Short-Term Electricity Demand Forecasting

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AGENDA

- Introduction
- Objective & Research Questions
- Data Description & Preprocessing
- Exploratory Data Analysis
- Modeling Approaches Used
- Model Performance Results
- Explainability with SHAP
- Website Overview
- Challenges Faced
- Future Work
- Conclusion
- References

Introduction

Problem Statement

- Accurate short-term electricity demand forecasting critical for power system operations,
- With generation scheduling, grid stability, and cost optimization.
- Electricity demand exhibits:
  - Strong daily and seasonal patterns
  - Non-linear behavior driven by weather and human activity
  - Large errors during peak demand hours
- Traditional statistical models struggle with non-linearities, interpretability and stability

Motivation

- Operational risk is highest during peak load periods,
- Studies optimize overall accuracy, but peak-hour performance is still underexplored
- Practical need to:
  - Compare classical and deep learning approaches
  - Improve peak-load forecasting
  - Combining statistical structure with neural flexibility

Ref: Generated by AI

Objectives & Research Questions

Objective: To systematically compare statistical and deep learning models for short-term electricity demand forecasting

RQ1 — Model Comparison

How do classical time-series models (SARIMA) and deep learning models (LSTM) differ for short-term electricity demand forecasting?

- Forecast accuracy
- Interpretability
- Computational and operational characteristics

RQ2 — Peak-Load Performance

Can hybrid SARIMA+LSTM or ensemble models:

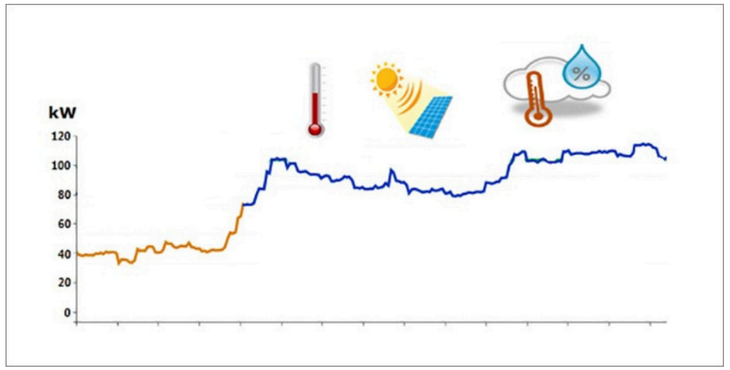
- Reduce forecast error variance
- Improve stability

  during peak-load periods, where forecasting failures are most costly?

RQ3 — Explainability & Trust

Do explainability methods (e.g., SHAP):

- Provide meaningful insights into LSTM and hybrid model behavior?
- Enhance trust and usability of forecasts for grid operators?



Ref: Load Forecasting

Data Description & Preprocessing

Raw Dataset

- Electricity Dataset Source : Open Power System Data
- Weather Dataset : Renewables.ninja
- Original Dimensions: 50,401 rows × 299 columns
- Time Range: 2014-12-31 to 2020-09-30 (hourly data)
- Coverage: ~35 European countries

Processsed Dataset

- Final Dimensions: 32,665 rows × 95 columns
- Time Range: 2015-01-08 to 2018-09-30
- Resolution: Continuous hourly intervals
- Data Quality: 100% complete after preprocessing

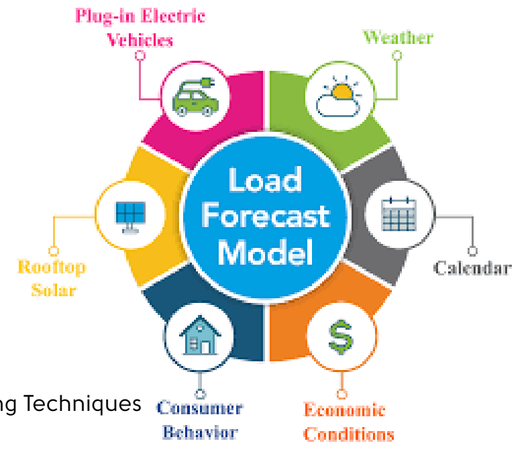


Figure: Load Forecasting Techniques
Ref: [6]

Key Variables

Energy Data

- Target: Electricity load (MW) - actual consumption
- Renewable generation: Solar and wind (actual, offshore, onshore)
- Capacity data: Installed solar and wind capacity
- Control regions: Four German TSO load data

Weather Data (Population-weighted for Germany)

- Temperature (°C) and humidity (%)
- Wind speed (m/s) and solar radiation (W/m²)
- Cloud cover (%) and precipitation (mm)
- Additional: Air density, snow mass, snowfall

Engineered Features

- Calendar: Hour, day, month, season, holidays, weekends
- Temporal: Lag features (1-168 hours), rolling statistics
- Special: Heating/cooling degree days, generation proxies

Data Preprocessing Pipeline

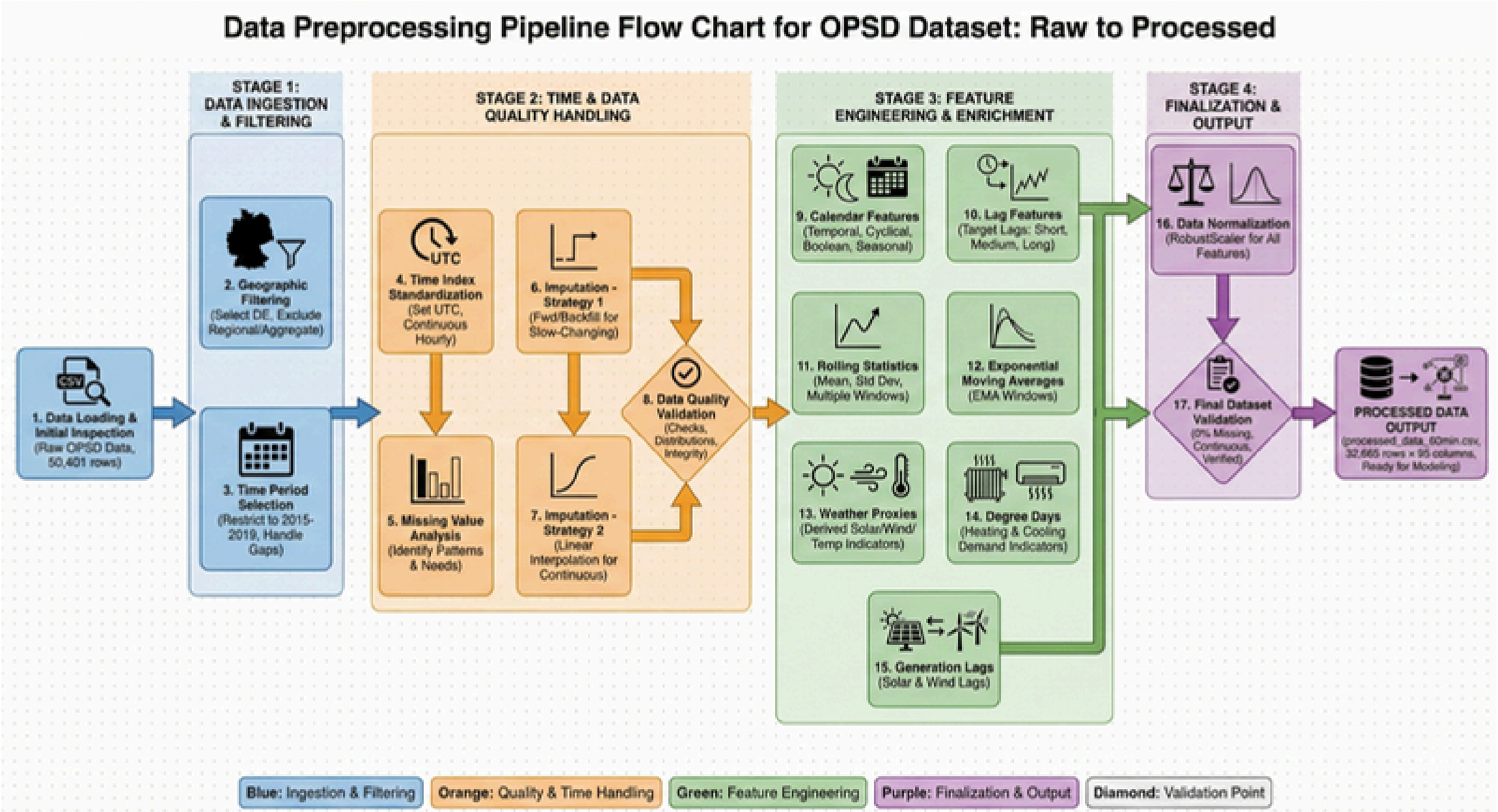


Figure : Preprocessing Steps (Ref: Generated by AI)

Exploratory Data Analysis

Dataset Summary

- Resolution: Hourly (60 min)
- Period: Jan 2015 – Sep 2018 (32,665 obs)
- Features: 95 (load, generation, weather, calendar)
- Data Quality: No missing values

Target Variable (Load)

- Mean: 55,705 MW | Range: 31,307–77,549 MW
- Distribution: Nearly normal (skew -0.04, kurtosis -1.15)
- Outliers: None (IQR method

Seasonality Patterns

- Daily: Peak 10 AM, Min 1 AM (strong diurnal cycle)
- Weekly: Peak Wed, Min Sun (week pattern)
- Monthly: Peak Feb, Min May (annual pattern)
- Weekday vs Weekend: +18.8% higher demand

Weather Impact

- Solar radiation TOA: 0.40 (strongest predictor)
- Surface solar: 0.35 | Wind: 0.28 | Temp: -0.02

Peak Load Analysis

- Threshold: 90th percentile = 68,857 MW (10% of data)
- Peak Timing: 9 AM, Wed, Jan
- Weather: Lower temp (-0.48), higher wind (+0.56)

Feature Importance

- Control region loads: 0.97–0.99
- Lagged loads: 1h (0.966), 168h (0.916)
- Rolling stats: 3h mean (0.9685), 6h EMA (0.9061)
- Calendar: Hour cosine (0.65)

Modeling Approaches

SARIMA

Model Overview

- Model: SARIMA (Seasonal ARIMA)
- Approach: Univariate time series (load only)
- Dataset: Hourly load data (2015–2018)
- Library: statsmodels ARIMA

Data Preparation

- Split: Time-based (no leakage)
  - Train: 2015–2017
  - Test: 2018
- Target: Normalized hourly electricity load

Model Architecture

- SARIMA(1,1,1) × (1,1,1,24)
- Training data: Last 1 year only (8,640 samples)
- Seasonality: Daily (s = 24)

LSTM

Model Overview

- Model: Multivariate LSTM Neural Network
- Dataset: Hourly data (2015–2018)
- Features: 94 engineered features
- Framework: TensorFlow / Keras

Data Preparation

- Time-based Split (no leakage):
  - Train: 2015–2017
  - Validation: 20% of training
  - Test: 2018
- Target: Normalized electricity load (MW)

Model Architecture

- layers: 64 → 32 units (stacked)
- Dense layer: 16 units (ReLU)
- Output: 1 neuron (linear)
- Regularization: Dropout = 0.2
- Parameters: ~30K trainable

Training Strategy

- Optimizer: Adam (lr = 0.001)
- Loss: MSE | Metric: MAE
- Batch size: 64
- Early stopping: Validation-based

Modeling Approaches

HYBRID

Model Overview

- Model: Hybrid SARIMA + LSTM
- Approach: Error-aware modeling for extreme demand hours
  - SARIMA captures linear trend + seasonality
  - LSTM learns nonlinear patterns left in SARIMA residuals
- Two evaluation regimes: All hours and Peak hours only

Data Preparation

- Scaling
  - Residuals normalized using MinMaxScaler
- Peak hours defined as:
  - Load ≥ 90th percentile of historical hourly demand

Model Architecture:

- Target: SARIMA residuals $Residual_t = y_t - y'_t SARIMA$
- Input features: Lagged residual sequences (lookback window)
- Output: Residual correction term
- Final Prediction

$$y'_t Hybrid = y'_t SARIMA + r'_t LSTM$$

ENSEMBLE

Model Overview

- Model: Combines forecasts from multiple models into one prediction to improve accuracy and peak-load stability.
- Dataset: Hourly data (predictions from SARIMA,LSTM,HYBRID)

Data Preparation

- Standardized data using StandardScaler for Ridge-based ensembles and SHAP explainability
- Peak hours defined as load > 90th percentile of evaluation data

Methods:

- **Mean(Simple Average):** Mean of all base models
- **Median**: Median of all base models
- **Stacked Ridge**: Ridge regression meta-learner
- **Weighted Ridge:** Performance-weighted combination
- **NNLS (Non-Negative Least Squares)**: Constrained optimization
- **Residual Corrector**: LSTM-based error correction
- **Switch Models:** Conditional model selection based on peak detection

Overall Model Performance Results

Performance Metrics	SARIMA	LSTM	HYBRID	ENSEMBLE (final_switch_residual)
MAE	11,526 MW	818.79 MW	16475 MW	**577.09 MW**
RMSE	13,362 MW	1,087.63 MW	18460 MW	**740.69 MW**
MAPE	19.56%	1.46%	28.70%	**1.10%**
ME (Bias)	–11,063 MW	–93.88 MW	-16351 MW	**-236.22MW**
MASE	6.04	0.43	8.63	**0.121**
R^2	–0.847	0.9877	-2.53	**0.99**
Directional Accuracy	82.89%	91.13%	80.97%	**92.59%**

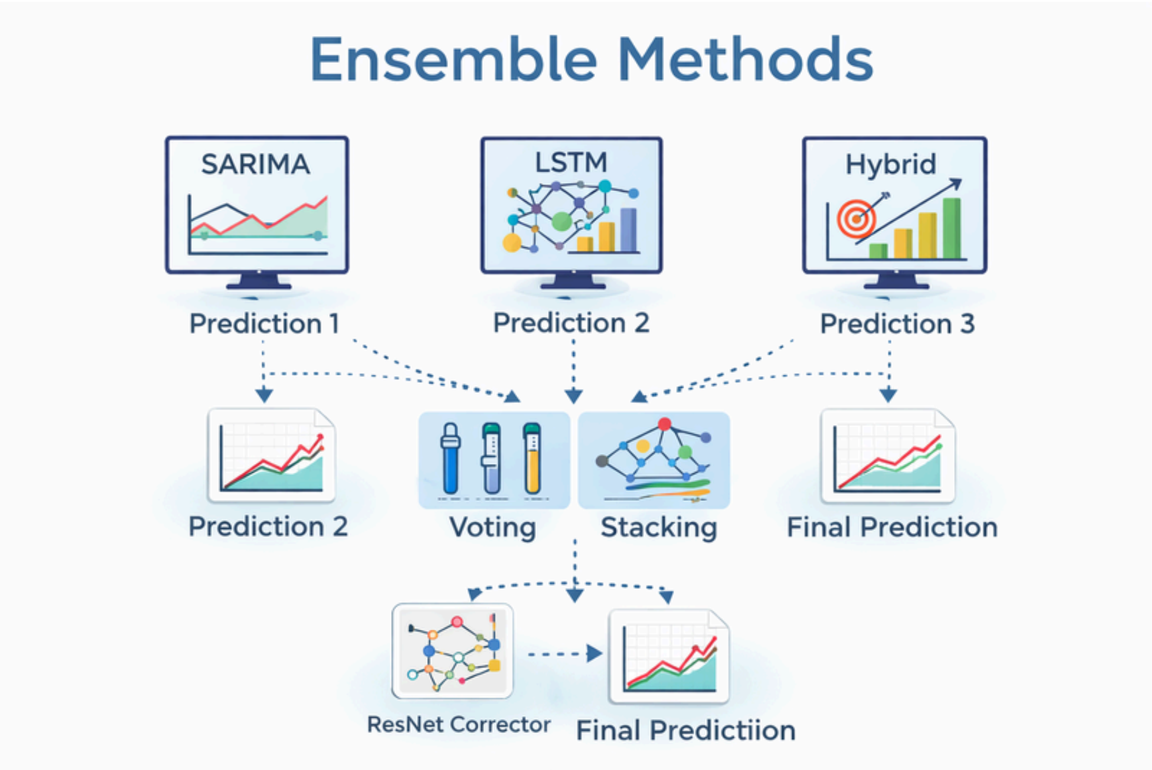
Ensemble Methods Performance Results

Best overall and peak model: final_switch_residual, lowest error overall and during peaks by learning and correcting residual forecast errors.

Strong alternatives: ens_residual_lstm and LSTM/NNLS consistently good, but slightly less accurate than residual correction.

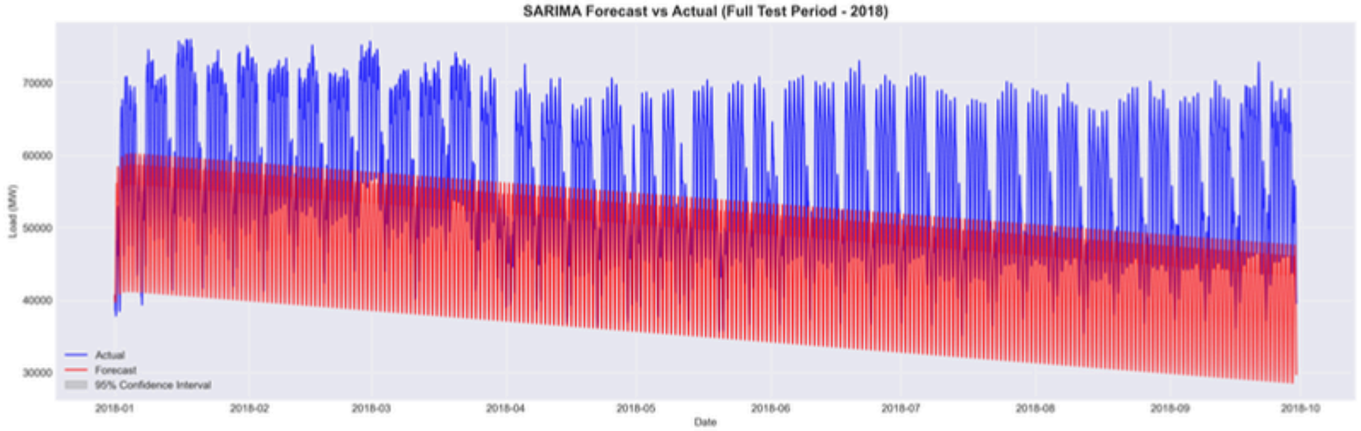
ens_weighted_ridge: strong peak performance by giving higher weight to better base predictors.

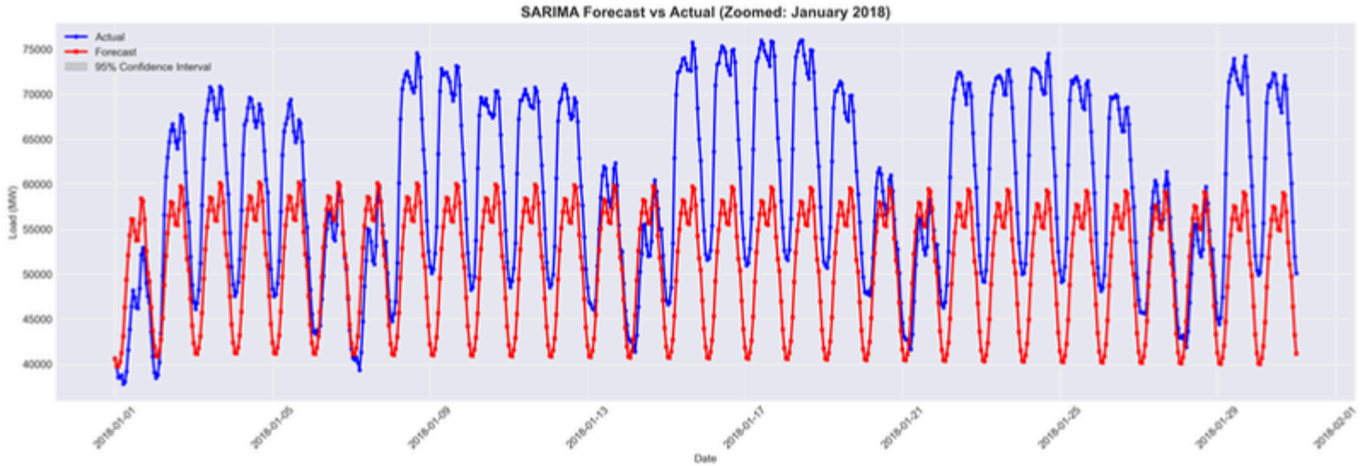
mean/median: mean and median ensembles, weak because poor base forecasts distort the combination and they cannot adapt to spikes.

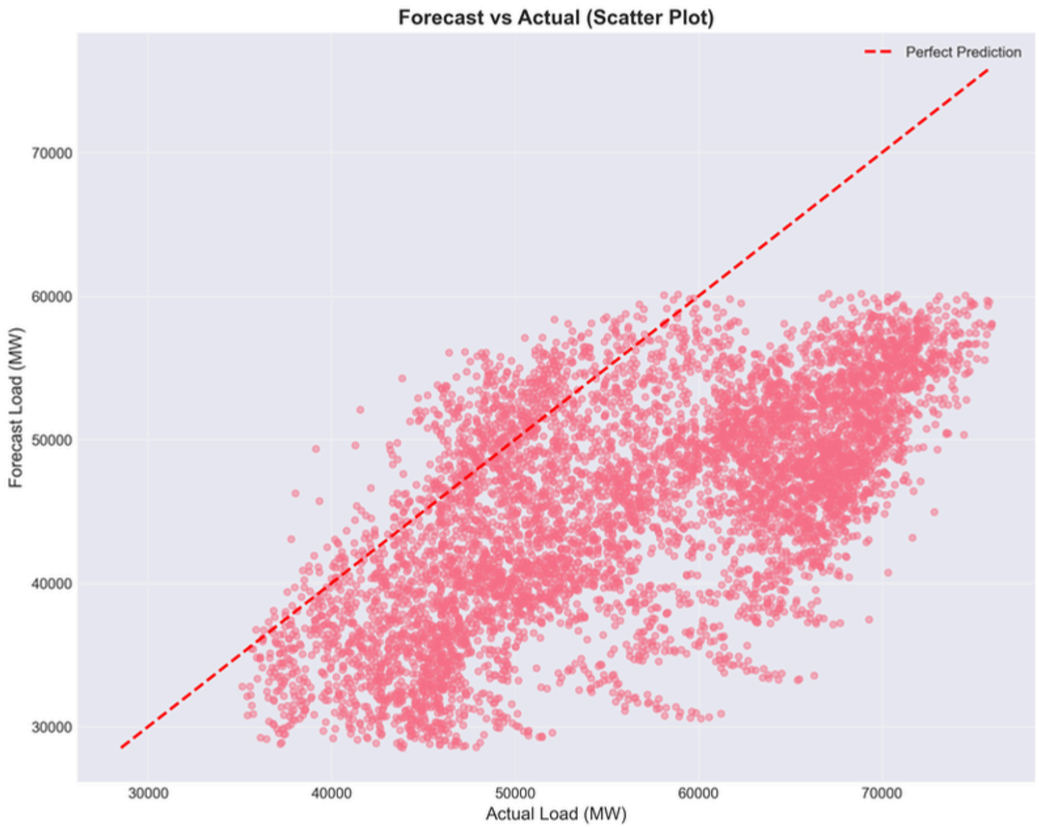


Ref: Generated by AI

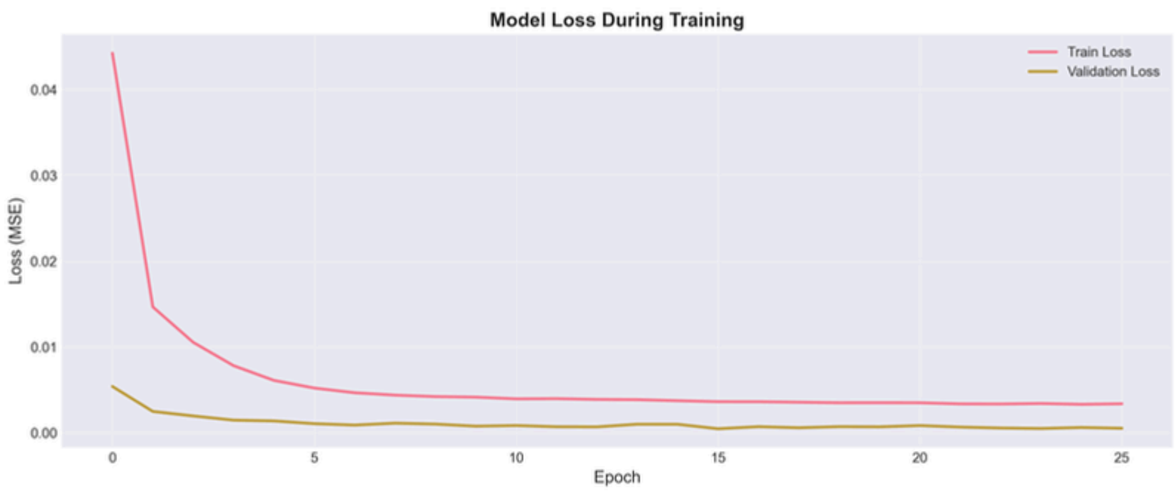
Graphs Analysis & Results: SARIMA

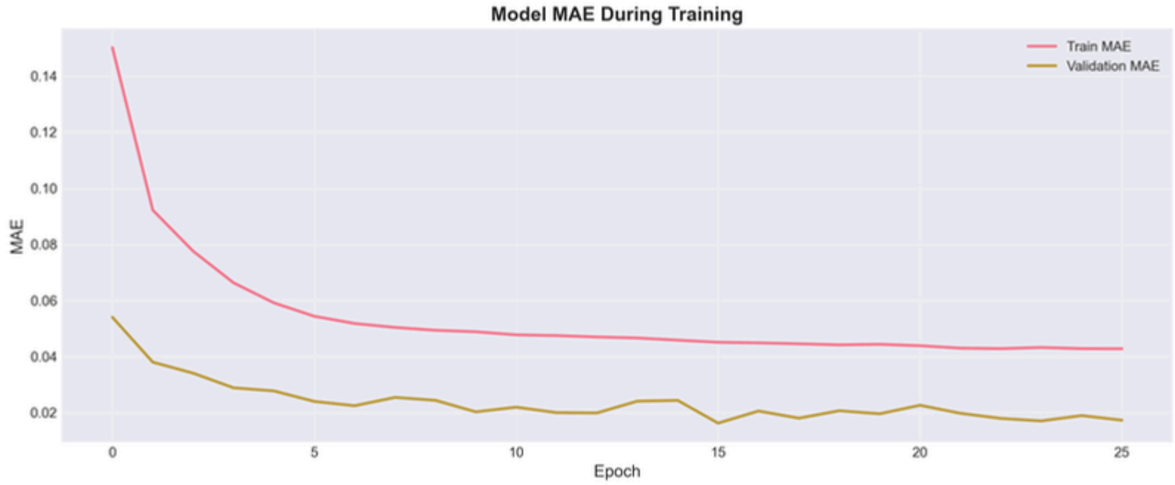


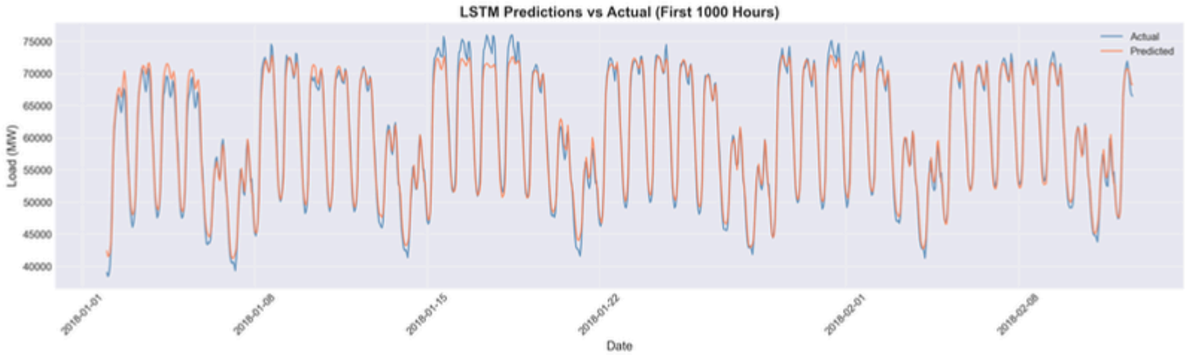


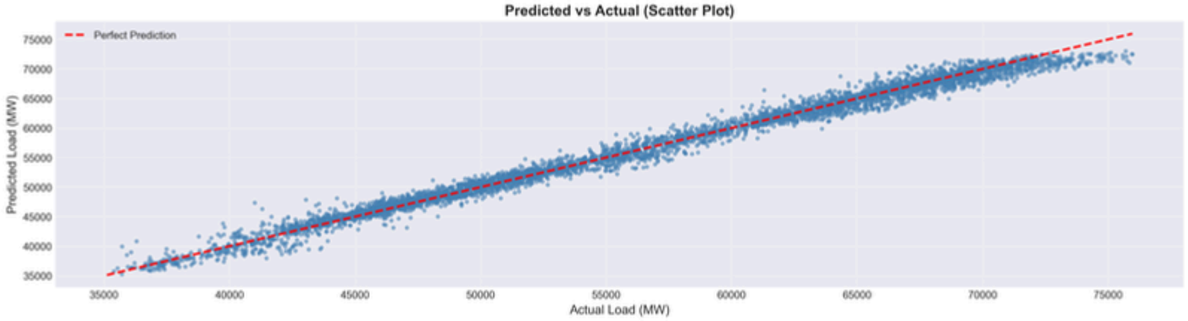


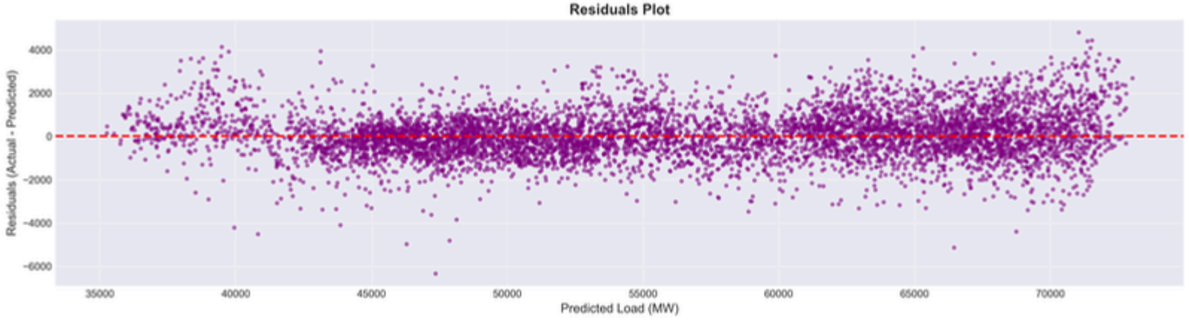
Graphs Analysis & Results: LSTM



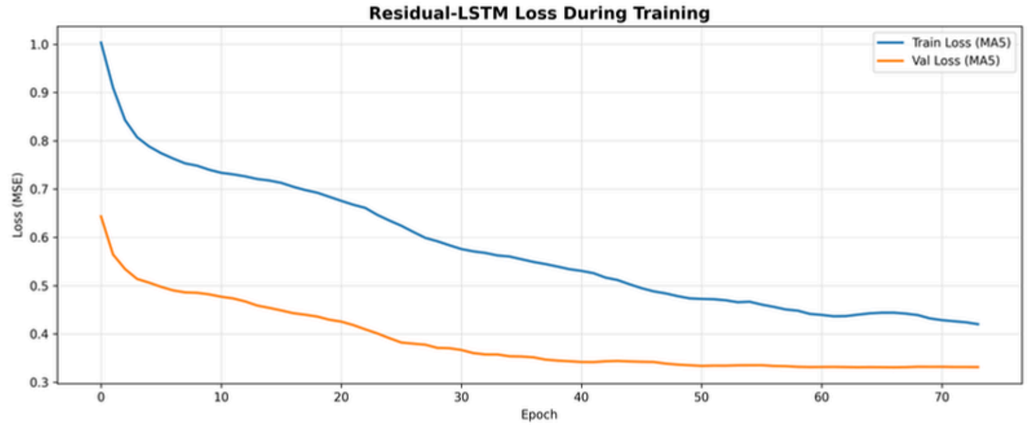


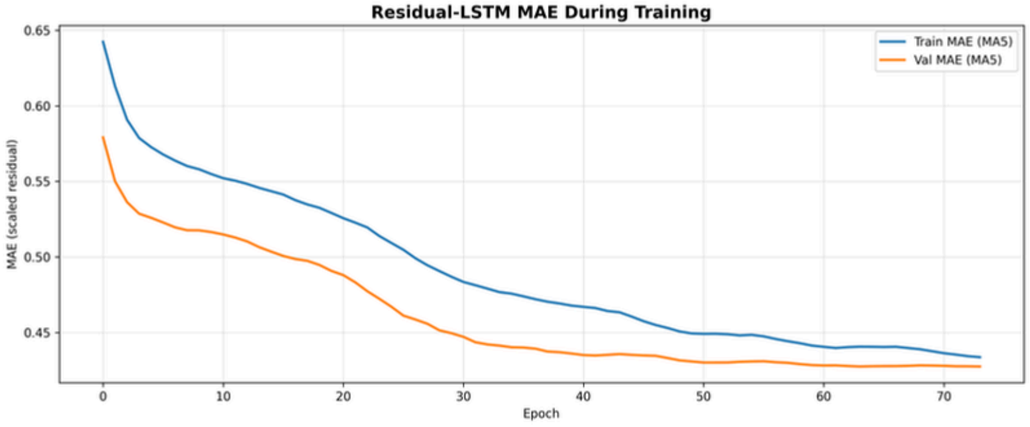


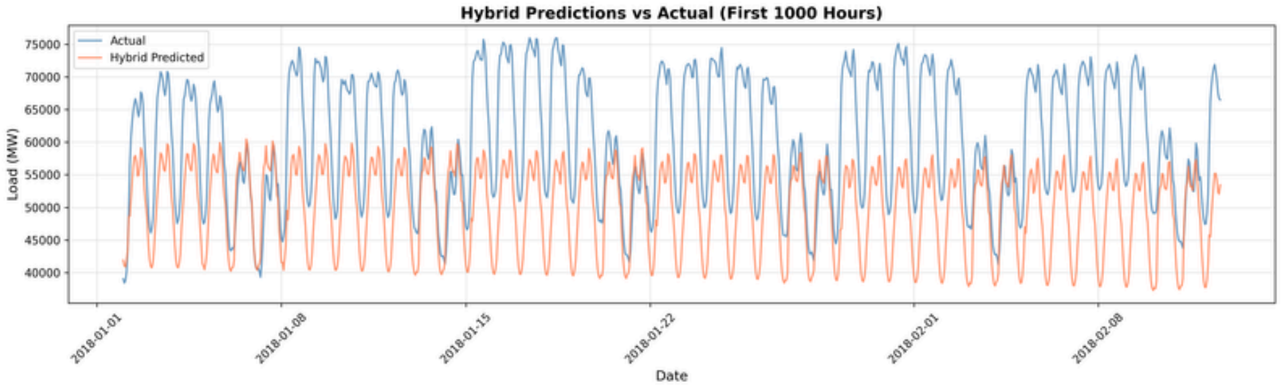


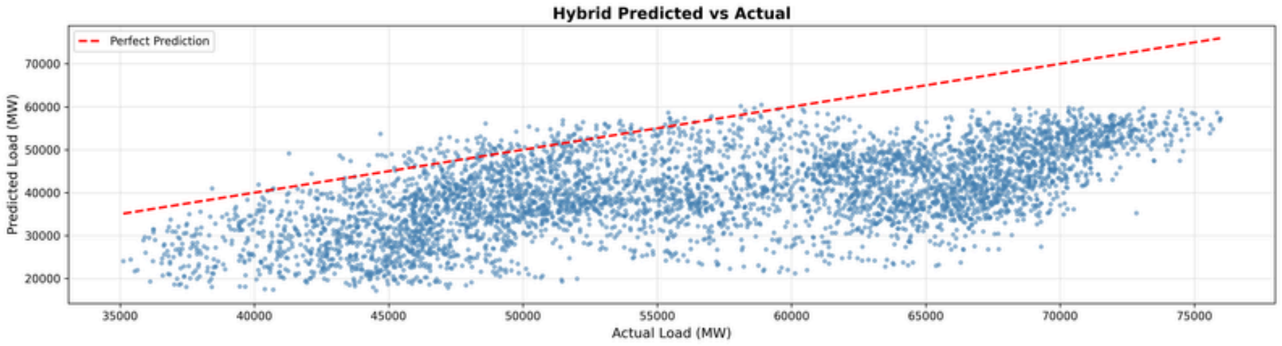


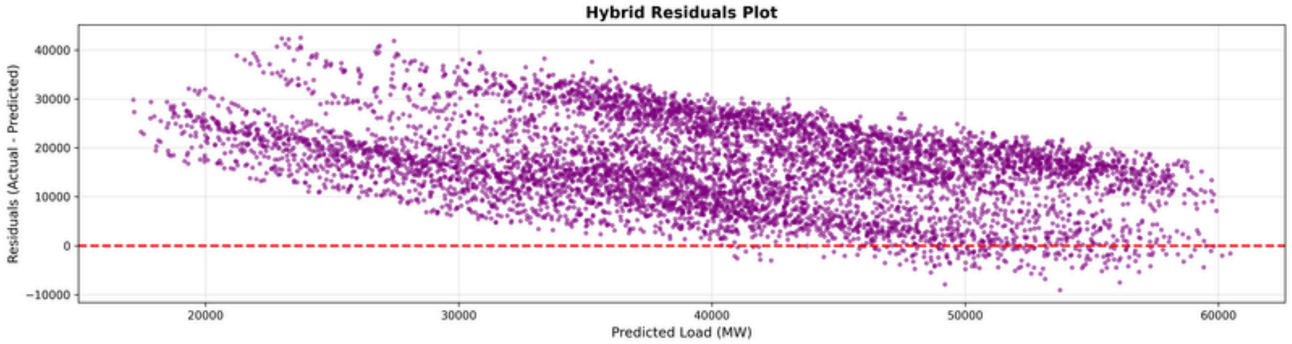
Graphs Analysis & Results: Hybrid



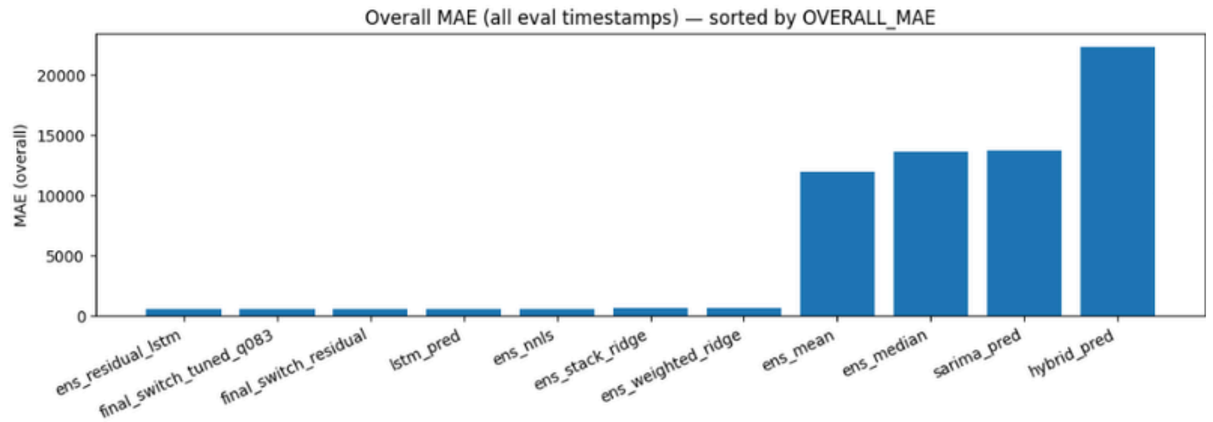


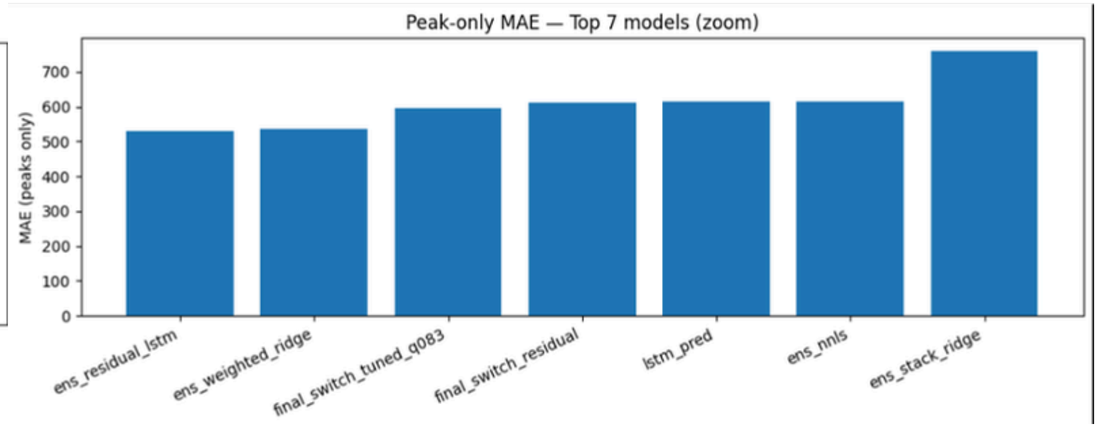


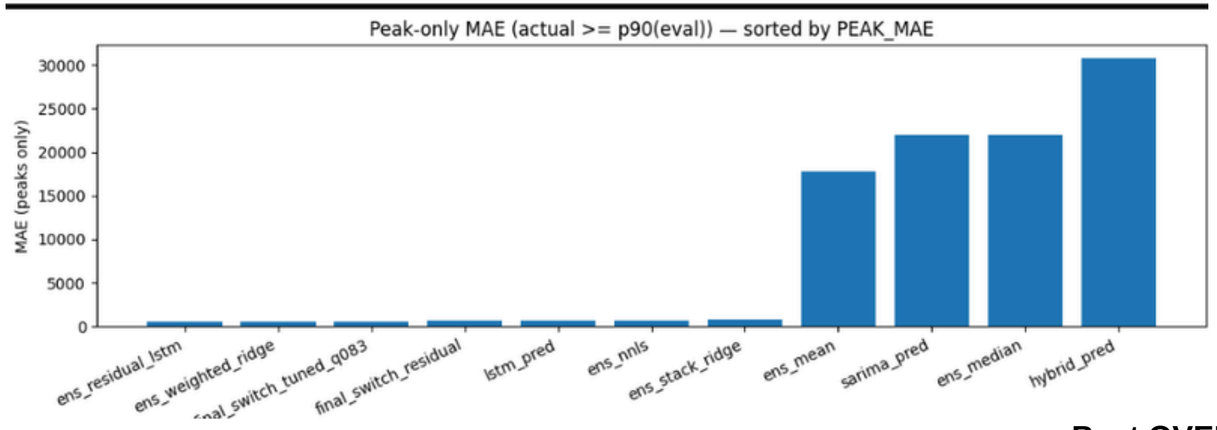




Graphs Analysis & Results: Ensemble Methods



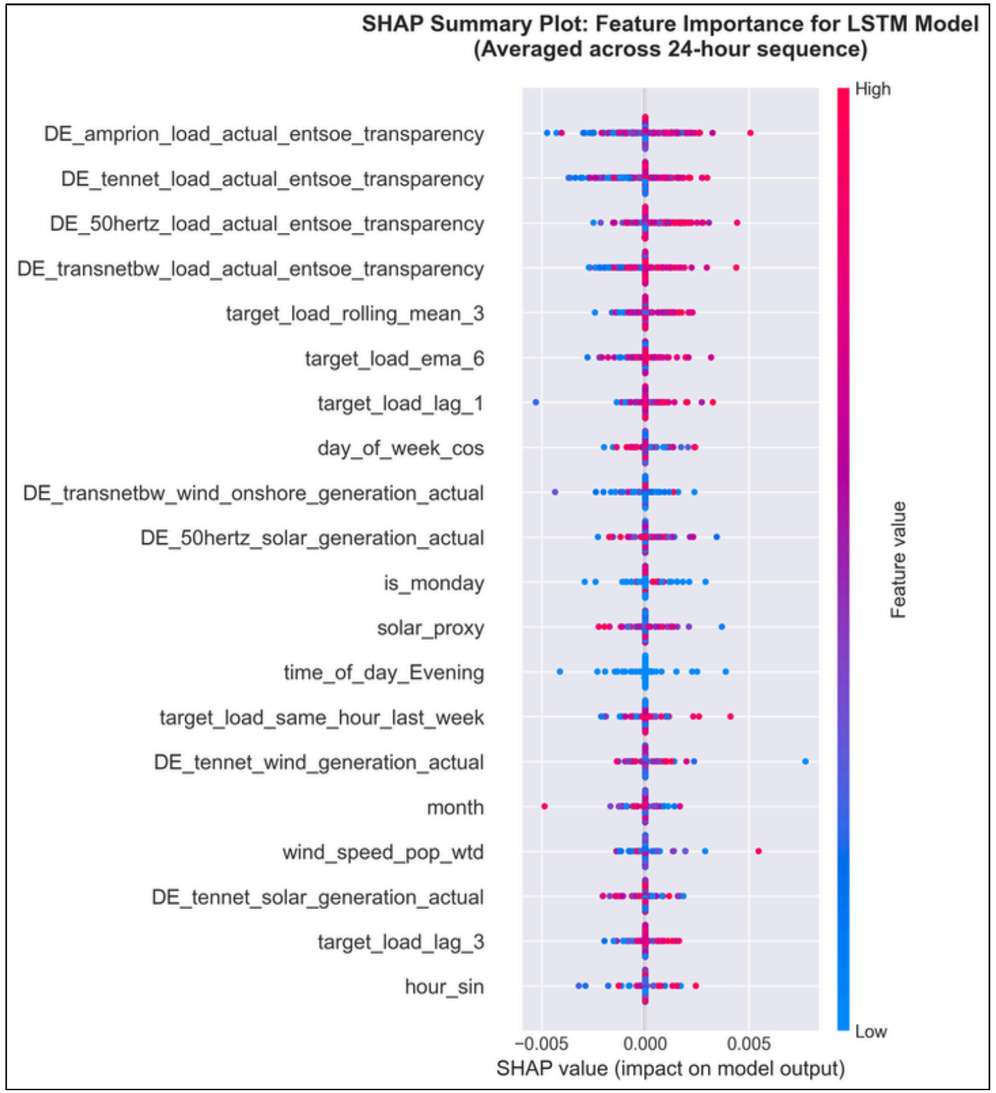




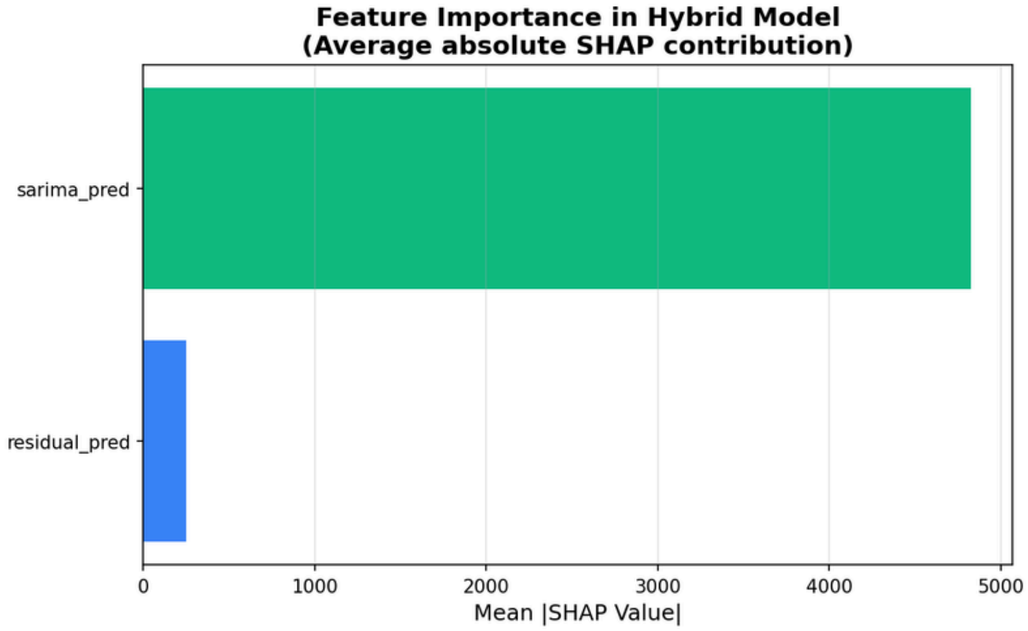
Best OVERALL: **final_switch_residual | OVERALL_MAE: 577.09 | PEAK_MAE: 529.9**

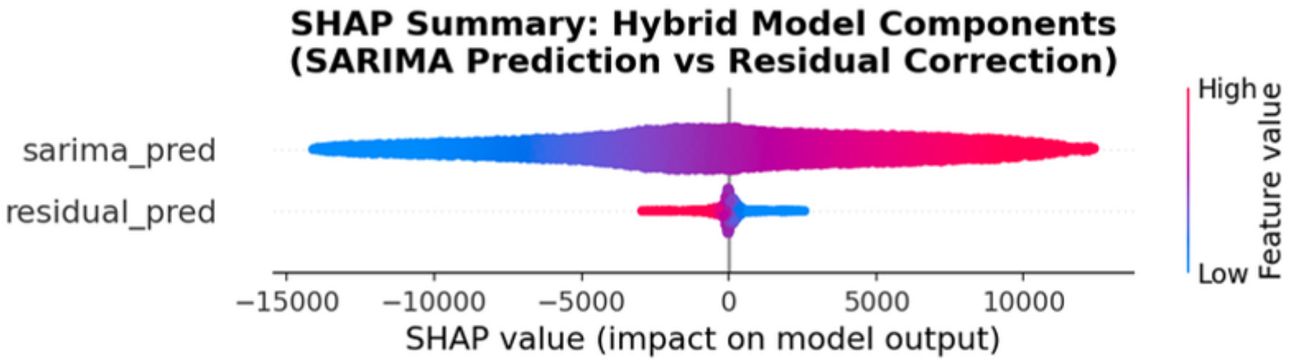
Best PEAK: **final_switch_residual | OVERALL_MAE: 577.08 | PEAK_MAE: 529.9**

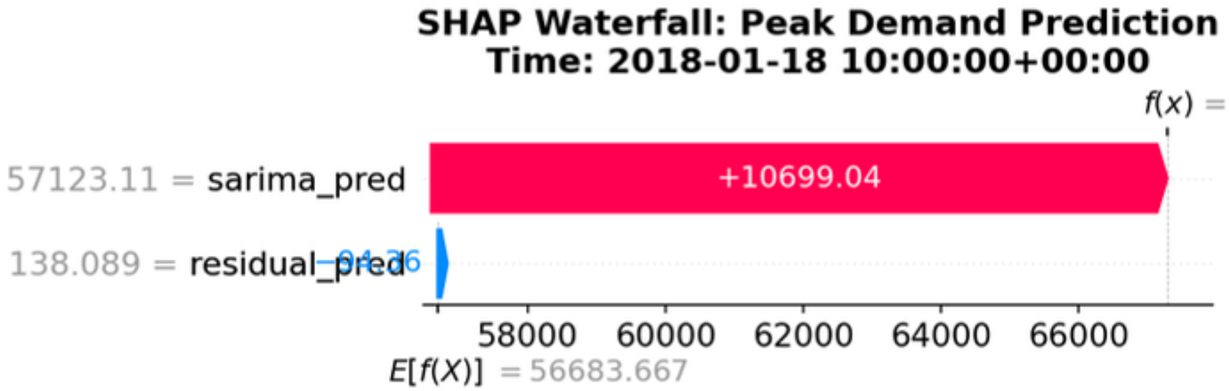
XAI with SHAP: LSTM

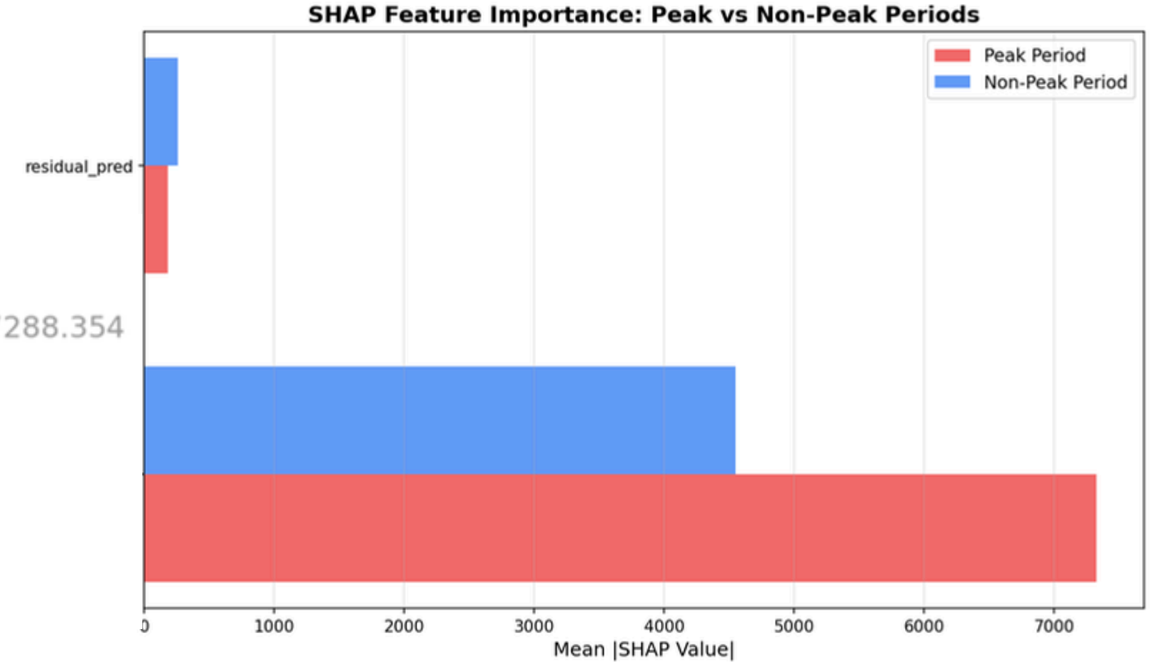


XAI with SHAP: Hybrid

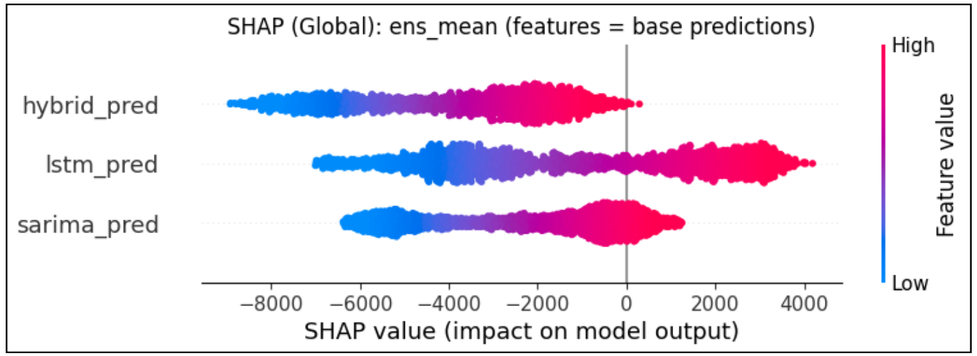


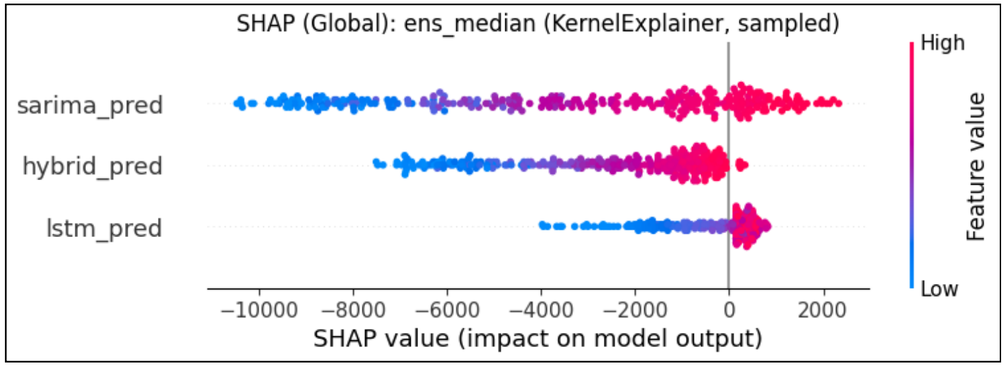


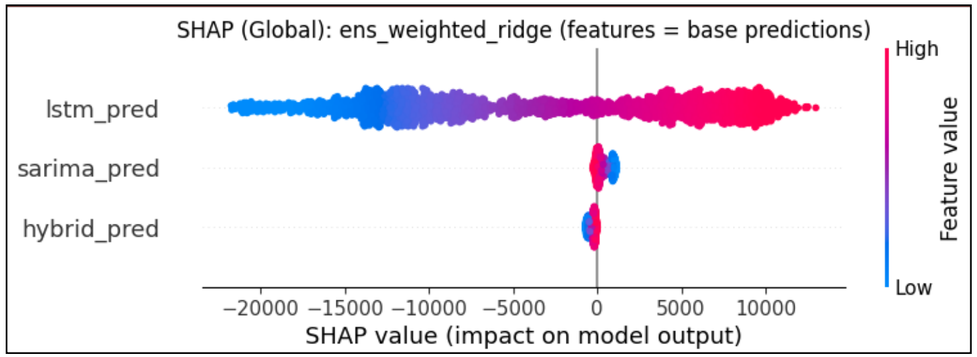


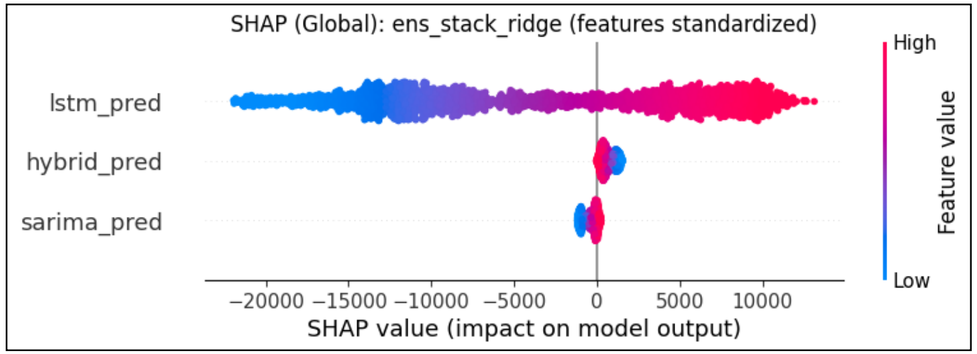


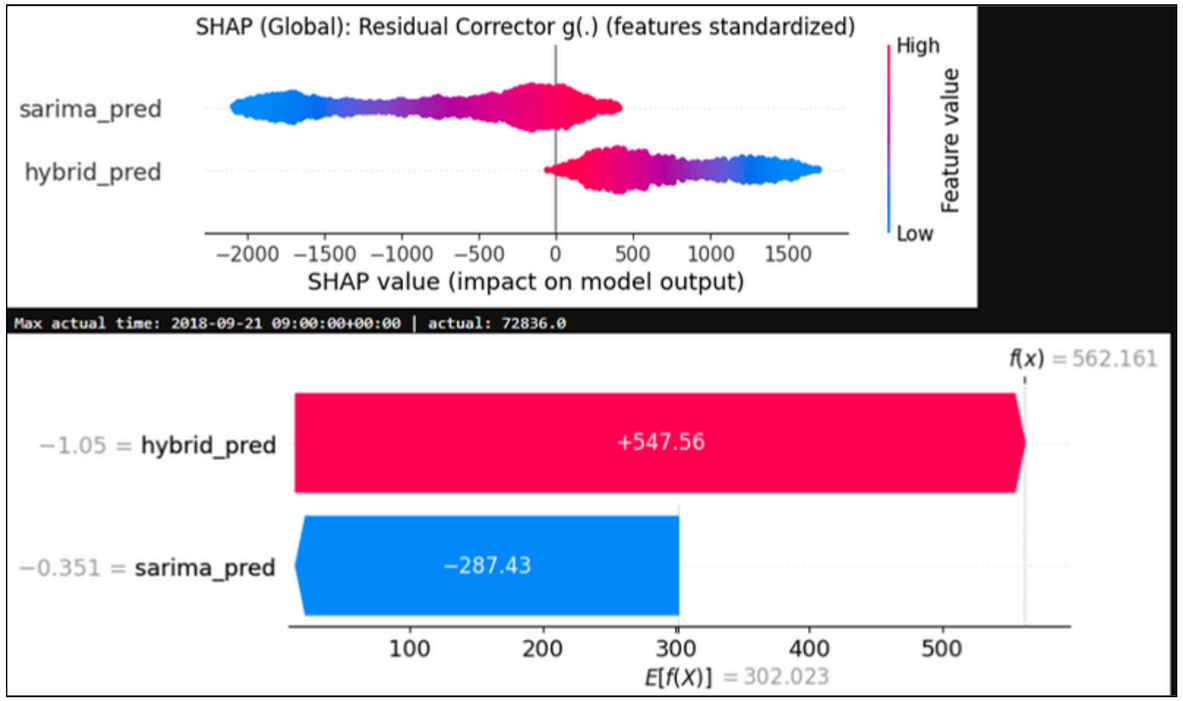
XAI with SHAP: Ensemble Methods





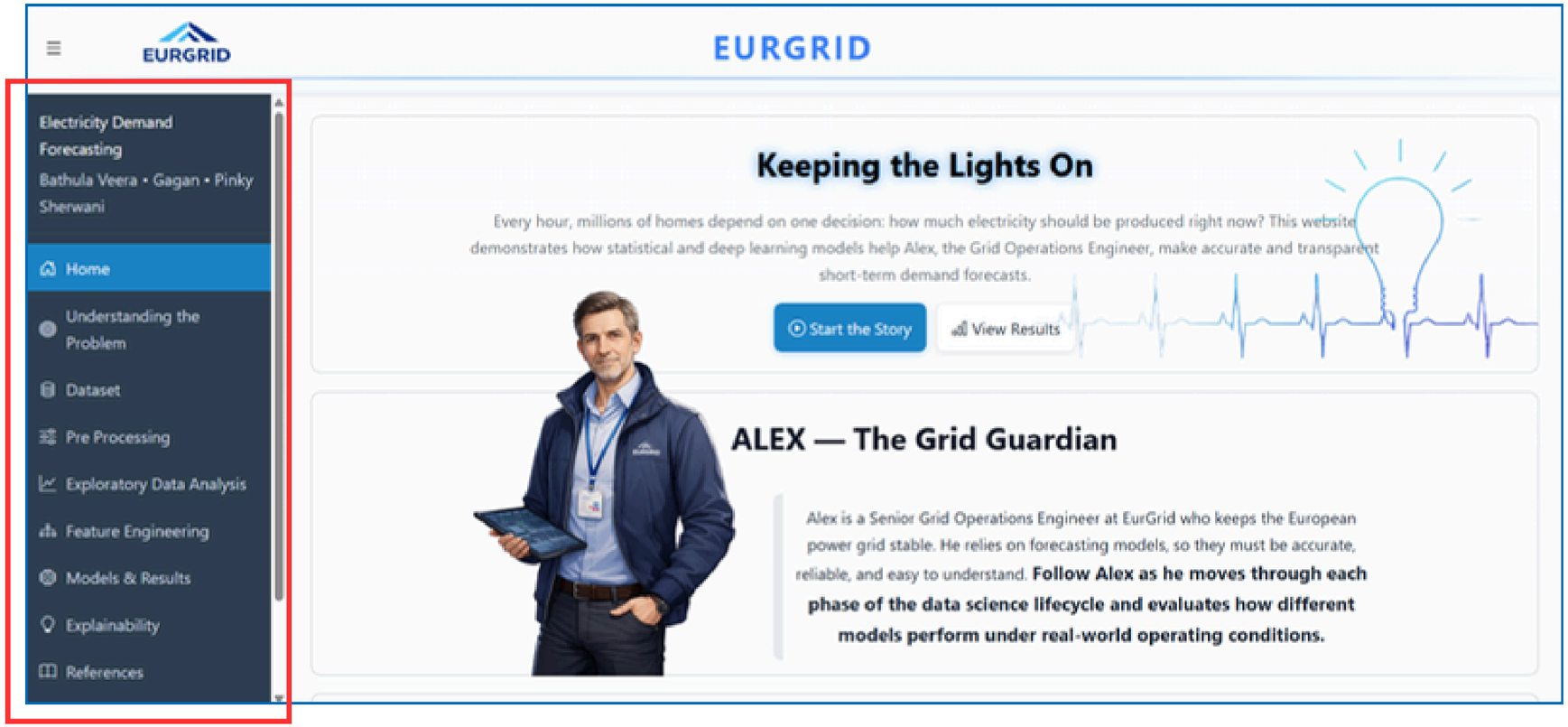






Website Overview

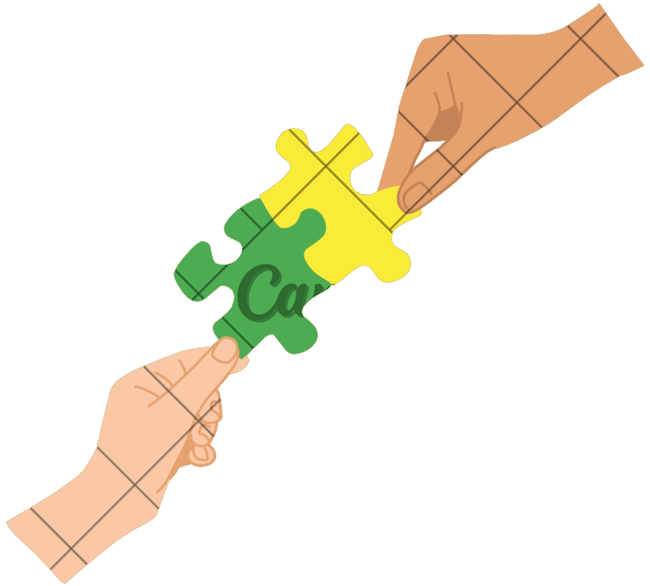
- Public narrative presentation for entire forecasting workflow
- Designed to tell a story from problem to results through interactive content and visuals
- The website uses a fictional grid operations engineer, **"Alex,"** to guide users through stages of the project
- Tailored narrative connects:
  - real grid challenges
  - data science workflow
  - forecasting results
- For audience to see the "why" behind each step



Work Done and Challenges Faced

How Work was Divided?

- Data Preprocessing and EDA - Gagan, Pinky, Raghav
- Modeling Approaches and their XAI Analysis:
  - SARIMA and LSTM: Gagan
  - Hybrid: Pinky
  - Ensemble Methods: Raghav
- Website: Pinky, Raghav, Gagan



Challenges Faced

- Dataset limitations where certain control regions were available after September 2018.
- Inclusion of weather data and creation of proxies.
- Full dataset and weekly seasonality causing memory constraint in Sarima.
- Increasing LSTM layers and bidirectional causing computational constraints.
- Implementation of SHAP for statistical model like Sarima.
- Due to lack of computational power, SARIMA model could not be used with seasonal period of 1 week~168 days

Conclusion &Future Work

Conclusion:

- SARIMA underfits badly and is only a weak seasonal baseline
- LSTM performs very well, capturing non-linear demand patterns
- Hybrid is worst and doesn't generalize here
- Switch-based ensemble is best model in both **Overall and Peak** with the lowest MAE/RMSE and highest R^2

Future Work:

- Use GRU/CNN hybrid ensembles
- Deploy for real-time use and update the model continuously with new data.
- Build a leakage-free setup and use SHAP to clearly explain predictions.

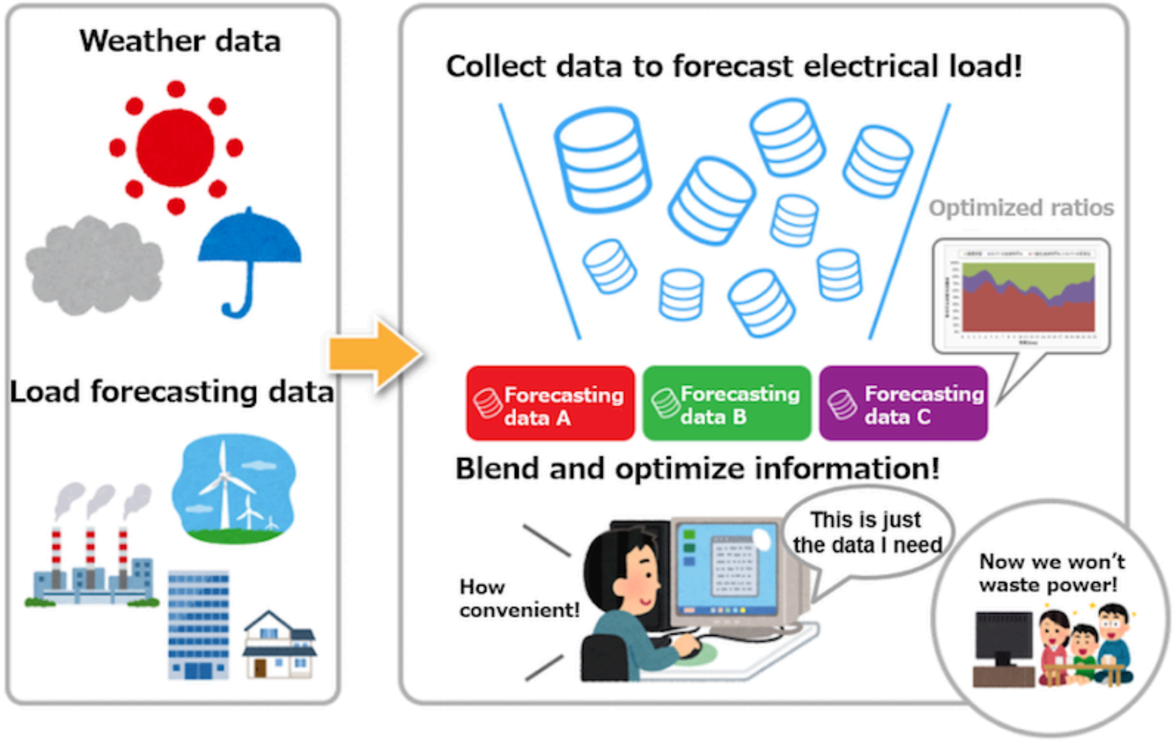


Figure: XAI intio Electricity Load Forecasting
Ref:Toshiba

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THANK YOU

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Q & A