



Vol. 3 No. 12 (December) (2025)

Deep Machine Learning to Predict Wind Speed through Temperature and Humidity

Naeem Sadiq

Institute of Space Science & Technology, University of Karachi, Karachi

Email: nsadiq@uok.edu.pk

Fida Hussain Khoso*

Department of computer Science, Dawood University of Engineering & Technology,

Karachi Email: fidahussain.khoso@duet.edu.pk

Asadullah Buledi

IMCS, University of Sindh Jamshoro Email: asad.buledi@usindh.edu.pk

Muhammad Shahid

Department of Electronic Engineering, Dawood University of Engineering &

Technology, Karachi Email: Muhammad.Shahid@duet.edu.pk

Shafique Ahmed Awan

Department of Computer Science and IT, Benazir Bhutto Shaheed University Lyari

Karachi Sindhi, Pakistan Email: Shafique.awan@bbsul.edu.pk

Muhammad Ahsan Riaz

Department of Electronic Engineering, Dawood University of Engineering &

Technology, Karachi Email: ahsan.riaz@duet.edu.pk

ABSTRACT

The paper aims to predict the wind speed of Karachi based on temperature and Humidity of he city. A deep machine learning technique through a double layer neural network has been employed to analyze the meteorological parameters. The model was trained to capture complex patterns and dynamics and after validation, testing followed. The performance evaluation of the outcomes is verified through statistical parameters like R^2 and RMSE which comes out as for single and for double layer. It is found that the double-layer results show improvement than the single layer results. The promising results show the potential of deep learning in enhancing the forecasting of wind speed.

Keywords: Machine Learning, Wind Speed Prediction, Temperature, Humidity, Neural Networks

INTRODUCTION

Wind velocity happens to be an important parameter with practical applications in renewable energy, agriculture, and meteorology. The correct prediction of the wind velocity will enable the optimization of wind energy production, climate predictability, and mitigation from damage by extreme weather occurrences. Of the most important atmospheric parameters that might influence wind speed, two are temperature and humidity. Recent work using deep machine learning models on forecasting wind velocity



Vol. 3 No. 12 (December) (2025)

with considerations to information about temperature and humidity is promising.

Wind speed can be affected by temperature and humidity as shown in a few studies. For instance, in China, it was studied that temperature has been a significant variable to predict wind speed (Samuel, et al., 2021). Similarly, a study explored that humidity was a good predictor of wind speed in Madison, Wisconsin, USA (El-Fouly et al., 2008).

Traditional ways of predicting wind speed are through physical models, statistical models, and machine learning algorithms. The physical models include complicated mathematical equations that have been used to represent parts of the atmosphere, for example, in a study of Yanbu, Saudi Arabia, it was revealed that out of the evaluated ML-based approaches the performance of SVR and RF is better than kNN (Faniband et al 2021). Historical meteorological data of the wind farm located at Sotavento, Spain, at different time horizons in different seasons, was used by Sarangi et al., (2023) through the probabilistic model for short-term wind speed intervals.

Many studies utilize Recurrent Neural Network (RNN) to predict wind speed through temperature and humidity. For example Senthil Kumar, P., (2019) and Khosravi et al., (2018) found in their studies that the output of machine learning is better than statistical methods. Further, more modifications to get better results than the original techniques were done by Lazarevska (2016) and de Figueiredo (2021), in which they utilized a deep machine learning method that further improves the forecasting of wind speed.

A few researchers also used some other techniques, for instance, In a China study, Wind speed prediction using a combination of principal component analysis along with short-term memory network was done by Geng et al., (2020). A study of mountainous regions comprised of 11 locations in the western Himalayan in India, showed the increased predictive accuracy of the developed ANN model (Ramasamy et al., 2015).

Despite the advancements in wind speed prediction using deep learning, there remains a gap in research focusing on the combined influence of temperature and humidity, particularly in coastal regions like Karachi. Coastal areas like Karachi, with their unique meteorological conditions, may present a valuable opportunity for optimizing renewable energy systems. This study leverages deep learning techniques to predict wind speed in Karachi city, aiming to contribute to the need of growing body of work on wind energy optimization and climate predictability. By focusing on temperature and humidity as key predictors, the study seeks to provide a reliable and efficient model for wind speed forecasting.

METHODOLOGY

Five years of wind speed data, i.e. from 2015-2019 has been used to build the model by employing deep learning techniques of Artificial Neural Networks. Through this approach, we utilized feed forward algorithm which terminates once the weights and then biases are optimized. This ensures the effective and efficient training process. Hence, the input data now includes temperature, relative humidity, and precursor values of wind speed. Other meteorological parameters, like pressure and wind direction, were not included in the analysis because these variables exhibited no significant correlation with wind speed. The ANN architecture consists of two hidden layers each having ten neurons. The output variable is the wind speed.

The equation of the ANN model is given by

$$v_k = f(T, H, v_{k-1})$$

Here v_k and v_{k-1} are the present and previous day's wind speeds, T is the average daily



Vol. 3 No. 12 (December) (2025)

temperature, and H is the relative humidity.

The choice of a double-layer architecture was motivated by its ability to provide increased representational power compared to a single-layer network. Single-layer ANN can capture linear relationships, while a double-layer ANN intends to modelled the more complex, non-linear patterns in the data. The resultant architecture comprises a balance between model complexity and computational efficiency, reducing the risk of overfitting while maintaining robust predictive performance

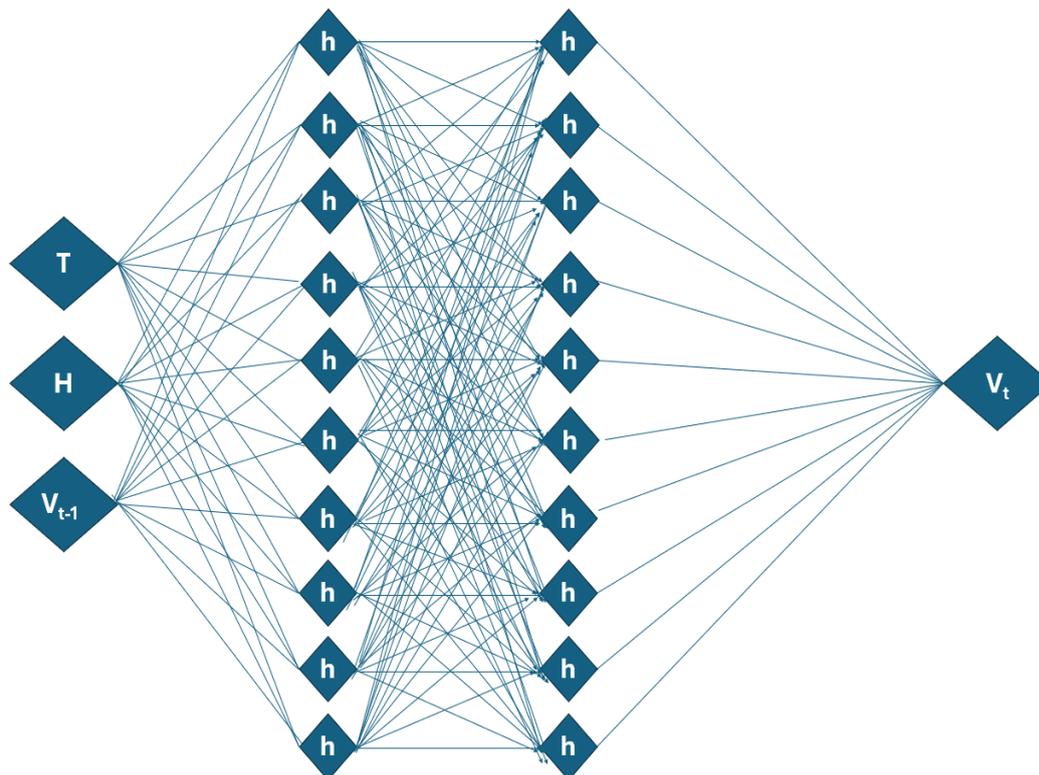


Figure 1: Neural network architecture featuring three inputs, two hidden layers, and one output

RESULT AND DISCUSSION

Renewable energy is the need of this era due to the increasing demand for electricity and the rapid depletion of fossil fuels. Many countries around the world have installed various renewable energy development plants to fulfill their energy demand. The biggest advantage of renewable energy is its green nature. Wind energy is one of the renewable energies that is available throughout the year in various regions of the world. Pakistan is blessed to have enormous potential for renewable energy e.g. solar, hydro, and wind energies, especially the coastal regions of Pakistan have great wind potential. Karachi is one of the cities which lies along the coastal belt of Pakistan. This work aimed to predict wind speed using its precursor values daily average temperature and relative humidity. A deep learning algorithm based on this input was developed to predict wind speed. The ANN architecture has two hidden layers each of which has ten neurons.

The ANN model uses five years of data from 2015 to 2019, the data is divided into three parts to train, validate, and test the network according to the use of data 75%, 15%, and 15%, respectively. The schematic diagram of the network is shown in Fig. 1. Figure 2 shows the results of the training, validation, testing, and overall fitting of the data using the ANN model. The value of R^2 is greater than 0.82 in each of these fitting phases.

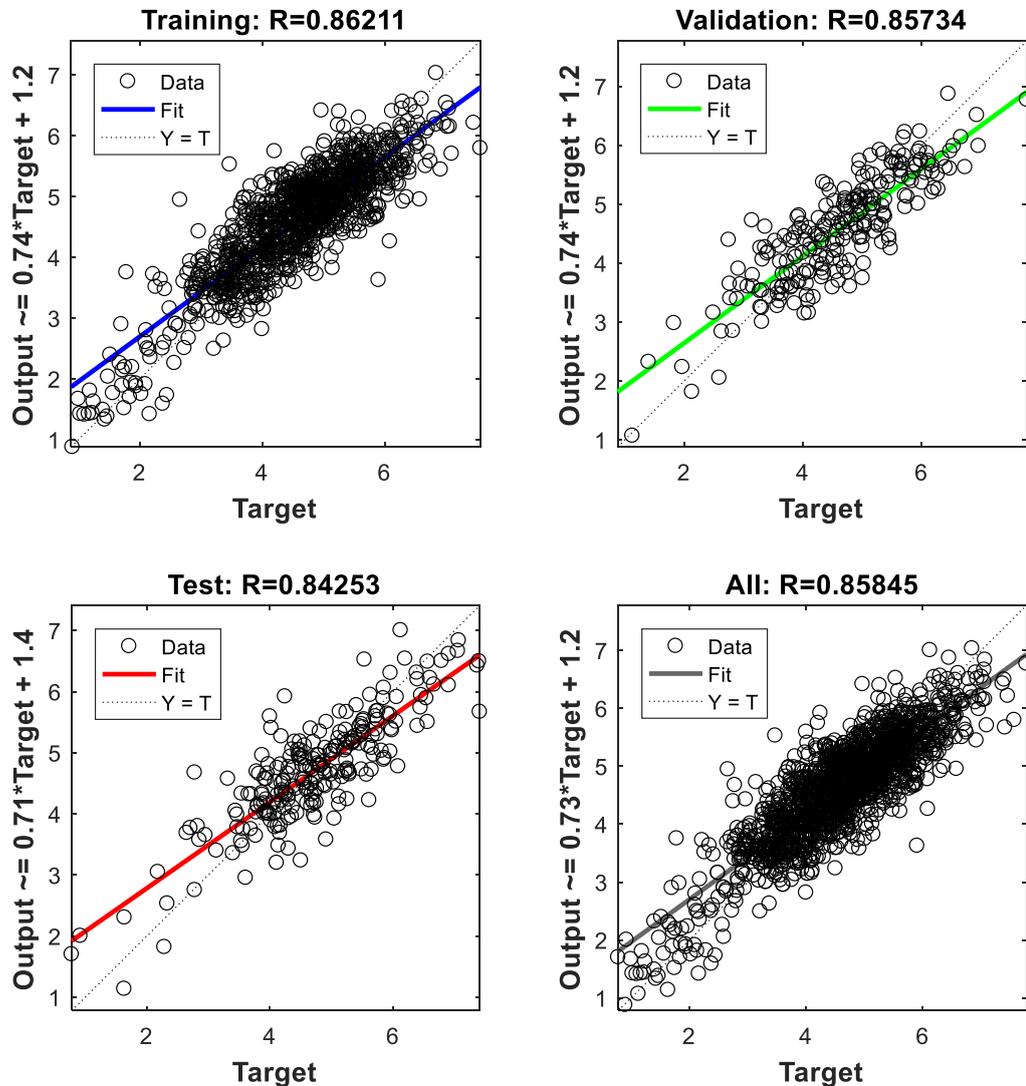


Figure 2: Regression models for training, validation, testing, and combination as ‘All’
 The trained network was used to predict the wind speeds, the results were compared an excellent agreement was found between the predicted and actual values of the wind speeds. Figure 3 depicts the comparison of the predicted values (red graph) and actual values (blue graph) of the wind speeds. The perfect overlapping of the graph indicates the performance of the ANN network. The same can be verified by the RMSE value which is 0.52. The weights of the input, hidden, and output layers are given in the appendix.

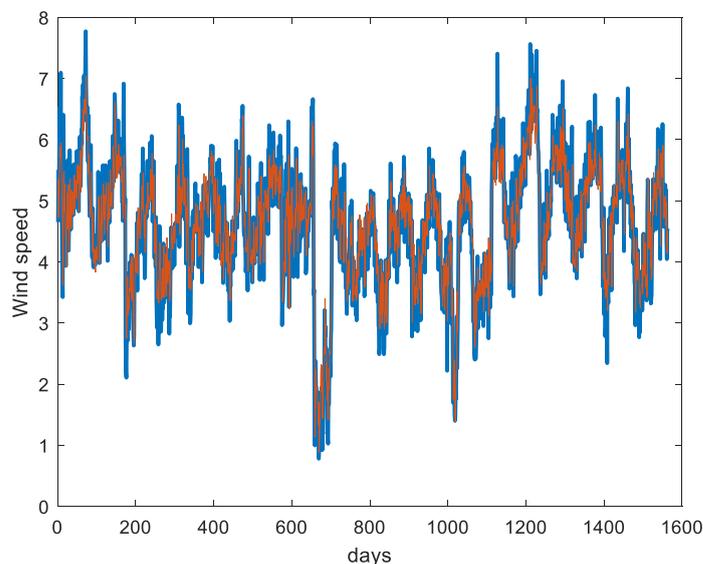


Figure 3: Comparison of predicted (orange) and actual (blue) wind speed

CONCLUSION

Wind speed has significant potential for renewable energy generation. Pakistan has great wind potential, especially in its coastal belt. Wind speed can be predicted using meteorological parameters. In this study, we used deep machine learning in the prediction of wind speed using its precursor values for the coastal city, of Karachi. We used five years of meteorological data on Temperature and humidity from 2015 to 2019 to train the ANN model. ANN with two hidden layers each having 10 neurons was employed in the prediction. Excellent fitting results were achieved with an RMSE value of 0.5426. The ANN network can predict the future value of wind speed using its precursor value and temperature and relative humidity values. Future research may be conducted by including additional relevant variables and alternative deep learning architectures.

REFERENCES

- Samuel, G.G., Salimath, G.F., Porselvi, T. and Karthikeyan, V., "Improved Prediction of Wind Speed Using Machine Learning." *Journal of Physics: Conference Series*, Vol. 1964, No. 5, p. 052005, 2021.
- El-Fouly, T.H., El-Saadany, E.F. and Salama, M.M., "One Day Ahead Prediction of Wind Speed and Direction." *IEEE Transactions on Energy Conversion*, Vol. 23, No. 1, pp. 191-201, 2008.
- Faniband, Y.P. and Shaahid, S.M., "Univariate Time Series Prediction of Wind Speed with a Case Study of Yanbu, Saudi Arabia." *International Journal*, Vol. 10, No. 1, pp. 257-264, 2021.
- Sarangi, S., Dash, P.K. and Bisoi, R., "Probabilistic Prediction of Wind Speed Using an Integrated Deep Belief Network Optimized by a Hybrid Multi-Objective Particle Swarm Algorithm." *Engineering Applications of Artificial Intelligence*, Vol. 126, p. 107034, 2023.
- Senthil Kumar, P., "Improved Prediction of Wind Speed Using Machine Learning." *EAI Endorsed Transactions on the Energy Web*, Vol. 6, No. 23, 2019.
- Khosravi, A., Machado, L. and Nunes, R.O., "Time-Series Prediction of Wind Speed Using Machine Learning Algorithms: A Case Study of Osorio Wind Farm, Brazil." *Applied Energy*, Vol. 224, pp. 550-566, 2018.
- Lazarevska, E., "Wind Speed Prediction Based on Incremental Extreme Learning Machine." In



Vol. 3 No. 12 (December) (2025)

Proceedings of the 9th EUROSIM Congress on Modelling and Simulation, EUROSIM, pp. 544-550, 2016.

de Figueiredo, Y.F.C. and de Campos, L.M.L., "Prediction of Wind Speed Time Series in Brazil." In International Conference on Soft Computing and Pattern Recognition, pp. 627-636. Cham: Springer International Publishing, 2021.

Geng, D., Zhang, H. and Wu, H., "Short-Term Wind Speed Prediction Based on Principal Component Analysis and LSTM." Applied Sciences, Vol. 10, No. 13, p. 4416, 2020.

Ramasamy, P., Chandel, S.S. and Yadav, A.K., "Wind Speed Prediction in the Mountainous Region of India Using an Artificial Neural Network Model." Renewable Energy, Vol. 80, pp. 338-347, 2015.

Appendix

Weights for input to the hidden layer		
2.7285	3.1136	-4.5200
4.9153	-3.0095	0.6729
-0.2034	6.4535	2.1978
2.3939	2.5077	-5.4385
1.3993	-5.7873	0.4005
4.7002	3.8210	0.8435
3.1056	3.1404	-3.5269
-3.3917	4.5411	0.6766
-3.3592	0.9072	-4.5303
-4.5179	0.6306	-3.7371

Weights for the first hidden layer to the second hidden layer									
0.1325	0.9647	2.1544	-0.6504	1.6757	0.3042	-0.1628	-0.1653	-0.2715	1.1648
-0.8573	0.0403	-1.7865	-1.3800	0.4136	-2.1771	0.1969	0.5060	1.3457	-0.5684
0.5771	-1.6215	0.3704	-1.5601	-2.4172	1.5514	0.9883	1.8896	0.6618	0.7941
-0.6146	-0.6715	-0.4872	-1.9750	2.4341	-0.2499	2.4756	0.4148	0.8324	0.5335
-1.2920	1.3136	-0.4377	-1.9186	1.2027	-2.0052	0.7467	-0.9201	-1.6746	0.7019
1.3937	-0.8344	-0.6988	0.1067	1.7362	-0.8416	0.0239	-1.2197	-0.1680	1.1580
0.7594	0.6910	-0.0128	-1.1452	-0.3483	-1.9513	2.3440	-0.6755	0.1577	0.0709
0.6453	2.0727	0.5418	1.5501	-0.2403	-1.4999	0.2842	1.8952	-0.6317	1.3513
1.0673	1.7665	2.0296	0.4107	-1.1722	-0.2918	-0.2686	0.1833	-0.0505	-1.3331
0.8359	-1.1260	-0.3732	1.4818	0.7234	-0.0237	1.2382	0.8927	-0.1414	1.3996
Weights for the second hidden layer to output									
-0.3986	-0.1955	-0.4458	0.8212	0.0107	-0.9938	-0.8929	0.1186	-0.7082	-0.6062