Phase 2: Innovation - Electricity Price Prediction

Introduction

In the previous phase, we outlined a systematic approach to building a predictive model for electricity price forecasting. In this phase, we will explore advanced time series forecasting techniques to further improve the accuracy of our predictions. Specifically, we will consider using the Facebook Prophet forecasting tool and deep learning models.

1. **Facebook Prophet**

Facebook Prophet is an open-source forecasting tool designed for forecasting time series data with strong seasonal patterns and multiple seasonalities. Here's how we will incorporate Prophet into our project:

Installation and Data Preparation: We will install the Prophet library and prepare our dataset, ensuring it meets Prophet's input requirements (i.e., date and target variable).

Model Training: Prophet allows us to model daily and yearly seasonality, holidays, and special events. We will use these features to capture the underlying patterns in electricity prices. The model will automatically detect changepoints, where the time series behavior shifts, and adapt to these changes.

Hyperparameter Tuning: We will fine-tune Prophet's hyperparameters to optimize forecasting accuracy. Parameters like seasonality, holidays, and changepoints will be adjusted to fit our data effectively.

Evaluation: As in the previous phase, we will evaluate the Prophet model's performance using metrics such as MAE, RMSE, and MAPE. We will compare these results with those obtained from the previous models (ARIMA, LSTM) to determine if Prophet offers an improvement.

2**. Deep Learning Models**

Deep learning models, particularly recurrent neural networks (RNNs) and variations like LSTM, are known for their ability to capture complex temporal dependencies in sequential data. Here's how we will incorporate deep learning into our project:

Data Preparation: We will format the dataset to suit the requirements of deep learning models. This involves creating sequences of historical data as input features and the corresponding electricity prices as the target variable.

Model Architecture: We will design and implement deep learning architectures, including LSTM-based models. These models will have multiple layers to capture both short-term and long-term patterns in the time series data.

Training: We will train the deep learning models on our preprocessed dataset. We will experiment with various configurations, batch sizes, and epochs to find the best-performing model.

Evaluation: Similar to the evaluation of Prophet, we will use metrics like MAE, RMSE, and MAPE to assess the accuracy of our deep learning models.

Conclusion

In this phase, we have introduced innovative approaches to improve the accuracy of our electricity price forecasting model. By exploring Facebook Prophet and deep learning models, we aim to capture intricate patterns and seasonality in the data, which can lead to more accurate predictions.

The updated notebook (ADS_Phase2) will include the implementation of Prophet and deep learning models, hyperparameter tuning, and a comprehensive evaluation of these models' performance. We will compare the results obtained from these advanced techniques with the previous models to determine which approach provides the best forecasting accuracy.