D2.2. Develop the models based on the outcome of D2.1

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1. *Develop the models based on the outcome of D2.1*

This document provides a brief summary of the methodological research conducted, which was developed using insights from D2.1 to address the grid-aware energy storage dispatch problem.

1.1. Develop the models based on the outcome of D2.1

Bulk, or large-scale, energy storage systems (ESSs) are indispensable elements of future energy networks approaching 100 % share of intermittent renewable energy. The rising contribution of intermittent renewable resources into energy networks entails deploying colossal flexibility sources, e.g., bulk energy storages, to retain real-time supply and demand equilibrium through peak shaving or load leveling. Yet, the extensive adoption of bulk ESSs in contemporary electricity grids faces obstacles due to their significant upfront investment costs (negative cash flow) and uncertain revenue streams (positive cash flows). Investment costs for bulk ESSs are influenced by numerous factors often perceived as beyond direct control. However, the allure of positive cash flows within deregulated energy markets serves as a crucial factor in enticing investors and promoting the widespread deployment of such resources. In this context, this research aims to tackle grid-aware operational challenges encountered during the daily functioning of a hybrid ESS, coupled Compressed Air Energy Storage (CAES) with Cryogenic Energy Storage (CES), namely, CAES-CES.

In this setup, the strategic CAES-CES facility aims to optimize its revenues by making strategic inter-temporal arbitrage choices, and in contrast, the power system operator strives to enhance the overall welfare of the electricity grid amidst the integration of renewable energy generation. This interaction between the storage facility and the market operator is depicted as a bi-level optimization problem. Here, the upper-level optimization aims to maximize the revenue of the storage facility, while the lower-level problem focuses on minimizing the electric grid cost based on Optimal Power Flow (OPF) principles. The suggested bi-level model is subsequently converted into a mathematical program incorporating equilibrium constraints, which can be reformulated as a mixed-integer programming problem. Nonetheless, the resultant mixed-integer programming problem is identified as an NP-hard optimization challenge owing to the sheer volume of discrete decisions associated with the charge/discharge operations of the storage system, as well as the optimality conditions based on Karush-Kuhn-Tucker (KKT) constraints within the market operator's problem. To address this challenge, we introduce a learning-to-optimize framework. This learning-to-optimize framework focuses on gaining insights into the attributes of discrete variables by warm-starting all discrete variables with a machine-learning predictor.

As for the machine-learning predictor, a deep feedforward neural network was selected as the machine-learning predictor due to its effectiveness with high-dimensional output spaces. The network architecture follows a standard design, with multiple densely connected ReLU layers and an output layer composed of sigmoidal neurons, each predicting a specific binary variable. Once the classifier’s parameters are optimized, the trained network is used to predict 0-1 values for all discrete variables in new, out-of-sample feature sets. These predictions serve as a warm-start for the MIP optimizer, providing an informed basis for the solver and reducing the need to search from scratch for optimal discrete solutions.

We employed trained neural networks to predict discrete variables for new, out-of-sample features, using these predictions as a warm-start for the on-call solver to maintain feasibility and global optimality. The main goal was to use these predictions to enhance computational efficiency. Effectiveness was assessed by time saved and reduced computational load, specifically in the iteration count required by Gurobi’s branch-and-cut algorithm. The warm-started optimization was compared to the traditional MIP approach to assess performance. Results showed substantial reductions in computation time and iterations, with time savings reaching 29.30% on the 24-bus system. This improvement did not compromise local optimality. Additionally, iteration reduction was proportional to neural network accuracy, indicating that higher accuracy leads to greater reductions. Time savings were also impacted by the number of continuous variables; for instance, the

118-bus system, with two orders of magnitude more continuous variables than the 6-bus system, saw relatively lower time savings despite greater iteration reductions.

Following publications outline the details of the conducted analysis revolving around the development of models based on the outcome of D2.1:

Khaloie, H., et al, (2024). Hybrid Energy Storage Dispatch: A Bi-Level Look-Ahead Learning-Assisted Model. Submitted to IEEE Transactions on Power Systems.