The European Union aims at reaching climate neutrality at horizon 2050 by achieving an economy with net-zero greenhouse gas emissions. Such ambitious policy target has implied and will continue to imply big changes in European energy systems, which accounted for 74% of European greenhouse gas emission in 2019. In this line, the electricity sector is currently rapidly shifting its supply mix towards less carbon-intensive energy sources, which conducts to growing shares of weather-dependent renewable energy sources (e.g., wind and photovoltaic power). The generation profile of these technologies differs from conventional ones (e.g., gas-fired units) by their high intermittency and uncertainty, which rises the difficulty of ensuring a continued, real-time balance between the electricity demand and supply.

This balancing requirement is vital when operating electricity systems since a mismatch between demand and supply automatically deteriorates the system frequency, which may trigger the disconnection of system components, and ultimately, lead to power blackouts. In the unbundled European electricity markets, the balancing management is supported via the balancing markets, which establish (amongst other) the market rules for the real-time trading of energy. While originally designed at national level, the European balancing markets are currently undergoing a harmonization process for fostering the cooperation between European countries. In this process, the favored option for pricing the real-time energy imbalances is the single price imbalance settlement, which provides financial incentives for market actors to adopt an imbalance position in the opposite direction of the total net system imbalance. When appropriately provided, this real-time balancing service is beneficial for the whole system as it reduces the total net system imbalance, which requires thus less costly corrective balancing actions.

This work is focused on developing novel forecast-driven strategies for fostering the provision of such real-time balancing services in European electricity markets. Practically, these strategies are studied using an integrated approach, where the entire value chain, i.e., from forecasting to the decision-making processes, is modeled for optimizing close-to-real-time the imbalance position of a market actor. In this setting, the methodological contributions principally concern the modeling of uncertainty and risk in their operational strategies. More specifically, novel probabilistic forecasting methods based on deep learning techniques have been proposed, aiming at better capturing the high volatility of the total net system imbalance. In complement, for exploiting at best the predicted probabilistic information, tailored stochastic decision-support tools (i.e., stochastic programming and robust optimization method) are developed, for which a new data-driven approach was designed for continuously adjusting the risk policy of the market actor. The implementation of the developed approaches on real-world market data from the Belgian power system corroborates the key goal of the single price imbalance settlement, by showing that the market actor can increase its operating profit by optimizing its imbalance position, while reducing the total net system imbalance. Additionally, advanced neural networks architectures based on attention mechanisms demonstrate top forecasting performance for predicting the total net system imbalance. Finally, the data-driven approach for continuously adjusting the risk policy shows promising economic benefits in comparison with a static (determined once and for all) risk policy.

The final research efforts of this work are devoted on interpretability of deep learning-based forecasting methods, which aim at accurately identifying the most important input features of the model and their interaction when returning the prediction. Combining the predictive power of deep neural models with interpretable outcomes is an essential step for fostering their practical adoption in the energy industry. To achieve interpretability in both feature and time dimensions, the attention-based neural architecture is here augmented with subnetworks dedicated to endogenously quantify the relative importance of each input feature. Outcomes using the data from the Belgian power systems show that adding interpretable components within the neural architecture does not hinder their prediction performance, while shedding light on its most important drivers.