

Failure Analysis of the New York City Power Grid

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Abstract—As U.S. power grid transforms itself into Smart Grid, it has become less reliable in the past years. Power grid failures lead to huge financial cost and affect people's life. Using a statistical analysis and holistic approach, this paper analyzes the New York City power grid failures: failure patterns and climatic effects. Our findings include: higher peak electrical load increases likelihood of power grid failure; increased subsequent failures among electrical feeders sharing the same substation; underground feeders fail less than overhead feeders; cables and joints installed during certain years are more likely to fail; higher weather temperature leads to more power grid failures. We further suggest preventive maintenance, intertemporal consumption, and electrical load optimization for failure prevention. We also estimated that the predictability of the power grid component failures correlates with the cycles of the North Atlantic Oscillation (NAO) Index.

Index Terms—failure analysis, power system reliability, prediction methods, reliability engineering, statistical analysis, machine learning.

I. INTRODUCTION

A Sustainable energy future depends on an efficient, reliable and intelligent electricity distribution and transmission system, i.e., power grid. As a critical infrastructure, power grid is the electricity distribution and transmission system that bridges the power generation and the electricity consumers. Despite huge investments in the U.S. to improve the power grid, it has become less reliable and more outage-prone in the past years. According to two data sets, one from the U.S. Department of Energy and the other one from the North American Electric Reliability Corp., the number of power outages greater than 100 Megawatts or affecting more than 50,000 customers in the U.S. almost doubled every five years in the past fifteen years, resulting in about \$49 billion outage costs per year [1].

One of the main causes of power grid failure is electrical component failure. These component failures may lead to cascading failures. In 2004, the U.S.-Canada Power System Outage Task Force released their final report on the 2003 U.S. Northeast blackout, placing the main cause of the blackout on some strained high-voltage power lines in Ohio that later went out of service, which led to the cascading effect that ultimately forced the shutdown of more than 100 power plants [2].

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We have collaborated with the Consolidated Edison of New York, the main power utility provider of New York City, and conducted a statistical analysis of the New York City power grid failures, especially in the electrical feeder component. We have identified several power grid failure patterns including: higher peak electrical load increases likelihood of power grid failure; increased subsequent failure among feeders sharing the same substation; underground feeders fail less than overhead feeders; cables and joints installed between 1970 and 1975 are more likely to fail. Because climate affects the power grid reliability, we also analyzed the climatic effects on the power grid failures including temperature, North Atlantic Oscillation (NAO), snowfall, hurricane and earthquake, and solar storm. To effectively prevent power grid failure, preventive maintenance, intertemporal consumption, and electrical load optimization can be used.

The paper is organized as follows. In the following section, we will present failure model and statistical methods. Then we will describe our findings in power grid failure patterns, followed by climatic effects on power grid failures. We will further describe failure prevention before conclusion.

II. FAILURE MODEL AND STATISTICAL METHODS

As a complex distributed system, power grid usually does not fail as a whole, except in some extreme occasions. The failure analysis of power grid focuses on the failures of the partial segments and the individual electrical components of the grid.

The failure rate can be defined as the total number of failures within an item population, divided by the total time expended by that population, during a particular measurement interval under stated conditions [4]. For the Weibull failure distribution, the failure density function $f(t)$ and cumulative failure distribution function $F(t)$ are

$$f(t; \lambda, k) = \begin{cases} \frac{k}{\lambda} \left(\frac{t}{\lambda}\right)^{k-1} e^{-(t/\lambda)^k}, & t \geq 0 \\ 0, & t < 0 \end{cases}$$

$$F(t; \lambda, k) = \begin{cases} 1 - e^{-(t/\lambda)^k}, & t \geq 0 \\ 0, & t < 0 \end{cases}$$

where $k > 0$ is the shape parameter and $\lambda > 0$ is the scale parameter of the distribution. The hazard function (or instantaneous failure rate) when $t \geq 0$ can be derived as

$$h(t; \lambda, k) = \frac{f(t; \lambda, k)}{F(t; \lambda, k)} = \frac{f(t; \lambda, k)}{1 - F(t; \lambda, k)} = \frac{k}{\lambda} \left(\frac{t}{\lambda}\right)^{k-1}.$$

A value of $k < 1$ indicates that the failure rate decreases over time. A value of $k = 1$ indicates that the failure rate is constant (i.e., k/λ) over time. In this case, the Weibull

distribution becomes an exponential distribution. A value of $k > 1$ indicates that the failure rate increases with time.

Mean time between failures (MTBF) is the predicted elapsed time between inherent failures of a system during operation. In practice, MTBF can be calculated as inverse of failure rate.

III. POWER GRID FAILURE PATTERNS

In New York City, underground primary feeders are one of the most failure-prone types of electrical components. In the following section, we will analyze the feeder failure data collected in New York City and describe our findings on the power grid failure patterns.

A. Higher Peak Electrical Load Increases Likelihood of Power Grid Failure

Seasonal electrical load and peak electrical load have a major impact on power grid failures. As show on Fig. 1, during summer heat waves, the city wide peak electrical load is significantly higher than the other times. The stress on the grid leads to more power grid component failures.

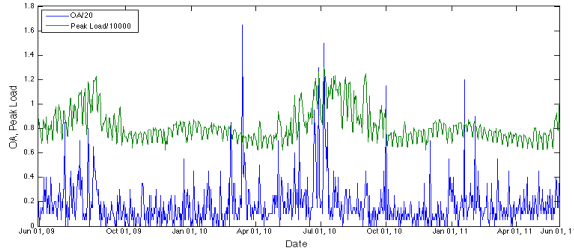


Fig. 1: Number of feeder failures (OA) and city wide peak electrical load from June 1, 2009 to May 31, 2011.

B. Increased Subsequent Failures Among Feeders Sharing the Same Substation

Given the effect of failures on other feeders in the same network we investigated the effect of failures on networks that were connected by a shared bus at the substation. The following graphs show the results of this study. The following graph shows the Weibull component of the fit to the histograms of the intervals between an failure and a subsequent failure on feeders in the same network, a subsequent failure on a feeder in the second network connected at the substation by a shared bus, and a subsequent failure on a network chosen at random. Each curve is normalized to 1000 initial failures. We see that the number of failures above random in the case of failures on the same network is significant on day one and is also significant on days 2-10. There is also a clean signal on day one in the Other Network case that we speculate is due to transient electrical effects. The minor signal on a Random network we speculate is due to occurrences of multiple failures on days of weather extremes or other artificially high coincidences such as those that occurred after 9/11, during the LIC event, and the steam explosion of 2007 in Manhattan [5].

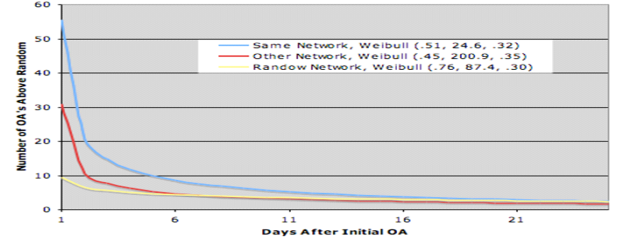


Fig. 2: Subsequent feeder failures after initial failures [5].

C. Underground Feeders Fail Less Than Overhead Feeders

New York City has mixed use of underground and overhead feeders in the five boroughs with Manhattan mostly use underground feeders. As illustrated in Fig. 3, the normalized data shows that the underground feeders fail less than other feeders in most years.

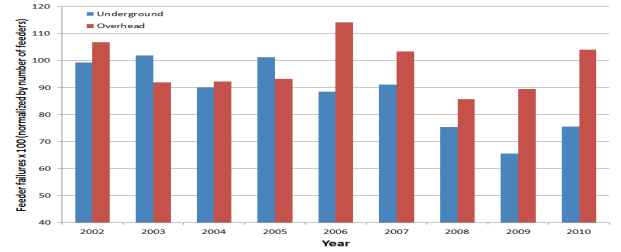


Fig. 3: Underground and overhead feeder failures normalized by number of feeders from 2002 to 2010.

D. Cables and Joints Installed Between 1970 and 1975 Are More Likely to Fail

Our analysis of the cable and joint failures data from March 1975 to August 2011 shows that the cables and joints installed between 1970 and 1975 are more likely to fail. Fig. 4 and Fig. 5 illustrate the number of failure incidents for the cables and joints installed from 1901 to 2011.

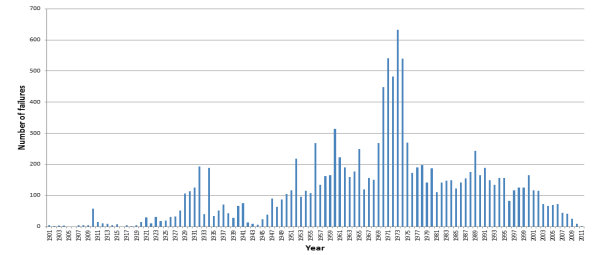


Fig. 4: Cable failures versus installation year.

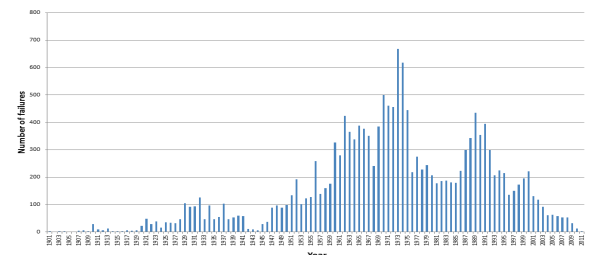


Fig. 5: Joint failures versus installation year.

IV. CLIMATIC EFFECTS ON POWER GRID FAILURES

The physical installation and operation of the power grid electrical components expose them to the influence of the weather. The climate affects the reliability of the New York City power grid. In the following section, we will describe climatic effects on the power grid failures.

A. Weather Temperature

During summer heat waves, the power grid in New York City is normally under higher load stress due to increased electricity demand. We have analyzed three years of electrical feeder failure data from June 1, 2009 to May 31, 2011 and compare them with the corresponding temperature variables, *i.e.*, the three hour weighted average of the highest temperature and wet bulb from the current forecast day and the actual from the two previous days. As shown in Fig. 6 and Fig. 7, the number of feeder failures increases as the temperature increases from 20 Fahrenheit degree to 75 Fahrenheit degree. The tail drop in Fig. 7 at above 75 degree is due to the limited data points in the extreme hot weather. While, Fig. 6 shows that the number of failures are even higher for the hot weather with temperature above 75 degree.

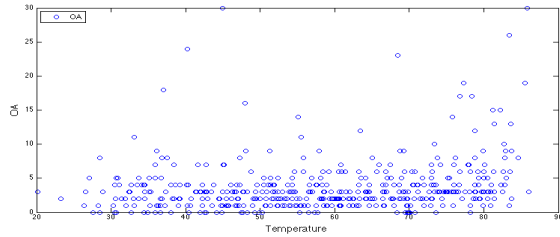


Fig. 6: Number of feeder failures versus temperature variable scatter plot (June 1, 2009 to May 31, 2011).

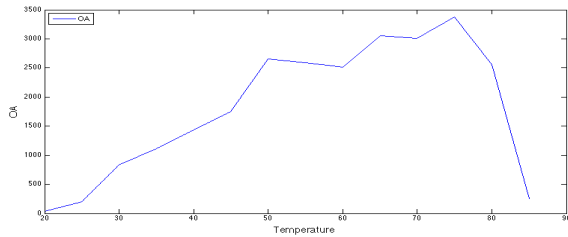


Fig. 7: Number of feeder failures in a 5-degree bucket versus temperature variable (June 1, 2009 to May 31, 2011).

B. North Atlantic Oscillation

The North Atlantic Oscillation (NAO) is a climatic phenomenon of fluctuations in the difference of atmospheric pressure at sea level between the Icelandic low and the subtropical high. Through east-west oscillation motions of the Icelandic low and the subtropical high, the NAO controls the strength and direction of westerly winds and storm tracks across the North Atlantic. It is the dominant mode of winter climate variability in the North Atlantic region ranging from central North America to Europe and much into Northern Asia. As defined by the National Weather Service, the daily NAO index

is constructed by projecting the daily (00Z) 500mb height anomalies over the Northern Hemisphere onto the loading pattern of the NAO, which is defined as the first leading mode of Rotated Empirical Orthogonal Function (REOF) analysis of monthly mean 500mb height during 1950-2000 period [6].

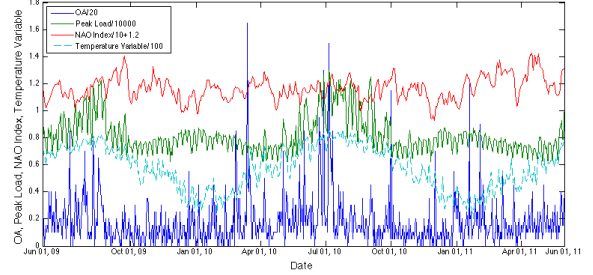


Fig. 8: Feeder failures (OA), NAO Index, temperature variable and peak electric load from June 1, 2009 to May 31, 2011.

The positive phase of the NAO reflects below-normal heights and pressure across the high latitudes of the North Atlantic and above-normal heights and pressure over the central North Atlantic, the eastern United States and Western Europe. The increased pressure difference results in more and stronger winter storms crossing the Atlantic Ocean on a more northerly track. The eastern US experiences mild and wet winter conditions. The negative phase reflects an opposite pattern of height and pressure anomalies over these regions. The reduced pressure gradient results in fewer and weaker winter storms crossing on a more west-east pathway. The US east coast experiences more cold air outbreaks and hence snowy weather conditions. Both phases of the NAO are associated with basin-wide changes in the intensity and location of the North Atlantic jet stream and storm track, and in large-scale modulations of the normal patterns of zonal and meridional heat and moisture transport [7], which in turn results in changes in temperature and precipitation patterns often extending from eastern North America to western and central Europe [8], [9], [10].

C. Snowfall

We have studied past snow storms and their effects on the power grid. We noticed the absence of any corresponding peak in secondary events during the snowfall. Instead of a sharp rise after a snow storm, we see a gradual rise in the number of secondary events. At the same time, the maximum temperature during and after the initial snow storm is well below freezing. The number of secondary events only peaks after a rise in temperature above freezing. These observations are consistent with the hypothesis that runoff water from melting snow is largely responsible for the rise in events. Fig. 9 shows the spatial distribution of the Manhattan secondary events on the snow and non-snow days [11].

D. Hurricane and Earthquake

New York City does not locate in a zone that hurricane and earthquake frequently visits. But in August 2011, Hurricane Irene and 5.8 earthquake affected New York City. On August

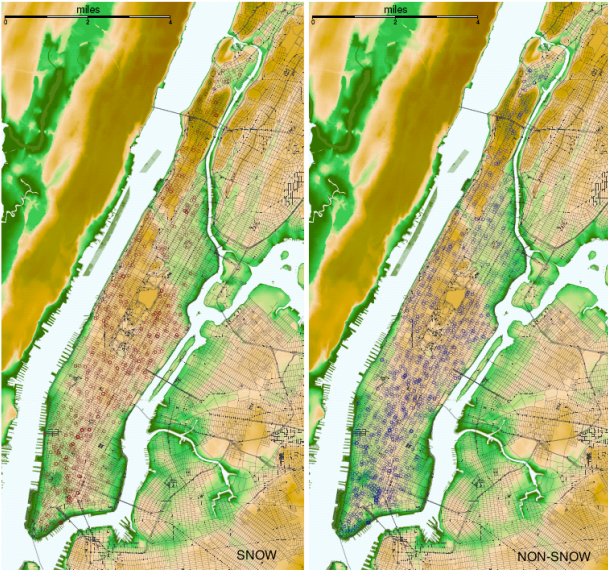


Fig. 9: Manhattan events on snow and ordinary days [11].

27, 2011, Hurricane Irene made landfall on Coney Island NY as a Category 1 hurricane. The weakened tropical storm surge reaches underneath the boardwalks in beach areas. There were 2 EF0 tornadoes that were confirmed by the National Weather Service. The low-lying areas in lower Manhattan and other boroughs were flooded. The hurricane Irene caused power outages in lower Manhattan, especially in the coastal Battery Park area, for several days. It was also reported that the Long Island Power Authority (LIPA) had over 400,000 power outages.

On August 23, 2011, a 5.8 earthquake centered in Virginia spread its shock wave to much of the East Coast, giving New York City its biggest shaking in decades. Two nuclear plants in Virginia shut down automatically as a precaution. Other than personnel evacuation from office buildings, New York City did not experience massive power interruption because of this earthquake.

E. Solar Storm

We are moving to an age with increasingly active and volatile space weather including solar storm. A recent research [12] analyzed the solar storm's potential catastrophic effect on the power grid. An eruptive event on the Sun, known as a coronal mass ejection, sends a powerful flux of charged particles, protons and electrons, into the surrounding space. If the Earth is on a line with the eruption, the charged particles interact with the Earth's radiation belts and geomagnetic field to produce currents in the ionosphere. The power lines which make up the electrical transmission grid act as antennae, to couple these ionospheric currents to the installed transformers which step up the voltage for long-distance transmission. The ionospheric or auroral currents produced by a powerful solar storm induce strong fluctuating direct currents in the power lines. Known as geomagnetically induced currents (GIC), when they reach the transformers, they piggyback on to the strong alternating current already flowing and cause the iron cores of the transformers to saturate and overheat from

hysteresis and reactive resonance effects in the transmission line. This can cause network-wide voltage regulation problems leading to blackouts, or complete transformer burnout. The greatest danger is to the more than 300 extra high-voltage (EHV) transformers located at power substations along the routes of major transmission lines. Because of the limited manufacturing capability for these large EHV transformers, it could take months or years to restore power in some areas [12], [13], [14].

V. FAILURE PREVENTION

Preventive maintenance, intertemporal consumption, and electrical load optimization can be used to effectively prevent power grid failures under non-catastrophic climate situation.

A. Preventive Maintenance Using Susceptibility Ranking

To improve the power grid reliability and reduce potential failures, we have developed several machine learning and data mining systems to rank some types of electrical components by their susceptibility to impending failure. The rankings can then be used for planning of fieldwork aimed at preventive maintenance, where the components should be proactively inspected and/or repaired in order of their estimated susceptibility to failure [3].

MartaRank [15], [16] and ODDS [17] are two online machine learning and data mining-based feeder-ranking systems for preventive maintenance. MartaRank employs Support Vector Machines (SVM), RankBoost, Martingale Boosting, and an ensemble-based wrapper. The ODDS ranking system uses ranked lists obtained from a linear SVM. In evaluating a ranked list of components, we use accompanying rank statistics such as the Area Under the Curve (AUC). The AUC is equal to the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one. It is in the range of [0, 1], where an AUC of 0.5 represents a random ordering, and an AUC of close to 1.0 represents better ranking with the positive examples at the top and the negative ones at the bottom. One phenomenon we identified is the AUC cyclicity that appears in both feeder-ranking systems (Fig. 10) [18]. Although the two AUC time series vary differently, they both possess an inherent cyclical pattern.

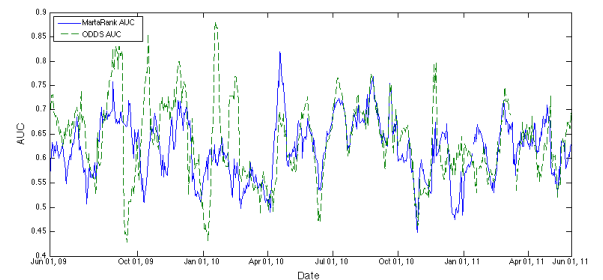


Fig. 10: MartaRank AUC and ODDS AUC from June 1, 2009 to May 31, 2011

To find out the cause of this cyclical pattern, we studied many possible factors and analyzed their corresponding data

including peak power load, temperature, load pocket weight (i.e., a measurement of intensive power use constraints on the transmission system in a big city like New York) and their derivatives such as delta values. Our finding shows that climate affects the reliability of the New York City power grid and the predictability of the power grid component failures is following the cycles of the North Atlantic Oscillation (NAO) Index (Fig. 8). Our analysis further shows a prominent 21 days peak and trough correlation between the NAO index, machine learning AUC and temperature variable (Fig. 11). As shown in the Fig. 11, the NAO index, temperature variable and two AUC time series fluctuate in tandem with each other in an approximately 21 days cycles from May 2010 to October 2010.

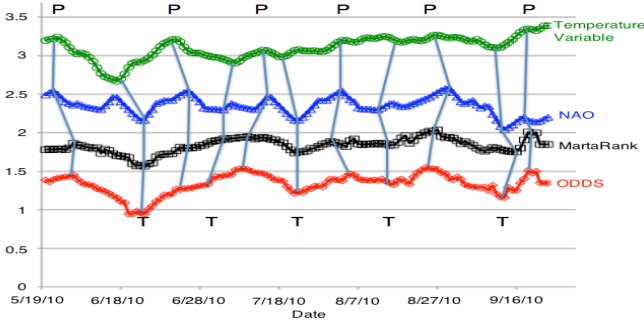


Fig. 11: Peak and trough correlation (approximately every 21 days)

We estimated that the climate affects the reliability of the New York City power grid and the predictability of the power grid component failures is following the cycles of the North Atlantic Oscillation (NAO) Index. However, the weather temperature and peak power load do not follow the predictability trend of the power grid component failures as close and as sensitive as the NAO Index. The close correlation between NAO Index and the predictability of the New York City power grid component failures derive from various climatic factors and the power grid components cyber-physical responses to them.

B. Intertemporal Consumption and Load Optimization

As we stated earlier, the higher peak electrical load inevitably leads to the stress of the power grid and higher likelihood of power grid failures. With the fixed electricity distribution and load capacity, electrical components often work in a stressful or overloaded mode, which is a major cause of electrical component failures. Intertemporal consumption and electrical load optimization are two ways to lower the peak electrical load and smooth the demand curve of the power distribution.

As an economic term, intertemporal consumption describes how an individual's current decisions affect what options become available in the future. An individual who saves today consumes less, causing his or her current utility to decline. Over time, the savings grow, increasing the amount of goods the individual can consume and, therefore, the person's future utility. Electricity consumers, including commercial, industrial, and residential customers, have the option to reschedule their

use of the power grid. For example, to move the heavy industrial use of the grid to the weekend may significantly reduce the overall area wide peak load demand. The intertemporal consumption may be incentivized through pricing rebate from the utilities. One example is the Electric Vehicle charging, which is likely to increase overall electrical load on the grid. The high peak power requirement of ten-minute charging can also stress the local power grid and might increase the risk of power outages or even black-outs during peak demand if enough vehicles choose to charge at these times. Using economic incentives to encourage EV users to charge during off-peak hours can help to reduce the demand during peak load time.

Electrical load optimization includes load curtailment and optimal load allocation. Load curtailment entails voluntary and involuntary cut down of electricity use by large consumers. It is an effective way to reduce consumption during peak electric demand period and would help to mitigate the stress on the grid and effectively reduce potential failures. Optimal load allocation requires improvement on how the utilities allocate and route the electrical load among the available supply network in some intelligent and proactive way, thus creating a better match between supply, demand and response. Use of energy storage system helps electrical load optimization and bridges the gap between the electricity demand and limited capacity of the power grid. The energy storage system suffers some efficiency drop and thus trades lower overall system efficiency in favor of higher peak demand capacity.

VI. CONCLUSION

In this paper, we did a statistical and holistic analysis of the New York City power grid failures. We identified several failure patterns and analyzed climatic effects on the power grid failures. We further suggested preventive maintenance, intertemporal consumption, and load optimization as some effective ways of preventing power grid failures.

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Cynthia Rudin is an Assistant Professor of Statistics at the MIT Sloan School of Management, and an Adjunct Research Scientist at the Center for Computational Learning Systems at Columbia University. Her research interests are in statistical learning theory and applications of machine learning. She has several projects that involve the application of machine learning to electrical grid maintenance, and also a project with Ford through the MIT-Ford Alliance. She is the recipient of an NSF CAREER award and an NSF Postdoctoral Research Fellowship. She received a PhD at Princeton University, and BS and BA degrees from the State University of New York at Buffalo.

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