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Addendum to the 2015 Eastern Interconnect Baselining and Analysis Report

BG Amidan
JD Follum

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Pacific Northwest National Laboratory
Richland, Washington 99352

Executive Summary

This report serves as an addendum to the report "2015 Eastern Interconnect Baselining and Analysis Report" (Amidan, Follum, and Freeman, 2015). This addendum report investigates the following:

- the impact of shorter record lengths and of adding a daily regularization term to the date/time models for angle pair measurements,
- additional development of a method to monitor the trend in phase angle pairs,
- the effect of changing the length of time to determine a baseline, when calculating atypical events, and
- a comparison between quantitatively discovered atypical events and actual events.

The purpose of the Date/Time Modeling approach is to calculate normal operation ranges for phase angle pairs. The model uses the effects due to the day of week and hour of the day to predict the next day's phase angle pair difference values and to create these ranges. A daily regularization term was added to the model. This term was the value of the phase angle pair at midnight (although any other time of day could also work). It was found that adding this term helped adjust to changes in the system configuration faster. This allowed the interval ranges to better track the changes in the system, resulting in less deviation from the normal operation ranges. When adding the regularization term, it is important to note that this term could be unintentionally masking a change in conditions that could have occurred at the same time.

Originally, the Date/Time Model used 4 weeks of data to help train the model to best capture the effects due to the day of week and hour of day. Using a 1 week, 2 week, and 3 week window was investigated. Results showed that 1 week and 2 week windows resulted in a lot more data being identified as abnormal (outside of the normal operational ranges). The 3 week window performed very similarly with the 4 week window. It is recommended that the window used to train the Date/Time Model be at least 3 weeks. Results from the 3 week and 4 week window ranges were compared to ranges determined by EPG. Ranges were generally tighter for the Date/Time Model and more variable as the ranges are dynamically calculated each day.

A complementary method to the date/time model is a method of indicating when the phase angle separation has a significant trend. Our initial look into this method showed promise. Further development of this method could help identify unusual grid behavior that develops over the course of several minutes or even hours.

Multivariate baselining was discussed in the previous report and is used to help identify unusual grid behavior. It was decided to investigate how the length of the baseline influences the identification of unusual data points. The use of 2 week, 1 month, and 2 month baselines were investigated. It was found that unusual events determined using the 2 month baseline were not the same as the 2 week or 1 month determined unusual events. This indicates that the baseline did not have enough time to stabilize. Further investigation should be performed to determine how much time is needed to stabilize the baseline. More data would be necessary to perform this investigation.

The last investigation looked at how the baselining determined atypical events compared to actual events. For this, BPA PMU data was used, because more data was available and lists of actual events were also available. The baselining algorithms were not very good at determining line outages, as these

type of outages are generally not noticed in PMU data. There were 3 line outages that were detected and these were considered major line outages. Frequency events were also compared. The baselining algorithms detected all the frequency events that happened within the footprint of the data. The baselining algorithms found an additional possible frequency event that looked like the others, but had not been detected. The baselining algorithms also found 3 other events that were not on any actual event lists. These events were voltage related and two of them were based on spikes in the voltage measurements. The other event was a gradual increase that resulted in a long time period of voltage measurements outside of the normal values. This anomaly was discovered relying upon multiple variables and would have most likely not been detected using a single variable baselining approach.

Acknowledgments

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1.0 Introduction

The proliferation of phasor measurement units (PMUs) in power systems has made new monitoring and analysis applications possible. Where supervisory control and data acquisition (SCADA) data is limited by its low reporting rate and lack of synchronization, PMU data can provide tremendous benefits. At the same time, these qualities tend to lead to vast volumes of PMU data that cannot be practically analyzed with conventional techniques. To address the data volume challenges of PMU data while developing new analysis capabilities, a DOE funded project pairing the research organizations Pacific Northwest National Laboratory (PNNL) and Electric Power Group (EPG) with Eastern Interconnection (EI) system operators PJM, MISO, NYSO, and ISO-NE was undertaken. Results of the PNNL portion of the project as of November 2015 were reported in (Amidan, 2015). This report serves as an addendum to (Amidan, 2015) to discuss additional analyses that were completed after the primary report was published.

One of the efforts detailed in (Amidan, 2015) was the development of date/time models for voltage angle pair measurements. These models, which took the day of the week and hour of the day as inputs, predict the following day's normal behavior with upper and lower ranges. In (Amidan, 2015), the model is developed using a sliding window of four weeks of past data. In this report, the impacts of shorter record lengths and of a daily regularization term are examined. The ranges are also compared with those produced by EPG's methods.

The results in (Amidan, 2015) for the date/time model were generated using a set of data spanning from December 15, 2013 to February 15, 2014. This set of data is referred to as the Winter 2014 dataset. In this addendum, results from application of the methods to the Fall 2014 dataset, which spans September 1, 2014 through November 1, 2014 are also presented.

Another contribution of this report is the description of a method to monitor the trend in phase angle pairs. The method, which is in the early stages of development, uses filtering to highlight large changes in the phase angle pair that take several minutes to develop. With further development, the method may prove useful in identifying unusual conditions that come about gradually and may otherwise go unnoticed.

Amidan et al (2015) discussed ways to determine a baseline and identify atypical system conditions using that baseline. This report will investigate the effect of changing the amount of time to determine a baseline. It will also do a comparison of atypical events to actual events to help provide insight into future precursor investigations.

The results presented in this report demonstrate the successful application of new analysis techniques to large quantities of PMU data. The analyses highlighted system events that may be of interest to system operators. With further development, the methods could be used to improve the situational awareness of system operators.

2.0 Date/Time Modeling

In power systems, abnormal phase angle values can be indicative of unusual, and possibly detrimental, system conditions. Thus, phase angle pairs can be monitored to improve the situational awareness of system operators. To distinguish between normal and abnormal phase angle pairs, the natural variation in the measurements that occur daily, weekly, and seasonally should be taken into account. The date/time modelling approach described in (Amidan, 2015) was developed for this purpose.

Mathematically, the date/time model in (Amidan, 2015) can be described as

$$\hat{A} = \mu + W_j + T_k + \varepsilon_{j,k}$$

where $\hat{A}$ is the predicted phase angle pair, μ is the average effect; W_j accounts for the day of the week with $j = 1, 2, \ldots, 7$; T_k accounts for the hour of the day with $k = 0, 1, \ldots, 23$; and $\varepsilon_{j,k}$ is an error term. The model explicitly accounts for weekly and daily variation with the W_j and T_k terms. By selecting the parameters based on a limited amount of data – a sliding window of four weeks was used in (Amidan, 2015) – there is no need for a seasonal term. The predicted phase angle pair $\hat{A}$ is actually of less interest than the prediction interval given by

$$\hat{A} \pm t_{\left(\nu, 1-\frac{\alpha}{2}\right)} SD(\hat{A}).$$

Here $t_{\left(\nu, 1-\frac{\alpha}{2}\right)}$ is the quantile function for a Student's t-distribution with ν degrees of freedom. The α term is the false positive rate, which is the rate at which normal data is falsely identified as abnormal. Though small values for α are desirable, if it is too small the interval will become very large and uninformative. In this report, a value of 0.001 is used for α. Finally, $SD\left(\hat{A}\right)$ denotes the standard deviation of the predicted phase angle pair. For a complete description of prediction intervals see (Draper and Smith, 1998).

In this application, the prediction interval is used to delineate between normal and abnormal data. Past data is used to fit the terms in the date/time model. Using the model, the prediction interval for each hour in the following day is generated. As the day progresses, measurements falling within the prediction interval are considered normal. Those falling outside the interval are considered abnormal. In the following sections, follow-on work to the date/time model described in (Amidan, 2015) is discussed.

2.1 Addition of a Regularization Term

A significant challenge with the date/time modeling approach is adapting to occasional changes in system topology. For example, generators are regularly taken out of service for maintenance. Such changes impact phase angle pair values and adjust the ranges that constitute normal system behavior. For example, consider Figure 1. This plot shows the Arcadian-Goodings phase angle pair from the Winter 2014 dataset in red along with the prediction interval generated by the date/time model in (Amidan, 2015) in black. Note that during day 47 a significant shift in the phase angle occurs. The cause of this change is unknown. As desired, the measurements quickly fall outside the prediction interval after the change. Note, though, that because four weeks of past data was used to build the model, the prediction interval does not adjust to the new phase angle pair values over the subsequent days. To increase the speed with which the model adapts, a regularization term was added to the date/time model.

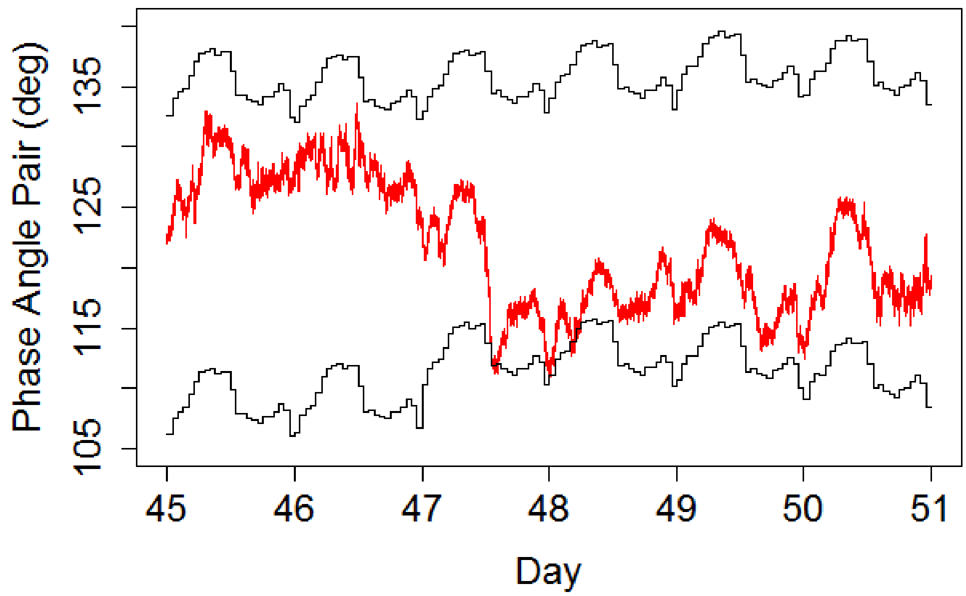

Figure 1. Example performance of the original date/time model after a change in the normal range for a phase angle pair. Data is from the Winter 2014 Arcadian-Goodings phase angle pair measurements.

Though prediction intervals for the upcoming day could be generated at any point, they were generated at midnight in (Amidan, 2015) as this should be a time of convenience for system operators due to low system stress. The value of a phase angle pair at midnight generally provides a strong indication of the range for normal values throughout the rest of the day. Based on this observation, it was hypothesized that providing the model with the phase angle pair's value at midnight would help it adjust to changes in system configuration faster.

With the additional regularization term, the model can be expressed mathematically as

$$\hat{A} = \mu + W_j + T_k + M \times \check{A}_0 + \varepsilon_{j,k}$$

where M is the regularization parameter, which is selected along with W_j and T_k using past data, and $\check{A}_0$ is the measured phase angle pair value at midnight. If $\check{A}_0$ is not available due to a problem in the data stream, the original date/time model is used for the day. The expression for the prediction interval is unchanged. At midnight, the day of the week, each hour of the day, and the phase angle pair's value at midnight are fed into the model. The model then produces predictions for the phase angle pair at each hour of the day along with prediction intervals. If the phase angle pair leaves the prediction interval during the day, abnormal system conditions are detected. When adding the regularization term, it is important to note that this term could be unintentionally masking a change in conditions that could have occurred at the same time. Further research could be done to determine ranges on changes to the regularization parameter that could be the result of abnormal system conditions.

By incorporating the phase angle pair's value at midnight into the model, the prediction intervals better track changes in the system. Consider Figure 2, which shows the same set of data in Figure 1 but with prediction intervals from the updated date/time model. Note that the initial system change is again detected during day 47, as desired. In the days following the system change, though, the model does a better job of adjusting to the new system conditions.

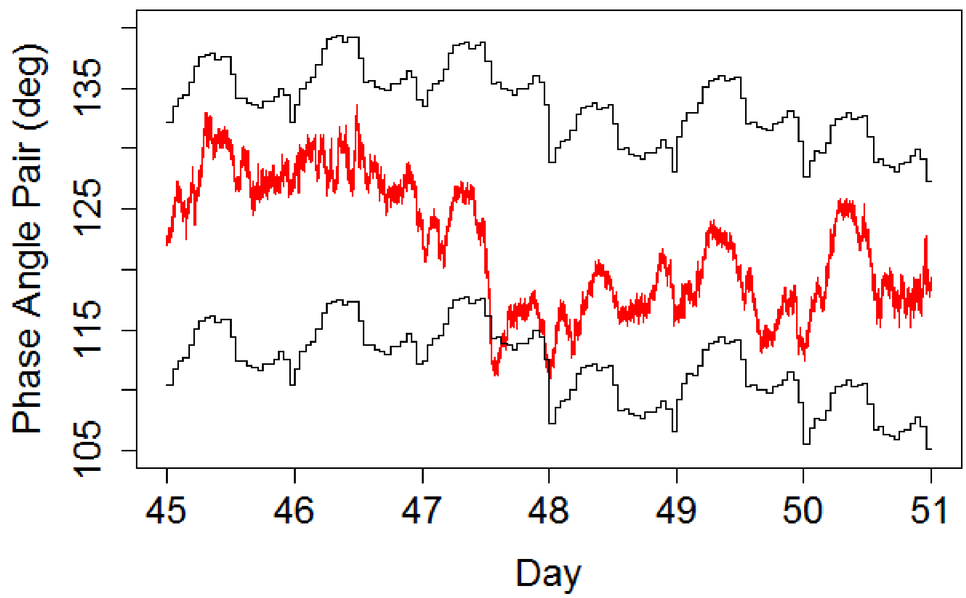

Figure 2. Example of performance of the updated date/time model after a change in the normal range for a phase angle pair. Data is from the Winter 2014 Arcadian-Goodings phase angle pair measurements.

As a general result, the updated date/time model was found to outperform the original. By incorporating the phase angle pair's value at midnight, the model is better able to indicate the range of normal values for phase angle pairs, even as system topology changes occur. The update does not hinder the method's ability to identify abnormal system conditions. Rather, it allows the model to adjust if those system conditions remain for multiple days, indicating that the change was planned and/or acceptable. Found to provide desirable performance using four weeks of past data, the updated date/time model was further tested to determine how much past data was required.

2.2 Impact of Window Length on the Date/Time Model's Performance

The amount of data used to fit the parameters of the date/time model has a direct impact on the approach's performance. Large quantities of data provide several observations of each day of the week and hour of the day, but they also make the model slow to adjust to topological changes in the system. Conversely, using smaller amounts of data can be problematic because too few observations are available for each day of the week and/or hour of the day. The results in (Amidan, 2015) for the date/time model were generated using a sliding window of four weeks of data. To validate this selection, performance of the method using from one to four weeks of data was evaluated.

The date/time model was used to generate prediction intervals for 33 days of data from the Fall 2014 dataset. The proportion of data from the 33 days that was deemed abnormal was then tabulated for each of the window lengths. Results are presented in Figure 3. The false positive rate, denoted as α, is also included in the figure. This rate, which is user-selected, determines how sensitive the method is to abnormal data. As is true for all problems of this variety, increasing sensitivity to abnormal data requires an increase in the amount of normal data misidentified as abnormal. For these experiments, a false positive rate of α=0.001 was used. If all 33 days of data were normal, proportions of 0.001 would be expected in Figure 3, but because some data is expected to be abnormal, the observed proportion should be somewhat higher, indicating that the approach was able to identify abnormal system conditions. However, the extremely high proportions of data deemed abnormal using one and two week windows are unacceptable. The relative similarity between results obtained using three and four week windows indicates that either window length may be an acceptable choice. For all angle pairs, the proportion of data deemed abnormal is greater for the three week window than for the four week window, but the shorter window provides faster adjustment as system topology changes occur.

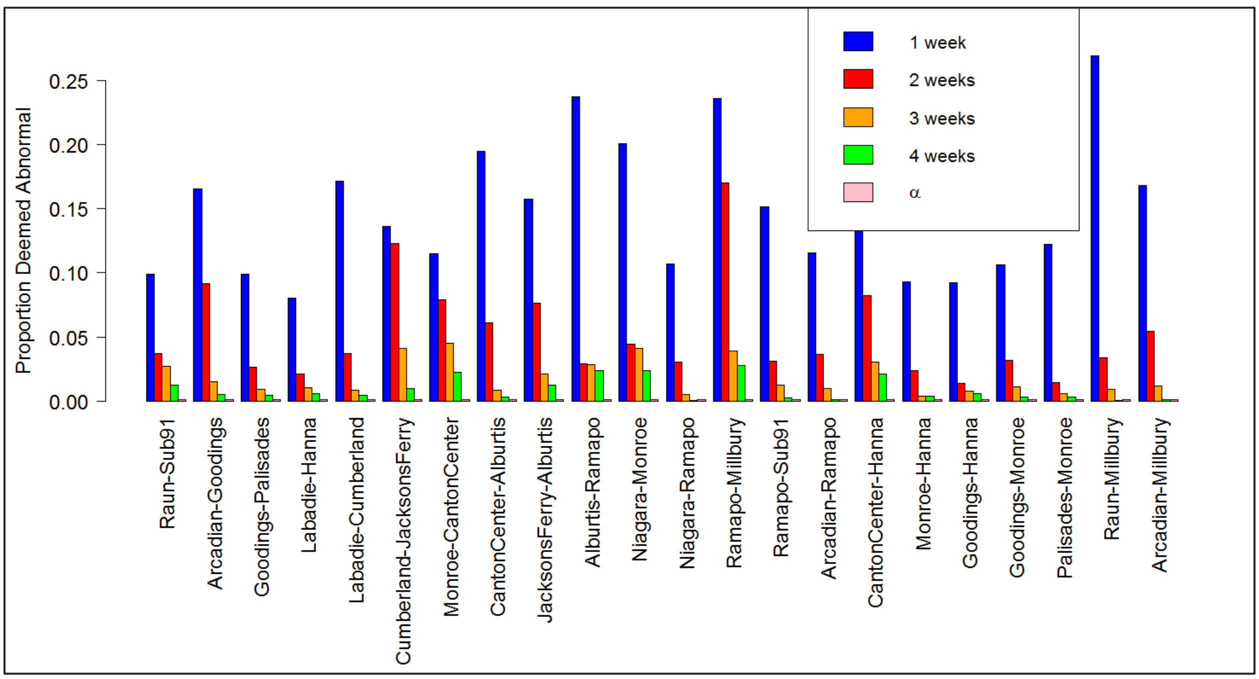

Figure 3. Results from applying the date/time model to 33 days of data using sliding windows of various lengths. The false positive rate, α, is included for reference.

An intuitive relationship exists between the proportion of data deemed abnormal and the range of the prediction interval. The range refers to the number of degrees between the upper and lower bounds of the prediction interval as a function of time. It constitutes the range of angles that are considered normal for a given time. For example, consider the interval ranges for the Goodings-Monroe phase angle pair in Figure 4. Note that the range of the prediction interval from a date/time model based on one week of data is significantly smaller than for four weeks of data. Smaller ranges are desirable because they more precisely specify the qualifications for normal data, but only if the proportion of data deemed abnormal is reasonable. Figure 4 was typical of the various phase angle pairs. The differences in range between prediction intervals from date/time models based on two and three weeks of data are relatively small. However, the impact on the proportion of data deemed abnormal is relatively significant, as can be seen in Figure 3 for the Goodings-Monroe phase angle pair. This result indicates that prediction intervals from three and four weeks of data provide improved performance over those from one and two weeks of data.

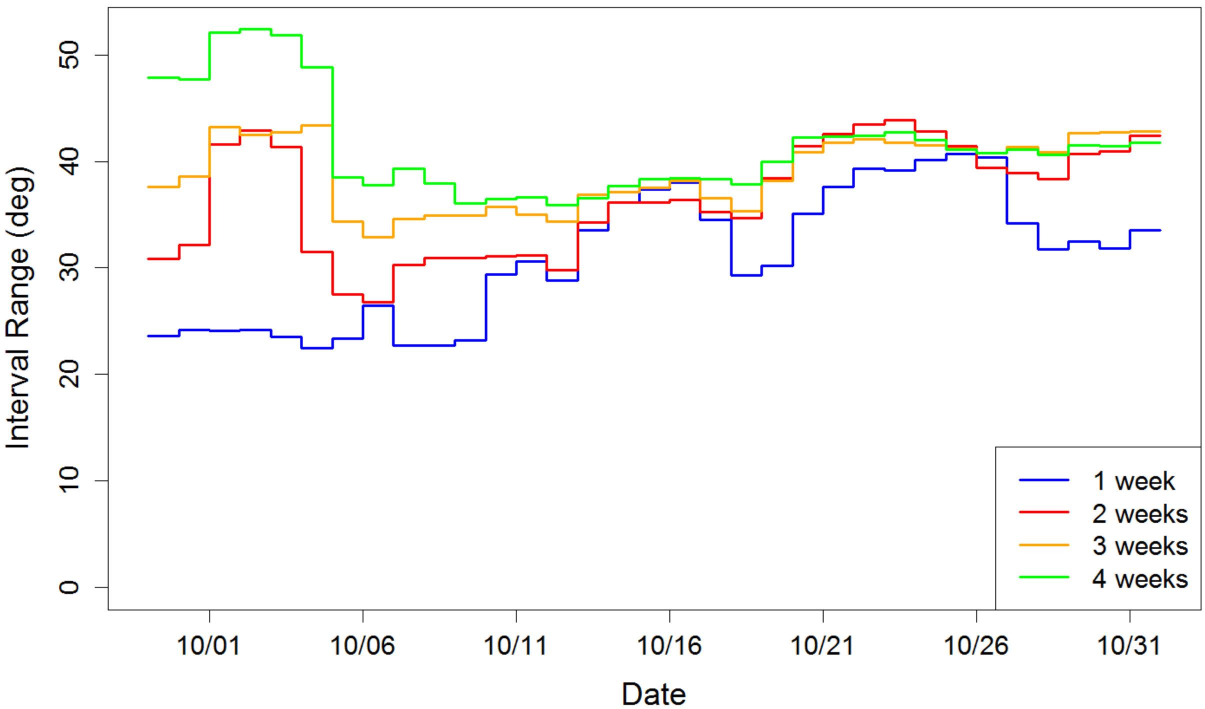

Figure 4. Prediction interval ranges based on one to four weeks of data from the Goodings-Monroe phase angle pair.

Figures 3 and 4 clearly demonstrate the impact the length of the window used to generate date/time models can have on results. When the window is too short, the model too frequently identifies data as abnormal. From the analysis, and further review of results, it was concluded that analyses with three and four week windows identified sets of events with significant overlap. Though a three week window is probably appropriate for use, to maintain consistency with (Amidan, 2015) and remain conservative in parameter selection, a four week window was used for all remaining results in this addendum.

2.3 Comparison with EPG Results

As mentioned previously, EPG also developed methods for identifying abnormal grid behavior by monitoring phase angle pairs. Like the date/time model, some of EPG's methods identified abnormalities in phase angle pair values by setting thresholds. In this section, a comparison between the thresholds is provided.

The approach implemented by EPG is similar to the one based on the date/time model. Based on an examination of several weeks of data, a time-varying interval is established to delineate between normal and abnormal data. Here, a brief description of the method is provided. First, data points from the entire dataset are broken up by hour of the day and whether the measurement was collected on a weekday or weekend. Next, the mean value corresponding to each combination of hour of the day and day type is calculated. Finally, intervals above and below the mean value are selected to include 99% of the data. The resulting interval, which varies with time, specifies the range of normal data. Measurements falling outside of the interval are deemed abnormal.

Both the date/time model approach and the EPG approach were applied to the Fall 2014 dataset. The following examples illustrate key findings when comparing the two methods. Generally, the two methods provided similar results. Consider, for example, the week of data with accompanying intervals in Figure 5. The data is from the Monroe-Hanna phase angle pair. Note the distinct similarity between the intervals produced by the date/time and EPG methods. The most significant excursion of the measurements from normal behavior (occurring near the 10/15 mark) is detected by both approaches. Note the five repetitions of the “weekday” interval followed by two repetitions of the “weekend” interval in the EPG results. In contrast, the interval from the date/time model is unique each day.

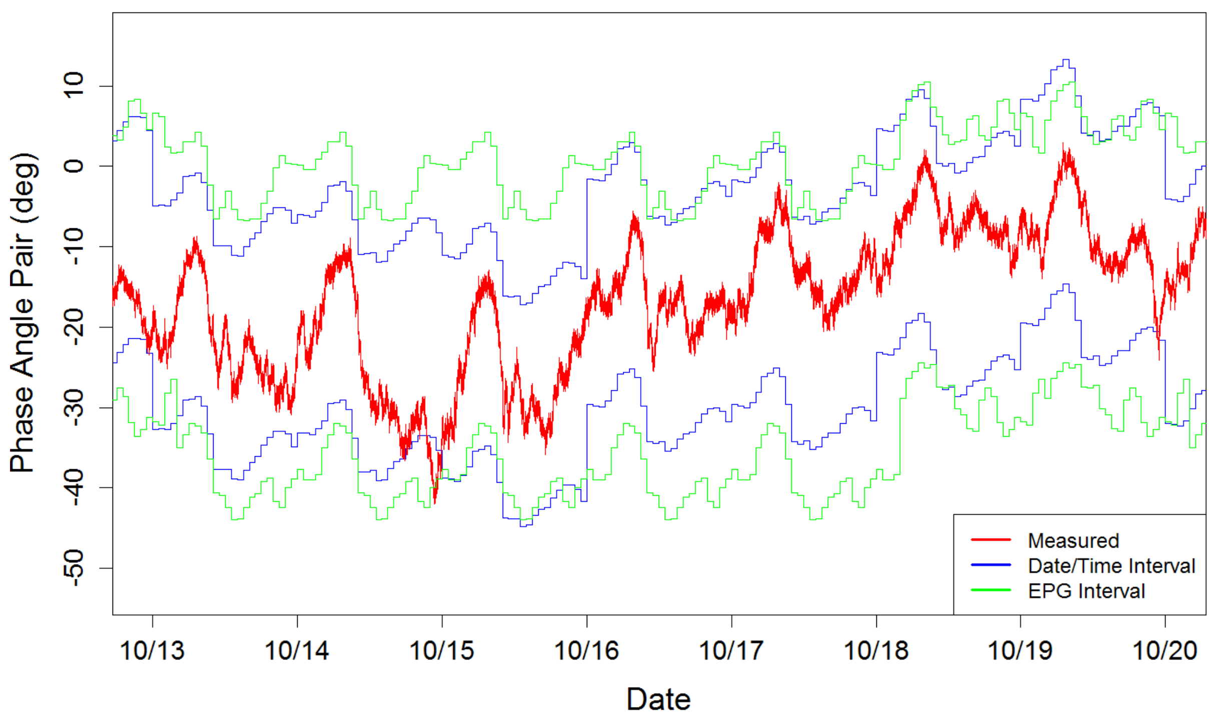

Figure 5. Comparison of results for one week of data. Measured data from the Monroe-Hanna phase angle pair are displayed along with upper and lower bounds from the date/time model and EPG approaches.

To compare each method’s sensitivity to abnormal data, the proportion of data that was deemed abnormal was examined. The methods were again applied to 33 days of data, and windows of three and four weeks were used to build the date/time models. Results are presented in Figure 6. For several phase angle pairs the methods perform quite similarly, but overall the EPG method tends to classify a smaller proportion of the data as abnormal. Note that the methods were not designed to be identical in this way, so it is not unexpected that they differ. To properly interpret the results in Figure 6, it is important to consider the ranges of the prediction intervals provided by the date/time and EPG methods.

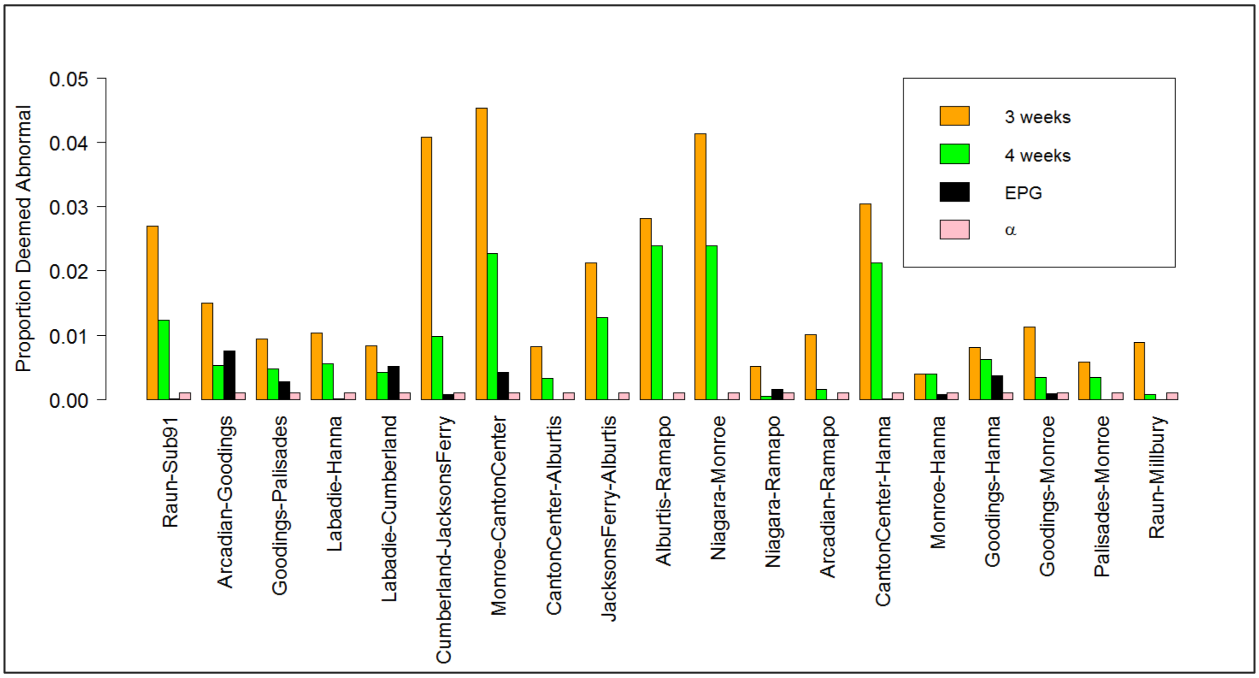

Figure 6. Comparison of proportions of data deemed abnormal from the EPG method and the date/time model based on three and four weeks of data. The false positive rate, α, is included for reference.

The interval ranges for each method were compared for the various phase angle pairs. For some angle pairs, such as the Goodings-Palisades pair in Figure 7, the ranges are similar. Note that the prediction interval ranges from the date/time model are unique each day and do not vary hourly. Conversely, the EPG prediction interval ranges vary hourly and are not unique. Instead, the same set of ranges can be observed for each day during the week and for each day during the weekend.

For most of the phase angle pairs the prediction interval ranges from the date/time model tended to be smaller than those from the EPG method. An example is presented in Figure 8. The increases in ranges from the date/time model for certain days correspond to the original model (without the regularization term described in Section 2.1) being used because measurements at midnight were not available. From Figure 8, the ability of the regularization term to tighten the bounds around the measured data is apparent.

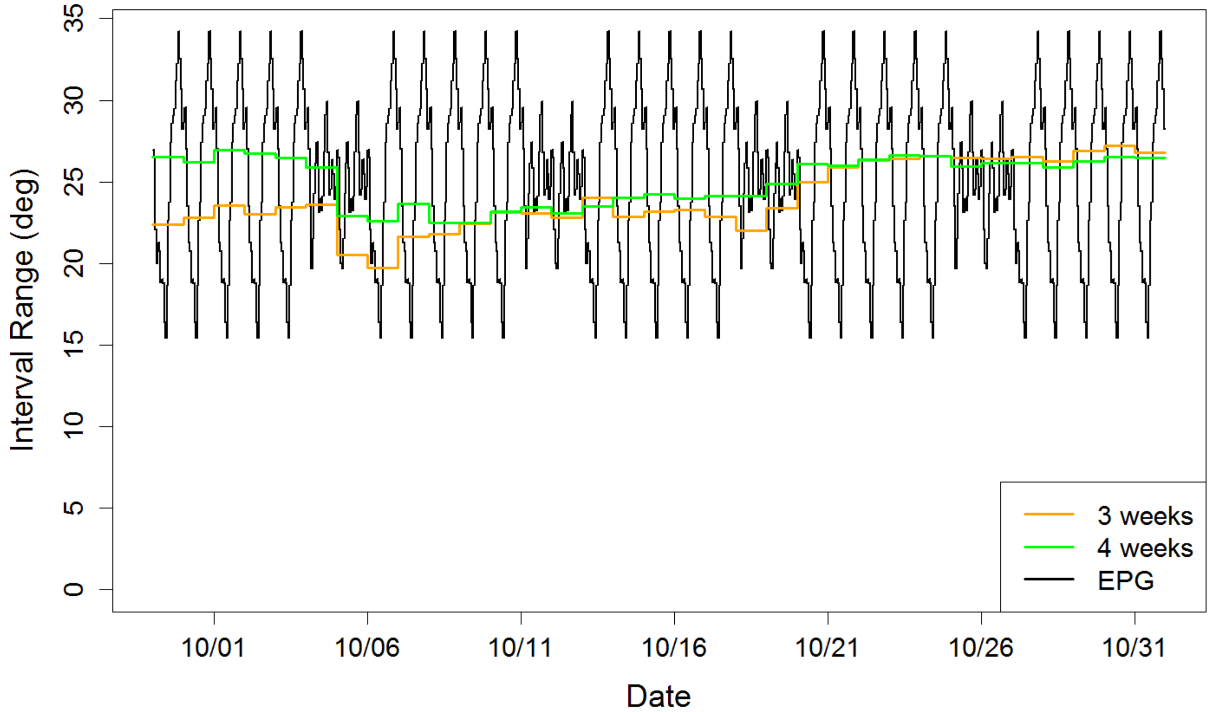

Figure 7. Ranges of prediction intervals from the date/time and EPG methods for the Goodings-Palisades phase angle pair.

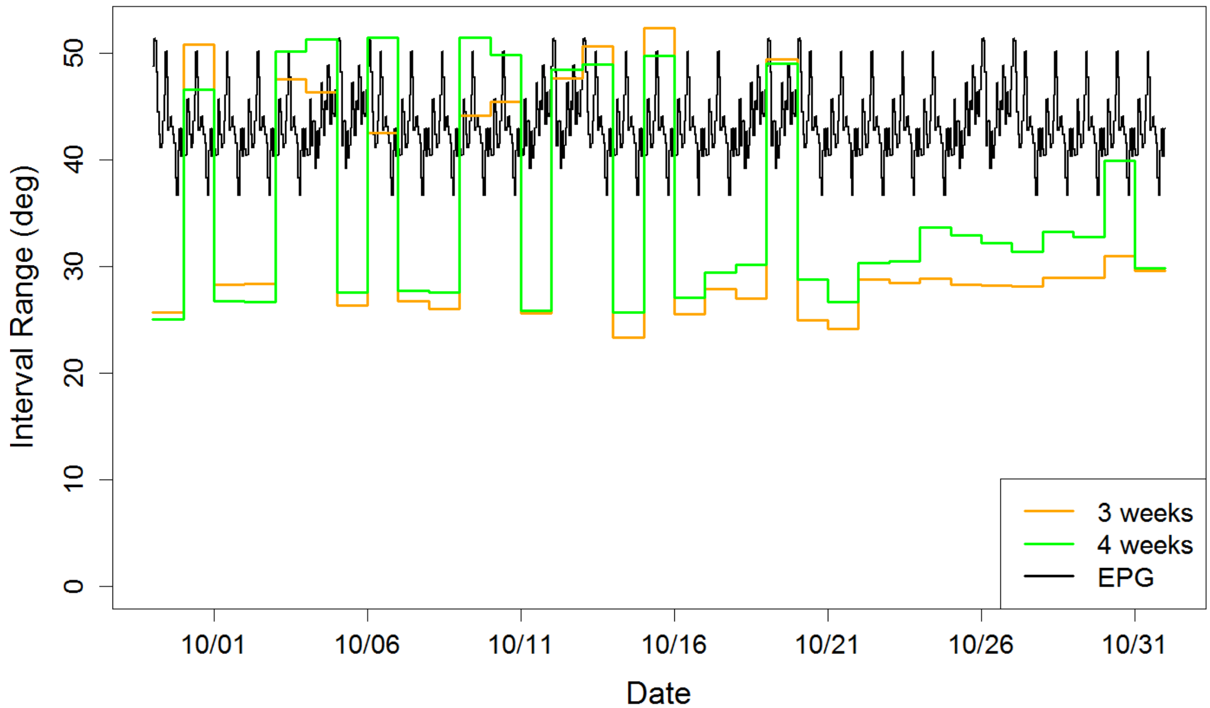

Figure 8. Ranges of prediction intervals from the date/time and EPG methods for the Ramapo-Millbury phase angle pair.

Examination of figures similar to Figures 7 and 8 for the remaining phase angle pairs indicated that the date/time model tended to produce prediction intervals with smaller ranges than the EPG intervals. This observation explains the increased amount of data deemed abnormal by the date/time model (see Figure 6) and reflects the intuitive tradeoff between tightening intervals and increased amounts of data being classified as abnormal. Both the date/time model and EPG methods can be tuned to narrow or widen the prediction interval, thereby increasing or decreasing the amount of data deemed abnormal.

Comparison of results with EPG's method helps to validate the date/time model approach to categorizing data. The methods perform similarly enough to support their use. Examining the amount of data needed to build the date/time model also helped to establish the usefulness of the approach. Based on three or four weeks of past data, the date/time model can effectively predict normal behavior for the following day's phase angle pairs, particularly when the value of the phase angle pair at midnight is incorporated into the model. Future efforts with the date/time model will utilize this parameterization.

3.0 Phase Angle Trend Monitoring

The date/time model described in the previous section is designed to inform system operators when the separation between two phase angle measurements has become abnormal. The method described in this section is intended to complement the date/time model by indicating when the phase angle separation has a significant trend. The motivation for this approach will be illustrated with an example.

Consider the Goodings-Palisades phase angle pair in Figure 9. After remaining primarily between 15 and 20 degrees for over 8 hours, the angle separation drops below 5 degrees over the course of approximately an hour. It was hypothesized that this type of behavior, where dramatic changes in the phase angle separation occur relatively quickly, could be indicative of important system changes. To identify such instances, the signal's noise must be ignored to focus on the signal's trend. This task is accomplished by first filtering the signal.

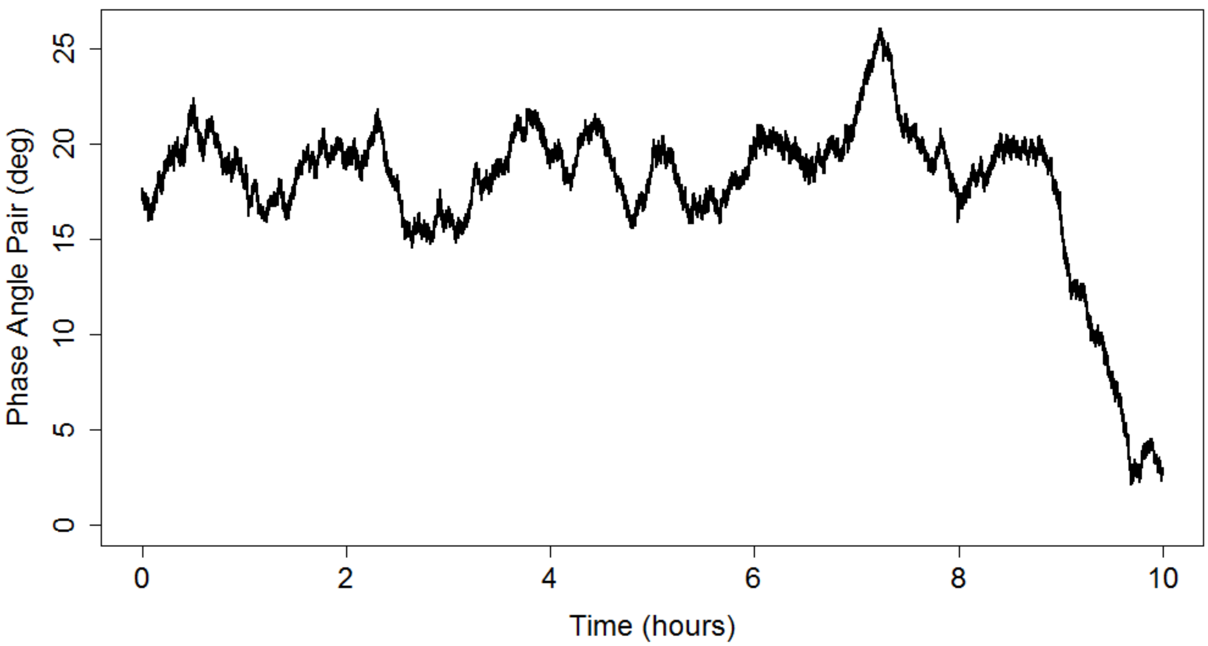

Figure 9. Example of a sudden decreasing trend in the Goodings-Palisades phase angle pair.

A low-pass finite-impulse-response (FIR) equiripple Parks-McClellan filter with order 484 was designed to remove the noise that obscures the signal trends. The filter's stop-band began at approximately 0.01 Hz. The impact of the filter can be seen in Figure 10, where the raw and filtered signals are plotted together. Note that the filtered signal captures the trend in the phase angle pair without being obscured by noise.

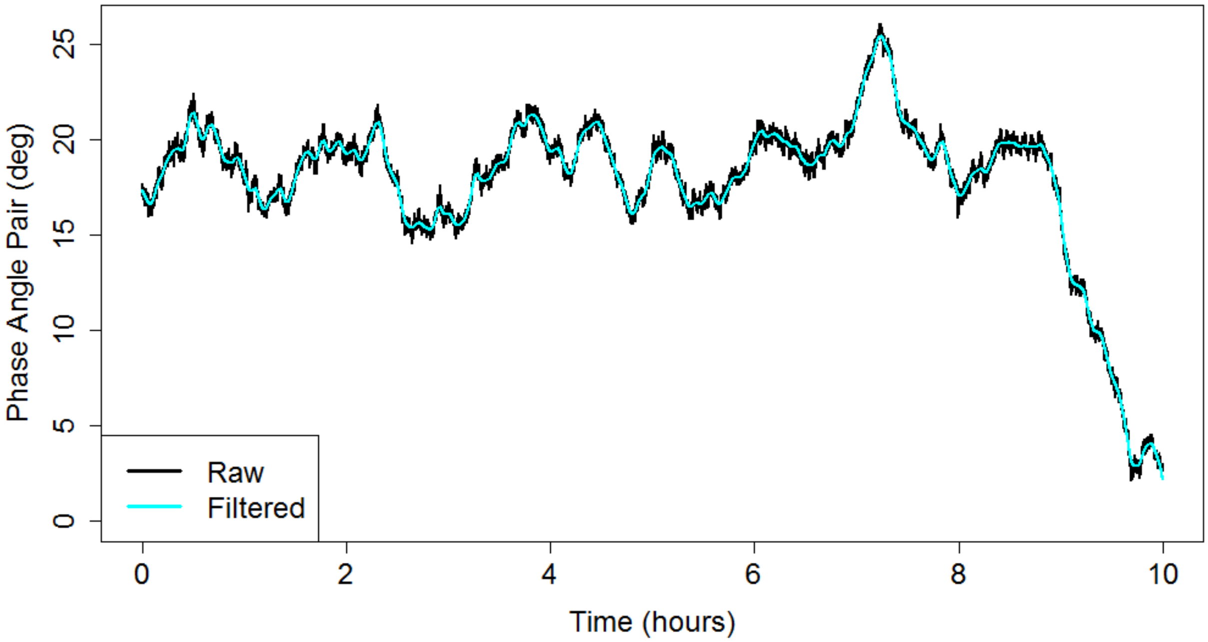

Figure 10. Raw and low-pass filtered data from the Goodings-Palisades phase angle pair.

To quantify the trend in the phase angle separation, this filtered signal was next broken into periods where the trend was increasing and decreasing. This operation is depicted in Figure 11, with increasing trends highlighted in blue and decreasing trends highlighted in red. As a final step, the individual trends in Figure 11 are plotted in succession in Figure 12. Note the continuation of the color coding from Figure 11 to Figure 12. In Figure 12, the trend is reset every time the filtered signal changes direction. In this way, periods of steady increase or decrease in the phase angle pair are highlighted. For example, the steady decrease in the phase angle pair that occurred between hours 9 and 10 in Figure 9 is apparent in Figure 12.

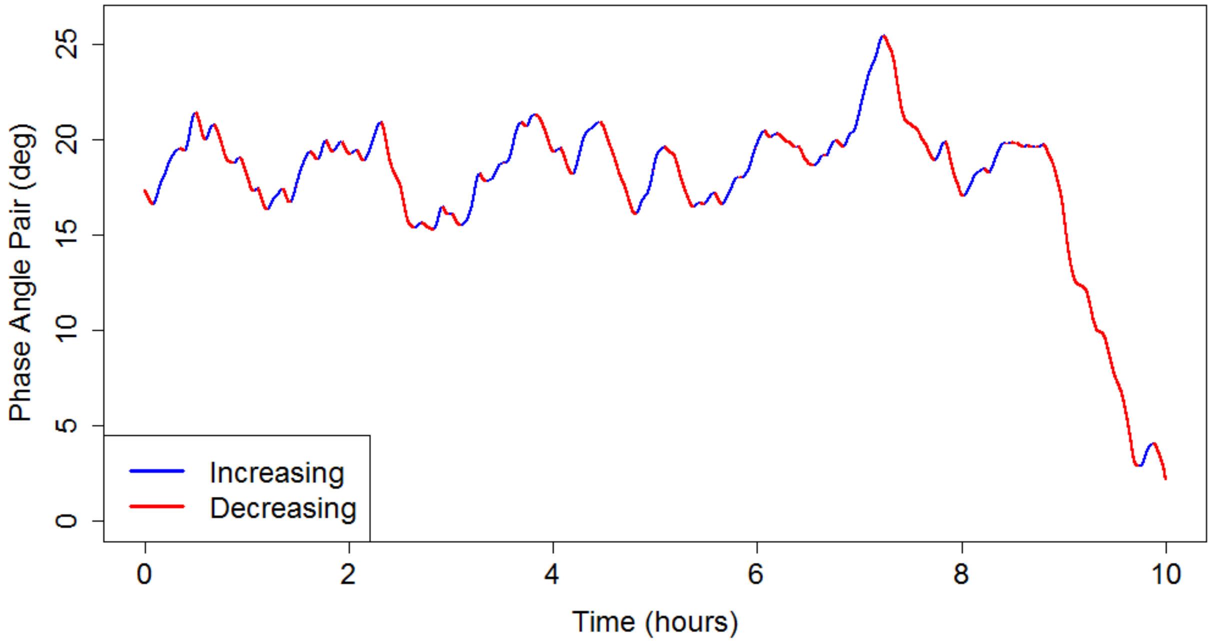

Figure 11. Filtered example data from the Goodings-Palisades phase angle pair with highlighted increasing and decreasing trends.

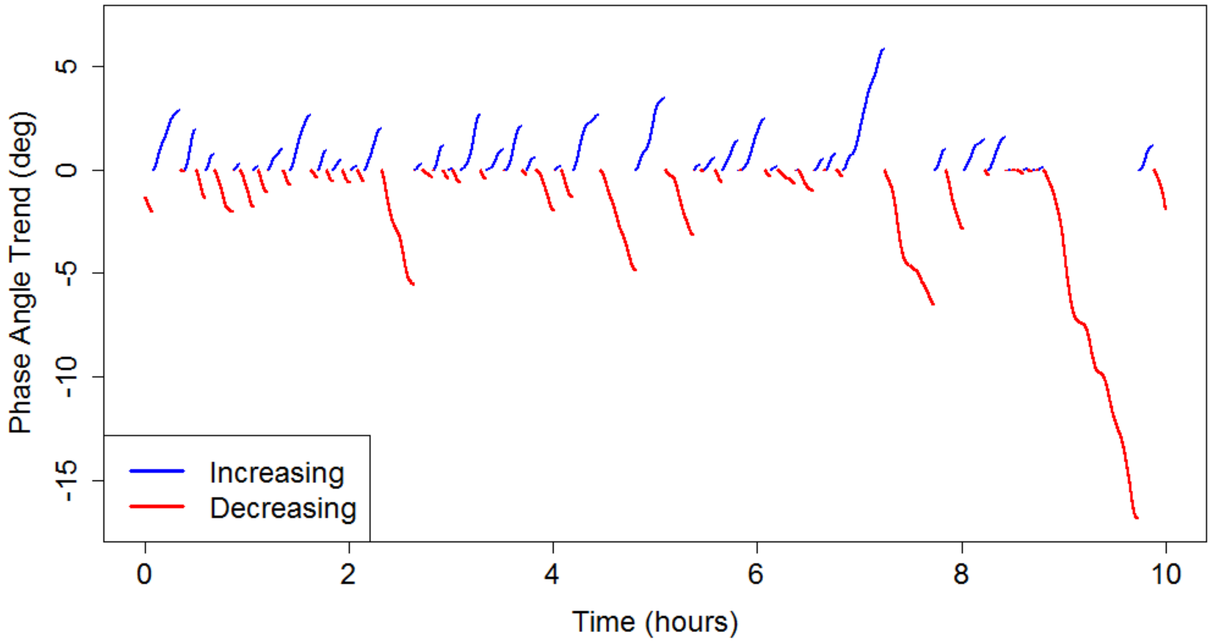

Figure 12. Trends in the example data from the Goodings-Palisades phase angle pair. Note the significant downward trend that occurs between hours 9 & 10. The trend is also apparent in Figures 9-11.

In examining the full two months of Fall 2014 data with the trend monitoring approach, several significant trends such as the one in Figure 12 were identified. The method is in the early stages of development, so further results are not yet available. With further development, the method could help identify unusual grid behavior that develops over the course of several minutes or hours. Such events may be of significant interest.

4.0 Investigation of the Effect of Window Size on Baselining

The Fall 2014 dataset was used to investigate the events that are discovered when using a 2 week baseline, a 1 month baseline, and a 2 month baseline. Comparison of these discovered events will help give insight into the effects of changing the length of time for a baseline. A baseline is a summary of typical behavior that future grid data can be compared to in order to determine if that data is unusual.

Figure 13 shows the atypicality scores (larger score indicates more atypical) as calculated using a 2 week baseline and a 2 month baseline for each minute (points on the scatterplot) of the 2 month dataset. The red rectangle identifies the most atypical minutes when based on a 2 week baseline, while the blue rectangle identifies the most atypical minutes when based on a 2 month baseline. If there is no effect in going from a 2 month baseline to a 2 week baseline, the same minutes should be most atypical for both baselines. As Figure 13 shows, that is not the case. Those minutes that were deemed most atypical using a 2 month baseline were not the same as those deemed most atypical using a 2 week baseline.

Figure 14 is similar to Figure 13, except that it compares the atypicality scores for each minute using a 1 month baseline and a 2 month baseline. Again, the minutes that were deemed most atypical using a 2 month baseline were not the same as those deemed most atypical using a 1 month baseline.

This investigation shows the volatility in the baseline when smaller time periods are selected. There is no stability in results when only looking at 2 weeks or 1 month of data. This investigation does not look beyond 2 months; therefore, there is no discussion of whether 2 months is even enough data to establish a stable baseline. Further research and more data would be needed to better understand the amount of time necessary to establish a stable baseline.

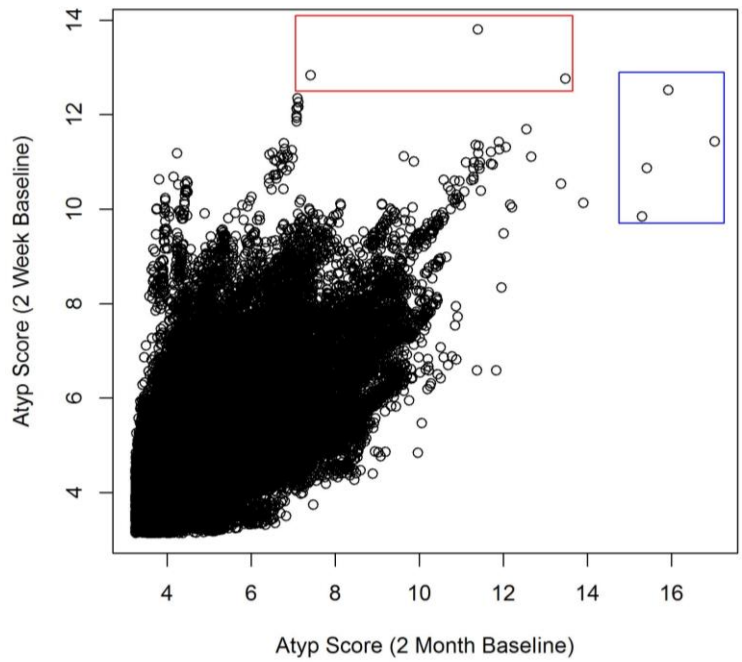

Figure 13. Atypicality Scores Using a 2 Week Baseline Versus Atypicality Scores Using a 2 Month Baseline

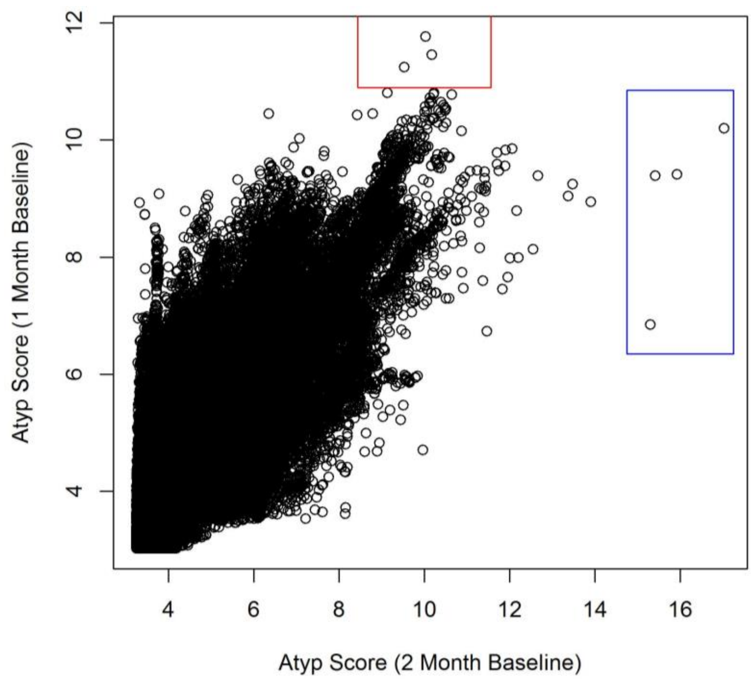

Figure 14. Atypicality Scores Using a 1 Month Baseline Versus Atypicality Scores Using a 2 Month Baseline

5.0 Baselining Atypical Event and Actual Event Comparison

This comparison was made at BPA (Bonneville Power Administration) using BPA PMU data. This was done because BPA detected events were available for a time period in which PMU data was also available. Also, there were a few years of PMU data available for analyses. It was decided to look at June and July of 2015 because there appeared to be more frequency related events during those months (according to WECC records). Analyses were performed using the DISAT tool, which was installed at BPA and uses the baselining algorithms developed by PNNL.

A list of 60 June and 49 July line outages was received from BPA. Of those, 13 June and 11 July line outages involved lines connected to PMUs and so these were further investigated. Line outages often are not noticeable in PMU data, so it was expected that the DISAT tool would not detect many line outages. The DISAT tool detected events during 2 of the June line outages and 1 of the July line outages. Figures 15 and 16 show how voltage behaves during these line outages. These plots are typical of behavior for many locations during these times. Note that date and location have been removed from plots in this section so that no identifying information is available. The line outage in July (Figure 16) was a major line outage, so it was not surprising that DISAT was able to detect it in the data.

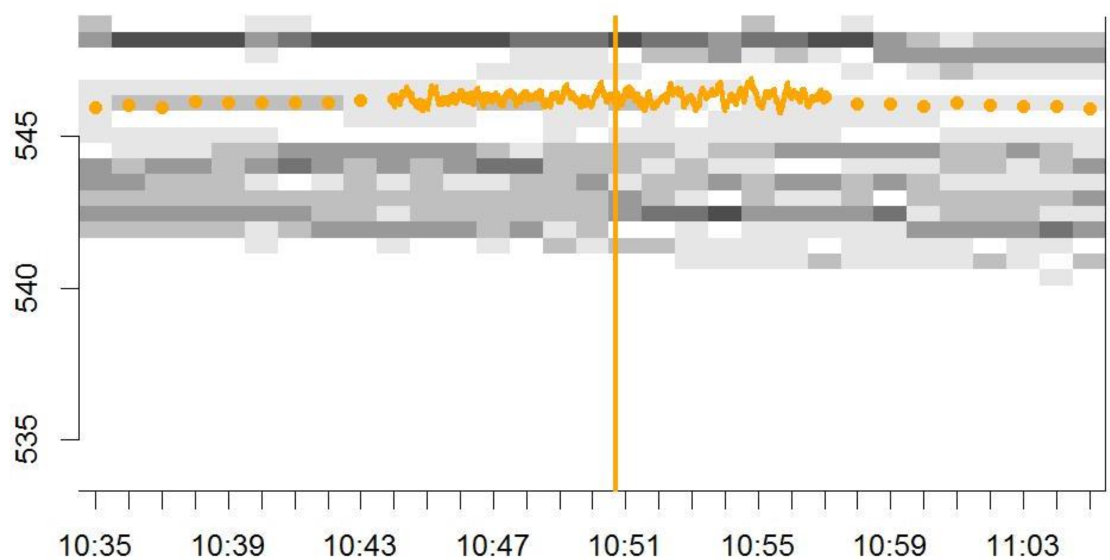

Figure 15. Example Voltage Behavior during a Line Outage in June

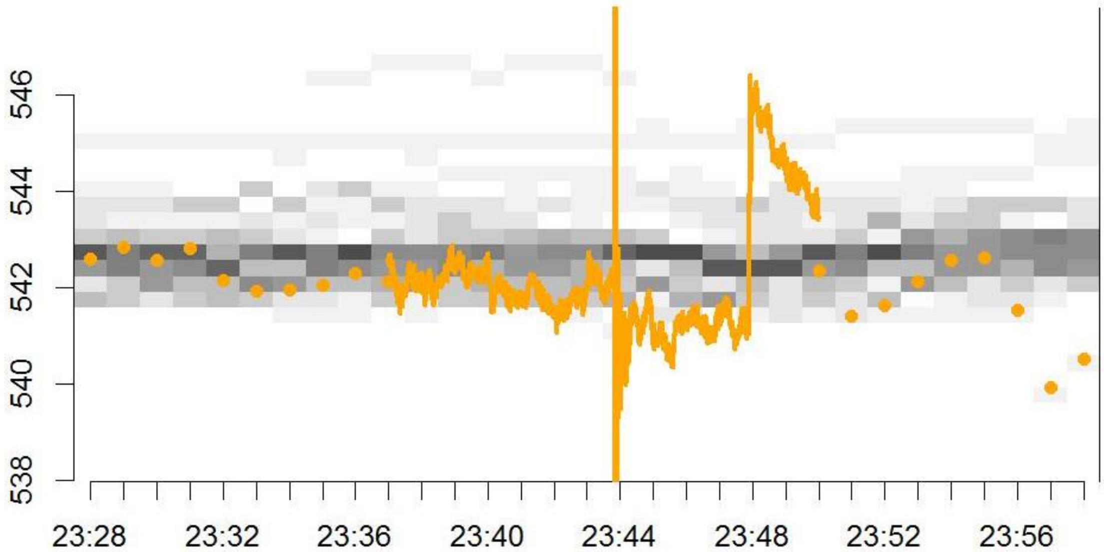

Figure 16. Example Voltage Behavior during a Line Outage in July

In addition to the line outage events, the DISAT detected events were compared to the frequency events that were determined by BPA during June and July 2015. The results of these comparisons are found in Table 1. Table 1 shows that DISAT was able to detect some of the frequency events in June and over half in July. Further investigation into this showed that many of these frequency events were actually outside of the BPA system, where PMU data were not available for these analyses. DISAT was able to detect each frequency event inside the BPA system (those PMUs that were available for analyses). In fact, DISAT detected each of the frequency events that were just outside of the BPA system. The frequency events that were more distance away from the BPA system were generally not detected.

Table 1. Numbers of Frequency Events Detected by BPA and the Number of Those Detected by DISAT

	Frequency Events	
Month	**Number of Detections**	**Detected By DISAT**
June 2015	15	3
July 2015	15	8

DISAT found an additional possible event that was frequency based, but not on the BPA list of frequency events. Figure 17 shows the behavior of a frequency variable for a given PMU at this time. This same behavior was seen in frequency for the other PMUs. This possible event was not on the BPA list of frequency events.

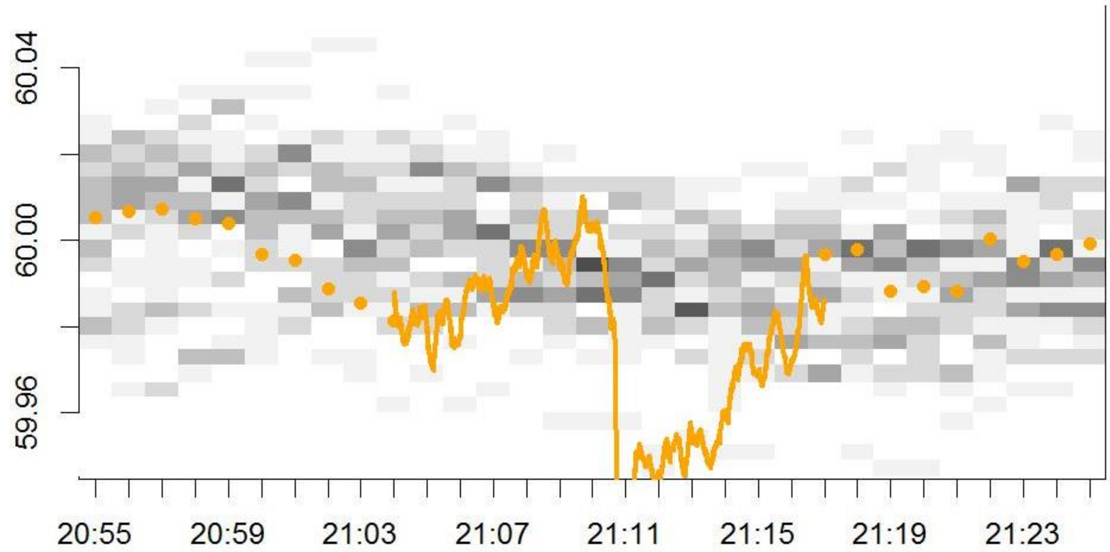

Figure 17. Example Frequency Behavior During a Possible Event

In addition to the frequency event that DISAT found that was not on the event list, there were 3 additional events that DISAT found that were not on any list for the two months of data and were not frequency based.

The first event was found in the voltage data (Event 1). There were two different unusual patterns in some of the voltage measurements that triggered an event by DISAT. The first pattern is very subtle and can be seen in Figure 18. At about 11:13 we see a subtle shift down in voltage and, more importantly, we see an increase in the variability of the voltage measurement. This was seen in voltage measurements for at least 5 PMUs. The second pattern is more distinct and noticeable and is demonstrated in Figure 19. This unusual behavior occurs around 11:15 and it only occurs at 1 PMU. We are not sure if these two patterns are related.

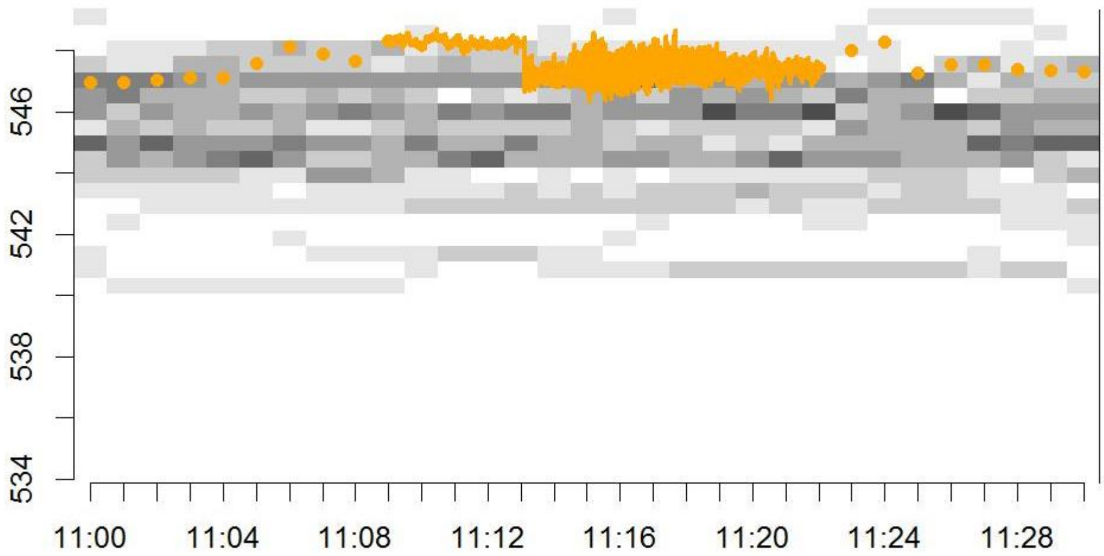

Figure 18. Example of Subtly Unusual Behavior in Voltage (Event 1)

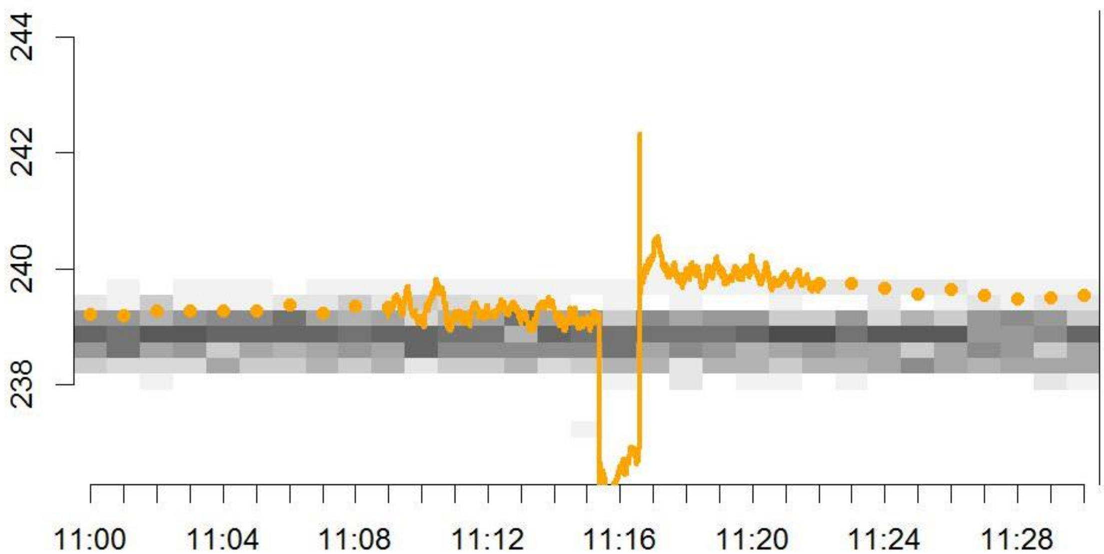

Figure 19. Example of Unusual Behavior in Voltage (Event 1)

The next event (Event 2) was also identified using voltage data. As Figure 20 shows, there was a disturbance that caused a spike in both directions. Figure 21 zooms in closer around the unusual activity. This was specifically noticed for at least 5 PMUs. As can be seen more clearly in Figure 21, there was also a small disturbance about 40 seconds before the larger one. Figure 22 shows voltage at a different site during this same time period. This also shows the slight disturbance about 40 seconds before the larger one, and it also shows another disturbance about 6 minutes previous and another disturbance about

5 minutes after the larger one. Further investigation would be necessary to determine if these disturbances were related. Investigations, like this one, could lead to better understanding of possible pre-cursors to events.

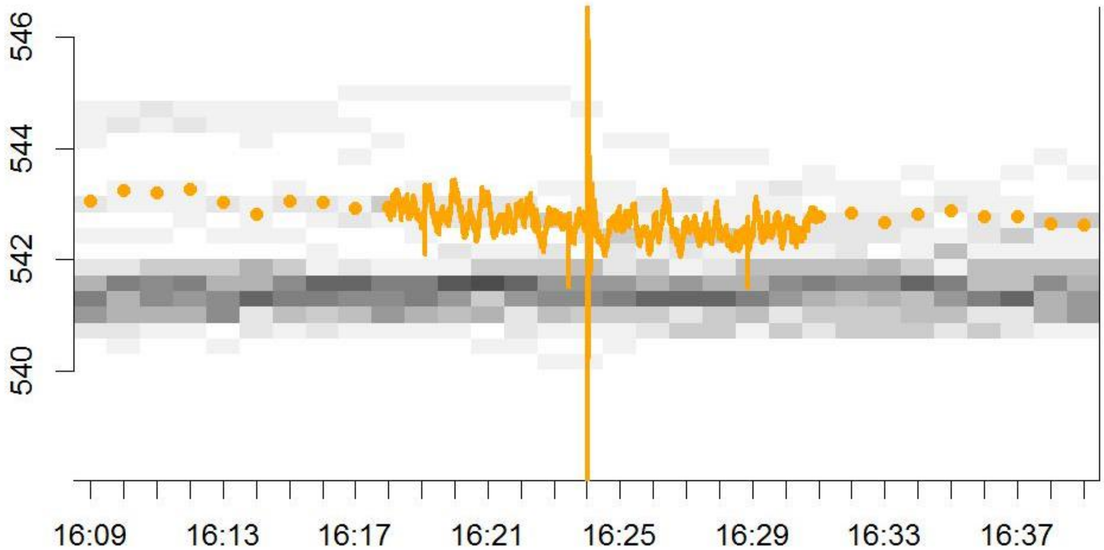

Figure 20. Example of Unusual Behavior in Voltage (Event 2)

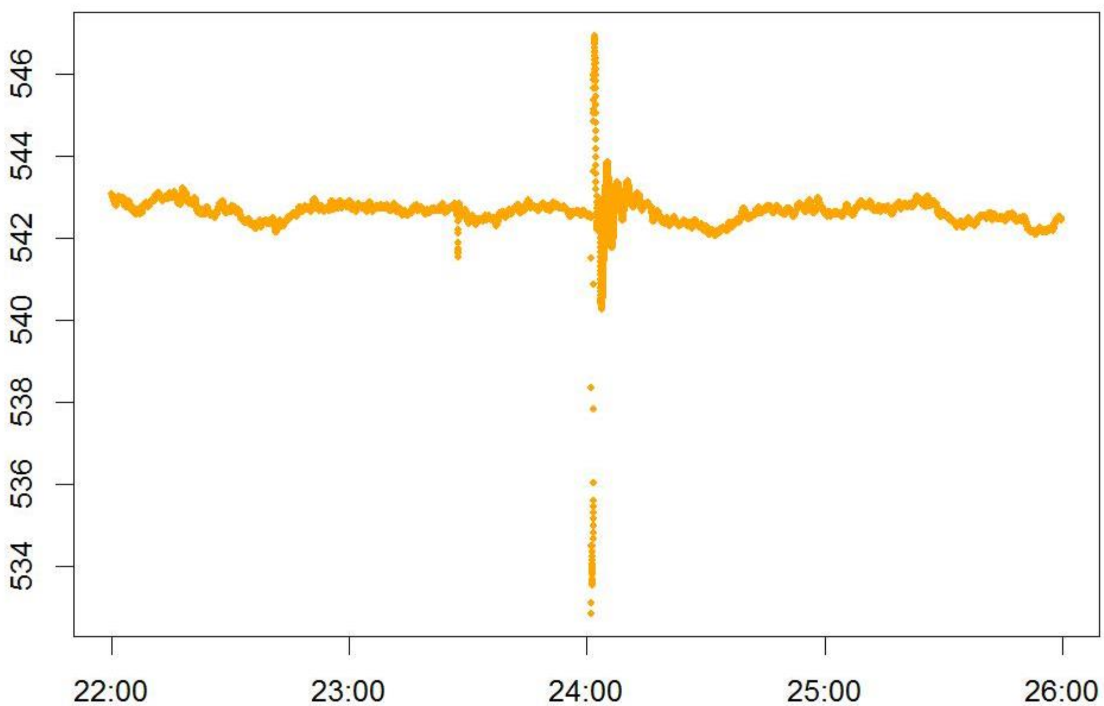

Figure 21. Zoom in of Unusual Behavior from Figure 20 (minutes:seconds).

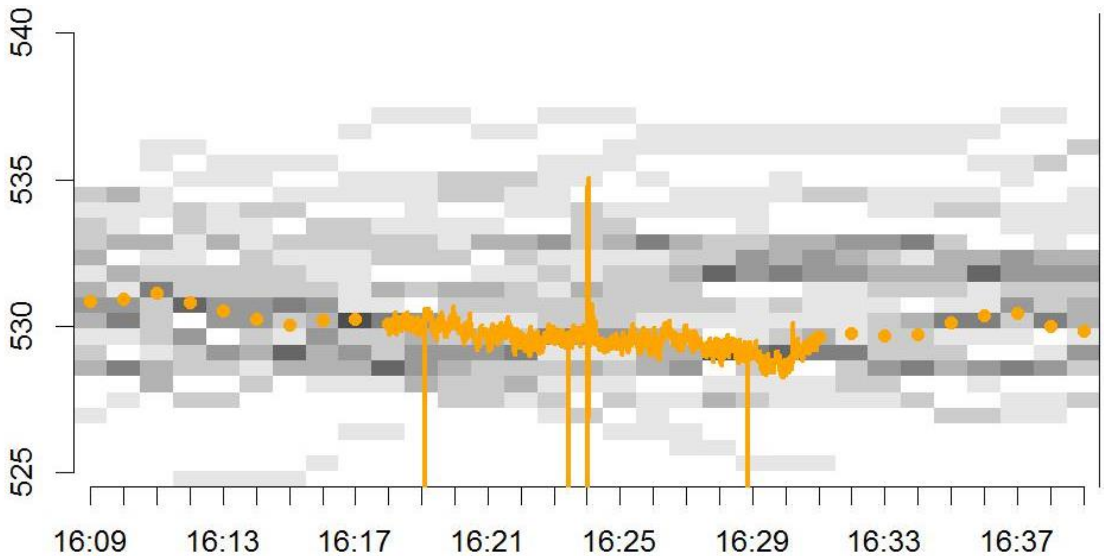

Figure 22. Example of Unusual Behavior in Voltage (Event 2)

The last detected DISAT event (Event 3) was discovered within the voltage data, but was unlike the first 2 events. In this case there were no spikes in the data. As Figure 23 and 24 show, the voltage values are well above the performance envelope (the gray area that defines the typical behavior). This was occurring with voltage values at many of the PMUs. Figure 23 shows the voltage values staying high and this was typically seen across many of the PMUs at this time. Figure 24 shows a bump up in value starting around 9:20 and this behavior was only seen at one PMU. The DISAT tool uses multivariate analyses to find unusual behavior, meaning that many variables are used, not just one variable. In this case, there are individual voltage measurements that are a little unusual, but not significantly unusual when looked at individually. Using multiple variables allows for considering the correlations between variables and how they are behaving collectively. In this case, it was considered very unusual behavior collectively, so it was labeled as an event.

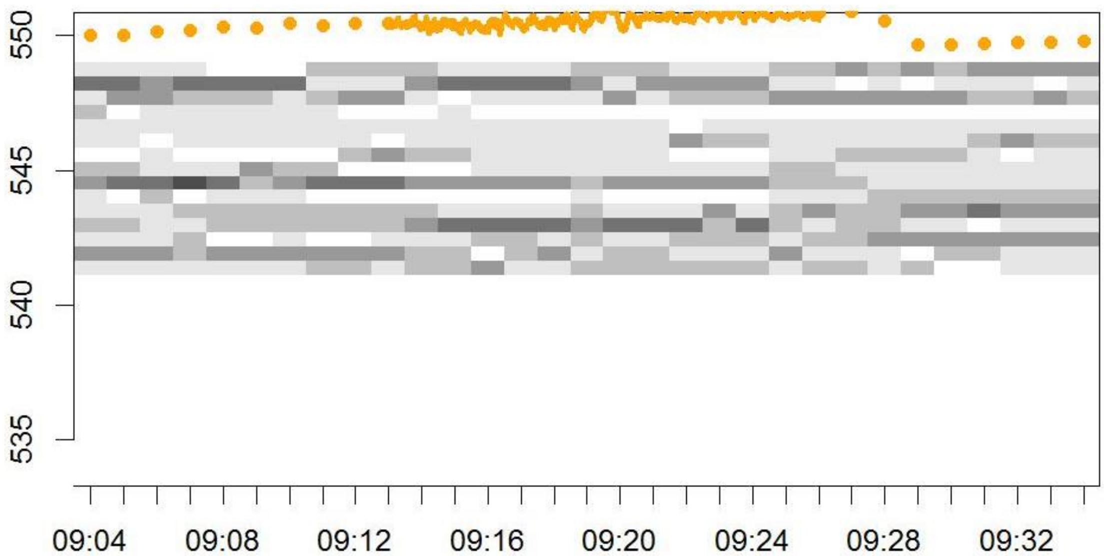

Figure 23. Example of Unusual Behavior in Voltage (Event 3)

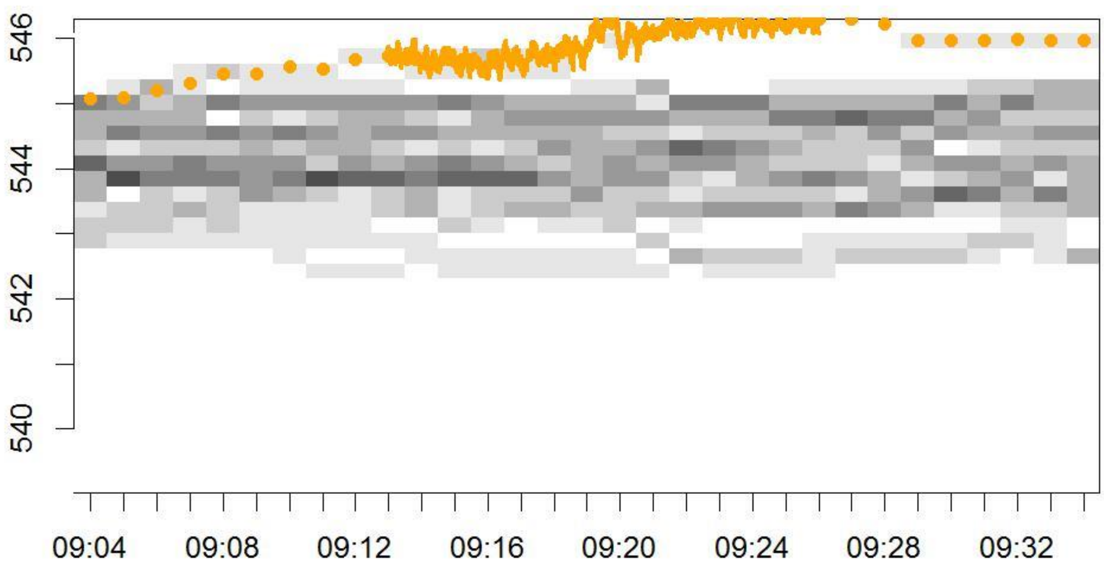

Figure 24. Example of Unusual Behavior in Voltage (Event 3)

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