Literature Review

The ability to predict renewable energy output reliably is crucial due to the increasing reliance on sustainable energy sources worldwide. Renewable energy forecasting involves the use of weather, environmental, and operational data to estimate future energy production, a complex task given the inherent variability of sources like wind and solar power.

Several studies have addressed the shortcomings of traditional statistical methods in this domain. Hyndman and Athanasopoulos (2018) highlighted that while classical time series models such as ARIMA and exponential smoothing have been widely used, they often fail to capture the non-linear dependencies present in renewable energy data. Consequently, machine learning methods, capable of modeling complex and non-linear relationships, have become the focus of contemporary research.

Random Forest and Gradient Boosted Trees (e.g., XGBoost) have emerged as effective ensemble methods for renewable energy forecasting. Rahman and Saha (2022) reviewed various machine learning techniques for predicting solar and wind power generation and concluded that ensemble learning techniques, especially Random Forest and XGBoost, often outperform traditional models due to their robustness against overfitting and ability to handle multicollinearity in data.

Deep learning methods, particularly Long Short-Term Memory (LSTM) networks, have gained popularity for their superior performance in sequential data modeling. LSTM networks are a type of recurrent neural network (RNN) specifically designed to address the vanishing gradient problem, allowing them to capture long-term dependencies in time series data effectively (Hochreiter and Schmidhuber, 1997). In the context of renewable energy, LSTM models have been applied successfully to predict both short-term and long-term energy generation trends.

In the M4 forecasting competition analyzed by Makridakis et al. (2020), hybrid models combining statistical and machine learning techniques outperformed standalone models, underscoring the importance of ensemble strategies. Similarly, Kramer and Kabele (2019) explored hybrid approaches that combine weather prediction models with machine learning techniques, reporting significant improvements in solar energy forecasting accuracy.

Moreover, recent advancements in feature engineering, such as the use of lagged variables, rolling averages, and interaction features, have significantly enhanced model performance. As noted by Khosravi et al. (2021), careful preprocessing and feature selection are critical to maximize the predictive power of machine learning models when applied to renewable energy datasets.

Despite their advantages, machine learning models are not without challenges. Issues such as data sparsity, sensor errors, and the requirement for large volumes of training data can affect model performance. Additionally, the black-box nature of some models, particularly deep learning networks, poses interpretability challenges which are critical in energy management applications.

Given this context, the current project leverages the strengths of Random Forest, XGBoost, and LSTM models to develop an integrated framework for renewable energy forecasting. By combining structured energy generation data with real-time weather information, and applying advanced machine learning techniques, this study aims to provide a more accurate and reliable prediction mechanism, contributing to better energy grid management and policy decision-making.

In summary, while previous studies provide strong evidence supporting the use of machine learning in energy forecasting, this project seeks to build on this foundation by integrating multiple models and comparing their performance on a real-world, multi-source dataset, thereby advancing the practical application of machine learning in renewable energy forecasting.

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