**PROJECT NAME : ELECTRICITY PRICES PREDICTION**

Phase 1: Problem Definition and Design Thinking

**Problem Definition:**

Defining the problem of electricity price prediction is a crucial step in any predictive modeling task. Here's how you can define the problem clearly Predict future electricity prices for a specific region or market based on historical data and relevant factors.

Key Elements of the Problem Definition:

1. Target Variable: The target variable is the one you want to predict, which in this case is "electricity prices." These prices could be hourly, daily, or at any other relevant time interval, depending on the scope of your prediction task.

2. Data Source: Specify the source of your historical data. This could be data obtained from energy market databases, government agencies, or commercial data providers.

3. Region or Market: Clearly define the geographical area or market for which you are predicting electricity prices. Electricity prices can vary significantly from one region to another.

4. Time Period: Determine the time period for which you want to make predictions. Are you predicting prices for the next day, week, month, or year? This choice depends on the specific forecasting needs.

5. Predictors/Features: Identify the factors that will be used to make predictions. These could include historical price data, electricity demand, weather conditions (e.g., temperature, humidity, wind speed), supply factors (e.g., generation capacity, renewable energy production), market indicators (e.g., gas prices, economic data), and any other relevant variables.

6. Forecasting Horizon: Specify the time horizon for your predictions. For example, you might want to predict prices for the next 24 hours, the next week, or even longer.

7. Evaluation Metric: Determine how you will measure the accuracy of your predictions. Common evaluation metrics for regression tasks like this include Mean Absolute Error (MAE), Mean Squared Error (MSE), or Root Mean Squared Error (RMSE).

8. Frequency of Updates: Specify how often you will update the prediction model. Electricity prices can change frequently, so understanding the update frequency is important for real-time applications.

A well-defined problem statement serves as the foundation for your electricity price prediction project. It guides data collection, feature engineering, model selection, and evaluation, ultimately leading to accurate and actionable predictions.

**Design Thinking:**

Design thinking is a human-centered approach to problem-solving and innovation that can be applied to the task of electricity price prediction. While it's commonly associated with product or service design, the principles of design thinking can help create more effective and user-focused prediction models. Here's how you can apply design thinking to electricity price prediction:

* Empathize (Understand the Problem): Begin by empathizing with the end-users or stakeholders. Understand their needs, pain points, and goals related to electricity price predictions. Conduct interviews or surveys to gather insights.
* Define (Frame the Problem): Clearly define the problem based on your understanding of users' needs. This is where you create the problem statement as discussed in the previous response.
* Ideate (Generate Solutions): Brainstorm potential solutions and approaches for predicting electricity prices. Encourage creativity and explore various data sources and modeling techniques.
* Prototype (Create a Predictive Model): Develop a prototype of your predictive model. This involves:
* Data collection and preprocessing: Gather historical data on electricity prices and relevant features (demand, weather, etc.). Clean and preprocess the data.
* Feature selection and engineering: Identify the most important features and create new ones that could improve predictions.
* Model selection: Choose appropriate machine learning or time series forecasting models.
* Initial implementation: Build a basic version of the prediction model.
* Test (Evaluate and Refine): Test the prototype's performance using historical data. Use evaluation metrics like MAE, MSE, or RMSE to assess accuracy.Gather feedback from potential users, data scientists, or domain experts to identify areas for improvement.
* Feedback (Iterate and Improve): Based on the feedback and evaluation results, iterate on your model. Refine data preprocessing, feature engineering, and model selection.Continuously improve the model to enhance its accuracy and reliability.
* Implement (Deploy the Model): Once you have a well-performing model, deploy it to start making predictions on future electricity prices. Ensure that it integrates with existing systems or workflows used by stakeholders.
* Monitor (Track Performance): Continuously monitor the model's performance in real-time. Detect anomalies or deviations from predictions and take corrective actions when necessary.
* Scale and Adapt (Respond to Changes): As electricity markets and conditions evolve, be prepared to scale your model and adapt it to changing circumstances. This may involve retraining the model with fresh data or adjusting its parameters.
* Communicate (Share Insights): Effectively communicate the predictions and insights to the intended audience. Provide easy-to-understand visualizations and reports that help users make informed decisions.

Design thinking emphasizes collaboration, user feedback, and iterative development. It ensures that the predictive model is not only accurate but also valuable and user-friendly for those who rely on electricity price predictions for decision-making.

A key point in electricity spot price modeling and forecasting is the appropriate treatment of seasonality.The electricity price exhibits seasonality at three levels: the daily and weekly, and to some extent - the annual. In *short-term forecasting*, the annual or long-term seasonality is usually ignored, but the daily and weekly patterns (including a separate treatment of holidays) are of prime importance. This, however, may not be the right approach. As Nowotarski and Weron have recently shown, decomposing a series of electricity prices into a long-term seasonal and a stochastic component, modeling them independently and combining their forecasts can bring - contrary to a common belief - an accuracy gain compared to an approach in which a given model is calibrated to the prices themselves.

In *mid-term forecasting*, the daily patterns become less relevant and most EPF models work with average daily prices. However, the long-term trend-cycle component plays a crucial role. Its misspecification can introduce bias, which may lead to a bad estimate of the mean reversion level or of the price spike intensity and severity, and consequently, to underestimating the risk. Finally, in the *long term*, when the time horizon is measured in years, the daily, weekly and even annual seasonality may be ignored, and long-term trends dominate. Adequate treatment - both in-sample and out of sample of seasonality has not been given enough attention in the literature so far.