Detection of Impending Ramp for Improved Wind Farm Power Forecasting

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***Abstract*—Detection of impending front-induced ramp events is studied as a new class of change detection problem - change detection for multiple time series with spatial dependency. A critical step to ramp event detection is to capture the spatial dependency between neighbor turbines' power output. To this end, a graphical model is utilized to model the dependency of turbine-level ramp events. Then, change point detection is carried out for the time series of individual turbines' power output, by using the belief from neighbor turbines in the dependency graph. Once an impending ramp is detected, the magnitude of ramp is then forecasted by using current measurement data. A key observation is that due to the movement of front, the best predictors for individual turbines' power output vary across three different regions of the wind farm. With this insight, different predictive models are adopted for forecasting power output from each region. Through numerical experiments, the proposed detection-based wind power forecasting method is proven to outperform conventional methods for wind power ramps.**

***Index Terms*—Ramp events, short-term wind power forecasting, wind farm.**

I. Introduction

With an objective to build a sustainable energy infrastructure, many states in the U.S. have adopted renewable portfolio standards (RPS) [1] that specify the anticipated penetration levels of renewable energy. A critical aspect in meeting these goals is the integration of wind power generation the bulk power grids. Particularly, wind power is expected to constitute a significant portion of all renewable generation being integrated to the bulk power grids of U.S. [2]. Specifically, U.S. Department of Energy has envisaged that the wind power will contribute to more than 20% percent of U.S. electricity demand by 2030 [3]. With increasing penetration into bulk power systems, wind power generation has posed significant challenges for power reliability [4], [5]. Unlike conventional energy resources, wind power generation is non-dispatchable, in the sense that wind energy could be not harvested simply by request. Further, wind power generation highly depends on geographical and meteorological conditions and thus exhibits greater variability across all timescales, which makes it challenging for system operators to obtain accurate knowledge of future wind power generation. Typically, power system operators will maintain an adequate amount of back up generation capacity or battery storage as reserves to compensate for small variations of wind power [6]. However, disruptive events - extreme wind power ramp could have significant impact on the availability of wind power, as well as the reliability and stability of power grid. As the bulk of wind energy sources, the reliable power out from wind farms is of paramount significance to power grids. It is therefore of great interest to investigate the use of real-time measurements collected from widely dispersed sensors deployed at wind farms, together with state-of-the-art data analytics tools, for securing wind farm against disruptive events.

This research was supported by the NSF project ECCS-1653922

The rest of the paper is organized as follows. Background on wind power ramp and key observations from real-world data of wind farm are given in Section II. Section III presents the proposed approach to wind power ramp detection and forecasting. Numerical experiments are carried out in Section IV. Finally, conclusions are given in Section V.

II. Wind Power Ramp and Key Observations from Wind Farm Real-world Data

A. Wind Power Ramp

Wind power ramp refers to the sudden and significant change in the aggregate power output of a wind farm [7]. Reference [8] formally defines wind power ramp as follows: Definition - A wind power ramp is considered to occur at time instant t, if the change in the aggregate power output P_ag of a wind farm over a time interval δt, with regard to the wind farm's rated capacity $\bar{P}_ag$, is greater than a threshold r_th:

$$|p_{ag}(t-\delta t) - P_{ag}(t)| \geq r_{th}\bar{P}_{ag}. \tag{1}$$

Based on [9], a change by over 20% of the rated capacity of wind farm in 10 minutes, i.e., r_{th}=0.2 and δ t=10 min, is referred to as an extreme ramp. Generally, a ramp can be either an up-ramp (upward change) or a down-ramp (downward change). However, it is of greater interest to study down-ramps. This is because that to accommodate an up-ramp, wind power producers can curtail the aggregate power output of wind farms as needed; when down-ramps occur, battery storage and/or operating reserves has to be utilized, at additional cost, to compensate the energy supply deficit.

B. Extreme wind power ramps are low-probability high-impact events

By using historical measurement data collected from a large wind farm in western U.S. during the years 2009-2012, which has a rated capacity of 300.5 MW and 273 turbines, we apply extreme value analysis to study daily largest ramp. Figure 1 illustrates the generalized extreme value distribution fitted to the data of daily largest down-ramps, which is a Frechet

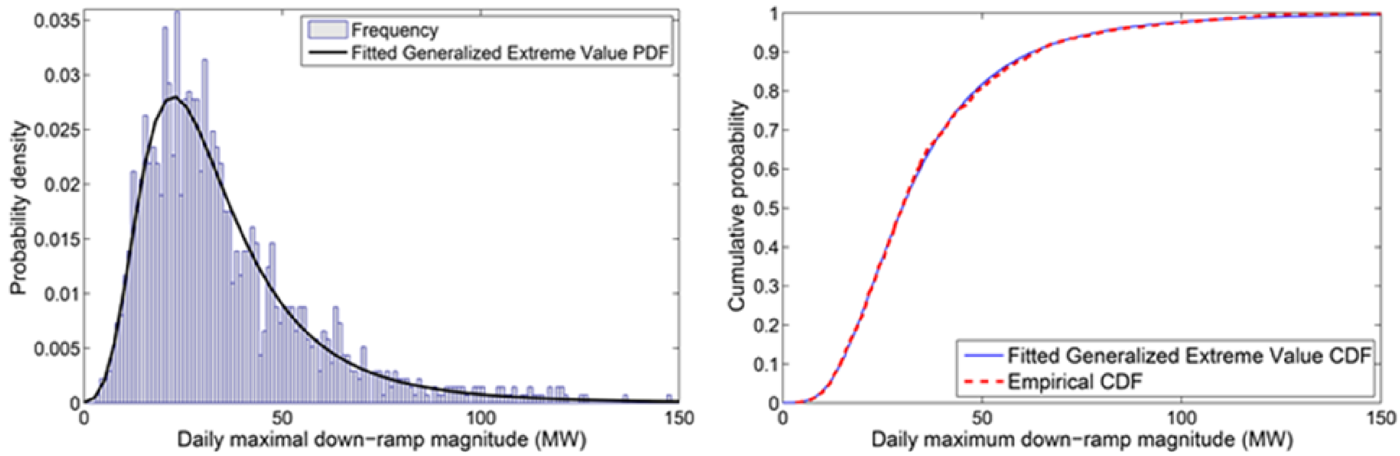


Fig. 1. Generalized extreme value distribution of daily largestdown-ramp.

distribution with shape parameter of 0.20, scale parameter of 13.36 MW and location parameter of 24.83 MW. It is observed from the Fig. 1 that an extreme down-ramp occurs daily with a probability of as low as 0.113.

State-of-the-art short-term wind power ramp forecasting approaches are not developed for extreme ramp events. Short-term wind power ramp forecasting aims to detect and quantify the impending ramp in a small lead time (5-15 min). The comprehensive literature survey [10] summarizes the approaches [8], [9], [11], which utilize historical aggregate wind power measurements and machine learning algorithms to induce a predictive model, as statistical-based short-term wind power ramp forecast approaches. Particularly, literature [11] applies data mining tools (boosting trees) and discoveries that the 10-min wind power ramps calculated from aggregate power measurements during the most recent 1 hour are the most significant predictors for short-term wind power ramp forecasting. Reference [8] develops a hidden Markov model for wind power ramp, with parameters estimated from historical data. The state-of-the-art statistical-based approaches can achieve reasonably high forecasting accuracy, when tested on a large data set by using mean absolute error as performance metric. However, it is noted from the above analysis and Fig. 1 that extreme ramps are rare events. Thus, data traces that consist of an extreme ramp event are usually treated as outliers when used to induce statistical-based predictive models. An example is illustrated in Fig. 2. The wind power generation during the 1-hour window before an extreme down-ramp on Aug 19th, 2012 is plotted. Another 201 wind power series are also plotted, which are "similar" to the extreme down-ramp in the sense that, the wind power at each time instant of the 1-hour forecasting window is different from that of the trace of the extreme wind power ramp by no greater than 5%. It is thus clear from Fig. 2 that statistical-based wind ramp forecast approaches would not work for extreme wind power ramps.

One key observation that motivates the proposed research is that, with new sensory data on turbine-level power measurements, extreme ramp events could be detected in advance

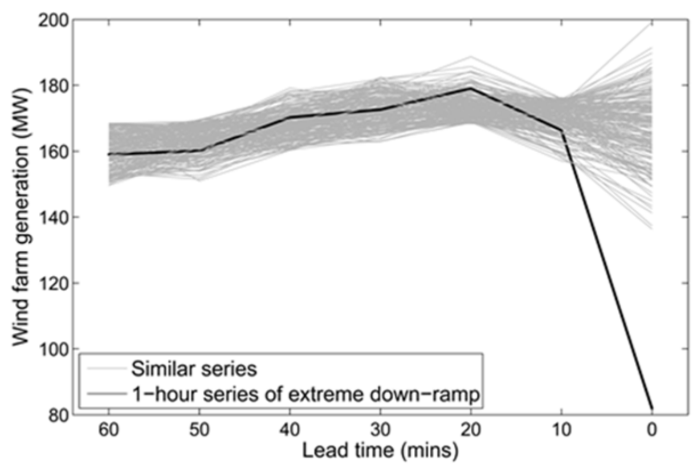
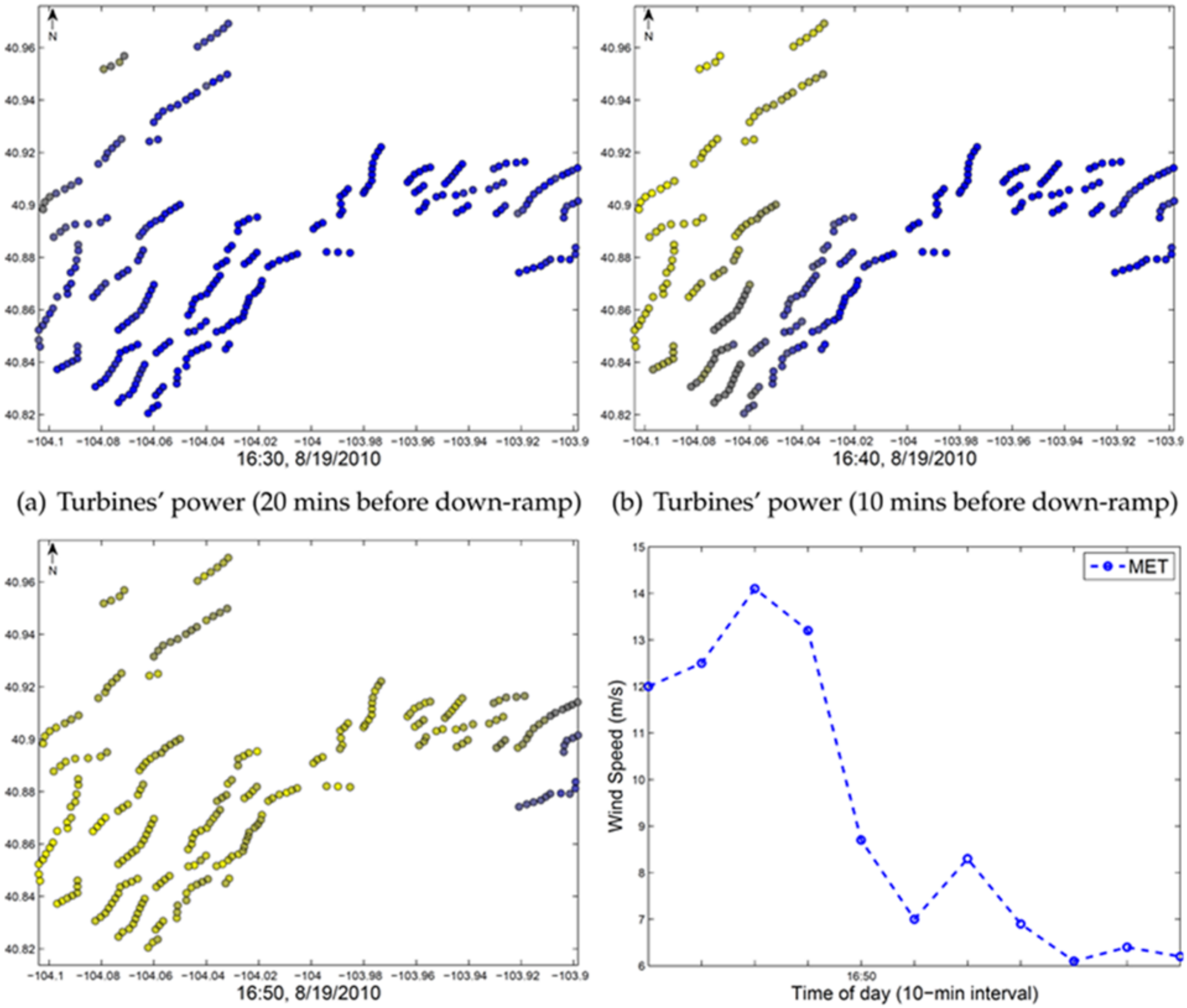


Fig. 2. An extreme down-ramp and "similar" series.

and accurately quantified. Wind power ramps are usually caused by sudden changes in weather conditions [12]–[14], including the passage of fronts, thunderstorms, and turbine shutdown due to gust or icing. The passages of fronts are results of the horizontal movement of large-scale weather systems or mesoscale/local circulations, after which the wind speed changes dramatically. By using turbine-level power measurements, Fig. 3 explains how the same extreme wind power ramp in Fig. 2 developed as the passage of a front. It is observed from Fig. 3 that a northwest weather front passed the wind farm, and induced an extreme down-ramp. As illustrated in Fig. 3(a) which was 20 min before the down-ramp, part of the turbines in the northwest area of the wind farm have less power output (denoted by yellow or green circles) than the rest turbines. Ten minutes later, as illustrated in Fig. 3(b), more turbines in the northwest area of the wind farm encountered significant drop in their power outputs. Finally, the wind behind the front, which has a less speed as illustrated in Fig. 3(d), covered the entire wind farm and induced an extreme down-ramp. From Fig. 3, we have two key observations:



(a) Turbines' power (20 mins before down-ramp) (b) Turbines' power (10 mins before down-ramp)

(c) Turbines' power (down-ramp has occurred!) (d) Wind speed

Fig. 3. A front-induced down-ramp (note: Each turbine is represented by a colored circle; the darker the color is, the higher the power output of the turbine is; the geographical information of each turbine is given in x-axis (longitude e) and y-axis (latitude)).

1) By using turbine-level power measurements, together with geographical information of turbines, front-induced extreme wind power ramps can be detected in advance, as suggested from development in Fig. 3(a) to Fig. 3(b) of the above example. Further, the moving direction and speed could also be estimated. Specifically, the moving direction could be determined from vector that is perpendicular to the boundary between wind turbines with power drop and the rest; and moving speed can be estimated from the turbines behind the front by using speed-to-power curves. 2) Wind speed measurement at a meteorological tower of wind farm is not sufficient for detection of front-induced ramps, as shown in the case of Fig. 3(d). Depending on the location of meteorological tower and the direction of front, the wind speed drop may occur simultaneously with or even after wind power ramp

III. Detection of Impending Front-induced Ramps

The proposed approach for data analytics of wind power ramps is comprised of three main steps. First, detection of impending front-induced ramps is formulated as a new class of change detection problem with spatial dependencies. Then, a support vector machine is utilized to classify turbines by using turbines' geographical information and corresponding turbine-level power ramp indicators, from which the moving direction and speed of front can be estimated. Finally, based on the results from the previous two steps, wind farm is partitioned into three regions, and magnitude of impending ramp is obtained from short-term wind power forecast of each region.

A. Detection of Impending Wind Power Ramp

1) Spatial Dependency Modeling: It is naturally to infer wind power ramp over the entire wind farm by observing the wind power ramp of individual turbines. Along this venue, a key observation is the turbine-level wind power ramp events are not independent, as illustrated in Fig. 3 of previous section. Since the movement of front is a spatio-temporal process, the turbine-level wind power ramp events have a specific spatial dependency structure. Intuitively, when all neighbors of a turbine encounter wind power reduction, it is highly likely the turbine also has a wind power down-ramp. In order to capture this spatial dependency, a Markov random field model is utilized.

Define the turbine-level power ramp indicator at time instant n as follows:

$$x_i^{(n)} = \begin{cases} +1 & \text{if } P_i(n) - P_i(n-1) < 0 \\ -1 & \text{o.w.} \end{cases} \tag{2}$$

Since the random field x is a binary vector, the following logistic model [15] is utilized:

$$p(\mathbf{x};\theta) = \exp\left\{\sum_i^m \theta_i x_i + \sum_i^m \sum_{j\neq i} \theta_{ij} x_i x_j - A(\theta)\right\}. \tag{3}$$

where $A(\theta)$ is the log partition function, and m is the number of turbines. By following the log determinant relaxation approach in [16], the parameter of the above Markov random field is estimated by exactly solving the following sparse maximum likelihood problem:

$$\hat{\theta}_{\text{exact}} = \arg\max_{\theta} \frac{1}{2}\langle R(\theta), R(\bar{\mathbf{x}})\rangle - A(\theta) - \lambda\|\theta\|_1 \tag{4}$$

where λ is the regularization coefficient used to penalize the l_1 norm of solution, $\bar{\mathbf{x}}$ is from historical data, and $R(\theta)$ is a matrix constructed by using the elements of θ. For the wind farm considered in previous examples, the solution to the above problems characterizes a sparse matrix $R(\theta)$, together with a spatial dependency graph of turbine-level wind power ramp indicators $\mathbf{x}$, as illustrated in Fig. 4. It can be seen that most neighbor nodes in the dependency graph are turbines in vicinity to each other, with few exception (possibly due to different local terrain conditions).

2) Turbine-level Wind Power Change Detection: Once the spatial dependency is characterized, turbine-level wind power ramp events can be detected by examining the posterior as below:

$$p(\mathbf{x}, \mu|\mathbf{P}) \propto p(\mathbf{x}) \prod_{i=1}^m p(\mu_i|\mathbf{x})\, p(\mathbf{P}|\mu), \tag{5}$$

in which recall that $\mathbf{x}$ is the vector of turbine-level power ramp indicators, P_i is an observation on the wind power of turbine i during the detection window, and u_i parameterizes the distribution on P_i. In the above posterior, it is assumed that conditioned on turbine-level ramp indicators $\mathbf{x}$,

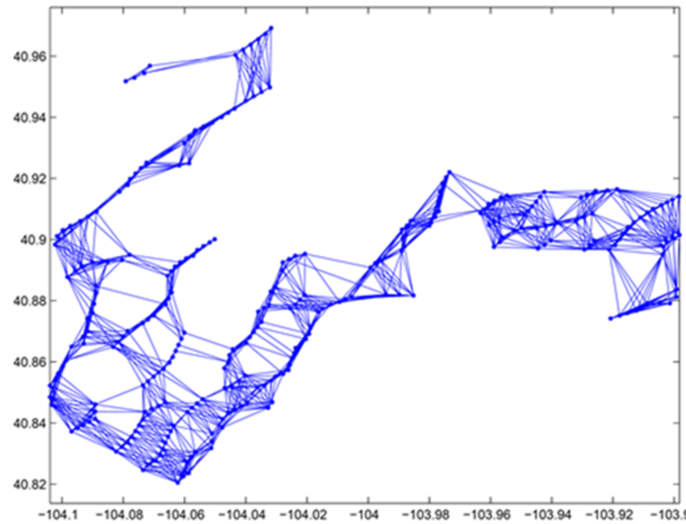


Fig. 4. Dependency graph of turbine-level wind power ramps.

u_i $(i = 1, 2, \cdots, m)$ are independent of each other. This assumption is adopted to account for the possible different types of wind turbines on the same wind farm. Specifically, the turbine-level ramp indicators could be highly correlated, but the absolute change in wind power varies depending on turbine type, hub height, and local terrain conditions. Further, it has been noted that extreme wind power ramps are "outliers," and thus a fixed prior on u_i is not appropriate. Instead, a Bayesian non-parametric approach [17] is adopted here. Specifically, the parameter u_i can be regularized by using Dirichlet priors or Pitman-Yor priors [17]. Finally, variational methods [18] or Markov chain Monte Carlo methods [17] could be utilized for model parameter learning from historical data.

B. Estimation of Front Moving Direction and Speed

By using the turbine-level power ramp indicators $\mathbf{x}$, together with the geographical information (latitude and longitude) of turbines, denoted by $\mathbf{c}$, the movement of front can be estimated by applying a linear classifier to (c, x). Let vector $\tilde{\mathbf{w}}$ denote the front moving direction. Intuitively, during a ramp event, the moving direction of the front would be perpendicular to the boundary between the region with mostly +1 (down-ramp) indicators and the rest of the wind farm. Thus motivated, the direction vector $\tilde{\mathbf{w}}$ can be found by solving the following soft-margin support vector machine problem:

$$\min_{\vec{W},\, \varepsilon, b} \frac{1}{2}\|\vec{w}\|^2 + C\sum_{i=1}^m \varepsilon_i \tag{6}$$

$$\text{s. t.} \qquad x_i(\vec{w}c_i - b) \geq 1 - \varepsilon_i, \forall i = 1, \cdots, m \tag{7}$$

An example of detected front with its moving direction is illustrated in Fig. 5. Specifically, the solid line clearly differentiates turbines with reduced power outputs from the rest. Then, the moving speed of the front can be obtained by estimated wind speeds at the support vector turbines that lie behind the front (e.g., the upstream region in Fig. 5).

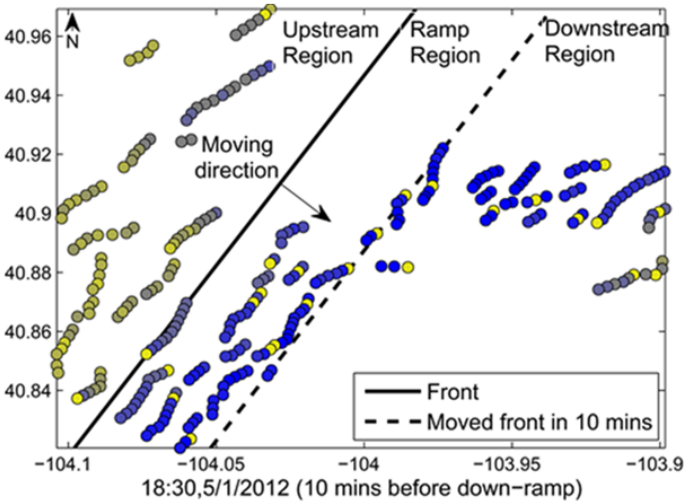


Fig. 5. Detected front and partitioned wind farm regions..

C. Quantification of Impending Wind Power Ramp

According to the detected location and estimated movement of front from the previous step, the wind farm is partitioned into the following three disjoint regions: 1) ramp region - the region of wind farm which is expected to be passed through by front (e.g., the region between the solid line and the dashed line in Fig. 5); 2) upstream region - the region of wind farm which lies behind the current front (e.g., the region behind the solid line against the moving direction); and 3) Downstream region - the region of wind farm which would not be covered by the front in the next time slot (e.g., the region in front of the dashed line along the moving direction in Fig. 5).

Wind power outputs from the three disjoint regions have different predictors, which motivates the partition into three regions before carrying out short-term wind power forecasting. Specifically, wind turbines in ramp region will be driven by totally different wind in the next timeslot, as can be seen from Fig. 5 or the example in Fig. 3. Therefore, the present and recent power measurements of ramp region cannot be used as predictors for wind power forecast of ramp region. However, it is noted that the present turbine-level power outputs in upstream region could be used as the predictors for future wind power output of turbines in ramp region, since they are or will be driven by the same wind. Further, it is easy to see that the all previous aggregate wind power generation in downstream region could be used as predictors for itself (i.e., auto-regression); while for upstream region, only the present aggregate wind power generation could be utilized, due to the passage of front. Accordingly, different forecasting models are applied for the three disjoint regions.

Ramp region forecasting: due to wake effect [19] (i.e., the effect of wind speed reduction when passing through a turbine) and turbine types, the power outputs of the turbines in ramp region and the upstream turbines may not have linear correlations. Therefore, non-linear regression models [20] are used for short-term forecasting for ramp region. It is worth noting that non-linear regression models are dependent on front moving direction $\tilde{\mathbf{w}}$. Further, a non-linear regression model is constructed for each turbine in ramp region, since not all turbine-level wind power measurements from upstream region would contain valuable information. To this end, optimal predictor would be discovered through correlation analysis or predictor important raking techniques (e.g., the regression tree and boosting tree methods used in [11]), by also taking into account turbines' locational information. Upstream region forecasting: since only the present aggregate wind power measurements could be utilized as predictors, first-order Markov chain models developed by the authors in reference [21] are applied to the present power output of the upstream region to provide short-term forecasts. Downstream region forecasting: since all previous measurement data can be used as predictors, high-order auto-regressive (AR) models with parameters obtained by recursive least square estimation [22], [23] is utilized.

IV. Numerical Experiments

A. Forecasting Models and Test Data

Two methods from literature are used as benchmark for performance evaluation and comparison. The first one is an autoregressive model that uses the measurement of actual wind power production from previous time. It is worth mentioning that for very-short-term wind power forecasting, autoregressive model is proven to be very effective to capture the variation in wind power [10]. Particularly, a class of adaptive-order autoregressive models are used to account for the different length of memory and dependency in the wind power time series, as well as to avoid possible over-fitting due to unnecessarily large orders. with their orders. The adaptive orders are determined by using the Box-Jenkins approach [24] through partial autocorrelation analysis. Basically, the Box-Jenkins approach can be regarded as to select the necessary number of predictors (from its past measurements) which would otherwise cause AR models to over-fit. The other benchmark approach is the data mining-based wind power ramp predictor developed in reference [25], which utilizes a set of recent wind power data as inputs to the trained support vector machines to categorize wind power ramp events into classes.

The historical data collected from the wind farm stated in Section II.A is used for numerical experiment. It is worth noting that the data mining-based benchmark approach [25] requires a large amount of training data, whereas the autoregressive model and the proposed approach requires only immediate recent wind power measurements. Therefore, among the four years of available data, data of the first two years is used to train the data mining-based benchmark approach, and those of the subsequent two years are used for testing of all approaches. Further, since the proposed approach is developed for wind power ramp only, the test data is then refined by picking the wind power ramp events. Specifically, wind power down ramps with r_{th}=0.2 and δ t=10 min, i.e., wind power production reduces by over 20% in a 10-min interval are chosen as the refined test cases. Here, it is worth mentioning that compared with up-ramp events, down-ramp events is of much more concern to wind power producers and power system operators [26]. Therefore, only wind power down ramps are tested here.

B. Performance Evaluation

Forecasting performance of the proposed approach and the benchmark approaches is quantified by using the mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE). Detailed definition of these metrics can be found in [21].

The performance of all approaches are measured by using test data, and these metrics are calculated, as shown in Table. I. It is observed that the proposed approach outperforms both the benchmark approaches. The data mining-based approach [25] works better than the autoregressive model, because its predictors are designed to classify wind power ramp levels and are trained by using extensive historical data. Further, for extreme ramps which are essentially rare events, historical data could be irrelevant, as illustrated in Fig. 2. Therefore, the data mining models built from these irrelevant historical data can fail to predict extreme ramps. On the other hand, since the proposed approach incorporates a step of extreme wind power ramp, and use differentiated forecasting models for separate wind farm regions, and is thus more accurate than generic data-mining approaches.

TABLE I
PERFORMANCE EVALUATION

Error	MAE	MAPE	RMSE
Proposed	10.86 MW	10.25 %	16.91 MW
AR	18.34 MW	16.86 %	30.42 MW
SVM [25]	14.81 MW	13.79 %	24.64 MW

V. CONCLUSION

This paper presents a novel approach for wind power ramp forecasting on a wind-farm level. The developed approach is comprised of a detection step followed by differentiated forecasting models for three disjoint regions of wind farm under wind power ramp events. The event detection-based approach requires little training data for operations, and is thus amenable for online applications. The more detailed characterization of wind power ramp events and more supplicated treatment for wind power forecasting per regions makes the proposed approach more accurate than state-of-the-art methods that using generic time-series, statistical, and data mining models. Finally, it is worth noting that the developed approach is exclusively developed for extreme wind power ramp events, and thus cannot replace general very-short-term wind power forecasting models for normal variational conditions of wind power.

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