Research Article

Raja Mohamed Kaja Bantha Navas*, Subramaniam Prakash, and Viktor Molnar

Analysis of short-term wind speed variation, trends and prediction: A case study of Tamil Nadu, India

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Abstract
Purpose – The purpose of this research article is to analyze the short-term wind speed and develop a framework model to overcome the challenges in the wind power industry.
Design/Methodology/Approach – Real data with a case study of wind speed is presented to illustrate the advantages of this new wind speed analytical framework. Hourly measurements of wind speed are observed, and the experiments are conducted using tools such as ANOVA, control charts, trend analysis, and predictive models. The August month data for over 13 years from modern era retrospective-analysis for research and applications (MERRA) National aeronautics and space administration (NASA) for Coimbatore and Erode locations in Tamil Nadu, India, have been used. The results were considered for the study to understand the wind speed data and the implementation of new wind power projects in India.
Findings – The essence of the proposed wind speed analytical framework is its flexible approach, which enables the effective integration of wind firms' individual requirements by developing tailor-made analytical evaluations.
Originality/Value – This article derives the wind speed analytical framework with the application of statistical tools and machine learning algorithms.

Keywords: wind speed, ANOVA, control chart, machine learning, predictive, ensemble, SPSS modeler

1 Introduction

Worldwide energy demand is growing rapidly in major domains of the energy market. The world has made remarkable progress and a high share of renewable energy sources. Due to a less carbon-intensive and sustainable energy system, the world is now moving toward renewable energy resources, which include biomass, hydropower, geothermal, wave, marine energies, and tidal [1]. The International Energy Agency's (IEA) Renewables Report 2019 shows clear trends and developments in renewable energy across different sectors. Renewable energy's share of global electricity generation is 26% (Renewables, 2019, Analysis and Forecast to 2024, IEA Report). The Ministry of Renewable Energy, Govt. of India Report [2] for India's wind projection states that India's wind power industry has greater scope. Kralova and Sjöblom [3] projected global renewable energy scenario status by 2030 and 2040. From this projection, wind and solar energies are indispensable sources of energy to satisfy power needs. Saidur et al. [4] discussed various literature about the

*** Corresponding author: Raja Mohamed Kaja Bantha Navas,** Department of Mechanical, Sathyabama Institute of Science and Technology, Jeppiaar Nagar, Rajiv Gandhi Salai, Chennai, 600119, India; Department of Fashion Technology, National Institute of Fashion Technology, Gandhinagar, Gujarat 382007, India, e-mail: sumai244@gmail.com
Subramaniam Prakash: Department of Mechanical, Sathyabama Institute of Science and Technology, Jeppiaar Nagar, Rajiv Gandhi Salai, Chennai, 600119, India, e-mail: prakash_s1969@yahoo.com
Viktor Molnar: Institute of Manufacturing Science, University of Miskolc, 3515 Miskolc, Hungary, e-mail: molnarv80@gmail.com

positive impacts of wind energy. They have also found that consumption reduction of water and CO_2 is a positive impact of wind energy. At the same time, Gao et al. [5] show that there is a slow decline in wind power potential in India due to climatic variation. Hence, an analytical study is required for wind speed. The aim of this research article is to analyze short-term wind speed variation, trends and prediction. This article explains the wind speed analytical framework for variation, trends and prediction based on the modern era retrospective-analysis for research and applications (MERRA) National aeronautics and space administration (NASA) portal data with the application of statistical tools and machine learning algorithms. Society 5.0 is a human-centered Industry 4.0. Society 5.0 is expected to create new value by developing advanced technology to bridge the gap between humans and future economic problems. Citations were included toward Society 5.0 (Hitachi – U Tokyo Laboratory [6] and Salgues [7]). The application of the proposed wind speed analytical framework, which is an aspect of Society 5.0, would enhance the performance of power industries toward economic advancement with the resolution of forecasting problems.

2 Theoretical background

Rehman et al. [8] investigated mean wind power density and mean energy content for three different cities Coimbatore, Erode, and Chennai in Tamil Nadu based on historical wind speed, direction, temperature, and pressure data. They found that Chennai is the most suitable site for wind energy production, followed by Coimbatore and Erode in Tamil Nadu. Moreno [9] defined big data techniques and their applications in smart city projects. They analyzed the region of Murcia data by integrating smart city applications and smart city campuses and derived the main features of the two architecture instantiations for smart campus and public tram service. Elattar et al. [10] proposed short-term electric load forecasting using locally weighted support vector regression and the modified grasshopper optimization algorithm in smart cities. They evaluated the proposed model with a traditional artificial neural network and support vector machine with six different real-world datasets. They found that hybrid models are giving better performance compared to traditional computational models. National center for atmospheric research (NCAR) and MERRA reanalysis data have been commonly used in wind resource analysis during the last decade. Lileo and Petrik [11] investigated the use of MERRA, National centers for environmental prediction reanalysis (NCEP)/climate forecast system reanalysis (CFSR), and NCEP/NCAR reanalysis data for wind resource analysis in the territory of Sweden. They have experimented with correlation analysis between the reanalysis data and mast measurements and the distance separating their locations. They found that MERRA grid data had a larger R square value compared to NCEP/NCAR and NCEP/CFSR. Navas Raja Mohamed and Prakash [12] discussed various neural network models for wind energy resource prediction. Navas Raja Mohamed et al. [13] predicted short-term wind speed using neural network models and categorical regression. Some scholars have listed ultra-short-term forecasting models with different applications. Navas and Prakash [14] worked out an ultra-short-term forecasting intelligence system with a hybrid neural network model for wind power, which is used to forecast 30 s to 6 h time horizon tasks. Katyal et al. [15] conducted wind speed forecasting experiments with a neural network-Design of Experiments – Data Envelopment Analysis. Krishnan [16] projected changes in temperature, rainfall, drought and sea level rise with India's climatic evidence. Mahmood et al. [17] analyzed temperature variability, trend and prediction. They found that 84% of the temperature time series have strong, increasing trends indication. Bastin et al. [18] have carried out the same experiments with city pairs for 520 major cities around the world. Murakami et al. [19] observed and analyzed climatic data for the global distribution of tropical cyclones. Girma et al. [20] investigated the annual precipitation and temperature time serious variability by using the innovative trend analysis method. NCAR and MERRA reanalysis data have been commonly used in wind resource analysis during the last decade. Asian et al. [21] analyzed 240 wind turbine accidents from around the world. The work focused on revealing the associations between several factors and deaths and injuries in wind turbine accidents. The article concluded that strong wind is the most relevant factor for natural causes. Boopathi et al. [22] investigated various Indian states' and regions' climatic variations with wind speed and extreme temperature variations. de Jong et al. [23] investigated Brazil's climate change toward wind and solar energy. Compared to the end of the twentieth century, there is significantly less rainfall and a higher temperature as a result. Chauke [24] looked at inter-annual variability (IAV) in wind speed in South Africa with trend analysis. Zhang et al. [25] investigated near-surface wind speed change in China during 1958–2015. Lee et al. [26] listed various parameters for wind speed variability. But it does not involve statistical approach. In this article, the researchers used a wind speed variability study with statistical approach. Bastin et al. [27] have done IAV, but the researchers carried out further microlevel inter-monthly variability for wind speed.

3 Methods and analysis

Tamil Nadu is one of India's most prominent states for wind resources. Tamil Nadu has four wind passes, i.e., Tamil Nadu continues to lead the way in the wind energy transition. While selecting the study location, we considered four wind passes in Tamil Nadu. We conducted a study trial for the major cities through wind passes. At the same time, the Ministry of Urban and Development, Govt. of India, identified 13 smart city projects in Tamil Nadu (http://smartcities.gov.in/content/). To implement smart city projects, requirements for the energy infrastructure are high, particularly renewable. A SMART city emerges when the urban infrastructure is evolved through the energy infrastructure, particularly renewable energy, with information and communication technology (Komninos [28]). Out of those 13 smart city project cities, we have chosen two cities that have strong wind passes. The wind speed MERRA data for the study was gathered from the NASA Giovanni portal [29]. The wind speed data collection is situated at 10.9675°N, 76.9182°E (Coimbatore) and 11.3410°N, 77.7172°E (Erode). The August month data from over 13 years' data have been used for this study. We have focused on wind speed recorded in August only since the wind speed is highest during that month.

Wind speed data attributes are given in Table 1. The wind speed analytical framework is an improvement system for existing processes falling below specification and looking for incremental performance. It included

Table 1: Data attributes for wind speed

S. No.	Parameters	Unit	Source of data	Temp. Res.	Spat. Res.
1	Wind speed	m/s	MEERA	Hourly	0.5 × 0.625°

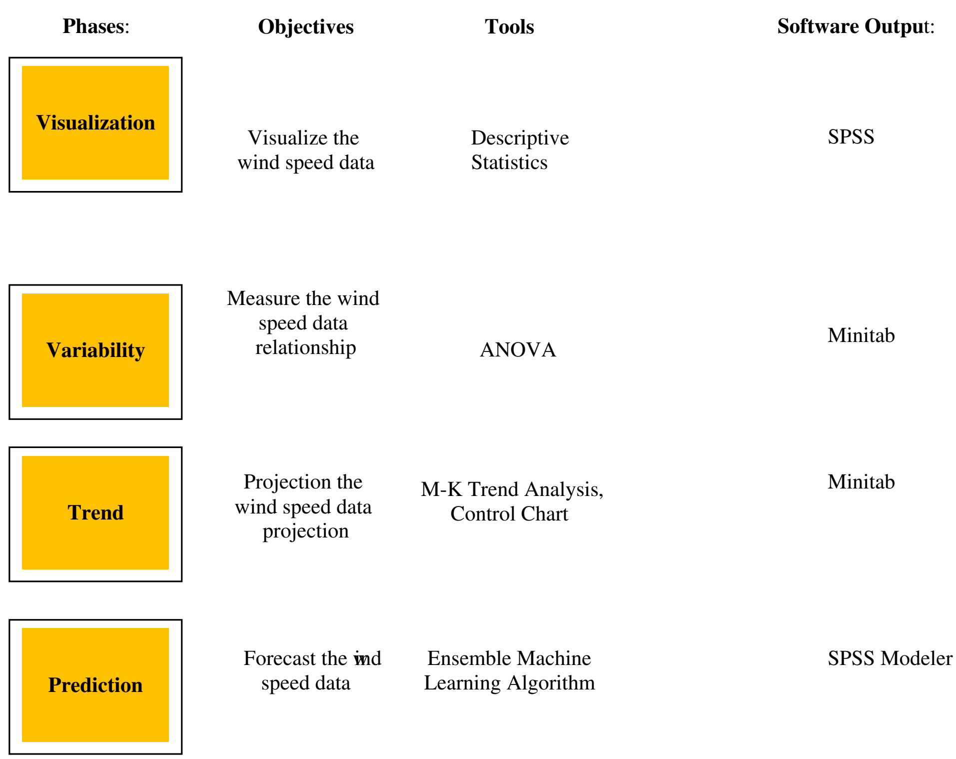

Figure 1: Methodology for wind speed analytical framework.

objectives, tools and output. The wind speed analytical framework methodology is shown in Figure 1. There are four phases in the wind speed analytical framework, i.e., descriptive, variability, trend and prediction. After finalizing the objectives, the tools selection is classified into two groups: one group is based on statistical tools like variation and trend analysis and based on the study conducted by Brower et al. [30], and the second group is based on the ensemble machine learning algorithm based on the IBM SPSS Modeler [31], which focused on auto-numeric function.

3.1 Descriptive statistics

The wind speed characteristics for each year are shown in Tables 2 and 3. In Table 2, mean scores and standard deviations of every year are calculated for the Coimbatore location, and in Table 3, mean scores and standard deviations of every year are calculated for the Erode location.

Table 2: Descriptive statistics for wind speed (Coimbatore)

Parameters/Year	2008	2009	2010	2011	2012	2013	2014
Mean	6.020	4.566	5.396	6.502	8.416	7.101	5.567
Minimum value	3.025	3.007	3.500	3.387	3.287	3.160	2.437
Maximum value	9.152	9.044	12.254	11.472	10.806	9.991	5.940
Std. deviation	0.297	1.297	0.845	0.244	0.054	0.233	0.233
Variance	0.08	0.299	0.401	0.451	0.716	0.038	0.395
Skewness	13.63	17.043	15.008	13.239	17.541	15.511	13.048

Parameters/Year	2015	2016	2017	2018	2019	2020
Mean	6.650	6.974	5.880	5.559	6.448	6.395
Minimum value	2.605	3.316	3.243	3.130	3.330	3.270
Maximum value	6.791	11.002	10.523	9.800	11.091	10.696
Std. deviation	0.383	0.324	0.264	0.449	1.096	0.238
Variance	0.506	0.152	0.158	0.072	0.473	0.234
Skewness	14.369	16.375	13.593	14.701	19.739	14.269

Table 3: Descriptive statistics for wind speed (Coimbatore)

Parameters/Year	2008	2009	2010	2011	2012	2013	2014
Mean	5.556	4.221	5.300	6.298	8.119	7.011	5.291
Minimum value	0.152	0.124	0.068	0.228	0.849	0.046	0.284
Maximum value	13.323	16.308	14.477	12.576	17.697	15.435	13.260
Std. deviation	2.828	2.936	3.407	3.371	3.176	2.998	2.528
Variance	7.998	8.618	11.606	11.363	10.086	8.991	6.389
Skewness	0.367	1.301	0.851	0.171	0.136	0.315	0.332

Parameters/Year	2015	2016	2017	2018	2019	2020
Mean	6.237	6.858	5.768	5.285	6.255	6.335
Minimum value	0.213	0.432	0.284	0.033	1.035	0.414
Maximum value	14.797	16.591	13.894	14.387	19.956	14.781
Std. deviation	2.695	3.302	2.937	3.061	3.391	3.249
Variance	7.264	10.902	8.626	9.369	11.502	10.557
Skewness	0.369	0.358	0.233	0.555	1.200	0.123

The descriptive statistics of wind speed such as the mean, standard deviation, coefficient of variation and skewness are discussed in Tables 1 and 2. The mean wind speed is highest for the year 2012 and lowest for the year 2009 for the Coimbatore and Erode sites. For the A1 site, standard deviation for wind speed is highest at 5.925 and lowest at 2.437. For Erode site, standard deviation for wind speed is highest at 3.371 and lowest at 2.828. It indicates that the data variance is very minimum. From the computed table for Coimbatore Site, it has been found that the average yearly wind speed variation ranges from 12.254 to 5.940%. The highest wind speed mean scores were in the year 2010. From the computed table for Erode Site, it has been found that the average yearly wind speed variation ranges from 11.606 to 6.389%. The highest wind speed mean scores were in the year 2010. Measures of skewness tell us the direction and extent of skewness. Skewness tells us about the direction of the variation or the departure from symmetry. It is an indication of the symmetry of the distribution. Kurtosis provides information about the peakiness of the distribution. Kurtosis refers to the degree of flatness or peakiness in the region about the mode of a frequency curve. All Skewness values of wind speed are positive, indicating the clustering of the scores at the low end (left-hand side of the graph) [32]. Kurtosis results are negative for most of the wind speed. The negative value for the kurtosis indicates that the distribution is rather peaked (clustered in the center) with long, thin tails. Kurtosis values below zero indicate a distribution that is relatively flat (too many cases in the extreme).

3.2 Analysis of variations

An orthogonal array was used to design the experiments with single factors (year) and 13 levels (each year) in Montgomery [33]. ANOVA experiments were carried out through Minitab. The experimental results are presented in Tables 4 and 5. Based on the wind speed mean, the following hypotheses have been formulated and tested:

Table 4: ANOVA result for wind speed (Coimbatore)

Sources	Sum of squares	df	Mean square	*F*	Sig.
Between groups	8123.356	12	676.946	68.452	0.000
Within groups	95521.171	9,659	9.889		
Total	103644.527	9,671			

Table 5: ANOVA result for wind speed (Erode)

Sources	Sum of squares	df	Mean square	*F*	Sig.
Between groups	8531.207	12	710.934	74.975	0.000
Within groups	91589.447	9,659	9.482		
Total	100120.654	9,671			

Null Hypothesis H_0: All year wind speed means are equal.

Alternative Hypothesis H_1: All year wind speed means are not equal.

From Tables 4 and 5 for both locations, the p-value in the ANOVA result is less than or equal to the significance level, so we have rejected the null hypothesis and concluded that not all the year wind speed is equal Montgomery [33].

3.3 Trend analysis

M–K method is the nonparametric test used to analyze if there is a monotonic upward or downward trend of the variable over time 2008–2020. M–K test results are shown in Figure 2 for Coimbatore location. Figure 2 shows that there is a trend in the yearly wind speed pattern. Statistically significant trends are detected for wind speed and also the result is statistically significant at a 99% confidence limit during the period of 2008–2020.

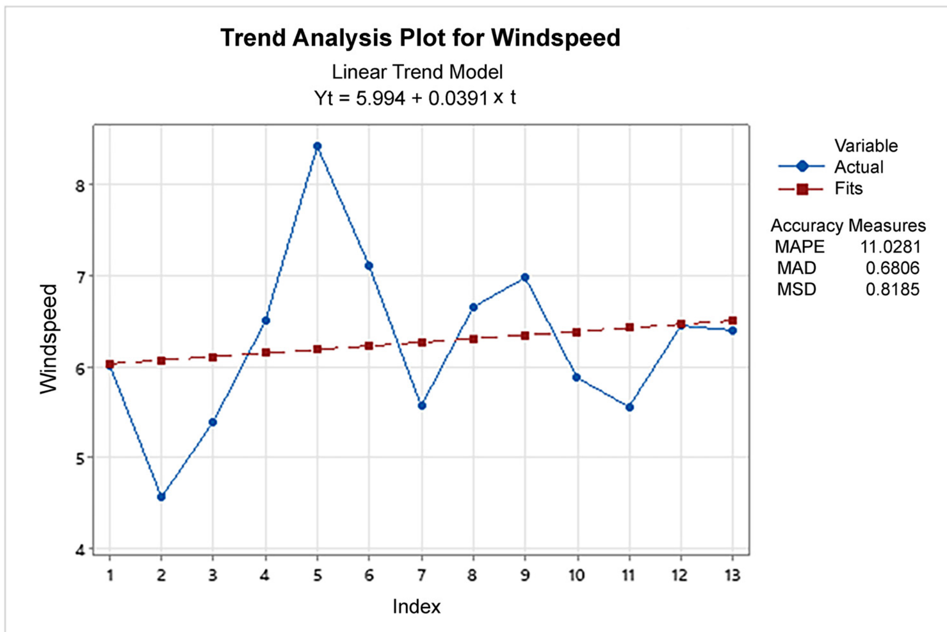

Figure 2: M–K trend result for wind speed (Coimbatore location).

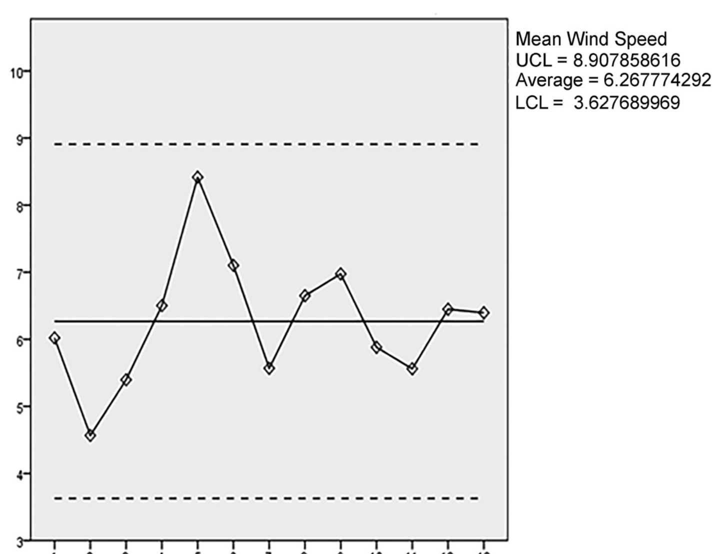

Figure 3: X-Bar chart for wind speed (Coimbatore).

3.4 Control charts

The control charts are a simple graphical tool that enables process performance and monitoring and identifies which types of variation exist within the process. Marton [34] and Suman and Prajapati [35] listed the various applications of control charts and provided guidance for the classification of control charts. We can also use X, R, C, U, P, and nP charts based on the data. But our data are variable, countable, not very large subgroup size, and constant sample size. So, we have chosen an X-bar chart for further analysis. In Figures 3 and 4, the X-bar control chart shows the mean of wind speed in subgroups varying year by year for Coimbatore and Erode. The mean of wind speed for all years is in control. It shows that the system is stable (i.e., in control).

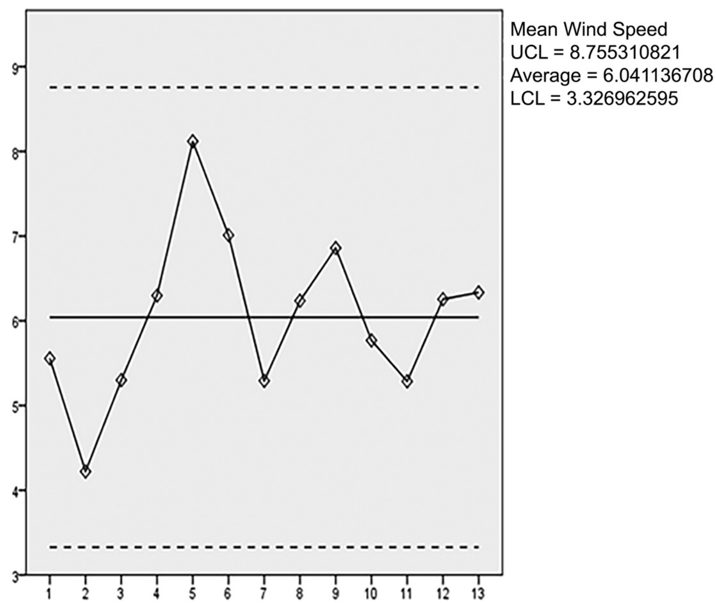

Figure 4: X-Bar chart for wind speed (Erode).

3.5 Predictive model

A time series is a set of observations of wind speed obtained by measuring a single variable regularly over a period of time. Time series forecasting is used for short-range forecasts such as wind speed. The predictive objective is to build ensemble methods that combine several base models for wind speed prediction and

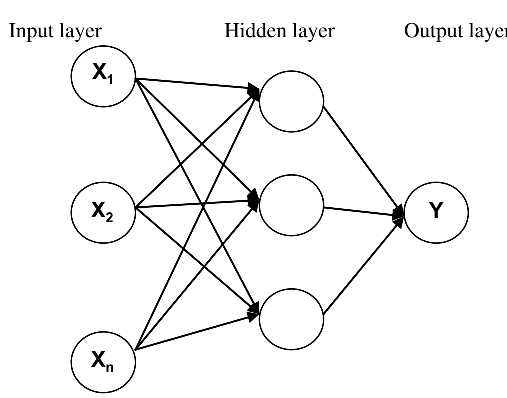

Figure 5: Input and output for ensemble model. Y = Wind speed @ 2020 (m/s); X_1 = Wind Speed (m/s) @ 2008 (m/s); X_2 = Wind Speed (m/s) @ 2009 (m/s); X_n = Wind Speed (m/s) @ 2019 (m/s).

produce a validated and acceptable prediction. The researchers have used auto-numeric through SPSS Modeler. Model input and output are shown in Figure 5. Forecasted wind speeds with different models for the period of August 2008 to August 2019 are compared with the actual measured wind speed data for the period of August 2020. According to the goodness-of-fit criterion, correlation and relative error are applied for performance analysis. The statistical indicators of wind speed estimation for Coimbatore location are presented in Table 6. Random forest, XGboost, Neural Network and CHAID are given reliable and minimum error. The results of the validation and comparative study indicate that the Random forest, XGboost, Neural Network and CHAID-based estimation techniques for wind speed are more suitable for predicting wind speed.

Table 6: Precision of the wind speed prediction by ensemble models (Coimbatore)

S. No.	Models	Correlation	Relative error
1	Random	0.994	0.015
2	XGboost	0.991	0.028
3	Neural network	0.972	0.055
4	CHAID	0.916	0.161

4 Conclusions

Wind speed could play a main role in the electricity market. This research has analyzed wind speed variability with two different locations in Tamil Nadu, India. Our results completely opposed the studies carried out by Gao et al. [5]. Furthermore, the collected data over 13 years were assigned with 30% testing partition and 70% training partition. The model's performance is measured with suitable data. The statistical performance criteria indicators are applied to carry out performance analysis. The performances of the models are analyzed using correlation, and relative error measures the average magnitude of the errors in a set of predictions without considering their direction. Hence, according to the performance indices random, XGboost, Neural Network and CHAID, it can be seen that the above models are reliable since they give minimal error. From the results, it can be found that the ensemble model is equally credible selection with other machine learning models. This study confirms the ability of random, XGboost, Neural Network and CHAID to predict wind speed values precisely. The performances of random, XGboost, Neural Network and CHAID were comprehensively investigated based on the wind data in Coimbatore. Their predictive performances are compared with suitable measured data. The correlation coefficient and relative error are applied for performance analysis.

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Conflict of interest: The author declares that there is no conflict of interest regarding the publication of this article.

Code availability: Not applicable.

Data availability statement: The data used to support the findings of this study are available from the corresponding author upon request.

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