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# The value of improved wind power forecasting: Grid flexibility quantification, ramp capability analysis, and impacts of electricity market operation timescales

Qin Wang, Hongyu Wu, Anthony R. Florita, Carlo Brancucci Martinez-Anido, Bri-Mathias Hodge *

*National Renewable Energy Laboratory, Golden, CO 80401, USA*

## HIGHLIGHTS

- The value of improving wind power forecasting accuracy at different timescales is analyzed.
- The grid flexibility of three studied systems is compared by selected metrics.
- Quantification of dynamic operational flexibility by real-time upward and downward ramp capacity.
- Generation resource mix plays a crucial role in evaluating the impacts of wind power forecasting accuracy.
- The annual operational electricity generation cost is mostly influenced by the dominant resource.

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## ABSTRACT

The value of improving wind power forecasting accuracy at different electricity market operation timescales was analyzed by simulating the IEEE 118-bus test system as modified to emulate the generation mixes of the Midcontinent, California, and New England independent system operator balancing authority areas. The wind power forecasting improvement methodology and error analysis for the data set were elaborated. Production cost simulation was conducted on the three emulated systems with a total of 480 scenarios considering the impacts of different generation technologies, wind penetration levels, and wind power forecasting improvement timescales. The static operational flexibility of the three systems was compared through the diversity of generation mix, the percentage of must-run base-load generators, as well as the available ramp rate and the minimum generation levels. The dynamic operational flexibility was evaluated by the real-time upward and downward ramp capacity. Simulation results show that the generation resource mix plays a crucial role in evaluating the value of improved wind power forecasting at different timescales. In addition, the changes in annual operational electricity generation costs were mostly influenced by the dominant resource in the system. Finally, the impacts of pumped-storage resources, generation ramp rates, and system minimum generation level requirements on the value of improved wind power forecasting were also analyzed.



## 1. Introduction

The variability and uncertainty of wind power can require changes to power system operating procedures as increasing amounts of wind generation are incorporated into the generation mix [1]. With increased investments in wind power fueled by state renewable portfolio standards [2] and declining wind power costs [3,4], the electric grids in the United States are starting to face operational challenges. One of the most efficient approaches to mitigating the negative impacts of wind power on system operations is to incorporate short-term wind power forecasting. With the application of new statistical and machine learning methodologies, as well as advancements in numerical weather prediction (NWP) models, the accuracy of wind power forecasting has been improved significantly in recent years. For example, the day-ahead (DA in tables) wind power forecasting mean absolute error (MAE) for a 100-MW nameplate capacity wind power plant has been reduced from 12% in 2006 to 10% in 2015, and the hour-ahead wind power forecasting MAE of the same site has been reduced from 12% in 2006 to 7% in 2015 [5]. A general review of

* Corresponding author.
*E-mail address:* bri.mathias.hodge@nrel.gov (B.-M. Hodge).

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the state of the art in the short-term prediction of wind power is shown in [6].

A plethora of wind power forecasting techniques currently exist, including NWP models, statistical models, machine learning methods, and space–time trajectories [7–10]. The NWP approach is primarily used to forecast wind speeds multiple hours to days ahead for given sites, and the wind speed is converted to wind power based on the wind turbine's power output curve [11–14]. The statistical models and machine learning methods attempt to adjust the relationships among a set of inputs, including the NWP model output and other meteorological data, and past measurements of the wind power output at a given location [15–17]. A recent trend in wind power forecasting is the emergence of probabilistic forecasting approaches, which are distinct from the traditional point forecasting approach in that the latter provides only a single estimated value (which is often the most likely outcome) for a given look-ahead horizon, whereas the former can provide probabilistic information about future events [18–20]. The trajectory method generalizes probabilistic forecasting by accounting for spatiotemporal dependencies [10]. In recent years, wind power ramp forecasting, which focuses on improving forecasts related to extreme events in the form of large power output variations, has attracted growing interest in the wind power forecasting community [21].

Recent research shows that standard wind power forecasts can be improved by 30% with advanced machine learning techniques [22], and the trend of expecting more accurate forecasts is expected to continue as wind power penetration rates increase; however, it is not clear how the improved accuracy will impact the operation of electric grids. It is difficult to precisely gauge the value attributed to a certain extent of wind forecast improvements because the relationship depends on multiple factors, such as market structure and size, wind penetration level, and forecasting timescales. Botterud et al. [23] reviewed the application of wind power forecasting in major U.S. electricity markets. Wang et al. [24] investigated the impacts of wind power forecasting uncertainty on the unit commitment process, but they did not measure the benefits from improved power forecasting. Hodge et al. [25] attempted to quantify the value of improved ultra-short-term wind power forecasting. A similar study also examined the value of day-ahead solar power forecasting improvements in the Independent System Operator New England (ISO-NE) power system [26]. McGarrigle et al. [27] studied the value of improved wind energy forecasts in the 2020 Irish electricity system with a 33% wind penetration level. Nevertheless, the majority of these studies have attempted to quantify the value of wind power forecasting only at a single time horizon, and they did not consider the impacts of grid flexibility and the system's ramp capability. The authors' previous study [28] quantified the benefits of wind power forecasting improvement in terms of production costs as well as grid reliability. The major difference between this article and reference [28] is that this article extends the scope in [28] by considering the impacts of grid flexibility, ramp capability, and electricity market operation timescales.

The techniques in this paper utilized the accuracy of wind power forecasts varied at different time horizons. For example, the MAE for 4-hour-ahead (4HA) forecasts is typically smaller than that for day-ahead forecasts because the 4HA forecast horizon is closer to real time, and thus more recent information is available. Improving the wind power forecasting accuracy at different time horizons can bring different benefits to the electric grid. From a utility's perspective, because the forecast accuracy and the resources required for the forecast vary at different timescales, there is a need to understand which timescale can bring the maximum benefits. This would guide investments in improving the forecast accuracy in day-ahead only, in intraday only, or in both day-ahead and intraday. In addition, the value of wind power forecasting improvement varies in systems with different flexibility levels and ramp capabilities. For instance, to date the California Independent System Operator (CAISO) power system has almost 20% renewable energy sources, and large ramp-up (and ramp-down) capability from the conventional generation fleet is required during the sunset (sunrise) period. This is illustrated by the "duck curve" [29], wherein the presence of solar energy makes the previous load shape (known as an "elephant curve") change to show the net load (i.e., load minus variable renewables) in the shape of a duck. However, the Midcontinent Independent System Operator (MISO) power system has approximately only 10% renewable energy sources (mostly from wind power) and has more than 60% coal [30]. Increasing the accuracy of wind power forecasting by the same amount in the two systems will incur different values. How to quantify the value of wind power forecasting improvements under different grid flexibility levels and ramp capabilities is a significant yet unresolved issue. To address these challenges, this article investigates the value of wind power forecasting improvements at different operation horizons as well as analyzes the impacts of grid flexibility and ramp capability. The study was performed by simulating the operation of an IEEE 118-bus test system[1] [31] as modified to emulate the generation mixes of the CAISO, ISO-NE, and MISO balancing authority areas (BAA). For each BAA, 10 wind power penetration levels and six wind power forecasting improvement scenarios are simulated. These scenarios are compared on an operational cost basis (called generation production costs) for all generators, including (1) start-up and showdown costs, (2) variable operation and maintenance (O&M) costs, and (3) fuel costs. The fixed O&M costs are not considered because they are generally used only for long-term generation capacity planning in PLEXOS. For the same reason, the levelized cost of electricity and the capital costs of generators are excluded when calculating the generation production costs. The impacts on wind power curtailment at different operation horizons are also compared. Moreover, operational impacts on conventional generators are analyzed.

The rest of the paper is organized as follows. Section 2 describes the process of generating the wind power forecasting improvement data in the different scenarios. Section 3 presents the production cost simulation model and the input data sources for the model. Section 4 demonstrates the study results. Finally, Section 5 concludes.

## 2. Wind power forecasting improvement methodology and error analysis

The National Renewable Energy Laboratory (NREL)'s Wind Integration National Dataset (WIND) Toolkit was the source of the wind power data used for different wind penetration scenarios. In the development of the tool kit, measured wind data sets served as reanalysis inputs to ensure realistic spatiotemporal correlations, ramping characteristics, and capacity factors of the simulated wind power plants. Further, these data are time synchronized with available load profiles. The WIND Toolkit is the most comprehensive publicly available data set that includes meteorological data, time series data of wind power production, and simulated forecasts. The data set was created using the Weather Research and Forecasting model run on an approximately 2-km by 2-km grid at 5-min resolution for the entire continental United States, with millions of meteorological data points narrowed down to 126,000 feasible land-based and offshore wind power production sites according

[1] The IEEE 118-bus test case represents a simple approximation of the American Electric Power system (in the U.S. Midwest) as of December 1962. The IEEE 118-bus system contains 54 generators, 186 transmission lines, and 91 loads [31].