FactoryElectricPrediction

April 16, 2025

1 Factory Electric Consumption Prediction

Forecast the electric consumption of a factory based on historical data. The goal is to develop a predictive model that provides accurate ele ctricity consumption forecasts to improve energy efficiency, plan resource allocation, and identify seasonal patterns or trends.

Objective - Predict Factory Electric Consumption using a regression model.

- Training data: 13,872 records
- Test data: 2,160 records
- Evaluation metric: RMSE

1.1 Libraries Used

[38]:
```
import pandas as pd
import numpy as np
import os
from xgboost import XGBRegressor
from sklearn.model_selection import train_test_split, cross_val_score,␣
↪GridSearchCV
from sklearn.linear_model import LinearRegression
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import PolynomialFeatures
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt
import seaborn as sns
```

1.2 Data Exploration

[39]:
```
# Upload the data
train_df = pd.read_csv("Data/train_df.csv")
test_df = pd.read_csv("Data/test_df.csv")

# Convert Date column to datetime
train_df['Date'] = pd.to_datetime(train_df['Date'])
test_df['Date'] = pd.to_datetime(test_df['Date'])
```

```python
# Statistics
print("====================================")
print("Train Data Statistics:")
display(train_df.describe())
display(train_df.info())
display(train_df.head())

print("====================================")
print("Test Data Statistics:")
display(test_df.describe())
display(test_df.info())
display(test_df.head())
```

```
====================================
Train Data Statistics:
       Electric_Consumption      Factor_A      Factor_B      Factor_C  \
count          13872.000000  13872.000000  13872.000000  13872.000000
mean               5.893120      2.262227     19.977867     40.332796
std                7.355969      1.457234      9.607866     24.324671
min               -0.009717    -74.220598     -5.422289      3.249366
25%                0.000000      1.105756     13.088434     20.396742
50%                0.086858      1.995936     20.187978     34.024351
75%               13.512742      3.261530     26.994172     57.191932
max               21.360638      8.392045     44.036205    101.706771

           Factor_D      Factor_E      Factor_F
count  13872.000000  13872.000000  13872.000000
mean     145.005668      0.209435     42.522214
std       94.993992      1.691576    280.466514
min    -1380.363752      0.000000      0.000000
25%      106.883078      0.000000      0.579665
50%      138.044038      0.000000      1.981719
75%      209.901463      0.000000     60.123072
max      312.895406     31.000006  31839.840610

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 13872 entries, 0 to 13871
Data columns (total 8 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Date                  13872 non-null  datetime64[ns]
 1   Electric_Consumption  13872 non-null  float64
 2   Factor_A              13872 non-null  float64
 3   Factor_B              13872 non-null  float64
 4   Factor_C              13872 non-null  float64
 5   Factor_D              13872 non-null  float64
 6   Factor_E              13872 non-null  float64
 7   Factor_F              13872 non-null  float64
```

```
dtypes: datetime64[ns](1), float64(7)
memory usage: 867.1 KB
```

```
None
```

```
                 Date  Electric_Consumption  Factor_A   Factor_B   Factor_C  \
0 2023-01-01 00:00:00              0.000000  1.242130  28.419739  13.720397
1 2023-01-01 01:00:00              0.000000  1.861285  29.840759  12.537668
2 2023-01-01 02:00:00              0.000000  4.212674  32.778036   9.408667
3 2023-01-01 03:00:00              0.000000  4.025251  32.624700   9.035601
4 2023-01-01 04:00:00             -0.000267  3.122659  31.931245   9.235502

    Factor_D  Factor_E  Factor_F
0  79.840600       0.0  2.386157
1  86.424903       0.0  1.473256
2  72.082793       0.0  1.583711
3  73.825705       0.0  1.706656
4  66.823956       0.0  0.987048
```

```
====================================
Test Data Statistics:
```

```
          Factor_A     Factor_B     Factor_C     Factor_D     Factor_E  \
count  2160.000000  2160.000000  2160.000000  2160.000000  2160.000000
mean      2.280775    23.913246    21.992996   134.518875     0.003495
std       1.277707     8.736639    13.721824    93.589285     0.034490
min       0.473873     0.766393     4.745143 -1012.946110     0.000000
25%       1.104193    18.239698    11.553210    98.235839     0.000000
50%       2.132809    23.942159    18.684433   128.545027     0.000000
75%       3.247832    31.062816    28.443607   192.731736     0.000000
max       6.805775    42.378972    99.802262   287.365535     0.450000

          Factor_F
count  2160.000000
mean     57.218186
std      82.329781
min       0.166857
25%       1.848734
50%      21.649669
75%      88.266094
max     561.087168
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2160 entries, 0 to 2159
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Date      2160 non-null   datetime64[ns]
 1   Factor_A  2160 non-null   float64
 2   Factor_B  2160 non-null   float64
```

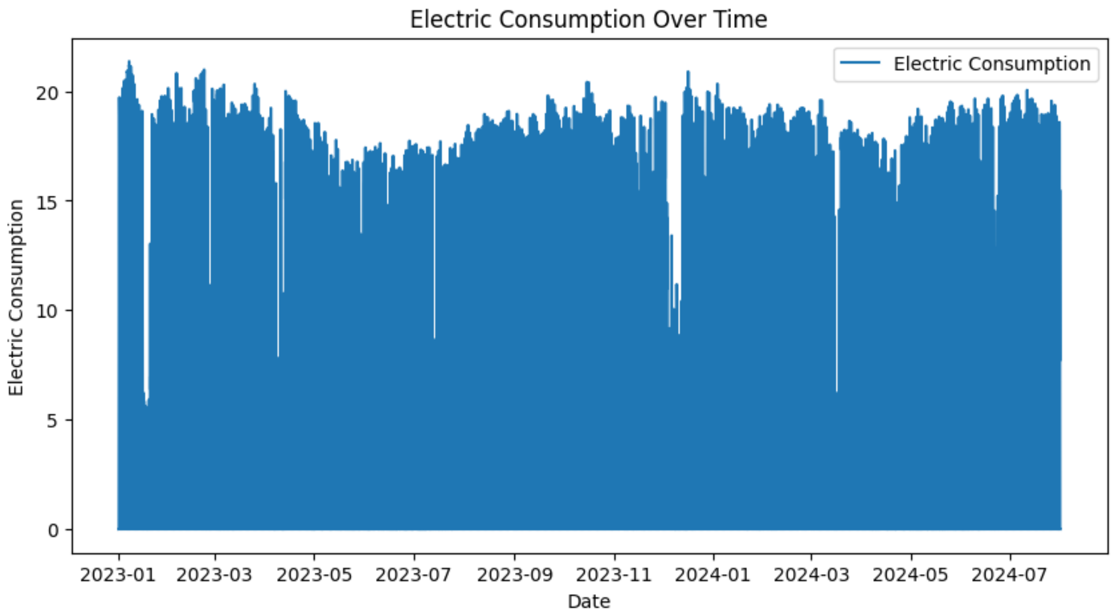
```
 3   Factor_C  2160 non-null   float64
 4   Factor_D  2160 non-null   float64
 5   Factor_E  2160 non-null   float64
 6   Factor_F  2160 non-null   float64
dtypes: datetime64[ns](1), float64(6)
memory usage: 118.2 KB
```

```
None
```

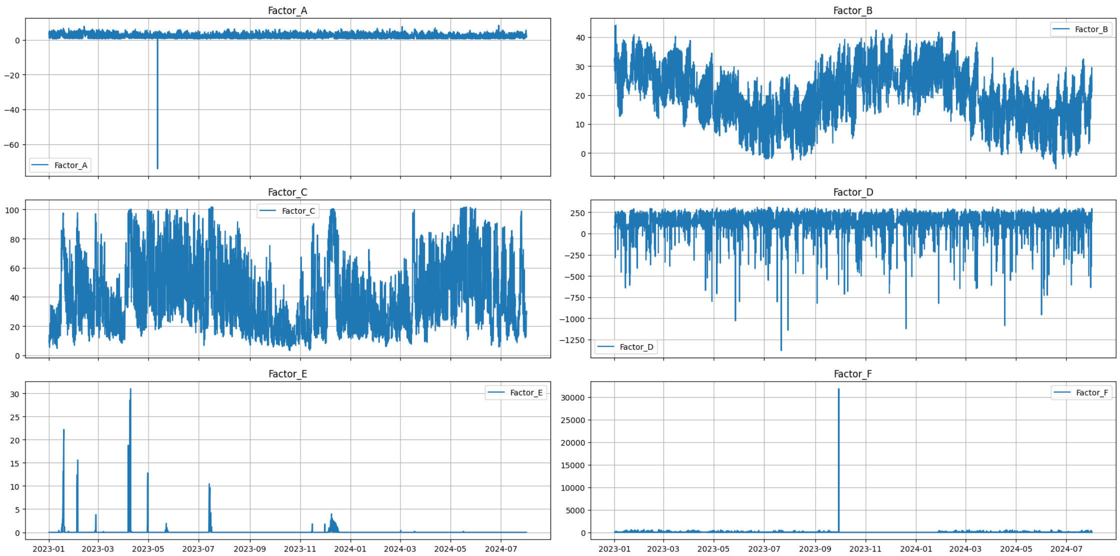
```
                 Date  Factor_A   Factor_B   Factor_C    Factor_D  Factor_E  \
0 2024-08-01 00:00:00  1.775026  21.729808  24.808146  249.474701       0.0
1 2024-08-01 01:00:00  2.176429  20.792287  25.128845  241.233210       0.0
2 2024-08-01 02:00:00  2.644089  20.041586  25.045506  239.540034       0.0
3 2024-08-01 03:00:00  2.759897  18.551710  26.976024  238.425577       0.0
4 2024-08-01 04:00:00  2.670419  16.689420  29.611734  240.139421       0.0

   Factor_F
0  1.808403
1  1.847753
2  1.967446
3  2.128126
4  1.945275
```

1.3 Plot the Data

[40]:
```
# Plot the Electric Consumption over time
plt.figure(figsize=(10, 5))
plt.plot(train_df['Date'], train_df['Electric_Consumption'], label='Electric␣
↪Consumption')
plt.title('Electric Consumption Over Time')
plt.xlabel('Date')
plt.ylabel('Electric Consumption')
plt.legend()
plt.show()
```



[41]:
```
# Feature Visualization: create subplots for different factors over time
fig, axs = plt.subplots(3, 2, figsize=(20, 10), sharex=True)
axs = axs.flatten()

factors = ['Factor_A', 'Factor_B', 'Factor_C', 'Factor_D', 'Factor_E',␣
↪'Factor_F']

for i, factor in enumerate(factors):
    axs[i].plot(train_df['Date'], train_df[factor], label=factor)
    axs[i].set_title(factor)
    axs[i].legend()
    axs[i].grid(True)
plt.tight_layout()
plt.show()
```



[42]:
```
# Missing Values Check
train_df.isnull().sum().sum()
```

[42]: 0

1.4 Data Processing

1.4.1 Features Extraction

[43]:
```
# Feature Extraction
for df in [train_df, test_df]:
    df['Hour'] = df['Date'].dt.hour
    df['DayOfWeek'] = df['Date'].dt.dayofweek
    df['Month'] = df['Date'].dt.month
    df['Day'] = df['Date'].dt.day

test_dates = pd.to_datetime(test_df['Date'])

# Drop the original Date column
train_df.drop('Date', axis=1, inplace=True)
test_df.drop('Date', axis=1, inplace=True)

features = ['Factor_A', 'Factor_B', 'Factor_C', 'Factor_D', 'Factor_E',␣
↪'Factor_F', 'Hour', 'DayOfWeek', 'Month', 'Day']

display(train_df.head())
```

```
   Electric_Consumption  Factor_A   Factor_B   Factor_C   Factor_D  Factor_E  \
0              0.000000  1.242130  28.419739  13.720397  79.840600       0.0
1              0.000000  1.861285  29.840759  12.537668  86.424903       0.0
```

```
2              0.000000  4.212674  32.778036   9.408667  72.082793       0.0
3              0.000000  4.025251  32.624700   9.035601  73.825705       0.0
4             -0.000267  3.122659  31.931245   9.235502  66.823956       0.0

   Factor_F  Hour  DayOfWeek  Month  Day
0  2.386157     0          6      1    1
1  1.473256     1          6      1    1
2  1.583711     2          6      1    1
3  1.706656     3          6      1    1
4  0.987048     4          6      1    1
```

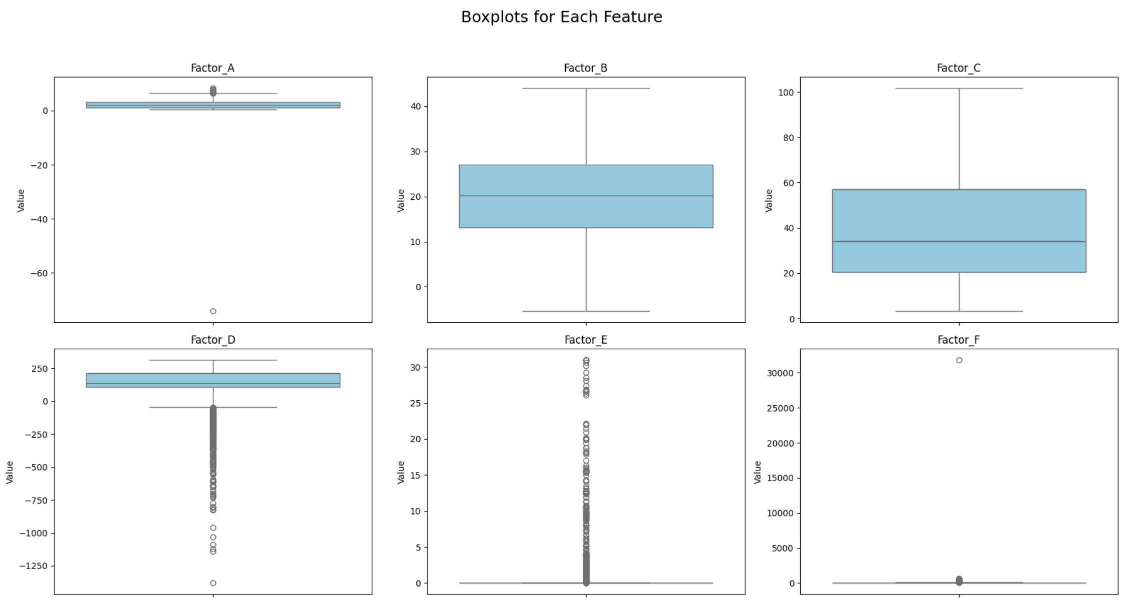
1.4.2 Outliers Analysis

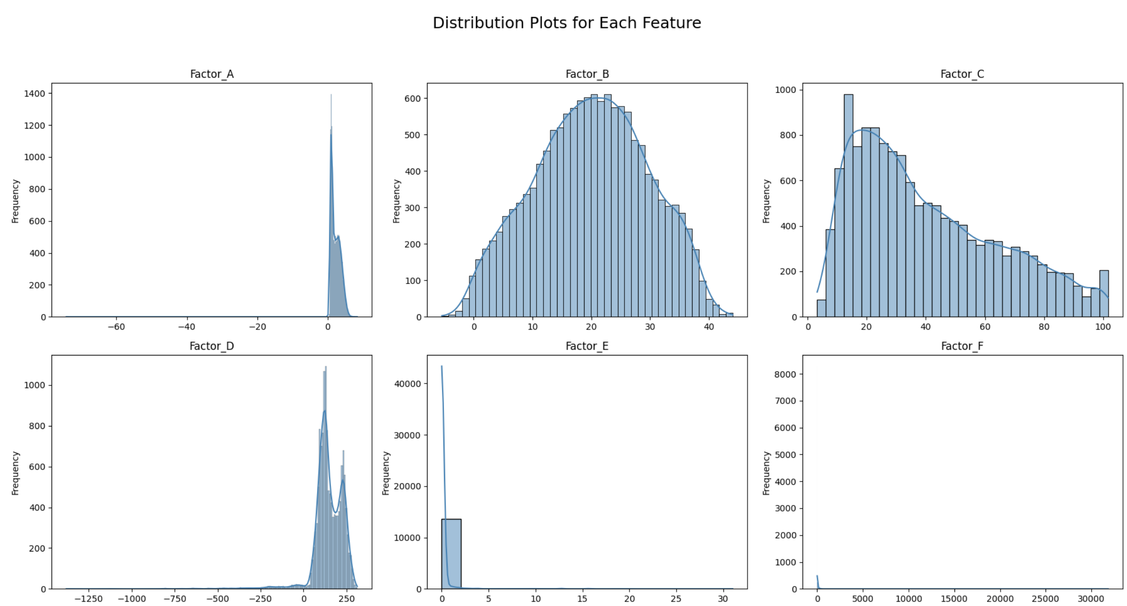
On numerical features: Factor_A, FactorB, Factor_C, Factor_D, Factor_E, Factor_F

[44]:
```python
# Helper functions to display outliers
def boxplt_display(factors):
    fig, axes = plt.subplots(2, 3, figsize=(18, 10))
    fig.suptitle('Boxplots for Each Feature', fontsize=18)
    axes = axes.flatten()

    for i, col in enumerate(factors):
        sns.boxplot(y=train_df[col], ax=axes[i], color='skyblue')
        axes[i].set_title(col, fontsize=12)
        axes[i].set_xlabel('')
        axes[i].set_ylabel('Value')


    plt.tight_layout(rect=[0, 0.03, 1, 0.95])
    plt.show()

def distribution_display(factors):
    fig, axes = plt.subplots(2, 3, figsize=(18, 10))
    fig.suptitle('Distribution Plots for Each Feature', fontsize=18)
    axes = axes.flatten()

    for i, col in enumerate(factors):
        sns.histplot(train_df[col], kde=True, ax=axes[i], color='steelblue')
        axes[i].set_title(f'{col}', fontsize=12)
        axes[i].set_xlabel('')
        axes[i].set_ylabel('Frequency')

    for j in range(len(factors), len(axes)):
        fig.delaxes(axes[j])

    plt.tight_layout(rect=[0, 0.03, 1, 0.95])
    plt.show()
```

[45]:

```
boxplt_display(factors)
distribution_display(factors)
```

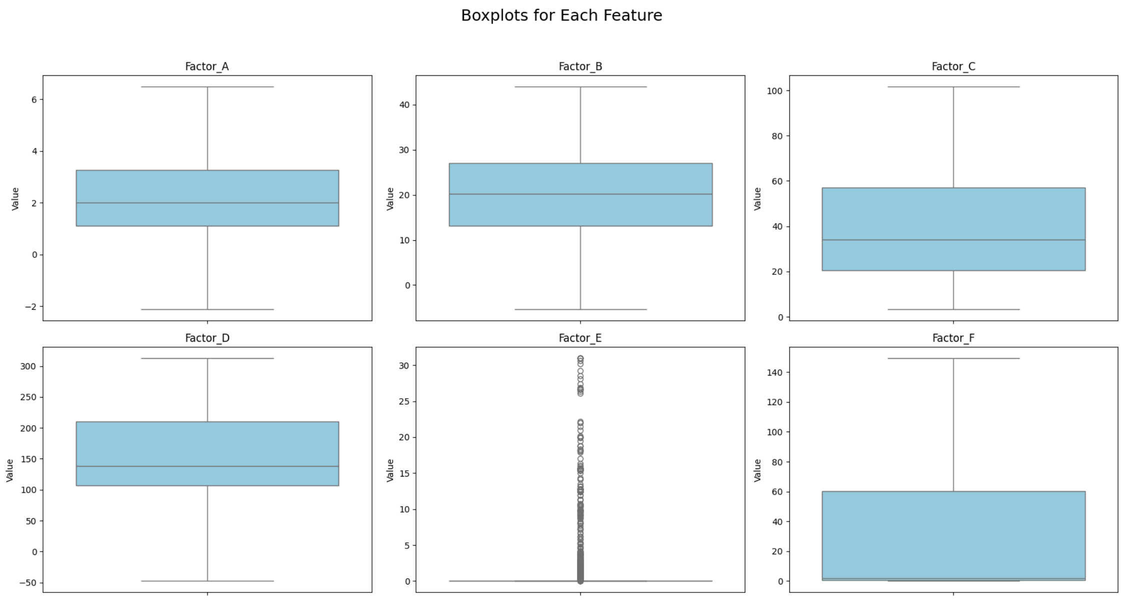


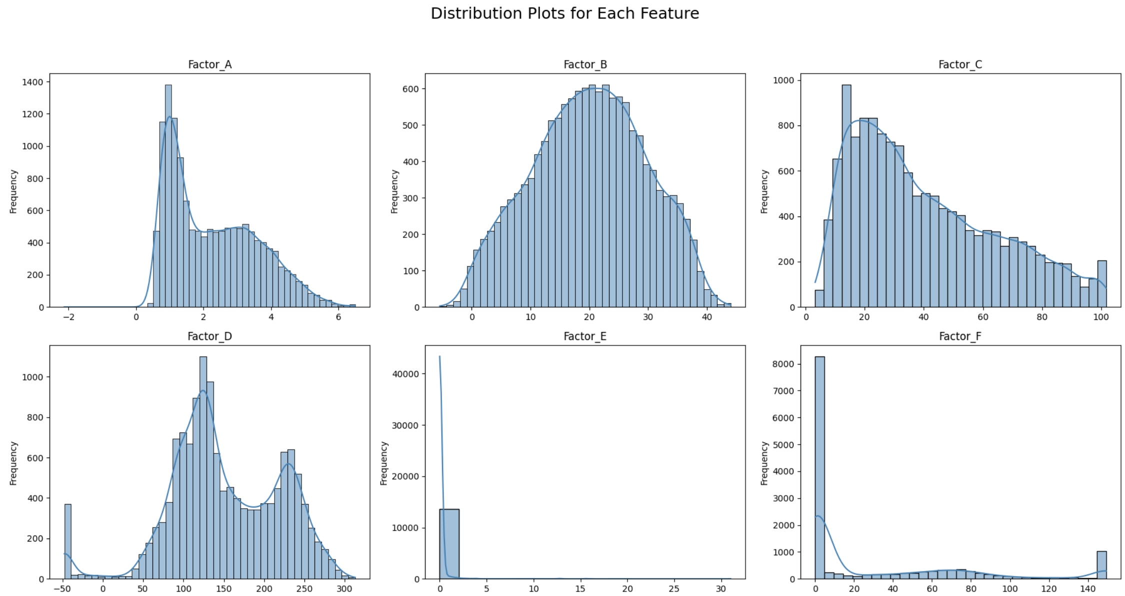


[46]:

```
# Detection and Treatment of Outliers in some Factors trhough IQR method
# Assuming that Factor_A, Factor_D and Factor_F are the ones with outliers␣
↪based on previous boxplot and distribution plots analysis
```

```
for col in ['Factor_A', 'Factor_D', 'Factor_F']:
    # IQR calculation
    Q1 = train_df[col].quantile(0.25)
    Q3 = train_df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower = Q1 - 1.5 * IQR
    upper = Q3 + 1.5 * IQR

    # Option 1: Clip outliers
    train_df[col] = train_df[col].clip(lower=lower, upper=upper)

    # Option 2: Apply log transform.
    # train_df[col] = np.log1p(train_df[col] - train_df[col].min() + 1)

    # Trying both methods to see which one works better but the second option
 ↪raised slightly the RMSE

# Check for outliers again
boxplt_display(factors)
distribution_display(factors)
```





1.4.3 Encoding of non-numerical features

[47]:
```
def add_cyclical_features(df):
    # Hour (0-23)
    df['Hour_sin'] = np.sin(2 * np.pi * df['Hour'] / 24)
    df['Hour_cos'] = np.cos(2 * np.pi * df['Hour'] / 24)

    # DayOfWeek (0-6)
    df['DayOfWeek_sin'] = np.sin(2 * np.pi * df['DayOfWeek'] / 7)
    df['DayOfWeek_cos'] = np.cos(2 * np.pi * df['DayOfWeek'] / 7)

    # Month (1-12)
    df['Month_sin'] = np.sin(2 * np.pi * df['Month'] / 12)
    df['Month_cos'] = np.cos(2 * np.pi * df['Month'] / 12)

    # Day (1-31) - opzionale
    df['Day_sin'] = np.sin(2 * np.pi * df['Day'] / 31)
    df['Day_cos'] = np.cos(2 * np.pi * df['Day'] / 31)

    return df

train_df = add_cyclical_features(train_df)
test_df = add_cyclical_features(test_df)

cols_to_drop = ['Hour', 'DayOfWeek', 'Month', 'Day']
train_df.drop(columns=cols_to_drop, inplace=True)
test_df.drop(columns=cols_to_drop, inplace=True)
```

1.5 Models Training and Evaluation

[54]:
```
# Dataset Preparation
features = ['Factor_A', 'Factor_B', 'Factor_C', 'Factor_D', 'Factor_E',␣
↪'Factor_F', 'Hour_sin', 'Hour_cos', 'DayOfWeek_sin', 'DayOfWeek_cos',␣
↪'Month_sin', 'Month_cos', 'Day_sin', 'Day_cos']
X = train_df[features]
y = train_df['Electric_Consumption']
X_test = test_df

X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

display(X_test.head())
X_train.head()
```

```
   Factor_A   Factor_B   Factor_C    Factor_D  Factor_E  Factor_F  Hour_sin  \
0  1.775026  21.729808  24.808146  249.474701       0.0  1.808403  0.000000
1  2.176429  20.792287  25.128845  241.233210       0.0  1.847753  0.258819
2  2.644089  20.041586  25.045506  239.540034       0.0  1.967446  0.500000
3  2.759897  18.551710  26.976024  238.425577       0.0  2.128126  0.707107
4  2.670419  16.689420  29.611734  240.139421       0.0  1.945275  0.866025

   Hour_cos  DayOfWeek_sin  DayOfWeek_cos  Month_sin  Month_cos   Day_sin  \
0  1.000000       0.433884      -0.900969  -0.866025       -0.5  0.201299
1  0.965926       0.433884      -0.900969  -0.866025       -0.5  0.201299
2  0.866025       0.433884      -0.900969  -0.866025       -0.5  0.201299
3  0.707107       0.433884      -0.900969  -0.866025       -0.5  0.201299
4  0.500000       0.433884      -0.900969  -0.866025       -0.5  0.201299

   Day_cos
0  0.97953
1  0.97953
2  0.97953
3  0.97953
4  0.97953
```

[54]:
```
       Factor_A   Factor_B   Factor_C    Factor_D  Factor_E      Factor_F  \
9205   3.358914  36.536203  12.820157  145.295411       0.0  0.000000e+00
6779   2.642509  34.672805   6.255283  251.108846       0.0  2.090000e-43
4148   1.239516  14.581460  41.370703  129.642411       0.0  1.550142e+00
4436   0.724160   7.163648  36.193505  233.031004       0.0  1.812564e+00
13219  1.676083  11.344591  39.577381  136.578953       0.0  1.976420e+00

       Hour_sin  Hour_cos  DayOfWeek_sin  DayOfWeek_cos     Month_sin  \
9205  -0.258819 -0.965926      -0.433884      -0.900969  5.000000e-01
6779   0.258819 -0.965926       0.781831       0.623490 -8.660254e-01
4148  -0.866025  0.500000       0.433884      -0.900969  1.224647e-16
```

```
4436   -0.866025  0.500000       0.781831       0.623490 -5.000000e-01
13219 -0.965926  0.258819       0.433884      -0.900969 -5.000000e-01

       Month_cos   Day_sin   Day_cos
9205    0.866025 -0.651372 -0.758758
6779    0.500000  0.897805 -0.440394
4148   -1.000000 -0.968077 -0.250653
4436   -0.866025  0.724793  0.688967
13219  -0.866025  0.724793  0.688967
```

[60]:
```
# Helper Functions
def rmse_cv(model, X, y):
    rmse = np.sqrt(-cross_val_score(model, X, y,␣
 ↪scoring="neg_mean_squared_error", cv=5))
    return rmse

def plot_feature_importance(model, features, model_name):
    importances = model.feature_importances_
    indices = np.argsort(importances)[::-1]

    plt.figure(figsize=(10, 6))
    plt.title(f"Feature Importances: {model_name}")
    plt.bar(range(len(importances)), importances[indices])
    plt.xticks(range(len(importances)), [features[i] for i in indices],␣
 ↪rotation=45)
    plt.tight_layout()
    plt.show()

def submission_dataset(predictions, name):
    name = name.replace(" ", "_")
    output_file = f"Data\\submission_data\\submission_{name}.csv"
    if os.path.exists(output_file):
        os.remove(output_file)
    submission = pd.DataFrame({
        'Date': test_dates,
        'Electric_Consumption': predictions
        })
    submission.to_csv(output_file, index=False)

    # print(f"File submission_{name}.csv salvato con successo!")
```

[61]:
```
# Models to Compare
models = {
    "Linear Regression": LinearRegression(),
    "Polynomial Regression": make_pipeline(PolynomialFeatures(),␣
 ↪LinearRegression()),
    "Random Forest": RandomForestRegressor(),
```

```
    "XGBoost": XGBRegressor(),
}

pr_param_grid = {
    'polynomialfeatures__degree': [2, 3],
    'polynomialfeatures__include_bias': [False, True],
}

rf_param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [6, 10, None],
    'min_samples_split': [2, 5],
}

xgb_param_grid = {
    'n_estimators': [500, 1000],
    'learning_rate': [0.01, 0.05],
    'max_depth': [4, 6, 8],
    'subsample': [0.8, 1],
    'tree_method': ['hist'],
    'predictor': ['cpu_predictor'],
}
```

[62]:
```
display(X_train.head())
display(X_test.head())
print("X_train shape",X_train.shape)
print("X_test shape",X_test.shape)
print("y shape",y.shape)
```

```
       Factor_A   Factor_B   Factor_C    Factor_D  Factor_E      Factor_F  \
9205   3.358914  36.536203  12.820157  145.295411       0.0  0.000000e+00
6779   2.642509  34.672805   6.255283  251.108846       0.0  2.090000e-43
4148   1.239516  14.581460  41.370703  129.642411       0.0  1.550142e+00
4436   0.724160   7.163648  36.193505  233.031004       0.0  1.812564e+00
13219  1.676083  11.344591  39.577381  136.578953       0.0  1.976420e+00

       Hour_sin  Hour_cos  DayOfWeek_sin  DayOfWeek_cos     Month_sin  \
9205  -0.258819 -0.965926      -0.433884      -0.900969  5.000000e-01
6779   0.258819 -0.965926       0.781831       0.623490 -8.660254e-01
4148  -0.866025  0.500000       0.433884      -0.900969  1.224647e-16
4436  -0.866025  0.500000       0.781831       0.623490 -5.000000e-01
13219 -0.965926  0.258819       0.433884      -0.900969 -5.000000e-01

       Month_cos   Day_sin   Day_cos
9205    0.866025 -0.651372 -0.758758
6779    0.500000  0.897805 -0.440394
4148   -1.000000 -0.968077 -0.250653
4436   -0.866025  0.724793  0.688967
```

```
13219  -0.866025  0.724793  0.688967

   Factor_A   Factor_B   Factor_C    Factor_D  Factor_E  Factor_F  Hour_sin  \
0  1.775026  21.729808  24.808146  249.474701       0.0  1.808403  0.000000
1  2.176429  20.792287  25.128845  241.233210       0.0  1.847753  0.258819
2  2.644089  20.041586  25.045506  239.540034       0.0  1.967446  0.500000
3  2.759897  18.551710  26.976024  238.425577       0.0  2.128126  0.707107
4  2.670419  16.689420  29.611734  240.139421       0.0  1.945275  0.866025

   Hour_cos  DayOfWeek_sin  DayOfWeek_cos  Month_sin  Month_cos   Day_sin  \
0  1.000000       0.433884      -0.900969  -0.866025       -0.5  0.201299
1  0.965926       0.433884      -0.900969  -0.866025       -0.5  0.201299
2  0.866025       0.433884      -0.900969  -0.866025       -0.5  0.201299
3  0.707107       0.433884      -0.900969  -0.866025       -0.5  0.201299
4  0.500000       0.433884      -0.900969  -0.866025       -0.5  0.201299

   Day_cos
0  0.97953
1  0.97953
2  0.97953
3  0.97953
4  0.97953

X_train shape (11097, 14)
X_test shape (2160, 14)
y shape (13872,)
```

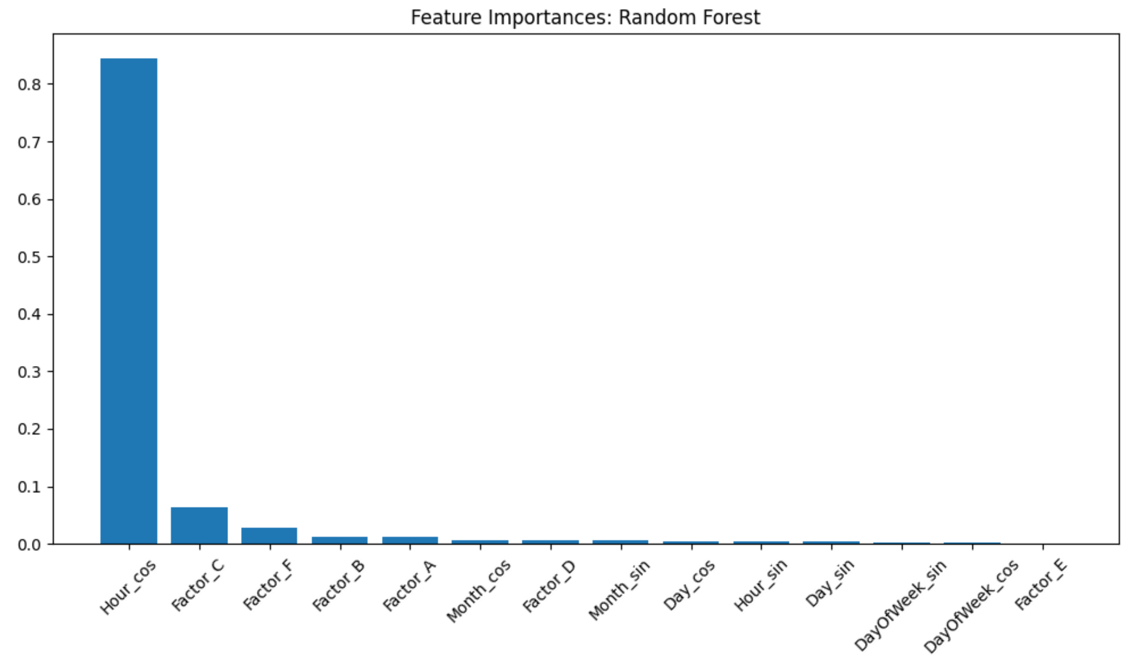
[63]:
```
# Training, Validation, and Results
results_dict = {}

for name, model in models.items():

    print(f"\n############      Training {name}       ############\n")
    results_dict[name] = {}

    # Cross validation RMSE
    cv_rmse = rmse_cv(model, X, y)
    print(f"{name} Cross-validated RMSE: {cv_rmse.mean():.2f} ± {cv_rmse.std():.
  ↪2f}")
    results_dict[name]["cv_rmse"] = cv_rmse.mean()
    results_dict[name]["cv_rmse_std"] = cv_rmse.std()

    if name == "Random Forest": param_grid = rf_param_grid
    elif name == "XGBoost": param_grid = xgb_param_grid
    elif name == "Polynomial Regression": param_grid = pr_param_grid
    else: param_grid = None

    if param_grid:
```

```
        # Hyperparameter tuning using GridSearchCV
        print(f"Performing grid search for {name} ...")
        grid_model = GridSearchCV(model, param_grid, cv=3,␣
↪scoring='neg_mean_squared_error', n_jobs=-1, verbose=1, error_score='raise')

        # Fit the model
        grid_model.fit(X_train, y_train)
        best_model = grid_model.best_estimator_
        best_params = grid_model.best_params_
        print(f"Best {name} parameters: {best_params}")

        results_dict[name]["best_params"] = best_params

    else:
        # Fit the model without hyperparameter tuning
        model.fit(X_train, y_train)
        best_model = model
        results_dict[name]["best_params"] = "Default"

    val_predictions = best_model.predict(X_val)
    val_predictions = np.clip(val_predictions, 0, None) # Ensure predictions␣
↪are non-negative (We actually have no explanations about the dataset so we␣
↪can't be sure that negative values are not possible)

    rmse = np.sqrt(mean_squared_error(y_val, val_predictions))
    print(f"{name} RMSE: {rmse}")
    results_dict[name]["rmse"] = rmse

    # Feature Importance
    if hasattr(best_model, 'feature_importances_'):
        plot_feature_importance(best_model, features, name)

    # I attempted to improve model performance by removing less important␣
↪features based on feature importance scores.
    # Specifically, I experimented with thresholds of 0.05, 0.02, and 0.01 to␣
↪filter out features with low importance values.
    # After selecting the most relevant features using each threshold, I␣
↪retrained the model and evaluated the new RMSE.
    # However, in all cases, the RMSE increased compared to the original model␣
↪using all features.
    # As a result, I decided to keep the full feature set for training, as␣
↪removing the lower-importance features consistently led to worse performance.
```

```python
    #     important_features = [feature for feature, importance in␣
↪zip(features, best_model.feature_importances_)
    #     if importance > 0.01]

    #     if len(important_features) > 0:
    #         # New dataset with important features
    #         X_train_imp = X_train[important_features]
    #         X_val_imp = X_val[important_features]
    #         X_test_imp = X_test[important_features]

    #         # Re-train the model with important features
    #         best_model.fit(X_train_imp, y_train)
    #         val_predictions = best_model.predict(X_val_imp)
    #         print(f"RMSE with selected features: {np.
↪sqrt(mean_squared_error(y_val, val_predictions)):.2f}")

    #         predictions = best_model.predict(X_test_imp)
    #     else:
    #         predictions = best_model.predict(X_test)
    # else:

    predictions = best_model.predict(X_test)

    # Ensure predictions are non-negative (We actually have no explanations␣
↪about the dataset so we can't be sure that negative values are not possible)
    predictions = np.clip(predictions, 0, None)
    submission_dataset(predictions, name)
```

```
############      Training Linear Regression       ############

Linear Regression Cross-validated RMSE: 3.48 ± 0.20
Linear Regression RMSE: 3.192344893933311

############      Training Polynomial Regression       ############

Polynomial Regression Cross-validated RMSE: 3.06 ± 1.11
Performing grid search for Polynomial Regression …
Fitting 3 folds for each of 4 candidates, totalling 12 fits
Best Polynomial Regression parameters: {'polynomialfeatures__degree': 2,
'polynomialfeatures__include_bias': True}
Polynomial Regression RMSE: 2.24130089440747

############      Training Random Forest       ############

Random Forest Cross-validated RMSE: 2.43 ± 0.45
Performing grid search for Random Forest …
```

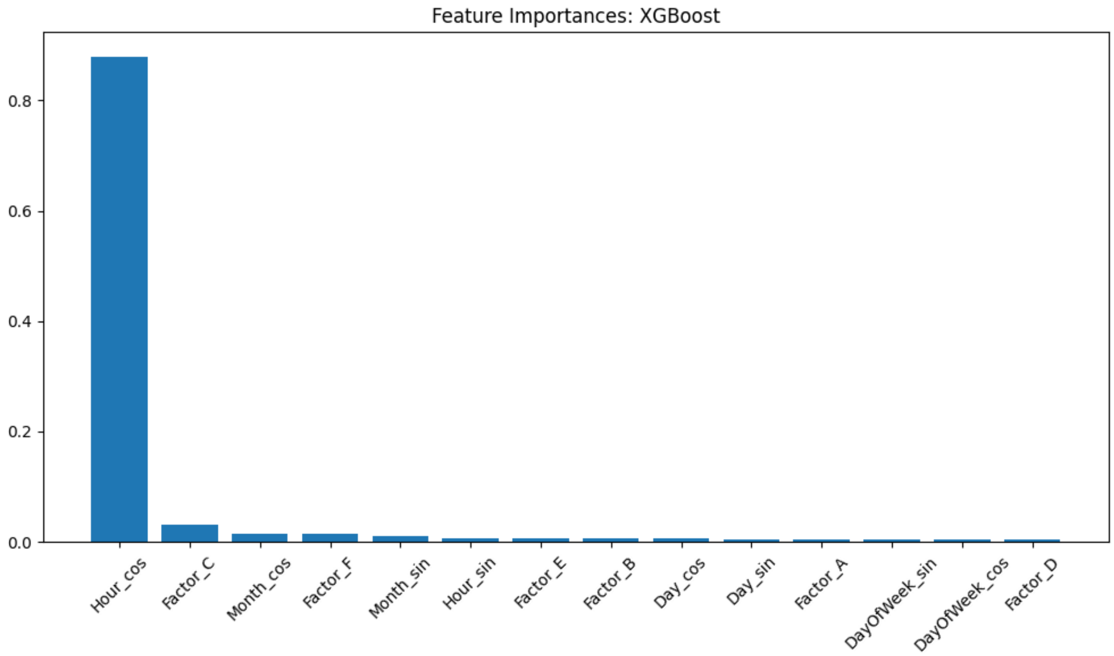
```
Fitting 3 folds for each of 12 candidates, totalling 36 fits
Best Random Forest parameters: {'max_depth': None, 'min_samples_split': 2,
'n_estimators': 200}
Random Forest RMSE: 1.6741349132053285
```




```
############      Training XGBoost       ############

XGBoost Cross-validated RMSE: 2.52 ± 0.43
Performing grid search for XGBoost …
Fitting 3 folds for each of 24 candidates, totalling 72 fits
```

```
c:\Users\irebu\AppData\Local\Programs\Python\Python39\lib\site-
packages\xgboost\core.py:158: UserWarning: [13:14:44] WARNING: C:\buildkite-
agent\builds\buildkite-windows-cpu-autoscaling-
group-i-08cbc0333d8d4aae1-1\xgboost\xgboost-ci-windows\src\learner.cc:740:
Parameters: { "predictor" } are not used.

  warnings.warn(smsg, UserWarning)
```

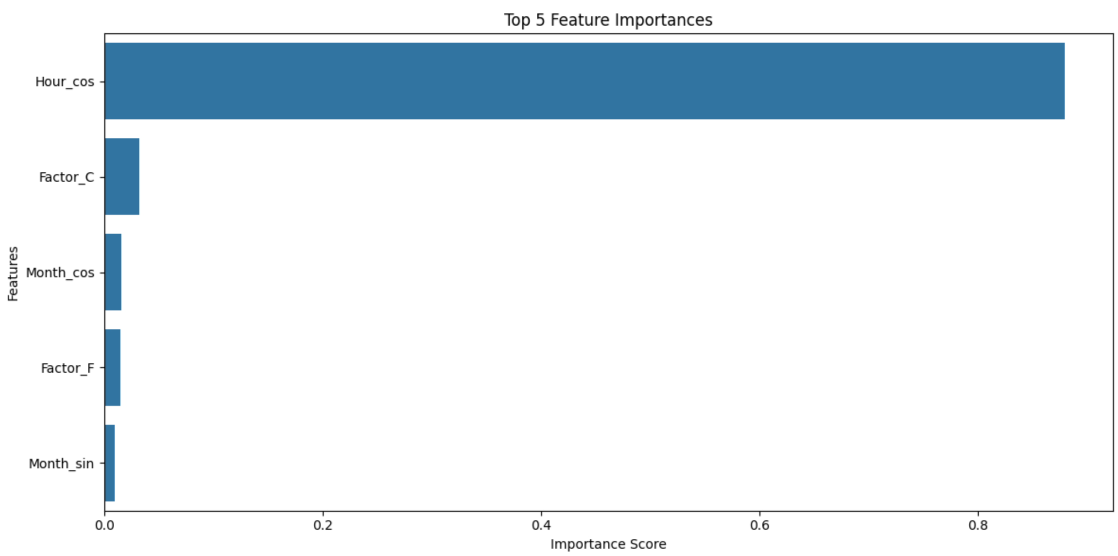
```
Best XGBoost parameters: {'learning_rate': 0.05, 'max_depth': 6, 'n_estimators':
1000, 'predictor': 'cpu_predictor', 'subsample': 0.8, 'tree_method': 'hist'}
XGBoost RMSE: 1.4940221702446124
```

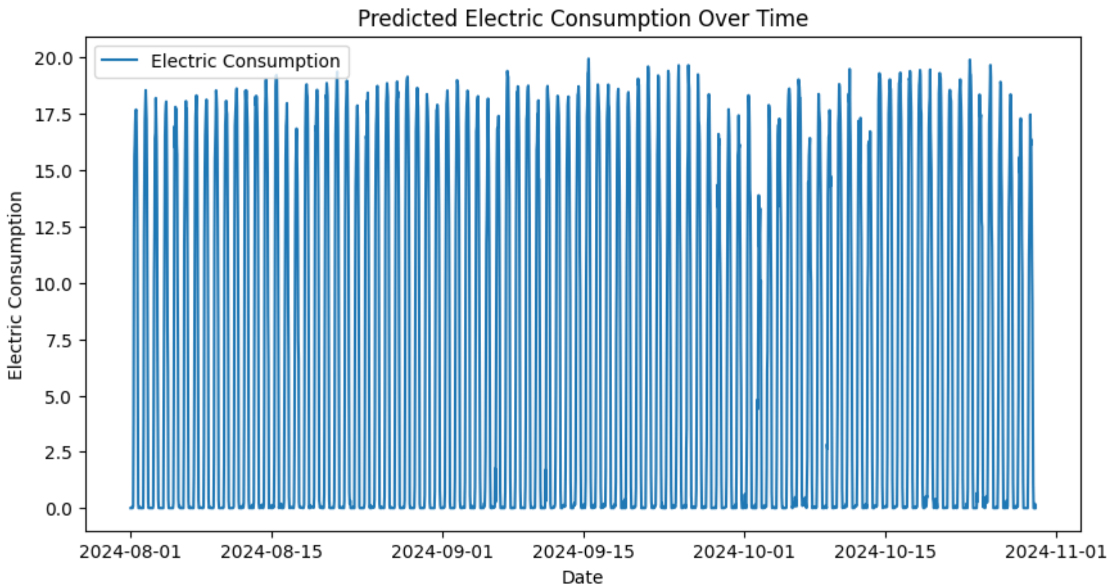


[64]:
```
# Get feature importances on the best optimized model - XGBoost
feature_importance = best_model.feature_importances_
features = X.columns

# Create a DataFrame with feature importances of the best model
importance_df = pd.DataFrame({'Feature': features, 'Importance':␣
↪feature_importance})
importance_df = importance_df.sort_values(by='Importance', ascending=False)

display(importance_df)

# Plot the features by importance using Seaborn of the best model
plt.figure(figsize=(12, 6))
sns.barplot(x='Importance', y='Feature', data=importance_df.head(5))
plt.title('Top 5 Feature Importances')
plt.xlabel('Importance Score')
plt.ylabel('Features')
plt.tight_layout()
plt.show()

# Plot the predictions
plt.figure(figsize=(10, 5))
plt.plot(test_dates, predictions, label='Electric Consumption')
plt.title('Predicted Electric Consumption Over Time')
plt.xlabel('Date')
```

```python
plt.ylabel('Electric Consumption')
plt.legend()
plt.show()
```

```
          Feature  Importance
7        Hour_cos    0.879457
2        Factor_C    0.032030
11      Month_cos    0.015145
5        Factor_F    0.014309
10      Month_sin    0.009729
6        Hour_sin    0.006914
4        Factor_E    0.006639
1        Factor_B    0.006341
13        Day_cos    0.005961
12        Day_sin    0.005455
0        Factor_A    0.004941
8   DayOfWeek_sin    0.004502
9   DayOfWeek_cos    0.004337
3        Factor_D    0.004238
```





[65]:
```python
# Compare results
df = pd.DataFrame(results_dict).T
df = df[['cv_rmse', 'cv_rmse_std', 'rmse', 'best_params']]
print(df.to_string())
```

```
                         cv_rmse cv_rmse_std      rmse
best_params
Linear Regression       3.476326    0.198908  3.192345
Default
Polynomial Regression   3.064045    1.112123  2.241301
{'polynomialfeatures__degree': 2, 'polynomialfeatures__include_bias': True}
Random Forest           2.434055    0.449658  1.674135
{'max_depth': None, 'min_samples_split': 2, 'n_estimators': 200}
XGBoost                 2.519667     0.42985  1.494022  {'learning_rate': 0.05,
'max_depth': 6, 'n_estimators': 1000, 'predictor': 'cpu_predictor', 'subsample':
0.8, 'tree_method': 'hist'}
```

[ ]: