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Comparative Analysis of Forecasting Models for Solar Wind Patterns: A Focus on Smoothing CNN-LSTM and a Hybrid Approach

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ABSTRACT

In this era of innovation, numerous researchers are striving to combat global warming and transform our planet into a greener and more sustainable environment. Their efforts focus primarily on reducing the release of harmful gases produced by conventional energy sources. This challenge can be mitigated by harnessing abundant renewable resources for various applications. This study explores the application of three distinct models, namely Convolutional Neural Network Long Short-Term Memory (CNN-LSTM), and Exponential Smoothing, for the prediction of solar wind patterns. The research aims to investigate the comparative performance of these forecasting techniques in capturing the dynamics of solar wind data. By leveraging the capabilities of deep learning through CNN-LSTM and the simplicity of Exponential Smoothing, we assess their effectiveness in providing accurate predictions for solar wind behavior. The results of this investigation have consequences for space weather forecasting and the understanding of solar-terrestrial interactions. Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and R-squared (R^2) are utilized for evaluating the manner in which a regression model performs. Wind speed and solar irradiation are predicted using four models are Exponential Smoothing model, LSTM model, CNN-LSTM model, and Smooth CNN-LSTM Model. The Exponential Smoothing model performs less well compared to the others, especially in terms of accuracy (MSE, RMSE) and explanatory power (R^2). "LSTM" and "CNN-LSTM" models have similar performance, with "CNN-LSTM" slightly outperforming "LSTM" with regard to RMSE and R^2. The "Smooth CNN-LSTM" model outperforms the other algorithms across all metrics, showcasing superior accuracy, precision, and explanatory power.

1. INTRODUCTION

Till now, our nation is a developing nation, many scholars have investigated the forecasting of available resources from wind and solar using different methodologies to make it a developed one. Tosun et al. [1] made wide research that underscores the efficacy of LSTM and CNN-LSTM models for the analysis and prediction of solar and wind energy data. This paper examines the factors influencing solar power generation and employs predictive models to achieve highly accurate intra-day solar power forecasts. These models successfully anticipate the forthcoming power output of the solar power facility, reaching an RMSE of less than 10%, all without the need for supplementary sensor data. In this work, a hybrid CNN-LSTM model is introduced for accurate forecasting of stable power generation in photovoltaic (PV) systems. This model excels in predicting power generation even in response to sudden weather condition shifts. By optimizing operations in PV power plants, this proposed model proves to be an efficient tool for forecasting solar energy production with precision, showcasing its effectiveness in achieving accurate predictions of solar energy output [2].

The author's primary focus lies in the realm of wind energy, where they introduce an LSTM model designed to forecast direction, speed, and the energy of the wind, yielding promising outcomes. Furthermore, they present a data analysis model that leverages the LSTM a model for monitoring power generation from Wind power. The results exhibit notable accuracy, a mean error of under 3% and an impressive R-Squared value of 0.95 [3]. Analyzes data on wind power time series and proposes a GA LSTM model for fluctuating wind energy prediction, demonstrating higher prediction accuracy compared to traditional methods. It proposes a wind power forecasting approach based on a deep learning model combining LSTM broadened using a GA [4].

LSTM emerges as a predictive model to predict the amount of solar radiation and photovoltaic power, surpassing the performance of traditional machine learning techniques. This study conducts a comparison between Separate LSTM and combined models that integrate LSTM, revealing LSTM's superiority in predicting solar energy when contrasted with other standalone models [5]. The paper presents a framework that synergizes a physics-based model with LSTM to enhance the accuracy of power output predictions for wind farms. Physics-based models such as FLORIS have the capability to estimate power generation based on atmospheric data over a given time series [6]. The authors concentrate on scrutinizing wind turbine data within a SCADA system. They utilize LSTM networks to project wind turbine performance, with the overarching goal of enhancing wind energy forecasting and operational efficiency. Through the utilization of LSTM models, the authors showcase the capacity to enhance prediction accuracy and actively contribute to the optimization of renewable energy sector wind turbine operations [7].

The authors conduct a comprehensive survey of various techniques employed in the discipline of anticipating renewable energy. The study explores a range of methods and approaches for predicting renewable energy generation, encompassing sources such as wind and solar power. This survey paper serves as a valuable resource for understanding the diverse techniques available for forecasting renewable energy production. It provides insights into the current state of research and offers an overview of the methodologies used in this important area of renewable energy management. It concludes that LSTM and RNN are advantages of forecast of solar and wind power generating time series [8]. The authors concentrate on the use of LSTM networks for predicting the power output of solar photovoltaic systems. Their study is centered around improving the accuracy of forecasts for solar energy generation. By utilizing LSTM networks, the authors demonstrate their effectiveness in enhancing the precision of solar photovoltaic power output predictions. This research contributes to the field of renewable energy forecasting, particularly in the context of solar power, offering valuable perceptions of the potential of LSTM-based prototypes for optimizing solar energy management and utilization. A key component of the deeper RNN is a layered LSTM network [9].

Wind and solar power forecasting are challenging, the authors delve into the critical domain of time series forecasting within the context of renewable energy. This work explores various techniques and methodologies for predicting renewable energy generation. By examining time series data, the study provides information about forecasting models and their application in renewable energy systems. It is a significant source of information for researchers and practitioners looking to deepen their comprehension of time series forecasting as it relates to renewable energy sources, contributing to the advancement of sustainable energy management and utilization [10].

The authors focus on predicting solar energy generation using LSTM profound understanding techniques. This research explores the utilization of LSTM models to forecast solar power output. The study demonstrates the effectiveness of LSTM-based deep learning in enhancing the accuracy of solar energy predictions. This work adds to the area of renewable energy forecasting by presenting the potential of advanced machine intelligence methods like LSTM for optimizing the utilization of solar energy resources. To precisely predict the generated power of solar photovoltaic power plants, deep learning methods are employed [11]. The author conducts a thorough analysis of hybrid models used to forecast wind power, with a specific focus on the application of LSTM networks. The paper provides an overview of various hybrid approaches that combine LSTM with other techniques to enhance the accuracy of wind power predictions. By reviewing the existing research, it offers insights into modern technology methods for predicting wind energy production. This survey is valuable for researchers and practitioners seeking to improve wind power forecasting models and strategies. Wind power's unpredictable nature has an enormous effect on the power system [12].

The study's main goal is to create a more effective technique for forecasting solar radiation in the near future, which is essential for optimizing the performance of solar energy systems. The authors propose the use of a hybrid model that combines CNN’s and LSTM networks. CNNs are effective at feature extraction from spatial data, while LSTMs excel in capturing temporal dependencies. A significant contribution of this research is the exploration of different time intervals for predicting solar radiation. The authors investigate various time intervals to identify the most suitable one for accurate predictions. The paper emphasizes the importance of both efficiency and accuracy in short-term solar radiation forecasting. The goal is to find a balance between computational efficiency and prediction precision. Compared to the SVR model, the CNN-LSTM hybrid model produced superior results [13].

PV and wind energy have enhancing results, the authors investigate the variability in the output of intermittent energy sources using data from NASA. Presented at the 2nd ICPRE Conference, the research explores the fluctuations in energy generation from sources such as solar and wind power. By leveraging NASA data, the authors offer insights into the patterns and characteristics of intermittent sources of energy. This study improves our knowledge of the difficulties and possibilities connected to harnessing renewable energy, particularly in addressing the intermittency and variability inherent to these sources [14].

The authors introduce a probabilistic forecasting model designed to provide precise estimates of power generation from photovoltaic (PV) solar and wind sources. The paper focuses on enhancing the accuracy of predictions for renewable energy generation, particularly from PV solar and wind systems. By incorporating probabilistic modeling, the authors aim to improve the reliability of forecasts, which is essential for efficient energy management and grid integration. This work contributes to the advancement of renewable energy forecasting techniques, addressing the variability inherent in solar and wind power generation. It is suggested to use a probabilistic method to estimate the solar irradiance and hourly wind speeds throughout a year [15].

The study's primary goal is to explore the relationship between coronal holes on the outermost layer of the sun and the solar wind's following actions, with the aim of improving solar wind forecasting. Areas on the surface of the Sun known as coronal holes where particles from the solar wind can more readily escape and the magnetic field is open. The paper examines how the presence and characteristics of these holes correlate with solar wind properties. The authors analyze observational data to identify and track coronal holes. They also investigate how the solar wind speed and other parameters change in response to the existence of these features. The study discusses the potential implications of using coronal hole observations for solar wind forecasting. Coronal holes may serve as valuable indicators for predicting solar wind conditions and space weather data. Up to 8.5 days ahead of time, the model can predict the Earth-directed solar wind velocity [16]. These papers focus on the use of SVR for predicting solar power. Author presents an SVR model for producing solar power forecasts up to 24 hours ahead. For energy forecasting, the effectiveness of various linear regression models and artificial neural networks is contrasted with the SVR model. The production of variable energy is rapidly increasing, especially from wind and solar energy resources [17].

The article offers a synopsis of the capabilities and challenges in the field of real-time solar wind forecasting. It highlights the crucial role of accurate solar wind predictions in mitigating the effects of space weather on Earth's technical infrastructure and underscores the need for collaboration and ongoing research to enhance forecasting capabilities. The main issue limiting the accuracy of solar wind models used for space weather research and prediction is the uncertainty in figuring out the physical parameters required for model inputs from real-time solar metrics [18].

This paper focuses on the establishment of a viable model for predicting the solar wind's behavior using numerical models. It highlights the importance of such forecasts for space weather prediction and their impact on various technological systems. This research contributes to the ongoing efforts to improve space weather forecasting capabilities. The Wang-Sheeley-Arge model that anticipates the solar wind speed time series most accurately [19]. This paper addresses the estimation of Uncertainties in the fast solar wind back mapping, an essential aspect of solar physics and space weather forecasting. It contributes to the ongoing efforts to enhance our understanding of solar wind behavior and its implications for space weather and astrophysical research. There is uncertainty in the fast solar wind's back mapping [20].

The authors provide a comparative analysis of the two forecasting methods, assessing their accuracy and performance in predicting wind energy generation. This paper presents a comparative study of wind energy forecasting techniques, specifically the ARIMA stochastic model and the FFANN neural network model. It contributes to the domain of renewable energy by providing perspectives on the relative effectiveness of these two approaches, ultimately seeking to increase wind energy's accuracy forecasts for better energy management and grid reliability. An examination is made between a neural network-based model and a stochastic model for predicting the output of electrical energy from renewable sources, including wind power [21].

The authors employ neural network techniques to create a forecasting model. Neural networks are renowned for their capacity to identify intricate links and patterns in data, making them appropriate for renewable energy forecasting. The prediction model is known as a Feedforward backpropagation neural network. This paper addresses the challenging task of forecasting the combined generation of wind and solar energy using neural network models. By providing a viable method for maximizing the integration of these renewable sources into the power grid for more sustainable energy management, the research advances the subject of renewable energy forecasting [22].

The survey highlights that forecasting solar and wind energy can effectively predict the availability of resources in a specific area, enabling efficient energy storage to meet future demands and establish renewables as a sustainable energy source.

Although various methodologies exist for forecasting, deep learning techniques have not been extensively utilized to enhance renewable energy forecasting. Hence, the decision was made to employ the CNN algorithm to optimize the parameters for renewable energy sources.

The upcoming sections are structured as follows: Section 2 discusses the methodologies, Section 3 focuses on wind prediction analysis, Section 4 addresses solar prediction analysis, and the study concludes in Section 5.

2. METHODOLOGY

The following subsections provide an overview of the algorithms used in this work to forecast wind and solar power.

2.1 Exponential smoothing model

A time period forecasting method called exponential smoothing gives different historical observations varying weights. Whenever examining time series data, SES works well when the recent past is more predictive of the future than the distant past. The current observation (Ot) and the prior forecast (Et-1) are weighted averages to create the forecast (Et), where α emphasizes more recent data.

$$Et = \beta Ot + (1 - \beta) \tag{1}$$

where, $0<\beta<1$ is the smoothing parameter.

2.2 LSTM smoothing model

The LSTM is an effective instrument for capturing dependency relationships in data sequences because of these equations, which enable it to store, update, and retrieve information selectively.

In order to solve the vanishing gradient issue that plagues conventional RNNs, LSTMs were created, which enhance their ability to recognize long-range dependencies in sequential data.

Memory cells are long-term information storage, is feature of LSTM memory cells, which enables them to recognize patterns over long periods of time. The input, output, and forget gates allow LSTMs to selectively store or discard data by managing information traveling into, out of, and within the memory cell. Instruction is BPTT, or backpropagation through time, is used to train LSTMs. They acquire the ability to reduce the discrepancy between the values that were expected and those that were actually by adjusting the weights of connections. Sequence Input is LSTM models can be built to forecast one future value given a sequence of values or a series of future values of input data. The number of layers and the rate are hyperparameters of learning, the amount of LSTM units, and the length of the sequence used for training constitute significant hyperparameters.

Xt-input

Ht-Hidden state

Ct-Cell state

It, *Ft*, *Gt*, and *Ot* are Input, forget, cell, and output gates, correspondingly.

W and *β* are input weight matrices and bias vectors for input, forget, cell, and output gates [23].

p and $tanh$ are Sigmoid and Hyperbolic tangent activation function.

$$It = p(Wii * Xt + \beta ii + Whi * ht - 1 * \beta hi) \quad (2)$$

$$Ft = p(WiF * Xt + \beta iF + WhF * ht - 1 * hF) \quad (3)$$

$$Gt = tanh(WiG * Xt + \beta iG + WhG * ht - 1 * hG) \quad (4)$$

$$Ct = Ft * Ct - 1 + It * Gt \quad (5)$$

$$Ot = p(WiO * Xt + \beta io + Who * ht - 1 * \beta ho) \quad (6)$$

$$Ht = Ot * tanh\ (Ct) \quad (7)$$

When given a series of input data, LSTMs can be made to forecast a single future value or the model with these metrics performs better than the one you previously mentioned, according to the lower values of MSE, RMSE, and MAE.

2.3 CNN-LSTM model

A powerful architecture that is frequently employed for sequence prediction tasks involves the combination of CNNs and LSTMs. This combination is especially advantageous when interacting with time series data or sequential data that has geographic characteristics. CNNs excel at obtaining features from spatial data and identifying patterns across different abstraction levels. LSTMs are good at photographing temporal patterns and modeling sequential dependencies.

Typical CNN components model is:

$$Ci = \alpha(\Sigma iWij * Xj + Bi) \quad (8)$$

$$Pi = \text{Pooling}\ (Ci) \quad (9)$$

$$F = \text{Flatten}\ (P) \quad (10)$$

Ci is Output feature map, Wij is Convolutional filter, Xj is Input feature map, Bi is Bias term, Pi is Pooled feature map and F is Flattened feature vector. The above CNN components model is combined with LSTM model.

2.4 Smooth CNN-LSTM model

When using smoothing together with a CNN-LSTM architecture, temporal as well as spatial characteristics from the CNN-LSTM are combined, and the smoothing attributes of exponential smoothing are utilized for time series data. To train the combined model, an appropriate optimization algorithm is applied. It is necessary to optimize the weights and parameters of the CNN-LSTM and exponential smoothing components simultaneously. A wide range of time series forecasting applications, such as sales, stock price, demand, traffic, and weather forecasting, can be applied with the Smooth CNN-LSTM model [24].

Figure 1 explains the Flowchart for Exponential smoothing CNN-LSTM model. Data Collection and Preparation: Gather and organize the time series data. Assemble the CNN architecture by specifying the number of convolutional layers, kernel sizes, and activation functions. Preprocess the data by normalizing or transforming it as necessary. Give the number of layers, LSTM units, and activation functions to define the LSTM architecture. CNN-LSTM Model Training: Utilize training data to train the model Make Predictions: Forecasts for new data are produced by using the trained model. Use the exponential smoothing method. CNN-LSTM forecasts are smoothed. Examine the model by contrasting the actual values with the smoothed forecasts [25].

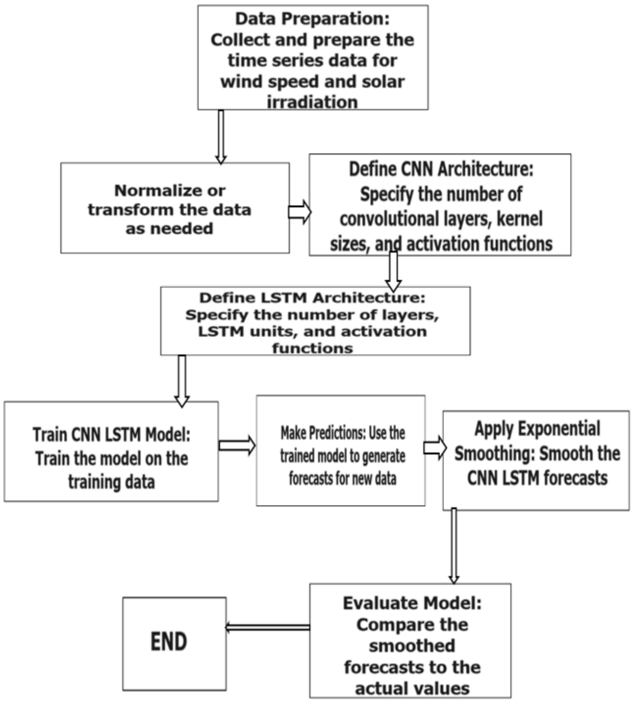

Figure 1. Flowchart for solar irradiation prediction and wind speed forecasting using smoothing CNN-LSTM model

3. ANALYSIS FOR WIND PREDICTIONS

The accuracy of solar and wind forecasting models can be impacted by various factors such as data quality, model complexity, geographic variability, and others. Therefore, meticulous attention to data quality, model architecture, and the training process is crucial for optimizing performance. In this study, various algorithms have been integrated to effectively forecast the availability of renewable resources. The Data was taken from NASA Native Resolution Powered by CERES/MERRA2.

Daily data: January 1, 2010, through June 30, 2024 (month, day, year).

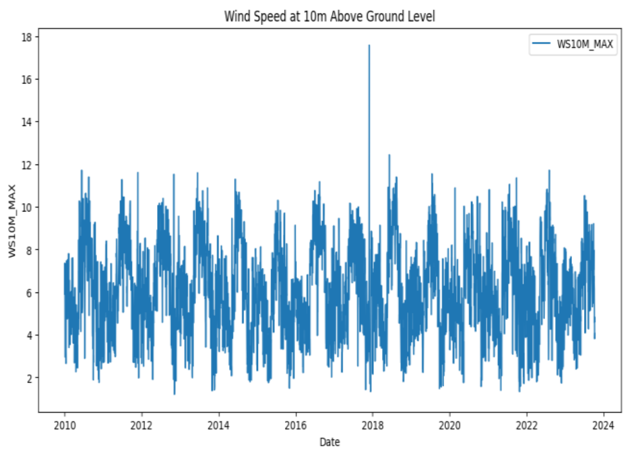

Figure 2. Wind speed at 10 m above ground level

Location: 77.5227 latitude, 8.2509 longitude and Figure 2 gives wind speed at 10m above ground level.

The term mean squared error (MS) refers to the average of the squared differences between the actual and expected values. Large errors are penalized more severely than little errors due to the squaring.

The root of the square root of the mean square error, or RMSE, is calculated. It offers a measurement of the typical size of the anticipated value errors. The dependent variable and it both have the same unit.

The mean absolute error, or MAE, is the average of the absolute differences between the expected and actual values. R-squared (R^2). The degree to which the model's predictions and the actual data agree is expressed by this statistic. It shows the percentage of the dependent variable's volatility that can be predicted based on the independent variable.

3.1 Exponential smoothing model for wind speed prediction

The Exponential smoothing model may not provide an optimal match for the data, or there may be potential for improvement, as shown by the lower R-squared values and the somewhat high MSE, RMSE, and MAE values. For a better-fitting model, a higher R^2 and lower MSE, RMSE and MAE value are often preferred.

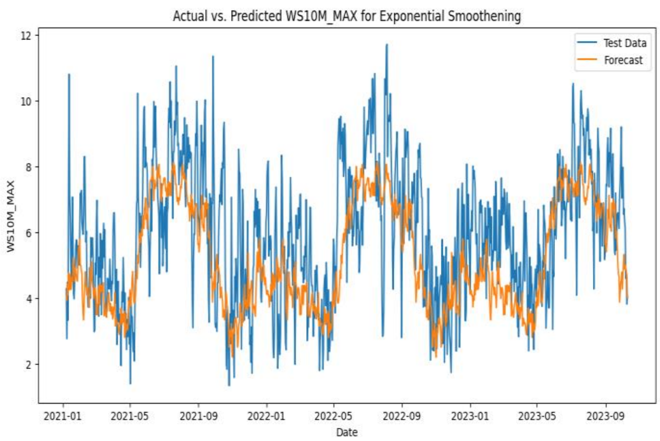

Figure 3. Actual vs. Predicted WS10M_MAX for exponential smoothing

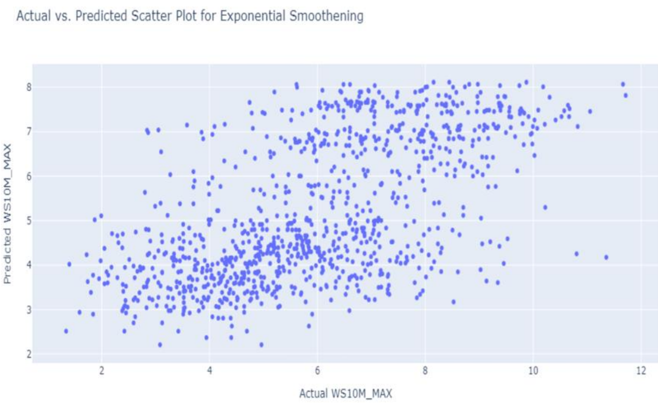

Figure 4. Actual vs. Predicted Scatter Plot for exponential smoothening

WS10M_MAX=Wind Speed at a Maximum Ten Meters (m/s)

The output taken using Exponential smoothing Model. Figure 3 gives Actual vs. Predicted WS10M_MAX for Exponential Smoothening and Figure 4 denotes Actual vs. Predicted Scatter Plot for Exponential Smoothening.

The dataset contains 5110 data points. In the four models, 79% (4015) of the dataset is used for training and 21% (1095 datasets) is used for testing. This is applicable for solar irradiation forecasting and wind speed forecasting.

3.2 LSTM smoothing model for wind speed prediction

The estimates are more likely to match the actual values when the MSE, RMSE, and MAE are lower. When compared to the Exponential smoothing model (R-squared of 0.20), the higher R-squared value (0.66) suggests this model explains a greater percentage of the variance in the variable that is reliant. A greater R^2 indicates a better fit. Figure 5 gives Actual vs. Predicted WS10M_MAX for LSTM Smoothening, and Figure 6 denotes Actual vs. Predicted Scatter Plot for LSTM Smoothening.

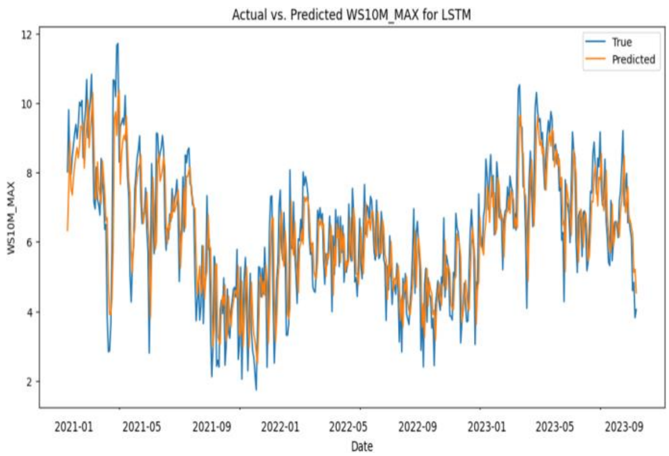

Figure 5. Actual vs. Predicted WS10M_MAX for LSTM

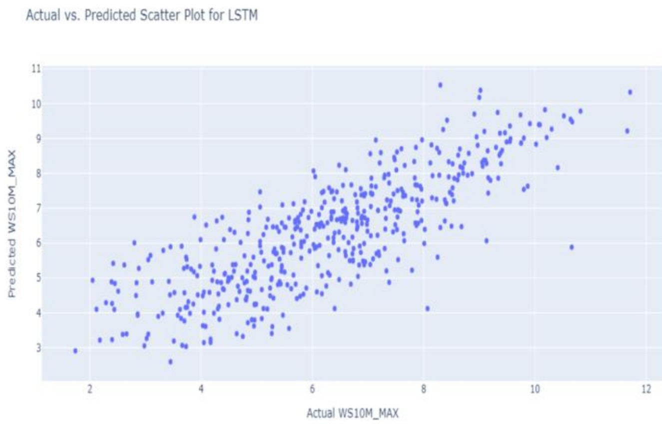

Figure 6. Actual vs. Predicted Scatter Plot for LSTM

3.3 CNN-LSTM model for wind speed prediction

The CNN-LSTM model seems to have an acceptable level of accuracy based on the MAE, MSE, and RMSE metrics. Since the values are not exceptionally high, the model's predictions are, on average, not sufficiently far off from the actual values. An appropriately good fit can be determined by the R-squared value of 0.67.

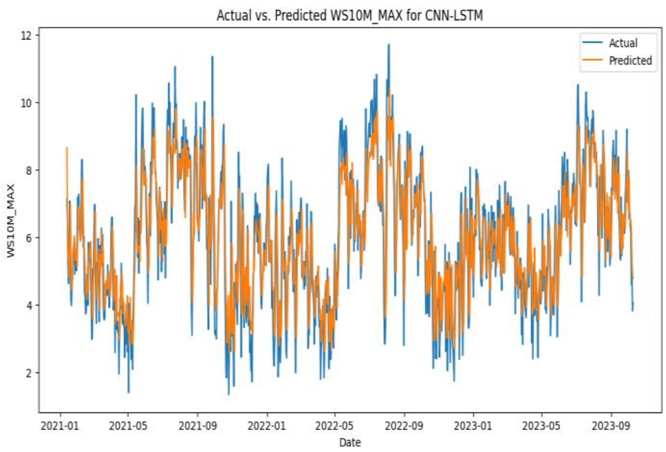

Figure 7. Actual vs. Predicted WS10M_MAX for CNN-LSTM

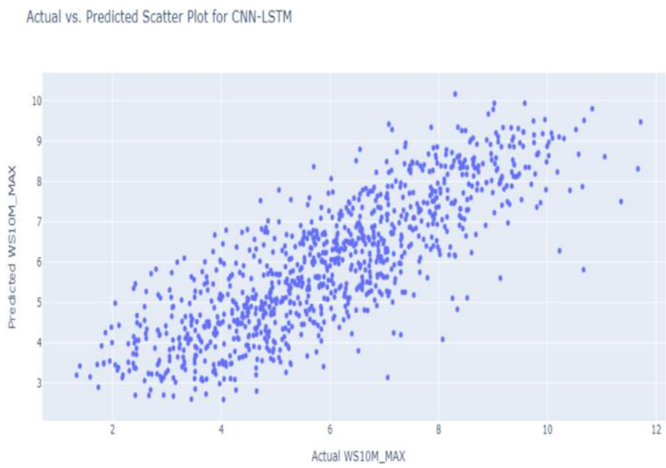

Figure 8. Actual vs. Predicted Scatter Plot for CNN-LSTM

This model handles a significant portion of the data variability, it might still be improved. Figure 7 shows Actual vs. Predicted WS10M_MAX for CNN-LSTM and Figure 8 denotes Actual vs. Predicted Scatter Plot for CNN-LSTM.

3.4 Smooth CNN-LSTM Model for wind speed prediction

Smooth CNN-LSTM model produces very accurate predictions with average error values that are very close to zero, as shown by the low MAE, MSE, and RMSE values. With a high R-squared value of 0.98. This model has a very strong explanatory power and appears to be catching practically all of the data's fluctuations and patterns.

Figure 9 gives Actual vs. Predicted WS10M_MAX for Smooth CNN-LSTM, and Figure 10 denotes Actual vs. Predicted Scatter Plot for Smooth CNN-LSTM.

Table 1. Comparison of evaluation metrics for wind forecasting

Algorithm	MAE	MSE	RMSE	R^2
LSTM	0.8962879619	1.282727664	1.132575677	0.6582805554
CNN-LSTM	0.8961970531	1.314920129	1.146699668	0.6752102337
Exponential Smoothening	1.439943771	3.271722413	1.808790318	0.1962437026
Smooth CNN-LSTM	0.1798849493	0.05209774487	0.2282493042	0.9791479698

All metrics show that the "Smooth CNN-LSTM" model operates more effectively than the other algorithms, demonstrating increased accuracy, precision, and explanatory power. When compared to the other models, the "Exponential Smoothing" model performs worse, particularly when it comes to explanatory power (R^2) and accuracy (MSE, RMSE). The "CNN-LSTM" model surpasses the "LSTM" model with regard to RMSE and R^2, but both models perform similarly. In conclusion, Smooth CNN-LSTM Model seems to be operating very well based on these metrics. The model accounts for a great deal of the variability in the data and is producing precise predictions with very little error.

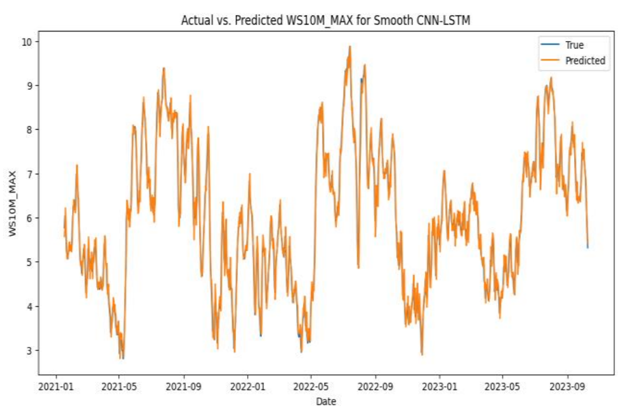

Figure 9. Actual vs. Predicted WS10M_MAX for exp Smooth CNN-LSTM

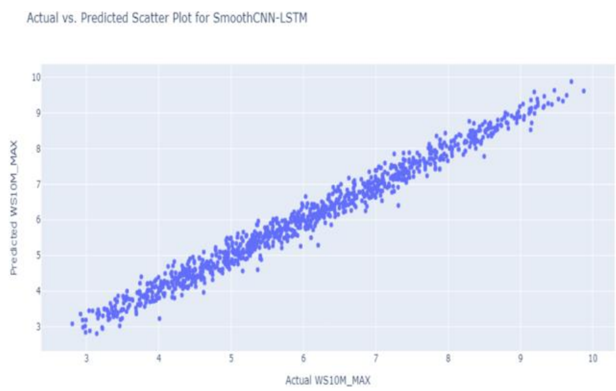

Figure 10. Actual vs. Predicted Scatter Plot for exp smooth CNN-LSTM

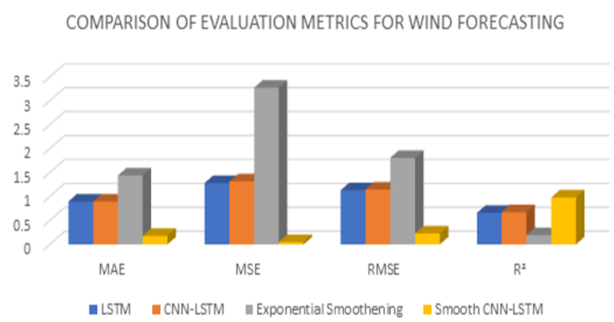

Figure 11. Comparison of evaluation metrics for wind forecasting

Figure 11 and Table 1 show the comparison of evaluation metrics for wind forecasting.

4. RESULT ANALYSIS FOR SOLAR PREDICTIONS

Interpret the performance metrics for each algorithm for solar prediction. Results are shown in Figures 12 to 16.

ALLSKY_SFC_LW_DWN means Total Longwave Downward Irradiance of the Sky Surface (W/m^2).

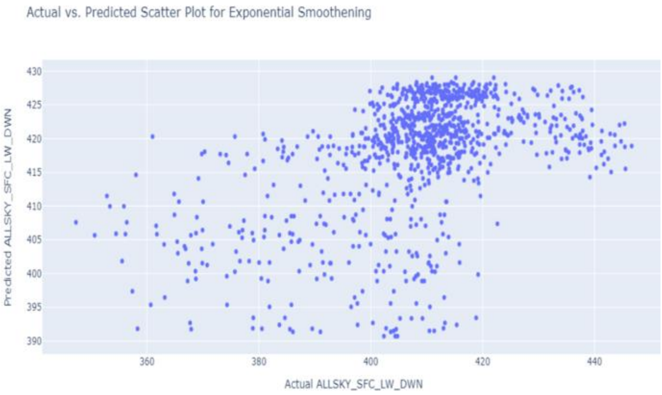

Figure 12. Actual vs. Predicted Scatter Plot for exponential smoothening

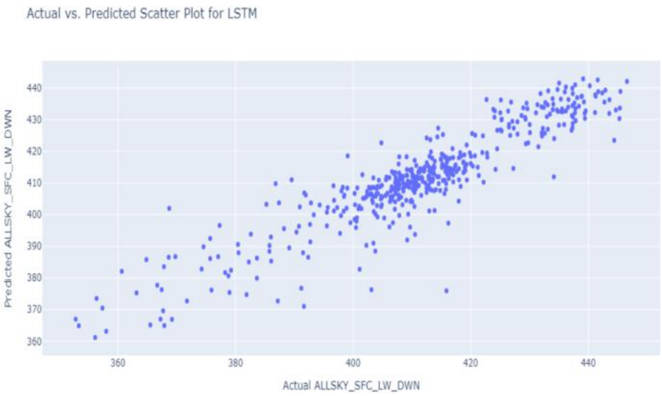

Figure 13. Actual vs. Predicted Scatter Plot for LSTM

It is preferable if the MAE is lower. The model "CNN-LSTM Exponential Smooth" shows the smallest average absolute errors (MAE). Larger errors are penalized with greater severity by MSE. Once more, "CNN-LSTM Exponential Smooth" has the lowest MSE, indicating predictions that are more accurate. Similar to MSE, but expressed in the target variable's original units is RMSE. With the lowest RMSE, "CNN-LSTM Exponential Smooth" suggests smaller average magnitude of errors. The dependent variable's predictable variance is expressed as a percentage, or R^2. Greater R^2 values are preferable. Out of all the models, "CNN-LSTM Exponential Smooth" has the highest R^2, suggesting the best explanatory. The metrics make it evident that "CNN-LSTM Exponential Smooth" is the model in this comparison that performs the best at predicting the sun irradiation (Table 2). But given the nature of solar prediction tasks, it's also critical to assess the models' capacity to identify patterns linked to solar cycles and meteorological conditions.

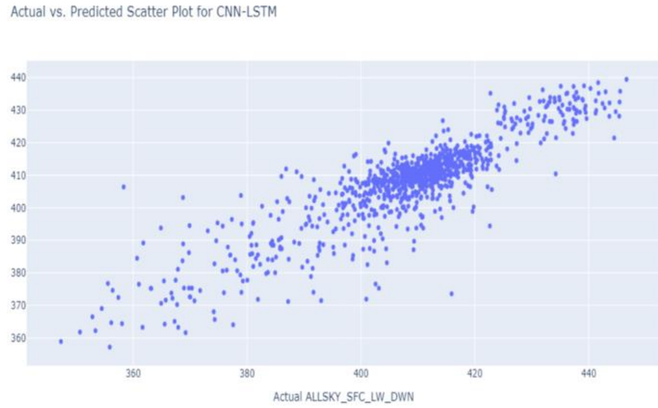

Figure 14. Actual vs. Predicted Scatter Plot for CNN-LSTM

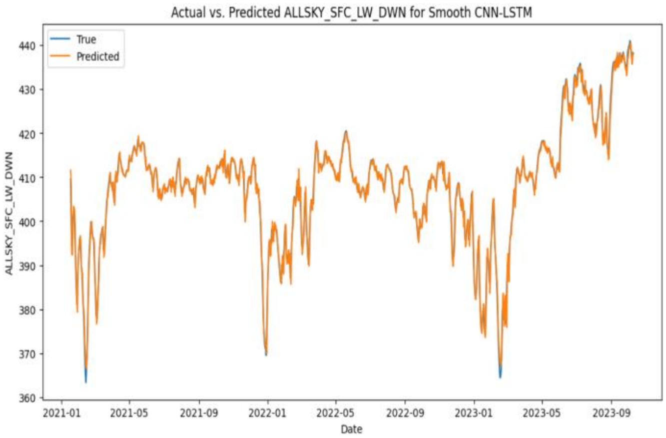

Figure 15. Actual vs. Predicted ALLSKY_SFC_LW_DWN for smooth CNN-LSTM

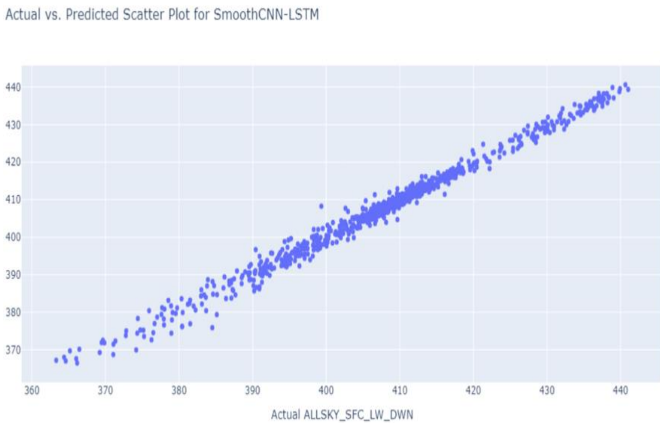

Figure 16. Actual vs. Predicted Scatter Plot for smooth CNN-LSTM

Table 2. Comparison of evaluation metrics for solar forecasting

Algorithm	MAE	MSE	RMSE	R^2
LSTM	5.128618012	52.26106388	7.229181412	0.8347565928
CNN-LSTM	5.274452091	56.68904962	7.529213081	0.7737642108
Exponential Smoothening	13.78351081	283.8759998	16.84862012	0.1395408998
Smooth CNN-LSTM	1.057548805	2.223535014	1.491152244	0.9874100766

5. CONCLUSIONS

Naturally, wind and solar energy power change at all times. As a result, it must be forecast beforehand using a variety of predictive models. This is done with the goal of implementing corrective actions that ensure the best possible output of electric power. The hybrid deep learning network, Smooth CNN-LSTM model, was presented by the authors, who obtained accuracy levels that were more significant than those of other models. Studies employing as input variables the 14-year historical meteorological solar and wind data for Aralvaimozhi. This can be applied to sun radiation and wind speed prediction. When data collected every four months was used to train the model, this performance was attained. The lower the MSE (2.2) in solar and (0.05) in wind, the better. In this regard, the Smooth CNN-LSTM model has the lowest MSE, indicating superior performance. Again, RMSE lower values (1.49) in solar and (0.22) in wind are better. The CNN-LSTM Exponential Smooth has the lowest RMSE, suggesting that it has the smallest average magnitude of errors. Similar to RMSE, lower MAE values are preferable. The Smooth CNN-LSTM model has the lowest MAE, indicating smaller average absolute errors. Higher R^2 (0.98) values are better in both solar and wind power forecasting. The Smooth CNN-LSTM model has the maximum R^2, signifying the finest explanatory power among the quartet of models. The proposed Exponential Smoothing-CNN-LSTM method outperforms existing techniques such as CNN-LSTM, LSTM, and Exponential Smoothing, as it effectively combines the strengths of all three approaches. The Smooth CNN-LSTM model, given its performance across multiple metrics, seems to be the most effective in this comparison. The limitation of this research lies in the fact that the predictive analysis of solar and wind data focuses exclusively on onshore climates. It remains uncertain whether the same methodologies would be applicable to offshore conditions. So, the future analysis may be on the weather forecasting for offshore environments.

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