Simulation Methods to Assess Long-Term Hurricane Impacts to U.S. Power Systems

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Abstract: Hurricanes have been the cause of extensive damage to infrastructure, massive financial losses, and displaced communities in many regions of the United States throughout history. The electric power distribution system is particularly vulnerable; power outages and related damages have to be repaired quickly, forcing utility companies to spend significant amounts of time and resources during and after each storm. Being able to anticipate outcomes with some degree of certainty allows for those affected to plan ahead, thus minimizing potential losses. This is true for both very short and very long time scales. In the context of hurricanes, utility companies try to correctly anticipate power outages and bring in the repair crews necessary to quickly and efficiently restore power to their customers. A similar type of planning can be applied to a long time horizon when making decisions on investments to improve grid reliability, resilience, and robustness. We present a methodology for assessing long-term risks to the power system while also incorporating possible changes in storm behavior as a result of climate change. We describe our simulation methodology and demonstrate the assessments for regions lying along the Gulf and Atlantic Coasts of the United States.

Keywords: Hurricane impact, Simulation, Power outages, Climate change.

1. INTRODUCTION

Tropical cyclones, and hurricanes in particular, have historically been some of the most destructive natural hazards for coastal areas [1, 2, 3]. Power outages caused by tropical cyclones are usually one of the biggest concerns as a storm approaches a region; widespread or long-lasting power outages can result in huge financial losses and health impacts. Utility companies are responsible for maintaining the electricity distribution system, and they are greatly concerned with the reliability of power for their customers and service area. Power outages have to be dealt with quickly, and this often comes at great expense to the utilities in the aftermath of a storm. Anticipating power outages in advance can help minimize these costs by ensuring that crews and equipment are available and sufficient. Any information that can assist in planning for oncoming storms is highly valued by utilities.

There is recent research into developing power-outage prediction models, and they have proven to be remarkably useful for local utility companies [4, 5, 6, 7, 8, 9]. This research addresses the problem of planning for tropical cyclones at a very short time scale: on the order of days as a storm is approaching. Planning for storms on a longer time scale is also critically important, but this problem presents very different challenges. A stronger, more robust power grid would better withstand strong winds from hurricanes and would suffer fewer power outages during a storm. Long-term planning raises questions regarding new investments in stronger utility poles or moving power lines underground, for example. These investments are potentially very costly and decision-makers want to ensure that they have the best available information in order to make appropriate decisions. The measured historical hurricane

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record is relatively short by long-term planning standards. New investments in infrastructure should be designed to withstand strong storms. The question of ”how strong?” is coupled with uncertainty about what future storms may look like. Analysis based on the historical tropical cyclone record is useful if the future climate remains stationary, but this technique can fail when the historical record is not long enough, since it doesn’t necessarily represent the full range of possible outcomes. Such is the case when planning for hurricanes.

To mitigate this issue, we present a simulation methodology that can be used to assess the expected impact of hurricanes on power systems in the United States. We simulate a large number of replications of hurricane seasons in order to assess the overall expectations of impacts in various regions of the coastal states. The simulation methodology can also be used to assess the potential for a future affected by climate change. The average behavior of tropical cyclones is expected to change as the climate warms, and these changes can be modeled to generate a range of possible impacts from hurricanes in a changing climate. We apply this methodology to the U.S. power system along the Gulf and Atlantic Coasts and present preliminary results of the capabilities of the model to assess local and regional changes in hurricane impacts.

By simulating a large number of virtual storms, we can assess the resulting impacts from tropical cyclones under a variety of climate assumptions. The baseline case assumes a static climate and uses static population data. This represents the current state of things, assuming that the observed storm behavior represents the natural variability in the climate and tropical cyclone behavior. We also simulate scenarios with stronger or weaker storms, scenarios with a higher or lower average annual frequency of storms, and scenarios in which the average distribution of where storms make landfall is shifted.

2. BACKGROUND

Planning for infrastructure investments involves an assessment of the conditions in which the system will operate. Many infrastructure systems have operating lives on the order of multiple decades, and accurately assessing conditions that far in the future is challenging. There is a high degree of uncertainty, and many forecast techniques make assumptions based on projections of the current conditions. Planning for tropical cyclones is especially challenging for two reasons: (1) our knowledge of the current conditions is based on a very limited history and (2) the uncertainty is compounded by the possible effects of climate change, which could change storm behavior significantly. Accurate recordings of hurricane activity are fairly recent. Prior to the 1960’s, there was not a lot of reliable scientific data on tropical storm behavior. Even with the older observations, the record is relatively short for tasks such as estimating the 100-year storm.

In addition to the limited data, planning for the future brings the challenge of unknown conditions. As the climate changes and warms, it is speculated that tropical cyclone behavior will also change. The relationship between tropical cyclones and climate has been studied extensively as researchers attempt to make projections about what future tropical cyclone seasons may look like around the world. However, there is still a great deal of uncertainty behind the results [2, 10, 11, 12, 13, 14, 15, 16]. Different models produce different projections, and different climate projections offer a variety of possible outcomes. For example, the results of the physics-based models developed by Knutson et al. suggest that the frequency of Atlantic hurricanes and tropical storms will likely be reduced in the future [13]. Results obtained by downscaling IPCC AR4 simulations also suggest a reduction in the global frequency of hurricanes in a warmer future climate scenario, with a potentially large increase in intensity in some locations [10]. Some statistical models developed suggest that the intensity and frequency of tropical cyclones will likely increase with a warmer future climate[17, 18].

The inherent uncertainty in future climate projections is coupled with uncertainty in the relationship between climate and tropical cyclones, especially since the relationship may vary in different regions of the world. Many traditional risk and decision analysis methods break down under such deep uncertainty [19]. Instead, for problems with such wide-reaching uncertainty, more robust planning tools are needed to deal with uncertainties that are changing with time. Without a strong understanding of the nature of the uncertainty, planning for the most likely scenario should be replaced with planning for short-term actions that perform well under a range of possible scenarios and that can be modified over time as conditions change and new information comes to light [20]. Long-term planning for major infrastructure projects, such as updates to the electric grid, should use scenarios to assess the robustness of possible actions and not as parameters to determine an optimal solution.

3. METHDOLOGY

Our simulation uses historical hurricane data dating back to 1900 gathered from the National Hurricane Center as the main input [21]. In addition, we use a wind-field simulation model and a power outage prediction model to assess the long-term impact of hurricane damage to the power grid. To explain the methods used, we first describe how virtual storms are created in the baseline case, in which future storms are assumed to resemble past storms. Next, we describe how scenarios influenced by potential climate change are incorporated into the simulations.

3.1. Baseline Simulation

For the baseline case, the simulation uses historical hurricane and tropical storm data as initial inputs. For each independent replication, we first randomly sample from a Poisson distribution to determine the number of storms that make landfall in the U.S. in that replicated year. The mean of the Poisson distribution represents the average number of tropical cyclones that make landfall each year, and this value is set equal to the historical mean as calculated from the measured storm record. Within each replication, each storm is treated independently. For each storm, we randomly sample a landfall location from a smoothed probability distribution that assigns a probability to each 50 km stretch of coastline from Texas through Maine. The historical record was smoothed so that each segment of coast had a non-zero probability of a storm making landfall. The smoothing was done to maintain the general shape of the distribution. From there we generate the path that the storm travels along, or the track. Again, we use historical hurricane tracks as a starting point, but simply sampling from past storm movement would severely limit the options of storm movement and would bias the simulation results. Instead, we use a simple statistical model to generate realistic track movement. Based on which section of the coastline the storm hits, we subset the historical tracks, keeping only those that made landfall in the same region. These remaining tracks are then used to train a random forest model, which predicts the x- and y-direction movement based on the previous direction of travel and previous location for each six-hour time step.

Concurrently with sampling a landfall location for each storm, we randomly sample a maximum wind speed. This represents the wind speed when the storm makes landfall, and the values are drawn from the maximum landfall wind speeds from the historical record. For each time step associated with the track movement, the wind speed decays according to the hurricane decay models of Kaplan and Demaria until the wind speeds fall below the tropical cyclone classification level [22].

Once the storm track and intensity for each point along the track are determined, these parameters are fed into a wind field model that generates the wind parameters for the entire storm as it moves along its track. For all areas within range of the storm, we estimate the maximum 3-second gust wind speed and the duration of wind speeds above 20 m/s for the centroid of each census tract. This wind field model is based on that developed by Huang *et al.* and used in Han *et al.* [1, 8, 9]. This wind data is then passed to a statistical outage prediction model, which uses a random forest model to predict the number of customers without power as a result of wind-induced power outages. This model has been trained and validated on past hurricanes in different areas of the U.S. It estimates outages from strong winds, but we do not account for outages caused by storm surge or flooding, so the estimates would be conservative for areas that are particularly prone to flooding, for example.

The outage predictions are compiled for each storm in each replication. We run the simulation for a large number of replications until we reach convergence. We run 1600 replications in order to achieve a 99% confidence on at least the 96th percentile according to the method proposed by Morgan and Henrion [23]. The aggregated results from 1600 simulated years worth of tropical cyclones allow us to calculate expected return periods for the output values. We calculate the 100-year, 50-year, 25-year, and 4-year, and 2-year return periods for maximum wind speed, duration of winds above 20 m/s, and the fraction (and number) of customers without power for each census tract. We also calculate the probability of each census tract having at least 5% of customers losing power in a given year.

3.2. Alternate Storm Scenarios

The simulation can also be used to assess the impacts and changes in impacts if the tropical cyclone behavior changes. Planning for a future with climate change, for example, will necessitate assessments of what the impacts could be if the warmer climate affects tropical cyclones. As mentioned in section refsec:background, climate change could affect the behavior of tropical cyclones in the North Atlantic Basin. Our simulation methodology can be modified to study these potential effects in terms of storm intensity, frequency, and location. We demonstrate this by selecting plausible scenarios in which we vary intensity, frequency, and location and running the simulation for each scenario. An overview of the methodology is shown in Figure 1.

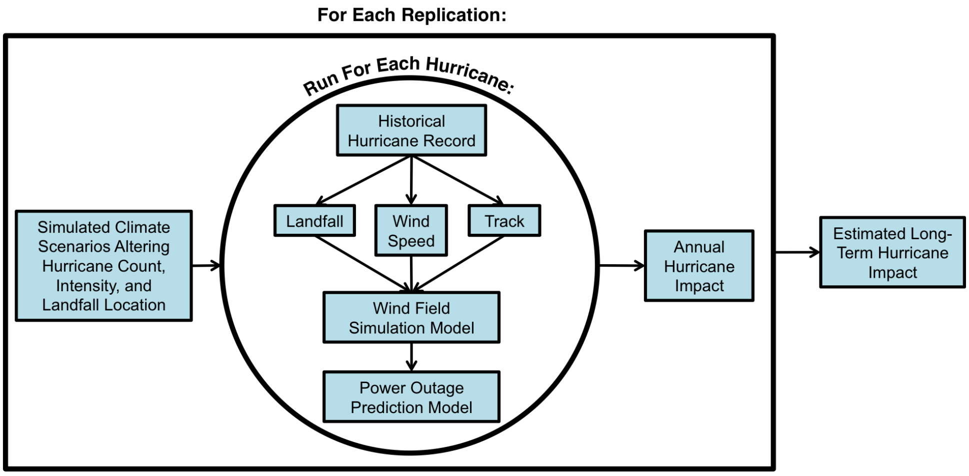
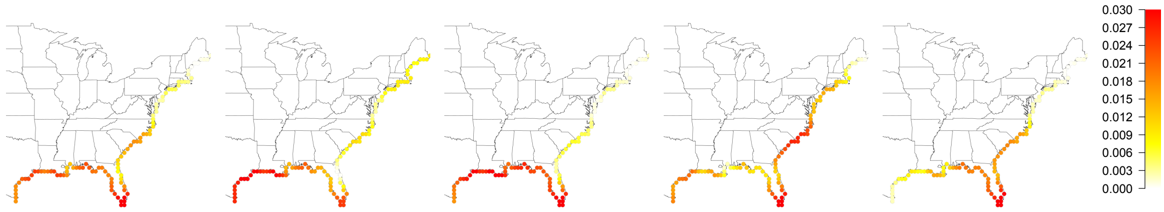


Figure 1: Schematic of the simulation methodology.

Running the simulation under these various scenarios requires very simple modifications. Each factor is varied individually within the simulation, and the overall structure is the same as that described for the baseline case above. We vary intensity by taking the randomly sampled maximum wind speed for each storm and multiplying it by a factor. We simulate scenarios for intensity factors of 0.8, 1.2, and 1.4, meaning a decrease in strength of 20%, an increase of 20%, and an increase of 40%. The results of these simulation runs show possible range of impacts for the intensity changes modeled. For scenarios of varying frequency, we adjust the mean of the Poisson distribution that is used to sample the number of storms in each replicated year. The baseline case has a mean of 2, and we simulate scenarios for means of 0.5, 1, 3, and 4. If there is a reduction or increase in the number of storms, the simulation can produce estimates for the expected impacts in each case.

The location scenarios are more subjective; starting from the smoothed baseline distribution, we adjust the probabilities for each 50-km segment of coastline. Each new distribution still retains the general shape of the baseline distribution, since it is based on actual geographical characteristics, but the individual probabilities are shifted. For example, some land areas are simply more prone to landfalling hurricanes because they jut out into the path of oncoming storms. We created four modified distributions to assess the changing impacts as storm genesis location may change. The first scenario shifts storms further up along the mid-Atlantic coast, the second shifts them further down into the Gulf of Mexico, the third spreads the distribution out more evenly to reduce the natural peak around Florida, and the fourth concentrates the peak around Florida, thereby reducing the probabilities in the Gulf and in the Northeast. The distributions are plotted along the coastline in figure 2.



(a) Baseline (b) (c) (d) (e)

Figure 2: Demonstrating the probability distributions used for shifting the landfall location of tropical cyclones. The distribution is shifted towards the mid-Atlantic in 2(b), towards the Gulf of Mexico in 2(c), spread more evenly along the coastline in 2(d), and concentrated on the Florida peninsula in 2(e).

For each scenario, we again ran the simulation for 1600 replications in order to reach convergence. From these results, we calculate the same wind speed and power outage parameters discussed previously. The scenario runs offer insight into the expected range of changes that could be brought on by climate change and its influences on tropical cyclones. For each scenario, the results from 1600 replicated years of hurricane seasons allows us to calculate the expected impacts in terms of wind speeds and power outages for all of the affected regions. These parameters portray the potential climate change impacts on both a large and small spatial scale.

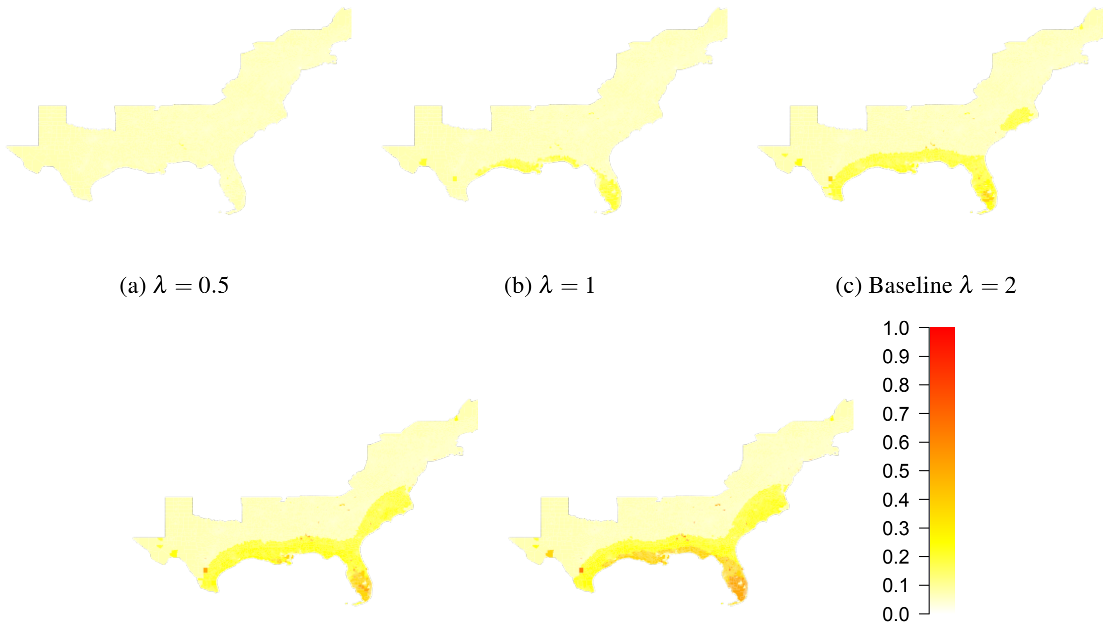
4. RESULTS

We applied this simulation methodology to hurricane-prone states in the U.S. along the Gulf and Atlantic coasts. We use all coastal states and some states stretching inland if they lay within potential hurricane impact areas. The baseline case models the impact for the current state of both meteorological and geographical conditions. Although we replicate 1600 virtual years of hurricane activity, these years do not represent any sort of future time period. The replications all use current conditions, and so the aggregation of this large number of replications represents the average impact for the current state of hurricane activity in the United States, subject to the assumptions and simplifications incorporated into the model. We use 2010 population numbers for all census tracts and assume that the electric grid is the same as its current state. For these reasons, our results offer useful insight into plausible impact scenarios, but they do not necessarily represent future impacts because we do not take into account possible infrastructure upgrades or population changes. This is a major assumption, but it allows us to simply demonstrate the simulation methodology and the capabilities of modeling changes in storm impacts. For example, we can look at the changes in wind speeds if the intensity of tropical storms changes in the North Atlantic Basin. Figure 3 plots the expected 50-year wind speed for the baseline case as well as scenarios with the average storm intensity is adjusted by a factor of 0.8, 1.2, or 1.4.

(a) Intensity Factor 0.8 (b) Baseline (c) Intensity Factor 1.2 (d) Intensity Factor 1.4

Figure 3: 50-year wind speed [m/s] for scenarios of varying tropical cyclone intensity.

Similarly, we can look at the expected impact for a different measure under different scenarios. Figure 4 plots the expected probability of each census tract having at least 5% of its customers losing power in a given year. This value is plotted for scenarios of varying storm frequency. We vary this by adjusting λ, the mean of the Poisson distribution that is used to sample the number of storms in each replication. The baseline value from the historical record is $\lambda = 2$, and we model scenarios for $\lambda = 0.5, 1, 3$, and 4 to assess the impacts from changes in tropical cyclone frequency.



(a) $\lambda = 0.5$ (b) $\lambda = 1$ (c) Baseline $\lambda = 2$

(d) $\lambda = 3$ (e) $\lambda = 4$

Figure 4: Annual probability of at least 5% of customers without power for scenarios of varying tropical cyclone frequency.

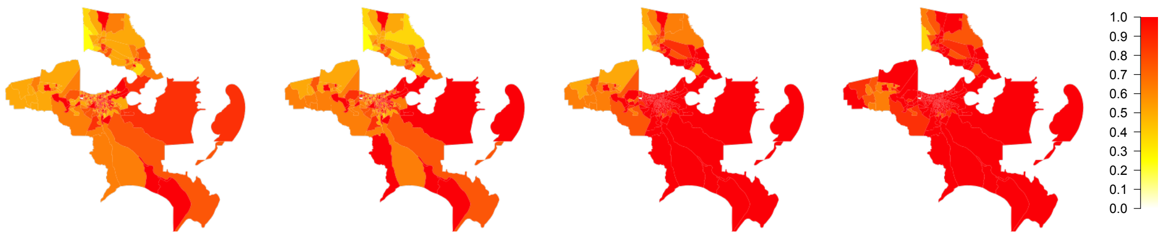
4.1. Local Impacts

One of the biggest advantages of this simulation methodology is the ability to look at local-area effects. We use census tracts as our area of analysis, and this allows us to study changes on a small scale. This is especially useful for agencies that are responsible for decisions regarding their own, often small, local area of influence. Utility companies, for example, are responsible for the poles and lines that make up the distribution system in the region that they serve. Any decisions that they make about strengthening the grid should be based on projections of conditions in their service area and not for the country as a whole.

To demonstrate this, we take a closer look at several metropolitan areas. Based on the scenarios that we selected, we can assess the impacts in terms of wind speeds and customers without power for scenarios of changing intensity, frequency, or location. For example, in figures 5 and 6 we plot the 100-year fraction of customers without power for the New York, NY and New Orleans, LA metropolitan areas as the average storm intensity varies.

(a) Intensity Factor 0.8 (b) Baseline (c) Intensity Factor 1.2 (d) Intensity Factor 1.4

Figure 5: 100-Year fraction of customers without power for the New York, NY metropolitan area for scenarios of varying storm intensity.



(a) Intensity Factor 0.8 (b) Baseline (c) Intensity Factor 1.2 (d) Intensity Factor 1.4

Figure 6: 100-Year fraction of customers without power for the New Orleans, LA metropolitan area for scenarios of varying storm intensity.

Some regions of the country are more affected by certain scenarios that were evaluated here. Overall, a large increase in storm intensity will cause the greatest changes in the number of people losing power. However, the strongest effects will be felt primarily in coastal areas where the wind speeds will be highest. Some inland areas may be more concerned with an increase in storm frequency, which will result in a greater chance of suffering power outages (although the overall number of customers out may be lower.) A shift in landfall location could change the expected impacts significantly in some regions, i.e. any region whose local probability of landfall shifts from low to high. While the impacts can be analyzed locally, it is also important to understand that different areas of the country may be more or less severely impacted depending on the climate-influenced scenario being assessed.

5. CONCLUSION

The simulation methodology presented here can serve as a tool for understanding the consequences of possible scenarios. This type of analysis is useful for quantifying the effects of the scenarios that may be used as part of a long-term planning process. To start, one can gain a deeper understanding of the potential impact of the current state of tropical cyclones and their impact on the United States. Looking at the big picture, the recorded hurricane record is very limited. Planning for future hurricanes based on the historical record alone would leave big gaps in terms of possible impacts and impacted regions. Decision-makers, such as utility companies, may be planning for upgrades to their local distribution grid to better withstand hurricanes. They need to incorporate information on the expected impact over the lifetime of the system. The wind-speed data produced as outputs from the simulation model will be critical in such planning decisions. Beyond this, our simulation allows for input conditions to be modified in order to model any possible changes to parameters including the meteorology as a result of climate change or population growth. While we demonstrated some plausible scenarios in which tropical cyclones are affected by climate change, this methodology is more general. It can be used for analyzing a large range of changing input conditions in terms of storm behavior. It can also be coupled with projections of population growth in the United States to study potential impacts as populations grow or change within each census tract. This tool can provide valuable assistance to decision-makers faced with long-term decisions about power system investments and upgrades.

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