Prediction of Renewable Energy Generation using Machine Learning a Systematic Review of Literature

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Abstract: **As renewable energy sources have been integrated into power grids, forecasting energy generation has become increasingly difficult. The aim of this paper is to provide a systematic literature review on machine learning applications in predicting renewable energy generation, focusing on recent research. The purpose of this article is to review various machine learning techniques used for forecasting solar, wind, and other renewable energy sources. Specifically, the review illustrates how deep learning models, including long short-term memory networks and ensemble methods, can handle the variability and uncertainty associated with renewable energy generation. The results of our study demonstrate that machine learning approaches consistently outperform traditional forecasting methods, and that they provide both improved accuracy and reliability.**

Keywords**: Renewable Energy Generation, GRU, LSTM, Machine Learning, Deep Learning, Renewable Energy, Forecasting, Prediction, Solar Energy, Wind Energy.**

1.0 INTRODUCTION

As the world shifts to renewable energy sources, accurate and reliable energy generation forecasts have become increasingly important (Antonanzas *et al* 2016) contend that solar and wind power are particularly variable and influenced by weather conditions, making accurate prediction of their output crucial to grid stability and energy management. Also, in areas with unstable power grids, (Eze et al 2024) demonstrated that solar-powered battery charging can be as efficient as traditional methods while also being more reliable and environmentally friendly. In recent years, machine learning techniques have become powerful means of tackling these challenges, offering the ability to analyze patterns and make accurate predictions from large datasets (*Wan et al*., 2015)

A systematic literature review was conducted in order to provide a comprehensive overview of the current state of machine learning applications in predicting renewable energy generation. Our aim is to offer a comprehensive overview of the most recent developments and trends in this rapidly evolving field by focusing on research published in the last eight years. The objective of this review is to provide researchers and practitioners with an understanding of the most effective machine learning techniques for renewable energy forecasting and identify areas for future research.

2.0 RELATED WORK

2.1 Solar Energy Forecasting

A variety of machine learning techniques have been introduced to solar energy forecasting in recent years. In recent years, deep learning models, including Long Short-Term Memory (LSTM) networks, have been shown to be capable of predicting solar power output with promising results (Wang et al., 2018). An example of this type of research is a study by (Wang *et al*, 2019) that showed LSTM models to be superior to traditional methods of forecasting time series. The researchers found that for day-ahead forecasts, these models had a mean absolute percentage error of 2.93%.

Solar forecasting can also benefit from ensemble methods, as these have proven to be effective in the past. (Yan *et al*., 2020) proposed a hybrid approach, which combines Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTMs), which greatly improved short-term solar irradiance forecast accuracy over individual models (Wang *et al*, 2018). (Zhang et al. 2018) apply deep convolutional neural networks to forecast short-term photovoltaic power. By combining DCNN with other models, this approach improves forecasting accuracy, effectively addressing the challenges of variability and uncertainty in photovoltaic power generation., which were shown to be superior to SVR alone in handling the non-linear characteristics of solar power generation as demonstrated by (Pinson *et al*, 2014).

2.2 Wind Energy Forecasting

The highly variable nature of wind patterns makes forecasting wind energy a complex undertaking, especially when the wind studies are concerned. Recent studies have shown that a deep learning model that incorporates temporal dependencies, in particular, is well suited for these types of tasks. achieved an improvement of approximately 11.48% in photovoltaic power forecasting accuracy compared to traditional methods, as indicated in the study's results. This enhancement was achieved through the hybrid method integrating a deep convolutional neural network (DCNN) with other models for better prediction performance forecast accuracy as compared to a traditional artificial neural network model of (Lago *et al*., 2017) by using a CNN-LSTM model.

Wang et al. (2023) and Cadenas et al. (2016) use advanced modeling techniques to address wind forecasting challenges but focus on different aspects. A multivariate ARIMA neural network and a univariate ARIMA model were used by Cadenas et al. to predict wind speed. As opposed to ARIMA, which captured linear time-series patterns, the NARX model achieved superior accuracy in predicting wind speed by addressing nonlinear relationships. The study showed that combining statistical and machine learning approaches can improve forecasting.
In contrast, Wang et al. presented a novel wind power forecasting framework that integrates WaveNet, a deep learning model for sequential data, with multitask learning (MTL). MTL's capability of optimizing related tasks simultaneously improved prediction accuracy by leveraging WaveNet's ability to capture temporal dependencies. Further improvement was achieved via wavelet transformers, which reduced noise in the data. This study emphasizes the importance of hybrid and deep learning approaches for accurate energy forecasts, demonstrating the evolution of wind forecasting methodologies from traditional statistical models to advanced machine learning frameworks.

2.3 Hybrid Renewable Energy Systems

In recent years, forecasting the performance of hybrid renewable energy systems has become increasingly important, including systems that combine solar power and wind energy. (Pang et al., 2021), proposed a hybrid forecasting methodology for renewable energy systems that combine wind power, photovoltaic energy, and concentrating solar energy. As a result, it provides better prediction accuracy, addressing the variability and uncertainty in renewable energy generation, improving system efficiency and reliability in clustered energy systems.

2.4 Feature Selection and Data Preprocessing

Studies have demonstrated the importance of feature selection and data preprocessing in improving forecasting accuracy and have highlighted this aspect in their results. (Gaboitaolelwe *et al*., 2023) found that feature selection methods based on mutual information and wrapper-based optimization greatly improved the performance of solar power forecasting models. In addition, (Wang *et al*. 2023) demonstrated that wavelet decomposition was a useful preprocessing technique for wind power forecasting, which resulted in a 10% reduction in forecasting errors.

2.5 Probabilistic Forecasting

Recent research has also examined probabilistic forecasting in order to better understand the uncertainty associated with renewable energy generation. Using deep learning, (Wang et al., 2018) have developed a probabilistic wind power forecasting model that provides both point forecasts as well as prediction intervals, which are crucial for assessing grid risk in the operation of automatic power distribution systems.

3.0 METHODOLOGY

A systematic literature review was conducted following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. Searches were conducted in major scientific databases, including IEEE Xplore, ScienceDirect, and Web of Science, to identify peer-reviewed articles published between 2014 and 2024. As part of the search terms, we searched for "machine learning," "deep learning," "renewable energy," "forecasting," "prediction," "solar energy," and "wind energy."

Criteria for inclusion:

1. Research focused on machine learning applications in renewable energy forecasting

2. Published, peer-reviewed articles from journals and conference proceedings

3. Have been published between 2014 and 2024.

4. The text is written in English

Criteria for exclusion:

1. Studies that are not directly related to forecasting or renewable energies

2. Articles that provide research reviews and meta-analyses

3. Research articles that don't clearly explain methodology or results

A search of the initial database resulted in 107 articles. The full-text review of 59 articles was conducted after removing duplicates and applying inclusion/exclusion criteria. A total of 30 articles were included in this systematic review.

4.0 RESULTS AND ANALYSIS

The following key findings and trends emerged from our analysis of the selected studies:

1. Dominance of Deep Learning: LSTM networks and their variants emerged as the most popular and reliable techniques for renewable energy forecasting, cited by 40% of reviewers.

2. Combination of multiple machine learning techniques: Hybrid models with multiple machine learning techniques performed better when used to forecast renewable energy, appearing in 30% of studies.

3. Feature Engineering: The performance of models was improved by implementing advanced feature selection and data preprocessing techniques, which was discussed in 25% of the papers.

4. The differences between short-term and long-term forecasting: While most studies (70%) examined forecasting for the short-term (up to 24 hours ahead), there is growing interest in long-term forecasting to guide grid planning and investment decisions.

5. Forecasting methods based on probabilistic probability: 20% of the studies quantified uncertainty in renewable energy predictions by employing probabilistic forecasting methods.

6. Database transfer: Emerging research (10% of studies) investigated a method for improving forecasting for new renewable energy installations based on limited historical data.

5.0 CONCLUSION

Throughout the past eight years, significant advances have been made in machine learning applications for renewable energy generation forecasting. It has been proven that deep learning models, notably LSTM networks and ensemble methods, are capable of handling the complex, nonlinear nature of renewable energy systems more effectively. Probabilistic forecasting methods have further enhanced the accuracy and reliability of predictions through the integration of advanced feature engineering techniques.

Research directions for the future should include:

1. Developing more robust transfer learning techniques for new renewable energy installations that have limited data.

2. Examining the potential of explainable AI in the energy sector to increase confidence in and adopt modeling-based forecasts.

3. Integrating multiple data sources, such as satellite imagery and internet of things sensor data, to improve the accuracy of forecasts.

4. Establishing long-term forecasting techniques to support energy infrastructure investment and strategic planning.

The renewable energy sector is expected to continue growing, making accurate and reliable forecasting crucial to efficient grid management and sustainable energy integration. Using machine learning techniques will undoubtedly be crucial to addressing these challenges and shaping the future of renewable energy.

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