Wind farm yaw-based wake steering control through deep reinforcement learning

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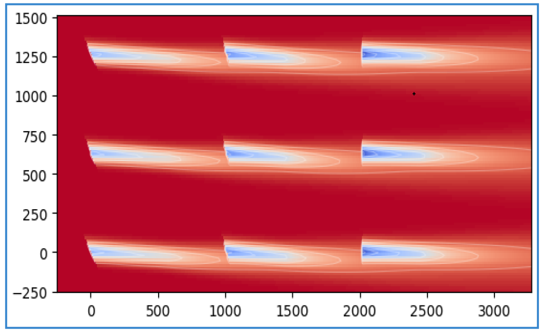
1. Introduction

Wake steering

Upstream wind turbines yaw → Wake center deviates from downstream wind turbine → Power output ↑ / Fatigue load ↓



Consider minute-level control

Wind Speed/Wind Direction

Wind turbine unit capacity

Yaw rate

Optimal Yaw Angles

May not be reached within minute

Initial position

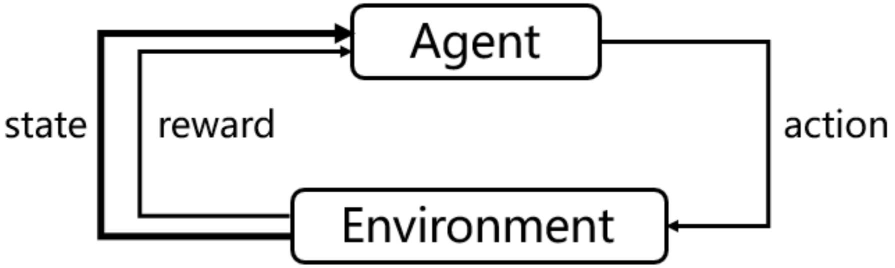
Range of action

2. Why choose DRL

Example : Optimal control of 72 wind turbines

	SLSQP	CMAES	Look-up table	DRL
Calculation type	Online Algorithm	Online Algorithm	Offline Algorithm	Offline Algorithm
Application computing time	100-200 s	120-250 s	<1s	<1s
Global optimal solution	N	Y	——	——
Coping with unknown initial position	Great	Perfect	Good	Excellent
Actual operation data feedback	None	None	None	Perfect
Practical application feasibility	Bad	General	Good	Perfect

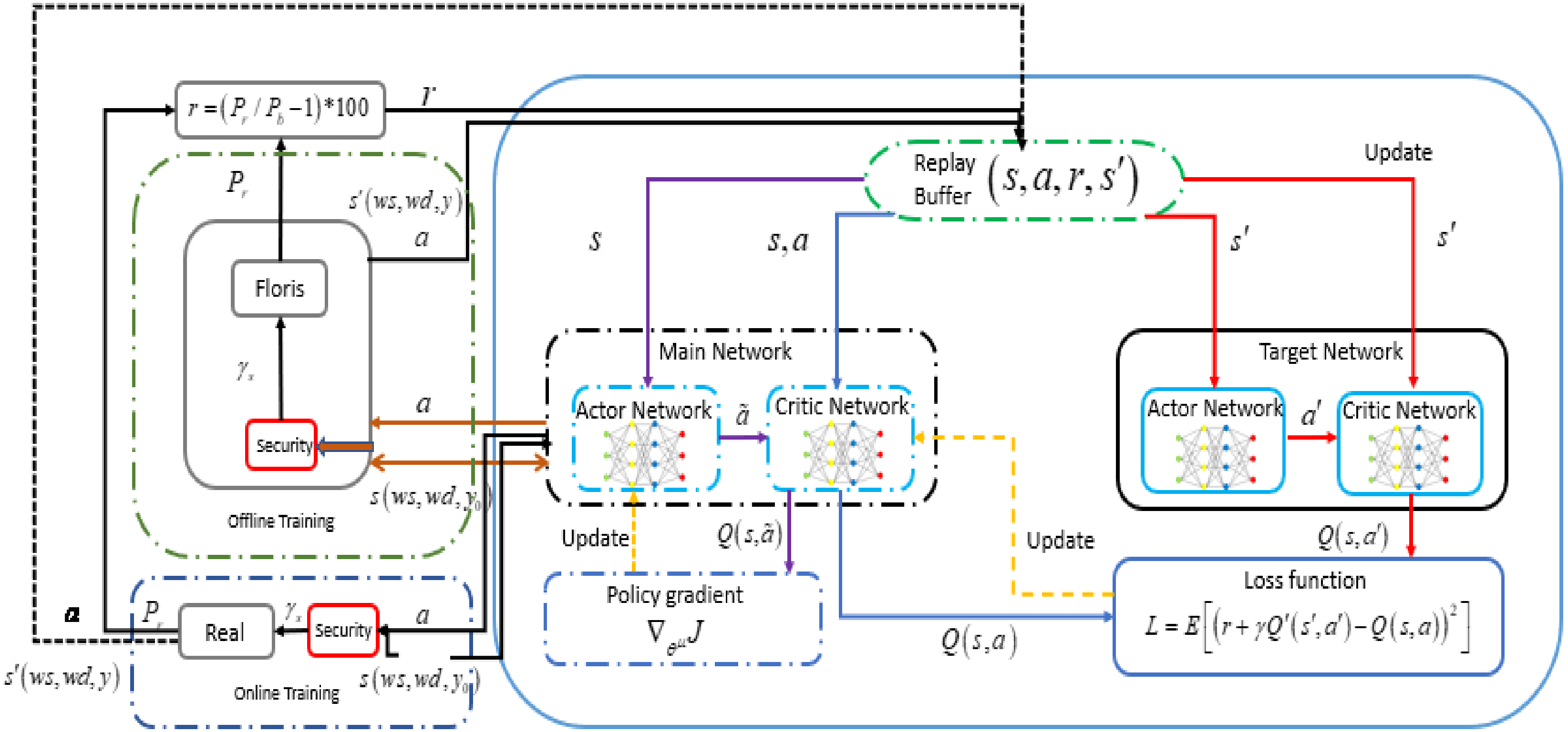
3. How DRL Works



Agents act in complex and uncertain **environments** to maximize **rewards**

Perception of Deep Learning
Decision-Making of Reinforcement Learning

- 1. **Offline training** to obtain network to guide agent action
- 2. Cope with initial position **uncertainty**
- 3. Actual data put in **Replay Buffer** for feedback update

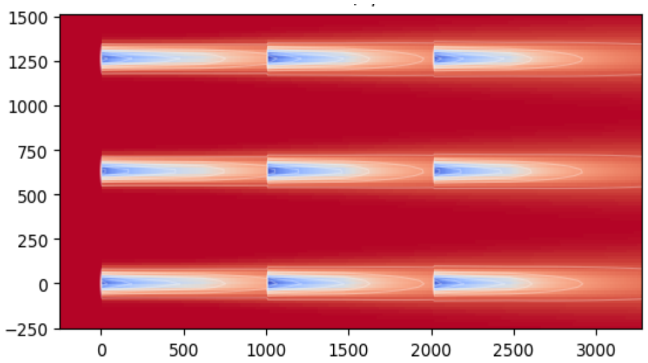


4. Case study

Environment settings

Nine NREL 5MW wind turbines

Row spacing 7D Column spacing 7D



Wake calculations with Floris

Model settings

Random

$s(ws, wd, y_0)$ y_0 is wind turbine yaw angles initial position

a Yaw angles change of wind turbines

$s'(ws, wd, y)$ y is wind turbine yaw angles final position

$r = (P_r / P_b - 1) * 100$ P_r The wind farm power when the yaw angle is y

P_b The wind farm power when wind turbine is controlled by MPPT

Model training

Train with 80 sets of random initial positions (-5,5)

a (-10,10)

4000 seconds of training per random initial state

5. Conclusion

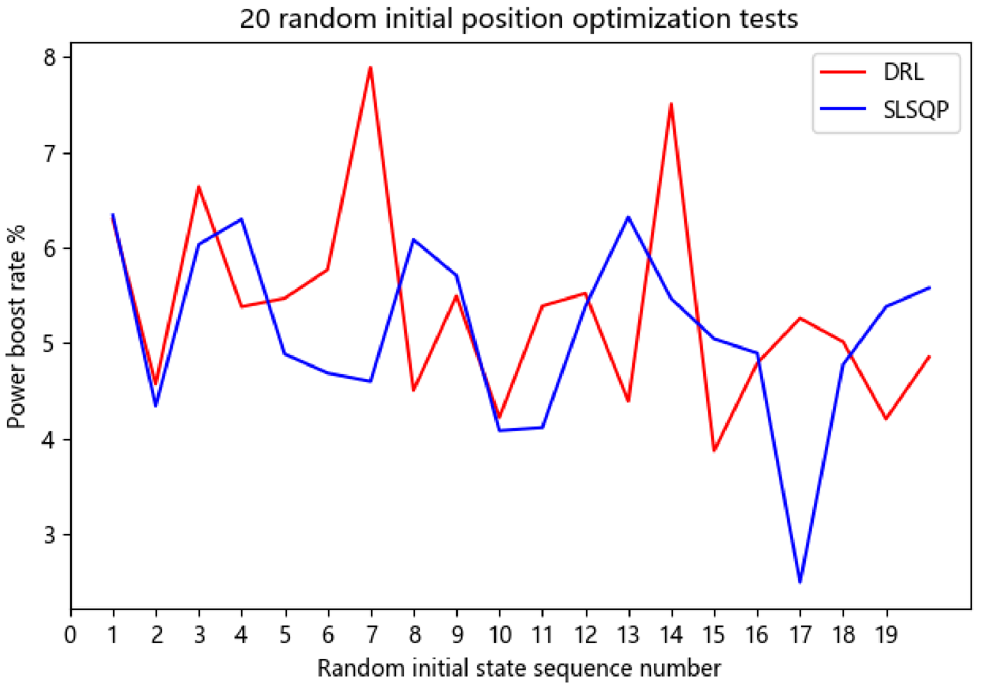
Results

Test with another 20 random initial positions

DRL: Optimizing with DRL

SLSQP: Optimizing with SLSQP

Average improvement rate:
DRL **3.3%** higher than SLSQP



Conclusion

- Can deal with uncertainty in initial position, get more power improvement
- Better use of actual data for feedback

Thank you for your attention!

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