# **Project Proposal**

**Team:** ETF

**Project Title:** Forecasting Energy Demand with Transformers

**Project Summary:**

Accurate forecasts of electricity demand are useful and necessary across many areas, such as operating power transmission systems, and wholesale energy pricing. This importance has only grown in recent years, with the introduction of renewable (and intermittent) energy resources. Forecasting on such data can be considered a sequence task, where given previous members of a sequence, we learn to predict the next member or members of said sequence, with additional complexity introduced from short-term fluctuations like seasonality and auto-correlation. Classical approaches to deal with such problems, such as ARIMA, have been successful for short term forecasts, but struggle when modeling more complex patterns of temporal dependence over longer periods of time. In this project, we aim to explore the performance of transformer architectures, which can better learn complex patterns from time series data, on this task, with the goal of potentially surpassing previous efforts in this space.

**Approach:**

For this project, we are utilizing a building energy demand dataset (obtained from IEEE [9]) to perform time-series forecasting of building power demand using a transformer-based architecture. To evaluate this approach, we will design a probabilistic model [6] as a benchmark. For further comparison, we aim to employ ARIMA (a commonly used time series forecasting approach and a Long Short-Term Memory (LSTM) [7] architecture alongside our transformer [2]. LSTM style architectures have been previously tried on this problem [8], with code examples provided, but to our knowledge, less work has been done for transformers. Therefore, much of our experimentation will be focused on constructing/tuning our transformer model. As our accuracy metric, we aim to use the root of mean squared error (RMSE) divided by the mean squared average of the demand [8], as presented below:

Since we are leveraging this metric alongside the build power demand dataset from [8], a stretch goal is to improve upon Taheri *et. Al's* results.

**Related Work:**

In general, time series forecasting for neural networks has seen a progression in the development of architectures which leverage past data to predict future information while also identifying the most appropriate past events to give proper attention. At first, specialized convolutional architectures, as well as recurrent neural network-based architectures [1][2], (given that time series, like text, can be viewed as sequences of inputs and targets), were employed to some success. However, RNNs, as well as LSTM architectures [3] which were designed to overcome RNN’s vanishing gradient issues, were later superseded by attention mechanisms [4][5], which have shown promise in time series forecasting (with improved performance over comparable recurrent networks [6]).

For our problem, current state of the art has involved hybrid approaches [7] that blend recurrent architectures and attention mechanisms with classical processes like Gaussian regression and wavelet decomposition. In particular, Taheri et. al [8] (the paper we aim to improve upon) show that a combination of an RNN architecture with Gaussian process regression outperforms classical approaches for electricity and heat demand forecasting.

**Resources:**

[1] B. Lim, S. Zohren and S. Roberts, "Recurrent Neural Filters: Learning Independent Bayesian Filtering Steps for Time Series Prediction," 2020 International Joint Conference on Neural Networks (IJCNN), 2020, pp. 1-8, doi: 10.1109/IJCNN48605.2020.9206906.

[2] Wang, Y., Smola, A., Maddix, D., Gasthaus, J., Foster, D. &amp; Januschowski, T.. (2019). Deep Factors for Forecasting. Proceedings of the 36th International Conference on Machine Learning, in Proceedings of Machine Learning Research 97:6607-6617 Available from https://proceedings.mlr.press/v97/wang19k.html.

[3] Luo, Xing, Dongxiao Zhang, and Xu Zhu. "Deep learning based forecasting of photovoltaic power generation by incorporating domain knowledge." Energy 225 (2021): 120240.

[4] Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. "Attention is all you need." In Advances in neural information processing systems, pp. 5998-6008. 2017.

[5] H. Zhou, Y. Zhang, L. Yang, Q. Liu, K. Yan and Y. Du, "Short-Term Photovoltaic Power Forecasting Based on Long Short Term Memory Neural Network and Attention Mechanism," in IEEE Access, vol. 7, pp. 78063-78074, 2019, doi: 10.1109/ACCESS.2019.2923006.

[6] Fan, Chenyou, Yuze Zhang, Yi Pan, Xiaoyue Li, Chi Zhang, Rong Yuan, Di Wu, Wensheng Wang, Jian Pei, and Heng Huang. "Multi-horizon time series forecasting with temporal attention learning." In Proceedings of the 25th ACM SIGKDD International conference on knowledge discovery & data mining, pp. 2527-2535. 2019.

[7] Wang, Kejun, Xiaoxia Qi, and Hongda Liu. "A comparison of day-ahead photovoltaic power forecasting models based on deep learning neural network." Applied Energy 251 (2019): 113315.

[8] Saman Taheri, Mohammad Jooshaki, Moein Moeini-Aghtaie, Long-term planning of integrated local energy systems using deep learning algorithms, International Journal of Electrical Power & Energy Systems, Volume 129, 2021, 106855, ISSN 0142-0615

**Dataset:**

[8 years of hourly heat and electricity demand for a residential building | IEEE DataPort (ieee-dataport.org)](https://ieee-dataport.org/open-access/8-years-hourly-heat-and-electricity-demand-residential-building) [9]

This dataset represents building energy audit results between December 2010 and November 2018, at a one hour aggregation level. We note that this is the same dataset used in [8], which offers a useful benchmark to compare our own work against. Electricity demand and heat demand are response variables. Below, please find a data dictionary of this dataset.

|  |  |  |  |
| --- | --- | --- | --- |
| **Column** | **Unit** | **Non-Null Row Count** | **Description** |
| Time | Datetime | 70080 | One Hour Aggregation |
| air\_pressure | mmHg | 69934 | Outside Air Pressure |
| air\_temperature | OC | 69903 | Outside Air Temperature |
| relative\_humidity | % | 69903 | Outside Air Relative Humidity |
| wind\_speed | m/s | 69125 | Wind Speed |
| solar\_irridiation | W/m2 | 70080 | Power Received from the Sun |
| total\_cloud\_cover | categorical | 69837 | 0-10 categorical |
| electricity\_demand\_values | kW | 70073 | HVAC System, convenience power, elevator, etc |
| heat\_demand\_values | kW | 70073 | Household Heating Load |

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