Forecasting the Future: Electricity Load and Price Prediction Based on Weather

Naga Vara Pradeep, Yendluri
nagavarapradeepyendluri@my.unt.edu

Prathyusha, Gangisetty
prathyushagangisetty@my.unt.edu

Sathwik Karthikeya, Mannava
sathwikkarthikeyamannava@my.unt.edu

Jayabhi Sankar Reddy, Illuri
JayabhiSankarReddyIlluri@my.unt.edu

Tarun Teja Nallan, Chakravertula
TarunTejaNallanChakravertula@my.unt.edu

Kartheek, Sure
KartheekSure@my.unt.edu

1. Introduction

The aim of this machine learning project is to develop a robust and accurate system for predicting electricity load based on a combination of weather, day, and hour data. By leveraging advanced machine learning algorithms, we intend to create a model that can forecast electricity consumption patterns, allowing for better resource planning, optimization of energy distribution, and contributing to a more sustainable and efficient energy ecosystem.

Python will serve as our programming language due to its capabilities and rich libraries. We plan to gather weather data from Kaggle datasets for electricity load, price and weather-related information. To preprocess data, we use Pandas and NumPy. When it comes to ML frameworks, we will explore tools like TensorFlow and PyTorch, including neural networks (DNNs), for their advanced model creation and training capabilities. The end-user interface will be developed using web technologies. Flask is used on back-end to serve the machine learning model and return predicted load and price details to users.

1.1. Project Milestones

- Data collection and Preprocessing
- ML Model Development
- Feature Engineering and Model Optimization
- Build User Interface and integrate the final model to serve user requests using Flask

1.2. Related Projects

- QuantRisk is a commercial software to predict electricity prices based on weather data.
- Linux Foundation Energy - OpenSTEF forecasts load on the grid for next 48 hours based on weather data and market prices
- While companies like IBM and Google offer solutions for energy prediction and optimization using ML algorithms, these options often come with high expenses and proprietary technologies that limit accessibility for smaller organizations or research purposes. Initiatives such as OpenSTEF provide open-source resources and data for energy forecasting.

2. Motivation

The project we are working on, which involves forecasting electricity prices, offers an intriguing chance to explore a crucial element of modern society with significant consequences. Electricity is more than just a commodity; it's the essential energy source driving households, businesses, industries, and vital services. Consequently, for numerous stakeholders involved, including enterprises, consumers, lawmakers, and energy providers, the capacity to precisely forecast electricity prices is of the utmost important.

This project's fundamental goal is to tackle the inherent uncertainty in electricity markets, especially in deregulated countries like Spain where a multitude of factors impact price dynamics. We want to build reliable forecasting models that can shed light on next price patterns by utilizing deep neural networks and other cutting-edge machine learning techniques. As a result of using these models, stakeholders in the energy industry may be able to improve market efficiency, optimize allocation of resources, and reduce risk.

There are far-reaching consequences for society as a whole related to this undertaking. A more stable market, more sustainable energy consumption habits, and easier grid integration of renewable energy sources are all possible outcomes of reliable power price forecasting. We may promote energy conservation and the use of more efficient technology by providing consumers with up-to-date information about our pricing dynamics. Furthermore, we may lessen our dependence on fossil fuels and mitigate the environmental impacts of power generation by letting energy suppliers predict changes in demand and alter generation accordingly.

As a team, we see this project as an opportunity to delve deeper into data science and machine learning. Improving our abilities in data preprocessing, model creation, and performance evaluation, while also applying our theoretical understanding to real-world challenges, is what this chance comes down to. In addition, it promotes a more thorough comprehension of how technological, environmental, and economic elements interact to shape the energy landscape.

Overall, this idea is extremely exciting since it could transform society for the better, give people what they need, and add to what we know about energy economics. Discover new opportunities and lay the groundwork for a more sustainable and resilient energy future by utilizing innovative technology and interdisciplinary approaches.

3. Evaluation

Several important factors must be carefully considered during the project's implementation. First off, a thorough analysis is made easier when data from multiple sources are combined into a single data frame. To ensure consistency and comparability across several families, however, the normalization process, which aggregates energy consumption data to a consistent day level per household is essential. By applying clustering techniques to weather data, it is possible to find the links between weather and energy use, which can provide important insights into possible patterns and correlations.

Here, to forecast energy consumption, two modeling approaches are going to be used: the LSTM [1] model and the ARIMA[2] model. After examining, the ARIMA model offers a conventional yet reliable framework for time series forecasting. The precision of electrical load predictions is greatly influenced by the level of noise present in the observed signal, emphasizing the importance of managing and reducing noise for more accurate forecasts.[1] The LSTM model has the capability to recognize sequential patterns within the data, offering predictions that could be complex. LSTM demonstrates remarkable performance in predicting electrical loads, primarily attributed to its effective modeling of past input features, specifically 6-hour intervals, in this study.[2]. Currently, the predominant approach in machine learning for price forecasting revolves around Recurrent Neural Networks (RNNs), with Long Short-Term Memory (LSTM) being a component of RNNs.[3] Evaluation of these models accuracy and reliability is done through metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE).

We may assess each model's predicting strengths and flaws by contrasting how well it performs with the other. Ultimately, the best method for precisely projecting energy consumption and guiding decision-making procedures must be determined by a thorough analysis of the ARIMA and LSTM models. A successful project outcome would be the creation of precise energy consumption forecasting models as well as the identification of important correlations between weather, holidays, and energy use.

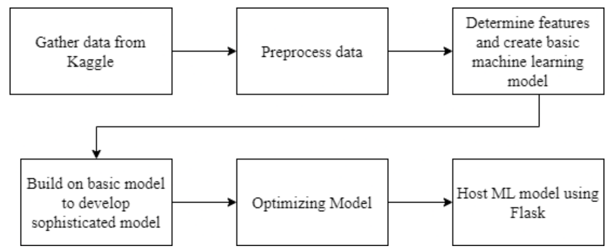

Figure 1. Process to create ML Model to predict electricity price and load

4. Resources

4.1. Computational Tools

- Programming Language: Python.
- Machine Learning Libraries: Scikit-learn, Keras.
- Data Preprocessing: Pandas, NumPy.
- Web Development: Flask.
- Data Visualization: Matplotlib, Seaborn.

4.2. Dataset

Kaggle

4.3. Computer Hardware

- Processor: Intel i5
- RAM: 8 GB
- GPU: NVIDIA 1650

5. Contributions

- Naga Vara Pradeep Yendluri - Introduction - Researched about open source and closed source services that are providing electricity load and price prediction. Identified milestones in project process.
- Kartheek Sure - Introduction - Researched about usage of load prediction in substations and listed technologies that can be used in the project.

[1]Long short-term memory (LSTM) network
[2]Autoregressive Integrated Moving Average (ARIMA)

- Tarun Teja Nallan Chakravertula - Motivation - Researched and described about why this project is exciting and described about its usage in broader societal impact.
- Sathwik Kartikeya Mannava - Motivation - Described about personal learning perspective of project in real world applications.
- Prathyusha Gangisetty - Evaluation
- Jayabhi Sankar Reddy Illuri - Researched about ARIMA model and Resources section

References

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