Grid Frequency Extreme Event Analysis and Modeling

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Maria Folgueras, Erin Wenger, Anthony Florita, Kara Clark, and Vahan Gevorgian
National Renewable Energy Laboratory

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Grid Frequency Extreme Event Analysis and Modeling

Maria Folgueras, Erin Wenger, Anthony Florita, Kara Clark, and Vahan Gevorgian
National Renewable Energy Laboratory
Golden, CO, USA

Abstract—Sudden losses of generation or load can lead to instantaneous changes in electric grid frequency and voltage. Extreme frequency events pose a major threat to grid stability. As renewable energy sources supply power to grids in increasing proportions, it becomes increasingly important to examine when and why extreme events occur to prevent destabilization of the grid. To better understand frequency events, including extrema, historic data were analyzed to fit probability distribution functions to various frequency metrics. Results showed that a standard Cauchy distribution fit the difference between the frequency nadir and pre-fault frequency \((f_{C-A})\) metric well, a standard Cauchy distribution fit the settling frequency \((f_B)\) metric well, and a standard normal distribution fit the difference between the settling frequency and frequency nadir \((f_B-C)\) metric very well. Results were inconclusive for the frequency nadir \((f_C)\) metric, meaning it likely has a more complex distribution than those tested. This probabilistic modeling facilitates more realistic modeling of grid faults.

Keywords—frequency; voltage; extreme events; probabilistic

NOMENCLATURE

- \(f_A\) – Avg. of freq. from -16s to 0s before an event [Hz] [17]
- \(f_B\) – Avg. of freq. from 20s to 52s after an event [Hz] [17]
- \(f_C\) – Freq. nadir, min. freq. achieved during a loss of gen. event [Hz] [17]
- \(f_{C-A}\) – Difference between \(f_C\) and \(f_A\) \((f_C - f_A)\) [Hz]
- \(f_{max}\) – Max. freq. prior to a loss of gen. event [Hz] [3]
- \(\Delta t\) – Freq. delta \((f_C - f_{max})\) [Hz] [3]
- \(T(0)\) – NERC-defined point at which a min. freq. change of at least 5 mHz occurs within a 1s time span [Hz] [17]
- \(\Delta f\) – Time duration of freq. event [s]
- \(t_c\) – Time at which \(f_C\) occurs [hh:mm:ss]
- \(t_{max}\) – Time at which \(f_{max}\) occurs [hh:mm:ss]
- RCOF – Rate of change of freq.; slope of the event [Hz/s]
- \(H\) – Inertia coefficient [MW-s]
- \(FR_{Current}\) – Measure of effectiveness of primary freq. response capabilities to correct freq. deviations during an event [MW/Hz] [15]
- \(f_{B-C}\) – Difference between \(f_B\) and \(f_C\) \((f_B - f_C)\) [Hz]

I. INTRODUCTION

The electric grid transmits and distributes electricity across the U.S. at a nominal frequency of 60 Hz [1]. Synchronous generators set the frequency and come equipped with primary control reserves [2]. These reserves, also known as primary frequency response (PFR), assist in recovering the grid frequency after it deviates from the nominal value sharply (i.e., the difference between the maximum and minimum event frequency exceeds 70 mHz in a 15-second rolling window) [3] or significantly (i.e., the frequency is less than 59.95 Hz or more than 60.05 Hz in the Western Interconnection) [4]. Secondary and tertiary frequency responses also act to correct frequency deviations to the nominal value (much like PFR), but they are delivered after PFR and during longer time periods [5]. Frequency deviations can result from an instantaneous loss of generation or load [6]. Frequency response controls are needed to prevent frequency deviation events.

Extreme frequency events are characterized “by non-linear responses, low probabilities, high consequences, and the potential for systems interaction that leads to catastrophic losses” [7]. They could be brought about by extreme weather, interrupting power generation and transmission, but also, in the near future, the impact of high penetrations of renewable power onto the grid. Renewable sources exacerbate challenges to frequency stability and grid reliability because of their variable and uncertain operation [8]. Renewable sources do not come equipped with synchronous generators or PFR capabilities [8], meaning that when large amounts of inverter-based renewable generation are brought onto the 60-Hz operating grid, PFR capabilities might be reduced unless the renewable power plants are equipped with special frequency responsive controls [9]. Instabilities in generation can cause extreme events such as underfrequency load-shedding, triggering under/overfrequency protection relays, and reaching the frequency nadir [1]. Reaching the frequency nadir can lead to cascading failures on the grid because at this point the grid frequency is no longer regulated and stabilized at its nominal value [10].

Issues of grid reliability have turned the focus of research to grid resilience during and after an extreme event. Generally, two factors affect infrastructure resilience after an extreme event: robustness and rapidity. Robustness is a measure of how much of the system remains functioning after an extreme event, and rapidity is a measure of how quickly the entire system can fully function again after the event [11]. The U.S. electric grid comprises countless power plants and millions of miles of transmission lines, thus it is the largest infrastructure in the world, and it can be categorized and studied in the vein of infrastructure.
resilience. Extreme events greatly stress the grid, and must be understood to allow for the integration of larger amounts of renewable energy penetration. By studying previous extreme events, outage frequencies, and outage durations, probability models were developed to attempt to predict these events happening in the future. The results suggest that these models can be used by system operators to approximate the probability of future frequency events, to plan generation and load balancing accordingly, and to possibly prevent frequency events from occurring as often as they do on the present electric grid.

II. DATA AND METHODOLOGY

A. Description of Data

Electric frequency data collected at NREL’s National Wind Technology Center (NWTC) was obtained, with date, time, and frequency, during an approximate 2-year time span. The monitoring system is a National Instruments model cDAQ-9171 chassis with a 9225 voltage measurement module (24-bit, 300 VRMS), and was plugged into a 110-V wall outlet and connected to a PC using a USB 2.0 cable (Figure 1) [12].

![Figure 1. Frequency monitoring system used at the NWTC to collect frequency data for this project. Reprinted from [12].](image)

Data were collected from August 1, 2014, until June 10, 2016, with occasional days of data missing because of unplanned device disconnections. The provided data were collected every 2 ms from August 1, 2014, to April 31, 2016, and collected every 1 ms from May 1, 2016 onward.

B. Data Validation

NWTC data were validated by comparing them to frequency event records provided by the North American Electric Reliability Corporation (NERC) [13]. At the time of the study, NERC had provided frequency event data only through March 31, 2016. For each frequency event recorded by NERC, the corresponding NWTC data were compared. The specific frequency decrease pattern before, during, and after the events were analyzed to determine a frequency event match. Events when frequency increased were ignored in this study; such events are not of interest as they represent a loss of load whereas this study focuses on loss of generation. In the subset of matched data, various frequency metrics were calculated from the NWTC data and compared to the corresponding NERC data. These metrics included $f_A$, $f_B$, $f_C$, and $f_C-A$. The metrics $f_{max}$, $\Delta f_A$, and $T(0)$ were also determined but not for comparison purposes (Figure 2) [14].

![Figure 2. Graphical representation of frequency event on November 13, 2015, from NWTC data (verified with NERC records) [14].](image)

After qualitative data analysis, a five-point moving average of the NWTC dataset was taken to smooth the data in an attempt to remove some of the variability and noise in the NWTC data that was not present in the NERC data. All previously mentioned values were again determined ($f_A$, $f_B$, $f_C$, $f_{C-A}$, $f_{max}$, $\Delta f_A$, and $T(0)$). This new five-point average dataset is referred to as the NWTC MA dataset. The percentage differences among the various NERC, NWTC, and NWTC MA values were calculated and used as comparison metrics (Table 1). The percentage differences between the NWTC and NWTC MA values were particularly important because they highlighted the impact of the applied five-point moving average on the data.

C. Calculation of Frequency Response Metrics

To calculate various frequency response metrics for each event recorded in the NWTC dataset, the time duration of the event (Equation 1) and the rate of change of frequency (Equation 2) were both determined.

$$\Delta t = t_C - t_{max} \quad (1)$$

$$ROCOP = \frac{\Delta f}{\Delta t} \quad (2)$$

The generation loss, $\Delta P$, that occurred during each event was provided by NERC [12]. This gave enough information to calculate the inertia coefficient (Equation 3) [5].

$$H = \left| \frac{f_A \Delta P}{2 \times ROCOP} \right| \quad (3)$$

Finally, the frequency response as defined by NERC was calculated for each event (Equation 4) [15].

$$FRC_{current} = \frac{\Delta P}{f_A - f_B} \quad (4)$$

Various combinations of the calculated data were plotted as scatterplots to identify causal patterns (Table 2). Linear regressions were performed and $R^2$-values compared. An evaluation was made of how the number of frequency events varied during different time frames. The number of events per month in the studied time frame (August 1, 2014, to March 31, 2016) and the number of events per season in the studied time frame were analyzed.
TABLE I. DETERMINED OR CALCULATED METRICS USED IN DATA VALIDATION FOR EVENT ON NOVEMBER 13, 2015

<table>
<thead>
<tr>
<th></th>
<th>NERC</th>
<th>NWTC</th>
<th>% Δ b/w NERC and NWTC</th>
<th>NWTC MA</th>
<th>% Δ b/w NERC and NWTC MA</th>
<th>% Δ b/w NWTC and NWTC MA</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_a$ (Hz)</td>
<td>60.019</td>
<td>60.019</td>
<td>4.17e-04%</td>
<td>60.019</td>
<td>5.33e-04%</td>
<td>1.17e-04%</td>
</tr>
<tr>
<td>$f_a$ (Hz)</td>
<td>59.950</td>
<td>59.951</td>
<td>1.00e-03%</td>
<td>59.951</td>
<td>9.84e-04%</td>
<td>1.67e-05%</td>
</tr>
<tr>
<td>$f_c$ (Hz)</td>
<td>59.924</td>
<td>59.922</td>
<td>3.39e-03%</td>
<td>59.923</td>
<td>2.39e-03%</td>
<td>1.00e-03%</td>
</tr>
<tr>
<td>$f_{c-a}$ (mHz)</td>
<td>-95.000</td>
<td>-96.780</td>
<td>-1.87e+00%</td>
<td>-96.110</td>
<td>-1.17e+00%</td>
<td>-6.92e-01%</td>
</tr>
<tr>
<td>$f_{max}$ (Hz)</td>
<td>NA</td>
<td>60.020</td>
<td>NA</td>
<td>NA</td>
<td>60.019</td>
<td>NA</td>
</tr>
<tr>
<td>$\Delta f$ (mHz)</td>
<td>NA</td>
<td>-97.700</td>
<td>NA</td>
<td>NA</td>
<td>-96.450</td>
<td>-1.28e+00%</td>
</tr>
<tr>
<td>$T(0)$ (Hz)</td>
<td>NA</td>
<td>60.005</td>
<td>NA</td>
<td>NA</td>
<td>60.004</td>
<td>2.57e-03%</td>
</tr>
</tbody>
</table>

TABLE II. SCATTERPLOTS USED TO ANALYZE CALCULATED DATA

| Scatterplots       | $H$ vs. $\Delta P$ | $H$ vs. $\Delta t$ | NERC $f_c$ vs. $\Delta t$ | NWTC $f_c$ vs. $\Delta t$ | NWTC MA $f_c$ vs. $\Delta t$ |

III. ANALYSIS

A. Linear Regression

An acceptable linear relationship was found between the calculated $H$-values and $\Delta t$ from the NWTC data (Table 3); i.e., an $R^2$-value of 0.7932. It should be noted a limited amount of data used: only 67 events, and of those 67 events, 22 did not have $\Delta P$ information from NERC, and 1 had too much noise in the NWTC data to properly analyze the event. As a result, only 44 events could be used in linear regression analysis. More data could help strengthen the $R^2$-value and thus the linear correlation between $H$ and $\Delta t$. It is also clear that the $H$ and $\Delta t$ $R^2$-value suggests a stronger linear correlation between $H$ and $\Delta t$ when compared to the other $R^2$-values obtained in this analysis (Table 3).

![Figure 3. Inertia coeff. $H$ vs. time duration of event $\Delta t$ for NWTC data](image)

B. Variation of Number of Events over Time

A correlation was found to exist between the number of events and the month in which they occurred. There seems to be a cyclical pattern: more events occur in the spring (March, April, May) and fall (Sept., Oct., Nov.) (Figure 4). Results suggest a relationship between extreme events and seasonality (Figure 4). More events occur during the “shoulder” or off-peak spring and fall months than during the peak summer and winter months (Figure 5). An explanation for this pattern might be that grid operators take advantage of off-peak seasons to commission facility maintenance, replacement, or new construction. As a result, fewer generators are online and supplying power to the grid during these seasons. A smaller pool of online generators lowers the inertia of the grid, making it more susceptible to instability with a sudden loss of generation or load [16].

![Figure 4. Number of frequency events per month in the studied August 1, 2014, to March 31, 2016, time frame](image)

TABLE III. LINEAR REGRESSION ANALYSIS OF VARIOUS SCATTERPLOTS

<table>
<thead>
<tr>
<th>Scatterplot</th>
<th>$R^2$-value</th>
<th>Slope of Regression Line</th>
<th>Intercept of Regression Line</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H$ vs. $\Delta P$</td>
<td>0.0023</td>
<td>185.72</td>
<td>2e+06</td>
</tr>
<tr>
<td>$H$ vs. $\Delta t$</td>
<td>0.7932</td>
<td>223636</td>
<td>231197</td>
</tr>
<tr>
<td>NERC $f_c$ vs. $\Delta t$</td>
<td>0.1094</td>
<td>0.0026</td>
<td>59.891</td>
</tr>
<tr>
<td>NWTC $f_c$ vs. $\Delta t$</td>
<td>0.1246</td>
<td>0.0028</td>
<td>59.885</td>
</tr>
<tr>
<td>NWTC MA $f_c$ vs. $\Delta t$</td>
<td>0.1125</td>
<td>0.0027</td>
<td>59.888</td>
</tr>
</tbody>
</table>

A positive linear correlation between $H$ and $\Delta t$ means that as the inertia coefficient of the system ($H$) increases, the time duration of the event ($\Delta t$) also increases (Figure 3). This is reasonable because $H$ and $\Delta t$ are directly proportional through the combination of (2) and (3):

$$H = \frac{f_a \Delta P}{2 \text{ ROCOF}} = \frac{f_a \Delta P}{2 \left( \frac{\Delta P}{f_a} \right)} = \frac{f_a \Delta P \Delta t}{2 \Delta f}$$

(5)
C. Probability Distribution Functions

From the density histogram of the normalized $f_{C-A}$ metric, a standard Cauchy distribution was determined to most closely fit the empirical density function of the dataset (Table 4, Figure 6).

<table>
<thead>
<tr>
<th>Dataset</th>
<th>$\mu$</th>
<th>$\sigma$</th>
<th>Interval of $\mu \pm 1\sigma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normalized</td>
<td>0</td>
<td>1</td>
<td>(-1, 1)</td>
</tr>
<tr>
<td>Original</td>
<td>-86.59831 mHz</td>
<td>37.41474 mHz</td>
<td>(-124.013 mHz, -49.18357 mHz)</td>
</tr>
</tbody>
</table>

This means that 68.2% of the normalized $f_{C-A}$ observations is contained within the interval (-1,1) and that 68.2% of the original $f_{C-A}$ observations is contained within the interval (-124.0 mHz, -49.2 mHz).

From the density histogram of the normalized $f_B$ metric, results were inconclusive in fitting a distribution to the empirical density function of the dataset (Figure 7). Consequently, the dataset likely has a more complex distribution than those tested.

Assuming a standard normal distribution, 68.2% of the $f_C$ observations are contained within the interval (-1,1). As such, 68.2% of the original $f_C$ observations are contained within the interval (59.87557 Hz, 59.95576 Hz).

From the density histogram of the normalized $f_{B-C}$ metric, a standard normal distribution was determined to best fit the empirical density function of the dataset (Table 6, Figure 9).
TABLE VI. PARAMETERS OF NORMAL DISTRIBUTION FOR NORMALIZED AND ORIGINAL $f_{B-C}$ DATASETS

<table>
<thead>
<tr>
<th>Dataset</th>
<th>$\mu$</th>
<th>$\Sigma$</th>
<th>Interval of $\mu\pm\sigma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normalized</td>
<td>0</td>
<td>1</td>
<td>(-1, 1)</td>
</tr>
<tr>
<td>Original</td>
<td>31.78 mHz</td>
<td>15.98 mHz</td>
<td>(15.80 mHz, 47.76 mHz)</td>
</tr>
</tbody>
</table>

Figure 9. Density of normalized NWTC $f_{B-C}$ with overlaid empirical and standard normal distributions

Again, 68.2% of the normalized $f_{B-C}$ observations are contained within the interval (-1,1), and 68.2% of the original $f_{B-C}$ observations are contained within the interval (15.80 mHz, 47.76 mHz).

Q-Q and P-P plots of both the normalized and original $f_{B-C}$ data supported the assertion that a standard normal distribution fits the metric very well (Figure 10). This suggests that the quantiles of the empirical distribution match the quantiles of the theoretical distribution for the normalized $f_{B-C}$ data well. Most points appear to lie close to the reference line, with greater deviations occurring at both tails. These deviations are caused by the few outliers in the normalized $f_{B-C}$ dataset, which correspond to outliers in the original $f_{B-C}$ dataset (Figure 11). Most of the data in the original $f_{B-C}$ dataset are clustered in the range from 4 mHz to 58 mHz, though three outlier points occur at $f_{B-C}$ values of -23.97 mHz, -13.81 mHz, and 74.61 mHz.

These outliers represent frequency events of greater “extremity,” indicating events that have larger frequency deviations from the nominal value. Fewer events of greater extremity are expected because adequate reserves are online and providing inertia to the grid. These reserves include generators that provide PFR, secondary frequency response, and tertiary frequency response to arrest frequency deviations quickly in most instances of a loss of generation or load.

Figure 10. Q-Q plot for normalized $f_{B-C}$ data with overlaid reference line $y = x$

Figure 11. Histogram of original $f_{B-C}$ dataset

With $\mu = 31.77815$ mHz and $\sigma = 15.97807$ mHz, the original $f_{B-C}$ data have the reference line $y = 0.03177815x + 0.01597807$ for a Q-Q plot, and the plotted points again lie closely (Figure 12). This suggests that the quantiles of the empirical distribution closely match the quantiles of the theoretical distribution for the original $f_{B-C}$ data. Similar to Figure 10, most points appear to lie closely to the reference line, with greater deviations occurring at the tails. The deviations correspond to the same outliers previously discussed from the original $f_{B-C}$ dataset (Figure 11). In fact, Figure 10 and Figure 12 are identical, except for the scale on the y-axis. This is significant because it suggests that a standard normal distribution is a good fit for the original $f_{B-C}$ data, not solely the normalized $f_{B-C}$ data.
Figure 12. Q-Q plot for original $f_{B-C}$ data with overlaid reference line $y = 0.03177815x + 0.01597807$

The normalized $f_{B-C}$ data considered in a P-P plot (Figure 13) suggests that the empirical cumulative distribution function (CDF) matches the theoretical CDF for the normalized $f_{B-C}$ data well. The middle points appear to lie closely to the reference line, with greater deviations occurring at the tails of the dataset. These deviations correspond to the three outliers previously analyzed in the original $f_{B-C}$ data (Figure 11).

Figure 13. P-P plot for normalized $f_{B-C}$ with overlaid reference line $y = x$

IV. CONCLUSIONS & RECOMMENDATIONS

Understanding past frequency events will help lower the risks associated with increased levels of renewable generation onto the grid. Using existing frequency event data, probability models of various frequency metrics have been developed. These models help assess frequency stability and grid reliability. The models suggest that more data are necessary for fitting. The data used in this analysis contained only 65 data points. Future work could include fitting probability density functions to the same frequency metrics but for a larger number of frequency events.

Frequency event data have been collected at the NWTC since June 16, 2011, and data collection is ongoing.

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