Decentralized Partially Observable Markov Decision Process for Power Grid Management

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1. Context

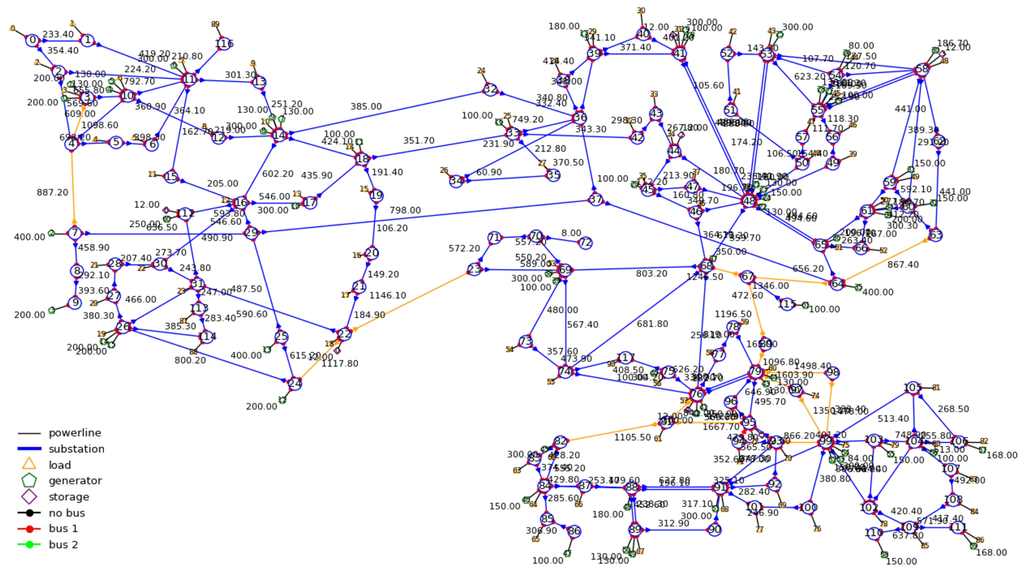
Renewable energy sources are forcing power grid operators to review their grid management strategies

Réseau de Transport d'Électricité (RTE) is developing new adaptive zonal automatons

- **Each automaton monitors a zone of the power grid** (up to 40 lines) thanks to an optimization algorithm.
- An automaton can act on the power grid configuration and on the electricity production.
- **Each automaton can receive a target path or additional information** from operators to decide the appropriate actions to be done. Examples of target path include (un)desirable configurations in future hours or information about other zones.

2. Objective

Design a decision support assistant for the supervision of zonal automatons able to **recommend relevant target paths/information for automatons** based on the power grid's configuration and constraints

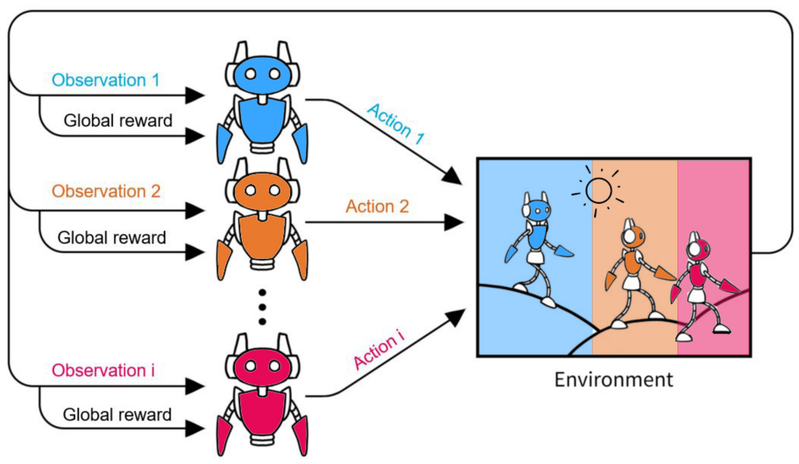


Example of a simulated power grid

3. Collaborative Multi-Agent Reinforcement Learning

A **decentralized approach can improve the scalability** compared to traditional reinforcement learning methods.

The supervision of automatons can be modeled as a **Decentralized Partially Observable Markov Decision Process** (Dec-POMDP) [1].



Decentralized multi-agent reinforcement learning

For example, each agent can be associated with a sub-group of automatons and their zones. At each timestep t:

1. Agent i gets an observation of the i^{th} sub-group of zones
2. Agent i chooses an action according to its observation. An action means here, transmitting a chosen target paths to the i^{th} sub-group of automatons.
3. Actions of agents are combined and executed on the environment
4. A global reward representing the safety of the hole grid is returned

Advantages and limits:

- A decentralized strategy would allow to **reduce the observation and action space and enable inference in parallel**.
- Literature lacks decentralized policies under stochastic conditions

4. How to emulate a zonal automaton?

To obtain **reasonable computation times** during training, we need a trade-off between speed and realism.

We will try to emulate an automaton with a RL agent able to:

1. Operate the grid
2. Follow a target setpoint

We designed an agent able to operate a 14-nodes power grid by controlling storage power

Performance of our agent on a 14-nodes simulated power grid

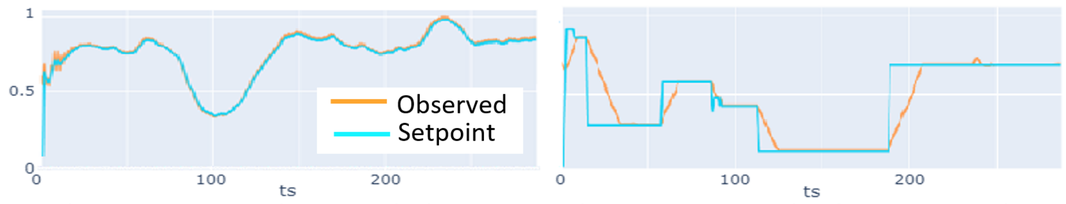
	DoNothing Agent	RL Agent
Average number of survived time steps per episode	206/288	**279/288**

We designed an agent able to follow a storage charge setpoint

We got interesting results about:

- how to penalize deviations from the setpoint.
- the impact of hyperparameters.
- the ability to **generalize to other shapes of setpoint** which is great as depicted in the figure below.

Normalized storage charge



Charge setpoint with a smooth shape | Charge setpoint with a function step shape

Comparison of observed charge with a smooth and a step function setpoint

Open questions

1. How to model network configuration under different levels of uncertainties and agents' objectives?
2. How do Dec-POMDP methods perform under transient network configuration and with hundreds of nodes?
3. How to combine model-based MARL and Dec-POMDP to have a performance independent of reward function and avoid reward hacking?

References

[1] Karl Johan Åström. Optimal control of markov processes with incomplete state information. *Journal of mathematical analysis and applications*, 10(1):174–205, 1965.