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Neural Network based wind energy model developed over Anantapur, Andhra Pradesh, India

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Abstract: Wind energy is a prominent renewable energy alternative to the conventional non-renewable energy source with a minimal environmental impact. Even though the fact that wind farms have grown in popularity, each one faces a unique set of challenges. Many sophisticated and new approaches are deployed for forecasting wind power genesis and wind power potential to pinpoint the low wind speed hours and schedule a time for turbine maintenance. This paper connotes wind power forecasting over a region using Artificial Neural Network (ANN) & Recurrent Neural Network (RNN) algorithms to address industry problems. In addition, various case studies were carried out with Meteorological variables includes Pressure, soil moisture, temperature, solar radiation, eastward wind (u10), northward wind (v10), and wind speed to assess the effectiveness of various models, and the best model with the highest degree of accuracy is recommended. This study deals with predicting the hourly wind speed at Anantapur, which is essential knowledge for the subsequent estimate of Wind Power Density (WPD). Short-range with statistical metrics of tiny Mean Absolute Error (MAE), low Root Mean Square Error (RMSE), and high Index Of Agreement (IOA) proving the predictability of the wind speed evolution, predictions made with ANN and RNN models at a lead time of 24 hours have been confirmed to be accurate. This study gives wind speed and wind electricity ability predictions that are useful for enterprises, government agencies, and industry in relation to wind harnessing.

1. Introduction

Energy is a fundamental input for both practical and physical activities in this world, and it is important to find the source of this production. It is further classified as renewable & non-renewable energy. The capacity of the energies to replenish itself is also reflected in their names. The preponderance of energy resources comes from non-renewable sources, and soon, it will be necessary to replace or substitute these sources. Arvesen and Hertwich (2011) [1] studied how the widespread use of wind energy might affect the environment. One of the primary environmental problems is the production of energy via fossil fuels. (A. Bilal Awan and Z. Ali Khan,2014) [2]. The installed wind energy capacity increased globally from 6100 MW in 1996 to over 238,000 MW in 2011, according to the Global Wind Report 2011.In India, about 20% of the total installed power currently comes from clean energy sources, falling short of the national target of 40% by 2030, according to a study by Bhatia and Gupta published in 2018.India has set ambitious goals to produce 100 GW of solar energy, 60 GW of wind energy, 250 GW of solar energy, and 100 GW of wind energy, respectively, by the years 2022 and 2030.The generation and consumption of energy are currently the most important indicators of a nation's growth rate. The energy production authorities focused a great deal of attention on renewable energy sources. Promoting renewable energy is necessary since it is a clean source of energy (Baúaranet al, 2015 [3], Jung et al, 2014 [4], Wang et al, 2011 [5] and Chang,2014 [6]) with significant growth potential for resolving environmental problems. By not producing the greenhouse gases that cause climate change or carbon emissions, renewable energy sources contribute to a more sustainable future. Different renewable energy sources with direct or indirect reliance on sunlight exist. It is predicted that renewable energy sources would produce the same amount of electricity as coal and natural gas by 2040.

Wind is the most abundant, clean, and environmentally friendly form of energy, along with solar and hydro energies. Wind energy is one of the best ways to combat global warming because it is completely pollution-free and emits no greenhouse gases. However, there are certain difficulties in running wind farms, such as predicting the whole quantity of electricity that must be generated to satisfy demand and not knowing the number of wind hours to plan a time for turbine maintenance. The operation planning of wind-generating plants producing electricity depends heavily on the study of short-term wind speeds and precise predictions. Researchers have used a variety of statistical, statistics mining, and system researching methodologies for constructing prediction models after realising the significance of forecasting the wind electricity era. (Ouyang et al. 2017 [7], Kusiak et al 2009 [8], Zhao et al 2011 [9], Sideratos and Hatziargyriou 2007 [10])

The most important factor in the forecasting method for wind power generation is the wind speed. It mostly determines how much power the wind turbine can convert. Over the years, a variety of single input techniques have been applied to artificial neural networks (ANN) to forecast wind speed. (Cadenas E., W.Rivera 2010 [11], Mabel M.C. and Fernández E 2008 [12], Liu et al., 1997 [13]) and with Linear Regression, support vector regression, Random Forest regression, time series analysis. As per the self-computing approach outperforms the regression technique according to Pao, 2008 [14]. These approaches have the disadvantage of producing forecasts that are not very precise since they simply take wind speed into account. Numerous geospatial variables are used in this study as inputs to calculate wind speed.

The goal of this study is to predict wind potential using continuous hourly temperature, soil temperature, solar radiation, pressure, u10, v10, and previous hour wind speed data. The best accurate model is recommended when using machine learning methods to anticipate the wind speed over the area, such as artificial neural networks and recurrent neural networks. The best thing about using these sophisticated models is they can update themselves in response to changes made to the input data received and give the most accurate forecast.

Satyanarayana et al. (2019) [15] found high wind energy zones over Telangana and Andhra Pradesh as well as predicted wind speeds at numerous levels under 120 m using 10-m wind speed observations for the period from 1979 to 2015 over the Telangana and Andhra Pradesh regions. Because of the higher wind speed in Anantapur, Andhra Pradesh, ANN and RNN models have been constructed in this study to anticipate the wind power potential over that area. This was done using data from the previous 10 years. The wind energy predictability using ANN and RNN models with a lead time of 24 hours. Wind energy planners and administrators can benefit greatly from wind energy predictions with a good lead time in terms of knowledge and direction.

2. Data

Meteorological data at 10-m level U-wind (eastward) and V-wind (northward) wind components, 2-meter level temperature, surface pressure, solar radiation, and soil temperature with a 1-hour interval (from 00:00 to 23:00 UTC) for a continuous period of 2011–2020 are collected from the ERA5 [ECMWF (European Centre for Medium-Range Weather Forecasts) Re-Analysis 5th generation] and used in this study for collecting Anantapur at latitude 14.5^0 N and longitude77.5^0 E (Figure 1).

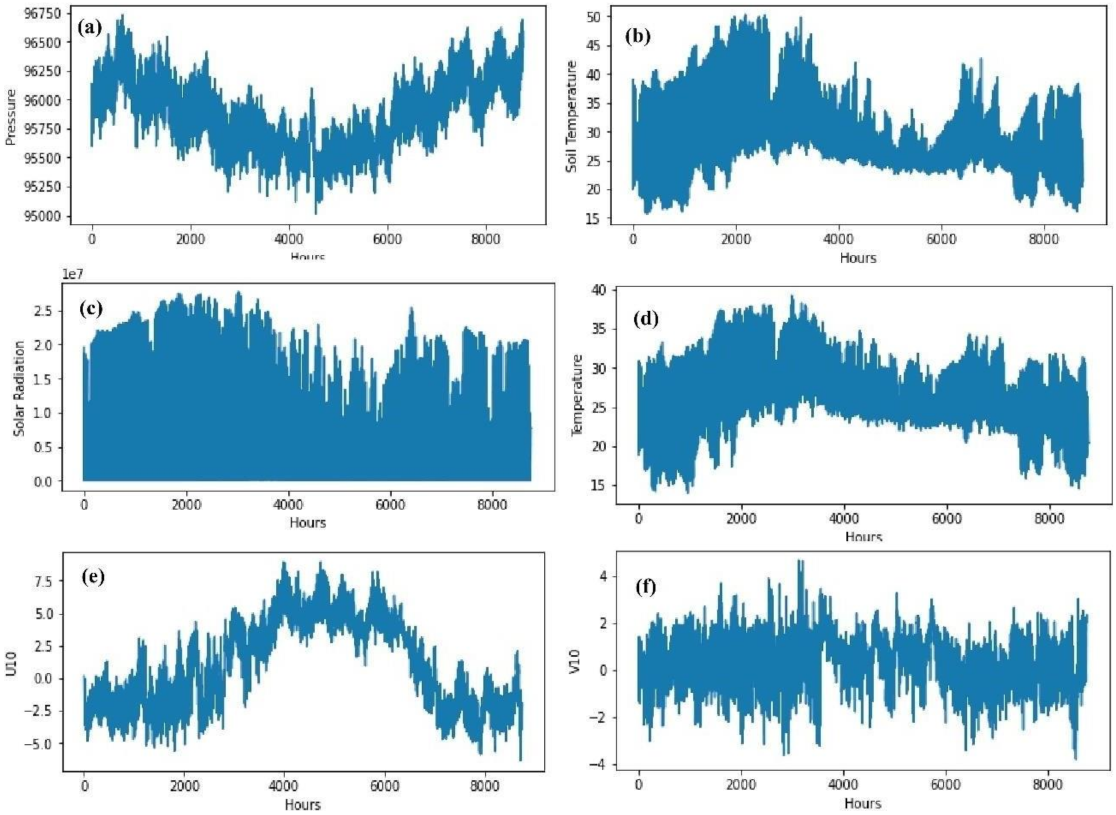

Figure 1: Time series of hourly data (a) Pressure, (b), Soil Temperature, (c) Solar Radiation, (d), Temperature, (e) eastward wind (u10m), (f) northward wind (v10m) at Anantapur, Andhra Pradesh for the period 2011 to 2020.

3. Methodologies

Artificial Neural Network (ANN):

The ANN is a group of algorithms that imitates how the human brain works to find hidden connections and patterns between different sets of data. Artificial neural networks are made up of various layers, each of which serves a distinct purpose. Information is initially sent to the input layer, which then sends it to the hidden layers. As a result of the link between these two layers, weights are randomly assigned to each input. The weighted total, which combines weights and bias, is then transmitted through the activation function once the bias has been applied to each input neuron. The intricacy of the network likewise grows as the number of hidden layers increases (Figure 2).

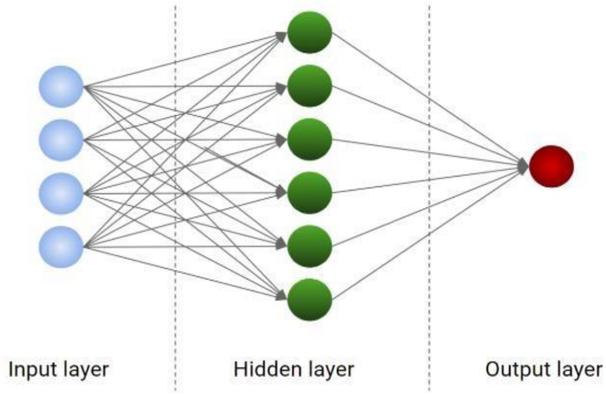

Figure 2: A Multilayered Feedforward ANN Schematic Diagram

Recurrent neural networks (RNN):

Recurrent neural networks are altered neural networks used to process time-series data or data that contains a sequence. In RNN, the output of the prior layer or neuron serves as the current layer's input, which is a key distinction between ANN and RNN. To produce the following output in a series, RNNs contain the idea of "memory," which enables them to store the states or information of prior inputs (Figure 3).

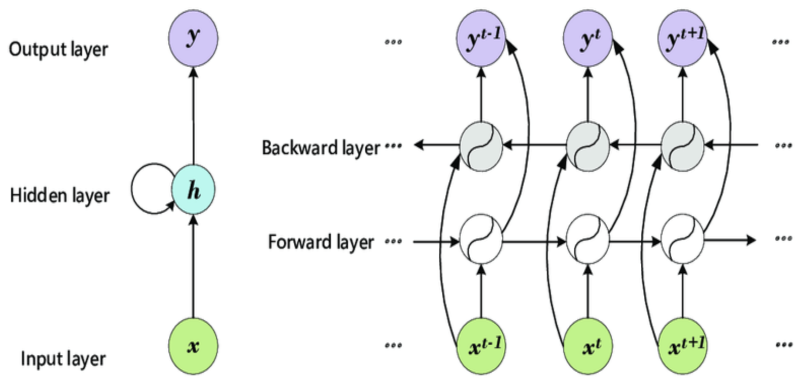

Figure 3: Schematic Diagram for the Recurrent Neural Networks (RNN)

Table 1: Different predicted variables with different test cases.

ASPECT	TEST-1	TEST-2	TEST-3	TEST-4
SOLAR RADIATION	✓	✓	✓	✓
TEMPERATURE	✓	✓	✓	✓
SOIL TEMPERATURE	✓	✓	✓	✓
PRESSURE	✓	✓	✓	✓
U10	✓	✓	✓	✓
V10	✓	✓	✓	✓
WIND SPEED		✓		✓

Develop the ANN model for Wind energy prediction

I. Test 1:
In the first case, the ANN model is trained with data on temperature, soil temperature, pressure, solar radiation, and u10 and v10 winds of the selected region to forecast the wind speed (Table 1).

II. Test 2:
Additional to the input parameters given in the first case, the previous hours predicted wind speed is given as input to the ANN model for forecasting the wind speed (Table 1).

III. Test 3:
In this case, the recurrent neural network model is trained with similar variables as given in case 1 and predicts the wind speed (Table 1).

IV. Test 4:
In addition to the input variables given in the first case, the previous hours predicted wind speed is given to the Recurrent Neural Network model to predict the wind speed (Table 1).

To compare the model outputs to daily observations, the statistical measures BIAS, MAE, IOA, RMSE, and correlation coefficient (COR) have been utilised. The equations and formulas are listed below. [Wilks, 2006]:

$$COR = \frac{\sum_{i=1}^{n}(f_i-\bar{f})(o_i-\bar{o})}{\sqrt{\sum_{i=1}^{n}(f_i-\bar{f})^2}\sqrt{\sum_{i=1}^{n}(o_i-\bar{o})^2}} \text{ ----------(1)}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|f_i - o_i| \text{ --------------------(2)}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(f_i-o_i)^2}{n}} \text{ ---------------------(3)}$$

$$\mathrm{IOA} = 1.0 - \frac{\sum_{i=1}^{n}(f_i-o_i)^2}{\sum_{i=1}^{n}(|f_i-\bar{o}|+|o_i-\bar{o}|)^2} \text{ ----------(4)}$$

Using the formula, the wind power density at the four selected levels was calculated. (Ramachandra and Shruthi, 2003)

$\mathbf{P_d = 0.5\ K_a\ D\ w_e^3}$-------------(5)

where Ka is the energy pattern factor

$\mathbf{K_e= [w_l^3/N_a]/w_a^3}$-----------------(6)

where Pd = power per unit area (watts/m2), D is the air density (1.29 kg/m3), whereas the wind speed in meters per second, and w_l is the wind speed in hours, N_a is the energy pattern factor and K_a is the number of wind speed hourly data (19).

4. Result and Analysis

All the test case models are trained on the past 7 years' data of Anantapur, which is located at (latitude 14.5 and longitude77.5.) and tested on 3 years of data. The data is split into training (63000 hours) and testing (27000 hours) parts (Figure 4).

Splitting of data into testing and training:

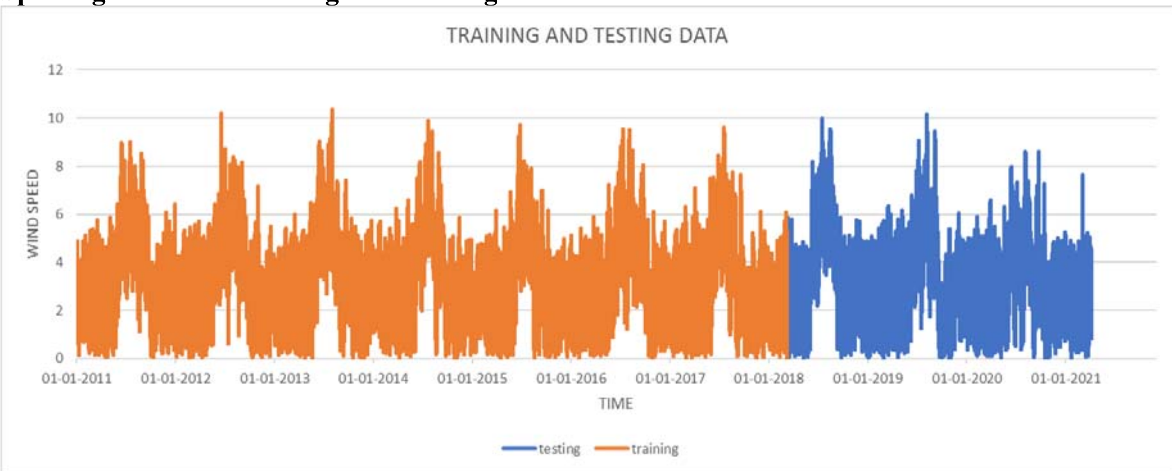

Figure 4: Time series of hourly wind speed orange shows training (70%) and the blue color indicates testing (20%) for the period 2011 to 2020.

All the four test cases are trained with the same computational parameters which includes epochs = 100, hidden layer=3, hidden layer activation function=relu, Dence layer activation function =Linear, optimizer =adam. Furthermore, model accuracy is measured by statistical analysis methods such as RMSE and MAE.

Forecasted values at 3 hours intervals, 6 hours intervals, 12 hours intervals, and 24 hours intervals are recorded for checking the continuous accuracy of the models.

TABLE 2: Evaluation of the statistical metrics of the ANN model predict wind speed at Anantapur, Andhra Pradesh during 2011-2020.

CASE 1	MAE	RMSE	R2
3 hrs	0.58	0.76	0.75
6 hrs	0.76	1.0	0.58
12 hrs	0.82	1.06	0.52
24 hrs	0.71	0.92	0.64
CASE 2	MAE	RMSE	R2
3 hrs	0.58	0.77	0.74
6 hrs	0.62	0.84	0.70
12 hrs	0.77	1.0	0.57
24 hrs	0.74	0.96	0.61

CASE 3	MAE	RMSE	R2
3 hrs	0.65	0.86	0.68
6 hrs	0.74	0.96	0.61
12 hrs	0.77	0.99	0.58
24 hrs	0.70	0.90	0.66

CASE 4	MAE	RMSE	R2
3 hrs	0.63	0.82	0.71
6 hrs	0.66	0.87	0.68
12 hrs	0.72	0.93	0.63
24 hrs	0.66	0.85	0.69

The results for all the performed test cases:

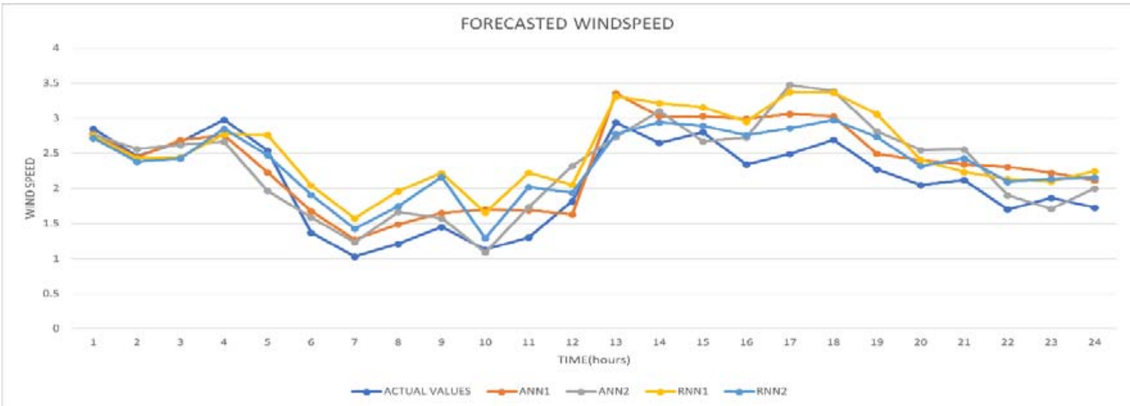

Figure 5: Time series of 24 hours wind speed prediction of different case studies at Anantapur

Analyzing the insights of the results has shown that RNN models suffered in the initial stage but have given good accuracy from the 12th hour's interval.

The Case 4RNN model has given promising results compared to the remaining test cases:

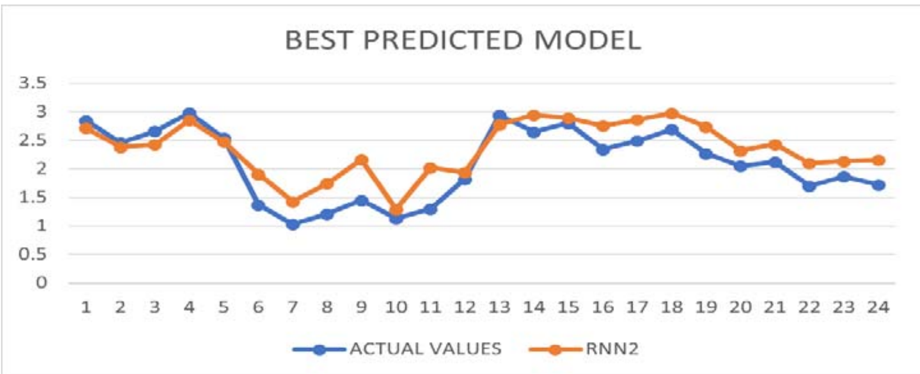

Figure 6: Time series of 24 hours wind speed prediction using the RNN model at Anantapur

Taylor Diagram for all the test cases has been calculated and the RNN model with inputs including the previous hour's wind speed (CASE 4) has shown a good correlation coefficient with the data and the results are more accurate than those of reaming test cases.

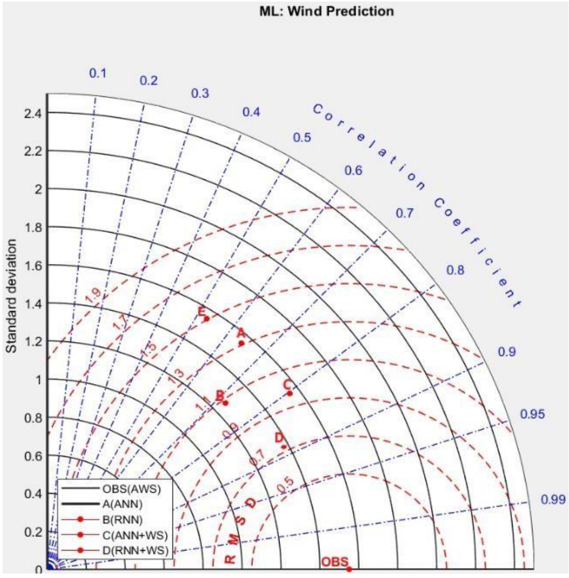

Figure 7: Taylor diagram for model evaluation performances.

5. Conclusion

Wind power is one of the most effective forms of popular and rising renewable energy. However, operating a wind farm has several difficulties, such as determining how much power will be generated each day and planning a maintenance window for the turbines, which helps with the simple operation of a wind farm. This study forecasts the potential for wind energy across the indicated region using a variety of machine learning approaches and predicts hours with less wind to conduct maintenance for the wind turbines.

To anticipate the wind power density in Anantapur, ANN and RNN models are utilised. In this study, we used ten years (2011-2020) of hourly wind speed data for developing prediction model. The findings demonstrate the strength and reliability of the prediction models created using a variety of training procedures, utilising a validation rate of 15% producing the best outcomes. Various statistical techniques, such as RMSE, R2 score, and correlation, are used to validate models' performance and choose the best method for predicting wind speed. Among the algorithms used, RNN provided with previous wind data (case 4) has shown good overall performance by achieving an RMSE of 0.82, 0.87, 0.93, and 0.85 for 3, 6, 12, and 24 hours respectively. ANN provided wind previous wind data (case 2) has given the next decent rmse score of 0.77, 0.84, 1.0, and 0.96 for 3, 6, 12, and 24 hours forecast respectively. ANN model (case 1) has an RMSE score of 0.76, 1.0, 1.06, and 0.92 for 3, 6, 12, and 24 hours forecast respectively. while RNN model (case 3) has an RMSE of 0.86, 0.96, 0.99, 0.90 for 3, 6, 12, and 24 hours forecast respectively. These stats suggest that RNN is the best algorithm to forecast wind energy and it is the preferred algorithm.

The key conclusion of the study is that forecasting wind speed is more accurate when using models with numerous inputs, including data from the previously projected wind. Additionally, machine learning is applicable in geoscience to forecast wind energy and speed over an uncharted region using historical data. The time and effort required to operate a wind farm are significantly reduced by this process, which can take the place of more conventional approaches.

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