Ramp Detection Methods for Renewable Energy Integration

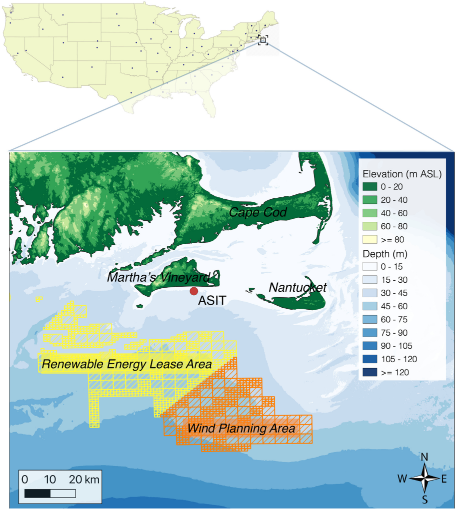
Zhe Wang[1], Malaquias Peña[2]

[1] Data Analytics, Denison University

[2] Department of Civil & Environmental Engineering, University of Connecticut

October 11, 2021

Offshore Wind Renewal Energy



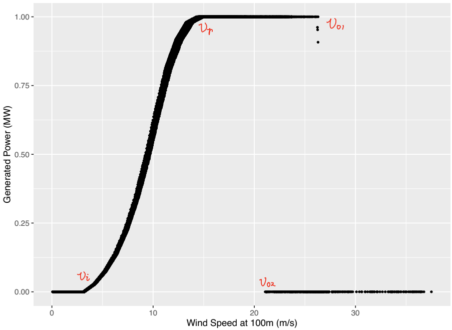
Wind Ramp

- **Ramp events** are described by sudden increases or decreases of wind speed in a short time period.
- For ramp-up events, the producer may shut down the turbines to avoid any damage. For ramp-down events, the operator may switch on fast hydro units.
- Ramp events have different definitions
  - e.g. 60% capacity change in 30 minutes
- Ramp events are defined on the generated power, however, ramp events detection should be performed on the **wind speed**.

Power Curve

- The *cut-in* speed (v_i) is the minimum speed at which the turbine deliver useful power.
- The *rated* speed (v_r) is the wind speed at which the maximum output power is obtained.
- The *cut-out* speed ($v_o = (v_{o1}, v_{o2})$) has two components:
  - v_{o1} is the maximum wind speed at which the turbine is allowed to produce power;
  - When the wind speed start decreasing from the highest speed, the maximum speed at which the turbine returns to normal operation is v_{o2}.

Power Curve



1. Step 1: detect the ramp events in wind speed;
2. Step 2: project the wind speed to generated power by 5-parameter logistic function;
3. Step 3: delete the ramp events outside of [**cut-in speed**, **rated speed**];
4. Step 4: add the rapid change around two cut-out speed.

Method 1: Wavelet Transformation and Ramp Function

The gradient of signal at different time scales can be captured by the **wavelet transform** based on the Haar function. λ is the sliding window length.

$$W_H^{t,\lambda} = \begin{cases} \lambda^{-1/2}\left(\sum_{j=1}^{\lambda/2} x_{t+j-1} - \sum_{j=1}^{\lambda/2} x_{t-j}\right) & \text{, if } \lambda \text{ is even} \\ \lambda^{-1/2}\left(\sum_{j=1}^{(\lambda-1)/2} x_{t+j} - \sum_{j=1}^{(\lambda-1)/2} x_{t-j}\right) & \text{, if } \lambda \text{ is odd} \end{cases}$$

Ramp function is defined by the sum of wavelet coefficients within the interval $\lambda_1 \leq \lambda \leq \lambda_N$

$$R_t(\lambda_1, \lambda_N) = \sum_{\lambda=\lambda_1}^{\lambda=\lambda_N} W_H^{t,\lambda}$$

*A common choice of λ_1 is 2.

Method 1: Wavelet Transformation and Ramp Function

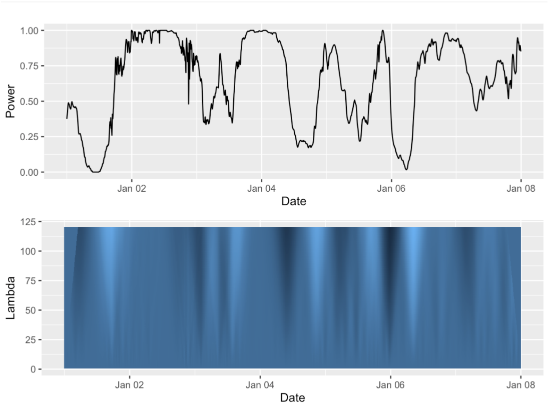


Figure: **Top**: Power output during an 8 days period. **Bottom**: Standardized wavelet transformation for different values of λ_N. Brighter shade shows positive gradients, which corresponds to the ramp up events. Dimmer shade shows negative gradients, which corresponds to the ramp down events. In this study, $\lambda_N = 24$ can capture ramp events with duration up to 4 hours.

Method 1: Wavelet Transformation and Ramp Function

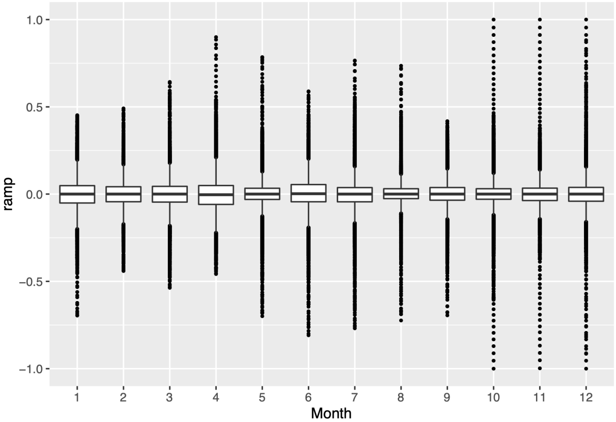


Figure: Distribution of standardized ramp function for each month.

- Ramp-up events are labeled by $R_t > Q_3^+ + 1.5IQR^+$ while ramp-down events are labeled by $R_t < Q_1^- - 1.5IQR^-$.

Method 1: Wavelet Transformation and Ramp Function

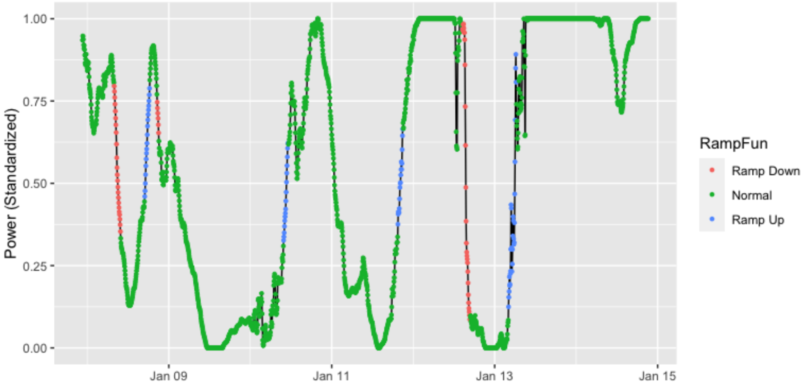


Figure: Ramp events captured by ramp function.

Method 2 : Kalman Filter Method

- Assuming the overall wind speed follows **Rayleigh** distribution. Then the wind speed in two orthogonal directions are **uncorrelated, normally distributed with equal variance and zero mean.**
- On each direction (X_t), apply Kalman filter:

$$\begin{array}{ll} \text{Observation Space:} & X_t = F_t\theta_t + u_t, u_t \sim N(0, U_t) \\ \text{State Space:} & \theta_t = G_t\theta_{t-1} + w_t, w_t \sim N(0, W_t) \end{array}$$

Estimate the parameter recursively, at time t:

- low posterior density in observation space $X_t|(X_1, ..., X_{t-1}) \sim N(f_t, Q_t)$ indicates outlier;
- low posterior density in state space $\theta_t|(X_1, ..., X_t) \sim N(m_t, C_t)$ indicates change point.

$$\begin{array}{cc} m_t = a_t + R_t F' t Q_t^{-1}(X_t - f_t), & a_t = G_t m_{t-1} \\ C_t = R_t - R_t F' t Q_t^{-1} F_t R_t, & f_t = F_t a_t \\ R_t = G_t C_{t-1} G_t' + W_t, & Q_t = F_t R_t F_t' + V_t \end{array}$$

Method 2: Kalman Filter Method

- Suppose $X_1, ..., X_n$ are *i.i.d.* random variables from any distribution $\mathcal{F}$. The extreme value probability(EVP) of x is defined as

$$P_{EV}\left(x|\{X_1, ..., X_n\}\right) = P(x \geq X_{(n)})$$

- By the Fisher and Tippett theorem, an EVP is expressed as the generalized extreme value distribution, which is generally not easy to evaluate.
- However, if the target distribution is assumed to be one-sided standard normal $|N(0,1)|$, the EVP is analytically obtained in the form of the Gumbel distribution

$$P_{EV}\left(z|\{Z_1, ..., Z_n\}\right) = exp[-exp(-\frac{z-\mu_n}{\sigma_n})]$$

$$\mu_n = \sqrt{2\ln n} - \frac{\ln(\ln n) + 2\pi}{2\sqrt{2\ln n}}, \sigma_n = (2\ln n)^{-1/2}$$

Method 2: Kalman Filter

- Since the EVP only dependes on current run length r_t. Stochastically

$$r_t = \begin{cases} 1, & \text{with } p = P_{EV}(t-1) \\ r_{t-1}+1, & \text{with } p = 1 - P_{EV}(t-1) \end{cases}$$

  and

$$P(r_t) = \begin{cases} P_{EV}(t-1), & \text{if } r_t = 1 \\ (1 - P_{EV}(t-1))\, P(r_{t-1}), & \text{otherwise} \end{cases}$$

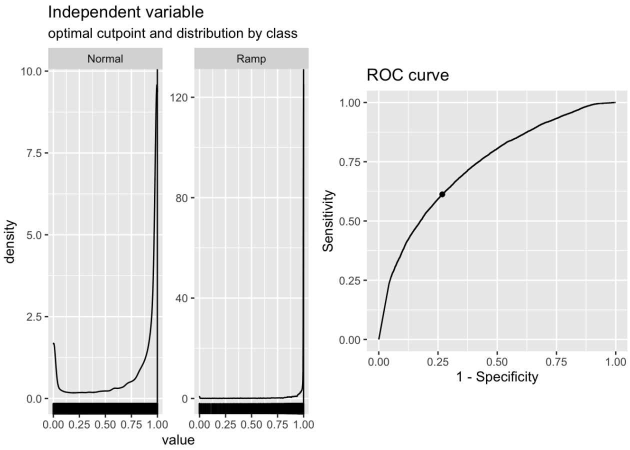
- To get the EVP at time t, we margin out the run length by

$$P_{EV}(Z_t) = \sum_{i=1}^{t} P_{EV}\left(Z_t | \{Z_t^{(r_t)}\}\right) P(r_t = i)$$

  where $\{Z_t^{(r_t)}\} = \{Z_{t-r_t+1}, ..., Z_t\}$ is the set of the most recent data since the last change point.
- Calculate the EVP for each point in the state space and observational space. A novelty flag is raised if it exceeds some threshold.

Method 2: Kalman Filter

- Ensemble Kalman filter outperformed Kalman filter in this case. To select the best cut-off point for the extreme value probability, use the results from Method 1 as benchmark,



Method 3: Swinging Door Algorithm

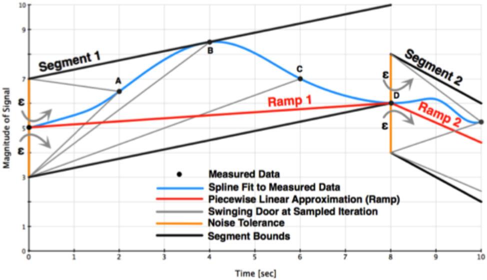


Figure: The tuning parameter is ϵ. The scales are arbitrary for illustration purposes. In this study, we choose $\epsilon = 0.025$.

- Use swinging door algorithm to have **segmentation** of the time series.
- Fit piece-wise linear regression on each segment. Label the whole segment as a ramp event if the slope go beyond the threshold.

Method 3: Swinging Door Algorithm

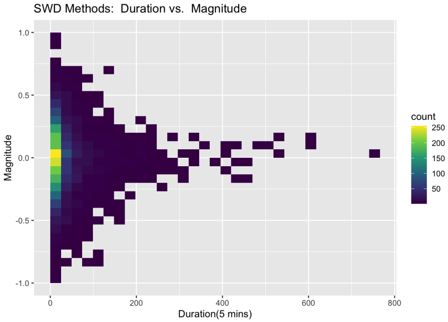


Figure: Distribution of segments.

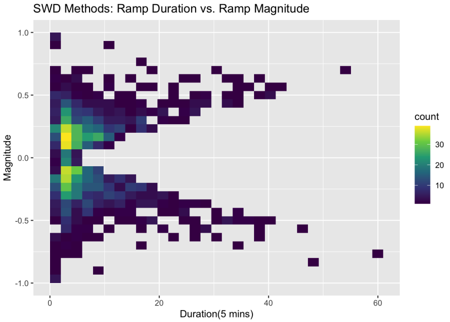


Figure: Distribution of ramps.

Method 4: Bayesian Online Changepoint Detection

- Bayesian online changepoint detection also focus on segmentation. We denote the run length since the last changepoint at time t by r_t, BOCD will recursively estimate the posterior $P(r_t|X_{1:t})$
- The predictive distribution can be written as

$$P(X_{t+1}|X_{1:t}) = \sum_{r_t} P\left(X_{t+1}|\{X_t^{(r_t)}\}\right) P(r_t|X_{1:t})$$

where $\{X_t^{(r_t)}\} = \{X_{t-r_t+1}, ..., X_t\}$ is the set of the most recent data since the last change point.

Method 4: Bayesian Online Changepoint Detection

- The posterior can be updated recursively by

$$P(r_t|X_{1:t}) = \frac{P(r_t, X_{1:t})}{\sum_{r_t} P(r_t, X_{1:t})}$$

where

$$\begin{aligned} P(r_t, X_{1:t}) &= \sum_{r_{t-1}} P(r_t, r_{t-1}, X_{1:t}) \\ &= ... \\ &= \sum_{r_{t-1}} P(r_t|r_{t-1}) P\left(X_t|r_{t-1}, \{X_t^{(r)}\}\right) P(r_{t-1}, X_{1:t-1}) \end{aligned}$$

Method 4: Bayesian Online Changepoint Detection

- To calculate the growth probability $P(r_t|r_{t-1})$, the run length at time t has two situations:

$$r_t = \begin{cases} 0, & \text{if } X_{t-1} \text{ is a changepoint} \\ r_{t-1}+1, & \text{else} \end{cases}$$

with the corresponding changepoint prior:

$$P(r_t|r_{t-1}) = \begin{cases} H(r_{t-1}+1), & \text{if } X_{t-1} \text{ is a changepoint} \\ 1 - H(r_{t-1}+1), & \text{else} \end{cases}.$$

where $H(.)$ is the hazard function.

- The occurrence of ramp events has memoryless property, thus a constant hazard function will be used.
- In our case, the projected wind speed follows (conjugated) normal distribution, the parameters can be updated sequentially.

Method 4: Bayesian Online Changepoint Detection

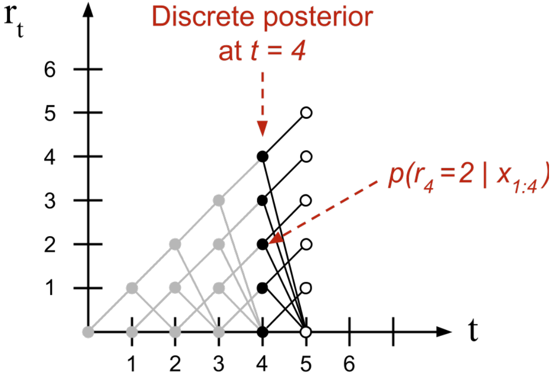


Figure: Diagram of the message-passing algorithm. $P(r_4 = 2|X_{1:4})$ is associate with the node indexed by $t = 4$ and $r_t = 2$.

Method 4: Bayesian Online Changepoint Detection

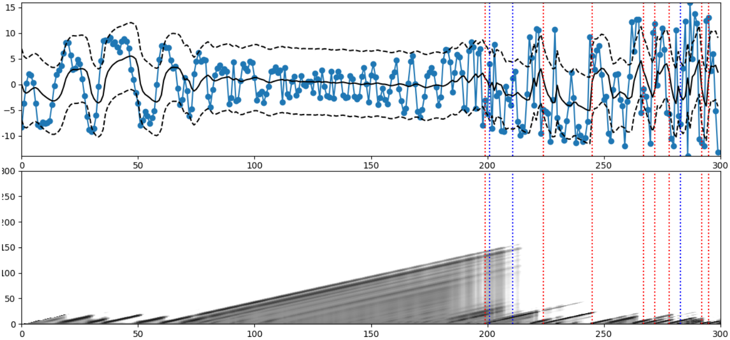


Figure: **Top:** Wind speed series with posterior mean and variance. **Bottom:** $P(r_t|X_{1:t})$ with changepoint detected by swinging door algorithm (blue) and BOCP(red.)

Summary

- Wavelet method (method 1) is offline detection method. While the other three are online detection methods.
- Wavelet method and Kalman filter method can provide binary labels to each time point(during a ramp or not).
- While swinging door algorithm and BOCP return to the segmentation of the data, which can provide the distribution of ramp duration and magnitude.