An Overview of Complementary Approaches for Grid Optimization

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1 Introduction

In the context of growing electricity consumption, and as the electricity mix evolves from predominantly centralized thermal power generation to decentralized renewable generation, electricity operators are increasingly confronted with congestion, and therefore increased risk of blackouts. To face these emerging risks, a number of initiatives have been launched by major players to devise innovative ways of operating the power grid based on optimization and machine learning.

In the United States, ARPA-E is organizing the GO competition (Grid Optimization) whose Challenge 3 [1] has just ended. In Europe, French TSO, RTE, is animating the L2RPN competition (Learning to Run a Power Network) [2] to encourage the development of solutions based on Reinforcement Learning approach. Other major European TSOs, such as TenneT also have in-house research project to tackle these issues by exploring different methods [3]. Artelys is actively taking part in these different initiatives with some slightly different problem formulations and different kind of approaches being investigated.

2 Overview of the approaches

2.1 Optimization - GO

Over the past few years, ARPA-E has launched a series of challenges with increasing complexity. The first one dealt with the computation of optimal powerflow under security constraints (SCOPF), while the second challenge added additional possibilities for action (transformers and shunts) and constraints (price reactivity, physical constraints on generator adaptation). The third challenge, just completed, added the different temporalities of electricity markets (week ahead, day ahead and real time).

After successful participation in the first two challenges, Artelys_Columbia team won the 4th prize in the 3^{rd} challenge. Their solution was derived from the solution built during the previous steps and uses Knitro [4] as a solver. The underlying optimization problem is hard as it is non linear, non convex and very large with millions of mixed variables. Their solution is based on trying to fix all integer variables using heuristics and by solving a relaxed problem with low precision. Once integer variables are fixed, the problem can be solved again with high precision. The optimization is done for all time periods at the same time.

2.2 Dynamic Programming - Tennet GridOptions

Artelys is a also key contributor to the development of GridOptions, TenneT's upcoming tool for decision support on topological remedial actions for congestion management. TenneT is the TSO from the Netherlands: the pilot project is focused on the area of Groningen-Drenthe, in the north-east region of the country, with high penetration of solar power and little consumption, causing recurrent congestion issues. The GridOptions tool is providing insights in day-ahead strategies to prevent or limit these congestion episodes.

The approach to build those strategies can be summarized as a dynamic programming algorithm combined with heuristics. In a first stage, load-flows are computed for a large selection of network topologies, using forecasts of power load and generation. This list of topologies is narrowed down with a heuristic favoring topologies with the longest period without congestion. Ultimately, a sequential decision graph of network states is built and strategies are derived from them using Dijkstra's algorithm.

2.3 Machine Learning - L2RPN

L2RPN is an open yearly challenge to build agents able to operate a synthetic grid network in real time during one-week scenarios. In addition to the planned evolution of the network (production, consumption, maintenance), forced outages are also simulated, creating overloads that need to be resolved. The agent is able to act on different levels on the grid : grid topology modification, production redispatch (ramp up or down plant production), curtailment (limit renewable production) or use available storage. Overall the agent is encouraged to optimize cost operation while avoiding blackouts and favoring low carbon emission energy source. The competition is based on the GridAlive software ecosystem to model the grid and the interaction of the agent [5].

For the past years, Artelys had been assisting RTE in the development of a set of tools for this competition (synthetic consumption and production data generation, baseline agents, visualization app to analyse agents) and this year, a team of Artelys of research engineers participated as a contender. They developed a multi-agent combining expert heuristics, machine learning based agent to act on the grid topology and optimization based agent to act on production levels. The agent mostly relies on grid topology modification as they are cheaper while being able to act on the production when the situation requires it. The topology agent is based on a curriculum learning approach [6, 7]. It is build in an iterative way, from greedy agents whose roles are to identify most relevant actions on the grid, to model-based agent trained by reinforcement learning to take into account the dynamic of scenarios. Artelys' solution ranked 1^{st} on the test leaderboard of the competition.

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