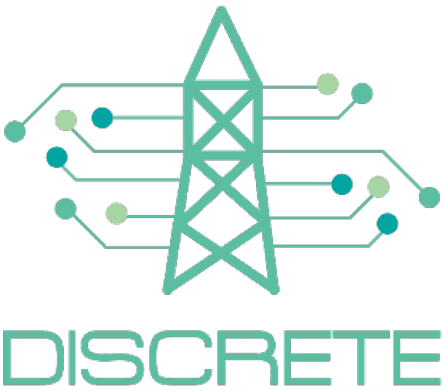

D2.1. Identify the most relevant supervised learning models able to handle the complex (non-linear, high-dimensional with discrete and continuous variables) characteristics of the problem

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1. Identification of machine learning models for the optimal power flow problem

This document provides a concise overview of the conducted academic research and offers insights into the identification of machine learning paradigms applicable to the Optimal Power Flow (OPF) problem.

1.1. Identification of machine learning models for the optimal power flow problem

The Optimal Power Flow (OPF) problem is the cornerstone of power systems operations, providing generators' most economical dispatch for power demands by fulfilling technical and physical constraints across the power network. To pledge safe and reliable operation of power systems, grid operators must steadily solve the nonconvex nonlinear OPF problem for immense power networks in near real-time, which pose tremendous computational challenges. The enormous amount of available data created by power systems digitalization and recent breakthroughs in machine learning have opened up new opportunities for grid operators to build shortcuts to predict or solve the OPF problem quickly in real-time. In this context, we overview recent attempts at leveraging machine learning algorithms to solve the transmission-level OPF problem. On this basis, we begin by laying the groundwork for commonly employed machine learning approaches leveraged to address the OPF problem which are classified into two classes: End-to-End (E2E) learning and Learning-to-Optimize (L2O). Within this context, we scrutinized this classification more closely and categorized L2O works into three groups: learning active sets of constraints, warm-start, and learning-assisted distributed/simplified optimization methods. On the other hand, when it comes to E2E learning models, their categorization hinges on the learning mechanism and the type of data they utilize. This leads to a primary classification of supervised mapping, unsupervised mapping, and reinforcement learning. These primary classes can be further categorized into subclasses such as unconstrained or constrained, and/or graph learning.

We then precisely analyzed 150 articles in the collected repository and performed a thorough comparative analysis across a wide range of factors, including the type of machine learning model, OPF type, network size, evaluation metrics, input parameters, dataset variations, dataset size, security analysis, learning algorithm, and open-source code availability. Next, we outlined frequently used performance evaluation metrics in learning-based OPFs to judge efficiency from diverse aspects (e.g., optimality in terms of the dispatched cost, feasibility concerning technical constraints, and computational efficiency) compared to conventional approaches. Further, we discuss the trend and progress of recently developed algorithms, and finally, we argue about challenges and open problems at the interface of machine learning and the OPF.

Summarizing the key takeaways from this academic work, several significant lessons emerge. First, unconstrained E2E learning models, despite their ease of implementation, offer predictions of power flow solutions that need reliable post-processing techniques to be applicable in real-world scenarios. Second, constrained E2E learning models, while more complex to implement, offer higher trustworthiness and practicality rates by respecting power flow constraints depending on the chosen architecture, but post-processing procedures may be necessary to enhance compliance with operational constraints. Thirdly, when it comes to topology awareness, graph-based learning approaches demonstrate exceptional performance, rendering them highly suitable for addressing concerns related to any form of grid contingency. Fourth, constrained reinforcement learning models are highly suitable for managing multi-period OPF while addressing inter-temporal constraints, as they naturally embrace the concept of sequential decision-making, though requiring customization for specific goals. Finally, it becomes evident that L2O frameworks offer greater practicality and trustworthiness for real-world implementation by adhering to power flow constraints, although their computational efficiency is somewhat restricted compared to E2E techniques. Consequently, the choice between E2E learning and L2O frameworks may be viewed as a trade-off between computational efficiency and solution trustworthiness.
Following publications outline the details of the conducted analysis revolving around the identification OPF learning schemes:

H. Khaloie, M. Dolányi, J-F. Toubeau, F. Vallée, “Review of Machine Learning Techniques for Optimal Power Flow”, 2023, submitted to journal *Renewable and Sustainable Energy Reviews*.