### **Energy Consumption Forecasts:**

#### **Data Used:**

The graphs and analysis are based on hourly energy consumption data for various utility companies, covering a period that spans multiple years. This timeframe allows for capturing the seasonal and trend components inherent in energy consumption patterns over time, such as daily usage fluctuations, monthly changes, and seasonal energy consumption peaks.

#### **Ultimate Takeaway:**

The root mean square error (RMSE) of most models indicates moderate success in predicting energy consumption. For most utilities, hyperparameter tuning resulted in slight or no improvement in RMSE values, but this doesn't necessarily imply that the model is ineffective. On certain datasets, RMSE values as low as 196 were achieved, while the highest observed RMSE was 1837. Even though the RMSE values aren't perfect, this model still holds value in its ability to provide insights into how different features affect energy consumption patterns.

#### **Why Random Forest and Time-Based Features Are a Good Choice:**

Random Forests are particularly effective for time-series forecasting because:

* Handling non-linearity: Random Forest can model complex, non-linear relationships between input features and the target variable (energy consumption in this case), which is often seen in time-series data.
* Feature importance: Random Forest inherently provides feature importance scores, allowing us to see which time-based features (hour of the day, day of the week, month of the year) are most influential in predicting energy consumption.
* Robustness to overfitting: Due to its ensemble nature (combining multiple decision trees), Random Forest helps prevent overfitting, which is crucial in time-series forecasting where the data may have patterns that are difficult to capture with a single model.

#### **Feature Importance Insights:**

Feature importance analysis revealed that, for most datasets, the hour of the day emerged as the most important feature, followed by month of the year in some cases. This suggests that energy consumption patterns vary primarily with the time of day, with some utilities also showing notable seasonal effects (as seen in the EKPC dataset, where the month of the year had a significant impact). This insight helps utilities better understand:

* When energy consumption peaks during the day.
* How seasonality affects energy demand throughout the year.