Summary Report

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Assignment 1: Power Calendar Function

Objective:
To calculate the number of hours that belong to specific trading blocks (onpeak, offpeak, flat, 2x16H, 7x8) for various Independent System Operators (ISOs) within specified periods. This analysis helps in understanding consistent electricity usage patterns across different periods and for different ISOs, which is crucial for planning and trading in the power market.

Key Findings:

1. Each ISO has specific definitions for peak types, affecting the calculation of hours for block trading. For example, MISO does not observe daylight-saving time, impacting hour calculations for certain months.
2. Onpeak hours generally correspond to high activity periods in household or industrial operations, reflecting the typical daily routine. The number of onpeak and offpeak hours can vary significantly with seasons due to changes in daylight-saving time and variations in daily activities.

Conclusions:
Understanding the distribution of onpeak and offpeak hours helps traders optimize their strategies and align their trading activities with periods of high and low demand, particularly during peak hours, leading to potential cost savings and reduced environmental impact.

Assignment 2: Meter Data Formatting

Overview:
This report provides an analysis of electricity consumption patterns based on the combined data from hourly residential electricity consumption and minute-by-minute appliance usage. The analysis covers variations in consumption by hour of the day, day of the week, and month. The objective is to identify patterns and any abnormalities in the data.

Data Overview:

- **Base Data:** Hourly electricity consumption for a resident (measured in kilowatts).
- **Appliance Data:** Minute-by-minute electricity consumption for a specific appliance (measured in watts).

Key Findings:

1. **Hourly Consumption Patterns:** The highest electricity consumption occurs around 10 AM, likely due to increased household activities and the use of high-power appliances during the morning hours. The lowest consumption is observed between midnight and 6 AM, and again after 8 PM, reflecting typical low activity periods in a household.

2. **Weekly Consumption Patterns:** Electricity consumption remains relatively stable across different days of the week, indicating consistent usage patterns without significant changes between weekdays and weekends. Several high consumption outliers were noted, possibly due to specific high-power activities or appliance usage on certain days.

3. **Monthly Consumption Patterns:** There is a noticeable increase in electricity consumption during the summer months (June, July, and August), likely due to the use of air conditioning or other cooling systems during hotter weather. Consumption remains relatively stable for the rest of the year.

Abnormalities:
The presence of outliers indicating very high consumption suggests occasional spikes in electricity usage, which could be attributed to specific high-power appliances or activities that occur sporadically.

Insights and Conclusions:
Electricity consumption is heavily influenced by daily routines, with peaks aligning with typical household activities. Seasonal changes, particularly in summer, significantly affect consumption patterns. Stable usage patterns across different days of the week suggest that daily routines do not vary significantly between weekdays and weekends. Understanding these patterns can help identify opportunities for energy efficiency improvements, such as shifting high-power activities to non-peak hours or improving insulation and cooling efficiency during summer months.

Assignment 3: EDA and Forecast Model

Objective:
The data spans various attributes such as hourly electricity consumption, real-time load, wind, and solar generation in the ERCOT region. The analysis aimed to evaluate electricity consumption patterns and predict the Real-Time Locational Marginal Price (RTLMP) using time series and machine learning models.

Methodology:

1. **Data Processing:** Loaded and cleaned the timeseries data, applied feature engineering techniques such as creating lagged features and rolling averages, and generated time-based features like hour, day of the week, and month.

2. **Exploratory Data Analysis (EDA):** Conducted EDA to understand data structure and correlations. Time series plots revealed distinct patterns and seasonal variations, with correlation analysis indicating that RTLMP is negatively correlated with wind and solar generation.

3. **Model Development:** Developed predictive models using LSTM (Long Short-Term Memory) neural networks. Evaluated model performance using metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE).

Findings:

- The correlation matrix showed that higher wind and solar generation could lead to lower electricity prices.

- The LSTM model provided effective predictions, with RMSE and MAE metrics indicating accurate performance in capturing time dependencies and seasonal patterns.

Insights and Conclusions:
The negative correlation between RTLMP and renewable generation suggests that increased renewable generation can lead to lower electricity prices, useful for planning and optimizing energy market strategies. The inclusion of time-based features made the model more robust in predicting daily and seasonal variations. The predictive models provided accurate forecasts for RTLMP, crucial for effective energy market operations and decision-making.