RISK ANALYSIS OF CORDOVA'S MICROGRID FROM A COMPLEX SYSTEMS VIEWPOINT

By

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Abstract

Cordova is a town of approximately 2,000 people located on the southern coast of Alaska. A power grid for a town this size, with a large seasonal fishing economy, is considered a moderate to large sized microgrid in terms of power produced. Understanding the vulnerabilities and risks of failures in such a grid is important for planning and operations and investigating these characteristics in the context of complex system dynamics is novel. The analysis of Cordova's microgrid is a case study relevant to a large class of microgrid communities that could benefit from this work. Our analysis of this grid began by looking at the distribution of all outages from 2003 - 2017 by size, followed by splitting up outages based on certain characteristics and again looking at outage size distribution based on different characteristics. Following this we correlated the outages with different weather patterns and then with the hourly load demand on the system. After doing these analyses we developed a risk metric to give a single numerical value to the risk of an outage occurring during certain time periods and under certain conditions. We looked at risk in the summer versus the winter due to the summer having a much larger load demand, and we also looked at the risk before and after all cables in the grid were buried underground. This gives us an idea of when/under what circumstances the most outages are likely to occur and allows us to run our model of the system, make changes, and determine if those changes were beneficial to the system or not.

Acknowledgments

I would first like to thank my advisor, Dr. David Newman. You are a very busy person, however I never felt like you didn't have time for me and my million questions. Not only did you make time for all of my questions, but you always gave me very thorough and informative answers, were extremely positive, and encouraged me and my ideas. You are one of the best teachers I have had and have been a great example of the type of teacher I would like to be.

Second I would like to thank all of the people at the Cordova Electric Cooperative. You were all so open with sharing your data with us and extremely helpful when it came to formatting the data for us to use. We could not have done the work we did without you.

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Finally, I would like to thank my husband, Grant, for always supporting me and especially for encouraging me to go back to school to study what I enjoy, physics. And then for further encouraging me when I decided I wanted to go to graduate school and move to Alaska to do it! I wouldn't be where I am today without you.

Contents

List of Figures

List of Tables

1 General Introduction

This project was done in order to analyze the resiliency of the power grid in the town of Cordova, AK. Cordova is a case study of a large class of microgrid communities/situations that could benefit from this work. Cordova is a town of approximately 2,000 people located on the southern coast of Alaska. Being a coastal town, it has a large fishing economy. Cordova's power grid is considered a microgrid, but is a moderate to large sized microgrid. There are a total of about 1,600 meters, 600 nodes, and 600 lines in this grid. There are 3 generation stations, two of which use hydro power and the third generation station uses diesel power. Through this project we aim to investigate conditions that may lead to a higher chance of an outage occurring on the grid. Then, we will use this information to create a risk metric for the system. This risk metric can then be used to improve the strength of the grid against potential causes of outages. To create a risk metric for the grid we need to first define risk and then we can evaluate the size of the risk to the grid during different conditions. Risk will be defined though a combination of cost to the community, which will depend on the size of an outage, and the probability that a certain condition will lead to an outage. In order to do our analysis and develop a risk metric we were given access to the last 15 years' worth of outage data as well as the last 13 years' worth of power usage data by the town from the Cordova Electric Cooperative (CEC).

We used the data given to us to first analyze the outages alone to look for characteristics of this grid behaving like a complex system, something that is seen often in larger power grids. To do this we had to come up with a way to measure the size of an outage. We were given the duration of each outage in minutes and the number of meters that were down on each feeder during an outage. We used these two measures of outage size separately along with a measure of size that included both of these measures multiplied together. We then came up with another measure that calculated the approximated energy demand that went unserved due to the outage. We interpreted the multiplied values measure and the energy unserved measure as being better, more encompassing measures of outage size than just the number of meters affected or the duration of an outage alone.

Once we developed our measures of sizes of outages, we used a variety of statistical methods to analyze the outages in order to get a well-rounded interpretation of the data. To better visualize the distribution of outages throughout the 15 years we first plotted a time series using each of the four measures described above. Beyond this nice visual representation we then sorted and grouped outages by size and plotted them as PDFs, CDFs, and CCDFs to see if a power law exists among the outages. If a power law does show up and the slope is between 0 and -1 that will indicate that larger outages are playing a higher role than just randomly being scattered throughout. This is significant because it would indicate that the system may be displaying characteristics of a complex system. We use these techniques throughout the analysis in order to get an idea of how big of a role the larger outages play in the system compared to the smaller, more frequent outages. We also performed an r/s analysis on our two main measures of outage size to look at any long time correlations of the outages in the grid.

The outage data also included cause codes that told us what category the cause of an outage fell into. Because of this we were able to look separately at planned and unplanned outages as well as look at which specific causes were the most common. Looking at causes individually made it possible to analyze whether or not there was a particular cause of outages that may have led to a disproportionate amount of larger outages, outages during a certain time of day or period in the year, etc. To do this, we again used PDFs and compared the slopes of each outage cause's plot.

Once we got an idea of the distribution of outages alone based on their sizes and causes we began correlating and comparing these outages with other factors. The main factors we looked at were weather conditions and the cycle of power demand. When looking at weather conditions we looked for correlations with both extreme weather events along with everyday weather. For example, we looked at outages that corresponded with high wind events, flooding, and heavy snowfall and also correlated outages with daily temperature and daily precipitation values. When looking at the cycle of power demand we noticed a day and night cycle as well as a very consistent, very large spike in power demand in the summer. Since this is a coastal town with a large fishing economy it makes sense to us that this summertime peak is due to the high power demand coming from the fish processing plants, which only operate during the summer. Because of this large seasonal difference in power demand we focus a lot of our analysis of the outages correlated with load demand by splitting it up into two seasons, summer vs winter, and comparing the distribution of outages that occur during each season. We look also at day vs night, but since this difference is not nearly as drastic as the seasonal change we don't focus as much on it.

To analyze the differences in the seasonal and the daily cycles we looked at the probability of an outage occurring during a certain time in the load demand cycle. For example, for summer we totaled up all outages that occurred between mid-June to mid-September every year and divided that by total number of outages. We did the same for winter and the same for day and night. Once we got these percentages we were able to compare these values with the percentage of an outage randomly occurring during these times. If the percentages were similar that would mean the outages are likely randomly occurring during this time. However if the first percentage is a significant amount higher that would indicate that there is something happening during a specific time period to cause more outages than one would expect. In this case we would expect that that something would have to do with the load demand cycle. We did this for overall outages that occurred during these times and then we went further and split the outages up in terms of small, medium, and large outages. We did this using the outage size measures of energy that went unserved, number of meters down times duration in minutes, and just duration in minutes. We chose to do this analysis for all of these measures because we thought that each one could tell us different important information. The results from these different measures of size could also be compared to determine if they were all consistent or if a certain measure produced vastly different results. Both situations in this case can tell us something about the behavior of the outages.

We were also told that in 2009 all of the lines were buried underground. While we assumed the burial of these lines might not help internal causes of outages, like load demand being too high, we figured that this would likely cause some external factors such as high wind storms to have much less of an effect of the grid. In order to see just how much this change helped the grid we split up and analyzed outages before 2009 and after to see if there was a difference in the distribution of the sizes of the outages. We combined this with the seasonal power demand change as well and looked at the differences in outages that occurred in the summer vs the winter before and after 2009 to see if this burial had a different effect on different times in the load demand cycle. We also looked at our risk metric before and after 2009 and in summer vs winter to get an idea of if the burial of the lines reduced the overall risk on the system.

After all of this we have a good idea of the outages and how they are distributed among season, time of day, and before or after the lines were buried. We use these factors to compare risk values. As described above, risk is defined though a combination of cost to the community, the probability that an outage will occur during the certain time period, and the frequency that outages normally appear during the certain time period. We will use this information to get a single value that we will call the risk index for each different time period. There is no scale to this risk value, but it is used rather as a comparison. If a risk index is higher for one season than the other that will indicate that there is more risk to the system during the season with the higher risk index. Furthermore, the farther apart the two risk indices are, the greater the difference of risk in the two time periods. These risk indices give a simple yet accurate representation of when the grid may be least or most likely to suffer from an outage. This is useful because they can be used to indicate points in the grid that may need the most attention the next time improvements are made and what points of the grid are already the strongest.

All of these processes and analysis methods listed here and the results from these are described in more detail in the following chapters.

2 Risk Analysis of Cordova's Microgrid From a Complex Systems Viewpoint [1]

2.1 Background

In order to create a more reliable power grid, it is important to look at outage causes and patterns that exist on the current grid. This has been done in depth on large power grids [1]-[17], but less so in microgrids. A grid that can be used to analyze microgrids is the Cordova grid. To do this sort of analysis for the town of Cordova, data on all outages and average hourly load demand for the town was provided to us by the Cordova Electric Cooperative. The data given looks at outages for the past 15 years (from 2003-2017) and the hourly load demand for the past 13 years (from 2005-2017). We analyze the outage data by itself first to get an idea of the system and then we compare and contrast this outage data to certain external factors that may influence outages, such as severe weather events or fluctuating customer demand. In the end, we use all of these analyses in order to create a risk metric for the system, similar to what was done in [17]-[18].

We start off in the first analysis sub-section using the outage size information to analyze characteristics and behaviors of the microgrid in this town, namely looking to see if it exhibited complex system dynamics. We see that some larger grids analyzed prior to this show power laws when looking at the distribution of the outage sizes [1]-[17]. The fact that power laws exist in the data and slopes of these power laws being between -1 and zero can tell us about the underlying dynamics in the system. When a power law exists, this suggests that the grid may be a complex system. The shallower the slope is in the power law means that the large events are occurring more frequently than we would expect and thus will play a dominating role when assessing blackout risk.

After investigating the characteristics of the microgrid's overall outage data by itself we look deeper into the causes of the outages. We look at individual causes of these outages in order to see if there is a particular cause or type of cause that is leading to a disproportionate number of outages. We then break down the outages further and look at the size distribution

[1] Prepared for submission. Authors: Anna Lipetzky Bowker, Dr. David Newman, Cordova Electric Cooperative

of outages from some of the major causes to see if there is a cause that is associated with more large or small outages compared to normal.

Because the Cordova grid is small enough to be contained in a single town, we can obtain weather history for this town and compare certain weather events to the outages. These weather events include blizzards, floods, and high wind storms. We also look at daily weather data such as precipitation, snowfall, and average temperature and correlate these events with the outages to look for any trends or periodicities.

Finally, we compare the outages with the hourly load demand. We see daily and yearly fluctuations in the load and analyze how this affects outages. We look deeper into outage size to determine if there is a certain time in the load demand cycles that cause more large or small outages than average.

2.2 Data

The data used for this project is all relevant to analyze the electric grid for the town of Cordova. The specific information relating directly to the power grid is provided to us by the Cordova Electric Cooperative. Any other information relating to the town of Cordova can be found online.

The first data we looked at was a summary of the outages that occurred within the power grid from the years 2003-2017. This information included the time of each outage, the duration, the specific feeder it occurred on, how many meters were affected by the outage, and the cause of the outage (if known). Besides when we are specifically analyzing the different feeders, it is assumed that outages that occur at the same time, for the same duration, and with the same cause, but on different feeders, are the same outage and are combined into one in the analysis.

When looking through the outage data we noticed a few outages that appeared to be cascading failures. We counted the failure as cascading if a second (or more) failure occurred on another feeder before the first was fixed and if the cause of the outage was unplanned. There were a total of 18 cascading failures from unplanned outages out of a total of 522 unplanned outages for the 15 years. This gives us 3.4% of unplanned outages appearing to be cascading. A majority of the cascading failures were due to “Power Supplier – Hydro” and “Distribution – Primary Cable.”

While still looking at the outages, we then found data on the weather history in Cordova.

This weather history included daily precipitation values, daily snowfall, daily current snow depth, floods, blizzards, and high wind events [19]-[20]. We looked at any similarities between when some of these stronger weather events occurred and when outages occurred.

Following this the load demand of the system was analyzed. We were given hour by hour load demand for each feeder for the years 2005-2017. This data consisted of an average of every second of the load demand over that hour in order to get a value for the specific hour. We were also given second by second data on the load generated in the system, split up by hydro power and by diesel power which could simply be combined to give total power generated. Because this was second by second data it was turned into hour by hour data both to match that given by the load demand data and because second by second data is too many data points to realistically handle.

2.3 Analysis

2.3.1 All Outages

2.3.1.1 Time Series

The outages are analyzed in terms of size. There are four different measures for size: the duration of the outage in minutes, the number of meters downed/out by the outage, the duration multiplied by the number of meters out, and an estimate of the amount of energy that goes unserved due to an outage. The time series of outages in terms of the four different size measures can be seen below. Unless there is something of interest in the first two measures that differs greatly from the third, most of the analysis looks at the third measure – (meters out)x(duration) – and the fourth measure - amount of average power unserved during the outage times the duration of the outage (where every time duration is measured in minutes). The reasoning for this assumption is that these measures give a more complete picture of the size and impact of the outages. The assumption that (meters out)x(duration) is a better measure than each measure individually can be seen in the first three time series in figure 2.1

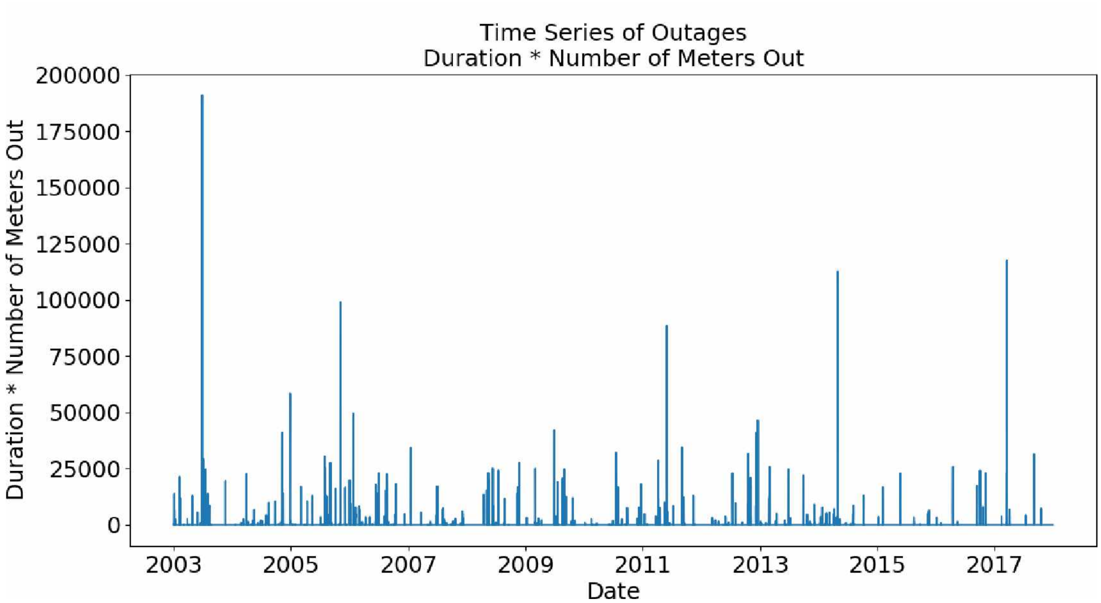

Figure 2.1: Time Series of Outages Measured by (meters out)x(duration)

Figure 2.1 shows the plot of outages in terms of meters times duration. The outages vary greatly in size and the larger outages seem to be spread and not all near the same time. Figure 2.2 is the time series plot in terms of duration. This plot somewhat reaffirms the fact that sometimes just looking at duration does not give any information on the magnitude of the outages in terms of how many customers are affected. For instance, a shorter duration outage may have a larger impact if it takes out hundreds of meters than a longer duration outage would if it only affects a few meters. We can see this if we look at the largest outage in terms of duration that occurs in early 2005; from the duration plot below we can tell it was a very long outage, however from the meters times duration plot above the event is seen but does not have nearly the same impact because it only affected one meter.

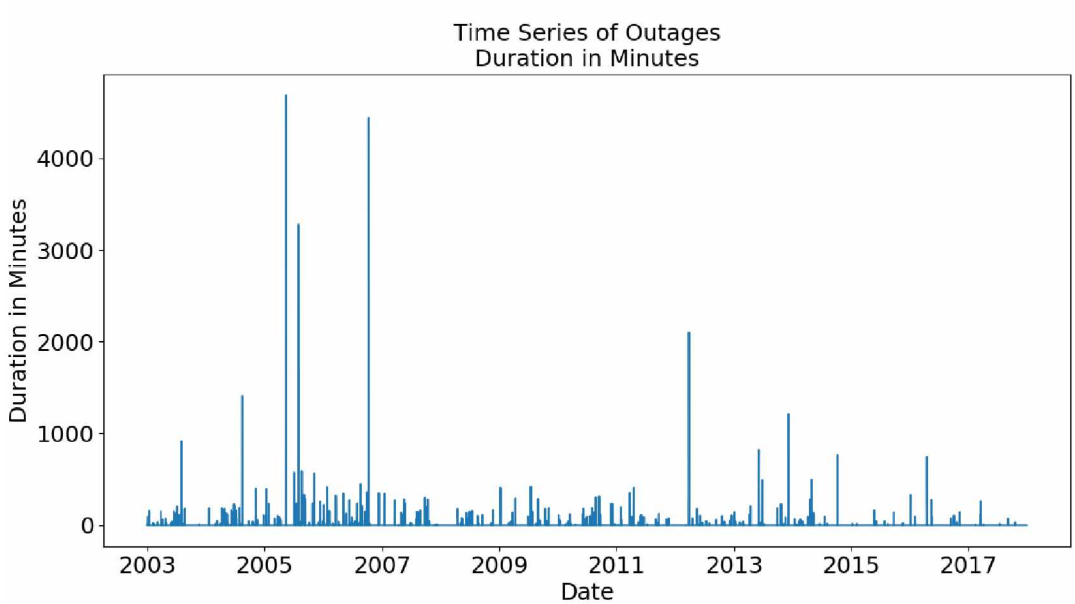

Figure 2.2: Time Series of Outages Measured by Duration in Minutes

Secondly, from the time series of the outages plotted in Figure 2.3 it becomes clear also that the number of meters out can be a limiting measure because different feeders get maxed out on certain distinct levels. These distinct levels seen are the total number of meters on each feeder, which gives a maximum value to how many meters can be affected by an outage on a particular feeder. The numbers of meters on each feeder are: Auxiliary – 104, 13 Mile – 226, Main Town – 317, Lake Avenue – 430, New Town – 517.

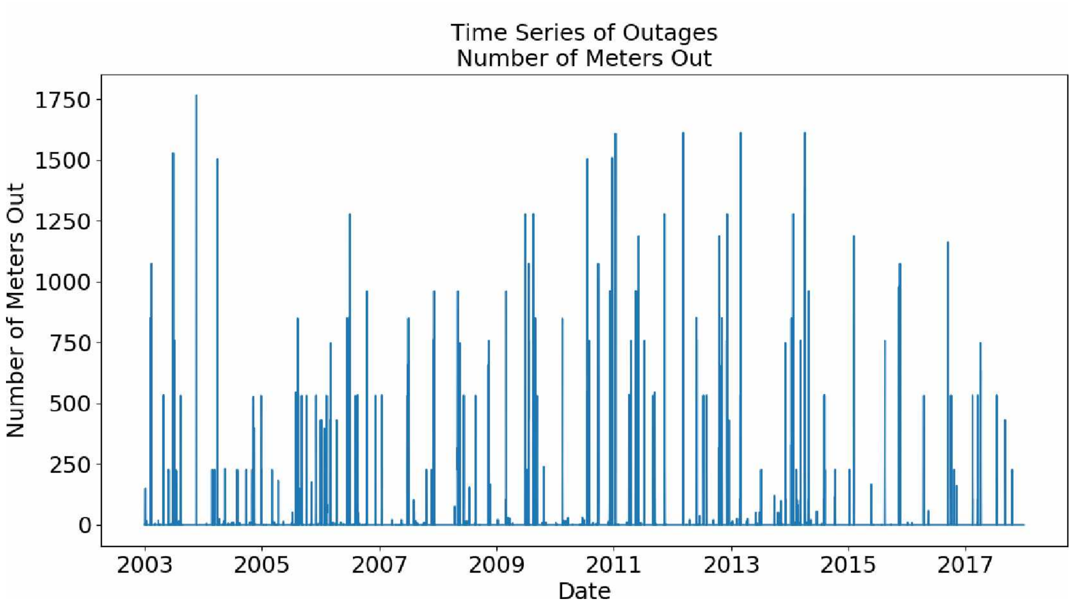

Figure 2.3: Time Series of Outages Measured by meters out

The duration of the outages and the number of meters out in each outage are straightforward measures and come right from the outage data. The energy unserved measure comes from the outage data in combination with the load demand data. To get the estimate of the size of an outage in terms of energy unserved we used the information from the load demand at a given time on the feeder that the outage occurred. Since there is no individual meter data, we assumed that all of the meters on a particular feeder used an equal amount of the total load on that feeder. The energy not served was calculated by:

$$Energy\ Unserved = meters \times load \times duration \tag{2.1}$$

where,

$$\begin{aligned} meters &= number\ of\ meters\ out\ on\ a\ feeder \\ load &= load\ per\ meter\ on\ that\ feeder \\ duration &= duration\ of\ the\ outage\ in\ minutes \end{aligned}$$

Since the load demand value sometimes goes down while there is an outage we used the load value from the hour before the outage began plus the load value from the hour after the outage ended and divided by 2. Since this is feeder dependent the energy unserved was calculated for each outage first and then the outages that occurred at the same time and for the same duration were combined.

In Figure 2.4 the time series for outages on the Lake Ave, New Town, Main Town, 13 Mile, and Auxiliary feeders in terms of energy unserved are shown.

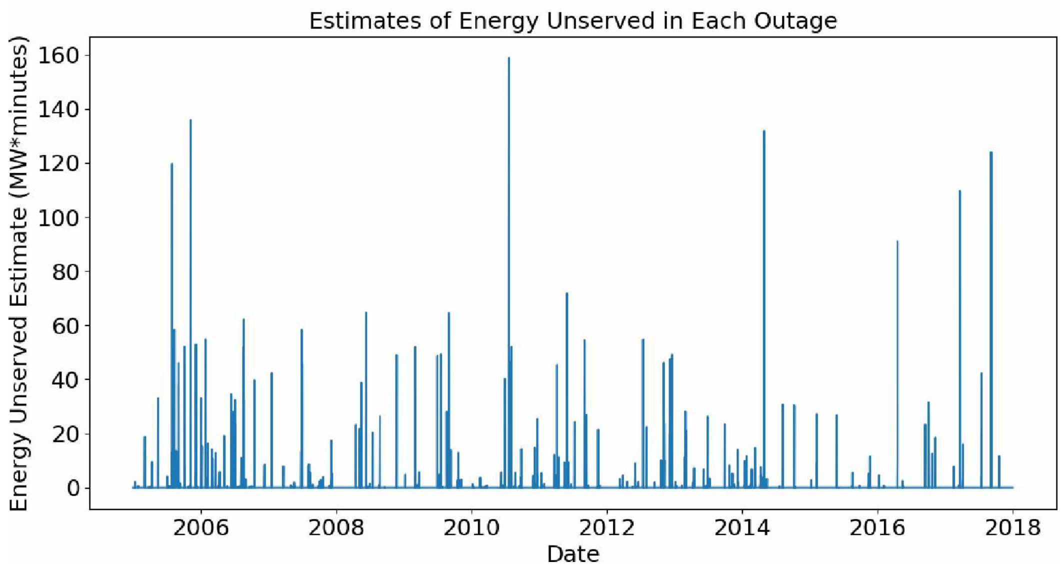

Figure 2.4: Time Series of Outages Measured by Energy Unserved

Even with the multiple assumptions made to calculate the estimate of the energy unserved we still have strong reason to believe this is the best measure for the size of an outage. This measure takes into account the duration of the outage, an estimate of how many customers the outage affected, and amount of power that is usually being consumed that is lost. This causes two outages that may have a similar duration and number of meters out to be sized differently depending on when during a load demand cycle they occur. This also means an outage during a peak demand time will hold more weight and be considered a larger outage. This discrepancy between two similar outages is beneficial because an outage that occurs during peak demand time will have the largest negative impact on customers.

When looking at the spread of the differently sized outages on the energy unserved and (meters out)x(duration) time series we notice there is a wide variety of outage sizes with small outages (and no outage) being by far the most common. While small outages are more common we do see large outages are occurring every one to two years and intermediate outages occurring at a rate somewhere in between the rate of small and large outages. This indicates that our system is showing characteristics of complex systems. Because of this, we look deeper into the analyses done on complex systems, in particular, looking for power law behavior in a probability distribution function (PDF) of the outages.

2.3.1.2 Probability Distribution Function (PDF) and Complimentary Cumulative Distribution Function (CCDF)

With the arrays of all outages using the four different measures of outage size we want to sort and group the different sizes of outages and plot them to determine the probability of having an outage of a particular size. This plot is called a probability distribution function (PDF) and can tell a lot about the system. In particular, we want to see if a power law occurs when these outages are sorted and grouped by size and then graphed on a log-log plot. To sort and group elements we want to put similar sized events together in the same bin and then each bin will be plotted with the average event size on the x-axis and the frequency that an event fell in that particular category on the y-axis. (The method for doing this is detailed in the appendix).

Once all outages are sorted and grouped in bins where every bin has a bin size and a frequency we plot bin size vs frequency on a log-log plot. This plot is the probability density function (PDF). If the plotted outages ever appear linear on this plot of the PDF this tells us that the data fits a power law. When a power law is present this indicates that large events occur more frequently than one would expect if outages were happening randomly, which would be shown in a plot by an exponential drop off. So it is the larger events that have a greater impact on the outages than the more frequent smaller events. Power laws can have varying slopes and the slope of this linear trend is also important. A shallower, less negative slope indicates that the larger events occur more frequently relative to the small event than with a steeper, more negative slope.

Looking at the PDF below in Figure 2.5 for all of the outages in terms of (meters out)x(duration) there is a power law. It occurs for events in the size range 25-26,000.

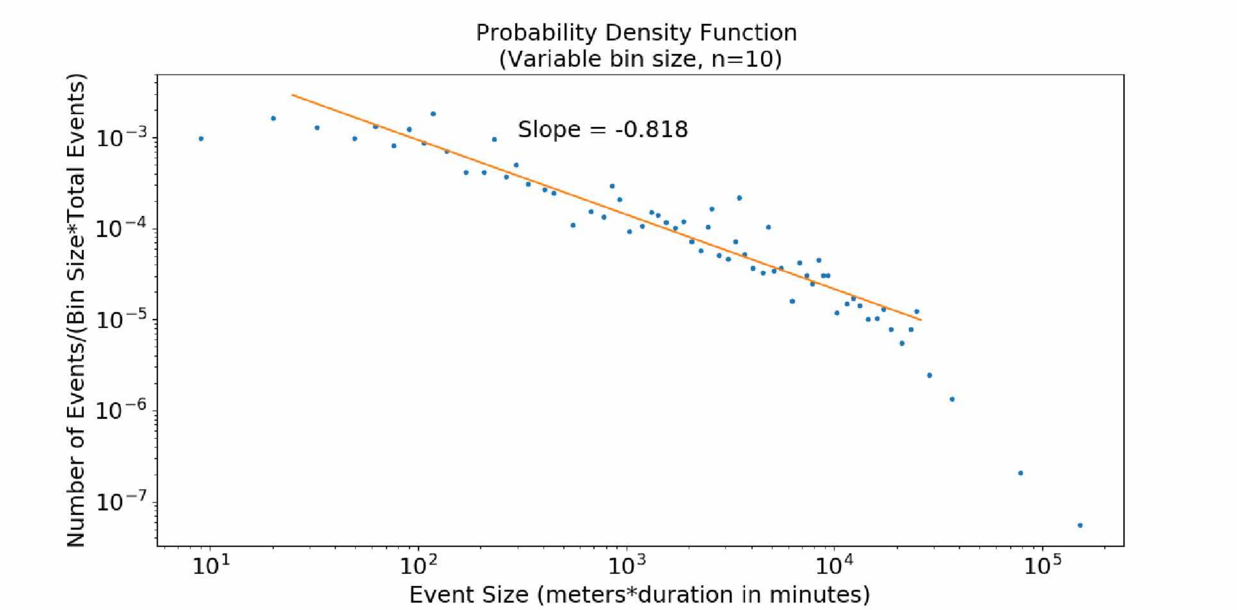

Figure 2.5: PDF of Outages Measured by $Meters\ Down \times Duration\ in\ Minutes$

The Complimentary Cumulative Distribution Function (CCDF) is another measure that can be calculated from the PDF. The CCDF is useful in that it shows the probability of having an event of a particular size or larger. This plot starts at one, indicating that there is a one hundred percent chance of an event being of the smallest size or larger. The CCDF is important because if a system is exhibiting a pure power law distribution then the CCDF will also show a power law which will have an exponent (slope on log-log plot) one greater than the exponent of the power law seen in the PDF.

There is a special version of the CCDF called the Survival Function. The survival function is the CCDF when there is only one event size per bin, $n = 1$ (i.e. only events of the same size are grouped together). This is a special case because it looks at each event size individually instead of getting probabilities for a group of events in a certain size range. For all outages measured by (meters out)x(duration) the CCDF and the survival function are shown in Figures 2.6 and 2.7.

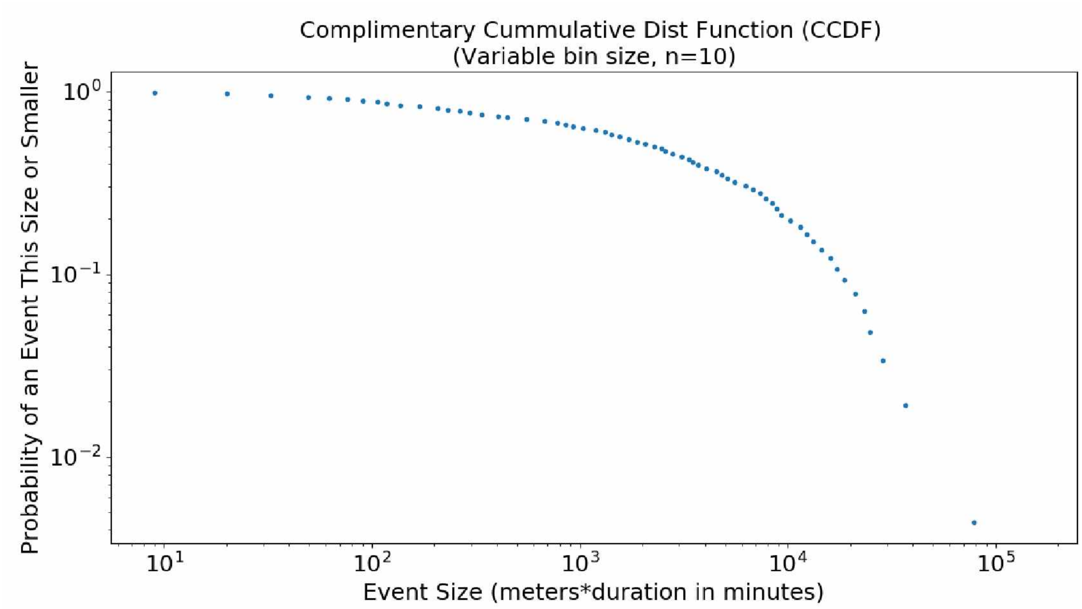

Figure 2.6: CCDF

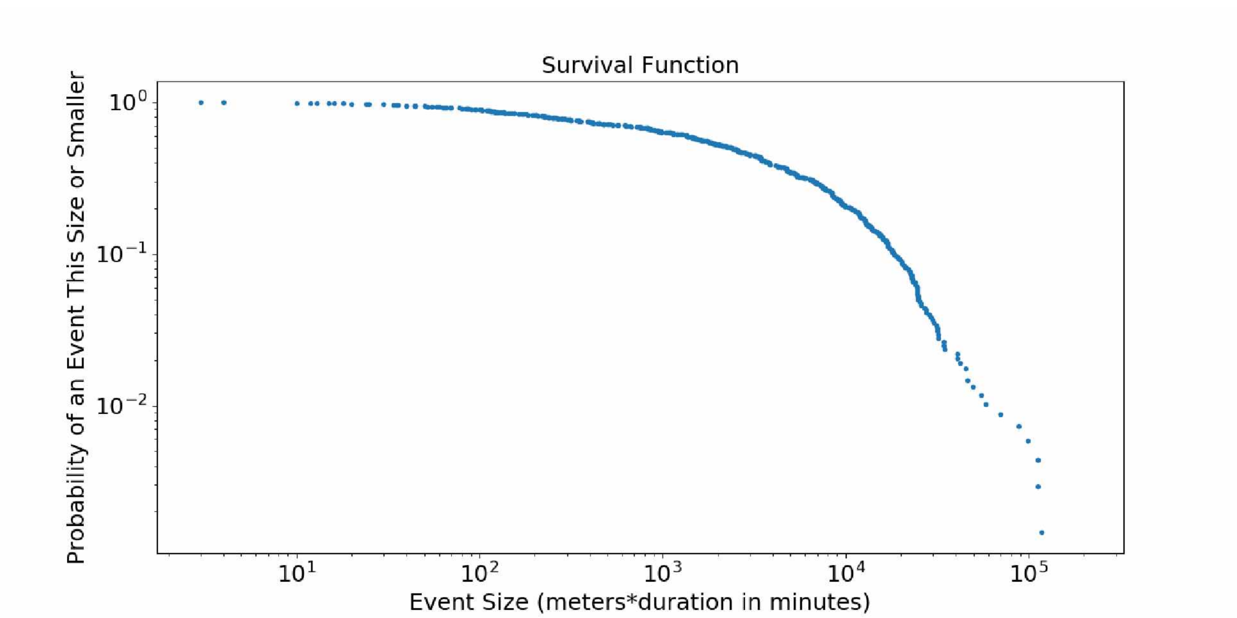

Figure 2.7: Survival Function of Outages Measured by (meters out)x(duration)

Comparing the CCDF and the Survival Function above it can be seen that they have very similar shapes which would be expected. Despite the similar shapes there are still some slight differences because the Survival function takes into account all outage sizes instead of having bins with outage size ranges. Because of this there are some parts of the Survival

Function that become blurred or nonexistent in the plot of the CCDF.

We also look at the PDFs using the other two measures of size – duration in minutes and number of meters out by the outage. Looking at these two PDFs as well can give us information like the relative importance that long or short outages have. Both plots are shown below in Figures 2.8 and 2.9.

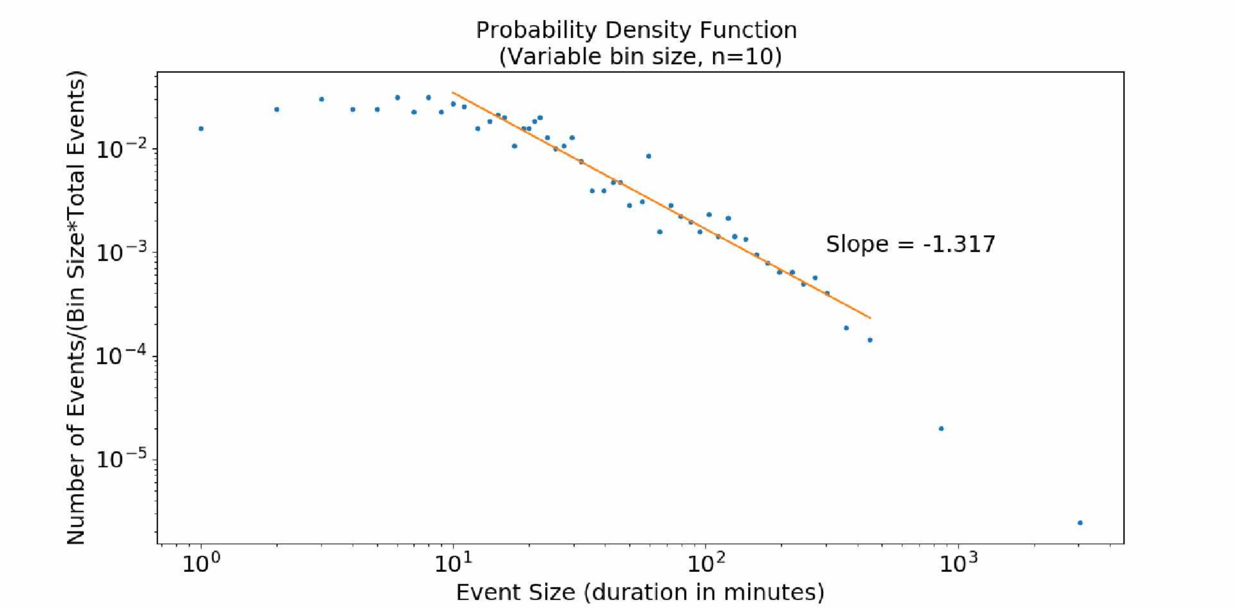

Figure 2.8: PDFs of Outages Measured by Duration in Minutes

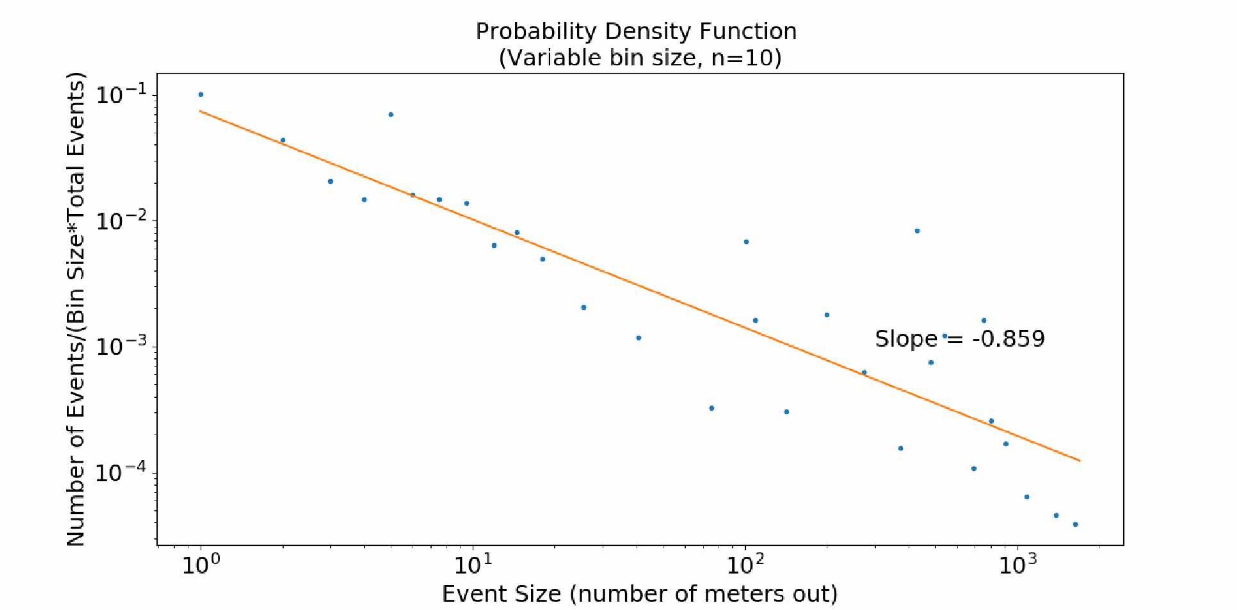

Figure 2.9: PDFs of Outages Measured by meters out

Because there is a power law in both plots we can see that larger events play a bigger role in the outages than one would expect if the outages were random. The steeper slope in the duration PDF tells us that these larger duration events are less common than the larger events in terms of the number of meters out, which has a shallower slope to its power law.

There are a number of outliers on the large event side when looking at the PDF of the number of meters out in each event. The original PDF with $n = 10$ can be seen above. We think these outliers may be caused by the fact that each feeder only has a certain number of meters associated with it and once all of those meters are down the event size cannot get any bigger. This will result in a disproportionate number of events of these sizes. These maximum values/total number of meters on each feeder are: Auxiliary – 104, 13 Mile – 226, Main Town – 317, Lake Avenue – 430, New Town – 517. We removed the events where all meters on the feeder were affected and analyzed the remaining 297 events. This caused the outliers to disappear, and so we believe the outages that effected all of the meters on a feeder were what caused outliers in the PDF. This filtering also caused a steeper and more accurate looking line of best fit. The filtered PDF is shown in Figure 2.10.

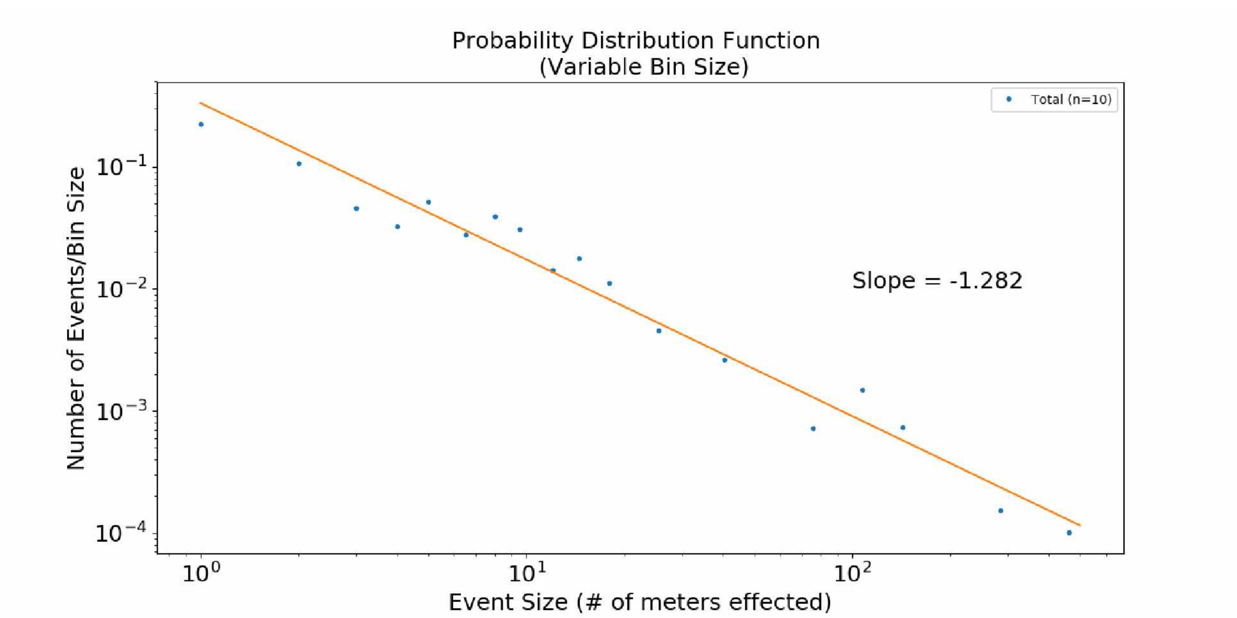

Figure 2.10: PDF of Outages Measured by Meters Out After Removing the Outages that Take Out All Meters on a Feeder

Looking at the PDF of the outages in terms of the energy unserved, shown in Figure 2.11, there is also a power law. This power law has a nearly identical slope as the plot shown in Figure 2.10 using the measure of (meters out)x(duration). From this we can see consistency in our two main measures of the outage size.

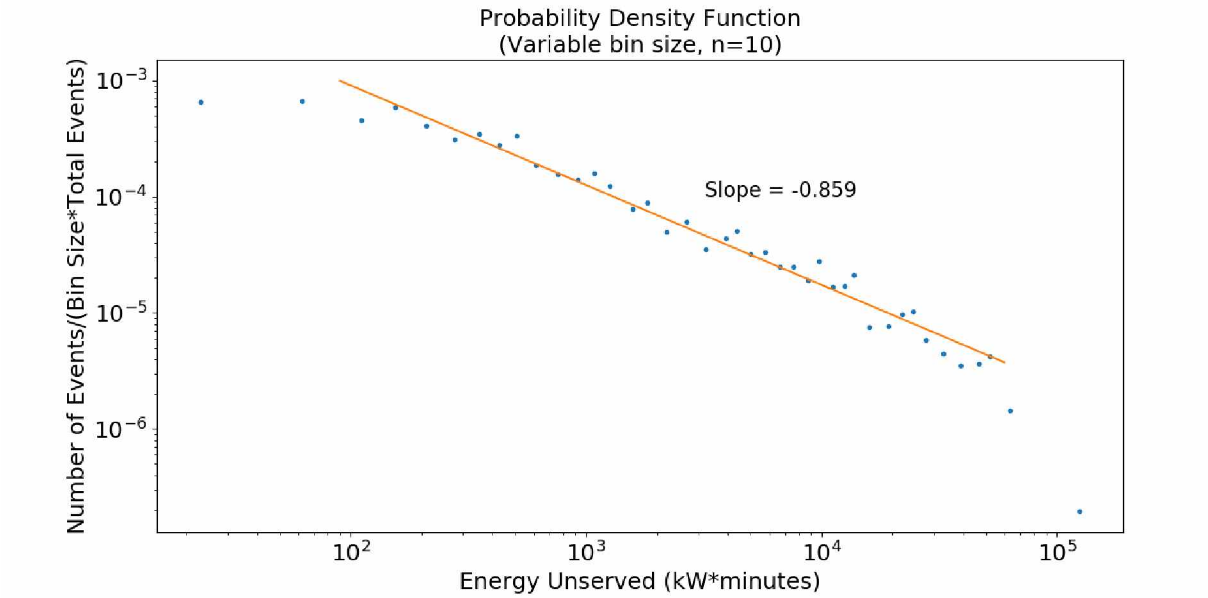

Figure 2.11: PDF of Outages Measured by Energy Unserved

Because of the difference in load demand in the summer versus the winter (see analysis section e.) it is useful to analyze outages in terms of these seasons. Separating outages into summer vs winter and estimating energy not served in the same manner as before, we plotted the PDFs for both summer (June 15 – Sept 15) and winter (the rest of the year) (Figure 2.12 and 2.13). The slope for summer was -0.704 and winter has a slope of -0.923. This means there is a higher amount of larger outages in the summer when the load demand is higher.

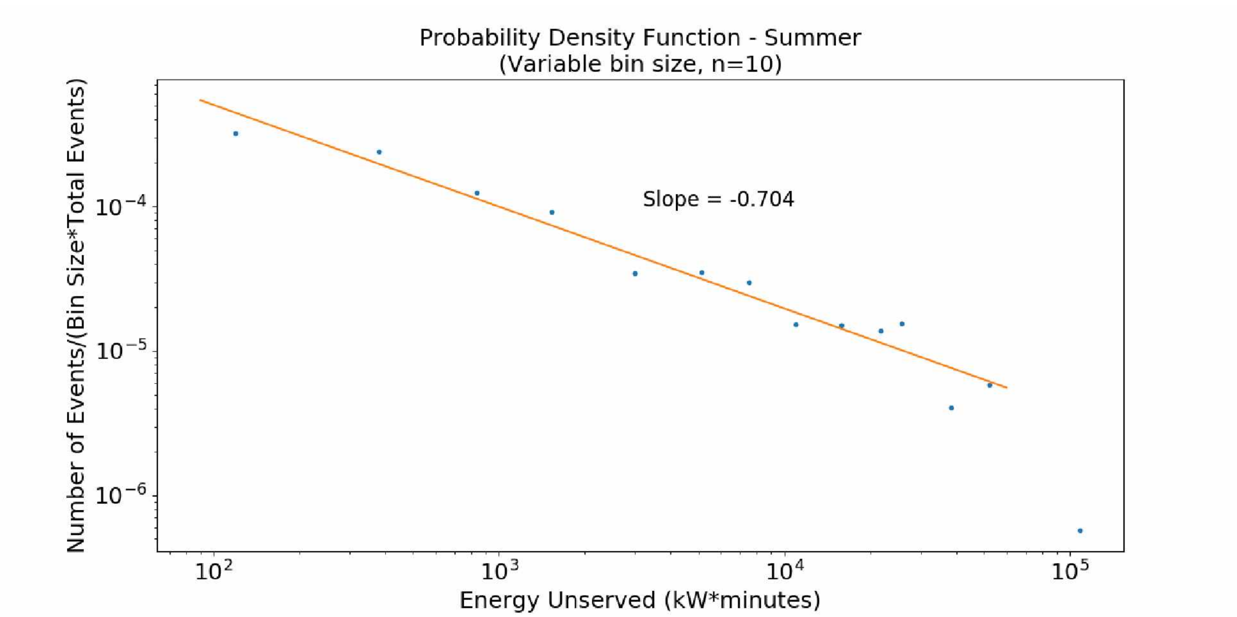

Figure 2.12: PDFs of Outages Measured by Energy Unserved During Summer

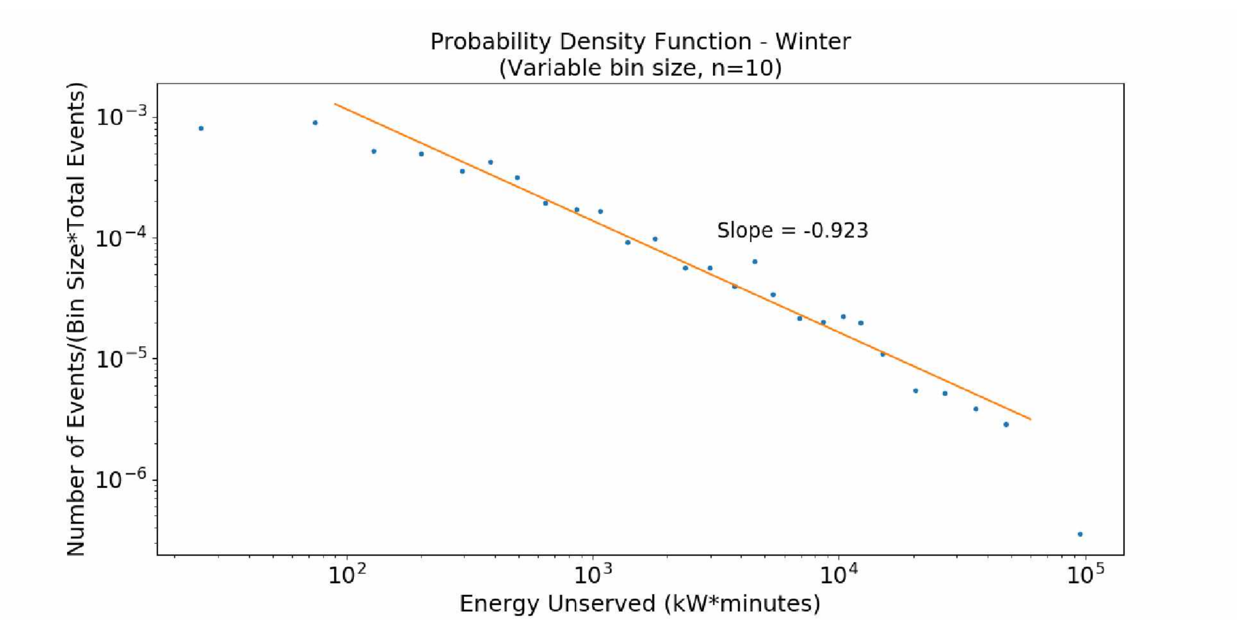

Figure 2.13: PDFs of Outages Measured by Energy Unserved During Winter

We notice power laws in our data in every different measure we use to quantify the sizes of our outages. This strongly suggests this grid is behaving like a complex system. We use an R/S analysis to determine the scale of any long time correlation of the outages.

2.3.2 R/S Analysis

Since we see characteristics of complex systems in our PDF analysis we now want to see if there is a long time correlation in the system's outage events. The correlations in complex systems between certain sized events can be measured using a Hurst exponent [17], [21]-[22]. The slope of this plot is called the Hurst exponent. A Hurst exponent larger than 0.5 means there is a positive correlation, meaning a blackout at one time may have an effect on a blackout that occurs on a later day. In contrast, a Hurst exponent below 0.5 means a negative correlation and a Hurst exponent equal to 0.5 shows no correlation.

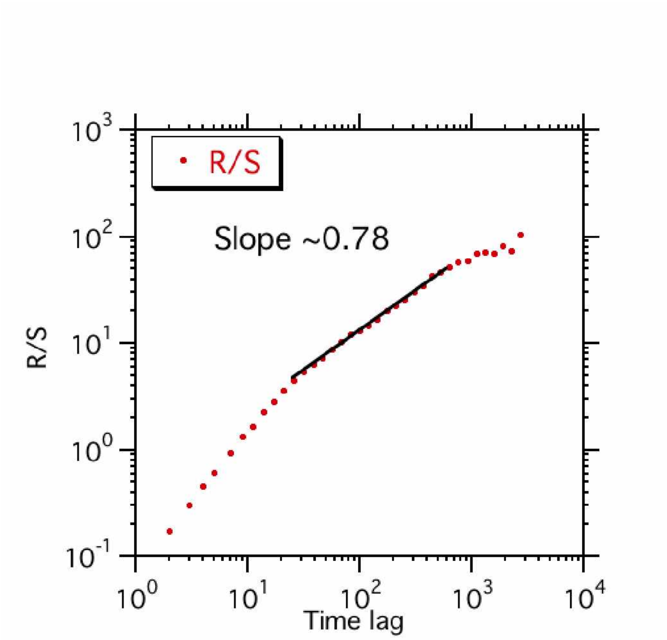

Figure 2.14: R/S Analysis of Outages Measured by (meters out)x(duration)

In Figure 2.14, we see a Hurst exponent of about 0.78 in the R/S plot which indicates a long time correlation. A long time correlation tells us that events happening today are affected by events that happened in the past, and similarly, events today will affect future events. From the plot we see that this correlation lasts between about 10 days to 3 years.

The power laws from the above section and the long time correlation found here suggest the microgrid behaves like a complex system. Because of this we dig deeper into possible underlying causes for our outages in the form of looking at the cause codes associated with each outage, followed by looking for correlations with the weather.

2.3.3 Outages with Different Causes

In our summary of all outages each outage is given a three digit cause code in which the first digit gives information on the broad category of the cause and the next two digits give more detailed information in the form of subcategories. The categories can be seen in Table 2.1. In order to determine if certain causes played more of a role than others for particular sized outages we next plotted time series and PDFs of the outages split up by cause code.

Table 2.1: Outage Cause Codes

Power Supplier		Distribution		Planned_Outage		Storm		Other	
Hydro	100	Substation	200	Construction	300	Wind Damage	400	Auto Accident	500
Diesel	101	Substation Fusing or Relay	201	Repairs	301	Water/Snow D	401	Boat Antenna	501
Operatio	199	Transformer Bad or Replaced	202	Replacement	302	Line Slap	402	Bird Contact	502
		Primary Cable	203	Operations	303			Animal Contact	505
		Transformer Fuse or Breaker	204					Damaged Wire -	503
		Secondary Cable or Pedestal	205					Dig In	504
								Unknown	666

As one would expect there are some outages that are much more prevalent than others. The number of outages due to each cause can be seen in Table 2.2. This difference in outages for each cause is taken into account when choosing the bin size of the PDFs. For instance, if a cause has less than ten events a bin size of two or three will be chosen rather than the usual bin size of ten events per bin. Another thing to be aware of is that less than ten events is a very small sample size and it can be hard to get a reliable trend from that amount of data.

Table 2.2: Number of Outages Associated with each Cause Code

Cause Code	# of Outages	Cause Code	# of Outages	Cause Code	# of Outages	Cause Code	# of Outages
100	82	203	105	303	9	502	13
101	148	204	26	400	2	503	5
199	24	205	15	401	12	504	29
200	5	300	15	402	10	Switching Error	1
201	11	301	91	500	1		
202	4	302	68	501	1	666	6

The top causes of outages are “Power Supplier – Diesel”,“Distribution – Primary Cable”, "Planned Outage – Repairs", "Power Supplier – Hydro", and "Planned Outage – Replacement". Because these 5 types of outages make up for about 72% of all outages we will focus on those causes to see if any of the trends deviate a significant amount from the total trend. This will also help show us if there is a certain cause that relates to more of the smaller or larger events than usual.

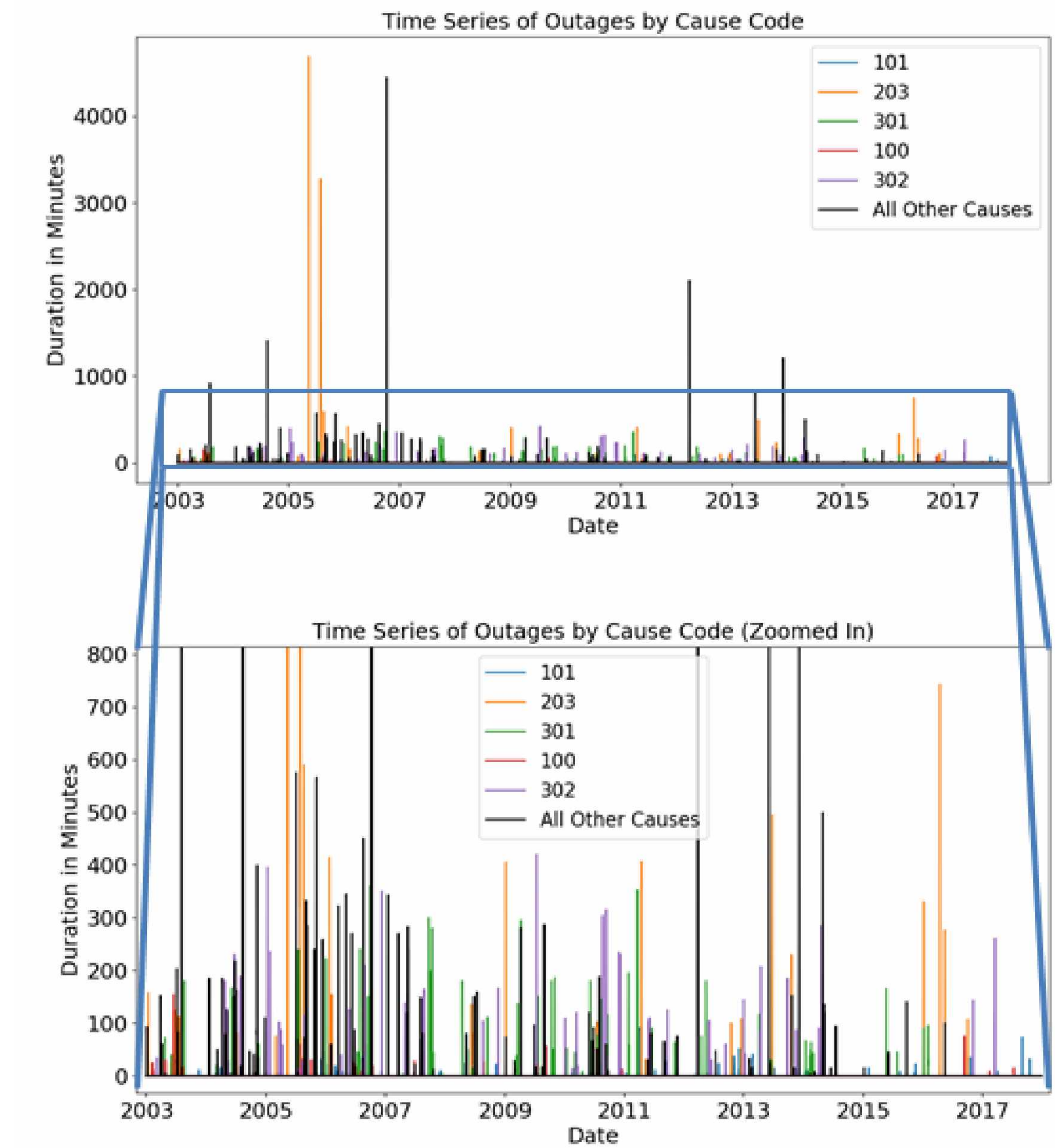

Figure 2.15: Time Series of Outages Associated with Different Cause Codes (Zoomed in below)

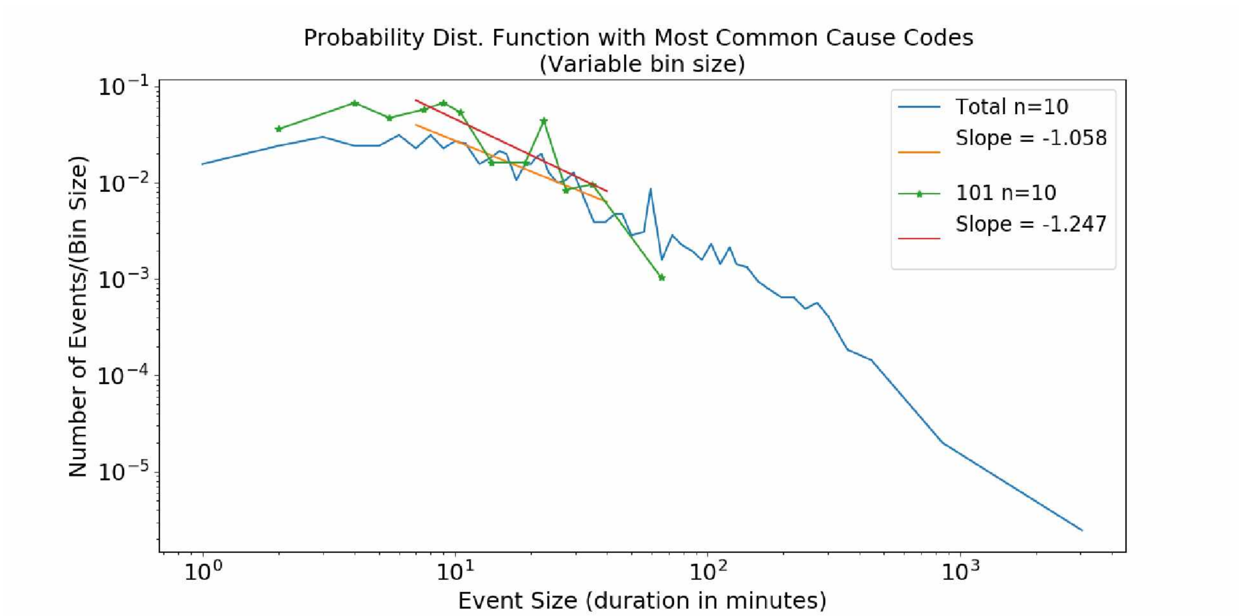

Figure 2.16: PDFs of Outages Associated with Cause Code 101

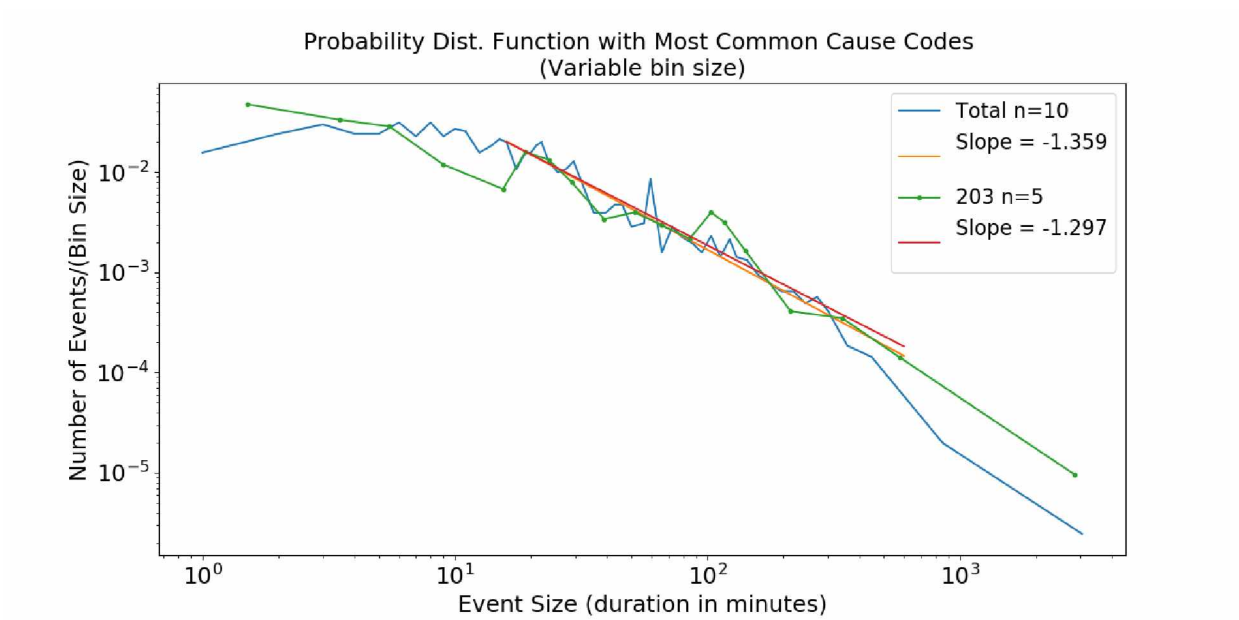

Figure 2.17: PDFs of Outages Associated with Cause Code 203

The plots in Figures 2.16 and 2.17 are PDFs of the top two unplanned outage causes compared with the total outages. The plots include the slopes of both in ranges where they appeared similar. The same was done for the remaining top five outage causes and the slopes for certain ranges are plotted and then recorded in Table 2.3.

Table 2.3: Summary of Slopes of PDF Plots for the Top Five Outage Causes

PDFs of top 5 outages compared to total (duration) and one for all other causes of events.			
Cause Code	**Number of Events**	**Range (minutes)**	**Slope**
Total	683	7-40	-1.058
101	148	7-40	-1.191
Total	683	17-600	-1.359
203	105	17-600	-1.297
Total	683	5-350	-1.177
301	91	5-350	-0.838
Total	683	6-30	-0.615
100	82	6-30	-0.449
Total	683	7-400	-1.252
302	68	7-400	-0.472
Total	683	14-400	-1.331
All Other Causes	189	14-400	-1.210

Of the top five causes of outages the only one that deviates significantly from the trend of the total outages is cause 302 – Planned Outage: Replacement. From the shallow slope of the power law in this PDF for this cause we can see that it accounts a higher than average percentage of the outages that occur in the duration range near 150-400 minutes. Cause 302 is a planned outage and is the cause that deviates the most from the total outages, followed by cause 301 - Planned Outage: Repairs, another planned outage cause. Because of this, we next plot the unplanned and the planned outage PDF, figure 14. From this plot it is noticeable that in the middle range (5-300 minutes) the planned outages have a shallower slope. In this range it is the planned outages that account for a higher percentage of longer outages. However since the unplanned outages PDF extends further out it is these outages that account for all outages that last longer than 600 minutes.

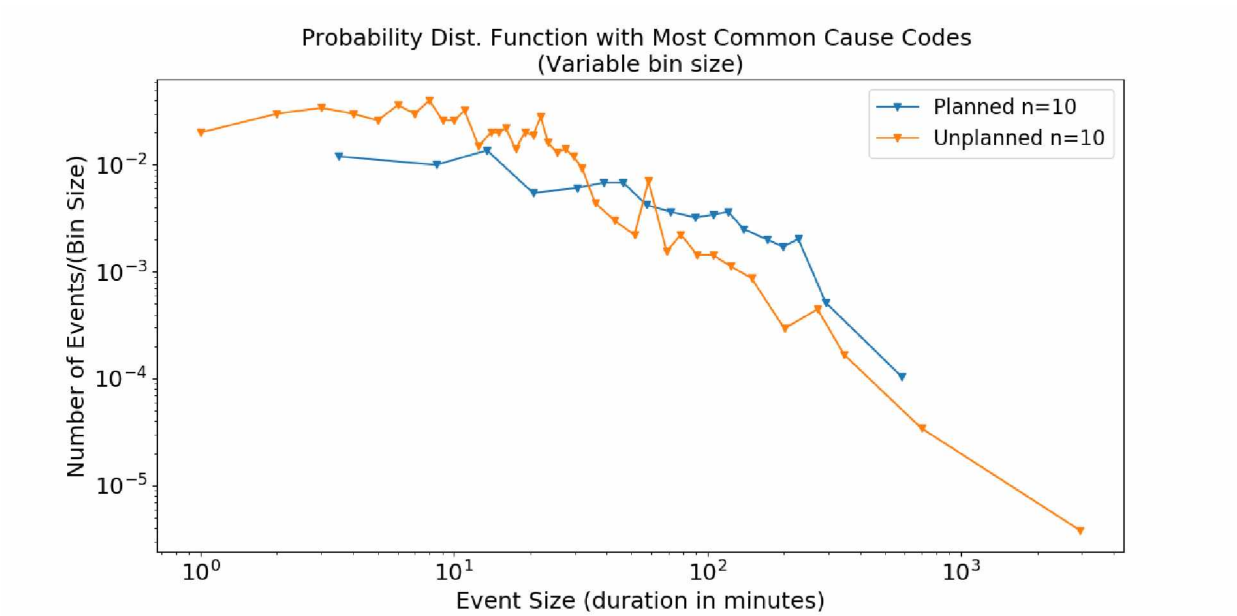

Figure 2.18: PDF of Planned vs Unplanned Outages

Another piece of historical data we have on this system is the fact that all lines were buried in 2009 and looked at different outage cause time series with this in mind. Like one would expect, this didn't seem to have a noticeable effect on any of the outage causes as a whole except the weather related causes. From the chart above we see that the category with the 400's cause codes is titled "Storm." The time series of outages from this category only is plotted below in Figure 2.18. On this plot we can see that there are no outages due to these cause codes after the year 2009.

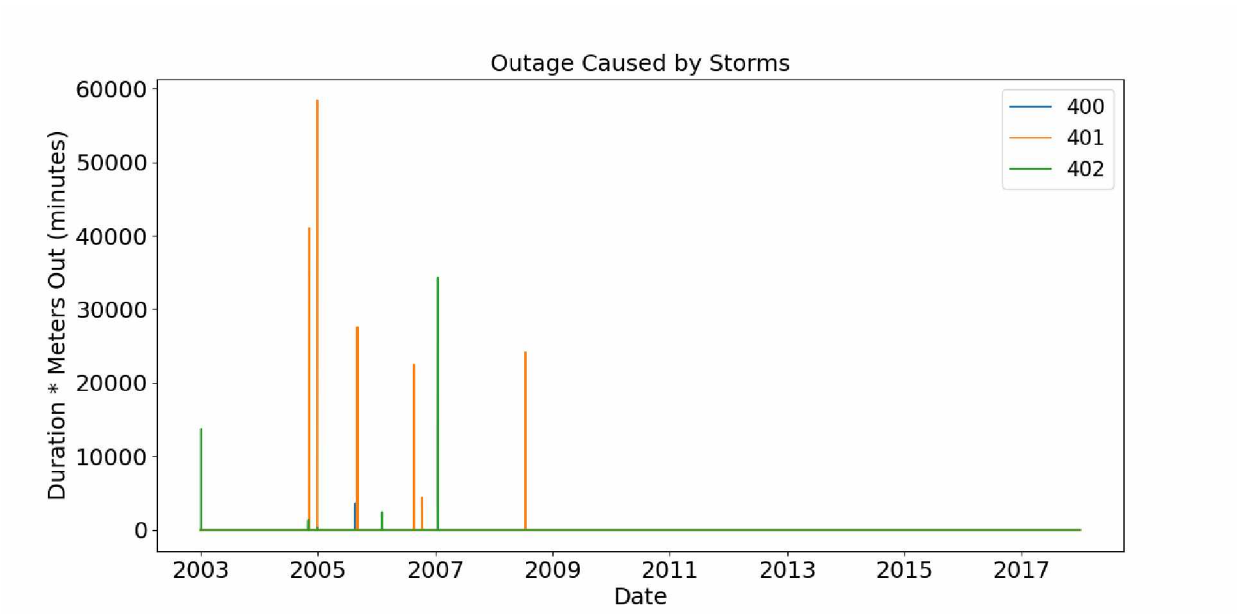

Figure 2.19: Time Series of Outages Caused by Storms

Even though we now know the buried lines protects from outages directly due to storms we still look at correlations of the outages with weather. We look still at weather because there may be indirect correlations of storms or severe weather that relates to outages. For example, extreme high or low temperatures may change normal demands, or large amounts of snow may make access to components difficult when it comes to repairs. These things would not be labelled as storm related outages even though weather or storms will still have an effect.

2.3.4 Weather and Seasonal Correlations

The weather factors we looked at include high winds, floods, blizzards, daily precipitation, daily snowfall, and daily temperatures. For each of these factors we plotted time series of the outages along with the weather category or categories that we are analyzing. Each condition has a plot for duration of events in minutes times the number of meters out. The plots are from Jan 1, 2003-Dec 31, 2016. Some of the daily data was marked 'M' which meant missing (sometimes a whole month had 'M' and sometimes just a day or two); those days were just changed to zeros and not plotted. The yellow bars highlight the precipitation and storm events that happen the same day (star at top) or the day before (dot at top) an outage event. Since there are many events and there is no way to say where the cause and effect lies we look at statistics in each of the plots below. Using probabilities we compare the chances of having an outage during certain weather events to the probability of randomly having an outage on any given day. There are 682 outage events in 5,114 days; this means that on any given day there is about a 13% chance of having an outage event.

2.3.4.1 High Winds

The National Weather Service Instruction PDF defined a high wind storm event as: Sustained non-convective winds of 35 knots (40 mph) or greater lasting for 1 hour or longer, or gusts of 50 knots (58 mph) or greater for any duration (or otherwise locally/regionally defined)[23]. From looking through the data filtered for the Cordova area [20] all wind event magnitude values given are the gusts (either measured or estimated) in knots. According to NOAA, Cordova falls in the Southeastern Prince William Sound (SERN P.W. SND) Zone, so all storm events in the plot (Figure 2.20) are taken from the data on that zone.

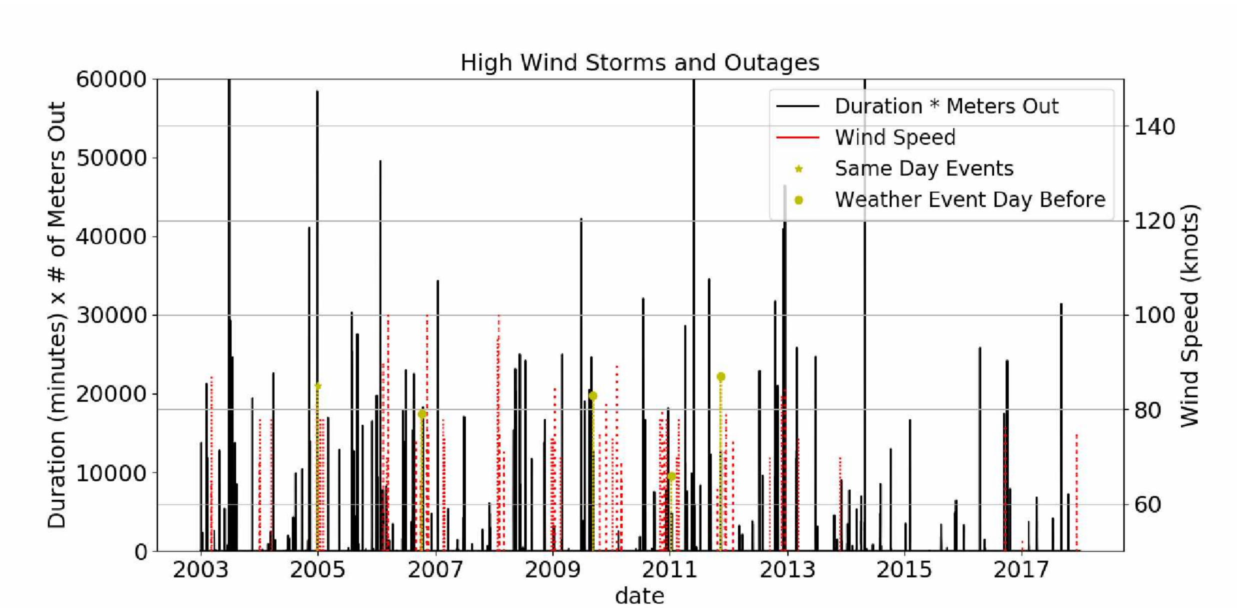

Figure 2.20: Time Series of Outages and High Wind Events

There are 59 wind storm events (see above for what qualifies). Of these 59 only 8 are on the same day as or the day before an outage event, this is 14%, almost the exact same likelihood of having an outage event randomly. Looking at events over 80 knots there are 14 events and 3 coincide with outage events, 21% which is slightly higher, but given this small sample this is very similar to the likelihood of just randomly having an outage event on a given day. This indicates that high winds likely do not have an effect on the number of outages. This result is somewhat expected and consistent with the fact that all lines were buried underground in 2009.

2.3.4.2 Precipitation and Snowfall

We plotted daily precipitation and daily snowfall together in Figure 2.21. Precipitation and snowfall data were found on the UAF GI climate page and there are two stations in Cordova, "Cordova North" and "Cordova Airport", for recording precipitation and snowfall [19]. For the plot we used both the "Cordova North" and "Cordova Airport" data and if there was a discrepancy in values I took the highest value of precipitation or snowfall on a given day and used that as the value. The y-axis on the left side of the plot is the precipitation in inches and it starts at 2 inches, assuming 2 inches and less will not have an impact on the grid.

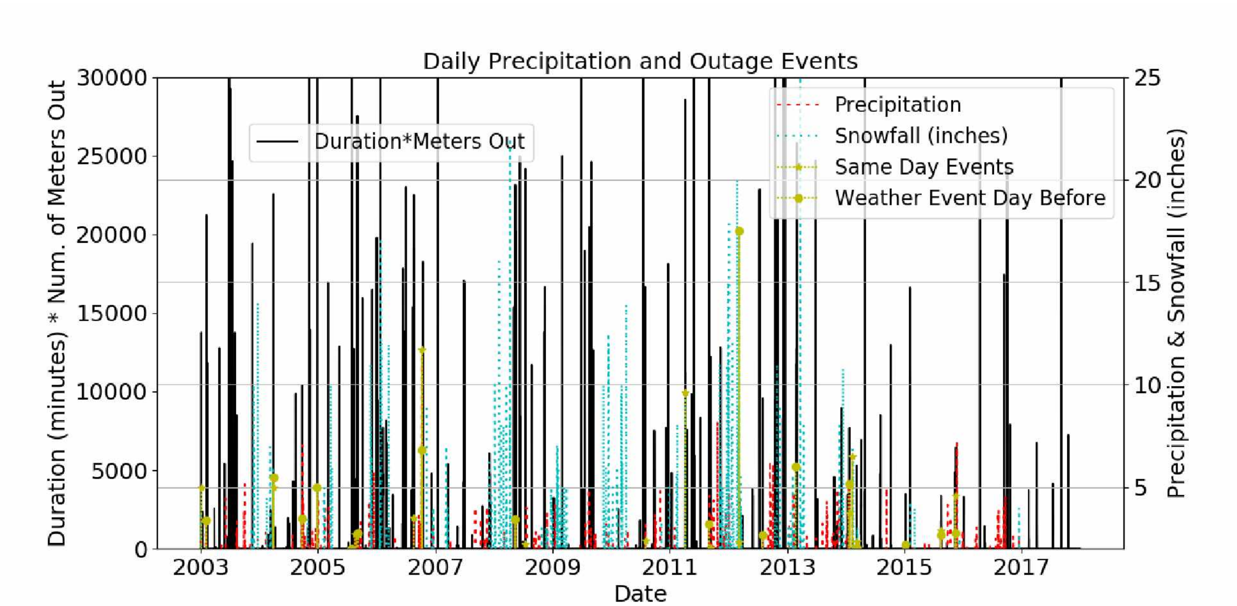

Figure 2.21: Time Series of Outages and Daily Precipitation and Snowfall

As with the plot of high wind events, here we also highlighted all precipitation and snowfall events above 2 inches that occurred on or one day before an outage event in order to see them better. Since there are many precipitation events it is hard to interpret if and when these events caused an outage or if they are just coincidental. For precipitation there are 211 events over 2 inches and 29 of them coincide with an outage event (about 14%), for snowfall there are 225 events over 2 inches and 32 of them coincide with an outage event (about 14%). Alone both of these seem coincidental, but for precipitation it seems there may be an effect for very large events.

There is a large outage event on 10/10/2006 with heavy rain the day of and the day before that shows up in the flood data as well; this is the largest amount of precipitation in the data at just under 12 inches in one day and 8 inches the day before. This suggests that extremely heavy rains for two consecutive days will have an effect on the power grid. The next largest precipitation events fall in the range of 5-8 inches, for which there are eight events and only one is the same day as an outage. This gives 12.5% of events in this range coincide with an outage event which is about the same as the chances of having an outage event in general; so this is probably just coincidental. For large amounts of snowfall, looking only at events that are over 10 inches, there are 23 events and only 2 coincide with outage events, 9% which seems just coincidental.

2.3.4.3 Floods and Blizzards

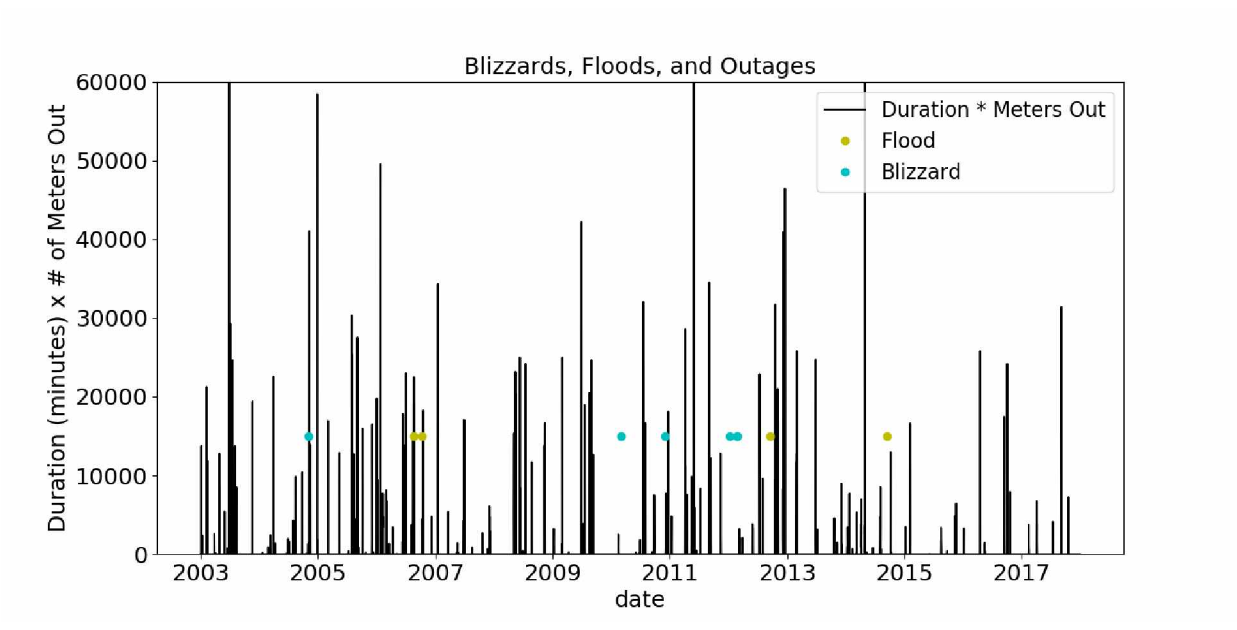

Figure 2.22: Time Series of Outages and Flood and Blizzard Events

From the past 15 years there have been 5 blizzard events and 4 flood events. The website does not have information regarding the size of these events, so we just plotted them all as either an event occurring or no event occurring. Of the 5 blizzards only one coincided with outages and one happened two days before, the other three blizzards were not the same dates as any outage events. Of the 4 floods, 3 of them coincide with an outage event, one being a very large outage event which also coincides with a large precipitation event. Even though the sample size is small, we think this may indicate that floods are likely to have an effect on outages, but blizzards do not seem to. The result of the floods is an interesting one, because this seems to be the only storm event that may still affect the grid even though the lines are buried.

2.3.4.4 Temperature

When looking at temperature data points, if any days had an 'M' (which indicated missing data) we changed those to be the same as the day before so we could still plot everything. Figure 19, below, shows the plot of the high and low temperature along with the duration of all outage events.

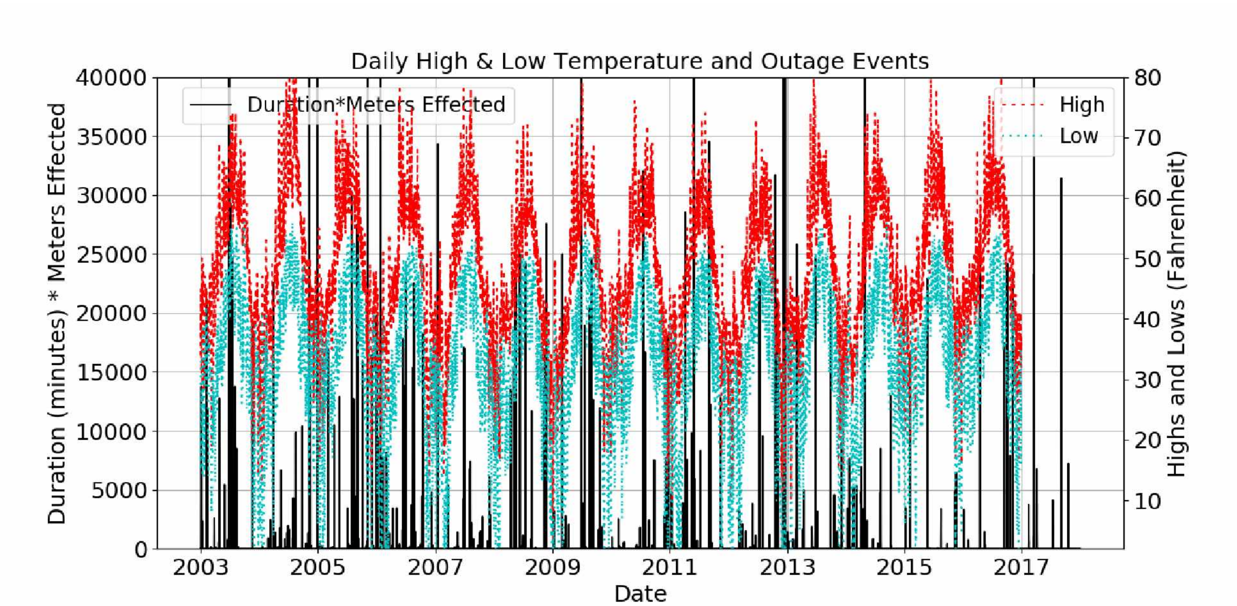

Figure 2.23: Time Series of Outages and Daily High and Low Temperatures

We saw a slight correlation with warmer temperatures. We believe this may be caused by the fish processing plants that only operate in the summer and thus increase the load demand in the summer. We will look at the correlation of outages with load demand in the next section.

2.3.5 Additional Plots

Also looking at temperature and precipitation we plotted events when it rained while the low was less than 32 degrees Fahrenheit assuming this would result in freezing rain. From this we found 23 times where this happened and only 3 that correspond with an outage for about 13%. So we found no link between cold temperatures and rain either. We also looked at different snow depths to see if that had an effect on the duration of outages assuming that it may be more difficult to get to wires for repairs if snow is too deep, but this also seemed to have no effect.

2.3.5.1 Correlation of Outages with Load Demand

The most telling metric we have used is comparing the outages with the load demand. We have the hourly load usage data (in MW) for the years 2005-2017 and the outage data for the years 2003-2017 for the 5 main feeders: Auxiliary, New Town, Main Town, Lake Avenue, and 13 Mile. We analyzed this data by plotting a time series of the load data and the outage data on each feeder to compare the two and were able to both estimate an average trend in the load data as well as zoom in on each outage to determine whether the outage happened during a peak demand time or not.

When plotting each feeder's load demand individually there are noticeable trends in the load demand that differ. It can also be seen in these plots that there was a major reconfiguration of the lines in 2013 causing some of the trends to change. The most immediately noticeable trend is that Auxiliary feeder has a peak demand in the summer and this is probably due to the fact that this feeder goes to the fish processing locations. This trend is also very noticeable in the Main Town feeder after the line reconfiguration in 2013. When zooming into the plots closer, the 13 Mile, Lake Avenue, Main Town, and New Town feeders all seem to have a daily cycle that peaks during the day, highest in the morning near 8am-noon and evening near 5-8pm and is at a low during the night near 10pm-6am. All feeders have slight peaks during the summer, but not as much as the Auxiliary and Main Town feeders.

To see an average year, in Figure 2.24 are the loads (in MW) on all feeders combined for 2014. In Figure 2.25 the average daily load demand cycle is shown.

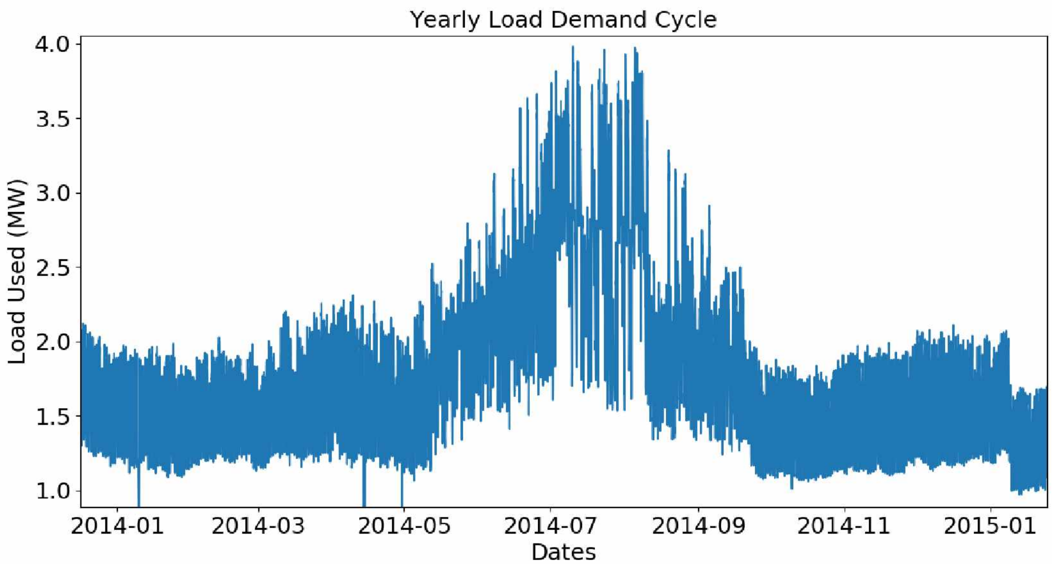

Figure 2.24: Annual Load Demand Cycles

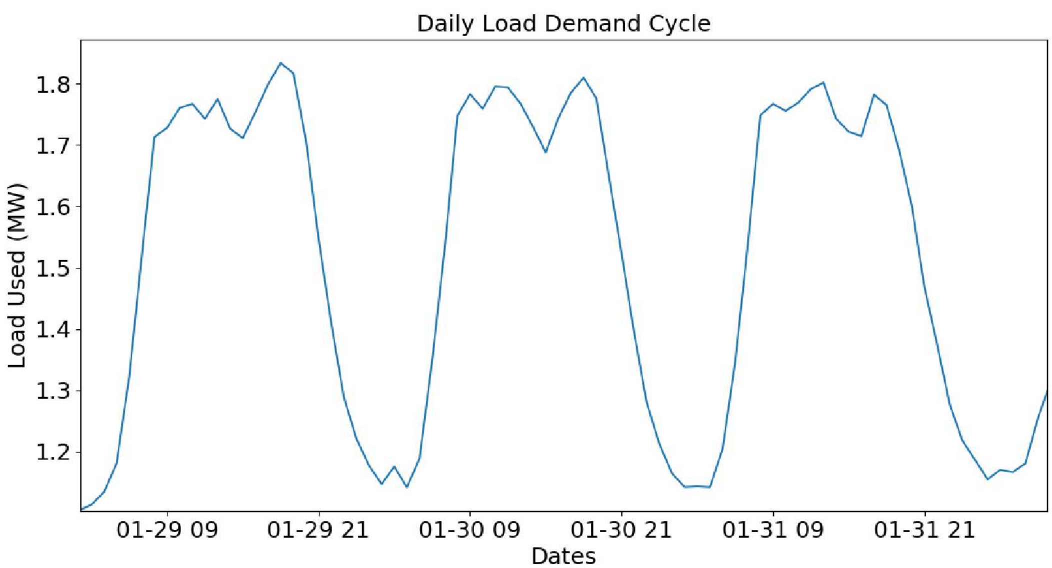

Figure 2.25: Daily Load Demand Cycles

When counting the outages that occurred during the day we assumed the day time peak was around 8am-10pm. When counting the outages during the summer time peak load demand we assumed that fell between mid-June until mid-September. We used these times and dates to analyze the outages, specifically the percentage of outages that took place during a daily peak, a nightly lull, and a summer time peak compared with the percentage of outages that would happen in those times if outages were happening randomly. The total tally for the number of outages can be seen in Table 2.4 below. Along with total outages we also looked at the amount of different sized outages (small, medium, large) during each period in terms of number of meters out, duration of outages in minutes, and (meters out)x(duration).

All outages, in terms of (meters out)x(duration) are plotted below in Figure 2.26. From this plot, we arbitrarily chose values to be cutoff values for the ranges of small, medium, and large outages. They are defined as:

- Small: less than 5,000
- Medium: between 5,000 and 15,000
- Large: greater than 15,000

The amount of small, medium, large, and total outages during each part of the load demand cycle are recorded in Table 2.4.

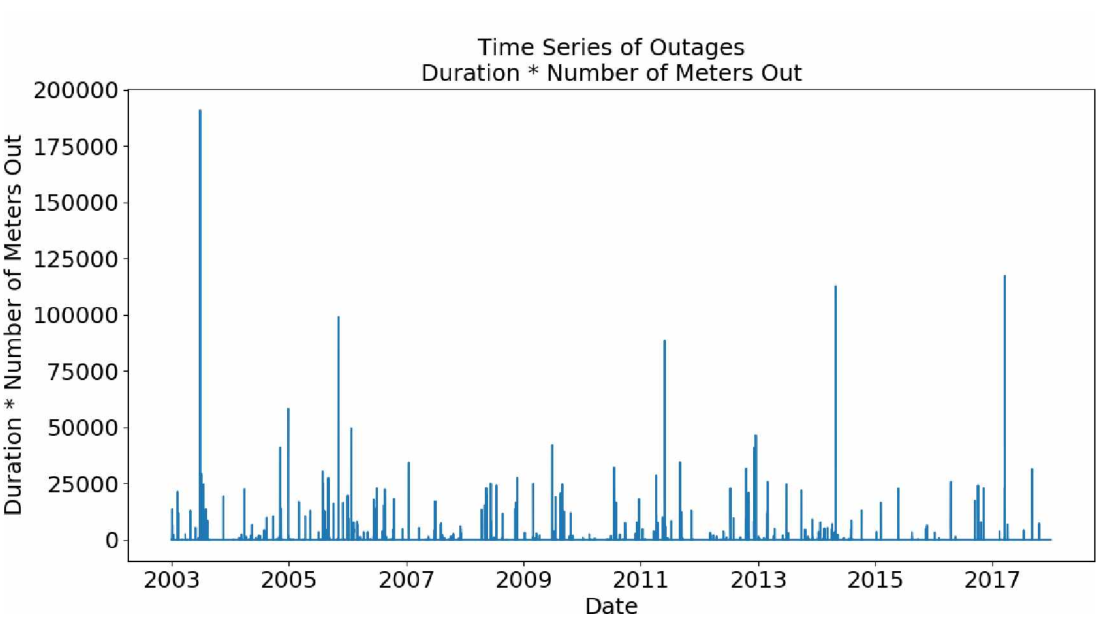

Figure 2.26: Time Series of Outages Measured by Meters Out × Duration in Minutes

Table 2.4: Summary of Probabilities of Outages During Different Points in Load Demand Cycle Measured by Meters Out$\times$ Duration in Minutes

Year	Total Outages				Daytime Peak				Nighttime Lull				Summer Peak			
	Large	Medium	Small	Total	Large	Medium	Small	Total	Large	Medium	Small	Total	Large	Medium	Small	Total
2005	9	11	28	48	7	9	22	38	2	2	6	10	6	4	24	34
2006	9	17	26	52	5	13	19	37	4	4	7	15	4	10	8	22
2007	4	5	19	28	1	2	15	18	3	3	4	10	2	3	8	13
2008	8	12	6	26	1	5	2	8	7	7	4	18	1	3	1	5
2009	6	10	15	31	5	7	15	27	1	3	0	4	4	10	9	23
2010	8	12	25	45	7	9	20	36	1	3	5	9	7	10	15	32
2011	5	14	19	38	1	8	13	22	4	6	6	16	1	5	3	9
2012	8	8	18	34	1	4	11	16	7	4	7	18	1	3	4	8
2013	2	6	17	25	2	2	14	18	0	4	3	7	1	0	2	3
2014	3	9	29	41	0	2	14	16	3	7	15	25	0	3	6	9
2015	1	1	13	15	1	1	11	13	0	0	2	2	0	0	3	3
2016	7	5	7	19	4	2	2	8	3	3	5	11	1	0	1	2
2017	3	2	15	20	3	1	15	19	0	1	0	1	3	0	6	9
total	73	112	237	422	38	65	173	276	35	47	64	146	31	51	90	172
Actual Percentage					52.05%	58.04%	73.00%	65.40%	47.95%	41.96%	27.00%	34.60%	42.47%	45.54%	37.97%	40.76%
Random Percentage								58.33%				41.67%				25.00%

In Table 2.4, when looking at total outages, we can see a clearly higher percentage of outages that happen during the summer than we would expect if outages were just happening randomly. There is also a slightly higher amount of outages that occur in the daytime than we would expect from them randomly happening, but the percentage is not much higher and this could just be due to chance. Because the yearly fluctuations in load demand are much more drastic, this suggests a correlation with more outages during higher load demand times which is expected.

This same process is repeated twice more except this time we are measuring the outages in terms of duration in minutes and then energy unserved. Below in Figure 2.27 is the plot of the outages in terms of duration in minutes. From here we chose the following values to represent small, medium, and large outages:

- Small: Less than 30 minutes
- Medium: Between 30 minutes and 120 minutes
- Large: Greater than 120 minutes (2 hours)

We chose these values based on the outages in the plot along with our own opinions on what we would consider to be a large, medium, or small outage.

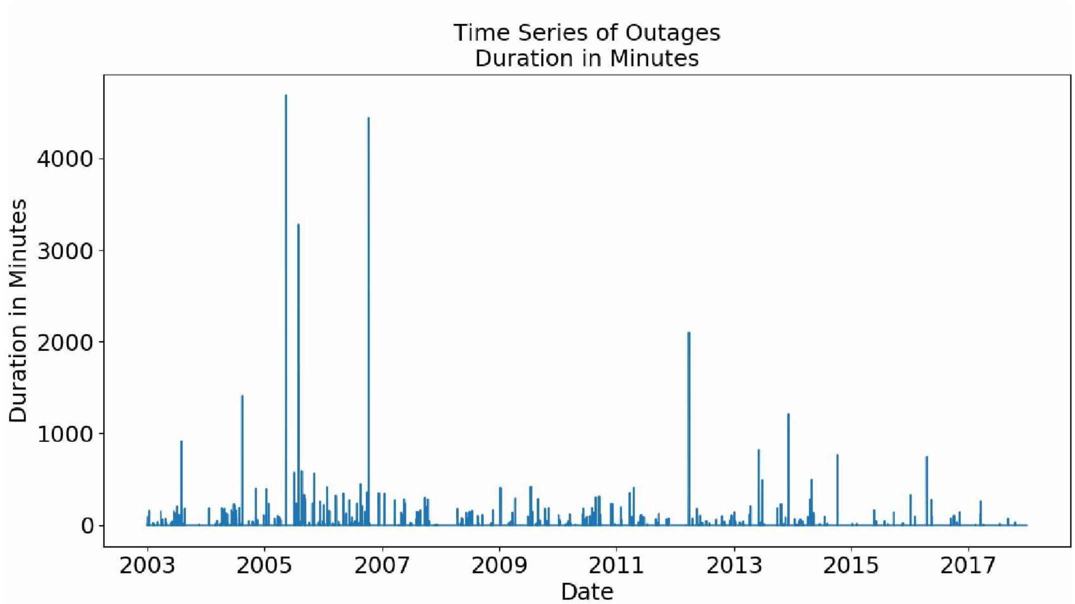

Figure 2.27: Time Series of Outages Measured by Duration in Minutes

Table 2.5: Summary of Probabilities of Outages During Different Points in Load Demand Cycle Measured by Duration in Minutes

Year	Total Outages				Daytime Peak				Nighttime Lull				Summer Peak			
	Large	Medium	Small	Total	Large	Medium	Small	Total	Large	Medium	Small	Total	Large	Medium	Small	Total
2005	12	18	18	48	7	13	18	38	5	5	0	10	8	14	12	34
2006	9	6	37	52	6	3	28	37	3	3	9	15	1	2	19	22
2007	4	3	21	28	2	2	14	18	2	1	7	10	0	1	12	13
2008	3	9	14	26	1	2	5	8	2	7	9	18	2	0	3	5
2009	4	7	20	31	4	4	19	27	0	3	1	4	2	5	16	23
2010	1	12	32	45	1	9	26	36	0	3	6	9	1	10	21	32
2011	1	9	28	38	0	4	18	22	1	5	10	16	0	2	7	9
2012	2	10	22	34	0	2	14	16	2	8	8	18	0	2	6	8
2013	7	5	13	25	7	1	10	18	0	4	3	7	1	1	1	3
2014	5	5	31	41	1	0	15	16	4	5	16	25	0	0	9	9
2015	1	1	13	15	1	1	11	13	0	0	2	2	0	0	3	3
2016	8	7	4	19	4	3	1	8	4	4	3	11	0	1	1	2
2017	0	5	15	20	0	4	15	19	0	1	0	1	0	4	5	9
total	57	97	268	422	34	48	194	276	23	49	74	146	15	42	115	172
Actual Percentage					59.65%	49.48%	72.39%	65.40%	40.35%	50.52%	27.61%	34.60%	26.32%	43.30%	42.91%	40.76%
Random Percentage								58.33%				41.67%				25.00%

For energy unserved we chose the following values for small, medium, and large outages based on the distribution of sizes in the time series.

- Small: less than 5 MW*min.
- Medium: 5-30 MW*min.

- Large: greater than 30 MW*min.

Table 2.6: Summary of Probabilities of Outages During Different Points in Load Demand Cycle Measured by Energy Unserved

Year	Total Outages				Daytime Peak				Nighttime Lull				Summer Peak			
	Large	Medium	Small	Total	Large	Medium	Small	Total	Large	Medium	Small	Total	Large	Medium	Small	Total
2005	9	12	24	45	7	9	21	37	2	3	3	8	5	9	13	27
2006	8	21	20	49	5	19	15	39	3	2	5	10	4	9	11	24
2007	5	9	19	33	1	6	18	25	4	3	1	8	3	5	4	12
2008	4	10	10	24	1	5	6	12	3	5	4	12	0	4	4	8
2009	4	7	16	27	3	5	16	24	1	2	0	3	3	5	4	12
2010	8	14	28	50	6	11	26	43	2	3	2	7	8	10	7	25
2011	3	11	18	32	1	7	16	24	2	4	2	8	1	3	1	5
2012	5	10	10	25	1	6	6	13	4	4	4	12	1	3	2	6
2013	0	12	20	32	0	9	18	27	0	3	2	5	0	1	3	4
2014	3	10	30	43	0	5	23	28	3	5	7	15	1	3	3	7
2015	0	6	8	14	0	6	6	12	0	0	2	2	0	1	2	3
2016	3	7	7	17	1	2	5	8	2	5	2	9	0	1	0	1
2017	5	6	6	17	5	5	5	15	0	1	1	2	2	2	1	5
total	57	135	216	408	31	95	181	307	26	40	35	101	28	56	55	139
Actual Percentage					54.39%	70.37%	83.80%	75.25%	45.61%	29.63%	16.20%	24.75%	49.12%	41.48%	25.46%	34.07%
Random Percentage								58.33%				41.67%				25.00%

One interesting thing that is seen here when loads are split up by size is that there are less large outages during the day and more during the night. Since the planned outages are filtered out already, this could possibly be due to a faster response time and/or more people working on the issue during the day. There is also a very large percentage of small outages that happen during the daytime peak in load demand. When comparing the tables using the two different measurements of outage we can see that the outages that happen during the nighttime lull tend to be much longer in duration.

Since the summer peak here is defined by mid-June to mid-September the probability of randomly having outages that fall in this time frame would be $\frac{3}{12}$ or 25%. The actual percentage of outages that fall in this range is just over 40%. Since we have 13 years of data this is enough to say that there is a significant amount more outages in the summer time. There are some years, such as 2016, which we know to be a low fish processing year (i.e. lower summertime demand) that had a lower percentage of outages in the summer. This helps reinforce our assumption that the higher demand in the summer, even if it is only on one or two feeders, leads to more outages overall during this time. This result is consistent with what we found when plotting the PDFs of the summer outages and winter outages (Figures 2.12 and 2.13).

For most days the daytime peak in the daily cycle falls around 7am-10pm. With this assumption/average the probability of an outage randomly falling in this time frame would be $\frac{15}{24}$ or 62.5%. The actual percentage of outages that fall during this time frame is 65%. While this is slightly higher than what random would predict, it is not a lot higher. Since there is 13 years of data I think this slight increase may be meaningful, but is not quite as significant as the summertime peak in load demand.

Between the greatly increased amount of outages in the summer and the slightly increased amount of outages in the day time, we can conclude that higher demands lead to a slightly higher chance of an outage. With this knowledge we look into the difference in outage size distribution at different times during the annual and daily cycles using slopes from PDFs. A summary of the results from the PDFs in terms of energy unserved (see section b) are shown in Table 2.7 below.

Table 2.7: Summary of Slopes of PDFs of Outages Measured by Energy Unserved During Different Points in Load Demand Cycle

Plot Measure	Slope
Total	-0.880
Summer	-0.704
Winter	-0.923
Day	-0.951
Night	-0.601
Before Lines Buried	-0.892
After Lines Buried	-0.888

These results are consistent with what was found in Tables 2.4 - 2.6 above. There are more large outages occurring at night and during the summer. Because the change in load demand in summer vs winter is much more drastic than the difference between day vs night we take the summer vs winter result to be more significant in terms of the effect of load demand on outages.

2.3.6 Risk

The reason for doing much of the above analysis on the system is to get a better idea behind what threatens the system in terms of outages, especially large outages, on the power grid the most. By becoming more aware of the factors surrounding a higher or lower than average amount of outages occurring one can have a better idea of where and how to make the grid more resilient. To quantify this we have come up with a risk metric that measures the risk to the grid during a certain time period compared to an opposing time period.

First we compare the risk in the summer when there is a peak in the power demand vs the risk in the winter when there is no peak in the power demand (See figure 20a. plot of average yearly cycle at the beginning of the previous subsection). Risk is calculated using probability of a certain event happening, P, and the estimated cost of that event [18]. Estimated cost is the approximated power demand that is not met because of the outage multiplied by the duration of the outage. These points are plotted on a log-log plot (see appendix section c) and then a single risk value, R, is found by integrating this plot and taking this value times the frequency of an event occurring. The value for R does not have an upper limit, but rather gives a single numerical interpretation of risk meant to allow a simple comparison between two numbers to understand the difference in risk between two different periods in time. A higher value for R represents a larger risk for the time period in question. The equations to obtain R are as follows:

$$R = (frequency) \times \Sigma Risk(i) \tag{2.2}$$

$$Risk(i) = Probability(i) \times Power\ Lost(i) \times Duration(i)) \tag{2.3}$$

$$frequency = \frac{(fraction\ of\ events\ that\ occur\ in\ this\ time\ period)}{(fraction\ of\ days\ in\ this\ timer\ period)} \tag{2.4}$$

Where the probability of events in bin i is calculated the same as it is in the PDF. When comparing winter and summer, the results for the risk index were what we expected; the summer had a much larger value for risk index than winter as shown in Table 2.8.

Table 2.8: Risk Index Values for Summer vs Winter

R Values	
Summer	1.608
Winter	0.705

Using the same methods of calculating values as above, we then calculated and plotted risk for before and after all lines were buried (this occurred in 2009) to determine whether or not this had an effect on the risk of an outage occurring. We see in Table 2.9 below that the lines being buried results in a much lower risk.

Table 2.9: Risk Index Values for Before vs After all the Lines were Buried Underground

R Values	
Before Burying	1.139
After Burying	0.803

We then combined the above two comparisons and looked at risk in the summer vs winter for both before and after the lines were buried. These risk values are listed in Table 2.10.

Table 2.10: Risk Index Values for Combined Summer vs Winter and Before vs After Line Burial

R Values		
	Summer	Winter
Before Burying	2.305	0.747
After Burying	1.171	0.679

Our results were consistent with above, risk was highest in the summer before the lines were buried and lowest in the winter after the lines were buried. From this we see that the system benefited from burying the lines and also that the system is less at risk of an outage when the load demand is lower.

2.4 Conclusions

This microgrid seems to behave similarly to larger grids. It exhibits power law behavior that suggests self-organized criticality within the system. This tells us that larger events tend to dominate the risk in this grid.

This system has a higher energy demand in the summer than the winter which can be attributed to the fish processing that occurs during these months. Due to the high energy demand in the summer we notice a higher risk in the system in the summer compared to the winter months when load demand is lower. We also noticed that the overall risk dropped significantly after the year 2009 which was when all of the lines were buried underground; this burial of the cables also resulted in an elimination of outages due to weather events.

3 General Conclusion

The microgrid in Cordova shows similar behavior to what is typical of larger grids that have been researched. Using multiple different measures of outage size, it displays power laws in the distribution of its outages. This tells us that large outages happen more often than expected and thus play a dominating role in the distribution of outages by size.

After getting an idea of the distribution of all outages we separated outages based on the cause of the outage. Broadly, we separated by planned and unplanned outages. Through this we found that although the unplanned outages accounted for some of the largest outages we saw, the planned outages held more weight in the amount of larger outages; i.e. the PDF of planned outages had a noticeably shallower slope than the PDF of the unplanned outages.

Even though we found storms to be on the lower end of the causes of outages we decided to next correlate outages with various weather events thinking that severe weather may still have an indirect effect on the grid such as through something like longer repair time for an outage. We looked at events such as high winds, daily and heavy precipitation, snowfall and more, and found little correlation. This lack of correlation with things like high winds, blizzards, etc. was somewhat expected due to the all of the lines being buried underground in 2009. The only severe weather event with potential correlation to outages would be flooding, where we found that 75% of the time that there was a flood there was also an outage. However, there were only 4 occurrences of flooding in the 15 years we were looking at so it is hard to tell from this small of a sample size. We were surprised that when comparing outages with the temperature we saw a larger portion of outages occurring when there were higher temperatures. Then we looked at the annual power demand and saw a large increase in power demand in the summer.

Since there is a much higher demand in power over the summer, due to the fish processing that occurs in Cordova, we attributed the larger portion of outages during higher temperatures to this. We also noticed a daily cycle in the load demand, but this was much less dramatic than the seasonal cycle. In the daily power demand cycle the demand at the bottom of this daily cycle in the summer was still much higher than the top of the peak demand in this cycle throughout the rest of the year. Due to this we saw much more discrepancy in the frequency of outages that occurred during the summer versus the rest of the year than we did in the daily demand cycle and so the seasonal cycle became our main focus.

Since we found a difference in the portion of outages that fell in the summer versus the rest of the year we decided to look deeper into that and split outages up by size (small, medium, large). We found that when using the measure of meters down times duration that slightly more of the summer time outages were of large and medium size, when using the measure of duration more of the outages were medium and small, and when using the energy unserved measure most of the outages were by far large outages. This tells us that outages are much more likely to occur when power demand is high and also tells us that these outages at these high demand times in the summer were able to be resolved slightly faster than average.

All of the conclusions above helped us form our risk index for the system and helped us determine what time frames to compare when looking at different risk values. The risk index showed us that the risk of the system having an outage is higher in the summer, when the load demand is highest, than it is during the rest of the year. The risk index also showed us that the risk of the system having an outage was higher before the lines were all buried in 2009 than after. This is consistent with what we thought would happen and it now gives us an index/value to quantify just how much different the risk is. We see that after the lines were buried the risk in the summer was nearly cut in half where the risk in the winter only went down by about 10%. The risk index provides an easy to interpret, single number scale for comparing risk to different areas of the grid and different time frames.

4 References

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5 Appendices

5.1 PDFs - Fixed Bins

The PDF is created when we sort and group the different sizes of outages and plot them to determine the probability of having an outage of a particular size. To sort and group elements we want to put similar sized events together in the same bin and then each bin will be plotted with the average event size on the x-axis and the frequency that an event fell in that particular category on the y-axis. To do this, there are two ways to define a bin; a fixed bin and a variable bin. In the analysis above the variable bin method is always used.

A fixed bin takes in the number of bins desired, N, and divides them all up to be equally sized. With fixed bins, some bins might have no events in them and some might have many events in them. With this method, it is important to choose an appropriate N that describes the whole PDF well. If N is chosen to be too large, there tend to be many bins with zero or one event in them as we get to the larger and rarer event sizes. If N is chosen to be too small this may cause a loss of information for the smaller, more probable events. In some cases it could be that there is not one value for N that provides adequate information for both ends of the PDF and this is where the variable bin method can provide a better option.

The second method, variable binning, results in a non-uniform bin size. This method sets the size of the bin to be based on the number of events in the bin, n. Once a value for n is chosen the smallest n events will be placed in the first bin and that bin size is set as the largest value in that bin divided by 2. Then the next n events will be placed in the next bin and the size of that bin is set by the largest value in that bin minus the largest value in the previous bin and that difference is divided by two. This continues until all events are placed in a bin. There will be one main instance when there will be more than n events in a bin, that is when n events have been placed in a bin and the size of the largest event in that bin is the same value as the next largest event. In this case, since the values are indistinguishable it would not make sense to separate them and because of this they are placed in the same bin and the number of events for that particular bin will be larger than n. This process takes place until the next largest number in the array is distinguishable from the largest in the bin. When plotting the variable bin assortment the bin sizes are shown on the x-axis and the number of events in each bin divided by the bin size multiplied by total events is on the y-axis. Commonly throughout this paper we choose $n = 10$, unless we are dealing with a very small number of events where $n = 10$ does not provide enough data.

5.2 CDF and CCDF

The Cumulative Distribution Function (CDF) is the integral of the PDF. For the discrete case here the plot is constructed by taking the sum of all points smaller than the point that is being calculated. The PDF is a probability function so the integral of the entire function must be one, because of this fact the CDF must asymptote to one.

From the CDF the Complimentary Cumulative Distribution Function (CCDF) can be formed by taking one minus the CDF.

The CCDF plots for both summer and winter are shown.

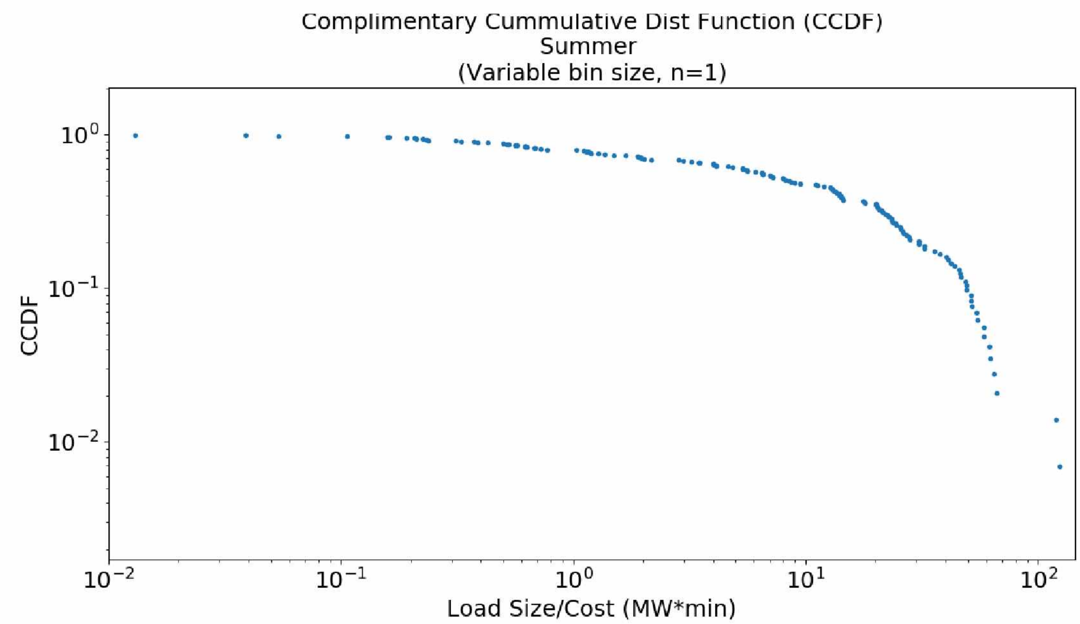

Figure 5.1: CCDF Plot for Outages that Occur in Summer

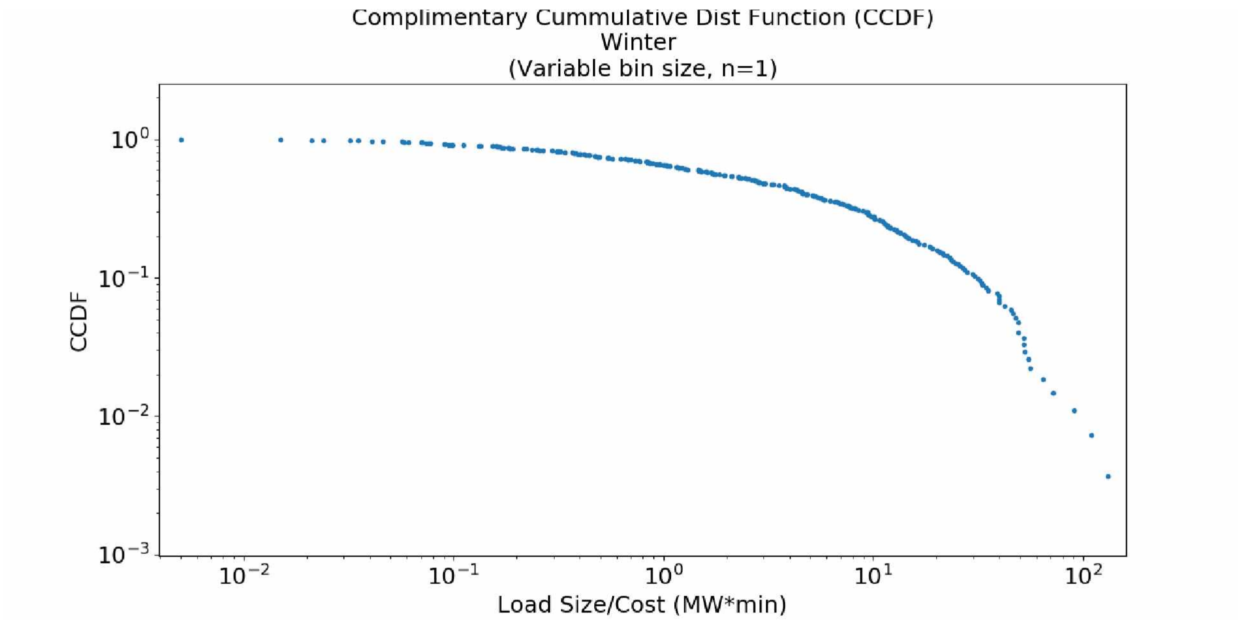

Figure 5.2: CCDF Plot for Outages that Occur in Winter

Below are the plots of the CCDF functions for before and after the lines were buried:

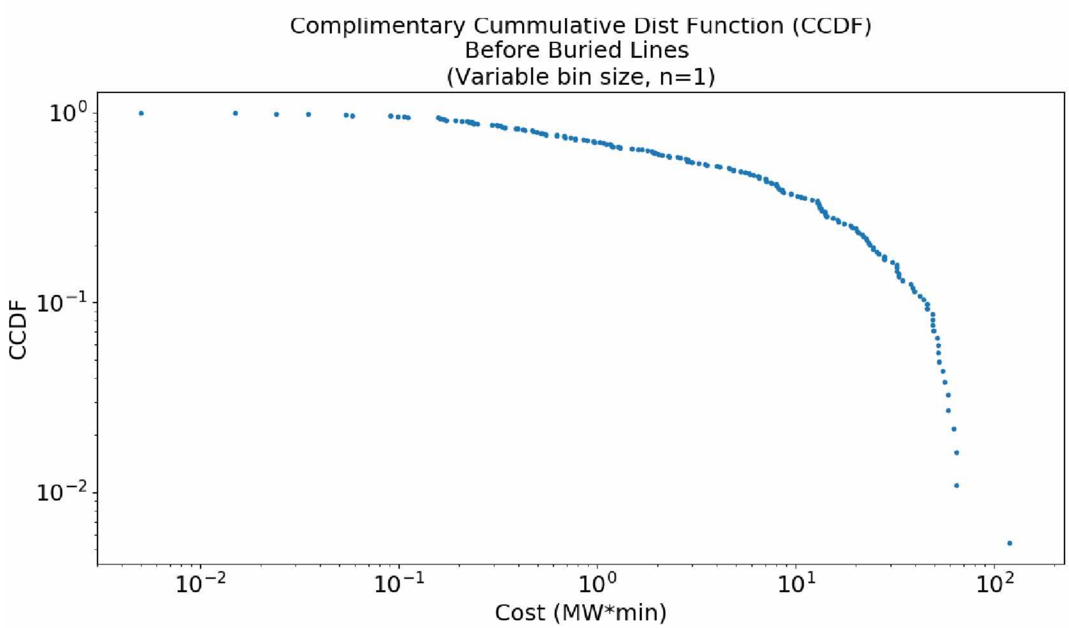

Figure 5.3: CCDF Plot for Outages that Occur Before Lines were Buried

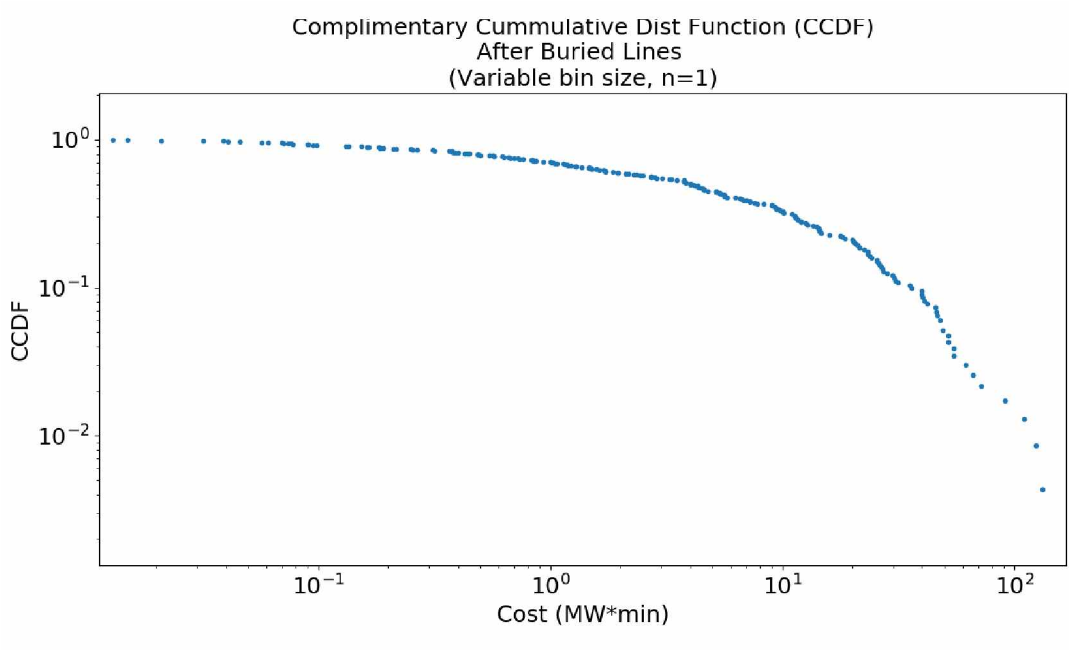

Figure 5.4: CCDF Plot for Outages that Occur After Lines were Buried

5.3 Autocorrelation and Cross Correlation

Cross correlating two sets/arrays of data shows how related the two sets are in terms of a value from -1.0 to +1.0, where +1.0 means perfectly correlated and -1.0 means perfectly anticorrelated. For each set of data the value for which correlation/anticorrelation would be considered significant differs and depends on the level of noise in the set. To cross correlate two sets of data use the following function:

$$C(\tau) = \frac{\int G(t)F(t+\tau)dt}{\left[\int G(t)^2 dt \int F(t)^2 dt\right]^{\frac{1}{2}}} = \frac{\sum G(t)F(t+\tau)dt}{\left[\sum G(t)^2 dt \sum F(t)^2 dt\right]^{\frac{1}{2}}} \tag{5.1}$$

where $G(t)$ is one array and $F(t)$ is the other array. All values in array G and array F have been averaged and then that average is subtracted from all values in the array. This equation shows that array G will be stationary, while array F will be the array that is shifting values to correlate.

Cross correlation can be used in two ways. One way is to determine if there is any meaningful periodic correlation between two sets of data. This will appear as a pattern when enough shifts (value of τ) are shown in the plot. For example, a yearly correlation might be seen after plotting about three or more years worth of tau values. The second is to determine potential causation. This is seen when looking closely at daily shifts near the center of the plot, around τ equal to -5 to +5 days. If there is a significant peak at, for example, +2 this tells us that perhaps whatever is happening today in array G could be caused by an event that happened two days ago in array F, and vice versa for negative numbers.

In our case, tau is the shift in days and will go from -5,114 to +5,114 before the data starts repeating because we have 15 years worth of data. Plotting the cross correlation of two functions can be done in two ways, one way is to shift one set of data by one day for each point until there are only two points left to correlate, this sometimes causes the ends to look strange as there are very few data points left to correlate the two functions. The second way is to wrap the data points back around after shifting them, this method we have labelled as "(Wrapping Array Values)" under the title of each plot in order to differentiate what method was used. However, this shouldn't make much of a difference because the important correlations will be seen closer to the middle which will look almost identical for the two methods. We look primarily at the middle because when dealing with things like weather correlations once we are a week or two away from a weather event there is almost no chance that any correlation seen between that event and an outage will be meaningful at all. Autocorrelating a set of data is the same as cross correlating except the second data set is the same as the first; this can show any periodicities in a set of data being looked at. When autocorrelating a function the time lag of $\tau = 0$ should always have a value of 1.0 meaning perfectly correlated. This is because when the data sets are being compared with no shift they will be identical for autocorrelation.

The autocorrelation for the outage data is shown below. The outage data is the array of values for outages in terms of meters affected times duration in minutes. In order to get the array of outage data to be the same length as the weather data, and to keep time lags consistently one day, I took the largest event on a given day if there was more than one event that fell on a particular day. From the plots there is a +1.0 correlation for $\tau = 0$ and then it falls to a value of around +0.02 after one shift and then fluctuates around -0.01 to +0.2 for the rest of the time. Because the ends get a little inaccurate I zoomed in to get plots of the middle $\frac{1}{3}$ shifts each way (about -2,000 to +2,000). It appears that most of the plot is just noise, indicating that the outages do not have an effect on each other from one day to the next and there is also no noticeable periodicity to the outages. This result of not seeing any outages affecting another might be expected for a system of this size. This is because any cascading failures that occur will likely occur in the same day and be resolved that day as well. This analysis would not pick that up because the time shift is a whole day and therefore doesn't go into fine enough detail to pick up outages that effect each other in the same day.

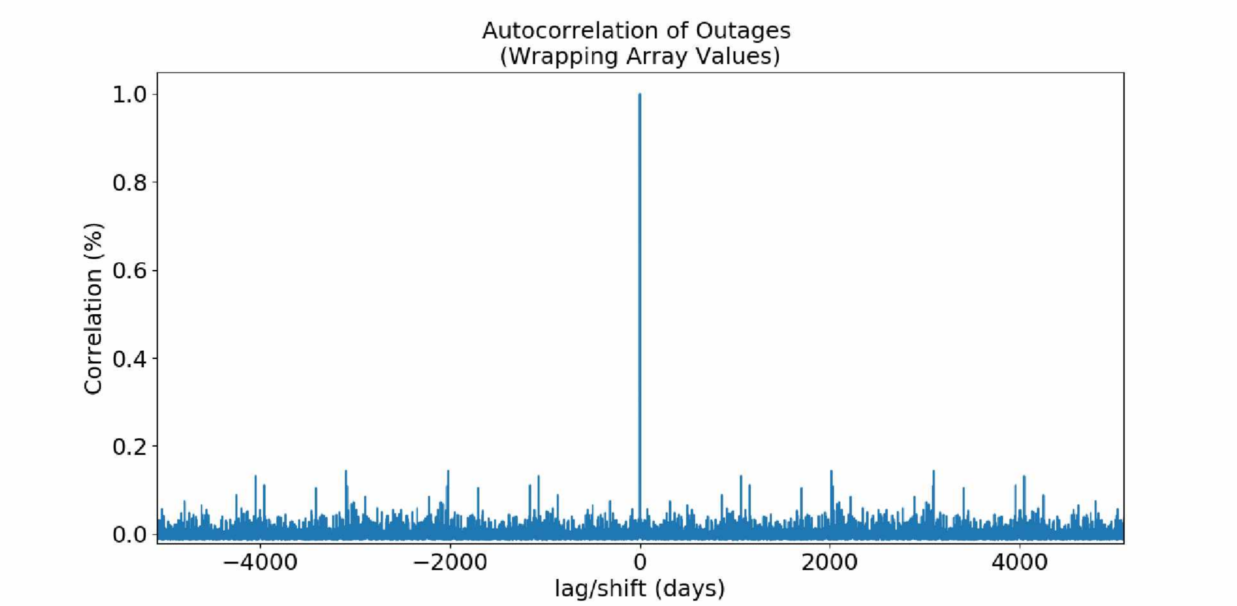

Figure 5.5: Autocorrelation of Outages Values

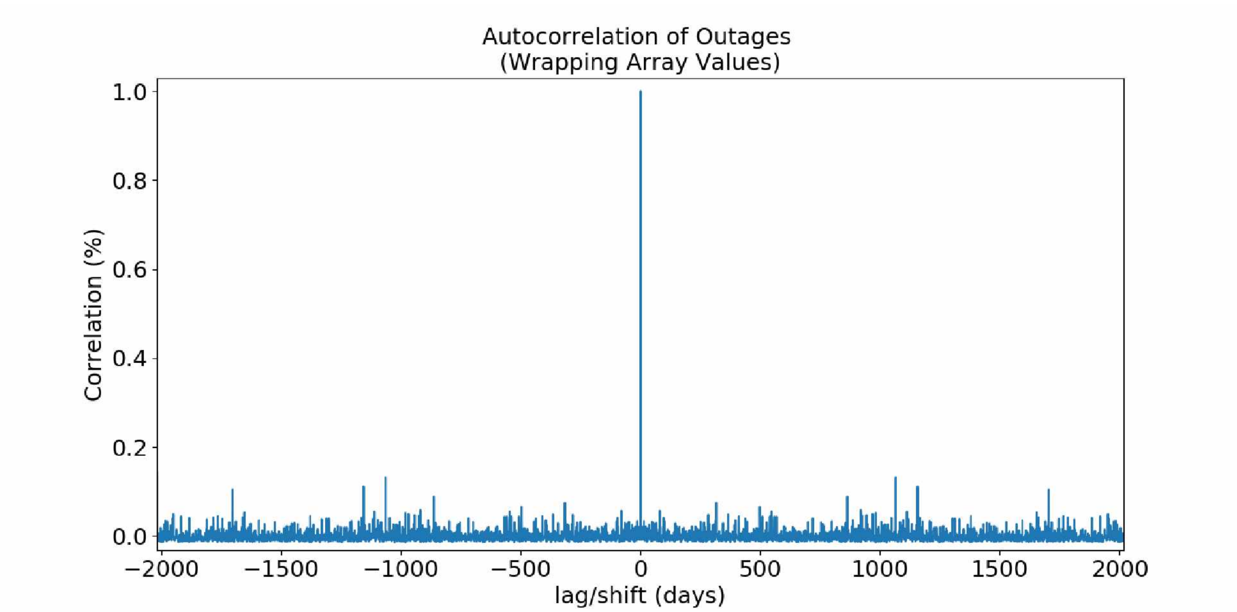

Figure 5.6: Autocorrelation of Outages Values Zoomed In

Following the autocorrelation, we cross correlated the outages with the daily high temperatures and found a slight seasonal correlation, shown in Figure 5.7. The plot is done with outages being the first array, G, and daily high temperatures being array F, shifted by the values indicated on the x-axis. There is periodicity in the plots with the values going between -0.04 to +0.04. The plot shows a trend/periodicity which indicates a correlation with the changing seasons.

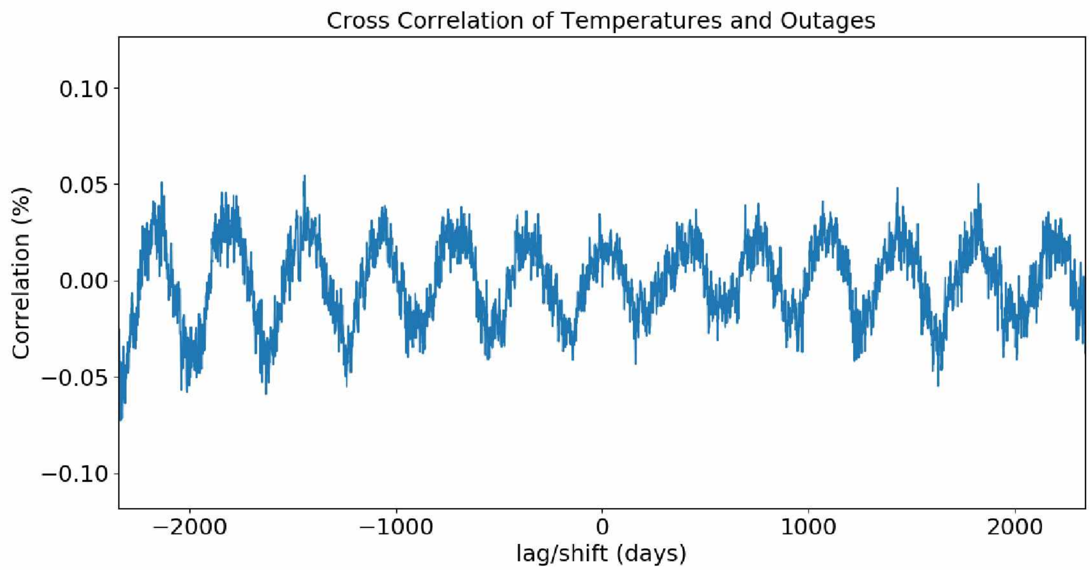

Figure 5.7: Cross Correlation Between Outages and Daily High Temperatures

Next, we cross correlated the outages (in number of meters affected times duration in minutes) with other weather events. Shown in Figures 5.8 through 5.11 are the correlation plots for daily precipitation and snowfall. Wind storms, floods, and blizzards were all cross correlated too, but due to the small number of data points there was no meaningful result from this method of analysis. In both cases shown below the array of outages is what is being shifted (amount of shift is given on x-axis). In all cases we show a plot zoomed into about the middle $\frac{1}{5}$ of all shifts and then zoom in closer to see the behavior around zero.

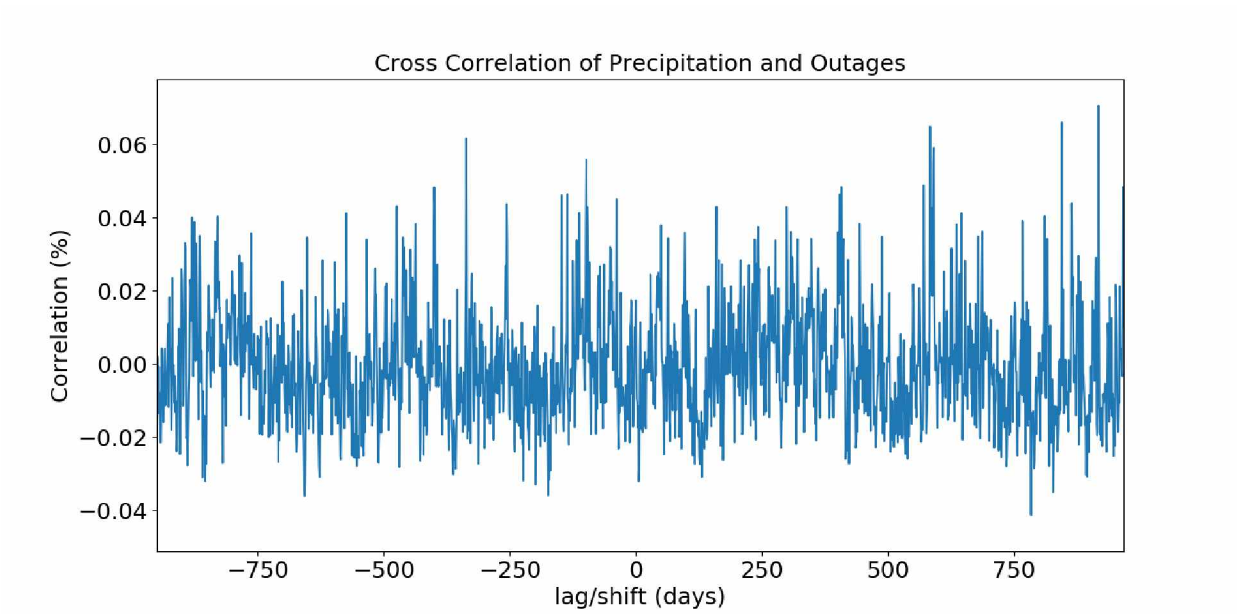

Figure 5.8: Cross Correlation Between Outages and Daily Precipitation - Middle 1/3 Values

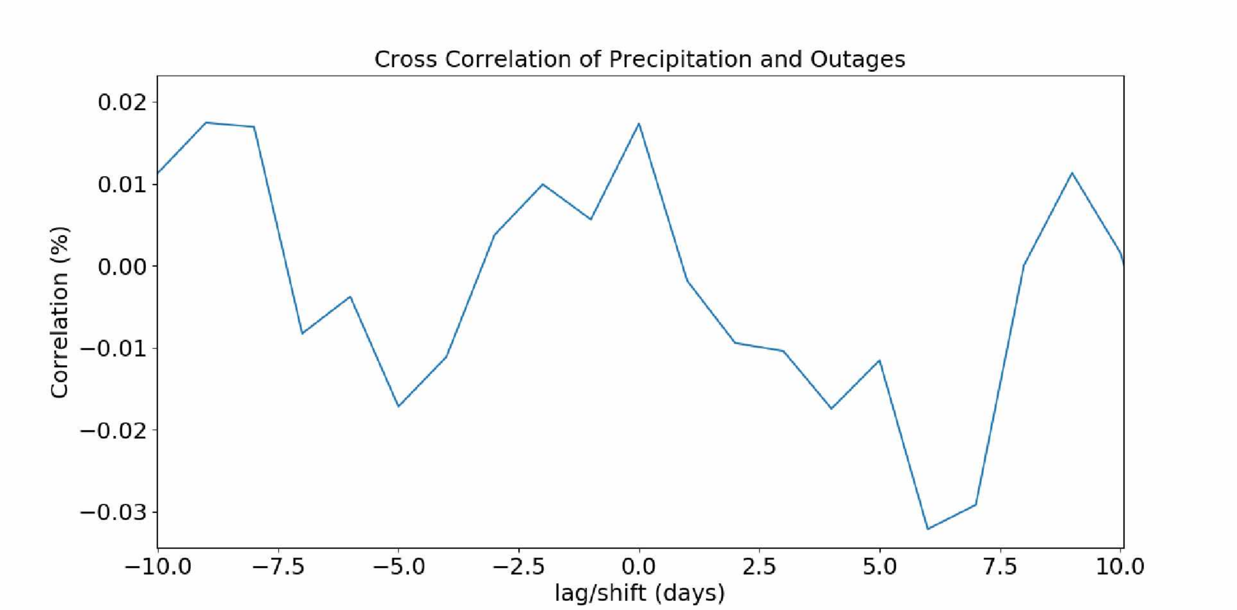

Figure 5.9: Cross Correlation Between Outages and Daily Precipitation - Zoomed In Further

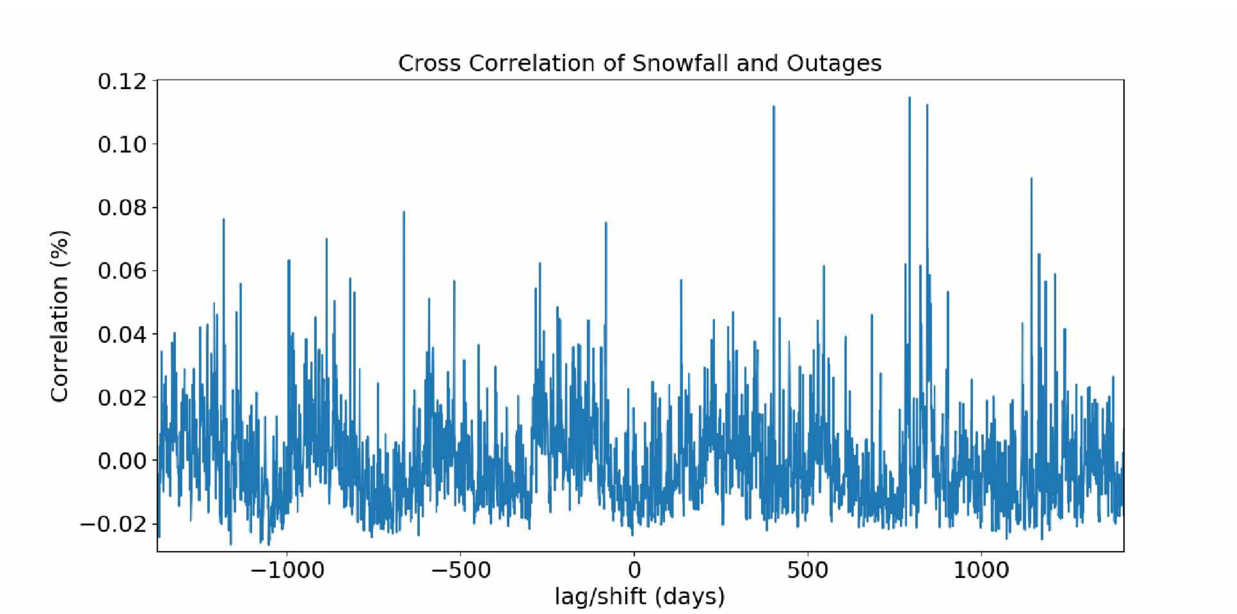

Figure 5.10: Cross Correlation Between Outages and Daily Snowfall - Middle 1/3 Values

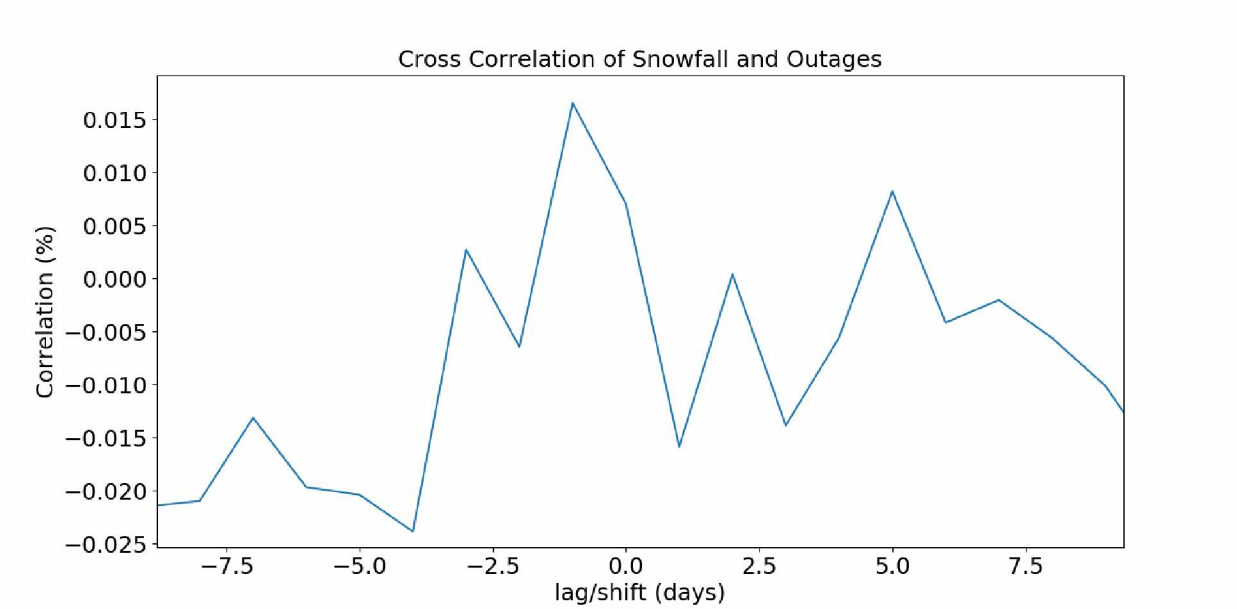

Figure 5.11: Cross Correlation Between Outages and Daily Snowfall - Zoomed In Further

There appears to be slight seasonal periodicity in both plots which may just be due to the seasonal periodicity of snow and rain. When looking at the center-most points we can see peaks, but these peaks don't go above the level of correlation that would be considered noise in these plots, so we cannot say anything about these other than the rain and snow do not appear to have an effect on the outages.

5.4 Outages Separated by Feeder

To further look into the duration PDF I split up events based on which feeder they were a part of. Then I plotted each feeder's events with the total events in one PDF (distribution) to compare them. I used a variable bin size with $n = 10$ events for the total (all events) and anywhere from $n = 2, 3, 4, 5$ events for each individual feeder, depending on the number of events associated with each feeder. In these PDFs the events that occur at the same time are not combined because I am looking at the different feeders.

The number of events for each feeder is:

- Auxiliary – 90
- 13 Mile – 176
- Express – 61
- HBC – 58
- Lake Avenue – 174
- Main Town – 84
- New Town – 194
- Power Creek – 0
- Total – 837

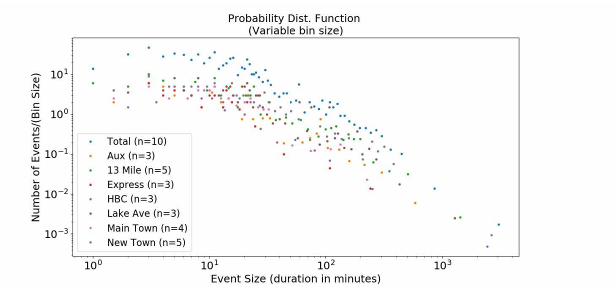

Figure 5.12: PDF of All Feeders Individually

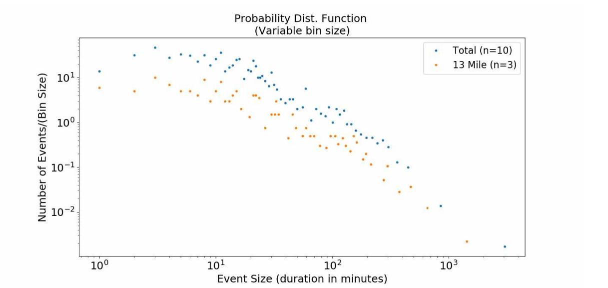

Figure 5.14: PDF of 13 Mile Feeder (n=3) Outages

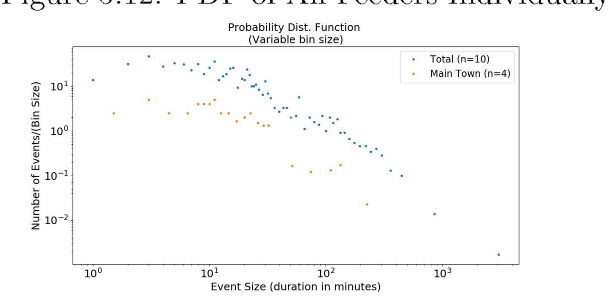

Figure 5.13: PDF of Main Town Feeder Outages

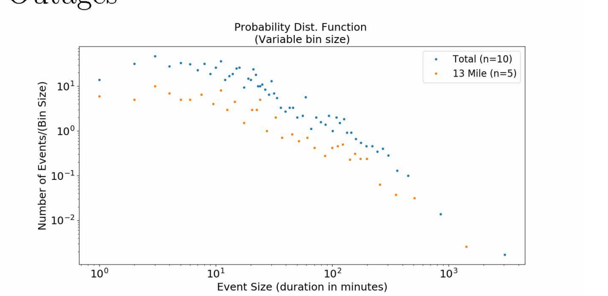

Figure 5.15: PDF of 13 Mile Feeder (n=5) Outages

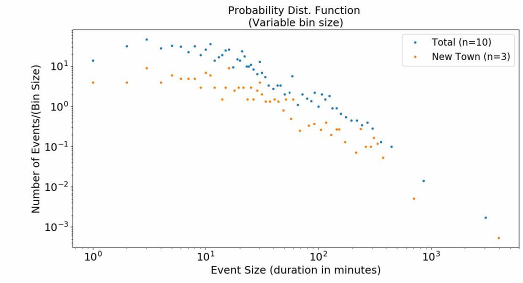

Figure 5.16: PDF of New Town Feeder (n=3) Outages

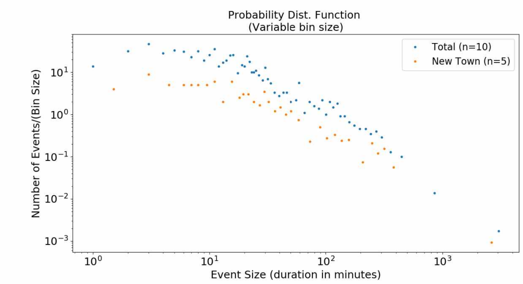

Figure 5.17: PDF of New Town Feeder (n=5) Outages

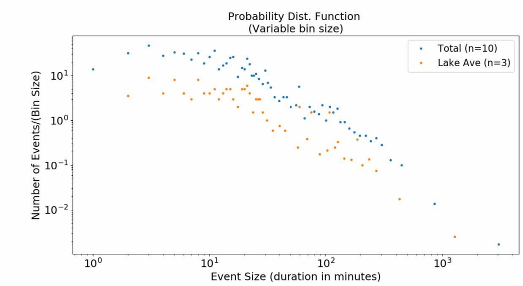

Figure 5.18: PDF of Lake Ave Feeder (n=3) Outages

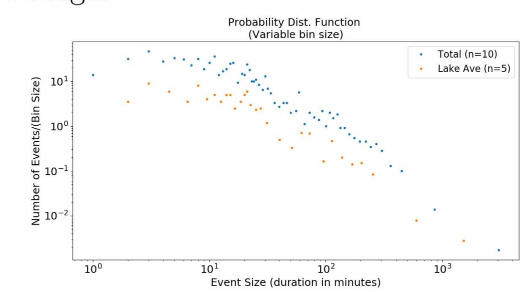

Figure 5.19: PDF of Lake Ave Feeder (n=5) Outages

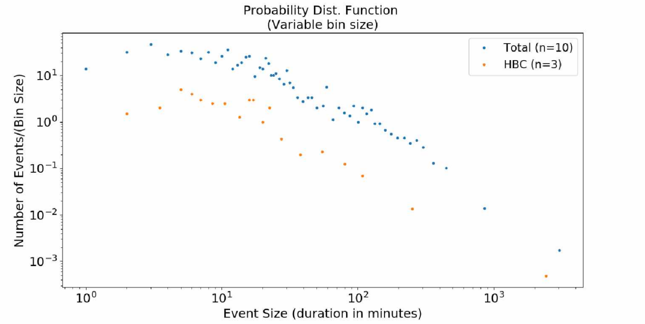

Figure 5.20: PDF of Humpback Creek Feeder Outages

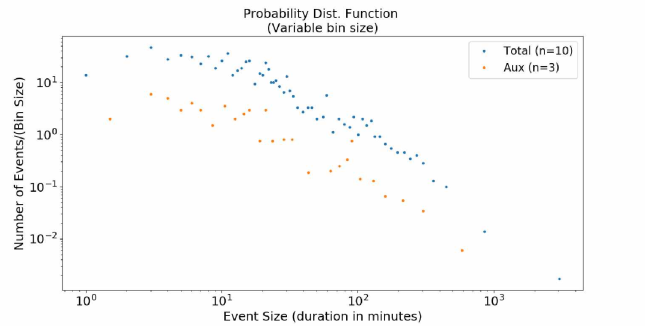

Figure 5.21: PDF of Auxiliary Feeder Outages

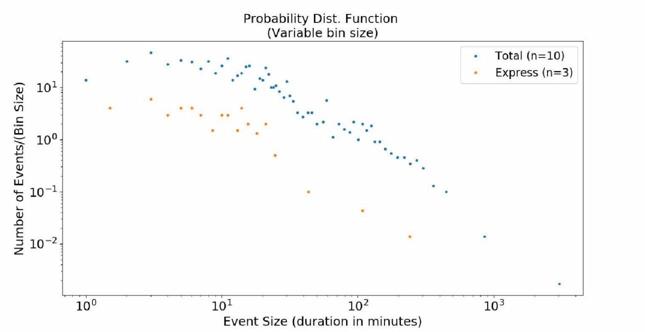

Figure 5.22: PDF of Express Feeder Outages

From Figures 5.12-5.22 it seems that all of the PDFs of the individual feeders share the same shape (at least roughly) as the PDF of all events. From this I would think the abnormal shape of the plot near 20-30 minutes is not due to a particular feeder.

5.5 Cascading Failures

Cascading failures of unplanned outages are listed in Table 5.1. I counted the failure as cascading if a second (or more) failure occurred on another feeder before the first was fixed.

Table 5.1: Potential Cascading Failures

Date	Line	Start Time	End Time	Cause		Num. of Lines
8/14/2003	New Town	3:03 PM	3:19 PM	Power Supplier	Hydro	531
	13 Mile	3:20 PM	3:23 PM	Power Supplier	Hydro	226
12/27/2004	New Town	3:58 AM	5:48 AM	Storm	Water/Snow Dam	531
	13 Mile	5:47 AM	6:27 AM	Storm	Water/Snow Dam	226
	New Town	2:15 PM	2:50 PM	Storm	Line Slap	10
	New Town	2:29 PM	2:30 PM	Distributor	Transformer Fuse	117
6/25/2006	New Town	2:16 PM	2:44 PM	Power Supplier	Hydro	531
	Lake Aven	2:22 PM	2:41 PM	Power Supplier	Hydro	430
	Main Town	2:26 PM	2:44 PM	Power Supplier	Hydro	317
7/3/2006	Lake Aven	7:39 PM	7:52 PM	Power Supplier	Hydro	430
	New Town	7:40 PM	7:52 PM	Power Supplier	Hydro	531
12/11/2006	Lake Aven	3:38 PM	3:47 PM	Power Supplier	Diesel	430
	New Town	3:39 PM	3:48 PM	Power Supplier	Diesel	531
5/6/2008	13 Mile	10:06 PM	10:30 PM	Power Supplier	Diesel	226
	New Town	10:14 PM	10:30 PM	Power Supplier	Diesel	531
	Lake Aven	10:14 PM	10:30 PM	Power Supplier	Diesel	430
	Main Town	10:14 PM	10:30 PM	Power Supplier	Diesel	317
5/15/2008	New Town	3:47 PM	4:12 PM	Distribution	Primary Cable	531
	Main Town	2:56 PM	4:11 PM	Distribution	Primary Cable	317
8/25/2008	Lake Aven	1:17 PM	1:44 PM	Distribution	Primary Cable	430
	13 Mile	1:21 PM	1:45 PM	Distribution	Primary Cable	226
	New Town	1:22 PM	1:44 PM	Distribution	Primary Cable	531
9/11/2009	13 Mile	1:00 AM	1:56 AM	Power Supplier	Hydro	226
	New Town	1:38 AM	1:56 AM	Power Supplier	Hydro	531
5/17/2011	Auxiliary	3:33 PM	3:37 PM	Distribution	Primary Cable	104
	Express	3:33 PM	3:37 PM	Distribution	Primary Cable	0
	New Town	3:33 PM	3:38 PM	Distribution	Primary Cable	531
	Lake Aven	3:33 PM	3:37 PM	Distribution	Primary Cable	430
	Main Town	3:33 PM	3:43 PM	Distribution	Primary Cable	317
	13 Mile	3:33 PM	3:43 PM	Distribution	Primary Cable	226
	Auxiliary	3:39 PM	3:40 PM	Distribution	Primary Cable	104
	Express	3:39 PM	3:41 PM	Distribution	Primary Cable	0
	New Town	3:39 PM	3:41 PM	Distribution	Primary Cable	531
	Lake Aven	3:39 PM	3:41 PM	Distribution	Primary Cable	430
7/14/2012	13 Mile	4:12 PM	4:59 PM	Power Supplier	Operations	266
	HBC	4:12 PM	4:28 PM	Power Supplier	Operations	5
	New Town	4:15 PM	4:58 PM	Power Supplier	Operations	531
	Lake Aven	4:28 PM	4:55 PM	Power Supplier	Operations	430
10/19/2012	Main Town	11:07 PM	12:47 AM	Distribution	Primary Cable	317
10/20/2012	Express	12:41 AM	12:47 AM	Distribution	Primary Cable	0
	New Town	12:41 AM	12:49 AM	Distribution	Primary Cable	531
	Lake Aven	12:41 AM	12:49 AM	Distribution	Primary Cable	430
	13 Mile	12:41 AM	12:49 AM	Distribution	Primary Cable	226
3/11/2014	HBC	9:31 AM	9:37 AM	Power Supplier	Operations	5
	Main Town	9:31 AM	9:37 AM	Power Supplier	Operations	317
	New Town	9:31 AM	9:38 AM	Power Supplier	Operations	531
	Lake Aven	9:31 AM	9:39 AM	Power Supplier	Operations	430
	13 Mile	9:31 AM	9:38 AM	Power Supplier	Operations	226
	Auxiliary	9:33 AM	9:36 AM	Power Supplier	Operations	104
	Express	9:33 AM	9:35 AM	Power Supplier	Operations	0
4/17/2016	13 Mile	1:06 PM	1:30 AM	Distribution	Primary Cable	33
	13 Mile	1:08 PM	4:54 PM	Distribution	Primary Cable	32
	13 Mile	1:08 PM	5:38 PM	Distribution	Primary Cable	91
	13 Mile	1:06 PM	8:30 PM	Distribution	Primary Cable	15
	New Town	1:16 PM	1:46 PM	Distribution	Primary Cable	531
	13 Mile	11:00 PM	1:30 AM	Distribution	Primary Cable	172
10/3/2016	New Town	12:35 AM	1:13 AM	Distribution	Primary Cable	531
	13 Mile	12:35 AM	2:22 AM	Distribution	Primary Cable	226
	HBC	12:36 AM	1:21 AM	Distribution	Primary Cable	5
	Lake Aven	12:43 AM	1:05 AM	Distribution	Primary Cable	430
	Main Town	12:48 AM	1:13 AM	Distribution	Primary Cable	317
2/14/2017	Auxiliary	9:40 AM	9:46 AM	Power Supplier	Hydro	104
	HBC	9:40 AM	9:49 AM	Power Supplier	Hydro	5
	Main Town	9:40 AM	9:48 AM	Power Supplier	Hydro	317
	Lake Aven	9:41 AM	9:47 AM	Power Supplier	Hydro	430
	13 Mile	9:40 AM	9:46 AM	Power Supplier	Hydro	226
	New Town	9:41 AM	9:48 AM	Power Supplier	Hydro	531
7/14/2017	13 Mile	10:50 AM	11:01 AM	Power Supplier	Hydro	226
	Auxiliary	10:50 AM	11:05 AM	Power Supplier	Hydro	104
	HBC	10:50 AM	11:05 AM	Power Supplier	Hydro	5
	Main Town	10:50 AM	11:03 AM	Power Supplier	Hydro	317
	New Town	10:55 AM	11:02 AM	Power Supplier	Hydro	531
	Lake Aven	10:55 AM	11:01 AM	Power Supplier	Hydro	430
9/4/2017	HBC	9:10 AM	10:04 AM	Power Supplier	Diesel	5
	Main Town	9:11 AM	10:08 AM	Power Supplier	Diesel	317
	Lake Aven	9:11 AM	10:24 AM	Power Supplier	Diesel	430
	13 Mile	9:11 AM	10:19 AM	Power Supplier	Diesel	226

Table 5.2 is a table of the different causes of cascading and total outages and the percentages of each.

Table 5.2: Summary of Percentage of Cascading Failures by Cause

Cause		Cascading		Total	
Power Supplier	Hydro	6	33.33%	85	16.28%
	Diesel	3	16.67%	154	29.50%
	Operations	2	11.11%	30	5.75%
Distribution	Substation	0	0.00%	5	0.96%
	Substation Fusing or Rela	0	0.00%	9	1.72%
	Transformer Bad or Repla	0	0.00%	3	0.57%
	Primary Cable	6	33.33%	112	21.46%
	Transformer Fuse or Brea	0.33	1.83%	28	5.36%
	Secondary Cable or Pede	0	0.00%	15	2.87%
Storm	Wind	0	0.00%	2	0.38%
	Water/Snow	0.33	1.83%	12	2.30%
	Line Slap	0.33	1.83%	10	1.92%
Other		0	0.00%	57	10.92%
Total		18		522	

There were a total of 18 cascading failures from unplanned outages. A majority of the cascading failures were due to "Power Supplier – Hydro" and "Distribution – Primary Cable."

5.6 Earthquakes

There were 130 earthquakes of size 4.0 or larger near Cordova in the last 100 years. Looking at the time series of these earthquakes it was clear that the equipment before the mid 1970's was not as good. From looking at the data it appears that only size 5.5 or larger earthquakes were recorded before then, and possibly only 6.5 and larger was recorded before the mid 1960's. Because of this we only used earthquakes after 1973 for our analysis.

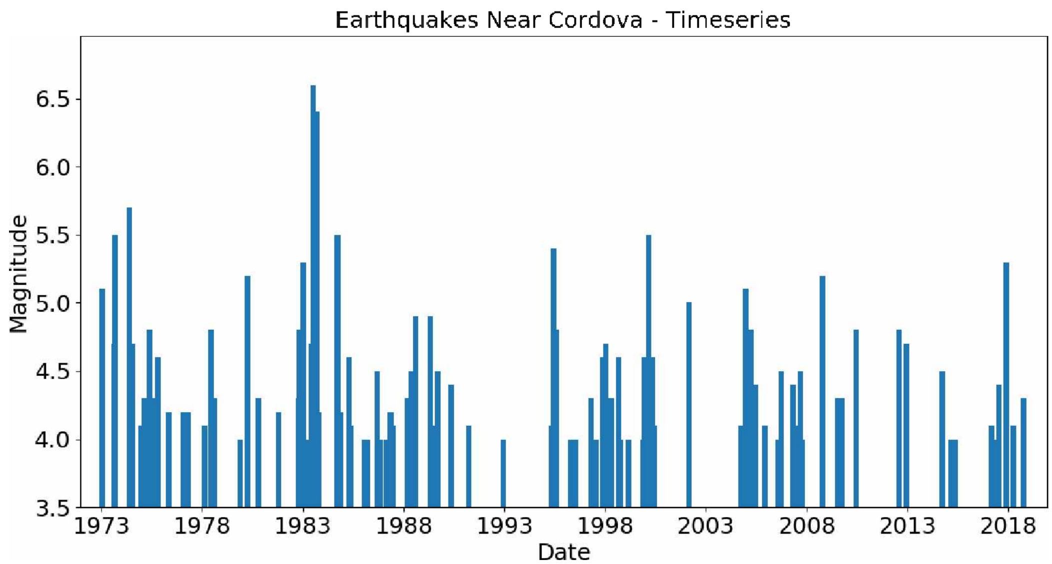

Figure 5.23: Time Series of Earthquakes Near Cordova

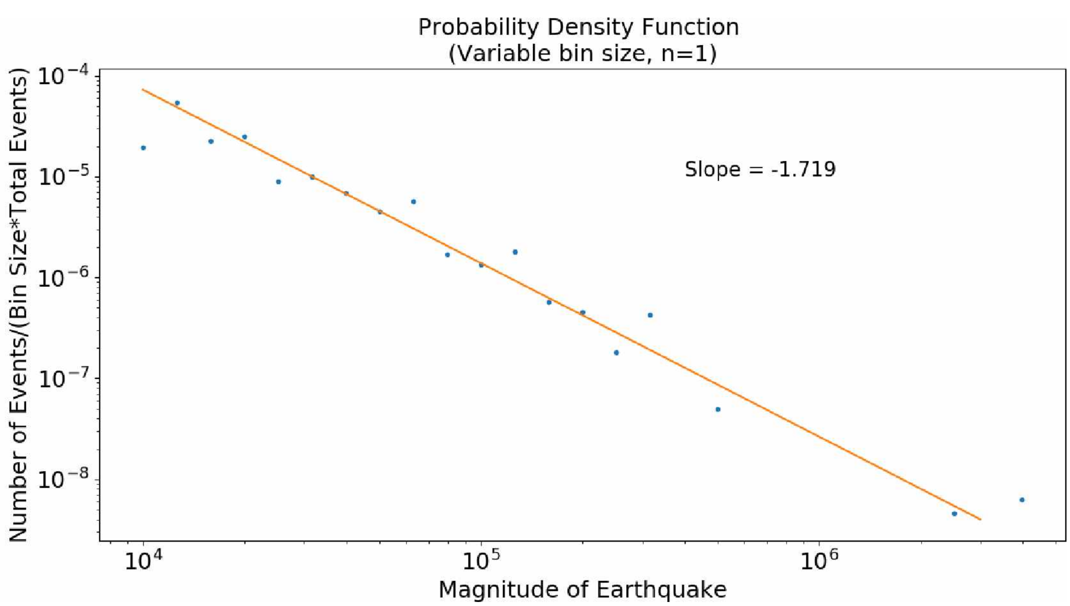

Figure 5.24: PDF of Earthquakes

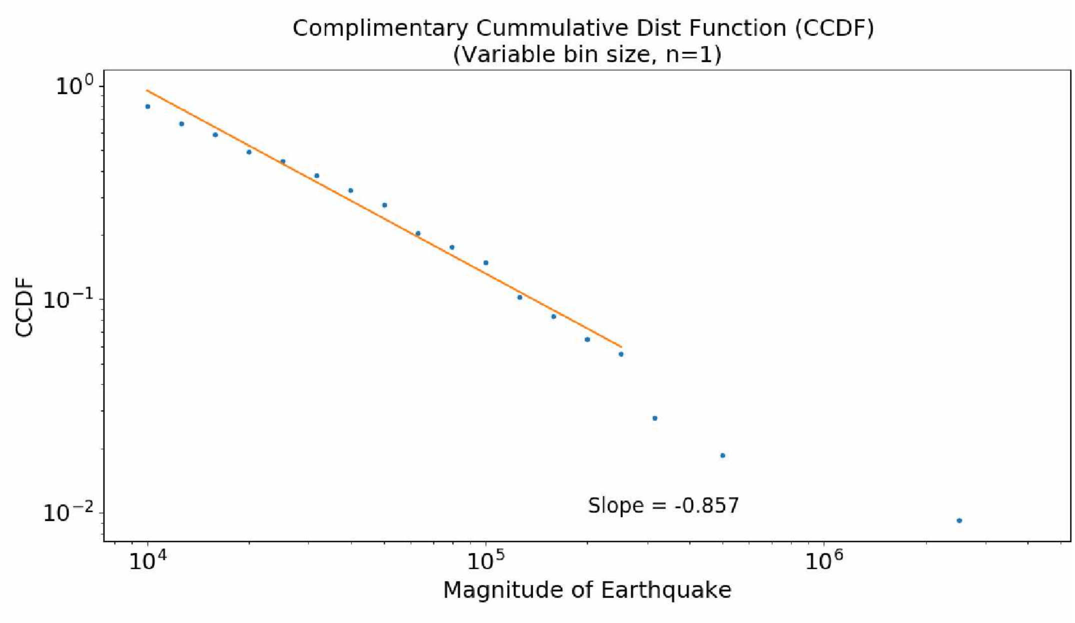

Figure 5.25: CCDF of Earthquakes

There appears to be a power law for the events of about size 4.0-5.5 in the CCDF.