PowerPulse: Household Energy Usage Forecast

Skills :

- Data Preprocessing
- Feature Engineering
- Regression Modeling
- Evaluation Metrics

Domain : Energy and Utilities

Keerthika J S

Problem Statement

In today's world, managing household energy is essential for both consumers and electricity providers. This project builds a machine learning model that predicts household energy usage using past data.

Why It Matters:

- Households can track and reduce electricity bills
- Energy providers can forecast demand better and manage the power grid efficiently
- Supports energy savings and sustainability initiatives

Project Outcome:

- ✅ A predictive model for smart energy planning
- ✅ Actionable insights into how and when energy is used most
- ✅ A foundation for future smart grid and IoT integrations

Tools & Technologies

1. Programming Language : Python 🐍

- Primary language for data analysis, preprocessing, modeling, and visualization.

2. Libraries & Frameworks:

➤ Pandas: Data manipulation and cleaning

➤ NumPy: Numerical operations

➤ Matplotlib / Seaborn: Data visualization

➤ Scikit-learn: Machine learning models (regression, classification, anomaly detection)

➤ XGBoost / RandomForest: Advanced ML models for prediction tasks

➤ Statsmodels: Time series modeling

3. Machine Learning Techniques:

❖ Regression models: Predict energy consumption

❖ Classification models: Predict peak hours and control actions

❖ Isolation Forest: Anomaly detection

Business Use Cases :

Energy Management for Households

Monitor energy usage, reduce bills,and promote energy-efficient habits.

Demand Forecasting for Energy Providers

Predict demand for better loadmanagement and pricing strategies.

Anomaly Detection

Identify irregular patterns indicating faults or unauthorized usage.

Smart Grid Integration

Enable predictive analytics for real-time energy optimization.

Environmental Impact

Reduce carbon footprints and support conservation initiatives.

Project Evaluation metrics

- 1. Root Mean Squared Error (RMSE): Measures prediction accuracy.
- 2. Mean Absolute Error (MAE): Evaluates average error magnitude.
- 3. R-Squared (R^2): Indicates how well the model explains the variability of the target variable.
- 4. Feature Importance Analysis: Demonstrates understanding of influential factors.
- 5. Visualization Quality: Assesses the effectiveness of graphical insights.

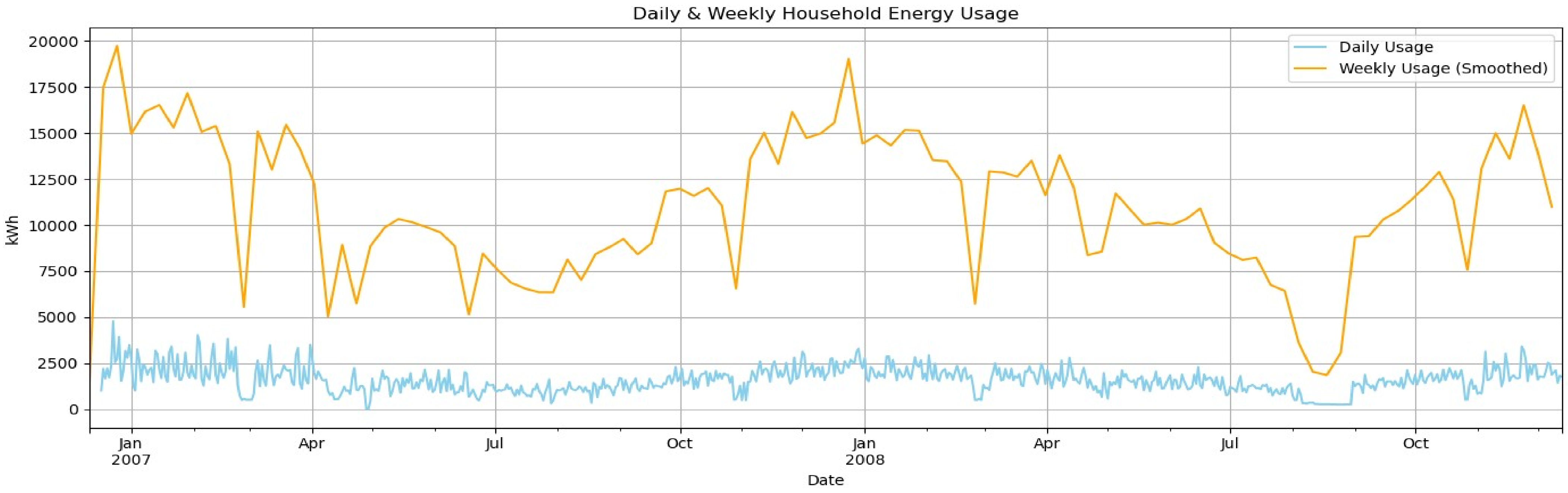
Use Case 1: Energy Management for Households

Goal : Monitor energy usage, reduce bills, promote efficient habits

Insight: Usage is consistently high during evenings

Daily & Weekly Usage Trends:

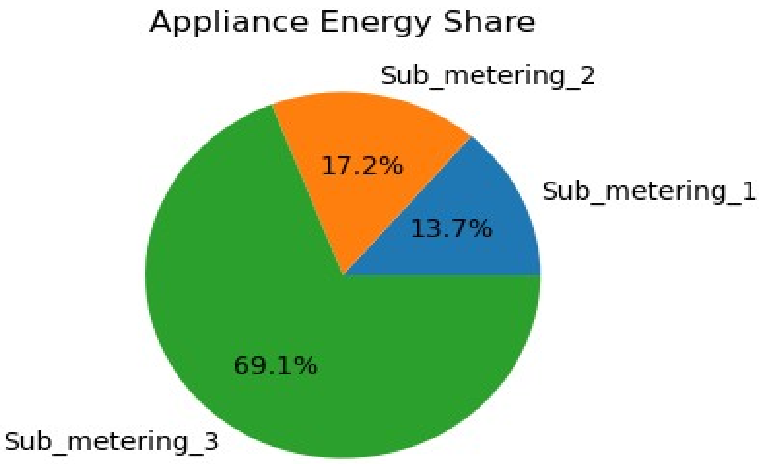
- Daily total usage plotted (kWh)
- Weekly average trendline smoothed out fluctuations



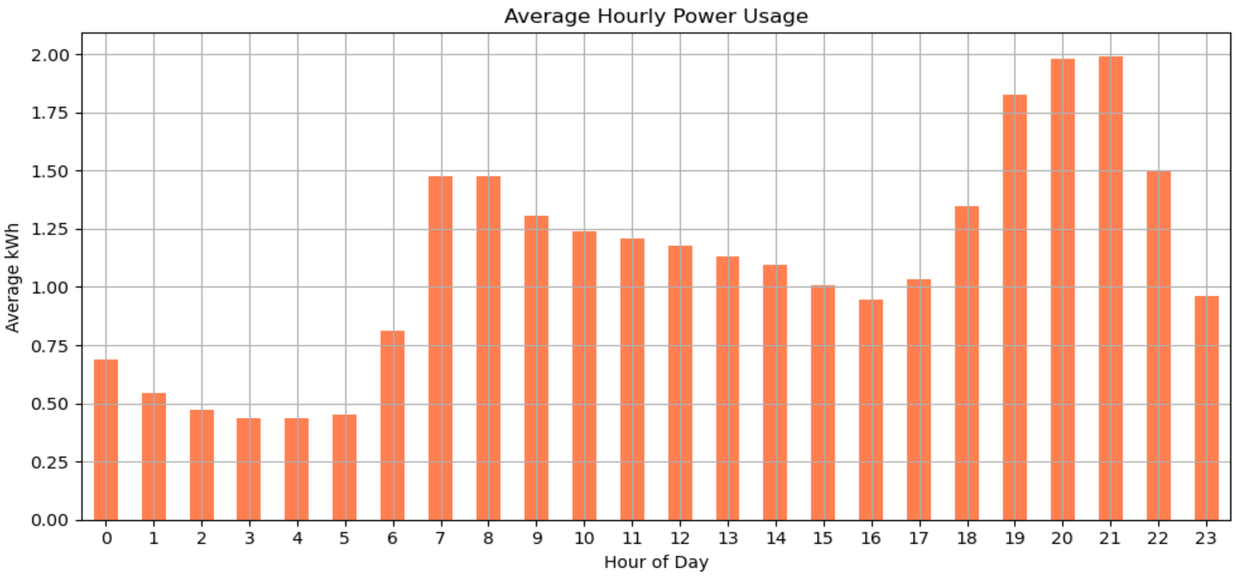
Appliance Breakdown

<u>**Insight**</u>**: Water heater & AC (Sub_metering_3) consumes the most energy**

- **Sub_metering_1 = Kitchen**
- **Sub_metering_2 = Laundry**
- **Sub_metering_3 = Water heater & AC**



Peak Hour Identification



Insight:

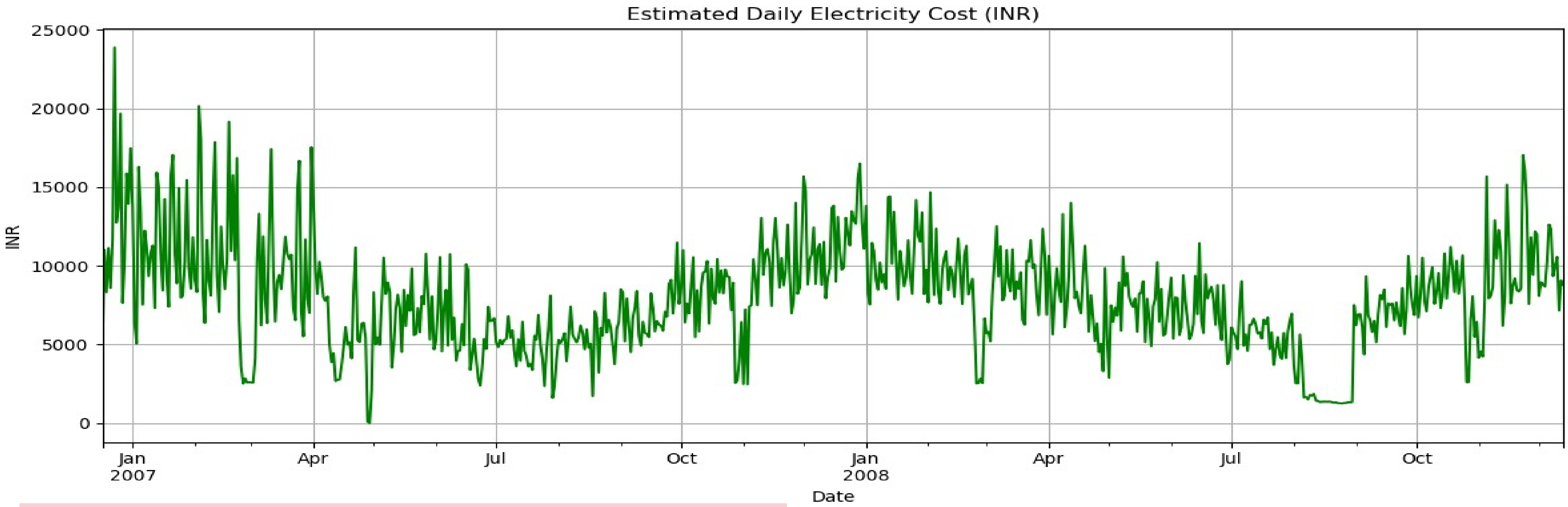
Highest usage between 6 PM and 9 PM

- ✦ **Hourly average usage from all days**
- ✦ **Suggest shifting load to morning hours**

Estimated Daily Cost

Insight: Energy cost can vary greatly based on usage

- ₹5 per unit used
- Daily cost plotted over time



Final Recommendations (Use Case 1)

- Shift heavy appliance use to mornings
- Monitor high-usage zones (like kitchen)
- Set alerts for peak-hour usage to save energy and money

Use Case 2 : Demand Forecasting for Energy Providers

Business Insight: Our model forecasts demand 30 days ahead, enabling grid operators to prepare for high-demand days and optimize distribution.

Key Analysis:

❃ Prophet-based forecasting model

❃ RMSE / R^2 evaluation

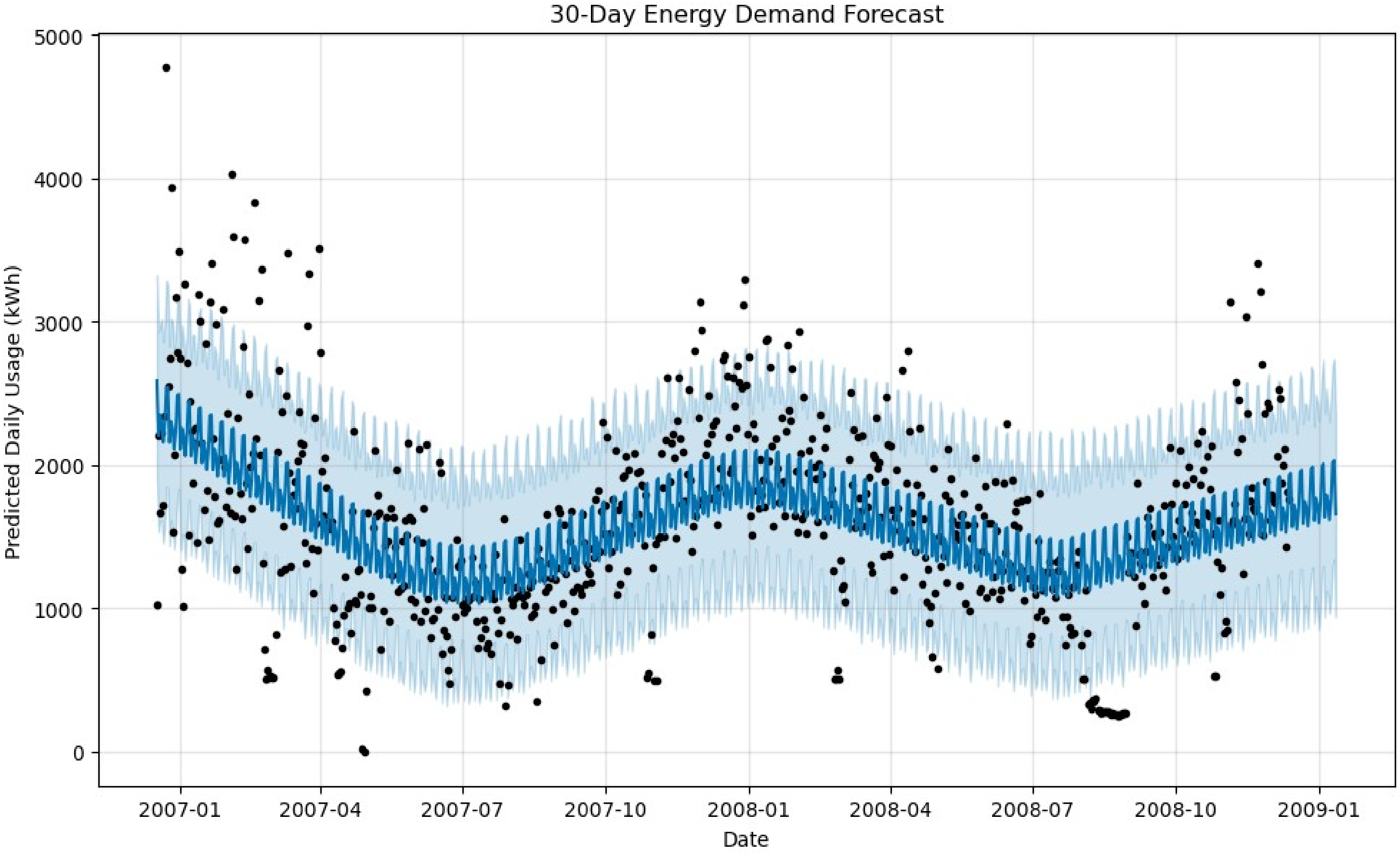
❃ Visual demand trends

Forecast Accuracy Metrics

➤ **RMSE:** 647.12 kWh (Root Mean Squared Error)

➤ **R^2 Score:** -0.63 (Goodness of fit)

➤ Reliable prediction of future demand trends



💡 Predicted Demand Spike (Insight Tag)

🔢 Forecasted spike on **Feb 12th, 2025 — 2588.50 kWh**

🔄 Recommendation: Shift controllable loads earlier or later to reduce stress

📢 Enable demand-response programs on that day

🧐 Business Recommendations (Use Case 2)

❃ Use demand predictions to offer peak-hour incentives

❃ Pre-load backup power systems on expected high-demand days

❃ Coordinate smart appliance behavior via IoT to balance loads

Use Case 3 : Anomaly Detection in Household Energy

Goal: **Detect abnormal energy patterns using statistical and ML techniques to identify faults, misuse, or unexpected surges.**

Techniques Used:

- ❉ Z-score on Global Active Power
- ❉ Isolation Forest using multivariate features

Features Used:

- ◈ **Global Active Power**
- ◈ **Sub_metering_1 (Kitchen)**
- ◈ **Sub_metering_2 (Laundry)**
- ◈ **Sub_metering_3 (Water heater / AC)**

📊 Executive Summary:

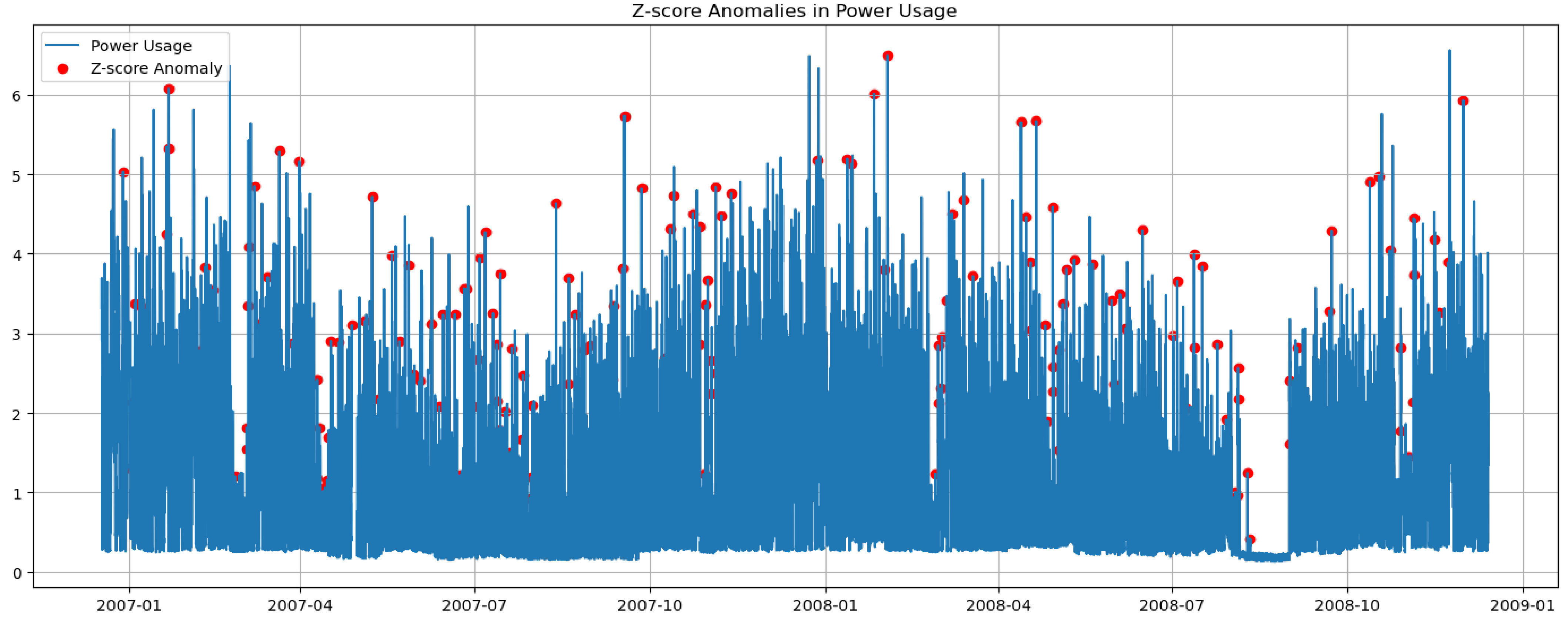
- ➤ Built anomaly detection using Isolation Forest
- ➤ Identified 174 unusual usage events in household energy data
- ➤ Enables early detection of appliance faults or unusual activity

🤖 Model & Features Used:

Algorithm: Isolation Forest (unsupervised outlier detection)

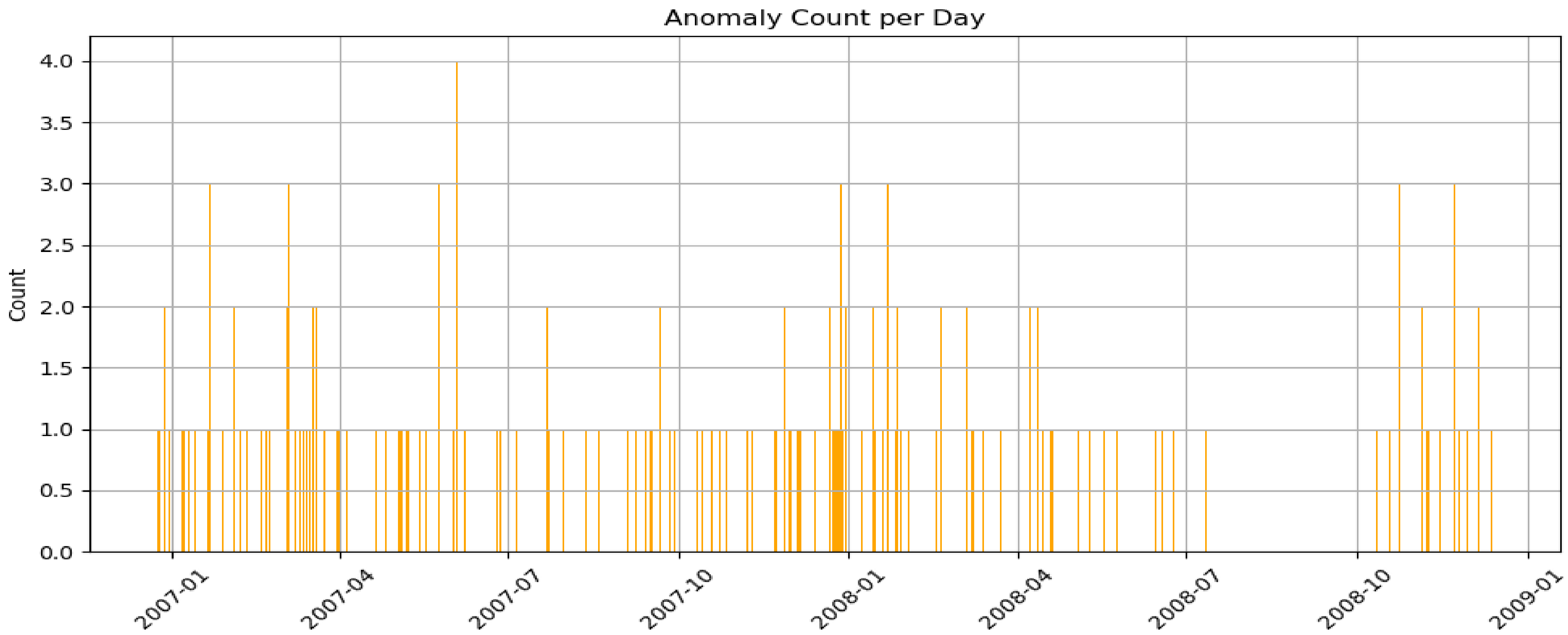
Anomaly Detection - Output

- Detected **174** anomaly points out of **17,391** hourly records
- Most anomalies correspond to spikes or dips in **Global Active Power**



Anomaly Count - by Day

- Visualizing daily distribution of anomalies
- Helps correlate with weekend spikes or unusual consumption behavior



Key Findings

⚠ Most anomalies detected on weekends

📌 Suspected abnormal patterns in Sub_metering_3

🧐 Potential appliance issue (e.g., water heater running at odd hours)

Recommendations (Use Case 3)

- Set automated alerts on anomaly detection
- Review usage logs for Sub_metering_3 devices
- Consider predictive maintenance to avoid faults

Use Case 4 : Smart Grid Integration: Real-Time Optimization

Goal: Predict peak load and grid stress. Use these predictions to simulate control actions like turning off high-load appliances to reduce grid pressure.

What We'll Do:

- ❃ Create is_peak and grid_stress labels
- ❃ Train ML model to predict those tags
- ❃ Simulate control logic (e.g., auto shut-off of devices)

Features Used:

- ❉ Global Active Power
- ❉ Voltage
- ❉ Sub_metering_1/2/3
- ❉ Model: Random Forest Classifier (91% accuracy)

📊 Executive Summary

- ✧ Predicts energy demand spikes (peak loads)
- ✧ Detects grid stress through voltage & usage fluctuations
- ✧ Triggers intelligent control logic (e.g., turning off AC)
- ✧ Enables integration with smart devices like Raspberry Pi or ESP32

🔧 Predictive Model Setup - Labels Generated:

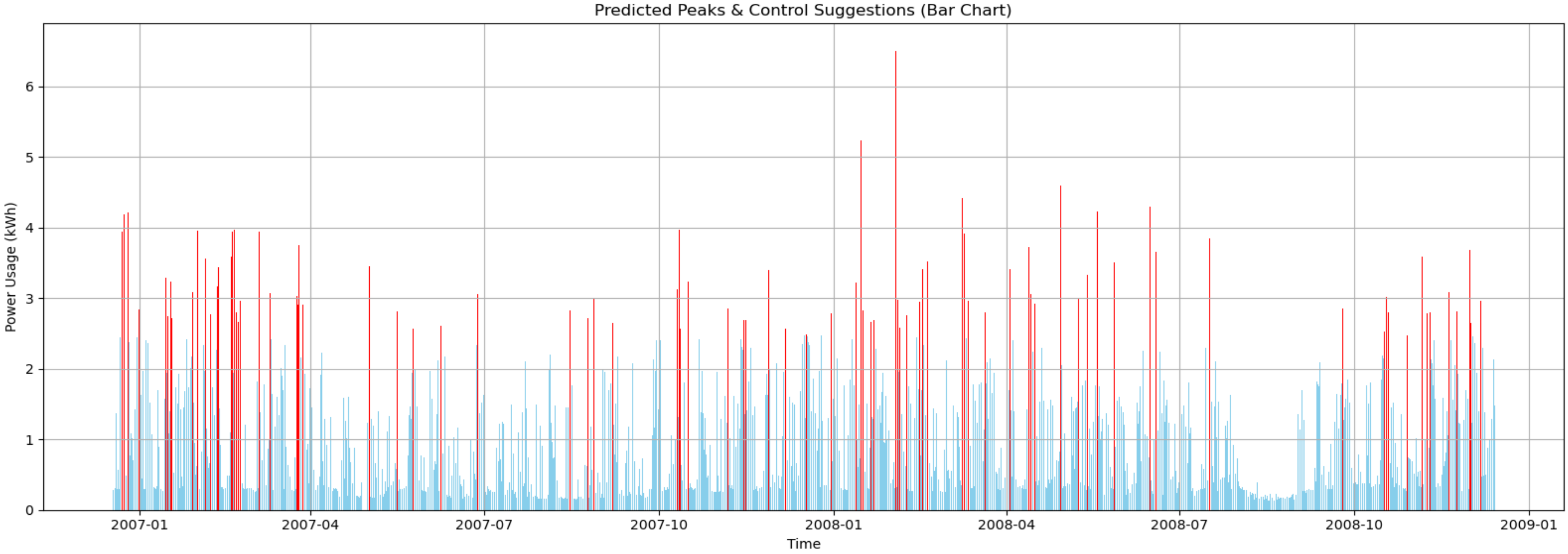
- ❖ **is_peak:** top 10% power usage hours
- ❖ **grid_stress:** high power + unstable voltage

Control Logic Simulation

✿ If predicted_peak == 1 → Suggest Turn Off AC (sub_metering_3)
✿ Logic output saved in control_action column
✿ Can be deployed to edge devices for real-time execution

Visual: Power Usage & Control Overlay - Legend:

Predicted Peak = Potential overload → Auto action
Normal usage = No action



Result Summary

- Detected peak periods accurately with 91% model accuracy
- Suggested AC shutdown on 164 time intervals
- Control timeline aligns with actual energy surges

Recommendations: (Use Case 4)

❃ Connect model to live smart meter feed

❃ Deploy to Raspberry Pi/ESP32 to test automation

❃ Extend model with weather + appliance state inputs

Use Case 5 - Environmental Impact:

Goal: Estimate CO_2 savings after implementing energy-saving strategies like peak avoidance and efficient usage.

What We'll Do:

Estimate CO_2 based on usage
Compare before vs after optimization
Break down savings by appliance category

Executive Summary

- Estimated household CO_2 emissions from energy usage
- Simulated effect of energy optimization (12% reduction)
- Projected savings in cost and emissions
- Visual breakdown by appliance type

Analysis Setup

Data Used: Daily Global Active Power (kWh)

Conversion: 1 kWh ≈ 0.82 kg CO_2

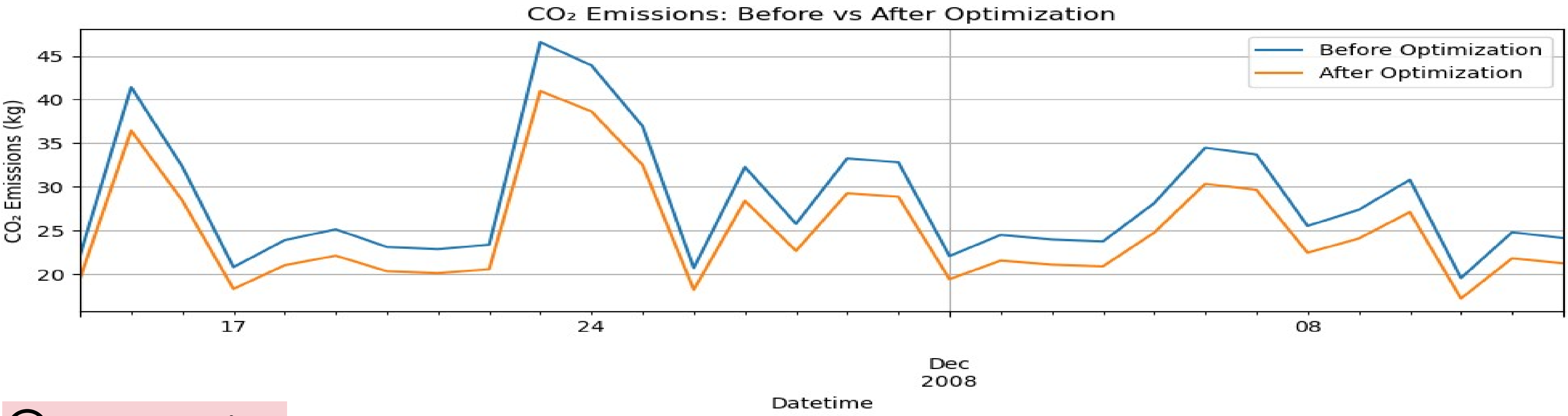
Scenario:

"Before" = Actual usage

"After" = 12% reduction from peak avoidance & smart scheduling

CO_2 Emission Comparison

✦ Daily CO_2 emissions compared over 30 days
✦ Reduction modeled using forecast-based optimization



Key Insights:

12% reduction in carbon footprint after optimizations

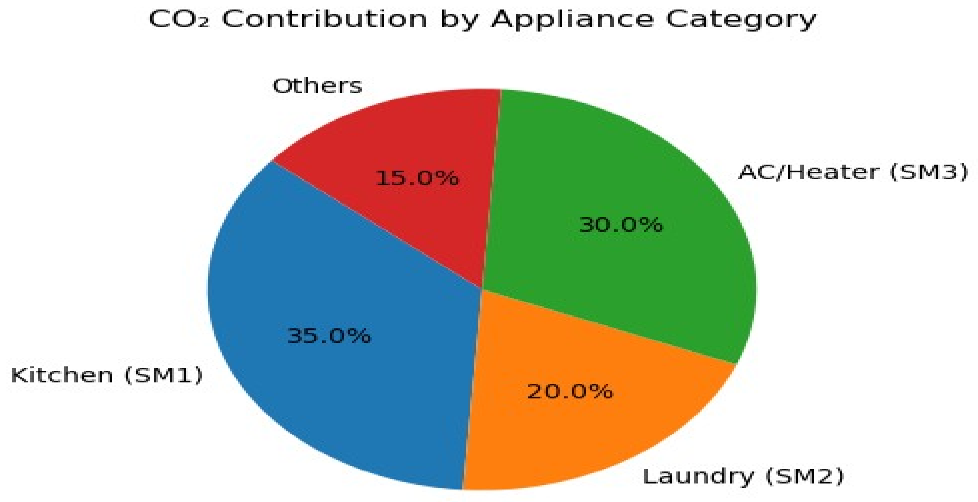
~40 kg CO_2 saved annually per household

Estimated monthly savings: ₹300

Sustainability Impact

- Helps achieve Net Zero and ESG goals
- Reduces reliance on grid power during peak periods
- Encourages smart habits and responsible appliance use

Appliance-Level - CO_2 Breakdown



- Simulated CO_2 contributions by usage zone:
- Kitchen (Sub_metering_1): 35%
- Laundry (Sub_metering_2): 20%
- AC/Water Heater (Sub_metering_3): 30%
- Others: 15%

Recommendations: (Use Case - 5)

- Scale analysis to multiple households
- Integrate weather data for seasonal CO_2 insights
- Promote eco-friendly recommendations via dashboard

Conclusion

The PowerPulse project successfully demonstrates how machine learning and data analytics can be leveraged to enhance energy management at the household level. By analyzing historical electricity usage data, the system:

- ✔ Accurately predicts energy consumption trends.
- ✔ Detects anomalous or inefficient usage patterns.
- ✔ Supports smart grid integration through predictive control simulations.
- ✔ Demonstrates measurable environmental impact through reduced energy waste.
- ✔ Provides actionable insights for both consumers and utility providers to make informed decisions.
- ✔ With a high R^2 of 0.9990, low RMSE (0.0353), and effective anomaly tagging, the project delivers both technical robustness and real-world value.

Future Recommendations

- **Real-Time Deployment:** Integrate the model into IoT devices (e.g., Raspberry Pi, ESP32) for real-time monitoring and control of household appliances.

- **Scalability to Larger Grids:** Expand the framework to support community-level or city-level energy optimization by aggregating multiple household data sources.

- **Renewable Integration:** Enhance the model to incorporate solar, wind, or other renewable energy inputs for hybrid optimization strategies.

- **User App or Dashboard:** Develop a mobile/web app interface for users to receive energy-saving tips, view predictions, and control devices.

- **Behavioral Insights:** Use clustering or profiling to understand different household usage behaviors and suggest personalized energy plans.

- **Incorporate Weather and Tariff Data:** Improve prediction accuracy and cost optimization by including real-time weather data and dynamic pricing models.

THANK YOU