Regional Wind Power Ramp Forecasting through Multinomial Logistic Regression

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***Abstract*—Wind power ramps are the abrupt yet significant change in wind power productions. The information on the ordinal levels of impending wind power ramp could help power system operator to arm operation or ramping reserves in a timely manner. This paper presents novel approaches for regional wind power ramp level forecasting using real-time meso-scale wind speed measurements. Motivated by the correlation of the meso-scale wind speed measurements with the regional wind power data, the proposed approach utilizes multinomial logistic regression for wind power ramp forecasting. An approach that combines the probabilistic output of individual regressive models in a weighted manner is proposed, with the weights calculated by minimizing the Brier skill score of the combined model. The proposed methods are tested by using real-world data, and is compared with benchmark methods. The results reveal the effectiveness of the proposed approaches.**

***Index Terms*—Multinomial logistic regression, sparse primary component analysis, wind power ramp forecasting.**

I. Introduction

Wind power ramps, which is referred to as the significant changes in the wind power production in a relatively short time period, is a result of the volatility in the wind or meteorological conditions at different geographical scales. Wind power ramps could refer to the abrupt power production change from a single-turbine level or a wind farm level, to regional level or system level. Combining with the uncertain nature of wind power, which makes wind power forecasting can attain a certain level of accuracy, large-scale wind power ramps have posed technical challenges for power system operations. Particulary, the electric reliability council of Texas (ERCOT) has adopted an approach that incorporates wind power ramp risks into the requirements of non-spinning reserves [1], [2]. Further, the ERCOT large ramp alert system (ELRAS) [3] utilizes numerical weather predictions to provide information (including timing, magnitude, direction, and likelihood) on potential large wind power ramps. The information on wind power ramps (magnitude and timing) could alert control room operators of future wind power conditions and energy forecasts so they can make well-informed scheduling decisions.

In spite of such an overall forecasting accuracy of numerical weather prediction models in practice [4], [5], these approaches and systems could fail on providing pertinent and timely information on large wind power ramp events [6]. One key reason is that it is an extremely computationally intensive procedure for global or regional numerical weather prediction models to produce forecasting data, which consists of the processing for synoptic data assimilation, solutions for complex mathematical and physical models (multiple sets of models in the case of ensemble forecasting) of atmospherical variables, and necessary post-processing. Therefore, the output data of numerical weather prediction models may not be generated in a timely manner for determining the timing of wind power ramps. In this context, the approaches and apparatus that utilize real-time measurement data (e.g., wind speed measurement from meteorological station) for wind power ramp forecasting and detection would be very useful.

Proven methods and cost-effective techniques for online wind power ramp forecasting that utilize real-time measurements and apply models trained offline could be found in the survey [7], [8]. More recently, advanced statistical models and data-mining models have also been applied. Sacrificially, an improved short-term wind power forecasting approach is proposed in reference [9] at different temporal and spatial scales, which applies an optimized swinging door algorithm to extract ramp events from actual and forecasted wind power time series. Reference [10] applies supervised learning approaches to predict wind power ramps, and particularly focuses on addressing the class imbalance issues (as large wind power ramps are low-probability events [11]). An empirical mode decomposition based ensemble learning technique that incorporates kernel ridge regression and a random vector functional link network is developed in reference [12] for short-term wind power ramp forecasting. Reference [13] utilizes an elaborate model that feeds input data to a support vector machine for wind power ramp classification. An innovative wavelet-based ramp characteristic function for wind power ramp detection from time series is proposed in reference [14], which is obtained by considering large power gradients evaluated for different time scales. A variety of machine learning techniques (support vector regression, multi-layer perceptrons, extreme learning machines) and Gaussian processes are explored by reference [15] that incorporates hybrid numerical-physical weather models for wind power ramp prediction in real-time systems. Reference [16] presents a data-driven method for probabilistic wind power ramp forecasting based on a large number of simulated scenarios generated from generalized Gaussian mixture models. Other approaches include orthogonal test [17], least-square support vector machines [18], hidden Markov model [19], autoregressive logistic model [20], and the reservoir computing technique [21].

In existing work, as presented in the aforementioned lit-

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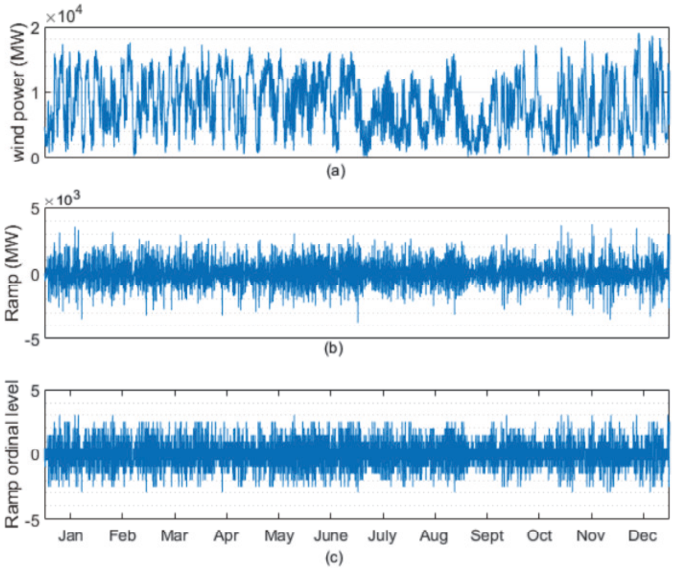

Fig. 1. ERCOT hourly data in 2018: (a) hourly wind power, (b) hourly wind power ramp, and (c) ordinal levels of wind power ramp.

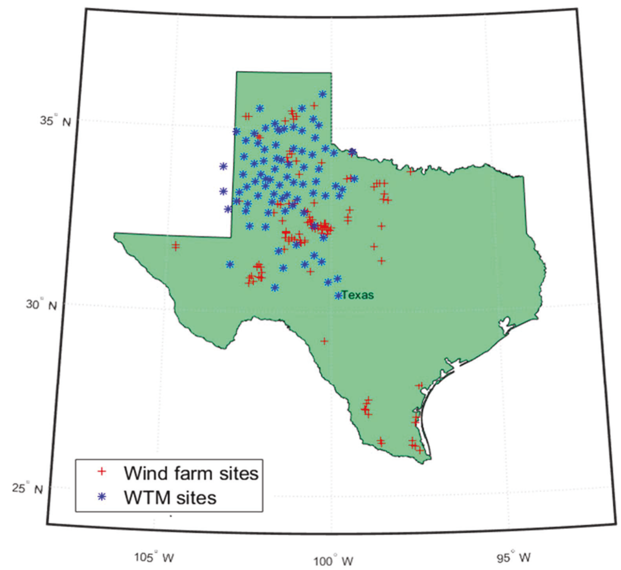

Fig. 2. West Texas Mesonet stations and ERCOT wind farms.

erature, the key predictors for wind power ramp forecasting or classification is mainly a univariate time-series of wind speed or wind power corresponding to real-time measurements collected from one location, meteorological state, or wind farm. For regional wind power ramps that cover an extended geographical region, there could be multiple sources of real-time measurements, which poses a new problem of wind power ramp forecasting with multi-variate measurements. Then, a challenging issue would be the effective fusion and combination of these multi-variate measurements. This paper studies this new problem for regional wind power data based on logistic classification models, by developing a weighted voting model to combine the decision of individual logistic classifiers. Further, the logistic classification models utilized are all multinomial, in the sense that they will predict the ordinal levels of wind power ramps.

The rest of the paper is organized as follows. Description and discussion of ERCOT regional wind power data and the Mesonet wind speed measurements are presented in Section II. Section III presents the proposed approaches to regional wind power ramp forecasting. The results of numerical experiments using real-world data are presented in Section IV. Finally, conclusions are given in Section V.

II. Data and Key Observations

A. Ordinal levels of wind power ramp

As mentioned above, numerical weather predictions models is capable of producing accurate forecasting of the magnitude of wind power ramps; however, the high computational complexity and low data refreshing rate of these models may compromise the timely delivery of these forecasts. Instead, predictive or classification models that utilizes real-time measurements can provide unrefined yet timely information on impending wind power ramps. One kind of this information would be the ordinal levels [21] of wind power ramps. More specifically, categorical or numerical labels could be assigned to the wind power ramps with magnitude falling into specific ranges. For example, a wind power ramp within the range $(2.5\text{GW}, 2\text{GW}]$ could be labeled as '2' or 'Large Up Ramp', and one in the range $[-3\text{GW}, \infty)$ could be labeled as '-3' or 'Extreme Down Ramp. By using the numerical labels for the hourly wind power ramps of ERCOT, the ordinal information is plotted in Fig. 1. It can be seen that the ordinal levels (represented by the numerical labels) could capture of the levels of wind power ramp with sufficient fidelity for the purpose of power system operations and ramping reserve acquisition. Therefore, this study aims at predicting the ordinal levels of hourly wind power ramp.

B. Real-time Mesonet measurements

The predictors used for wind power ramp forecasting are the wind speed measurements from West Texas Mesonet [22]. The West Texas Mesonet is comprised of 120 stations that monitor key meteorological attributes, including wind (speed, direction, and gust speed), temperature, solar radiation, humidity, air pressure, etc. The measurement devices take measurements every 3 second, and report 1-minute (or 5-minute for old stations) and 15-minute average values to data center. The coverage of West Texas Mesonet in the West Texas and Panhandle regions, as well as on the ERCOT's grid-connected wind farms in these regions, could be seen from Fig. 2.

To reveal the relevance of the Mesonet wind speed measurements to the hourly wind power ramp in the West Texas and Panhandle region, the hourly average wind speed data of Mesonet is calculated and the regional wind ramp data for West Texas and Panhandle regions is obtained from ERCOT's hourly averaged wind power data by geographical region [23]. Then, correlation analysis is carried out between the hourly

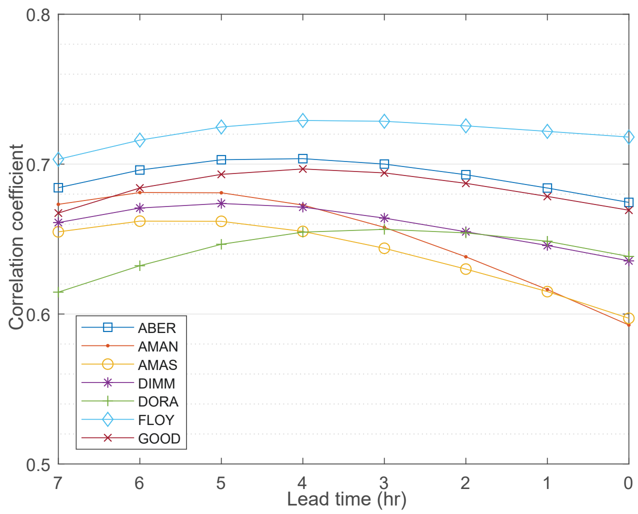

Fig. 3. Correlation between wind speed measurements and wind power data.

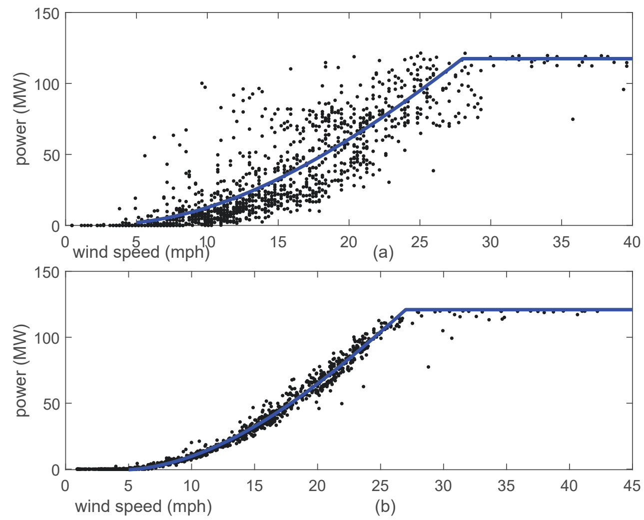

Fig. 4. Power curves of wind farms (a) 'CHAMPION', and (b) 'CSEC'.

wind data from each of the Mesonet site and the regional wind power data for different values of lead time. The results for a few representative sites are shown in Fig. 3. Two key observations could be drawn from Fig. 3: 1) the wind speed measurements at the Mesonet sites are highly correlated with the regional wind power data, with correlation coefficients ranging from 0.6 to 0.8; 2) the correlation coefficients for different Mesonet sites could peak at different lead time. For example, for the Mesonet site 'FLOY' in Fig. 3, the regional wind power data has the highest correlation (with a coefficient of 0.76) with the wind speed measurements of 4 hours ago at Mesonet site 'FLOY'. This is because the Mesonet sites are dispersed in this extended geographical region, and thus the variations in the aggregate regional wind power could lag that of the wind speed measurements at a single Mesonet site. This also explains that different sites may have different lead time for maximal correlation to the regional wind power, depending on their relative location to the wind farms of the region.

C. Logistic regression for wind power ramp forecasting

From the observation on the high correlation as illustrated in Fig. 3, it would be effective to apply a linear regressive model [24] to the log-odds of wind power ramp, by using the Mesonet wind speed measurements within a lead time window of up to N hours as the predictors, which is given by

$$\log\left(\frac{\Pr(\tilde{Y}_t=1)}{\Pr(\tilde{Y}_t=0)}\right)=\beta_1 w_{m,t-1}+\cdots+\beta_Q w_{m,t-Q}, \quad (1)$$

in which $\Pr(\tilde{Y}_t{=}1)$ is the forecast probability that wind power ramp occurs at time slot t, the predictors (i.e., $w_{m,t-1}$,$w_{m,t-2}$,$\cdots$, $w_{m,t-Q}$) are the wind speed measurement at the m-th Mesonet site within a time window of Q hours (Q could be chosen to be 6 based on the observation from Fig. 3) immediately ahead of the time slot t, and β are the corresponding regressive coefficients of the predictors. It is worth mentioning that logistic regression has been applied to wind power ramp forecasting (e.g., in literature [20] and the references therein). However, the prior studies apply regression to the same wind power time-series for wind power ramp forecasting in an autoregressive manner, and the predictors are univariate (in the sense that they are from the same time-series). In sharp contrast, this paper is focused on utilizing multi-variate predictors which are wind speed measurements from dispersed locations in an extended geographical region. It is noted that by using multiple sources of data as multi-variate predictors, the regressive models have significant potentials for improving the performance of wind power ramp forecasting. However, due to the complex nature and the distinct lead time for the Mesonet measurements from different sites, there is no existing approaches for efficient fusion or combination of the multi-variate predictors for regional wind power forecasting. This work will fill this gap by developing a combination of individual logistic regressive models.

D. Hourly average of wind speed measurements

In (1), the regressive variables are the hourly wind speed measurements at a Mesonet site. The raw wind speed measurements reported by Mesonet sites are 5-minute or 1-minute data, and thus, averaging of the measured wind speed data is needed. Note that similar to the manufacture's power curve of wind turbines, the fitted power curve of wind farms could also be comprised of a cubic region followed by a rated-power region, as can be seen from the two examples in Fig. 4. Therefore, for ramp events where the wind speed is typically in the cubic region, the wind power is fundamentally related to the cube of wind speed. Further, preliminary statistical analysis of historical wind speed measurements of Mesonet sites reveal that the wind speed measurements very well follow Weibull distributions, as illustrated by the two example on the site 'AMAN' (1-minute data, a scale parameter of λ=4.9 m/s and a scale parameter of k=1.7) and the site 'SASU' (5-minute data, a scale parameter of λ=3.6 m/s and a scale parameter

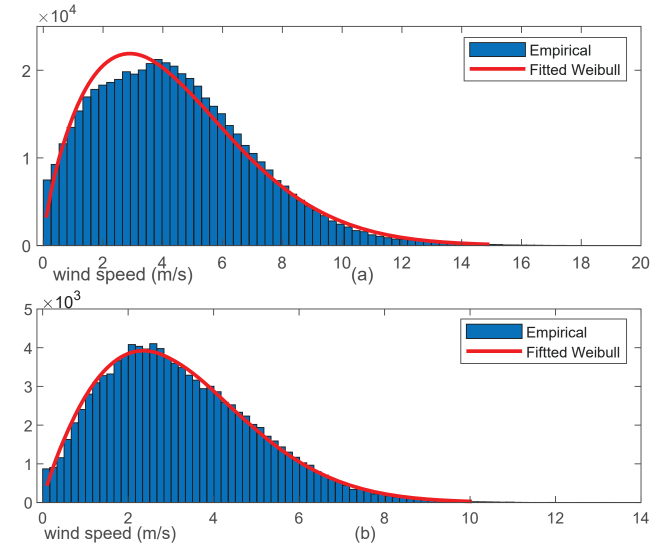

Fig. 5. Weifull distribution of wind speed (a)'AMAN' and (b) 'SASU'.

of k=1.8) using the year 2015 data. With these observations, let $\bar{w}_{n,t}$ denote the hourly mean of the 1-minute or 5-minute wind speed measurements. Then, the hourly mean of the cube of 1-minute or 5-minute wind speed measurements is given by:

$$\overline{w^3}_{n,t} = \bar{w}^3_{n,t}\frac{\Gamma(1+3k^{-1})}{\Gamma^3(1+k^{-1})}, \tag{2}$$

where $\Gamma(\cdot)$ is the gamma function. Therefore, in the Logistic regressive model of (1), it is more appropriate to use the hourly mean of the cube of 1-minute or 5-minute wind speed measurements $\overline{w^3}_{n,t-1},\cdots,\overline{w^3}_{n,t-Q}$ as the regressive variables. To this end, all the 1-minute or 5-minute wind speed measurements of Mesonet are pre-precessed according to (2).

III. Proposed Approach

In what follows, multinomial logistic regression for predicting the ordinal levels of wind power ramps is first introduced. A scheme for combining multiple logistic regressive models through weighted voting is developed, and the weights are obtained by minimizing a probabilistic forecast skill score.

A. Multinomial logistic regression for ordinal forecasting

Let K be the number of wind power ramp levels. For example, Fig.1.(c) illustrates 10 levels of wind power ramp. Then, the objective of the ordinal wind power forecasting model is to assign a label $\tilde{Y}_t$=k to indicate that the forecast ramp level for time slot t is k ($k \in \{1,\cdots,K\}$). By applying multinomial logistic regression [25] to the wind speed measurement at the m-th Mesonet site, the forecast probability of an ordinal level k is given by

$$\Pr(\tilde{Y}_{mt}=k) = \frac{1}{z}e^{\boldsymbol{\beta}^T_{mk}\mathbf{w}_{mt}}, \tag{3}$$

in which $\mathbf{w}_{mt}$=$(w_{m,t-1},\cdots,w_{m,t-Q})^T$ is a vector of the wind speed measurements at the m-th Mesonet site in the forecasting time window with a window size of Q, $\boldsymbol{\beta}_{mk}$ is a vector of corresponding regressive coefficients for the k-th ordinal level, and z is partition function [26] that normalizes the forecast provability which is given by z=$\sum_{k=1}^{K} e^{\boldsymbol{\beta}^T_{mk}\mathbf{w}_{mt}}$. The set of regressive coefficients in each vector $\boldsymbol{\beta}_{mk}$ are obtained by fitting the above models to the training data through maximum a posteriori (MAP) estimation [27].

B. Combination of multiple regressive models

With the multinomial logistic regressive models built for the wind speed measurements from each Mesonet site, the forecast decision could be combined to produce an aggregate forecasting model that is more accurate than any individual ones. By adopting a weighted voting scheme, the forecast probability of the aggregate forecasting model is given by:

$$\Pr(\tilde{Y}_t=k) = \sum_{m=1}^{M} a_m \Pr(\tilde{Y}_{mt}=k) = \sum_{m=1}^{M}\frac{a_m}{z_m}e^{\boldsymbol{\beta}^T_{mk}\mathbf{w}_{mt}}, \tag{4}$$

where a_m is the voting weight of the regressive model built by using wind speed measurements from the m-th Mesonet site, and $\sum_{m=1}^{M} a_m$=1 is chosen to normalize the forecast probabilities. Then, a natural question would be how to find the voting weights a_m so that the aggregate forecasting model has optimal performance. To this end, the multi-class Brier skill score [28] for probabilistic forecast is utilized to quantify the performance of the aggregate model:

$$S(\mathbf{Y},\tilde{\mathbf{Y}};\mathbf{a}) = \sum_t \sum_{k=1}^{K}(\mathbf{1}_{\{Y_t=k\}} - \Pr(\tilde{Y}_t=k))^2, \tag{5}$$

where t is the index of training data, $\mathbf{1}_{\{\cdot\}}$ is the indicator function, and Y_t is the actual ordinal level of the wind ramp occurring at time slot t. Therefore, it holds that $\mathbf{1}_{\{Y_t=k\}}$=1 only when a level-k wind ramp occurred at time slot t. Therefore, the the vector of voting weights $\mathbf{a}$ could be obtained by minimizing the probabilistic forecast skill score:

$$\mathbf{a}^* = \operatorname*{argmin}_{\mathbf{a}} S(\mathbf{Y},\tilde{\mathbf{Y}};\mathbf{a}) \tag{6}$$

subject to the constraint that $\sum_{m=1}^{M} a_m$=1. For brevity, let y_{kt} denote $\mathbf{1}_{\{Y_t=k\}}$, p_{mkt} denote $\Pr(\tilde{Y}_{mt}=k)$ (note that the values of y_{kt} and p_{mkt} are already known). Further, let $\mathbf{p}_{kt}$ be the vector of p_{mkt} $(m=1,\cdots,M)$. Then,

$$\Pr(\tilde{Y}_t=k) = \sum_{m=1}^{M} a_m \Pr(\tilde{Y}_{mt}=k) = \mathbf{a}^T\mathbf{p}_{kt}. \tag{7}$$

Then, the Lagrangian for the problem in (6) is given by:

$$L(\mathbf{a},\lambda) = \frac{1}{2}\sum_{kt}(y_{kt}-\mathbf{a}^T\mathbf{p}_{kt})^2 + \lambda(1-\mathbf{e}^T\mathbf{a}), \tag{8}$$

where $\mathbf{e}$ is an M-by-1 all-one vector. The gradient of the Lagrangian has the following components:

$$\frac{\partial L(\mathbf{a},\lambda)}{\partial \mathbf{a}} = \sum_{kt}(\mathbf{a}^T\mathbf{p}_{kt}\mathbf{p}^T_{kt} - y_{kt}\mathbf{p}^T_{kt}) - \lambda\mathbf{e}^T, \tag{9}$$

$$\frac{\partial L(\mathbf{a},\lambda)}{\partial \lambda} = 1 - \mathbf{e}^T\mathbf{a}. \tag{10}$$

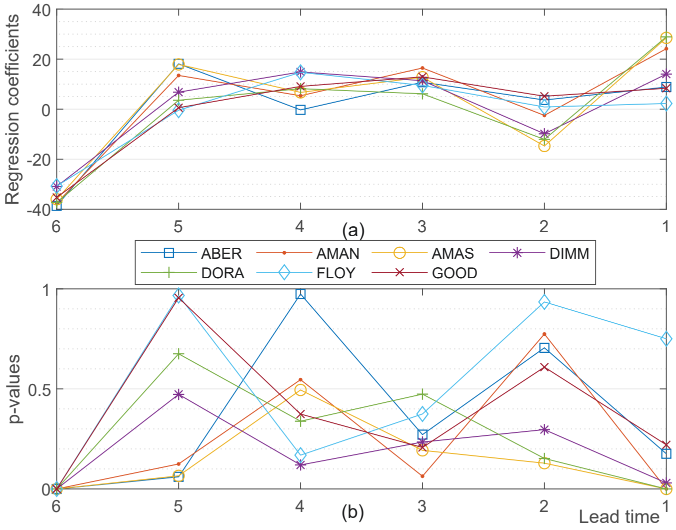

Fig. 6. regressive models: (a) regressive coefficients, and (b) p-values.

Solving for $\mathbf{a}$ and λ such that the gradient is zero, yielding:

$$\lambda^* = \left(1 - \mathbf{e}^T\mathbf{P}^{-1}\sum\nolimits_{kt} y_{kt}\mathbf{p}_{kt}\right) / \mathbf{e}^T\mathbf{P}^{-1}\mathbf{e}, \tag{11}$$

$$\mathbf{a}^* = \mathbf{P}^{-1}(\lambda^*\mathbf{e} + \sum\nolimits_{kt} y_{kt}\mathbf{p}_{kt}), \tag{12}$$

where $\mathbf{P}=\sum_{kt}\mathbf{p}_{kt}\mathbf{p}_{kt}^T$ is non-singular when a sufficient amount of training data is used.

IV. Case Study

A. Training and Testing Data

The year 2015 hourly wind power data for the region of West Texas and Panhandle, together with the year 2015 Mesonet wind speed measurement data, is used for training. The trained logistic regressive models are then tested using corresponding 2016 data. The number of forecasting ordinal levels is set to 6, among which two level corresponds to extreme ramps (>3GW and <-3GW), and four levels for evenly distributed between [-3GW, 3GW]. To account for the seasonality and diurnal non-stationary, as revealed in prior work [29], [30], the logistic regressive models are built for data corresponding to each month and each of the four 6-hour intervals of a day.

B. Regressive analysis

For each model, the hourly wind speed measurements within a 6-hr time window is used as the predictors. By following the proposed approach, individual regressive models are built by using the measurement from a single site only. The parameters of the trained regressive models (for ordinal level k=2, i.e., up ramp within (1.5GW, 3GW]) for 7 representative sites are shown in Fig. 6. In Fig. 6(a), a higher positive regressive coefficient indicates that the probability of a level-k wind power ramp could increase more significantly w.r.t. that wind speed measurement. In Fig. 6(b), a higher p-value indicates that the wind speed measurement is statistically less significant, and thus could be excluded from the regression model. Note that the p-value for the intercept term is not plotted in Fig. 6(b). One key observation from Fig. 6 is that not all wind speed measurements within the same 6-hour window are significantly relevant to wind power ramp forecasting. This also raises the needs for feature extraction of the wind speed measurements from multiple Mesonet sites through sparse PCA. Based on the observations from Fig. 6(b) for the seven models built by using the data from seven sites, a threshold of 0.05 is adopted for the p-values, and it turns out that 112 of the 516 (6×86) regressive variables are statistically significant.

C. Performance Evaluation

The proposed approach is tested and compared with a benchmark approach. For the benchmark approach, multinomial logistic regressive models are built by using wind speed measurements from a single site (which is consistent with the practice in state-of-the-art work, e.g., [21]). The performance metric for ordinal wind power ramp forecasting is the multi-class Brier skill score defined in (5). Two performance measures are produced for the benchmark approach: 1) the lowest Brier skill score of all models, and 2) the average of the lowest Brier skill score per each test data point. Note that the latter is unattainable in practice, since which individual model produces the best forecast is not known a priori. The results are shown in Table. I. It can be seen that the proposed approach has the minimum score, indicating that it outperforms the existing approach (Benchmark 1 and 2). The Brier skill scores for the training data is also shown in Table. I, wherein the lower score basically indicates that the model fits the training data better (yet unnecessarily generalizes better though). Further, the impact of the ordinal level K on the forecasting performance is illustrated in Table. II. The proposed method have performance degradation as the number of forecast ordinal levels increases, which shows the tradeoff between forecasting accuracy and refined ordinal levels.

TABLE I
Performance Evaluation

	Benchmark 1	Benchmark 2	Proposed 1
Brier score (training)	0.016	0.015	0.017
Brier score (testing)	0.089	0.065	0.071

TABLE II
Impact of Level Number k

K	2	4	6	10	16
Proposed	0.056	0.062	0.071	0.083	0.122

V. Conclusion

A new approach for predicting the ordinal levels of regional wind power ramp in ERCOT by using real-time wind speed measurements from multiple Mesonet sites are proposed in this paper. The proposed approach builds multinomial logistic regressive models by using separate Mesonet data, and combines only the forecast output of individual models. The work presented in this paper provides examples and insights of using dispersed measurement data as multi-variate predictors for regional wind power forecasting.

VI. Acknowledgment

This research was supported in part by NSF under grant ECCS-1653922 and in part by ERCOT.

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