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Integration of a Self-Coherence Algorithm into DISAT for Forced Oscillation Detection

February 2015

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U.S. DEPARTMENT OF ENERGY

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Summary

With the increasing number of phasor measurement units on the power system, behaviors typically not observable on the power system are becoming more apparent. Oscillatory behavior on the power system, notably forced oscillations, are one such behavior. However, the large amounts of data coming from the PMUs makes manually detecting and locating these oscillations difficult. To automate portions of the process, an oscillation detection routine was coded into the Data Integrity and Situational Awareness Tool (DISAT) framework.

Integration into the DISAT framework allows forced oscillations to be detected and information about the event provided to operational engineers. The oscillation detection algorithm integrates with the data handling and atypical data detecting capabilities of DISAT, building off of a standard library of functions. This report details that integration with information on the algorithm, some implementation issues, and some sample results from the western United States' power grid.

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Acronyms and Abbreviations

BPA	Bonneville Power Administration
DFT	Discrete Fourier Transform
DISAT	Data Integrity and Situational Awareness Tool
Hz	Hertz
MSC	Magnitude Squared Coherence
PDC	Phasor Data Concentrator
PMU	Phasor Measurement Unit
PNNL	Pacific Northwest National Laboratory
PSD	Power Spectral Density

Contents

Summary iii
Acknowledgments v
Acronyms and Abbreviations vii
1.0 Introduction 1
2.0 Method 1
  2.1 Self-Coherence Algorithm 2
  2.2 DISAT Implementation 3
  2.3 Implementation Lessons 4
3.0 Results 5
4.0 Conclusion 9
5.0 References 9

1.0 Introduction

The deployment of phasor measurement units (PMUs) and other measurement devices continues to increase the insight into and understanding of the power grid. These higher sampling rate devices are revealing behaviors in the underlying grid, especially related to oscillatory behavior on the system. However, the increased fidelity of the measurements also results in significantly more data being streamed into power operations centers, often at rates beyond a normal operator's ability to examine and parse. Methods of detection and effectively filtering the data are needed to get the useful information out of this collection and presented to the operators and engineers of the power system.

One method for managing the information flow is to detect conditions like oscillatory behavior and flag that data set for review. The Data Integrity and Situational Awareness Tool (DISAT) being developed at the Pacific Northwest National Laboratory (PNNL) is one tool to detect such conditions. Utilizing historical data and statistical analysis techniques, DISAT examines the PMU data and looks for abnormal behavior. That is, DISAT looks for conditions on the system that either do not match historical, baseline-analysis expectations. This anomaly detection is based on the combination of different measurements to form an atypicality score. Events that are uncommon or differ from an expected norm receive a higher atypicality score, prompting review and closer examination of that data.

Oscillatory behavior on the power system represents a condition where atypical or abnormal behavior can represent larger grid issues, or equipment failures or misoperations. Oscillatory conditions have become more observable with the deployment of PMUs. Behaviors like inter-area oscillations have been a research topic for many years, providing greater understanding of the larger power system. The PMUs have also increased the observability of other oscillatory behaviors, such as forced oscillations. Forced oscillations, unlike modal oscillations, are not a natural characteristic of the power system. They are often induced by equipment operating between limit cycles, misoperating controls, or equipment behaviors in less desired regions of operation. The ability to detect and diagnose these forced oscillations aids power grid operators in providing power more efficiently, as well as potentially preventing any costly, longer outages associated with an unexpected, catastrophic equipment failure.

The project implements a method of oscillation detection into the DISAT framework. Built upon a Fourier-based method, the oscillation detection routine creates atypicality values for the DISAT program. Using these atypicality flags, DISAT provides the time and observation channel information to the power system operator. This reduces the amount of data the operating or planning engineer needs to examine to track down the problem, and allows them to focus their efforts.

This report describes the underlying oscillation detection algorithm, as well as its integration into the DISAT framework. Implementation lessons and some initial findings from the algorithm are outlined near the end of that section. Analysis examples from PMU data obtained on the western United States' power system are shown, highlighting the oscillation detection results. The report concludes with some overall conclusions and future work for the project.

2.0 Method

The signal processing literature offers many suggestions for the detection of signals in noise. Several of these methods could be used directly or with some adjustment to detect the presence of forced oscillations in power systems, but to the authors' knowledge the only published works describing the use of such algorithms are [Follum, 2013], [Zhou, 2013], and [Zhou, 2015]. For use in this application, the self-coherence algorithm developed in [Zhou, 2015] was selected for its robust nature and ease of implementation. In this section, an overview of the self-coherence algorithm will first be presented. Next, some specifics of the algorithm's implementation with the DISAT tool will be provided. Finally, lessons learned during implementation will be shared.

2.1 Self-Coherence Algorithm

The self-coherence algorithm is based on estimates of the magnitude squared coherence (MSC), also known as the spectral coherence. The MSC is a real valued function of frequency that is bounded between zero and one. The value of the MSC at a particular frequency reflects how linearly correlated the two time-series are at that frequency. For two time-series $x(t)$ and $y(t)$, the MSC at frequency f is defined as

$$C = \frac{\left|P_{xy}(f)\right|^2}{P_{xx}(f)P_{yy}(f)} \quad , \tag{1}$$

where $P_{xx}(f)$ and $P_{yy}(f)$ are the power-spectral densities (PSDs) of the individual time-series, and $P_{xy}(f)$ is the cross-spectral density between the time-series.

The MSC can be estimated for sampled time-series by replacing $P_{xx}(f)$, $P_{yy}(f)$, and $P_{xy}(f)$ with their estimates. In this work, as with [Zhou, 2015], estimates were generated using Welch's method. Welch's method operates by averaging together simple spectral estimates from overlapping segments of time-series measurements. These simple spectral estimates are based on the discrete Fourier transforms (DFTs) of the sampled time-series. Let the time-series measurements sampled at an interval of T_s seconds, which corresponds to a sampling rate of $F_s = \frac{1}{T_s}$ samples per second, be given by

$$\begin{matrix} x[n] = x(t = nT_s) \\ y[n] = y(t = nT_s) \end{matrix} \quad n = 0,1, \dots, N-1. \tag{2}$$

For data segments of length L with 50% overlap, the required DFTs are

$$X_m(f_k) = \frac{1}{\sqrt{U}} \sum_{n=(m-1)L/2}^{(m+1)L/2-1} w[n]x[n]e^{-\frac{j2\pi kn}{L}} \quad , \tag{3a}$$

$$Y_m(f_k) = \frac{1}{\sqrt{U}} \sum_{n=(m-1)L/2}^{(m+1)L/2-1} w[n]y[n]e^{-\frac{j2\pi kn}{L}} \quad , \tag{3b}$$

where $m = 1,2, \dots, M$ and $M = \frac{2N}{L} - 1$. The sampled frequency is given by $f_k = \frac{kF_s}{L}$ for $k = 0,1, \dots, L - 1$. The scaling term

$$U = \sum_{n=0}^{L-1} w^2[n] \quad , \tag{4}$$

where used to account for the effects of the data window $w[n]$. Using the DFTs in (3), estimates of the cross-spectral density are calculated as

$$P_{xy}(f_k) = \frac{1}{M}\sum_{m=1}^{M} P_{xy}^{(m)}(f_k) \quad , \tag{5}$$

where

$$P_{xy}^{(m)}(f_k) = \begin{cases} 2T_s X_m(f_k) Y_m^*(f_k) & 0 < f_k < \frac{F_s}{2} \\ T_s X_m(f_k) Y_m^*(f_k) & f_k = 0 \end{cases} . \tag{6}$$

The PSD estimates are calculated as special cases of (5) and (6) where both time-series are identical, i.e., both time-series are $x[n]$ for $P_{xx}(f_k)$ or both time-series are $y[n]$ for $P_{yy}(f_k)$.

As mentioned previously, the MSC indicates how linearly correlated two time-series are as a function of frequency. To detect forced oscillations, [Zhou, 2015] suggested examining the MSC between a set of PMU measurements and a time-delayed version of those measurements, prompting the term *self-coherence*. When a forced oscillation is present in both the original and delayed versions of the signal, the self-coherence will be near one at the frequency of the oscillation. When a forced oscillation is not present, the PMU measurements are primarily composed of ambient noise and the coherence can be expected to be near zero when a sufficient delay is used.

In [Zhou, 2015], a detection threshold was used to determine whether or not a forced oscillation was present. If the self-coherence exceeded the threshold at some frequency, then an oscillation was detected at that frequency. The threshold approach is standard for implementing detection algorithms. In this application, however, the DISAT tool was used to determine whether self-coherence values indicated atypical system behavior, i.e., the presence of a forced oscillation. In the following section, details on this implementation strategy will be provided.

2.2 DISAT Implementation

Implementation of the self-coherence algorithm was strongly guided by the existing framework of the DISAT tool. DISAT was implemented using the R programming language [R Core Team, 2014]. The user interface was developed using the Shiny package within R. In this section, details regarding this implementation will be given, including a description of the available data, an overview of the DISAT tool's operation, and the approach to detection of forced oscillations as atypical events.

Data was stored in files containing one minute of measurements collected at 60 samples per second from 31 PMUs. The self-coherence algorithm was applied to each minute separately. After loading each minute, a filter was applied to remove bad data corrupted by PMU malfunction, communication failure, or phasor data concentrator (PDC) error. To avoid interpolating through bad data, only the largest section of contiguous data for each channel was analyzed. Positive sequence voltage angle measurements were used to derive measurements of the system's frequency deviation from the nominal 60 Hz synchronous frequency. This calculation was performed by applying a first-order derivative filter, multiplying by the sampling rate, and dividing by 360 degrees. Finally, a high-pass detrending filter with a cutoff frequency of 0.1 Hz was applied to remove low-frequency trends in the data. Application of these preprocessing steps helped the algorithm to detect the oscillations of interest.

Rather than directly detecting forced oscillations using self-coherence values, parameters from the self-coherences were passed to DISAT for analysis. For each minute and every available PMU channel, the peak value of the self-coherence, the frequency associated with that peak, and the median of the self-coherence values across a frequency range of interest were passed to DISAT. Within DISAT, each minute of data was grouped into clusters based on these parameters. As will be discussed later, clustering the data provided insight when examining atypicalities.

Beyond clustering the data, the peak, frequency, and median value parameters were also used to calculate an atypicality score for each minute. In most cases, high atypicality scores indicated that a forced oscillation may be present in the system during that minute. A threshold was selected to distinguish minutes with high atypicality scores from the rest. After determining that a minute had a high atypicality score, the variables (PMU channels) contributing most to the high atypicality score were identified. These PMU channels were listed in DISAT's user interface to indicate where the forced oscillation was most observable, which, in many cases, is also where the oscillation likely originated.

To communicate the forced oscillation's distribution in the system, maps were created for each atypical minute. The maps marked the location of all utilized PMUs with a circle. The color of each circle corresponded to the frequency of the peak in the self-coherence spectrum. The radius of the circles was made proportional to the value of the peak. Thus, a collection of large and similarly colored circles indicated PMUs at which a common forced oscillation was observable. Examples of these maps are given in the Results section. In the user interface, the maps are plotted alongside graphs of the atypicality score over time. These combination figures were created for each of the 30 minutes preceding and following the atypical minute. By displaying the maps and atypicality scores sequentially, the oscillation's progression could be observed.

2.3 Implementation Lessons

Several lessons were learned during the implementation of the spectral coherence component of DISAT; two will be discussed here. An initial implementation allowed for an examined frequency range extending to the highest possible value, 30 Hz. It was observed that a disproportionately large number of peaks in the self-coherence spectrum fell between 20 Hz and 30 Hz. This phenomenon can be attributed to the extremely small spectral content in this frequency band, which leads to numerical errors when calculating the self-coherence. In response, the examined frequency range was limited to frequencies below 20 Hz.

Early implementations of DISAT also considered all voltage angle measurements from the PMUs, i.e., three individual phases and the positive sequence component calculated from them. After examining results, it became clear that inclusion of the individual phases was redundant. For the spectral coherence algorithm, DISAT now only operates on positive sequence components.

3.0 Results

The spectral coherence portion of the DISAT tool was applied to 227 days of PMU data provided by BPA, resulting in 117 minutes being flagged as atypical. After being flagged, the atypical minutes were examined using periodograms to seek corroborating evidence of forced oscillations. Periodograms are often used to detect sinusoidal signals in noise [Kay, 1998][Stoica & Moses, 2005]. Clear evidence supporting DISAT's flags was found in 110 of the atypical minutes. In four of the remaining seven cases, the self-coherence algorithm provided strong evidence of forced oscillations (peaks were in excess of 0.82), but the periodograms did not. This disparity may indicate that the forced oscillation's source was a stochastic system disturbance with frequency content spread over a band of several Hertz. Methods based on the MSC are better suited than periodograms in this scenario. The peaks in the self-coherence for these four cases were primarily located between 16 and 20 Hz, suggesting that the oscillations may have had a common cause.

Two of the remaining minutes were flagged due to large peaks in the self-coherence at the lowest examined frequency, 0.1 Hz. In both cases, the high self-coherence was due to significant frequency content that exists in power systems below approximately 1.0 Hz. Examining only frequencies above 1.0 Hz would solve the problem, but at the cost of the ability to detect forced oscillations in the important range between 0.1 and 1.0 Hz. As only 2 minutes out of 227 days were incorrectly flagged due to this problem, adjustment is probably unnecessary.

The final minute flagged as atypical by DISAT showed little evidence of a forced oscillation in either the self-coherence or the periodogram. In this case, the atypical nature of the data appeared to be unrelated to the presence of a forced oscillation.

The clusters corresponding to all 117 of the atypical minutes are listed in Table 1. Note that seven atypical minutes (marked in red) belonged to clusters characterized by low peak value means. Though it is counterintuitive that minutes from such clusters would contain forced oscillations, examination of the atypical minutes from the clusters with periodograms verified the flags from DISAT in most cases. Still, flagged minutes from clusters characterized by low peak values probably deserve extra scrutiny.

Table 1. List of atypical minutes by cluster

Atypicalities in Cluster	Clustering Parameters: Peak Value (mean)	Frequency (standard deviation)	Median Spectral Coherence (mean)
65	High	Normal	Normal
18	High	Normal	High
11	High	Low	High
5	High	Low	Normal
5	Low	Normal	Low

4	Normal	Normal	Low
2	Normal	Low	High
2	High	Low	Low
2	Normal	Low	Low
2	Low	Low	Low
1	Normal	Normal	High

After performing the atypicality analysis, results were displayed in an interactive application developed and run within R. After the user selects an atypical minute, a map of the western United States is displayed along with a plot of the atypicality score. An example of the display for an atypical minute is presented in Figure 1. The locations of the dots on the map correspond to geographic locations of the PMUs used for analysis. The peak values of spectral coherences and their corresponding frequencies are indicated by the radius and color of the dots, respectively. Thus, the map in Figure 1 indicates that a forced oscillation with a frequency of 16.7 Hz (green color) was observable in many parts of the system, particularly along the Washington-Oregon border (large dots). The atypicality score plot shows that atypical behavior began at approximately 01:15 and persisted intermittently until at least 01:57.

Maps and plots are generated for the 30 minutes preceding and following the atypical minute so that the user can observe how the forced oscillation progressed with time. For example, compare Figures 1 and 2. Figure 2 was generated using data that preceded the flagged atypicality by 17 minutes. The map indicates that peak spectral coherence values for various PMUs tended to be small and widespread in frequency. As a result, the atypicality score for the minute, which is indicated by a vertical red dashed line, is quite low. Examination of the minutes following the flagged atypicality revealed that the 16.7 Hz forced oscillation returned to the system several times and caused the high atypicality scores plotted in Figures 1 and 2.

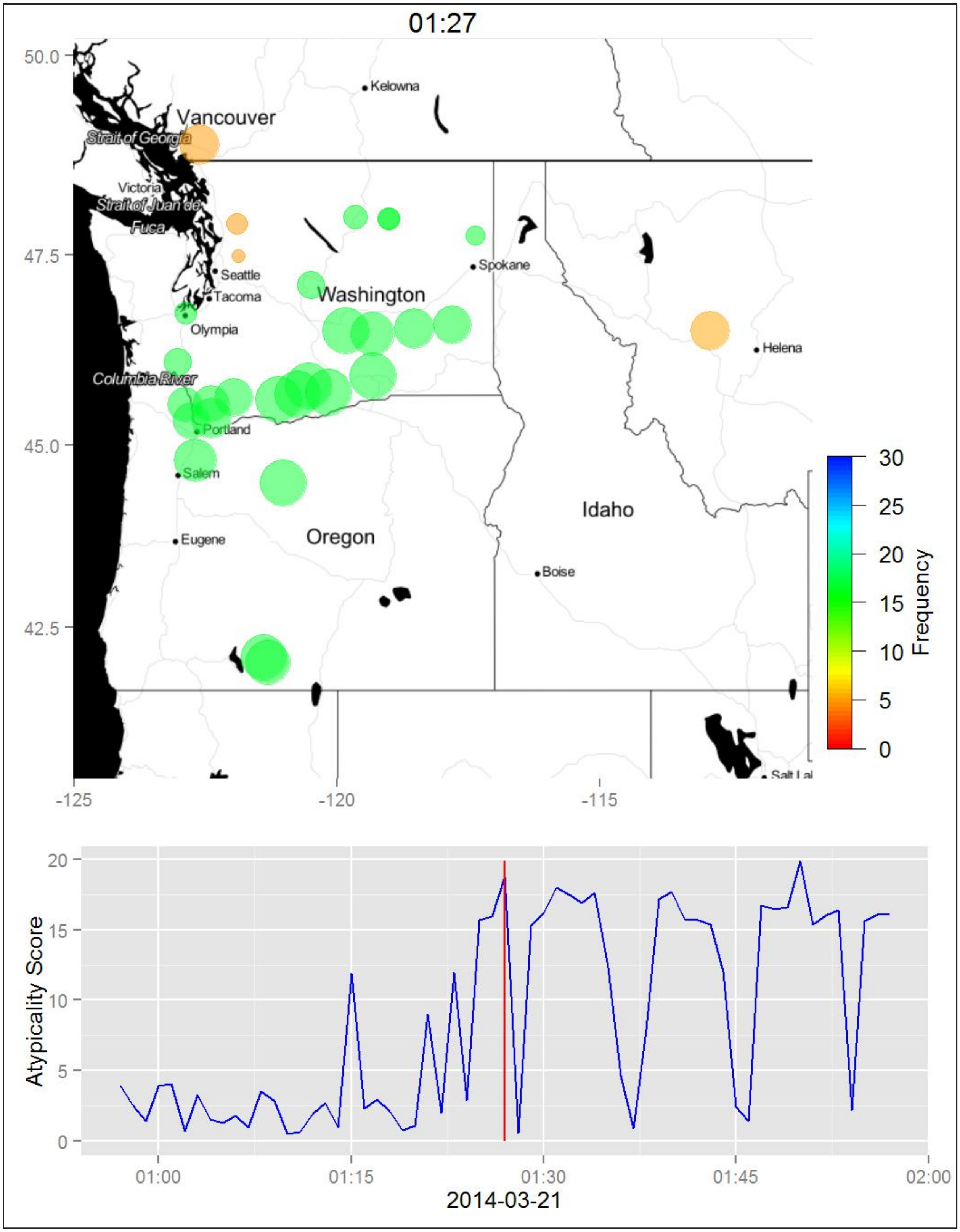

Figure 1: Example display from the DISAT application for an atypical minute. The solid red vertical line in the atypicality score plot indicates the atypical minute, as does the time above the map.

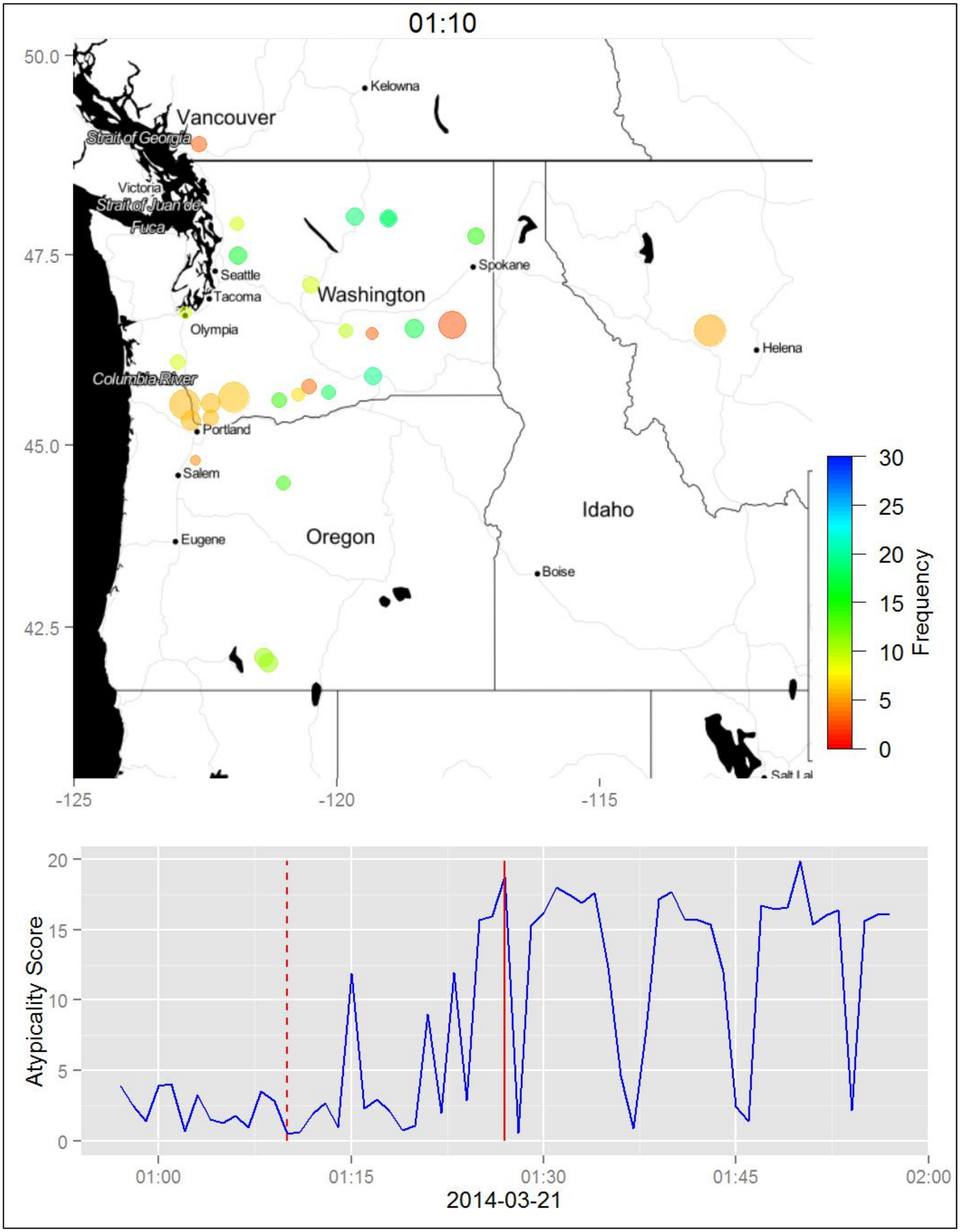

Figure 2: Example display from the DISAT application. This display is associated with the atypical minute from Figure 1, but the map was generated based on data preceding the flagged atypicality by several minutes (note the vertical dashed line at 01:10 in the atypicality score plot).

4.0 Conclusion

Integration of the self-coherence algorithm into the DISAT framework allows forced oscillations to be successfully detected. By highlighting the minutes and PMU locations where forced oscillations are observed, the tool circumvents the need for each minute and channel of data to be examined individually, a prohibitively large and arduous task. Informing operational engineers of when and where forced oscillations are present will improve their ability to correct the equipment misoperation or failure leading to the oscillation. In this way, the incorporation of the self-coherence algorithm into DISAT can have a positive impact on the reliable and efficient operation of the power system.

Currently, PNNL is continuing development of algorithms to be used for the detection of forced oscillations. This development includes investigation of algorithms with better detection capabilities and expansion of the algorithms into multi-channel methods. Eventually, the multi-channel nature of these algorithms may lead to improved methods of locating the sources of forced oscillations. Work will also continue to refine visualizations, such as those in Figures 1 and 2. Improving the visualizations based on feedback from operational engineers will help detection tools achieve their full potential impact.

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