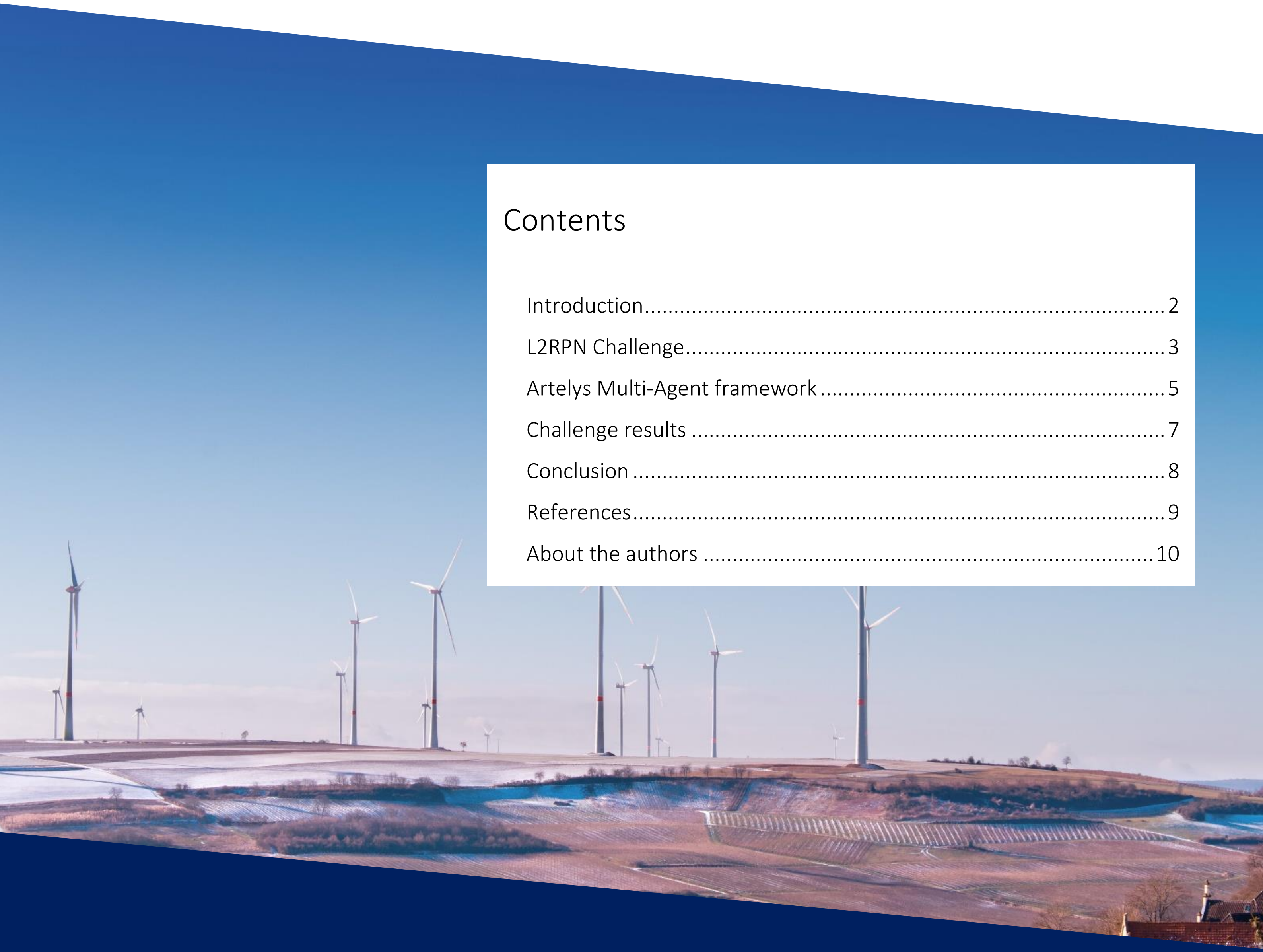
WHITE PAPER

# Artificial agents designed to run a power network



## Contents

# Introduction

As the electricity mix evolves from predominantly centralized thermal power generation to decentralized renewable generation, grid operations become increasingly complex. **Operators are faced with with more frequent congestions, and therefore with greater risks of blackouts**.

The role of grid operators is to ensure the grid security at any time. They can rely on production and load forecasts for the next hours, and on the current state of the grid. Day-ahead forecasts allow to anticipate probable congestions and prepare a day-ahead operation plan that consists of preventive remedial actions to maintain grid security.

However, due to forecast errors or unexpected contingencies (failure of grid element), the grid still requires to be operated in real time when it deviates from the initial plan. In such cases, the operator needs to quickly perform curative remedial actions to avoid contingencies.

Operators have several types of actions at their disposal:

- **Flow control mechanisms**: operators can directly act on the grid to reroute the flow from congested grid elements. This can be done through topological reconfigurations (substation configuration and decoupling, line disconnection, etc.) or Phase Shifting Transformers (PST). These actions are mostly considered as uncostly but the space of possible actions is extremely large and it can be hard to determine the correct action to do given a congestion.
- **Flexibility mechanisms**: This class of actions consists in modifying how the current is injected and consumed through the grid. This can be done through countertrading, load shedding, load balancing, re-dispatching, renewable energy sources curtailment or storage. These actions are very costly for TSOs as the involved producers and consumers are compensated for their actions.

Operators mainly rely on their own experience and on grid simulation tools to help them make the best decision to maintain grid security. The development of Renewable Energy Sources increases the uncertainty on the grid operation plan and makes it harder to anticipate the long-term effect of an action. **Recently, Transmission System Operators (TSOs) have started to investigate how advanced AI techniques can help the operators cope with the increasing complexity of grid operation.** Recent works have demonstrated that optimization [1]-[3] or reinforcement learning [4]-[8] techniques can be leveraged to suggest actions and strategies to operators and contribute to significantly reduce congestions.

For a few years now, Artelys has been actively contributing to this field of development in collaboration with European TSOs. Artelys is involved in the CorNet Program that aims at developing a day ahead operation plan for coordinating the TSOs response to congestion to maximize social welfare. Artelys is also working with TenneT B.V. on the Control Room Of the Future (CROF), an ambitious project to design the next generation of tools for grid operators. In this context, Artelys is developing a decision support tool that computes day ahead plans of topological configurations for the operators. For real time operation of the grid, Artelys has been involved in the past years in the development of the GridAlive framework developed by RTE. This framework was used to organize L2RPN (Learning to Run a Power Network) competition where participants develop AI agents that operate a synthetic, yet representative, network on a 5-minutes time scale. **In the 2023 edition of the competition, Artelys' agent scored as the best performing on the leader board.** In this White Paper, we present the main ideas that drove the development of this solution.

# L2RPN Challenge

## Problem description

For some years now, the French Transmission System Operator RTE organizes L2RPN challenge, where participants submit artificial agents to demonstrate their abilities to operate a grid in real time one-week scenarios. The agent must quickly solve congestions on lines before they lead to a blackout. The origins of congestions are manifold: they can be consequences of the scenario's production plan, but also result from contingencies due to planned maintenances or unexpected line failures (represented by *an adversarial agent*). The uncertainty caused by unexpected contingencies forces the agent to elaborate strategies that are robust to worst-case scenarios. Over the years, the challenge has been evolving to tackle more and more complex situations.

## The 2023 edition setup

### *Grid description*

In 2023, the challenge, co-organized by RTE and Ile de France Region, used an adapted version of the IEEE118 synthetical grid. It is made up of 118 substations and 186 lines connecting 62 generators, and 99 loads, representing points of electricity production and consumption. The distribution of generators type is tailored to meet France 2035 electricity mix, containing 30% renewables. The grid is also equipped with storage assets that allow for some additional flexibility. **A key objective of the 2023 challenge was to design agents that could take into account the carbon emissions associated to the grid operation and favor strategies that would limit the added carbon emissions of curative actions**.

Agents can access a wide variety of information about the state of the grid and its expected state in the next hour. In particular, the agent can know:

- The current load flow on every line, allowing to identify the congested ones;
- The current topological configuration*;*

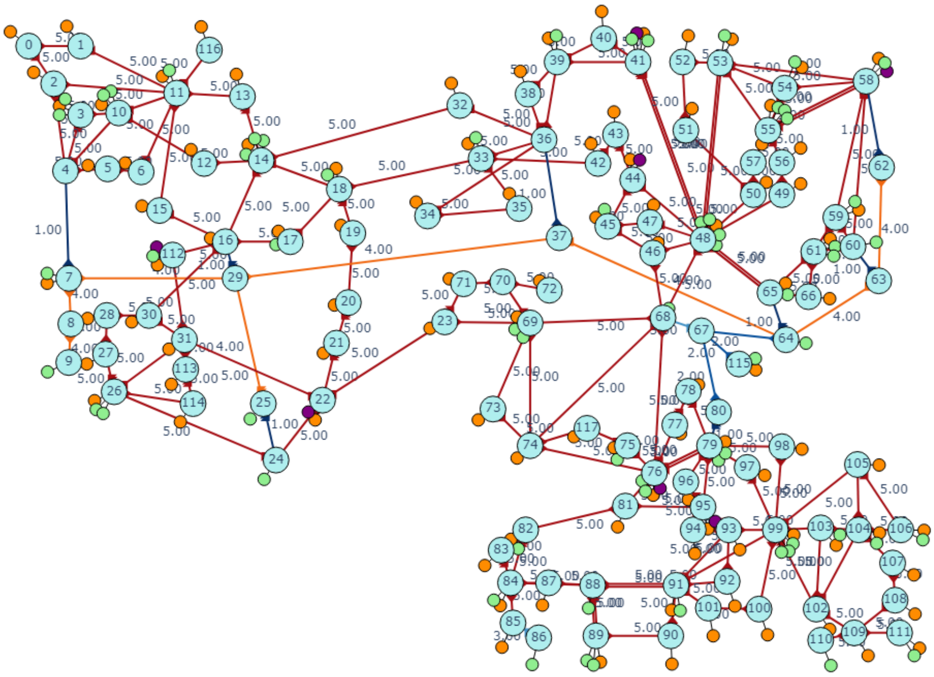


*Figure 1 Representation of the two voltage levels (in red, lines 138kV / in orange, lines 345kV) and the network transformers (in blue), from the L2RPN_idf_2023 challenge's environment.*

- The current and expected future active and reactive power injections of loads and generators

The environment also provides 832 scenarios that describe the evolution of the network over a week, using generator production and load consumption chronicles with a 5-minutes time step. These represent almost 16 years of data covering every month of the year in a homogeneous manner.

### *Acting on the grid*

In the usual setup, the possibilities of actions (i.e. the action space) are extremely large. The agent can modify the grid topology by changing the configuration of a substation (“free action”), representing around 75k different actions, but also make use of costly flexibility mechanisms like redispatching, renewable production curtailment and storage, which are continuous actions. A novelty introduced by the 2023 edition is the split of the grid into 3 connected zones. An agent is then able to act on each zone independently, making the topological action space even much larger!

### *Assistant and Sim2Real Track*

In addition, the 2023 edition added two more dimensions to the challenge:

- Assistant Track measures *trustfulness*. Agents are asked to raise alerts when they anticipate that a contingency happening in the next hour may not be handled. The track is tightly linked to the agent’s skills: a perfect agent should not raise any alert while a poor agent should raise alerts much more often. **Self-awareness of agents’ fallibility is key in the perspective of using them as assistants for human operators in the control room**.
- Sim2Real Track measures *adaptability*. In this track, agents are built and trained using a simple power grid simulator. They are then tested on a more realistic one, unknown to contenders. During the test phase, they are able to fine-tune their policy on a few scenarios. **This track evaluates how an agent that has learned on synthetic data may generalize to real data**.

## The GridAlive eco-system

These challenges have fostered the emergence and active development of the GridAlive framework. Centered around the open source Grid2Op library, it allows to simulate electrical grids in real time while acting on it. It also comes with a set of libraries to facilitate the development of agent and their analysis. From its beginning Artelys has been deeply involved in the development of this ecosystem alongside RTE. The framework is also compatible with the Gymnasium API making it easy to integrate to classical RL framework such as RLlib from Ray or Stable-Baselines3.

# Artelys Multi-Agent framework

## Solution Overview

The agent developed by Artelys is based on a **multi-agent cooperation framework** in which multiple specialized agents are collaborating and orchestrated by an expert agent. This framework allows decomposition of the large and hard problems posed by the challenge in subproblems that can be handled with the best suited approaches and technologies. The overall strategy is summarized in the Figure 2 below. The agent first determines whether the grid requires an intervention, identifies a relevant curative action if necessary (topological, if possible, supplemented by redispatch, if necessary), and combines it with a reversionary action. Actions are simulated to validate their effect on the grid before being implemented. In the following paragraphs, we elaborate on the inner working of each agent.

## Multi-Agent description

### *Parsimonious Agent*

To limit operation costs and benefit from the optimal power production plan initially scheduled, the agent **only intervenes when conditions require it to resolve congestions**. This may involve a simple pre-designed strategy, such as thresholding the maximum load rate currently observed, or foreseen, on all network lines. More ambitious strategies may involve more elaborated, learned models underlined by a dedicated agent deciding for curative actions to take place.

### *Topology Agent*

When a curative action is needed, the agent first looks for a topological action to resolve the contingency. As mentioned before, topological actions are considered uncostly. As the space of topological reconfiguration actions is extremely large, especially in this 3 zones setup, it would be nearly impossible for the agent to choose an action in real-time without reducing the action space. In that regard, Artelys built its Topology Agent upon a **curriculum training approach** to tackle those limitations. The approach is inspired by Lehna et al. [5] and adapted to the large grid and the 3 zones setup. It follows the sequence:

- ***Topological action space reduction***: *Actions selection* is performed simulating many curative actions and selecting the most consistently effective ones. Business heuristics are used to prioritize actions investigation based on their potential relevance.
- ***Greedy agent based on action space selection***: *Collection of a learning database* consisting of pairs linking a network state observation and the optimal curative action taken from the subspace build in the first phase.
- ***Learning by imitation***: *Learning of a statistical model* (e.g. a neural network) *in a supervised way*, based on the learning set constituted in the second phase. This agent is then able to act very quickly in the environment.

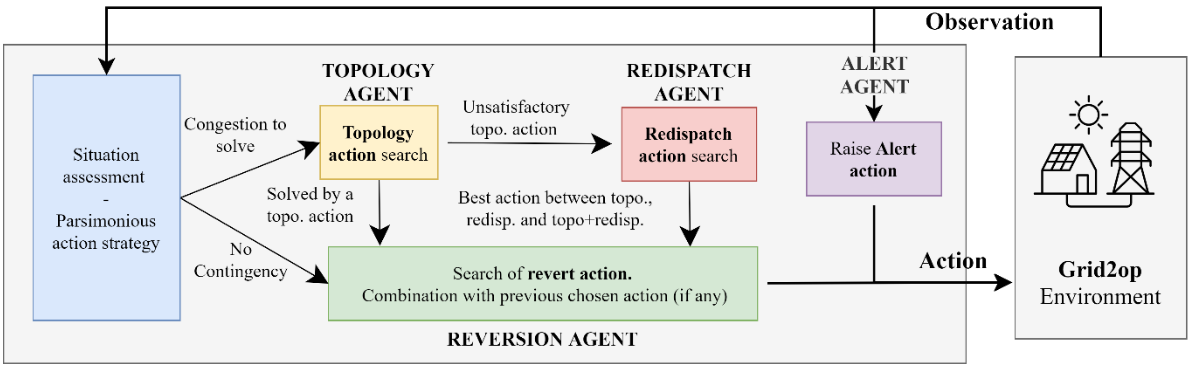



*Figure 2 - Multi-agent overview*

- ***Reinforcement learning:*** *Learning to interact with the environment by reinforcement*. The agent is re-trained using a PPO algorithm and the reduced action space. The actor function is based on the neural network learned by imitation to boost learning performance from the start. This final step allows the agent to adapt to the dynamics of scenarios.

### *Redispatch Agent*

A redispatch agent is consulted when the solution provided by the Topology Agent in the previous step is deemed insufficient. Redispatch agent provides near-optimal redispatch and curtailment actions across the whole grid by solving a convex optimization problem to reduce the load flow on congested lines while minimizing the associated costs and carbon emission. The problem is first solved in the current topology of the grid. If the proposed action is also unsatisfactory, the Redispatch Agent tries to solve the optimization problem in the top topological configurations proposed by the Topology Agent. The best combination of actions is finally implemented on the grid. Redispatch and curtailment are carefully used as they highly increase carbon emission and costs. Also, the Redispatch agent favors redispatch action over curtailment to limit its impact on carbon emission.

### *Reversion Agent*

When the network is in normal operation conditions, the agent takes advantage of this time to carry out **reversionary actions, bringing the network back to its initial configuration**. These reversionary actions concern both topological and redispatch changes made previously, and the restoration of lines that may have been disconnected. This reversion strategy is also used when a curative action is required. In this case, the agent investigates which reversionary actions can be combined with and improve the curative action imposed by one of the other agents. For instance, a zone of the grid may need a curative action while another may allow a reversionary action.

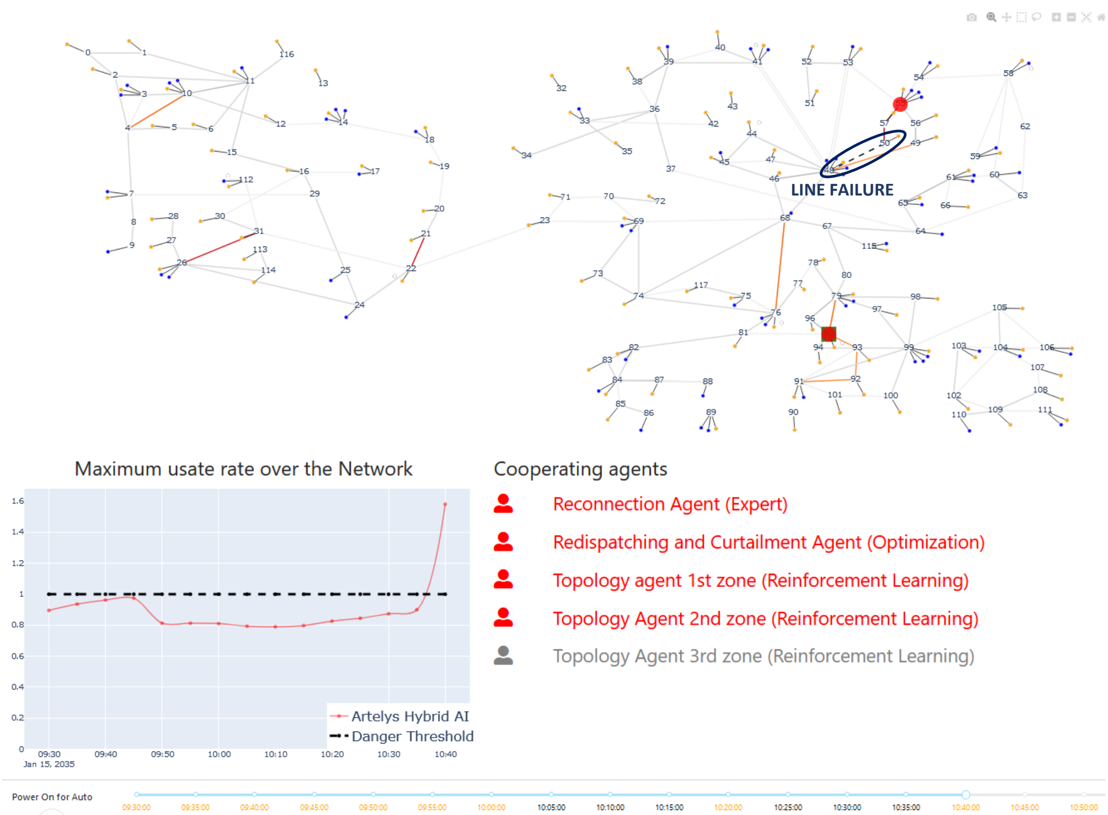



*Figure 3 - Example of a successful cooperation between agents to face an unexpected line failure (line 48-50)*

# Challenge results

## Main evaluation – Assistant Track

The participants were evaluated on a 3-fold score combining an ***operational*** score (evaluating costs of energy losses, flexibilities and blackouts), a ***RES*** score (the less curtailment the better), and a new feature ***assistant*** score (linked to the Assistant Track) where the agents were evaluated regarding their ability to anticipate situations where they fail to survive to line attacks for a reasonable amount of time required for human operators' response.

**Artelys agent reached the 1st position on the test scenarios of the private leaderboard at the end of the competition**. It reached state-of-the-art survival rates, with top operational score. While not being the best agent in terms of avoided carbon emission, it is significantly better on the assistant score. It reveals the ability of the agent to better foresee his failures to manage the power network safely in case of unexpected lines disconnection.

## Secondary evaluation – Sim2Real Track

The agents' adaptability was also evaluated in a different modality for the Sim2Real Track, allowing to assess how their abilities generalized to somehow more realistic power network operation conditions. In this track, agents were not evaluated against other challenger agents, but against themselves by comparing the performance of an agent before and after re-training. The performance of Artelys agent shown in Table 2, indicates that the agent is **robust** as its performance drop is less than 10% when the grid simulator is refined. After re-training on the new grid simulator, the agent increases its score by 3%, achieving almost on-par performance with its performance on the main track.

| Participant | Score | Operational | RES | Assistant |
|---|---|---|---|---|
| Artelys | 64.96 | 61.52 | 85.1 | 61.13 |
| Contender #2 | 64.11 | **61.93** | **98.1** | 48.97 |
| Contender #3 | 60.82 | 59.44 | 90.14 | 46.55 |

*Table 1 - Final scores from the 3 top participants*

| | Main Track | New grid simulator Before re-training | After re-training | Change (%) |
|---|---|---|---|---|
| Score | 66.24 | 61.74 | **63.29** | 3% |

*Table 2 - Sim2Real Artelys agent performance.*
*For this track, the score takes into account Operational and RES Score, but not Assistant*

# Conclusion

Innovation for grid operation is key on the road to the massive integration of renewables and electrification of usage that are needed for the energy transition. The L2RPN competition is a great opportunity to foster the emergence of solutions to a critical real-life problem faced by operators.

In that regard, Artificial Intelligence is one of the most promising technologies to help operators manage this transition. For many years now, Artelys is combining both its expertise in Energy and Artificial Intelligence, to support key actors in the development of the next-generation tool for grid operation. The proposed solution to 2023 L2RPN edition validated the great potential of our collaborative multi-agent framework combining expert business knowledge with state-of-the-art AI algorithms. While developed under hard time constraint, it showed the promising qualities to be

- An efficient Grid Operator that can limit cost and carbon emission in case of contingencies,
- A Real Time Tool with very fast response time
- A Trustful Assistant issuing warning to operators before failing.

## Perspectives

There are still many challenges to be met before these technologies can be used in real-life conditions by operators.

The development of human-machine interfaces that facilitate operator decision-making is probably the most crucial one. The actions taken by operators are critical to securing the country's power supply. The agent acts as an assistant, suggesting and informing the operator's actions. It empowers him to anticipate and explain his choices. The design of human-machine interaction will thus be at the heart of future work to guarantee the acceptability of these new technologies in such operational processes. Artelys is already working alongside TenneT B.V. and its operators on the development of a decision support tool for operators.

The L2RPN challenge is based on a synthetic network, which speeds up the development of technologies by making available large volumes of data. Further work will validate the results on real networks and data. Finally, the agent's promising performance has also enabled us to identify a number of avenues for improvement, which form an integral part of future work to make our agents more robust before putting them in the hands of operators.

# References

[1] F. Pourahmadi, H. Heidarabadi, S. H. Hosseini, and P. Dehghanian, "Dynamic Uncertainty Set Characterization for Bulk Power Grid Flexibility Assessment," *IEEE Syst. J.*, vol. 14, n° 1, pp. 718-728, March 2020, doi: 10.1109/JSYST.2019.2901358.

[2] E. Little, S. Bortolotti, J.-Y. Bourmaud, E. Karangelos, and Y. Perez, "Optimal Transmission Topology for Facilitating the Growth of Renewable Power Generation", in *2021 IEEE Madrid PowerTech*, June 2021, pp. 1-6. doi: 10.1109/PowerTech46648.2021.9495032.

[3] M. Heidarifar, P. Andrianesis, P. Ruiz, M. C. Caramanis, and I. Ch. Paschalidis, "An optimal transmission line switching and bus splitting heuristic incorporating AC and N-1 contingency constraints," *Int. J. Electr. Power Energy Syst.* vol. 133, p. 107278, Dec. 2021, doi: 10.1016/j.ijepes.2021.107278.

[4] M. Lehna, J. Viebahn, C. Scholz, A. Marot, and S. Tomforde, "Managing power grids through topology actions: A comparative study between advanced rule-based and reinforcement learning agents." arXiv, April 17, 2023. doi: 10.48550/arXiv.2304.00765.

[5] A. Marot *et al*, "Learning to run a Power Network Challenge: a Retrospective Analysis". arXiv, October 21, 2021. doi: 10.48550/arXiv.2103.03104.

[6] J. Viebahn, M. Naglic, A. Marot, B. Donnot, and S. H. Tindemans, "Potential and challenges of AI-powered decision support for short-term system operations: CIGRE Session 2022", 2022.

[7] S. Zarrabian, R. Belkacemi, and A. A. Babalola, "Reinforcement learning approach for congestion management and cascading failure prevention with experimental application", *Electr. Power Syst. Res.* vol. 141, pp. 179-190, Dec. 2016, doi: 10.1016/j.epsr.2016.06.041.

[8] M. Subramanian, J. Viebahn, S. H. Tindemans, B. Donnot, and A. Marot, "Exploring grid topology reconfiguration using a simple deep reinforcement learning approach", in *2021 IEEE Madrid PowerTech*, June 2021, pp. 1-6. doi: 10.1109/PowerTech46648.2021.9494879.

# About the authors

**Nicolas Lair is an experienced AI engineer and Project Manager**. He holds a PhD at the crossroads of Reinforcement Learning and Natural Language Processing. He has extensive experience of working in research-industry environments. At Artelys, he leads both R&D projects at a very early stage of development and projects aimed at industrializing tools developed in R&D. He is also working with Dutch TSO Tennet on the *CROF* project*: Control Room of the future.*
During the challenge, Nicolas coordinated the team's work and contributed to the specification and development of the curriculum-based topological agent, notably the Junior and Senior.

**Arthur Bossavy is an expert engineer in AI**. He holds a PhD on short-term and probabilistic forecasting of renewable energy production. His work with various players in the energy sector (RTE, CRE, ENGIE, ADEME) has enabled him to acquire a good understanding of business issues, as well as recognized expertise in the modeling and analysis of energy-related time series (RE production, electricity and gas consumption). Today, he works as a consultant at Artelys, where he develops statistical modeling (Machine Learning and Deep Learning) and data analysis methods.
During the challenge, he led the development of the Track Assistant alert mechanism and set up the Tutor and Junior.

**Paul Champion is an experienced AI engineer**. At Artelys, he is a specialist in data analysis and machine learning in the transport and energy sector (RTE, ADEME, RATP). Paul is coordinating the development of a decision-support application for the Dutch electricity grid operator TenneT. In collaboration with the TenneT teams, he implemented an algorithm for selecting network topologies and optimal control according to several operational criteria.
During the challenge, he contributed to the design and implementation of the Teacher action space reduction and exploration heuristics, and to the development of the Tutor and Junior.

**Vincent Renault is Project Director and AI Expert.** He has extensive mathematical expertise in statistical and probabilistic modeling, proven skills in the development of Machine Learning and data visualization software modules, and in-depth knowledge of data issues in Energy, consolidated through the customer and research projects he supervises. As coordinator of Artelys' foresight and R&D activities, he understands the complex challenges posed by the influx of new data sources in a wide range of industrial contexts. He was a direct contributor to the GridAlive environment during the preparation of previous editions of L2RPN. Vincent is currently working with Dutch TSO Tennet on the *CROF* project*: Control Room of the future.*
During the challenge, he developed the Redispatch agent, helped adapt grid2viz to the challenge environment and analyzed the performance of our agents.

For further information,
Tel : +33 (0)1 44 77 89 0
Fax : +33 (0)1 42 96 22 610
contact@artelys.com