Spring 5-14-2020

A review of methods to better predict and reduce the risk of hurricane damage to the energy sector

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This Master's Project

A review of methods to better predict and reduce the risk of hurricane damage to the energy sector

by

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is submitted in partial fulfillment of the requirements for the degree of:

Master of Science

In

Environmental Management

at the

University of San Francisco

Submitted:		Received:	
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Abstract

In the event of a hurricane, electricity is the most important utility as it provides heat, water, food, light, communication, and medical care to communities. Research predicts an increase in frequency and strength of hurricanes with time due to climate change, which requires communities and electric utility companies to be prepared for the inevitable. This paper assesses existing methods of hurricane preparation and restoration of the electric power grid in hurricane prone locations with regards to the electric utility companies and electric distribution systems. In this study, I perform a comparative analysis between different methods of planning and forecasting electrical power outages for a hurricane event. Previous research analyzes single models and methods, where this paper compares the many different models and methods to synthesize the most promising results for electric utility companies to implement. Results from this study indicate that hardening the electrical grid and optimizing the electrical forecast models with more promising variables (Estimated maximum wind speed, duration of high winds, previous outages, and tree densities) and model types (General Additive Models and Bayesian Additive Regression Tree models) will reduce response and recovery time of the electrical grid after a hurricane. This study is important as it will guide electrical utility companies on better methods to prepare and respond to hurricanes to facilitate fewer power outages and quicker recovery times after a hurricane, saving money and lives of affected communities and service areas.

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1. Introduction

Hurricanes are one of the most destructive forces that coastal communities in the United States face. They give little time to react and require communities to work together for solutions as no single person can protect themselves. Research predicts an increase in frequency and strength of hurricanes with time from climate change (Webster et al. 2005). With climate change comes changes in the ocean that create optimal conditions for hurricanes to form. A relationship between hurricane frequency and ocean surface water temperature has been found, and a surface temperature of 26°C is needed to create optimal hurricane conditions (Webster et al. 2005). Increasing ocean surface water temperatures due to climate change means that optimal hurricane conditions will be easier to create and more frequent than in the past. Between 1880 and 2012, a trend has shown land and ocean surface temperature warming by .85°C (Pachauri et al. 2014). With the ocean surface temperature already almost 1°C higher than they were almost one hundred years ago, it will continue to rise in temperature as humans continue to pollute.

More hurricanes will lead to more destruction along the coasts of the United States in the future. Hurricanes bring destruction to multiple facets of life. Hurricanes damage homes, spread waste, destroy the environment, disable communication, hinder transportation, and take down electricity. Even though all these different parts of communities are important after a hurricane, this paper will be focusing on the damage to the electrical grid caused by hurricanes. In our current society, electricity is a necessary part of life. Electricity provides heat to homes, is used to cook and store food, provides light to homes and streets, allows communication throughout the world, and is needed to provide medical support to the sick.

Reed et al. (2010) discuss how electricity is one of the most important factors after a hurricane and is often prioritized as electricity is needed to rebuild and remove debris as well as communicate with the community. Without electricity, rebuilding communities takes longer because of reduced infrastructure and communication. As hurricanes increase in strength and frequency, hurricane susceptible communities along the coasts of the United States need to be even more prepared than ever before. Hurricane Katrina in 2005 was devastating to Florida, Louisiana, Alabama, and Mississippi. As seen in Figure 1, there were over 1 million power outages on the first day of Hurricane Katrina in Florida, and many more days after in Louisiana, Alabama, and Mississippi because of the lack of infrastructure to protect the power grid (Reed et al. 2010). With as many power outages as there were in 2005 from Hurricane Katrina, we must review possible solutions to decrease the number of power outages from hurricanes to in the future to reduce destruction and loss.

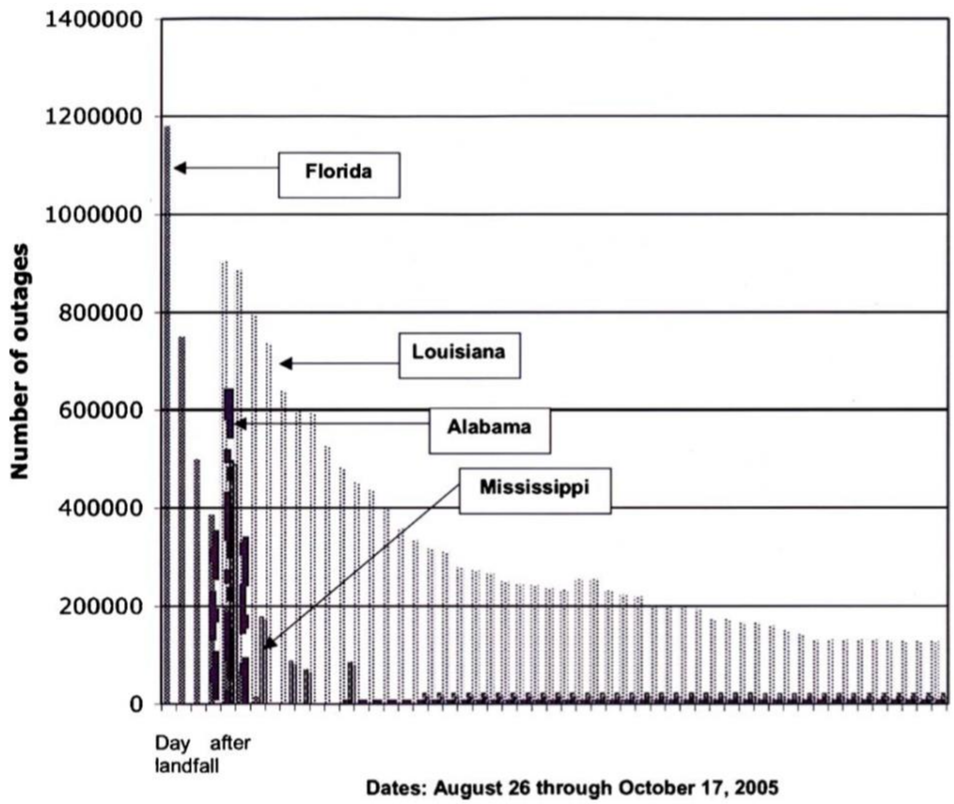

Figure 1 Reed et al. 2010; Bar chart showing power outages for the states affected by hurricane Katrina between August 26 and October 17, 2005

There is little that can be done to stop hurricanes once they have been created, but measures can be taken to reduce the damage and recovery time. This paper assesses existing methods of hurricane preparation and restoration of the electric power grid in hurricane prone locations to improve hurricane preparedness and response. This research will benefit communities susceptible to hurricanes as it will give an analysis of different methods that can be used to prepare and recover the electrical grid from hurricanes as quickly as possible. This information will save communities lives and money as well as facilitating quicker recovery times. Existing knowledge on this topic reviews singular methods and variables on forecasting whereas this study will review the different methods and variables against each other to understand the strongest predictors and models for hurricane power outage predictions. With these comparisons will come recommendations that will guide utility companies to have better protected electrical grids, better plans in place for post hurricane recovery, and more reliable power outage estimation models.

To assess existing methods of hurricane preparedness and response with respect to the electric grid, this paper performs a comparative analysis of methods and variables used to prepare, respond, and predict power outages of past hurricanes in the United States to find ways that electric utility companies can respond to current and future hurricanes. Through reviewing literature and data of electrical power grid failures from hurricanes, I will create a synthesis table reviewing the different methods of preparation and response that can be improved by electrical utility companies. The purpose of this approach is to find best methods and variables in hurricane preparedness and response to assess the best possible solutions for electrical utility companies to integrate with regards to their own power grids. From this research, I discuss the effectiveness of the solutions and models to recommend the best ones for electric utility companies to adopt.

The remainder of this paper is divided as follows. Chapter II reviews background information about hurricanes and the electrical grid. Chapter III goes into the methods of the literature review and data collection. Chapter IV reviews the evidence found in the literature discussing risks of hurricanes to the energy sector, methods of preparedness, and electrical grid forecast models. Chapter V discusses the future direction of research and recommendations for electric utility companies to better prepare and respond to hurricanes.

2. Background

2.1 Hurricanes

2.1.1 Background on Hurricanes

A hurricane is a natural phenomenon that is produced over warm ocean surface waters. As the warm moist air rises, the cooler ocean air replaces it until storm clouds are created. These storm clouds then rotate with the earth until enough speed has been built up and a hurricane is created. The minimum speed required to be considered a hurricane is 74 mph. Hurricanes are classified according to the Saffir-Simpson Hurricane Wind Scale, which rates hurricanes from one to five. Schott et al. (2019) classify hurricanes on a scale from 1-5 as follows: A category one hurricane has sustained winds between 74 and 95 mph which will damage lighter buildings and trees with some power outages. A category two hurricane has winds from 96 to 110 mph which will damage buildings due to debris and power outages are expected for days to weeks. A category three has winds from 111 to 129 mph and will cause devastation in the area that is affected with power outages expected for days to weeks. A category four has wind speeds from 130 to 156 mph and will cause catastrophic devastation making the area uninhabitable for weeks to months. A category five has wind speeds 157 mph and higher which will cause power outages from weeks to months and require total rebuilding of the area. Even though they are categorized on a one to five scale, every hurricane that approaches a community can be extremely dangerous, with many other factors affecting the damage caused.

2.1.2 Effects of a hurricane

Hurricanes are destructive as their high-speed wind vortexes can be strong enough to demolish buildings and trees, but corresponding effects from hurricanes can be equally destructive. Hurricanes carry and drop debris which under the right circumstances can destroy buildings, trees, and electricity towers. Hurricanes also cause storm surge, which is the sea-level rise caused by the wind and pressure of the hurricane. Storm surge can be dangerous because it causes significant flooding on the mainland that can destroy homes, cars, small structures like electrical poles, and can unexpectedly drown people.

This combination of damage to all sectors creates a large monetary loss to communities that were otherwise doing well. Pielke et al. (2008) performed a normalized hurricane damage analysis for the United States and found that since 1900, the monetary damage of hurricanes has steadily increased as shown in Figure 2. This increase in damage is related to increased coastal housing, increased wealth, and increases in frequency of hurricanes. From this analysis, Pielke et al. (2008) extrapolated that following these trends, the monetary loss would double every 10 years in the future. A recent study by Smith et al. (2019) shows that between 2016 and 2018 there were six hurricanes that each costed more than a billion dollars totaling to $329.9 billion. The average loss per year over those three years was $110 billion dollars, which follows the trend of damage doubling every 10 years. With increased yearly damage, Pielke et al. 2008 also estimated that losses from a single hurricane could increase drastically. The 1926 Great Miami Hurricane caused $140 billion worth of damage, and it is estimated that a hurricane like that is bound to happen in the 2020s that could reach $500 billion in damages.

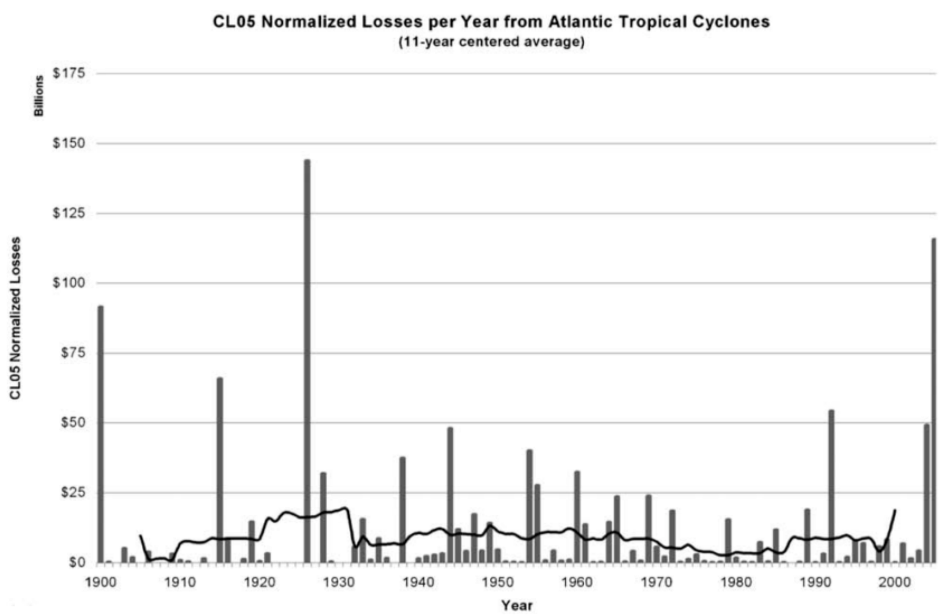

Figure 2 Pielke et al. 2009; Total monetary losses from hurricanes in the Atlantic adjusted for inflation and changes in housing

2.1.3 Climate change and hurricanes

As with most natural disasters, when the climate changes at extraordinary rates so will the occurrence and strength of hurricanes. Collins et al. (2010) performed in-depth research on climate models of the recent decades and found that all climate models show that global air and sea surface temperatures are and will continue warming because of greenhouse gas emissions. According to Emanuel (1987) small changes in sea temperatures will cause large intensity changes in hurricanes and tropical cyclones. Emanuel (1987) calculated that a 3°C change in surface temperature of the ocean can cause an increase of up to 15-20% maximum wind speed of hurricanes. This increased maximum speed would likely bring increased averages speeds of hurricanes and thus increase the damage that could potentially be caused by a hurricane dramatically. Bender et al. (2010) improved hurricane intensity simulations with scientific estimations for climate change. Results from this study indicate that the Western Atlantic Ocean between 20°N and 40°N will have the largest increase of very intense hurricane activity with climate change in the 21st century. This area aligns with the south-eastern part of the United States that has been hit with strong hurricanes like Hurricane Katrina, Isaac, Irma, Maria, and Harvey in the past. With these projections, it is increasingly important to focus on preparing and responding to hurricanes in the United States as there is no doubt that they will be increasingly common and destructive in the future.

2.2 Electrical power grid need and use

2.2.1 Different parts of the electrical grid

There are four parts of the electrical power grid which are generation systems, transmission systems, electrical substations, and distribution systems. Generation stations are the plants producing the power such as hydro-electric plants or natural gas plants. These plants generally have few points of failure and many redundant systems to prevent a blackout. Transmission systems carry high voltage electricity from the generation station to other transmission stations and substations. Transmission systems are composed of well reinforced towers and thick aluminum wires with tree setbacks in place so that wind will not easily cause a blackout. Electrical substations convert the voltage and power it up or down depending on whether it is going to a transmission line or distribution line. Substations are in well protected fenced off areas that are not easily harmed by a hurricane. Distribution systems carry power from the transmission lines to residential homes and businesses. Distribution systems are composed of wooden or metal poles with much thinner wires than transmission wires. They are placed along most roadways and are at risk of being harmed by hurricanes because trees and wind can knock over distribution poles and lines causing a blackout for the area (Kaplan 2009).

According to Panteli and Mancarella (2015), even though the generation, transmission, and substation parts of the electric grid would impact customers in a major way if disturbed by a natural disaster, there is a low chance of that happening. This low chance high impact scenario is considered low enough risk that the benefits of using resources to harden, prepare, and repair the distribution system makes it a much more worthwhile endeavor. Bie et al. (2017) back up this claim that historically, 90% of electrical outages occur on the distribution systems of the electric power grid. Because of the researched fact that the most vulnerable part of the electric grid is indeed the distribution system, the majority of electric grid research that relates to reducing the number of power outages due to hurricanes focuses on the distribution system. This comparative analysis reviews different potential weaknesses and solutions on the distribution system with regards to hurricanes to recommend utility companies best practices to reduce post disaster blackouts in their service area.

2.2.2 Risks of Hurricanes to the electric grid

Hurricanes create multiple environmental dangers that can cause damage to the electric grid. Hurricanes produce high speed winds, increased rainfall, and sudden storm surge that can destroy land, buildings, and the electric grid if proper preparations are not made. Once Hurricane Isaac made landfall in Louisiana, 47% of the state lost power even though the storm was only a category one hurricane (Guikema et al. 2010). According to Wang et al. (2016) there have been 933 power outage events in the United States between 1984 and 2006. Table 1 shows that hurricanes/tropical storms were the cause of 4.2% of the power outages in the United States between 1984 and 2006 but resulted in the largest mean size of customers affected, 782,695.

Cause	% of events	Mean size in MW	Mean size in customers
Earthquake	0.8	1,408	375,900
Tornado	2.8	367	115,439
Hurricane/tropical storm	4.2	1,309	782,695
Ice storm	5.0	1,152	343,448
Lightning	11.3	270	70,944
Wind/rain	14.8	793	185,199
Other cold weather	5.5	542	150,255
Fire	5.2	431	111,244
Intentional attack	1.6	340	24,572
Supply shortage	5.3	341	138,957
Other external cause	4.8	710	246,071
Equipment failure	29.7	379	57,140
Operator error	10.1	489	105,322
Voltage reduction	7.7	153	212,900
Volunteer reduction	5.9	190	134,543

Table 1 Modified from Wang et al. 2016; Largest contributors to blackouts in the United States between 1984 and 2006

Tonn et al. (2016) reviews the damage sources to the electric grid that Hurricane Isaac caused in Louisiana in 2012 to determine the causes of the power outages. The paper focused on the three main hazards of a hurricane which are wind, rainfall, and storm surge. The data for the paper came from electric companies, the national climatic data center, the US census, storm surge models, and wind models to accurately depict the events of the hurricane on an hourly basis. Tonn et al. (2016) used GIS analysis to find spatial trends throughout the state of Louisiana and the model. Through this analysis, Tonn et al. (2016) was able to find spatial variations in impacts of using four different variables. The analysis used cumulative precipitation, wind speed, maximum storm surge and previous outages as variables to find spatial trends of hourly power outages found from Hurricane Isaac. Relative importance was found for each of the four variables and then the data was mapped in GIS. The relative importance of cumulative precipitation and wind speed were moderate to high at predicting power outages from Hurricane Isaac in the east central and southwestern parts of Louisiana. Previous power outages tended to have moderate to high relative importance throughout the state but had higher relative importance in areas with low to moderate hourly power outages. Maximum storm surge was found to be of low relative importance throughout the state as the other variables were much better predictors of risk than storm surge was. This analysis showed that the risk of variables can vary throughout the state but areas with high wind or high cumulative precipitation tended to have an increased amount of hourly power outages due to Hurricane Isaac.

2.2.3 Distribution systems before a hurricane

Crowther et al. (2007) defines electric utility companies as essential parts of a community and must be included in planning for hurricane events. This was especially shown after Hurricane Katrina where in Louisiana the levees broke, pumping stations failed, equipment was damaged, utility companies were understaffed, and extended power outages were seen. Because of all the damages, businesses that relied on electricity, gas, and water were unable to operate causing lives, revenue, and property to be lost. Power outages in Louisiana increased in the days after the hurricane because of the flooding from the levees and rain, which lead to 1.1 million power outages. Preparedness plans and resilient strategies are crucial in the energy sector before a hurricane to be able to overcome challenges that hurricanes bring.

There are many challenges for electric utility companies to overcome with regards to the electric grid and distribution systems. The distribution systems hardware including the wooden poles are aging which increases the vulnerabilities in the distribution system to natural disasters (Salman et al. 2015). Salman et al. (2015) discusses how creating new distribution system with stronger poles will result in lower costs throughout the life cycle of the grid, but it is not worthwhile to replace wooden distribution poles with stronger ones. It is more worthwhile to invest in targeted hardening resources. Targeted system hardening is one way that a utility company can invest its budget to make the distribution system less prone to being harmed by hurricane events. Examples of system hardening techniques that have been studied are undergrounding the distribution grid, upgrading the distribution poles, elevating critical distribution infrastructure, vegetation management around electric distribution poles, and creating more redundancies in the grid. Smart grid technology is also a newer method of reducing risk to the distribution grid as the faults and problems in the grid can be isolated and further harm reduced in real time and electricity can be redirected to critical infrastructure using distributed generation (Bie et al. 2017). This paper will provide background of some of these preparation strategies to determine which are worthy endeavors for electric utility companies to invest time and money into to reduce the damage of hurricanes.

2.2.4 Distribution systems after a hurricane

Even though distribution systems are susceptible to hurricanes, there are safety systems in place to prevent greater risk during and after the event. These safety systems inevitably lead to power outages but protect the community from further electrical damage. When a distribution line is interrupted by a tree or pole falling, a fuse cutout will occur, or a circuit breaker will active. A fuse cutout occurs when there is overcurrent in the distribution line due to the electricity having nowhere to go along its path from a disruption along the distribution line. The fuse melts and electricity is cutout from the distribution line along its path. To fix a fuse cutout, the distribution pole and line must be fixed if either of them were harmed and the fuse needs to be replaced. A circuit breaker is a similar system to fuses except the breakers can be reset without replacement and they can protect higher voltage circuits. Fuses are placed all along the electrical distribution grid while the circuit breakers are placed at substations and along primary distribution poles. This is because circuit breakers are more expensive to install than fuses as they do not need to be replaced but can accept higher currents than fuses (Davidson et al. 2003).

With these safety systems in place, fallen trees and downed distribution poles create power outage scenarios throughout communities. To repair the distribution grid after these power outages, electric utility companies hire additional staff from around the country to decrease recovery times. To estimate the amount of damage and additional resources needed for optimal repair they use electric forecast models. These models are created by the utility company using past outage data and current weather data to estimate where the damage will be. It is critical for these models to be accurate so that the utility company has proper resources as too many or too little would put a burden on the utility company or the community.

While there are power outages caused directly by the hurricane, there are also indirect power outages caused by the electric utility company for the good of the people. After the hurricane event, power generation may be at a reduced capacity and load shedding may be necessary. Load shedding is the deliberate power disruption by electric utility companies to reduce electricity usage in non-critical locations when the generation cannot keep up to the usage. Load shedding is used to provide continuous electricity to critical infrastructures like hospitals, water utilities, stop lights, and any other location that is deemed important for human life after a hurricane (Gao et al. 2016). Load shedding is a temporary measure to keep electricity available to industries and customers who need it most but is an integral part of post-hurricane recovery and planning.

3. Methods

This study uses a comparative analysis methodology to review the different methods of preparation and prediction of the electric power grid used or proposed after severe hurricane events. To create this comparative analysis, I used Scopus and Environment Complete to gather peer reviewed articles discussing hurricanes and their effects on the electric grid. Common journal types reviewed were natural hazard reviews, risk analysis, and electric power systems review journals. The hurricanes that appeared most often in this research were Hurricane Ivan, Katrina, and Isaac as they were some of the costliest and destructive hurricanes in the past twenty years. From these research papers I created a synthesis tables of the different proposed methods and variables used in predicting power outages. To create the synthesis table, I searched for papers that would review different model types and variables. When reviewing those papers, I focused on the methods of the model, the variables they chose, which variables ended up being significant, and which variables ended up being considered insignificant. Creating this table allowed me to synthesize and understand methods and variables important in predicting power outages after a hurricane.

4. Evidence

4.1 Electrical grid planning

Electric grid planning and improvements are important in preventing electric distribution systems from being harmed by a hurricane causing a loss of power to the service area. These actions should occur before any hurricane is forecasted so that the electric utility company can prevent unnecessary and unforeseen power outages. Electric grid planning activities are often referred to as system hardening. The electric utility companies have a set yearly budget that they must allocate to disaster repair, general repairs, and upgrades to the grid. By budgeting for hardening properly, the utility company can save lives and money in the event a hurricane occurs in their service area. Hardening activities can be as large as overhauling the entire electric grid with distributed generation or undergrounding the distribution grid. It can also be as small as updating the infrastructure, increasing vegetation management, elevating critical infrastructure, or reassessing the utility poles throughout their service area.

Many different components make up the electrical distribution grid. One such component are the distribution poles that hold the wires together and provide electricity to the customers. Throughout the United States, these poles are most often made of yellow pine because it has proven to be sturdy under load, through weather, and is cost effective. The issue with having these poles made of wood is that like any material, wood has its limits to how much abuse it can handle before it fails. Research on upgrading and understanding the resilience of current electric utility poles is minimal, but Alam et al. (2019) presented a framework to understand how much wind damage these poles can take from a hurricane before failing. This framework is meant to help electric utility companies save money and prevent power outages due to poles that are showing signs of failure. The framework considers the angular deflection of the distribution poles with simulated wind models. The angular deflection is the degree of deviation that the pole is from being perfectly straight in the ground like when it was installed. The greater the angular deflection, the weaker the pole is and the more likely it is to fail due to the sustained wind of a hurricane.

This framework developed by Alam et al. (2019) is used with a cost-benefit analysis to determine the economic loss of a hurricane on distribution poles. The case study is performed on twenty-two random poles in Beaumont, Texas which have experienced harsh wind and flooding from hurricanes in the past twenty years. The twenty-two poles were measured for their angular deflection and the sample was propagated with a binomial distribution to create one thousand sample poles. Alam et al. (2019) emulated a category 3 hurricane (120mph) to simulate the costs and savings of different scenarios of preparations. After the model calculated the angle of deflection of the poles after the storm, it determines which would now be in a damaged stated that would need to be replaced through cost benefit analysis. The cost to replace a pole before the hurricane is only $2500, but after a hurricane that raised to $4000 per pole as disaster pay increases the cost of replacement. With having increased costs after the hurricane to replace the pole, there is also significant economic loss to all the people who are without electricity because of the pole failing that is considered in this analysis.

The framework used by Alam et al. (2019) tests three different scenarios of preparation: no replacement, replacement of current unhealthy poles, and the replacement of current and predicted unhealthy poles. The strategies that consist of replacing poles before they fail comes with upfront cost, but that upfront cost pays off with cost savings after the hurricane for the utility and community. Scenario one where nothing is replaced lead to a cost of $8.5 million. Scenario two where only the unhealthy poles are replaced had an initial investment of $0.3 million but reduced the post-hurricane cost to $3.6 million. Scenario three replaces current unhealthy poles as well as predicted ones with an upfront cost of $0.3 million but it ideally prevents all damage after the hurricane that would have occurred from distribution poles being damaged. These results are promising showing that by inspecting and replacing damaged distribution poles, damages costs due to failures decrease. Though these results seem to be able to reduce the cost and damage from a hurricane to the distribution poles drastically, the study was preliminary to see what this framework could do. The analysis did not consider other variable besides wind, but the researchers planned to continue the research in the future to acknowledge a wide variety of variables.

The model by Tian and Li (2014) uses a system dynamics (SD) based approach to review the cost effectiveness of long-term (50 year) distribution pole maintenance. An SD approach analyzes a complex system with its interactions from multiple socioeconomic viewpoints to understand how any why the it may change throughout its lifespan. This SD model represents distribution poles in Miami County, Florida which are prone to occasional hurricanes that can cost the utility money to replace the distribution pole. This SD model used by Tian and Li (2014) calculates the cost effectiveness 50-year life span by replacement ratios and cumulative cost ratios with three variables on a multipole system. The first variable used was maximum annual wind speed which varies linearly with climate change over the 50-year lifespan. Another variable used was the cost of replacement, which varied over the 50-year lifespan with different discount rates from 0% to 8%. The last variable used was the population growth rate which ranged from 0-2.5%. Population growth is used because as a population grows, their demand for electricity grows and the need for more distribution poles also increases.

The 50-year lifespan of the distribution poles was simulated by Tian and Li (2014) with the SD model and every combination of these variables with a sensitivity analysis. Figure 3 and 4 shows the range curves of cumulative costs and replacement ratios over the 50-year lifespan of the three factors. The most significant factor for cumulative cost in Figure 3 was the discount rate which drastically increases the cumulative cost 2/3 into the life of the distribution pole. Wind speed and growth rate both have significant influence on the replacement ratio in Figure 4. This demonstrates that utilities should keep a close eye on the change in wind speed and the growth rate towards the latter part of the 50-year lifespan of the distribution poles to control the costs involved with replacing the distribution poles. To counteract these influences of discount rate, wind, and discount rate utilities should look into other methods of resilience for their distribution poles in the early years to have them in place by the time the variables have a large influence.

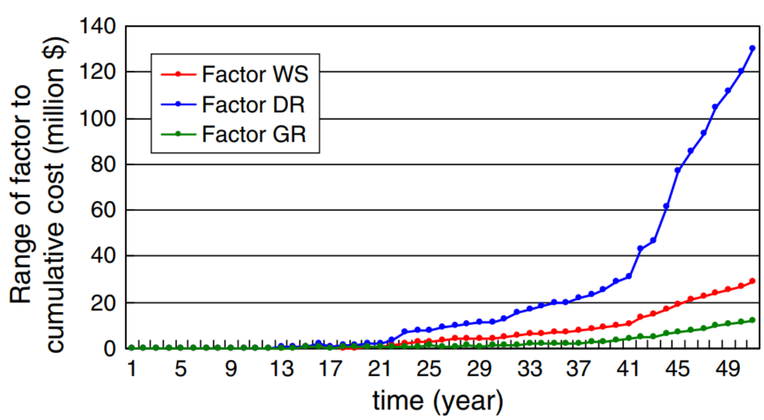

Figure 3 Tian and Li 2014; Range curve of cumulative cost from years 0-50; wind speed (WS), discount rate (DR), growth rate (GR)

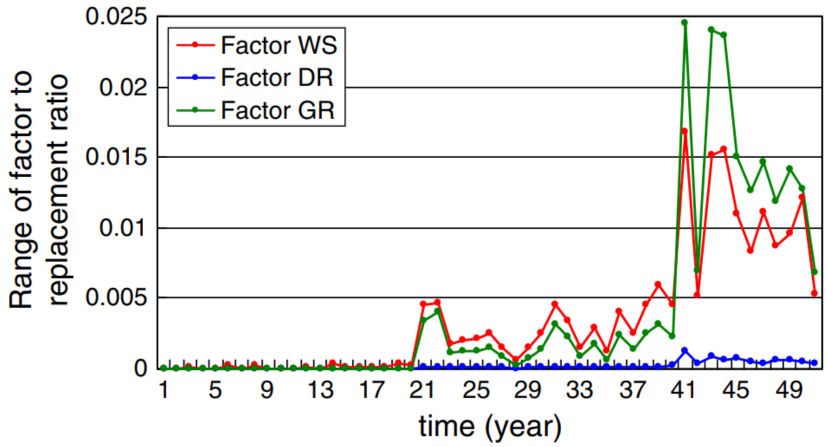

Figure 4 Tian and Li 2014; Range curves of replacement ratio from years 0-50 wind speed (WS), discount rate (DR), growth rate (GR)

Another method of planning and protecting the electric grid before a hurricane is by undergrounding the electric grid. Francis et al. (2011) performed an analytical life cycle analysis of burying the electric grid underground. With climate change and increasing populations living near the coasts, alternative measures need to be taken to protect communities from the loss of electricity from the power grid. In hurricane prone areas, undergrounding electricity has many the benefit of being more reliable because it is less vulnerable to wind and rain that hurricanes bring with them compared to traditional systems. Undergrounding electrical equipment is not done traditionally because the cost to implement underground electrical grids is $1.3 million per circuit mile for little yearly savings, being $4,000 per circuit mile compared to $4,500 per circuit mile in traditional systems. This analysis reviews the life cycle costs with undergrounding all electric equipment, undergrounding only equipment in commercial zones, and making no changes. The analysis then looks at each of those scenarios with and without wetlands and with or without economic/environmental costs as to find out whether it would be beneficial for communities prone to hurricanes to bury their electric grids.

Francis et al. (2011) combine multiple different models to create their own framework, called the economic input–output life-cycle assessment framework (EIO-LCA disaster mitigation framework) to perform this analysis. This framework combines the life cycle analysis and an extended life cycle analysis and adds supply-chain environmental impacts and other societal disaster risk mitigation impacts to it. The final model considers the planned costs by the agency, costs on society because of the agency, unplanned costs by the agency, and unplanned costs on society. By combining the costs of creating wetlands and burying electrical equipment compared to the benefits that each of them would give to society and the environment, they were able to model each scenario. The findings from this study were that the most cost-effective method in all scenarios was to not underground the electrical grid and to not invest in wetland restoration, seen in Table 2. Table 2 shows that Scenario 3: No Undergrounding of the electric grid costs the least amount of money for society and private businesses in all scenarios. This means that repairing damaged electric grids above ground in the long run, is justifiable to keeping the costs of hurricane induced electrical damage down. Francis et al. (2011) state that more research needs to be done to replicate these results with a larger model, use more sophisticated storm surge models, include ecological benefits, and a review of social costs with regards to wetland restoration and undergrounding the electric grid.

Case:	1	2	3
Wetland restoration:	Excluded	Included	Included
Induced economic output:	Excluded	Excluded	Included
Environmental impacts:	Excluded	Excluded	Included
Scenario	E[NPV]	E[NPV]	E[NPV]
1: Underground all eligible components	($9,294)	($0.0396)	($1,500,000)
2: Underground only the commercial district	$(1,969)	($0.0280)	($1,418,000)
3: No undergrounding	($0.543)	($0.006)	($1,402,000)
Preferred alternative	Do nothing	Do nothing	Do nothing

Costs are in million of US dollars

Table 2 Francis et al. 2011; Results from Infrastructure hardening

Fenrick and Getachew (2012) found that undergrounding electric distribution lines on average costs $559,293 while traditional overhead lines cost $196,628 per circuit mile. The increased cost is not always valuable, but undergrounded distribution lines do provide the benefit of lower operation and maintenance costs and increased reliability. The reliability is one of the most important points as unlike overhead electrical lines, underground lines are not at risk to natural dangers like animals, trees, or natural disasters. If there are damages found in the underground system, it can be harder to locate and repair. The Electric Power Research Institute (2013) performed a review on undergrounding electric distribution grids and came to similar conclusions. It was found that the cost of undergrounding equipment was five to fifteen times as expensive when compared to traditional electric grid placement. Even with undergrounding the equipment, severe flooding from hurricanes could cause certain parts of the grid that are underground to fail which would then increase repair time because of the difficulty to get to the undergrounded power lines. A more economical solution to increase the durability of the distribution grid at less cost would be to underground portions of the distribution lines that are more prone to power outages or are critical to staying powered. Locations that this would benefit are areas with lots of vegetation coverages and feeder circuits that would otherwise remove power to entire sections of the grid if disturbed (Electric Power Research Institute 2013). Though underground is an option, more research is needed on the true benefits going forward and currently other hardening options should be investigated

Yuan et al. (2016) conducted a study about hardening of the electric grid through optimization. Mathematical optimization models are often used to determine where to best allocate resources, identify critical components, and sectionalizing the electric grid into microgrids with distributed generation (DG). DG can improve resilience of electric grids if placed properly as they can improve the supply of power, reliability of power, and reduce loss. These systems are often used as back up but are not always optimal placed. Yuan et al. (2016) follows the defender-attacker-defender model which is similar to two-stage optimization. In this model, the electric utility planner designs and updates the system before knowledge of any natural disaster. Then after the natural disaster is recognized, immediate action is done to prepare and protect the best they can. Then lastly the disaster happens, and the utility reacts and responds with repairs to minimize load shedding. Load shedding is when power companies reduce electricity consumption by switching off the power supply to groups of customers because the entire system is at risk.

Yuan et al. (2016) discusses defender planning to make the network more resilient. This includes hardening power lines and optimizing placement of DG resources. In the model it is assumed that any electric distribution lines that are hardened will survive the disaster and the amount of lines hardened is set by a budget formula. A budget formula is created to place the DG resources as optimally as possible to reduce the load shedding required after the hurricane. The DG resource defends as best as it can, but the utility must defend again after the hurricane attacks which involves load shedding. The more money put into DG resources, the less load shedding is needed. Figure 4 shows the amount of predicted load that will be necessary to shed after a hurricane due to the electric grid being overwhelmed based on the budget that is spent on hardening the grid. The more money that the utility is willing to spend on placing DG resources, will cause less load shedding required. The worst-case scenario with no money spent on hardening would cost the electric utility company to shed between 9000 KV and 9500 KV. Any amount of the budget that then goes toward DG resources reduces the amount of load shedding that the utility has to incorporate after the hurricane. This optimization formula is useful in helping utilities determine how much of their budget to spend on hardening their electric grid. Figure 5 shows how load shedding can be reduced drastically with a hardening budget and DG placement, both randomly and strategically. The figures show that in all scenarios, if some amount of the hardening budget is put towards placing DG, then the amount of load shedding will be substantially lower than if DG are not place and involved in the hardening budget.

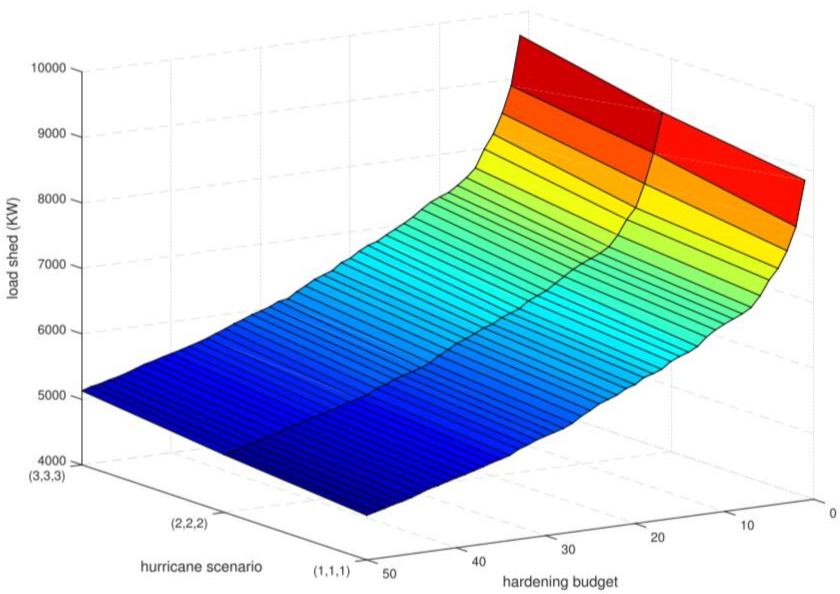

Figure 5 Yuan et al. 2016; Load shedding with different budgets for the 123-Node System

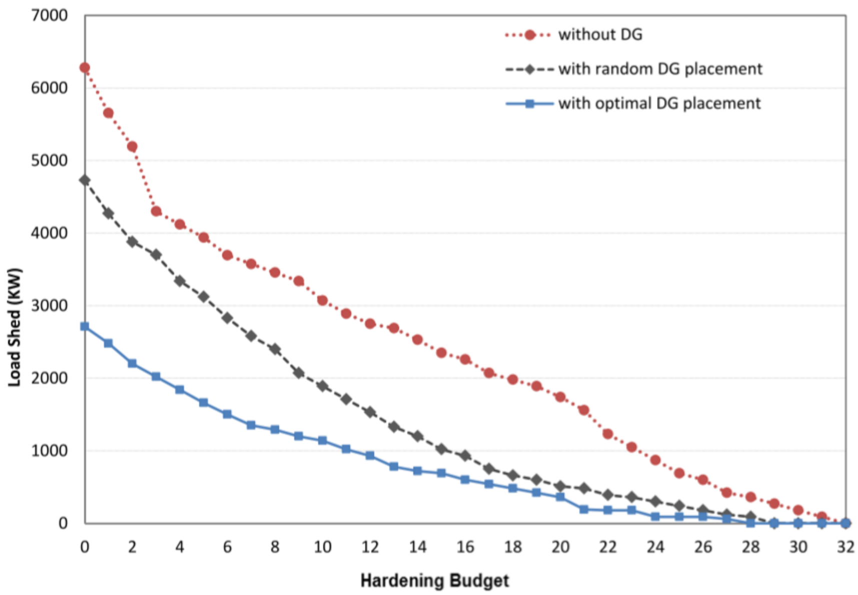

Figure 6 Yuan et al. 2016; The different impacts of DG on resilience of the distribution system by hardening budgets

Like DG resources, microgrids are a newer technology that can help protect the electrical distribution grid from short-long term power outages from severe storms. Schneider et al. (2017) describes the three different kinds of microgrids that could be crucial in the coming future where the earth is hit with more severe storms that create blackouts. Microgrids are a powerful resource for maintaining or redirecting power when there are blackouts. There are three types of microgrids discussed. The first is as a local resource meant to supply energy to critical infrastructures like hospitals, military bases, and wastewater treatment facilities. These types of microgrids are like large individual generators, not meant for long term use. They are expensive and inefficient but effective for keeping critical infrastructure online. The second type of microgrids are community resource microgrids. These microgrids are similar to local microgrids but the power created from them can be redirected to other critical infrastructure away from the generation source through the traditional distribution lines. This type of microgrid is useful when there is an extended power outage and energy can be supplied to locations that need it to survive for an extended period like a military base supplying a hospital with temporary electricity from its generators. The last type of microgrid is a black start microgrid. This type of microgrid is for when there is an extremely severe weather event that has cut almost all power. Most thermal power plants like coal plants cannot flow electricity through a transmission line that is not already energized. That’s where the black start unit like a hydroelectric plant starts producing energy to help re-energize other generation plants. These microgrids are crucial for restoring an electric grid that has experienced total failure.

4.2 Utility Company Electric Grid Forecast Models

When a hurricane is forecasted to make landfall, electric utility companies must prepare to repair any outages immediately afterwards so that communities are not without power for an extended period. According to Davidson et al. (2003), utility companies do not have the staffing to repair the entire electric grid after a hurricane hits, so they must hire external workers in the electric utility sector. Hiring additional workers can be costly for an electric utility company so they must optimize deployment locations and staffing requirements. To do this, the utility company runs rudimentary simulations based off past hurricane outages and data about the upcoming hurricanes to create a rough estimate of how much staff they need and where to place them. The issue with this is that often these estimations are not accurate and the electric utility company either has too much staff which costs them excess money, or they do not have enough staff and cannot repair the electric grid in their community quick enough. This inaccuracy in the current systems modeling and estimation leads to research that tries to better understand what variables are linked to these power outages and how these models can be improved to create more reliable estimations on where to place restoration crews and how much they need.

Papers forecasting electric power outages after a hurricane focus primarily on the distribution system. The distribution system is the primary focus because around 90% of power outages after a hurricane occur on the distribution system (Yuan et al. 2016). According to Davidson et al. (2003) the distribution system is more vulnerable because the wires and poles transporting electricity to homes and businesses are much lower to the ground and are not designed to be as strong as the transmission lines. Distribution systems are created weaker because they must take up less space and be more easily repairable than transmission lines. Transmission systems must be placed with a large open space around them with trees set back away from them so that they run uninterrupted as they move high amounts power from the generation plant to the distribution lines. These transmission systems are created to be able to withstand high winds and have many redundancies so that if an outage at one point were to occur, it does not harm the entire power grid. On the other hand, distribution systems do not have nearly as stringent standards for setbacks as they line streets with little to no room to move objects out of their way. Because of these design differences between transmission systems and distribution systems, it is expected to have to repair many distribution systems after a hurricane, which must be planned and prepared before the hurricane.

Through research of the literature, Table 3 synthesizes a wide variety of proposed models to better forecast power outages after hurricanes. These models build off previous research and test their models against previous models. They each use different variables and model types. Columns c, d, and e display the variables used in the models and which variables ended up being the most and least significant.

Reference	**Model types**	**Variables used**	**Significant Variable**	**Insignificant Variables**
Davidson et al. 2003	GIS, Statistics	land cover, wind speeds, rainfall, power failures, trees	maximum wind gust, precipitation	
Han et al. 2009	GAM	geographical, climate, wind, storm		
Guikema et al. 2010	GLM, GAM, BART, CART	damaged utility poles, number of poles, miles of line, duration of wind, mean precipitation, land cover type	damaged utility poles	
Tonn et al. 2016	Quantile Regression, Random Forest Model	wind, precipitation, previous outages, storm surge	wind speed, cumulative precipitation, previous outages	storm surge, wind duration
Quiring et al. 2015	CART	37 soil parameters, topographic, wind, precipitation	maximum wind gust, duration of strong winds	soil, topographic data
McRoberts et al. 2018	SGHOPM	wind, elevation, land cover, soil, precipitation, vegetation	maximum wind speed, strong winds duration, average wood density, mean elevation,	topographic, root zone depth

Table 3 Synthesized methods and variables used in studies focusing on forecast models of the electric grid after a hurricane event

Wang et al. (2016) define forecast models as a tool used by electric utility companies to estimate where electrical power outages will be after a hurricane. There are statistical models and simulation models. There are multiple different statistical models, but they rely on damage from past hurricanes and environmental data to be accurate. Data fitting models such as Generalized Linear Models (GLM) use equations to model how certain actions like tree trimming will affect the total power outages. Accelerated Failure Time (AFT) models are useful for estimating the duration of power outages. Tree based data mining models such as CART and BART use regression trees to develop relationships between data. For each of these models, the mean absolute error (MAE), mean absolute deviation (MAD), mean squared error (MSE), and root mean squared error (RMSE) are used to describe the accuracy of different models, with a smaller error being more accurate.

In studying and optimizing forecast models, researchers use various methods and models to either build upon previous models or repurpose existing models to better fit the data. The most basic method of modeling hurricane damage to the electric power grid was by Davidson et al. (2003) . In their research, a combination of statistical analysis and GIS was used to compare variables to power outages to find correlation between variables. The analysis reviewed five different hurricanes in North and South Carolina using data such as land cover, wind speeds, rainfall, and power failures to create basic models that are more accurate than the ones that were used at the time. The data was compiled and visually displayed with GIS. From GIS they were able to statistically compare power outages to the different variables to learn the importance of each. Figure 7 shows one such set of maps they created to visualize the correlation between damage and different covariables. Their analysis showed that through relatively simple statistics and GIS mapping, predictor variables can be found for each service area to better support hurricane power outage models. GIS was good for finding correlations between variables but is not great at estimating power outages after a hurricane.

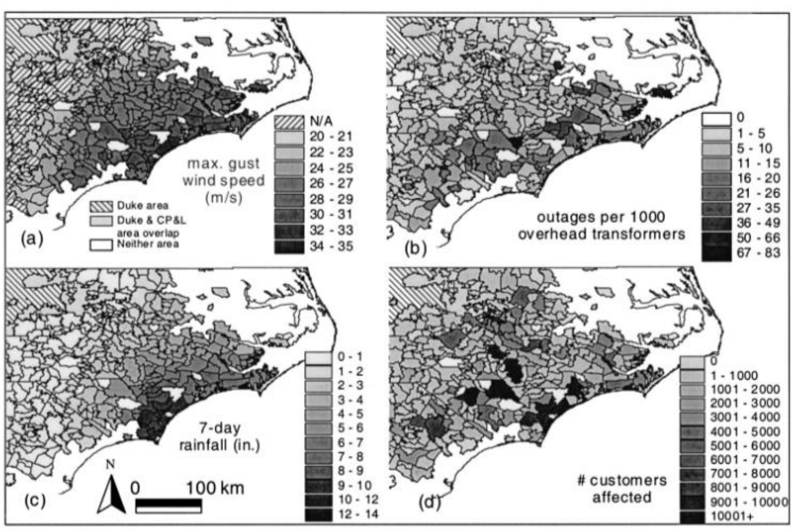

Figure 7 Davidson et al. 2003; GIS maps after Hurricane Bonnie (1998)in Nort Carolina a) Maximum gust wind speeds (m/s); b) number of outages per 1,000 transformers; c) 7-day rainfall (mm); and d) number of customers affected

A common method referenced by Han et al. (2009) and Guikema et al. (2010) is the generalized linear model (GLM). This model assumes a linear relationship between the dependent and independent variables but often overestimates power outages because it does not account for nonlinear relationships as well Han et al. (2009). Han et al. (2009) build upon this model with the generalized additive model (GAM) which can account for nonlinear relationships by adding a randomness factor to the previous GLM. By using this GAM on the same dataset as the GLM, Han et al. (2009) was able to reduce the mean absolute error (MAE) thus increasing the predictive accuracy of the model seen in Table 4.

		Danny (1997)	Georges (1998)	Ivan (2004)	Dennis (2005)	Katrina (2005)
Actual number of outages		627	1,075	13,568	4,840	10,105
	μ_{outages}	0.0938	0.1609	2.0308	0.7244	1.5125
MAE_{GLM}	$0 \sim 1_{\text{outages}}$	1.3	0.14	1.7×10^{-7}	0.39	0.21
	$1 \sim 10_{\text{outages}}$	6.0	17.6	2.7	3.7	2.0
	$10 \sim 50_{\text{outages}}$	8.3	50.1	17.4	808.4	75.8
	$>50_{\text{outages}}$	–	–	72.2	–	57.3
MAE_{GAM}	$0 \sim 1_{\text{outages}}$	0.09	0.10	3.8×10^{-9}	0.38	0.08
	$1 \sim 10_{\text{outages}}$	1.8	1.4	2.7	2.0	2.1
	$10 \sim 50_{\text{outages}}$	5.4	13.8	17.4	10.6	15.9
	$>50_{\text{outages}}$	–	–	72.2	–	51.5

Table 4 Han et al. 2009; Mean absolute error (MAE) for GLM and GAM in five different hurricanes

Tree models like classification and regression trees (CART) and bayesian additive regression trees (BART) use regression trees to develop relationships between data (Wang et al. 2016). CART uses a single tree to develop a relationship between variables while BART models use many smaller trees together to develop a more in-depth relationship between variables (Guikema et al. 2010). To further optimize and increase predictive accuracy, Guikema et al. (2010) uses both GAM and GLMs used previously by Han et al. (2009) but also includes CART and BART in their analysis to compare which methods work best together. From these models, Guikema et al. (2010) calculated the mean square errors (MSE) using each different method and by averaging multiple methods, as seen in Table 5. From this table, the BART, BART/CART, and BART/CART/GAM average models have the lowest mean squared error values. The BART/CART and BART/CART/GAM average models also have statistically significant p-values, which make them the best choice for this data set used. This means that by using the averages of multiple statistical tree models, you can have the lowest amount of error and significant data to predict where power outages will be. When comparing their data to Han et al (2009) in Table 6, the use of geographic data, detailed pole damage, and tree modeling created consistently more accurate models at predicting damaged electrical poles after a hurricane.

Model	Mean MAE	*p*-Value: (2)	*p*-Value: (3)	*p*-Value: (4)	*p*-Value: (5)	*p*-Value: (6)	*p*-Value: (7)	*p*-Value: (8)
(1) BART	11.5	0.69	$\mathbf{1.01 \times 10^{-5}}$	$\mathbf{2.27 \times 10^{-4}}$	$\mathbf{2.82 \times 10^{-7}}$	$\mathbf{2.87 \times 10^{-5}}$	0.43	$\mathbf{5.68 \times 10^{-21}}$
(2) CART	11.7		$\mathbf{4.70 \times 10^{-6}}$	$\mathbf{1.39 \times 10^{-4}}$	$\mathbf{2.65 \times 10^{-9}}$	$\mathbf{3.03 \times 10^{-6}}$	0.52	$\mathbf{4.38 \times 10^{-25}}$
(3) GLM	21.4			$\mathbf{8.23 \times 10^{-5}}$	$\mathbf{6.17 \times 10^{-7}}$	$\mathbf{1.14 \times 10^{-6}}$	$\mathbf{8.46 \times 10^{-8}}$	0.46
(4) GAM	13.6				$\mathbf{6.01 \times 10^{-9}}$	$\mathbf{2.02 \times 10^{-11}}$	$\mathbf{5.08 \times 10^{-4}}$	$\mathbf{3.03 \times 10^{-15}}$
(5) BART \ CART	10.3					0.61	$\mathbf{1.23 \times 10^{-3}}$	$\mathbf{1.41 \times 10^{-27}}$
(6) BART \ CART \ GAM	10.4						3.40×10^{-3}	$\mathbf{2.58 \times 10^{-26}}$
(7) BART \ CART \ GAM \ GLM	12.0							$\mathbf{1.84 \times 10^{-19}}$
(8) Prediction by the Mean	20.0							

Note: Bold values are statistically significant comparisons at an overall 5% significance level for the family of simultaneous tests.

Table 5 Guikema et al 2010; Comparison of MAE based on detailed pole damage within 150 random holdout samples

	Ivan (2004)	Dennis (2005)	Katrina (2005)
Actual number of damaged poles (mean/grid cell)	2,364 (2.99)	144 (0.17)	834 (1.47)
Actual number of damaged transformers (mean/grid cell)	709 (0.90)	107 (0.13)	602 (1.06)
MAE, poles	243	148	64
MSE, poles	69,862	117,116	10,371
MAE, transformers	73	61	57
MSE, transformers	6,285	17,460	11,024

Table 6 Guikema et al 2010; Comparison of holdout MAE using GLM damage estimation models from Han et al. 2008

CART models are also good at comparing models with different variables to each other to determine if the addition or subtraction of variables has a significant effect on the predictive accuracy of the model. Quiring et al. (2011) used CART models to understand whether soil and topographic data increases the predictive accuracy. Based on the CART analysis, the MAE of the addition of soil data, which was between 0.370 and 1.750, did not significantly improve the predictive capacity of the original model with a MAE between 0.372 and 1.744. Based on their CART comparisons of the original model and the addition of topographic and elevation data, the MAE were both between .372 and 1.744 for both. This meant that the inclusion of topographic and elevation data did not improve the predictive power of the model. They also compared a CART model with reduced variables which gave an MAE between .224 and 1.760 when compared to the original models MAE between .372 and 1.744. Overall, this meant that the addition of topographic and soil data did not make a significant difference in the predictive accuracy of these CART models, but the reduced model containing a similar MAE as the original, could lead to optimizations of the CART model and less data needed to get accurate results.

Tonn et al. (2016) performed a quantile regression analysis and random forest modeling on Hurricane Isaac in Louisiana. They analyzed physical variables of wind, storm surge, and rainfall over time to understand the most important variables to focus on in future models. They performed quantile regression forests to estimate a conditional distribution of the data for 10 zip codes in Louisiana and concluded that there was little accuracy in smaller delta outages (0-2), fairly high accuracy at predicting mid-range (2-75) delta outages, and significant accuracy at predicting delta high outages (>75). From this analysis, they decided that because of the low accuracy of predicting delta outages less than 2, they only used data with delta outages greater than 1. This increased the reliability of the data by increasing the amount of data within the 80% confidence interval. After quantile regression forests, they performed a random forest model on key covariates on a zip code basis. Using the model, they were able to output variable importance and a partial dependence plot for the covariates. Variable importance is like correlation strength, the more important a variable is the higher the correlation shown by the variable.

A different type of model used by McRoberts et al. (2018) was the spatially generalized hurricane outage prediction model (SGHOPM). This model adds new variables and is split into 2 stages. The first stage of the model, binary classification (BC), uses random forest classification modeling to determine if there are outages or not. The second stage of this model, non-zero outage (NOZE), uses a random forest regression model to predict how many outages there are in spots where it has been predicted that there are outages. The model developed by McRoberts et al. 2018 uses topography, land cover, soil characteristics, soil moisture, wind speed, and precipitation. The model is compared to a similar SGHOPM by Guikema et al. (2010) that only used 3 variables (census tract population, maximum 3-sec wind gust, and duration of sustained winds exceeding 20 m/s). Compared to the baseline model, it can be seen in Figure 8 that McRoberts et al. 2018 model outperformed in over 71% of the census tracks and the mean accuracy increased by more than 25% within two-fifths of census tracts across all storms. Of the 994 census tracts 113 of them had no power outages. McRoberts et al. (2018) model correctly predicted 78 (70%) of them while the baseline model predicted 315,000 outages within those 78 tracts. This two-step model improved the accuracy of the original model by 17%, where 9% of that improvement came from implementing a 2-step process. The addition of the first step that recognizes and addresses the census blocks with zero power outages was critical to this method to get more accurate numbers of power outages.

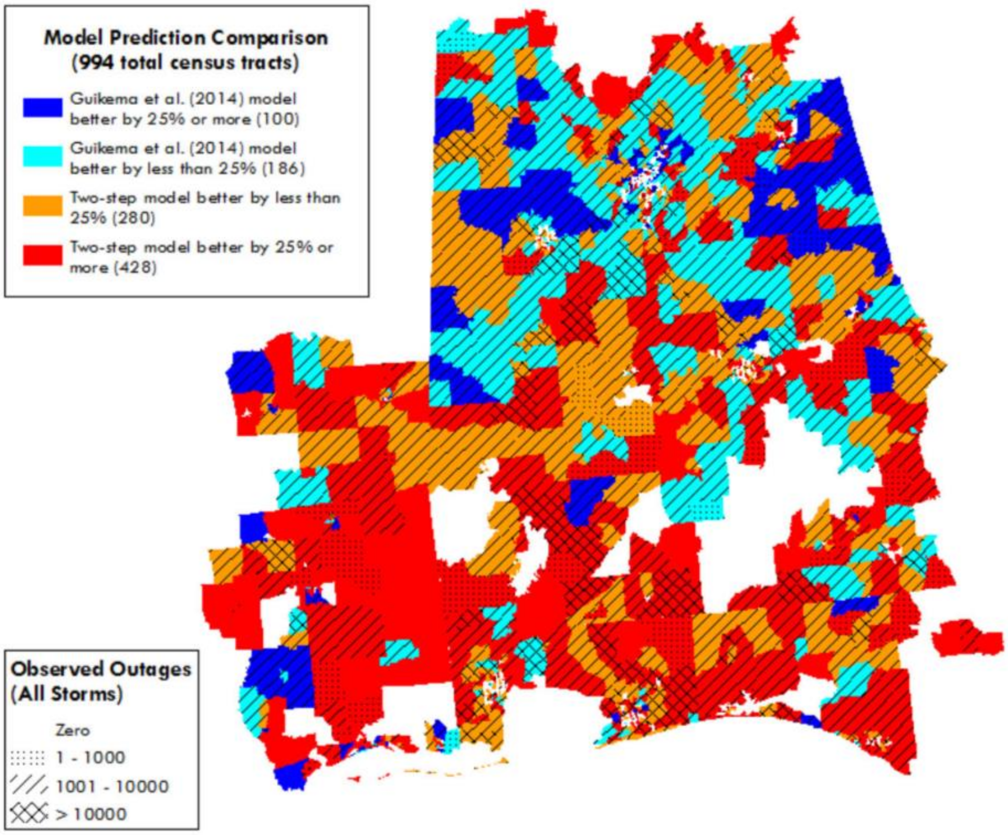

Figure 8 McRoberts et al. 2018; Comparison of model performance between McRoberts and Guikema et al. 2014 models

In the development of these models, much of the research goes about trying to evaluate if the addition of certain variables would be significant and beneficial if they were added to current forecast models used by electric utility companies. The response variable used in nearly all the papers was electric power outages experienced. The explanatory variables can be divided into two categories, static and dynamic. Static variables are ones that do not change over time. Examples of static variables used in the literature are previous outages, past damaged utility poles, soil characteristics of an area, and topographic data such as land cover and elevation. Dynamic variables change over time and are usually effects of the hurricane. Examples of dynamic variables used are wind data such as maximum wind speed and the duration of strong winds, precipitation, and storm surge.

Throughout the literature, some of the variables used and tested were found to be more significant than others. One of the most important variables found useful in predicting electrical outages after hurricanes was maximum wind speed. Maximum wind speed is the highest speed of the wind during the hurricane by hour. Tonn et al. (2016), Quiring et al. (2011), and McRoberts et al. (2018) all found maximum wind speed to be one of the most important variables in hurricane power outage predictions. Figure 9 modified from Tonn et al. (2016) shows the variable importance of each variable they tested which is measures the contribution of each variable to their accuracy in predicting power outages given the data set averaged over all random forest trees. From the figure, the variable importance of maximum wind speed is one of the highest for their data. Table 7 modified from Quiring et al. (2011) shows the percent variable importance for predicting power outages for all the variables that they tested, with maximum windspeed (WS) being first or second important for four of the five hurricanes they modeled at 100%, 94.8%, 89.7%, 87%, and 30.4% importance. Table 8 modified from McRoberts et al. (2018) shows the variable importance of maximum wind speed to be highest in both phases of their analysis at 100% importance.

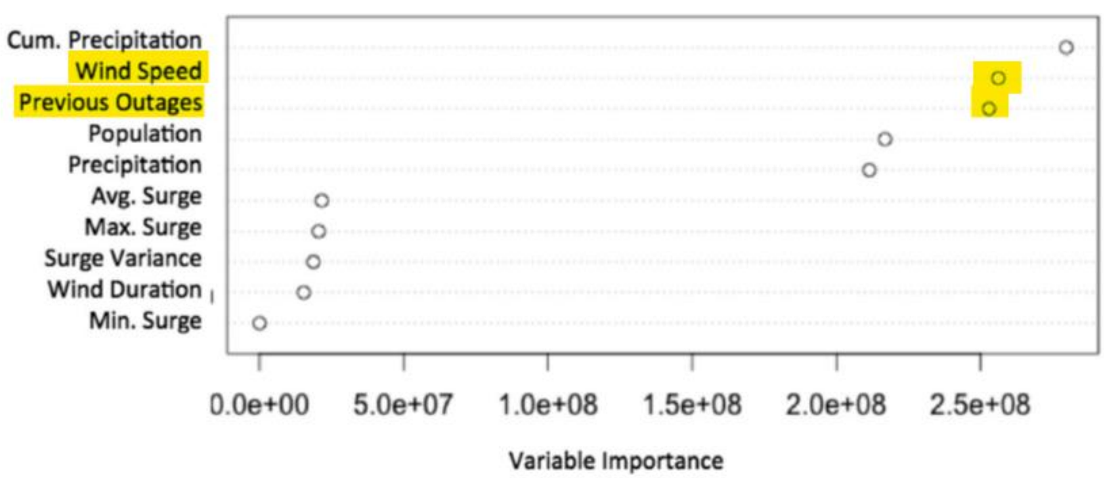

Figure 9 Modified from Tonn et al 2016; Variable importance of all variables

Rank	Danny	Dennis	Georges	Ivan	Katrina
1st	WS	WS	WS	TIME	DUR
	100.0	100.0	100.0	100.0	100.0
2nd	DUR	DUR	DUR	WS	WS
	89.7	94.8	87.0	50.1	98.3
3rd	COM	CAT	CAT	LC22	TIME
	71.2	88.9	58.3	47.8	94.5
4th	TIME	COM	COM	COM	COM
	65.2	50.8	56.9	41.1	78.2
5th	LC21	TIME	LC22	LC5	LC5
	44.8	48.7	55.3	37.4	76.9
6th	LC5	LC22	TIME	LC23	LC22
	39.8	45.2	44.1	31.5	70.9
7th	LC22	MAP	LC5	LC21	MAP
	37.9	37.0	43.8	30.5	48.9
8th	CAT	LC5	MAP	DUR	LC21
	34.5	34.9	37.8	30.4	44.4
9th	SURF	SURF	LC23	LC4	SURF
	31.5	33.6	31.3	23.9	32.5
10th	LC23	LC23	LC21	LC8	LC23
	28.1	24.9	28.8	13.6	31.3

Table 7 Modified from Quiring et al 2011; Percent variable importance for all variables in reduced model; DUR duration of strong winds; WS maximum wind speed

Table VI. Variable Importance in the BC Model, Originally Measured as the Decrease in the Gini Index (g)

Rank	Type	Variable	VI
1	Baseline	Max wind speed	100.00
2	Tree	Average wood density	89.63
3	Baseline	Strong winds duration	87.19
4	Elevation	Mean elevation	85.77
5	Elevation	Max elevation	76.54
6	Elevation	Median elevation	71.91
7	Tree	Average crushing strength	59.14
8	Elevation	Min elevation	57.99
9	Land cover	Wetlands land cover	55.14
10	Tree	Percentage taproot	51.66
11	Baseline	Population density	47.85
12	Tree	Percentage deep	44.85
13	Elevation	Elevation stdev	42.04
14	Land cover	Developed land cover	41.83
15	Tree	Average max tree height	39.09
16	Land cover	Scrub land cover	37.78
17	Tree	Average Janka hardness	36.99
18	Land cover	Barren land cover	31.23
19	Land cover	Pasture land cover	30.28
20	Land cover	Forest land cover	29.15
21	Tree	Average maximum DBH	28.26
22	Tree	Grassland land cover	26.84
23	Root zone depth	Root zone mean depth	26.70
24	Land cover	Water land cover	25.98
25	Tree	Percentage treed	24.61
26	Root zone depth	Root zone majority depth	1.10

Table VII. Variable Importance in the NOZE Model, Originally Measured as the Residual Sum of Squares

Rank	Type	Variable	VI
1	Baseline	Max wind speed	100.00
2	Baseline	Strong winds duration	87.45
3	SPI	SPI12	70.16
4	Baseline	Population density	41.05
5	Soil moisture	Soil CDF 2	38.54
6	Soil moisture	Soil CDF 1	38.42
7	SPI	SPI3	37.75
8	SPI	SPI24	35.69
9	SPI	SPI6	33.33
10	Tree	Average wood density	33.01
11	Soil moisture	Soil CDF 3	30.38
12	SPI	SPI1	30.32
13	Land cover	Wetlands land cover	28.69
14	Elevation	Max elevation	27.63
15	Tree	Percentage deep	26.83
16	Tree	Percentage taproot	26.83
17	Root zone depth	Root zone mean depth	26.58
18	Tree	Average Janka hardness	26.20
19	Tree	Average max tree height	25.73
20	Land cover	Forest land cover	24.52
21	Tree	Percentage treed	23.64
22	Land cover	Grassland land cover	22.89
23	Elevation	Median elevation	22.19
24	Tree	Average crushing strength	22.14
25	Tree	Average maximum DBH	6.76

Table 8 Modified from McRoberts et al 2018; a) Variable importance in the BC model b) Variable importance in NOZE model

Another important variable found was the duration of strong winds (winds > 20m/s). Quiring et al. (2011) and McRoberts et al. (2018) found it to be among the most important. Table 7 by Quiring et al. (2011) show duration of strong winds (DUR) as first and second highest percent variable importance for four out of five of their case studies. Similar results can be found in Table 8 by McRoberts et al. 2018 with it being the third and second highest variable importance in their models at predicting whether there will be power outages and how many outages there are.

Another important variable found was damaged utility poles and previous power outages. This data is not as often recorded on a highly accurate scale by all utility companies but Guikema et al. (2010) and Tonn et al. (2016) had found reliable accurate data for previous power outages and damaged utility poles and found them to be important. Tables 5 and 6 (Guikema et al. 2010) shows the difference in predictive accuracy of Han et al. (2008) model compared to Guikema et al. (2010). The MAE for the mean number of electrical poles damaged per grid cell is much higher in Han et al. (2008) GML based estimation model with 243 electrical poles for Hurricane Ivan, 148 electrical poles for Hurricane Dennis, and 64 electrical poles for Hurricane Katrina. respectively. The MAE for all methods used by Guikema et al. (2010) is between 10 and 21.4, which is significantly less error. Figure 9 by Tonn et al. (2016) shows the variable importance of previous power outages being among the top three important variables in predicting electrical power outages after a hurricane in their sample data.

Davidson et al. (2003) and McRoberts et al. (2018) included data about trees and tree density within the scope of their study areas and found it to be among the topmost important variables. Table 8 (McRoberts et al. 2018) shows tree density being the second most important variable in their BC model in determining whether there will be a power outage after a hurricane and tenth most important in determining how many power outages there will be. McRoberts et al. (2018) found that an average wood density greater than 650 kg/m^3 predicted outage increases, most notably because the loblolly pine in the study area had a density of 570 kg/m^3 and is more susceptible to being uprooted and knocking power lines and utility poles down. Table 9 by Davidson et al. (2003) shows that from their statistical analysis, between 42% and 61% of power outages in the Carolinas for these three storms in this specific area was related to trees and danger trees (large trees further than 15 feet from the power line that must be uprooted to cause damage).

Cause/Hurricane	Opal (%)	Fran (%)	Floyd (%)
Trees	36.3	18.8	50.6
Danger trees	5.7	42.3	7.1
Other/unknown	58.0	38.9	42.3

Table 9 Davidson et al. 2003; Percentage of power outages by external cause for 3 hurricanes in the Carolinas

Though there were many important variables, there were also some that were found to not be beneficial to add to forecast models. These variables include storm surge, soil properties, and topographic data. Tonn et al. (2016) found that all variables they used that had relation to storm surge were not significant as shown in Figure 9 with them being four of the five lowest scoring in terms of variable importance. Their explanation for this low variable importance was that a low portion of the state of Louisiana experienced storm surge as a result of Hurricane

Isaac, thus for their data set and hurricane it was of little importance. The main purpose of Quiring et al. (2011) study was to determine if the addition of 37 soil factors and topographic data would increase the predictive accuracy of hurricane power outage modeling. They concluded that even with the addition of the soil and topographic data, there was no significant difference between their model that included these variables and the models that did not. McRoberts et al. (2018) added topographic data including root depth, soil moisture, and tree characteristics and found that they had little variable importance for estimating power outages after hurricanes in their testing.

5. Conclusions and Recommendations

5.1 Future Direction of Research

Future directions of this work include using this research in practice with an electric utility company and working with weather stations for data. It is easy to use statistics and previous data to show that a model is viable and better than a previous model, but without testing these models and variables viability with in the moment data, it would be difficult to implement as it needs to undergo a strenuous process of checks and balances before it is approved and solely used. The first issue it would have to overcome is making sure that the method could work accurately with only a couple days lead time rather than months. The best method to test if the method and variables would work in a real-world scenario would be to work alongside an electric utility company operator during hurricane season to run the hypothetical model alongside the ones currently used by the utility. By doing this, the model can be tested to its full extent for practicality without worrying of it not working and further putting liability on the electric utility. If the model did prove to work as well or better than the one used by the utility, the model would have to be set up in a system that is simple to plug in variables to get responses without having to mess around with the data, including sources of weather data instantaneously. To acquire reliable sources of weather data including maximum forecasted wind speed, forecasted durations of winds, and cumulative forecasted precipitation, the utility company would have to find and acquire datasets from local and reliable weather sources and fit them to the specific model. Performing a real-world scenario like that would truly validate or invalidate whether a combination of models and variables is proven effective for an electric utility plant to invest in implementing it.

Another direction for this research to take in the future is on hardening the electric distribution grid by reducing load shedding needed and researching utility-poles with new policies. The past research by Yuan et al. (2016) shows that depending on the budget spent to harden the grid, it is possible to reduce the load shedding required after a hurricane. To achieve this goal of reducing load shedding by investing in hardening the grid, electric utility companies would have to perform cost benefit analyses on their service area to find out how much grid hardening would be worthwhile to invest in. To better protect distribution poles, studies and tests have to be performed to find the strongest cost effective pole materials to reduce the number of distribution power outages due to hurricanes. Tests would have to be conducted for utility poles on different setbacks distances of trees, types of woods structures, types of grounding structures.

5.2 Recommendations

From this research, it is necessary to implement changes or start to change how things are done in the energy sector with regards to hurricane preparedness and response. Electric utility companies can attack this issue in more than one way. The first way is by hardening the grid and protecting the distribution system already in place. This involves taking accurate pole by pole data after a hurricane on which poles needed repair and figuring out if there was a flaw in the pole or the area it is in is a high hurricane risk area which needs extra reinforcement for future storms. With taking accurate data and assessing problems from previous storms, the utility company should also perform more periodic inspections of their electric distribution poles. They should look at poles to check if they are splintering, leaning, being uprooted, or have fundamental flaws that if fixed will prevent power outages due to that specific pole. With taking more data, it is also important to implement new hardening technology such as distributed generation resources and sectionalized microgrids to reduce load shed after hurricanes. To implement this new technology, electric utility companies will need to perform separate cost benefit analysis for technology that is feasible for their location.

After hardening the grid to prepare for hurricanes, electric utility companies need to reassess their current methods of hurricane forecasting by implementing different models and variables that will provide more accurate predictions. Variables that have shown increased accuracy in power outage predictions have been estimated maximum wind speeds, duration of high wind speeds, cumulative precipitation, and areas that previously had outages. To use this data, the electric utility companies need to use accurate weather prediction models from local weather stations. They also need to take accurate data after a hurricane to better help with predicting the outcome of a future hurricane. With these variables, electric utility companies should also investigate using different models than the currently do. New models will bring more accurate results on where and how many people to deploy to repair the distribution system after a hurricane. The best method of implementing new models would be to develop a combination model using a data fitting model such as GAM and a tree model such BART to take advantage of looking at the situation through multiple angles.

If these recommendations are followed, electric utility companies will see a reduction in power outages after a hurricane within their service area and be better equipped to combat outages. This will result in a reduction of deaths and financial loss for the service area of the utility company. It will also save the electric utility companies and taxpayers money allowing resources to be spent on medical attention, debris cleanup, and construction shortly after the hurricane has stopped.

6. References

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