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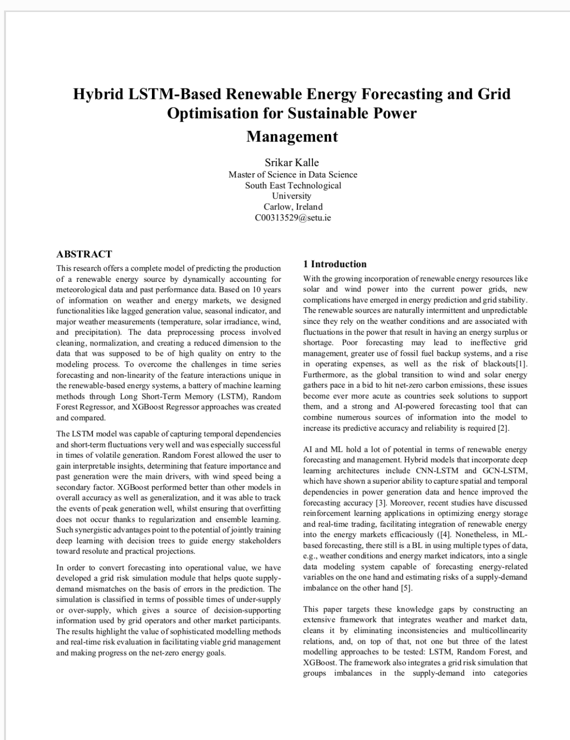

Hybrid LSTM-Based Renewable Energy Forecasting and Grid Optimisation for Sustainable Power Management

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ABSTRACT

This research offers a complete model of predicting the production of a renewable energy source by dynamically accounting for meteorological data and past performance data. Based on 10 years of information on weather and energy markets, we designed functionalities like lagged generation value, seasonal indicator, and major weather measurements (temperature, solar irradiance, wind, and precipitation). The data preprocessing process involved cleaning, normalization, and creating a reduced dimension to the data that was supposed to be of high quality on entry to the modeling process. To overcome the challenges in time series forecasting and non-linearity of the feature interactions unique in the renewable-based energy systems, a battery of machine learning methods through Long Short-Term Memory (LSTM), Random Forest Regressor, and XGBoost Regressor approaches was created and compared.

The LSTM model was capable of capturing temporal dependencies and short-term fluctuations very well and was especially successful in times of volatile generation. Random Forest allowed the user to gain interpretable insights, determining that feature importance and past generation were the main drivers, with wind speed being a secondary factor. XGBoost performed better than other models in overall accuracy as well as generalization, and it was able to track the events of peak generation well, whilst ensuring that overfitting does not occur thanks to regularization and ensemble learning. Such synergistic advantages point to the potential of jointly training deep learning with decision trees to guide energy stakeholders toward resolute and practical projections.

In order to convert forecasting into operational value, we have developed a grid risk simulation module that helps quote supply-demand mismatches on the basis of errors in the prediction. The simulation is classified in terms of possible times of under-supply or over-supply, which gives a source of decision-supporting information used by grid operators and other market participants. The results highlight the value of sophisticated modelling methods and real-time risk evaluation in facilitating viable grid management and making progress on the net-zero energy goals.

1 Introduction

With the growing incorporation of renewable energy resources like solar and wind power into the current power grids, new complications have emerged in energy prediction and grid stability. The renewable sources are naturally intermittent and unpredictable since they rely on the weather conditions and are associated with fluctuations in the power that result in having an energy surplus or shortage. Poor forecasting may lead to ineffective grid management, greater use of fossil fuel backup systems, and a rise in operating expenses, as well as the risk of blackouts[1]. Furthermore, as the global transition to wind and solar energy gathers pace in a bid to hit net-zero carbon emissions, these issues become ever more acute as countries seek solutions to support them, and a strong and AI-powered forecasting tool that can combine numerous sources of information into the model to increase its predictive accuracy and reliability is required [2].

AI and ML hold a lot of potential in terms of renewable energy forecasting and management. Hybrid models that incorporate deep learning architectures include CNN-LSTM and GCN-LSTM, which have shown a superior ability to capture spatial and temporal dependencies in power generation data and hence improved the forecasting accuracy [3]. Moreover, recent studies have discussed reinforcement learning applications in optimizing energy storage and real-time trading, facilitating integration of renewable energy into the energy markets efficaciously ([4]. Nonetheless, in ML-based forecasting, there still is a BL in using multiple types of data, e.g., weather conditions and energy market indicators, into a single data modeling system capable of forecasting energy-related variables on the one hand and estimating risks of a supply-demand imbalance on the other hand [5].

This paper targets these knowledge gaps by constructing an extensive framework that integrates weather and market data, cleans it by eliminating inconsistencies and multicollinearity relations, and, on top of that, not one but three of the latest modelling approaches to be tested: LSTM, Random Forest, and XGBoost. The framework also integrates a grid risk simulation that groups imbalances in the supply-demand into categories