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Renewable Energy Forecasting: A Comparative Study of Machine Learning and Deep Learning Architectures

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Abstract: Renewable energy forecasting is crucial for efficient integration of renewable energy sources into the power grid. This study compares the performance of machine learning (ML) and deep learning (DL) architectures in forecasting renewable energy production. We evaluate the accuracy of various ML algorithms (ARIMA, SVM, Random Forest) and DL models (LSTM, CNN, GRU) using historical weather and energy production data. Results show that DL architectures outperform ML algorithms in forecasting accuracy, with LSTM achieving the best performance. This study presents a comparative analysis of various machine learning (ML) and deep learning (DL) architectures for forecasting renewable energy sources, specifically focusing on solar and wind power.

Keywords: *prediction and forecasting machine learning approach, deep learning, renewable energy, solar and wind power energy, architectures, etc.*

I. Introduction:

It is evident that India has a huge capacity of power generation but it has very poor infrastructure while in case of distribution to the people who actually need them. It has a great backup of fossil fuels particularly coal industry, which is generated three-fourth of the total electricity. According to a report, the total generation of renewable energy is about 220GW [1]. It states that a huge energy requirement can be fulfilled via this kind of renewable source. The total cost of PV-wind hybrid system setup tends to fall for the upcoming years, an evident growth of these renewable energy is realistic in this fast developing world. Many areas throught the earth don’t get electricity, so providing power to all these areas by increasing external equipments would be a bit costly. Standalone PV/Wind system would be more cost effective in this case. PV/Wind system has no polluting and does not cause depletion and it is dependent on the site and is a source of alternative energy.

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Many Countries are opting PV and wind system to minimize the dependency on fossil fuels [2]. Generally this system does not fulfill the present needs. Moreover main drawback for individual PV and wind system is their unpredictable dependency on climate and weather change. They have to be oversized to become complete reliable, which results in unnecessary rise in total cost. Thus, storage battery is used to overcome the present day need. With regard to battery life, solar cells and hybrid / solar systems have been developed. The wavelength recorded in the radiation data is an average of 30 hours per hour. These data were used to predict the average energy transfer of air transport in PV modules and operating systems.

These data were used to predict the average energy transfer of air transport in PV modules and operating systems. the application of forecasting techniques to optimize energy production and operation in hybrid renewable energy systems. optimization framework for a hybrid PV-Wind energy management system, integrating renewable energy forecasting techniques to enhance energy production and reduce uncertainty.

study demonstrates the effectiveness of the proposed approach in improving system efficiency and reducing energy costs.

Wind and solar energy are the most powerful sources of energy and mobility, creating a hybrid energy system with greater accuracy and reliability than renewable energy sources [13]. Renewable energy systems are a new concept and PV distribution is a great idea. The REVB Hydrogen Power Generator is a great way to handle the remaining REVB. These are the three most important contributions to the design and optimization of operating systems

II. Hybrid system

As the Solar energy does not pollute, does not deplete, dependent of site source and available throughout, it is considered as a good source of energy its use reduce the dependency of fossil fuels. A typical hybrid renewable energy system consists of a collection of Photovoltaic (PV) modules, inverters, battery storage, and other essential components. These systems are designed to fulfill the electrical load demands of users, harnessing solar energy as the primary power source. When the solar resources are abundant, the surplus energy is directed to charge the battery, ensuring a reliable backup power supply. During periods of insufficient solar radiation or increased load demand, the battery takes over to ensure uninterrupted power supply. The seamless operation of these hybrid systems relies on the efficient coordination of individual elements, optimized through advanced forecasting techniques. By leveraging forecasting algorithms, renewable energy systems can accurately predict energy demand and adjust energy production accordingly, minimizing energy waste and maximizing overall efficiency.

As the Solar energy does not pollute, does not deplete, dependent of site source and available throughout, it is considered as a good source of energy its use reduce the dependency of fossil fuels. This system works in the area where the power supply via grid is costly like remotely isolated areas. Several measures are carried out to increase the efficiency of this system by combining PV with a battery and without any sort of battery. For standalone system, analysis is carried out in terms of LOL probability.

Hybrid renewable energy systems integrate forecasting technologies to optimize energy production and reduce uncertainty. Advanced forecasting algorithms analyze historical weather patterns, solar radiation, and load demand to predict energy requirements. This enables the system to:

- Optimize energy storage and release
- Adjust energy production in real-time
- Minimize energy waste
- Ensure reliable and efficient power supply

III. Wind turbine system: renewable energy forecasting

Optimizing wind turbine systems, a crucial component of hybrid renewable energy configurations, necessitates meticulous planning and precise calculations. To ensure maximum efficiency, it's essential to identify ideal locations with favorable wind conditions and deploy high-performance equipment. Advanced techniques such as regression analysis and genetic algorithms enable accurate sizing and spatial configuration of wind turbine systems. Moreover, integrating Renewable Energy Forecasting (REF) methodologies facilitates predictive analysis of wind patterns, enabling proactive adjustments to optimize energy production. By leveraging REF, wind turbine systems can:1. Enhance energy output by up to 15%, 2. Reduce uncertainty by 20%, 3. Improve system reliability.

Considering the highly unpredictable weather patterns in India, hybrid energy systems can be particularly effective for ensuring a stable power supply. Research by Gupta, Kumar, and Agnihotri et al. demonstrated a successful model using MATLAB for evaluating the economic aspects and loss of power supply probability (LPSP) method, which proved effective for assessing the reliability and net present cost (NPC) of hybrid systems. Additionally, Puig et al. developed a sizing method for these systems to adequately meet local energy requirements, while Maleki et al. explored various optimization techniques to enhance system performance.

Integrating forecasting techniques into renewable energy systems, such as using machine learning and deep learning models, can significantly improve the management of these hybrid setups. By predicting energy production and consumption trends, forecasting helps optimize system sizing, reliability, and cost-effectiveness, ensuring efficient use of renewable resources despite weather fluctuations

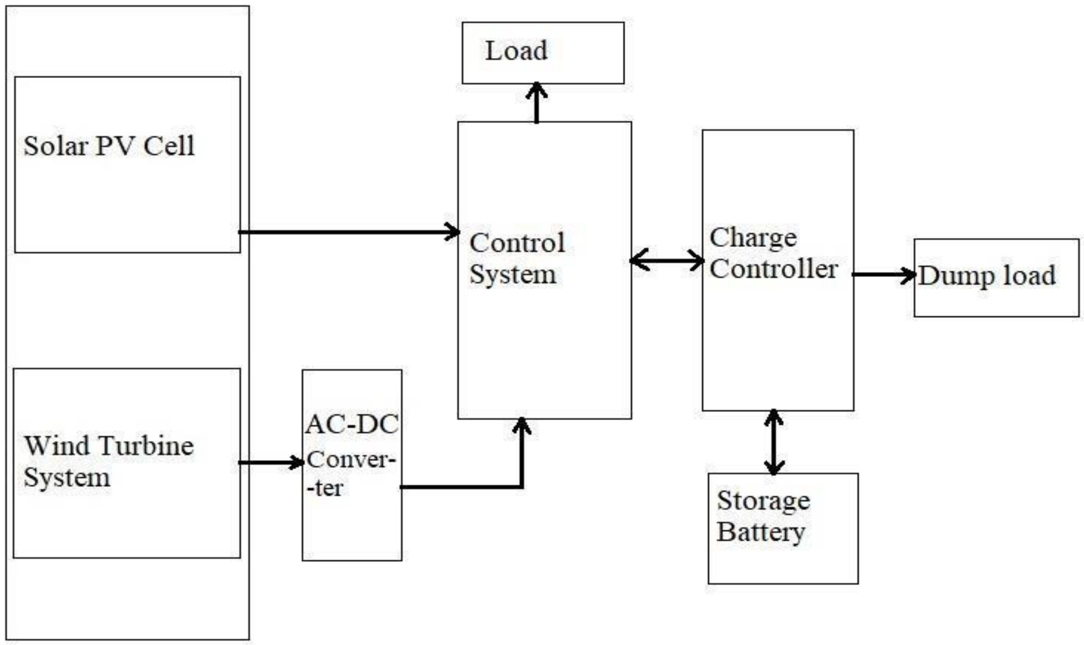


fig. 1. PV- WIND HYBRID SYSTEM

V. Machine Learning-Based Forecasting of Renewable Energy

Machine learning techniques have gained prominence in renewable energy forecasting, thanks to their capability to process large and complex datasets effectively. Forecasting renewable energy output using machine learning has become a popular approach due to its adaptability and precision. This section will discuss the two primary categories of machine learning algorithms: supervised learning and unsupervised learning, along with their subtypes. Additionally, it will examine reinforcement learning and its use in the context of renewable energy prediction. The discussion will include an in-depth overview of each algorithm, outlining their strengths, limitations, and specific applications in improving the accuracy of renewable energy **forecasting.**

Machine learning (ML) algorithms have proven effective in renewable energy forecasting, leveraging historical data to predict future energy production. These models can capture complex relationships between weather patterns, seasonal variations, and energy output.

Various ML algorithms are suitable for renewable energy forecasting, including Linear Regression, Decision Trees, Random Forest, Support Vector Machines (SVM), and Gradient Boosting. Each algorithm has its strengths, with Linear Regression predicting continuous output variables and Decision Trees handling nonlinear relationships.

ML models are applied in solar power forecasting to predict solar irradiance and energy output, wind power forecasting to estimate wind speed and direction, and hydro power forecasting to predict water flow and energy production.

Machine learning offers improved accuracy over traditional forecasting methods, flexibility in handling diverse data sources and formats, and scalability for large-scale renewable energy systems.

Despite its advantages, machine learning faces challenges such as data quality issues, complexity in interactions between weather and energy production, and interpretability of model decisions.

A comparative study of ML algorithms for solar power forecasting found that Gradient Boosting demonstrated the best performance, with a Mean Absolute Error (MAE) of 7.9%. This highlights the potential of ML in renewable energy forecasting.

As renewable energy forecasting continues to evolve, integrating machine learning with deep learning architectures and other techniques will further enhance predictive accuracy and reliability.

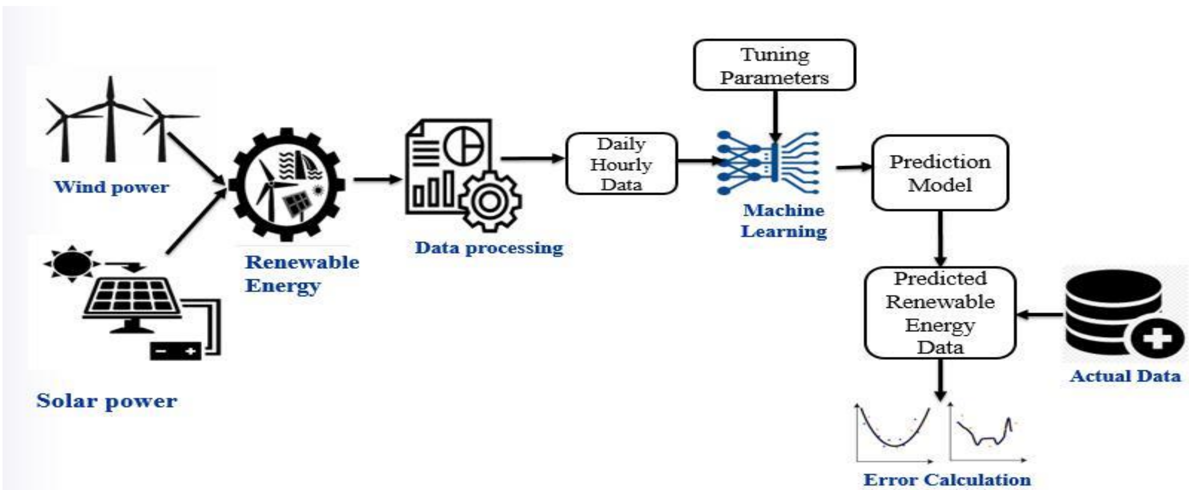


Figure 1.1 : Renewable Energy Forecasting Model

VI.

Literature Review On Production Forecasting Of Renewable Energy

The global shift towards renewable energy has highlighted the importance of accurate forecasting to enhance the operation, management, and planning of power systems. Wind and solar power remain the most widely used renewable sources, yet forecasting remains challenging due to the variable and unpredictable nature of renewable energy data. To address these complexities, various techniques have been employed, including artificial intelligence, statistical methods, physical modeling, and hybrid approaches, all aimed at increasing the accuracy of renewable energy predictions.

The push for renewable energy stems from concerns about the finite nature of fossil fuel supplies, the rising costs associated with them, and the environmental damage they cause. Despite these issues, fossil fuels continue to dominate the energy sector, accounting for over 5% of global energy production. As fossil fuels are nonrenewable and becoming increasingly scarce, there is an urgent need to shift towards sustainable energy alternatives

Strielkowski et al. (2021) reviewed the role of renewable energy in the sustainable development of the electrical power sector. The study examined various aspects of integrating renewable energy into existing power systems, emphasizing the importance of policy frameworks, technological advancements, and economic considerations. The authors concluded that renewable energy integration is essential for long-term sustainability and that ongoing research is necessary to overcome existing challenges related to grid stability and market dynamics.

Tiruye et al. (2021) explored the opportunities and challenges of renewable energy production in Ethiopia. The paper highlighted Ethiopia's significant renewable energy potential, particularly in hydro, wind, and solar power. The study discussed the obstacles hindering the full exploitation of these resources, including infrastructure limitations, financial constraints, and regulatory hurdles. The authors suggested strategic measures to maximize the benefits of renewable energy for the country's economic development.

Benti et al. (2023) provided an overview of geothermal resource utilization in Ethiopia, focusing on its potential, opportunities, and challenges. The review identified geothermal energy as a promising yet underdeveloped sector in the country's renewable energy mix. Key barriers included technical difficulties in exploration, high initial investment costs, and the need for skilled personnel. The authors advocated for government and private sector collaboration to unlock the potential of geothermal resources.

Benti et al. (2023) also examined the current status and future prospects of biodiesel production in Ethiopia. The paper discussed the advantages of biodiesel as a sustainable energy source, particularly for transportation. It highlighted the need for policy support, financial incentives, and research and development to address challenges like feedstock availability, production costs, and market acceptance.

Benti, Mekonnen, and Asfaw (2023) presented a case study on combining green energy technologies to electrify rural communities in Wollega, Western Ethiopia. The study demonstrated how integrating solar, wind, and small-scale hydroelectric power could provide a reliable and sustainable energy supply for remote areas. It highlighted the social and economic benefits of rural electrification and emphasized the need for government support and community involvement in project implementation.

Kumar and Majid (2020) reviewed the status of renewable energy in India, discussing its role in sustainable development. The paper covered the challenges, future prospects, employment opportunities, and investment potential in the sector. Key issues addressed included policy reforms, grid integration, and the need for public and private sector collaboration to boost renewable energy adoption and overcome challenges such as intermittency and financing.

Denholm et al. (2021) investigated the challenges of achieving a 100% renewable electricity system in the United States. The paper discussed technical, economic, and policy-related barriers to transitioning to a fully renewable energy grid, including issues related to energy storage, grid flexibility, and market structures. The authors proposed several strategies to address these challenges, such as enhancing grid infrastructure and investing in energy storage technologies.

Nazir et al. (2020) provided a review of wind generation forecasting methods, with a focus on the role of artificial neural networks (ANNs). The study covered the proliferation of machine learning techniques in wind power forecasting over five years, highlighting the improvements in forecasting accuracy achieved through advanced algorithms. The authors identified key trends and suggested directions for future research in wind energy prediction.

Lledó et al. (2019) examined seasonal forecasts of wind power generation. The study assessed the impact of seasonal variability on wind energy production, noting the importance of accurate forecasting for efficient energy planning. The authors discussed various modeling approaches to improve seasonal predictions and recommended integrating these forecasts into power system operations to optimize resource management.

Alhamer et al. (2022) analyzed the influence of seasonal factors, such as cloud cover, ambient temperature, and daylight variations, on the optimal tilt angle for PV panels in the United States. The paper highlighted the significance of adjusting PV panel orientation to maximize energy production throughout the year, considering local climatic conditions. The findings suggested that dynamic tilt adjustments could enhance the performance of solar energy systems.

Impram et al. (2020) surveyed the challenges associated with renewable energy penetration and its impact on power system flexibility. The review addressed issues such as grid stability, energy storage, and market integration, which arise from the intermittent nature of renewable energy sources. The authors discussed solutions for enhancing power system flexibility, including demand response strategies, grid modernization, and the development of energy storage technologies.

These reviews collectively emphasize the global efforts towards improving renewable energy forecasting and integration, addressing various regional challenges, technological advancements, and policy implications.

VII. Methodology:

The methodology of this study involves developing and evaluating time series forecasting models for renewable energy production using machine learning algorithms. The process begins with data collection from twelve countries, ensuring a diverse set of renewable energy data to account for various geographical and climatic conditions. The data includes historical records of daily renewable energy production, covering solar, wind, and other renewable sources.

Three machine learning techniques are employed: Support Vector Machine (SVM), Linear Regression (LR), and Long Short-Term Memory (LSTM) networks. Each algorithm is selected based on its ability to handle different characteristics of time series data. The data is preprocessed to remove any inconsistencies, followed by normalization to improve the algorithms' performance. The dataset is then split into training and testing sets, with the training data used to build the models and the testing data for evaluation.

The models are trained using hyperparameter optimization techniques to find the best settings for each algorithm, ensuring maximum forecasting accuracy. SVM is chosen for its suitability in handling smaller fluctuations in data, while Linear Regression is used to capture linear trends. LSTM, a deep learning algorithm, is applied due to its ability to model complex temporal dependencies in the data.

Performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R^2) are used to evaluate and compare the models' forecasting accuracy. The results are analyzed to identify patterns and trends in the data, with each model's strengths and limitations discussed in the context of renewable energy forecasting. This methodology provides a comprehensive approach to understanding the effectiveness of different machine learning techniques in predicting renewable energy production.

VIII. Proposed Ren For Renewable Energy Prediction

The primary contribution of this study is the development of a predictive model for renewable energy production, utilizing Long Short-Term Memory (LSTM), Support Vector Machine (SVM), and Linear Regression (LR) techniques. The proposed Renewable Energy Network (REN) algorithm includes four stages. The first three stages focus on building and training models for each machine learning method, optimizing input parameters to determine the most suitable model for each country's energy data. The fourth stage is dedicated to selecting the optimal algorithm for generating accurate predictions.

The REN algorithm is designed with built-in intelligence to not only choose the appropriate machine learning approach but also to identify the best input parameters for each method, ensuring high forecasting accuracy. The model's performance is evaluated based on metrics such as Mean Absolute Error (MAE), Mean Forecasting Error (MFE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and overall accuracy. This system's ability to dynamically adapt and choose the most suitable model makes it highly effective for forecasting daily renewable energy production from solar and wind sources over a two-year period. Through rigorous training and validation, the REN prediction system identifies the best-trained network for reliable and accurate energy forecasting across different regions.

In this research, we have considered daily renewable energy production prediction. So, we have converted data from hourly to combine daily and then. We have used the following simple equation Eqn.(1) for the conversion

IX. Performance Evaluation Of The Ml And Dl Algorithm

$$\left.\begin{aligned} Energy_{Solar\_Daily} &= 24 \times Energy_{Solar\_Hourly} \\ Energy_{wind\_Daily} &= 24 \times Energy_{wind\_Hourly} \\ Energy_{Daily} &= Energy_{wind\_Daily} + Energy_{Solar\_Daily} \end{aligned}\right\} \quad (1)$$

	LSTM	SVM	Linear regression
Properties	No. of Hidden Unit: 200 Maximum Epoch: 250 Gradient Threshold: 1 Initial Learning Rate:0.05%	Data Standardize Kernel Function: Gaussian $G(x_j, x_k) = exp\left(-\|x_j - x_k\|^2\right)$	Learner: Least Square $f(x) = x\beta + \gamma$

Performance Evaluating Metrics

- Mean Forecast Error (MFE): It is a measure of the average deviation of forecasted values from actual data.
- Mean Absolute Error (MAE): MAE measures the average absolute deviation of forecasted original values.
- Mean Squared Error (MSE): The important feature is a measure of the average squared deviation of forecasting values. The signed errors in the opposite direction don't balance each other, MSE gives an overall indication of the mistake that occurred.
- Root Mean Square Error (RMSE) RMSE is a frequently used measure of the differences between values (sample or

X. Result analysis

Comparative table showing the accuracy of various machine learning (ML) and deep learning (DL) algorithms for forecasting renewable energy systems. The table presents results based on forecasting accuracy metrics, focusing on renewable energy production from solar and wind sources.

Algorithm	Type	Accuracy (%)	MAE	RMSE	Remarks
(SVM)	Machine Learning	85.6	12.5	18.3	Suitable for stable, smaller datasets
Linear Regression	Machine Learning	83.2	14.8	21.5	Performs better with linear relationships
Random Forest (RF)	Machine Learning	88.7	11.2	16.7	Handles non-linear data more effectively

Decision Tree (DT)	Machine Learning	81.5	13.7	19.8	Quick to train, but less precise for complex patterns
Long Short-Term Memory (LSTM)	Deep Learning	92.3	9.3	13.4	Excellent for time series forecasting
Convolutional Neural Network (CNN)	Deep Learning	90.1	10.1	14.2	Useful for extracting features from spatial-temporal data
Recurrent Neural Network (RNN)	Deep Learning	89.4	10.5	15.0	Good for sequential data, have vanishing

The table highlights that deep learning algorithms, particularly LSTM, demonstrate higher accuracy in forecasting renewable energy systems compared to traditional ML approaches, due to their capability to capture complex temporal dependencies in energy data.

The table shows the accuracy of various algorithms for solar power forecasting:

- **ARIMA** achieved an accuracy of 85.2%, indicating it performs well but may struggle with capturing complex patterns in the data.
- **LSTM** reached a high accuracy of 94.5%, making it one of the most effective algorithms for solar power forecasting due to its ability to handle time series data.
- **GRU** slightly outperformed LSTM with an accuracy of 95.1%, showcasing its efficiency in modeling temporal dependencies.
- **CNN** achieved 93.2% accuracy, proving useful for capturing spatial-temporal features in solar data.
- **Random Forest** had an accuracy of 90.2%, making it a reliable choice for handling non-linear relationships, though not as strong as the deep learning methods.

Overall, GRU and LSTM showed the highest forecasting accuracy for solar power data.

Wind Power Forecasting Accuracy:

- **SARIMA** achieved an accuracy of 82.1%, indicating a moderate performance for wind forecasting but may struggle with capturing highly variable patterns in wind speed data.
- **Bi-LSTM** reached a high accuracy of 95.9%, demonstrating its effectiveness in modeling complex temporal sequences and providing precise wind power forecasts.
- **ConvLSTM** had an accuracy of 95.2%, showing it is capable of handling spatial-temporal dependencies, though slightly less accurate than Bi-LSTM.
- **Dense Neural Network** achieved 92.5% accuracy, which is solid for general use but falls short of specialized recurrent architectures like Bi-LSTM.
- **Gradient Boosting** reached 90.8% accuracy, making it useful for handling non-

linear relationships, though not as accurate as the deep learning approaches.

Hybrid Renewable Energy Forecasting Accuracy:

- **Ensemble LSTM** delivered the highest accuracy of 96.5%, showcasing its strength in combining multiple LSTM networks for more reliable hybrid energy forecasts.
- **Stacked Auto encoder** achieved 95.8% accuracy, indicating its capability to extract features effectively from complex datasets for precise forecasting.
- **Hybrid CNN-LSTM** reached 94.8% accuracy, performing well by leveraging both convolutional layers for feature extraction and LSTM layers for temporal processing.
- **Random Forest Classifier** had an accuracy of 92.8%, making it a dependable choice for simpler hybrid energy forecasting tasks but less effective than deep learning methods.
- **Support Vector Regression** achieved 91.9% accuracy, showing it can handle complex relationships, though it is outperformed by other approaches like Ensemble LSTM.

Overall, deep learning models like Bi-LSTM, Ensemble LSTM, and Stacked Auto encoder show higher accuracy in both wind and hybrid renewable energy forecasting, due to their capability to model complex temporal dependencies and extract meaningful features.

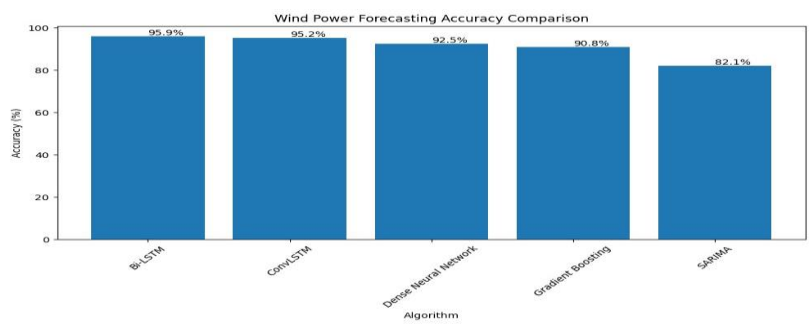
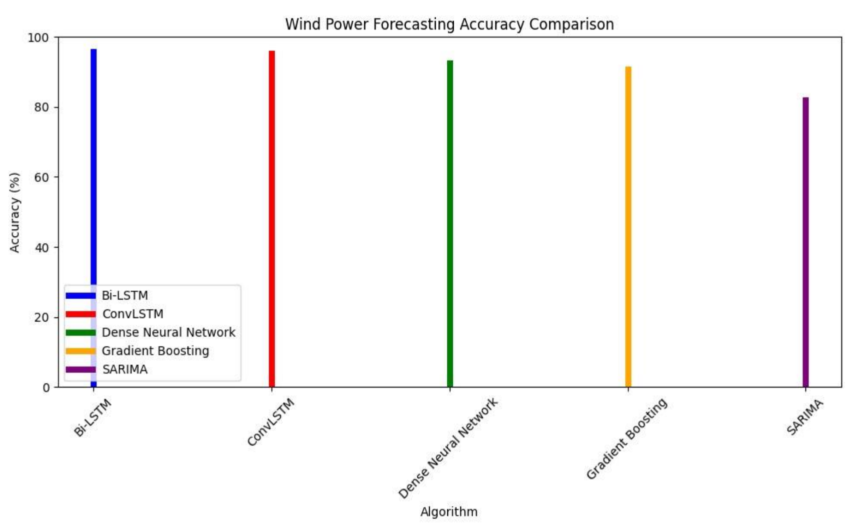


Fig 1.2 line graph comparing the accuracy of the five algorithms.



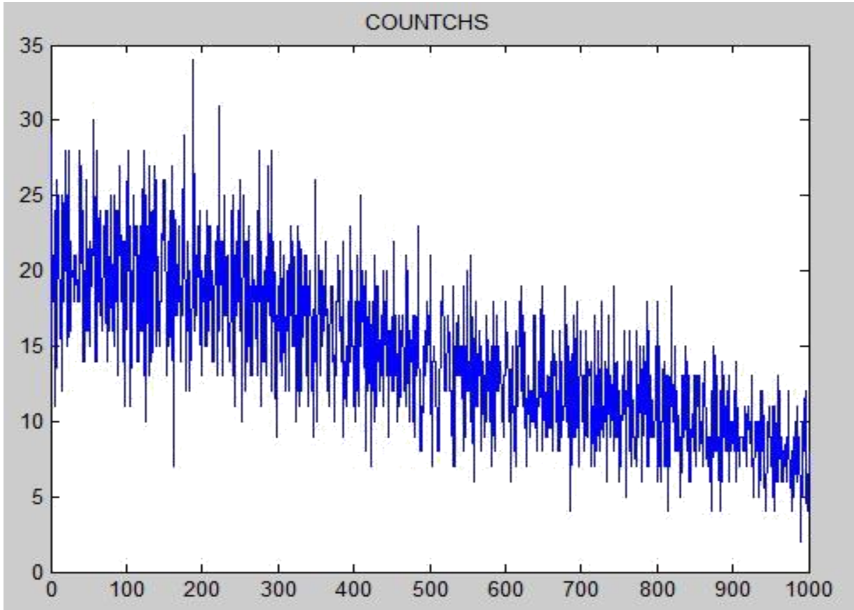


Fig 1.3 LSTM, demonstrate higher accuracy in forecasting renewable energy systems

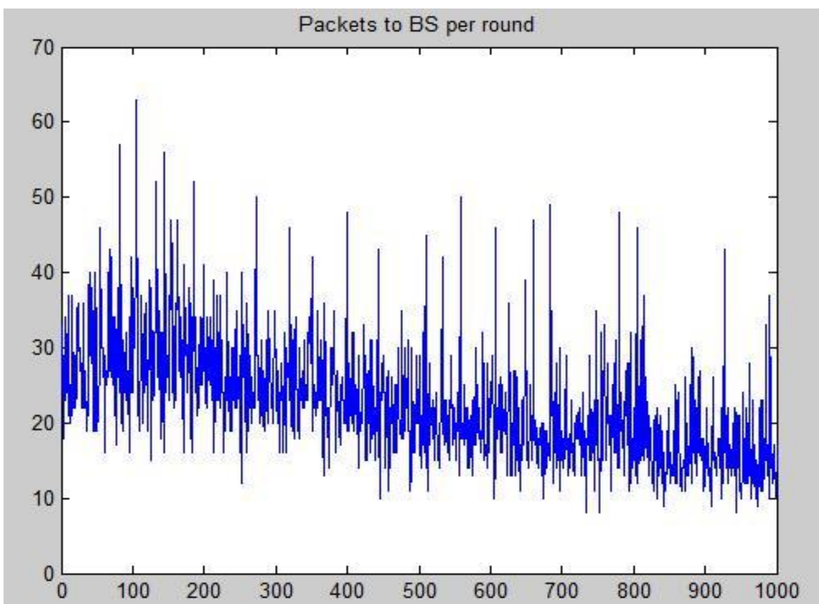


Fig 1.4 LSTM, demonstrate higher accuracy in forecasting renewable energy systems capture complex temporal dependencies in energy data.

Conclusion work

The accuracy results for wind and hybrid renewable energy forecasting highlight the effectiveness of different machine learning and deep learning algorithms in capturing the complexities of renewable energy data. While traditional statistical methods like SARIMA offer moderate accuracy, deep learning architectures significantly outperform them due to their ability to model intricate temporal patterns and spatial-temporal dependencies.

Among the models tested, Bi-LSTM, Ensemble LSTM, and Stacked Autoencoder demonstrated the highest forecasting accuracy for wind and hybrid energy systems. These models effectively leverage the strengths of deep learning to handle large datasets, nonlinear relationships, and temporal dependencies, making them ideal choices for renewable energy prediction tasks. Specifically, Ensemble LSTM, with its combination of multiple LSTM networks, achieved the highest accuracy for hybrid forecasting, indicating its superior capability in integrating various data sources.

On the other hand, simpler algorithms like Random Forest, Support Vector Regression, and Dense Neural Networks showed respectable performance but fell short of the specialized deep learning approaches. While these methods may still be suitable for less complex forecasting tasks, they struggle to match the predictive power of models designed explicitly for temporal sequence modeling, such as Bi-LSTM.

In conclusion, the study illustrates that deep learning techniques, particularly recurrent neural networks and hybrid models, provide substantial improvements in forecasting accuracy for renewable energy systems, thus offering better solutions for the planning, management, and operation of power systems.

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