The Evolving Electric Power Grid

-Energy Internet, IoT and AI

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@CURENT Strategic Planning Meeting

Outline

1. Recent Development: Energy Internet and IoT
2. The New-gen. AI Technologies
3. Challenges and Opportunities

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Unbalance in Resources and Load

Fig. West to east power transmission

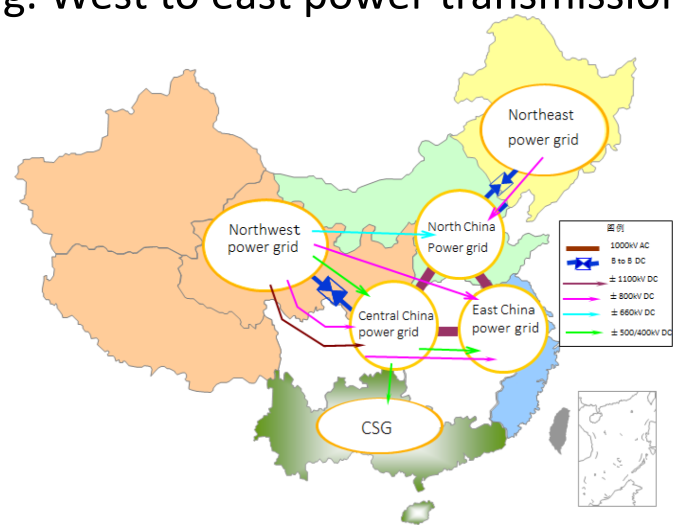


Fig. China power transmission framework

Resource

- 76% of coal in North and Northwest
- 80% of hydropower in Southwest, mainly in upper stream of Yangtze River
- All inland wind in Northwest
- Solar resources mainly in Northwest

Load

- 70%+ of load in Central and Eastern parts

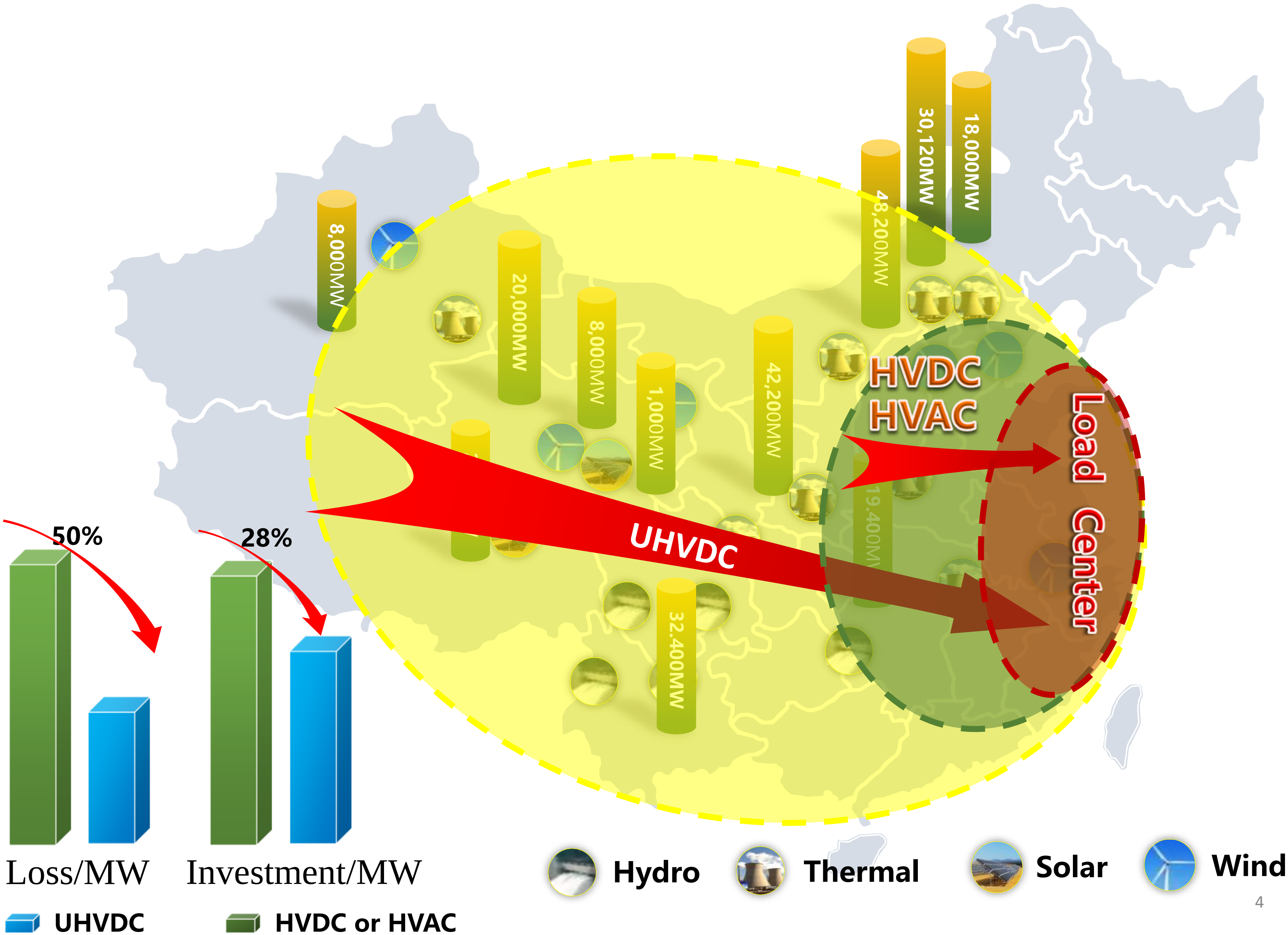
Transmission

- Distances between resource and load center reaches up to 2000+km
- UHVDC and UHVAC are good options to transfer huge amount of power over long distance

Challenges

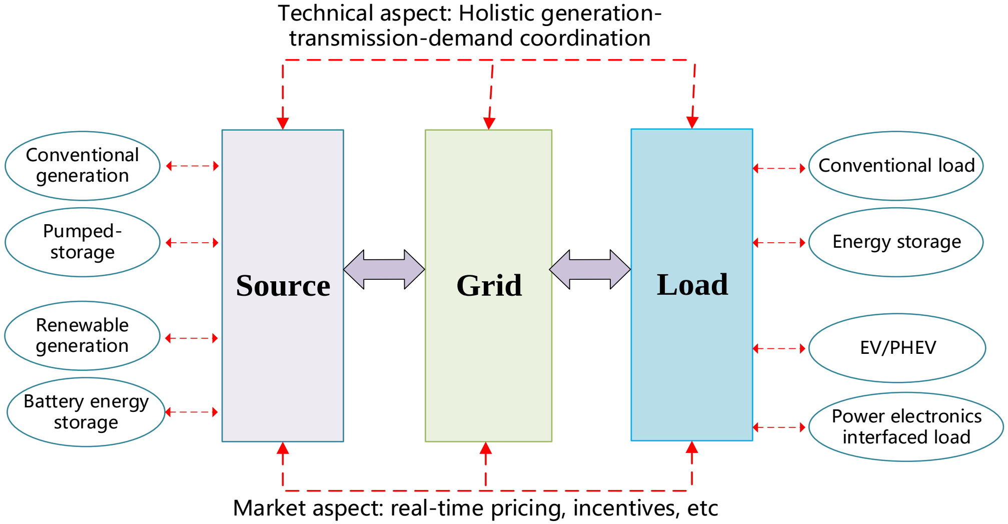
- Hybrid operation of AC and DC systems
- System stability, security, and reliability

UHVDC

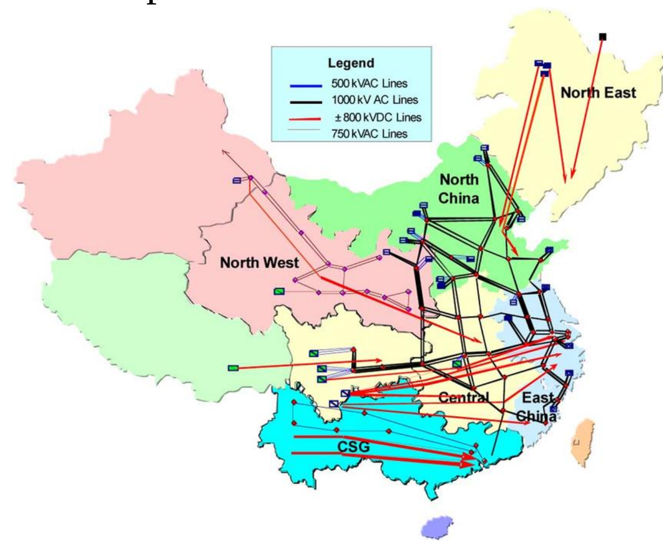

8,000MW
20,000MW
8,000MW
1,000MW
42,200MW
48,200MW
30,120MW
18,000MW
19,400MW
32,400MW
HVDC
HVAC
Load Center
UHVDC
50%
28%
Loss/MW
Investment/MW
UHVDC
HVDC or HVAC
Hydro
Thermal
Solar
Wind

Developmental Trend: Source-Grid-Load Interaction

Source-Grid-load interaction proposed by SGCC Jiangsu

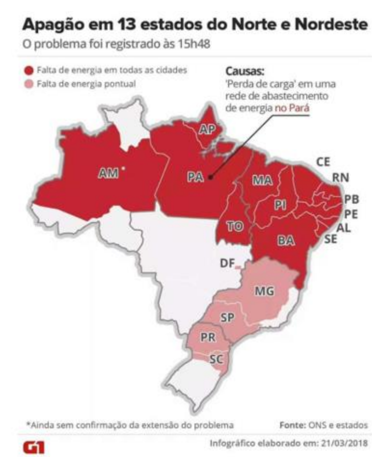


UHVDC/UHVAC/HVDC/HVAC development in China



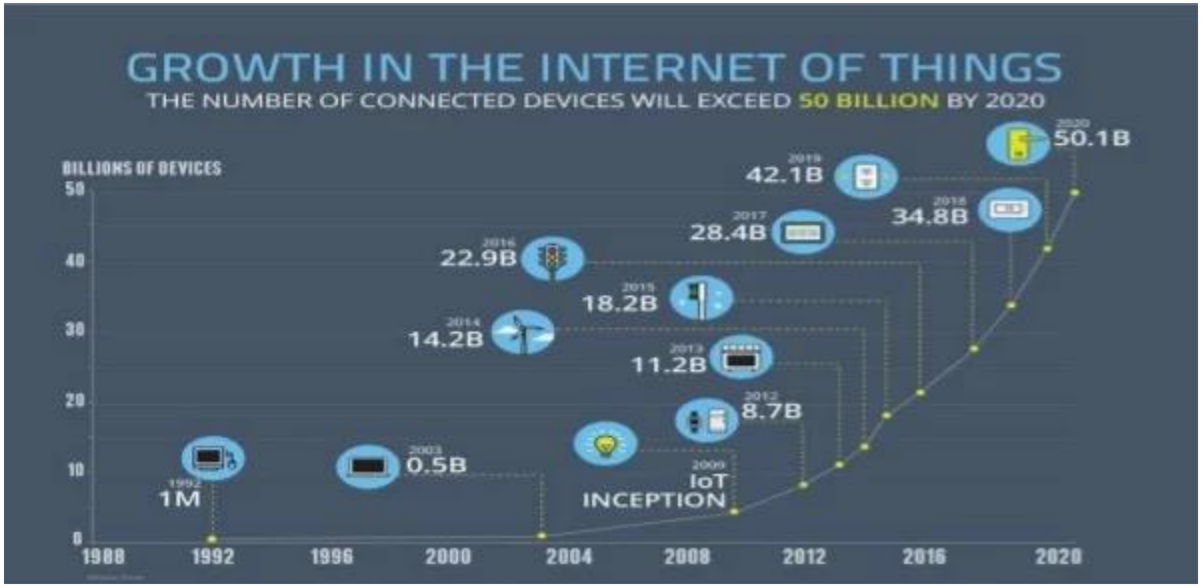
- **The existing load control methods are of low granularity, and the load response is slow.**
- **The load monitoring/control is highly dependent on the SCADA network and it costs much to extend to end-user level.**
- **It is urgent to develop cost-effective methods to integrate higher levels of renewable generation.**

UHVDC Fault Caused Outage in Brazil



G. Wen, G. Hu, J. Hu, X. Shi and G. Chen, "Frequency Regulation of Source-Grid-Load Systems: A Compound Control Strategy," in *IEEE Transactions on Industrial Informatics*, vol. 12, no. 1, pp. 69-78, Feb. 2016.

Developmental Trend: Internet-of-Things (IoT)



Pic from: https://www.valuecoders.com/blog/technology-and-apps/11-mobile-app-development-trends-stay-2017/

- Advanced metering infrastructure (AMI)
- SCADA (supervisory control and data acquisition)
- Smart inverters
- Remote control operation of energy consuming devices
- Various type of interconnected sensors

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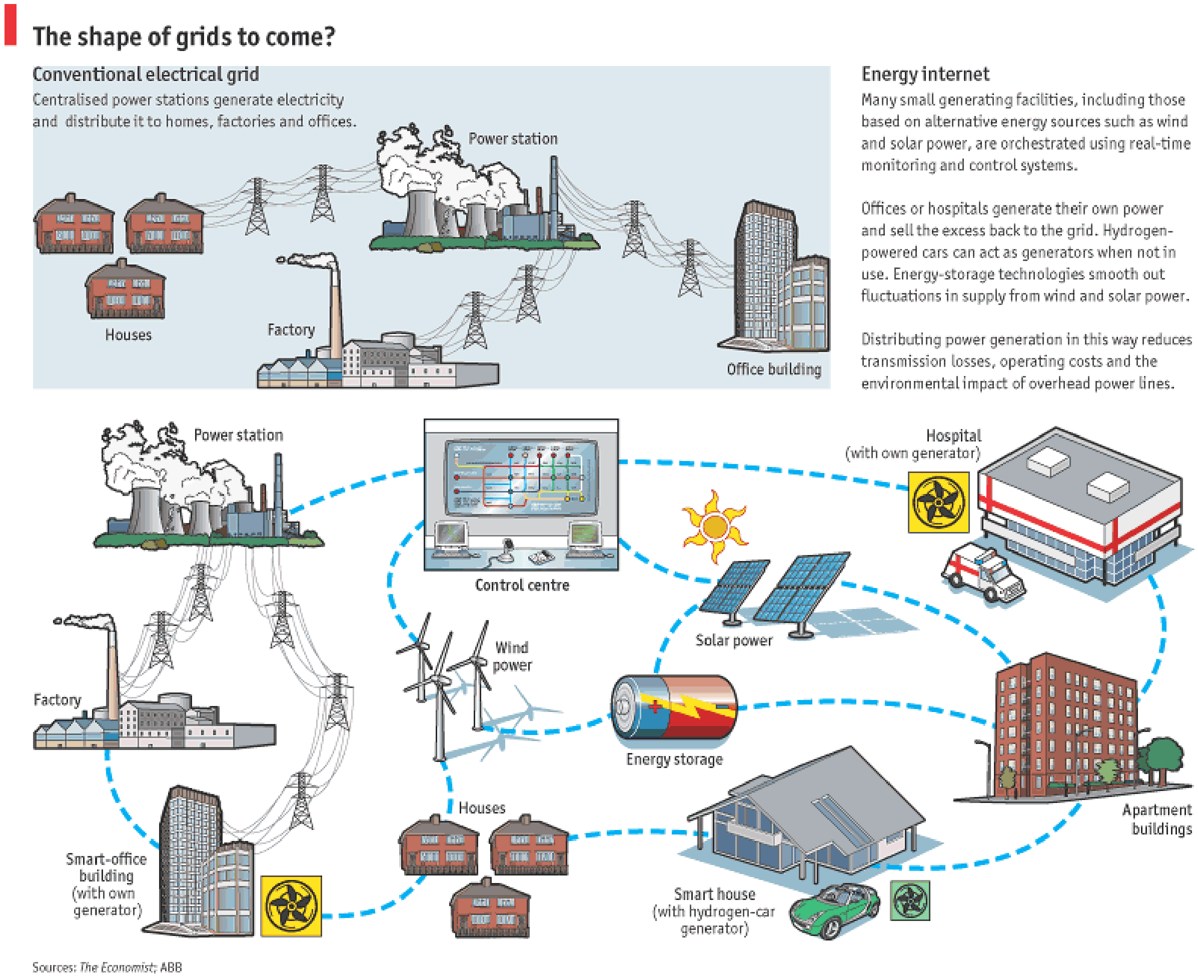
Developmental Trend: Energy Internet (Interconnection)



Pic from: https://www.economist.com/technology-quarterly/2004/03/13/building-the-energy-internet

Known Challenges and Opportunities

Challenges

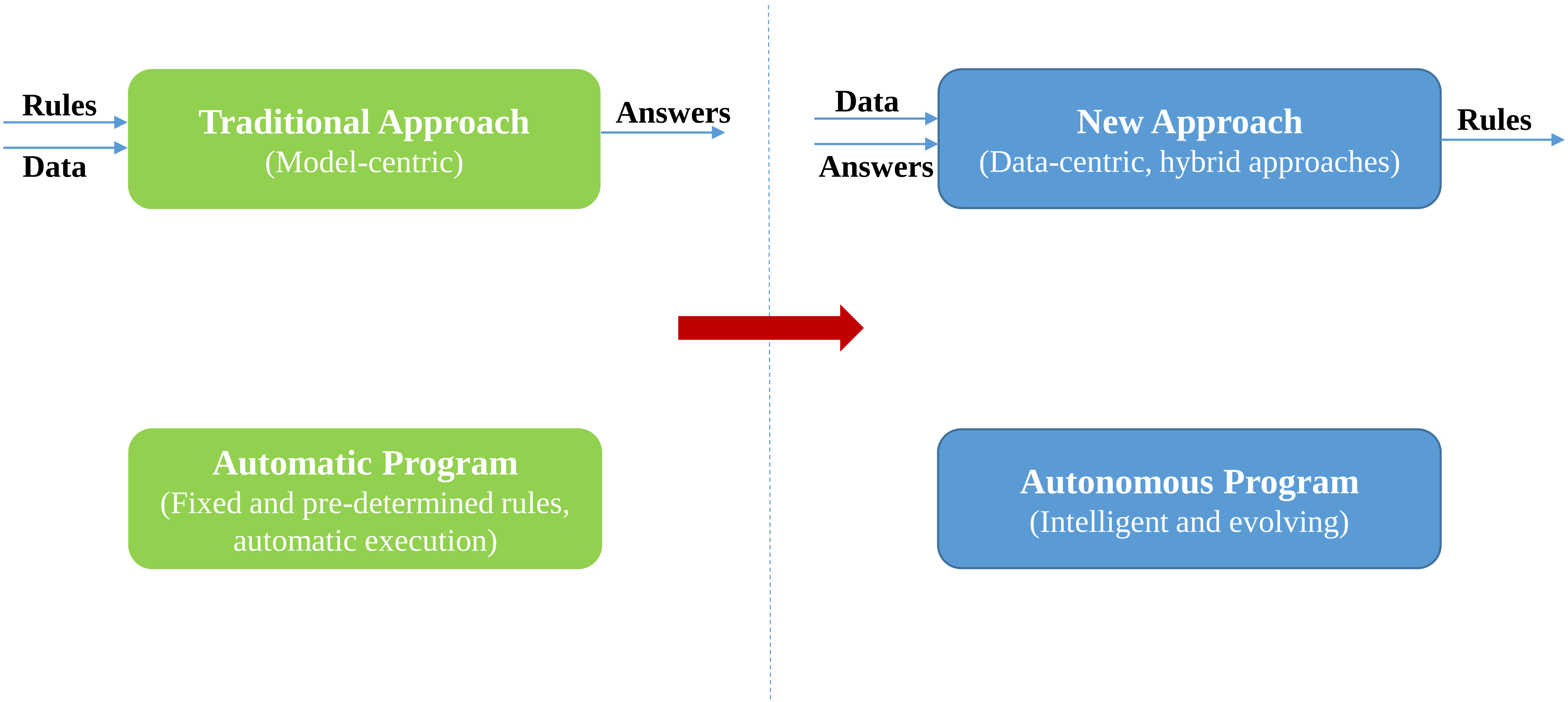
- ➢ Increasing dynamics and stochastics.
- ➢ Traditional operational rules and procedures, which are derived from offline studies or historical experiences, tend to be less optimal (over-conservative or risky).
- ➢ Limited capabilities to adapt to various, including unknown, system operating conditions.
- ➢ Causes
  - Increasing penetration of DERs
  - Transportation electrification
  - Fast demand responses
  - New market behaviors
  - Inaccurate grid models

Opportunities

- ➢ The need for faster and enhanced system situational awareness tools/platforms.
  - WAMS with good coverage of PMUs
  - Point-on-wave measurements/devices
  - Progress in computation/simulation
  - Recent progress in AI (Deep learning)
- ➢ The need for faster, preferably real-time, decision-support tools/platforms.
  - Most existing operational rules are offline determined considering the worst-case scenarios
  - Lack of preventive/corrective measures to mitigate operational risks
  - Proven capability of AI in decision making/support under highly complexed situations.

Lack of approaches to collect and synthesize **overwhelming amounts of data** from **millions of** smart sensors **nationwide to make timely decisions** on how to **best allocate** energy resources.

Changes in Way of Thinking



The New-gen. AI Technologies

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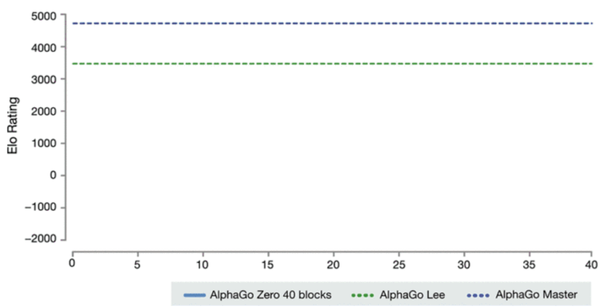
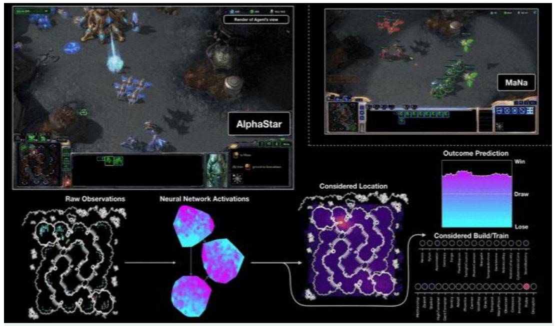


Oct. 2017, 《Nature》, AlphaGo Zero beat AlphaGo Lee with a score of 100:0, after 3 days' training by learning from scratch.



Dec. 2018, AlphaStar mastered the real-time strategy game StarCraft II and beat top teams, by learning from human and then self play.

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

Credit of pics: Google

Core technologies: 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

Notes:

- No/limited labeled data (raw data input), play against itself for improvement.
- Learn from human, and then play against itself for improvement.

Hints for power system applications:

- Lack of large amount of labeled data, especially event data.
- Generate reasonable data sets based on existing/typical data/operating conditions.
- Combine AI with classical power system theories/computations/metrics.

Deep Learning

Deep Learning is part of the machine learning family based on artificial neural network with many layers. Deep learning can be supervised, unsupervised and semi-supervised.

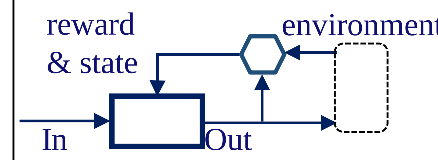
Supervised Learning

Unsupervised Learning

Semi-supervised Learning

o k-Near
o Linear
o Logisti
o Decisi
o Naïve
o Suppor (SVM)
o Neural

Reinforcement Learning

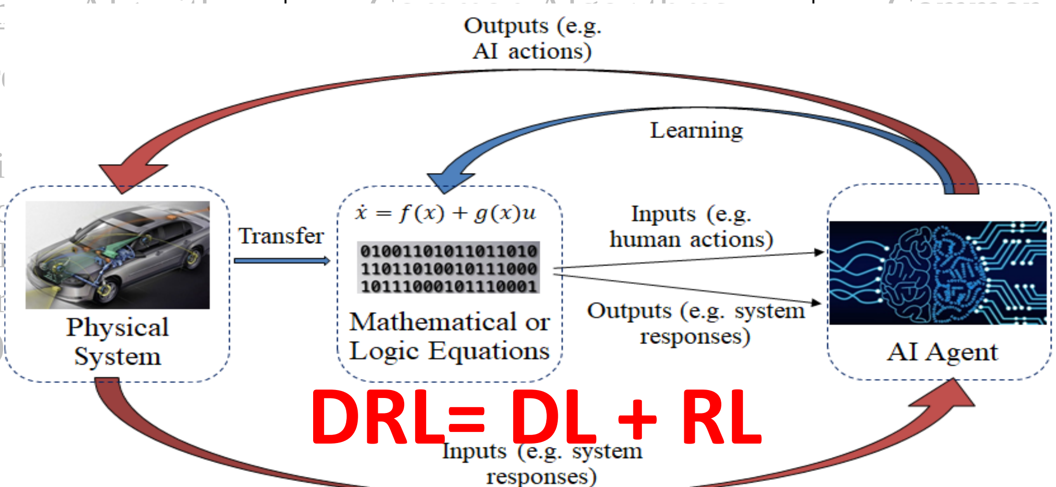


Application

- ✓ DeepMind's AlphaGo
- ✓ AlphaZero
- ✓ AlphaStar
- ✓ Fire-extinguish robots

Common Algorithms

- o Dynamic programming
- o Monte Carlo
- o Q-Learning
- o SARSA
- o Deep Q Network (DQN)
- o Asynchronous Actor-Critic Agent (A3C)
- o Deep Deterministic Policy Gradient (DDPG)



DRL= DL + RL

Credit: Elena Mocanu, TU/e

The Grid Mind Vision

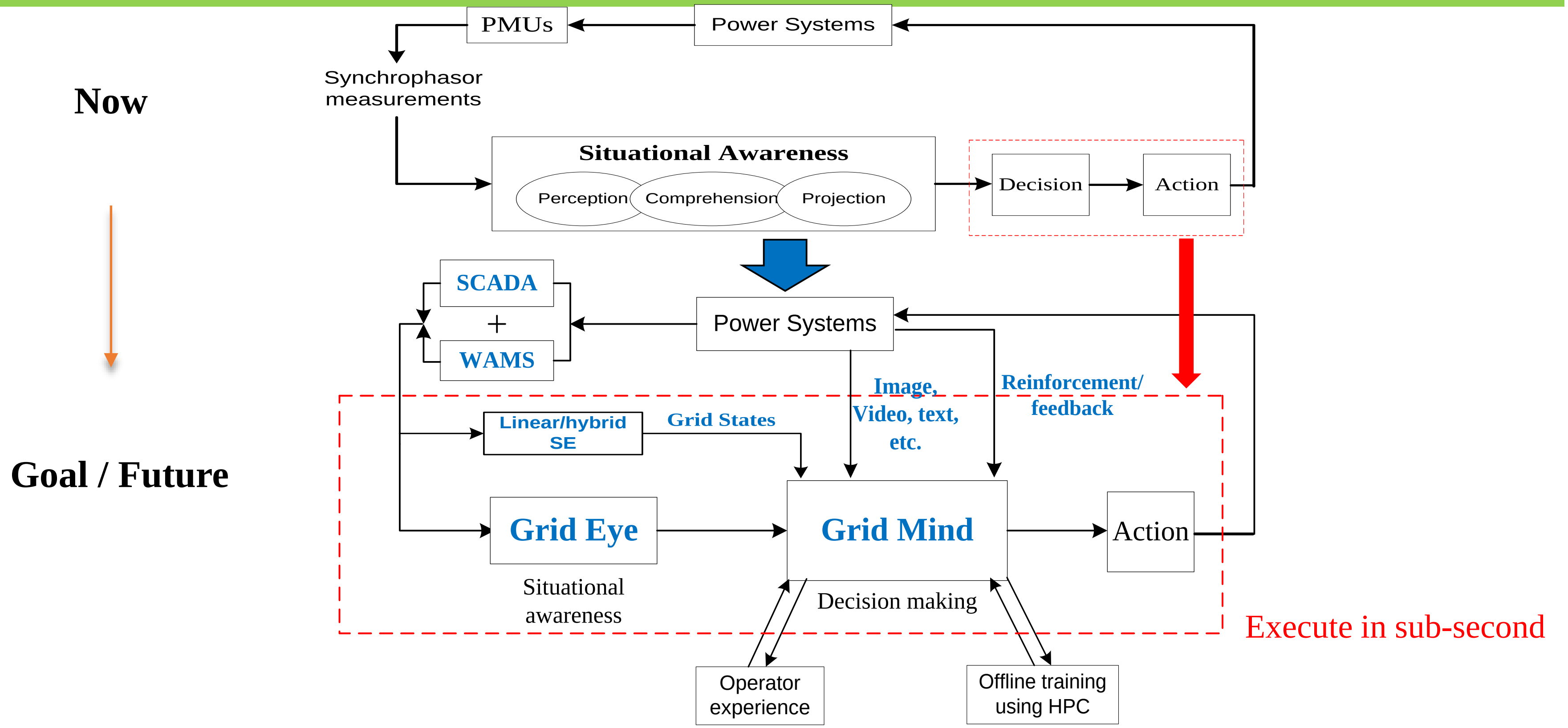
- **Grid Mind:** A measurement-driven, grid-interactive, self-evolving, and open platform for power system autonomous dispatch and control.

❑ In the short term, create EXAMPLES of AlphaZero in power systems.

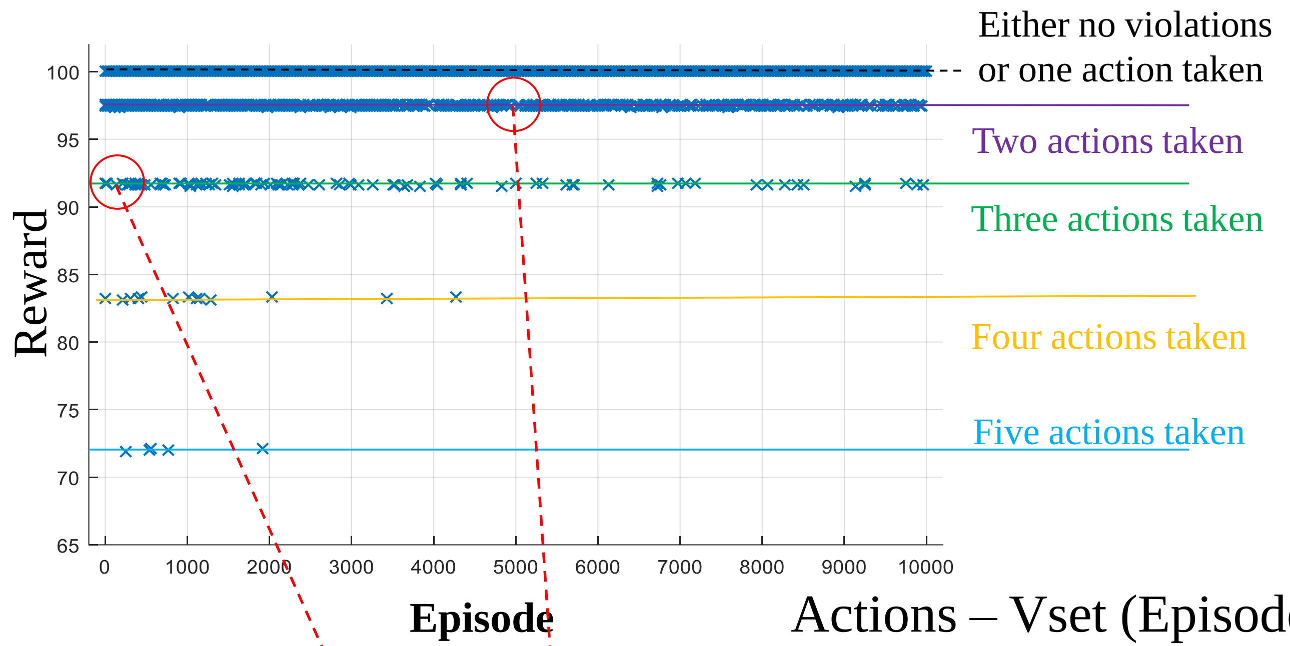
❑ In the mid-term, Grid Mind serves as an assistant to grid operators.

❑ In the long term, Grid Mind will be the core of power system operation ROBOT.

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



Autonomous Voltage Control (AVC) on IEEE 14-Bus System



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

AVC: DQN and DDPG Agents for Illinois 200-bus System

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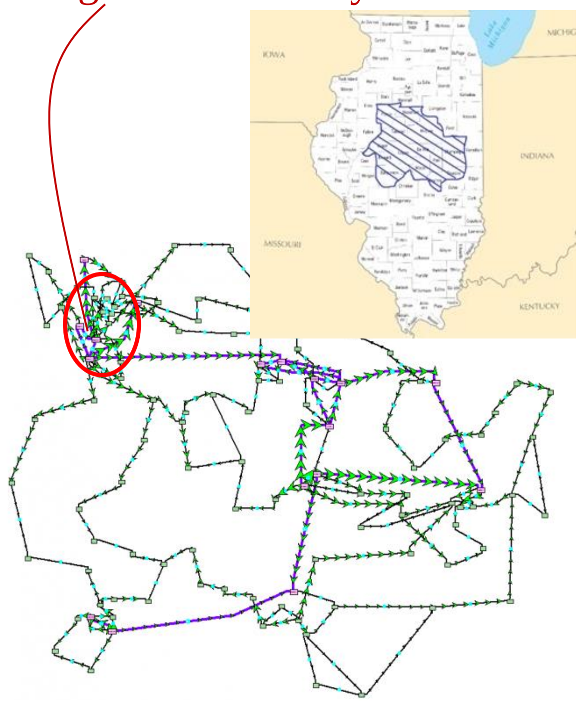
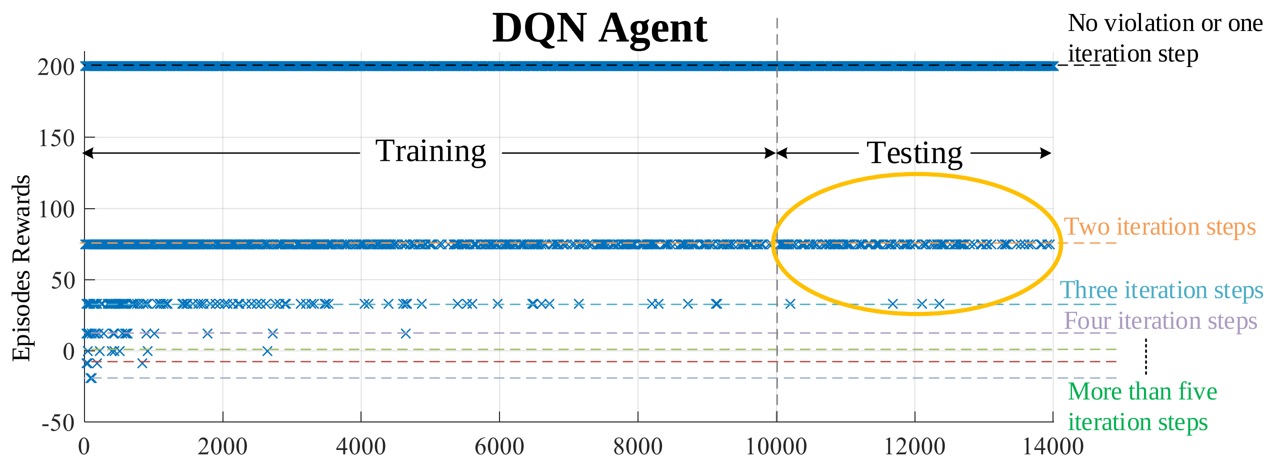
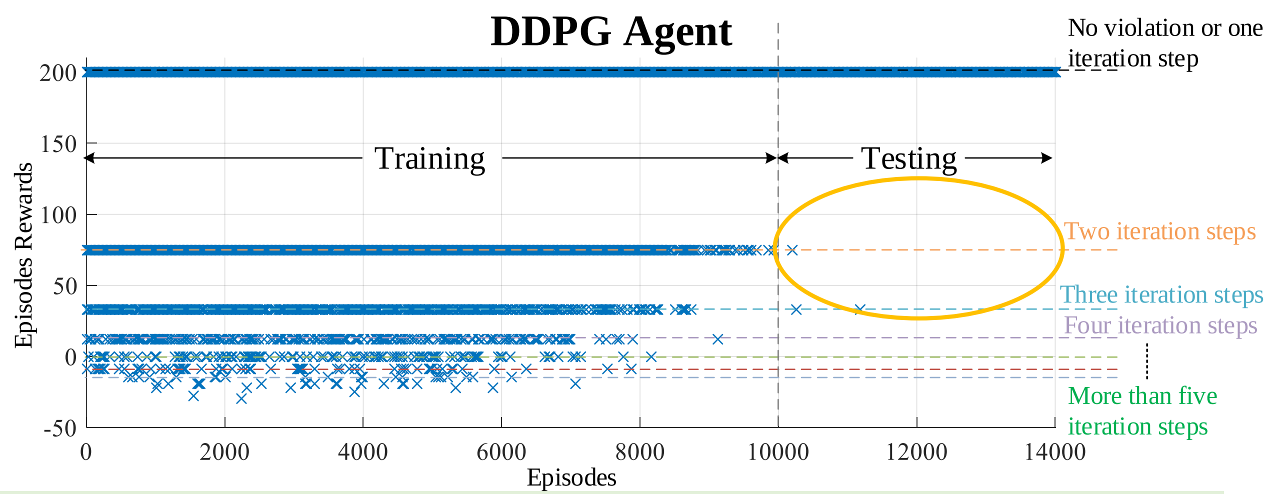
60%-120% random load changes are applied to each episode

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.

*The Illinois 200-bus system model is from https://egriddata.org/dataset/illinois-200-bus-system-activsg200

Further Testing-200 Bus System with Random N-1

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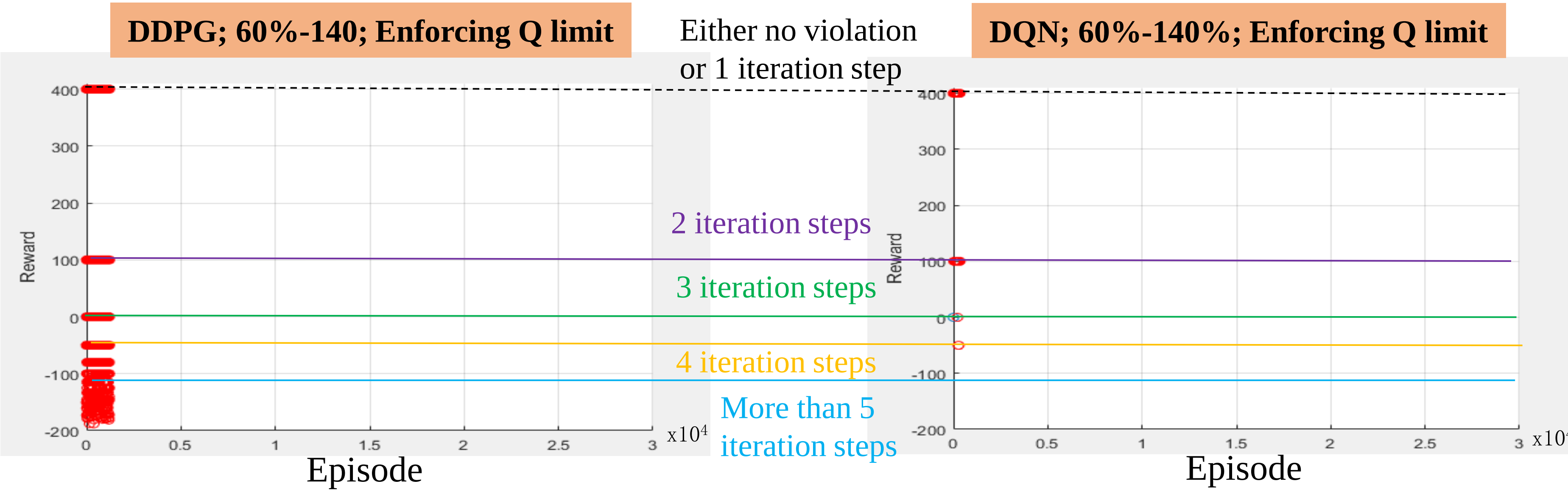
- Test the DRL agent under different loading conditions: heavily loaded, fully loaded, and lightly loaded.
- **Consider different topological changes. For example, random line tripping contingency or N-1 conditions.**

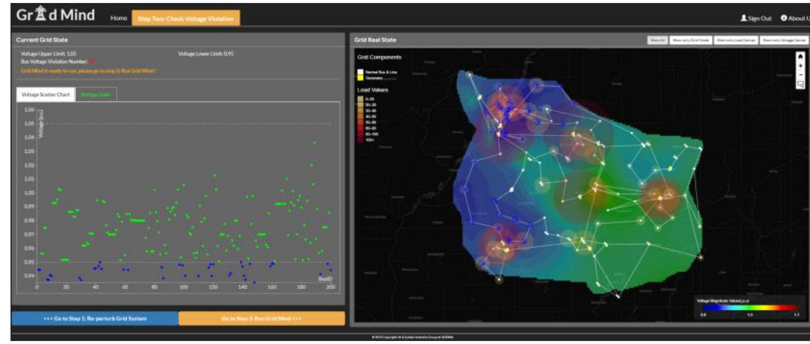


Observations:

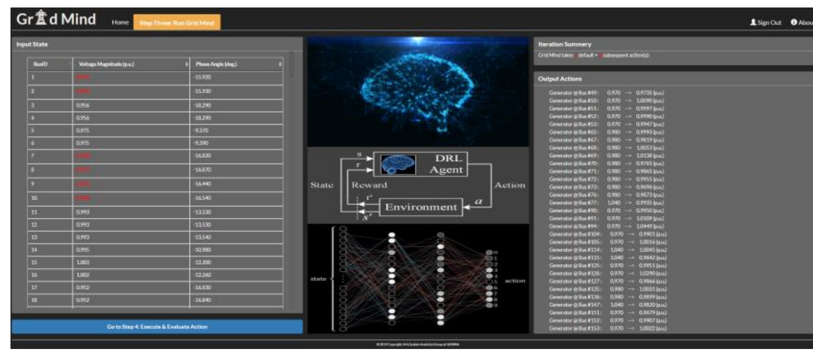
1. With little human interference, the designed agents work very well under all testing conditions.
2. The results comply with basic power system principles and engineering judgement very well.
3. The proposed framework is promising for power system autonomous operation and control.

Demo

Step 1: Perturb the system



Step 2: Check for voltage violations



Step 3: Run Grid Mind

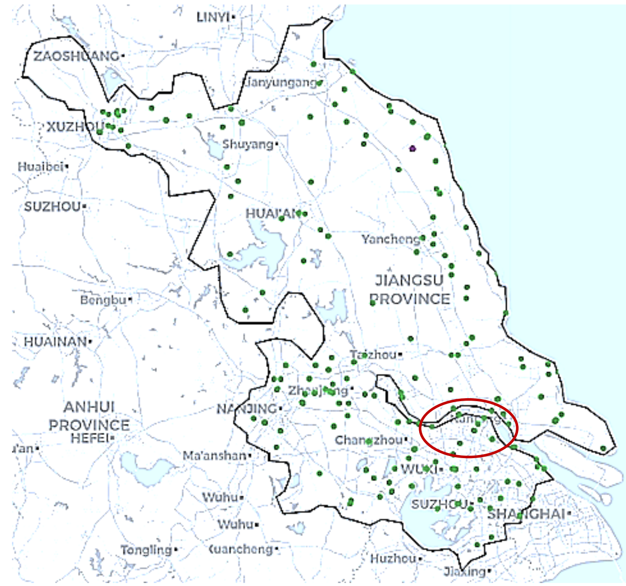
Step 4: See the results

Check the following links for the demo: https://geirina.net/assets/pdf/GridMindDemo_JD4.mp4
https://geirina.net/assets/pdf/JiangsuDemo.mp4

Deployment of Grid Mind at Jiangsu Grid

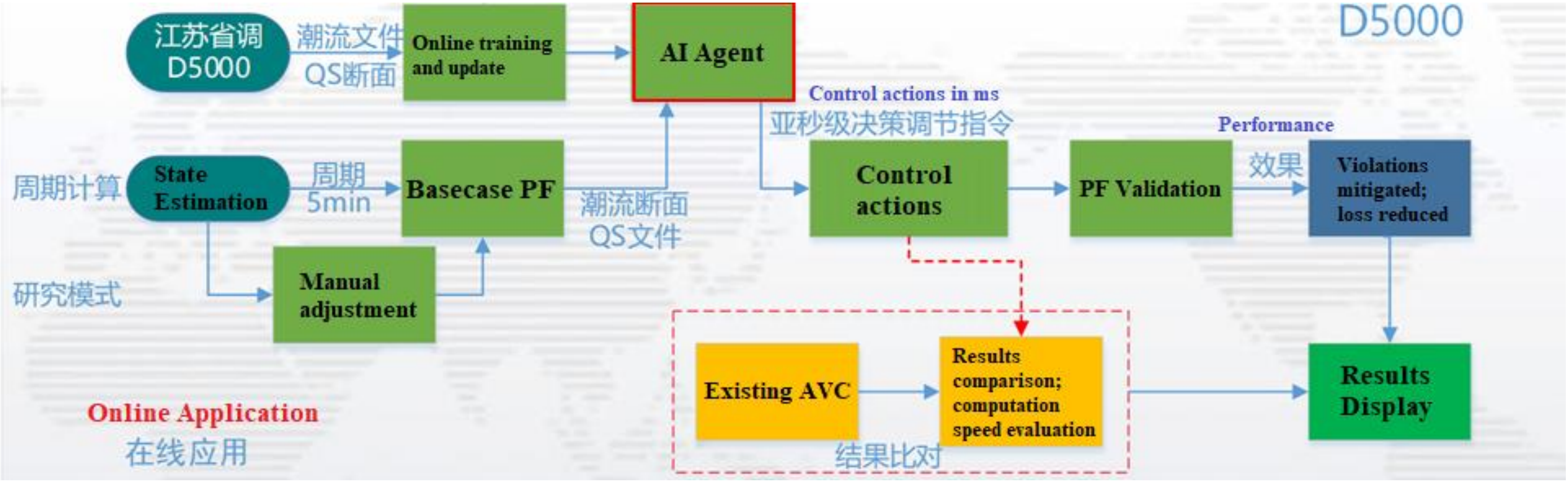
220kV and Above at ZhangJiaGang

Two Pilot Projects at ZhangJiaGang and NingBei of Jiangsu



- ➢ 45 substations and power plants
- ➢ 12 generators
- ➢ 3 500kV substations
- ➢ 37 220kV substations
- ➢ ~100 T-lines
- ➢ 50 buses
- ➢ Max load 3500MW
- ➢ Max gen. 5800MVA

Interface with Existing EMS and Data Flows



Pre-deployment Training and Testing

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➢ Generate Reasonable Data Sets based on Existing Data

- Perturb the following data files 2019-07-30-10-00， 2019-07-30-13-00， 2019-07-30-15-00， 2019-07-30-17-00， 2019-07-31-13-00 (of entire Jiangsu Grid)，by changing its load between 80%-120%, with N-1 and N-1-1
- Generate a total of 24000 system snap shots，use 12,000 of them as the training data and the rest for testing

➢ Control Objectives

- Bus voltages of 220kV and above stay within range
- 220kV-and-above lines should not be overloaded
- Reduce the loss for all lines at 220kV and above

Offline training & online execution：

Train the AI agent from scratch offline to "college" level, the agent has to learn itself in the online environment to "graduate"

➢ Testing Results are shown in the table

No. of Iterations	No. of Cases	Percentage (%)
1	11670	97.25
2	90	0.75
3	19	0.16
4	8	0.067
5	5	0.042
6	3	0.025
7	3	0.025
8	1	0.0083
10	1	0.0083
20	200	1.67

➢ Summary of Results

- ❑ Success rate in term of voltage control: 99.9917% (for only one case, voltage issue got relieved but not completely solved, 1/12000)
- ❑ Success rate in term of line flow control： 100%
- ❑ Success rate in term of loss reduction： 98.33%, averaged loss reduction at 1.27%

Possible causes (needs further investigation)：

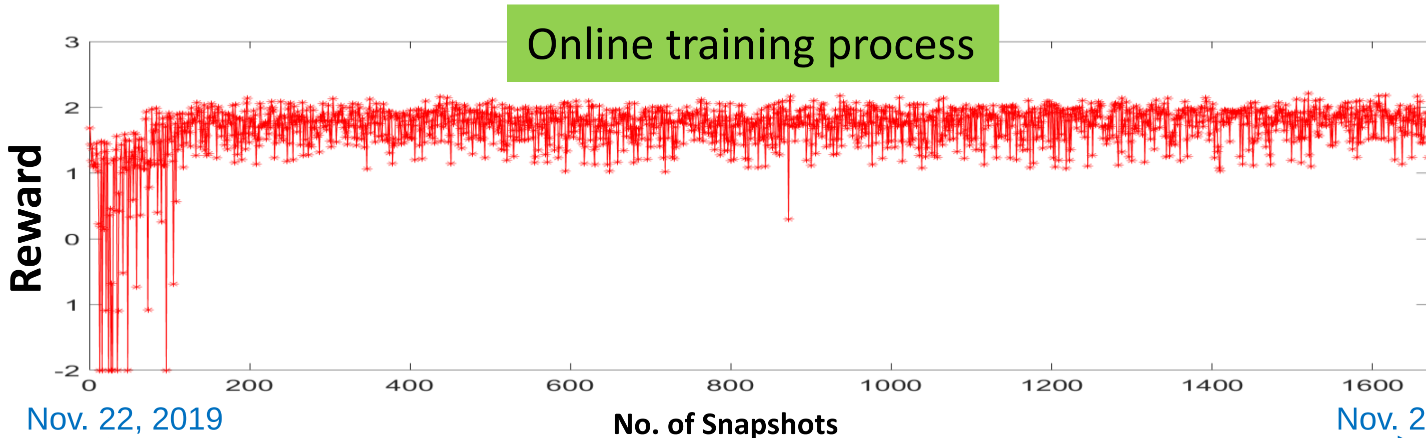
1）Unreasonable data set （random load perturbation was considered)

2）Action space can be enlarged （shunts and Xfrm taps)

3）The case itself is difficult to solve (potential byproduct critical snapshot identification)

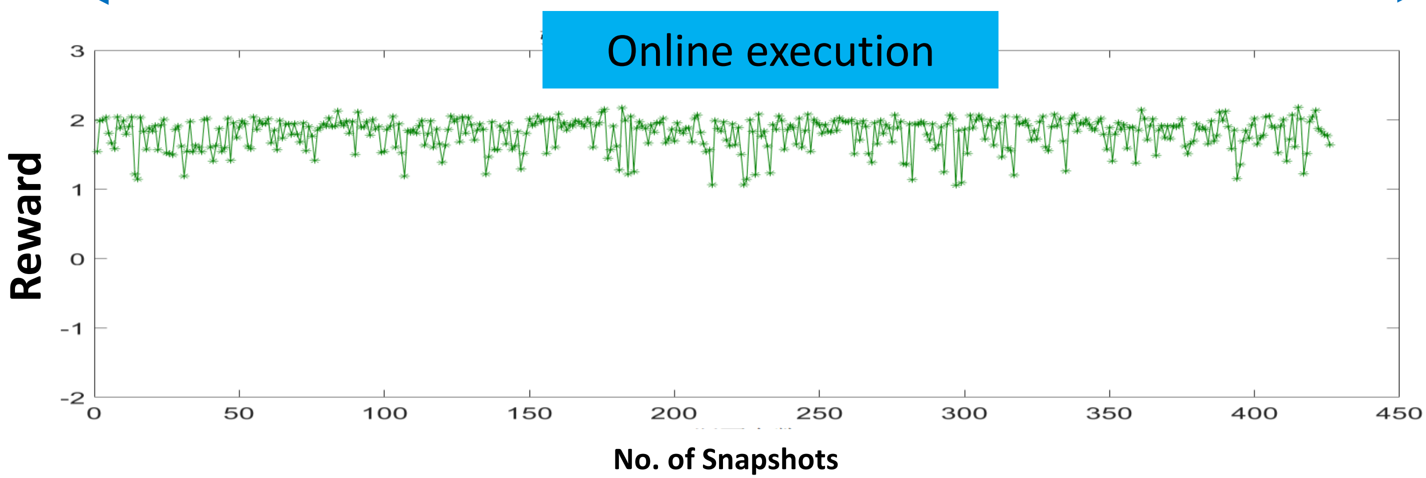
Online Deployment with REAL Data

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



During online training, 571 snapshots have violations, all solved by AI agent

Nov. 22, 2019 — Nov. 29, 2019

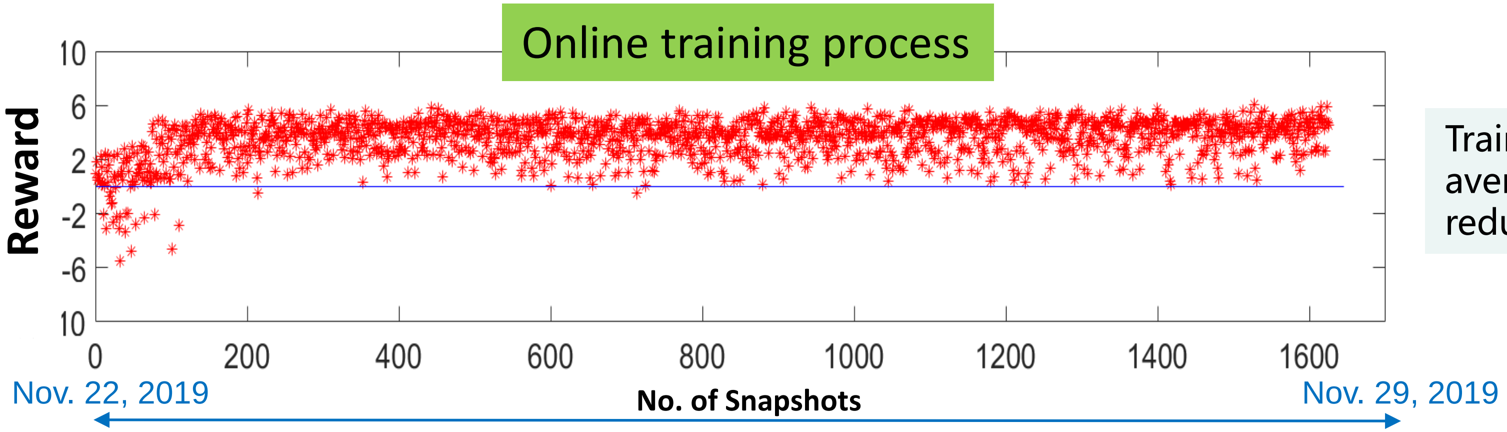


During online execution, 239 snapshots have violations, all solved by AI agent

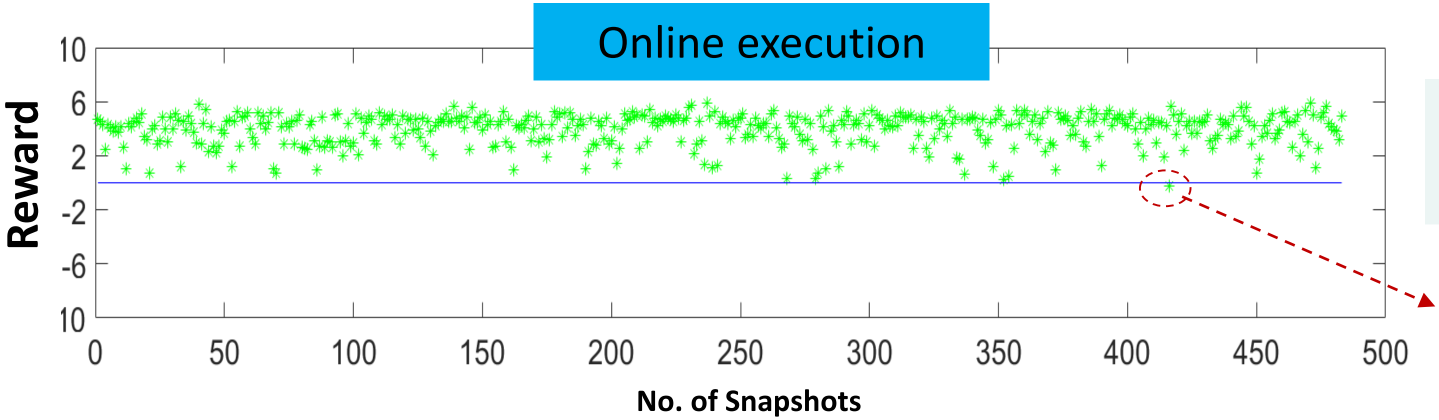
During online training, after ~200 snapshots, AI agent start to converge, and continue to evolve afterwards;

During online execution, all cases are solved, validated by the EMS (D5000);

For all cases, voltage and line flow violations are solved, with an average reduction in system loss of 3.87%。



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



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

Voltage violations solved, loss increases slightly

Observations: validated by the EMS

1) following the decisions of the AI agent, all voltage violations are solved;
2) for 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 flow is observed。

Display of one event (screen shots from one video)...

- Performance

Voltage violations at two Substations

Actions suggested

- Computation time

Decision takes 2.2 ms

Problem solved after taking the suggestion from AI agent

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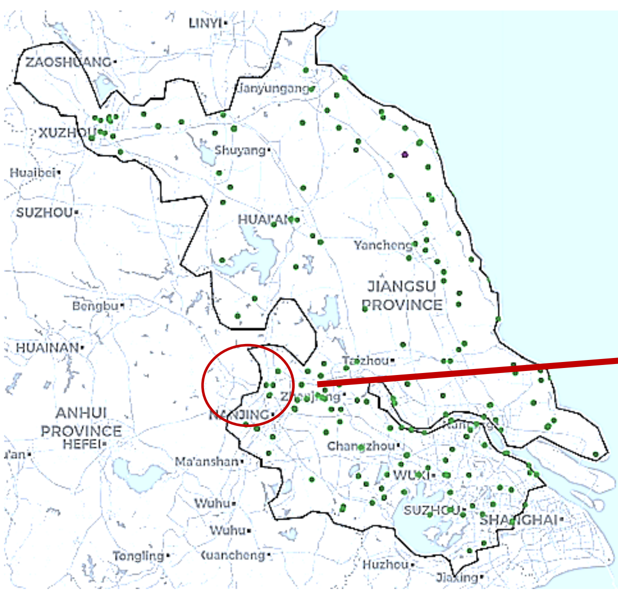
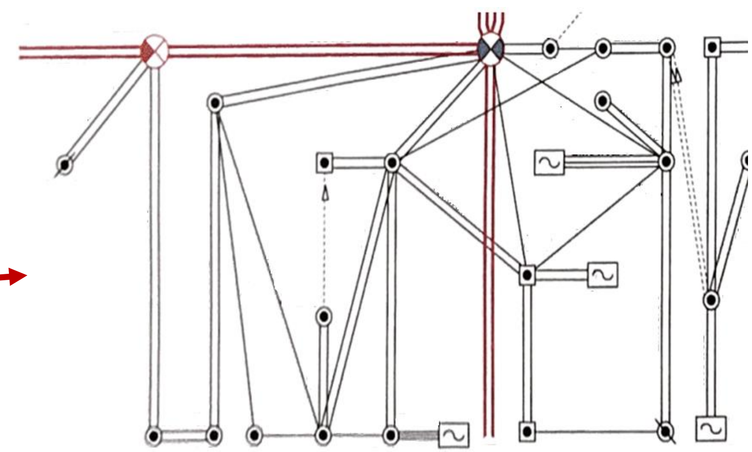
Deployment at NingBei

- **Objective:** to relieve the high-voltage problem during the Spring Festival and national holidays
- **Special operating conditions**
  - ✓ Close to HVDC terminal station
  - ✓ Forecasted load of Jiangsu Grid during this period drops to 1/3 of peak load (~33,500MW)
  - ✓ One transformer being maintained, 4x60MVar shunt reactors offline
  - ✓ Multiple generators operates in under-excitation mode with negative Q

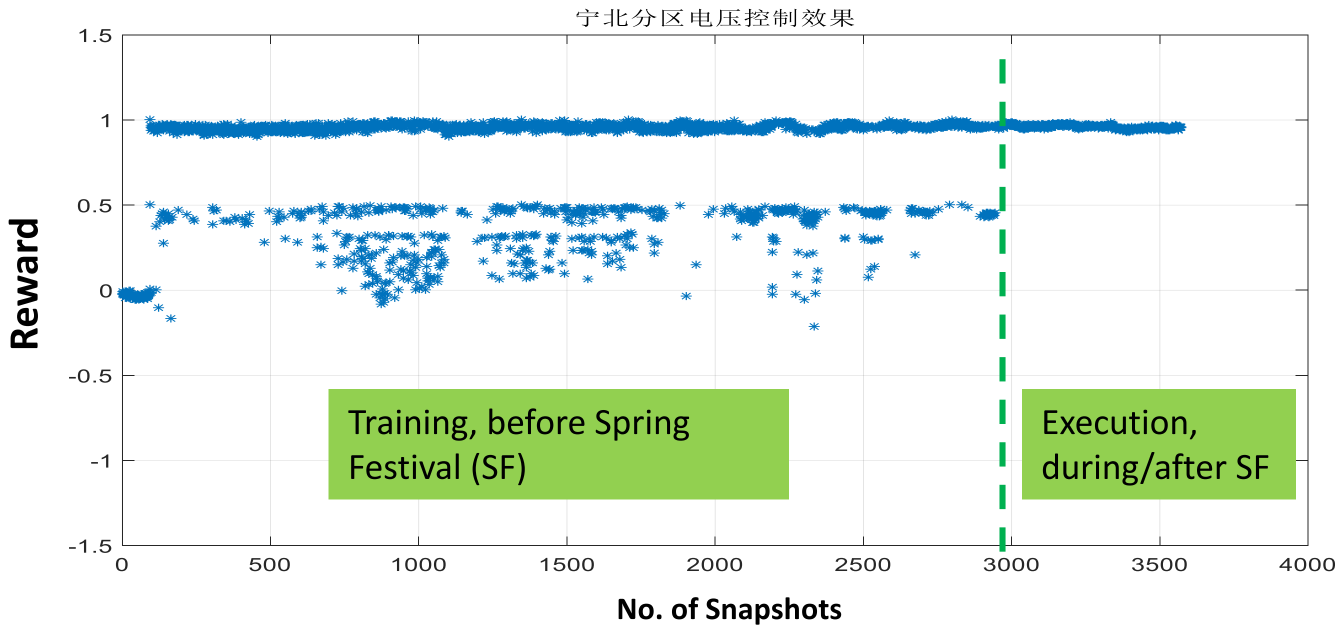




NingBei Area

Results

Jan. 1, 2020-Feb. 12, 2020, a total of 10919 snapshots



- **Training**: 2864 snapshots with violations
- **Execution/testing**: 707 snapshots with violations
- **100% success rate**

Bus Voltages

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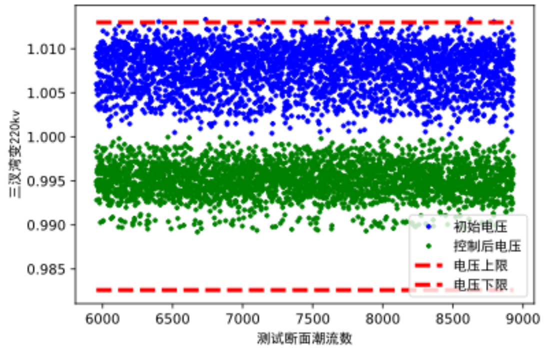
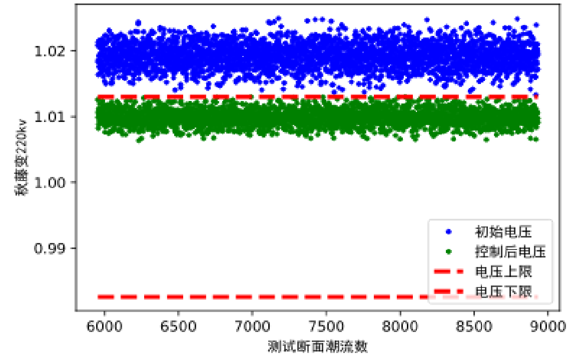
220kV-and-above buses

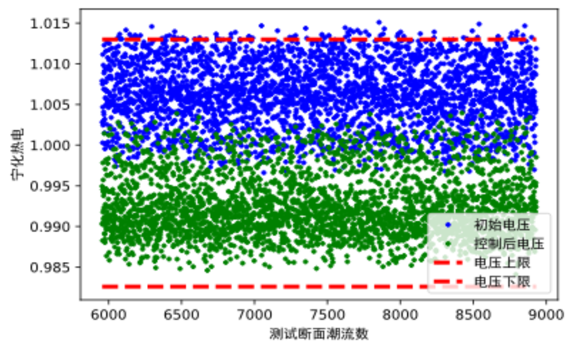
SanChaWan 220kV



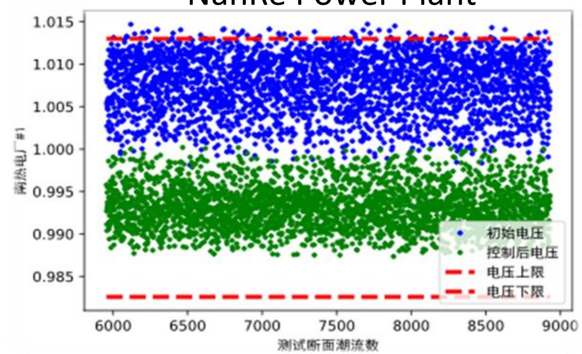
QiuTengBian 220kV



NingHua Thermal Plant



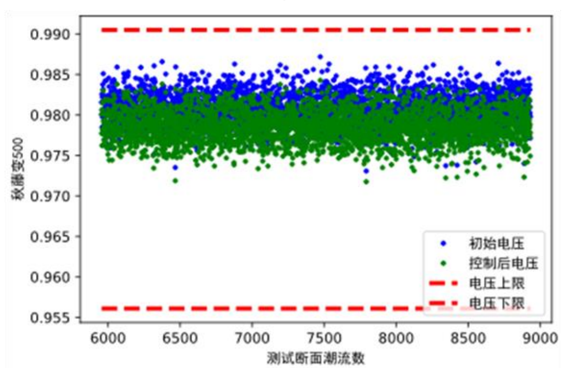
NanRe Power Plant



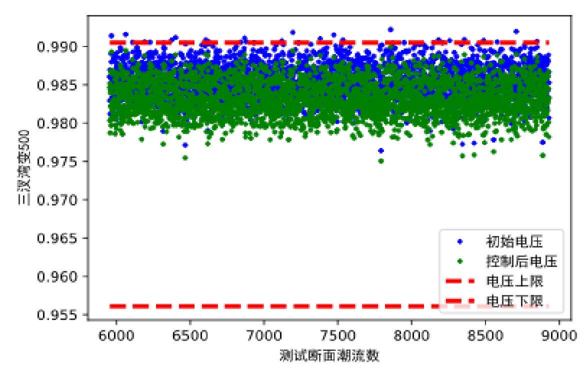
- before
- after

500kV-and-above buses

QiuTengBian 500kV



SanChaWanBian 500kV



Real Time Optimal Topology Control (L2RPN) -- Problem Formulation

- **Time-Series Optimal Control through Topology Adjustment**

Optimization problem:

- Input Data

Obj. *Min/Max (Objective)*

s.t. *Constraint_1*
Constraint_2
Constraint_3
…
Constraint_i
Constraint_j
…

Single-timestep Constraints (Constraint_1, Constraint_2, Constraint_3)

Multi-timestep Constraints (Constraint_i, Constraint_j)

- Decision Variables

Goal: Maximize the remaining power transfer capability of the entire system (all lines) over **all time steps for all 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

Node Splitting/Rejoining (**156** for 14 nodes)

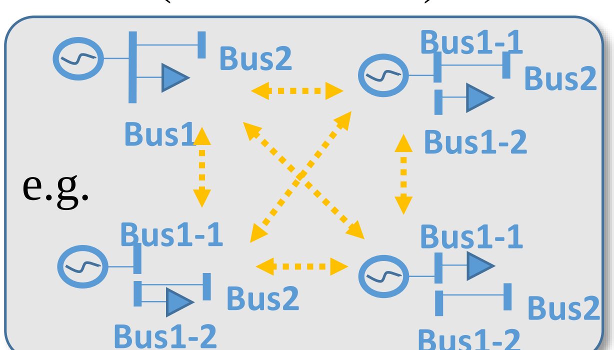
\+

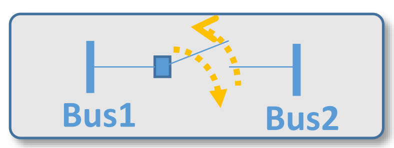
Line Switching On/Off (**20** lines)

\+

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

e.g.





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

A total of 3120 possible actions in a single timestep!

Constraints

- **Game Over** if any of the following "**hard**" constraints is violated:
  - Load should be met over all time steps of all scenarios
  - No more than 1 power plants get disconnected over all time steps of all scenarios
  - The grid should not get split apart into isolated sub-grids over all time steps of all scenarios
  - AC power flow solution should converge over all time steps of all scenarios

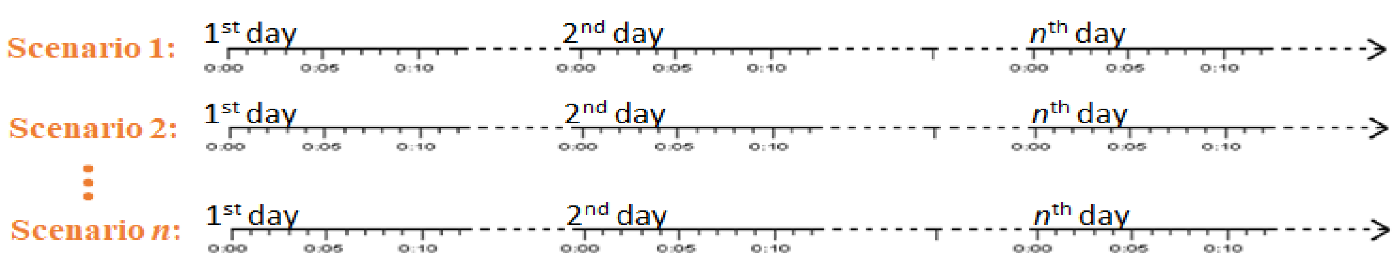
Single-timestep Constraints

- Violation on "**soft**" constraints may lead to **certain consequences** though not immediate "game over":
  - Line overload should be controlled over all time steps of all scenarios:

Scenario	Consequence	Time Steps to Recover
Line Flow >= 150%	Line immediately broken and disconnected	10
100% < Line Flow < 150%	Wait for 2 more timestep to see whether the overflow is resolved; If not, line gets disconnected	3

  - Cooldown should be considered: 3 steps of cooldown is required before a line or node can be reused, the violation on this will cause: 1) step score to be 0; 2) the action will not be taken, resulting in no action.

Multi-timestep Constraints



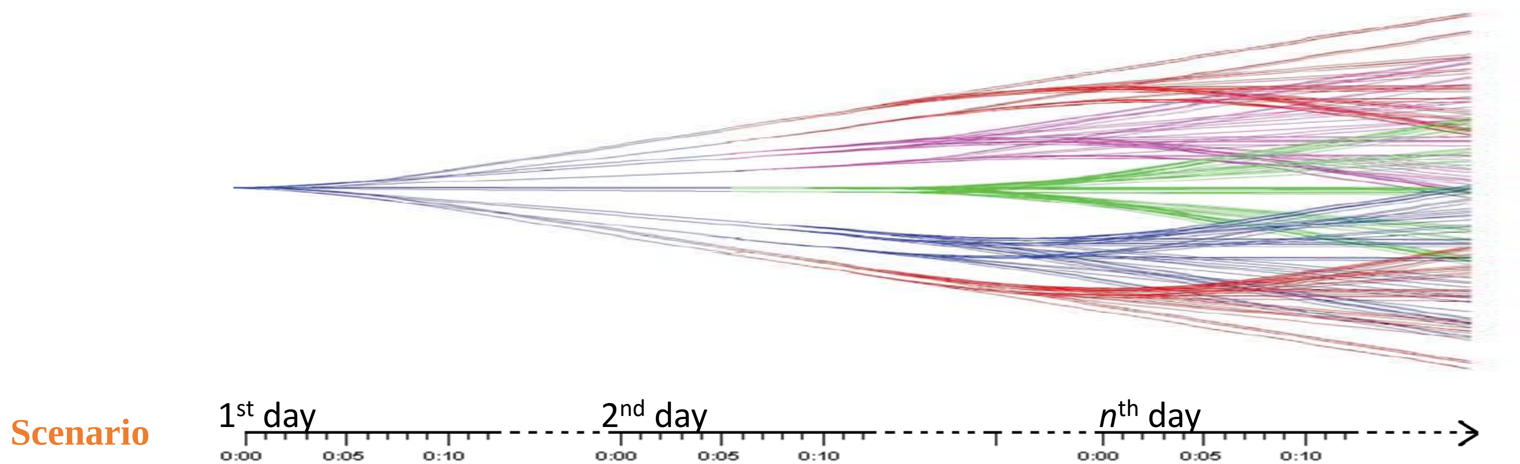
Problem Complexity

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)



Solve this Using Conventional Optimization Approach?

Formulation for a single-time-step (without considering multi-time-step constraints):

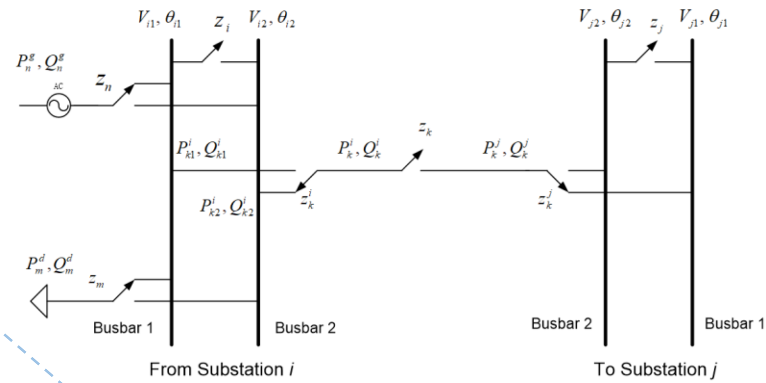
The objective is to maximize the system available transmission capacity, an auxiliary variable λ_k is introduced.

Objective Fun.:

$$\max \sum_{k \in \Omega_k} \lambda_k$$

$$\lambda_k \geq 0, \forall k$$

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



Generalized model for network topology change

Constraints:

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

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

$$P_{m1}^d = (1-z_m)P_m^d, \forall m \in \mathcal{D}$$
$$P_{m2}^d = z_m P_m^d, \forall m \in \mathcal{D}$$

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

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

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

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

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

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

$$S_k \geq S_k^i, \forall k$$
$$S_k \geq S_k^j, \forall k$$

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

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

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

Dueling DQN with Imitation Learning and Early Warning

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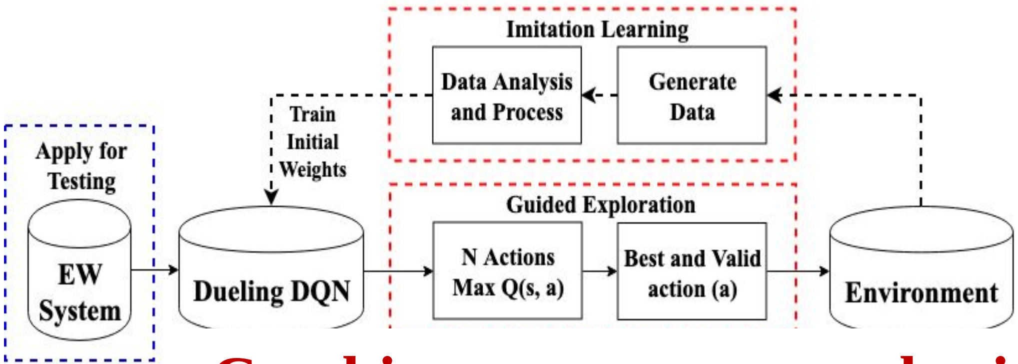
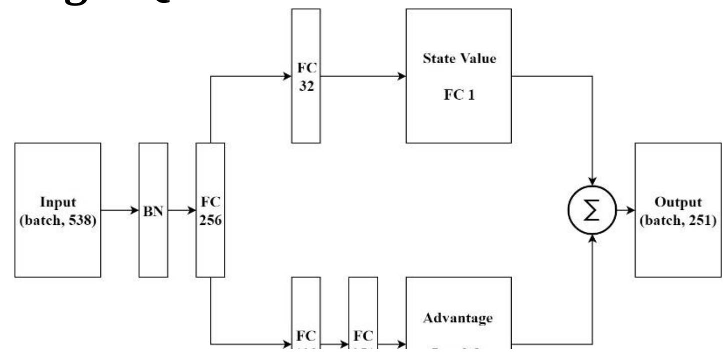
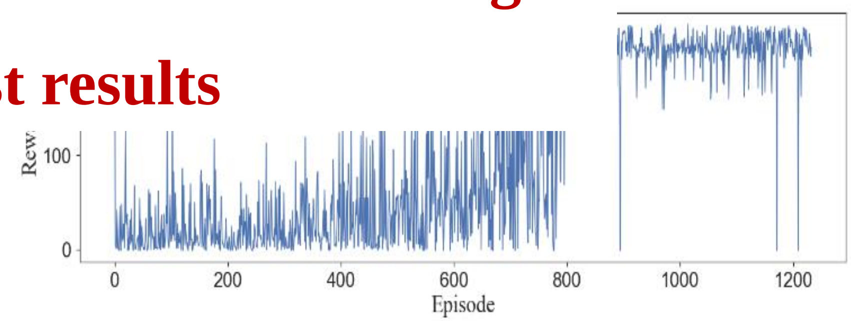
- **Architecture design**



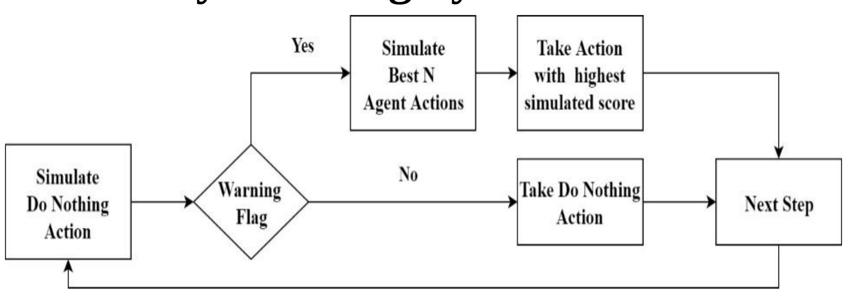
- **Dueling DQN structure and Performance**



Combine power system physics with AI technologies to obtain the best results



- **Early Warning System**



$$Warning\ Flag = \begin{cases} True & \text{if } \dfrac{lineflow_i}{thermallimit_i} > \theta,\ \forall i \in \{1,2,\ldots,20\} \\ False & otherwise \end{cases}$$

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

Agent	Game Over	Mean Score All	Mean Score w/o Dead
EW $\theta = 0.90$	17	75491.63	82504.51
EW $\theta = 0.91$	15	76345.36	82535.52
EW $\theta = 0.92$	15	76353.23	82544.03

Autonomously controlling the grid for up to a month!!!

Demo on A Hard Sample Case

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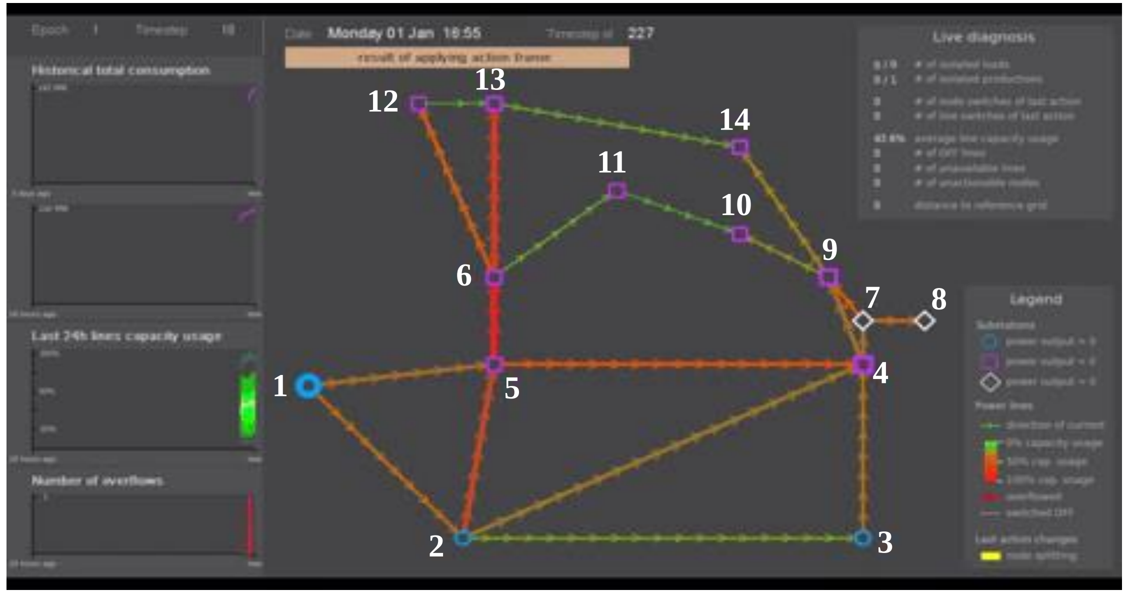
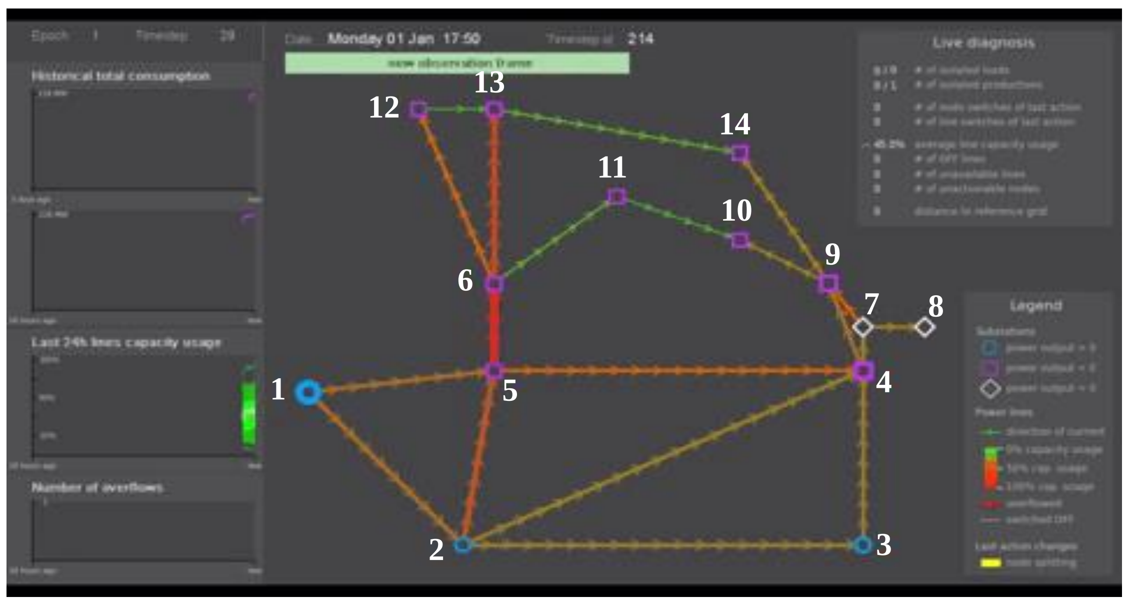
If Agent does nothing …

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



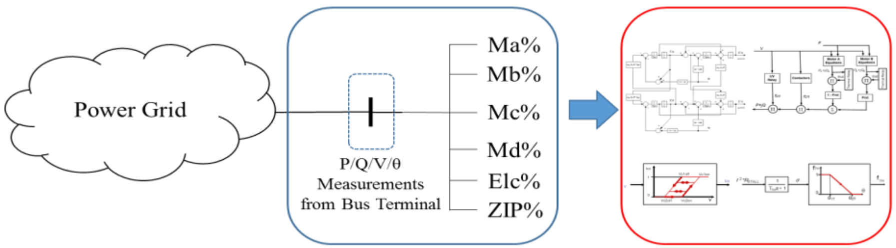
Trained Agent

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



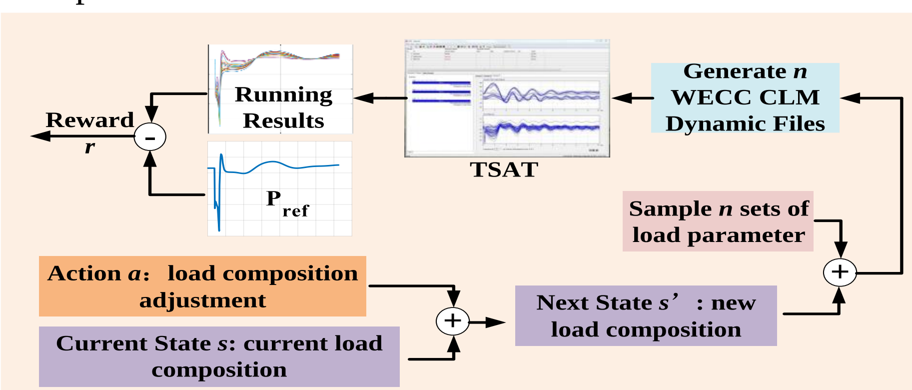
Learn Load Dynamics using AI - WECC CLM

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



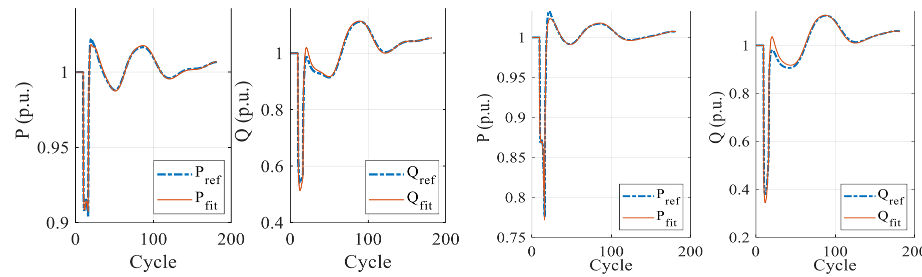
Stage I: solve load composition   Stage II: identify load parameters

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

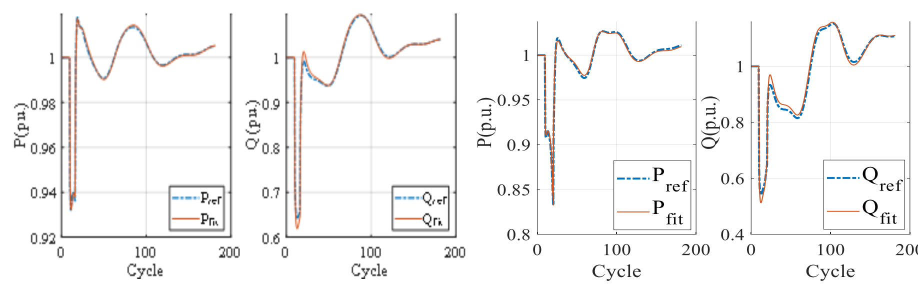


The approach is robust for fault at different locations, different fault types, different fault clearing times. The results using the identified model match the dynamic response of the system.

For one Fault   Diff. Fault Locations



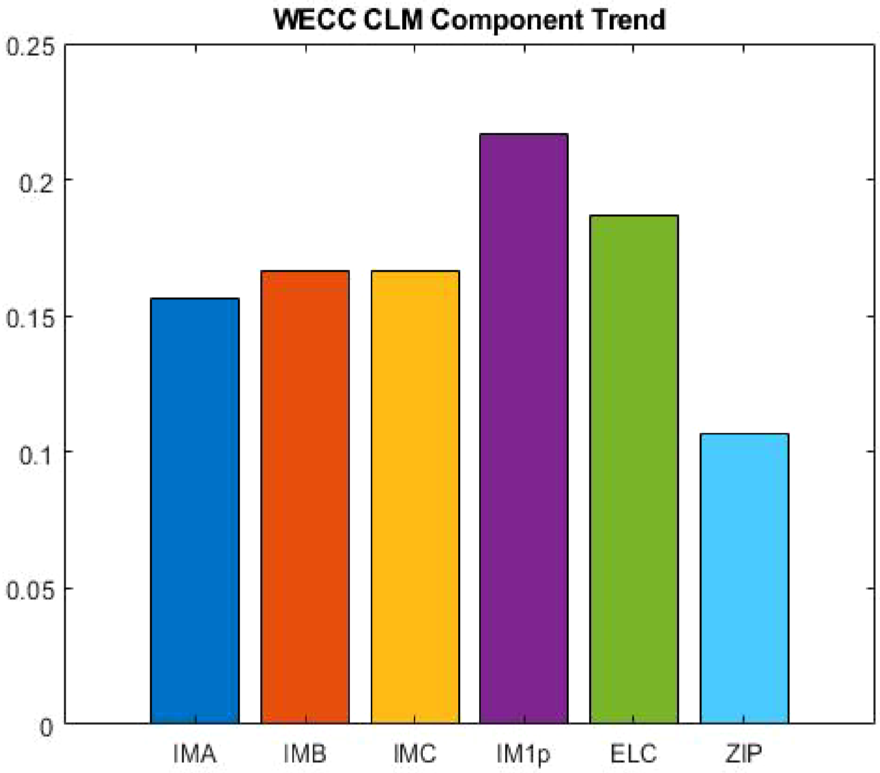
Diff. Fault Types   Diff. Fault Clearing Time

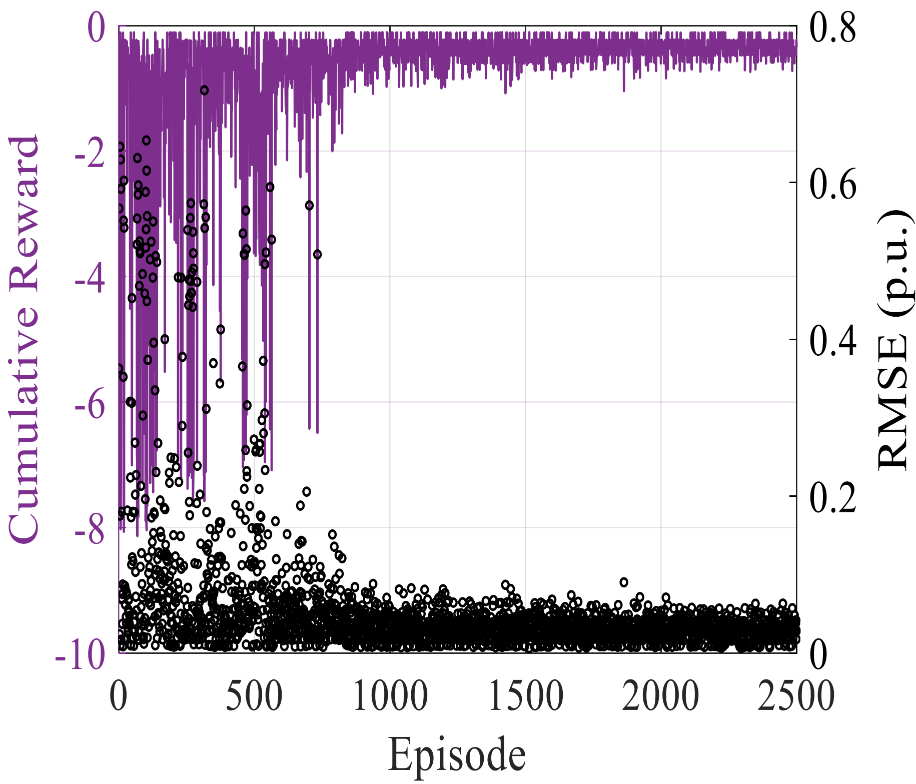


Accuracy for P, RMSE 0.12%
Accuracy for Q, RMSE 0.64%

Method Validation

The left animation shows the identification process of different load components of the WECC CLM; the right one shows the tracking error. The algorithm converges pretty fast.





Other Applications We've Developed/Are Developing

- Online learning for AI agents in face of significant topology and operating pattern changes
- Autonomous line flow control
- Learn generator/load dynamic model & parameters
- Data-driven AC OPF
- Multi-agent cooperative control for larger systems

Multiple Cooperative Dispatch Robots

Developmental Trend

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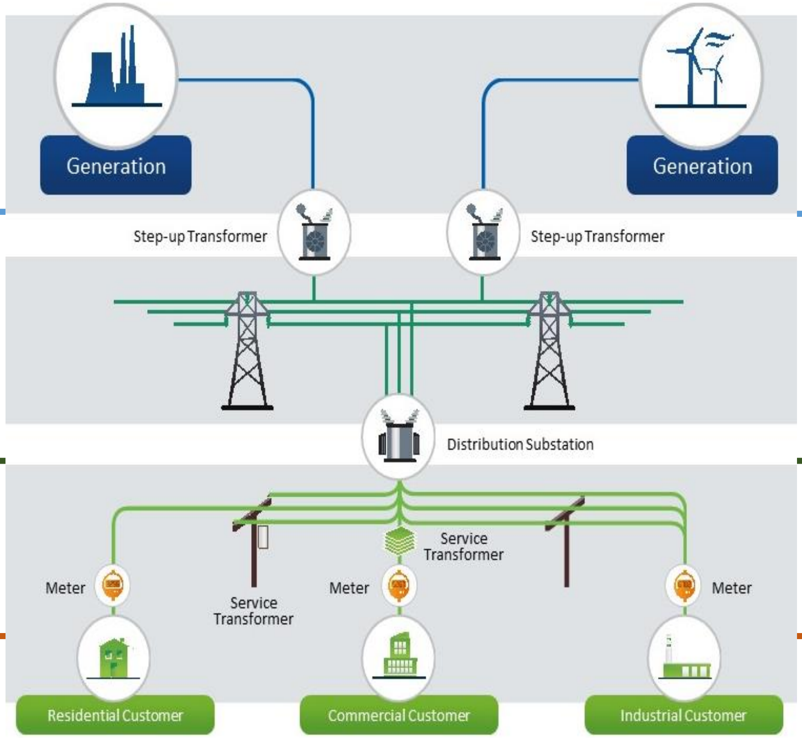
- Model validation and calibration
- Excitation and damping control
- Maintenance Scheduling
- Renewable Forecasting

- Intelligent monitoring & early warning
- Intelligent diagnosis of equipment
- Image recognition of power lines
- Situational awareness

- Knowledge map & intelligent reasoning
- Fault detection and location
- Intelligent analysis and self-healing ctrl

- Demand forecasting
- Load clustering and par. identification



Generation

Transmission

Distribution

End user

Trend of AI in Power Systems

Monitoring
Diagnosis
Forecasting

- RNN
- LSTM
- CNN
- GAN
- GNN
- SVM…

Reasoning/planning
Decision making
Autonomous control

- (D)DQN
- PPO
- DDPG
- SAC
- A3C
- TRPO…

Potential Applications

- Power system operation and control
- Power system planning
- Power system asset management
- Power system economics and market

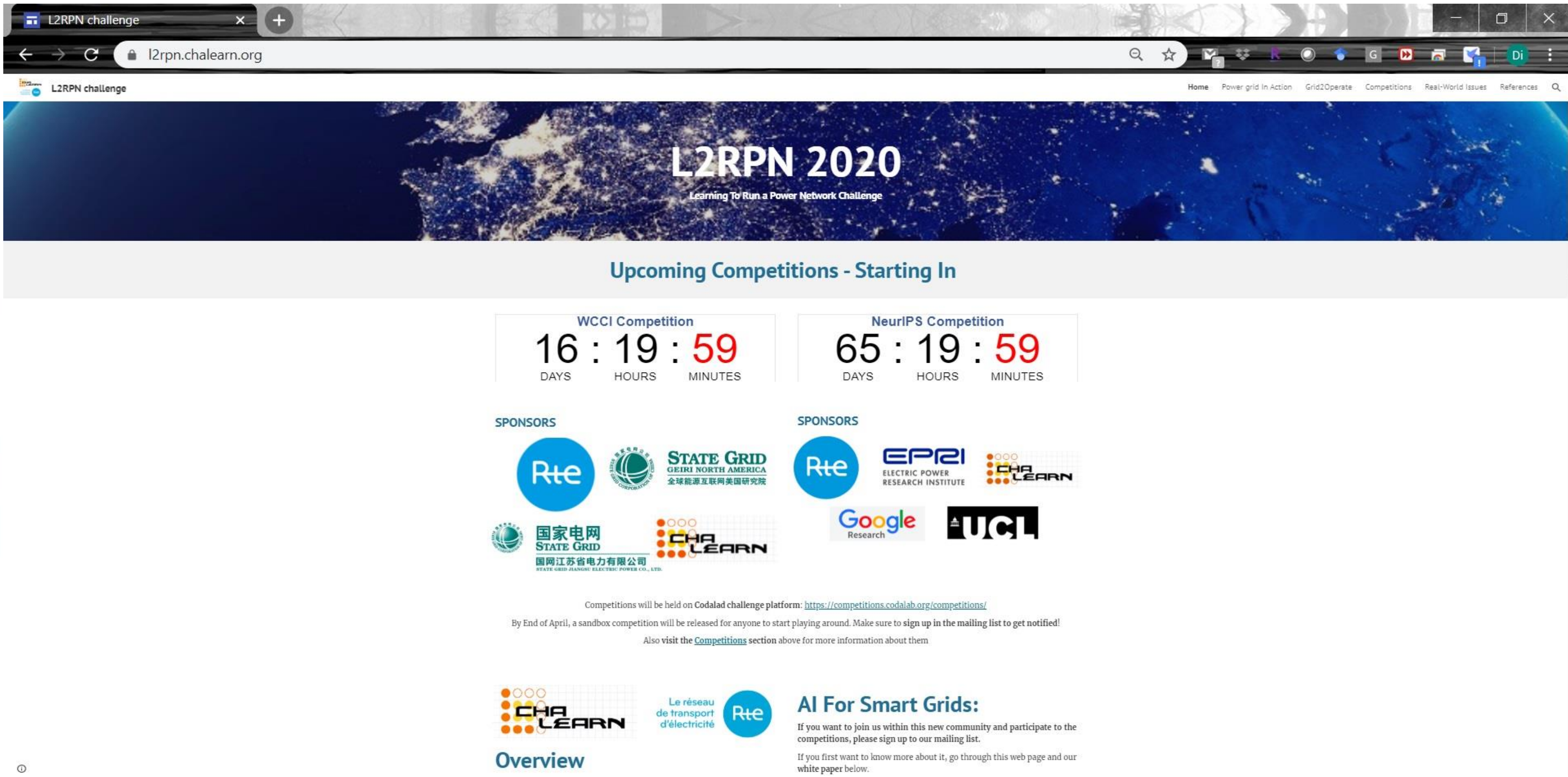
Challenges & Opportunities

- Data sets
- Platform
- Competitions based on common data sets & platform

White Paper – RL for Electricity Network Operation

RTE France, Google Brain, EPRI, ASU, GEIRINA, etc. published a White Paper 《Reinforcement Learning for Electricity Network Operation》, Introducing applications of RL in Power Systems, https://arxiv.org/abs/2003.07339

In 2020, two Power System AI Competitions will be hosted: https://l2rpn.chalearn.org/



Related Publications

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1. X. Wang, Y. Wang, D. Shi, J. Wang, and Z. Wang, “Two-stage WECC Composite Load Modeling: A Double Deep Q-Learning Networks Approach,” IEEE Transactions on Smart Grid, 2020.
2. S. Wang, J. Duan, D. Shi, C. Xu, H. Li, R. Diao, Z. Wang, “A Data-driven Multi-agent Voltage Control Framework Using Deep Reinforcement Learning,” IEEE Transactions on Power Systems, 2020.
3. Z. Yu, D. Shi, J. Li, Y. Wang, X. Zhao, Z. Wang, and J. Li, “Using Transfer Learning to Distinguish between Natural and Forced Oscillations,” IEEE PES General Meeting, 2020.
4. Z. Xu, Y. Zan, C. Xu, J. Li, D. Shi, Z. Wang, B. Zhang, and J. Duan, “Accelerated DRL Agent for Autonomous Voltage Control Using Asynchronous Advantage Actor-critic,” IEEE PES General Meeting, 2020.
5. G. Tian, Y. Gu, X. Lu, D. Shi, Q. Zhou, Z. Wang, and J. Li, "Estimation Matrix Calibration of PMU Data-driven State Estimation Using Neural Network," IEEE PES General Meeting, Montreal, 2020.
6. B. Zhang, X. Lu, R. Diao, H. Li, T. Lan, D. Shi, and Z. Wang, "Real-time Autonomous Line Flow Control Using Proximal Policy Optimization," IEEE PES General Meeting, Montreal, 2020.
7. T. Lan, J. Duan, B. Zhang, D. Shi, Z. Wang, R. Diao, and X. Zhang, “AI-Based Autonomous Line Flow Control via Topology Adjustment for Maximizing Time-Series ATCs,” IEEE PES General Meeting, 2020.
8. X. Wang, Y. Wang, J. Wang, and D. Shi, “Residential Customer Baseline Load Estimation Using Stacked Autoencoder with Pseudo-load Selection,” IEEE Journal on Selected Areas in Communications (J-SAC) issue on Communications and Data Analytics in Smart Grid, 2019
9. J. Duan, D. Shi, R. Diao, H. Li, Z. Wang, B. Zhang, D. Bian, and Z. Yi, “Deep-Reinforcement-Learning-Based Autonomous Voltage Control for Power Grid Operations,” IEEE Transactions on Power Systems, 2019.
10. 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.
11. J. Duan, H. Li, X. Zhang, R. Diao, B. Zhang, D. Shi, X. Lu, Z. Wang, and S. Wang, "A Deep Reinforcement Learning Based Approach for Optimal Active Power Dispatch," IEEE Sustainable Power and Energy Conference, 2019.
12. 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]
13. 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]

Thank You!

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