Energy Forecasting with Transformer and LightGBM

This project focuses on forecasting urban energy consumption based solely on historical usage and temperature data from Chicago (2011–2018). Two model architectures are compared: a LightGBM ensemble model and a Transformer-based neural network (based on the Moments Time Series Transformer). The goal is to predict hourly electricity demand and analyze model performance, interpretability, and generalizability.

The project also simulates a real-time setting, where hourly predictions are made sequentially to mirror operational deployment. The modular design allows for adaptation to other urban contexts, assuming a compatible data structure.

The modular structure is transferable to similar forecasting tasks such as load prediction or material flow analysis in industrial systems. Full repository available at: https://github.com/dlajic/energy-forecasting-transformer-lightgbm

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Overview

- **Goal**: Predict hourly energy consumption using timestamp, temperature, and historical consumption features.
- **Models**: LightGBM and Time Series Transformer Model (moements).
- **Results**: Both models perform well; LightGBM achieves the best overall performance.
- **Dashboard**: Live forecast simulation via Streamlit interface.
- **Usage Context**: Developed as a prototype for real-time hourly forecasting, with a modular structure that supports adaptation to similar operational settings.

Results

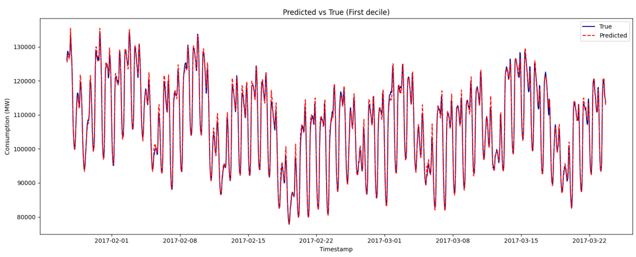
Evaluation Metrics

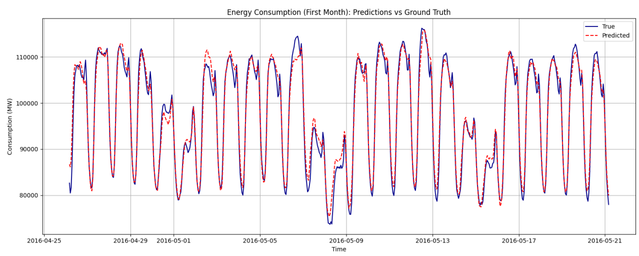
Model	RMSE	R^2	MAPE
Transformer	3933.57	0.972	2.32 %
LightGBM	1383.68	0.996	0.84 %

> **Note:** All values are in megawatts (MW). Hourly consumption typically ranges from 100,000 to 200,000 MW.

- LightGBM achieves the best trade-off between performance and resource efficiency.
- The Transformer model generalizes well to temporal patterns and may scale better in more complex or multi-network scenarios.
- Both models show no signs of overfitting, supported by learning curves, consistent evaluation metrics, and additional diagnostics such as residual distribution analysis and noise-feature validation.

Forecast Plots

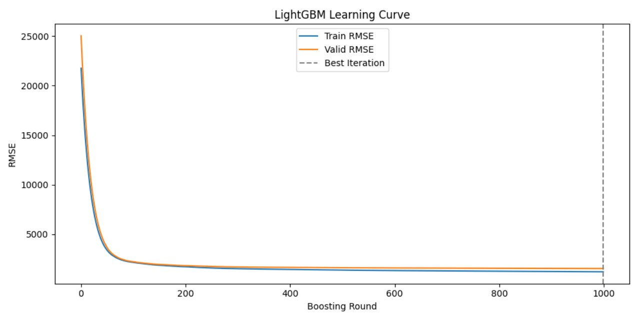


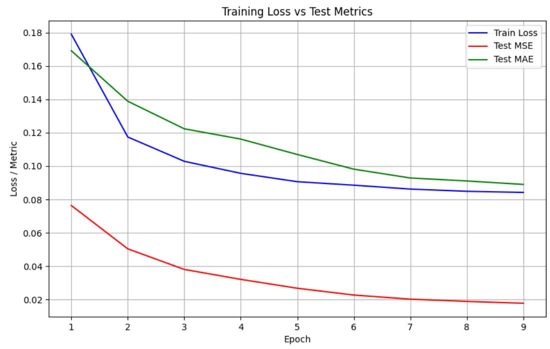


> **Note:** Example forecast windows are shown (LightGBM: 3 months, Transformer: 1 month).
> LightGBM maintains highly consistent performance over time, while the Transformer shows occasional over- or underestimation on special peak days.

Learning Curves

These plots visualize training dynamics and help detect overfitting.





- The LightGBM curve shows a stable gap between training and validation RMSE, indicating low overfitting.
- The Transformer learning curve also converges smoothly without divergence, supporting generalizability.
- In addition to visual inspection, further checks like residual analysis and a noise feature test confirmed robustness.

> **Note:** The LightGBM curve shows boosting rounds with validation RMSE,
> while the Transformer plot tracks training loss and test metrics per epoch.

More plots are available in the respective `/results` directories.

Streamlit Simulation Dashboard

- Live hourly forecast simulation
- Uses the trained models
- Repeats predictions sequentially for each hour to simulate real-time data flow
- Hosted on Hugging Face (CPU only, slower prediction speed)

You can try the model predictions interactively in the Streamlit dashboard:

Try it here: Launch Streamlit App

Data

- **Source**:
  - COMED Hourly Consumption Data
  - NOAA Temperature Data
- **Time range**: January 2011 – August 2018
- **Merged file**: `data/processed/energy_consumption_aggregated_cleaned.csv`

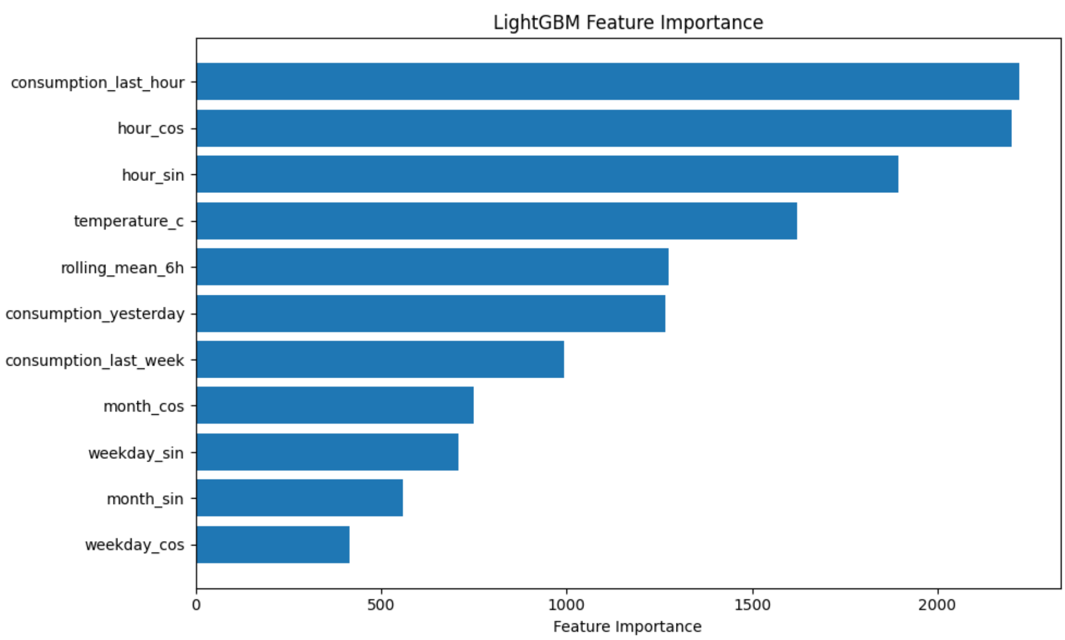
Feature Engineering

The models rely on timestamp and temperature data, enriched with derived time-based and lag-based features:

- hour_sin, hour_cos
- weekday_sin, weekday_cos
- month_sin, month_cos
- rolling_mean_6h
- temperature_c
- consumption_last_hour
- consumption_yesterday
- consumption_last_week

Feature selection was guided by LightGBM feature importance analysis. Weak features with nearly no impact like "is_weekend" were deleted.

Final LightGBM Feature Importance



Model Development

LightGBM

- Custom grid search with over 50 parameter combinations
- Parameters tested:
  - num_leaves, max_depth, learning_rate, lambda_l1, lambda_l2, min_split_gain
- Final Parameters:
  - learning_rate: 0.05
  - num_leaves: 15
  - max_depth: 5
  - lambda_l1: 1.0
  - lambda_l2: 0.0
  - min_split_gain: 0.0
  - n_estimators: 1000
  - objective: regression

Overfitting was monitored using a noise feature and RMSE gaps. See grid search results: `notebooks/lightgbm/lightgbm_gridsearch_results.csv`

Transformer (Moments Time Series Transformer)

- Based on pretrained Moments model
- Fine-tuned only the forecasting head for regular training
- Also tested variants with unfrozen encoder layers and dropout
- Final config:
  - task_name: forecasting
  - forecast_horizon: 24
  - head_dropout: 0.1
  - weight_decay: 0
  - freeze_encoder: True
  - freeze_embedder: True
  - freeze_head: False

Project Structure

```
energy-forecasting-transformer-lightgbm/
├── data/                    # Raw, external, processed datasets
├── notebooks/               # EDA, lightgbm and transformer prototypes, including
hyperparameter tuning and model selection
├── scripts/                 # Data preprocessing scripts
├── lightgbm_model/          # LightGBM model, scripts, results
├── transformer_model/       # Transformer model, scripts, results
├── streamlit_simulation/    # Streamlit dashboard
├── requirements.txt         # Main environment
├── requirements_lgbm.txt    # Optional for LightGBM
├── setup.py
└── README.md
```

Reproducibility

You can reuse this pipeline with any dataset, as long as it contains the following key columns:

```
timestamp,       # hourly timestamp (e.g., "2018-01-01 14:00")
consumption,     # energy usage (aggregated; for individual users, consider adding
an ID column)
temperature      # hourly
```

Notes:

- Transformer model training is **very slow on CPU**, also with AMD GPU
- Recommended: use **CUDA or Google Colab + CUDA GPU runtime** for transformer training
- All scripts are modular and can be executed separately

Run Locally

Prerequisites

- Python 3.9–3.11 (required for Moments Transformer)

Installation

```
git clone https://github.com/dlajic/energy-forecasting-transformer-lightgbm.git
cd energy-forecasting-transformer-lightgbm
pip install -r requirements.txt
```

Preprocess Data

```
python -m scripts.data_preprocessing.merge_temperature_data  # merges raw temperature and energy data (only needed with raw inputs)
python -m scripts.data_preprocessing.preprocess_data         # launches full preprocessing pipeline; use if data already matches expected format
```

Train Models

```
python -m lightgbm_model.scripts.train.train_lightgbm
python -m transformer_model.scripts.training.train
```

Evaluate Models

```
python -m lightgbm_model.scripts.eval.eval_lightgbm
python -m transformer_model.scripts.evaluation.evaluate
python -m transformer_model.scripts.evaluation.plot_learning_curves
```

Run Streamlit Dashboard (local)

```
streamlit run streamlit_simulation/app.py
```

For editable install:

```
pip install -e .
```

Author

Dean Lajic GitHub: dlajic

References

- Moments Time Series Transformer
  https://github.com/moment-timeseries-foundation-model/moment
- COMED Consumption Dataset
  https://www.kaggle.com/datasets/robikscube/hourly-energy-consumption
- NOAA Weather Data
  https://www.ncei.noaa.gov