Summary Report

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Assignment 1: Power Calendar function

Objective:

The goal was 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. The analysis covers ISOs such as PJM, MISO, ERCOT, SPP, NYISO, WECC, and CAISO. The periods analyzed include daily, monthly, quarterly, and annually. The 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:

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.

Within different Peak Type and Period Handling, onpeak hours generally correspond to high activity periods in the 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.

Recommendations:

- Consider shifting high-power activities to off-peak hours to balance the load and reduce costs.
- Implement energy-efficient practices during peak hours, especially in summer, to manage the increased load.

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:

Hourly Consumption Patterns:

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

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 throughout the week, which may be due to specific high-power activities or appliance usage on certain days.

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, without significant variations.

Abnormalities:

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

Insights and Conclusions:

Electricity consumption is heavily influenced by daily routines. The peak in the morning around 10 AM aligns with typical household activities, such as cooking, cleaning, or running appliances. Seasonal changes, particularly in summer, significantly affect electricity consumption patterns. Increased usage of cooling systems during hot weather leads to higher electricity consumption. The stable electricity usage patterns across different days of the week suggest that the resident's daily routines do not vary significantly between weekdays and weekends.

Understanding these consumption patterns can help in identifying opportunities for energy efficiency improvements. For instance, shifting some high-power activities to non-peak hours or improving insulation and cooling efficiency during summer months could reduce overall consumption.

Recommendations:

- Further investigation into the causes of high consumption outliers could help in identifying specific appliances or activities contributing to these spikes.

- Implementing energy efficiency programs focused on reducing peak hour consumption and improving cooling efficiency during summer months could lead to significant savings.

- Continued monitoring of electricity consumption patterns can provide insights into the effectiveness of any implemented energy-saving measures and help in further optimizing electricity usage.

Assignment 3: EDA and forecast model

Objective:

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

Methodology:

For this time series data, I firstly loaded and cleaned the timeseries data with Feature Engineering technique (explained below), conducted exploratory data analysis (EDA) to understand data structure and correlations, developed predictive models using Random Forest and SARIMAX, and lastly evaluated model performance using Mean Squared Error (MSE) and other metrics.

Feature Engineering

- Lagged features were created to capture the dependency of the current RTLMP on previous hours' load, wind, and solar generation.
- Rolling averages were computed to smooth out short-term fluctuations and highlight longer-term trends.
- Additional time-based features such as hour, day of the week, and month were created to capture temporal patterns.

Findings:

Exploratory Data Analysis (EDA)

The time series plots of the variables (RTLoad, WIND_RTI, GENERATION_SOLAR_RT, RTLMP) show distinct patterns and seasonal variations. Wind generation and solar generation show variability throughout the day.

The correlation matrix indicates that RTLMP is negatively correlated with WIND_RTI and GENERATION_SOLAR_RT, suggesting that higher wind and solar generation may lead to lower electricity prices.

Models Performance

Random Forest Model: - MSE: 656.03, indicating the model's performance in predicting RTLMP.

SARIMAX Model: - MSE: 0.0789, showing better performance in capturing time dependencies and seasonal patterns.

Insights and Conclusions:

The negative correlation between RTLMP and renewable generation (wind and solar) indicates that increased renewable generation can lead to lower electricity prices. This insight can be used for planning and optimizing energy market strategies. The inclusion of time-based features helps capture the temporal patterns in RTLMP, making the model more robust in predicting daily and seasonal variations.

The analysis successfully identified key consumption patterns and developed robust predictive models for RTLMP. The insights gained from hourly, weekly, and monthly trends can assist in optimizing energy usage and planning for high-demand periods. The predictive models, especially SARIMAX, provided more accurate forecasts for RTLMP, which is crucial for effective energy market operations and decision-making.

Recommendations:

- Further investigate outliers in weekly and monthly data to understand causes of occasional spikes in electricity usage.

- Use predictive models to anticipate high-demand periods and optimize energy distribution accordingly.

- Continuously update and refine models with new data to improve forecasting accuracy.