kWh Energy Forecasting Project

1 - Importing Libraries

In [378…

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
import matplotlib.dates as mdates
from datetime import datetime
import prophet as Prophet
from sklearn.model_selection import train_test_split
from statsmodels.tsa.api import ARIMA, SARIMAX
import pmdarima
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from sklearn.tree import DecisionTreeRegressor, export_text
from sklearn.metrics import mean_squared_error, root_mean_squared_error
from sklearn.ensemble import RandomForestRegressor
from statsmodels.tsa.holtwinters import ExponentialSmoothing
```

2 - Features

In [379…

```
def features(df):
    daily_data = pd.read_csv('daily - Sheet1.csv')

    daily_data = daily_data.rename(columns={'Start': 'date'})


    daily_data['date'] = (pd.to_datetime(daily_data['date'], format='%m/%d/%Y

    daily_data['day'] = daily_data['date'].dt.day_name()
    day_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Satu
    daily_data['day'] = pd.Categorical(daily_data['day'], categories=day_order

    daily_data['day_number'] = daily_data['date'].dt.day_of_week
    weekdays = daily_data[daily_data['day_number'] < 5]
    weekends = daily_data[daily_data['day_number'] >= 5]

    daily_data['month'] = daily_data['date'].dt.month_name()
    daily_data['month_number'] = daily_data['date'].dt.month  # <-- Added this
    daily_data['weekday'] = (daily_data['day_number'] < 5).astype(int)

    daily_data = daily_data.set_index('date', inplace=False)
    return daily_data
```

In [380…

```
df = features('daily - Sheet1.csv')
```

```
df.head()
```

Out[380…

	kWh	day	day_number	month	month_number	weekday
date						
2025-06-01	5.05	Sunday	6	June	6	0
2025-06-02	6.86	Monday	0	June	6	1
2025-06-03	9.10	Tuesday	1	June	6	1
2025-06-04	7.32	Wednesday	2	June	6	1
2025-06-05	12.88	Thursday	3	June	6	1

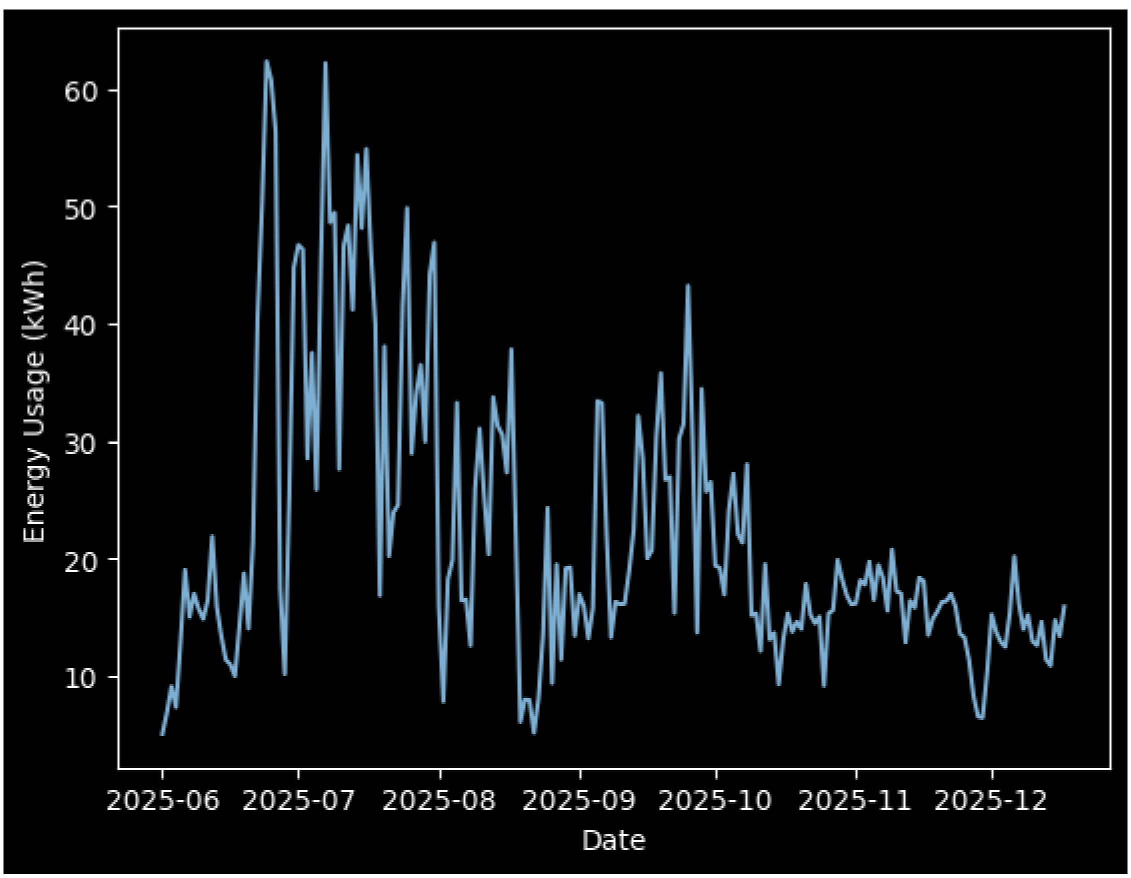
3 - Exploratory Data Analysis

3.1 - kWh Time Series Graph

In [386…

```
sns.lineplot(df['kWh'], color = sns.color_palette()[4])
plt.xlabel('Date')
plt.ylabel('Energy Usage (kWh)')
plt.figure(figsize=(18,6))
```

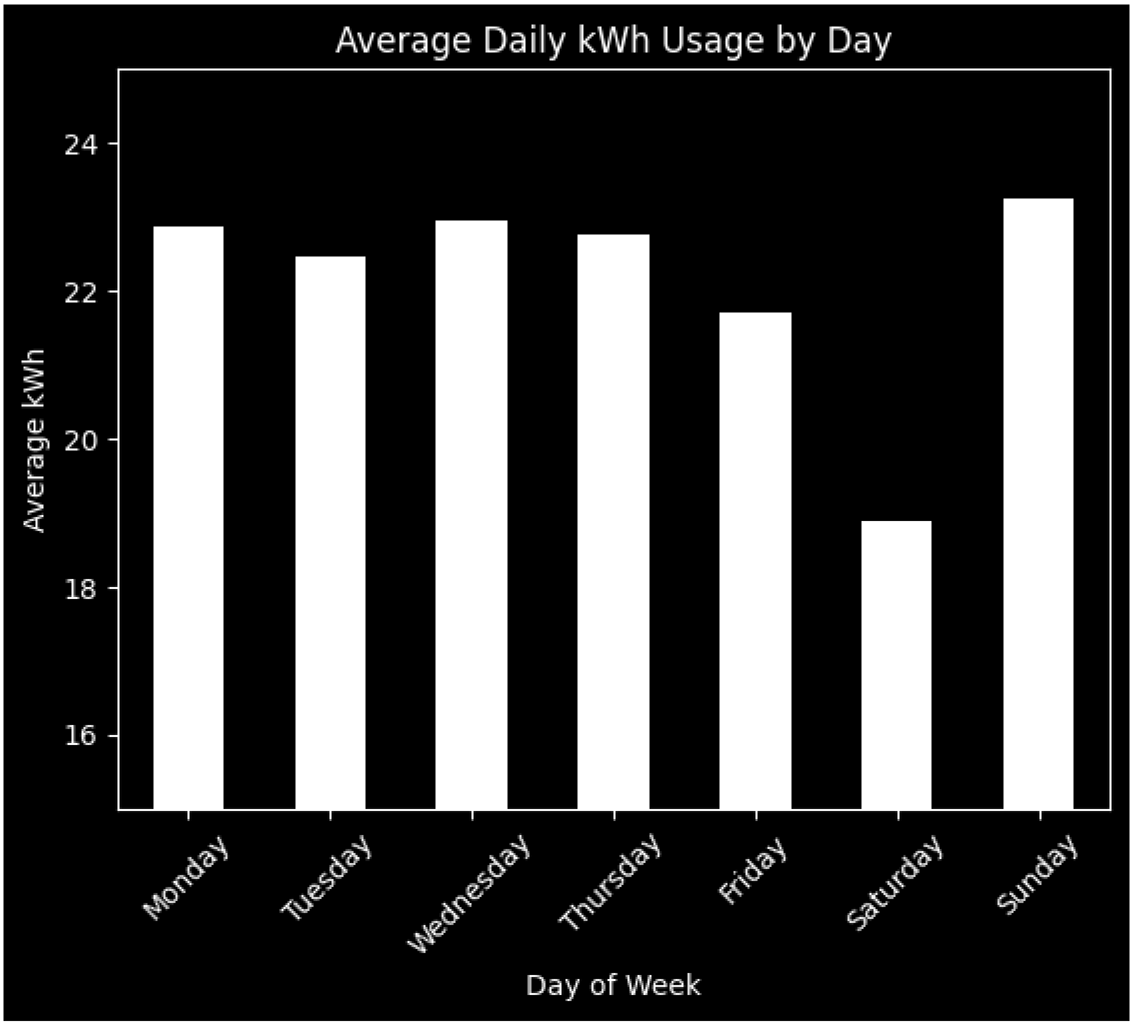
Out[386… <Figure size 1800x600 with 0 Axes>



<Figure size 1800x600 with 0 Axes>

3.2 - Average kWh Per Day

In [387…
```
df.groupby('day', observed = True)['kWh'].mean().plot(kind='bar', color='white
plt.ylabel('Average kWh')
plt.xlabel('Day of Week')
plt.title('Average Daily kWh Usage by Day')
plt.xticks(rotation=45)
plt.ylim(15,25)
plt.show()
(df.groupby('day', observed = True)['kWh'].mean())
```

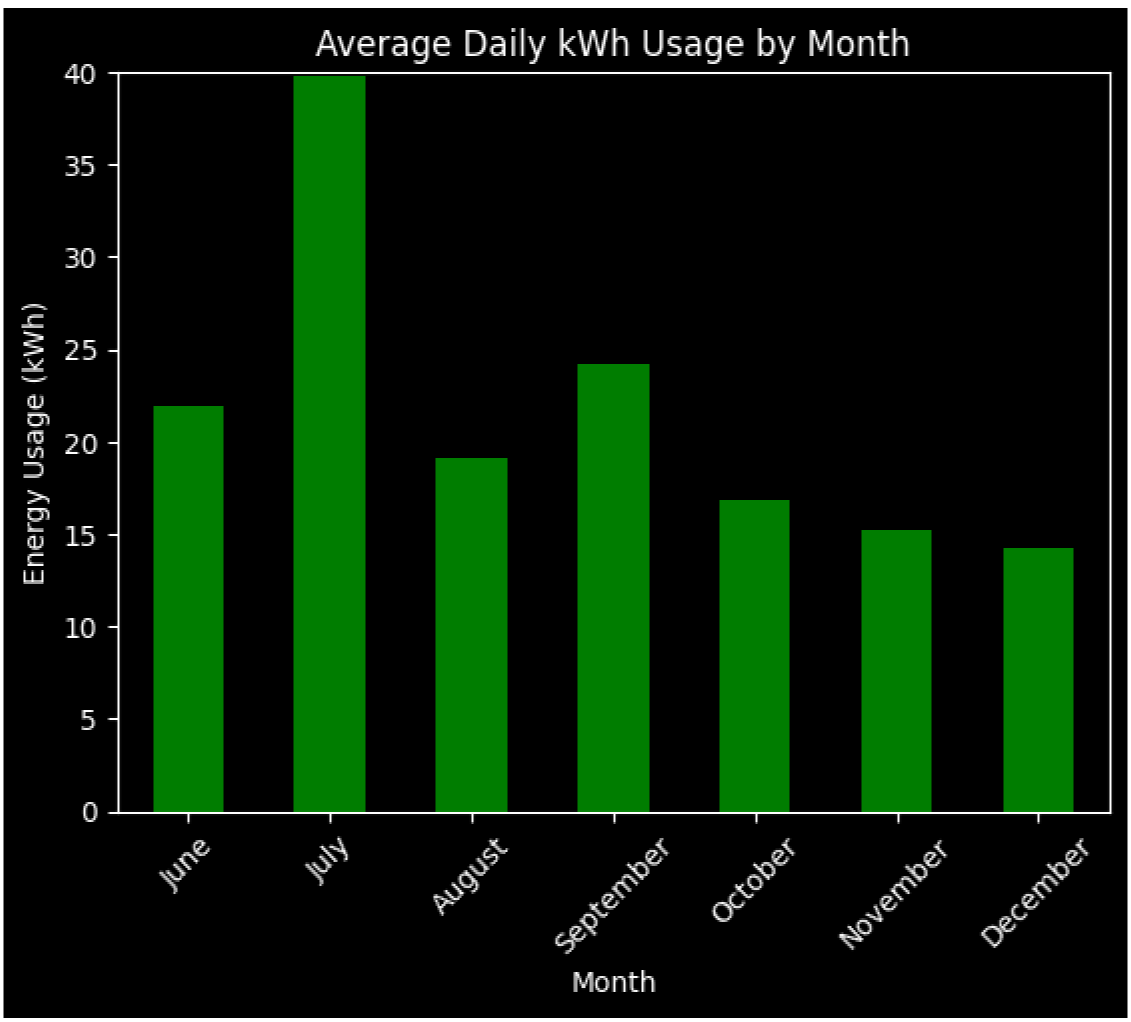


Out[387…
```
day
Monday       22.879310
Tuesday      22.468621
Wednesday    22.941379
Thursday     22.770357
Friday       21.705714
Saturday     18.884643
Sunday       23.262069
Name: kWh, dtype: float64
```

3.3 - Average kWh by Month

In [389…

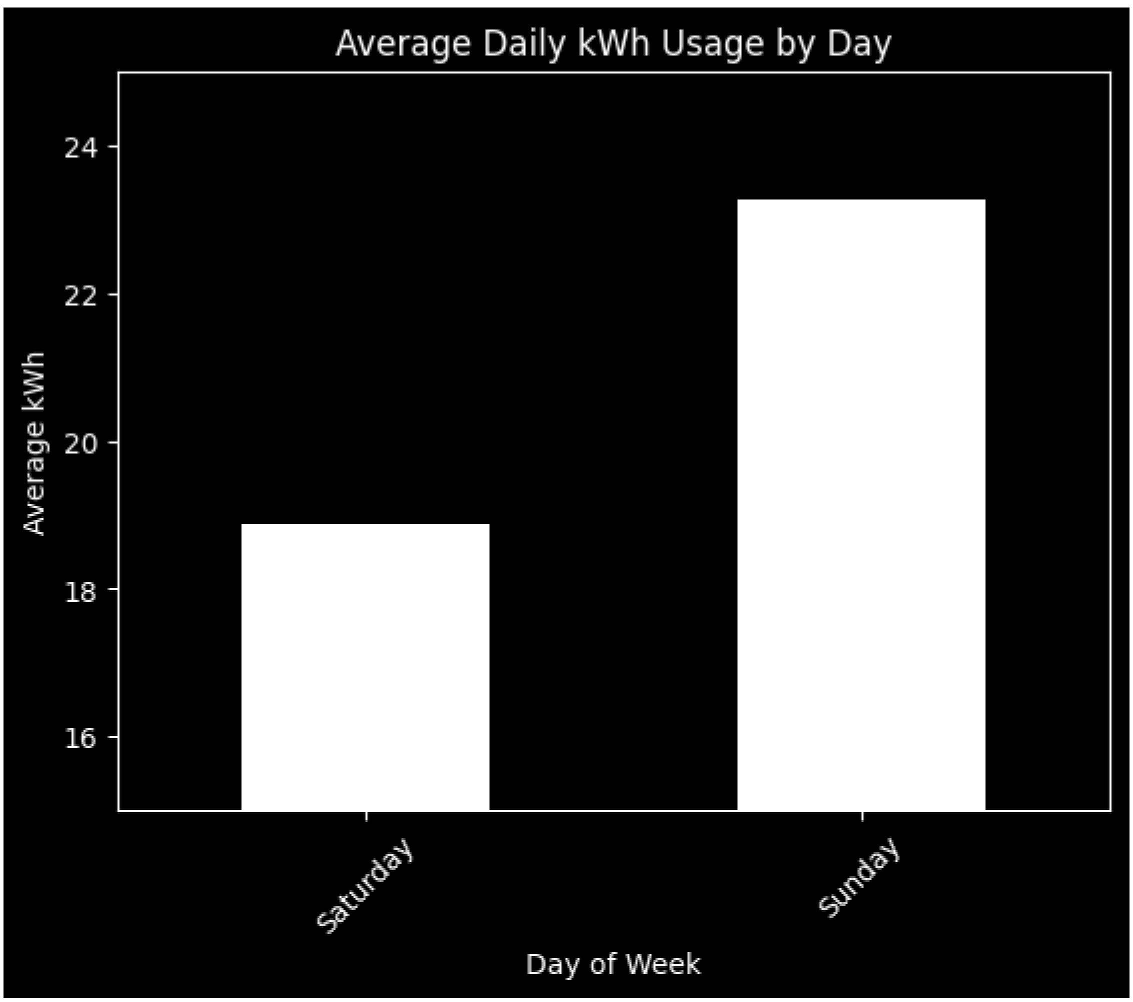
```
month_order = [
    'June',
    'July', 'August', 'September', 'October', 'November', 'December'
]

(
    df.groupby('month')['kWh']
      .mean()
      .reindex(month_order)
      .plot(kind='bar', color='Green')
)

plt.ylabel('Energy Usage (kWh)')
plt.xlabel('Month')
plt.title('Average Daily kWh Usage by Month')
plt.xticks(rotation=45)
plt.ylim(0, 40)
plt.show()
```

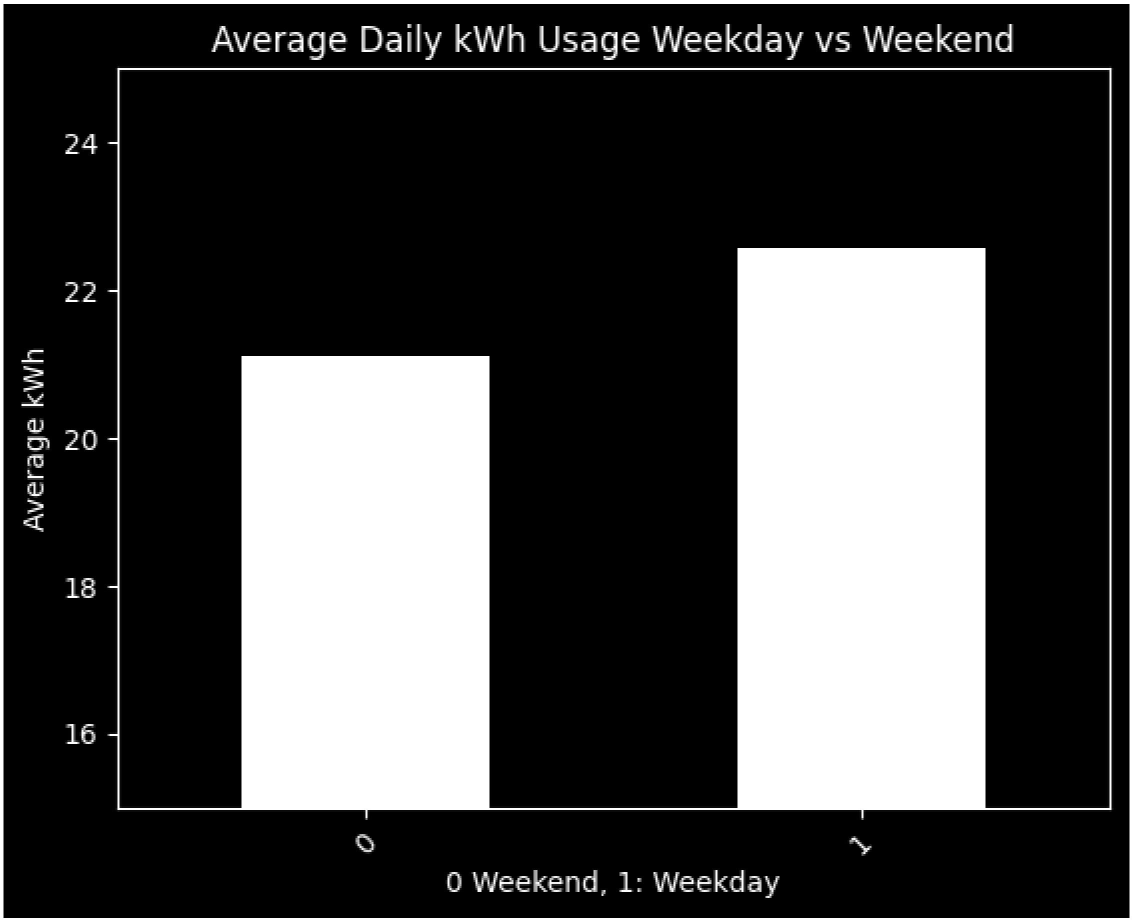


3.4 - Weekends vs Weekdays

In [418…

```
weekends = df[df['day_number'] > 4]
weekends.groupby('day', observed = True)['kWh'].mean().plot(kind='bar', color=
plt.ylabel('Average kWh')
plt.xlabel('Day of Week')
plt.title('Average Daily kWh Usage by Day')
plt.xticks(rotation=45)
plt.ylim(15,25)
plt.show()


(df.groupby('weekday', observed = True)['kWh'].mean()).plot(kind='bar', color=
plt.ylabel('Average kWh')
plt.xlabel('0 Weekend, 1: Weekday')
plt.title('Average Daily kWh Usage Weekday vs Weekend')
plt.xticks(rotation=45)
plt.ylim(15,25)
plt.show()
```





4 - Train / Split

In [399…
```
X = df.drop(columns=['kWh', 'day','month'])   # all real predictors
y = df['kWh'].values

split_point = int(len(X) * 0.8)

X_train = X.iloc[:split_point]
X_test  = X.iloc[split_point:]

y_train = y[:split_point]
y_test  = y[split_point:]
```

5 - Arima

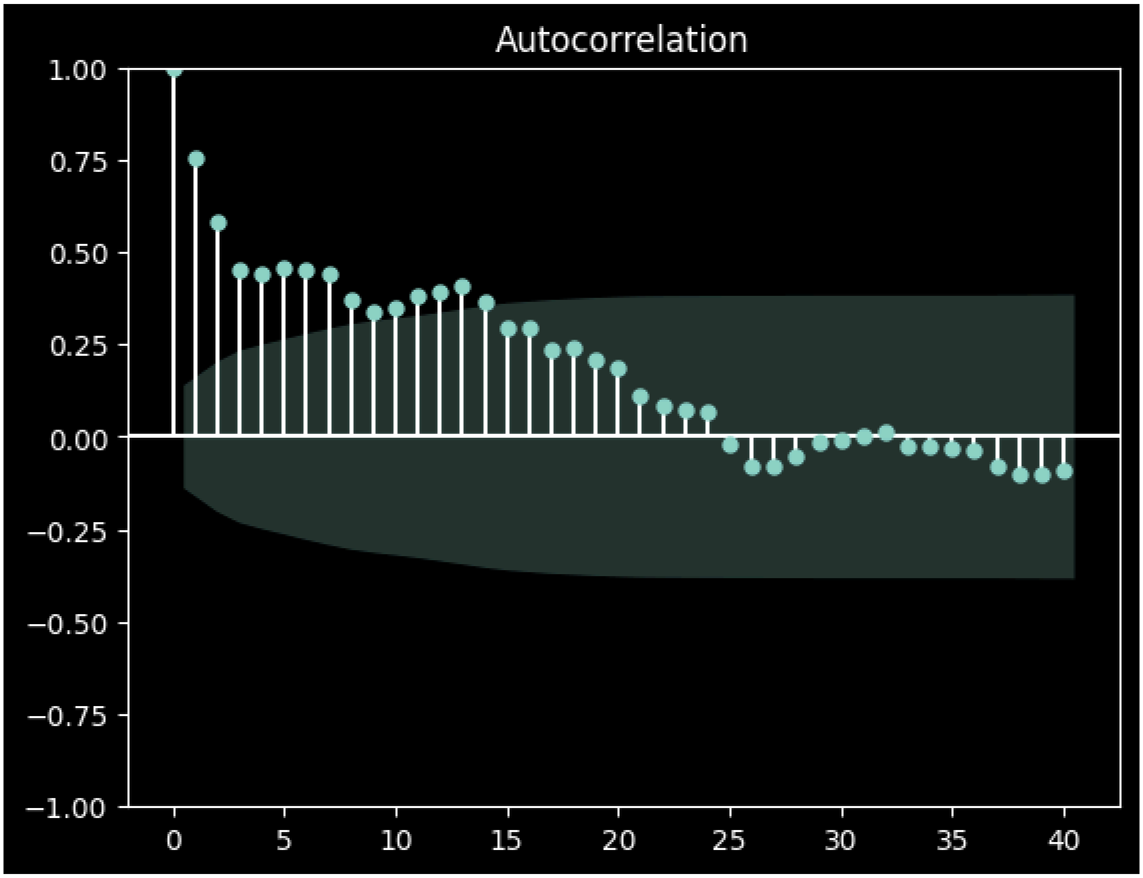
5.1 - ADF Test for Stationarity

In [400…
```
adf_test = adfuller(df['kWh'].values)
# Output the results
print('ADF Statistic: %f' % adf_test[0])
print('p-value: %f' % adf_test[1])
```

```
ADF Statistic: -2.886002
p-value: 0.047000
```

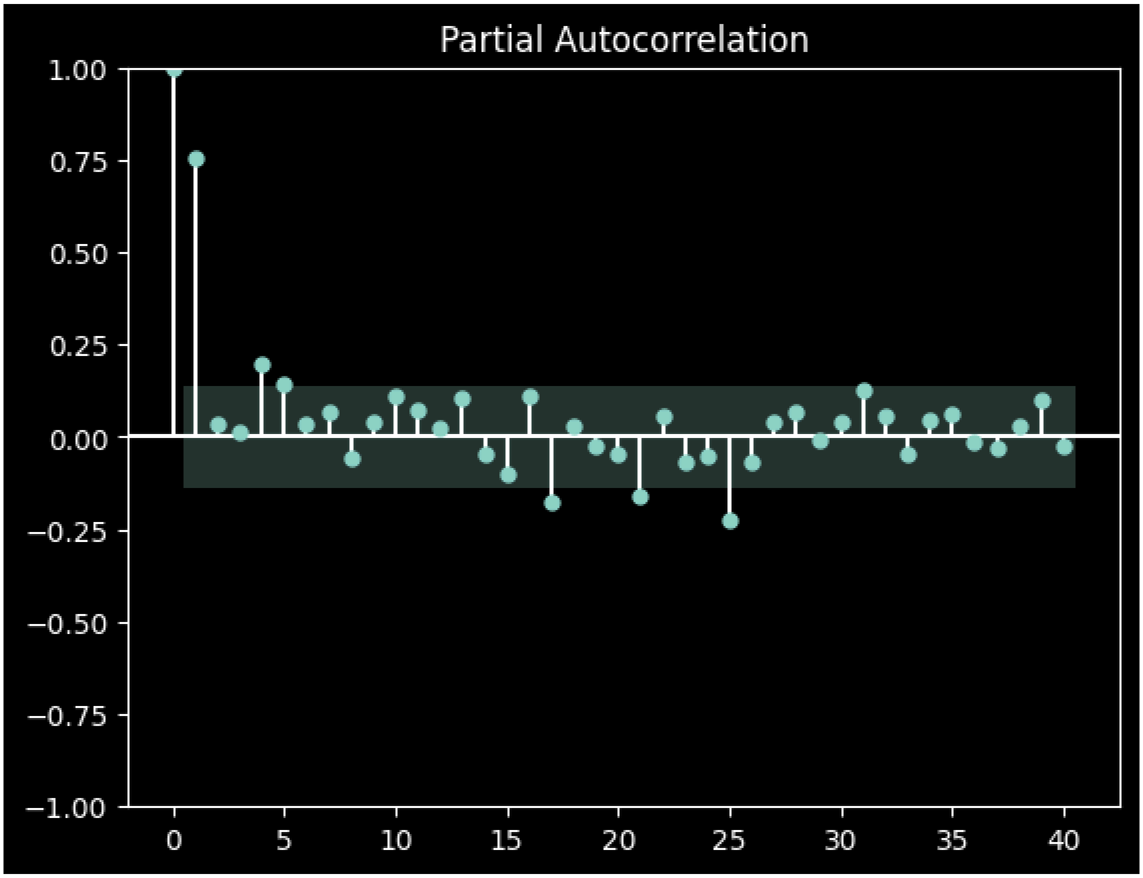
5.2 - Autocorrelation Function

In [401…
```python
plot_acf(df['kWh'].values, lags=40)
plt.show()
```



5.3 - Partial Autocorrelation Function

In [402…
```python
plot_pacf(df['kWh'].values, lags=40)
plt.show()
```



5.4 - Auto Arima

In [404…

```
from pmdarima import auto_arima

optimal_model = auto_arima(y_train, start_p=0, start_q=0,
                           test='adf',
                           max_p=3, max_q=3,
                           m=1,
                           d=None,
                           seasonal=True,
                           start_P=0,
                           D=0,
                           trace=True,
                           error_action='ignore',
                           suppress_warnings=True,
                           stepwise=True)

print(optimal_model.summary())
```

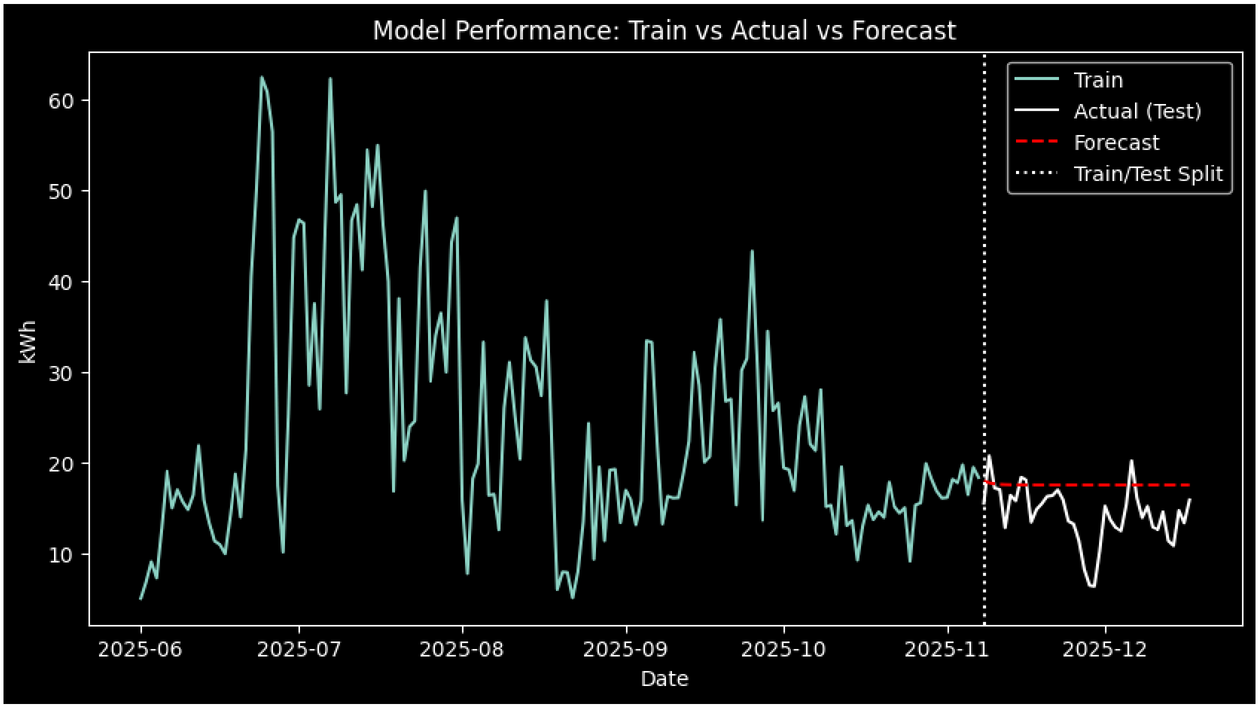
```
Performing stepwise search to minimize aic
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=1173.051, Time=0.04 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=1171.196, Time=0.01 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=1169.277, Time=0.01 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=1171.063, Time=0.00 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=1153.876, Time=0.03 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=1154.521, Time=0.03 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=1155.066, Time=0.02 sec
 ARIMA(0,1,2)(0,0,0)[0] intercept   : AIC=1158.878, Time=0.01 sec
 ARIMA(2,1,0)(0,0,0)[0] intercept   : AIC=1171.193, Time=0.01 sec
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=inf, Time=0.08 sec
 ARIMA(1,1,1)(0,0,0)[0]             : AIC=1151.910, Time=0.02 sec
 ARIMA(0,1,1)(0,0,0)[0]             : AIC=1167.299, Time=0.01 sec
 ARIMA(1,1,0)(0,0,0)[0]             : AIC=1169.212, Time=0.01 sec
 ARIMA(2,1,1)(0,0,0)[0]             : AIC=1152.564, Time=0.02 sec
 ARIMA(1,1,2)(0,0,0)[0]             : AIC=1153.105, Time=0.01 sec
 ARIMA(0,1,2)(0,0,0)[0]             : AIC=1156.930, Time=0.01 sec
 ARIMA(2,1,0)(0,0,0)[0]             : AIC=1169.212, Time=0.01 sec
 ARIMA(2,1,2)(0,0,0)[0]             : AIC=inf, Time=0.06 sec

Best model:  ARIMA(1,1,1)(0,0,0)[0]
Total fit time: 0.399 seconds
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  160
Model:               SARIMAX(1, 1, 1)   Log Likelihood                -572.955
Date:                Sun, 21 Dec 2025   AIC                           1151.910
Time:                        15:40:50   BIC                           1161.117
Sample:                             0   HQIC                          1155.649
                                - 160
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.5345      0.081      6.603      0.000       0.376       0.693
ma.L1         -0.8713      0.047    -18.727      0.000      -0.963      -0.780
sigma2        78.7210      7.327     10.744      0.000      64.361      93.082
================================================================================
====
Ljung-Box (L1) (Q):                   0.29   Jarque-Bera (JB):                1
2.29
Prob(Q):                              0.59   Prob(JB):
0.00
Heteroskedasticity (H):               0.27   Skew:
-0.33
Prob(H) (two-sided):                  0.00   Kurtosis:
4.19
================================================================================
====

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
```

In [421…

```
import warnings
warnings.filterwarnings("ignore", category=UserWarning, module="statsmodels.ts
model = SARIMAX(y_train, order=(1,1, 1))
model_fit = model.fit()
```

In [431…

```
n_test = len(y_test)
forecast_values = model_fit.forecast(steps=n_test)

test_index = df.index[-n_test:]

forecast = pd.Series(forecast_values, index=test_index)
y_test_series = pd.Series(y_test, index=test_index)


plt.figure(figsize=(10, 5))

plt.plot(df.index[:-n_test], df['kWh'].iloc[:-n_test], label='Train')
plt.plot(test_index, y_test_series, label='Actual (Test)', color = 'white')
plt.plot(test_index, forecast, label='Forecast', linestyle='--', color = 'red'

plt.axvline(df.index[-n_test], linestyle=':', label='Train/Test Split')

plt.title('Model Performance: Train vs Actual vs Forecast')
plt.ylabel('kWh')
plt.xlabel('Date')
plt.legend()
plt.show()


from sklearn.metrics import mean_absolute_error, root_mean_squared_error, r2_s

print("Test RMSE:", root_mean_squared_error(y_test_series, forecast))
print("Test MAE:", mean_absolute_error(y_test_series, forecast))

naive_forecast = np.repeat(y_train[-1], len(y_test))

print("Naive RMSE:",
      root_mean_squared_error(y_test, naive_forecast))
```




```
Test RMSE: 4.459848125927703
Test MAE: 3.592938531099827
Naive RMSE: 5.07309939780407
```

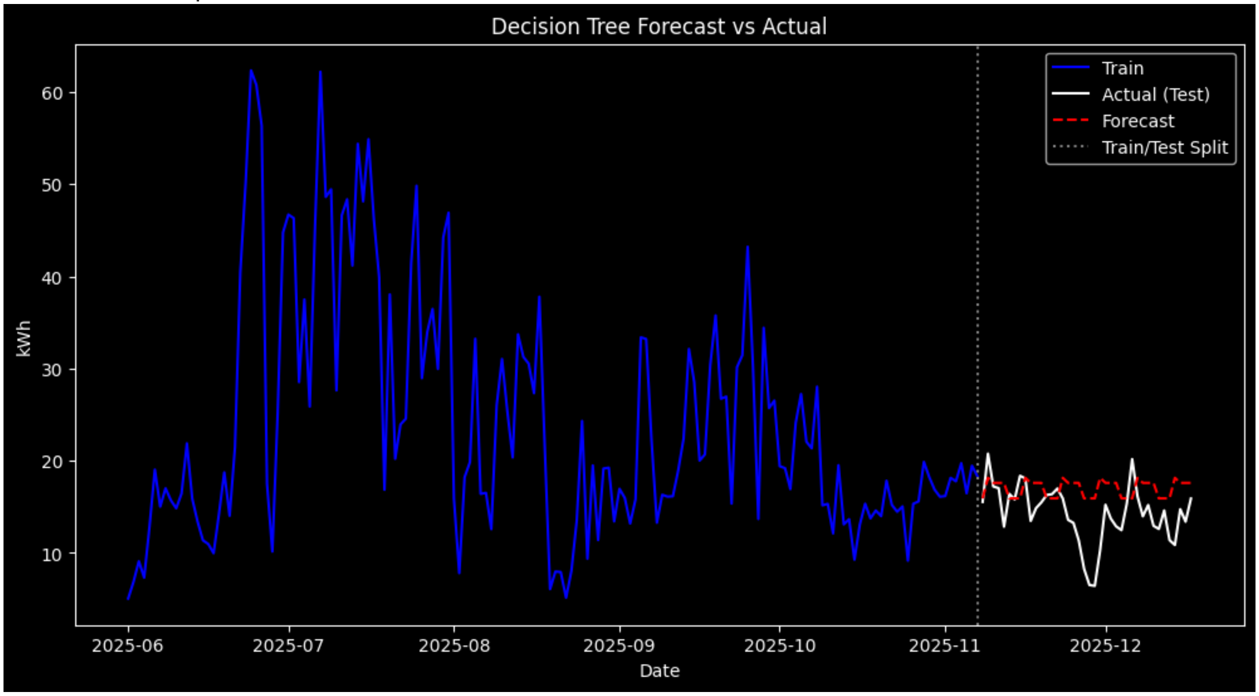
6.0 Regression Trees

In [429…

```python
y_train_series = pd.Series(y_train, index=df.index[:split_point])
y_test_series  = pd.Series(y_test,  index=df.index[split_point:])

regressor = DecisionTreeRegressor(max_depth=4, random_state=42)
regressor.fit(X_train, y_train_series)
y_pred = regressor.predict(X_test)

mse = root_mean_squared_error(y_test, y_pred)
print(f"Root Mean Squared Error: {mse:.4f}")

plt.figure(figsize=(12,6))


plt.plot(y_train_series.index, y_train_series, label='Train', color='blue')


plt.plot(y_test_series.index, y_test_series, label='Actual (Test)', color='Whi


plt.plot(y_test_series.index, y_pred, label='Forecast', color='red', linestyle


plt.axvline(y_train_series.index[-1], color='gray', linestyle=':', label='Trai

plt.title('Decision Tree Forecast vs Actual')
```

```
plt.xlabel('Date')
plt.ylabel('kWh')
plt.legend()
plt.show()
```

```
Root Mean Squared Error: 4.1153
```



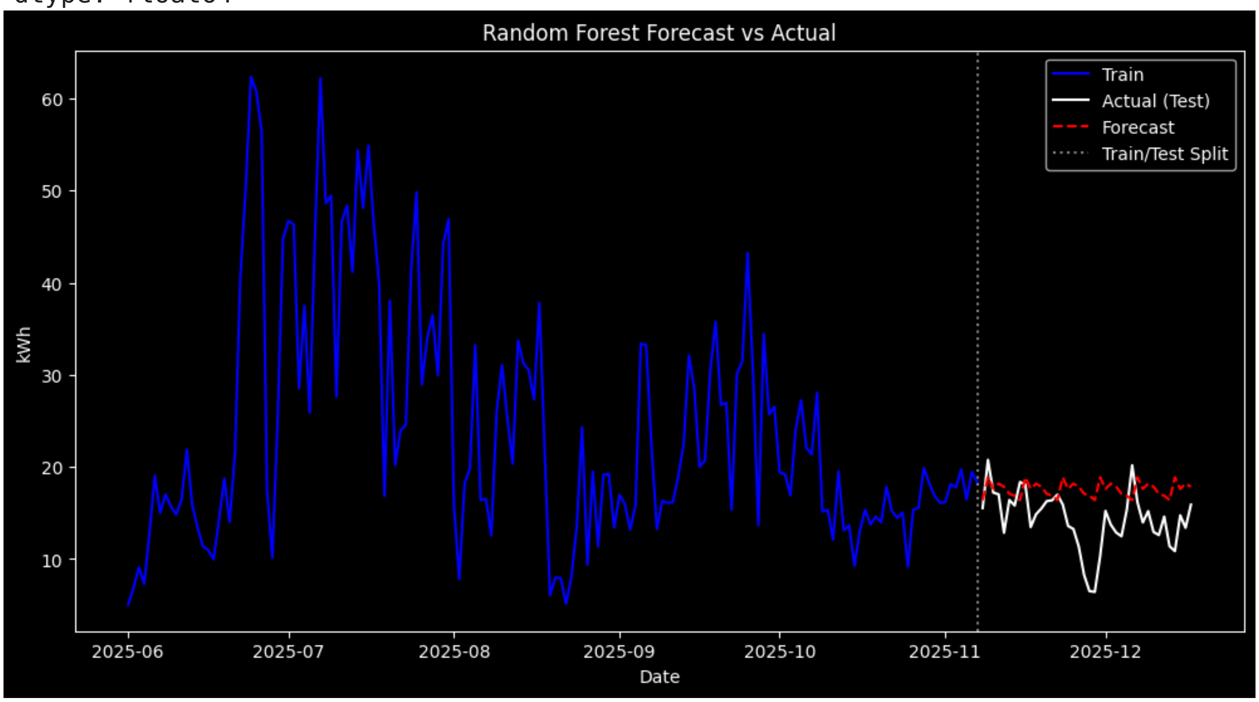
7.0 - Random Forrest

In [424…

```
rf_regressor = RandomForestRegressor(
    n_estimators=100,
    max_depth=4,
    random_state=42
)
rf_regressor.fit(X_train, y_train_series)

y_pred = rf_regressor.predict(X_test)

#Metrics
rmse = root_mean_squared_error(y_test, y_pred)
mae  = mean_absolute_error(y_test, y_pred)
print(f"Random Forest RMSE: {rmse:.4f}")
print(f"Random Forest MAE: {mae:.4f}")

feature_importance = pd.Series(
    rf_regressor.feature_importances_,
    index=X.columns
).sort_values(ascending=False)
print("\nFeature Importance:")
print(feature_importance)

plt.figure(figsize=(12,6))
```

```
plt.plot(y_train_series.index, y_train_series, label='Train', color='blue')
plt.plot(y_test_series.index, y_test_series, label='Actual (Test)', color='whi
plt.plot(y_test_series.index, y_pred, label='Forecast', color='red', linestyle
plt.axvline(y_train_series.index[-1], color='gray', linestyle=':', label='Trai

plt.title('Random Forest Forecast vs Actual')
plt.xlabel('Date')
plt.ylabel('kWh')
plt.legend()
plt.show()
```

```
Random Forest RMSE: 4.5074
Random Forest MAE: 3.6762

Feature Importance:
month_number    0.771722
day_number      0.215202
weekday         0.013076
dtype: float64
```



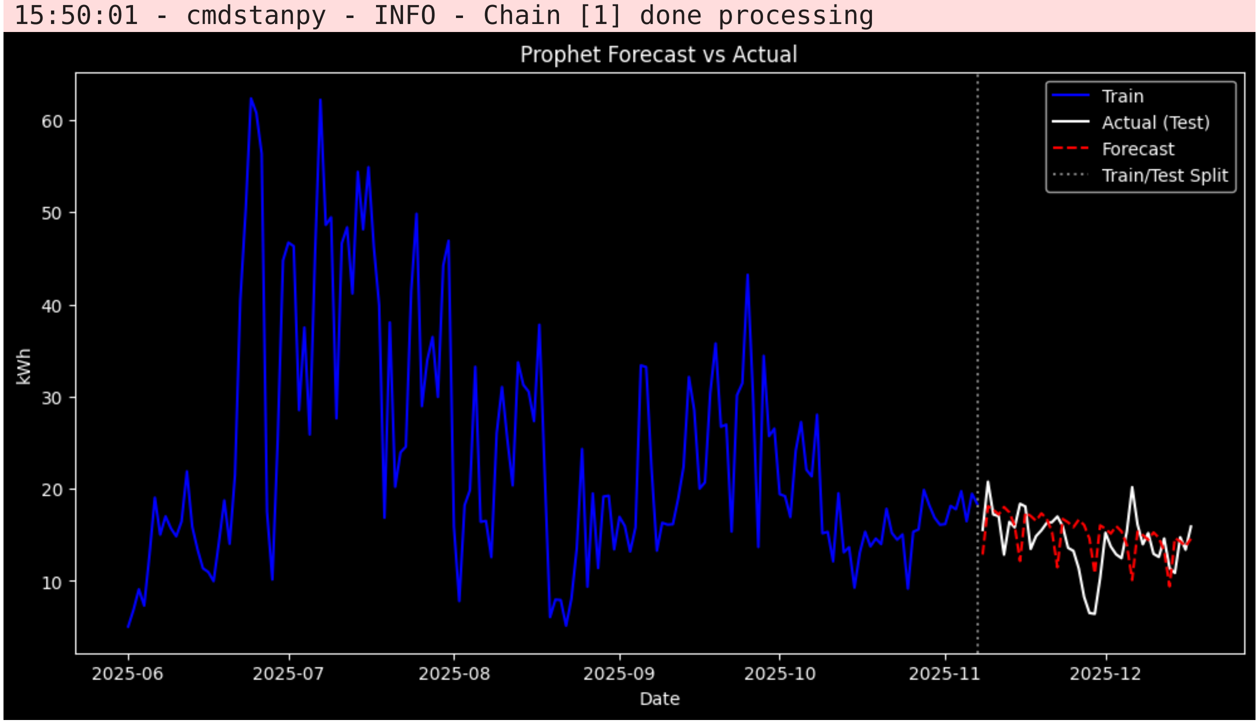
8.0 - Prophet

In [425…

```
prophet_df = df.reset_index()[['date', 'kWh']].rename(columns={'date':'ds', 'k


split_point = int(len(prophet_df) * 0.8)
train_df = prophet_df.iloc[:split_point]
test_df  = prophet_df.iloc[split_point:]


model = Prophet(daily_seasonality=False, weekly_seasonality=True, yearly_seaso
```

```python
model.fit(train_df)


future = test_df[['ds']].copy()
forecast = model.predict(future)


plt.figure(figsize=(12,6))
plt.plot(train_df['ds'], train_df['y'], label='Train', color='blue')
plt.plot(test_df['ds'], test_df['y'], label='Actual (Test)', color='White')
plt.plot(forecast['ds'], forecast['yhat'], label='Forecast', color='red', line
plt.axvline(train_df['ds'].iloc[-1], color='gray', linestyle=':', label='Trair
plt.title('Prophet Forecast vs Actual')
plt.xlabel('Date')
plt.ylabel('kWh')
plt.legend()
plt.show()

#Metrics
rmse = root_mean_squared_error(test_df['y'], forecast['yhat'])
mae  = mean_absolute_error(test_df['y'], forecast['yhat'])
print(f"Prophet RMSE: {rmse:.4f}")
print(f"Prophet MAE: {mae:.4f}")
```

```
15:50:01 - cmdstanpy - INFO - Chain [1] start processing
15:50:01 - cmdstanpy - INFO - Chain [1] done processing
```




```
Prophet RMSE: 3.5739
Prophet MAE: 2.6618
```

9.0 - Holt Winters Exponential Smoothing

In [428…

```python
y_train_series = y_train_series.asfreq('D')
```

```
y_test_series  = y_test_series.asfreq('D')

from statsmodels.tools.sm_exceptions import ConvergenceWarning
warnings.filterwarnings("ignore", category=ConvergenceWarning)


hw_model = ExponentialSmoothing(
    y_train_series,
    trend='multiplicative',
    seasonal='additive',
    seasonal_periods=7
).fit()


y_pred = hw_model.forecast(len(y_test_series))

rmse = root_mean_squared_error(y_test_series, y_pred)
mae  = mean_absolute_error(y_test_series, y_pred)
print(f"Holt-Winters RMSE: {rmse:.4f}")
print(f"Holt-Winters MAE: {mae:.4f}")

plt.figure(figsize=(12,6))
plt.plot(y_train_series.index, y_train_series, label='Train', color='blue')
plt.plot(y_test_series.index, y_test_series, label='Actual (Test)', color='Whi
plt.plot(y_test_series.index, y_pred, label='Forecast', color='red', linestyle
plt.axvline(y_train_series.index[-1], color='gray', linestyle=':', label='Trai
plt.title('Holt-Winters Forecast vs Actual')
plt.xlabel('Date')
plt.ylabel('kWh')
plt.legend()
plt.show()
```

```
Holt-Winters RMSE: 3.5696
Holt-Winters MAE: 2.5214
```