# Quantifying Risk of Wind Power Ramps in ERCOT

Jie Zhao, *Student Member, IEEE,* Sajjad Abedi, *Student Member, IEEE,* Miao He, *Member, IEEE,* Pengwei Du, *Senior Member, IEEE,* Sandip Sharma, *Member, IEEE,* Bill Blevins, *Member, IEEE*

***Abstract*—Hourly wind power ramps in ERCOT are studied by applying extreme value theory. Mean excess plot reveals that the tail behavior of large hourly wind power ramps indeed follows a generalized Pareto distribution. The location, shape and scale parameters of generalized Pareto distribution are then determined by using mean excess plot and the least square technique, from which risk measures including $\alpha$ quantile VaR and CVaR are calculated.**

***Index Terms*—ERCOT, extreme value theory, generalized Pareto distribution, risk assessment, wind power ramp.**

## I. Introduction

Grid-connected wind power generation in ERCOT has increased dramatically in the past decade, with installed capacity increased from 2GW in 2006 to 16GW by 2015. Particularly, there were 464 hours in total in 2015 when over 30% of system load in ERCOT was served by wind power. As wind power generation is intermittent, uncertain and not fully dispatchable, wind power ramps pose grand operational challenges. Probabilistic models and risk measures for hourly wind power ramps would provide invaluable information for scheduling generation resources and acquiring adequate reserves [1].

Recently, there has been a vast amount of effort directed toward statistical modeling and analysis of wind power ramps (see [2], [3] and the references therein). However, it is noted that for $\alpha$ (e.g., 5% or more conservatively, 1%) quantile risk measures, statistical models that characterize the tail distribution of large wind power ramps are more pertinent. Indeed, recent study [4] has demonstrated that real-world wind power ramp data exhibits heavier tails than common parametric probabilistic models fitted to these data. Therefore, quantitative risk assessment of wind power ramps requires different treatment and models from those in literature.

In this paper, extreme value theory is applied to examine the tail characteristics of wind power ramp data, and generalized Pareto distribution is utilized to model large wind power ramps. The data used in this study is the ERCOT hourly wind power ramp data from 2011 to 2015, normalized to corresponding installed capacity, resulting in a knowledge base of 43,824 data points in total. The proposed probabilistic modeling and subsequent risk assessment is carried out for wind power up ramps and down ramps separately. Further, modeling and risk assessment of wind power ramp is carried out for each month and each hour of day, to account for seasonality and diurnal non-stationarity.

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Jie Zhao, Sajjad Abedi, and Miao He are with Department of Electrical and Computer Engineering, Texas Tech University, Lubbock, TX 79409, USA (e-mail: Jie.Zhao@ttu.edu; Sajjad.Abedi@ttu.edu; Miao.He@ttu.edu). Pengwei Du, Sandip Sharma, and Bill Blevins are with Electric Reliability Council of Texas, Tayler, TX, 76574, USA (e-mail: Pengwei.Du@ercot.com; Sandip.Sharma@ercot.com; Bill.Blevins@ercot.com).

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## II. Wind Power Ramp Modeling

Large wind power ramps are low-probability events. As revealed in the prior work [5], less than 5% of hourly wind power ramps in ERCOT had a magnitude greater than '$3\sigma$' (where $\sigma$ is the standard deviation). Therefore, in order to quantify typical risk measures, e.g., $\alpha$ ($\alpha\leq 5\%$) quantile value at risk (VaR) or conditional value at risk (CVaR), accurate models for the tail distribution of wind power ramps is the key. To this end, extreme value theory provides useful tools.

Specifically, according to extreme value theory [6], the conditional probability distribution of the magnitude of an up or down ramp $X$, given that it exceeds a large threshold $\mu$, can be well approximated by a generalized Pareto distribution, i.e.,

$$\Pr\left\{X-\mu\leq x|X>\mu\right\}\approx G_{\mu,\epsilon,\beta}\left(x\right), \tag{1}$$

where $\mu$, $\epsilon$, $\beta$, and $G_{\mu,\epsilon,\beta}\left(\cdot\right)$ denote the location parameter, shape parameter, scale parameter, and cumulative distribution function of a generalized Pareto distribution, in which

$$G_{\mu,\epsilon,\beta}\left(x\right)=1-\left(1+\epsilon(x-\mu)/\beta\right)^{-1/\epsilon}. \tag{2}$$

Two technical issues arise when generalized Pareto distribution is to be applied: 1) whether large hourly wind power ramp data follows a generalized Pareto distribution, and 2) what is an appropriate threshold $\mu$, beyond which large wind power ramps exhibit the tail behavior dictated by generalized Pareto distributions. Mean excess plot can address both issues. Specifically, the mean excess function, $e(\nu)\triangleq \mathrm{E}(X-\nu|X>\nu)$, could be characterized by using (1) and (2), as follows:

$$e(\nu)=\left(\beta+\epsilon(\nu-\mu)\right)/(1-\epsilon),\ \nu\geq\mu. \tag{3}$$

This unique property, which is a result of 'threshold stability' [6] of generalized Pareto distribution, shows that $e(\nu)$ is linear in terms of $\nu$. Thus, the plot of $e(\nu)$ against $\nu$ is a line with slope $\epsilon/(1-\epsilon)$ and intercept $(\beta-\epsilon\mu)/(1-\epsilon)$ for $\nu\geq\mu$. With this insight, empirical values of $e(\nu)$ for all wind power ramp data are calculated and plotted. If the plot contains a linear tail, then generalized Pareto distribution is applicable, and the point at which linearity begins in the plot is the threshold $\mu$. An example of applying this mean excess plot-based approach is illustrated in Fig. 1. It can be seen that the threshold $\mu$ is 4% (647MW out of 16GW), and wind power down ramps greater than $\mu$ follow a clearly linear mean excess function, which indicates the applicability of generalized Pareto distribution.

Once the location parameter $\mu$ is determined, the shape parameter $\epsilon$ and the scale parameter $\beta$ could be estimated

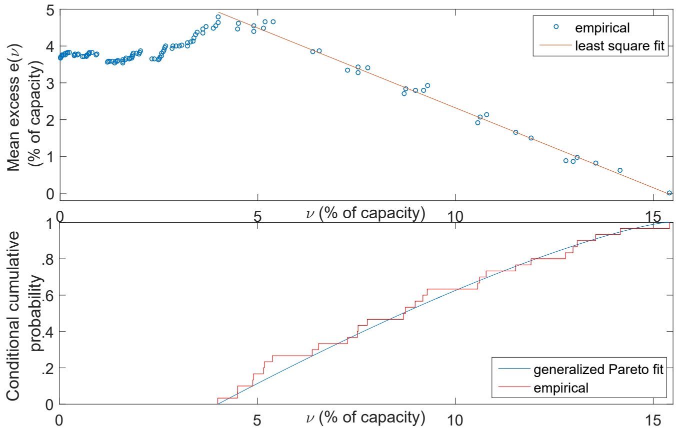


Fig. 1. mean excess plot (least sqaure fit RMS error 0.103) and Pareto type II fitted tail of wind power down ramp for November 17:00PM.

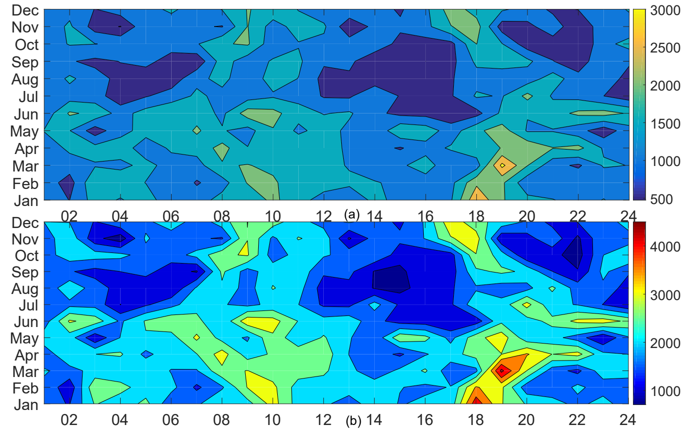


Fig. 2. 5% VaR (MW) of hourly wind power down ramp for installed capacity (a) 16GW and (b) 24GW, by month and by hour of day.

by applying maximum likelihood methods to the data that is greater than $\mu$. However, a more straightforward yet equally effective approach is to fit a straight line to the data on the mean excess plot using the least square technique, as shown in Fig. 1. Using the slope $a$ and intercept $b$ of the fitted line, the shape and scale parameters are then calculated as follows:

$$\epsilon = a/(1+a), \quad \beta = (b + a\mu)/(1+a). \tag{4}$$

Once all the parameters are known, the conditional cumulative probability could be calculated, and compared with empirical values to verify the capability of generalized Pareto distribution in characterizing the tail behavior of large wind power ramps. This is also shown in Fig. 1. Note that the generalized Pareto fit starts at the threshold 4%, and does not model any wind power down ramp that is lower than this threshold. Therefore, compared with common parametric models that aim to model entire data set, generalized Pareto distribution is more suitable for large wind ramp modeling and risk assessment, to which there are two main reasons: 1) small wind power ramps may have arbitrary distribution while large wind ramps follow generalized Pareto distribution, and thus a model for both could undermine its fitness to large wind power ramps; 2) the distribution of small wind power ramps contains little information for quantifying $\alpha$% risk measures.

## III. Risk Assessment

The $\alpha$ quantile VaR implies that with $1-\alpha$ confidence hourly wind power ramp is no greater than $\text{VaR}_\alpha$. Let $F$ denote the cumulative probability distribution of hourly wind power ramp, then $\alpha$ quantile VaR is given by $\text{VaR}_\alpha = F^{-1}(1-\alpha)$. As the tail of $F$ has been characterized by generalized Pareto distribution, it follows from (1) and (2) that VaR is given by:

$$\text{VaR}_\alpha = \mu + \beta\left(((1-F(\mu))\alpha)^{-\epsilon} - 1\right)/\epsilon, \tag{5}$$

for which the empirical value of $F(\mu)$ could be used. The $\alpha$ quantile CVaR is defined as the conditional mean of hourly wind power ramp, given that its magnitude exceeds $\text{VaR}_\alpha$, i.e., $\text{CVaR}_\alpha \triangleq \text{E}(X|X > \text{VaR}_\alpha)$. By definition, it can be seen that $\text{CVaR}_\alpha = \text{VaR}_\alpha + e(\text{VaR}_\alpha)$. Thus, by using the mean excess function in (3), the $\alpha$ quantile CVaR is given by:

$$\text{CVaR}_\alpha = (\text{VaR}_\alpha + \beta - \epsilon\mu)/(1-\epsilon). \tag{6}$$

Note that both $\text{VaR}_\alpha$ and $\text{CVaR}_\alpha$ are also normalized values to capacity. These values times projected installed capacity would produce the risk measures of hourly wind power ramp for future years. The 5% quantile VaRs for wind power down ramps are presented here. Numerical results for two scenarios: a) the contemporary 16GW capacity and b) a projected 24GW capacity are illustrated in Fig. 2. It can be seen that large wind power down ramps are very unlikely in afternoon of warm seasons, due to convection or low-level jets; whereas a considerable portion of largest down ramps are concentrated around early evening in winter season, as a result of rapid slackening of pressure gradient, which is aggravated by the fact that load could ramp to peak within the same time frame.

## IV. Conclusion

An interesting finding by this work is that large ramps in system-level wind power indeed follow a tail behavior that can be characterized by generalized Pareto, more specifically, Pareto type II distributions, which builds the foundation for calculating $\alpha$ quantile VaR and CVaR in a rigorous and computationally efficient manner. Note that extreme value theory has proven to be applicable to extreme wind speed [7] and farm-level wind power ramp [4]. Therefore, the proposed approach for risk assessment could also be useful to other power systems with wind power generation at different scales. It is necessary to point out that a majority of increased wind generation in ERCOT in the past decade is from West Texas and Panhandle area, which have homogenous geographical and climate characteristics. However, the emerging wind resources in other in-land and coastal areas may bring new statistical signatures to wind power ramps.

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