AI-POWERED FUTURE ENERGY SYSTEMS

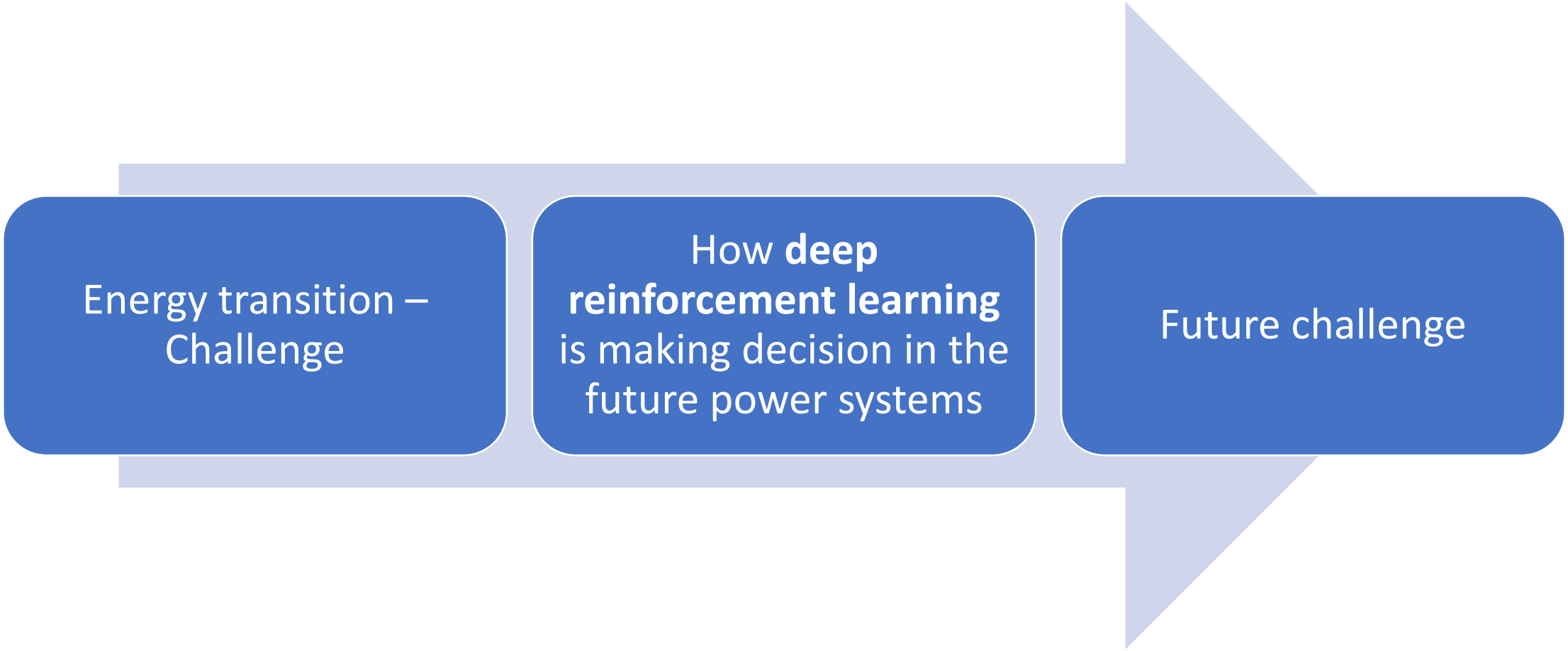
Sustainable Energy Systems (SES) Group
Intelligent Clean Energy Systems (ICES) unit
Luxembourg Institute of Science and Technology (LIST)

Dr Jun Cao

April 29th 2022

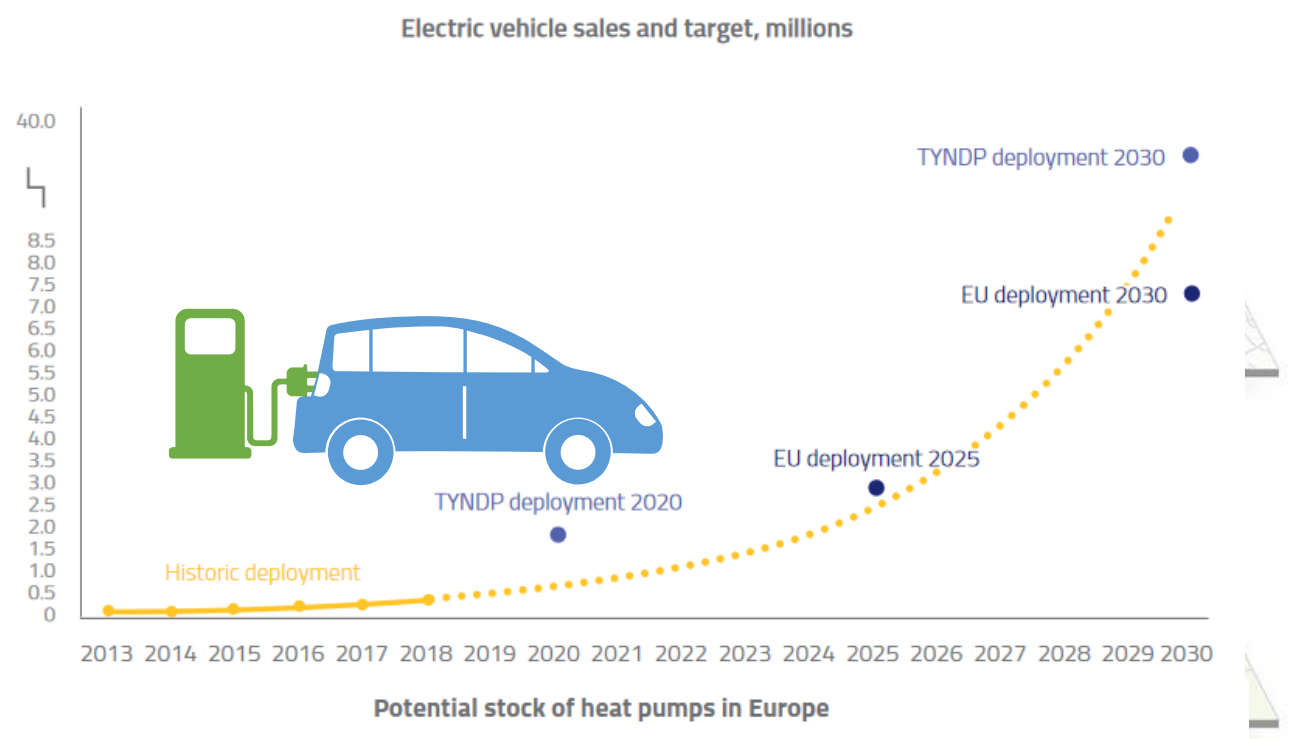
LUXEMBOURG INSTITUTE OF SCIENCE AND TECHNOLOGY | LIST

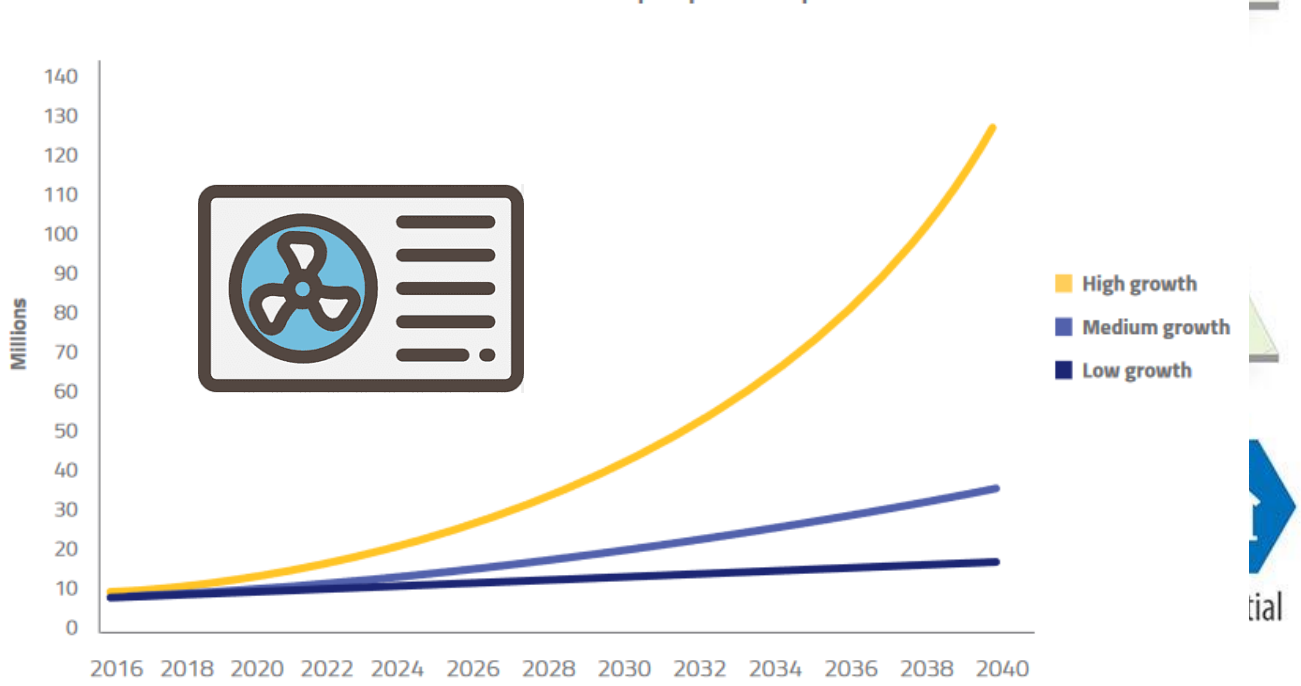
Outline


Energy transition – Challenge
How **deep reinforcement learning** is making decision in the future power systems
Future challenge

Energy Transition

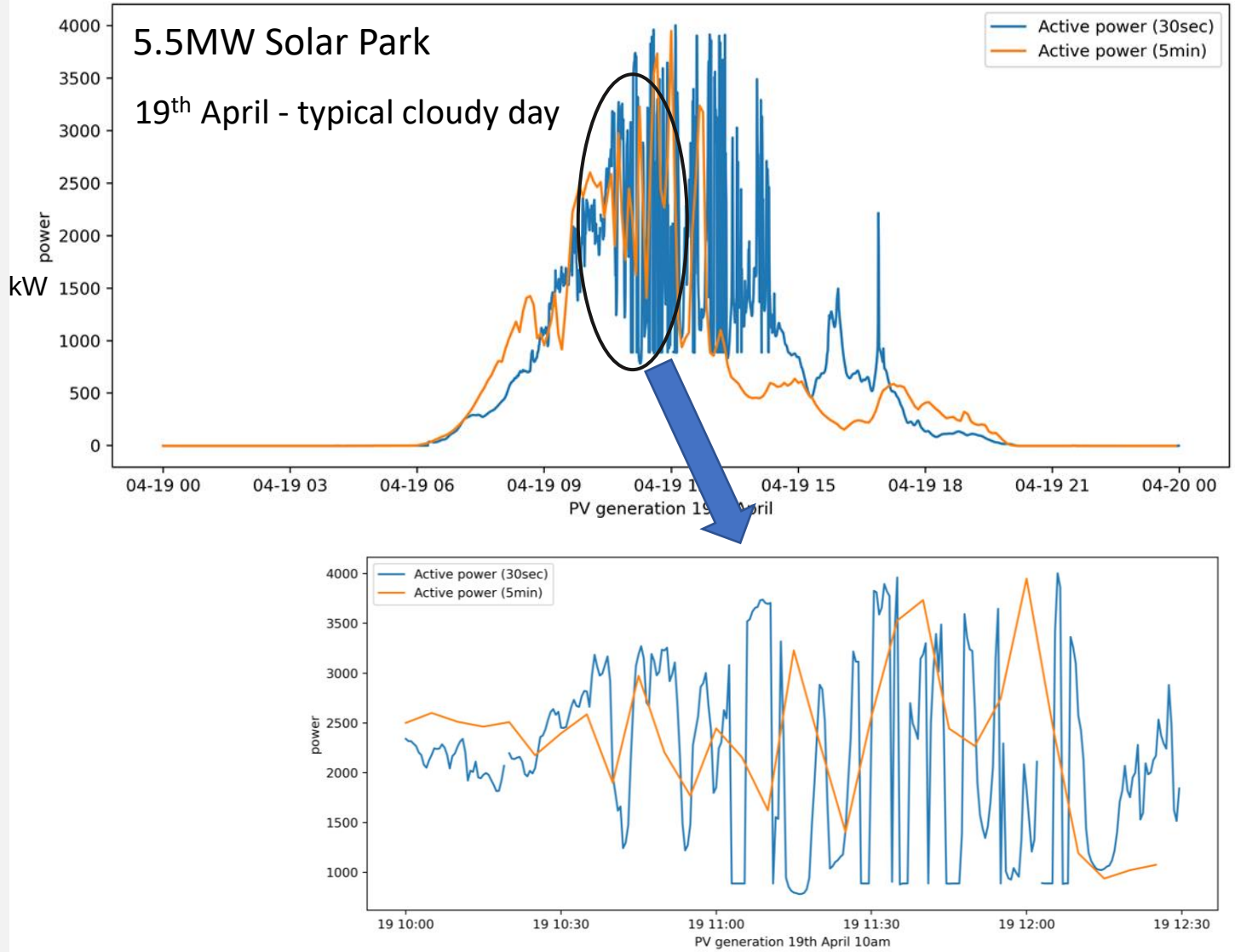
- Huge amount of distributed energy resources.





Energy Transition

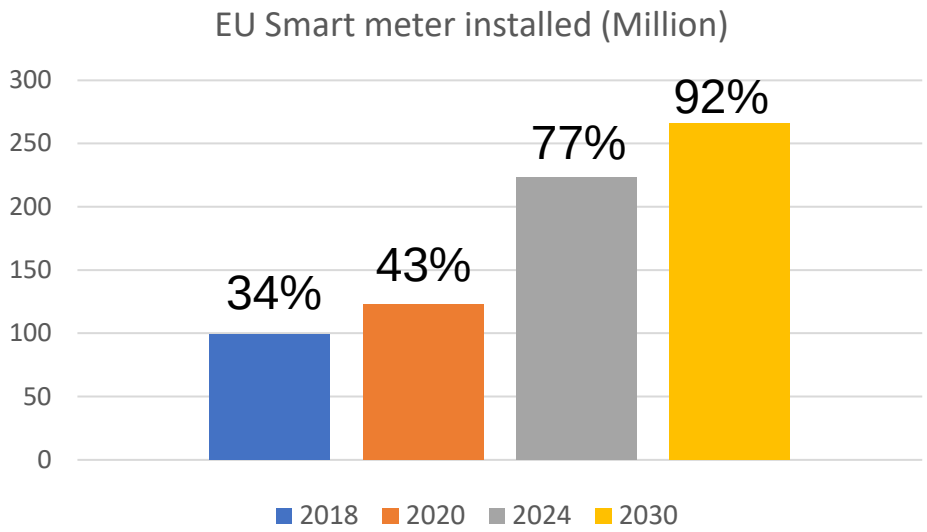
- **Renewable generation**



Real-time operation from seconds to minutes

Energy Transition

- **Big data-Huge amount of data volume.**



Data volume (1 year)

Collection frequency	1/day	1/h	1/30min	1/15min
Records	365 m	8.75 Billon	17.52 Billion	35 Billion
Volume	1.82 TB	730 TB	1460 TB	2920 TB

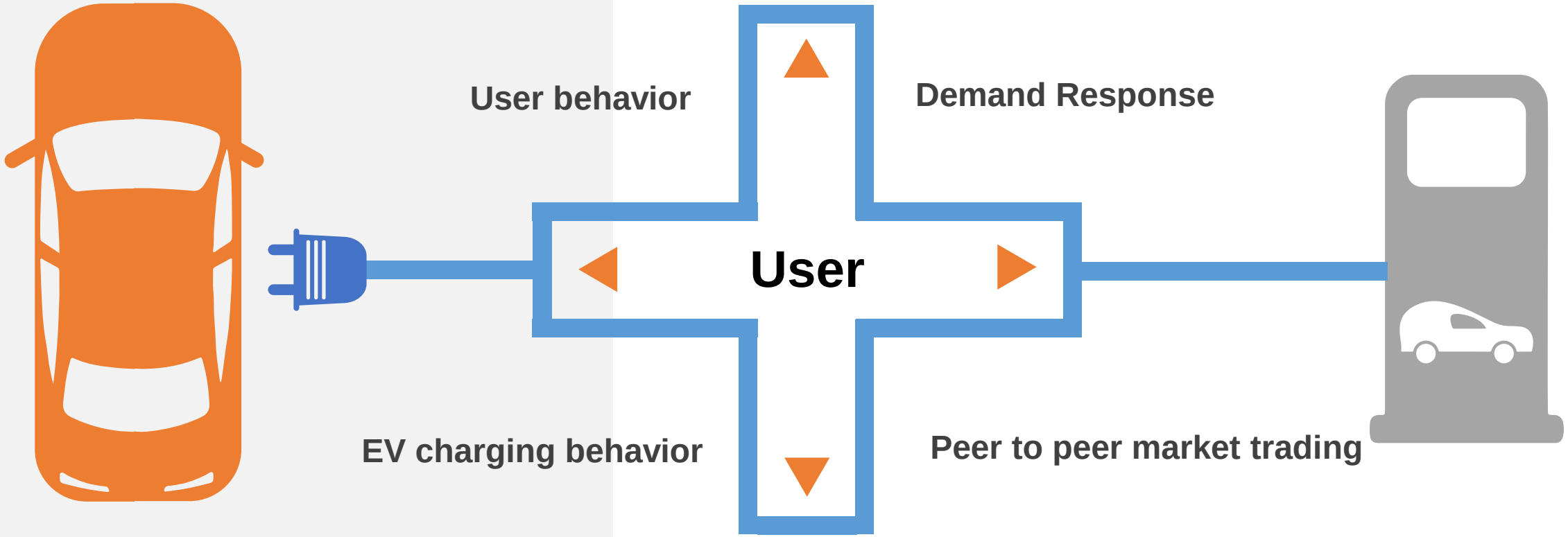
❑ Data variety

AMI's data recording frequency increases from **once a month** to one reading **every 15 minutes to one hour**.

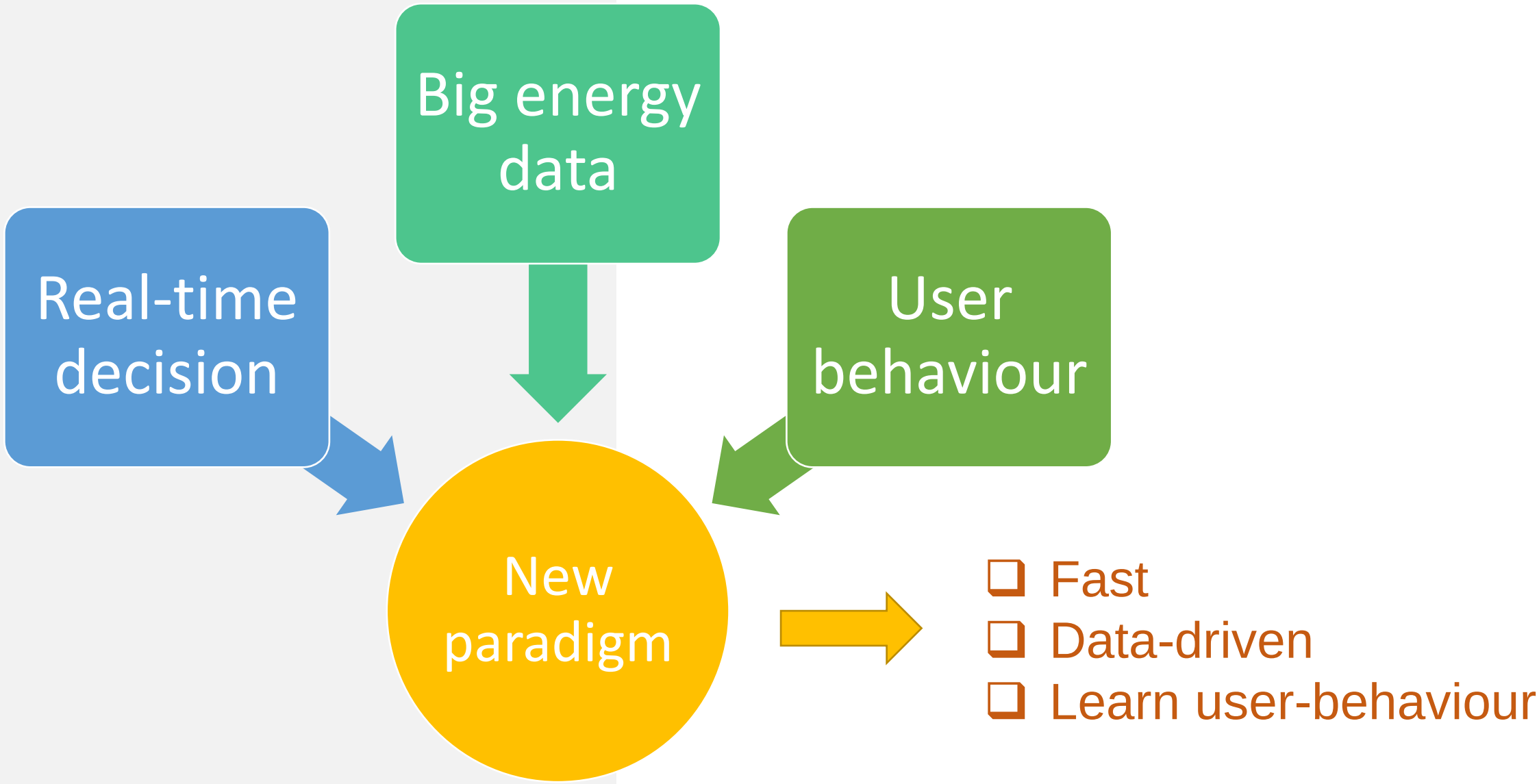
Micro-PMU hundreds (512) of samples per cycle at 50/60 Hz

How to utilize the big energy datasets

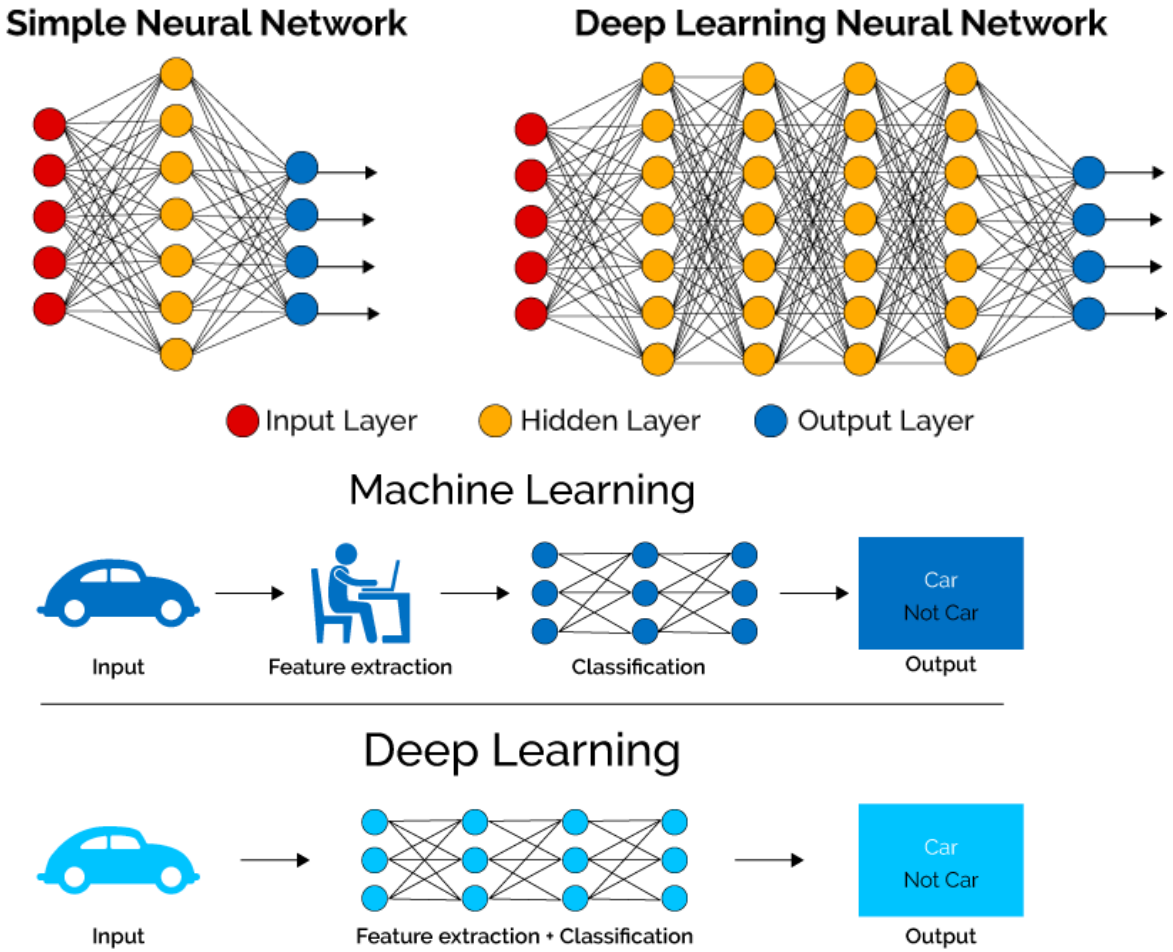
Energy Transition: User centric



Model and learn the user behaviour


Big energy data
Real-time decision
User behaviour
New paradigm
Fast
Data-driven
Learn user-behaviour

Artificial Intelligence – Deep Learning



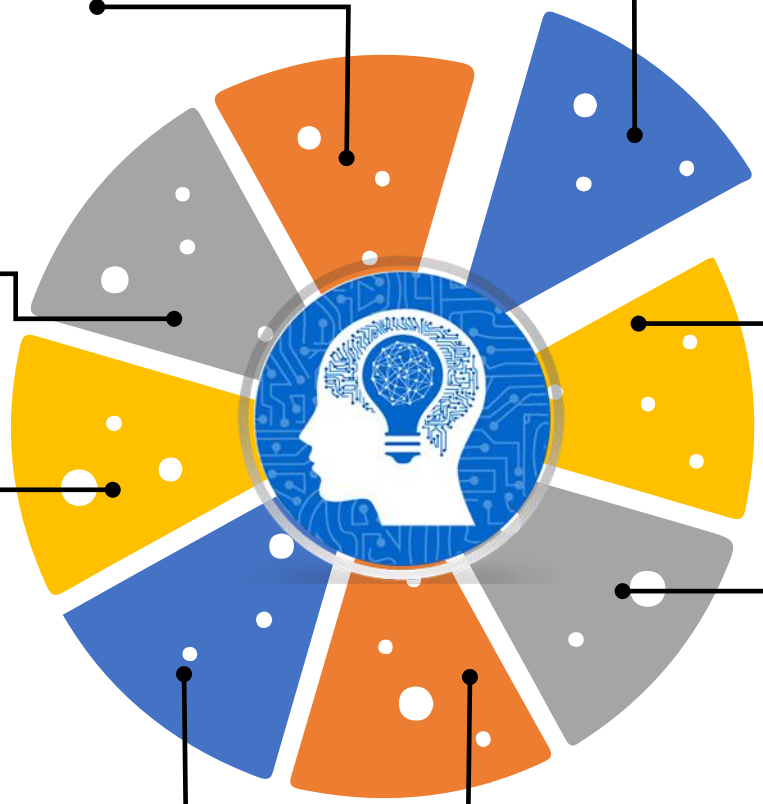
- Big data
- Computational power
- Open-source ecosystem

TensorFlow

PyTorch

AI is driving innovation across businesses of every size and scale

Applications of AI/ML in Energy



Forecasting
Electric Load / Short-Term / Long-Term

Market
Energy trading, Deep reinforcement learning

Anomaly Detection
Outliers//data attacks

System Monitoring
State Estimation & Visualization

Power System Controls
Deep reinforcement learning

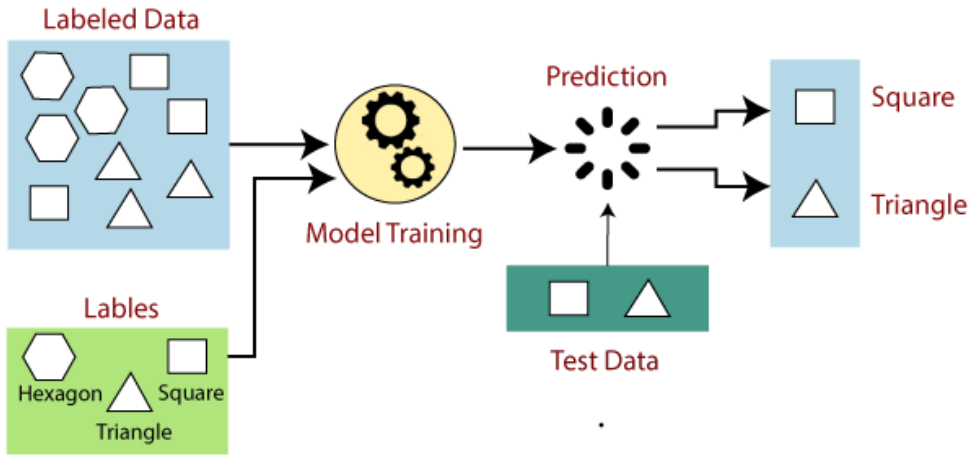
Network Topology and Parameter Identification
Transformer-to-customer, Phase connectivity, Impedance estimation

Equipment Monitoring
Predictive Maintenance
Online Diagnosis

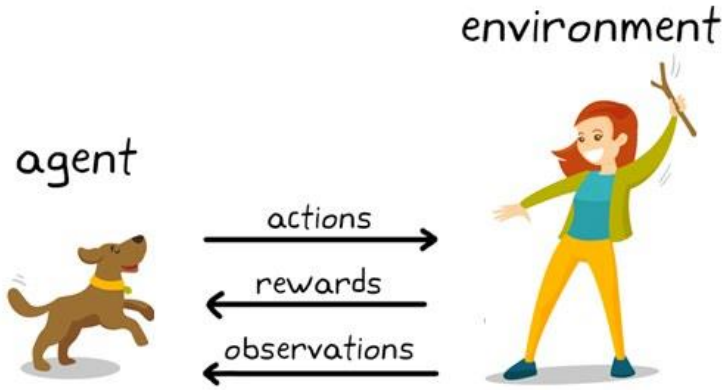
Customer Behavior Analysis
Customer segmentation, nonintrusive load monitoring, demand response

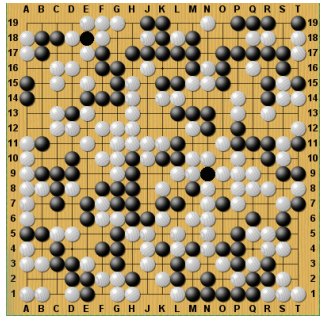
Reinforcement Learning in a nutshell

Supervised learning



Reinforcement learning



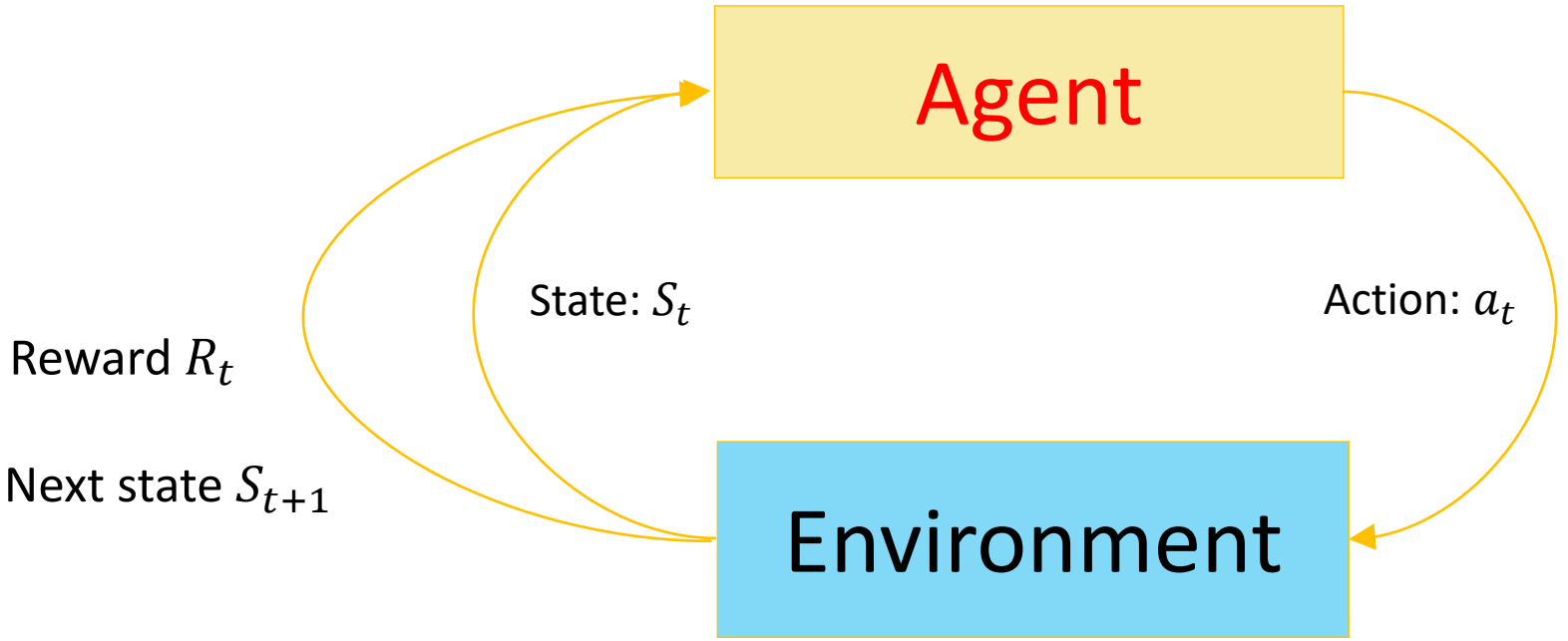


AlphaGo

Real-time decision making for complex process

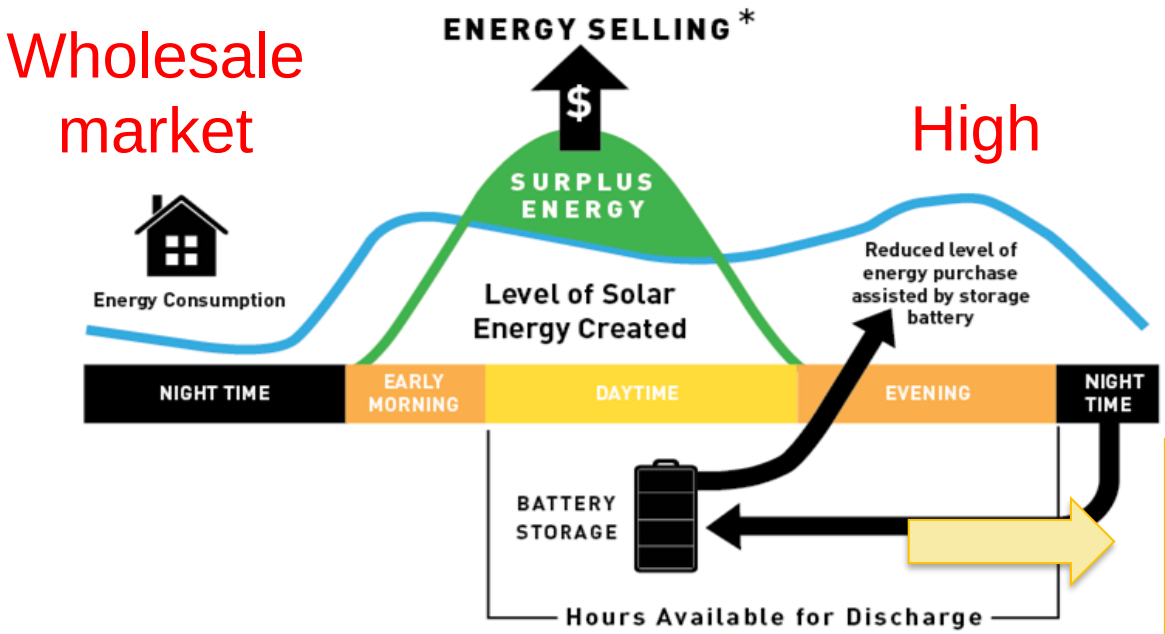
Reinforcement Learning in a nutshell

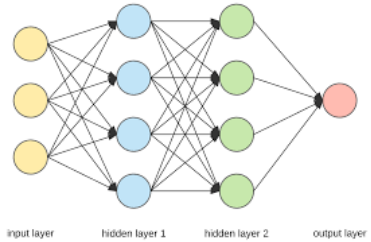
- Reinforcement Learning(RL): Problems involving an **agent** interacting with an **environment** to learn how to take **actions** in order to maximize **reward** (optimal policy).



Deep reinforcement learning in Battery Energy Arbitrage

- Overall goal: Design a optimal control strategy to maximise the profit of battery owner participating in the wholesale energy market.





Agent

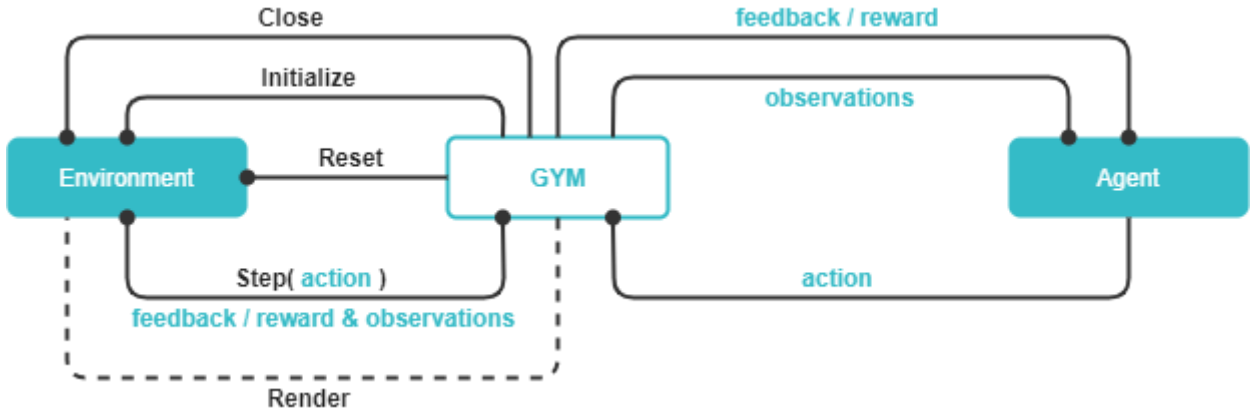
- Battery model

Environment

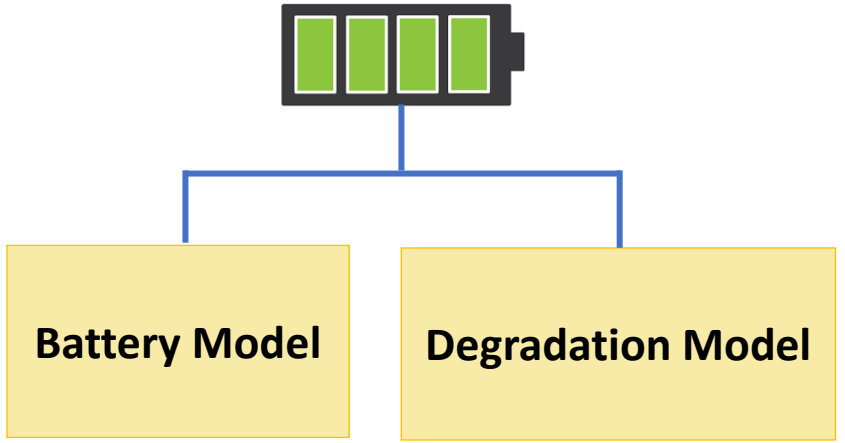
Source: http://css.umich.edu/factsheets/us-grid-energy-storage-factsheet

Battery environment

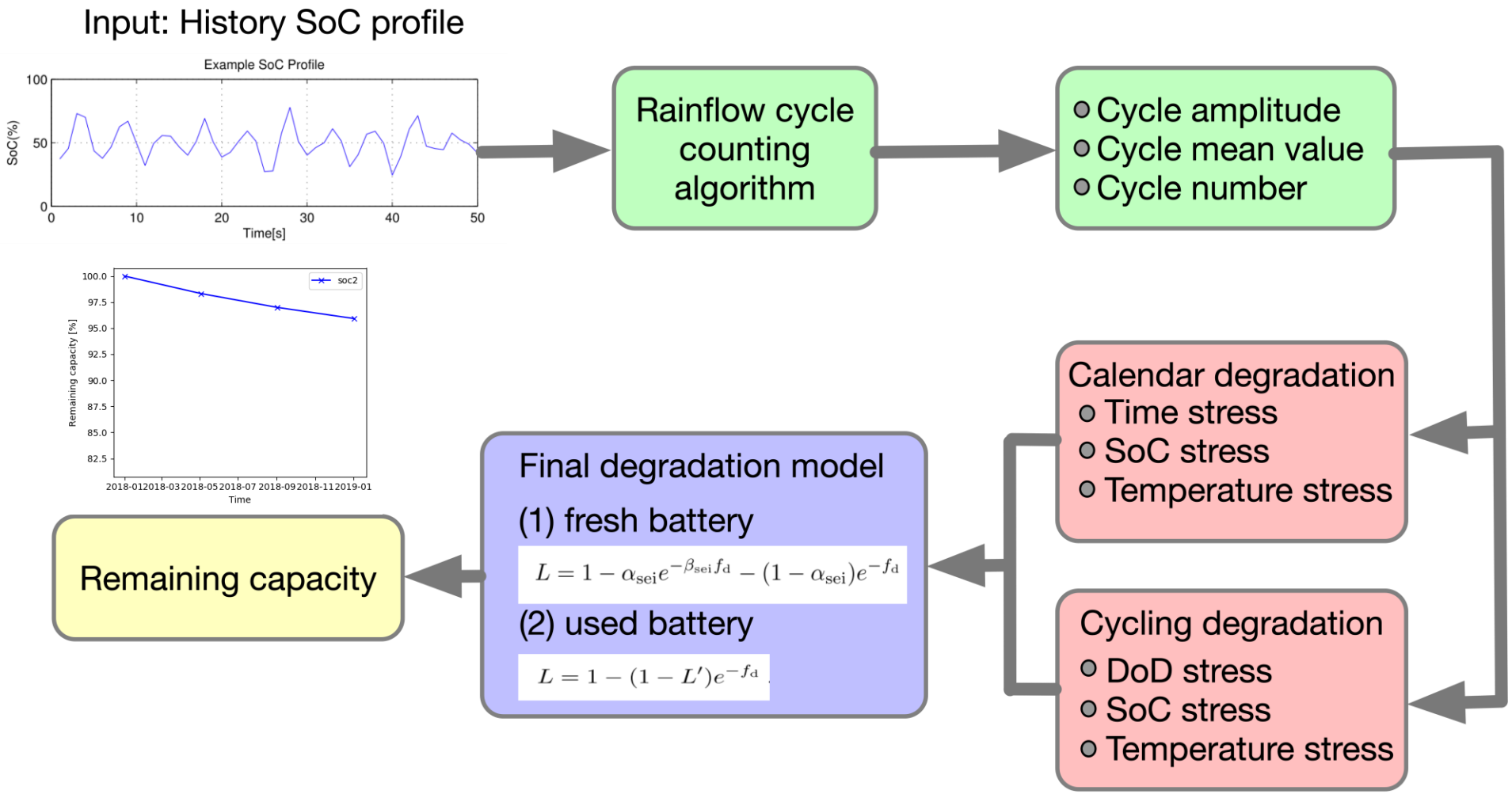
Open AI Gym



Battery Env



Battery degradation



Bolun Xu et.al, “Modeling of lithium-ion battery degradation for cell life assessment,” IEEE Transactions on Smart Grid, vol. 9, no. 2, pp. 1131–1140, 2018.

State and Observation

A state *s* is a complete description of the state of the world.

An observation *o* is a partial description of a state, which may omit information.

- Battery state of charge *SoCt:* Battery's current charging situation
- Prices from wholesale market: historical prices, prediction

State space $s_t \in \mathcal{S}$

Reward and action

The goal of the agent is to maximize some notion of cumulative reward over a trajectory.

$$R_t = c_t \cdot \frac{P_{e,t}}{P_e^{max}} - \alpha_d \cdot \frac{|P_{e,t}|}{P_e^{max}}$$

Revenue

Degradation costs

Reward function

$$\mathcal{R} : \mathcal{S} \times \mathcal{A} \mapsto \mathbb{R}$$

$$r_t \sim \mathcal{R}(s_t, a_t)$$

Battery charging/discharging:

- Discrete:

$$a = (-P_e^{max}, -0.5P_e^{max}, 0, 0.5P_e^{max}, P_e^{max})$$

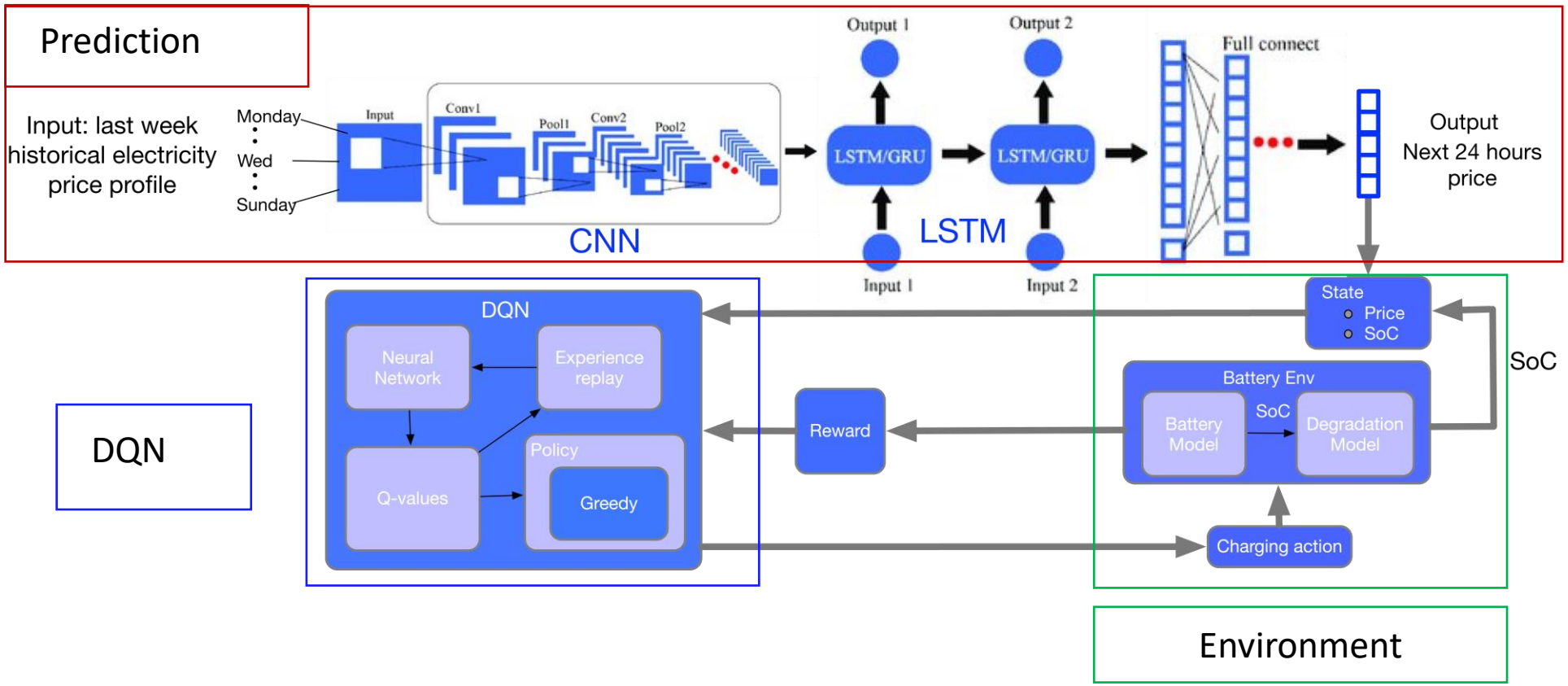
- Continuous:

$$[-P_e^{max}, P_e^{max}]$$

Action space

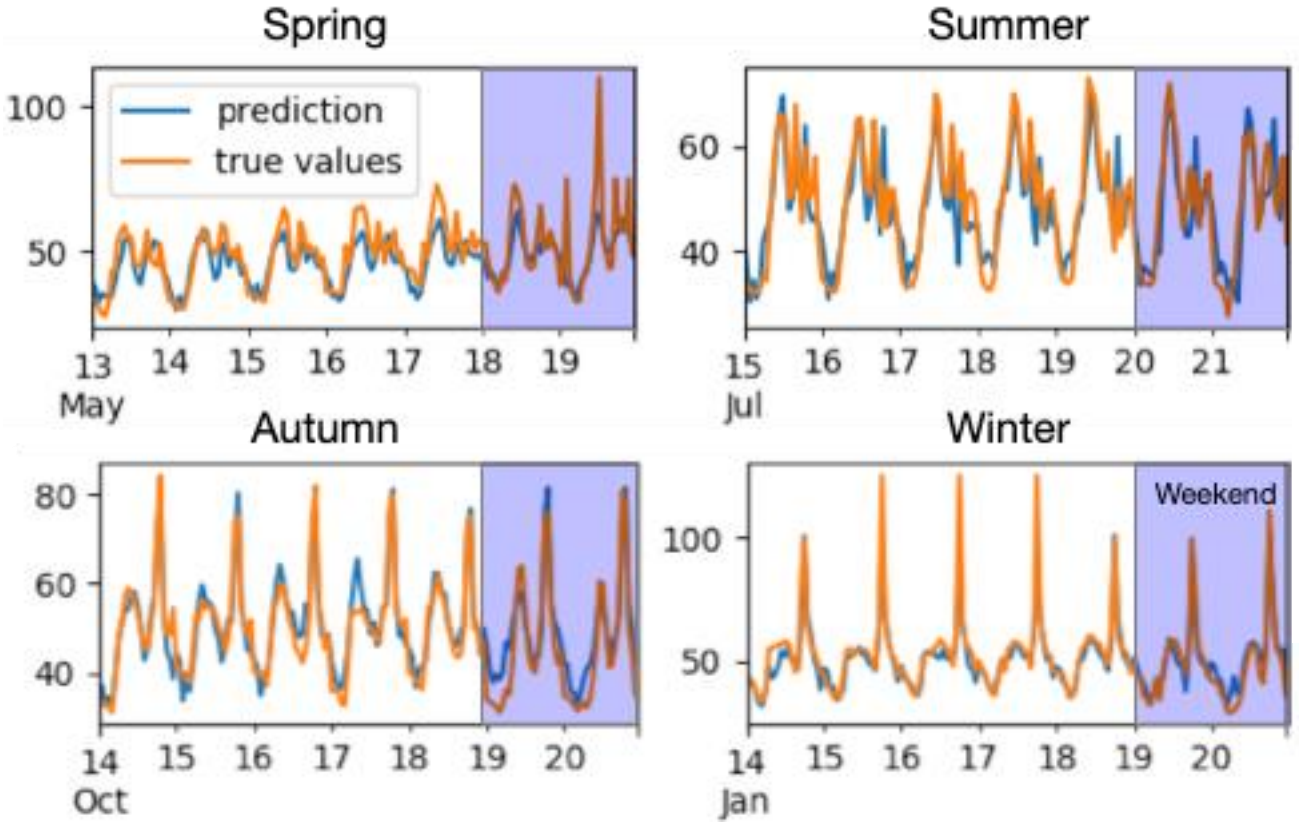
$$a_t \in \mathcal{A}$$

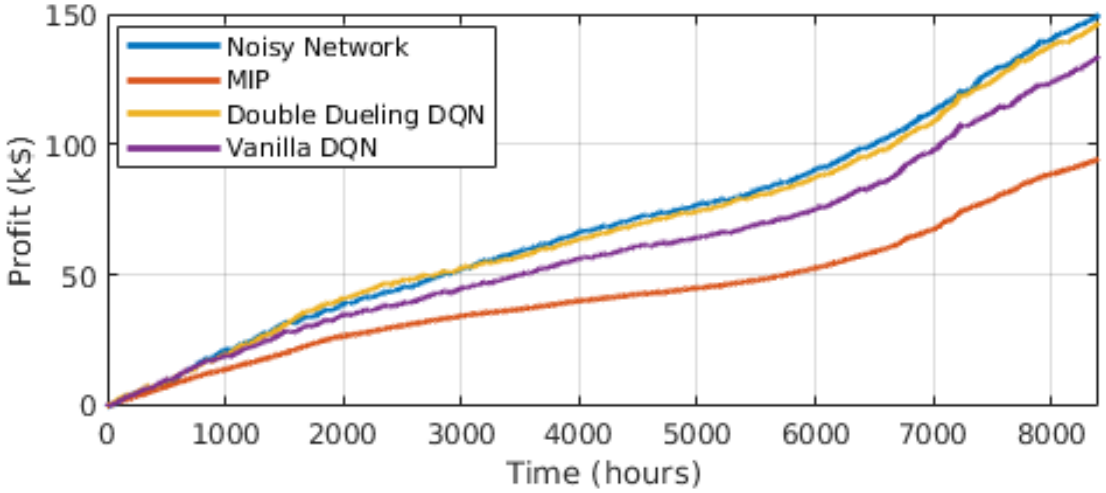
Deep Q Network (DQN)



Jun Cao, Zhong Fan, “Deep Reinforcement Learning-Based Energy Storage Arbitrage With Accurate Lithium-Ion Battery Degradation Model”, IEEE Tran. on Smart Grid, vol. 11, no. 5, pp. 4513-4521, Sept. 2020.

Results

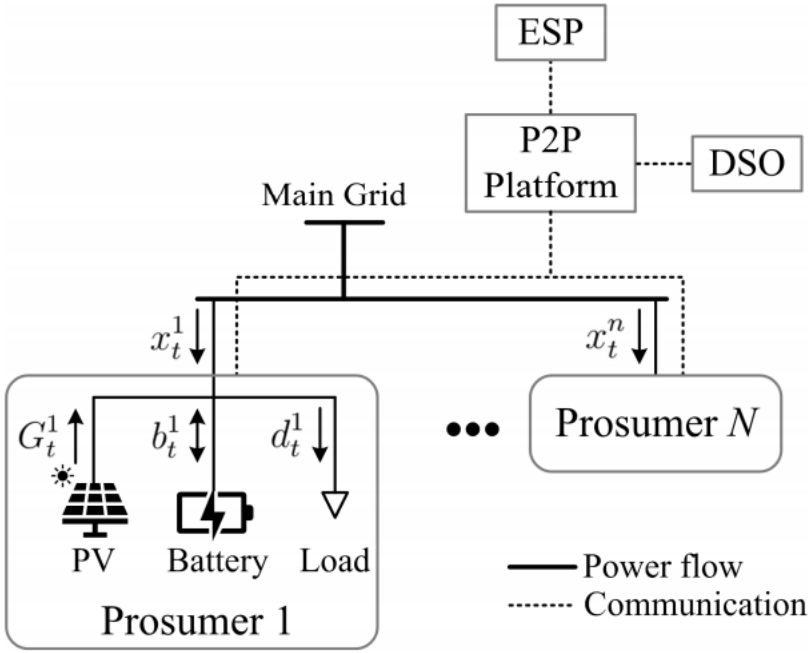


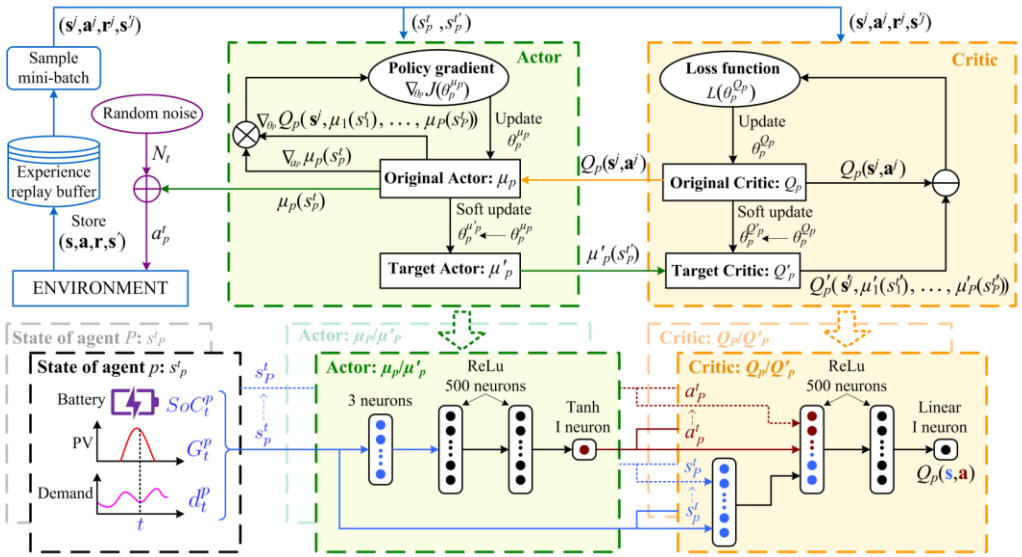


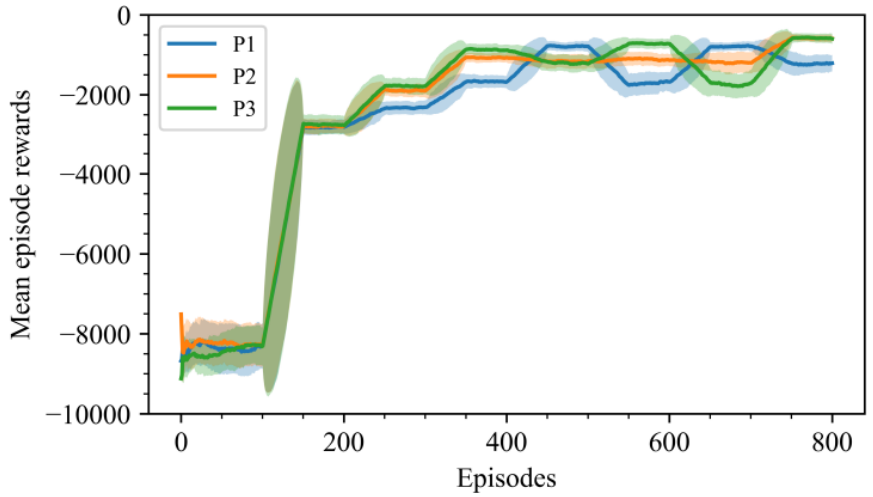
Profit

MAE(mean absolute error) 4.7

Automatic Peer to Peer trading







Multi-Agent Deep Reinforcement Learning

Cephas Samende, Jun Cao, Multi-Agent Deep Deterministic Policy Gradient Algorithm for Peer-to-Peer Energy Trading Considering Distribution Network Constraints, Applied energy, in press, 2022.

Future direction

Trustworthy AI

Explainable

Transparency

Technical Robustness and Safety

Diversity, non-discrimination and fairness

Data in Digital Energy

- Data availability
- Data quality
- Data privacy
- Data market

Thank you!!