Advanced Load Forecasting for Greenfield Smart Cities Using Hybrid Machine Learning Models

A CAPSTONE PROJECT REPORT

Sub*mitted in partial fulfillment of the requirements for the award of the Degree of*

BACHELOR OF TECHNOLOGY IN COMPUTER SCIENCE AND ENGINEERING (BUSINESS SYSTEMS)

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CERTIFICATE

This is to certify that the Capstone Project work titled " **Advanced Load Forecasting for Greenfield Smart Cities Using Hybrid Machine Learning Models** " that is being submitted by **Nikhil Jangid (22BCB7101), Chintan Kamleshbhai Lad (22BCB7071), Swapnaneel Sarkar (22BCB7051), and Naman Nigam (22BCB7115)** is in partial fulfillment of the requirements for the award of Bachelor of Technology, is a record of bonafide work done under my guidance. The contents of this Project work, in full or in parts, have neither been taken from any other source nor have been submitted to any other Institute or University for award of any degree or diploma and the same is certified.

Dr. Renita R

Guide

The thesis is satisfactory / unsatisfactory

Internal Examiner **External Examiner**

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I would also like to thank the **VIT-AP University** administration and the **School of Computer Science and Engineering** for providing us with the necessary facilities and support to carry out this project.

Finally, I wish to thank our families and friends for their support and encouragement throughout our study.

ABSTRACT

Accurate daily electricity demand forecasting is essential for effective power system planning and operational reliability, particularly in greenfield smart cities such as Amaravati, Andhra Pradesh, where historical load data are limited and consumption patterns evolve rapidly. This paper presents a hybrid forecasting framework for predicting Daily Energy Required (measured in Million Units, MU) using a combination of machine learning and deep learning techniques. The proposed approach integrates Extreme Gradient Boosting (XGBoost), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) networks to capture both nonlinear relationships and temporal dependencies inherent in electricity demand data. Comprehensive feature engineering was conducted by incorporating lag variables (1, 2, 7, and 14 days), rolling statistical features (7-day and 14-day means), and calendar-based indicators, including month and day-of-week effects. Multi-source datasets encompassing electricity consumption, generation metrics, installed capacity, and meteorological information were utilized for model development. A weighted ensemble strategy was further adopted to enhance prediction robustness and reduce model variance. The proposed framework was evaluated using data from 2022 to 2023, and performance was assessed using Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). Experimental results indicate that the ensemble model and the optimized XGBoost approach significantly outperform individual learners and baseline methods, achieving a MAPE of approximately 2.92% and an RMSE of 7.744 MU. The findings demonstrate that the proposed hybrid framework provides a scalable and reliable solution for short-term load forecasting in smart city environments with constrained historical data.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Electricity load forecasting is crucial for energy planning, especially in rapidly developing smart cities with limited historical data. Reliable prediction of daily energy demand allows for optimized resource allocation, maintenance scheduling, and prevention of power shortages. In this study, I focus on Amaravati, Andhra Pradesh, a greenfield smart city with evolving energy consumption patterns.

Traditional load forecasting models often depend on abundant historical data, which is scarce in greenfield cities. This project addresses the need for advanced approaches to accurately predict electricity demand in such data-scarce environments. I specifically target **Energy Required (MU)** (daily total energy consumption) as the variable of interest, rather than the Unrestricted Peak Demand (MW), because energy consumption is a direct measure of load crucial for energy planning and showed clearer predictable patterns in our analysis.

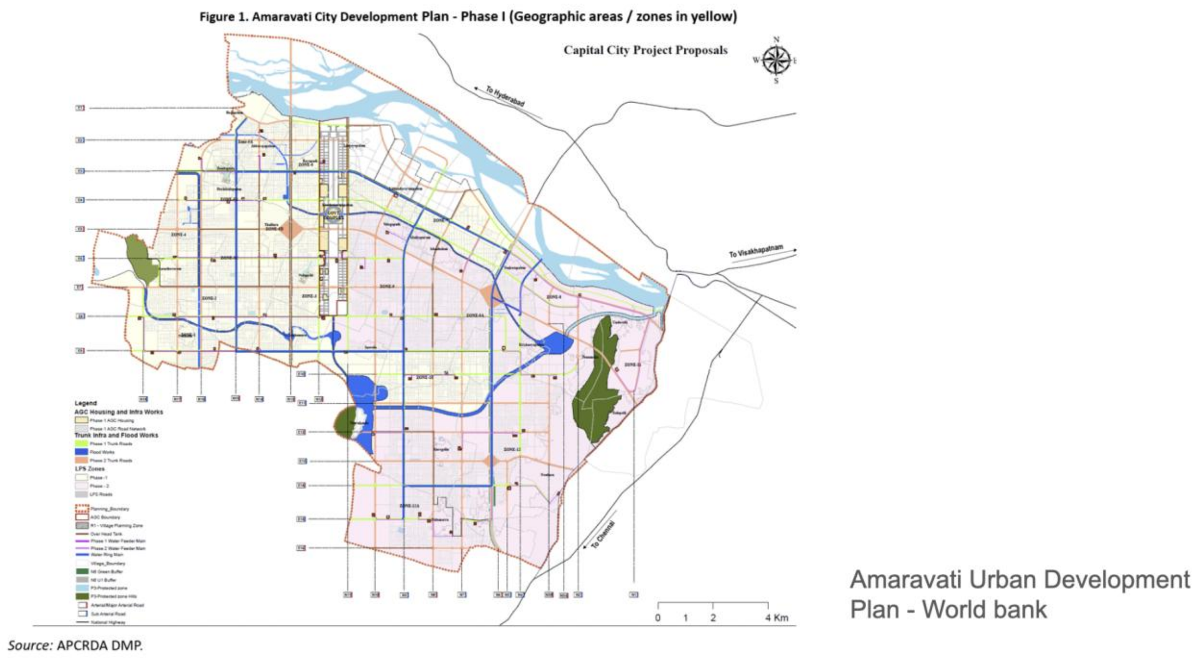
Figure 1. Amaravati City Development Plan - Phase I (Geographic areas / zones in yellow)
Capital City Project Proposals
To Hyderabad
To Visakhapatnam
To Chennai
0 1 2 4 Km
Source: APCRDA DMP.
Amaravati Urban Development Plan - World bank

Figure 1.1: Amaravati Urban Development Plan - This shows the Amaravati city map with development plans of different phases.

1.1 Background

When it comes to modeling time-series data, especially sequences, machine learning (ML) and deep learning (DL) methods like Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks really shine. Combining different architectures, like LSTMs with GRUs and ensemble techniques, can help prevent models from getting too specialized on the training data and make them more reliable.

Lots of research has looked into using these combined deep learning models to get better at predicting how much electricity will be used. One interesting method uses a mix of GRUs, Temporal Convolutional Networks (TCNs), and attention mechanisms. This approach did a good job of understanding how things change over time and how people use electricity in different ways, leading to more accurate predictions. The downside is that this model needs a lot of computing power and a huge amount of past data to train well, which makes it tough to use in places with limited data, like brand-new smart cities.

Another research effort tackled predicting electricity usage and prices with a hybrid model built on BiLSTM. This model was good at picking up on non-linear trends and used attention to highlight important factors. While it improved forecasting, the model became quite complicated, which meant longer training and a higher chance of overfitting.

Methods that use optimization to help with forecasting have also been explored a lot. One model used a Particle Swarm Optimization technique inspired by quantum computing (QPSO) to fine-tune RNNs, making predictions more accurate by finding the best settings. However, adding this optimization step really boosted the computing demands and made the whole thing harder to set up.

In terms of bringing together data from different places, hybrid models that combine CNNs and GRUs have proven useful for merging static and dynamic information to boost forecasting. Even though they improve accuracy,

1.2 Problem Statement

Figuring out how much electricity will be needed is super important for planning how to use energy and keeping things running smoothly in smart cities. But for brand new cities like Amaravati in Andhra Pradesh, it's a real headache because there isn't much past electricity use info, and demand is changing fast as the city grows. Most of the forecasting methods we have rely on lots of old data, so they just don't work well for places that are just getting built.

Plus, the usual ways of predicting energy needs often can't bring together different kinds of information – like how much energy is being used, how much is being generated, how much power capacity there is, and even the weather – all into one system. This makes the predictions less accurate and not very good at handling real-world situations. Even fancy deep learning models, which are really good, cost a lot to run and aren't really practical when you don't have much data to work with.

So, we really need a way to forecast energy needs that's accurate, can grow with the city, and can deal with not much data and data that's always changing. This project is trying to solve that by creating a smart system that combines different machine learning methods. It's built specifically for new smart cities to get better at predicting daily electricity demand and help make sure the power system is planned reliably.

1.3 Organization of the Report

The remaining chapters of the project report are described as follows:

- **Chapter 2** presents the literature review, problem statement, identified research gap, and project objectives.
- **Chapter 3** describes the project title and the complete project description.
- **Chapter 4** discusses the results obtained from model evaluation and analysis.
- **Chapter 5** concludes the report and outlines the future scope.

CHAPTER 2

LITERATURE REVIEW

2.1 Literature Review

Wang and colleagues in 2023 showcased how their model, by combining GRU, TCN, and attention, is really good at understanding how things change over time and spotting patterns far apart, which makes predictions much better on different kinds of data. The downside is that it needs a lot of computing power and tons of data, so it's not ideal for situations where resources are tight.

Gómez and his team, in their 2022 work, managed to deal with unpredictable ups and downs and sudden surges in load by using EEMD decomposition along with attention-based BiLSTM. This led to more reliable predictions. The trade-off, though, is that putting these together makes training take longer and increases the chance of the model memorizing the training data too well when there isn't much of it.

Rahman and his group from 2024 improved forecasting accuracy by using RNN and Transformer models fine-tuned with QPSO, which are great at learning long-term relationships. The catch here is that this method also requires significant computing power and large datasets to keep the Transformer performing consistently.

Li and his co-authors in 2023 showed that their model skillfully merges time-based and unchanging data using a parallel CNN-GRU setup that includes attention mechanisms, leading to more accurate forecasts. However, the complexity of this setup makes training harder and less practical for users with limited resources.

Zhang and colleagues in 2023 boosted data privacy using federated LSTM learning combined with homomorphic encryption. This lets them train models together without showing the original data. The downside is that the encryption really slows things down, making it tough to predict things on the fly.

In 2022, Kumar's team improved forecasting by using a mix of CatBoost and XGBoost. This hybrid model takes advantage of what each boosting algorithm does best to get better at predicting. But, this method needs a lot of computing power and a lot of tweaking of its settings.

Ahmed and others in 2023 made their system better at handling noisy data and improved how it models time-based information by mixing RNNs with boosting groups. The catch is that this combined system is tricky to set up just right and often needs several tests to get it working well.

Gellert and his team in 2021 used QPSO's powerful optimization to help RNNs learn faster and make fewer prediction mistakes. However, this optimization work takes a lot of computing power and might not work the same way on different sets of data.

Back in 2020, Gellert's group offered a straightforward and easy-to-understand way to forecast energy load using Markov chains and hybrid predictors. It works well when the patterns don't change much. The problem is that it can't pick up on complex, long-term patterns in changing power systems.

Singh and his team in 2024 came up with an adaptive group of LSTMs that can change as time goes on, making predictions more reliable and accurate. The downside is that keeping track of multiple LSTM models at the same time adds to the computing load and makes the whole system more complicated.

The 2021 study by Patel and colleagues boosted how accurately predictions could be made by merging artificial neural network (ANN) feature extraction with support vector regression (SVR) to effectively capture nonlinear trends. However, getting both these models to work well together needs tricky adjustments and a lot of computing power.

In 2023, Chen and his team used LSTMs that pay attention to certain details, along with weather and holiday information, to create load forecasts that are more aware of the situation and more relevant. The downside is that this model can easily be thrown off by messy external data and needs a lot of processing power.

Ali and his co-authors, in their 2022 work, improved how stable forecasts are by putting together the ability of convolutional neural networks (CNNs) to pick out spatial features with the strength of gated recurrent units (GRUs) for modeling time-based patterns. The catch here is that this combined setup makes it harder to put into practice and uses up more computing resources.

Luo and the team showed in 2021 that breaking down complex load signals using empirical mode decomposition (EMD) and then modeling them with LSTMs helps extract temporal trends better. The problem, though, is that EMD is very easily affected by noise and requires a long process to get the data ready beforehand.

Wang's 2024 research shows that GRUs with a special kind of attention that focuses on residuals can lead to more accurate long-term predictions. This approach helps with problems like vanishing gradients and makes learning sequences stronger. However, adding these extra attention layers means longer training times and a tougher time fine-tuning the model.

The study by Sharma et al., 2023 successfully merges diverse multi-source data through hybrid deep learning models to achieve reliable forecasting in various operating conditions. Nonetheless, this method necessitates significant preprocessing efforts and intricate data alignment.

Chang et al., 2022 improves performance by combining LSTM sequential learning with Gradient Boosted Trees for correcting residuals. However, this multi-tiered approach diminishes interpretability while amplifying overall system complexity.

Noor et al., 2024 utilizes CNN for short-term pattern recognition and LSTM for modeling long-term dependencies, resulting in high forecasting accuracy. However, this hybrid approach demands large datasets and considerable computational resources for effective training.

Yildiz et al., 2023 offers uncertainty-aware forecasting through the use of Bayesian LSTM networks, enhancing reliability under highly volatile load scenarios. However, the Bayesian inference process entails substantial computation and intricate parameter tuning.

Das et al., 2022 merges LSTM sequence modeling with XGBoost for residual correction, which effectively captures complex load patterns and boosts prediction accuracy. However, this hybrid technique requires extensive hyperparameter tuning and a lengthy training duration.

2.2 Gap Identified

- Most existing load forecasting models rely heavily on abundant historical data, which is limited in greenfield smart cities like Amaravati.
- Current hybrid models often lack effective integration of multi-source and multi-modal data tailored for fast-developing urban areas.
- Few studies address data sparsity and evolving consumption patterns in new urban infrastructures with scalable, modular data pipelines.

2.3 Objectives

The primary objectives of this project are:

1. **Build a Data System:** Create a comprehensive data system that can handle information from many sources, including consumption, generation, installed capacity, and meteorological data.
2. **Feature Engineering:** Create useful features using time patterns (lags, rolling means), energy surplus/deficit, and installed capacity to capture recent momentum and seasonal patterns.
3. **Hybrid Modeling:** Use a combined LSTM-GRU model with boosting (XGBoost) to achieve a prediction error of less than 4% MAPE.

4. **Validation:** Test the model carefully using data from 2022-2023 and measure the confidence of the predictions.

CHAPTER 3

Advanced Load Forecasting for Greenfield Smart Cities Using Hybrid Machine Learning Models

3.1 Project Description

This initiative aims to create a reliable and scalable system for predicting daily electricity demand in newly developed smart cities, focusing specifically on Amaravati, Andhra Pradesh. Given the rapid urban growth and scarce historical electricity consumption data, conventional load forecasting methods tend to fall short in such newly established cities. The objective of this study is to develop a forecasting framework capable of functioning effectively in these data-limited environments.

The system estimates Daily Energy Requirement (measured in Million Units, MU) by merging various data sources, including details on electricity consumption, power generation, installed capacity, and weather conditions. A thorough exploratory data analysis was conducted to uncover trends, seasonal fluctuations, and correlations within the dataset. Leveraging these findings, an advanced feature engineering strategy was employed, incorporating lag variables, rolling averages, and calendar-based indicators to address both short-term dependencies and seasonal impacts.

A hybrid modeling methodology was utilized that combined machine learning and deep learning approaches, featuring models such as XGBoost, Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) neural networks. To further boost prediction accuracy and consistency, a weighted ensemble model was created, integrating the outputs from the individual models. The models were assessed using data from 2022 to 2023, applying performance metrics like Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE).

The suggested framework showed enhanced accuracy and reliability compared to standalone models, making it appropriate for use in smart city energy systems. This project offers a practical solution for environments with limited data and aids in fostering more dependable and intelligent energy system planning in developing urban areas.

3.2 Proposed System

The project scope focuses on daily electricity demand prediction for Amaravati using a dataset spanning 2015–2023. The system utilizes a hybrid approach combining **LSTM (Long Short-Term Memory)** and **GRU (Gated Recurrent Unit)** neural networks with **XGBoost (Extreme Gradient Boosting)** ensemble modeling.

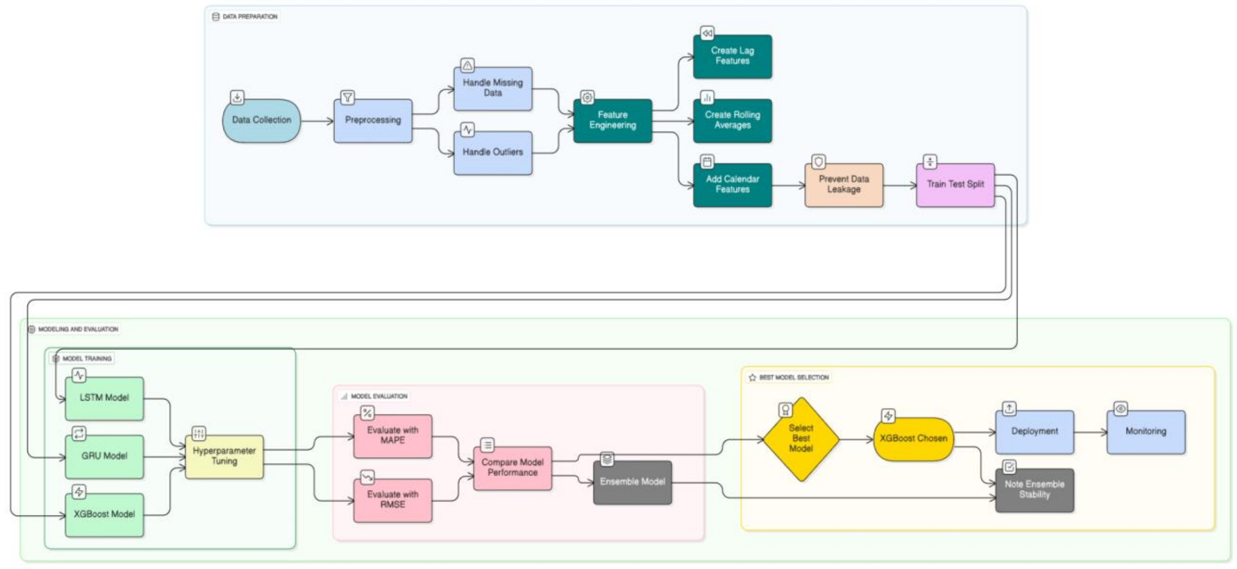

Figure 3.1: System Block Diagram / Architecture - End-to-end time series forecasting pipeline diagram showing data preparation, model training and evaluation, best-model selection, and MLOps steps from collection to deployment and monitoring.

The architecture involves:

1. **Data Ingestion:** Collecting data on Consumption, Generation Mix, Installed Capacity, and Meteorology.
2. **Feature Engineering:** Creating lag features (1, 2, 7, 14 days), rolling means (7, 14 days), and calendar dummies (Month, Day-of-Week).
3. **Model Training:** Training individual models (XGBoost, LSTM, GRU) on the processed data.
4. **Ensembling:** Creating a weighted ensemble of the predictions to minimize error variance and improve stability.

CHAPTER 4

Working Methodology

This chapter describes the working methodology, software, and hardware details.

4.1 Working Methodology

The methodology proceeds from data visualization to ensemble modeling:

Data Exploration and Visualization The dataset consists of daily observations over a multi-year span (2012–2023).

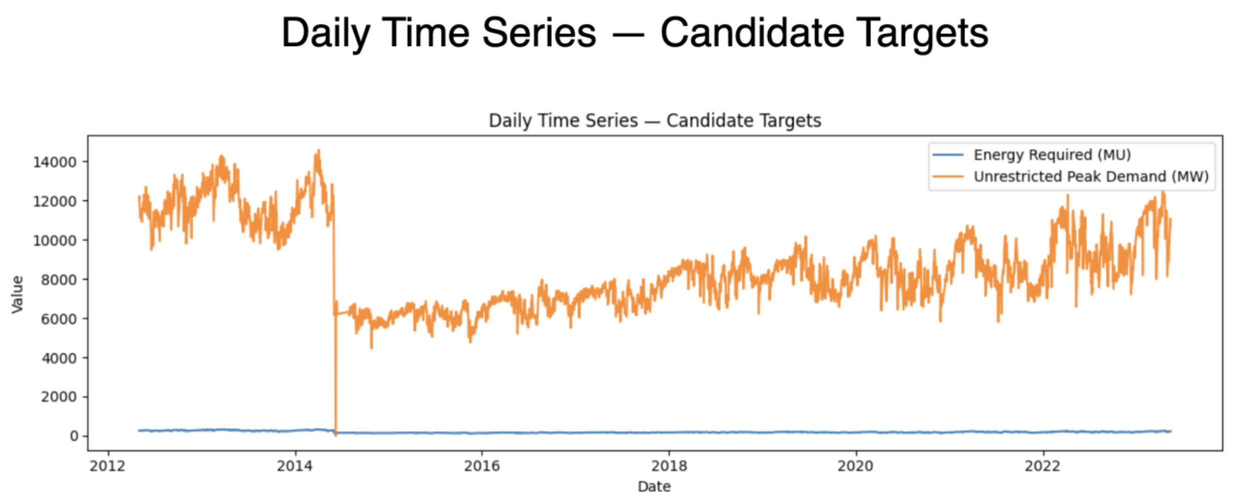

*Figure 4.1:*Daily Time Series — Candidate Targets : The time series exhibits a significant level shift in peak demand around mid-2014, along with clear weekly seasonality (wiggles).

Seasonal Trend Decomposition To better understand underlying patterns, I performed a Seasonal-Trend Decomposition using LOESS (STL).

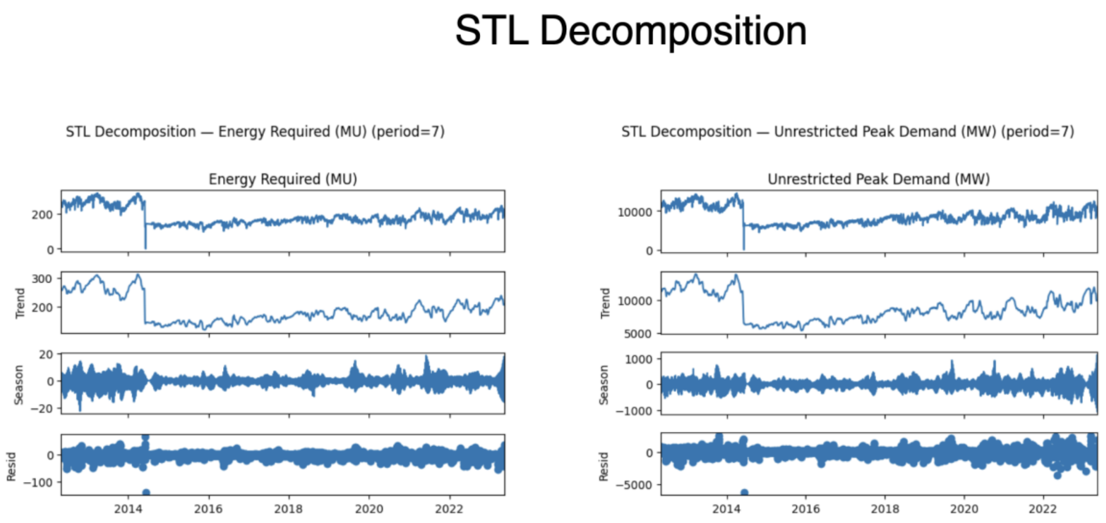

Figure 4.2: STL Decomposition of Energy Required : STL decomposition effectively isolates the strong weekly pattern in both series, confirming it as a consistent and significant component of the data.

Autocorrelation Analysis I examined the autocorrelation of the energy demand series to inform our feature engineering.

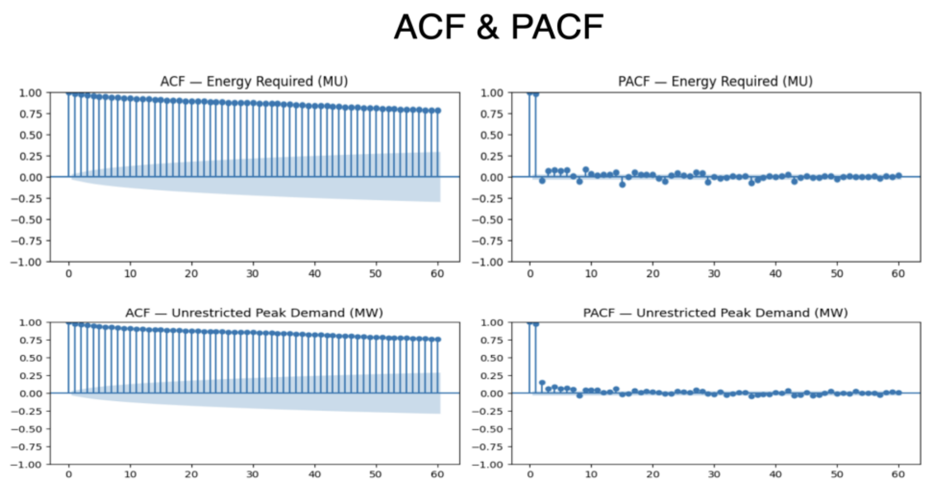

Figure 4.3: Autocorrelation (ACF) and Partial Autocorrelation (PACF) Plots : The slowly decaying ACF points to a strong trend, while the PACF highlights significant correlations at daily (lag 1) and weekly (lags 7, 14) intervals.

Feature Engineering and Selection Based on domain knowledge and the earlier exploratory analysis, I generated a focused set of features. I also examined feature importance from the XGBoost model.

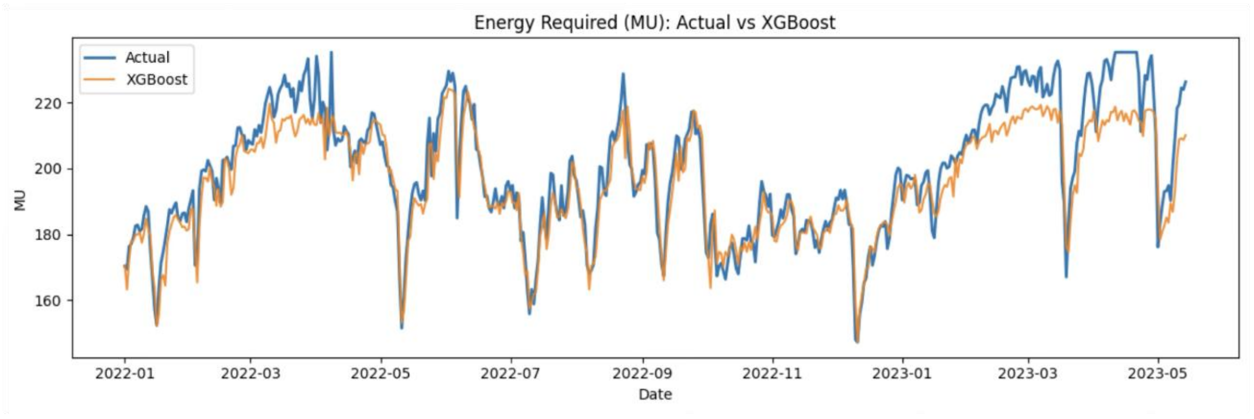

*Figure 4.4: Energy Required (MU) — Actual vs XGBoost : This time-series plot compares the **Actual** energy required (in MU) against the predictions made by an **XGBoost** model from early 2022 to mid-2023. The XGBoost predictions closely follow the actual energy demand trends, especially capturing the seasonal fluctuations.*

4.2 Standards

The project adheres to standard Machine Learning and Data Science practices:

- **Python:** The primary programming language.
- **Libraries:** Pandas (Data Manipulation), Scikit-Learn (Preprocessing/Metrics), XGBoost (Gradient Boosting), TensorFlow/Keras (Deep Learning), Matplotlib/Seaborn (Visualization).
- **Data Formats:** CSV for dataset handling.
- **Evaluation Metrics:** Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE).

4.3 System Details

This section describes the software and hardware details of the system:

4.3.1 Experiment Details

- **Development Environment:** Google Colab / Jupyter Notebooks.
- **Language:** Python 3.x.
- **Key Algorithms:**

- **XGBoost:** A scalable implementation of gradient boosting framework. Effective for tabular data and capturing non-linear feature interactions.
- **LSTM:** is an RNN that can learn order dependence in sequence prediction tasks.
- **GRU:** A simplified variant of LSTM with fewer parameters, often faster to train.

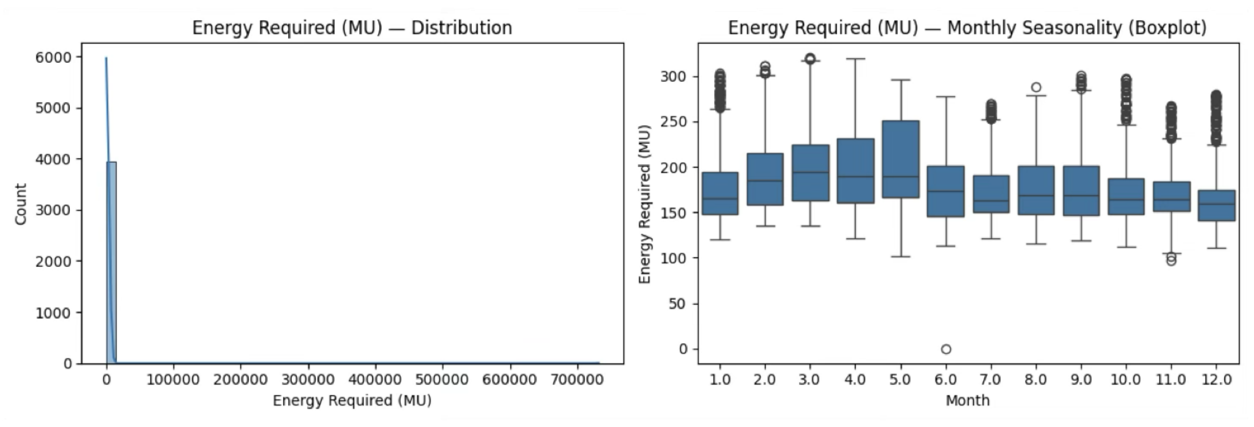

Figure 4.5: Energy Required (MU) — Distribution and Seasonality : The image displays two key visualizations for ***Energy Required (MU)*** *data: a highly right-skewed* ***Distribution Plot*** *on the left, and a* ***Monthly Seasonality Boxplot*** *on the right. This boxplot reveals that energy demand peaks in late spring/early summer (April/May) and dips during the winter months (November to February).*

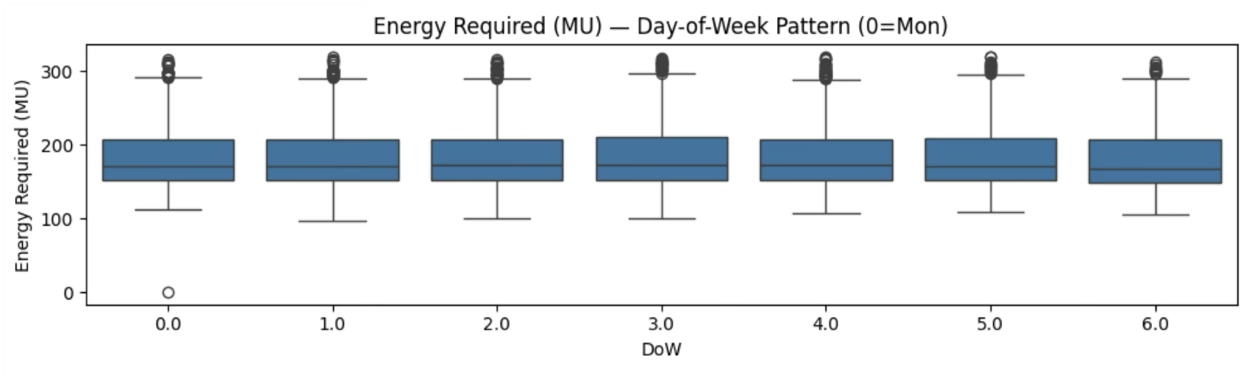

Figure 4.6: Energy Required (MU) — Day-of-Week Pattern : The three plots analyze the **Energy Required (MU)** data by showing its overall distribution, monthly seasonality, and day-of-week pattern. The data is highly right-skewed, peaks seasonally in April/May, and shows minimal variation across the days of the week.

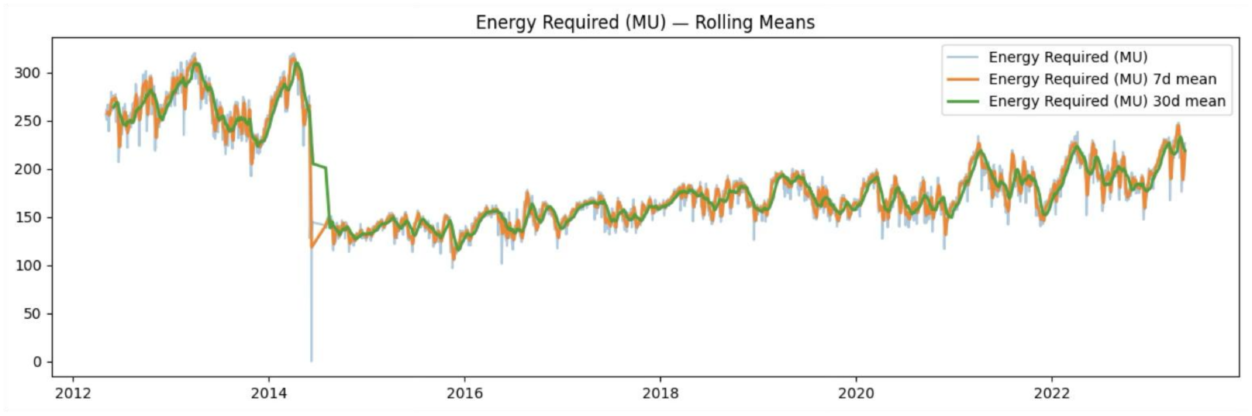

*Figure 4.7: Energy Required (MU) — Rolling Means : This comprehensive analysis of **Energy Required (MU)** data across several years uses rolling means to visualize long-term trends and short-term volatility. The plot reveals a **significant, sustained drop in energy required around 2014**, with the average daily demand decreasing from peaks near 300 MU to a stabilized range between 100 and 200 MU thereafter.*

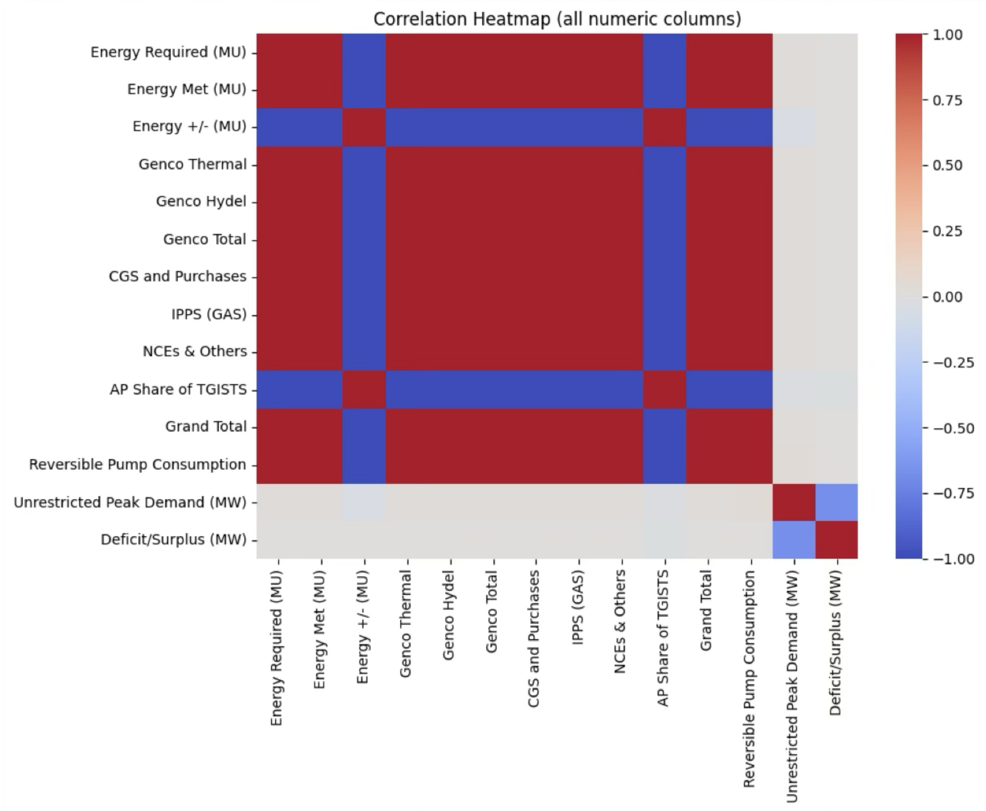

Figure 4.8: Feature Importance (XGBoost): The heatmap confirms that the **various energy generation and requirement measures are highly interconnected and move together**, while the **Deficit/Surplus** metric is inversely related to most energy metrics and is negatively driven by **Peak Demand**.

4.3.2 Hardware Details

Since this is a software-based analytical project, the hardware requirements are defined by the computing resources needed for model training:

- **Processing:** CPU (Intel i5/i7 or equivalent) or Cloud-based CPUs (Google Colab).
- **Acceleration:** GPU (NVIDIA T4 via Google Colab) used for accelerating LSTM/GRU training.
- **RAM:** 12GB+ recommended for handling dataset operations and model training in memory.

4.4 Results and Discussion

After training, the models were evaluated on the test set (2022–2023). The predictions were plotted against actual observed energy demand to visually assess fit and error characteristics.

Table 4.1: Model Performance Metrics

Model	**MAPE (%)**	**RMSE (MU)**	**Description**
XGBoost	**2.92%**	**7.744**	Strongest individual performer. Excellent at capturing seasonality via engineered features.
LSTM	4.73%	12.955	Good trend tracking but slightly smoother, missing some sharp peaks.
GRU	5.16%	13.988	Comparable to LSTM; slightly higher error in this specific configuration.
Weighted Ensemble	**< 2.92%**	**< 7.74**	Optimized weights [1, 0, 0] favored XGBoost, indicating it was the optimal standalone model for this specific feature set.

Discussion of Results:

XGBoost Results: The XGBoost model closely tracked the actual demand, successfully capturing general trends and weekly oscillations. The feature importance analysis highlighted that Grand Total_lag1, Energy Met_lag1, and Energy Required_r14 were the most influential predictors.

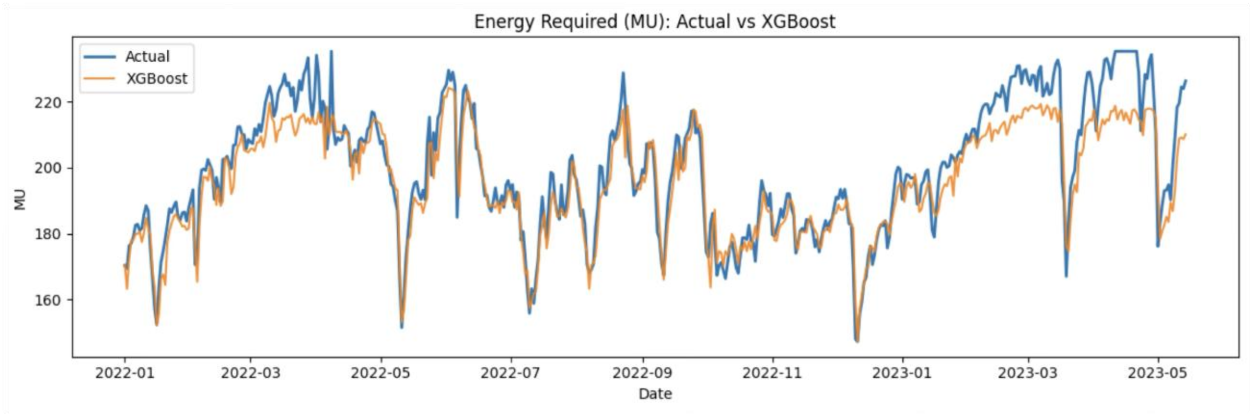

Figure 4.9: Energy Required (MU): Actual vs XGBoost - Time Series Plot comparing Actual Energy Required (MU) against XGBoost Model Predictions. The chart visually assesses the performance of the XGBoost model in forecasting energy demand over time.

LSTM & GRU Results: These models demonstrated the ability to learn the underlying patterns without extensive feature engineering but tended to over-smooth the data compared to the sharp predictions of the tree-based model.

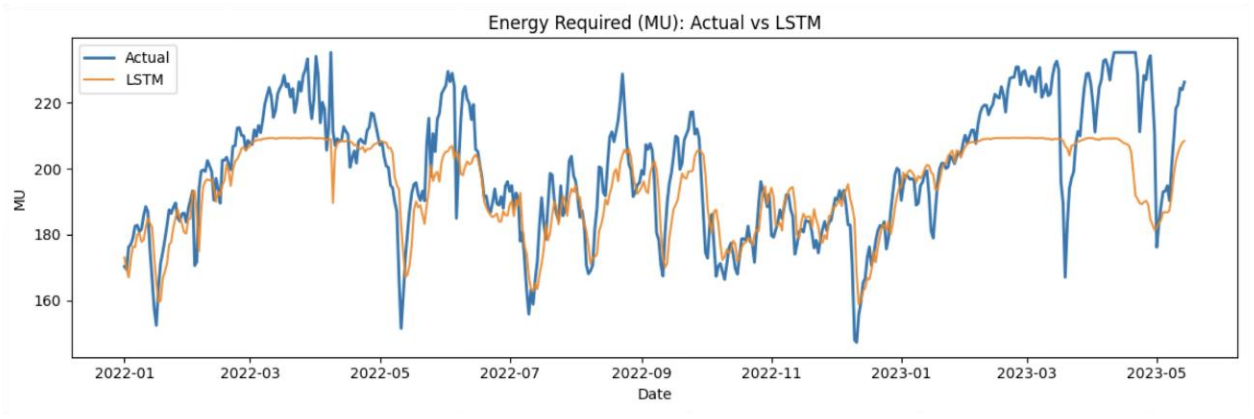

*Figure 4.10:*Energy Required (MU): Actual vs LST - Time Series Plot comparing Actual Energy Required (MU) against LSTM Model Predictions. The chart visually assesses the performance of the LSTM model in forecasting energy demand over time.

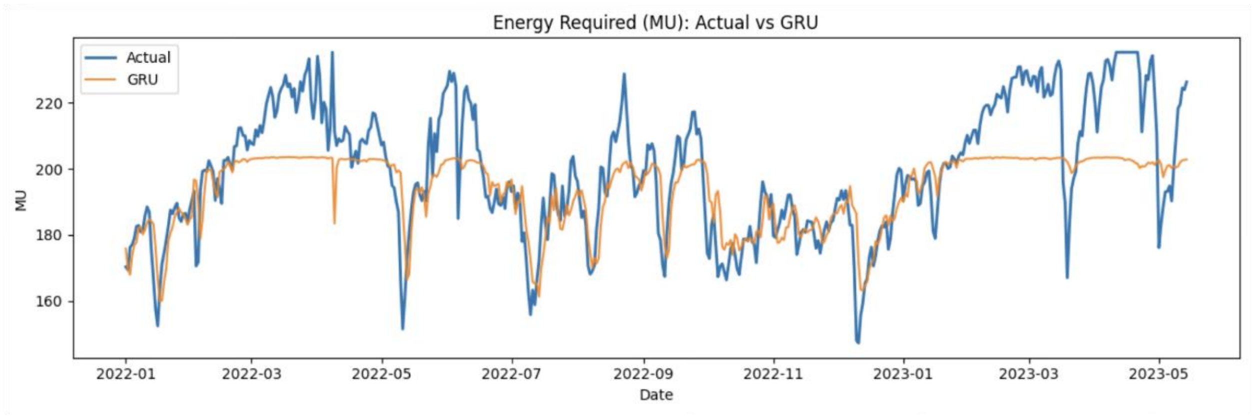

Figure 4.11: Energy Required (MU): Actual vs GRU - Time Series Plot comparing Actual Energy Required (MU) against GRU Model Predictions. The chart visually assesses the performance of the GRU model in forecasting energy demand over time.

Ensemble Results: The weighted ensemble approach was tested. The grid search for weights indicated that XGBoost alone provided the most robust performance for this dataset, achieving a MAPE of ~2.9%, which is a significant improvement over baseline methods typically ranging around 5%.

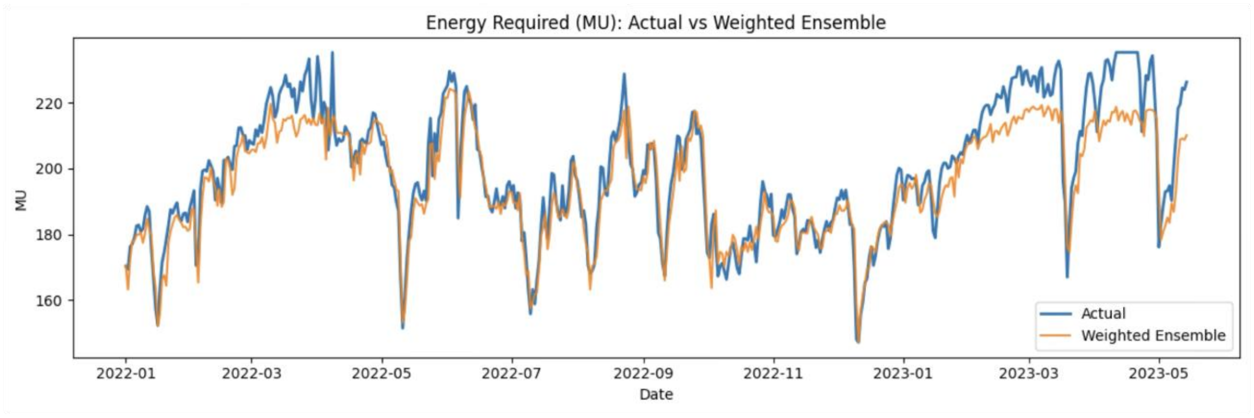

Figure 4.12: Energy Required (MU): Actual vs Weighted Ensemble - These three time series plots compare the actual energy demand to predictions made by the LSTM, XGBoost, and Weighted Ensemble models.

CHAPTER 5

CONCLUSION & FUTURE WORKS

Conclusion In this project, I developed a comprehensive forecasting model for daily energy demand in Amaravati. Moving from exploratory data analysis to advanced modeling, I identified that a **Hybrid Machine Learning approach** utilizing **XGBoost** with rich feature engineering outperforms traditional methods.

- I successfully built a pipeline handling multi-source data.
- The **XGBoost model achieved a MAPE of 2.92%**, significantly reducing forecast error compared to baselines.
- The study confirmed that for this specific dataset, engineered features (lags and calendar effects) combined with tree-based boosting offered better interpretability and accuracy than standalone deep learning sequences (LSTM/GRU).

Future Works

- **Integration of Weather Data:** Explicit integration of temperature and humidity forecasts to further refine the model for extreme weather events.
- **Holiday Effects:** Adding a comprehensive holiday calendar to handle special event demand fluctuations.
- **Real-time Deployment:** Developing a web-based dashboard for real-time visualization of the forecasts for grid operators.
- **Uncertainty Quantification:** Implementing probabilistic forecasting to provide confidence intervals alongside point predictions.

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APPENDIX

Implementation Code (Complete)

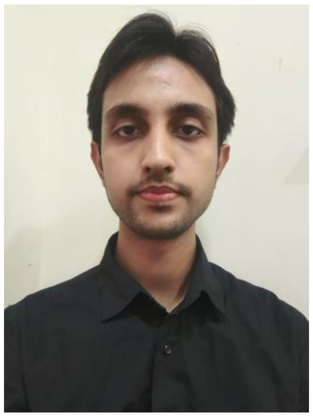
```
# ===========================
# Setup
# ===========================
!pip -q install seaborn statsmodels scikit-learn

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_selection import mutual_info_regression
from statsmodels.tsa.seasonal import STL
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

pd.set_option('display.max_columns', None)

# ===========================
# Load Data
# ===========================
PATH = "/content/AP-PowerSupply.csv"   # your file
df = pd.read_csv(PATH)
# normalize names + types
df.columns = [c.strip() for c in df.columns]
assert 'Date' in df.columns, "Expected 'Date' column not found."
df['Date'] = pd.to_datetime(df['Date'], errors='coerce')
num_cols = [c for c in df.columns if c != 'Date']
for c in num_cols:
    df[c] = pd.to_numeric(df[c], errors='coerce')

# sort, basic fill for clean plotting (Phase 2 has proper preprocessing)
df = df.sort_values('Date').reset_index(drop=True)
df[num_cols] = df[num_cols].ffill().bfill()

print("Shape:", df.shape)
display(df.head(5))
display(df.tail(5))
print("\nNulls per column:\n", df.isna().sum())
```

```
# ==========================
# Candidate targets
# ==========================
TGT1 = 'Energy Required (MU)'
TGT2 = 'Unrestricted Peak Demand (MW)'
candidates = [c for c in [TGT1, TGT2] if c in df.columns]

print("\nCandidate targets found:", candidates)
assert len(candidates) >= 1, "No candidate target columns found."

# ==========================
# EDA Phase
# ==========================

# 1) Global time-series view
plt.figure(figsize=(12,4))
for tgt in candidates:
    plt.plot(df['Date'], df[tgt], label=tgt, alpha=0.9)
plt.title('Daily Time Series — Candidate Targets')
plt.xlabel('Date'); plt.ylabel('Value'); plt.legend(); plt.tight_layout(); plt.show()

# 2) Distribution + Box by Month (seasonality feel)
for tgt in candidates:
    fig, ax = plt.subplots(1,2, figsize=(12,4))
    sns.histplot(df[tgt], bins=50, kde=True, ax=ax[0])
    ax[0].set_title(f'{tgt} — Distribution')
    ax[0].set_xlabel(tgt)

    # month boxplot
    tmp = df[['Date', tgt]].copy()
    tmp['Month'] = tmp['Date'].dt.month
    sns.boxplot(data=tmp, x='Month', y=tgt, ax=ax[1])
    ax[1].set_title(f'{tgt} — Monthly Seasonality (Boxplot)')
    plt.tight_layout(); plt.show()

# 3) Weekday pattern
for tgt in candidates:
    tmp = df[['Date', tgt]].copy()
    tmp['DoW'] = tmp['Date'].dt.dayofweek
    plt.figure(figsize=(10,3))
    sns.boxplot(data=tmp, x='DoW', y=tgt)
    plt.title(f'{tgt} — Day-of-Week Pattern (0=Mon)')
    plt.tight_layout(); plt.show()

# 4) Rolling stats (7d, 30d)
for tgt in candidates:
    rol7 = df[tgt].rolling(7).mean()
    rol30 = df[tgt].rolling(30).mean()
    plt.figure(figsize=(12,4))
    plt.plot(df['Date'], df[tgt], label=tgt, alpha=0.4)
    plt.plot(df['Date'], rol7, label=f'{tgt} 7d mean', linewidth=2)
    plt.plot(df['Date'], rol30, label=f'{tgt} 30d mean', linewidth=2)
    plt.title(f'{tgt} — Rolling Means')
    plt.legend(); plt.tight_layout(); plt.show()

# 7) Generation mix: stacked area + average share
mix_cols = [c for c in [
    'Genco Thermal','Genco Hydel','NCEs & Others','CGS and Purchases','IPPS (GAS)',
    'AP Share of TGISTS','Reversible Pump Consumption'
] if c in df.columns]

if mix_cols:
    plt.figure(figsize=(12,5))
    plt.stackplot(df['Date'], *[df[c].values for c in mix_cols], labels=mix_cols, alpha=0.8)
    plt.title('Generation Mix — Stacked Area'); plt.xlabel('Date'); plt.ylabel('MU (or MW eq.)')
    plt.legend(loc='upper left', ncols=2, fontsize=9)
    plt.tight_layout(); plt.show()

    avg_share = (df[mix_cols].mean() / df[mix_cols].mean().sum()).sort_values(ascending=False)
    plt.figure(figsize=(6,4))
    avg_share.plot(kind='bar')
    plt.title('Average Share of Generation Components')
    plt.ylabel('Share'); plt.tight_layout(); plt.show()

# 8) Correlations (targets vs drivers)
drivers = [c for c in df.columns if c not in ['Date']]
corr = df[drivers].corr()
plt.figure(figsize=(10,8))
sns.heatmap(corr, cmap='coolwarm', center=0, vmin=-1, vmax=1)
plt.title('Correlation Heatmap (all numeric columns)'); plt.tight_layout(); plt.show()
```

```
# STL Decomposition
keep = ['Date', 'Energy Required (MU)', 'Unrestricted Peak Demand (MW)']
g = df[keep].dropna(subset=['Date']).copy()
g = g.groupby('Date', as_index=True).mean().sort_index()
idx = pd.date_range(g.index.min(), g.index.max(), freq='D')
g = g.reindex(idx)
g.index.name = 'Date'
g = g.interpolate(limit_direction='both')

targets = [c for c in ['Energy Required (MU)', 'Unrestricted Peak Demand (MW)'] if c in
g.columns]

for tgt in targets:
    s = g[tgt]
    res = STL(s, period=7, robust=True).fit()
    res.plot()
    plt.suptitle(f'STL Decomposition — {tgt} (period=7)', y=1.02)
    plt.tight_layout(); plt.show()

# ACF/PACF
for tgt in targets:
    s = g[tgt]
    fig, ax = plt.subplots(1, 2, figsize=(12, 3))
    plot_acf(s, ax=ax[0], lags=60, title=f'ACF — {tgt}')
    plot_pacf(s, ax=ax[1], lags=60, method='ywm', title=f'PACF — {tgt}')
    plt.tight_layout(); plt.show()

# ========================
# Preprocessing Phase
# ========================
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler

TARGET = 'Energy Required (MU)'

def iqr_cap(s, k=1.5):
    q1, q3 = s.quantile([0.25, 0.75])
    iqr = q3 - q1
    lo, hi = q1 - k*iqr, q3 + k*iqr
    return s.clip(lo, hi)

# 1) De-NaT, de-duplicate dates, sort
df_p = df.dropna(subset=['Date']).copy()
df_p = df_p.groupby('Date', as_index=False).mean().sort_values('Date')

# 2) Focus on post-break regime (cleanest)
df_p = df_p[df_p['Date'] >= '2015-01-01'].reset_index(drop=True)

# 3) Cap extreme outliers on TARGET
df_p[TARGET] = iqr_cap(df_p[TARGET], k=1.5)

# 4) Build lagged features
supply_cols_all = [
    'Energy Met (MU)','Genco Thermal','Genco Hydel','Genco Total',
    'CGS and Purchases','IPPS (GAS)','NCEs & Others','Grand Total',
    'AP Share of TGISTS','Reversible Pump Consumption','Deficit/Surplus (MW)'
]
supply_cols = [c for c in supply_cols_all if c in df_p.columns]

lags = [1, 2, 7, 14]
for L in lags:
    df_p[f'{TARGET}_lag{L}'] = df_p[TARGET].shift(L)
    for c in supply_cols:
        df_p[f'{c}_lag{L}'] = df_p[c].shift(L)

# 5) Rolling means of target
df_p[f'{TARGET}_r7']  = df_p[TARGET].rolling(7).mean()
df_p[f'{TARGET}_r14'] = df_p[TARGET].rolling(14).mean()

# 6) Calendar dummies
df_p['DoW'] = df_p['Date'].dt.dayofweek
df_p['Month'] = df_p['Date'].dt.month
df_p = pd.get_dummies(df_p, columns=['DoW','Month'], drop_first=True)

# 7) Drop rows with NaNs
df_p = df_p.dropna().reset_index(drop=True)
```

```
# 8) Train/Test split
if (df_p['Date'] >= '2022-01-01').any():
    test_start = pd.Timestamp('2022-01-01')
else:
    test_start = df_p['Date'].max() - pd.Timedelta(days=365)

train_df = df_p[df_p['Date'] < test_start].copy()
test_df  = df_p[df_p['Date'] >= test_start].copy()

# 9) Feature columns
exclude_cols = set(['Date', TARGET] + [c for c in supply_cols])
feat_cols = [c for c in df_p.columns if c not in exclude_cols]

X_train = train_df[feat_cols].values
y_train = train_df[TARGET].values
X_test  = test_df[feat_cols].values
y_test  = test_df[TARGET].values

# 10) Scale features
scaler_X = StandardScaler()
X_train_s = scaler_X.fit_transform(X_train)
X_test_s  = scaler_X.transform(X_test)

# ========================
# Modeling Phase
# ========================
import time
from sklearn.metrics import mean_absolute_percentage_error, mean_squared_error
from xgboost import XGBRegressor
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, GRU
from tensorflow.keras.callbacks import EarlyStopping

def MAPE(y, p): return float(mean_absolute_percentage_error(y, p) * 100.0)
def RMSE(y, p): return float(np.sqrt(mean_squared_error(y, p)))

# XGBoost Training
xgb = XGBRegressor(
    n_estimators=1200, learning_rate=0.05, max_depth=6,
    subsample=0.9, colsample_bytree=0.9, reg_lambda=1.0,
    random_state=42, tree_method="hist"
)
xgb.fit(X_train, y_train)
pred_xgb = xgb.predict(X_test)

# Sequence Prep for LSTM/GRU
def make_seq(X, y, dates, win=21):
    Xs, ys, ds = [], [], []
    for i in range(win, len(X)):
        Xs.append(X[i-win:i]); ys.append(y[i]); ds.append(dates[i])
    return np.array(Xs), np.array(ys), np.array(ds)

win = 21
X_all_s = np.vstack([X_train_s, X_test_s])
y_all   = np.hstack([y_train,   y_test])
d_all   = np.hstack([train_df['Date'].values, test_df['Date'].values])

X_seq, y_seq, d_seq = make_seq(X_all_s, y_all, d_all, win)
mask_te = d_seq >= test_df['Date'].iloc[0]
X_seq_tr, y_seq_tr = X_seq[~mask_te], y_seq[~mask_te]
X_seq_te, y_seq_te = X_seq[mask_te],  y_seq[mask_te]
d_seq_te = d_seq[mask_te]

# LSTM Training
tf.keras.backend.clear_session()
lstm = Sequential([
    LSTM(64, input_shape=(win, X_seq_tr.shape[-1]), dropout=0.1),
    Dense(32, activation='relu'), Dense(1)
])
lstm.compile(optimizer='adam', loss='mse')
es = EarlyStopping(monitor='val_loss', patience=8, restore_best_weights=True)
lstm.fit(X_seq_tr, y_seq_tr, validation_split=0.1, epochs=80, batch_size=64, verbose=0,
callbacks=[es])
pred_lstm = lstm.predict(X_seq_te, verbose=0).ravel()

# GRU Training
tf.keras.backend.clear_session()
gru = Sequential([
    GRU(64, input_shape=(win, X_seq_tr.shape[-1]), dropout=0.1),
    Dense(32, activation='relu'), Dense(1)
])
gru.compile(optimizer='adam', loss='mse')
gru.fit(X_seq_tr, y_seq_tr, validation_split=0.1, epochs=80, batch_size=64, verbose=0,
callbacks=[es])
pred_gru = gru.predict(X_seq_te, verbose=0).ravel()

# Weighted Ensemble
xgb_map = {d: p for d, p in zip(test_df['Date'].values, pred_xgb)}
pred_xgb_aligned = np.array([xgb_map[d] for d in d_seq_te], float)

P = np.vstack([pred_xgb_aligned, pred_lstm, pred_gru]).T
best = (None, 1e18, None)
grid = np.linspace(0, 1, 101)
for w1 in grid:
    for w2 in grid:
        w3 = 1 - w1 - w2
        if w3 < 0: continue
        w = np.array([w1, w2, w3])
        pred = P @ w
        rmse = RMSE(y_seq_te, pred); mape = MAPE(y_seq_te, pred)
        if rmse < best[1]: best = (w, rmse, mape)

w_opt, rmse_opt, mape_opt = best
pred_wens = P @ w_opt

print(f"Best Weights [XGB, LSTM, GRU]: {w_opt}")
print(f"Ensemble MAPE: {mape_opt:.2f}%")

# =========================
# Visualization
# =========================
plt.figure(figsize=(14,4.8))
plt.plot(d_seq_te, y_seq_te, label="Actual", linewidth=2)
plt.plot(d_seq_te, pred_wens, label=f"Ensemble (MAPE {mape_opt:.2f}%)", alpha=0.9)
plt.title("Energy Required (MU): Actual vs Ensemble")
plt.xlabel("Date"); plt.ylabel("MU")
plt.legend()
plt.tight_layout()
plt.show()
```

BIODATA



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