



NeurIPS 2020 L2RPN Robustness and Adaptability Tracks Competition Winning Approach

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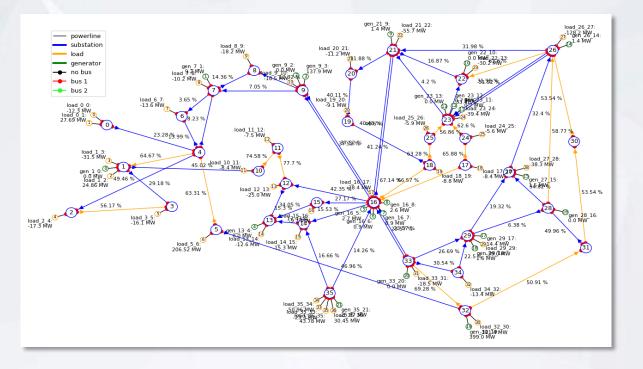
Track1: Robustness Track

Problem description

Methodology

Tricks

Results





An adversarial opponent will attack some lines of the grid everyday randomly.

- ➤ **Goal:** Develop agent to be robust to unexpected events and keep delivering reliable electricity everywhere even in difficult circumstances.
- > Operation Cost: Operate the grid as long as possible, minimize the operation cost including powerlines losses, redispatch cost and blackout cost (penalty).



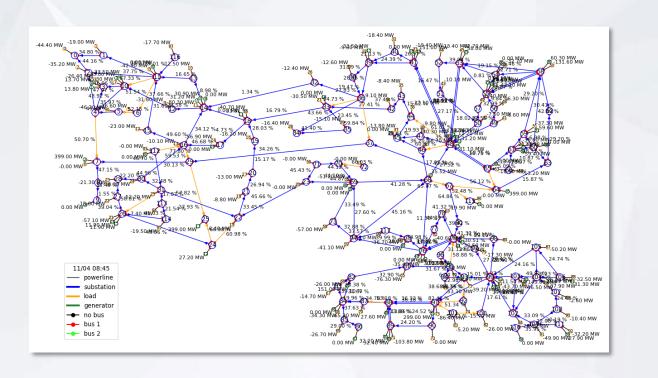
Methodology

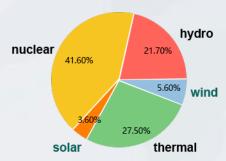
Tricks

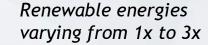
Results

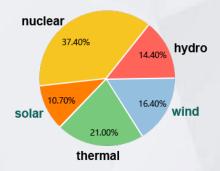


Track2: Adaptability Track









- ➤ **Goal:** Develop agent to adapt to new energy productions in the grid with an increasing share of renewable energies which might be less controllable.
- > Operation Cost: Operate the grid for as long as possible, minimize the operation cost including powerlines losses, redispatch cost and blackout cost (penalty).



Rules and Score

Problem description

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Rules and Constraints

- > Demand-supply balance should be met at any time without load shedding.
- Tripping power plant is not allowed.
- > Electrical islands are not allowed.
- > Any action has a certain cool down time.

•••

Score

The agent with less blackouts and less operation costs will be given higher score.

$$C_{operations}(t) = C_{loss}(t) + C_{redispatching}(t)$$

$$C_{blackout}(t) = Load(t) * \beta * p(t), \beta \ge 1$$

$$C(e) = \sum_{t=1}^{t_{end}} C_{operations}(t) + \sum_{t=t_{end}}^{T_e} C_{blackout}(t)$$

$$Score = \sum_{i=1}^{N} C(e_i)$$





Methodology

Tricks

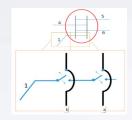
Results



Do-Nothing action



Powerline Status action: reconnecting / disconnecting a power line



Substation Topological action: switching busbar connection between double busbars for each substation object.



Generation redispatch action: modifying the production set point with redispatching





Methodology

Tricks

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State chosen:

- Some states (such as prod_p, load_p, topology_vect, time_next_maintenance, line_status, rho etc.) are necessary in our action selecting process.
- Inherent properties in power grid (e.g thermal_limit of lines) and some properties of generators (e.g max_ramp_up)

State unchosen:

Another part of states (such as date, time, prod_q, load_q etc.) which have no contribution to our action selecting process.



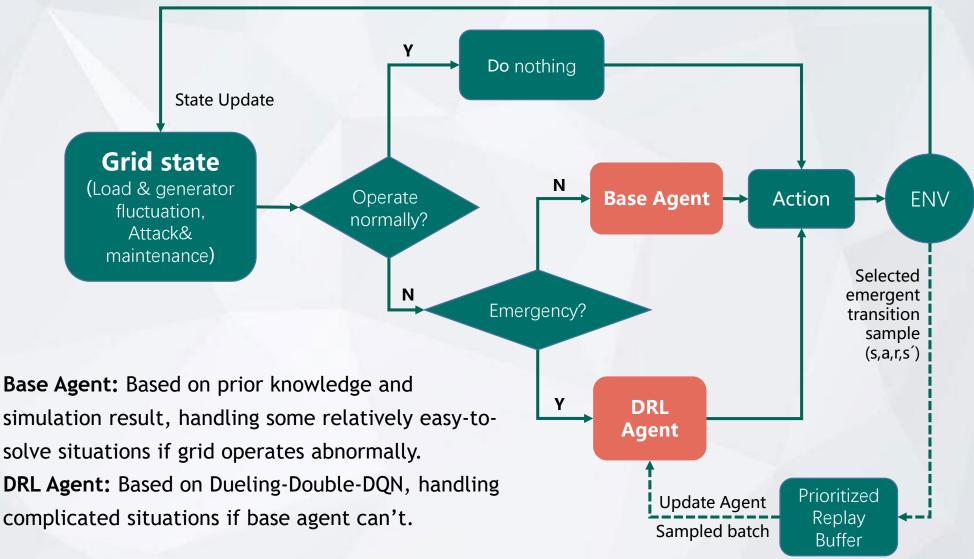
Methodology

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Dual-agent strategy





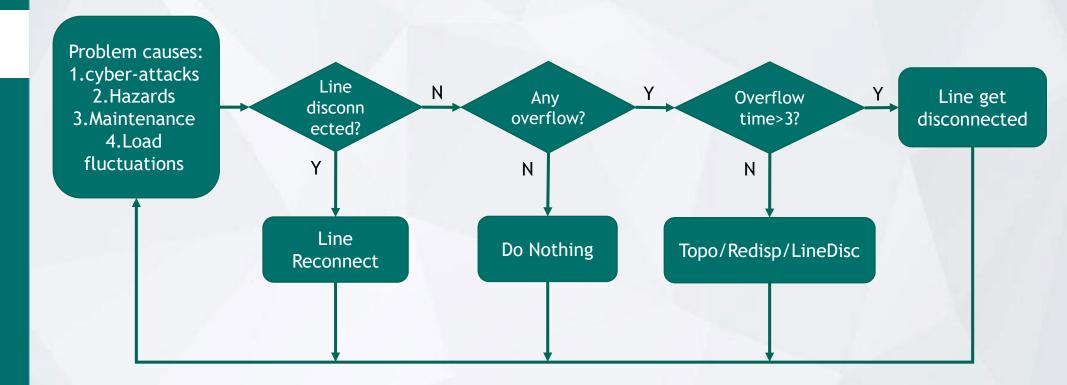




Methodology

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Results





DRL agent

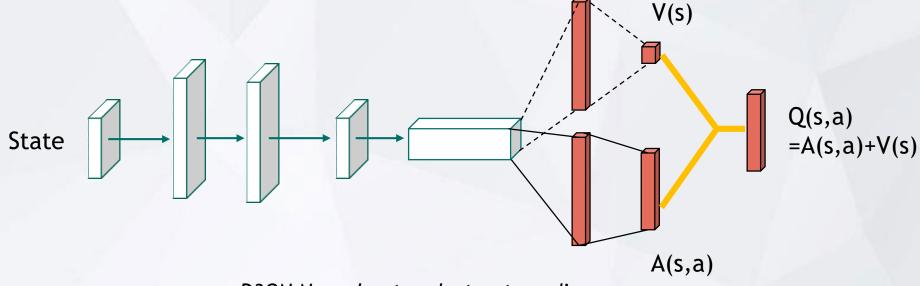
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We adopt the Dueling-Double-DQN(D3QN) algorithm for our DRL agent, a kind of value based algorithm which can handle discrete action-space problems.



D3QN Neural network structure diagram

Robustness Track: State size=744, Action size=885

Adaptability Track: State size =2300, Action size =1164





Methodology

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Rewards: (factors considering)

- 1.Sandbox economic
- 2.Close-To-OverFlow overflow
- 3. Distance difference with initial topology
- 4.Line-capacity available transfer capacity



Robustness Track (Track1)

- Sandbox-Reward
- Close-To-OverFlow-Reward
- Distance-Reward

Adaptability Track (Track2)

- ➤ Sandbox-Reward
- ➤ Close-To-OverFlow-Reward
- ➤ Distance-Reward
- ➤ Lines-Capacity-Reward

Reward= Σ Weight(i)*Reward(i),i \in (Sandbox, CloseToOverflow, Distance, LineCapacity)



Methodology

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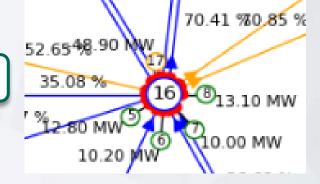
Reduced Action-space

- Robustness Track (Track1)
- \triangleright Before reduce: 130k (2¹⁷ = 131,072)
- > After reduce: 885
 - 58 line, 786 topo, 40 redisp, 1 donothing

- Adaptability Track (Track2)
- Before reduce: even more!
- > After reduce: 1164

185 line, 978 topo, 1 donothing

Why action-space need to be reduced?



- > The topology action number is huge due to complex action combination.
- Difficult for system simulation and agent training.
- > We reduce them according to domain knowledge and experiments.



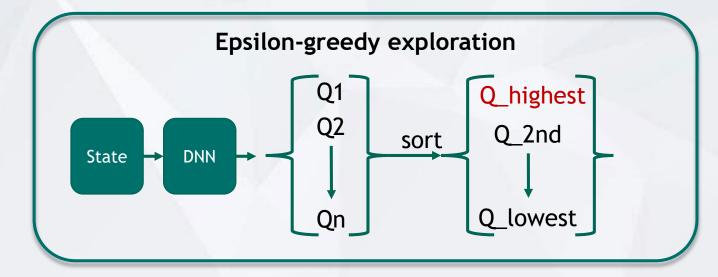
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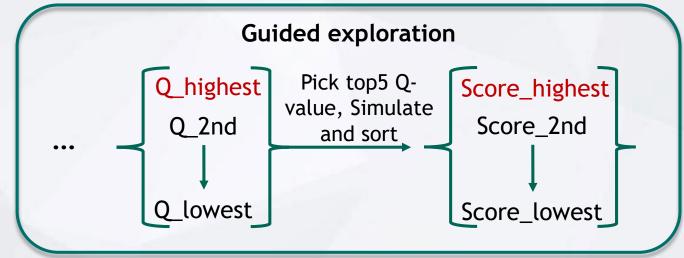


Guided exploration





- Large Action-space
- Long MDP chain
- Local optimum





- Stable
- Better experience
- Efficient

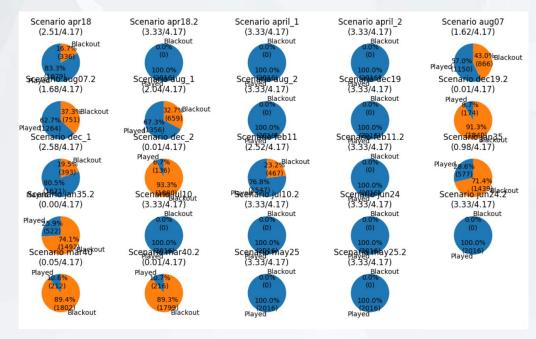




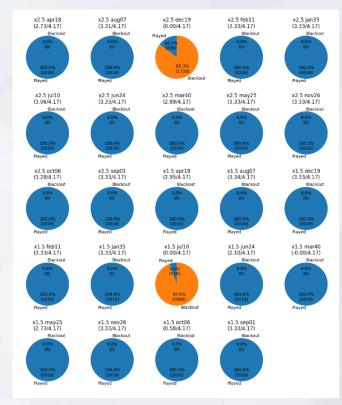
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Adaptability Track Test Result

- > 50-year simulated training data and 24-week test data for each competition track.
- Blue indicates scenarios passed, orange indicates scenarios black-out.
- > We will optimize our agent for the failed cases in future work.



Methodology

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Robustness Track:

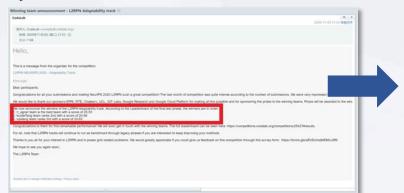


 $1.rl_agent\ team\ is\ the\ best\ team\ with\ a\ score\ of\ 59.26$

2.binbinChen team ranks 2nd with a score of 46.89

3. lujixiang team ranks 3rd with a score of 44.62

Adaptability Track:



1.rl_agent team is the best team with a score of 25.53

2.kunijeTang team ranks 2nd with a score of 24.66

3.lujixiang team ranks 3rd with a score of 24.63

We are one of top performers in both NeurIPS Robustness Track and Adaptability Track competitions.





Thanks!

