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

Authors: Hooman Khaloie, François Vallée

This deliverable is based on the following publication:

Khaloie, H., et al, (2025). Hybrid Energy Storage Dispatch: A Bi-Level Look-Ahead Learning-Assisted Model. in IEEE Transactions on Energy Markets, Policy and Regulation, vol. 3, no. 3, pp. 376-392.

Table of Contents

1. Purpose within the project

This paper was carried out to investigate how supervised learning can support the solution of complex optimisation problems arising in the operation of future renewable-dominated power systems. A central objective of DISCRETE is the development of data-driven decision-support tools capable of producing high-quality operational decisions within the limited time available to transmission system operators. The objective of this work was therefore to explore how machine-learning techniques can be integrated with optimisation models to improve computational tractability while preserving operational reliability and physical consistency.

The paper addresses one of the key challenges identified in DISCRETE: enabling real-time or near-real-time optimisation in systems characterised by high renewable penetration, and large numbers of discrete and continuous decision variables. The case study focuses on the strategic dispatch of a hybrid Compressed Air Energy Storage (CAES) and Cryogenic Energy Storage (CES) facility participating in electricity markets.

The developed methodology serves as a representative test case for learning-assisted optimisation approaches that can later be transferred to broader transmission-system applications.

Aspect	Summary
Main objective	Improve the computational scalability of optimisation-based decision support
Methodological focus	Learning-to-Optimize using supervised learning and optimisation warm-starting
Operational challenge	Large-scale mixed-integer optimisation under uncertainty and market interactions
Operational value	Strategic dispatch of hybrid energy storage systems that supports real-time, risk-aware operation

2. Methodological contribution

The work develops a look-ahead dispatch formulation for hybrid energy storage systems. The hybrid facility combines the high efficiency of above-ground compressed-air storage with the large storage capacity of cryogenic energy storage through bidirectional conversion between compressed and liquid air.

The dispatch problem explicitly models charging, discharging, state-of-charge evolution, internal energy transfers between storage technologies, and participation in day-ahead electricity markets. To capture strategic market behaviour, the storage operator is modelled as a leader in a Stackelberg game, while the market-clearing process acts as a follower. This structure results in a bi-level optimisation problem capable of determining profit-maximising dispatch strategies over multi-day look-ahead horizons.

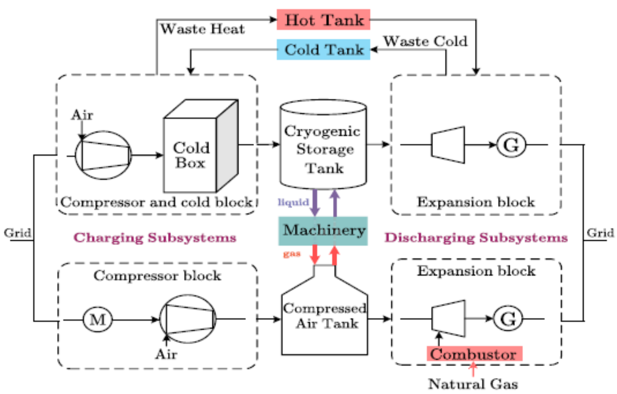

Figure – Hybrid CAES-CES dispatch and bi-level optimisation framework

A key methodological contribution of the task is the transformation of the bi-level problem into a tractable single-level mixed-integer optimisation model. The lower-level market-clearing problem is reformulated through Karush–Kuhn–Tucker (KKT) conditions and complementarity constraints. Although this transformation preserves the original optimisation logic, it generates a very large number of binary variables associated both with storage operating modes and with the linearisation of complementarity conditions. For realistic power systems and multi-day look-ahead horizons, the resulting optimisation problems contain hundreds of thousands of effective binary variables, creating significant computational challenges.

To address this issue, the work proposes a Learning-to-Optimize framework based on supervised learning. Rather than replacing the optimisation process, machine learning is used to predict high-quality initial values for binary decision variables before the optimisation solver is launched. The proposed methodology consists of three stages, as represented in the Figure below:

1. Data acquisition, where optimisation problems are solved offline under many operating conditions to generate labelled datasets;
2. Learning, where a deep feedforward neural network is trained to learn the relationship between system conditions and optimal binary decisions;
3. Warm-start assisted optimisation, where the trained model predicts binary-variable configurations for unseen operating conditions and provides these predictions as initial solutions to the optimisation solver.

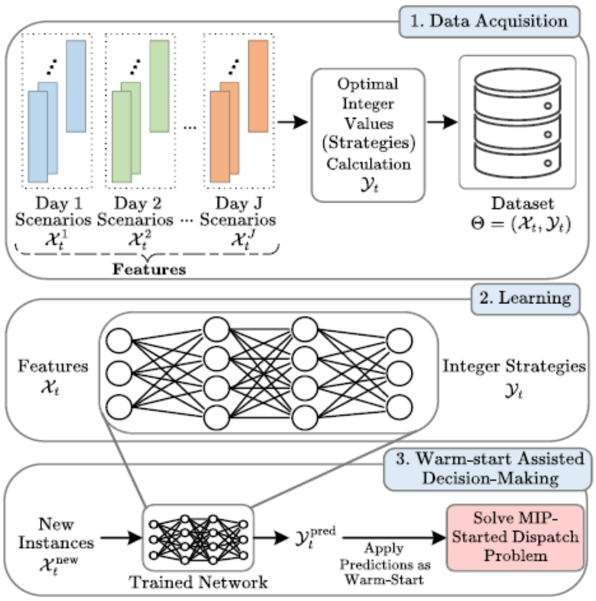

Figure – Learning-assisted optimisation framework based on warm-start prediction

The proposed machine-learning model assists the optimisation algorithm by guiding its search process. Consequently, the framework retains the feasibility guarantees and optimality properties of mathematical optimisation while benefiting from the capabilities of supervised learning. The proposed architecture therefore represents a practical implementation of the Learning-to-Optimize paradigm within a complex power-system application.

3. Main results

The numerical studies demonstrate both the operational value of the hybrid storage concept and the effectiveness of the learning-assisted optimisation strategy.

From an operational perspective, the results show that extending the look-ahead horizon changes the strategic behaviour of the hybrid storage facility. As shown in the Figure below, the storage system discharges more aggressively and offers energy at lower prices during selected periods, increasing its market participation and influencing market-clearing prices. This behaviour affects the distribution of social welfare among market participants.

Figure - Hourly hybrid storage commitment (bars, MW) and market-clearing price (lines, € /MWh) on day 6

For four different cases (further highlighted in the paper) summarized in the Table below, the results show that the hybrid CAES-CES facility can achieve profit improvements of up to 9.08% compared with standalone alternatives when operating under extended look-ahead horizons. These gains originate from the coordinated use of the two storage technologies and from the ability to optimise state-of-charge trajectories over multiple days rather than treating each day independently.

Table - Profitability assessment of standalone and hybrid systems

System	Profit [€]			
	Case 1	Case 2	Case 3	Case 4
Standalone Facilities	64,110	90,345	80,301	120,732
Hybrid Plant	65,491	98,076	81,339	130,031

From a computational perspective, the learning-assisted framework significantly reduces optimisation effort. The neural network successfully learns patterns associated with optimal binary decisions and provides effective warm-start solutions to the mixed-integer solver. Across the studied systems, computation times are reduced by approximately 29.3% for the 24-bus network and 13.35% for the 118-bus network while maintaining solution quality. These results demonstrate that supervised learning can meaningfully accelerate optimisation procedures even when the optimisation model itself remains unchanged.

4. Takeways

Overall, this paper contributes to the DISCRETE project by demonstrating how supervised learning can complement, rather than replace, mathematical optimisation. The proposed learning-assisted framework provides a practical pathway for accelerating large-scale optimisation problems while preserving the robustness and feasibility guarantees required for operational deployment. The results show that machine learning can effectively support the solution of complex mixed-integer optimisation problems involving nonlinear dynamics, discrete decisions, and market interactions, thereby creating a foundation for the development of scalable real-time decision-support tools in future renewable-dominated power systems.

The work also highlights several important research directions for future developments. First, more advanced learning architectures, including graph neural networks and transformer-based models, may further improve prediction quality and scalability. Second, uncertainty-aware learning strategies could be integrated to account explicitly for renewable variability, market uncertainty, and forecast errors. Third, the methodology could be extended beyond binary warm-start prediction toward active-constraint prediction, decomposition strategies, or adaptive solver control.