

BIG DATA IN POWER SYSTEMS: A STATISTICAL APPROACH ON
SYNCHROPHASOR APPLICATION

BY

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THESIS

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ABSTRACT

Phasor Measurement Units (PMUs) are regarded as one of the most valuable device on the power system. PMUs, being devices that are found on buses of the power system, are capable of supplying both detailed and broad situational information.

The data produced by PMUs, which are synchronized by GPS timing, are referred to as synchrophasor data, and have plethora of information about the power system that has traditionally not been observed. The general trend in the use of synchrophasor data is offline, such as model validation and post-event analysis.

This thesis aims to provide a significantly different approach in the synchrophasor usage. Rather than considering synchrophasor data as extra sensor data that allows for enhancement of models, this thesis treats synchrophasor data as a type of big data, and utilizes statistical methods to find solutions and insight to synchrophasor data. The chapters of this thesis start with applying statistical methods to offline usage, and continue to consider statistical methods in real-time application.

ACKNOWLEDGMENTS

I would like to acknowledge many people for making this research possible. It was in June 2012 that PhD student, and retired Army Colonel, Karl Reinhard brought me into the synchrophasor effort sponsored by Professor Peter W. Sauer and TCIPG. Words are not sufficient to express my gratitude to Karl, as he is the one who let me start this endeavor and develop all the engineering intuition I have right now. I also greatly appreciate Professor Sauer for his support and the degree of freedom in studying the research he has provided me throughout both of my degrees. From TCIPG, I would like to thank Tim Yardley and Jeremy Jones for providing me with the necessary research resources, and Al Valdes for providing me with some insight on statistical methods.

There are many others I would like to thank from industry. I thank Jim Kleitsch from American Transmission Company for providing the data for this research as well as giving me in for an internship during my undergraduate degree; Brett Amidan for allowing me to use his application for the beginning part of my research and providing support for statistics concepts; and Dr. Yutaka Kokai for allowing me to intern at Hitachi America Big Data Labs where I was able to develop a wider view on the issue.

Lastly, I would like to thank my family for their support while I worked toward earning this degree.

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CHAPTER 1: INTRODUCTION

1.1 Background

The U.S. Power System is perhaps one of the most robust and interconnected system in the world. With 3092 generators interconnected through many iterations of transmission lines and transformers [1], each having an embedded control and multiple centralized control per subsystem, the complexity, resources, time, and man-power exerted on the system is unarguably one of the most significant systems built by humans. The reliability provided by this system is far beyond that of any other everyday social infrastructure utilized: one expects a loss of signal in a mobile device; one expects a loss of communication in internet usage; one expects a delay in transportation; however, one does not expect a loss of electricity. Electricity service provided by the U.S. Power System is developed to a point at which the quality of the service became a social norm: no other infrastructure has achieved this state of operation in the span of a century.

The fundamental challenge in the power system is due to this developed social norm for the reliability. Electricity supply is reliable at this point; however, changes in methods of generation and increase in load make it difficult to maintain this reliability to the social norm. The social demand for renewable energy adds variability to system stability [2]. Meanwhile, the demand for electricity continues to increase over the years [3]. In parallel to all of these factors, the aging of components in the power system also adds to the complexity of this challenge. These factors combined propose the challenge to this issue.

The task is how to overcome this fundamental challenge of the system. One method is to add extra modes of controllability to the system. This however, is not often the issue in the modern power grid, as many devices are controllable. The concern exists in the observability of the system, both in wide area and single point granularity. Together, these are referred to as wide area situational awareness (WASA) in the power system [4]. The lack of WASA, as a matter of fact, is one of the primary causes of the Northeast blackout of 2003 [5]; the state estimator did not provide sufficient and correct information about the power grid, and thus caused a chain reaction to occur throughout the grid [6]. The affected region can be seen in Figure 1.1.

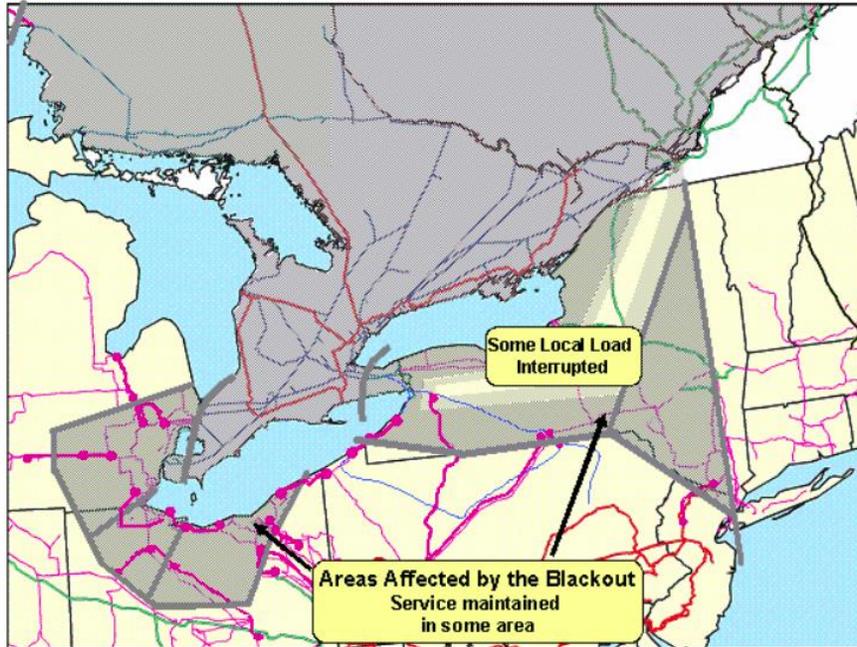


Figure 1.1: Affected region for Northeast blackout [6]

Devices and systems that allow WASA are referred to as the Wide Area Measurement System (WAMS). One of the most critical devices within WAMS is a Phasor Measurement Unit (PMU). PMU is a device that measures and creates phasor representation of the voltage and current on an AC system with a synchronized timestamp at 30 to 60 Hz [7]. The data created is often referred as synchrophasor data. The benefits that PMUs bring about are the following: (1) the synchronized timestamp allows the exact observation at each observation point at a given time and (2) high-frequency reporting of phasor data allows for granularity of information and allows behavior that have traditionally been unobservable to be seen. As a result, many entities have installed PMUs into their systems, as shown in Figure 1.2.

However, with benefits, PMUs bring about challenges related to data. According to calculations done by Hitachi, each PMU in a system produces a minimum of 80 GB of synchrophasor data per year [9]. Given a system with 100 PMUs, the data produced is over 8 TB per year. Along with the 30 Hz reporting rate, the analysis of the synchrophasor data is definitely a type of big data analysis. With the bandwidth of synchrophasor data and the static nature of the power system, seeking meaningful data out of the stream is no elementary task. To accomplish such a feat requires significant resources, manpower, and knowledge in several fields such as, but not limiting to, power system dynamics, statistics, and computer science.

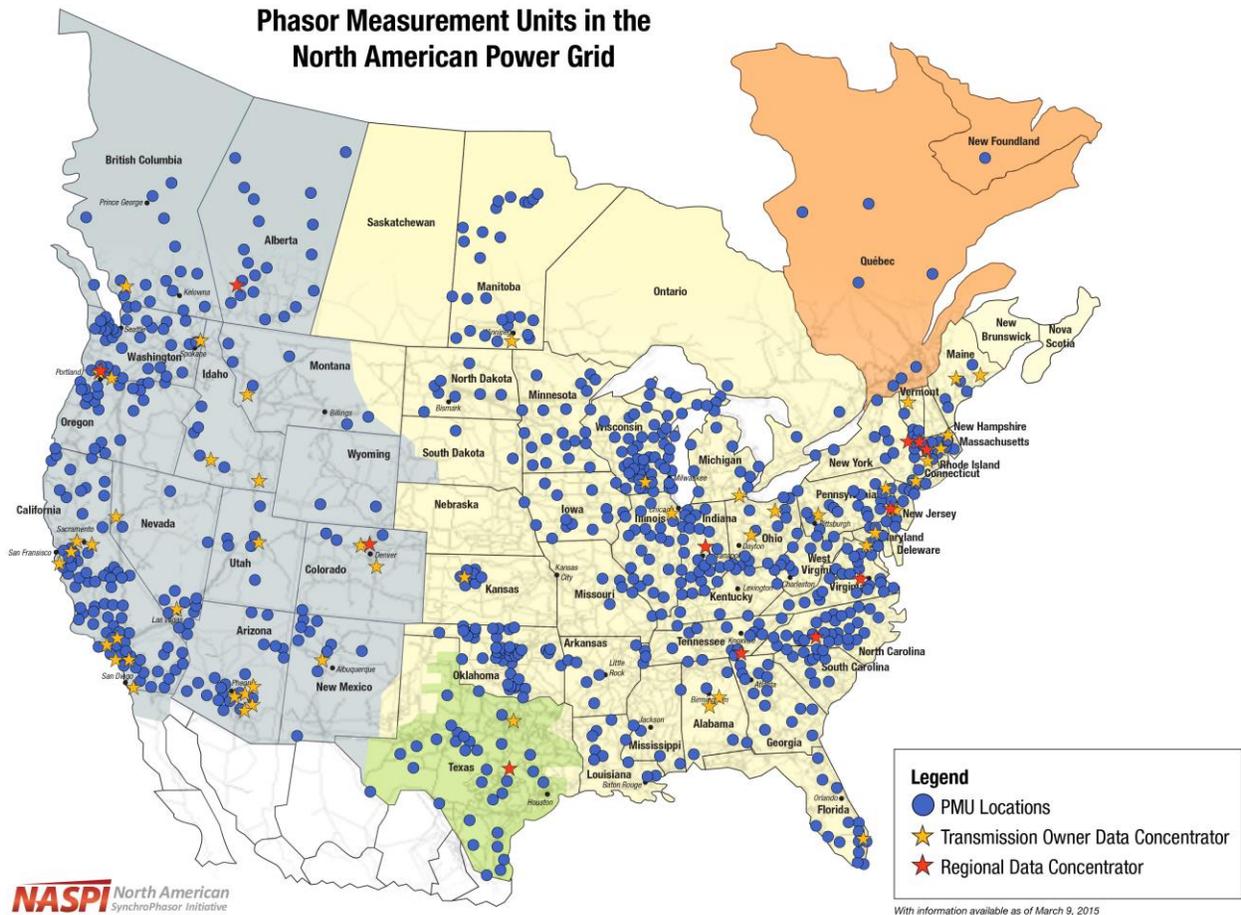


Figure 1.2: PMU deployment in North American power grid [8]

The limiting reagent causing deferment in the advancement of synchrophasor analysis is the disconnection between the above factors. Power system experts, such as operations engineers, often lack the time and computational resources preferable to advance analysis of the synchrophasor data. Since PMU data is only a segment of the operations engineer’s duties and responsibilities, difficulty exists in dedicating time into cost-inefficient modes of analysis. Meanwhile, those with computational resources and duties dedicated for data analysis, often lack the access to the data itself due to the proprietary of the data in power systems.

In order to investigate effective and meaningful ways to utilize synchrophasor data, the University of Illinois at Urbana-Champaign (UIUC), through the funding of Trust-worthy Cyber Infrastructure for Power Grid (TCIPG), has signed a NDA with American Transmission Company (ATC) for usage of ATC archive synchrophasor data. The thesis overviews the major efforts made in identifying the challenges and solutions in synchrophasor usage from a statistical perspective.

1.2 Thesis Overview

In this thesis, statistical techniques will be applied to synchrophasor Big Data to seek a way to overcome some of the challenges in usage of the data. First and foremost, background on data structure and resources available for this research is discussed in Chapter 2. In Chapter 3, preliminary signature detection is presented. Chapter 4 presents a specific Java application of synchrophasor. Chapter 5 discusses the extended work that foresees developments beyond the other chapters. Finally, Chapter 6 provides a conclusion.

CHAPTER 2: SYNCHROPHASOR DATA AND RESOURCES

2.1 Synchrophasor Data Description

Before further discussion is made, it is important to understand the concept of synchrophasors. As briefly mentioned in the introduction, synchrophasor data is a time-synchronized form of voltage and current measurements. What this entails is shown in Figure 2.1.

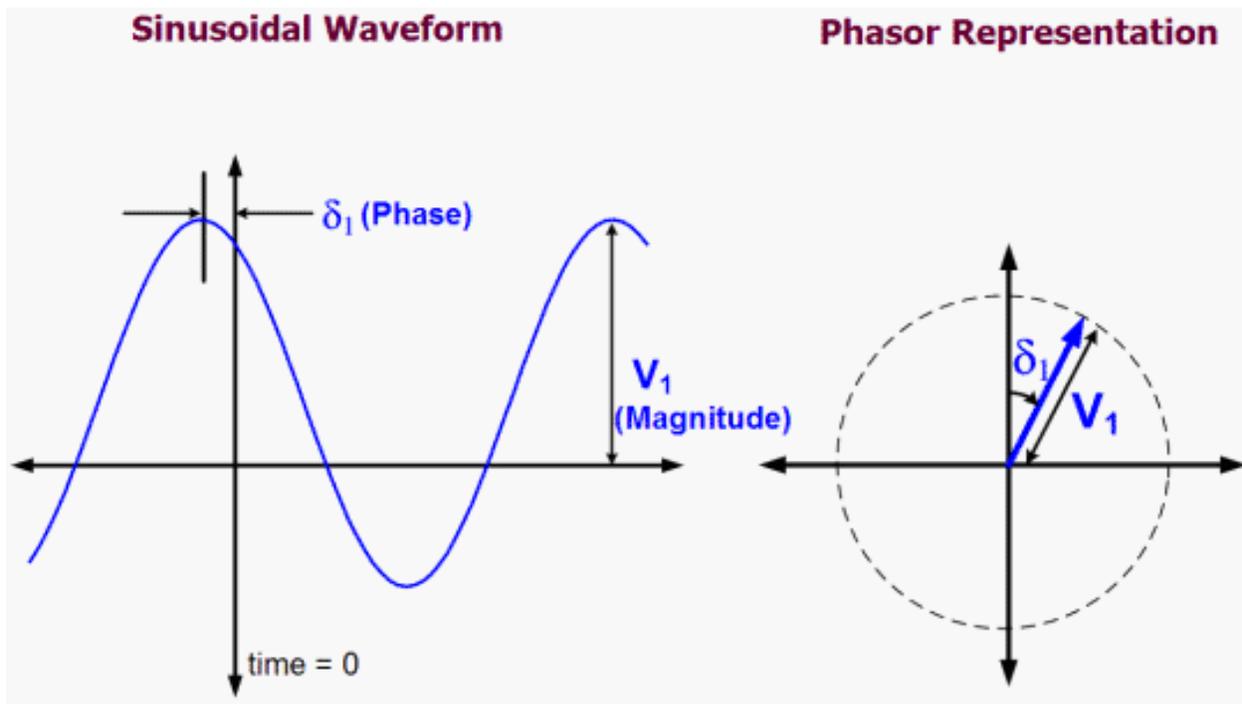


Figure 2.1: Phasor representation [10]

In the respective figure, the sinusoidal waveform (left) is representative of the raw voltage (or current) measurement sampled at a very high frequency for a 30th of a second. From this waveform of the length of a 30th of a second, the magnitude of the waveform and a phase of the waveform with respect to a 60 Hz signal is calculated. The resultant operation creates a phasor representation of the waveform during this time window shown on the right. Along with this operation, the frequency of the waveform is calculated by processing the waveform to a Fourier domain. The respective phasors for voltage and current as well as frequency are timestamped by the end of the 30th of a second. The operation is repeated for each phase. In the end, each synchrophasor contains the metrics shown in Table 2.1.

Table 2.1: All metrics to each synchrophasor

	Voltage Magnitude	Voltage Angle	Current Magnitude	Current Angle	Frequency	Timestamp
Phase A	-----	-----	-----	-----	-----	-----
Phase B	-----	-----	-----	-----		
Phase C	-----	-----	-----	-----		

These 17 metrics, together are referred as one synchrophasor at a given location and time. Due to the time window being a 30th of a second, naturally, these synchrophasors are generated at 30 times per second at a particular location by a PMU.

How this synchrophasor data flows throughout the network is shown in Figure 2.2. First, synchrophasors are generated at each PMU. The synchrophasors from several PMUs are then reported to a Phasor Data Concentrator (PDC), and then to the control center and archives. Finally, the synchrophasor is reported to the regional entity's PDC. The whole process is done in a continuous stream to provide a real-time informatic of the system from each PMU location.

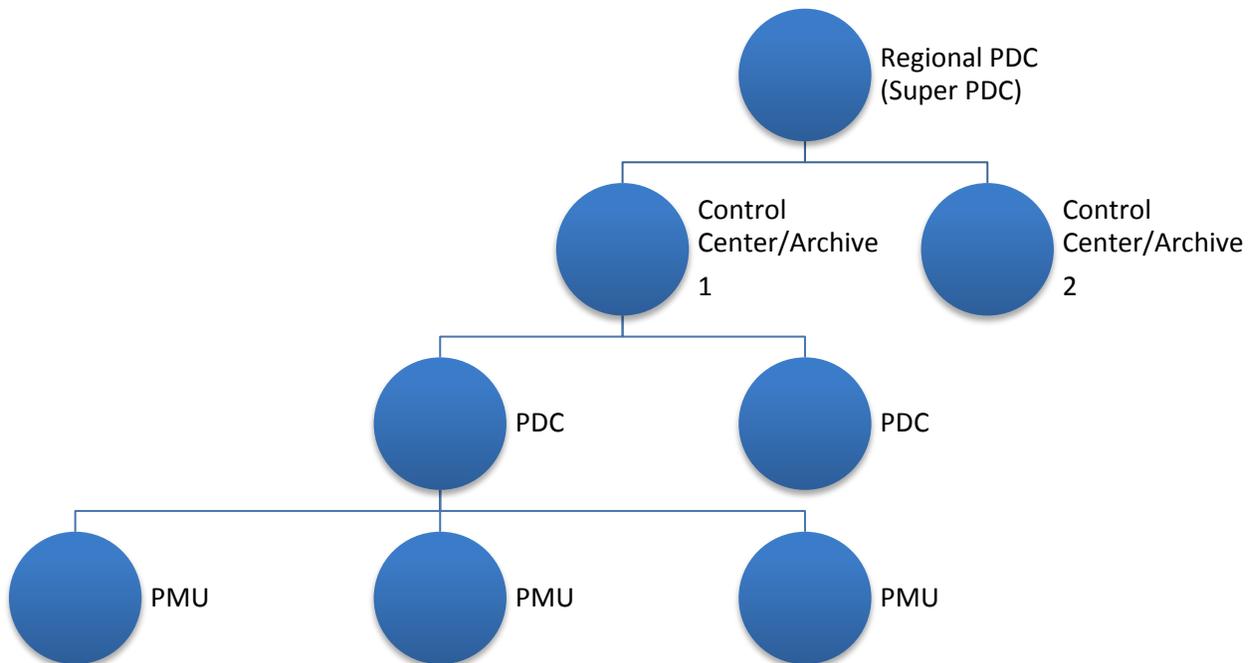


Figure 2.2: Synchrophasor flow map

2.2 Resources

To conduct this research, appropriate resources are necessary. The resources available for research are the following:

- 20 TB of ATC Synchrophasor Data Full Archive
- 2 Intel i7 Quad-Core Windows Machines
- 1 Intel i7 Dual-Core OSX Machine
- 26-Node Hadoop Cluster

The description of each resource will be discussed individually in detail.

2.2.1 ATC Synchrophasor Data Archive

As the primary resource to this project, 20 TB of ATC synchrophasor data archive is located on an OSIssoft PI server. The OSIssoft PI server is a SQL-based relational database [11]. Since synchrophasor data is a high-frequency time series data, it is likely stored in either one long table, or many long tables. One possible storage mode of these data in the server itself is shown in Table 2.1.

Table 2.2: Possible table for synchrophasor storage

Timestamp	Metric	Value	PMU Location
Time A	Voltage Magnitude Phase B	-----	Somewhereville
Time A	Voltage Magnitude Phase C	-----	Somewhereville
Time A	Voltage Magnitude Phase A	-----	Hereville
Time A	Voltage Magnitude Phase B	-----	Hereville
Time A	Voltage Magnitude Phase C	-----	Hereville
Time A	Frequency	-----	Hereville

Essentially, for each new timestamp, synchrophasor data is divided into 17 different rows, and stored individually. As this is a basic structure for a relational database, it is highly plausible that the data is organized in this fashion or similar to where each PMU location can be a different long table. However,

unlike open-source databases, such as MySQL, the PI server does not reveal the physical—in this case physical in a digital sense—structure of the database. To avoid the possible uncertainty of the database structure and for ease of analysis, a small subset of the data in CSV is used. The data structure of the data is as such in Table 2.3.

Table 2.3: CSV data structure

Timestamp	Frequency	VA A	VM A	VA B	VM B	VA C	VM C	IA A	IM A	IA B	IM B	IA C	IM C
-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----

Instead of each synchrophasor being separated, as it would be in a relational database, each synchrophasor is presented as a row. This is often referred to as a wide-table format. Although inefficient for database storage, since each column signifies a continuous time series data stream, analysis across variables and time reduces the overall effort necessary.

2.2.2 Windows Machines

Two Windows machines, both of which contains quad-core i7 processors are utilized for the computational power. Since i7 processors are capable of hyper-threading, the processing power of the machines would be anywhere between 10-20% higher than that without hyper-threading technology. Also, the availability of two sets of quad-core CPUs allows a desirable environment for parallel processing. This is utilized through the use of multicore parallel processing to achieve a psuedo-cluster for testing the environment.

2.2.3 26-Node Hadoop Cluster

As a precaution and preparation for when more computational power is necessary, access to a 26-node Hadoop cluster was granted from TCIPG. However, due to the simplicity of the task that can be done on Hadoop, which is marginally more complex than a SQL command, the platform was available mainly as a final effort for processing data.

CHAPTER 3: PRELIMINARY SIGNATURE DETECTION

One of the most promising functionalities of synchrophasor data is the time series signature that can be generated. Unlike the traditional SCADA system, the higher reporting rate of the system allows for “patterns” to be recognized in the system. Figure 3.1 shows one example of such a pattern that was observed on the Dominion system. SCADA system was able to identify an issue with the power output out of the generator, however, was unable to identify the full “picture.” Such a phenomenon is caused by the SCADA system’s reporting frequency, which is far below that of the power system event frequency; meanwhile, synchrophasors are capable of reporting much higher than the Nyquist frequency of known system events, so these “signatures” can be observed.

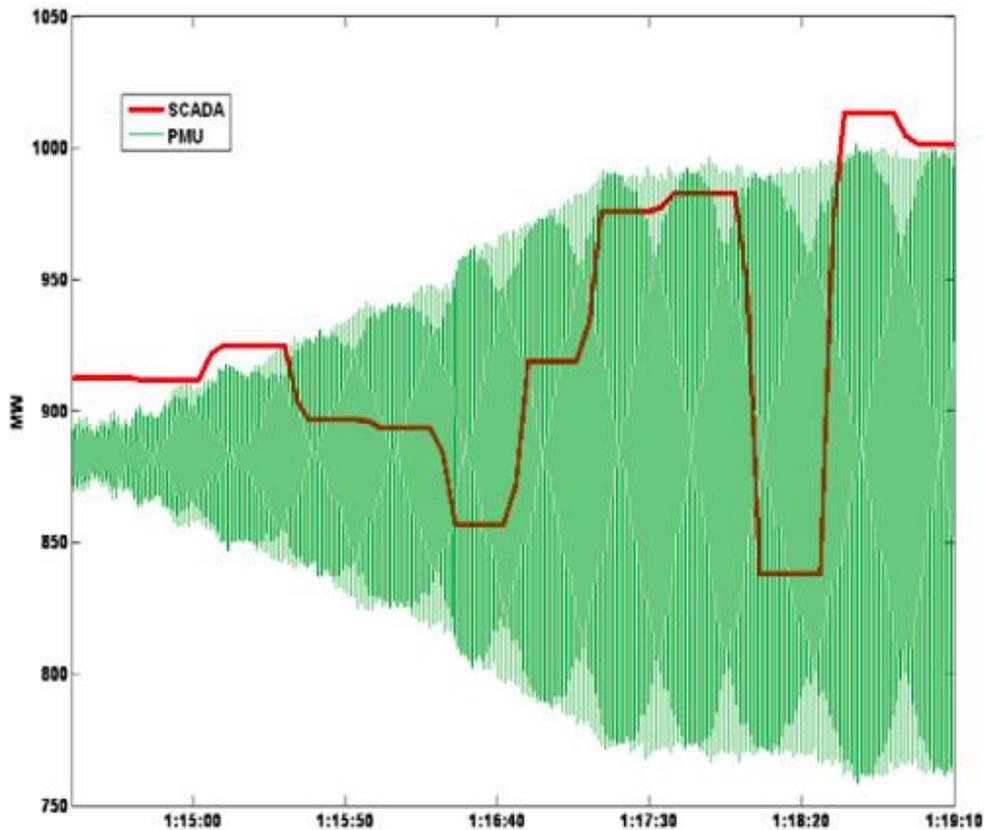


Figure 3.1: Twelve-minute oscillation at a nuclear power plant [12]

The work presented in this chapter is adapted from “Investigating Synchrophasor Data Quality Issues” from IEEE Xplore publication presented at *Power and Energy Conference at Illinois 2014* at Champaign, IL authored by Kenta Kiriara, Karl E. Reinhard, Andy K. Yoon, and Peter W. Sauer [13].

This chapter puts emphasis on finding signatures from the large scale of synchrophasor data using preliminary and advanced analysis in the R-project statistical analysis program (R). R is an open-source program optimized for statistical application. Due to R being a direct successor to the S-language, which is C-based, a wide range of analysis can be done. If necessary, additional packages can be downloaded or scripted with C, C++, or Fortran to extend the functionality. R is chosen over other programming languages such as Python, C++, or Java in this analysis due to the flexibility that is available.

As a guideline to this search for signature detection, ATC proposed several possible events analysis categories:

- Unit trips and/or loss of significant loads
- System fault
- Capacitor bank failures
- Predecessor events to trips
- Imbalanced line phase angle differences

By searching for these signatures in the synchrophasor data, the validity of using a data-driven approach is confirmed. Signatures are confirmed with ATC archive information to link the signature.

3.1 Baseline Approach

As a way to understand the baseline behavior of the system, principal statistical values of the time-series data are computed. Since computation time is non-linear, a particularly small section is used. Shown in Figure 3.2 is an extraction of 5 days of phase voltage magnitude for a particular substation. The principal statistical values are shown in Table 3.1.

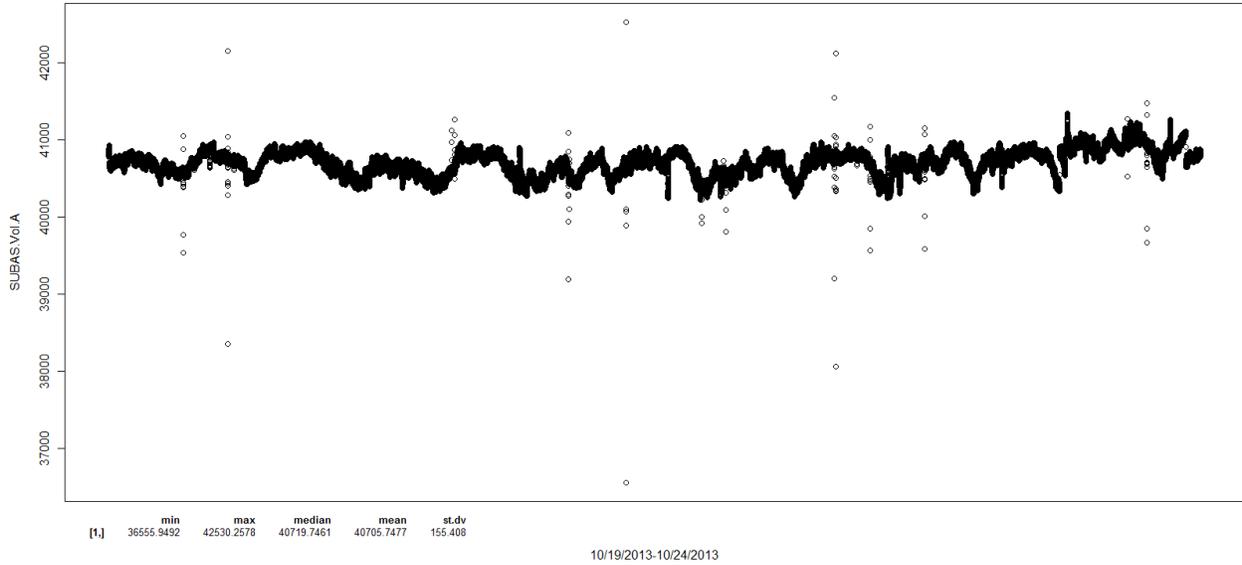


Figure 3.2: Time-series plot of 5 days of voltage magnitude

Table 3.1: Principal statistical values for the time-series data

Min	36555.9492
Max	42530.2578
Mean	40710.7461
Median	40705.7477
Standard Deviation	155.408

From Table 3.1 and Figure 3.2, it is apparent that most of system is stable. The difference between the mean and the median is insignificant, and thus, most of the data follows a normal distribution. From the exclusion-inclusion principle, these points that lie outside of expected normal operation are unusual behaviors. However, as seen from the Figure 3.2, many points exist outside of this standard deviation, but the cause is unknown; a more advanced method of analysis is necessary to identify if these are actual signatures or a synchrophasor data quality issue caused by the PMU.

3.2 High-Performance Clustering Technique

Situational Awareness and Alerting Report (SitAAR) is a big data analysis tool developed by Brett Amidan at Pacific Northwest National Laboratory (PNNL). Using k-means clustering methods, and other preprocessing to clean the data, the tool allows signatures to be clustered together and outliers to be found [14]. In other words, the tool allows a separation of system events by comparing them to different modes of system operation.

In detail, SitAAR first divides the time series into one-minute intervals and adds a quadratic model to the interval. The one-minute interval, which equates to 1800 PMU data points assuming a 30 Hz-reporting rate, allows for robust analysis. As of October 2013, ATC system has 92% of the PMUs delivering 99.9% reliable data with a 99.9% success rate [15]. Using this data and averaging all of the PMUs, the expected value of reliable data per PMU is 1600 data points per minute: an accurate quadratic regression can be made with this number of points. This allows the tool to recognize the pattern of the interval such as gradual change or sudden changes in the reported value, in quadratic model parameters. The parameters of each model is used to signify a point on an n-dimensional space to determine which cluster the interval belongs to.

Since most of the power system is rather static, with AVR applying a gradual change in voltage, the number of clusters the analysis needs is rather arbitrary. In practice, when considered different modes of operation, the following cases can be considered:

1. System is operating within the standard deviation
2. System is operating at peak capacity or on low demand
3. System is shifting from one operating to another or in transience

Taking into consideration these cases, it is trivial that case 3 is the one that would fall into an outlier. To account for several different modes of case 1 and 2, the number of clusters SitARR would generate was set to 30.

Figure 3.3 shows one of the results that SitAAR was able to capture in the data. This particular instance, a line trip was found through the current magnitude data. The event is captured due to the high atypicality score of the interval.

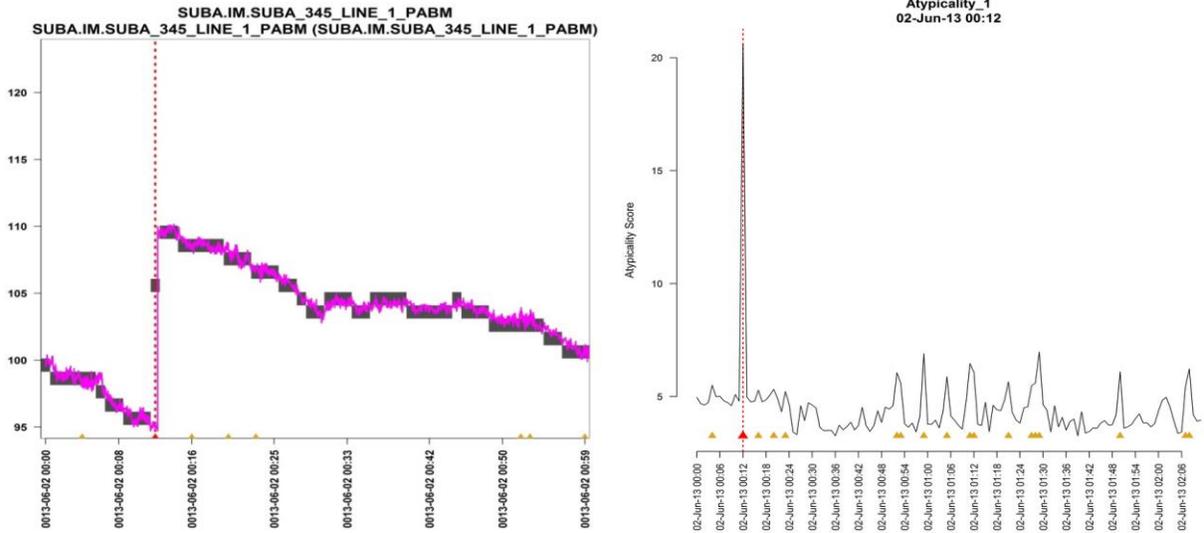


Figure 3.3: Found signature (left) and atypicality score (right)

Similarly, SitAAR was able to identify several other types of signatures in the system as shown in Figures 3.4, 3.5, and 3.6. In Figures 3.4 and 3.5, the same event is captured through different metrics in the data: one being current magnitude and other being frequency. Since current flow is interrupted on a line during a line trip, when the line is restored, the current flow is also restored. This sudden change in behavior has been detected through the current flow changing across the system and frequency of the system at the point of measurement to alter.

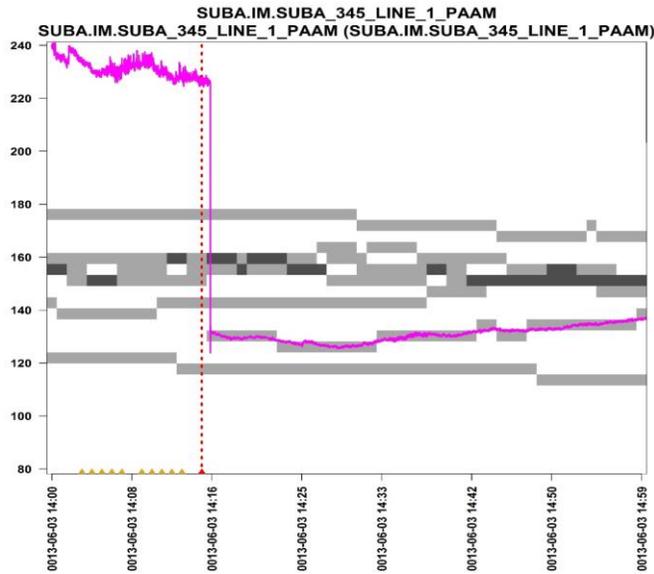


Figure 3.4: Another example of a line trip

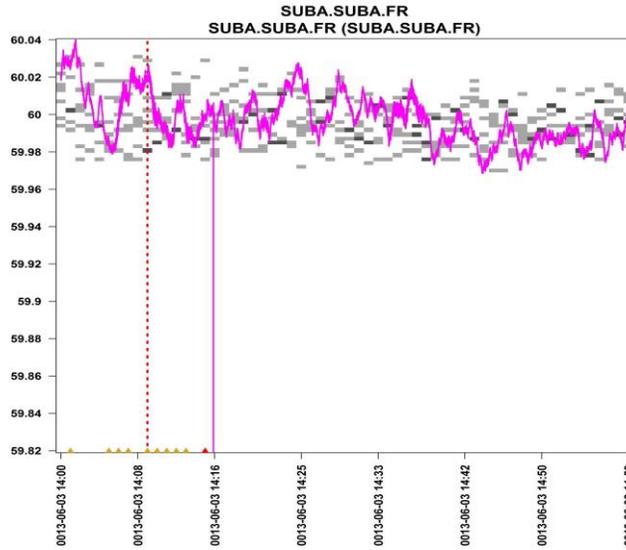


Figure 3.5: SitAAR detecting frequency disturbance in the same event as Figure 3.4

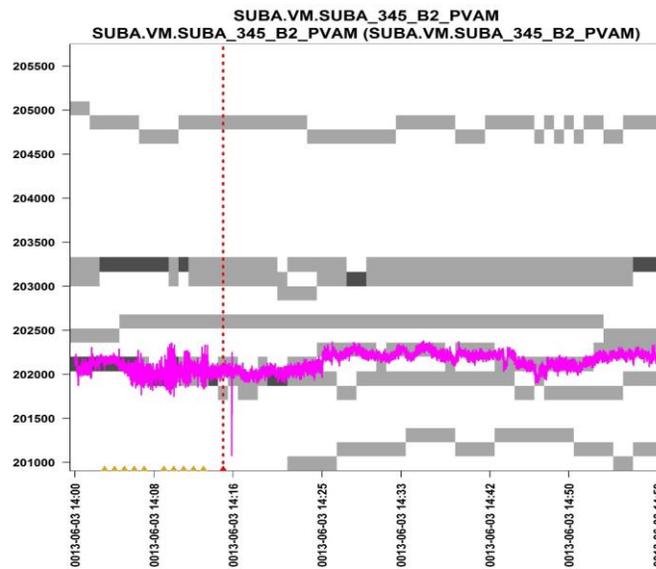


Figure 3.6: Voltage magnitude capturing another line trip

Figure 3.6, shows the voltage magnitude data capturing another line trip. From pattern recognition or the signature detection use case, which SitAAR is responsible for, finding signatures through the use of voltage magnitude, current magnitude, and frequency measurements indicate that the use of voltage and current magnitudes are the more reliable ways of finding faults.

3.3 Drawbacks

The use of SitAAR was effective in finding signatures in the system. However, major drawbacks exist in extending to a more dynamic use case. It is undeniable that the k-means clustering technique is effective in finding the signatures in a system when used in an offline case. The problem exists in the physical limitation in computation. With a data size of 20 GB, which was approximately the size of the data that was used for the preliminary test, the time necessary for computation was approximately 12 hours with one i-7 Windows machine. To process 20 TB of the data using the same exact hardware would take a minimum of 1000 times, or 18 months assuming a linear processing time.

First, having a program executing for 18 months is an implausible task, and it is apparent from common experience that most operating systems are incapable of being able to run for such an extent without resetting. Second, the amount of RAM necessary to keep the clustered data would quickly deplete, and virtual RAM will be required. The memory swapping necessary will impact the CPU overhead, and thus, cause a larger process to complete at a nonlinear time.

Using the exact same method online, as in clustering streaming data, would again lead to the same issues regarding physical hardware. The k-means centroid would be fairly static, but the overhead necessary to keep track of these centroid maybe expensive. For a practical usecase, such as online usage or large-scale analysis of the whole archive data, a more efficient and dynamic algorithm for signature detection is necessary.

CHAPTER 4: SYNCHROPHASOR VISUALIZER

Online usage, otherwise referred to as “real-time” usage, is one of the two end goals of synchrophasor technology. The October 2014 North American Synchro Phasor Initiative (NASPI) identified the status of the synchrophasor development in North America. Out of the 13 entities listed in the NASPI Recovery Act Smart Grid Investments Synchrophasor Project Status, WECC is the only entity which has successfully implemented all of the applications of synchrophasors, both in real-time and study mode application as of the summer of 2014 [16]. Many of the projects are still in research stage, and have yet to be implemented. As mentioned in the introduction, the fundamental challenge with the synchrophasor effort is the lack of designated engineers solely working on the synchrophasor task. Oftentimes, these engineers are expert engineers from both operations and system planning, but the problem lies in the possible time commitment of these engineers. Though Smart Grid Initiative funds and their efforts in terms of resources, the human resources necessary for the tasks are vastly lacking.

To remedy this challenge and to simulate an environment where statistical methods can be implemented, a baseline application in which entities can build upon is proposed. Synchrophasor Visualizer (SPV) is a Java-based application that covers the essential functionality of the synchrophasor network. Although called “Synchrophasor Visualizer”, to experiment with statistical methods, SPV puts more emphasis on the data processing than the visualization.

4.1 SPV Overview

Figure 4.1 shows the functional design of the SPV. Data is fed in through two sources, either from a live stream or through a database; however, the functionality of SPV does not differ between the two modes of operation: archived data is played back as if the data is streamed. Once the data is secured in the program, the data is utilized in two ways: visualization of raw information and event detection. The two sections work independently and are displayed upon user control.

The work presented in this chapter is adapted from “Synchrophasor visualizer” from IEEE Xplore publication presented at *Power and Energy Conference at Illinois 2015* at Champaign, IL authored by Kenta Kirihara, Karl E. Reinhard, Yang Liu, and Peter W. Sauer [17].

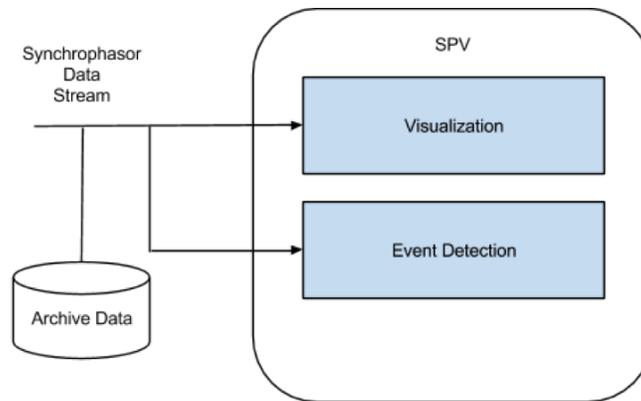


Figure 4.1: SPV functional design

In Figure 4.1, the program design of SPV is shown. In SPV, the most essential task is to visualize data continuously. That is, data should be processed in such a way that the continuous stream of information is uninterrupted. To accomplish this, the program is divided into four different processes:

- Data retrieval
- Data processing
- Data visualization
- User control

The concept is elementary in modular programming. Creating independent sections allows for multiple tasks to be processed independently of each other. However, increase in the number of parallel processing brings about challenges when handling data stream of synchronphasors. In the process of building SPV, it is essential to understand the nature of threads in general. Any task that requires a query will benefit from having more threads and opposed to computation to require less threads. SPV is a combination of these two types of operations and thus utilizes both a task requiring more threads and another that requires fewer threads through the use of Java programming.

4.2 SPV Data Retrieval

As with any program, data retrieval is an essential functionality in bringing data into the system. In the data retrieval block of the SPV, two modes of operation are present: one where data is streamed from a

PDC and one where data is queried from a database and played back. The switching between the two modes is user controlled.

4.3 SPV Data Processing

In this process, data processing and computation is executed. Data processing takes on two roles: one is to stream the data into the section and the other is to analyze the data to send the result to the visualization block. There are two separate types of computation that are executed in parallel. One is a Fast Fourier Transform (FFT) and another is an anomaly detection through a variation of one-dimensional moving distribution. Both are tasks that require less thread and more dedicated CPU core.

4.3.1 Fast Fourier Transform

FFT is an algorithm in which time-series data can be converted into a Fourier domain. Conceptually, from a Big Data perspective, the transformation from time-series domain to Fourier domain is similar to quadratic regression. The algorithm is relatively computationally inexpensive, and is suited for running in real-time. FFT is utilized to capture an oscillation that may occur in the power system: as this is a fairly common method of detecting oscillation, this feature is left in the back-end. Since oscillation is fairly uncommon in a power system, except for the case of wind farms [18], this feature will not be used as heavily.

In SPV, 3000 data points of synchrophasor voltage magnitude for one phase are collected and an FFT is performed after zero-padding. The advantage of using this many points is that it allows a detection of slower frequency oscillation by having many data points to reference. If an oscillation were to be detected, a signal is sent to the visualization process.

4.3.2 Moving Distribution-based Anomaly Detection (MDAD)

The core of the processing in the synchrophasor data is in moving distribution-based anomaly detection (MDAD). This process is a one-dimensional version of k-means clustering detection through the

combination of rule-based statistical methods. First, the latest 3000 points, or 100 seconds of synchrophasor voltage measurement data is collected. The mean and the standard deviation of the data points are calculated. The calculation is repeated for every new data point that enters the system. If more than three latest data points lie beyond four standard deviations from the mean, then an alarm is triggered.

Figures 4.2, 4.3, and 4.4 illustrate the algorithm in use on voltage magnitude data. For each figure, the right shows the original time-series data and the left shows the distribution in the hundred second time interval. In stability, which is shown in Figure 4.2, the distribution of the voltage magnitude is pseudo-normal. However, when stability is lost, the normality is lost, and the distribution begins to form a multi-modal distribution as shown in Figure 4.3. Once a new stability is reached, the distribution of the measurement will form an obvious multi-modal distribution. The moving distribution-based anomaly detection captures this shift from one stable point to another.

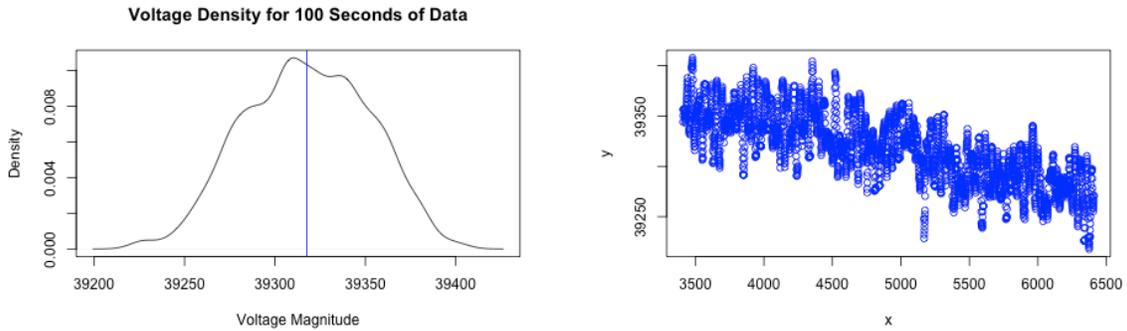


Figure 4.2: Distribution (left) and raw data (right) before transience.

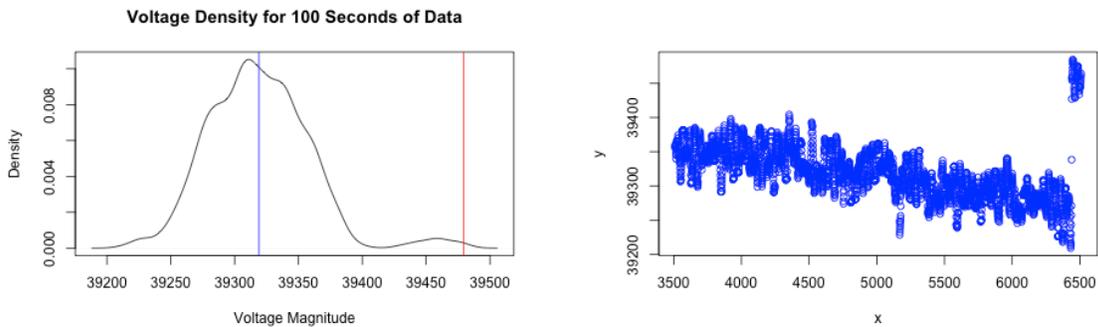


Figure 4.3: Distribution (left) and raw data (right) during transience. Red line indicates fault detected.

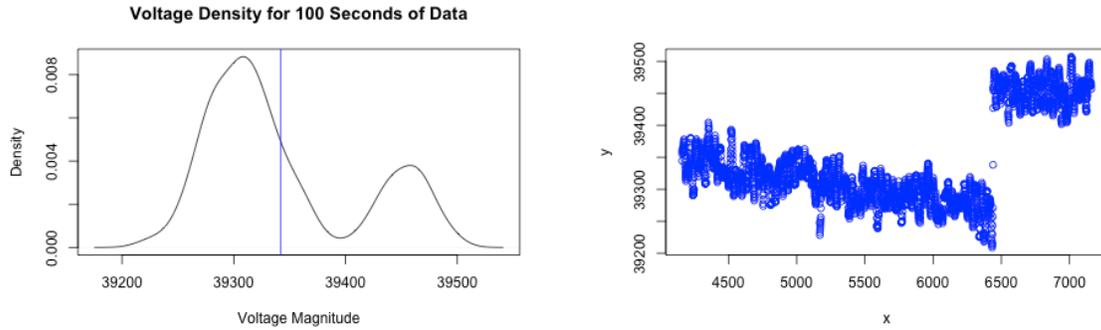


Figure 4.4: Distribution (left) and raw data (right) after transience.

The advantage of this algorithm is the computational efficiency that is brought along. As opposed to an FFT, which is in itself light, MDAD only computes low-level operations that can be processed in simple programs. For instance, computing the result for one hour of data in Excel consumes less than half a minute.

Testing of this algorithm’s effectiveness was performed on several cases identified beforehand through SitAAR. As mentioned in the previous section, SitAAR is very effective in identifying events, and suitable for comparison. Table 4.1 summarizes the type of event and the effectiveness of the MDAD compared to SitAAR. As shown, MDAD yields effectiveness, which matches the k-means clustering method to find an outlier or system event.

4.4 SPV Visualization

By default, data is visualized as shown in Figure 4.5. On top of a Google Map API, PMU locations are added. Each circle on the map represents a PMU location. Selecting a PMU will reveal the real-time measurements of voltage magnitude and angle.

When an overview is necessary, using the buttons on the upper-right corner, the user is able to choose whether the voltage magnitude or voltage angle is mapped out using a gradient map for immediate wide-area system awareness as in Figure 4.6. Like with the concept of one-line diagrams, the voltage magnitude at each point is normalized to a per-unit convention. By doing such operation, the operator is able to observe the relative voltage levels at each section of the map instantaneously. Also, when a system event is found through the data processing section, the event is displayed as in Figure 4.7 to signify the user where the fault is located.

The visualization is mapped out and refreshed at a rate of 10 Hz. There are two reasons why this is done. First, since opinions from operators revealed that excess information are non-preferable, the refresh rate is set lower to accommodate such demands [19]. Second is to reduce the computational stress on the machine so more threads can be utilized for analysis.

Table 4.1: Effectiveness of MDAD

Substation	Time	Measurement Type	Suspected Cause	MDAD Effectiveness
SUBA	0013-06-03 12:59	PA-IM	Load Change	Effective
SUBA	0013-06-03 12:59	PB-IM	Load Change	Effective
SUBA	0013-06-03 12:59	PC-IM	Load Change	Effective
SUBA	0013-06-03 14:16	FR	Unknown	Effective
SUBA	0013-06-03 14:16	PA-IM	Line Trip	Effective
SUBA	0013-06-03 14:16	PB-IM	Line Trip	Effective
SUBA	0013-06-03 14:16	PC-IM	Line Trip	Effective
SUBA	0013-06-03 14:16	PA-VM	Line Trip	Effective
SUBA	0013-06-03 14:16	PB-VM	Line Trip	Effective
SUBA	0013-06-03 14:16	PC-VM	Line Trip	Effective
SUBA	0013-06-04 02:16	PA-VM	Line Trip	Effective
SUBA	0013-06-04 02:16	PB-VM	Line Trip	Effective
SUBA	0013-06-04 02:16	PC-VM	Line Trip	Effective
SUBAY	0013-10-31 06:08	PA-VM	Double Capacitor Switching	Effective
SUBBJ	0013-10-31 21:08	PA-VM	Capacitor Bank Switching In & Out	Effective

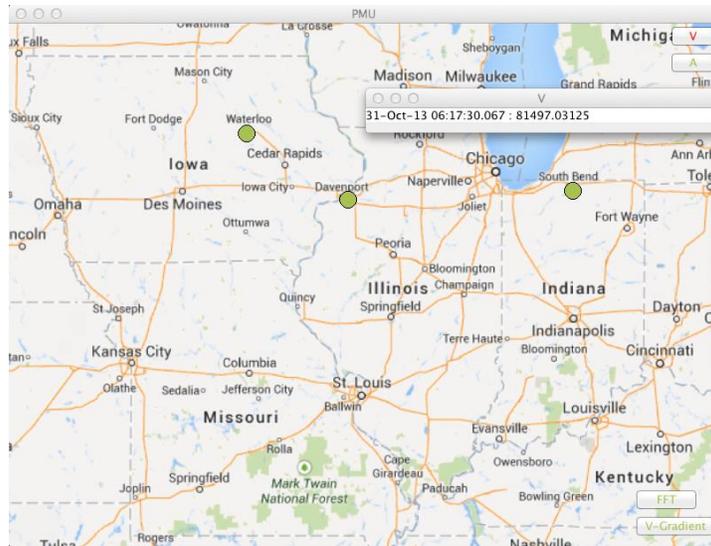


Figure 4.5: SPV default page

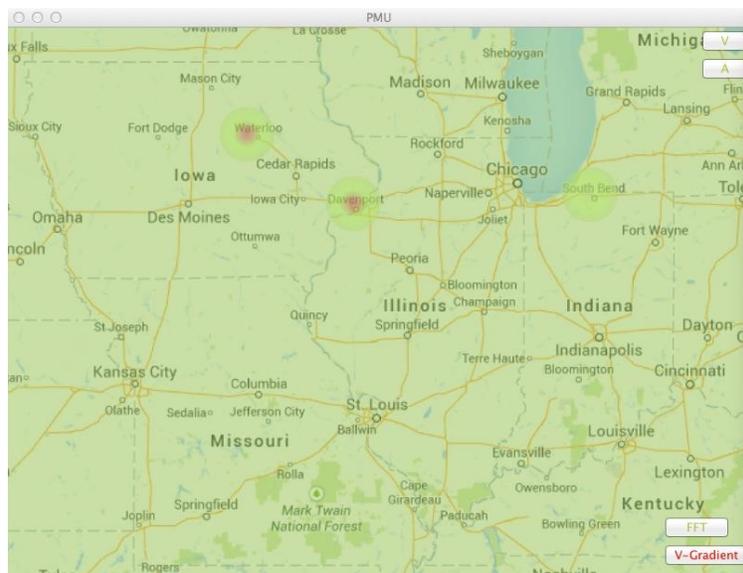


Figure 4.6: SPV gradient

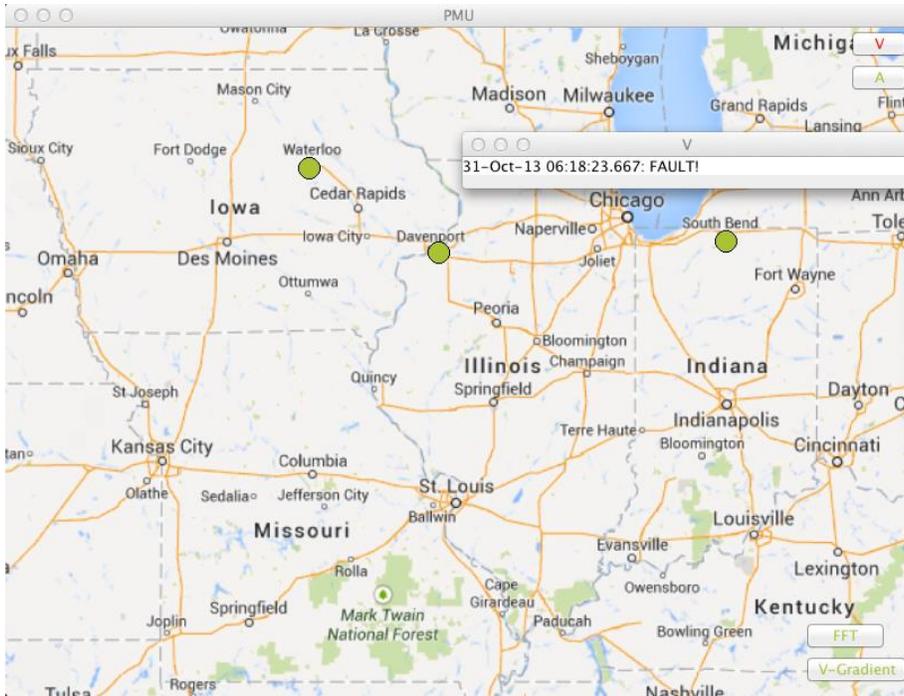


Figure 4.7: SPV detecting fault

CHAPTER 5: EXTENDED WORK

The ultimate goal of synchrophasor usage is to combine all aspects, both online usage and offline usage into an application such as SPV. When considering real-usage, there will be edge cases that come about that must be considered. Furthermore, the capabilities of the application may need to be extended. This chapter will discuss the next step of synchrophasor usage, considering the edge cases not discussed in the previous chapters.

5.1 Data Quality Issues

In the previous chapter, where real-time usage was discussed, the issue with data quality was not considered. With regards to data quality, several cases must be considered:

- Case 1: Data is correct and available.
- Case 2: Data is incorrect and available.
- Case 3: Data is unavailable.

Case 1 is an ideal case, and further processing or handling of the data is unnecessary. Case 2 is when data is faulty due to measurement, networking, or vulnerability issues. Case 3 is a special case of case 2.

When considering cases 2 and 3, several actions can be taken. One action is to omit the faulty data for analysis; another is to correct the data; and the last action is to recover data. Depending on the situation, different combinations of the method can be used. From a data usage standpoint, however, the three methods are fundamentally equal, and can be derived from the correlation of the data.

5.1.1 Pair-Wise Correlation in the PMU Data

When events are captured on a synchrophasor data, it is extremely rare for one PMU only to capture the event. This is due to the inherent correlation that exists in the synchrophasor data. Figures 5.1 to 5.3 show the pair-wise correlation of each metric for 7 PMUs.

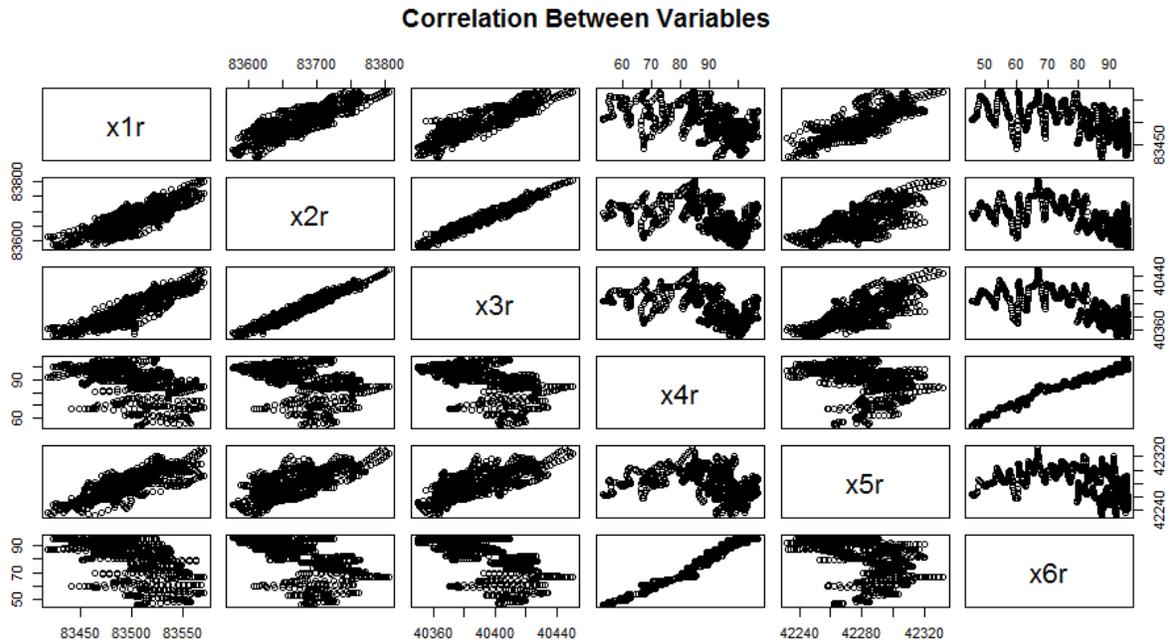


Figure 5.1: Pair-wise correlation of synchrophasor data (voltage magnitude)

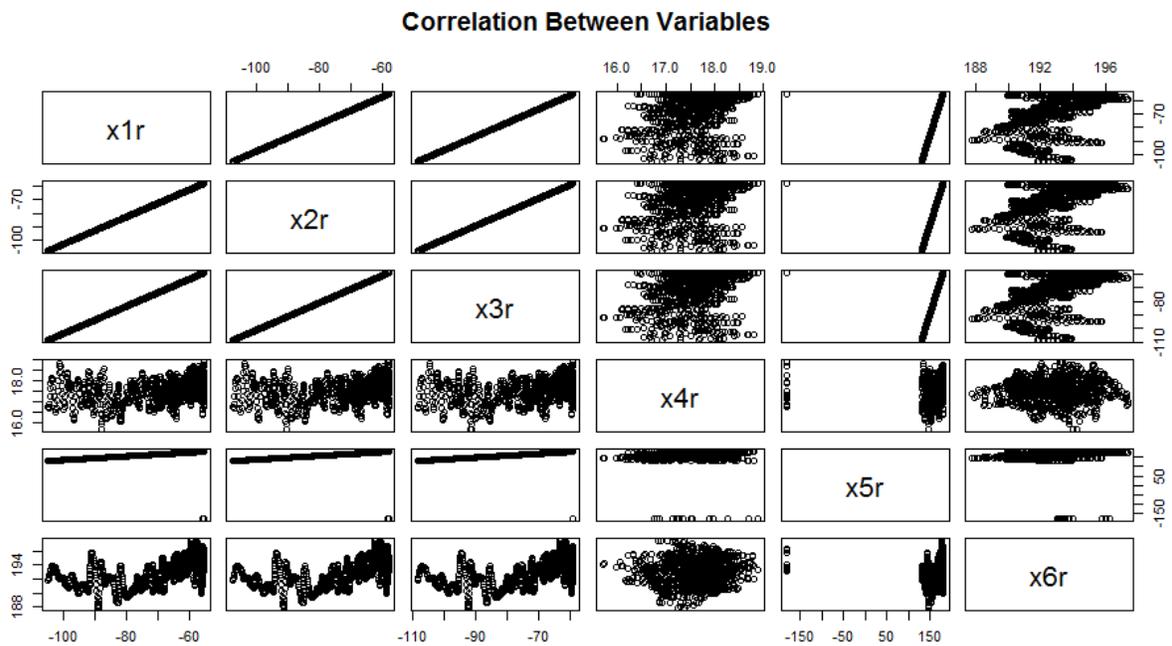


Figure 5.2: Pair-wise correlation of synchrophasor data (voltage angle)

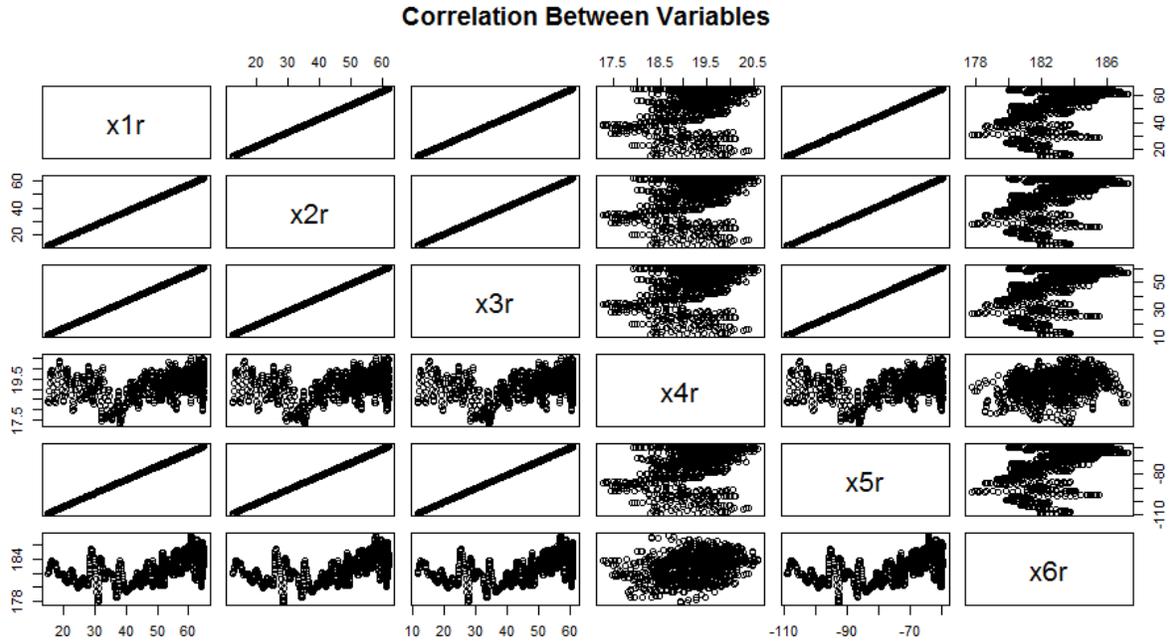


Figure 5.3: Pair-wise correlation of synchrophasor data (frequency)

The pair-wise correlation listed in Figures 5.1-5.3 show an important aspect in synchrophasor data. Those with high correlation form a linear relationship with each data. For example from this specific sample dataset, it is apparent that PMU locations x1r to x3r and x5r are highly correlated, and others are not. Conceptually, these PMUs observe the same location in the power system and are semi-redundant.

In a paper presented by Wang, Chow, et al., method of data recovery is discussed using a singular value decomposition and matrix re-creation [20]. For ease of discussion, this will be referred to as the RPI method for data re-creation in this thesis. However, instead of using singular value decomposition, the pair-wise correlation from the previous figures show that the use of multivariate linear models is another valid method for re-creating data. Using a combination of MDAD and the use of correlation models, an alternate approach to correcting and re-creating missing data is proposed.

5.1.2 Data Re-Creation from Multi-Variate Model

As one method of data re-creation, a multi-variate statistical model is utilized. The concept between the RPI method and the multi-variate model is similar. The RPI method essentially uses matrix transformation to solve for a system of differential equation, and recover the missing data based on

present surrounding data. The multi-variate model approach is very similar to the RPI method; with difference being the way the relationship between the data is described.

Consider the case where data from one or more PMUs are lost due to some error or fault in the communication system. Surrounding PMUs in the system are still available and assumed to be correct. In a multi-variate model, the missing PMU parameters are expressed as a linear model of other PMU parameters.

The specific steps taken to re-create the missing data are as follows:

1. A multi-variate linear model for each parameter is created based on pre-data loss relationship.
2. A model is reduced using the Akaike Information Criterion (AIC).
3. A multi-variate model is utilized to re-create missing data.

To test this method, a set non-defective synchrophasor data from seven different locations were utilized. Masking and removing certain sections of data, the residual data was used to conduct the above method. Figures 5.4, 5.5, and 5.6 show a sample re-creation of missing data.

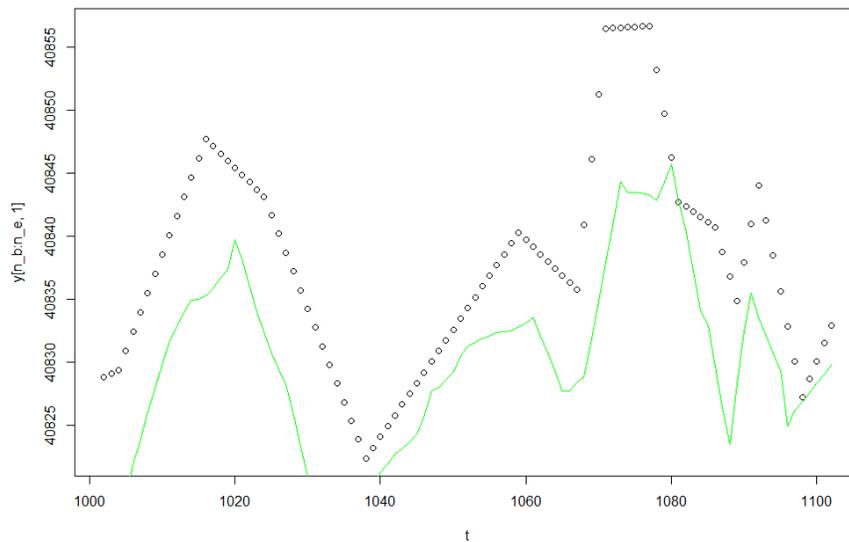


Figure 5.4: Voltage magnitude data re-creation (line indicates re-created data, points indicate simulated missing data) with 0.01957% average residual error

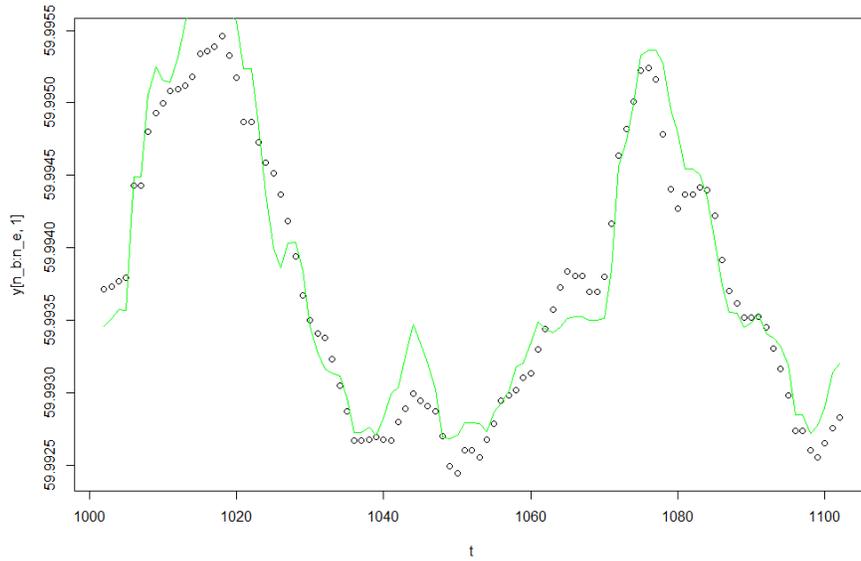


Figure 5.5: Frequency data re-creation (line indicates re-created data, points indicate simulated missing data) with 0.000327% average residual error

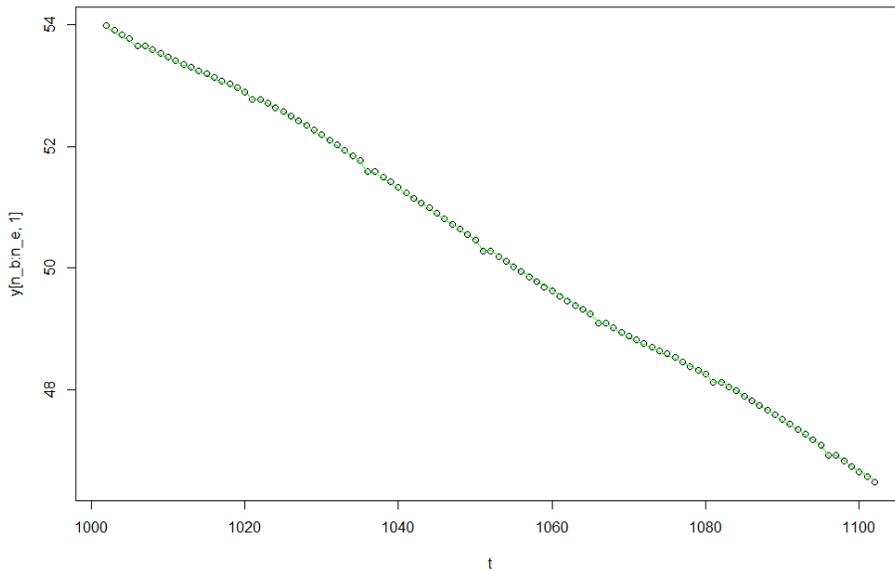


Figure 5.6: Phase data re-creation (line indicates re-created data, points indicate simulated missing data) with 0.0232% average residual error

The respective error for each metric is as shown in the figures. As shown in the Figures 5.1 to 5.3, those with relatively high correlation yield a lower residual error. The question still remains whether the residual error is more accurate than the state estimation or RPI method.

The multi-variate model method does propose a few benefits over the RPI method. As opposed to the RPI method, data can be processed linearly and in real-time. Since the statistical model has to be created before the re-creation of the data, there is an initial cost to the computation. However, every consecutive loss in data can be recovered with the same amount of time as the previous ones since it is a one-way function. When recovering larger amounts of data, the linear computation time definitely brings about benefits compared to the RPI method.

5.1.3 PMU Security and Data Correction

Using the combination of the statistical methods in this thesis; correlation, MDAD, and multi-variate model, it is plausible to detect and correct faulty or spoofed PMU measurement data.

Consider the following case. A PMU on a particular system has been injected with significant false data to attack the system. This can be either spoofing the GPS as presented in [21] or simply modifying measurement with some other form of cyber-attack to the PMU. Such action is taken to jeopardize the validation of security based on PMU measurements [22] or simply to disturb wide-area situational awareness. Regardless of the intention, PMU location is assumed to be under a cyber-attack, and is assumed to be inaccurate.

Under this situation, the pair-wise correlation and MDAD can be observed to determine whether the data has been tampered with. When MDAD observes an anomaly, but only in one PMU; other highly correlated PMU does not detect within a reasonable propagation delay; it can be assumed that the data at that point has been tampered with. To correct this data, the multi-variate model can be utilized.

5.2 Future Work

Although available, one tool that was not utilized during the research was the 26-node Hadoop cluster. This is due to the fact that Hadoop has certain drawbacks that make it difficult to perform complex analysis. In other words, leveraging the clustering method presented in Chapter 3 directly is a difficult task that cannot be performed with ease.

However, the next step that is done would be to utilize MDAD and k-means clustering to characterize power system behavior into signatures through the use of the historical archive. Specifically, what must be done is to use MDAD on Hadoop to filter static behavior of the synchrophasor data, and categorize different signatures to each power system event using the k-means clustering.

The roadmap to extend the work presented in this thesis is as follows:

1. Categorize synchrophasor signatures.
2. Embed the functionalities of Chapter 5.1 and synchrophasor signature categorization to SPV.
3. Extend UI capabilities of SPV.
4. Develop an adaptive algorithm to further enhance all features presented in this thesis.

Following this roadmap and creating a more feature-rich version of the SPV is the immediate future work that is necessary.

CHAPTER 6: CONCLUSION

With over a decade of synchrophasor technology available to the industry, time is quickly approaching for synchrophasor applications to reach the control room. Whether the method is centralized or distributed, utilizing the myriad of synchrophasor data is a feature that is necessary in the further advancement of synchrophasor deployment. Upon doing so, the use of statistical methods is favorable. Since statistics is one of the methods to emulate the way of a human mind, while organizing data in a mathematical way, it is beneficial in aiding the operation of the present power system.

There are two forms of synchrophasor applications that can be developed. One that acts as a replacement to the current SCADA software and another that is stand-alone which enhances the operation done by SCADA presently. The work presented here in the paper is a basis of the latter which uses a data-driven approach rather than a physical model based approach, which has been traditionally used in the industry. Production of an application, which would essentially be the ultimate form for SPV, would be such application that defines uniqueness in an industry that is model based.

The work presented in this thesis should ideally give insight to implementing these statistical methods to actual systems. Beginning with the elementary methods to look at the data structure, advanced statistical methods and real-time usage scenarios were considered to propose the computational and functional challenges of implementing statistics into synchrophasor application. Due to reasons that are not discussed naturally when considering synchrophasor usage, statistical methods in synchrophasor application is a challenge that still needs more effort to make reality.

Although work has been done in this paper, further work can also be implemented to investigate a more complete form of such application. Such include, but not limited to, the more efficient use of computational cores and distributed platform, research on an artificial intelligence, more efficient detection algorithm, and perhaps more advanced ways to visualize material leveraging different statistical methods.

REFERENCES

- [1] U.S. Energy Information Association, "Electric Power Annual 2013," Washington, D.C., 2015.
- [2] National Renewable Energy Laboratory, "NREL: Transmission Grid Integration - Frequency Response," 2014. [Online]. Available: http://www.nrel.gov/electricity/transmission/frequency_response.html
- [3] U.S. Energy Information Association, "Electricity data browser," 2015. [Online]. Available: <http://www.eia.gov/electricity/data/browser>
- [4] S. Matsumoto, et al., "Wide-area situational awareness (WASA) system based upon international standards," *Developments in Power Systems Protection, DPSP 2012. 11th International Conference on*, pp. 1, 6, April 23-26 2012.
- [5] J. E. Chadwick, "How a smarter grid could have prevented the 2003 U.S. cascading blackout," *Power and Energy Conference at Illinois (PECI), 2013 IEEE*, pp. 65, 71, Feb. 22-23 2013
- [6] NERC Steering Group, "Technical Analysis of the August 14, 2003, Blackout: What Happened, Why, and What Did We Learn?," North American Electric Reliability Council, Princeton, NJ, 2015.
- [7] A. Phadke, "Synchronized phasor measurements in power systems," *Computer Applications in Power*, IEEE, vol. 6, no. 2, pp. 10–15, April 1993.
- [8] North American Synchro Phasor Initiative, "Phasor measurement units and synchrophasor data flows in the North American power grid" presented at March 2015, North American Synchro Phasor Initiative Work Group Meeting, 2015.
- [9] Hitachi Ltd., "Realization of big data platform for PMU to improve control center," presented at March 2015, North American Synchro Phasor Initiative Work Group Meeting, 2015.
- [10] Consortium for Electric Reliability Technology, "Phasor Advanced FAQ," 2015. [Online]. Available: http://www.phasor-rtdms.com/phaserconcepts/phasor_adv_faq.html.
- [11] Osisoft. "PI Data Access," 2015. [Online]. Available: http://www.osisoft.com/software-support/products/PI_Data_Access.aspx
- [12] A. Silverstein, K. Thomas, J. Kleitsch, "Using synchrophasor data to diagnose equipment mis-operations and health," presented at October 2014, North American Synchro-Phasor Initiative (NASPI) Work Group Meeting, Houston, Texas, Oct. 22, 2014 [Online]: <https://www.naspi.org/site/Module/Meeting/Forms/Export/ExportAttachments.aspx?meetingid=327>
- [13] K. Kiriwara, K. E. Reinhard, A. K. Yoon, P. W. Sauer, "Investigating synchrophasor data quality issues," in *Power and Energy Conference at Illinois (PECI), 2014*, pp. 1, 4, Feb. 28-March 1 2014.

- [14] A. Brett. "Baselining studies and analyses," presented at 2013 Transmission Reliability Program Peer Review, Washington, D.C., 27 June 2013 [Online]. Available: <http://energy.gov/sites/prod/files/2013/07/f2/2013TRR-2Amidan.pdf>
- [15] J. Kleitsch, "Smart grid investment grant update," presented at October 2013, North American Synchro Phasor Initiative Work Group Meeting, Rosemont, IL, Oct 22-24 2013. [Online]. Available: <https://www.naspi.org/File.aspx?fileID=1177>
- [16] K. Kiriwara, K. E. Reinhard, Y. Liu; P. W. Sauer, "Synchrophasor visualizer," in *Power and Energy Conference at Illinois (PECI), 2015 IEEE* , pp. 1, 4, Feb. 20-21, 2015
- [17] North American Synchro Phasor Initiative, "Recovery act smart grid investments synchrophasor project status," June 2014 [Online]. Available: [https://www.smartgrid.gov/sites/default/files/synchrophasor project status 061014-1.pdf](https://www.smartgrid.gov/sites/default/files/synchrophasor%20project%20status%20061014-1.pdf)
- [18] Y. Wan, "Synchronized phasor data for analyzing wind power plant dynamic behavior and model validation," U.S. Department of Energy, Oakridge, TN, 2013. [Online]. Available: <http://www.nrel.gov/docs/fy13osti/57342.pdf>
- [19] J. Obradovich, "NASPI phasor tools visualization workshop: A quick summary," Atlanta, 2012. [Online]. Available: [http://www.nerc.com/pa/rrm/hp/2012%20Human%20Performance%20Conference/NASPI%20Viz%20Workshop%20Summary NERC%20HP JHObradovich.pdf](http://www.nerc.com/pa/rrm/hp/2012%20Human%20Performance%20Conference/NASPI%20Viz%20Workshop%20Summary%20NERC%20HP%20JHObradovich.pdf)
- [20] M. Wang, J. H. Chow, et al., "A low-rank matrix approach for the analysis of large amounts of power system synchrophasor data," *System Sciences (HICSS), 2015 48th Hawaii International Conference on*, pp. 2637, 2644, 5-8 Jan. 2015.
- [21] X. Jiang, J. Zhang, B. J. Harding, J.J. Makela, A. D. Dominguez-Garcia, "Spoofing GPS receiver clock offset of phasor measurement units," *Power Systems, IEEE Transactions on*, vol. 28, no. 3, pp. 3253, 3262, Aug. 2013.
- [22] Y. V. Makarov, et al., "PMU-based wide-area security assessment: Concept, method, and implementation," *Smart Grid, IEEE Transactions on*, vol. 3, no. 3, pp. 1325, 1332, Sept. 2012.