Discussion on improving efficiency in machine learning wind power forecast for operational purposes

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Objective & Background

Power forecasting for wind farms, due to their large scale and non-programmability, is crucial for continuously balancing supply and demand and maintaining the safety of electric grid. Wind is also a particularly challenging variable to predict due to its intermittent nature. Therefore, various techniques, such as machine learning, are used to improve the accuracy of wind power forecasting. On top of these, forecast needs differ between research case study and a real-world operational scenario, where computational costs must be considered as a priority.

The aim of this study is to improve the efficiency of the forecasting based on machine learning, by means of a properly selected training period.

Method

The study involves several steps. First, the power of 8 wind farms located in Southern Italy was acquired and properly validated. Then, forecast of meteorological variables, affecting wind production, were derived using high resolution limited area numerical weather (NWP) models (Weather Research and Forecasting Model [WRF] and Regional Atmospheric Modeling System [RAMS]) initialized using two different global drivers (Integrated Forecast System [IFS] and Global Forecast System [GFS]). Two machine learning models (Random Forest and Gradient Boosting Machines) were trained with five years of hourly power data, to obtain hourly power forecast till three days ahead. Each month was then classified using Weibull distributions of the forecasted wind. These classifications were used to obtain a lower-size training dataset. Performances of wind power forecasts implemented with reduced and non-reduced training dataset were finally compared.

Principal Findings

With this approach the computational cost of hyperparameters tuning has been reduced by 15 and that of machine learning training by 7. This result has been obtained without a significant loss in performances.

Conclusion

The key benefit of this methodology is that it allows to obtain a relevant reduction in execution time without a significant loss in forecasting performance. This condition makes it possible to implement other machine learning methods highly performant but often not operable due to their high computational costs. Furthermore, this improvement in efficiency enables to frequently update the forecasting models. Finally, it’s easier to implement a forecast based on an ensemble of different models, leading to a spectrum of predictions. The resulting range of variability indirectly gives an indication on the uncertainty of the provided forecast.