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Long Term Wind Power Forecasting using Deep Learning Techniques

Surbhi Mann[1]
Department of Electrical Egnineering
Suresh Gyan Vihar University
Jaipur, Rajasthan

Nishant Saxena[2],
Assistant Professor,
Department of Electrical Engineering,
Suresh Gyan Vihar University
Jaipur, Rajasthan

Hari Ram Tanwar[3],
Assistant Professor,
Department of Electrical Engineering
Suresh Gyan Vihar University
Jaipur, Rajasthan

Abstract— **Supply and demand balancing is one of the most crucial duties for any power system. A dynamic equilibrium exists here. Based on previous trends, an amount is estimated for the need for power. The system operator will use this demand prediction to decide how much power to provide to satisfy demand or cut waste. Demand seems to change throughout time, necessitating a matching change in supply. Wind power facilities have a far harder difficulty altering their output than conventional fossil-fired power plants. Thermal power facilities' output can be programmed to adapt to changes in demand. Like the majority of renewable energy sources, wind power is prone to erratic fluctuations. Unlike natural gas - fired power facilities, wind turbines cannot transmit electricity. The present wind conditions have a major role in determining the maximum wind power production. We have put out a cutting-edge Deep Learning method for predicting wind in Dewas, Madhya Pradesh, India. For the comparison research on MATLAB, the forecasts for wind power were made using machine learning regression and the long short term method, with the results showing that they were more accurate than predictions made using conventional statistics and other methods.**

Keywords— Wind power, wind power forecasting, support vector machines, regression methods, deep learning, machine learning, and the weibull's probability density function.

I. Introduction

One of the peculiarities is the sporadic wind. There's many times when the wind is hardly noticeable, and other times when it is easy to know it is windy just by hearing it. Wind is significantly impacted by geography. Wind is typically stronger at the beach due to the difference in atmospheric temperature between the land and the ocean. A similar situation—a temperature difference, in this instance between a mountain and a valley—results in a similar occurrence, increased wind speed around specific valleys. Seasonal variations in wind patterns result in stronger winds being more frequently observed in India in the spring. The role of wind power forecast has grown increasingly important as the rate of wind penetration increases. Every power system has a reasonable ability to react to changes in demand since demand estimation is never precise. Power systems do not need to be worried with the fluctuation of the wind power supply when the penetration rate is low. This is due to the fact that, for instance, a decline in wind speed that results in a reduction in the supply of wind energy is quite comparable to an increase in demand, which even the power system can handle..

A. *Very Short Term Wind Power Predictions*

The time scale for very short-term prediction normally ranges from one minute to thirty minutes, although it can even be as brief as a few seconds. The results of prediction can be used for real-time power grid [3], wind turbine control [2], and other applications. The computation time for this method was likewise quite short.

B. *Short-term Wind Power Predictions*

Short-term wind power predictions include time horizons between 30 minutes and 6 hours. In addition to making wind power more commercially feasible, this collection of techniques is primarily used to plan load dispatch. Predictions for very short-term wind power.

C. *Medium- and Long-term Wind Power Predictions*

Medium-term predictions are those that range in duration from 6 hours to 1 day, while long-term predictions are those that last longer than 1 day. In addition to other factors, these projections can be helpful in making decisions about unit commitment, reserve needs, and maintenance [19]. It's important to note that less research has been done on long-term predicting than on shorter-term forecasting.

II. Data Description

The site of a wind farm close to Dewas, Madhya Pradesh, served as the source of the data for this project. Because of its relatively high wind speed and capacity to produce enough electricity to help with peak power demand, the Dewas location was selected. The NASA Surface and Meteorological Prediction of Worldwide Energy Resources Power program was used to collect the wind data. As shown in fig. 1, which shows the wind speed data gathered from 1 January through December 31, 2021, the wind speed at 50 meters at the site, or the average daily of wind speed at 50 meters has been taken into account.

Along with this information, the location's temperature and humidity have been taken into account as predictors, and the problem's response variable—wind power—has been computed using Weibull's probability distribution. Fig. 2 displays the temperature information for the area gathered over the same time period. The daily average wind power is shown in Fig. 3 and was estimated using the scale and shape parameters of 3 and 6 for Weibull's probability distribution.

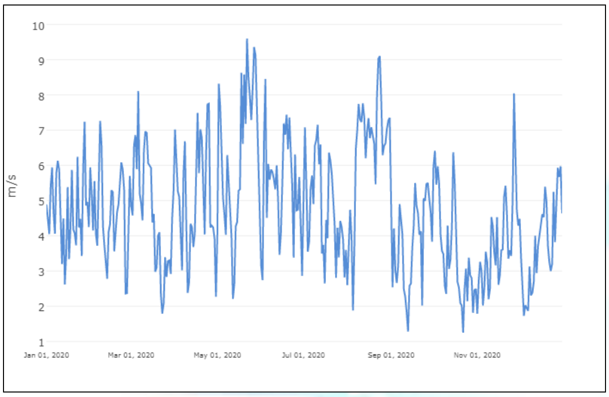

Fig. 1 Wind Speed at 50 meter from 1st Jan. 2021 to 31st Dec. 2021 AT DEWAS, MP

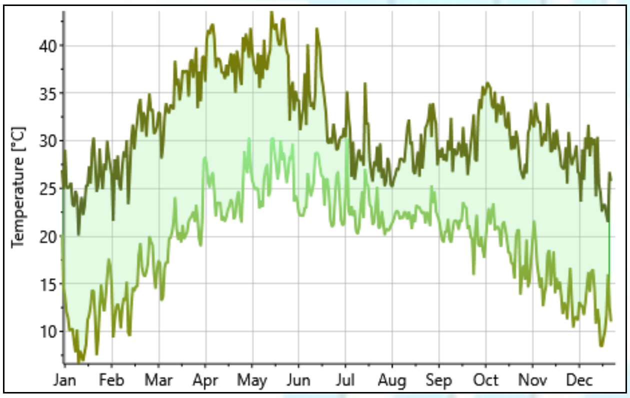

Fig. 2 Daily Minimum and Maximum Temperature from 1st Jan., 2021 to 31st Dec., 2021 AT DEWAS, MP

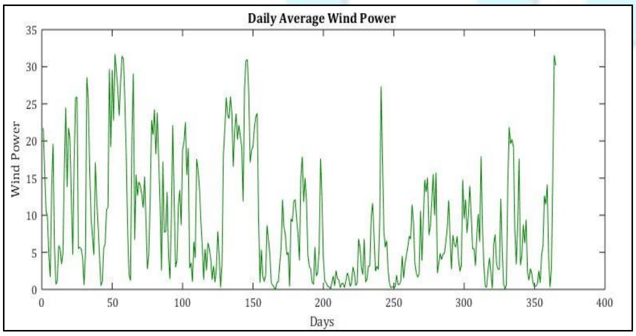

Fig. 3 Daily Average Wind Power

III. Proposed SVM based wind power prediction model

The Support vector machines (SVMs) are unsupervised machine learning techniques that may be applied to both regression and classification. They are used most frequently, though, in classification problems. SVMs were created in the 1960s, but they saw improvements in the 1990s. SVMs differ from other machine learning techniques in that they use a different implementation strategy. Due to their ability to manage various continuous and categorical variables, they have lately garnered a lot of interest. An SVM model is only a hyperplane in multi - dimensional space that represents a number of classes. In order to lower the error, SVM will iteratively construct the hyperplane. The goal of SVM is to classify datasets so that a maximal marginal hyperplane may be obtained (MMH). An SVM seems to be limited to describing a linear connection among input and output when determining support vectors to identify a linear hyperplane. On the other hand, the initial input data can be changed into a more complex format with several dimensions. In this new feature space, the linear relation that may be articulated may be found.

$$\hat{P}_q = w_0 + \sum_{i=1}^{m} w_i \phi_i(\mathbf{e_q}) \tag{1}$$

where {Ø_i }_(i=1)^mis a set of non-linear mapping to the new feature space. When transferred back to the original feature space, the non-linear relationship between input eqn and prediction Pˆ q is obtained accordingly.

IV. Proposed Deep Learning Method based wind power prediction model

One of the machine models that needs work to train is the ANN; the DNN, which has several hidden layers, requires more effort to learn. However, the ability to comprehend more intricate and complex relationships is advantageous. A deep neural network that employs recurrent neural networks is called the recurrent neural network (RNN) (RNNs). Building and improving artificial neural networks (ANNs) has been done [23]. The use of RNN, a time series-based sequence model, to train and features extracted from time series inputs is possible. It may be utilized in a variety of applications with time series inputs. Here, it is applied to forecast wind energy using time series sequences. On the other hand, due to the exponentially fast dropping gradient norm toward 0 and blast difficulties, RNN experiences gradient evanescence and has a limited capacity to learn long-term temporal correlations. To deal with the issue of fading gradients, the LSTM neural network was developed [31].

As shown in the figure, the LSTM network consists of an input layer, an output layer, and several recursive concealing layers in between. Each memory module in a recursive concealing layer has one or more self-contained memory units that are managed by the input gate, forgetting gate, and output gate. Figure 4 depicts the LSTM network's

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fundamental structure. Additionally, a schematic representation of neurons is displayed, defining the various network gates. Output gate values are calculated as follows for time period t:

$$i_t = \text{Sigmoid}\ (IW_t \times X_t + RW_i \times h_{t-1} + b_i \quad (2)$$

$$f_t = \text{Sigmoid}\ (IW_f \times X_t + RW_f \times h_{t-1} + b_f \quad (3)$$

$$o_t = \text{Sigmoid}\ (IW_o \times X_t + RW_o \times h_{t-1} + b_o \quad (4)$$

$$c_t^* = \text{TanH}\ (IW_c \times X_t + RW_c \times h_{t-1} + b_c \quad (5)$$

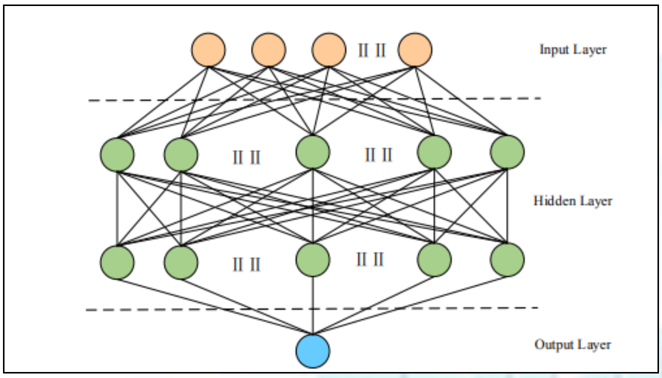

Fig. 4 Multi Neuron LSTM Structure

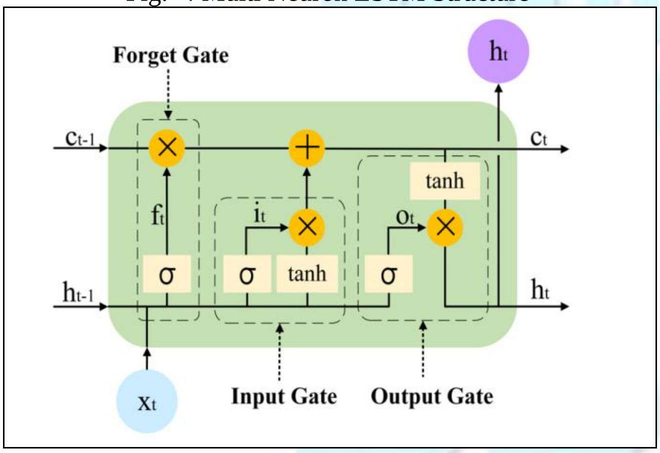

Fig. 5 LSTM Neuron Structure

The output of a neuron in regard to one or more inputs is described by the activation function, which is a smooth nonlinear function. The LSTM structure in TABLE I is activated using the hyperbolic tangent (TanH) and sigmoid functions, which are detailed in the following.

TABLE I: VARIOUS LSTM ACTIVATION FUNCTIONS

Activation function	Formula
Sigmoid	$Sigmoid\ (x) = \frac{1}{1+e^{-x}}$
TanH	$TanH\ (x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$

In order to forecast the wind power for the previously specified area, we have used both the Support Vector Machine (SVM) using Regression Learner and Deep Learning Method utilizing Long Short Term Memory (LSTM) framework in this study.

V. RESULTS AND DICUSSIONS

A. *Estimators and Evaluators:*

In the study and analysis purpose several indicators are identified and used as an estimator for the evaluation of methods and accuracy of predictions made. Some have been used here like, mean absolute error, mean square error, and root mean square error discussed in brief below.

a) *Mean Absolute Error:* The Normalized Mean Absolute Error (NMAE), a measure of error that examines the forecast's mean absolute error, is defined in equation 11.

$$NMAE_k = \frac{1}{N}\sum_{t=1}^{N}|\epsilon_{t+k|t}| \quad (11)$$

Another well-known name for Mean Absolute Error is Mean Absolute Deviation (MAD) (MAE). This number should be as small as is practical and represents the overall amount of inaccuracy that has been introduced as a result of prediction. This error depends on the scale and is affected by the data processing and measurement scale.

b) *Mean Squared Error:* The Normalized Mean Squared Error (NMSE), which examines the average of the squared errors, is an error quantity that is derived using the Normalized Sum of Squared Error (NSSE) defined in 12:

$$NMSE_k = \frac{1}{N}\sum_{t=1}^{N}\epsilon_{t+k|t}^2 \quad (12)$$

c) *Root Mean Square Error:* The NMSE is squared by an error called the Normalized Root Mean Squared Error (NRMSE). Equation defines it.

$$NRMSE_k = NMSE_k^{1/2} = \left(\frac{1}{N}\sum_{t=1}^{N}\epsilon_{t+k|t}^2\right)^{1/2} \quad (13)$$

B. *Support Vecvtor Machine (SVM) Results*

The SVM method is applied on the dataset in a custom MATLAB program. Two different SVM methods—Linear SVM and Medium Gaussian SVM—have been used to the given dataset

(GMSVM). The suggested methods have been evaluated using the aforementioned evaluation indices, and the results are shown in TABLE II. Figure 7 shows the prediction plot for the linear SVM approach, while Figure 8 shows the prediction plot for the Gaussian median SVM methodology.

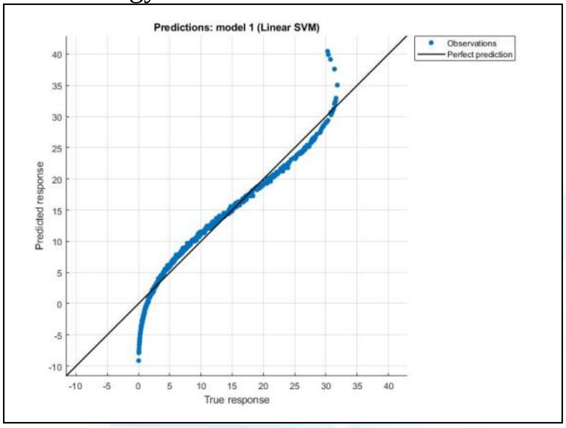

Fig. 7 Regression Plot for Linear SVM

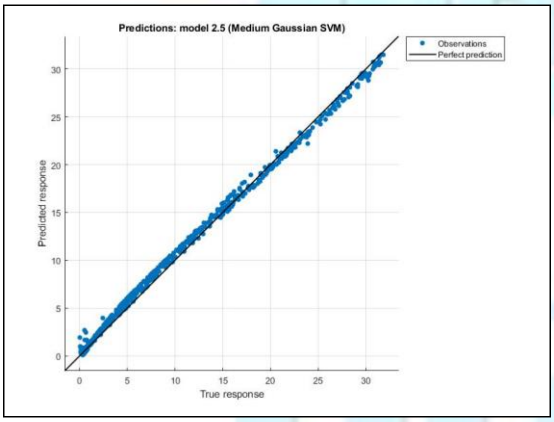

Fig. 8 Regression plot for Medium Gaussian SVM

It can be clearly seen that, GMSVM method gives the better prediction with less error which are also been verified by the Error comparison table for both the models. The GMSVM Method provides the RMSE value of 0.62 which is much lesser than comparative to Linear SVM method as 2.012.. Furthermore, the training time required in the GMSVM is also better then Linear SVM method.

TABLE II RESULTS OF SVM METHOD

Evaluator Indices	Linear SVM	GMSVM
RMSE	2.012	0.62
R SQUARED	0.95	1.00
MSE	4.051	0.39771
MAE	4.15	0.55
TRAINING TIME	5.59 sec	0.06512 sec

Furthermore, response plots for the linear SVM and Gaussian median SVM method is shown in fig. 9 and fig. 10. It can be clearly seen that, The GMSVM methods response with wind Speed is better and more nearer to the true values. The Predictions of the Power is more accurate towards the wind Speed. The fig. 11 and fig. 12 shows that residual plots of both Linear SVM and Gaussian Median SVM method. The figures clearly depict the no. of residuals generated for the predicted and true values.

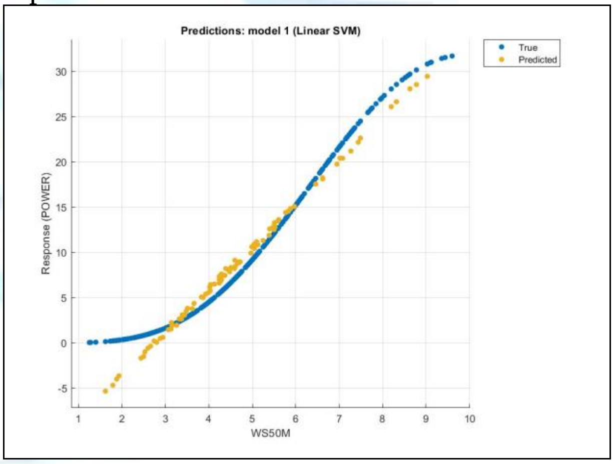

Fig.9 Response plot of Linear SVM

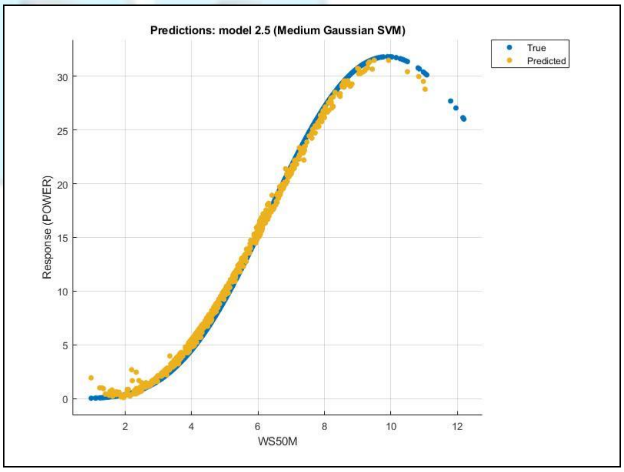

Fig. 10 Response Plot for Gaussian Median SVM Method

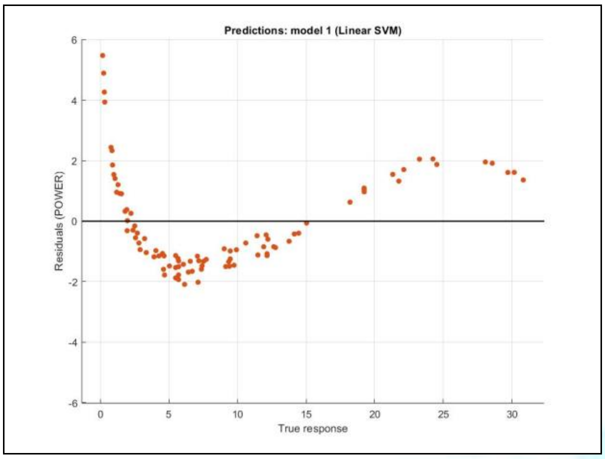

Fig. 11 Residual Plot of Linear SVM method

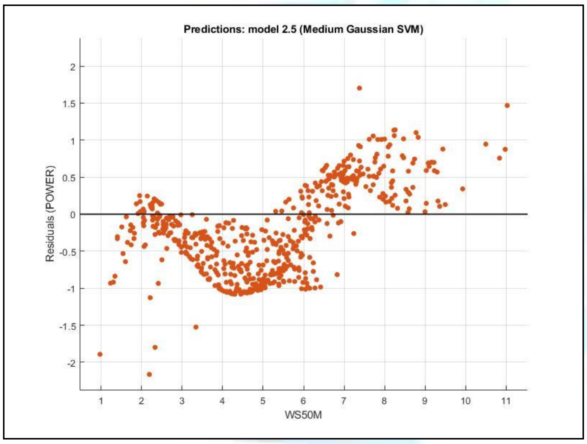

Fig. 12 Residual Plot of Gaussian Median SVM method

C. Long short term memory (LSTM)method results

RNN - LSTM methods has been implemented on the MATLAB for the forecasting of wind power for next interval. The same dataset of wind power, Temperature and Wind Speed has been applied and the method machine learning model has been developed using MATLAB Deep learning toolbox. The Training has been done to the 70 percent of the data and remaining is been kept for the testing. Furthermore, the parameters for the model were tested with trial and error method and conclusive parameters utilized are shown in TABLE III

TABLE III : LSTM TRAINING NETWORK PARAMETER

Sr. No.	Parameter	Value
1	Training cycle Epochs	250
2	Iterations	250
3	Learning rate	0.005
4	Learning Rate Schedule	Piecewise
5	No. of hidden layers	100
6	Learning Rate drop factor	0.2
7	Learning Rate drop Period	125
8	Solver	ADAM

After the Implementation and setting of above parameters the results were obtained and shown from fig.13 to fig. 15. It can be clearly seen from fig. 13 that the root mean square error reached to below 0.2 with and loss of the training of less then 0.05 defining the better performance than previously discussed two regression methods viz. Linear Support Vector Machine and Gaussian Median Support Vector Machine methods.

Fig. 14 shown the forecasted values of the wind power for the testing data which can also be verified by the fig. 15. The Fig. 16 shows that the forecasted value of Wind power are obtained as similar to the wind power actual during the same period of the days.

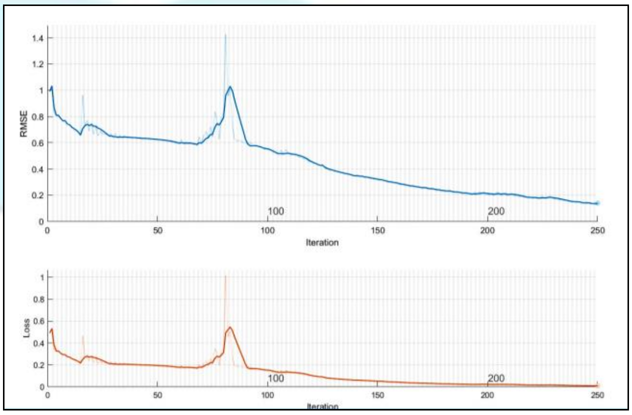

Fig. 13 Training Progress of Machine Learning Model with 250 Iterations

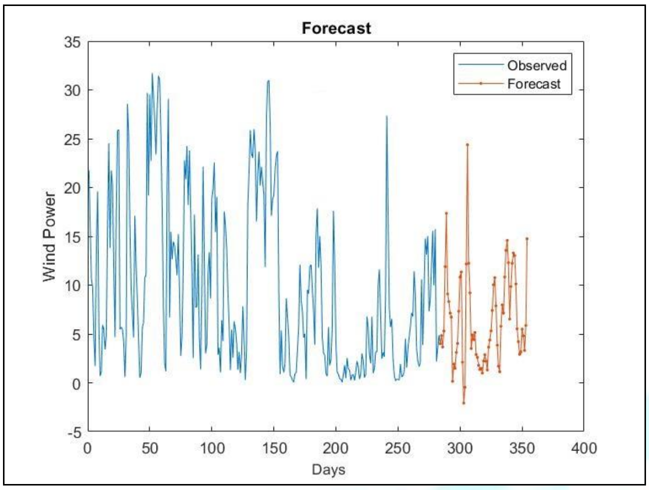

Fig. 14 Forecast plot of the wind power for 30% Testing data

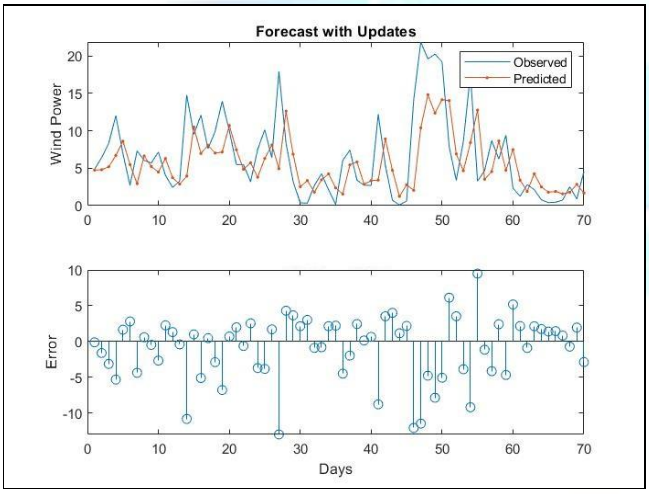

Fig. 15 Forecast with update plot for wind power using LSTM method

D. Long short term memory (LSTM)method results:

It has been discovered that the Deep Learning based LSTM method is more sophisticated and generally predicts more accurate outcomes when compared to Regression based SVM Methods after determining the predicted errors for both suggested approaches. Table 4.3 displays the findings in comparison. The graphical comparison of the various strategies employed in the suggested ways is presented in Fig. 4.10.

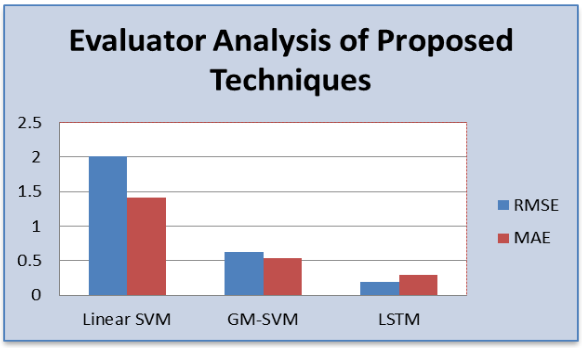

Fig 16. Comparison graph for the proposed methods and results

TABLE IV COMPARATIVE ANALYSIS OF PROPOSED METHODS

Error	Linear SVM	GM-SVM	LSTM
RMSE	2.012	0.62	0.2005
MAE	4.15	0.55	0.31

VI. CONCLUSION

Using cutting-edge support vector machine and deep learning methods, the study offers more accurate forecasting with fewer prediction mistakes. In compared to SVM, the Deep learning method is proven to be more dependable. In contrast to Linear SVM and Gaussian Median SVM, the RMSE error for deep learning approaches is reduced, as shown in Comparative Table 4.3. Using a similar process, we can create machine learning models to anticipate solar and wind energy for various sites in India, improving the accuracy of scheduling and power prediction in the area. More precise prediction models would be needed for forecasting with shorter lead times and greater accuracy as a consequence of the rise in the demand for renewable energy and initiatives implemented by the government of India.

REFERENCES

[1] Saroha, S., Aggrawal, S. K., “A Review and Evaluation of Current Wind Power Prediction Technologies, WSEAS Transactions on Power Systems, 2015
[2] Colak, I., Sagiroglu, S., Yesilbudak, M., “Data mining and wind power prediction: A literature review”, Renewable Energy, 2012, 46, 241-247
[3] Chang, W.-Y., “A Literature Review of Wind Forecasting Methods”, Journal of Power and Energy Engineering, 2, 161-168. http://dx.doi.org/10.4236/jpee.2014.24023, 2014
[4] Chen, K. & Yu, J., “Short-term wind speed prediction using an unscented Kalman filter based state-space support vector regression approach”, Applied Energy, 113, 690-705, 2014.

[5] Catalao, J. P. S., Pousinho, H. M. I. & Mendes, V. M. F., "Hybrid wavelet-PSO-ANFIS approach for short-term wind power forecasting in Portugal", IEEE Transactions on Sustainable Energy, 2 (1), 50-59, 2015

[6] Potter, C. W. & Negnevitsky, M., "Very short-term wind forecasting for Tasmanian power generation", IEEE Transactions on Power Systems, 21 (2), 965-972. 2006

[7] Damousis, I. G., Alexiadis, M. C., Theocharis, J. B. & Dokopoulos, P. S., "A fuzzy model for wind speed prediction and power generation in wind parks using spatial correlation", IEEE Transactions on Energy Conversion, 19 (2), 352-361, 2004.

[8] Monfared, M., Rastergar, H. & Kojabadi, H. M., "A new strategy for wind speed forecasting using artificial intelligent methods" Renewable Energy, 34, 845-848, 2009

[9] Chang, W.-Y., "Application of Back Propagation Neural Network for Wind Power Generation Forecasting" International Journal of Digital Content Technology and its Application, 7, 502-509, 2013

[10] Liu, D., Niu, D., Wang, H. & Fan, L., "Short-term wind speed forecasting using wavelet transform and support vector machines optimized by genetic algorithm", Renewable Energy, 62, 592-597, 2014

[11] Fan, S., Liao, J. R., Yokoyama, R., Chen. L. & Lee, W.-J., "Forecasting the wind generation using a two-stage network based on meteorological information", IEEE Transactions on Energy Conversion, 24 (2), 474-482, 2009

[12] Zeng, J. & Qiao, W., "Support vector machine-based short term wind power forecasting", Power Systems Conference and Exposition (PSCE), Phoenix, AZ, pp. 1-8, 2011.

[13] Mao, M., Cao, Y. & Chang, L., "Improved Fast Short-term Wind Power Prediction Model Based on Superposition of Predicted Error", Power Electronics for Distributed Generation Systems (PEDG), 2013 4th IEEE International Symposium on, Rogers, AR, 2013, pp. 1-6.

[14] Kusiak, A., Zheng, H. & Song, Z., "Short-Term Prediction of Wind Farm Power: A Data Mining Approach" IEEE Transactions on Energy Conversion, 24 (1), 125-136. 2009.

[15] Chang, W.-Y., "A Literature Review of Wind Forecasting Methods" Journal of Power and Energy Engineering, 2, 161-168. http://dx.doi.org/10.4236/jpee.2014.24023, 2014.

[16] Rzui, P. C. & Eremia, M., "Prediction of wind power by artificial intelligence techniques. Intelligent System Application to Power Systems", (ISAP), 2011 16th International Conference on, Hersonissos, 2011, pp. 1-6.

[17] R. Akash, A. G. Rangaraj, R. Meenal, and M. Lydia, "Day-Ahead Wind Power Forecasting Using Machine Learning Algorithms," in Computational Methods and Data Engineering, Singapore, 2021, pp. 329–341. doi: 10.1007/978-981-15-6876-3_25.

[18] B. Alonzo, R. Plougonven, M. Mougeot, A. Fischer, A. Dupré, and P. Drobinski, "From Numerical Weather Prediction Outputs to Accurate Local Surface Wind Speed: Statistical Modeling and Forecasts," in Renewable Energy: Forecasting and Risk Management, Cham, 2018, pp. 23–44. doi: 10.1007/978-3-319-99052-1_2.

[19] Banerjee, J. Tian, S. Wang, and W. Gao, "Weighted Evaluation of Wind Power Forecasting Models Using Evolutionary Optimization Algorithms," Procedia Comput. Sci., vol. 114, pp. 357–365, Jan. 2017, doi: 10.1016/j.procs.2017.09.046.

[20] H. Demolli, A. S. Dokuz, A. Ecemis, and M. Gokcek, "Wind power forecasting based on daily wind speed data using machine learning algorithms," Energy Convers. Manag., vol. 198, p. 111823, Oct. 2019, doi: 10.1016/j.enconman.2019.111823.

[21] J. Heinermann and O. Kramer, "Machine learning ensembles for wind power prediction," Renew. Energy, vol. 89, pp. 671–679, Apr. 2016, doi: 10.1016/j.renene.2015.11.073.

[22] Lahouar and J. Ben Hadj Slama, "Hour-ahead wind power forecast based on random forests," Renew. Energy, vol. 109, pp. 529–541, Aug. 2017, doi: 10.1016/j.renene.2017.03.064.

[23] J. Maldonado-Correa, J. Solano, and M. Rojas-Moncayo, "Wind power forecasting: A systematic literature review," Wind Eng., vol. 45, no. 2, pp. 413–426, Apr. 2021, doi: 10.1177/0309524X19891672.

[24] Nishant Saxena, Souvik Ganguli, "Solar and Wind Power Estimation and Economic Load Dispatch Using Firefly Algorithm" ,Procedia Computer Science, Volume 70, 2015, Pages 688-700,

[25] S. Saroha and S. Aggarwal, "A Review and Evaluation of Current Wind Power Prediction Technologies," 2015.

[26] S. Saroha and S. K. Aggarwal, "Wind power forecasting using wavelet transforms and neural networks with tapped delay," CSEE J. Power Energy Syst., vol. 4, no. 2, pp. 197–209, Jun. 2018, doi: 10.17775/CSEEJPES.2016.00970.

[27] Gupta, K. Gupta, and S. Saroha, "Solar Irradiation Forecasting Technologies: A Review," Strateg. Plan. Energy Environ., pp. 319–354–319–354, 2020, doi: 10.13052/SPEE1048-4236.391413.

[28] S. Saroha and S. K. Aggarwal, "Wind Power Forecasting Using Wavelet Transform and General Regression Neural Network for Ontario Electricity Market," Recent Adv. Electr. Electron. Eng. (Formerly Recent Patents Electr. Electron. Eng., vol. 13, no. 1, pp. 16–26, Mar. 2019, doi: 10.2174/2352096512666190118160604.

[29] P. Singla, M. Duhan, and S. Saroha, "A comprehensive review and analysis of solar forecasting techniques," Front. Energy 2021, pp. 1–37, Mar. 2021, doi: 10.1007/S11708-021-0722-7.

[30] M. Syed Ali, G. Narayanan, S. Saroha, B. Priya, and G. K. Thakur, "Finite-time stability analysis of fractional-order memristive fuzzy cellular neural networks with time delay and leakage term," Math. Comput. Simul., vol. 185, pp. 468–485, Jul. 2021, doi: 10.1016/J.MATCOM.2020.12.035.

[31] H. Demolli, A. S. Dokuz, A. Ecemis, and M. Gokcek, "Wind power forecasting based on daily wind speed data using machine learning algorithms," Energy Convers. Manag., vol. 198, p. 111823, 2019, doi: https://doi.org/10.1016/j.enconman.2019.111823.