Interactive dashboard with machine learning on electricity demand forecasting for insightful planning

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INTRODUCTION

Electricity demand forecasting is a fundamental activity for both regional and national energy supply planning. Recent studies have employed several different approaches for electricity demand forecasting over varying timelines, however, it appears little has been done to present the results in an intuitive and interactive interface. As such, this study outlines an approach for electricity demand forecasting using various machine learning models and present the results in an easy to understand, interactive dashboard to aid end users with efficient, data driven decision making. The proposed models were developed using an historical electricity consumption and weather data sets. The resulting dashboard facilitates improved energy planning and more efficient production and resource utilization.

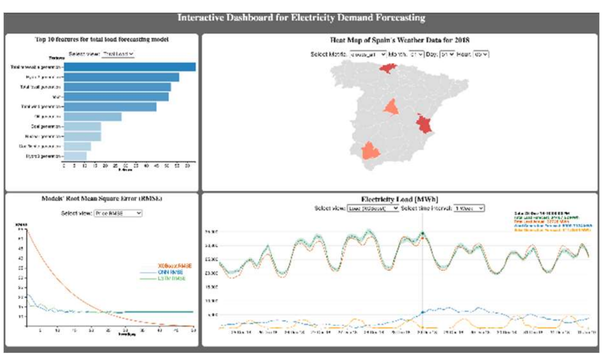

Figure 1. Screenshot of interactive dashboard for electricity demand forecasting.

PROBLEM DEFINITION

Ever increasing awareness about responsible environmental stewardship continues to highlight the need for effective and efficient energy management practices. We have seen more pressing demands for increasingly accurate energy consumption forecasting models to support the optimization of electricity supply planning in residential, commercial, and industrial spaces. Coupled with this need for more accurate models is the not so apparent, yet crucial need to present the forecasted results and underlying models in a manner which is easily understood by end users [1].

Our study leveraged previous works by implementing big data technologies together with deep learning AI models to forecast energy consumption [2], [3], [4]. In addition, our approach built on previous works with the aim of enhancing and simplifying the end user experience. The following paragraphs detail what is new in our approach compared to previously reviewed works.

There are several earlier studies which show comparisons between different analytical models used to forecast energy consumption [5], [6], however, in majority of these cases the results and underlying models were presented in a manner which undoubtedly are difficult to understand for anyone without specialized knowledge. In our approach we present both the models and their results via an interactive dashboard. End users can interact with the visualizations in order to view explanations (tooltips) of the results. The main idea is that by helping users better understand the underlying models and results, it facilitates willingness to incorporate models in their decision making. Further, it enables them to give constructive feedback for improvement of the models.

LITERATURE SURVEY

From our review of related works, it is evident that energy forecasting is a prominent topic. The following sections will detail some notable studies in this area.

Machine learning approach

One approach is estimate consumption of energy using commonly accessible features as opposed to having diverse and complete data. They have used CBECS survey data and validated their model with NYC Local Law 84 energy dataset [3]. It is also common for papers to present various models like CDT, FitcKnn, LRM and Stepwise-LRM for both weekly and monthly basis and compare the results [7]. Many of the related studies focused on achieving some level of consistency in deployed solutions by checking for data drift or shift via an automated and statistically based method [8].

Energy forecasting methods

There is an abundance of forecasting methods and one such study showed forecasting methods from 2005 to 2015. It focused on energy and demand forecasting using traditional time series models along with soft computing methods [6]. There is also review of energy performance prediction and suggestions for further research. In addition to these methods, we focus on the user-interactivity and interpretability [9]. As outline in one study which proposes a forecast system based on user-defined parameters using more interpretable kNN model. It is accompanied with an interactive visualization [1]. Energy and electricity data, being mostly time-series based, either daily, weekly, or annual, has been the subject of various papers. ARIMA, ANN, GM, and hybrid models are some of the popular forecasting techniques employed [5], [10]. The results can be aggregated for variants of fuel sources, geothermal heat, electricity and solar which are then aggregated as the total energy in Turkey [11].

Deep learning and neural networks

Various deep learning-based models are employed using neural networks. LSTM for aggregated load forecasting to select best features and optimize performance has been employed [12]. proposed a forecasting model for monthly residential electricity demand with social and weather-related variables [4]. LSTM has several variants, and one approach is to tune and pit them against one other for comparison [13]. Abstraction can be employed to increase accuracy as well as extracting trends and perform separate predictions of both tendencies using neural networks [14], [15].

PROPOSED METHOD

<u>INTUITION:</u>

When considering state-of-the-art forecasting tools used in Europe [16], a key feature in our tool that we believe may contribute to better decision making in energy planning is our multi-model forecasting. Our intuition is that there cannot be one machine learning model that can generalize predictions for all weather and energy demand scenarios.

To this point, our tool offers descriptions and comparisons of different models and their performance with respect to RMSE and displays this interactively. It is precisely this visibility of model comparison which leads energy planners to know which model is appropriate in each decision scenario.

<u>APPROACH DESCRIPTION:</u>

Given our intuition, the literature survey and review of past work performed in this area, we believe our approach builds on their results to add significant value in the following key areas:

1. Our approach utilizes multi-model training on the same data pipeline and provides interactive visuals to end-user who then selects different models to compare their performance.
2. Our approach provides a dashboard with actionable and insightful visuals that can help utility planners forecast energy generation and usage. We achieve this by consolidating weather and energy datasets and presenting them in meaningful visuals.

Figure 2 below depicts the methodology which was utilized to achieve the results generated by our study and subsequent paragraphs outline the details of each stage of our process.

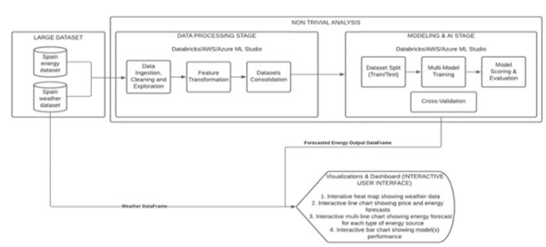

Figure 2. Project methodology

<u>LARGE DATASET:</u>

The dataset selected for our research consists of 35,046 records of Spain's energy data (29 features) for the period 2015 to 2018 and 178,397 records of Spain's weather (17 features) corresponding to the same period previously mentioned. This dataset adheres to the definition of 'a large dataset' as defined in the project description.

NON-TRIVIAL ANALYSIS:

The non-trivial analysis performed consisted of six main stages in the data pipeline.

Stage 1: Data Ingestion, Cleaning and Exploration

In this stage we introduced the data to the data pipeline. The energy dataset which was not location specific, and the weather dataset which was location specific both shared a common datetime key.

For the weather dataset, each city had varying number of rows where different dates were duplicated for each. Multiple classifiers were used to identify the correct label from duplicate entries which had varying labels. This duplicate data equated to 8.8% of the original weather dataset. In the case of the energy data, 46 entries with null values were present and these were imputed to the mean of the respective columns.

During our exploratory analysis, we observed somewhat expected characteristics of seasonality, trends, and cyclical information in the prices and energy datasets.

Data exploration was done on Databricks, while the models were developed and run in Azure ML lab.

Stage 2: Feature Transformation

As our final dataset was considerable (consisting of 100 features) it was decided to only introduce elementary data engineering on the dataset, as our final dataset was comprehensive. Furthermore, it was decided to pursue multivariate analysis where applicable, since we knew it to provide a richer analysis and we can derive temporal links between variables. In some instances, univariate analysis was sufficient with the selected dataset. We employed PCA as feature reduction technique.

Stage 3: Data Consolidation

In this stage we consolidated the energy and the weather datasets to produce a single dataframe containing the most relevant features. This resulted in a complete dataset which we then used for ML processing.

Stage 4: Dataset Split

In this stage we split the dataset from stage 3 into train and test sets. Data for the period 2015-2017 was used for training, while data for 2018 was reserved for our test dataset. This resulted in a train-test split ratio of 75%-25%. We further employed cross-validation to measure model's performance and to reduce overfitting.

Stage 5: Multi Model Training

After exploring various models, multivariate regression and neural networks were chosen as the models in the back-end of our dashboard, specifically XGBoost, LSTM, and CNN. In addition to the initial data preparation stage, we had to convert some of the features into numeric values before using them with the models.

Stage 6: Model Scoring & Evaluation

After each model was trained, they were evaluated against the test dataset and scored using the RMSE metric. The models' performance were compared against each other using RMSE. In addition, we compared our models' predictive performance using RMSE against published results from Spain's Transmission System Operators (TSO) website.

VISUALIZATIONS AND DASHBOARD:

The combined data from Stage 3 of the non-trivial analysis together with forecasted values and model performance measures from Stages 5 & 6 served as input to the visualization dashboard. The interactive dashboard was developed using React + D3.js. The following visualizations are included in the interactive dashboard:

Viz 1. Interactive Heat Map for weather data

The heat map provides visual representation of various weather parameters which impact electricity demand. This heat map permits user interaction including click to zoom for select locations, tooltips displaying selected location information. The heat map also allows users to select display metrics and date via a drop down.

Viz 2. Interactive Bar Chart showing top 10 most importance features.

The interactive bar chart shows the top 10 most important features affecting the XGBoost model's performance for total wind generation forecast, total solar generation forecast, total load forecast and price forecast. Feature importance is assessed based on calculated f-score. This bar chart helps users to quickly assess the features which have the highest impact on the forecasted value in question. Users can select different views from a drop down menu and a hover tooltip gives a clear layman's explanation of f-score to aid users in better understanding the dashboard and underlying models.

Viz 3. Interactive Line Chart showing and comparing underlying models' performance.

The interactive line chart shows RMSE value for the XGBoost, LSTM and CNN models which were used to forecast total load, total solar generation, total wind generation and price. Users can select different views from a drop-down menu and a hover tooltip gives a clear layman's explanation of RMSE to aid users in better understanding the dashboard and underlying models.

Viz 4. Interactive Multi-Line Chart showing actual and forecasted values for various energy sources and price.

The interactive multi-line chart shows day ahead forecasted values for total load, total wind generation, total solar generation, and price. This chart also shows actual total load, actual price and total actual generation for different energy sources. Users can select different time periods (1 week, 1 month, 3 months, 6 months, 1 year) on this chart. Users can mouseover the chart to see a display of the date and corresponding value of the features shown on the graph. Users can select different models and view the actual and forecasted values corresponding to that model.

EXPERIMENTS AND EVALUATION

<u>TEST BED:</u>

Following is a list of questions our experiments were designed to answer:

1. How accurately do our machine learning models forecast load and price?
2. How do our models' predictive performance compare to existing research/state of the art?
3. How well does our interactive user interface meet the needs of end users? Is it intuitive and easy to understand? Will it be accepted as an integral part of their energy planning process?

<u>DETAILS OF EXPERIMENTS:</u>

Modeling:

1. We assessed the impact of different features on the target response. This was measured using F-score as shown on viz #2.
2. We worked with the final consolidated data (union of energy and weather and their related features) for training our model and measure its performance.
3. Feature engineering has improved the model's performance, for instances breaking down the time into hour, week, year and creating city-specific features.
4. We have used feature reduction and normalization to speed up and optimize the neural network-based models.
5. Grid search was employed for XGBoost to look for the best set of parameters. GridSearchCV from Scikit-learn proved to be an intuitive package for hyperparameter tuning.
6. For all models, we used cross validation to reduce overfitting and measure their performance.
7. In addition, we have used various platforms, such as Databricks, Jupyter, Anaconda and packages including xgboost, tensorflow, sklearn for our modeling.

Visualization:

1. We created an interactive dashboard to display the output data results from ML modeling. The dashboard displays 4 main viz.

2. Viz 1 (Interactive heat map) presents users with a visual aid to help them understand the potential effect of different weather parameters on energy demand.

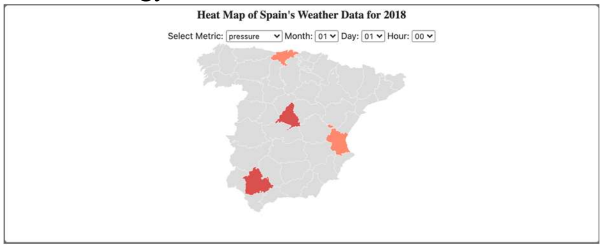

Figure 3. screenshot of interactive heat map

3. Viz 2 (Interactive bar chart) displays top 10 features impacting model prediction. Where possible, this information can help utility planners to action any adjustments of these high impact features which may be within their control. This can be done in order to optimize generation and cost.

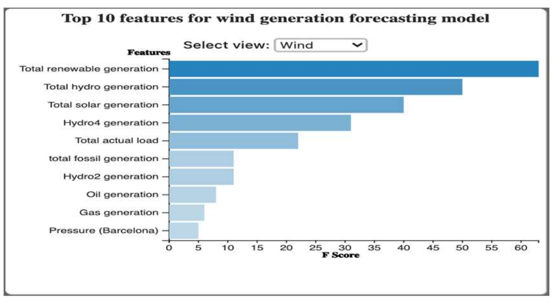

Figure 4. Screenshot of interactive bar chart showing top 10 most important features

4. Viz 3 (Interactive line chart) chart allows users to easily compare model accuracy thereby enabling them to select the best model and corresponding forecasted value for the feature (eg. total load forecast) under consideration

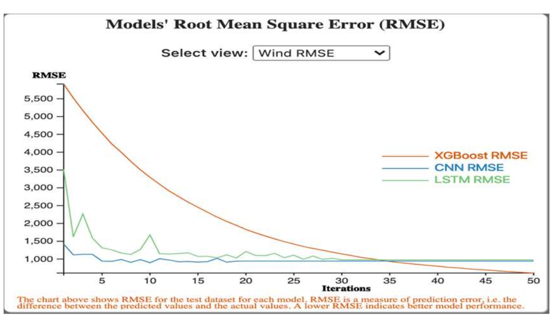

Figure 5. Screenshot of interactive line chart showing model's performance for total wind generation prediction.

5. Viz 4 (interactive multi-line chart) allows for easy and intuitive visualization of actual loads against forecasted load and trends in the data. Based on forecasted day ahead loads, forecasted day ahead solar generation and forecasted day ahead wind generation, utility planners can schedule backup load generation as required to meet expected demands.

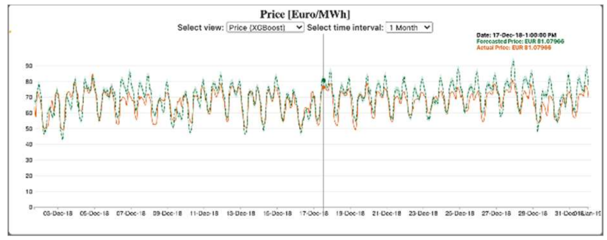

Figure 6. Screenshot of Viz 4. – this view of the multi-line chart shows forecasted price vs actual price.

EVALUATION CRITERIA

We employed a two-step strategy to evaluate our experiments.

1. In terms of usability and helpfulness, we interviewed Mr. Alhamede Emad Eldin, Sr. Specialist in Dubai Electricity & Water Authority – MOROHub, who is a domain expert in IoT, AI & Energy Planning. We requested him to provide his feedback on the dashboard our team has created for Energy Demand Forecast.
2. We compared the error difference (using RMSE) between the forecasting algorithms used by TSO and our algorithms.

RESULTS

The industry expert rated our tool against the conventional energy forecasting tool used in their operations. The results shown in Figure 7 below clearly demonstrate that we have successfully developed a helpful tool.

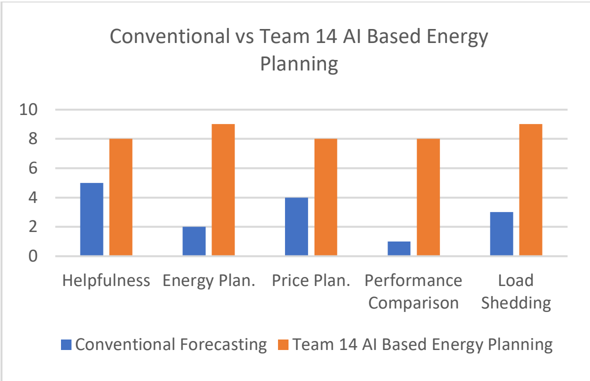

Figure 7. Conventional vs Team 14 AI based energy forecasting tool

For the second evaluation criteria, we evaluated the models' performance using RMSE. We compared TSO (the utility operator), XGB, LSTM, and CNN's predictive performance for each of the response variable: price, total load, total solar generation, and total wind generation. From the results it was seen that we achieved better performance in 3 out of 4 areas. For price and total solar generation (LSTM and CNN outperformed TSO); for total wind generation (XGB outperformed TSO). For total load forecast TSO showed better predictive performance than our models. Total load prediction warrants further investigation, we recommend further work be done in this area.

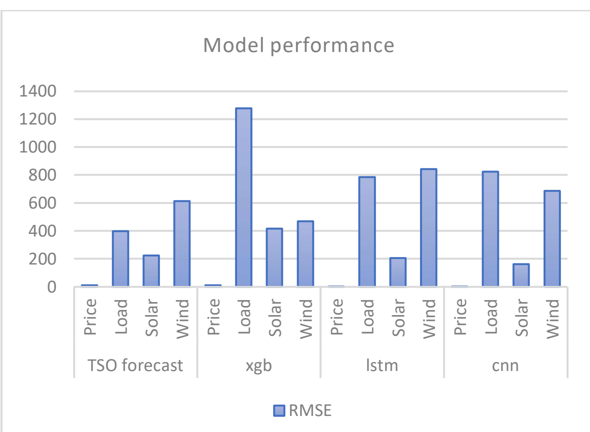

Figure 8. Showing the RMSE performance of different models

DISTRIBUTION OF TEAM MEMBERS EFFORTS

All team members contributed similar amount of effort to the project.

CONCLUSIONS AND DISCUSSION

Having set out to develop an effective and interactive tool for use in electricity demand forecasting we believe our work has materialized into a final product which will be proven to be extremely useful to utility providers.

By developing a dashboard backed by multiple ML models it was shown that our tool exhibited overall better prediction accuracy as compared to existing state of the art (TSO). Based on the high accuracy of our forecasted values, utility planners will be able to have a high level of confidence in planning decisions made based on our tool's predictions. In addition, expert feedback from a major utility provider (Dubai Electricity and Water Authority) attested to the expected usefulness of our interactive dashboard for planning purposes. Because our dashboard was developed using open-source and highly scalable software (React + D3.js and packages like Scikit-learn for modeling) we expect this will noticeably reduce implementation cost when compared to some other data visualization tools. In addition, the software used in our project allows the dashboard to be specifically tailored to individual user needs.

In closing, we believe further work in the following areas will enhance the work already undertaken in this project:

1. Use APIs to provide real-time data to the interactive dashboard.
2. Perform further model tuning to improve predictive performance.
3. Investigate the use of other big data ML/AI platforms to simplify the model pipeline. Assess the ability of other platforms to report the best set of parameters and run event-driven task (i.e., when performance is down, the platform can initiate re-training / parameter tuning)
4. Partner with a utility provider throughout the product develop process. Maintaining a continuous feedback loop with an intended end user should result in a very effective development process and a final product highly tailored to the individual user's needs.

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