Short-term trading of wind energy production using data-driven prescriptive optimization.

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Abstract

The participation of Wind Power Plants (WPPs) in competitive electricity markets requires several forecasting and decision-making tools. WPP operators submit offers in market auctions, which are closed ahead of delivery (e.g. the day before), therefore the uncertainty of wind production should be accurately taken into consideration in the offering strategy. This constitutes a stochastic optimization problem that needs to be solved conditioned on observations of explanatory data, e.g. weather conditions at the WPP site. The standard approach to tackle this conditional stochastic optimization problem is to first deploy a forecasting model to predict uncertain parameters like wind production and market prices and, subsequently, use those predictions as inputs in an optimization module. This constitutes a modelling chain, which generally requires substantial tuning effort in order to obtain optimal trading decisions. Furthermore, the relationship between offering decisions and explanatory data is indirect, making it difficult to analyze the impact of those conditions on the trading revenue.

In this work, we present an alternative approach based on data-driven deterministic optimization, which integrates forecasting and optimization tools with the goal of using predictive algorithms to directly prescribe optimal decisions. Specifically, we consider the problem of a WPP offering energy in a day-ahead (DA) market, subject to imbalance costs. In this case, the optimal offering strategy relies on the estimation of the conditional distribution of wind production [1] given explanatory data. Following recent advances in data-driven optimization and prescriptive analytics [2], we train predictive machine learning algorithms to estimate local weights for a new observation point, which are then used to derive a weighted sample average approximation (SAA) of the original problem. This approach effectively links explanatory data to decisions, which are termed Predictive Prescriptions.

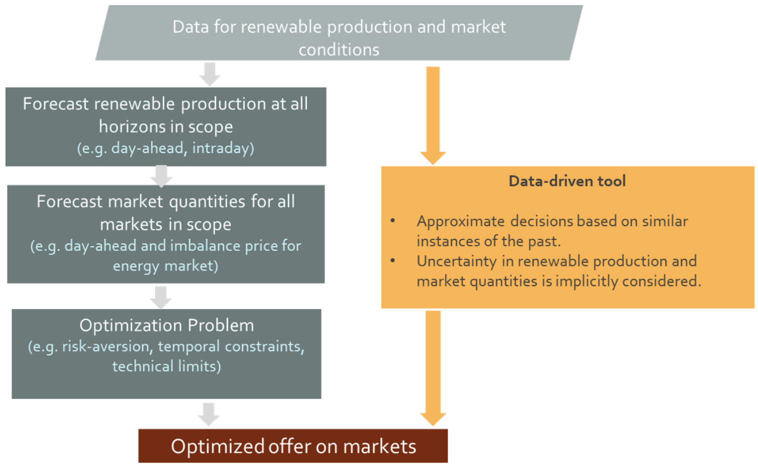

Fig. 1. High level description of case study.

A high level description of the two approaches is presented in Figure 1 below. A use case of a virtual power plant (VPP) participating in a DA market under a dual price balancing mechanism is presented. We consider the more general case of a VPP composed of wind and PV power plants (though with a higher share of wind). First, we train different local learning algorithms, such as k-Nearest Neighbors, kernel regression, and variants of decision trees, to predict uncertain production and assess the impact of features on predictive accuracy based on the permutation importance. Second, based on the local weights obtained, we form and evaluate predictive prescriptions and compare against the standard two-step approach. We conduct numerical experiments to study the sensitivity of derived prescriptions to the size of the training sample. Finally, we measure the impact of explanatory variables on the forecast value, i.e., trading costs, by expanding the permutation importance in a prescriptive analytics framework. Results with real data indicate that the proposed approach achieves similar performance in terms of trading revenue with the standard approach, without the need of explicitly modeling the full distributional uncertainty. Furthermore, it allows to directly measure the impact of explanatory variables in forecast value.

References

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[2] D. Bertsimas and N. Kallus, "From predictive to prescriptive analytics," *Management Science*, vol. 66, no. 3, pp. 1025–1044, 2020.