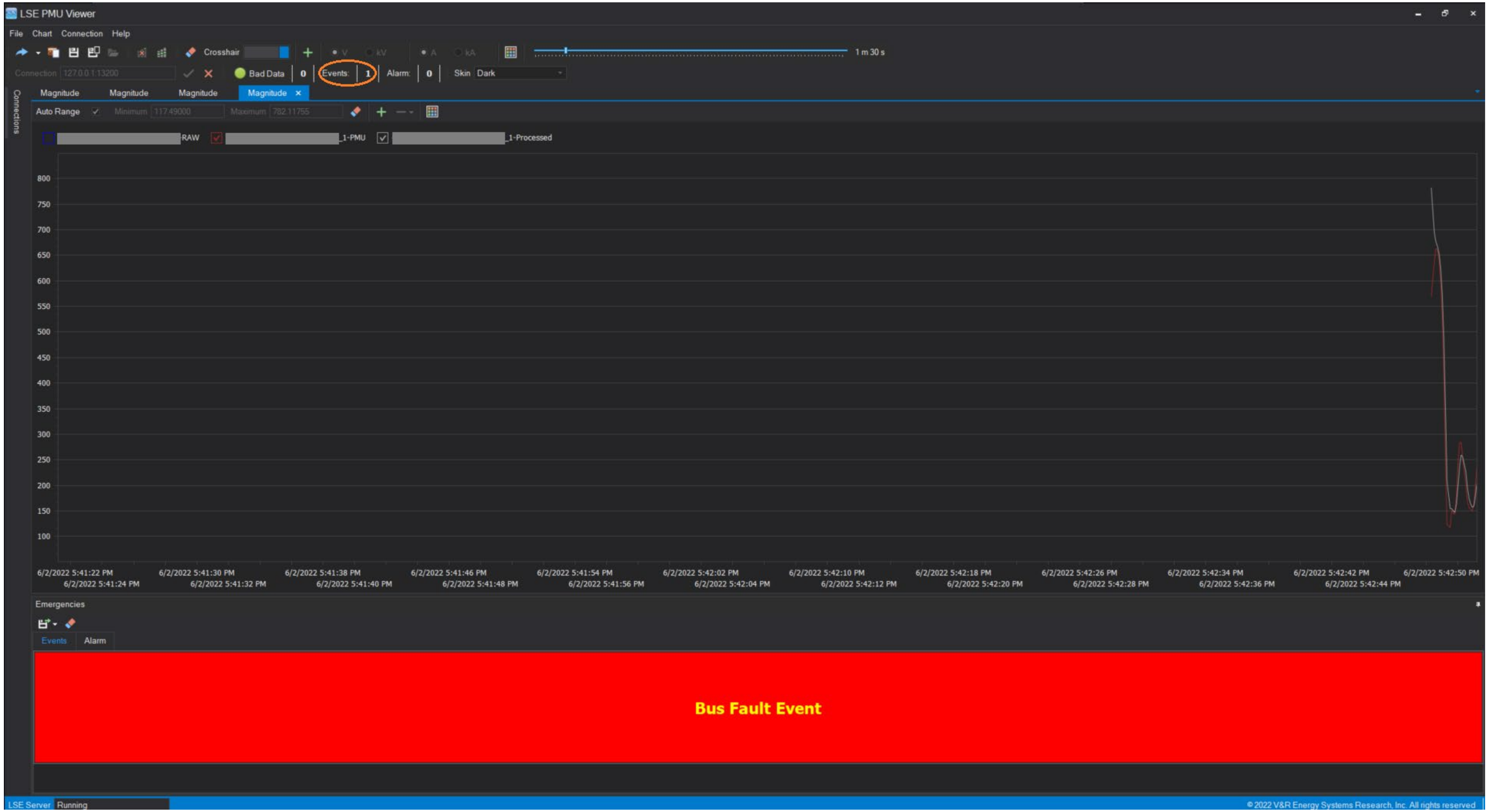


LSE POM Server for Demonstration – 2

- LSE functionalities for demo include:
  - Bad data detection and conditioning;
  - Filtering & smoothing;
  - Weighted Least Squares Methods (WLS);
  - Event detection;
  - Alarming;
  - Archiving;
  - Visualization.



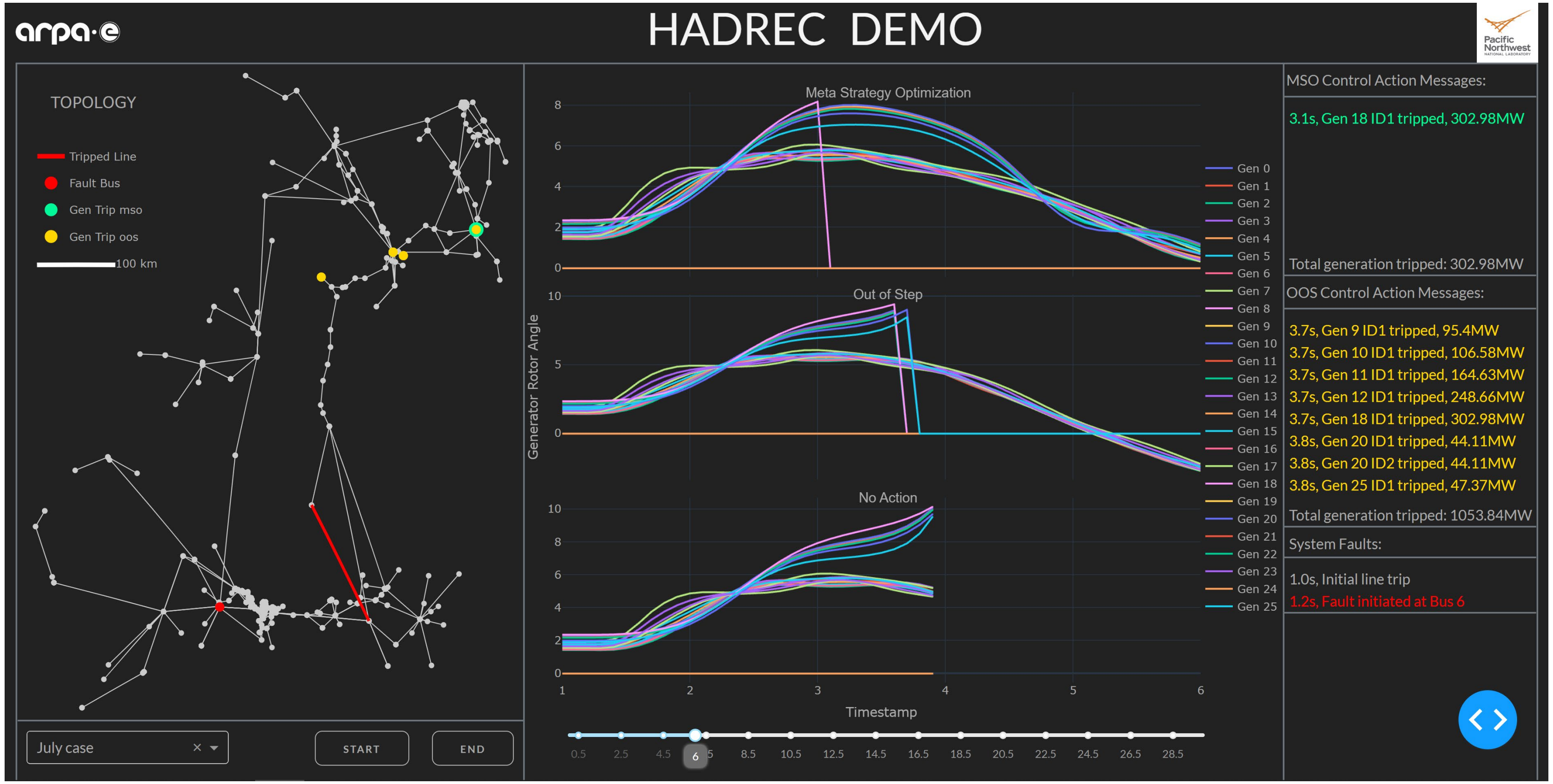
LSE PMU Viewer for Real-Time Situational Awareness



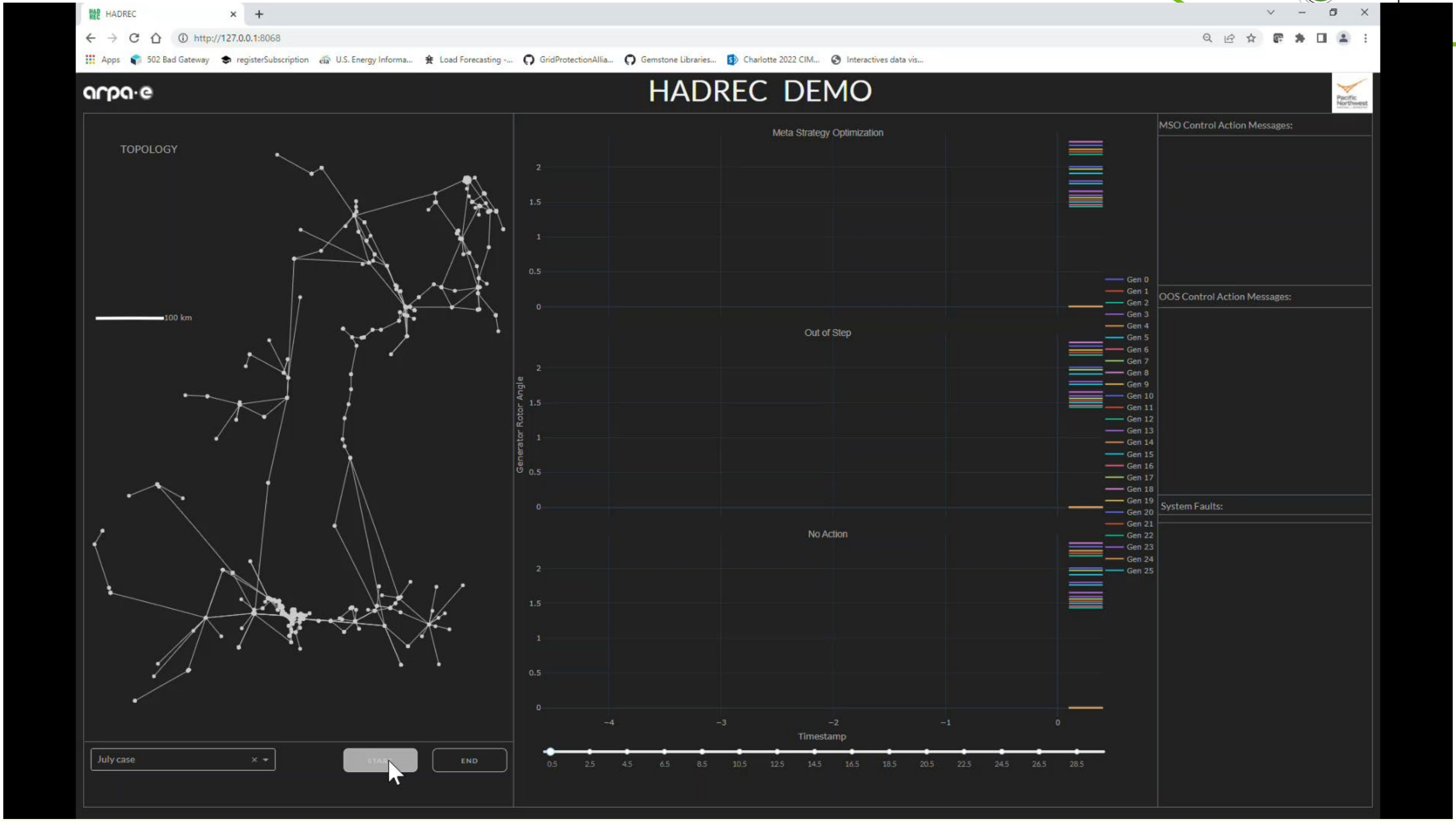
LSE POM Server identified a bus fault event in PacifiCorp system and PMU Viewer displayed an alarm

- Visualizes:
  - PMU measurements
  - Data processed by LSE
- Displays:
  - Events
  - Alarms
  - Bad Data

HADREC performance on the PacifiCorp system



- HADREC: 1 generator tripped, 300MW total
- Out of Step (OOS): 8 generators tripped, 1 GW total
- ~20% improvement in responding time and 70% improved in tripped generator output
- HADREC technology integrated with V&R’s real-time situational awareness tool (ROSE)


HADREC
http://127.0.0.1:8068
Apps
502 Bad Gateway
registerSubscription
U.S. Energy Informa...
Load Forecasting -...
GridProtectionAllia...
Gemstone Libraries...
Charlotte 2022 CIM...
Interactives data vis...
arpa·e
HADREC DEMO
TOPOLOGY
100 km
July case
START
END
Meta Strategy Optimization
Out of Step
No Action
Generator Rotor Angle
Timestamp
Gen 0
Gen 1
Gen 2
Gen 3
Gen 4
Gen 5
Gen 6
Gen 7
Gen 8
Gen 9
Gen 10
Gen 11
Gen 12
Gen 13
Gen 14
Gen 15
Gen 16
Gen 17
Gen 18
Gen 19
Gen 20
Gen 21
Gen 22
Gen 23
Gen 24
Gen 25
MSO Control Action Messages:
OOS Control Action Messages:
System Faults:

The AI Algorithms and Grid Simulation Environment are Open-sourced

- AI algorithms and training source codes
  - https://github.com/pnnl/HADREC/

- High-performance grid simulation environment based on GridPACK
  - https://github.com/GridOPTICS/GridPACK
  - Python wrapper for OpenAI-gym interface: https://github.com/GridOPTICS/GridPACK/tree/master/python

Recent progress in AI for Grid Operation

PNNL's Recent progress in AI for power systems

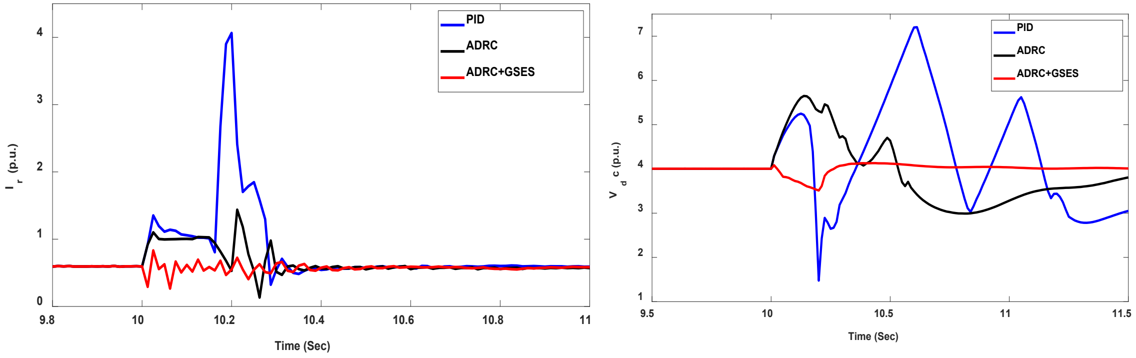
AI/ML – Capabilities:

- DOE PMU "Big Data Analytics" FOA. Anonymized and placed in dedicated cloud environment
  - ~30 TB data, 600B records, 394 PMUs
  - Full blown PMU network could be >1 petabytes/year.
- EIOC dedicated "reliability grade" streaming data storage and curation
  - Approaching petabyte capacity to support research and industry collaboration
- ARPA-E data repositories (real and synthetic data)
- Positioned to provide NAERM support and hosting as the real-time system is developed

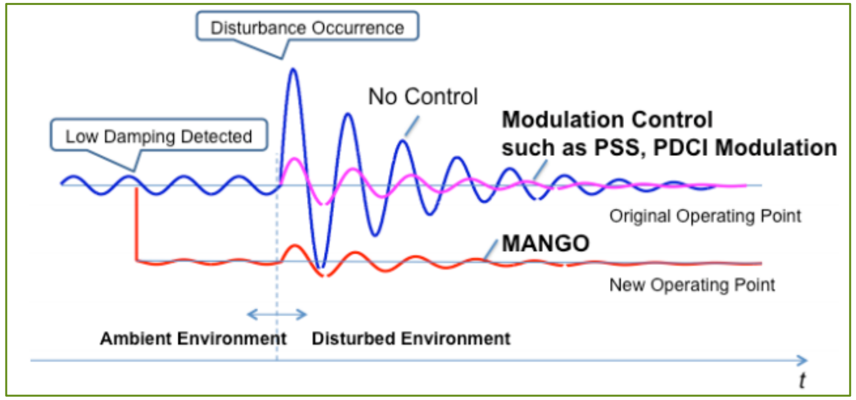
AI/ML – Accomplishments:

- Operation and Control
  - LACC: Reduce overshot magnitude during fault by more than 10X
  - MANGO: Adjust real-time operating points for damping improvement
  - TRAST: Actively learning preventive measure in real time for graceful degradation
- Planning
  - HIPPO: 35x faster optimal solutions for $Bs energy savings

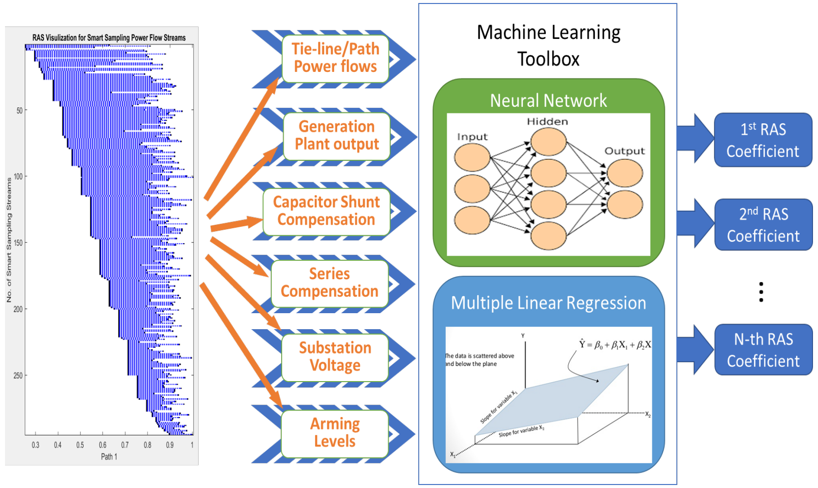
PNNL Applies AI to Increase System Transparency and Grid Reliability, Security and Efficiency



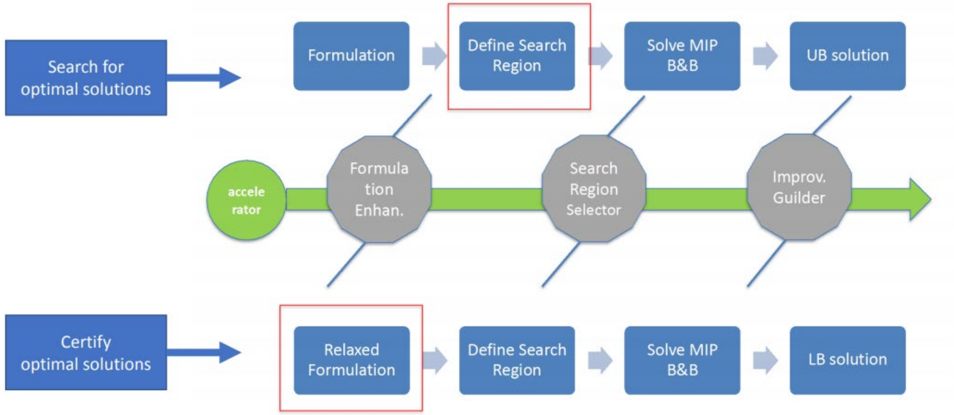
LACC: AI-based online controller parameter optimization and adaption



MANGO: Grid damping improvement through AI-enabled active operating point adjustment

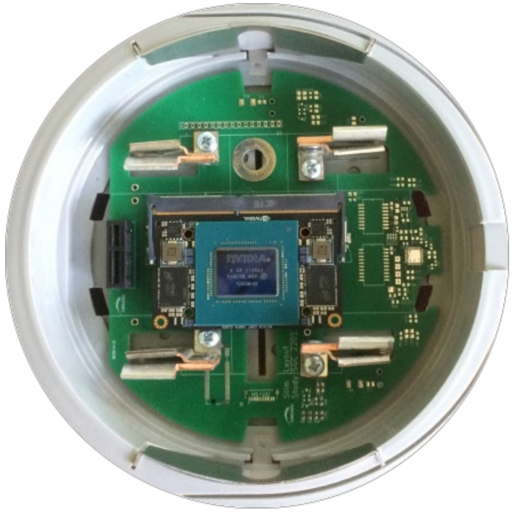


Transformative Remedial Action Scheme Tool (TRAST)

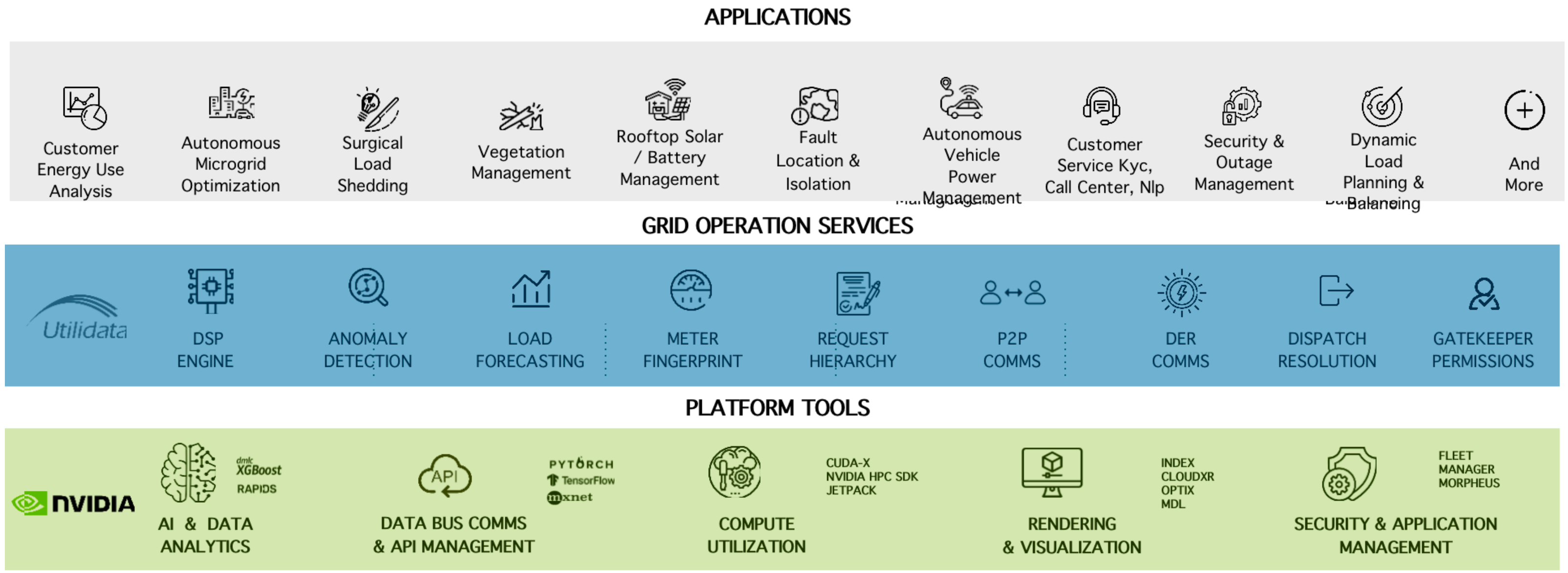


HIPPO: AI accelerates solving power market clearing problems

New Hardware and Software Ecosystem for Grid Edge Intelligence



Smart grid chip with GPU for edge computing and AI



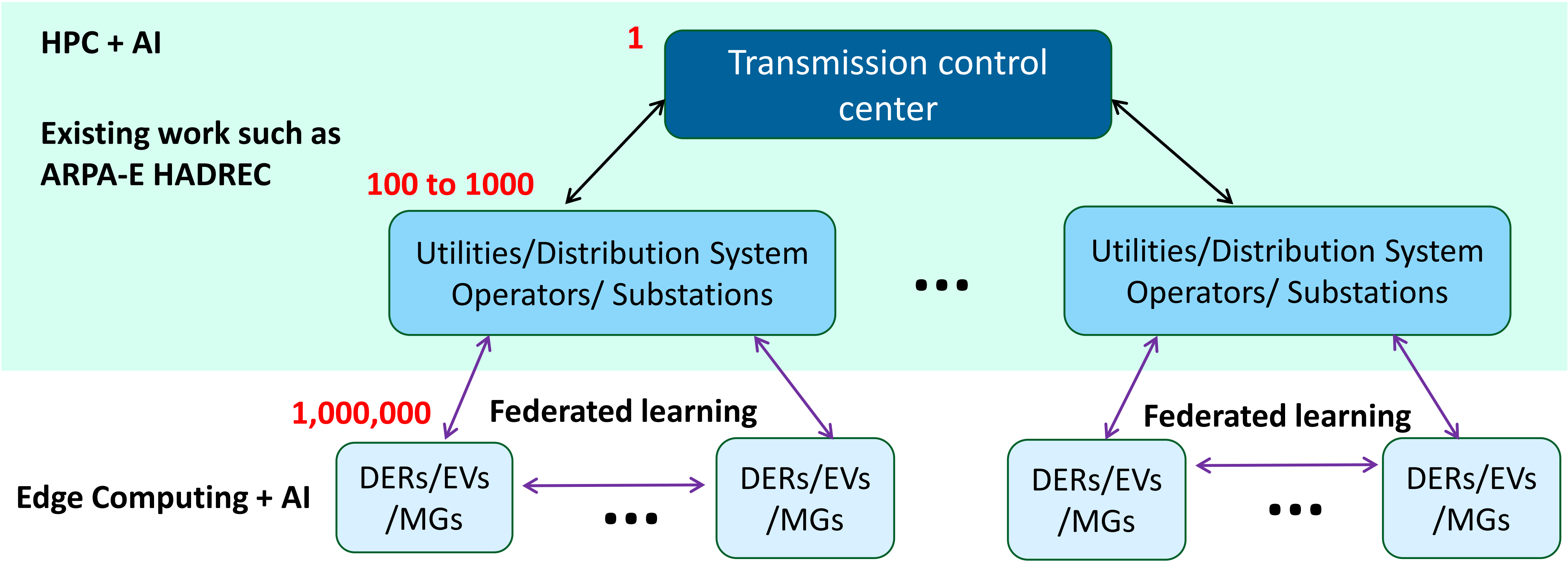
Open-source software ecosystem for the grid edge intelligence

Summary

- Fast and intelligent control and decision-making at the control centers and the edge is required to operate the grid reliably and efficiently.
- AI such as DRL, when combined with physics and advanced computing, can be an essential part of the solution.
- We demonstrated fast and intelligent emergency controls for a Texas-size system and WECC system is achievable through fusing AI, physics, computing, control.
- We developed datasets and AI-based solutions for enhancing renewable integration, system operation, reliability management and market solution.

Perspective: Distributed Control with Edge AI and Coordination with Centralized Control

- Distributed control with edge computing and AI helps manage and coordinate up to millions of DERs.
- Coordinating centralized and distributed control as well as computing is critical for large-scale clean energy integration and FERC 2222 compliance.
- Federated learning and control can help overcome the data privacy and security concerns.

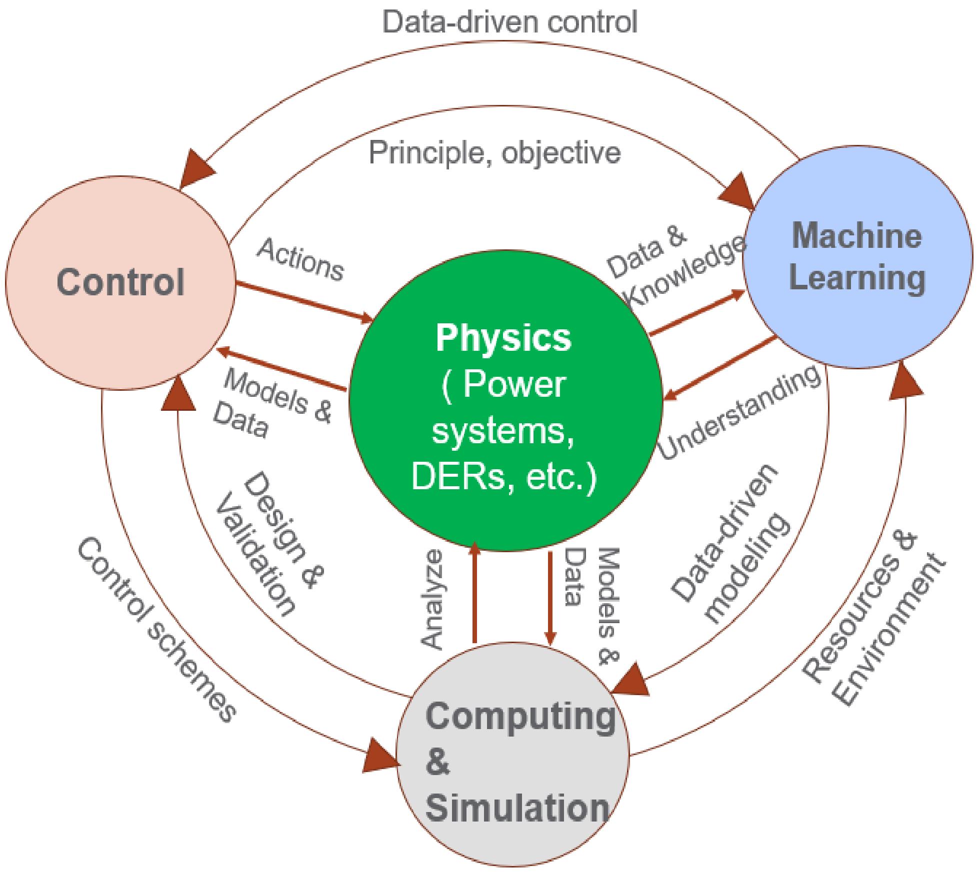


Perspective: Convergence of Physics, AI, Computing and Control for the Future Grid

- The technology advancements required for operating the future grid can be achieved through the convergence of key technologies including physics, AI, computing and control.

- The ARPA-E HADREC project demonstrated promising results in this direction.

- This framework is good for both centralized and distributed applications.



Thank You!

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qhuang@utilidata.com