Time Series Prediction for the European Electricity Market

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1. Introduction
2. Data Preperation
3. Modeling
4. What's Next

Motivation

- The European electricity market involves complex dynamics due to varying demand and supply.
- Short term Accurate time series prediction is crucial due to the signal unstability.
- The potential of spatio-temporal graph neural networks and their interpretability.

Objectives

- Collect and model European electricity data as graph-structured data.
- Train a spatio-temporal model able to make accurate node level regression.
- Apply several explainability techniques to interpret the model.

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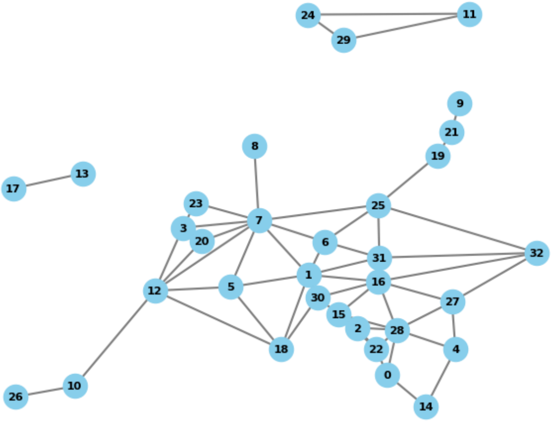
Data Collection

- Data were collected from ENTSOE platform [1] and oikolab [2] using scraping scripts from 2020 to 2023, fine grained hourly.

Target Vector	Feature Vector
Day-ahead Total Load (MW), Energy Price (EUR/MWh)	Weather Data, Electricity Generation, Historical Load Data, Day-of-Week, Time-of-Day, Transmission Data, Public Holidays Indicator

Data Modeling

The collected data were preprocessed into a static graph using Pytorch Geometric Temporal [3], where $D = \{(G_t, X_t)\}_{t=1}^{T}$



Data Normalization

Before training, X_t, Y_t for $t = 1, \ldots, T$ are normalized by dividing by N (population in million):

$$\hat{X}_t = \frac{X_t}{N}, \quad \hat{Y}_t = \frac{Y_t}{N}$$

After training, the predictions are denormalized by multiplying by N before evaluation:

$$\tilde{Y}_t = \hat{Y}_t \times N$$

Baseline

As a baseline we train a a *XGBRegressor* and *Linear Regression* on $D' = \{(X_t, Y_t)\}_{t=1}^{T}$.

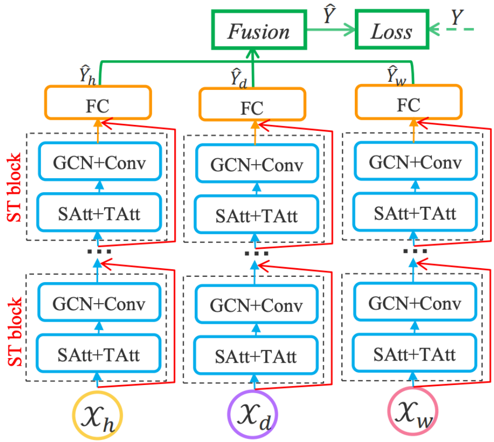
Model	MSE	MAE
XGBRegressor	2.077×10^7	**1270**
LinearRegression	$\mathbf{1.603} \times 10^7$	1782

A date feature was included, which was converted to radians for each time step t.

$$\text{Date Feature}_t = \sin\left(\frac{2\pi t}{365}\right)$$

Spatio-Temporal Model Architechture

We propose an Attention Based Spatial-Temporal Graph Convolutional Network (ASTGCN) [4].



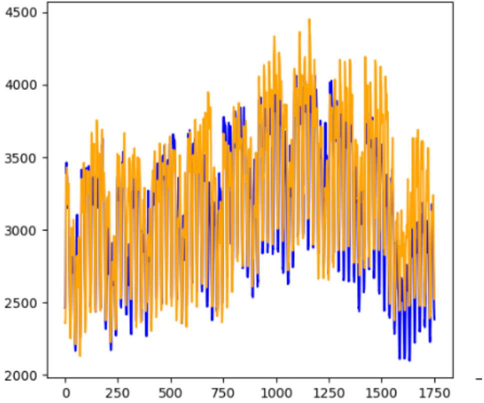
Spatio-Temporal Model Details

The model is trained on 32 mini-batches, $D = \{D_1, D_2, \ldots, D_{32}\}$, where each $D_i \subseteq D$ represents a mini-batch.

Length of X ($\mathbf{X}$)	8760
Length of Nodes ($\mathbf{N}$)	37
Length of Input ($\mathbf{x}$)	23
Number of Parameters	44457
Hidden size	128
Epochs	400

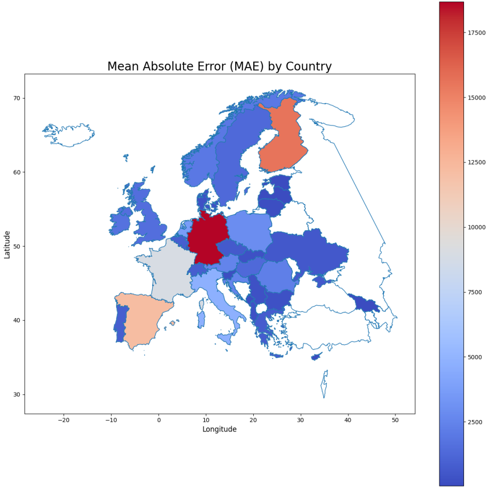
Spatio-Temporal Model Performance

Predicted signal (orange) compared with actual signal (blue) after 400 epochs for a node.



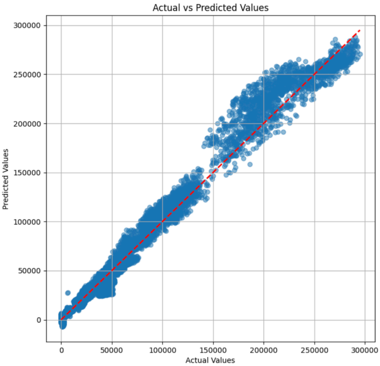
Spatio-Temporal Model Performance

MAE per country.



Models Comparison

Model	MSE	MAE
XGBRegressor	2.077×10^7	1270
LinearRegression	1.603×10^7	1782
ASTGCN	**1.36** $\times 10^5$	**147**



New target and Explainability

1. The model could be more fine tuned and then trained to predict the energy price.
2. We will also aim to explain our model using:
   - Gradient or feature-based methods
   - Perturbation methods
   - Decomposition methods

Kolmogrov-Arnold Networks ?

$$\text{KAN}(\mathbf{x}) = (\Phi_3 \cdot \Phi_2 \cdot \Phi_1)(\mathbf{x})$$

instead of

$$\text{MLP}(\mathbf{x}) = (\mathbf{W}_3 \cdot \sigma_2 \cdot \mathbf{W}_2 \cdot \sigma_1 \cdot \mathbf{W}_1)(\mathbf{x})$$

- Can KANs be adapted for spatio-temporal data?
- Would they perform better than MLP based models?
- Are they actually more interpretable?

[1] ENTSOE platform

[2] OikoLab

[3] B. Rozemberczki et al, "PyTorch Geometric Temporal: Spatiotemporal Signal Processing with Neural Machine Learning Models", *Proc. 30th ACM Int. Conf. on Info. and Knowledge Management*, 2021, pp. 4564–4573.

[4] Guo, Shengnan et al, Attention Based Spatial-Temporal Graph Convolutional Networks for Traffic Flow Forecasting, *Proceedings of the AAAI Conference on Artificial Intelligence*, 2019,pp. 922-929

Thanks! Questions ?