Multivariate Time Series Forecasting of Appliance Energy Usage

Appliances Energy Prediction Dataset (UCI)

August 1, 2025

Dataset and Problem Statement

The Appliances Energy Prediction Dataset contains **19,735 time-series measurements** collected at **10-minute intervals** over **4.5 months** in a low-energy smart home. Each sample consists of **28 features** derived from:

- **Indoor conditions:** Temperatures T1–T9, Humidities RH_1–RH_9
- **Weather station:** T_out, RH_out, Pressure, Windspeed, Visibility, Tdewpoint
- **Other:** lights, rv1, rv2 (random vars)
- **Target:** Appliances (Wh)

The dataset is clean (no missing data), collected via ZigBee sensors and M-Bus meters, and merged with weather data from Chievres Airport (Belgium).

Data Characteristics and Goals

- The dataset exhibits **daily and sub-daily seasonality**, **bursty behavior**, and **weak linear correlations** with the target.
- Goal: **Forecast future appliance energy consumption** using historical multivariate data.
- Challenges: **Non-stationarity**, **random peaks**, **heterogeneous features**.
- Strategy: Deep learning models trained via **sliding windows** for sequence-to-sequence forecasting.

Data Integrity and Missing Values

- Verified dataset has **no missing or NaN values**.
- All columns are continuous, time-indexed, and ready for modeling.

Temporal Trends (First Week)

Daily cycles are clearly visible in indoor temperatures and humidity. The **Appliances** target exhibits **bursty, irregular usage** often aligned with human routines.

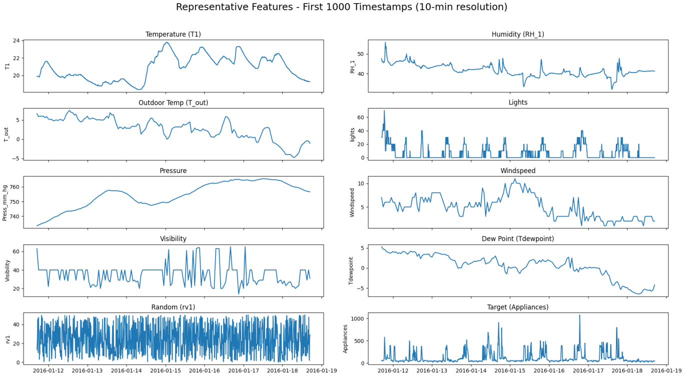
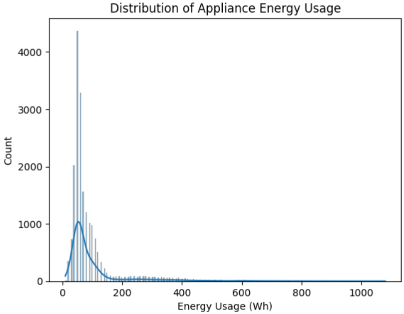
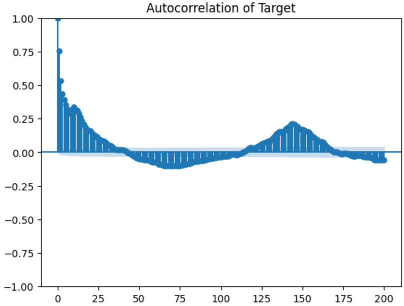


Figure: Time series representation (one week)

Target Distribution and Autocorrelation

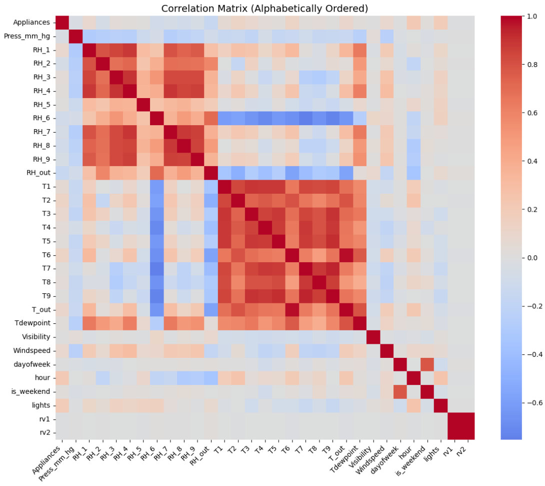
- Right-skewed distribution of **Appliances** with rare spikes > 1000 Wh.
- Autocorrelation reveals strong **daily periodicity** (lag $= 144$ steps).





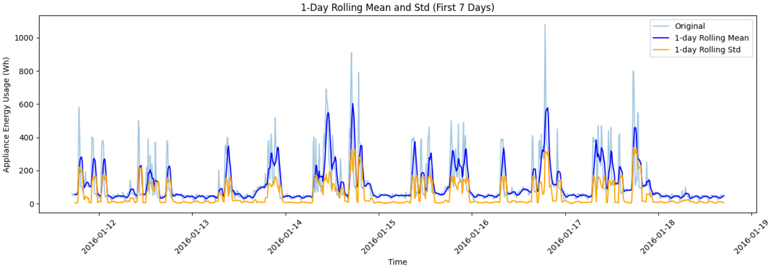
Correlation and Non-Linear Dependencies

- Strong correlation between **T1–T9** and between **RH1–RH9**.
- **Appliances** has weak linear correlation with all inputs.
- Suggests that **nonlinear models** are better suited.



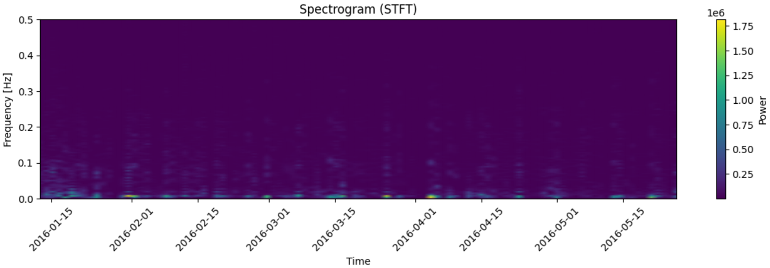
Non-Stationarity: Rolling Statistics

- Rolling mean and std deviate over time.
- Indicates **non-stationary** behavior.



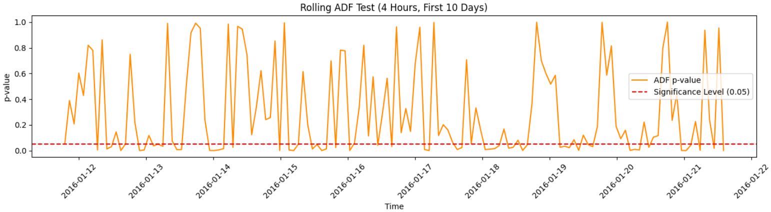
Spectrogram and FFT Analysis

- Frequency domain shows **dominant daily periodicity**.
- FFT confirms strong **24h cycles** and secondary harmonics.



ADF Stationarity Tests

- Global ADF: $p < 0.05 \rightarrow$ Stationary.
- Rolling ADF: p-values fluctuate $\rightarrow$ **Local non-stationarity**.
- Recommends **seasonal decomposition or transforms**.



Forecasting Task Definition

- Input: last **720 steps** (5 days) of multivariate features.
- Output: next **100 steps** of **Appliances**.
- Sliding window: stride = 72 steps (12 hours).
- Time-aware categorical features added (hour, dayofweek).

Train/Test Split & Normalization

- No shuffling to preserve temporal order.
- First 80%: training; Last 20%: test.
- Features/target scaled using **StandardScaler** fit on train split only.

Models Trained

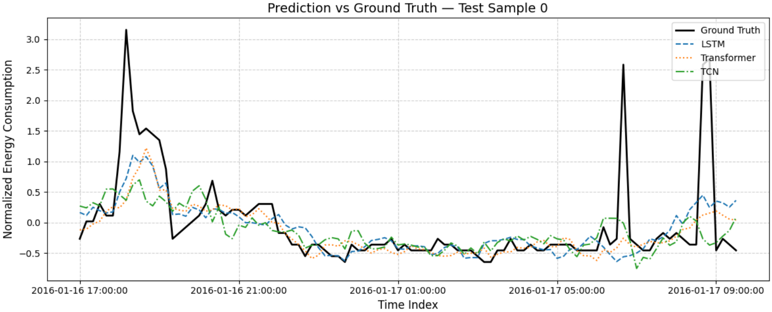
- **LSTM:** Recurrent network for long memory.
- **Transformer:** Attention-based global model.
- **TCN:** Dilated causal convolutions.
- All trained for 200 epochs using MAE loss and Adam optimizer.

Model Performance (Test Set)

Model	MAE	RMSE
LSTM	0.485	0.899
Transformer	**0.458**	**0.869**
TCN	0.553	0.930

Prediction Visualization

- Transformers follow temporal trends best.
- All models struggle with **unpredictable peaks**.



Next Steps

- Add classical models: ARIMA, SARIMA, Exponential Smoothing
- Hybrid models: ARIMA + DL for residuals
- Deeper DL architectures, multi-scale inputs, hyperparameter tuning
- Explore dimensionality reduction (PCA/UMAP), anomaly detection
- Rolling-origin CV, confidence intervals, uncertainty estimation