DOI: http://doi.org/10.5281/zenodo.5048479
U.S. ISSN 2768-1025

How COVID-19 Impacted CO2 Emissions Based on Electricity Usage: A Machine Learning Approach

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Abstract— The goal of this study is to determine the difference in CO2 emissions between 2019-2020 and 2020-2021, more specifically during lockdown periods during the COVID-19 pandemic. In the beginning of the pandemic, most countries were forced into lockdowns, and a countless number of people had to continue their daily work from home in isolation. Previously, people would go to an office or to school and leave their houses empty for eight hours, without having lights or any electronics on. Because of this, there should be a direct correlation between electricity usage before and during lockdowns, as a private residence should have higher electricity consumption during 2020-2021, when they are at home. Using machine learning, we will investigate to see if COVID-19 affected CO2 emissions as a result of more electricity usage in private residences. A model will be made to predict what the CO2 emissions would be for 2019-2020, based on electricity usage data from 2020-2021. Then, the real CO2 emissions from 2019-2020 will be compared with the model's predicted values, and the difference will indicate if COVID-19 caused an inconsistency between actual and predicted CO2 emissions. Factors that were taken into account when making a model were independent variables relating to outdoor conditions, the number of people living in the house, and the temperature that the thermostat is set at, making the response variable CO2 emissions.

Keywords—COVID-19, electricity consumption, CO2 Emissions, Deep Learning Neural Network

I. INTRODUCTION

Electricity consumption can be dependent on several different factors. For example, it can be affected by the building insulation, outdoor weather factors, and how many appliances are requiring electricity. The only data being observed and assessed in this paper is electricity, however, the literature review will go into depth on the other factors not quantified. After determining what factors increase or decrease electricity consumption, we will discuss relevant statistics that will show how COVID-19 lockdowns led to many people to work from home, rather than at an office, and how much private residence energy consumption rose as a result. Furthermore, we will also explain how COVID-19 had an overall decrease in global carbon emissions and why. And, as well as looking at how electricity consumption can lessen based on weather conditions and individual energy conservation methods, we will look into the new paths that can produce electricity. Next, we will investigate how companies are beginning to use wind and solar resources to harness electricity in a sustainable way. Sustainable energy allows people to use electricity without the consequence of carbon emissions. Lastly, in addition to the following background research that will be conducted, we will also introduce background on machine learning and the process we used for this study.

II. HUMAN FACTORS AFFECTING ELECTRICITY CONSUMPTION

People's daily lives contribute to electricity consumption and there are several other factors that can increase or decrease this consumption. Residential factors that most affect electricity consumption are air conditioning, heating, water heating, electrical appliances, lighting, and TV and media equipment. According to Direct Energy [1], air conditioning and heating use up to 46 percent of electricity per month, water heating 14 percent, electrical appliances 13 percent, lighting 9 percent, and TV and Media Equipment 4 percent.

The thermostat setpoint can have a great effect in monthly electricity consumption as well: "Without reducing satisfaction levels, by increasing the cooling setpoint of 22.2°C (72°F) to 25°C (77°F), an average of 29% of cooling energy and 27% total HVAC energy savings are achieved. Reducing the heating setpoint of 21.1°C (70°F) to 20°C (68°F) saves an average of 34% of terminal heating energy. Further widened temperature bands achieved with fans or personal controls can result in HVAC savings in the range of 32%–73% depending on the climate" [2]. This shows that even moderate changes to the thermostat temperature can drastically affect a household's monthly electricity consumption.

III. NATURAL FACTORS AFFECTING ELECTRICITY CONSUMPTION

External, outdoor weather factors can also affect energy consumption, specifically if wind, humidity, precipitation, and temperature truly make a difference for a private residences' electricity consumption.

An example of how outdoor weather factors can have a great impact on energy consumption was in 2006 when there was a heat wave that spread across the United States and "All seven U.S. regional independent electric grid operators set new record demands in July as they met the challenge of record high temperatures without incident" [3]. As the outdoor temperature increases, the more likely people are to decrease their thermostat temperature setpoint to achieve some thermal comfort. The weather plays an important role in energy consumption, "it directly affects the thermal loads and thus energy performance of buildings" [4]. If a person lives somewhere where it is typically very hot or very cold, they are more likely to use more energy to heat or cool their homes to their individual comfort. The time of day and season also affects electricity consumption: "the sensitivity of energy use to weather depends on the season and specific time of the day/night" [5]. This again proves that weather plays an important role in electricity consumption and demand. Therefore, energy consumption will be different in residences who live in different climate zones.

Next, a study [6] showed how indoor temperature is related to humidity and human comfortability. Humidity is a factor that does not have a direct effect on temperature, however, it can affect thermal comfortability for people. In a study done by the Civil Engineering department at Hunan University in Changsha China, experimenters determined if humidity increased or decreased comfortability and air quality for people. It is known that good air quality and comfort is beneficial for both psychological and physiological health. Nowadays, there is an increasing attention to quality of life; because of this the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) has proposed “acceptable indoor air quality” based on both subjective and objective evaluations. Comfort is a consequence of the interaction between people and their environment, and subjectively comfort is determined by two factors: the objective environment (environmental factors) and the subjective feeling (body sensory organs). Furthermore, the two most important environmental factors, observed in this study, are temperature and humidity. In general, ~70 degrees Fahrenheit (21 degrees Celsius) is an ideal temperature for humans, and ideal humidity is between 30-50%. The article mentioned how an earlier study from the 1960s found that a decrease in relative humidity by 10% equals an increase of air temperature by 0.3 degrees Celsius, however the air felt stuffier as humidity increased, this is an example of how subjective and objective traits are observed and collected.

The experiments were then carried out in a laboratory in Hunan University with controlled conditions: subjects would sit at a desk with five radiant cooling panels around them, and the rest of the environment was controlled with another air conditioning system. The indoor temperature and relative humidity was continuously monitored by the TR-72Ui temperature and humidity sensor, and air velocity was also measured with an air velocity meter, TSI-8347. There were a total of 24 subjects for this study, 12 females and 12 males, and they all were similar in height, weight, and health condition. The subjects were also asked not to exercise, drink coffee, or drink alcohol before the experiment. Another consistent factor for all the participants was the clothes they were wearing, as they all wore summer clothing with the insulation being around 0.5clo. For data collection, the indoor temperatures were maintained at 26, 28, and 30 degrees Celsius, with relative humidity levels at 60% and 80%, giving a total of 6 combinations for 6 trials. The results of this experiment showed how humidity affected the participants’ comfort at different temperatures. Fig.1 shows how there was little thermal comfort difference at 26 degrees with different relative humidity, but how at 28 and 30 degrees thermal comfort did change as relative humidity was changing. Fig. 2 shows how more people preferred the dried environment when in warmer temperatures, however at the cooler temperature, humidity did not have as much significance.

This experiment relates to this study because thermostat temperature setpoints and humidity will be used as factors for the machine learning dataframe. This relates to electricity consumption because if it is hot and humid, a resident may be more likely to increase the air conditioning, compared to if there is lower humidity. For this reason, humidity will be observed and assessed on how the humidity of different regions of the country can affect electricity consumption, by way of excess air conditioning

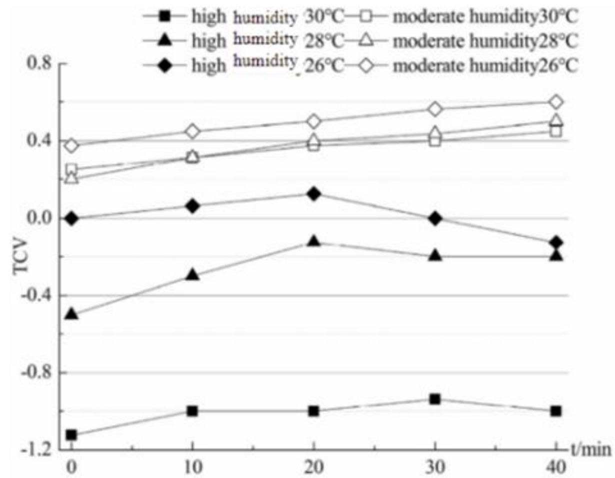

Figure 1: Overall Thermal Comfort

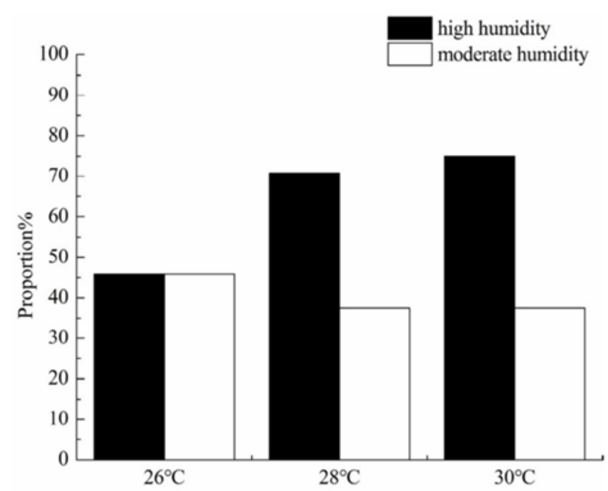

Figure 2: People Who Preferred Drier Environments

IV. How COVID-19 Affected Electricity Consumption

Now that it has been determined how consumption habits and climate factors affect electricity consumption, we will elaborate on how COVID-19 may have increased the electricity consumption for private residences. COVID-19 has made some impact on global CO2 consumption as people were traveling less and staying home more; “Daily global CO2 emissions decreased by –17% (–11 to –25% for ±1σ) by early April 2020 compared with the mean 2019 levels" [7]. People all around the world were forced into lockdown and this greatly impacted global CO_2 emissions. In an article from Stanford University [8], it was said that CO_2 emissions dropped 7% from 2019 fossil emission levels, that is a decline of approximately 2.4 billion tons of CO_2 in 2020. This was a record drop in the global history of fossil fuel consumption.

Moreover, COVID-19 has made an impact with residential energy use. People are spending much more time at home, either from working from home, or just being home because of unemployment caused by business shutdowns from the pandemic. With so many people working from home, there has been an increase in "heating and cooling systems, and lamps and printers running all day. Compared with the same months from 2016–19 and adjusted for weather differences, the second quarter of 2020 saw a 10 percent increase in residential electricity usage, a 12 percent drop in commercial usage, and a 14 percent drop in industrial usage" [9]. Since so many people are now at home because of shutdowns, they are using more electricity to power their homes, whether it is for lighting, thermostat control, or for common household appliances. As private residential usage went up, commercial and industrial usage went down.

Working from home has no doubt increased monthly residential electricity consumption, but compared to working in an office, energy consumption overall relatively stays the same. Working from home "may lead to unpredictable increases in non-work travel and home energy use that may outweigh the gains from reduced work travel. The available evidence suggests that economy-wide energy savings are typically modest, and in many circumstances could be negative or non-existent" [10]. Whether people are working from home, or working in an office, they are using electricity, however, it was found that the amount of electricity they are using is relatively the same.

Based on global temperature, 2020 has been the warmest year on record: "Climate change continued its relentless March in 2020, which is on track to be one of the three warmest years on record. 2011-2020 will be the warmest decade on record… Despite the COVID-19 lockdown, atmospheric concentrations of greenhouse gases continued to rise, committing the planet to further warming for many generations to come because of the long lifetime of CO_2 in the atmosphere, according to the report" [11]. Even though CO_2 emissions have gone down because of COVID-19 travel restrictions, greenhouse gas emissions continue to rise. A rising global temperature could have an effect on thermostat setpoints which in turn could have an effect on electricity consumption.

V. FUTURE DIRECTIONS TOWARDS SUSTAINABLE ENERGY

Iberdrola is an energy focused group that works on making energy switches from nonrenewable to renewable energy to see how they are conserving and converting energy to promote a low carbon economy. Their goal is to reduce the global carbon footprint by installing renewable energy systems such as solar and wind; "The Iberdrola group has undertaken to reduce its emission intensity to 50 gCO_2/kWh globally by 2030, thus achieving an 86% reduction in three decades, in addition to being carbon neutral globally by 2050" [12]. Their group has made great progress over the years in meeting renewable energy targets and have made significant goals to meet for the future in hopes of decreasing the need for fossil fuels for energy.

VI. DEEP LEARNING

Deep learning is a branch of machine learning. It is an algorithm that uses artificial neural networks as the architecture to characterize and learn data. Deep learning is an algorithm in machine learning based on characterization learning of data. Observations can be represented in a variety of ways, such as a vector of the intensity value of each pixel, or more abstractly represented as a series of edges, regions of a specific shape, and so on. It is easier to learn tasks from examples using certain specific representation methods. The advantage of deep learning is to use unsupervised learning or semi-supervised feature learning and hierarchical feature extraction efficient algorithms to replace manual feature acquisition.

There have been several deep learning frameworks, such as, deep learning neural networks, convolutional neural networks, and recurrent neural networks, which have been applied in the field of computer vision, speech recognition, natural language processing, audio recognition and energy field, etc. All of them can have excellent results by using deep learning frameworks.

VII. THESIS STATEMENT

From the collected data, the group hypothesizes that COVID-19 affected CO_2 emissions. There will be more electricity usage in private residences in 2020-2021, specifically during lockdown periods. Predicted CO_2 emission values will be determined with a deep learning neural network. The effect COVID-19 had on private residential electricity usage will be determined by comparing the predicted and actual CO_2 emission values.

VIII. METHOD/DATA COLLECTION/ STRATEGY - DATA COLLECTION

First, data was collected out of a class size of 39 undergraduate and graduate students from the University of Dayton in Dayton, OH, where each student provided information for the following factors: monthly electricity usage in their residence, the number of people residing in that household, the average thermostat setpoint temperature, and what city and state they live in. Additional data was collected and organized into a data frame: monthly average outdoor temperatures [13], monthly average percent humidity [14], wind speed [15], annual precipitation days and inches [16], average days of cloud coverage [17], average days with fog [17], and CO_2 emissions for 2019 and 2020 [18], [19]. These features were chosen, as they are factors that could all affect electricity consumption in a house. A data frame was then made by organizing the features collected from students and national weather data records. The dataframe was then processed into the program RStudio, a programming language for statistical computing and graphics, where machine learning was implemented. Fig.3 displays the theoretical process used to make the prediction model. A deep learning neural network (DNN) model was used to predict 2019 CO2 emission data based on the electricity consumption present in the dataframe. A "What-If" simulation was used, and the question that was asked was "what if the coronavirus never happened?" by altering the electricity usage. The model will show the difference between the actual and predicted CO2 emission data for 2020, which will reveal whether the pandemic caused carbon emissions to lower. A figure will also be developed to display the difference between hypothetical carbon emissions for a non-COVID-19 and the actual carbon emissions per year.

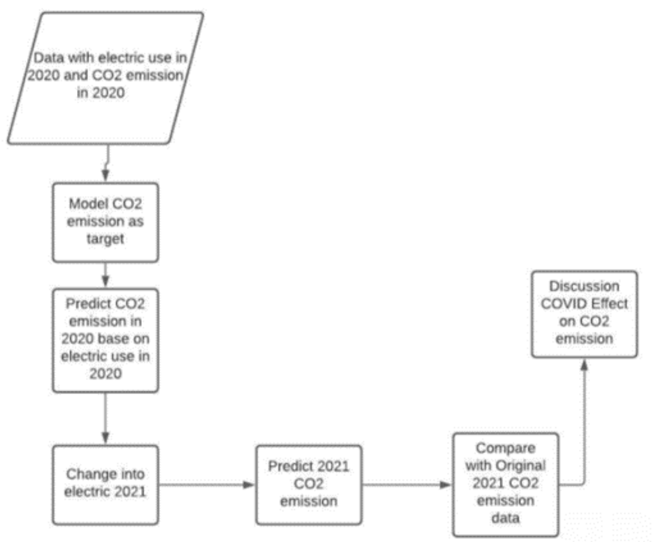

Figure 3: Strategy for Machine Learning Process

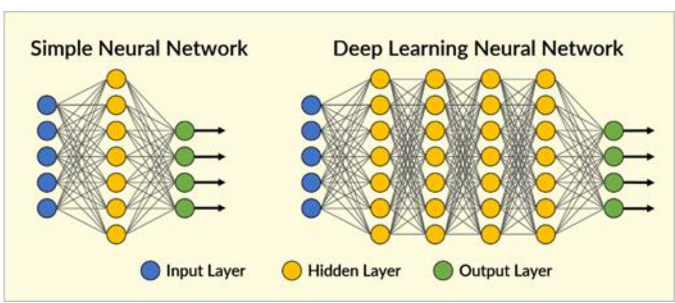

Figure 4: Model Considerations

Fig. 4 shows the difference between a simple neural network and a deep learning neural network. Deep learning (DL) is a method of machine learning based on the representation of data. It is a machine learning method that can simulate the neural structure of the human brain. The concept of deep learning comes from the research of artificial neural networks. The artificial neural network (ANN) abstracts the human brain neuron network from the perspective of information processing, establishes a certain simple model, and forms different networks according to different connection methods, referred to as neural networks or similar neural networks.

The deep learning neural network is the most common and effective algorithm used to train artificial neural networks. Divided from previous neural networks and other machine learning algorithms, one of the main advantages of deep learning is that it can introduce new features from the limited feature set contained in the training set. Deep learning has the ability to create features without being explicitly told to do so, this means that data scientists can save months of work by relying on these networks. Therefore, in this research, the deep learning neural network will be considered as the model to predict the CO2 emissions.

Here, H2O.flow is the tool being used to build the deep learning neural network. In the model, there are two hidden layers with 200 neurons in each layer by adding K-fold to increase the training data.

A. *What-If*

The what-if assumption has been widely used in different areas, such as finance, energy, and etc. A what-if hypothesis sets up different conditions and compares the results, which can help people to simulate the expected results. In this case, the what-if hypothesis is changing the value for electricity use in 2019-2020 into 2020-2021 to estimate if the electricity usage gets higher and also to determine what the predicted CO2 emissions will be in 2020-2021. Then, by comparing the results of the simulated consumption with the real consumption for 2020-2021, CO2 emissions will display how the COVID-19 effect on CO2 emission.

IX. RESULTS

Fig.5 shows the validation metrics of the model which include the R-squared value, mean absolute error, etc.

model	deeplearning-7dca7a4f-30f4-4040-8a6b-08f0f0117016
model_checksum	2682664355833531288
frame	Key_Frame__Model_dataset.hex
frame_checksum	1987217394261798044
description	Metrics reported on full validation frame
model_category	Regression
scoring_time	1619143113663
predictions	·
MSE	0.175952
RMSE	0.419466
nobs	431
custom_metric_name	·
custom_metric_value	0
r2	0.940081
mean_residual_deviance	0.175952
mae	0.296405
rmsle	0.147273

Figure 5: Validation Metrics

Therefore, from the validation metrics, Deep Learning Neural Network has been established which has 0.94 on R-squared value and 0.29 Mean Absolute Error. If the R-squared

DOI: http://doi.org/10.5281/zenodo.5048479
U.S. ISSN 2768-1025

value is close to 1 and the Mean Absolute Error value is below 0.5, then the model is accurate enough to be viable. For the range of the target, CO2 emission in 2019 ~2020 is from 0 to 5 for monthly individual residential CO2 emission. Therefore, the model build for this dataset is acceptable.

This Deep Learning Neural Network model will apply for the What-if simulation to predict the CO2 emission in 2020 ~ 2021 by only changing the electricity consumption for individual residential houses. Fig. 6 shows the What-If Simulation plot from our model.

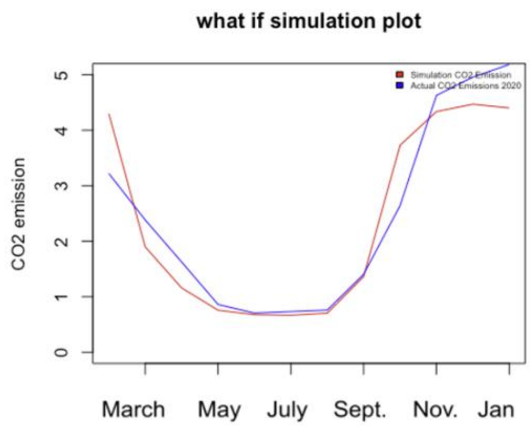

Figure 6: What-if Simulation Plot

In this research, the electricity usage values were set from 2019~2020 into 2020~2021 to simulate the condition if the COVID-19 did not happen. This was done by applying the model which is built for 2019 ~ 2020, and comparing the simulated and actual CO2 emissions for 2020 ~ 2021. Fig. 6 shows the difference between simulated CO2 emissions and the real CO2 emissions in 2019~ 2020. In the spring, when lockdowns were in place, the simulated CO2 emissions were lower than the actual. This shows that private electricity consumption during the lockdown period was greater than expected, because people were at home all day, consuming their own electricity, rather than going to work all day. As soon as September came, the simulated CO2 emissions became higher than the actual CO2 emissions, this is because the model predicted a higher consumption for private residences than the actual consumption, as lockdown restrictions began to lift. And, during the summer season, the simulated CO2 emissions are a little bit lower than the actual CO2 emissions in 2020. The reason why there is not a big difference is because during the summer time, most people have their air conditioning running all day even when they are not home. However, the actual consumption was still slightly higher than the simulated because people may have still been working from home and using more electricity from their electronics in that way. Therefore, based on the whole plot, COVID-19 did affect CO2 emissions in 2020-2021 compared to CO2 emissions in 2019-2020, depending on when lockdown restrictions were in place and when they began to lift. Fig. 7 shows how when the actual was higher than the predicted people were at home, and when the simulated was higher than the actual, things were normal and people were going to public buildings.

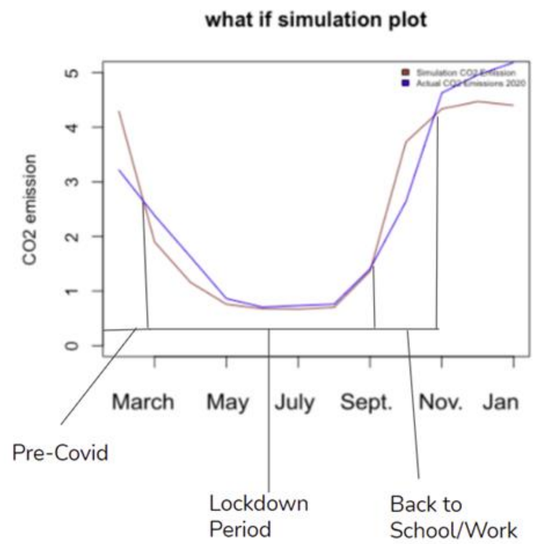

Figure 7: What-If Simulation with Annotation

X. CONCLUSION AND DISCUSSION

A. *Conclusion*

From our model and what-if assessment, we found that in the months of March through May the predicted CO2 emissions were lower than the actual; these were the months during a lockdown period. This supports our hypothesis because it shows that when COVID-19 was at its peak in the United States and everyone was in isolation, the actual CO2 emissions were greater than the predicted CO2 emissions, based on a non-covid model. The actual CO2 emissions stayed higher than the simulation CO2 emissions until people began to go back to work and school in September. This month was when people began to return to school and work, and the predicted CO2 emissions were lower than the actual CO2 emissions for private residences. This makes sense because once lockdown restrictions eased up, people were spending less time at home, thus using less electricity during the day. Our model and the comparison between the predicted and actual CO2 emission levels supports that COVID-19 did increase electricity consumption during lockdown periods, and that consumption was lower again once people went back into public buildings during the day.

B. *Global CO2 Emissions During Covid*

As previously stated, COVID-19 caused 2020 to have a record drop in CO2 emissions globally, the largest decrease the world has ever seen, as we are constantly increasing our fossil emissions annually. However, our data shows that during lockdown periods private residences experienced an increase in CO2 emissions from electricity usage. A possible reason for this could be as people were forced to continue and live their normal lives at home, private consumption increased, while at the same time, since people were not going to work or school everyday, commercial consumption plummeted. The difference between the decrease in commercial and industrial CO2 consumption vastly outweighed the increase of CO2 consumption of home, thus, leading to an overall drop in global CO2 consumption.

C. Future Suggestions for Global CO2 Emissions

Despite COVID-19 lowering global CO2 emissions, 2020 was actually the warmest year in recorded history. And, as people must go back to their normal lives, which includes working from an office and going to school, this will greatly increase CO2 emissions compared to what they were during COVID-19 lockdowns. With the environment and people's livelihoods at stake, due to CO2 emissions and COVID lockdowns, there needs to be a solution where people can still consume electricity, but in a sustainable way. As previously mentioned in our background research, there are many things people can do to lower their fossil consumption and live their lives more efficiently. However, transitioning to a renewable energy economy is the only way that we will be able to lower our carbon emissions in a substantial way. Companies like Iberdrola that are helping transition energy sources to be renewable are greatly influential for this to happen. One thing that can be said about COVID-19 is that it made people more aware of the energy they consume at home. As residential energy consumption rose, the world saw how much CO2 emissions dropped, and global consumption decreased. If there is any takeaway from the pandemic, it serves as a warning for our fossil consumption and a hope that diminishing CO2 emissions can help fight climate change.

D. Future Suggestions the Study

Although we were able to use machine learning to understand the impact COVID-19 had on electricity consumption of private residences, there were some limitations to our study, for which we have suggestions about. The data we collected from students in our class may not have been consistent or accurate, so we would first like to gather electricity consumption data from a single energy provider source for more consistency. In addition, to verify our findings, we would like to add more features or columns to our dataframe. More households added to the dataframe, that would add up to at least 2000 rows of data, would also allow for a more accurate model with less assumptions. We would also like to add the square footage of each home, since the space affects how much energy will have to be used to heat or cool rooms. Next, we would suggest adding more concrete features relating to utility consumption, such as natural gas and water consumption. From our data collection, we did have some students insert their water and natural gas consumption data, but there was not enough data to be able to make a machine learning model. All of the features that we added were all environmental features, which we would keep, and we would also like to have more features directly related to consumption. This would allow us to further understand if general utility consumption increased due to COVID-19, not just electricity consumption, and it would allow us to go deeper into the question: Is it more sustainable for people to work from home or go to an office, in terms of energy consumption? In conclusion, we recommend having one singular source for all of the consumption data, data from more households (rows for dataframe), and more consumption features (columns of dataframe), to make a more accurate model.

Conflicts of Interest: The authors declare no conflicts of interest.

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