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Using Convolutional Neural Networks to Understand the Impact of COVID-19 on Electricity Demand in Texas

Vincent Li[1,2], Xiaonan Wang[1]

1 Tsinghua University, Beijing, China

2 Horace Mann School, U.S.A.

ABSTRACT

Economic consequences have been felt around the world as a result of COVID-19, among which have been changes in electricity demand. In this project, we use a convolutional neural network (CNN) to investigate whether there was a change in electricity demand in the state of Texas, located within the United States, during the pandemic, as compared to before it. Training the model on electricity demand and weather data, we were able to achieve a relative RMSE, relative MAE, and R2 of 0.049, 0.041, and 0.92, respectively, on a testing set that represented a normal, pre-pandemic year. The CNN showed better performance, as compared to a plain artificial neural network (ANN). Based on the predictions of the CNN and the actual demand in 2020–2021, we find that the hypothesis that demand decreased during the pandemic was partially supported. A larger decrease was present due to extreme weather events; therefore, we recommend that Texas fortify its electricity generation facilities against such events.

Keywords: COVID-19, convolutional neural network, electricity demand, machine learning, lockdown policy

1. INTRODUCTION

The COVID-19 pandemic has been going on for nearly two years. Ever since the beginning, much has changed in the lives of many. For example, electricity demand has decreased in places around the world, as studied in many previous works, such as the state of New York in the United States (Li et al., 2021); Spain, Italy, Belgium, the United Kingdom, and the Netherlands (Bahmanyar et al., 2020); and the United States (as a whole) and Brazil (Zhong et al., 2020).

In contrast to the artificial neural networks (ANNs) used by Li et al. (2021), the convolutional neural networks (CNNs) in this study made predictions for the electricity demand each day based not only on temperature information during that day, but also during previous days. While CNNs can be used for image recognition, they can also be used to solve regression problems, such as the problem of predicting electricity demand.

In this study, we use a CNN to predict the demand in the state of Texas in the United States during 2020–2021 as if the pandemic had not occurred and compare the prediction to the actual demand during that time period. Because of the decrease in demand that was seen by places around the world (Li et al., 2021; Bahmanyar et al., 2020; Zhong et al., 2020), we hypothesize that in Texas, there will also be a decrease in demand, as compared to before the pandemic.

Our study adds on to the contributions of previous studies. For example, Snow et al.

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(2020), who studied the impact of COVID-19 on Australian households, used statistics to measure the significance of changes to demand during lockdown. Halbrügge et al. (2021) studied the impact of COVID-19 on electricity systems in Germany and other European countries. Our study adds to the contributions of Snow et al. (2020) and Halbrügge et al. (2021) by using more recent data and incorporating neural networks, rather than only statistics.

2. MATERIALS AND METHODS

2.1 Data

For this study, we downloaded data from the Energy Information Administration (EIA, 2021) on the electricity demand patterns in Texas. The data was given in an hourly format, which was aggregated into a daily one. We also downloaded data from the National Oceanic and Atmospheric Administration (NOAA, 2021) about the daily temperatures in three cities in Texas: Houston, San Antonio, and Dallas. These cities were chosen because they are the three most populous cities in the state. Therefore, any change in the temperatures there would affect the largest numbers of people, and thus have the largest effect on electricity demand in Texas. The input data into the model also included the day of the week (represented by an integer from 0–6, inclusive) and whether a day was a weekend (represented by a boolean value). This was done to ensure that the CNN could pick up on weekly cycles of electricity demand, if any such cycle existed.

2.2 CNN Model

The architecture of the CNN model was as follows: the data was inputted into a 1D convolutional layer with 20 filters of kernel size 3, then passed into a second layer with 200 neurons, and then to a final layer of a single neuron, which was the output layer. All of the layers, except for the output layer, had an activation function of ReLU. The model trained for 100 epochs.

2.3 ANN Model

Using the methods described by Li et al. (2021), we also created an ANN model, whose performance we compared to that of the CNN model. The ANN model architecture was the same as that of the CNN minus the convolutional layer, which was simply replaced by an input layer.

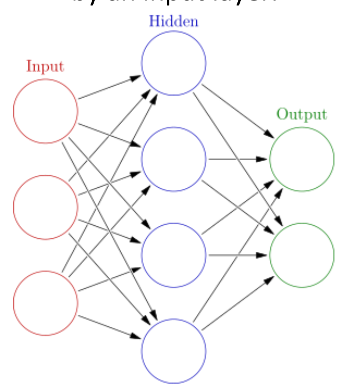

Figure 1. A diagram of the ANN. Although there are different numbers of neurons in each layer than shown in the diagram, it illustrates the general structure of the ANN. Image by Glosser.ca (2013).

3. RESULTS

Demand vs. Time

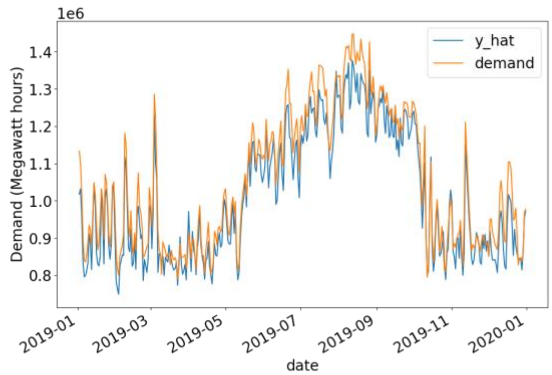

Figure 2. The CNN's prediction (blue) compared to the actual demand (orange) in Texas during 2019. The prediction was based on the temperatures in Houston, San Antonio, and Dallas, the day of the week, and whether each day was a business day. The CNN trained on data from 2017–2018.

In Figure 1 above, for the CNN, the relative root mean square error (relative RMSE, defined as the RMSE divided by the mean demand) was 0.049 and the relative mean absolute error (relative MAE, defined similarly) was 0.041. The R^2 was 0.92. For the ANN on the same task, the relative RMSE, relative MAE, and R^2, were 0.056, 0.048, and 0.89, respectively, which were respective relative changes of –0.13, –0.15, and 0.033, when changing from the ANN to the CNN. By all measures, the CNN had a better performance than the ANN.

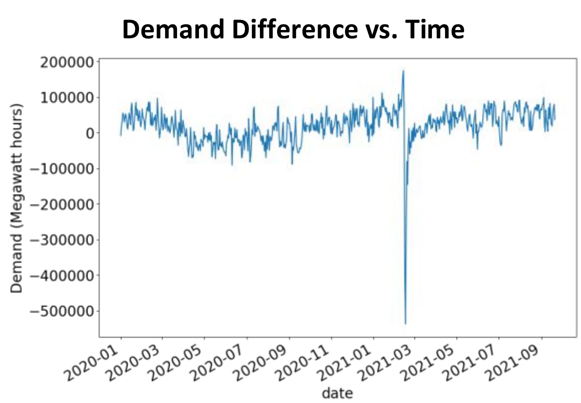

Figure 3. The difference (actual – predicted) between the actual demand and the CNN's predictions (both graphed in Figure 1) is plotted here. Notably, in February 2021, there was a large downward spike in the difference. During that time period, there was a large power outage in Texas that affected over 4.5 million people (Wikipedia, 2021c).

4. DISCUSSION

In a previous study on New York state, Li et al. (2021) found that the demand decreased during the pandemic, especially from March–June 2020, which was indicated by the difference being below 0. By examining Figure 2, we see that the difference appeared to be below 0 from April–September 2020 in Texas, which supports the hypothesis that the demand would decrease during the pandemic. This decrease in demand, as compared to that of New York state, occurred later and lasted longer, which makes sense when analyzing from a policy standpoint. The downward spike in Figure 2 can be explained from extreme weather events.

In general, the policies in Texas pertaining to restricting the spread of COVID-19 were put into place later and lifted earlier than their counterparts in New York. For example, in New York, the mask mandate came on April 15, 2020 (Wikipedia, 2021a), while in Texas, it came two and a half months later on July 2, 2020 (Wikipedia, 2021b). On the topic of reopening, New York introduced its reopening plan on May 7, 2020 (Wikipedia, 2021a), whereas Texas had done so in the previous month, on April 17, 2020 (Wikipedia, 2021b). The more relaxed policies of Texas are consistent with its dip in demand coming later, as quarantine measures are associated with decreases in demand during the pandemic.

In Figure 2, there is a large downward spike in February 2021 whose magnitude greatly surpasses that of all of the other variations in the difference. Around that time, there also was a power outage that affected more than 4.5 million people in Texas caused by the failure of electricity generation due to winter storms (Wikipedia, 2021c). Because the difference was large in magnitude and negative, the actual demand was much lower than predicted, which is consistent with the idea that power generation fell from the outage to an extent that the model did not predict.

In this study, it is important to recognize that the data does not imply that the pandemic caused the decrease in demand in Texas from April–September 2020, per se. Rather, only an association can be inferred from the data. Furthermore, as evident in Figure 2, in other time periods, the difference was actually positive, and in general, the variability of the difference is substantial compared to its magnitude, implying that we cannot be certain that there even necessarily was much of a change at all. Nevertheless, the downward spike in February 2021 appears to be large enough that the aforementioned limitation does not apply.

5. CONCLUSION

The hypothesis that the demand in Texas would decrease during the pandemic was partially supported because the difference was negative from April–September 2020, but was positive in other parts of the 2020–2021 period. However, we also found that the power outages in February had a much more drastic (albeit much shorter lasting) effect on the demand. Given that the sudden nature of these storms make them harder to anticipate than a pandemic that lasts for multiple years, and given that it is harder for people to adjust with less warning, we recommend that Texas focus on better preparing its electricity generation facilities against cold weather.

Future studies in this area may focus on different regions in the United States, accounting various climate conditions or may attempt to establish whether a causal relationship exists between the pandemic and the demand difference. They may also examine power outages in Texas or other regions in the United States to ascertain whether it is necessary for other states to better protect their electricity generation facilities against extreme weather events.

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Date accessed: 25 September 2021

National Oceanic and Atmospheric Administration (NOAA)
Global Historical Climatology Network - Daily (GHCN-Daily), Version 3
https://www.ncdc.noaa.gov/cdo-web/datasets/GHCND/stations/[station_code]/detail
Replace [station_code] with "GHCND:USW00012921", "GHCND:USW00003971", or "GHCND:USW00094728" for the individual data sets. Date accessed: 25 September 2021

8. IMAGES

Glosser.ca (2013, February). Colored neural network. License: CC BY-SA 3.0 <https://creativecommons.org/licenses/by-sa/3.0>, via Wikimedia Commons. https://commons.wikimedia.org/wiki/File:Colored_neural_network.svg