Impacts of Weather on Electricity Reliability : A case study for MA

Abstract

With rapid urbanization, there is an increase in demand for energy which resulted in greenhouse gas emissions and extreme weather changes. Electrical outages have a negative impact on the population's economic well-being. This project presents the scientific relationship between Massachusetts outages related to weather using the regression analysis and measures the electricity impacts using the System Average Interruption Duration Index(SAIDI). The data is collected from public sources, which are freely available. This study visualizes the major reasons for outages and proves that the SAIDI and weather related variables are statistically significant, while helping the policymaker think through the policy implemented so far.

Keywords: Weather; Climate; Impacts; Power outages.

1. Introduction

With the shift in population to urban areas, there is rapid urbanization, increasing demand for energy individuals cannot anticipate climate change, greenhouse gas emissions, and decarbonization [1]. From the deadly floods in Pakistan and severe ongoing droughts in the horn of Africa to wildfires worldwide, climate change has become a global phenomenon. The severe impacts of climate change increased the stress on urban areas. The most concerning impacts are those that have significant repercussions, such as Hurricane Ike (2008) and Superstorm Sandy (2012) [2,3]. Supporting climate action plans and achieving more sustainable cities became one of the critical concerns in today's work.

Electrical outages have a significant negative effect on daily living and can have a negative impact on a population's economic well-being as well. According to researchers, the annual direct cost of electrical outages across the US ranges from 5 to 75 billion dollars. Though indirect cost is difficult to predict it is estimated that US economic production reduces by 1% because of electricity outages[4].

According to Commonwealth's climate, there is a warming trend in Weather conditions affecting snow or rainfall [5]. The typical risks of Massachusetts(MA) state include heat, storms, etc[6]. There are constant efforts from researchers to understand the electricity reliability impacts measures [7]. There are also weather-related impacts on power outage studies [8], they used Pearson correlation coefficients to understand the relationship between weather events and the number of outages. The case study on Hurricane Harvey, a category 4 hurricane mentioned in the paper[8], found the correlation coefficient of outages and weather conditions in Harris and Nueces County to understand the features' relation.

This paper will seek to identify major reasons for power outage in Massachusetts from 2019 to 2021. Then identify if the weather related variables are statistically significant to System Average Interruption Duration Index (SAIDI) [9], a common measure for the duration of power outages using ordinary least square model [10,12,14]. Finally to spatially visualize where is the major cluster of top 20 towns affected in MA. What we want to achieve from this study is to present the scientific method of MA outages related to weather. So that the energy sector and customers are aware of the weather-related impacts during this climate change. This can also help the policymakers to reflect on the already established plan if there is any increase or decrease in outages due to weather.

2. Data:

2.1 Data collection:

MA OUTAGE DATA:

Historical MA outage data by MA Office of Energy and Environmental Affairs from Unitil, National Grid, and Eversource companies which are the major power source utilities in MA from 2019 to 2021. The data include the city or town where the outage occurred, the number of customers affected, outage duration, the time the outage occurred, and reasons for the outage. The data can be found here :

https://www.mass.gov/info-details/power-outages#historic-power-outages-

WEATHER DATA :

We can get weather data from the National Centers for Environmental Information, which has daily summaries of data, and observations provided by the World Meteorological Organization, Cooperative, and CoCoRaHS networks. The dataset is downloaded from years 2019 to 2021 and features includes latitude, longitude, station, max and minimum temperatures, total precipitation, snowfall, and average wind speed, 2 min fastest wind speed(all units in standard metric units). Observed that only 19 stations have data recoded those can be seen in Fig 1.

The data can be found here :

https://www.ncdc.noaa.gov/cdo-web/search?datasetid=GHCND

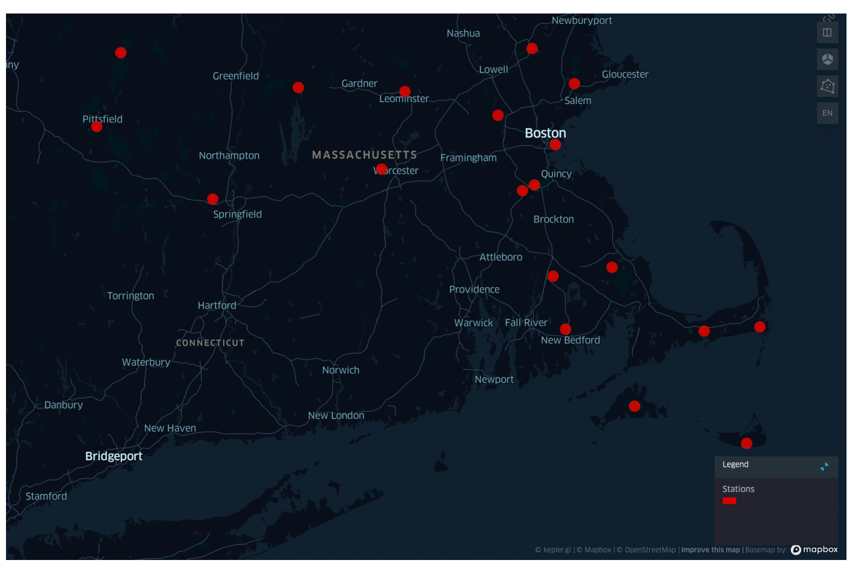

Fig 1 : Weather Stations

2.2 Data cleaning :

We have used spatial join in ArcGIS pro to find the outage towns located nearest to weather stations and also merged MA census tract data available from living atlas of ArcGIS Pro to get total population of town. Then merged weather and outage data in Python and granularity of data is town. Checked the weather variables for normality using probability density function[12] and QQ plots[13]. Few variables are shown in Fig 2,3 and all remaining variables are added as supplementary figures.

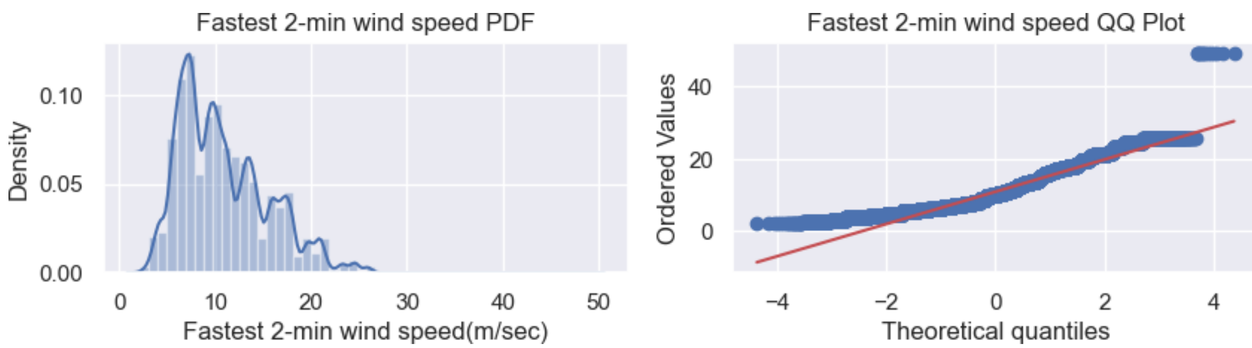

Fig 2: Normality curve for Fastest 2-min Wind Speed

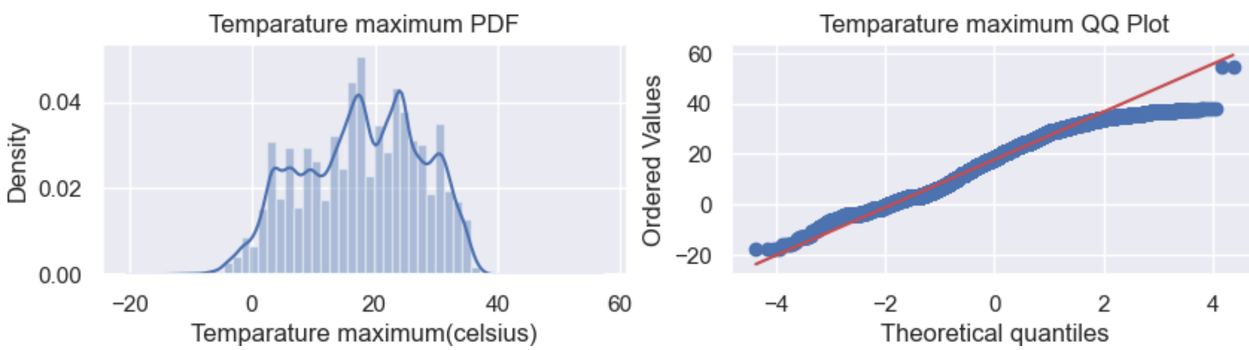

Fig 3: Normality curve for Temperature maximum

The outage data collected seems imbalanced with respect to years. 2020 we have higher percentages of outages nearly 53.5% compared to the 2019 and 2021 which are 27.5% and 19% respectively. Since I am using visualization to know the major reasons for outages and normalizing the outage reliability parameter with respect to population this data limitation can be ignored.

3. Methodology:

3.1. Metrics for Reliability:

A variety of indices for measuring electricity reliability are described in the IEEE 1366 standard [9]. Some metrics measure the duration of outages while others measure the frequency of outages. In this section, we go through metrics that utilities use to measure the impact of electricity outages. If the outage duration is given by S and customers affected given by C the total number of customers served is given by N then the System Average Interruption Duration Index (SAIDI) is given by :

$$SAIDI = S*C / N$$

3.2. Weather-outage analysis:

To determine the correlation weather relate to power outages, we are going to use ordinary least square linear model. As mentioned in paper[8] which used Pearson correlation to find the degree of linear relation between variables, We used OLS[14] modeling which shows statistical correlation relation between two or multiple variables. Both the Pearson constant method and

ordinary least square model infer the same linear relationship between the variables, but the Pearson coefficient can also be used to find the correlation between two variables so using OLS to find correlation between multiple variables and the response variable, SAIDI.

The estimated model equation is given by :

$$y=\sum\beta*x+\varepsilon$$

Where y is response variable, SAIDI

X is the independent variables, weather related features β is the coefficients of the independent variables
ε is the irreducible error

4. Results:

From the Fig 4 we can see that most of the outages causes are because of tree contact, which are the indirect cause of weather conditions like high winds and seasonal storms[16]. Though the extreme weather related outages are less, since tree contact is indirect cause of weather conditions looked into correlation factors of weather variable to outage resilience metric.

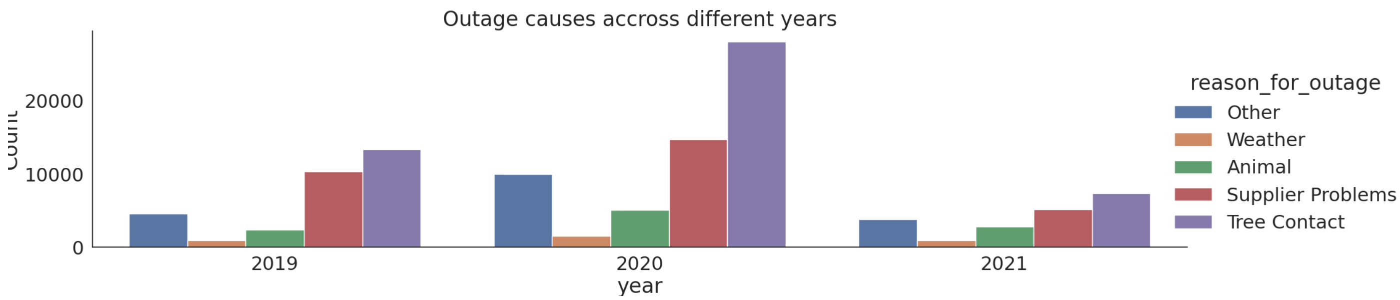

Fig 4 : Outage reasons

From the Fig 5, we can see that most of the weather variables have no major correlation except fastest 2-min wind speed & average wind speed, temperature minimum & temperature maximum.So removed temperature minimum and average wind speed variable to do OLS model, multiple regression analysis.

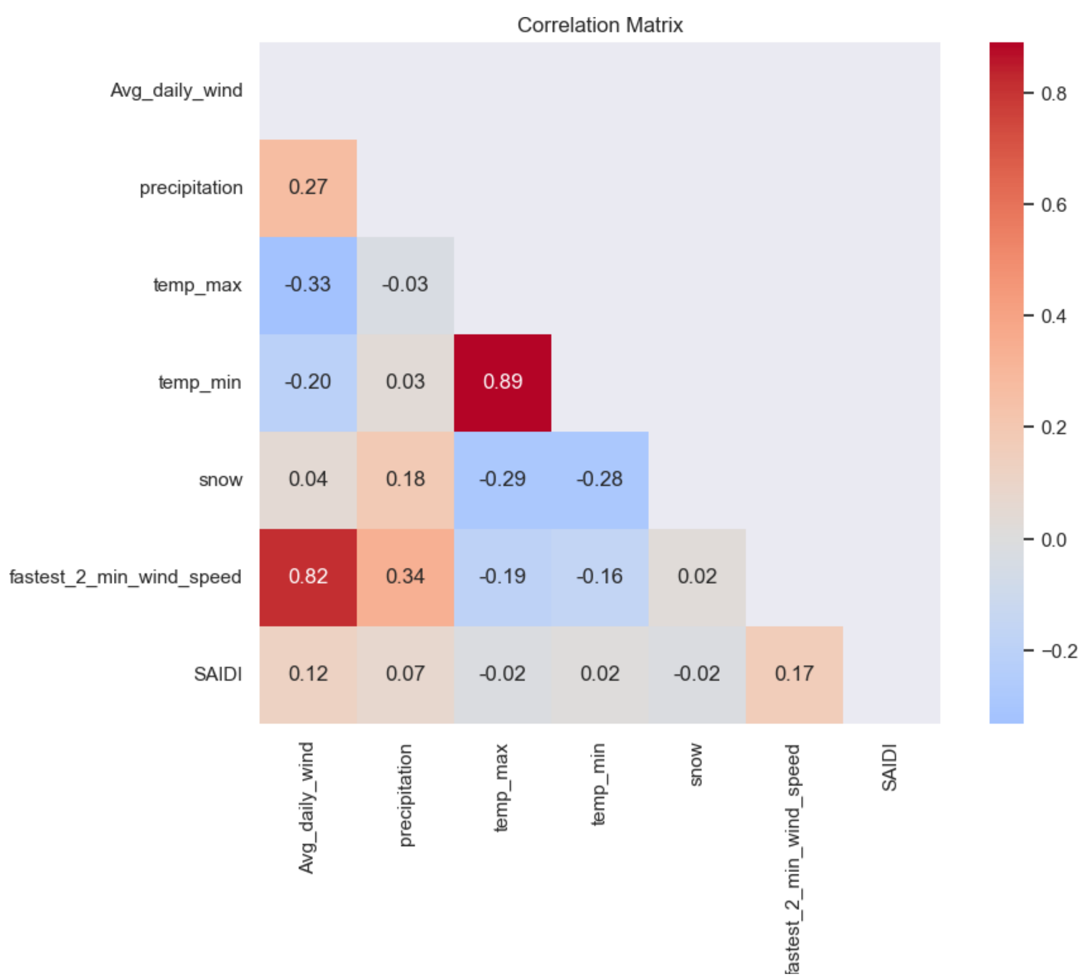

Fig 5 : Correlation Matrix

4.1 Statistical Analysis

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                            OLS Regression Results
==============================================================================
Dep. Variable:                  SAIDI   R-squared:                       0.030
Model:                            OLS   Adj. R-squared:                  0.030
Method:                 Least Squares   F-statistic:                     862.8
Date:                Sat, 10 Dec 2022   Prob (F-statistic):               0.00
Time:                        22:33:58   Log-Likelihood:                -66735.
No. Observations:              111212   AIC:                         1.335e+05
Df Residuals:                  111207   BIC:                         1.335e+05
Df Model:                           4
Covariance Type:            nonrobust
============================================================================================
                              coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------------
precipitation               0.0006      0.000      5.745      0.000       0.000       0.001
temp_min                    0.0019      0.000     11.991      0.000       0.002       0.002
snow                       -0.0003   6.59e-05     -4.407      0.000      -0.000      -0.000
fastest_2_min_wind_speed    0.0162      0.000     52.183      0.000       0.016       0.017
Intercept                  -0.0969      0.004    -24.489      0.000      -0.105      -0.089
==============================================================================
Omnibus:                   245118.145   Durbin-Watson:                   1.419
Prob(Omnibus):                  0.000   Jarque-Bera (JB):       2925004633.528
Skew:                          20.057   Prob(JB):                         0.00
Kurtosis:                     796.485   Cond. No.                         72.0
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
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Fig 6 : OLS model results

From fig 6 we can see that the p-value is <0.05 which means the weather variables are statistically significant to the SAIDI. Which proves our hypothesis.

4.2 Spatial Analysis

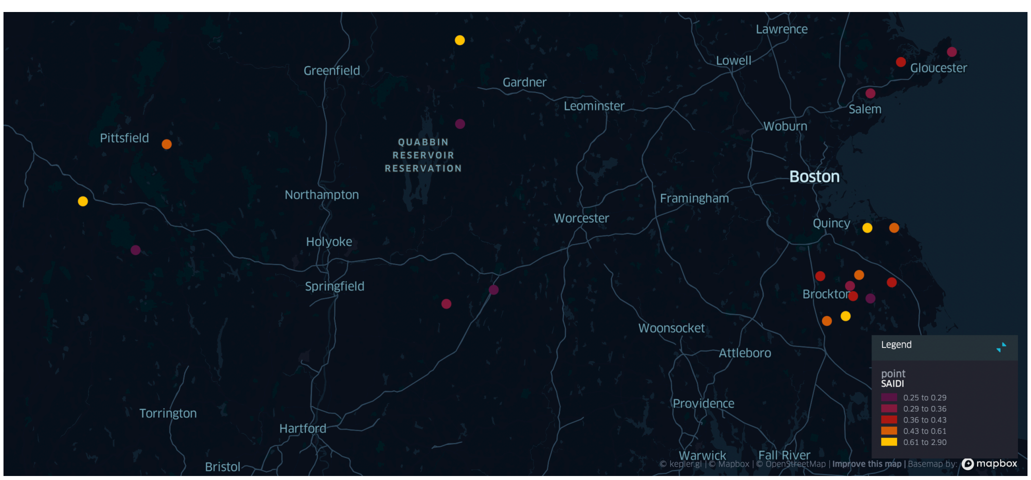

Fig 7 : Top 20 towns based on SAIDI

Found top 20 towns based on the mean of SAIDI of all 3 years, which are spatially visualized in kepler.gl tool. Which can be seen in Fig 7, Top 20 towns are mostly clustered around the brockton area.

5. Policy Implications:

The results show that the impacts using the SAIDI metrics we can see that reasons caused for power outages are mostly because of a tree falling, and slightly because of severe weather or some human activity, etc, knowing this information the city planners can concentrate on the areas where the tree of contact outages are more. The planners can do the trees trimming[1] near the grid lines to reduce power outages. The other result can be a correlation between weather and power outages. If the correlation is positive then the government should Implement strategies such as planning for underground transmission lines, enhancing power system operations and control with Smart Grid, and improving utility maintenance methods. However, the majority of these proposed remedies have large costs, which must be weighed against the predicted advantages in order to mitigate losses and plan sustainably.

6. Conclusion & Future work:

Conclude that tree contacts are the major reasons for outages and weather variables are statistically correlated to SAIDI. Though are statistically correlated adjusted R^2 is too low to say that that weather variables are in linear relation to SAIDI, so for future trying more advance machine learning models like splines is better solution. Other direction for future work can be knowing the tree distribution of the MA and seeing how the outages are affected at densely populated tree areas and sparsely populated areas.

7. Appendix:

A special thanks to Prof. Sunter for giving us project pitches for our data science for sustainability class. This project is based on the direction she guided. My four other teammates in class are planning on working with the same dataset but different research question. I would like to also thank Prof. Sumeeta for her help in using ArcGIS methods in this project.

8. Supplementary Figures:

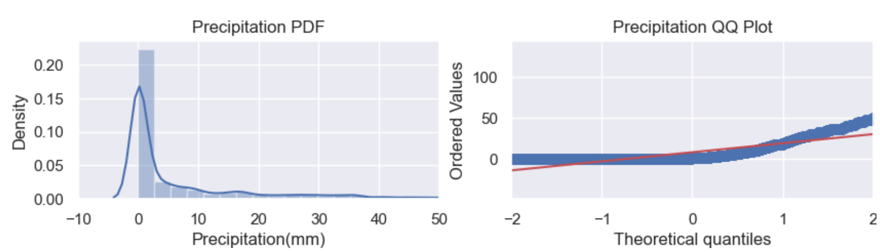

Fig a : Normality curve for Precipitation

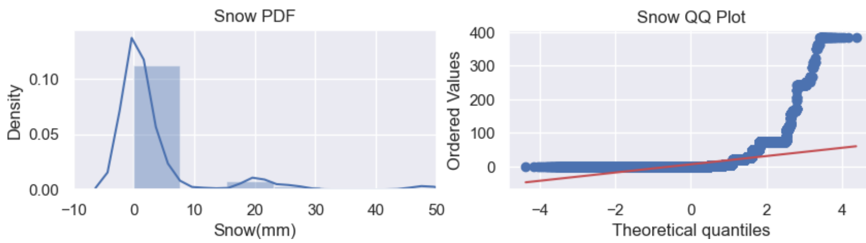

Fig b : Normality curve for Snow

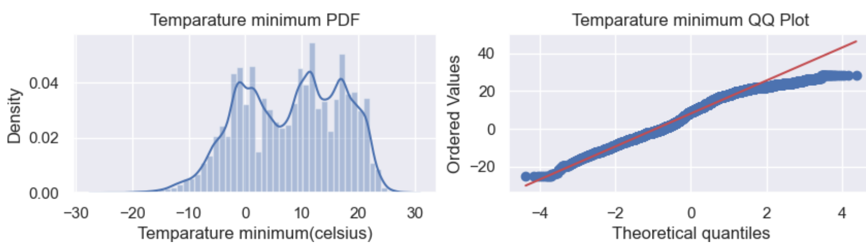

Fig c : Normality curve for Temperature minimum

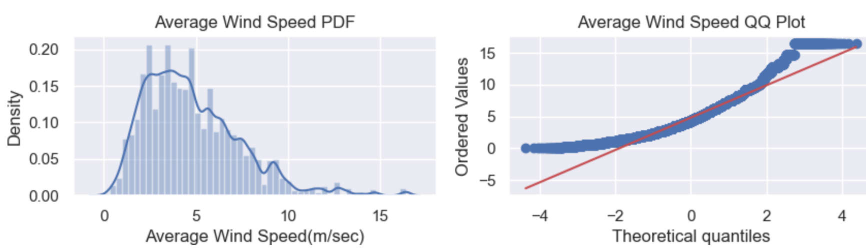

Fig d : Normality curve for Average Wind Speed

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