1. Abstract

Energy Consumption at a household level can impact ecosystems as well as the environments around them. Environmental factors such as land quality, biodiversity and ecosystem health are directly impacted by the production and consumption of energy. Previous studies have shown that high energy use without the correct infrastructure can lead to environmental and humanitarian disasters such as those seen in California and Texas which has led to the lack of access to electricity, destruction of property, and deaths. Budgeting for energy consumption continues to be an issue at a regional level, ensuring that energy demands are met can be modeled and forecasted. Energy consumption data from the United Kingdom Power Networks on household energy use will be used to forecast energy usage using a Long Short Term Memory (LSTM) Model, a neural network capable of tracking and selecting dependencies for new observations using past observations. Results show that it is possible to determine Energy Budgets given certain variables as they relate to energy such as temperature and weather conditions.

1. Intro/Background

Global energy consumption affects nearly all people as energy and environmental problems are closely related. Environmental factors and events directly impact energy production and consumption which include temperature, climate change, pollution, and waste disposal. Burning fossil fuels, such as coal, oil, and natural gas, is one of the highest contributors to our energy grids but is also one of the largest contributors to Greenhouse Gas Emissions (GHG). The use of fossil fuels leads to a multitude of environmental problems such as water and land pollution which not only negatively impacts local ecosystems but can lead to long term problems for human health and productivity.

High energy use without the necessary infrastructure to provide such a commodity could lead to both environmental and humanitarian disasters. Recently, we witnessed energy infrastructure failures in California as well as Texas which led to blackouts, environmental destruction, and fatalities. These energy issues were not only related to the given energy infrastructure but also to climate effects. The 2021 Power Crisis in Texas was the result of severe winter storms which had swept across the United States leaving 4.5 million without power as well as estimates of 702 deaths as a result from the storms. The result of the lack of preparedness as well as energy infrastructure in Texas led to an estimated $20.4 billion in damages. To understand the relationship between energy consumption and climatic variables, we need to be able to model and understand data on the relationship between Energy Consumption and variables such as daily temperatures.

1. Methods

Energy consumption data was be retrieved from UK Power Networks, which samples 5,567 London Households which took part in the UK Power Networks Low Carbon London project between November 2011 to February 2014. Energy reading were retrieved in half-hourly intervals and data is measured in kWh, household identifier, date, and time. The purpose of this dataset was government policies to install smart meters in every home in the United Kingdom to analyze how the energy infrastructure is utilized to tackle supply chain demands regarding climate change. While data is structured in 30-minute intervals, Data was then converted to average household data use per day. Data was formatted in a CSV file with a total of 3536007 rows between 829 days from November 23rd, 2011 - February 28th, 2014.

Weather data will be received from the meteomatics Weather API which is able to retrieve current and historical climate data in a time series format for any location in the world from 1979 onwards. Weather API data will retrieve standard weather parameters such as temperature, humidity, and Visibility.

Data was than imported into python and R where it was cleaned and analyzed using various libraries. Data was then formatted into time-series, as well as undergone feature selection to ensure best results for the LTSM model.

1. Data Exploration and Manipulation

After importing, cleaning, and manipulating the data, we were able to make some decisions before applying our data to our model. Multiple time series charts showed the relationship between Energy Consumption and various weather variables. Figure 1 shows that there is strong inverse relationship between Energy Consumption and Temperature whereas Temperature Increases, Energy usage decreases. This indicates temperature as a good indicator for energy usage. Figure 2 shows that there is a positive correlation between energy usage and relative humidity. Figure 3 shows that Energy Consumption and Visibility carry a positive correlation as well. This indicates that Temperature Visibility and Relative Humidity could be good indicators for determining the amount of energy consumption in a household. Combining these values into a weather cluster would be important to reach an accurate prediction for household energy use. Figure 4. Shows 6 as the optimal number of clusters given an elbow curve when grouping Relative Humidity and Visibility while using Maximum Temperature as a separate indicator for energy usage.

Chart, line chart

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Figure : Energy Consumption vs Temperature

Chart

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Figure : Energy Consumption vs Humidity

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Figure : Energy Consumption and Visibility

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Figure : Optimum K Clusters

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Figure : Weather Cluster

1. Results

Data was fitted, scaled, and applied to the LSTM model, which produced interesting results. The average household vs predicted household energy use was predicted accurately with a Root Mean Squared Error of 0.624. This means that the model was able to predict the average household energy use with an accuracy of +- .624 Kilowatt Hours. Figure 6 indicates that our predictions were not totally accurate but were able to predict a daily average household electricity consumption for households in the UK. The average electricity produced by 1 kWh costs around 12.55 cents in the US. This metric is essentially the amount of energy used by keeping 1,000 watt appliances running for 1 hour. Figure 7 shows a table of the predicted and actual values of household electricity consumption using our LSTM model. Figure 8 shows the loss in the model which contained 50 epochs with minimal loss of prediction towards our true labels.

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Figure : LSTM Model Results

|  | **predicted** | **avg\_energy** |
| --- | --- | --- |
| **0** | 3.693668 | 3.705790 |
| **1** | 3.700994 | 3.757952 |
| **2** | 3.707747 | 3.716657 |
| **3** | 3.754201 | 3.834259 |
| **4** | 3.756873 | 3.573996 |
| **5** | 3.674609 | 3.515900 |
| **6** | 3.564569 | 3.615430 |
| **7** | 3.560658 | 3.628714 |
| **8** | 3.651751 | 3.477669 |
| **9** | 3.548311 | 3.668540 |
| **10** | 3.630450 | 3.872832 |
| **11** | 3.718781 | 3.568842 |
| **12** | 3.671705 | 3.628209 |
| **13** | 3.618959 | 3.702192 |
| **14** | 3.618986 | 3.573859 |
| **15** | 3.581329 | 3.749295 |
| **16** | 3.662187 | 3.638854 |
| **17** | 3.670417 | 3.672708 |
| **18** | 3.636604 | 3.476525 |
| **19** | 3.574478 | 3.415168 |
| **20** | 3.541205 | 3.377993 |
| **21** | 3.460115 | 3.346477 |
| **22** | 3.512124 | 3.325300 |
| **23** | 3.419443 | 3.414958 |
| **24** | 3.442120 | 3.638111 |
| **25** | 3.510547 | 3.292925 |
| **26** | 3.407245 | 3.258093 |
| **27** | 3.339891 | 3.225993 |
| **28** | 3.291487 | 3.277377 |

Figure 7: LSTM Model Results (Table)

Shape

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Figure 8: Loss in model training

1. Discussion/Conclusion

Using a Long Short Term Model we were able to predict with a +- 0.624 kWh of the amount of energy a household in London uses given previous days energy usage, temperature, visibility, and relative humidity. Given the right data, this model shows that is entirely possible to predict energy consumption given specific variables. The challenge lies in predicting and creating energy budgets in the future which are capable of withstanding natural disasters to prevent infrastructure failure in delivering electricity to constituents. The next step would be to use similar models to predict energy budgets for future years using historical data as well as applying infrastructure improvements to already existing electrical infrastructure.

1. Acknowledgments
2. References

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