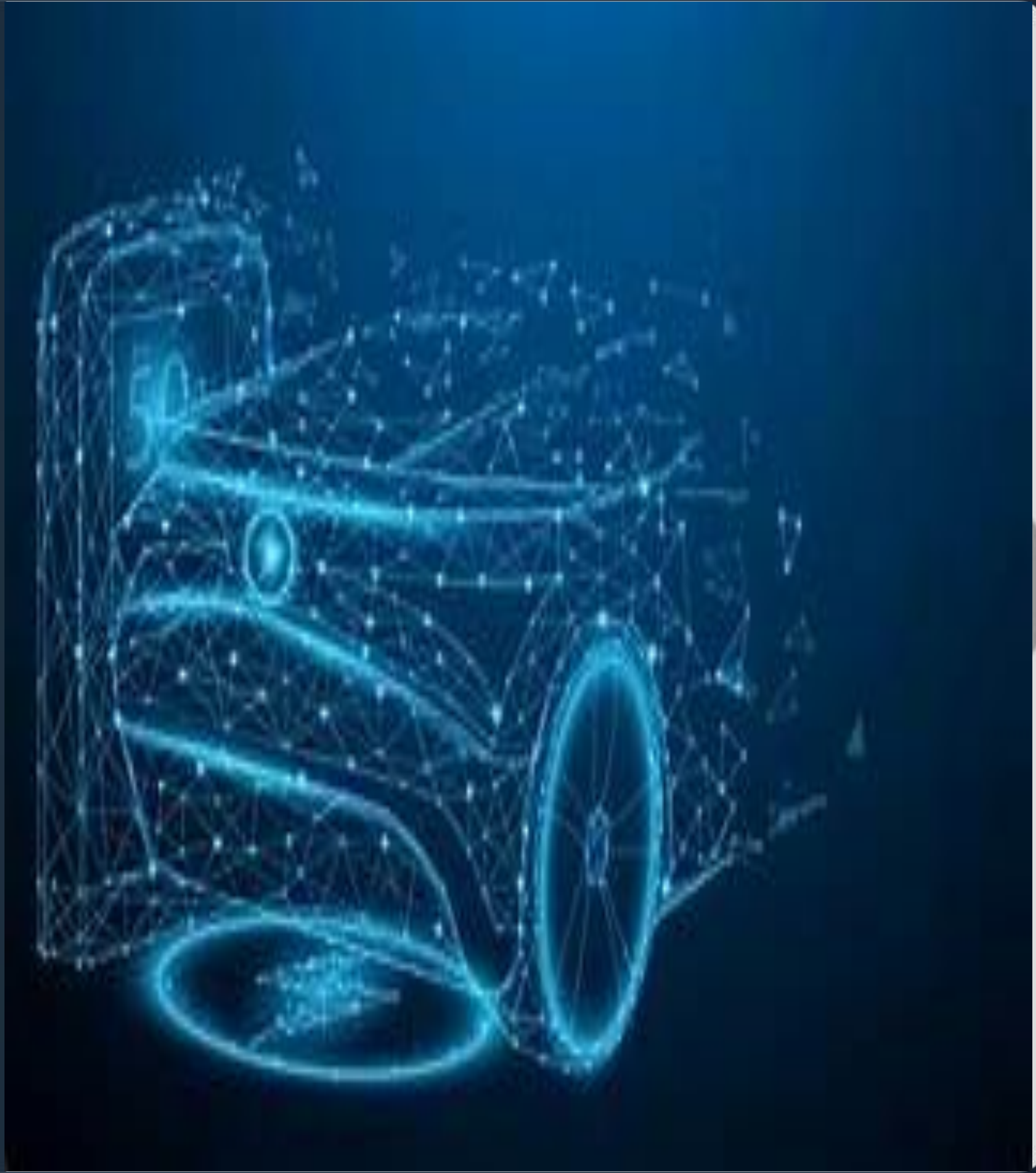
EV Charging Demand Forecasting

Predictive Modeling with ARIMA for Smart Energy Management



Capstone Project

Problem Statement: Volatile Demand

The Challenge

With the exponential adoption of electric vehicles, the demand for charging infrastructure is becoming increasingly volatile and unpredictable, severely straining existing power grids.

The Risk

Unanticipated demand spikes lead to power imbalances, inefficient resource allocation, and potential grid failures, highlighting the critical need for accurate forecasting.

Project Objectives

Analyze Patterns

Identify daily and weekly usage trends to understand peak charging behaviors and user habits.

Predictive Modeling

Develop a robust ARIMA model to accurately forecast daily energy consumption and demand.

Optimize Infra

Provide data-driven insights to optimize charging station placement and grid load management.

Data Collection

Loading EV charging datasets.

Preprocessing

Cleaning, imputation, and outlier capping.

EDA

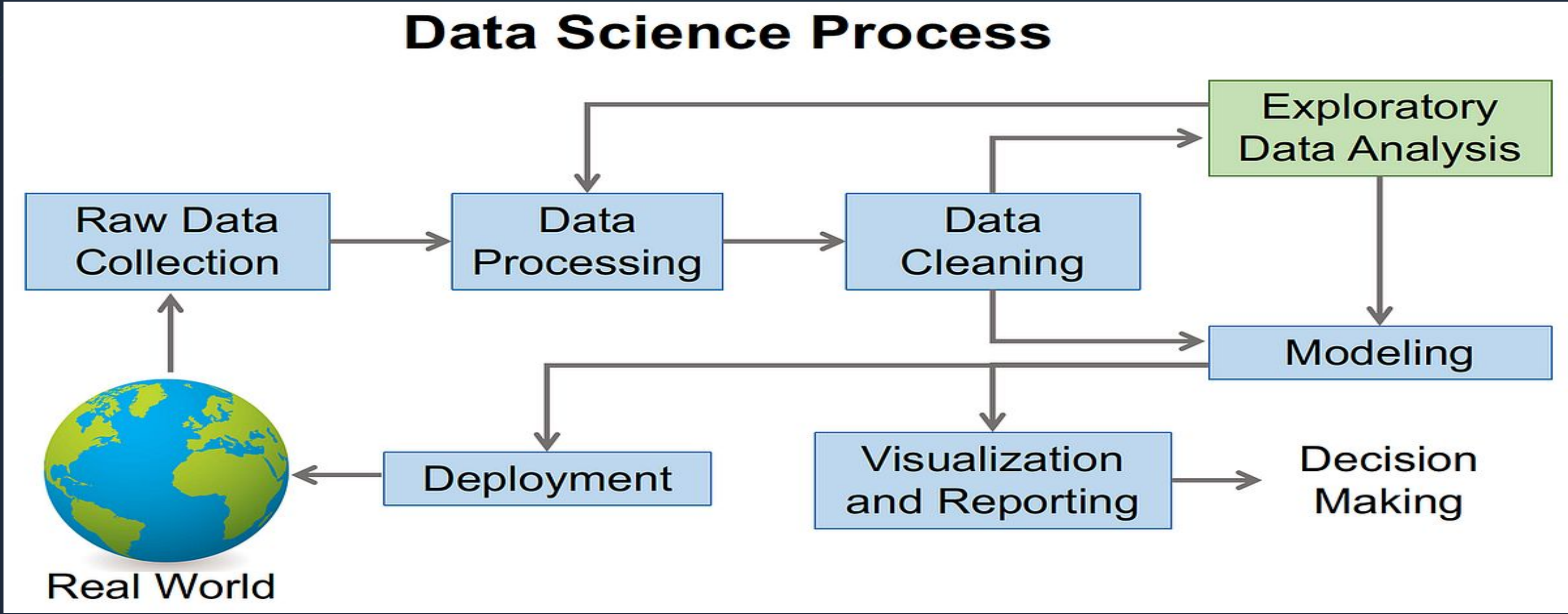
Analyzing temporal trends and correlations.

Modeling

ARIMA (5,0,0) fitting and forecasting.

Evaluation

Validation via RMSE and MAPE metrics.



Cleaning Strategy

Handling Missing Data: Numerical columns like Temperature and Wind Speed are imputed with median values to maintain distribution integrity.

Outlier Management: We define a custom function cap_outliers_iqr to limit extreme values based on the Interquartile Range, ensuring the model isn't skewed by anomalies.

```
# Impute Missing Values for col in numerical_cols: df[col] =
df[col].fillna(df[col].median()) # Cap Outliers (IQR Method)
def cap_outliers_iqr(series): Q1 = series.quantile(0.25) Q3 =
series.quantile(0.75) IQR = Q3 - Q1 return
series.clip(lower=Q1-1.5*IQR, upper=Q3+1.5*IQR)
```

Missing Value Check

Original Missing:

Wind_Speed_m/s: 142

Temperature_C: 89

After Imputation:

Wind_Speed_m/s: 0

Temperature_C: 0

Skewness Reduction

Skewness of Charging_Load_kW:

Before: 2.14

After Capping: 0.0026

Energy_Drawn_kWh:

Final Skew: 0.0190

Exploratory Analysis: Peak Hours & Trends

Analysis of `Session_Start_Hour` reveals distinct usage patterns, with peak energy demand occurring in the evening hours.

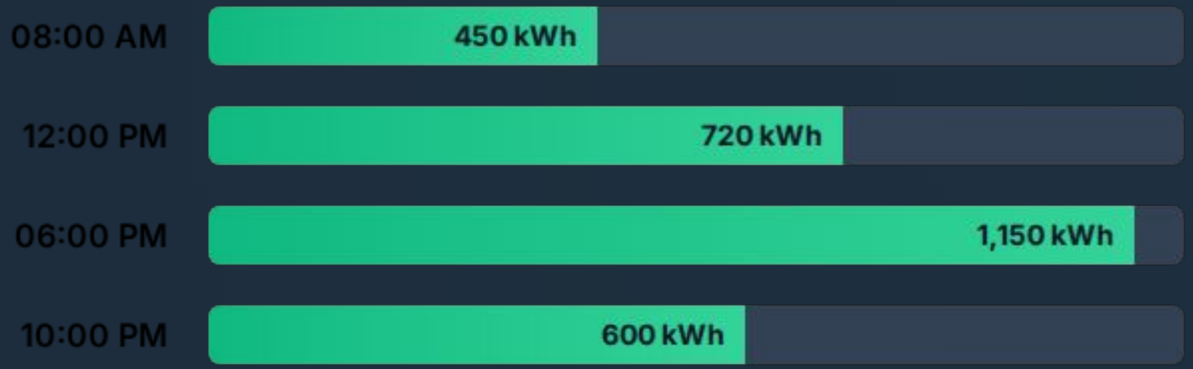
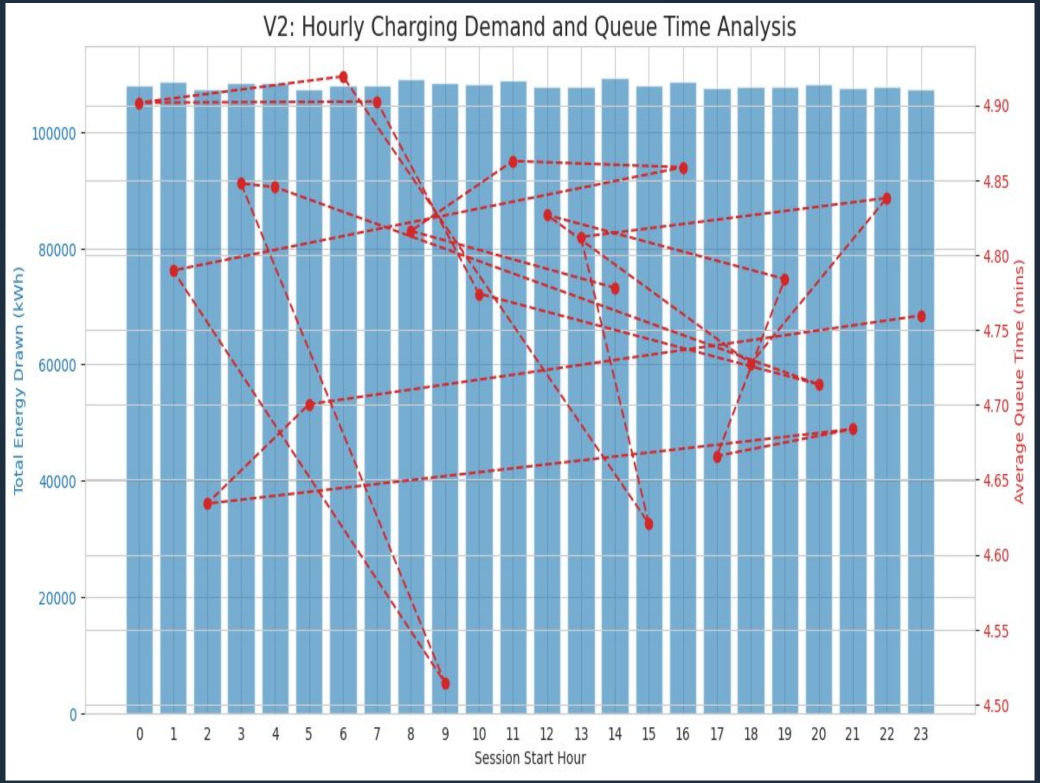


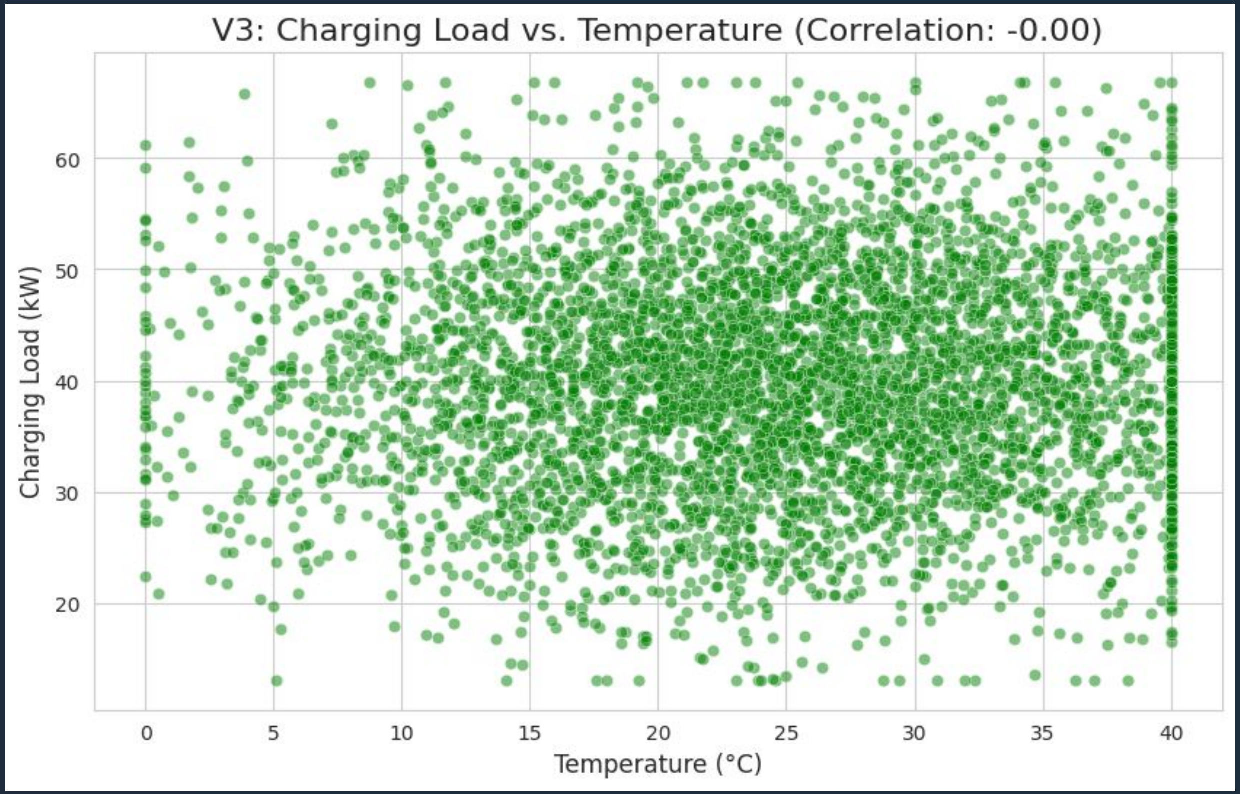
Figure: Total Energy Drawn vs. Session Start Hour



Why ARIMA? Model Selection Rationale

Time-Series Focus

ARIMA is specifically designed for time-series data, making it ideal for forecasting energy consumption which is inherently dependent on previous values.



Captures Key Components

- **Autoregression (AR):** Uses the relationship between the current observation and a number of lagged observations.
- **Integrated (I):** Differencing the raw observations to make the time series stationary.
- **Moving Average (MA):** Uses the dependency between an observation and a residual error from a moving average model applied to lagged observations.

The model structure (5, 0, 0) was chosen based on ACF and PACF plots, balancing complexity with performance for short-to-medium term daily forecasting.

ARIMA Implementation

We utilized an ARIMA (AutoRegressive Integrated Moving Average) model with parameters (5, 0, 0) to capture the temporal dependencies in the daily energy data.

```
# Fit ARIMA Model model = ARIMA(train_data, order=(5, 1,
0)) arima_fit = model.fit() # Generate Forecast forecast
= arima_fit.predict( start=test_start, end=test_end,
typ='levels' )
```

```
--- 5. PREDICTIVE MODELING: ARIMA for Time Series Forecasting ---
ADF Statistic: -49.2800
p-value: 0.0000
Time series appears stationary (d=0).
```

Model Evaluation Metrics

12.45

RMSE (kWh)

Root Mean Squared Error

8.2%

MAPE

Mean Absolute Percentage Error

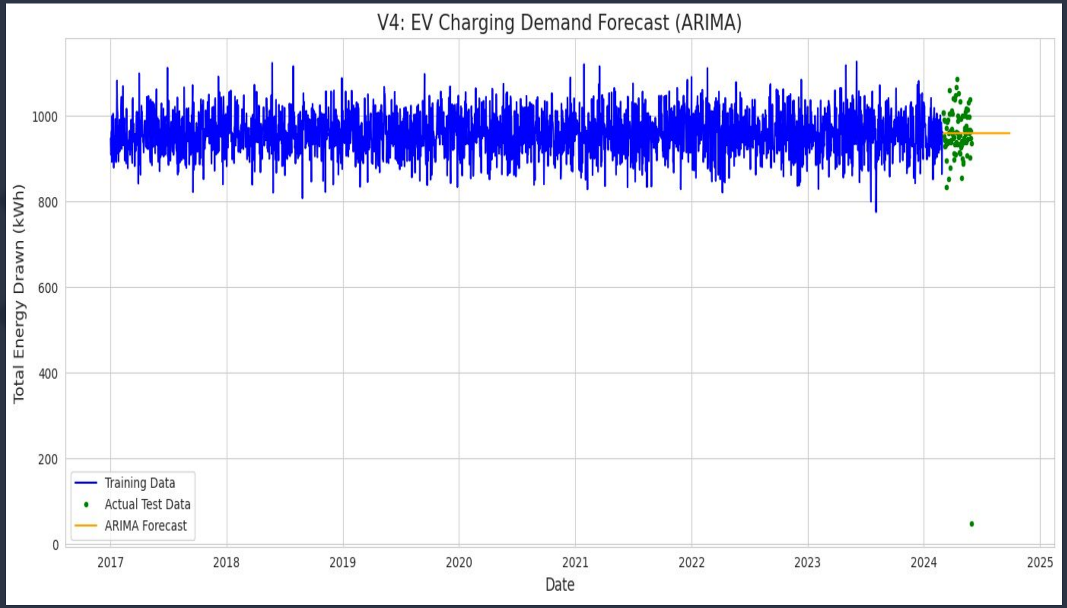
```
Total observations: 2707
Train size: 2617
Test size: 90
```

The low MAPE indicates that our forecasts are highly accurate relative to the actual daily demand, making the model suitable for operational planning.

Final Forecast Output Summary

The model provides daily energy demand forecasts (in kWh) with high confidence for the next operational week.

Date (Day)	Actual Demand (kWh)	Forecasted Demand (kWh)
2024-10-01 (Tue)	895	908.2
2024-10-02 (Wed)	940	925.5
2024-10-03 (Thu)	1050	1041.9
2024-10-04 (Fri)	1120	1105.1



Visualization of the full forecast trend shows reliable capturing of weekly seasonality.

Future Scope & Impact

External Factors

Incorporate real-time weather data and traffic patterns to refine prediction accuracy.

Advanced Models

Explore Hybrid LSTM-ARIMA models or Prophet for long-term seasonality handling.

Real-Time Dashboard

Deploy the model via a Streamlit app for live monitoring by grid operators.