Unsupervised Clustering on PMU Data for Event Characterization on Smart Grid

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Abstract: In the past decade, with the world-wide initiative of upgrading the electrical grid to smart grid, a significant amount of data have been generated by the grid on a daily basis. Therefore, there has been an increasing need in handling and processing these data efficiently. In this paper, we present our experience in applying unsupervised clustering on PMU data for event characterization on the smart grid. We show that although the PMU data are time series in nature, it is more efficient and robust to apply clustering methods on carefully selected features from the data collected at certain instantaneous moments in time. These features are more representative at the moments when the events have the most impact on the grid. Experiments have been carried out on real PMU data collected by Bonneville Power Administration in their wide-area monitoring system in the pacific northwest, and the results show that our instantaneous clustering method achieves high homogeneity, which provides great potentials for identifying unknown events in the grid without substantial training data.

1 INTRODUCTION

The emerging smart grid technology provides opportunities to implement a more reliable, intelligent, and highly automated energy delivery network, harnessing the advances in communication and information technologies. A key component in the smart grid is the *Phasor Measurement Unit (PMU)*, or *synchrophasor*, which measures phase angles and magnitudes of the electrical waves in real time, at a high frequency, ranging from 30 measurements per second to hundreds of measurements per second. Data generated by these devices contain valuable information about the operation status of the power grid. A significant amount of work has been done to detect or monitor certain conditions of a power grid by leveraging information extracted from PMU data. Potential applications include fault detection (Liang et al., 2014), localization (Jiang et al., 2000), tracking (Chang et al., 2008), and oscillation detection (Liu and Venkatasubramanian, 2008). A comprehensive survey on vaious applications using PMU data can be found in (Singh et al., 2011).

Over the last 5 years, the PMU deployment has been significantly increased in the U.S., from 200 PMUs in 2009 (North American Electric Reliability Corporation, 2014) to approximately 1700 in 2014 (Americans for a Clean Energy Grid, 2014). However, with the number of PMUs rapidly increasing, the volume of the data generated by those PMUs presents challenges for efficient processing. An installation of 100 PMUs produces data in the scale of 3-4TB per month, which will quickly become inaccessible for traditional workflow. A more automated and efficient approach for data processing is essential, in order to take advantage of the valuable information in PMU data. The efficiency of the data processing is even more critical for real-time monitoring of the power grid.

Machine learning techniques provide potentials for automated information extraction from large data sources, and therefore become the most widely used approach for address the big data challenge. Among machine learning techniques, clustering (Bailey, 1994) is an exploratory approach which can potentially identify unknown signatures by grouping data objects based on their similarities. In this paper, we apply various clustering methods on PMU data streams collected from a large power grid in pacific northwest. The goal is to explore the applicability of

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different clustering technique in identifying known or unknown events which occur in the power grid.

The remainder of the paper is organized as follows. Section 2 reviews related work in applying machine learning techniques on PMU data. Section 3 introduces the dataset we use in this research, as well as the feature selection for the clustering method. Section 4 presents our work in applying hierarchical clustering on PMU time series, and the experimental results. Section 5 presents a different approach for clustering instantaneous data, as well as experimental results. Section 6 concludes the paper and proposes future directions for this work.

2 RELATED WORK

PMUs are widely used to monitor the operational status of a power grid with the aim of enhancing the situation awareness for power system operators. A significant amount of work has been done to detect or monitor certain conditions of a power grid by leveraging information extracted from PMU data. Jiang et al. propose an online approach for fault detection and localization using SDFT (smart DFT) (Jiang et al., 2000). Liu et al. use Frequency Domain Decomposition for detecting oscillations (Liu and Venkatasubramanian, 2008). Kazami et al. propose a multivariable regression model to track fault locations (Chang et al., 2008). Besides voltage and current magnitudes, which are the most commonly used features in detecting faults, phase angle measurements can also be used in detecting outages (Tate and Overbye, 2008).

Most recently, with the emergence of big data analytics, new technologies are introduced to PMU data storage and processing. Most importantly, a variety of machine learning techniques have been applied to analyze PMU data for the purpose of recognizing patterns or signatures of events. Two widely adopted techniques are classification and clustering.

Classification methods employ supervised learning and therefore, after training, can identify known signatures or patterns. In (Nguyen et al., 2015), Nguyen *et al.* develop a decision tree based on the J48 algorithm, for the purpose of detecting line events on the power grid using PMU data streams. Zhang *et al.* propose a classification method for finding fault locations based on pattern recognition (Zhang et al., 2011). The key idea is to distinguish a class from irrelevant data elements using linear discriminant analysis. The classification is carried out based on two types of features: nodal voltage, and negative sequence voltage. Similar classification techniques are used to detect voltage collapse (Diao et al., 2009) and disturbances (Ray et al., 2014) in power systems. Specifically, Diao et al. develop and train a decision tree using PMU data to assess voltage security (Diao et al., 2009). Ray et al. build Support Vector Machines and decision tree classifiers based on a set of optimal features selected using a genetic algorithm (Ray et al., 2014). Support Vector Machine-based classifiers can also be used to identify fault locations (Salat and Osowski, 2004), and predict post-fault transient stability (Gomez et al., 2011).

Although classification methods usually can provide high accuracy, they require a substantial amount of labeled data for training. Unlike classification, clustering methods with unsupervised learning do not require labeled training data. Antoine et al. propose to identify causes for inter-area oscillations by clustering a number of parameters provided by PMUs, including mode frequency, the voltage angle differences between areas and the mode shapes (Antoine and Maun, 2012). It has been shown that by clustering these parameters, changes in inter-area oscillations can be explained. Clustering methods have also been proven to be effective in identifying different types of disturbances (Dahal et al., 2014).

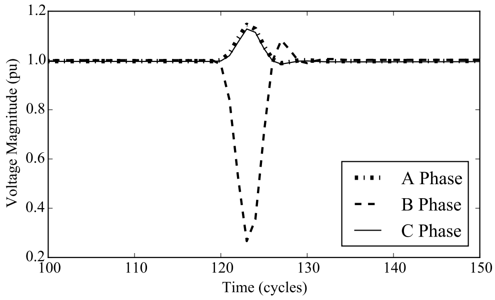
In this paper, we investigate PMU data collected from a wide-area monitoring system, extract useful features, and evaluate different unsupervised clustering methods on PMU data for the purpose of events characterization. To the best of our knowledge, this is the first work which applies unsupervised clustering methods to real PMU data for this characterizing line events.

3 DATASET AND FEATURE SELECTION

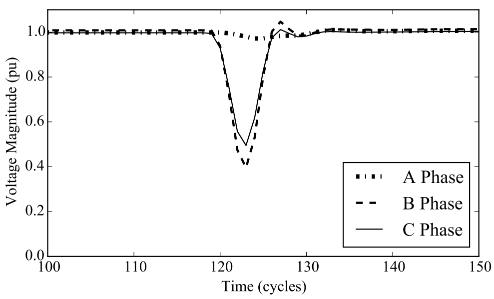
Our dataset was obtained from Bonneville Power Administration (BPA), one of the first transmission operators to adopt synchrophasor technology. In this section, we describe the dataset we use in this research, as well as the features we extracted for the clustering methods.

3.1 Dataset

At the time our data was collected, BPAs installation base contained 31 phasor measurement units from across the pacific northwest. These PMUs measure line and/or bus voltage across all three phases. They also record positive sequence voltage and current phasors, frequency and rate-of-change of frequency. At each PMU, the data is recorded at 60Hz. Measurements from our dataset are primarily from



(a) A Typical Single-Line-to-Ground Fault



(b) A Typical Line-to-Line Fault

Figure 1: Typical Line Events on a Smart Grid.

500KV and 230KV buses, although a small number of smaller voltage transmission lines are also covered. Our dataset was collected from the period October 17, 2012 to September 16, 2013 and contains 114 documented faults that occur at a bus or on a transmission line instrumented with at least one PMU. The faults include instances of single-line-to-ground faults, line-to-line faults, three-phase faults, in that order of relative frequency, and no-fault data. The data set used for clustering contains 100 of the 114 documented fault events and 19 no fault events, i.e., 119 events in total. Since not all events or locations on the electrical grid have all the required data for calculating of the features required for our clustering, those events and locations were dropped. On average we gathered data at 56 different locations on the electrical grid for each of the 119 events, resulting in 6676 data points in total. Of the 6676 data points 4935 are Line to Ground faults, 331 are Line to Line, 196 are Three Phase, and 1214 are marked as No Fault.

3.2 Feature Selection

In our dataset, the measurements recorded by the PMUs are voltage magnitude and phase angle (positive sequence and A, B, C phases), current magnitude and phase angle (positive sequence only), and frequency (60Hz). It has been shown in previous work that the per-phase voltage magnitude is an effective measurement to identify different types of line events (Liang et al., 2014).

Figure 1 shows the per-phase voltage magnitude over time for two typical line events, single-line-to-ground fault, and line-to-line fault. Note that the voltage magnitude values are normalized based on the *steady state voltage*. As shown in in Figure 1, the voltage sags behave differently in different types of events, which provides potentials for separating events into different groups via clustering. This observation serves as the guideline for developing features for our the clustering method.

To enable efficient clustering in a two dimension space while retaining all the information contained in the three phase voltage magnitudes, we developed two new features, $RelativePhase2over1$, and $RelativePhase3over1$, by synthesizing the three per-phase voltage values. These two features are calculated in 3 steps. First, we calculate the relative phase deviations (RP) from steady state for three phases, as shown in equation 1, 2, and 3.

$$RP_a = |1.0 - \frac{v_a}{ss_a}| \tag{1}$$

$$RP_b = |1.0 - \frac{v_b}{ss_b}| \tag{2}$$

$$RP_c = |1.0 - \frac{v_c}{ss_c}| \tag{3}$$

In the above equations, v values are per-phase voltage magnitudes, ss values are steady state voltages on the corresponding phases, and the values are normalized based on the steady state voltages. We then sort these relative phase deviations in ascending order, resulting in a tuple, as shown in equation 4.

$$[RP_3, RP_2, RP_1] = sort([RP_a, RP_b, RP_c]) \tag{4}$$

Note that sorting the relative phase deviations simplifies the complexity of our feature space. Although by doing that we lose the information about deviations on specific phases, the relative deviation magnitudes among three phases are captured, which still enable us to differentiate fault types.

In the last step, we use the values in the relative phase deviation tuple to calculate the two new features, as shown in equation 5, and 6.

$$RelativePhase2over1 = \frac{RP_2}{RP_1} \tag{5}$$

$$RelativePhase3over1 = \frac{RP_3}{RP_1} \tag{6}$$

These two features retain the information contained in the three per-phase voltage values, yet provide a simplified two dimensional space for the clustering methods. In addition, by normalizing the magnitudes based on the steady state voltages, we eliminate the bias introduced by the absolute magnitude deviations, so that the characteristics, or patterns of different events can be better captured by the clustering methods.

4 TIME SERIES CLUSTERING

Given the fact that PMU data are time series data in nature, we have applied the time series clustering method (Liao, 2005) to our dataset. The technical details and experimental results are described in this section.

4.1 Data Processing and Distance Metric

Time series clustering takes data on a window of time as one data entry. For our case, one data entry is a time window of data collected by one PMU. This approach provides an opportunity for clustering based on the shape of the event over time, instead of a single data point. However, events with longer duration present challenges in data handling. To simplify the data processing without losing the advantages of time series clustering, we have applied the widely used Piecewise Aggregate Approximation (PAA) (Keogh and Pazzani, 2000) to reduce the number of points in each time window. Specifically, each data window is divided into n time slices. Then, the mean of each time slice is calculated. These mean values are used to replace of the actual data collected during the corresponding time slices.

Another challenge in time series clustering is to define a meaningful similarity metric of two data entries. One basic method is to calculate the euclidean distance between the two time series. However, this method can be inaccurate, as the same event can appear at different sites where one site sees the fault a few cycles after the other, which results in the time series on two sites out of sync. Therefore, it is critical to use a method that can take slight offsets in time into account. To this end, we utilize Dynamic Time Warping (DTW) (Keogh and Pazzani, 2000), a well researched solution to this problem. DTW aligns the sequences by locally stretching and shrinking one sequence to obtain the optimal fit to the other sequence and then calculates their relative distance given the optimal alignment. This causes the time series to be compared in a non-linear fashion instead of in lock-step.

4.2 Clustering Results

For clustering, we chose the hierarchical clustering algorithm (Rokach and Maimon, 2005), because it is the most suitable method for the time series model, and it allows customized distance metric, for which we used the DTW distance metric described above.

In order to apply the hierarchical clustering method to our data, we need to transform each event into time series data with a fixed window size. Since most of the line events in our dataset last approximately 6 cycles (1/10th of a second), we choose a window size of 10, which gives us extra space to capture steady state data before and after the event. Specifically, we process each event as follows. First, for each event which lasts less than 8 cycles, we add steady state data to both sides until the duration is greater or equal to 8. Second, we perform PAA (Keogh and Pazzani, 2000) with a window size of 8 to each event, so that the data is divided into 8 slices, or time steps. Third, we add a steady state data point to each side of the event, forming a time series data with a fixed size 10.

After obtaining the 10 time steps for each event, we calculate the features described in Section 3.2 for each time step. Finally we apply the hierarchical clustering method on these data points. Due to the limited space of the paper, we only present the result time step 5. We chose time step 5 because it is located in the middle of the event window, and carries the most representative features of the event. The clustering result for this time step is shown in Figure 2. Different colors represent different groups of data entries. To associate the groups generated by the clustering method with the event types in our dataset, we have calculated the percentage breakdown of each event type in the 4 groups, and the results are shown in Table 1.

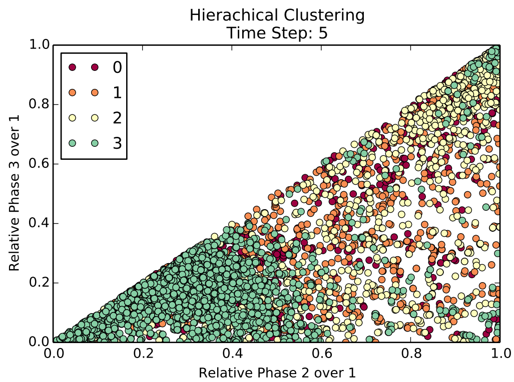


Figure 2: Hierachical Clustering at Time Step 5.

Table 1: Time Series Hierarchical Clustering % Breakdown.

	LG	LL	TP	NF
0	14.08%	9.37%	44.39%	28.25%
1	14.23%	29.00%	11.23%	29.41%
2	18.70%	38.37%	35.71%	40.94%
3	52.99%	23.26%	8.67%	1.40%

As shown in the results, half of the single-line-to-ground (LG) events are clustered in group 3 while the rest are split among the other three groups. Majority of the Line-to-line (LL) events are split among three groups 1, 2, and 3. Majority of the three-phase (TP) events are split among groups 0 and 2. Finally, most of the no-fault (NF) data entries are split between groups 0, 1, and 2. Overall, hierarchical clustering on PMU time series data does not work well, which can be reflected by the low homogeneity score of 0.156. Note that the homogeneity score (Rosenberg and Hirschberg, 2007) is a metric indicating how well data points which belong to the same class are assigned to the same cluster. A perfectly homogeneous solution has a homogeneity score of 1.

Since it has been shown that the combined voltage deviations, as illustrated in equation 7, is an effective metric for representing the impact of the event on the PMU site (Liang et al., 2014). A greater value of ΔV represents higher impact of an event on a PMU. In order to remove the events which occur at locations that are far away from the PMUs, we filtered our dataset by removing all the data entries with ΔV values less than 0.018, a threshold suggested in (Liang et al., 2014). After this filtering process, our dataset contains 2211 data points. That is to say, 4462 data points are filtered out. These data points are signals captured by PMUs which are far away from the location where the event occurred.

$$\Delta V = \frac{\sqrt{(v_a - ss_a)^2 + (v_b - ss_b)^2 + (v_c - ss_c)^2}}{3} \tag{7}$$

We then carried out the hierarchical clustering on the filtered dataset, and the results are shown in Figure 3 and Table 2.

Table 2: Time Series with ΔV filter Hierarchical Clustering % Breakdown.

	LG	LL	TP	NF
0	15.24%	44.36%	0.00%	0.00%
1	19.52%	21.77%	31.43%	0.00%
2	27.80%	15.32%	58.10%	33.33%
3	37.44%	18.55%	10.47%	66.67%

The results of the hierarchical clustering on filtered dataset are similar to those on the original

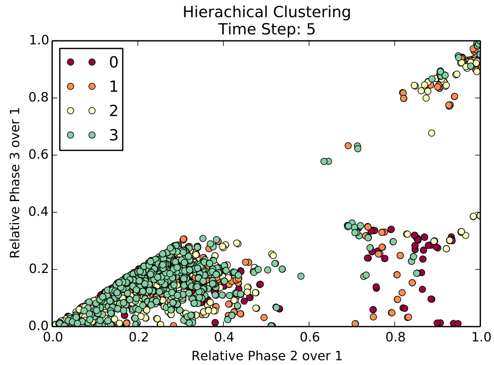


Figure 3: Hierarchical Clustering on Filtered Data at Time Step 5.

dataset, with an even lower homogeneity score of 0.027. This indicates that although PMU data are time series, it is challenging to apply clustering methods on these time series.

5 INSTANTANEOUS CLUSTERING

Besides time series clustering, an alternative solution is to represent each event using one single data point at an instantaneous moment in time, and apply clustering methods on these data points. In this section, we describe our work in this direction.

5.1 Data Processing

In order to apply instantaneous clustering methods to our data, we first need to choose a data point to represent each event. As shown in the typical line events in Figure 1, the best candidate is the moment when the maximum voltage deviation is reached. However, even though a given site may have a minimum at a given cycle, that does not guarantee that another site's minimum is located at the same cycle. Instead of choosing one site to represent all sites we developed a better method that takes all sites into account. In our method all sites vote on what cycle they say is the minimum cycle of a given fault. The cycle with the most votes from the sites is the one that is chosen. This method allows us to get the point in time where we see the largest deviation for the most sites. Note that in order to take into consideration all three phases, we use the metric ΔV shown in equation 7 in the voting process. In other words, for each event, the cycle during which the largest number of sites observe their greatest ΔV value is chosen to represent that event across the grid. We then apply instantaneous clustering methods on these data points.

5.2 Clustering Results

For instantaneous clustering, we choose two widely used methods, k-means (Wagstaff et al., 2001) and DBSCAN (Density Based Spatial Clustering of Applications with Noise) (Ester et al., 1996) to perform the clustering on our data points described above, based on the two features presented in Section 3.2.

The results of the k-means clustering are shown in Figure 4. The data points are divided into 4 different groups, each of which is represented by a different color. The percentage breakdown for different even types are shown in table 3.

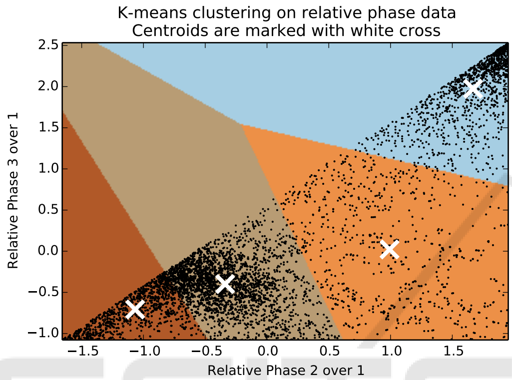


Figure 4: K-menas Clustering on Instantaneous Data.

Table 3: K-menas Clustering % Breakdown.

	LG	LL	TP	NF
Blue	1.72%	0.60%	98.98%	74.79%
Gray	64.84%	7.86%	0.00%	4.53%
Orange	3.49%	91.54%	1.02%	20.02%
Brown	29.95%	0.00%	0.00%	0.66%

In general, k-means clustering performs well in separating different events into groups. Particularly, three-phase (TP) events are well isolated from the rest event types. However, some single-line-to-ground (LG) events are mixed with line-to-line (LL) events, and the no-fault (NF) data points are separated into two main groups. Note that the over all homogeneity score of k-means clustering on the instantaneous PMU data is 0.60, showing a major improvement over the hierarchical clustering on time series data.

We then applied the density-based DBSCAN clustering method on the same dataset, and the results are shown in Figure 5 and Table 4.

When using DBSCAN the user does not provide the number of clusters. Instead the algorithm breaks down the data into as many clusters as it sees fit. On top of this it also adds an additional cluster for what DBSCAN has determined to be noise in the data. In this case DBSCAN divided the data into 16 groups. Despite the large number of groups, DBSCAN performs well in dividing LG and TP from the other two type of events. However, instead of grouping LL into a single cluster, DBSCAN has divided it into 7 groups. Also, most of the LL data are identified as noise. Most of the No Fault data points are grouped in the same cluster as TP, but a good portion of it is also marked as noise. This clustering has a homogeneity of 0.628.

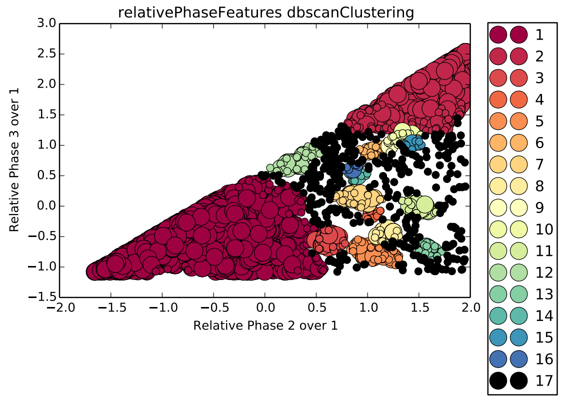


Figure 5: Relative Phase Features.

Table 4: DBSCAN clustering % breakdown.

	LG	LL	TP	NF
1	95.16%	8.16%	0.00%	5.93%
2	1.62%	0.60%	98.98%	69.44%
3	0.55%	3.32%	0.00%	0.66%
4	0.00%	4.23%	0.00%	0.08%
5	0.04%	15.11%	0.00%	0.41%
6	0.10%	0.00%	0.00%	1.40%
7	0.16%	8.46%	0.00%	0.66%
8	0.04%	6.65%	0.00%	0.00%
9	0.00%	0.00%	0.00%	0.74%
10	0.04%	0.00%	0.00%	1.32%
11	0.00%	9.67%	0.00%	0.16%
12	0.63%	0.00%	0.00%	1.48%
13	0.00%	5.74%	0.00%	0.00%
14	0.06%	0.00%	0.00%	0.91%
15	0.02%	0.00%	0.00%	0.91%
16	0.10%	0.00%	0.00%	0.33%
Noise	1.48%	38.07%	1.02%	15.57%

We observed that there is quite a bit of data being labeled as noise. If we could reduce the amount of noise, then that could help DBSCAN preform better. In addition, reducing the amount of noise could help separate no fault data from TP. With most faults a higher ΔV signifies that signal is closer to the location of the fault.

Therefore, we execute the two instantaneous clustering method on the filtered dataset which contains only data points with ΔV values greater than 0.018.The clustering results of k-means are shown in Figure 6 and Table 5.

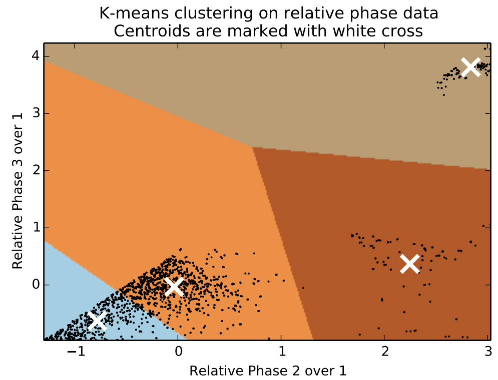


Figure 6: K-means Clutering on Filtered Instantaneous Data.

Table 5: Filtered K-means Clustering % Breakdown.

	LG	LL	TP	NF
Blue	37.18%	0.00%	0.00%	0.00%
Gray	0.56%	0.81%	100%	100%
Orange	62.21%	0.00%	0.00%	0.00%
Brown	0.05%	99.19%	0.00%	0.00%

The results here show some improvements over those on the non-filtered data, although LG is still split between two clusters. LL is predominately in one cluster. Interestingly, all of TP is in a single cluster with all NF data points. This is because that after the ΔV filtering, only a small number of NF data points are left in the dataset. The homogeneity score of this method is 0.932, much higher than the results on the non-filtered dataset.

On the same filtered dataset, we have also applied the DBSCAN clustering method, and the results are shown in Figure 7 and Table 6.

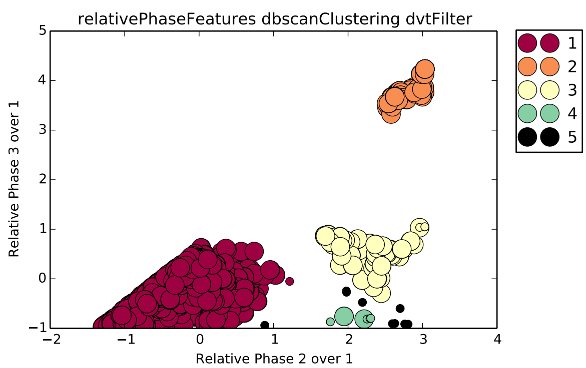


Figure 7: Relative Phase Features.

Table 6: Filtered DBSCAN clustering % breakdown.

	LG	LL	TP	NF
1	99.34%	0.00%	0.00%	0.00%
2	0.56%	0.81%	100%	100%
3	0.00%	84.68%	0.00%	0.00%
4	0.00%	6.45%	0.00%	0.00%
Noise	0.10%	8.06%	0.00%	0.00%

Comparing to the results on the original dataset, this set of results show significant improvement, because the filtering help remove most of the noise. With the filter DBSCAN preformed excellently well, illustrated by its homogeneity score of 0.933. It was able to cluster most of LG in cluster 1, LL in cluster 3 and 4, and all of TP in cluster 2. Similar to the k-means method, No Fault data are mixed with TP in cluster 2, because of the limited number of data samples after the filtering.

6 CONCLUSION

Synchrophasor technology is widely used in modern power systems, resulting in increasing amounts of data being generated on a daily basis. Machine learning methods represent the future directions in processing these data. Although supervised learning methods have been applied for this purpose, in order to prepare the training datasets for those methods, labeling data requires a significant amount of effort.

In this paper, we present our experience in apλplying unsupervised clustering methods on PMU data collected on a smart grid. We have evaluated multiple clustering methods on two distinct representations of PMU data: time series and instantaneous data points. Specifically, hierarchical clustering method is used to cluster time series data, and both k-means and DBSCAN are used to cluter instantaneous data points. Interestingly, although PMU data are time series data in nature, our results show that clustering on instantaneous data points with carefully selected features performs much better in terms of homogeneity score. Among all the clustering methods we have evaluated, DBSCAN achieves the highest homogeneity score. This work demonstrates potentials of identifying unknown events on a smart grid without substantial training data. For future work, we will apply the clustering methods on a dataset which contains unknown events, namely generator faults, for the purpose of characterizing new events. In addition, we will develop type-specific classification methods on different clusters to better classify events.

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