Learning to Operate Distribution Grids with Extreme Penetration of Renewables

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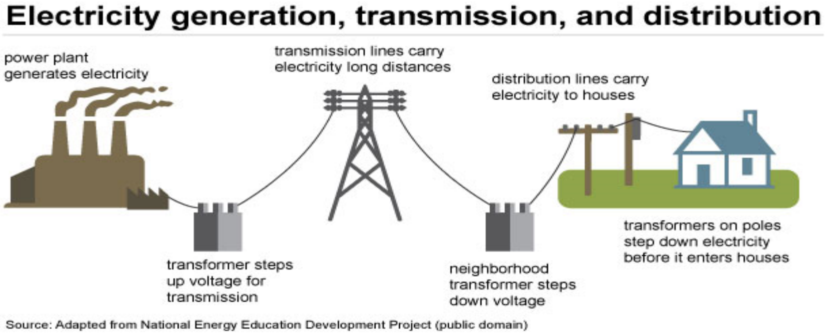
Outline

- Operational challenges caused by DERs
- How AI & ML can help?
- Several case studies
- Research needs

Transformation of Power Systems

Past

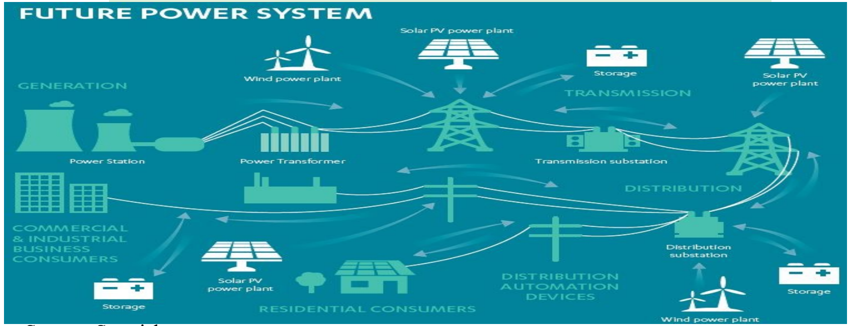
Large, centralized, unidirectional



flow of energy

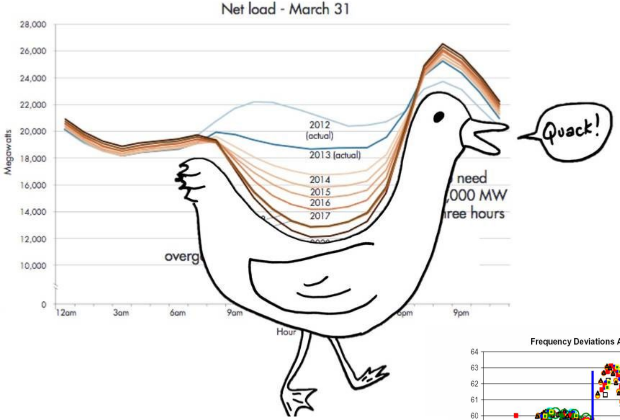
Now & Future

Clean, localized, multi-directional



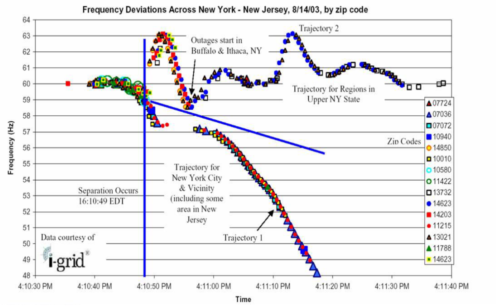
Source: Scottish energy news

flow of energy



The well-known Californian duck curves showing abrupt changes in system net load

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 IBRs, ESS, etc.
- Demand response
- New market behavior
- Experience/model-based control suggestions using limited studied cases are either conservative or risky for operation

Challenges - cont.

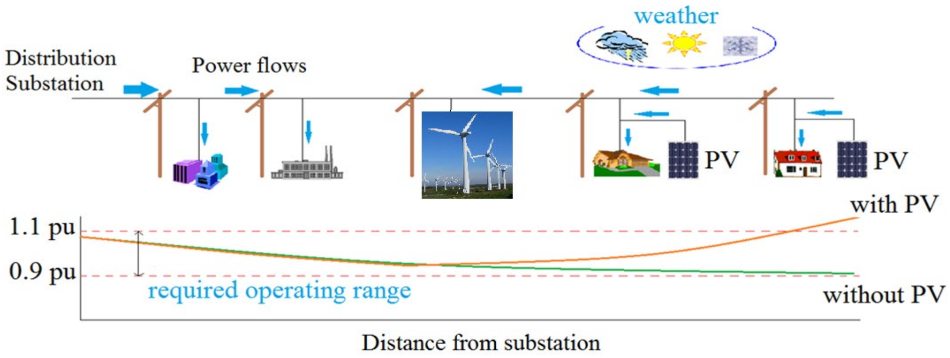


Fig. 1 Voltages become more difficult to control

- Bi-directional power flow causes grid voltage instability
- Over-voltage and fluctuation
- PV/Wind are highly intermittent
- Power quality issues
- Equipment failure
- Challenging for grid operator

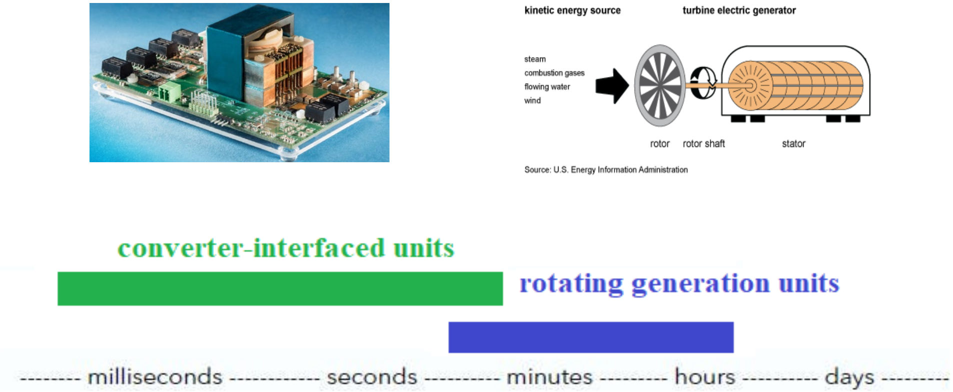
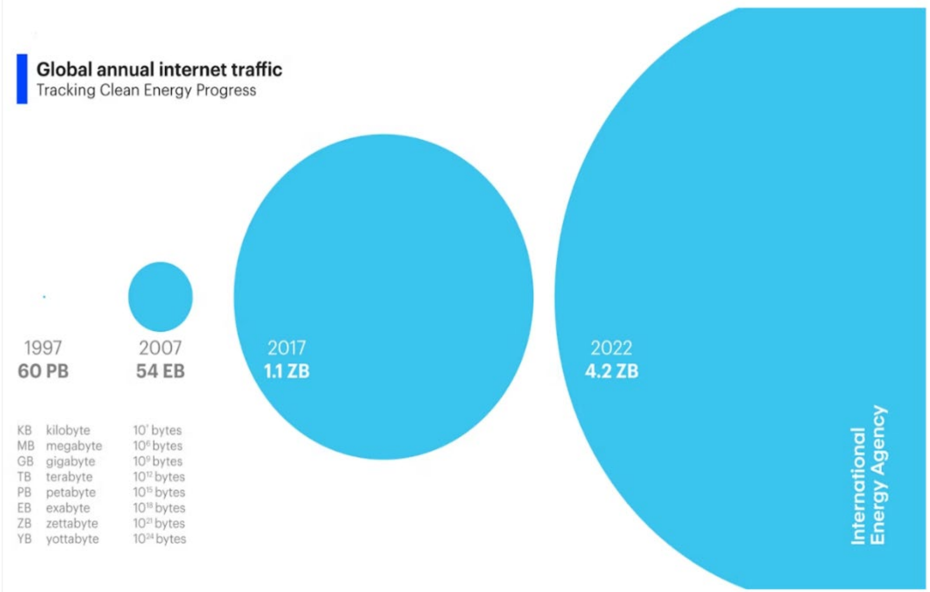
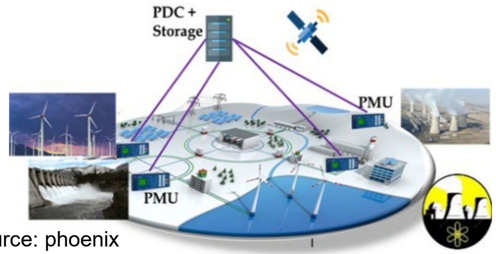


Fig. 2 Time constants of IBRs and turbine electric generators

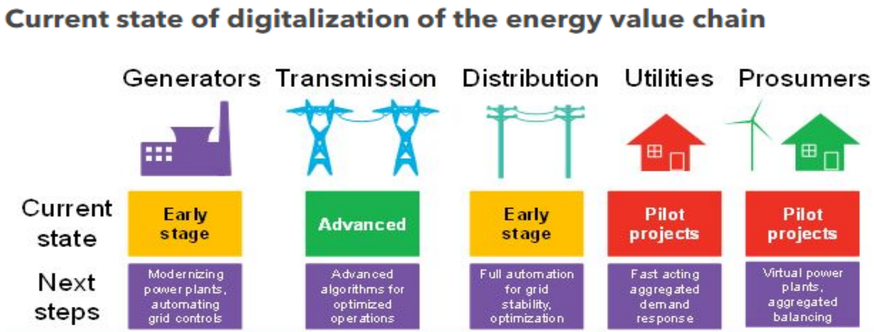
- Time constants of synchronous machines are in seconds or longer
- Time constants of power electronic converters are in the order of milliseconds or shorter
- System dynamics are becoming faster and faster as the penetration DER increases
- Faster decision support is much needed

Opportunities





Source: phoenix



Source: Bloomberg New Energy Finance

Increasing DERs
increasing communication
increasing controllable devices
increasing measurements

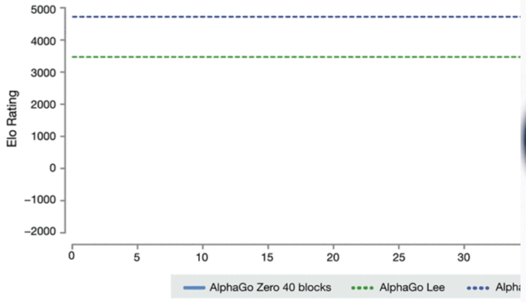
→

The ubiquity of data, connectivity and devices

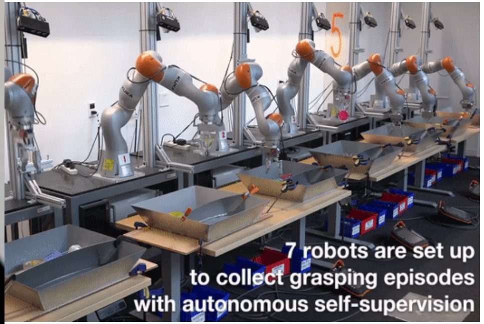
→

Digital technologies are set to make energy system around the world more connected, intelligent, efficient, reliable, and sustainable.

Recent Advancement in AI & ML



Oct.2017, 《Nature》, AlphaGo Zero
AlphaGo Lee with a score of 100:0,
days' training by learning from scratch.



ot arms learn to pick things up, hard
soft objects in different ways, with
human interference.

Credit of pics: Google

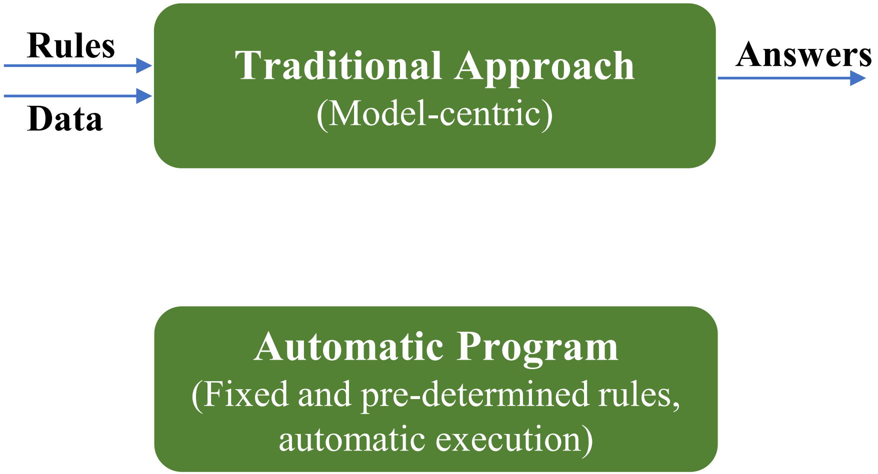
Core technology: Deep learning + Reinforcement learning

2010	2014	2015-2017	2018	2019
Deep Mind Founded	Google acquired Deep Mind	2015, AlphaGoFan (5:0 vs Hui Fan) 2016, AlphaGoLee (4:1 vs Lee Sedol) 2017, AlphaGoMaster (3:0 Jie Ke)	2017, AlphaZero 2018, AlphaStar	2019, MuZero

Hints: Power systems have lots of data, but much less event data, and very few of them are labeled.
How about ML + Classical power system analysis and computation approaches?

Self learning/self-supervised learning?

AI/ML vs Traditional Approaches



Flexibility: offer greater flexibility and adaptability in dealing with complex and non-linear control problems. Unlike traditional control methods that often rely on well-defined mathematical models, AI/ML can learn control strategies directly from data, making it more capable of handling systems with uncertainties and varying dynamics effectively.

Shift in Methodology - cont.

NM STATE

Continuous learning: AI/ML algorithms can continuously learn and refine their control policies as they interact with the system. This dynamic learning ability enables them to adapt to changing conditions or evolving system requirements over time, ensuring superior performance in dynamic scenarios.

No need for explicit models: Unlike traditional control methods that frequently require a priori knowledge of the system's dynamics and model parameters, AI/MLmethods do not depend on explicit models. Instead, they can learn control policies directly from experience, making them well-suited for systems with unknown or difficult-to-model dynamics. This characteristic provides AI/ML with a notable advantage in addressing real-world problems where precise system models may not be readily available.

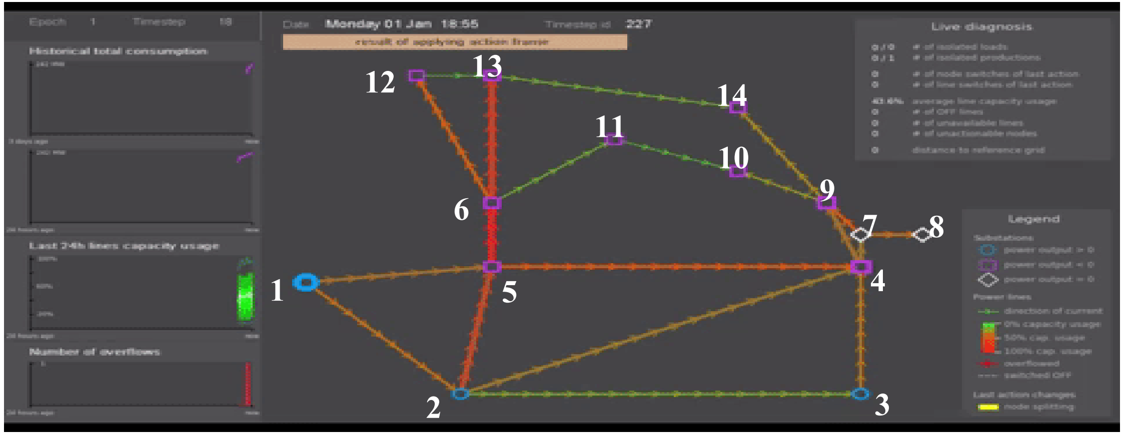
Lack of approaches to synthesize **massive number of measurements** from thousands of smart sensors from **wide areas** to make **timely decisions** on how to **best allocate** energy resources.

Real-time Optimal Network Topology Optimization/Reconfiguration with Renewables

NM STATE

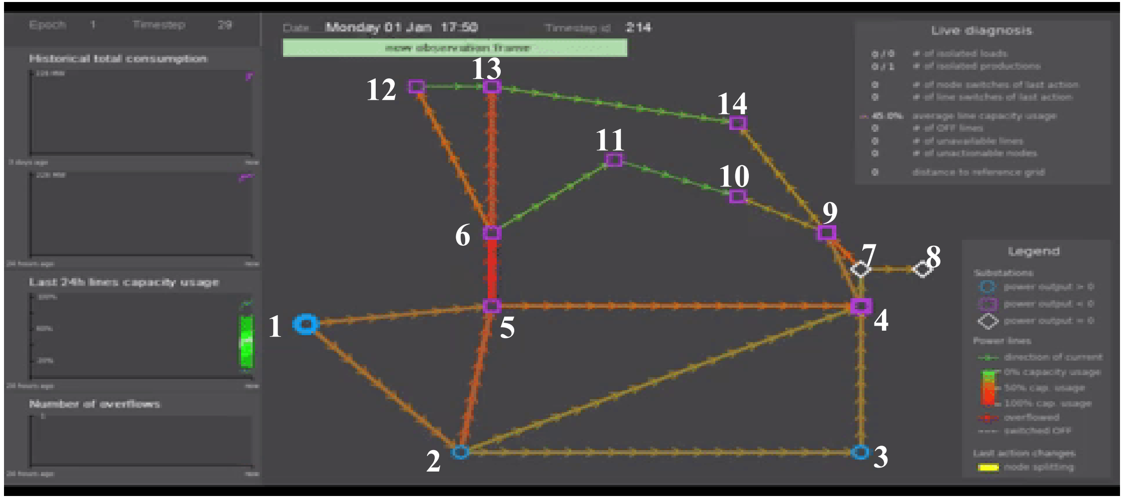
Do Nothing Agent

- Line 5-6, 4-5, 4-7, 4-9 are forced to switch off continuously, leading to grid failure.



Trained Agent

- switch-off line 10-11, line 5-6 overflow alleviated
- switch-off line 13-14, line 2-5 overflow alleviated
- Successfully goes through the system peak-load time



Series of power system AI competition ***L2RPN***: https://l2rpn.chalearn.org/

Problem Formulation and Complexity

Optimization problem:

- Input Data

Obj. *Min/Max (Objective)*

s.t. *Constraint_1*
Constraint_2
...
Single-timestep Constraints

Constraint_i
Constraint_j
...
Multi-timestep Constraints

- Decision Variables

Goal: Maximize **ATCs** of the entire system over all **time-steps** and **scenarios**

Transfer Capability at a Time Step:

Step_single_line_margin = Max(0, 1-Flow/ThermalLimit)**2)
Step_single_line_score = 1 – (1-Step_singel_line_margin)**2
Step_total_score = Sum(Step_single_line_score) over lines

Transfer Capability for one Scenario:

Scenario_Score = 0, if Game Over (when certain constraints are violated
= Sum(Step_total_score) over all timesteps, otherwise

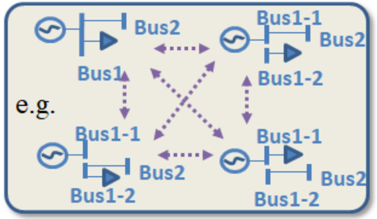
Transfer Capability of All Scenarios:

Total_score = Sum(Scenario_Score) over all scenarios

Action Space/Decision Variables:

Node Splitting/Rejoining

e.g.



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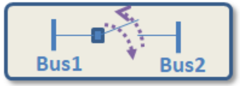
Line Switching On/Off (**20** lines)



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Combination of Node Splitting/Rejoining and Line Switching on/off

***Note: A Maximum of 1 action at the node + 1 action at a line per timestep is allowed**

Huge number of combination in a single timestep!

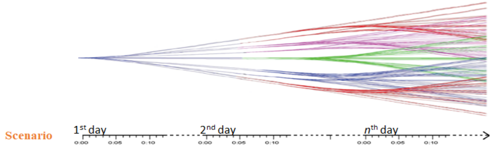
Problem Complexity:

Total number of possible trajectories:

3120^{5184}

Action space for each time step

Total time steps of 1 scenario (18 days with 5 mins intervals)



Comparison of Solutions

Conventional Approach

Vs.

The objective is to maximize the system available transmission capacity, an auxiliary variable λ_k is introduced.

Objective Fun.: $\max \sum_{k \in \Omega_k} \lambda_k$

$$\lambda_k \geq 0, \forall k$$
$$\lambda_k \geq 1 - \left(\frac{S_k}{S_k^{\max}}\right)^2, \forall k$$

Constraints:

$$-M^{\theta}(1-z_i) \leq \theta_{i1} - \theta_{i2} \leq M^{\theta}(1-z_i), \forall i$$
$$-M^{V}(1-z_i) \leq V_{i1} - V_{i2} \leq M^{V}(1-z_i), \forall i$$

$$P^g_{n1} = (1-z_n)P^{g,0}_n, \forall n \in \mathcal{G}/\mathcal{G}_{sl}$$
$$P^g_{n2} = z_n P^{g,0}_n, \forall n \in \mathcal{G}/\mathcal{G}_{sl}$$
$$-(1-z_n)M^P \leq P^g_{n1} \leq (1-z_n)M^P, \forall n \in \mathcal{G}_{sl}$$
$$-z_n M^P \leq P^g_{n2} \leq z_n M^P, \forall n \in \mathcal{G}_{sl}$$
$$-(1-z_n)M^Q \leq Q^g_{n1} \leq (1-z_n)M^Q, \forall n \in \mathcal{G}$$
$$-z_n M^Q \leq Q^g_{n2} \leq z_n M^Q, \forall n \in \mathcal{G}$$

$$P^d_{m1} = (1-z_m)P^d_m, \forall m \in \mathcal{D}$$
$$P^d_{m2} = z_m P^d_m, \forall m \in \mathcal{D}$$

$$-(1-z_k^{i(j)})M^l \leq P_{k1}^{i(j)} \leq (1-z_k^{i(j)})M^l, \forall k$$
$$-z_k^{i(j)}M^l \leq P_{k2}^{i(j)} \leq z_k^{i(j)}M^l, \forall k$$
$$-(1-z_k^{i(j)})M^l \leq Q_{k1}^{i(j)} \leq (1-z_k^{i(j)})M^l, \forall k$$
$$-z_k^{i(j)}M^l \leq Q_{k2}^{i(j)} \leq z_k^{i(j)}M^l, \forall k$$
$$-z_k M^l \leq P_{k1}^{i(j)} \leq z_k M^l, \forall k$$
$$-z_k M^l \leq Q_{k1}^{i(j)} \leq z_k M^l, \forall k$$
$$z_k^{i(j)} \leq z_k, \forall k$$

Constraints on bus voltage, generators, lines, and loads at a substation

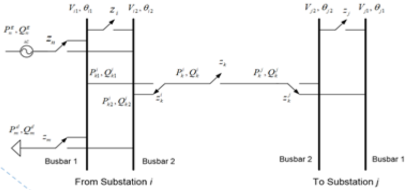
$$P_k^{i(j)} = P_{k1}^{i(j)} + P_{k2}^{i(j)}, \forall k$$
$$Q_k^{i(j)} = Q_{k1}^{i(j)} + Q_{k2}^{i(j)}, \forall k$$

$$-z_k^{i(j)}M^V \leq V_k^{i(j)} - V_{k1}^{i(j)} \leq z_k^{i(j)}M^V, \forall k$$
$$-(1-z_k^{i(j)})M^V \leq V_k^{i(j)} - V_{k2}^{i(j)} \leq (1-z_k^{i(j)})M^V, \forall k$$
$$-z_k^{i(j)}M^{\theta} \leq \theta_k^{i(j)} - \theta_{k1}^{i(j)} \leq z_k^{i(j)}M^{\theta}, \forall k$$
$$-(1-z_k^{i(j)})M^{\theta} \leq \theta_k^{i(j)} - \theta_{k2}^{i(j)} \leq (1-z_k^{i(j)})M^{\theta}, \forall k$$

$$-(1-z_k)M^l \leq g_k(V_k^i)^2 - V_k^i V_k^j (g_k \cos(\theta_k^i - \theta_k^j) + b_k \sin(\theta_k^i - \theta_k^j)) - P_k^i \leq (1-z_k)M^l, \forall k$$
$$-(1-z_k)M^l \leq -(V_k^i)^2(b_{k0} + b_k) - V_k^i V_k^j (g_k \sin(\theta_k^i - \theta_k^j) - b_k \cos(\theta_k^i - \theta_k^j)) - Q_k^i \leq (1-z_k)M^l, \forall k$$
$$-(1-z_k)M^l \leq g_k(V_k^j)^2 - V_k^j V_k^i (g_k \cos(\theta_k^j - \theta_k^i) + b_k \sin(\theta_k^j - \theta_k^i)) - P_k^j \leq (1-z_k)M^l, \forall k$$
$$-(1-z_k)M^l \leq -(V_k^j)^2(b_{k0} + b_k) - V_k^j V_k^i (g_k \sin(\theta_k^j - \theta_k^i) - b_k \cos(\theta_k^j - \theta_k^i)) - Q_k^j \leq (1-z_k)M^l, \forall k$$

$$S_k^i = \sqrt{(P_k^i)^2 + (Q_k^i)^2}, \forall k$$
$$S_k^j = \sqrt{(P_k^j)^2 + (Q_k^j)^2}, \forall k$$
$$S_k \geq S_k^i, \forall k$$
$$S_k \geq S_k^j, \forall k$$

Constraints on real and reactive power, volt., power flow, apparent power of a line



Generalized model for network topology change

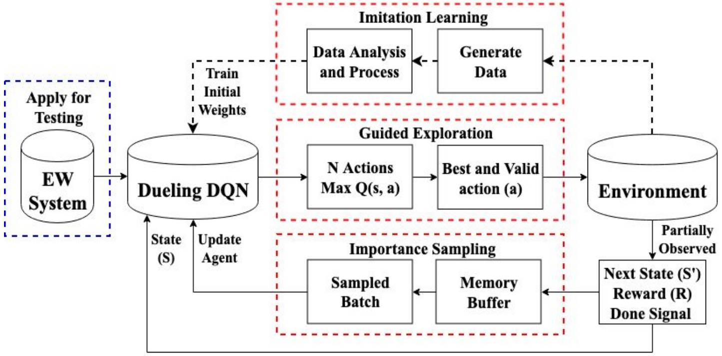
$$\sum_{n \in \mathcal{G}_i} P^g_{n1} - \sum_{m \in \mathcal{D}_i} P^d_{m1} - \sum_{k \in f(i)} P^l_{k1} + \sum_{k \in t(i)} P^l_{k1} = 0, \forall i$$
$$\sum_{n \in \mathcal{G}_i} Q^g_{n1} - \sum_{m \in \mathcal{D}_i} Q^d_{m1} - \sum_{k \in f(i)} Q^l_{k1} + \sum_{k \in t(i)} Q^l_{k1} = 0, \forall i$$
$$\sum_{n \in \mathcal{G}_i} P^g_{n2} - \sum_{m \in \mathcal{D}_i} P^d_{m2} - \sum_{k \in f(i)} P^l_{k2} + \sum_{k \in t(i)} P^l_{k2} = 0, \forall i$$
$$\sum_{n \in \mathcal{G}_i} Q^g_{n2} - \sum_{m \in \mathcal{D}_i} Q^d_{m2} - \sum_{k \in f(i)} Q^l_{k2} + \sum_{k \in t(i)} Q^l_{k2} = 0, \forall i$$
$$z_i + z_n \leq 1, \forall i, n \in \mathcal{G}_i$$
$$z_i + z_m \leq 1, \forall i, m \in \mathcal{D}_i$$
$$z_i + z_k^l \leq 1, \forall i, k \in f(i) \cup t(i)$$
$$\sum_{k \in \Omega_k} (1 - z_k) \leq 1$$
$$\sum_{i \in B} (1 - z_i) \leq 1$$

Constraints on power balance at a bus bar, number of bus splitting, and number of line switching.

Without considering constraints over multiple steps

Solution Time: Hours or tens of mins (with dc approximation)

Machine Learning based Approach



Test trained models on 200 unseen chronics, each has 5184 continuous steps

Agent	Game Over	Mean Score All	Mean Score w/o Dead
EW θ = 0.90	17	75491.63	82504.51
EW θ = 0.91	15	76345.36	82535.52
EW θ = 0.92	15	76353.23	82544.03
EW θ = 0.93	**12**	**77725.94**	**82687.17**
EW θ = 0.94	15	76386.96	82580.49
EW θ = 0.95	24	72256.32	82109.45

Autonomously controlling the grid for weeks!!

Solution Time: Sub-second

Our code has been open sourced at: https://github.com/shidi1985/L2RPN

Autonomous Voltage Control (AVC)

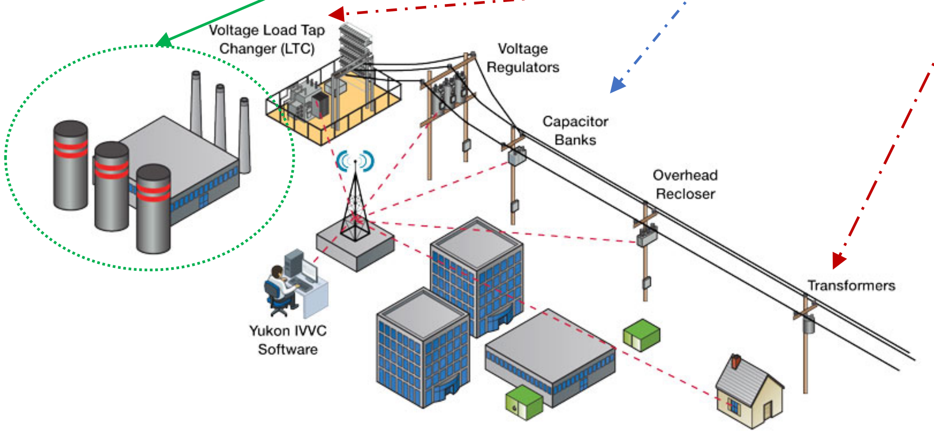
(Considering load variation, renewable intermittency and contingency conditions)

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.

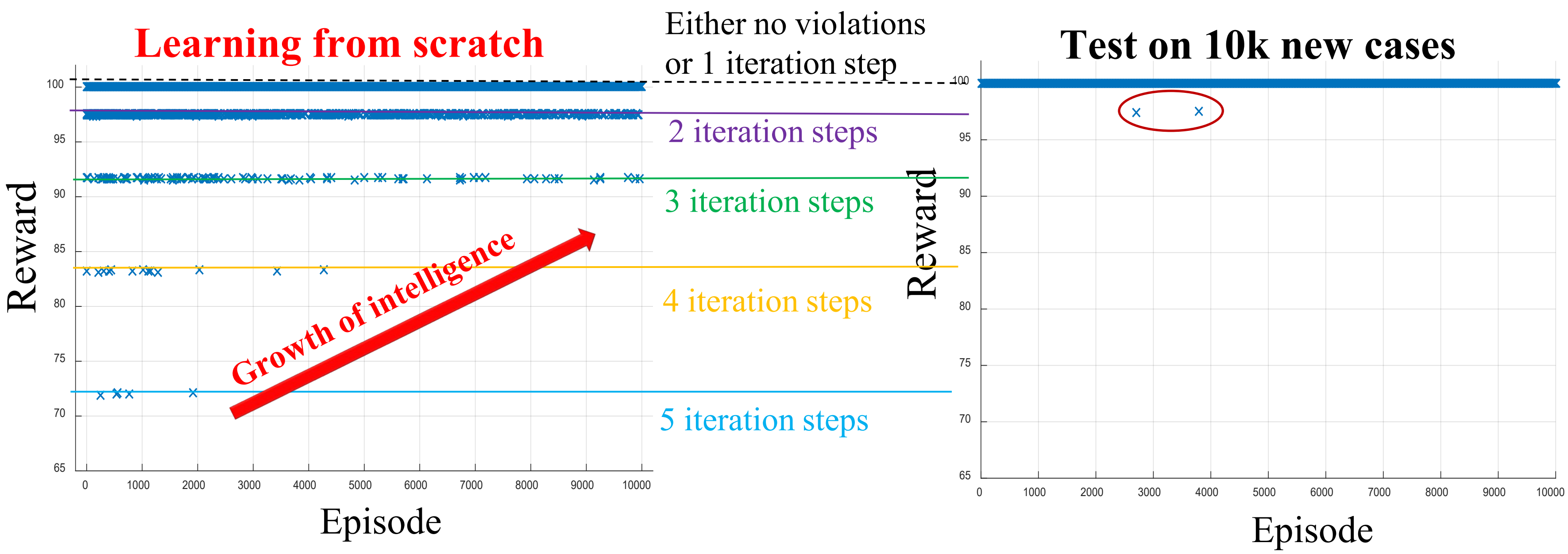
Bus Voltages → Voltage Controller →

- ✓ Change generator voltage set point
- ✓ Switchable shunts on & off
- ✓ Adjust transformer tap ratios

→ All buses stay within a secure range



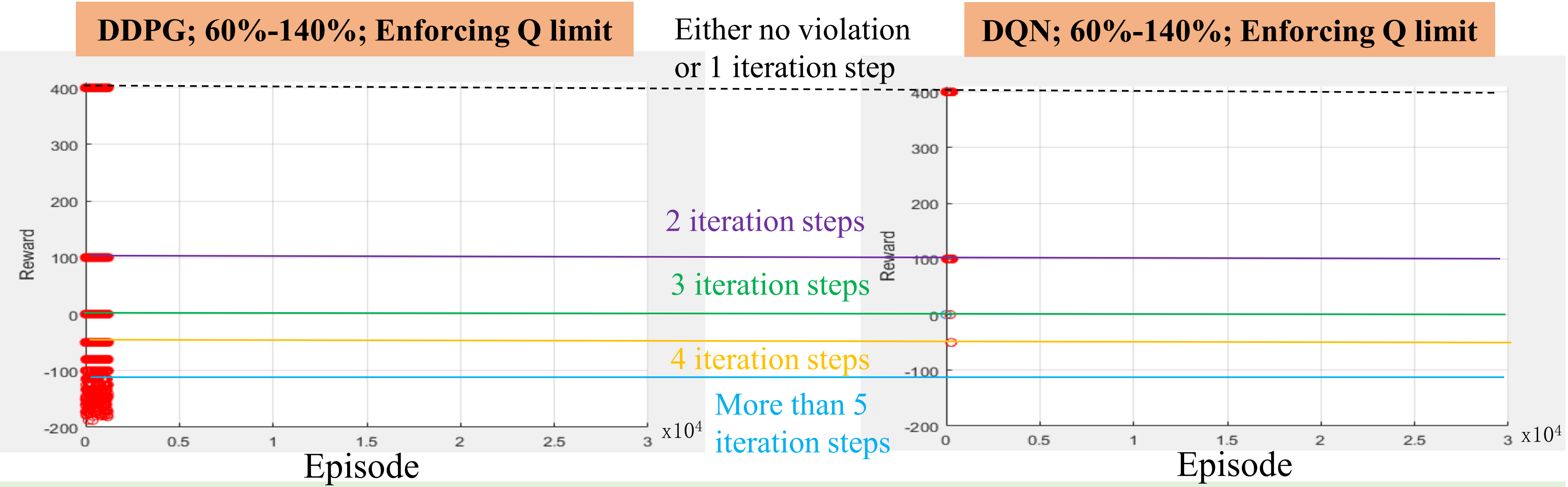
DQN Agent for IEEE 14-bus System



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

Further Testing with Topological Changes-200 Bus System

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



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.

Deriving Model-free Fast AC OPF Solutions

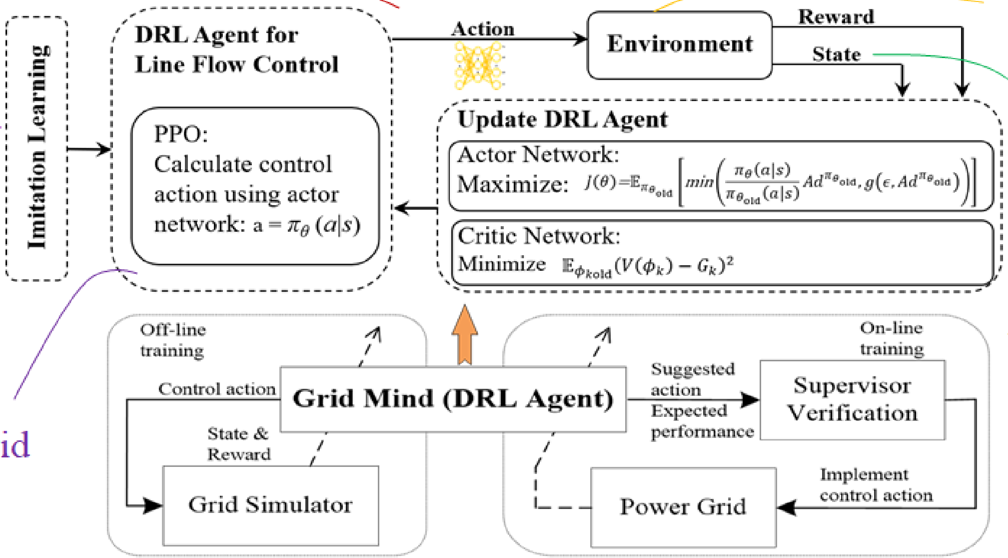
Objective: Minimize system-level generation cost without violating security constraints or shedding load, by controlling the voltage setpoints and power outputs of generators <u>under various loading conditions</u>.

Advantage: 1) **real-time application** for system control; 2) no dependence on accurate system models.

Active power adjustments of generators $[\Delta P_1, \Delta P_2, \ldots, \Delta P_n]$

Voltage adjustments of all generators $[\Delta V_1, \Delta V_2, \ldots, \Delta V_n]$

Power System

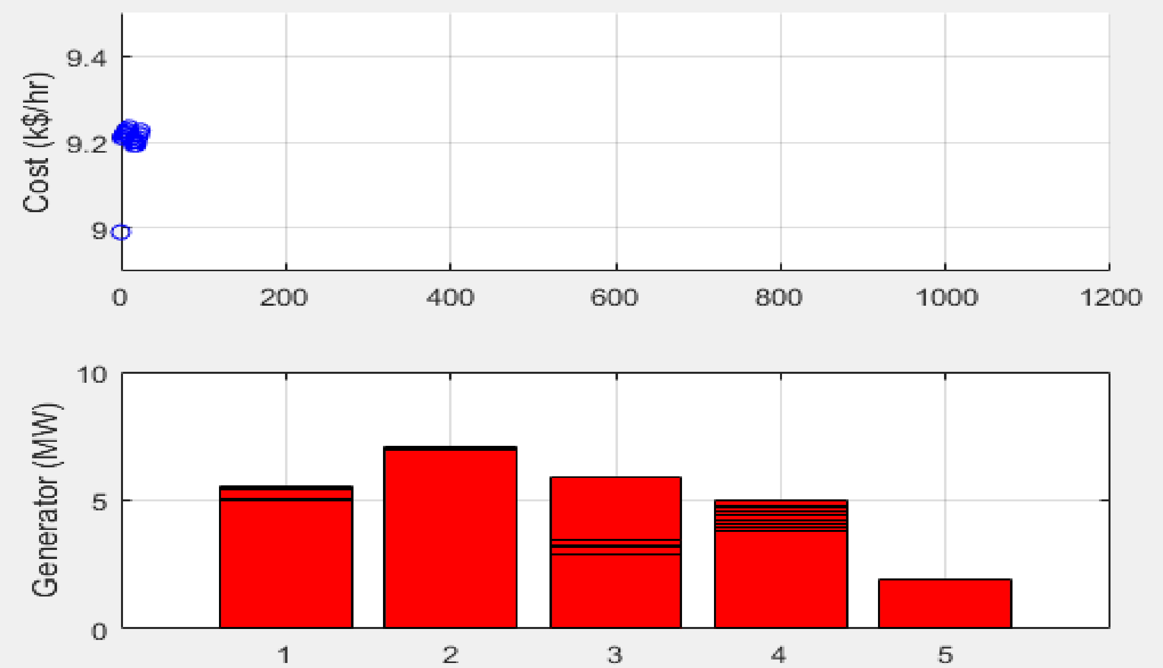


V_{gi}, P_{gi} of all generators

P_{di}, Q_{di} of all loads

App of Grid Mind

The Learning Process of AC-OPF



Generator ID

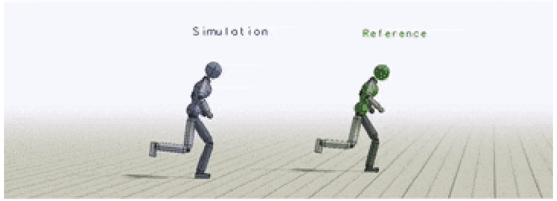
DRL + Imitation Learning (IL): Example Guided DRL

Why: large action space and sparse reward; no simulator.

$$\min_{\theta} \sum_{(s_t,\hat{a}_t)\in D_{train}} \frac{1}{N_{IL}} \left\| \hat{a}_t - \mu_\theta(a_t|s_t) \right\|_2^2$$

Using IL to initialize the weights of neural networks used by DRL.

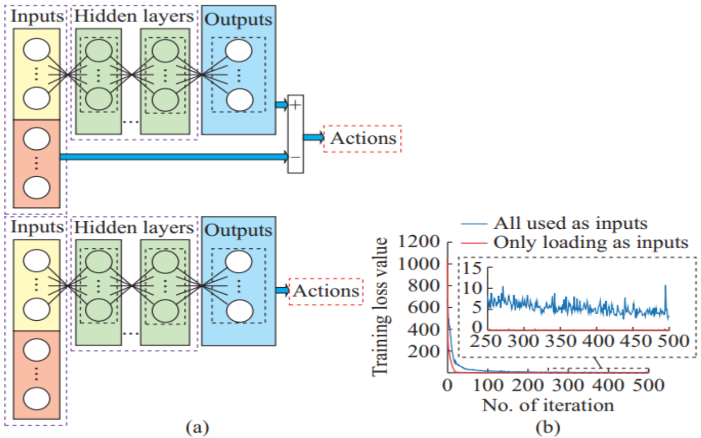
Humanoid: Run



Policy trained to imitate a running clip.

Source: https://medium.com/analytics-vidhya/imitation-learning-from-why-to-how-7b713a079501

Selection of network structures



IL comparisons based on 2 different NN structures. (a) NN structure. (b) Training loss.

$$\kappa = \frac{cost_{ips} - cost_{agent}}{cost_{ips}}$$

Cost calculated by using interior-point AC OPF solver

Testing systems and data sets

Test system	No. of training dataset	No. of testing dataset I	No. of testing dataset II
IEEE 14-bus system	55000	17364	2000
Illinois 200-bus system	60000	20000	5000

Average solution time: 170ms.
10x Faster

IEEE 14-bus system

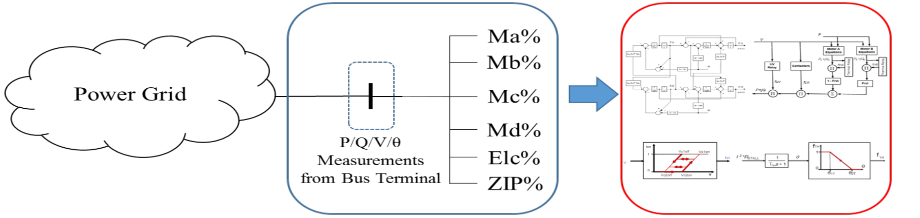
Training method	No. of success data	No. of failure data	Success rate (%)	Maximum $\lvert\kappa\rvert$ among success data (%)	Minimum $\lvert\kappa\rvert$ among success data (%)	Average $\lvert\kappa\rvert$ among success data (%)
IL	7138	10226	41.11	0.33	1.93×10^{-5}	1.29×10^{-2}
PPO	15944	1420	91.82	17.55	0.56	3.27
PPO with IL	17364	0	100.00	1.75	0.21	0.597

Illinois 200-bus system

Training method	No. of success data	No. of failure data	Success rate (%)	Maximum $\lvert\kappa\rvert$ among success data (%)	Minimum $\lvert\kappa\rvert$ among success data (%)	Average $\lvert\kappa\rvert$ among success data (%)
IL	11298	8702	56.49	1.28	8.60×10^{-4}	0.12
PPO	16004	3996	80.02	10.52	0.83	4.92
PPO with IL	19990	10	99.95	1.65	0.11	0.61

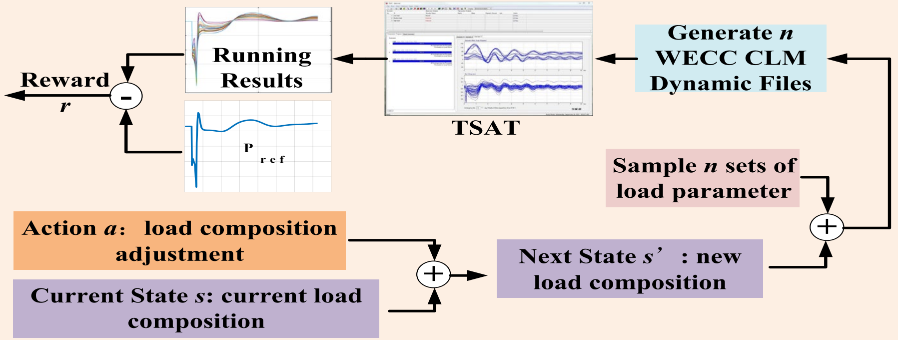
Power System Model Validation & Parameter Identification

A two-stage approach is proposed for ZIP+IM, CLOD, and WECC CLM with as many as 130+ parameters.



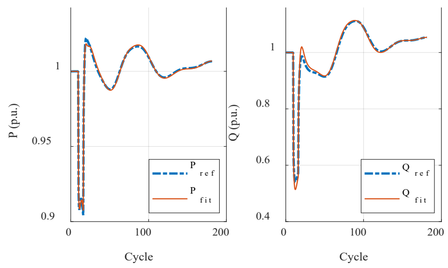
Stage I: solve load composition   Stage II: identify load parameters

In the **1st** stage, DRL is utilized to identify the percentage of each component; in the **2nd** stage, parameters of each component can be identified.

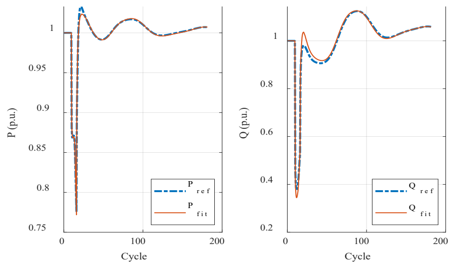


The approach is robust for faults at different locations, different fault types, different clearing times.

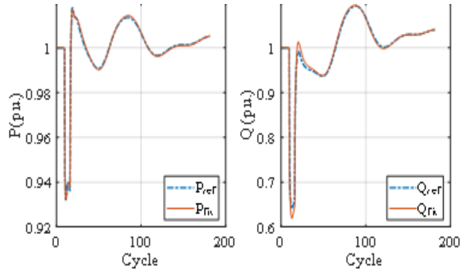
For one Fault



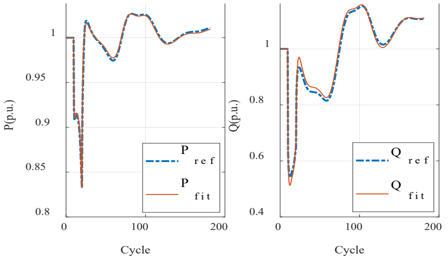
Diff. Fault Locations



Diff. Fault Types



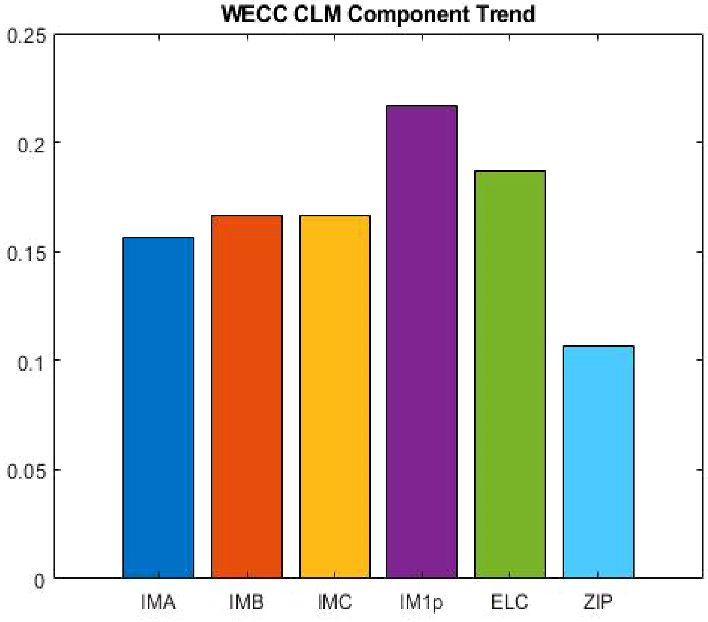
Diff. Fault Clearing Time



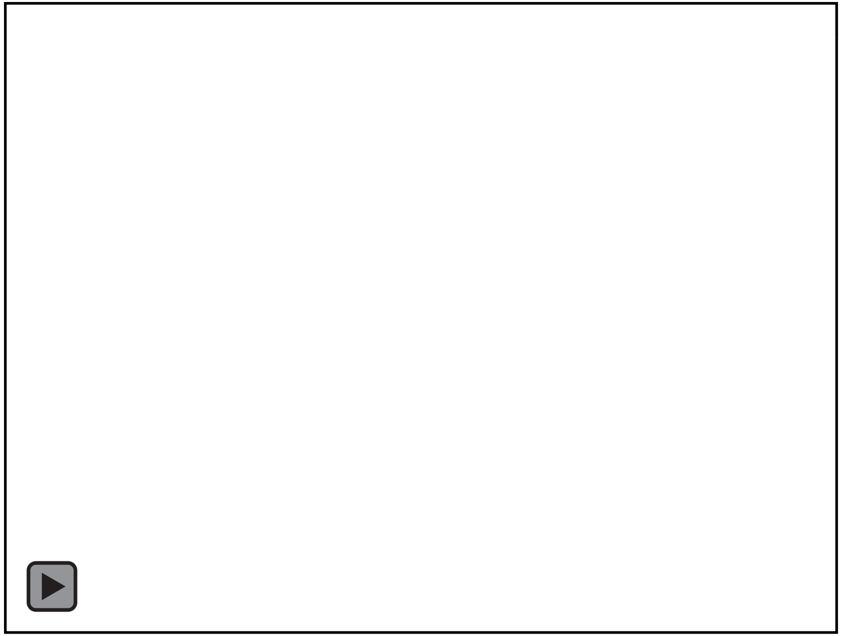
Accuracy for P, RMSE 0.12%
Accuracy for Q, RMSE 0.64%

Results - Model and Parameter Identification

DRL-based WECC Model Identification & Validation



DRL-based Generator Model Identification & Validation

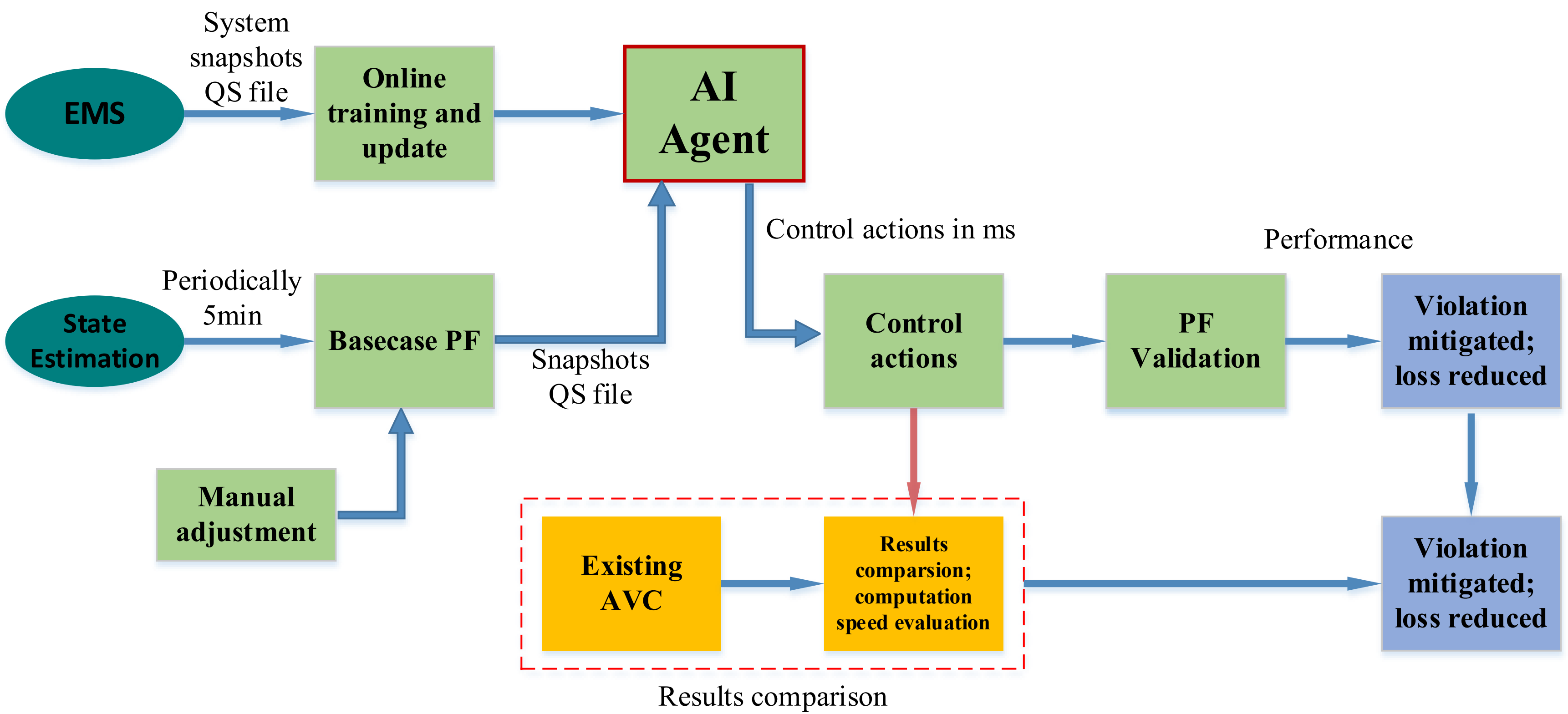


Pilot Projects at Real-world Power Systems

- ~50 substations/plants
- 12 generators
- 3 500kV substations
- 37 220kV substations
- 96 transmission lines
- Max load 3500MW
- Max gen. 5800MVA

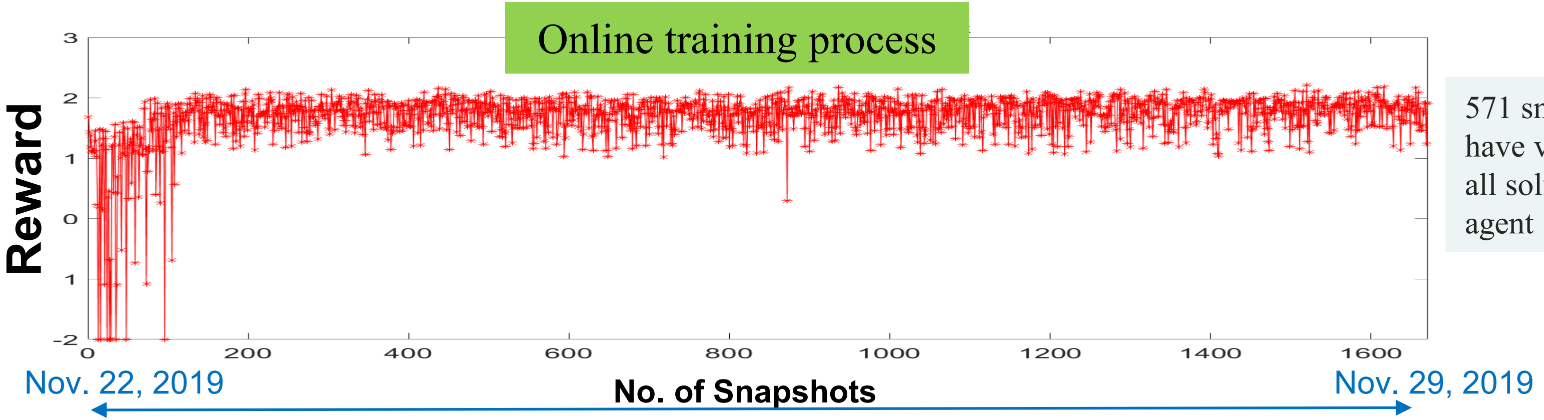
Multiple Control Objectives: voltage + line flow + system loss

Interface with Existing Energy Management System (EMS)

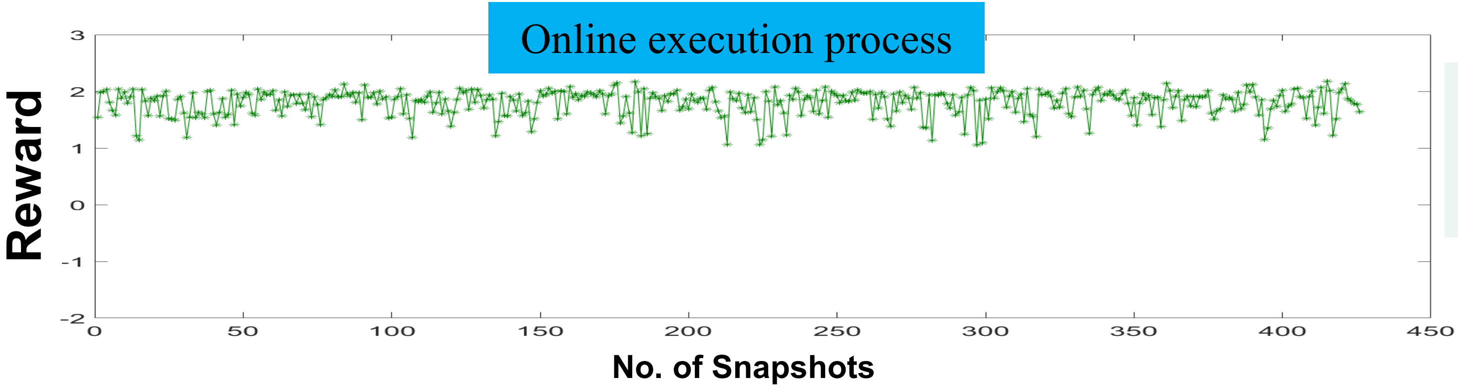


Online Deployment with REAL Data

Reward: positive if violations in Vs and Flows are solved; negative otherwise; the more loss it reduces, the higher the reward

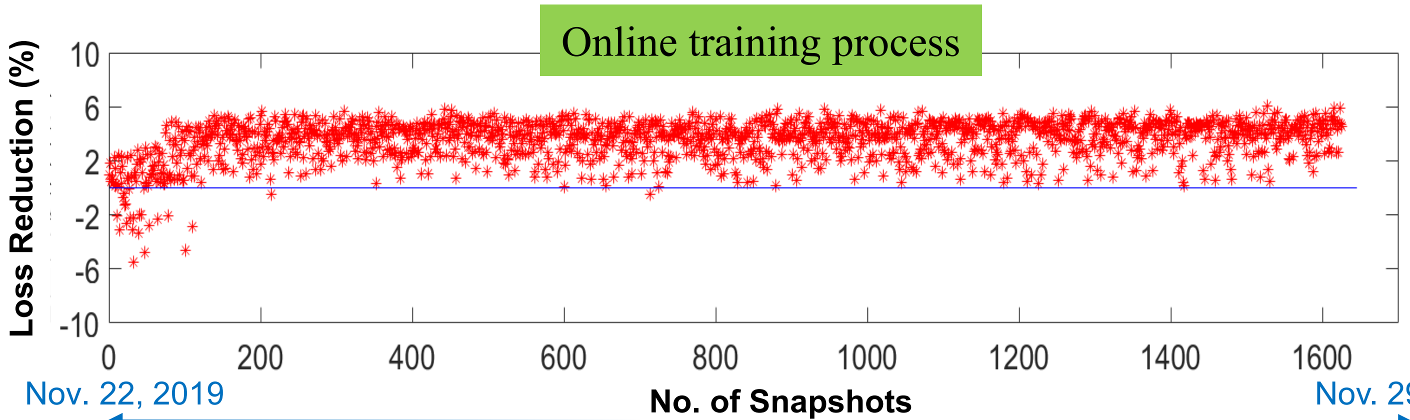


571 snapshots have violations, all solved by AI agent



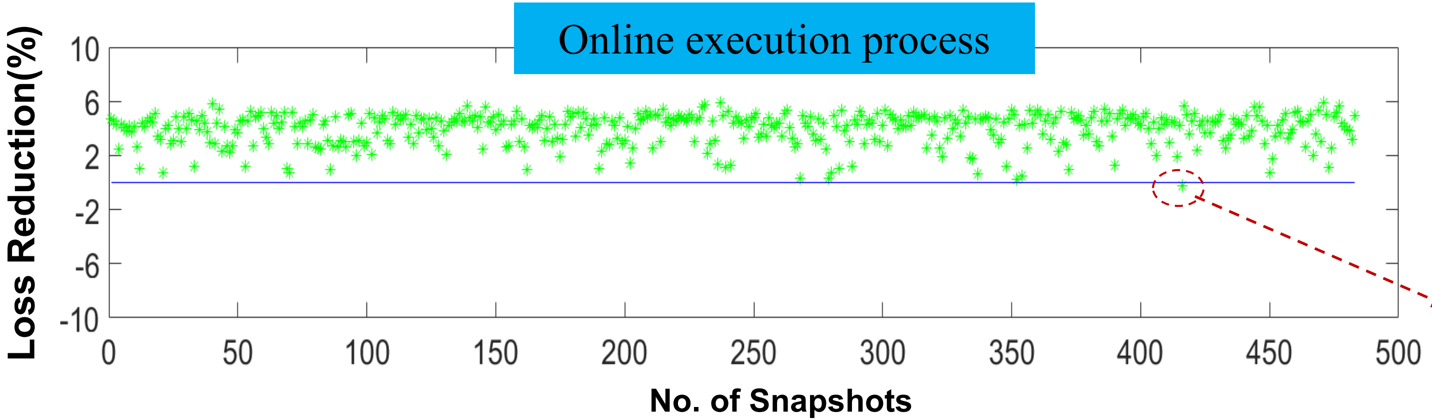
239 snapshots have violations, all solved by AI agent

Results-cont.



Nov. 22, 2019

Nov. 29, 2019



Training period: average loss reduction: **3.4525%**

Execution period: average loss reduction: **3.8747%**

Voltage violations solved, loss increases slightly

Observations

Validated by EMS,

1) following the decisions of the AI agent, all voltage violations are solved;
2) for only one snapshot, voltage violations are solved, loss slightly increases;
3) other than the one case, loss reductions are observed, with highest number reaching ~6%;
4) for all snapshots, before and after control, no violation in line flow is observed.

several million dollars' saving per year.

The Research Needs

- Highly sample efficient algorithms.

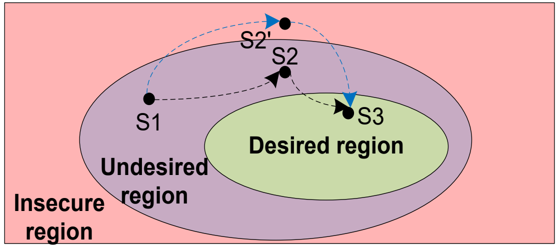
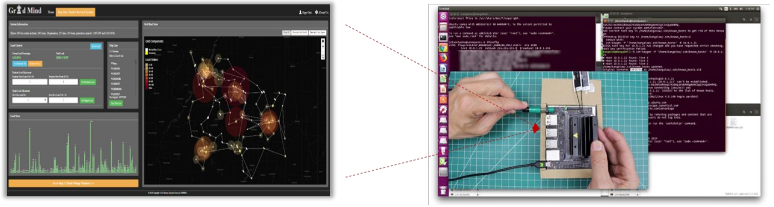


Fig. Illustration of the safety issue of machine learning algorithms

- Safety guaranteed inference.



- Edge AI for distribution grids.

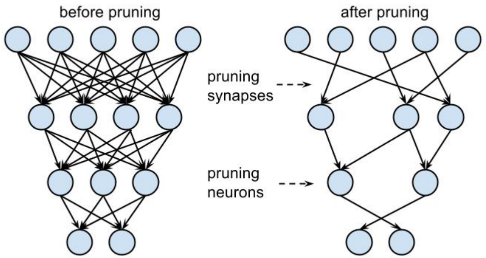


Fig. Edge AI - distributed & light-weight

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Thank you!

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