Proceedings of the 8th International Conference on Trends in Electronics and Informatics (ICOEI-2025)
DVD Part Number: CFP25J32-DVD; ISBN: 979-8-3315-4459-1

Hybrid Approaches to Renewable Energy Forecasting for Grid Stability Enhancement

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Abstract - Renewable energy forecasting is crucial for maintaining grid stability, reducing curtailment, and optimizing energy utilization. However, forecasting wind and solar energy is challenging due to their intermittent and variable nature, influenced by complex weather patterns, non-linear dependencies, and seasonal variations. Additionally, issues like data quality, geographical differences, and computational constraints further complicate accurate predictions and integration with grid systems. This paper discusses the importance of renewable energy forecasting and evaluates the effectiveness of three predictive models: Long Short-Term Memory (LSTM), Facebook Prophet (F-Prophet), and AutoRegressive Integrated Moving Average (ARIMA) using real-world solar and wind energy data. The experimental results demonstrate that LSTM achieved a Mean Absolute Error (MAE) of 4.19, representing a 98.74% and 98.89% improvement over F-Prophet and ARIMA, respectively. For wind forecasting, LSTM recorded a remarkably low MAE of 0.056, outperforming F-Prophet and ARIMA by 99.99%. In terms of Root Mean Square Error (RMSE), LSTM also showed superior performance improving over F-Prophet and ARIMA by 71.05% and 76.88% in solar forecasting, and by 91.01% and 91.24% in wind forecasting. These results emphasize LSTM's effectiveness in capturing complex, non-linear relationships and temporal dependencies in energy generation data.

***Keywords** - Time-series prediction, machine learning, statistical modeling, seasonality modeling, performance evaluation*

I. INTRODUCTION

The increasing integration of renewable energy sources, such as wind and solar, into power grids is essential for sustainable energy development and reducing carbon emissions. However, the intermittent and variable nature of these energy sources presents significant challenges to grid stability and reliability [1]. Accurate forecasting of renewable energy generation is crucial for effective grid management, curtailment reduction, and energy optimization. Traditional forecasting methods often struggle with capturing non-linear dependencies, seasonal variations, and complex weather patterns associated with renewable energy [2]. Solar and wind energy are two of the most prominent sources of renewable power worldwide. As the demand for clean and sustainable energy continues to grow, accurate forecasting of solar and wind energy generation has become crucial. Solar energy depends on sunlight intensity and cloud coverage, while wind energy relies on wind speed and direction [3]. Both sources are inherently variable and weather-dependent, making accurate predictions challenging but essential for efficient energy management [4].

Traditional statistical models, such as AutoRegressive Integrated Moving Average (ARIMA), have been widely used for short-term energy forecasting due to their effectiveness in modeling linear relationships and stationary time series data. Studies have demonstrated ARIMA's capability in providing reliable short-term predictions for stable datasets; however, its limitations in capturing non-linear patterns and complex dependencies are well-documented [5]. By identifying the most effective forecasting method, this paper aims to contribute to optimizing renewable energy utilization, reducing grid instability, and advancing the sustainability of energy systems worldwide. Improved forecasting accuracy will not only enhance energy planning and distribution but also facilitate the transition to a more resilient and efficient renewable energy infrastructure.

The paper is structured as follows: Section II presents the related works. Section III details the proposed methodology for solar and wind energy forecasting. Section IV provides a detailed discussion of the experimental results. Finally, conclusion is given in Section V.

II. RELATED WORKS

Over the years, various forecasting techniques have been developed to address these challenges, ranging from traditional statistical models to advanced machine learning algorithms. Solar forecasting for renewable energy integration through different methods such as ARIMA, time-series regression, and other classical forecasting approaches are used for output prediction [6]. This research highlighted the vital role of precise solar forecasting as a standard practice to connect solar power generation with the electric grid while reducing power variability. The authors established that energy management required both numerical weather prediction modeling and statistical techniques to maintain grid stability.

A renewable energy forecasting enhancement by introducing Numerical Weather Prediction (NWP) models was investigated [7]. The research found that upper echelon weather predictions benefited from the application of statistical methods for more accurate short-term predictions. The researchers discovered that merging these hybrid strategies helped control renewable resources more efficiently and minimized forecasting inaccuracies, particularly under high renewable energy integration scenarios.

A data-driven forecasting approach that used deep feature selection to predict short-term wind patterns was experimented [8]. Deep learning models paired with feature selection techniques produced substantial improvements in wind power prediction accuracy, which developed into a better method for integrating wind power into the energy grid. The study demonstrated that predictive tools needed data-based strategies to develop superior forecasting models and achieve optimized energy management outcomes.

A forecasting of renewable power over very short time frames, focusing on rapid changes in energy production levels was tested using time-series models like ARIMA, Prophet, and hybrid approaches [9]. Their findings demonstrated that precise short-term predictions were necessary to prevent power grid instability caused by abrupt power output fluctuations. The research showed that improved forecasting technologies helped reduce power output volatility, thus enhancing renewable integration in power systems.

A direct and indirect renewable energy forecasting approaches incorporating hybrid models that combine ARIMA, LSTM, and Prophet was proposed and evaluated their roles in grid operational systems [10]. The researchers compared the advantages and disadvantages of both approaches, revealing conflicting levels of complexity and precision in their results. They concluded that combining direct and indirect approaches in renewable energy forecasting provided more accurate and dependable predictions. A residential electric vehicle (EV) operation optimization using DNN and clustering-based energy forecasting approaches [11]. Their research demonstrated that EVs held significant potential for optimizing energy consumption by enabling demand forecast analysis for planning optimal charging sessions. The findings suggested that advanced forecasting methods facilitated EV integration into the grid, enhancing grid stability and efficiency.

A various prediction techniques to improve renewable energy system optimization were experimented. A Predict+ Optimize methodology, integrating statistical forecasting techniques such as ARIMA and machine learning models was used to improve decision-making in renewable energy management. [12]. Their research analyzed different forecasting approaches and assessed their operational effectiveness in renewable energy prediction. The study concluded that a predictive optimization framework combining several forecasting approaches enhanced reliable operation and efficiency of renewable energy systems.

A recursive forecasting method specializing in value-based prediction of renewable energy generation using LSTM and Prophet was proposed [13]. Their research showed that an iterative learning process enhanced model accuracy by incorporating newly available data for prediction refinement. The study suggested that this approach improved renewable power system management and facilitated renewable energy integration within power grids.

A deep generative method to predict spatio-temporal renewable energy scenarios was proposed [14]. The study demonstrated that deep generative models effectively forecasted renewable energy generation at various spatial and temporal levels. The researchers highlighted the potential of deep generative models in analyzing complex renewable energy systems and enhancing forecasting outcomes.

A stochastic predictive energy management for renewable energy-integrated systems was proposed [15]. Their study revealed that stochastic approaches improved renewable energy prediction when combined with energy storage system control. The findings indicated that predictive models managing randomness enhanced renewable energy system efficiency by better handling production unpredictability.

Numerous studies have explored different forecasting techniques and their impact on renewable energy integration and grid stability. Research has highlighted the importance of precise solar and wind energy forecasting for efficient grid operations and energy optimization. Studies have also emphasized the role of numerical weather prediction models, data-driven deep learning techniques, and hybrid forecasting strategies in enhancing forecast accuracy. Despite these advancements, challenges remain in selecting the optimal model combinations and balancing computational complexity with accuracy.

This paper builds upon existing literature by evaluating the performance of three widely used forecasting models—LSTM, F-Prophet, and ARIMA—using real-world solar and wind energy datasets. It also explores the potential of a hybrid approach to enhance forecast accuracy and grid stability. By examining these models' strengths and limitations, this study contributes to the ongoing development of robust renewable energy forecasting methods, supporting the integration of renewable energy sources into power grids.

III. PROPOSED METHODOLOGY

A hybrid forecasting approach that combines ARIMA, LSTM, and F-Prophet models is proposed and explained in this section. The rationale behind this hybrid methodology lies in leveraging the complementary strengths of each model: ARIMA's accuracy in short-term stable forecasts, LSTM's ability to learn complex dependencies and handle fluctuations, and F-Prophet's effectiveness in capturing seasonal patterns and trends.

By integrating these models, the proposed hybrid approach aims to enhance forecasting accuracy, stability, and reliability. The methodology begins with data collection, data pre-processing, including cleaning, normalization, and feature selection, using real-world solar and wind energy datasets. Each model—ARIMA, LSTM, and F-Prophet—is then individually trained and evaluated to understand its performance in different scenarios. ARIMA is employed for short-term forecasts on stable datasets, LSTM is used for capturing non-linear dependencies and handling fluctuations, while F-Prophet focuses on modeling seasonality and long-term trends. The hybrid model is developed by combining the forecasts from these three models. Various ensemble techniques, such as weighted averaging and stacking, are explored to merge the predictions, aiming to minimize errors and improve overall accuracy.

A. Data Collection

The researchers have utilized genuine power output measurements from solar photovoltaic (PV) systems together with wind turbine facilities operating in different climatic zones. The datasets hold essential information about solar radiation, wind speed, temperature and power output records measured on an hourly or daily basis for detecting renewable energy generation pattern

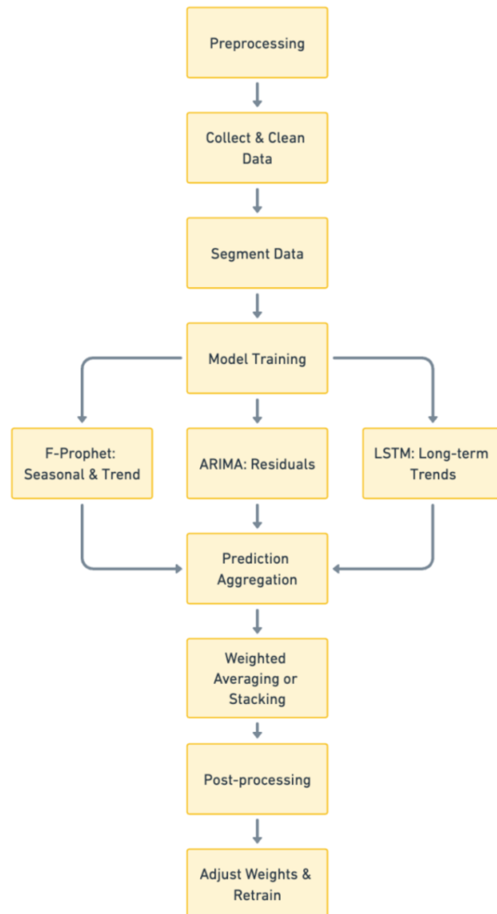

Fig. 1: Proposed Hybrid System Architecture

B. Data Preprocessing

The data collection process requires preprocessing to achieve a clean sufficient dataset that works for analysis. The data preparation includes addressing missing information and separating outliers while performing normalized transformation to scale all variables on a comparable level. All models receive their evaluation data from separate training, validation, and test sets that avoid the use of previously seen information for unbiased rating assessment.

- Load the dataset and inspect for missing values.
- Handle missing values using imputation techniques.
- Normalize continuous features to ensure uniformity in data distribution.
- Encode categorical variables (if any) for compatibility with machine learning models.

- Identify and remove outliers using statistical methods such as the Z-score or IQR method.
- Perform feature selection using Recursive Feature Elimination (RFE) or SelectKBest to retain only the most relevant features for forecasting

C. Model Training and Evaluation

To accurately forecast renewable energy generation, this study utilizes three predictive models—Long Short-Term Memory (LSTM), Facebook Prophet (F-Prophet), and AutoRegressive Integrated Moving Average (ARIMA). Each model is chosen for its unique strengths in handling time-series data complexities.

LSTM: A deep learning neural network called LSTM serves as the foundation to capture extended dependencies which exist between the non-linear time-series data elements. LSTM operates within TensorFlow framework to conduct its training process which learns to predict energy generation through analysis of historical data. The optimization process of hyperparameters including layer number together with learning rate and batch size takes place through experimental trials.

F-Prophet: The Facebook Prophet model functions to detect seasonal variations and transform patterns together with celebrating holidays. The model proves its worth when applied to energy production forecasting in practical scenarios because it retains clear interpretation of the results. The seasonal characteristics in renewable energy data are successfully identified through Prophet's modeling capabilities which help detect patterns and fluctuations.

ARIMA: Short-term predictive tasks employ the ARIMA model as their classical time-series forecasting technique. The ARIMA methodology establishes linear patterns in the data while showing effectiveness when short-term data stability prevails in a dataset. The parameters of ARIMA including autoregression order (AR) and differencing (I) along with moving average (MA) must be adjusted by statistically proven methods such as AIC (Akaike Information Criterion).

D. Performance Evaluation

The system's performance was rigorously evaluated using a variety of metrics to ensure its reliability and accuracy. The predictive models' accuracy level is evaluated through the combination of performance metrics including Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and R^2 score. Under this evaluation framework these metrics show the difference in predicted results compared to actual energy generation data to direct performance assessment.

IV. RESULT ANALYSIS AND DISCUSSION

A. Forecasting using ARIMA Model

This study employed the Open Power System Data (OPSD) dataset, a publicly available resource known for its comprehensive and high-quality information on power systems. The dataset provides detailed records of renewable energy generation, specifically solar and wind power output, along with relevant weather variables such as temperature, wind speed, and solar radiation. It served as the foundation for training and evaluating the predictive models—LSTM, Facebook Prophet (F-Prophet), and ARIMA—by leveraging its historical energy generation data. The dataset comprises 50,821 data points, combining both hourly and aggregated energy production values, and features 16 distinct attributes categorized into timestamps, production values, and installed capacity data. This rich time-series structure enabled the models to effectively capture complex temporal dependencies, seasonal trends, and non-linear relationships. Moreover, the inclusion of varying weather conditions and production scenarios allowed for a realistic and robust assessment of model performance.

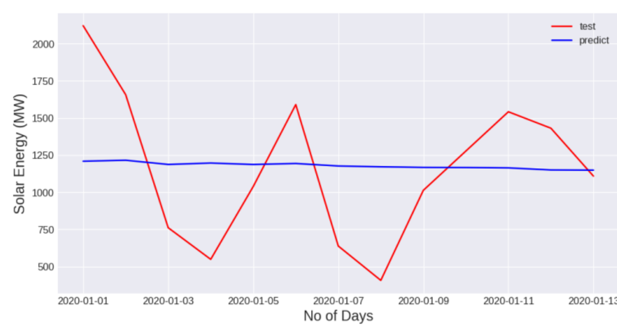

Fig. 2 ARIMA prediction for Solar Energy

Time-series forecasting heavily uses the AutoRegressive Integrated Moving Average (ARIMA) model when linear trend patterns without seasonal fluctuations appear in the dataset. ARIMA proves its best performance by predicting short-term patterns thus a 14-day prediction period was used for this analysis. The brief time frame enables the ARIMA model to detect energy generation linear patterns which makes it perform well for predictable datasets. ARIMA analyzes historical data effectively to forecast energy production at short durations because it produces trustworthy predictions in renewable energy systems for short-term forecasting. Figure 2 and 3 shows ARIMA prediction for and solar and wind energy respectively.

For the LSTM model, key hyperparameters included a learning rate of 0.001, a batch size of 32, 50 training epochs, a dropout rate of 0.2, and two LSTM layers. The Adam optimizer was used for efficient learning, with hyperparameters tuned through a trial-and-error approach to prevent overfitting and ensure faster convergence. Facebook Prophet was configured with a changepoint prior scale of 0.05 to control trend flexibility and used a multiplicative seasonality mode, which is better suited for energy-related trends. Holidays and special events were also included to capture fluctuations in energy demand, and grid search was applied to optimize seasonality settings and trend components. The ARIMA model's order parameters (p, d, q) were auto-selected based on the Akaike Information Criterion (AIC), with the differencing term (d) determined using KPSS and ADF statistical tests. AIC-based model selection was used to identify the optimal configuration and avoid overfitting.

Fig. 3 ARIMA prediction for Wind Energy

B. Forecasting using Facebook Prophet (F-Prophet) Model

Facebook Prophet (F-Prophet) stands as a robust forecasting model which effectively addresses seasonal patterns and long-term cycles with holiday effects thereby becoming appropriate for both short-run and extended-duration predictions. The adaptation features of Prophet differ from those of ARIMA because it detects alterations in trends and seasonality patterns which enables longer duration predictions. Figure 4 and 5 depicts the F-Prophet prediction for and solar and wind energy respectively.

Prophet model served as the forecasting model to predict renewable energy generation because its capacity enables it to detect extended patterns in energy manufacturing. Prophet stands as an excellent choice for forecasting renewable power generation since it understands essential seasonal patterns and enduring trends which help optimize energy distribution throughout power networks.

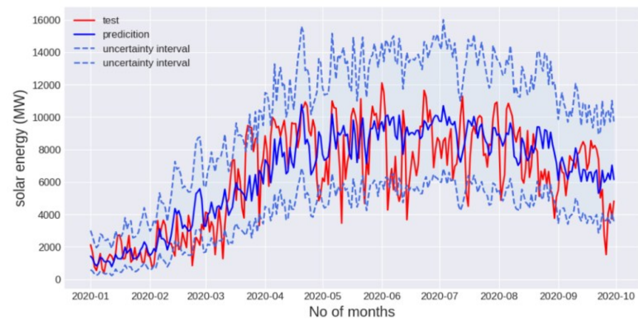

Fig. 4 F-Prophet prediction for Solar Energy

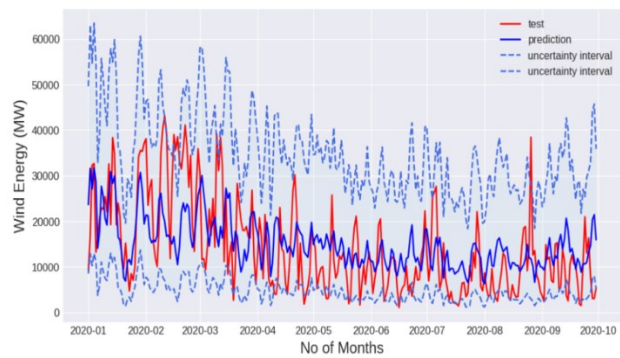

Fig. 5 F-Prophet prediction for Wind Energy

C. Forecasting using LSTM Model

The Long Short-Term Memory (LSTM) network demonstrates a strong ability to capture complex non-linear dependencies and long-term relationships in sequential energy generation data. In this analysis, LSTM was utilized to forecast renewable energy generation using hourly data, effectively capturing short-term variations. The wind power graph shows that the model closely follows actual generation trends, accurately predicting fluctuations with minimal deviation. Figure 6 and 7 depicts the LSTM prediction for and solar and wind energy respectively.

Similarly, the solar power graph indicates that the LSTM model effectively tracks the predictable daily pattern of solar energy production, aligning well with peak and low periods. LSTM's ability to retain long-term dependencies makes it well-suited for forecasting renewable energy, especially in fast-changing conditions like wind and solar power generation. The model delivers precise short-term predictions, supporting grid stability and efficient energy management.

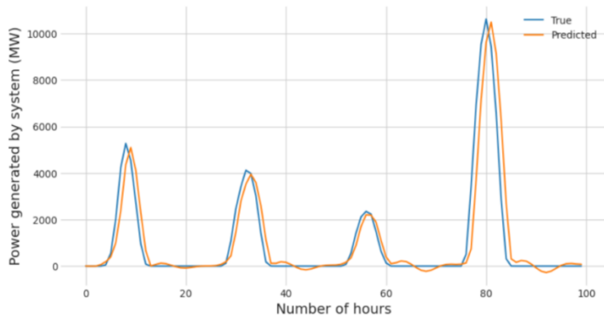

Fig. 6 LSTM prediction for Solar Energy

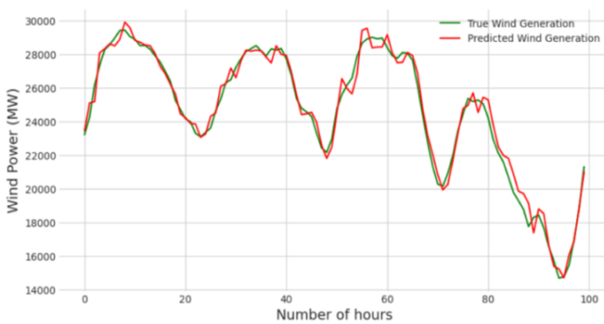

Fig. 7 LSTM prediction for Wind Energy

To enhance forecasting accuracy and improve the performance, multiple techniques were implemented, including data preprocessing, feature engineering, hyperparameter tuning, and model selection. Data preprocessing and feature engineering involved handling missing values using forward-fill methods to maintain data continuity, performing stationarity checks (KPSS & ADF tests) for ARIMA to determine the need for differencing, and extracting key features such as datetime attributes (year, month, day, hour), weather parameters (solar radiation, wind speed, temperature), and historical energy production data to enhance model input quality. Hyperparameter tuning and model optimizations were conducted for each model to enhance predictive performance.

D. Forecasting Error metric

Forecasting error metrics play a vital role in assessing the performance of these models by quantifying the differences between predicted and actual values. These metrics provide valuable insights into model accuracy, consistency, and reliability, helping to identify strengths and weaknesses in different forecasting approaches. Common error metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-Square Score are widely used to evaluate predictive accuracy. The MAE provides evaluation of error magnitudes by measuring average differences between predicted and actual values. This common measure helps establish direct insight about the regularity of prediction error intervals from actual measurement values. The predictive model performs well for forecasting purposes because it generates predictions that match actual values closely thus providing reliable output from the system.

The RMSE error serves as the main measure to determine how effectively the model controls big prediction errors. The Root Mean Square Error has higher sensitivity to deviations and affects models that generate major prediction mistakes negatively. The application of RMSE enables detection of model performance related to outlier and extreme value handling for maintaining realistic forecast values. The ability of models to predict with less error becomes more noticeable when their RMSE values drop because it shows better accuracy in forecasting without excessive discrepancies thus helping reduce energy waste and optimize renewable energy system management.

Table 1: Forecasting Error metrics of Solar Energy

Evaluation Metrics	**ARIMA**	**F-Prophet**	**LSTM**
Mean Absolute Error (MAE)	375.8117	333.5221	4 .18
Root Mean Square Error (RMSE)	520.8006	415.8739	120.42
R-Square Score	-0.4369	0.23	0.72

The R^2 score indicates the extent to which the model describes the data variations. In statistical terms a higher R^2 value shows that the model effectively understands patterns in the data analysis. The R^2 score of this project enables analysis of different forecasting models to determine their accuracy when fitting data patterns. The model requires higher R^2 to show genuine relationships while understanding renewable power effects on energy grid stability because accurate predictions depend on these relationships. Table 1 and 2 summarizes the forecasting error metrics for and solar and wind energy respectively.

The Lasso Regression, Ridge Regression, Decision Tree, Random forest, Support vector machine (SVM) are used to enhance prediction accuracy, reduce overfitting, and handle high-dimensional data effectively. Regression is particularly useful for high-dimensional datasets where only a few features are important, as it performs feature selection by shrinking some coefficients to zero, simplifying the model and reducing overfitting. These models are selected based on the dataset's nature, the problem requirements, and the trade-offs between accuracy, interpretability, and computational efficiency.

Table 2: Forecasting Error metrics of Wind Energy

Evaluation Metrics	ARIMA	F-Prophet	LSTM
Mean Absolute Error (MAE)	7182.29	6931.3293	0.05
Root Mean Square Error (RMSE)	8874.5958	8642.3231	776.9177
R-Square Score	-0.2247	-0.1614	0.9914

E. Performance of Machine Learning Models

Table 3: Comparison of Machine learning models for Solar Energy

Evaluation Metrics	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)	R-Square Score
Lasso Regression	32.91	58.73	0.99
Ridge Regression	1818.73	3873.79	0.69
Decision Tree	1800.10	3812.83	0.57
Random forest	33.07	68.11	0.99
SVM	6304.49	6818.35	-0.31

Table 4: Comparison of Machine learning models for Wind Energy

Evaluation Metrics	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)	R-Square Score
Lasso Regression	347.25	547.51	0.99
Ridge Regression	3458.21	6626.62	0.45
Decision Tree	2912.71	4946.91	0.61
Random forest	7906.52	10167.47	0.99
SVM	0.316	0.526	0.99

Lasso Regression is useful for selecting essential features while discarding irrelevant ones, enhancing feature selection in solar and wind forecasting. Ridge Regression reduces instability and overfitting, thus improving prediction generalization for variable energy datasets. Decision Trees analyze energy patterns effectively, making them suitable for short-term energy predictions involving environmental factors. Random Forests boost model accuracy by detecting non-linear relationships and reducing prediction errors in solar and wind energy generation. SVM efficiently handles complex, high-dimensional datasets, making it ideal for accurate wind energy forecasting amid fluctuating wind patterns. The table 3 and 4 summarizes which machine learning models work best for wind energy prediction. The SVM model delivers both the lowest prediction errors and best R-square score which together demonstrate superior accuracy when compared to other tested models alongside Random Forest.

V. CONCLUSION

This study evaluated the forecasting capabilities of ARIMA, Facebook Prophet, and LSTM for renewable energy prediction. ARIMA showed strength in short-term, stable trend scenarios, while Facebook Prophet effectively captured seasonality and long-term variations. LSTM, leveraging its deep learning architecture, outperformed both models by effectively handling complex non-linear patterns and temporal dependencies, particularly in high-frequency data. In solar forecasting, LSTM achieved a MAE of 4.19, improving over F-Prophet and ARIMA by 98.74% and 98.89%, respectively. For wind forecasting, it recorded a MAE of 0.056, with a 99.99% improvement over both models. RMSE results further confirmed LSTM's superiority, with gains of over 70% in solar and over 91% in wind forecasting. These findings highlight LSTM's accuracy and robustness. Additionally, the SVM model delivered the lowest prediction errors and highest R^2 scores, outperforming Random Forest and others. The study suggests that combining these models in a hybrid approach may further enhance forecasting accuracy and support more reliable renewable energy management systems.

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