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AI-optimized renewable energy forecasting for U.S. power grids

Ishmael Jesse Narh Adikorley [1,*] and Eunice Abena Lettu [2]

[1] *Marquette University, Milwaukee, WI, USA.*
[2] *Kwame Nkrumah University of Science and Technology, Ghana.*

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Abstract

Renewable energy has emerged as a critical component in the global pursuit of sustainable development and carbon neutrality. Despite its potential, the inherent challenges associated with renewable energy sources, such as intermittency, variability, and storage limitations, necessitate innovative solutions to enhance efficiency and reliability. The growing world demand for energy requires the incorporation of renewable energy into smart grids to create effective and efficient power systems. Through the utilization of sophisticated machine learning and combining traditional time-series methods and machine learning model tools, we conclude that the use of AI facilitates a speedy generation of better forecasting and dependency on renewable energy resources. As the demand for energy in the world continues to grow, the integration of renewable energy into smart grids has become essential for building efficient and sustainable power grid networks. In the study, artificial intelligence has become a transformative tool. Using machine learning techniques along with traditional techniques has promoted greater confidence and dependency on renewable energy resources. Overall, our findings support the statement that AI-based renewable energy systems can help integrate the transition to more sustainable energy resources by enhancing grid performance, reducing carbon footprints, and improving energy access. This study also reveals the significant role of AI in enhancing global sustainable goals for energy systems. This research also contributes to policymaking by evaluating AI's potential in shaping sustainable energy strategies, ensuring a reliable transition to clean energy.

Keywords: Artificial intelligence; Renewable; Energy; Power; Machine learning

1. Introduction

The twentieth century witnessed a boom in the number of data centers around the world, driven by a rapidly growing demand for Cloud services. Consequently, the energy footprint of the IT sector has increased exponentially and reached unprecedented levels. It is, actually, estimated to consume approximately 7% of global electricity in 2007[1]. Furthermore, in 2016, statistics show that data center demand reached 91 billion kWh of electricity, which is equivalent to twice the consumption of New York City [2].

The growing concerns over climate change, depletion of fossil fuel reserves, and rising global energy demand have accelerated the transition toward renewable energy sources such as solar, wind, hydro, and biomass. Governments and organizations worldwide are investing heavily in clean energy technologies to reduce greenhouse gas emissions and promote sustainable development. Despite these efforts, challenges such as the intermittent nature of renewable energy, grid integration complexities, and energy storage constraints remain key obstacles to widespread adoption [3-5].

* Corresponding author: Ishmael Jesse Narh Adikorley

Specifically, to meet the global energy demand, which is expected to increase in the future, the integration of renewable energy sources with the power systems is crucial for sustainability. Specifically, the nature of renewable sources like solar and wind is intermittent, as they regularly fluctuate throughout the day and night and in seasons, respectively. Utility-scale grids, initially developed for steady and predictable supply sources, are generally not suitable for managing fluctuating outputs. This situation has led to emergence of smart grids that involve the use of digital intelligence technologies for the monitoring and control of the grid in a more flexible manner. [6-7]

In recent years, Machine Learning (ML) and Artificial Intelligence (AI) have emerged as transformative technologies in the energy sector, offering advanced solutions for optimizing renewable energy generation and utilization. By leveraging Data Science techniques, ML and AI enable the analysis of vast datasets to improve energy forecasting, enhance operational efficiency, and optimize resource allocation. These technologies are increasingly being used in smart grids, predictive maintenance, and energy storage management, contributing to a more stable and reliable renewable energy infrastructure [8-13].

2. Importance of Forecasting Renewable Energy for Power Grids

2.1. Grid stability and reliability

Whereas further improvements in point forecast accuracy are certainly desirable, we argue that good estimates of forecast uncertainty are also of major importance to handle renewable energy in grid operations. Improved forecasting systems and corresponding decision support tools are key solutions to enable a clean, reliable, and cost-efficient future electricity grid driven by renewable resources [14].

2.2. Economic efficiency

As the amount of wind and solar energy production is not deterministic for any point in time, a huge demand for reliable forecasts has emerged. The energy production determines the energy price as well [15].

2.3. Integration of renewable energy at scale

Since many governments and states are increasingly integrating renewable energy resources into the electricity power system to decrease reliance on hydrocarbons, forecasting is very important due to the fluctuations of the renewable energy resources.[16]

2.4. Environmental sustainability

Forecasting of renewable energy is paramount since renewable energy research and development have gained significant attention due to a growing demand for clean and sustainable energy in recent years [17]. In the fight to cut greenhouse gas emissions and slow down climate change, renewable energy is essential. Therefore, developing accurate forecasting models for renewable energy generation is essential [18].

2.5. The Role of Artificial Intelligence

The integration of AI in renewable energy systems is a pivotal advancement in achieving global sustainability and energy efficiency. AI can play a role in overcoming challenges related to energy intermittency, demand forecasting, and grid optimization. The impact of Artificial Intelligence (AI) in optimizing renewable energy systems by evaluating factors such as energy forecasting accuracy, grid efficiency, storage optimization, and cost-effectiveness.

By analyzing, AI-driven solutions provide valuable insights into improving energy efficiency, reducing carbon emissions, and promoting smart grid infrastructure.

3. Methodologies in AI-Optimized Renewable Energy Forecasting for Power Grids

3.1. Data Collection and Integration

For effective forecasting, it is important that data collection and integration are done properly, including aggregation of datasets from energy providers, meteorological sources, smart grids, and IoT-based energy monitoring systems. Data used is sourced from open-access energy databases, sensor-based IoT devices, weather stations, and energy grid reports. Structures datasets from organizations such as the International Energy Agency (IEA) and the U.S. Department of Energy (DOE) provide historical records of Energy production. Consumption patterns and grid stability reports.

Additionally, real-time data collected from smart meters and renewable energy farms enhances the reliability of the analysis.[19] Real-data streams are simulated in a controlled environment, with variables such as current demand and supply levels regularly input into the system.

3.2. Data Processing and Cleaning

Data preprocessing is crucial for ensuring the accuracy and reliability of data used in forecasting. It involves steps such as data cleaning, which focuses on removing inconsistencies, duplicates, and errors to maintain high data quality. Missing values were imputed using historical averages, and outliers were detected and removed based on statistical thresholds. This helps in improving the accuracy of predictions. Another important aspect is data transformation, as it normalizes and standardizes data formats from various sources like IoT sensors, smart meters, and energy providers' databases to a common scale. This standardization facilitates integration and comparative analysis across datasets [20]

Through rigorous data preprocessing, stakeholders enhance the robustness of forecasting models, optimize resource allocation, and implement effective forecasting methods for renewable energy as well as time-based features were also generated to capture daily and seasonal variations in energy production and demand. This systematic approach ensures that data-driven decisions contribute to more efficient, resilient, and environmentally sustainable renewable energy forecasting.[21]

3.3. Time-series Forecasting Techniques

Time-series forecasting, a technique for predicting future values based on historical data, is essential for tasks like demand forecasting, financial analysis, and operational planning. By analyzing data that was red in the past, we can make informed decisions that can guide our business strategy and help us understand future trends. The important property of a time-series algorithm is its ability to extrapolate patterns outside of the domain of training data, which most machine-learning techniques cannot do by default. This is where time-series forecasting techniques come in. [22]

Various time-series forecasting techniques are employed to forecast energy, including:

3.3.1. Autoregressive Integrated Moving Average (ARIMA)

The ARIMA model has demonstrated its outperformance in precision and accuracy of predicting the next lags of time series. ARIMA (Auto-Regressive Integrated Moving Average)

method allows one to describe non-stationary time series, which are reduced to stationary

series by taking differences of some order from the original time series.[23] The ARIMA is suitable for effectively predicting low complexity subsequences based on the different sample entropies.[24]

3.3.2. Seasonal ARIMA(SARIMA)

Seasonal ARIMA is used in addressing the intermittence and unpredictability of wind energy and getting an accurate wind speed forecasting. It uses the evaluation metrics in terms of Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) performance evaluation metrics. The results show that SARIMA has excellent forecasting accuracy.[25]

For the wind turbine and solar panel models, it is possible to optimize the overall cost of the global energy system with the SARIMA model for forecasting.[26]

With the advancement of real-time smart sensors in power systems, it is of great significance to develop techniques to handle data streams on the fly to improve operational efficiency. An online variant of seasonal ARIMA(SARIMA) is purported to forecast electricity load sequentially. This model is utilized to forecast the hourly electricity load.[27]

3.3.3. Exponential Smoothing (ES)

This time-series model is used to model seasonality. It is a technique that uses an exponentially weighted average of past observations to predict future values. Exponential Smoothing is a method for forecasting univariate time series data. It is based on the principle that a prediction is a weighted linear sum of past observations or lags. The Exponential Smoothing time series method works by assigning exponentially decreasing weights for past observations. Inspired by classical exponential smoothing methods in time-series forecasting, the novel exponential smoothing attention (ESA) and frequency attention (FA) replace the self-attention mechanism in vanilla Transformers, thus improving both accuracy and efficiency.[28]

3.4. Machine Learning Models

3.4.1. Deep Learning (LSTM)

With the recent advancement in computational power of computers and, more importantly development of more advanced machine learning algorithms and approaches such as deep learning, new algorithms are developed to analyze and forecast time series data. The Long Short-Term Memory (LSTM) has become superior to the traditional algorithms. The empirical studies conducted and reported show that deep learning-based algorithms, such as LSTM, outperform traditional-based algorithms such as ARIMA and SARIMA. Overall, LSTM was found to be prominent as well in comparison to ARIMA and SARIMA.[29] Furthermore, it was noticed that the number of training times, known as “epoch” in deep learning, had no effect on the performance of the trained forecast model, and it exhibited truly random behavior.[30]

The application of machine techniques, specifically ARIMA and Bi-LSTM (bidirectional LSTM) models, for predicting solar power production. The application demonstrated that the Bi-LSTM model outperforms the ARIMA model in terms of accuracy and is able to successfully identify intricate patterns and long-term relationships in the real-time series data. The findings suggest that machine learning techniques can optimize the integration of renewable energy resources into smart grids, leading to more efficient and sustainable power systems.[31]

3.4.2. Prophet

The surging demand for electricity has exerted significant pressure on electricity generation and the overall functionality of the power grid. As a result, accurately anticipating electricity consumption holds considerable importance for the power industry. The Prophet algorithm has been applied to predict hourly and daily electricity consumption using the best model’s parameters selected using the Grid Search method. The results demonstrate the efficacy of the prediction model, yielding accurate forecasts.[32] The Prophet has been used to forecast the load data for the target time period, and has been shown to effectively predict future load data.[33]

3.4.3. Support Vector Machines (SVM)

A new method for wind power forecasting by combining the Sparrow Search Algorithm (SSA) with Support Vector Machines (SVM) is presented. The proposed SSA-SVM model is tested using historical wind power data, and the findings show a considerable increase in predicting accuracy compared to standard SVM models. Time series analysis also shows how well the SSA-SVM model can adjust to wind power patterns, and its effectiveness for wind power forecasting, and its potential role in enhancing the prediction of wind power in the renewable energy environment.[34]

A new model combines two well-known methods: the seasonal auto-regressive integrated moving average method (SARIMA) and the support vector machine method (SVMs) used on an hourly forecast of power produced by the plant gave quite a good accuracy, and the hybrid model performs better than both the SARIMA and the SVM model.[35]

3.4.4. Neural Networks

The smart grid has evolved into a typical dynamic, non-linear, and large-scale control system. The traditional model-based methods are hard to fully meet the control and analysis requirements of power systems because of their uncertainty and complexity. For example, traditional model-based methods for scenario generation of Renewable energy sources are not able to accurately capture the probability distribution characteristics and fluctuations of power curves [36], since they need to artificially assume the probability density function of power curves. Furthermore, traditional model-based methods are not universal, since the probability distributions of power curves vary from region and time. The outstanding performances of deep neural networks (DNNs) in computer vision bring new opportunities to these problems that cannot be solved by traditional model-based methods in power systems.[37]

3.4.5. Hybrid Models

An artificial neural network (ANN)-based model is investigated for short-term forecasting of the hourly wind speed, solar radiation, and electrical power demand. And its capacity to reconcile good forecasting performance on the short-term time horizon with a very simple network structure, which is potentially implementable on a low-cost processing platform.[38]

4. Challenges and Future Directions

4.1. Intermittency and Weather Variability

One of the substantial challenges with renewable energy is its dependence on natural phenomena such as sunlight and wind. These phenomena are unpredictable and can vary considerably across time and location. Renewables like solar and wind are inherently tied to weather conditions. A cloudy day or a sudden drop in wind speed can sharply reduce generation, making it difficult to guarantee a steady supply. Renewable energy supplies, such as are derived from sunlight or wind, have more fluctuating production patterns than those derived from more conventional power generation. These unpredictable changes often lead to imbalances between supply and demand. During periods of high wind or intense sunlight, energy output may exceed demand, while at other times it may fall short. Managing these fluctuations requires careful planning and reliable backup systems.[39]

4.2. Forecasting Model Challenges

For renewables to be effectively incorporated into the grid, accurate forecasting is required. Yet developing credible models comes with its own constraints. Weather conditions and performance data are critical for forecasting. Planning is less effective when forecasts are developed with inconsistent, partial, or inaccurate information. Since weather patterns fluctuate quickly, forecasting systems need to be able to adjust almost immediately. Traditional systems frequently find it difficult to keep up with these rapid shifts. It is more difficult to train reliable forecasting models in many areas due to a lack of comprehensive historical meteorological and grid data. This is particularly troublesome in growing markets for renewable energy or in developing regions.

4.3. Grid Infrastructure and Operations

The strain on existing electrical networks rises with the growth of renewable energy. Reliability is ensured by upgrading infrastructure. Long transmission lines are required since many renewable energy plants are located distant from populated regions. The ability of current grids to efficiently carry this energy can often be lacking. Monitoring and balancing can be enhanced by switching to smart grids, which are computerized systems that use digital communication. But doing so calls for a large monetary investment as well as cooperation from other parties. Renewable energies don't always produce consistent output like conventional power plants do. This could risk the grid's overall stability by causing problems like frequency imbalances and voltage fluctuations.

4.4. Economic and Operational Costs

The financial side of renewable integration is just as important as the technical challenges. Real-time supply and demand balancing often requires battery storage or backup from fossil fuel plants, raising operating costs. The production of renewable power can occasionally outpace the grid's ability to handle it. Operators are compelled to reduce—or stop—generation in certain situations, which results in wasted possibilities and monetary losses. Large batteries are an instance of energy storage devices that can reduce volatility and increase reliability, although the initial cost is still expensive. For renewable energy sources to be viable in the long run, more scalable and inexpensive storage options are essential.

5. Conclusion

This research emphasizes the favorable role of AI-integrated systems in enhancing both the efficiency and effectiveness of renewable energy integration in smart grids. Bu using advanced machine learning models for renewable energy generation and demand forecasting, the study demonstrates significant improvements in predictive accuracy especially for volatile energy sources such as solar and wind. Compared to traditional forecasting approaches, AI-driven models are better equipped to predict patterns, seasonal variations, and the inherent uncertainties in renewable energy production.

These advancements improve the reliability of grid operations, better resource planning, and increased capacity to utilize renewable energy without compromising grid stability. Enhanced forecasting capability enables utilities to optimize energy storage usage, reduce curtailment, and improve demand-response coordination, thereby supporting a resilient and adaptive grid infrastructure. Subsequently, the proper integration of AI technologies reduces dependency on fossil fuels, contributes to lower carbon emissions, and strengthens the overall sustainability of energy systems. The findings of this research reaffirm that AI-optimized smart grids hold substantial potential for accelerating the global transition toward clean and renewable energy futures.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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