A comparative evaluation of timeseries prediction algorithms for Energy Demand Forecasting

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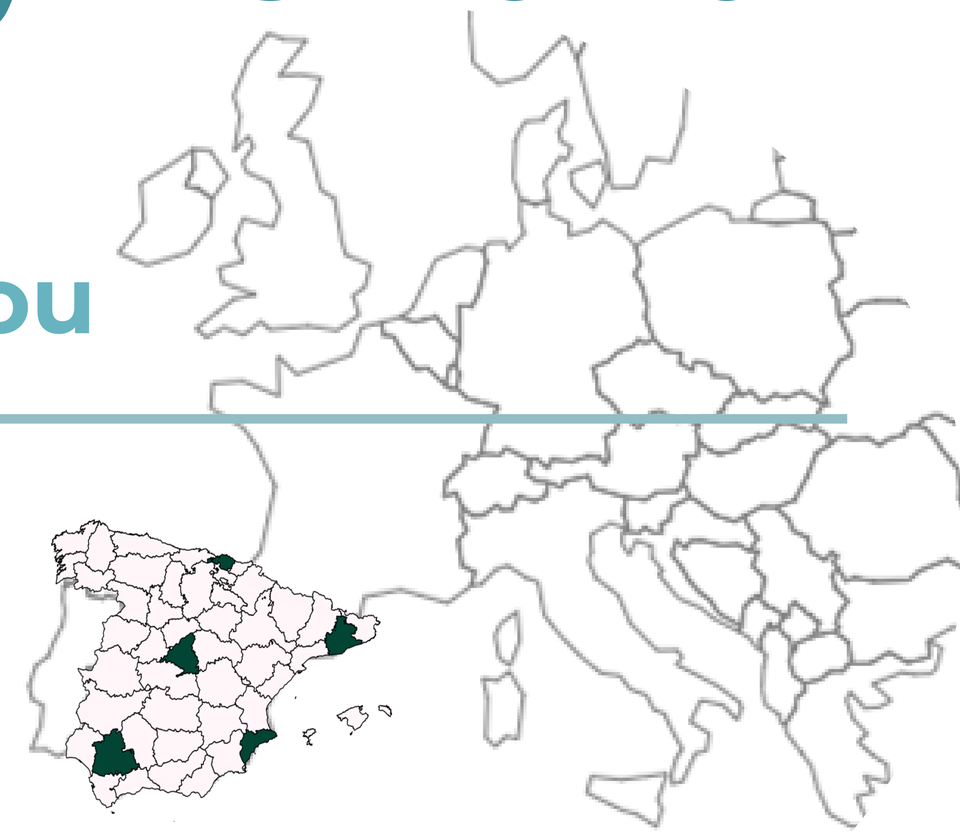

Introduction

- Energy Load Prediction utilizing machine and deep learning models along with weather and calendar data.
- **Short-term Forecasting:** Timeseries prediction including horizons from a few minutes up to a few days ahead.
- **Feature Engineering:** Selecting, manipulating and transforming raw data into features that can be used in supervised learning.

Motivation

- **Environmental Impact:** Accurate short-term forecasts can contribute to the reduction of polluting standby plants and the efficient management of the increasing amounts of renewable sources.
- **Financial Impact:** On-target energy demand forecasting can help the providers stay within the desired range.

CHECK IT OUT

Combining interpretability and knowledge attained from different models can lead to improved performance in energy demand forecasting.

Data

Hourly Energy Demand:
The dataset [1] contains 4 years of electrical consumption, generation, pricing, and weather data from Spain. Consumption and generation data was retrieved from ENTSOE. Settlement prices were obtained from the Spanish TSO Red Electric España. Weather data were produced utilizing the Open Weather API for the 5 largest cities in Spain.

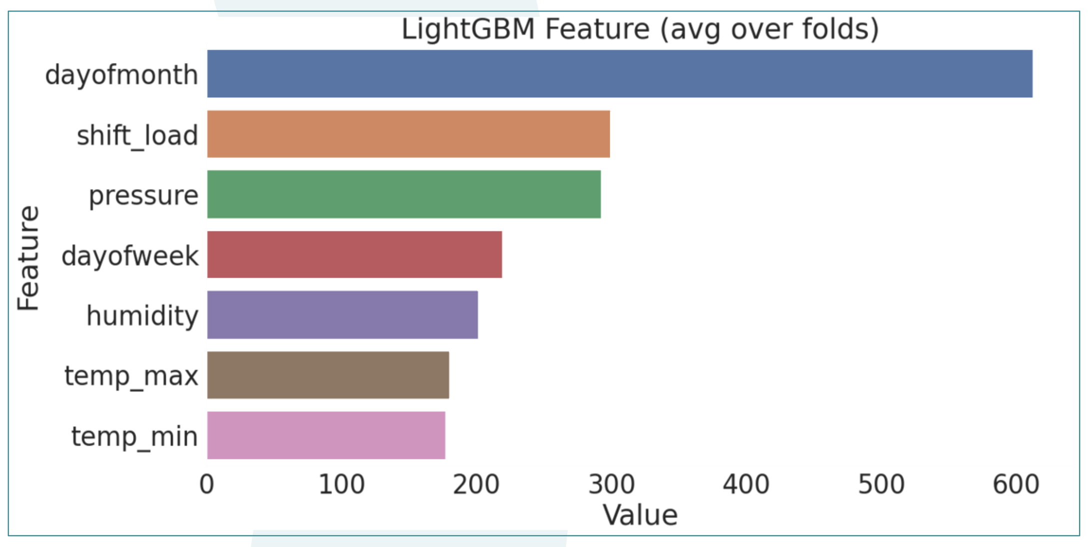

Figure 1: *Feature importance bar plots derived from LightGBM.*

Methods

- **ARIMA:** Autoregressive integrated moving average [2].
- **PROPHET:** An additive regression forecasting model released by Meta's research team [3].
- **LightGBM:** A gradient boosting framework that uses tree-based learning algorithms [4].
- **Transformer:** Deep learning attention-based model originally designed for influenza ratio forecasting [5].

Results

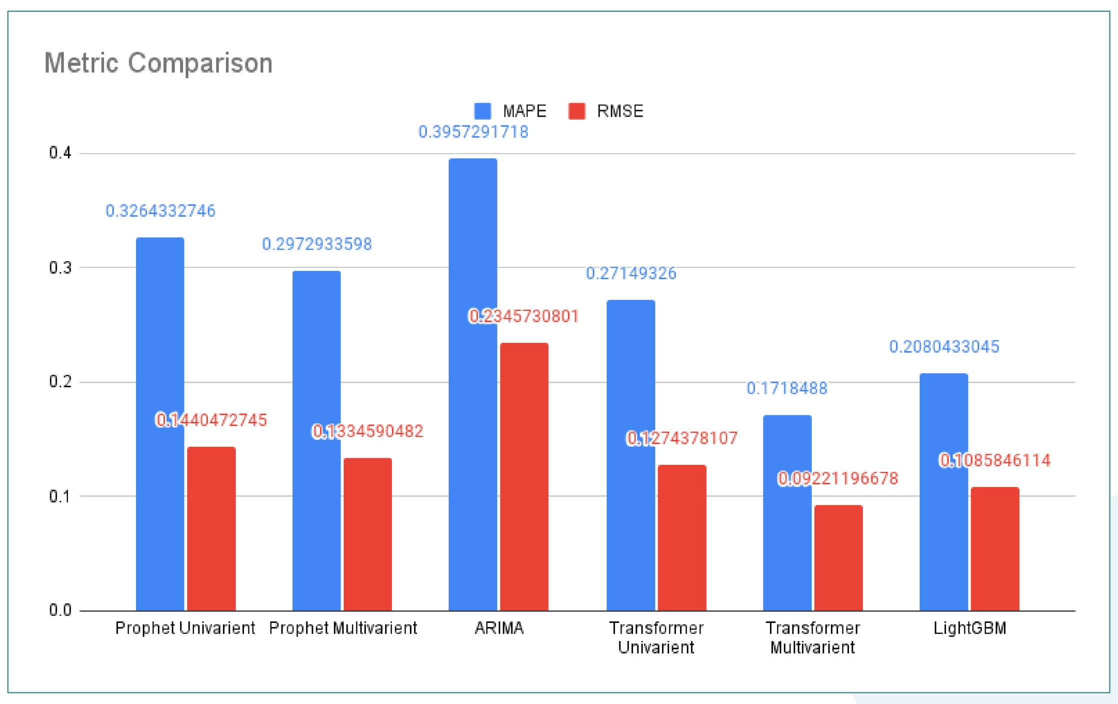

Figure 3*: Grouped bar plots from error (MAPE, RMSE) representation per model.*

Both Prophet and Transformer showed boosted performance after adding important features based on interpreting the LightGBM model.

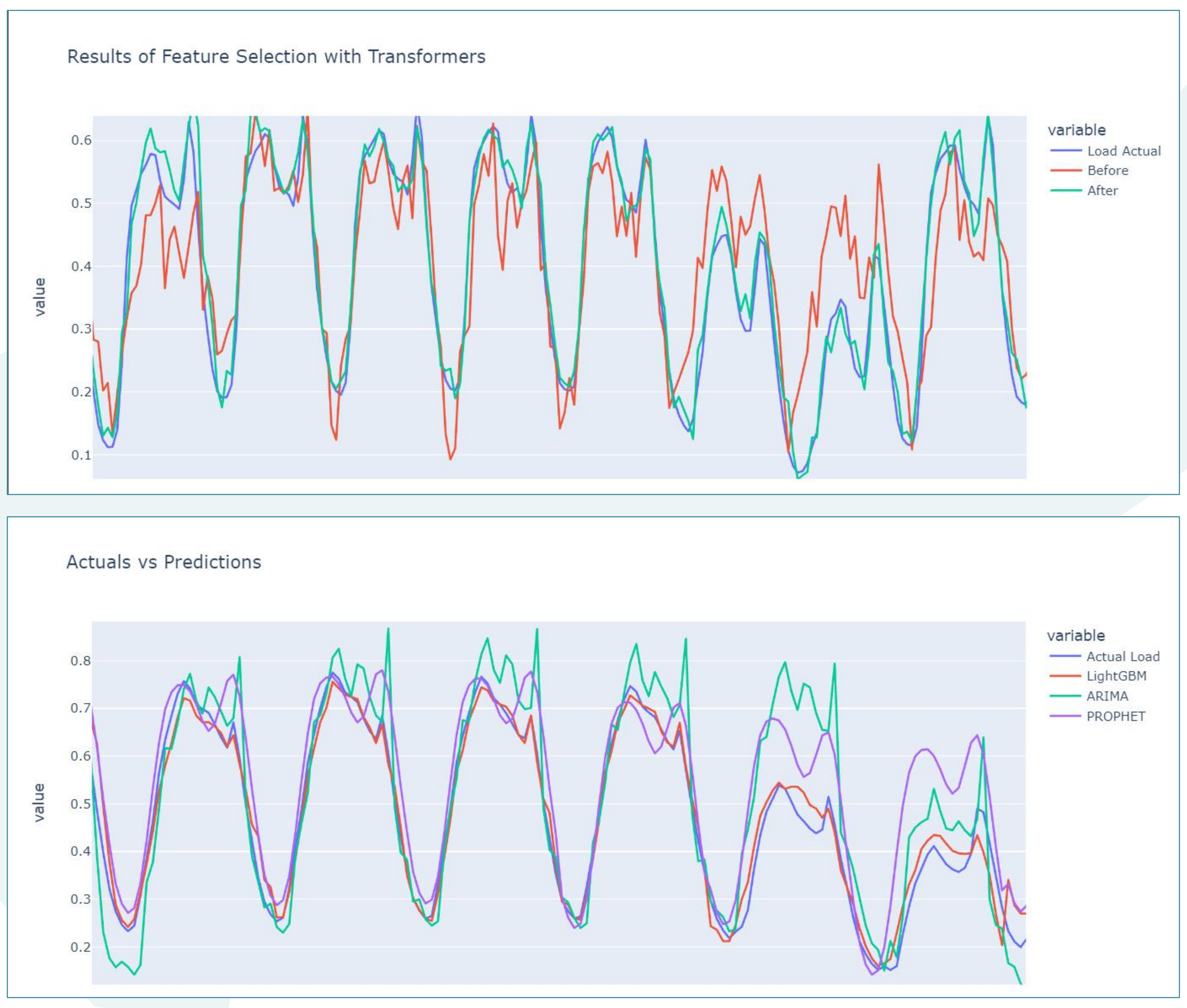

Figure 2:
Above: Comparison of the Transformer model before and after using the engineered features via line charts.
Below: Comparison between the ARIMA, PROPHET and LightGBM models via line charts.

[1] Jhana N. 2019. Hourly energy demand generation and weather. Retrieved April 8, 2022 from *https://www.kaggle.com/datasets/nicholasjhana/energy-consumption-generation-prices-and-weather/metadata?select=energy_dataset.csv*
[2] Box GEP, Jenkins GM, Reinsel GC, Ljung GM. 2015. Time Series Analysis: Forecasting and Control. *John Wiley and Sons Inc*, pp. 712. ISBN: 978-1-118-67502-1.
[3] Letham B, Taylor SJ. 2017. Prophet: forecasting at scale. [Blog] Meta Research. *https://research.facebook.com/blog/2017/02/prophet-forecasting-at-scale/ [Accessed April 8, 2022]*
[4] Wu N, Green B, Ben X, O'Banion S. 2020. Deep transformer models for time series forecasting: The influenza prevalence case. *arXiv preprint arXiv:2001.08317*.
[5] Ke G, Meng Q, Finley T, Wang T, Chen W, Ma W, Ye Q, Liu TY. 2017. Lightgbm: A highly efficient gradient boosting decision tree. *Advances in neural information processing systems*, 30.

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