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Machine learning-based simplified methods using shorter wind measuring masts for the time ahead wind forecasting at higher altitude for wind energy applications

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Abstract. Since wind is a fluctuating resource, the integration of wind energy into the electricity grid necessitates precise wind speed forecasting to maintain grid stability and power quality. Machine learning models built on different algorithms are widely used for wind forecasting. This requires a vast quantity of past wind speed data collected at the hub levels of the wind electric machines employed. Tall met masts pose a variety of practical issues in terms of installation and long-term maintenance, which will grow more challenging as next-generation wind turbines come with larger capacities and higher hub heights. In this paper, we propose four non-conventional methods for the time ahead forecasting of wind speed at a higher height by utilizing the wind speed data collected with relatively shorter wind measuring masts. We employ machine learning-based models and rely on the principle of interrelation between wind speeds at different altitudes in our investigations. Wind speed forecasts generated by the new methods at an altitude of 80 m above the ground level using wind speed data measured at lower altitudes of 50 m and 20 m are of industrially acceptable accuracy. The simplified physical requirements such methods demand far outweigh the marginal fall in prediction accuracy observed with these methods.

Keywords: Wind energy / wind speed forecasting / wind mast / machine learning / power law

1 Introduction

As a clean and renewable energy source, the wind continues to play a significant role in addressing the global energy crisis. The global wind power installations reached 743 GW in 2020 with the addition of 90 GW in 2020 alone, showing the phenomenal progression of this energy segment [1]. Going by the trends in wind energy development and utilization, the wind is expected to provide 20% of the global electricity production by 2030 [2]. Since wind is an intermittent resource, precise wind forecasting is essential for the proper integration of the varying wind energy into the electricity grid for ensuring grid stability and power quality. Accurate wind forecasts on different lead time scales assist wind farms in real-time grid control, efficient load dispatch planning, deciding on reserve requirements, market trading, maintenance scheduling and the like. Effective wind forecasting and planning can result in better exploitation of useful wind energy [3]. As the energy produced from the wind scales with the cube of wind velocity, even small errors in the assessment of wind speed can contribute to larger errors in the energy production estimate [4,5]. Because of these concerns, wind forecasting continues to be a field of great research interest to the wind energy sector.

Extensive research has been conducted in the past in the area of short-term wind prediction, giving attention to forecasting methods, types of models as well as meteorology [6]. Diverse investigations carried out in wind forecasting have yielded appreciable results for wind energy applications [7,8]. Based on the adopted methodology, wind forecast models are primarily classified into physical, statistical, data learning, and hybrid models. The physical models employ various atmospheric parameters and are useful to identify recurring trends and to make long-term predictions. Statistical models assume that the variations in wind speed are stochastic. Recent studies have however shown that the complex stochastic-like fluctuations in wind conditions arose from the chaotic dynamics of the underlying system [9–11]. One study has validated a method of nonlinear autoregressive network

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with exogenous input (NARX) for the hourly forecasting of wind speed [12]. Short-term wind power forecasting using linear and non-linear data mining algorithms has also been demonstrated with successful field trials [13]. Various artificial neural network-based data learning techniques are also gaining prominence in the recent literature for wind forecasting. A layer recurrent neural network (LRNN) method has been demonstrated for the prediction of wind speed up to 5 days ahead in 5 min steps [14]. Another study designed an adaptive neuro-fuzzy inference system (ANFIS) based intelligent machine for utility operators to fulfill the forecasting obligations as per Indian electricity grid code (IEGC) 2010 regulations [15]. Random Forest model has been shown in one particular study to yield better wind speed prediction accuracy over the classical neural network prediction method [16]. Hybrid models developed by combining various methods like physical, statistical and machine learning methods are found to improve predictive accuracy [17–20]. Simple auto regressive (AR) wind speed forecast models have been found to improve prediction accuracy when combined with the wavelet decomposition [21]. Short-term wind forecasting by combining different variants of support vector regression (SVR) with wavelet decomposition has also been reported [22]. Another study has attempted wind speed data analysis by combining wavelet transform, support vector machines and genetic algorithms [23], wherein wind speed data has been analyzed by decomposing it into several components and integrating it with a genetic algorithm parameter optimized support vector machine. A method of correcting the wind speed forecast errors by building a correction topography through statistical means from measured data and then applying the same to the wind forecasts generated by a conventional model has also been reported [24]. Another study has demonstrated very short-term wind forecasting by using a vector autoregressive model integrated with large-scale meteorological information [25]. A new enhanced ensemble method has shown improved performance in the short-term probabilistic forecasting of wind speed [26]. Hybrid models involving a combination of time series models with pressure, temperature and precipitation as inputs to predict monthly average wind speed values have also been investigated [27]. A hybrid model that uses ensemble empirical mode decomposition for noise reduction and a modified wind-driven optimized backpropagation neural network has been employed for predicting 10-min-ahead and 30-min-ahead wind speed [28]. One study has analyzed wind speed data with three different machine learning algorithms namely radial basis support vector machine, multilayer feed-forward neural network and adaptive neuro-fuzzy inference system and demonstrated the supremacy of support vector machine (SVM) variant over the neural network and neuro-fuzzy techniques [29]. Another study has shown Improved performance of machine learning-based wind forecast models with the inclusion of atmospheric stability parameters in them [30]. It has been shown that the gradient boost machine learning regressor is more accurate compared to any of the existing analytical models for the runtime performance prediction whenever the range of the prediction follows that of the training. However, the two analytical models namely the 2D-plate model and the fully-connected model outperform the machine learning regressor when using the extrapolation method [31]. Our recent study [32] has demonstrated the spatio-temporal independent applicability of one time trained machine learning wind forecast models within a wind regime, which has been applied in this research.

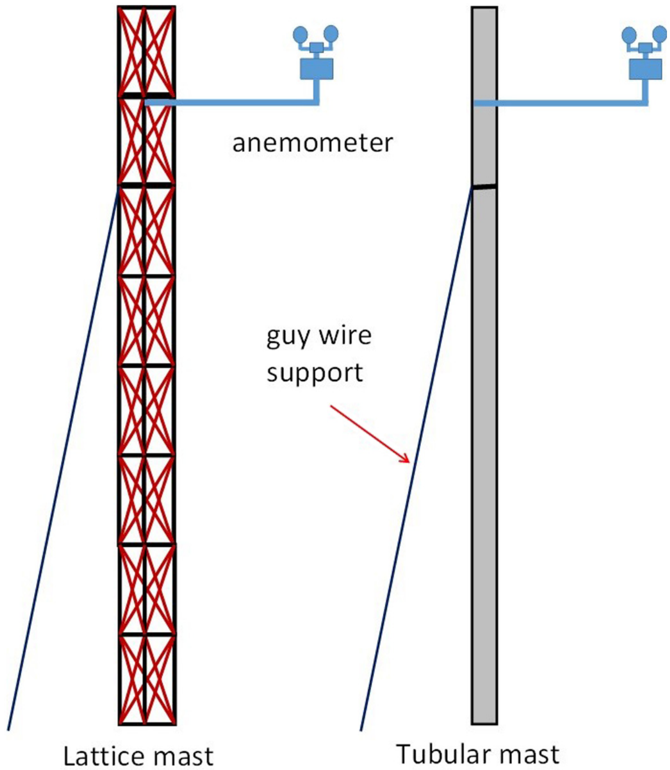


Fig. 1. Schematic representation of tubular and lattice-type wind masts.

Even as different methods are available for the effective forecasting of wind speed at an altitude of interest, a considerable quantity of historical wind speed data at the same location and altitude is necessary for the modeling and prediction, which is usually accomplished by establishing and retaining tall wind masts at the location of interest. The wind masts are tubular or lattice-type steel towers as shown schematically in Figure 1. Tubular towers are made of galvanized steel or stainless steel tubes with customizable heights. Lattice masts are made of steel lattice structures, usually connected one above the other to reach the required height. Tubular masts are normally preferred for 30 m to 85 m altitudes while the lattice masts are chosen for altitudes above 100 m. The installation and prolonged maintenance of high-altitude wind measuring masts give rise to several practical difficulties from an engineering standpoint. The tendency to lose the structural stability of mast in heavy wind load, the need for vast guy wire support for wind mast, the requirement of a larger area for the high mast together with the supporting guy wires, the propensity of component failures due to various reasons like lightning strikes, high cost associated with the de-erection and restoration of wind masts for rectifying the issues with malfunctioning anemometers and sensors, etc. are a few of such practical challenges usually to be addressed. Cost escalation with the increase in mast height is yet another disadvantage. All these practical difficulties get more complicated when wind forecasting is required to be done at increased heights as the new age wind turbines come with enhanced capacities and increased hub heights since the increased energy production by taller wind turbines far offsets the increased tower cost [33].

Time ahead wind speed forecasting at higher altitudes by using relatively shorter and less challenging wind measuring masts in place of the taller masts has not been reported in the literature so far. In this paper, we investigate the possibility of predicting future wind speeds at a higher altitude using machine learning predictive models by processing the present and past wind speed data measured at relatively lower heights. In this respect, four non-traditional methods are investigated in this study.

In the usual practice, the machine learning models are trained with a substantial quantum of historical wind data at an altitude and the trained model is subsequently employed for generating the values ahead at the same altitude. In contrast, we, in one of our methods, train the model by inputting each set of past data on the wind speed time series at a lower altitude against the succeeding value on the wind speed time series at a higher altitude. This has been attempted, keeping in view the fact that each wind speed value at a higher altitude is directly dependent on the corresponding value at a lower altitude at the same geographical position. In yet another approach, we attempt to incorporate the power law of wind shear for wind speed forecasting at a higher altitude by utilizing wind speed data measured at two lower heights. The wind speed values are first predicted at two lower altitudes using the machine learning model and the corresponding future value at the higher altitude is then calculated using the power law. We also investigate the combined application of the above two approaches towards achieving further simplification of the wind measuring physical setup for the forecast of wind speeds at higher altitudes. We further examine the applicability of the machine learning model trained with data from one location for making forecasts at a different location within the geographical area of the wind regime, with a view to simplifying the wind measuring mast systems required to be set up in the field. The study establishes the prospect of employing low-height wind measuring masts in the field for reliable wind forecasting at higher altitudes, wherein the practical advantages offered by such simplified physical systems more than compensate for the marginal falls in forecast accuracies brought about by these new methods.

2 Machine learning

Machine learning is an area of artificial intelligence that works by identifying patterns from past data and predicting upcoming information. It is a method of improving the performance of a computational software program by itself with experience. According to a widely accepted definition [34], 'A computer program is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P improves with experience E'. In machine learning, past experience is fed to the machine as input, and it gives the output as a typical model capable of solving future problems of the same nature. Here, past experience is collected for the purpose of imparting training. An abstract target function is determined that well describes the relationship between existing input and desired output. Subsequently, a suitable machine learning model is selected to approximate the target function. In the end, a suitable algorithm is used to build the model from the training examples.

Numerous learning algorithms are available to select from for this purpose and new ones are also being put forth by researchers. Based on the different approaches of learning methods, machine learning can be grouped into four categories; supervised, unsupervised, semi-supervised and reinforcement. Supervised learning can be further divided into classification and regression methods. In unsupervised learning, either clustering or reducing the dimensionality of the input information is followed. The different categories of machine learning are illustrated in Figure 2.

In supervised learning, the algorithm determines the optimal function that describes the relationship between the input and output target variables through an iterative process of predictions and adjustment until the prediction and the targeted value reach a maximal efficiency. Supervised learning can be grouped into two categories of classification and regression methods. The classification problem aims to predict labels or classes into which the new data will fall. Classification is better suited for problems that can be broken into categorical decisions (e.g. clinical trials). It can be applied to both structured and unstructured data. The regression method aims at determining a score on a continuous scale based on the value of one or more predictor variables. The output in a regression model has a quantitative value that can be ranked (e.g., energy market modeling).

Unlike in supervised learning, there is no target value in an unsupervised learning environment. Instead, it attempts to detect underlying structures in the data. Unsupervised learning can be either through a clustering approach or a dimensional reduction approach. The clustering approach of unsupervised learning is an analytical technique to develop meaningful subgroups from enormous samples based on the similarities amongst them (e.g., grid-mapping used in image recognition). When the number of features significantly outnumbers the number of observations, a dimensional reduction method is suitable to reduce the visual complexity. In this method, the number of random features under consideration is reduced by replacing it with a principal set (e.g., shape descriptors in text recognition problems).

Semi-supervised learning is used when target variables are not available for the entire data. In such cases, semi-supervised learning allows the model to integrate the available unlabelled features for supervised learning. This method is employed in predicting difficult-to-measure quality variables (e.g., melt index and octane number in determining the quality of ammonia extraction).

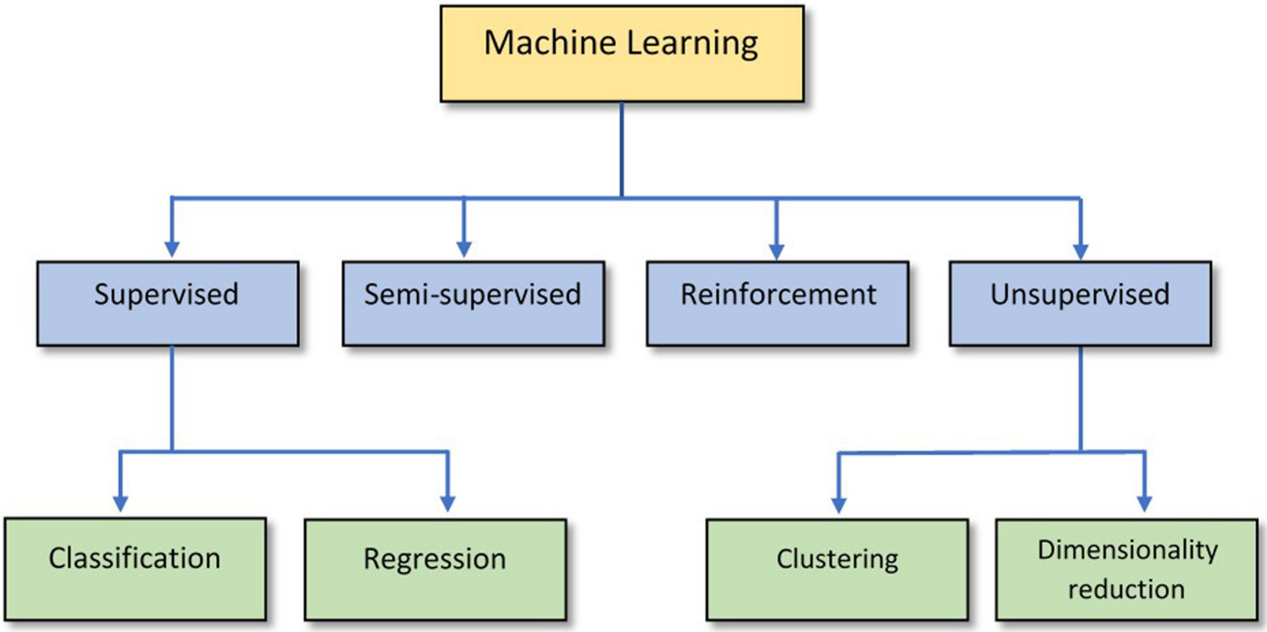


Fig. 2. Different types of machine learning approaches.

Reinforcement learning enables an agent to learn from the interactions in its environment by trial and error using feedback from its own actions and experiences (e.g., autonomous control of vehicles). While in supervised learning, the agent gets the correct set of actions for doing a task, reinforced learning uses a sequence of rewards and penalties as signals depending on whether the decision is towards the required final goal.

3 Power law of vertical wind shear

The availability and speed of wind resources are highly influenced by the geography and climate of the area. The wind speed is found to increase with altitude owing to the thermal gradient formation. At far away elevations of the order of one kilometer, the impact of land cover on wind speed is almost negligible [35]. The surface friction characteristic, on the other hand, has a substantial impact on wind speed in the air layers close to the land. The terrain's surface roughness creates wind shear, which causes vertical wind speed variations. In the assessment of wind shear, accurate measurement of surface roughness is a major challenge [35]. To characterize wind shear in the lowest layers of the atmosphere, some analytical models based on long-standing experience in wind engineering are commonly used.

Extrapolating wind speed from a relatively lower height to a required higher height is a typical strategy used in the wind energy sector when dealing with wind turbines with high hub heights [36]. Different methods named power law, logarithmic law and log-linear law are commonly used for vertical wind speed extrapolation [37–42]. These methods are based on combined hypothetical and experiential approaches and are therefore vulnerable to significant errors due to varying features such as ambient temperature, atmospheric pressure, humidity, terrain type, surface roughness, elevation, time of the day, seasons of the year, atmospheric stability, mean wind speed, wind direction and the like [43–47]. There has been a lot of work done in the past to improve these methods in order to get more reliable results. A data-driven method using symbolic regression has been proposed recently for improved vertical wind speed extrapolation [48]. Among these different methods, the power law of vertical wind shear is widely accepted in the wind energy industry across geographies as the simplest method for vertical wind speed extrapolation.

The power law is expressed as:

$$\frac{v_2}{v_1} = [\frac{h_2}{h_1}]^\alpha \tag{1}$$

where v_1 and v_2 are the wind speeds at a lower reference height h_1 and a higher reference height h_2 respectively and α is the coefficient of wind shear [49]. The coefficient of wind shear is also known as the Hellmann exponent [50] and this empirical constant is usually derived over the range of heights of practical interest. The coefficient of wind shear α is derived from equation (1) as:

$$\alpha = \frac{\log v_2 - \log v_1}{\log h_2 - \log h_1} \tag{2}$$

The wind shear coefficient α essentially combines all of the influential components into a single feature. It is normally assumed as constant for a given set of height levels, even though this is not exactly the true scenario [49]. As a thumb rule, α is often assumed as $1/7$, or 0.143, and the power law, in that case, is called the $1/7$th power law. As per recommendations of the American Society of Civil Engineers, the value of α is taken as $1/9$ for flat, unobstructed areas and water surface, $1/6.5$ for open

Table 1. Geographic coordinates of the wind mast locations.

Location code	Location name	Latitude	Longitude	Elevation AMSL (m)	Topography	Landscape	Roughness class
S1	Kulathumedu	$09^0 45' 30.2''$	$77^0 10' 41.3''$	1095	Hilly	Shrubs	2
S2	Malambuzha	$10^0 48' 57.7''$	$76^0 40' 10.3''$	83	Plain	Grass land	1

terrain and 1/4 for urban and suburban areas [51]. The value of α for a given site has been found to vary significantly with the variations in height levels, ambient temperature, land features, time of the day, the month of the year, etc. [52–54]. When no significant obstacles are present on the ground, wind shear coefficient α obtained from equation (2) by inputting the wind speeds at the two heights can be taken as the most reliable value at that instant, particularly in the altitudes ranging from 10 up to 100–150 meters [35]. The wind speed v_3 at that instant at a higher altitude h_3 is estimated by substituting the computed wind shear coefficient α in the equation:

$$v_3 = v_1 [\frac{h_3}{h_1}]^{\alpha}. \tag{3}$$

4 Study area and application strategy

The hourly wind speed time series at the altitudes of 80 m, 50 m and 20 m at two different windy locations S1 and S2 in the state of Kerala in India, assessed over two years (2013 and 2014) by employing tubular type wind measuring masts have been exhaustively analyzed in this research. These locations, distanced by 136 km, are detailed with corresponding geographic coordinates and physical conditions in Table 1 and shown for better visualization on a map in Figure 3. Depicting the massive nature of a typical wind measuring mast structure, Figure 4 shows the 80 m high, tubular-type wind measuring mast used for wind data collection at the location S1, with the inset picture showing a closer view of the wind anemometer fitted at 50 m height. The location S1 is a hilly terrain whereas the location S2 is almost a plain terrain. The wind flow patterns as measured at the height of 80 m at these locations from June 2013 to May 2014 are illustrated in Figure 5. The relevant particulars of the instruments used for wind data collection are given in Table 2. The five methods involving varying wind mast arrangemernts are investigated for the wind forecasting at the highest height of 80 m in this study by using machine learning modeling and the prediction accuracies are compared.

Support Vector Regression (SVR), K-Nearest Neighbours (KNN) regression and Gradient Boosting Machine (GBM) regression models are commonly used in machine learning-based wind forecasting [32]. The Support Vector Machine (SVM) algorithm attempts to find a hyperplane in an n-dimensional space that clearly classifies the data points. In SVM-based regression (called SVR), the straight line required to fit the data is referred to as the hyperplane. KNN regression is a simple, non-parametric machine learning regression technique. KNN method predicts new

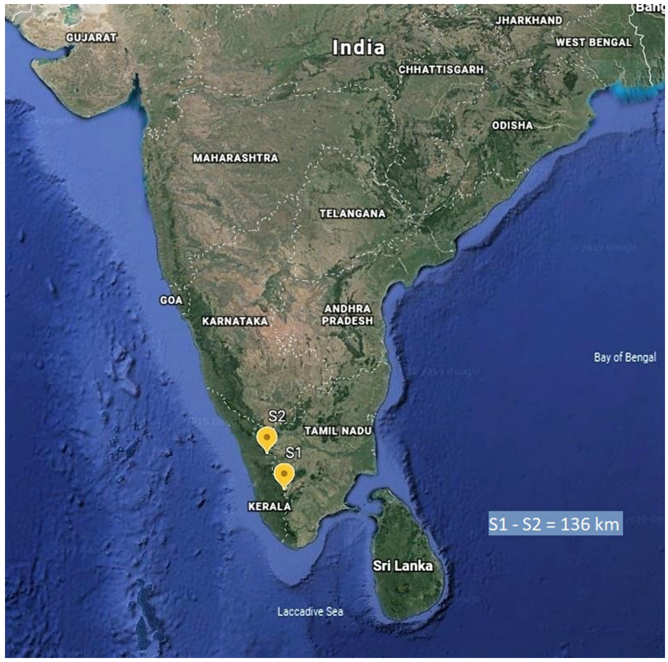


Fig. 3. Geographical positions of the wind masts (Courtesy: Google Maps).

data point values using the concept of "feature similarity". The new point's value depends on how closely it matches the training data. The training dataset identifies a new data point's k nearest neighbours. The projected data point is the average of k-neighbours. KNN calculates the distance between training and testing datasets. Next, the k-nearest neighbours with the k-smallest training data set distances are picked. The final estimate uses a weighted average. Boosting algorithms in classification problems combine several simple models ("weak learners") iteratively, resulting in a "strong learner" with improved prediction accuracy. Mostly, the boosting algorithm consists of weak learners, an additive model and a loss function. The GBM regression algorithm tries to find an additive model capable of minimizing the loss function, thereby improving the regression accuracy. The SVR model has been used in the first phase of this study. The e1071 package in R is used in this work to develop, train and test the models [55]. In the subsequent phases of the study, the KNN model and the GBM model are also employed to corroborate the research findings.

In the initial phase of the study by employing the SVR modeling, the first part of this phase is concentrated at location S1. The wind speed data at the three altitudes in the first year (2013) have been used to train and validate the SVR models to make sure successful learning of the

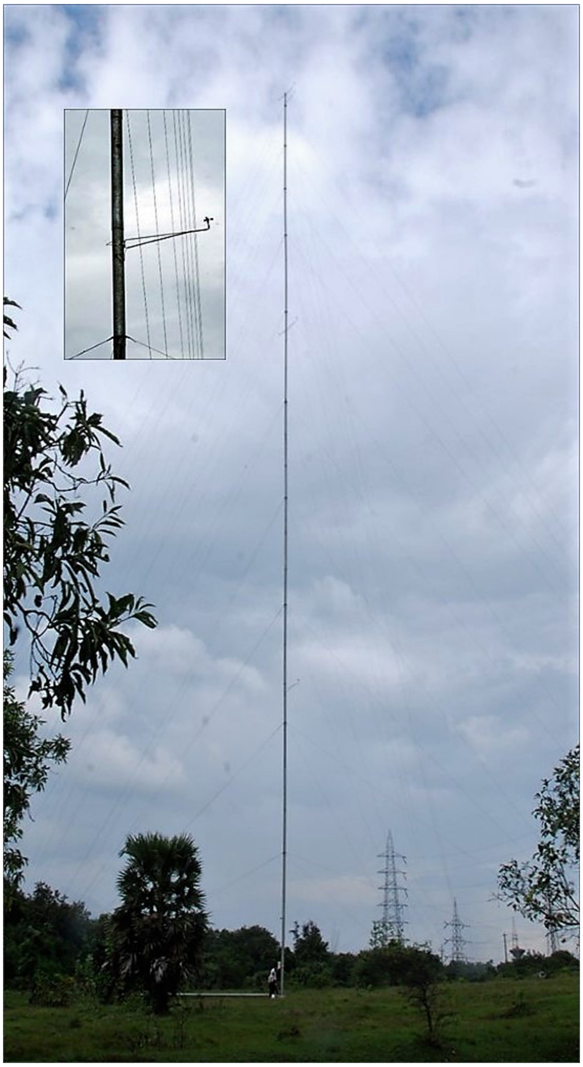


Fig. 4. Tubular, 80 m high wind measuring mast used for wind data collection at one of the locations S1; inset picture gives a closer view of the wind anemometer fitted at 50 m height.

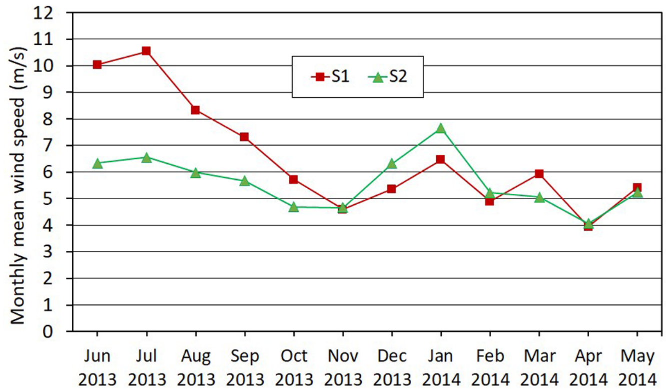


Fig. 5. The wind flow patterns at the locations S1 and S2 depicting the mean monthly wind speeds at the height of 80 m from June 2013 to May 2014.

dynamics of wind flow variability over a full period of seasonal variations. Subsequently, one step (one hour) ahead forecasts have been obtained along the second year (2014) time horizon at the height of 80 m using the trained models. The training and testing of the models are carried out optimally as detailed in the subsequent section. In one of the methods of wind mast configuration, data from the location S2 is used for model training for forecasting at the location S1. We use the error metric of RMSE for assessing and comparing the performance of the different models investigated. RMSE is a measure of the short-term performance of a model by making a term-by-term comparison of the difference between the estimated and the actual values [56]. The smaller the RMSE value, the better the model accuracy. An RMSE value of zero represents no deviation at all, all along the estimated and actual data series. A drawback of this test is that a few large deviations can result in a significant increase in RMSE. It follows that the smaller the RMSE value, the same itself truly indicates better model performance. Apart from determining the RMSE over the whole prediction timeline, we also follow a new approach of breaking the prediction timeline into segments and assessing the percentage of such segments qualifying against pre-set threshold RMSE values. This approach is adopted to minimize the misleading effect of outlier data on the RMSE values calculated and to enable better interpretation of the model performance. In the next part of the study, all the above-stated investigations have been repeated for the second location S2 to validate the location-independent functioning of the proposed predictive models. In the final phases of the study, KNN and GBM regression models are also employed for the forecasting in place of the SVR models, and the results are compared.

5 Methods of forecasting

The five methods involving different wind mast configurations investigated in this study are described here. All these methods are first analyzed extensively using SVR-based machine learning forecast models as detiled below.

5.1 Method 1

In this method, which is the conventional method of wind speed forecasting using machine learning models, the historical data in the year 2013 at the altitude of 80 m have been used for training the model, which is then used to predict at the same location at the same altitude in the year 2014. In a finite time series, the state of the system at a particular point of time always depends on some time-lagged events. The extent of dependence of one value on the previous values in a given time series can be estimated by obtaining the mutual information between delayed time series [57]. Based on this, it is assumed that the number of past wind speed values that each occurrence depends on can be determined from the time delayed mutual information function. The mutual information comes down with the increase in time delay and after a certain limit, it

Table 2. Details of instrumentation used for wind data collection.

Sl. No.	Instrument feature	Particulars
1	Type of anemometers	NRG 40C – 3 Cup Anemometers
2	Sensor range of anemometers	1 m/s to 96 m/s
3	Operating temperature range	–55 °C to 60 °C
4	Type of wind data loggers	Nomad 2

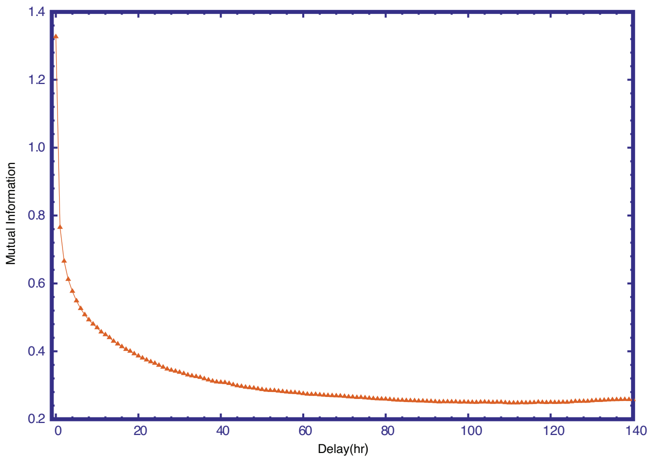


Fig. 6. The mutual information of hourly wind speed time series as function of delay.

starts to level-off as illustrated in the typical plot in Figure 6. It is taken in the present analysis that this leveling-off starts with 72 data points and hence it is assumed that every data point on the wind speed time series is a function of its previous 72 data points. Accordingly, the training of models with the past data has been done in such a way by inputting the preceding 72 continuous values against each wind speed value ahead.

Each of the one-step ahead predictions over the testing period (the year 2014) is generated by inputting the preceding 72 continuous data points into the trained model. The predicted values are appended in sequence and compared with the actual values for the initial 1000 data points in Figure 7a.

5.2 Method 2

In this method, we rely on the fact that each wind speed value at a higher altitude is directly dependent on the corresponding value at a lower altitude. Consequently, instead of training the model with a definite set of past data against each data ahead along the wind speed time series at the height of 80 m, we use the past data on the wind speed time series at the lower altitude of 50 m against the succeeding value at the height level of 80 m. Predictions at 80 m altitude over the test period are generated in a similar fashion by inputting values from the time series at 50 m altitude into the trained model. Training of the model and generating the forecasts are illustrated using block diagrams in Figure 11. The closeness of predictions in this method is shown for the initial 1000 data points in Figure 7b.

5.3 Method 3

In this method, the wind speeds are predicted separately along the wind speed time series at 50 m and 20 m altitudes as per procedures followed for 80 m altitude in Method 1, and then the corresponding value at the height of 80 m is determined using the power law . The profile made with one step ahead predictions in this method is shown in relation to the actual values for the initial 1000 data points in Figure 7c.

5.4 Method 4

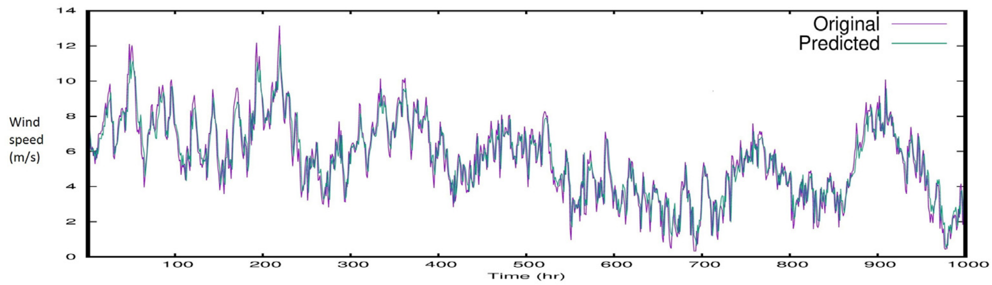
This method combines the procedures followed in Methods 1, 2 and 3 above in such a way that one model is used to predict one step ahead predictions at the height of 20 m using past data at the same height and another model is employed to predict along the 50 m altitude using past data at the 20 m altitude. The values thus predicted at the altitudes of 50 m and 20 m are then extrapolated to 80 m altitude by using the power law method. The block diagram in Figure 12 illustrates the forecasting process in this method. Figure 7d compares the predicted values at the height of 80 m in this method against the actual values for the initial 1000 data points.

5.5 Method 5

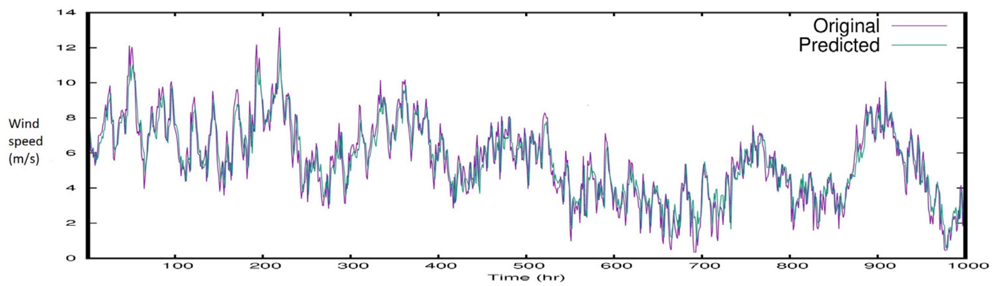
This method follows the same principle relied upon in Method 2, with the difference that the training of the model is carried out using the data from one location, termed the reference location, and that the trained model is used to generate forecasts at another location at a distance from the reference location. Whereas steps (a) and (b) in Figure 11 are performed for the same location in Method 2, in the present method, these two steps are carried out at two different locations. The data at location S2 is used here to train the model before applying the same to generate forecasts at location S1. The predicted values in this method are shown in relation to the actual values for the initial 1000 data points in Figure 7e.

6 Results and discussion

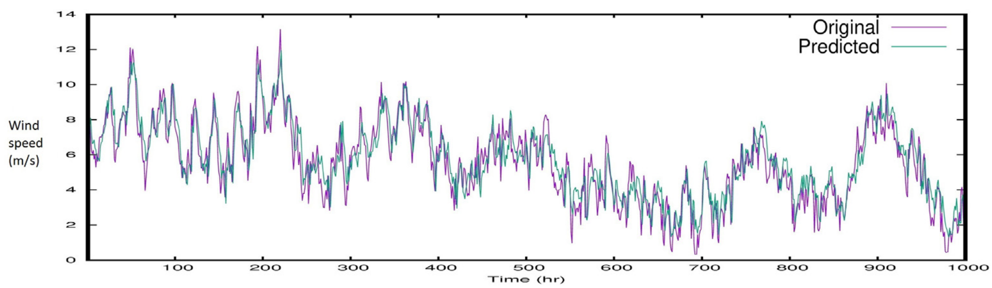
In the analyses of the forecast results, the forecast profile made of one step ahead predictions appended over the one-



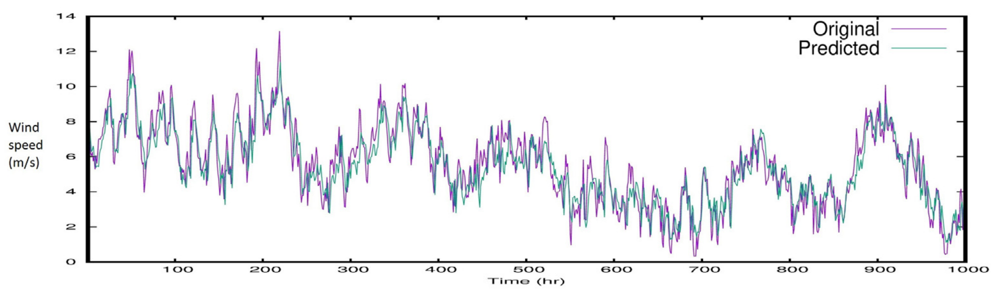
(a) Method 1



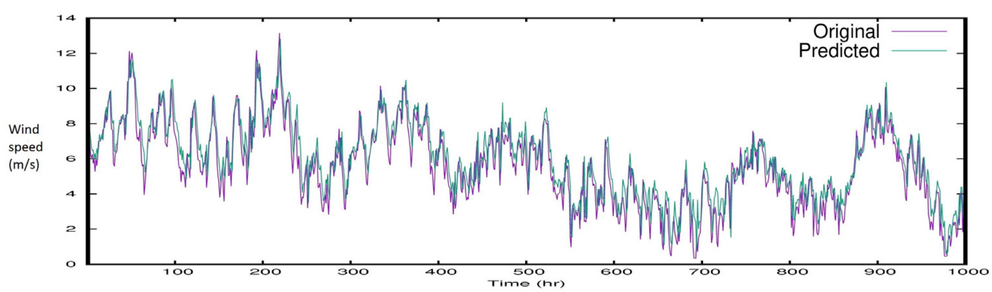
(b) Method 2



(c) Method 3

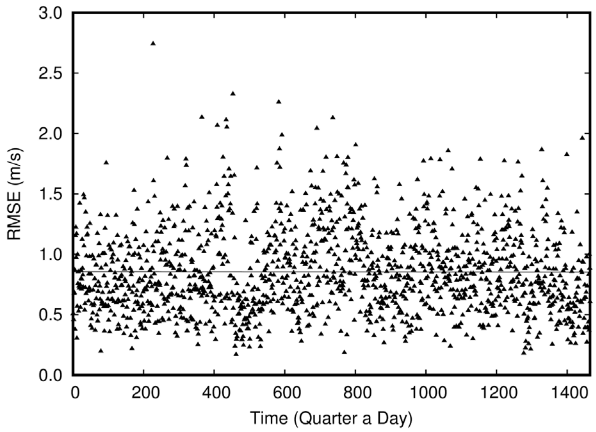


(d) Method 4

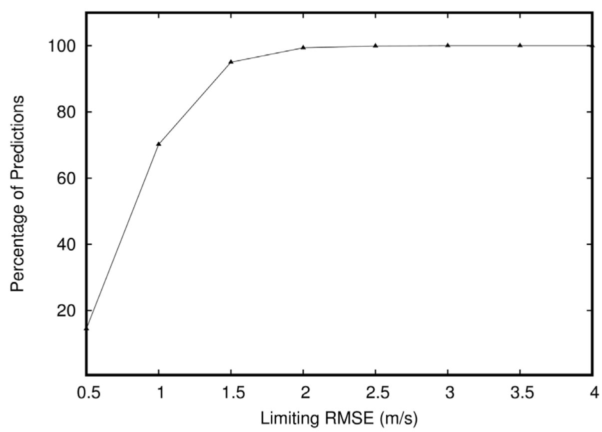


(e) Method 5

Fig. 7. Actual wind speed time series (for the initial 1000 hours) in comparison with the repeated one-step SVR predictions at the height of 80 m at location S1 by employing the different methods.



(a)



(b)

Fig. 8. Distribution of RMSEs of segment (quarter-a-day) wise SVR predictions along the one year test period (on the left side) and percentage-wise distribution of the same coming below different limiting RMSE values (on the right side) for the location S1 using the Method 1.

year prediction horizon in each method is considered. The RMSE values of these forecast profiles over quarter-a-day time segments along the one year test period are plotted against time in respect of the Methods 1 to 5 in Figures 8a, 9a, c, e and 10a respectively. Additionally, the percentage-wise distribution of these prediction segments with RMSE values below different limiting thresholds for these methods are plotted in Figures 8b, 9b, d, f and 10b. These plots are combined for easy comparison in Figure 14a. Apart from these assessments, the RMSE values over the year-long forecast period in the five methods are also determined, which are compared in Figure 14c.

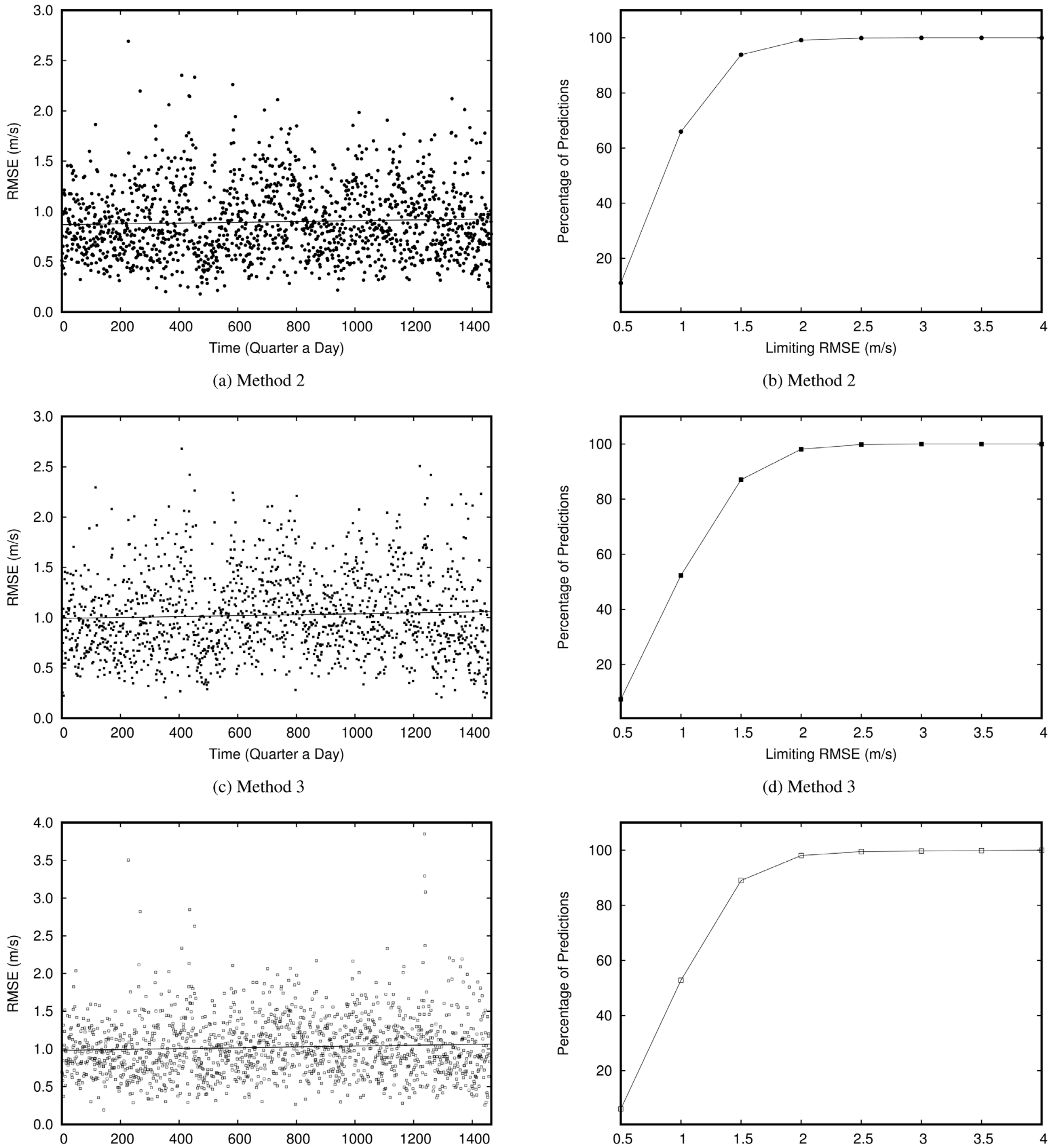
The straight lines given in Figures 8a, 9a, c, e and 10a show the lines of best fit for the scatter plot of RMSE values in the respective cases, which are almost parallel to the time axis in all instances, with near-zero slopes as given in Table 3. This clearly shows the time-independent characteristic of the trained machine learning models in wind speed forecasting, as the models one time trained with data for a definite period can be employed for forecasting tasks along the respective wind speed time series near as well as far away in time from the training data.

Method 1 is the conventional route of machine learning-based forecasting along a given wind speed time series. Intelligent training and testing of the model have been carried out in this process by determining the optimum data size that has an influence on the succeeding wind speed value and designing the training and testing of the model in such a way to fully absorb this interdependency. This approach has yielded better model performance, obtaining an RMSE value of 0.93 m/s for the one-step (one hour) ahead predictions mapped along the one-year forecast period. It is further seen in this case in Figure 8b that when a limiting RMSE of 1 m/s is taken, RMSE values of 70.18% of quarter-a-day prediction segments over the one year test period fall below this mark. When limiting RMSEs of 1.5 m/s and 2 m/s are taken, the percentage of such prediction segments to qualify increases to 95.03% and 99.39% respectively. Though this conventional method is the most accurate one among all the five methods investigated, it is essential in this method to construct and maintain a wind measuring mast system of 80 m height for the model training period as well as during the entire forecast timeline.

In Method 2, the RMSE of one step ahead predictions along the one-year period is found to be 0.97 m/s, which is slightly more than that in Method 1. When a limiting RMSE of 1 m/s is benchmarked, as shown in Figure 9b, 65.96% of quarter-a-day prediction segments along the prediction period of the year 2014 are found to possess RMSE values below this limiting value. Though the model error in this method is marginally higher compared to Method 1, this method, on the other hand, provides considerable relief in the field preparedness as a wind mast of 80 m height is required during the initial one year training period only, after which a wind mast of 50 m height only needs to be retained for the subsequent forecast periods.

The complexity of the wind measuring mast system is further simplified in Method 3 as this method requires a wind mast of 50 m height only to be used throughout the training and subsequent testing periods with anemometers fitted at 50 m and 20 m height levels. This relaxation, however, is accompanied by a fall in model accuracy compared to those achieved in the above two methods. The RMSE of one step ahead predictions along the one-year period is obtained in this method as 1.17 m/s and as illustrated in Figure 9d, 53.34% of the quarter-a-day prediction segments only qualify when a limiting RMSE of 1 m/s is insisted.

Method 4 requires the most simplified wind mast set up to be established and retained as a mast of 50 m with anemometers fitted at 50 m and 20 m height levels is required in this method to cover the training period and the



(a) Method 2 (b) Method 2

(c) Method 3 (d) Method 3

(e) Method 4 (f) Method 4

Fig. 9. Illustrations as in Figure 8, for the location S1 using the Methods 2, 3 and 4 based on SVR predictions.

same can be replaced with a mast system of 20 m height for generating forecasts during the subsequent test periods. This simplified physical arrangement can be pursued if relaxed prediction accuracy is acceptable as the RMSE of one step ahead predictions over the one-year period obtained in this method is 1.67 m/s, the highest among the corresponding values obtained in all the methods. Further, as provided in Figure 9f, only 52% of the quarter-a-day prediction segments along the one-year prediction timeline is found to have RMSE values below 1 m/s in this case.

Method 5, which is a reorganized version of Method 2, is slightly less accurate compared to Method 2 as the RMSE of one step ahead predictions over the one-year test period

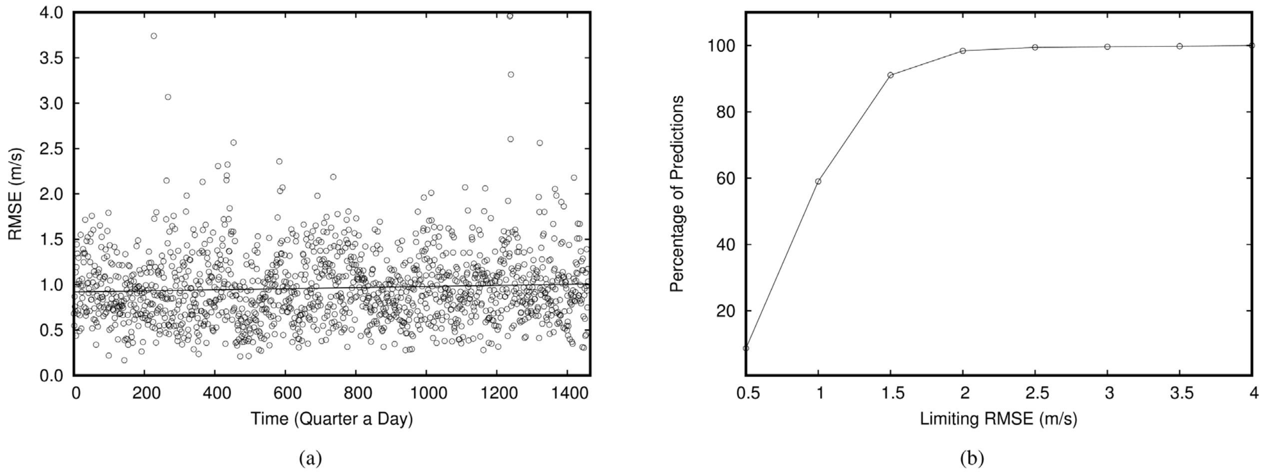


Fig. 10. Illustrations as in Figure 8, for the location S1 using the Method 5 based on SVR predictions.

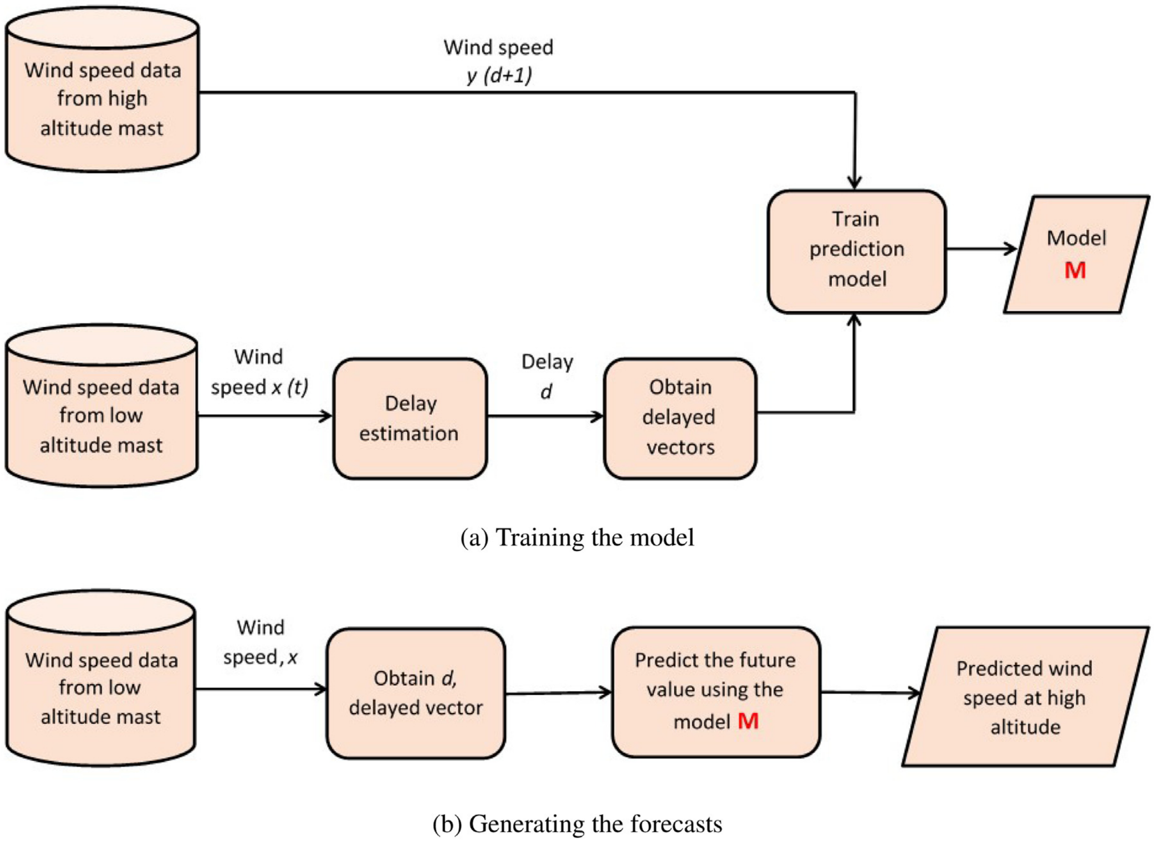


Fig. 11. Block diagram showing (a) training of the model and (b) testing of predictions in Method 2.

is 1.06 m/s in this method whereas the same value obtained in Method 2 is 0.97 m/s. When the predictions over quarter-a-day segments along the one-year prediction timeline is considered, as depicted in Figure 10b, 59.04% of such segments, in this case, are found to be with RMSE values less than or equal to 1 m/s, compared to the respective value of 65.96% in Method 2. This method, however, needs to erect only a 50 m high wind mast at the location of interest, as the model already trained with data from a different reference location generates the forecasts using this low-height wind speed data at this test location.

The prediction accuracies of the different methods are compared in Figure 13 based on performance in generating predictions of quarter-a-day segments with RMSE values

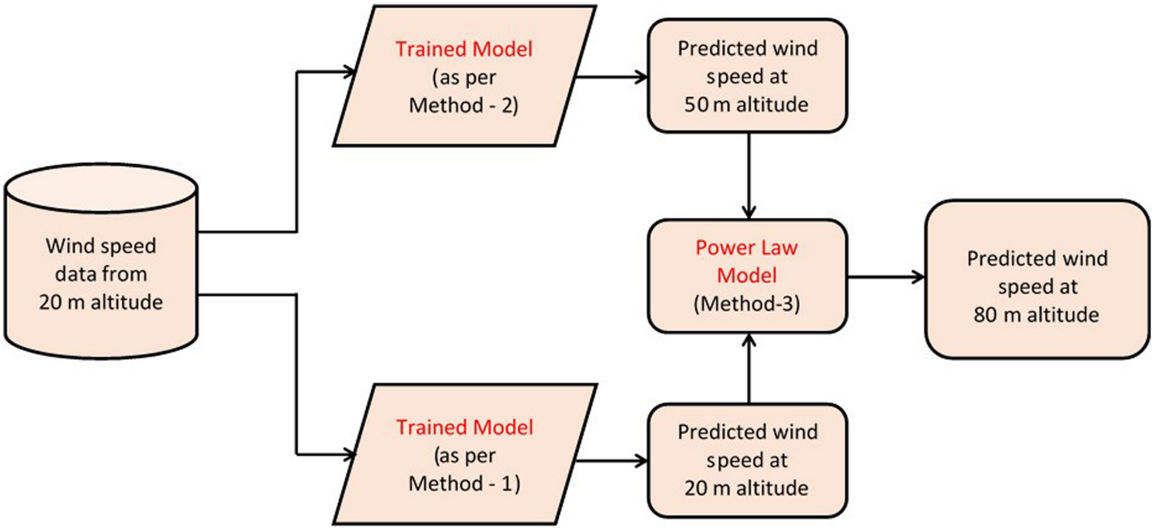


Fig. 12. Block diagram showing the forecasting process in Method 4.

less than two benchmarks of 1 m/s and 1.5 m/s. Here, a higher percentage of prediction segments with RMSE values less than a given benchmark indicates better model performance. Accordingly, this plot clearly ranks the Methods 1, 2, 5, 3 and 4 in the increasing order of model performance error. This position is reiterated in Figure 14a which compares the performance of the different methods in terms of the percentage of prediction segments with RMSE values below various limiting values. This order of accuracy is obvious in Figure 14c also, which compares the performance of the different methods investigated in this research in terms of the respective RMSE values of one step ahead predictions repeated along the one year forecast period, where a lower RMSE value indicates better model performance. All the five methods are listed in the increasing order of RMSE values of predictions over the one-year test span in Table 4, with the corresponding RMSE values specified thereon. The advantageous aspects from the practical standpoint in setting up and maintaining the physical structures of wind measuring mast systems for these methods in relation to the levels of model accuracies are briefly described in this table.

The five methods yield results of similar nature and trend when employed for identical analyses at location S2 as well, as illustrated in Figure 14b and d. The location S1 is taken here as the reference location for model training in Method 5 in this case. Based on both the yardsticks of (i) RMSE over the whole forecast period and (ii) RMSE values of segmented prediction periods, as in the case of location S1, the Methods 1, 2, 5, 3 and 4 emerge as options in the increasing order of RMSE values in the case of location S2 also, which implies that the research findings are location-independent.

After the analyses using SVR models as described above, models based on KNN and GBM algorithms are also employed in place of the SVR models. The RMSE values of predictions for the two locations using the five different methods, each based on the three machine learning models over the one year test period are compared

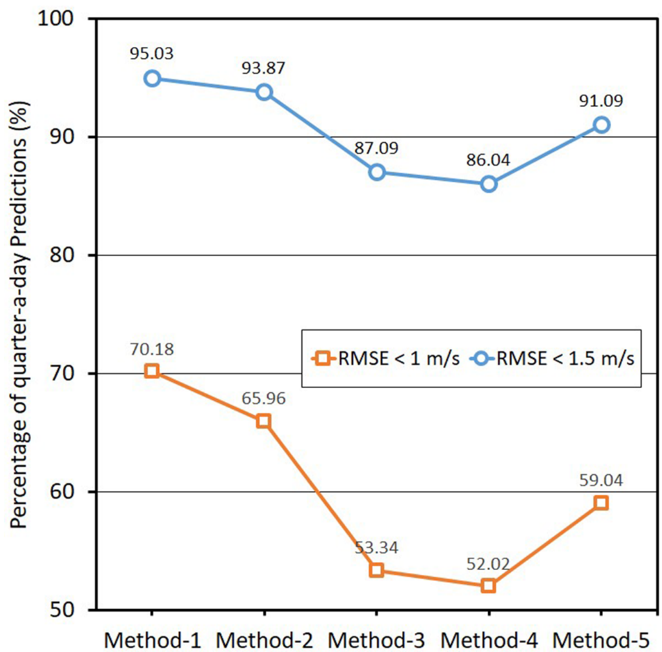
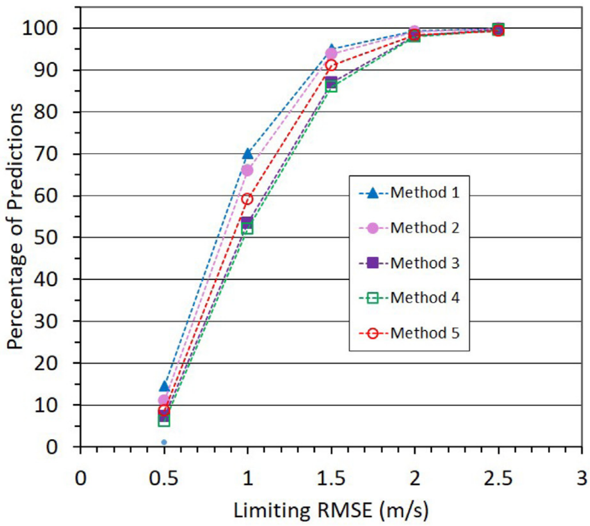
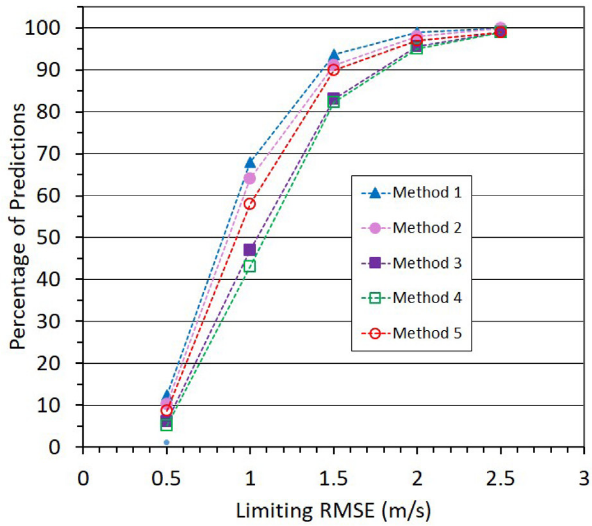


Fig. 13. Comparison of performance of the different methods in generating predictions of quarter-a-day segments in the one year test period with RMSE values less than two benchmarks of 1 m/s and 1.5 m/s based on SVR models.

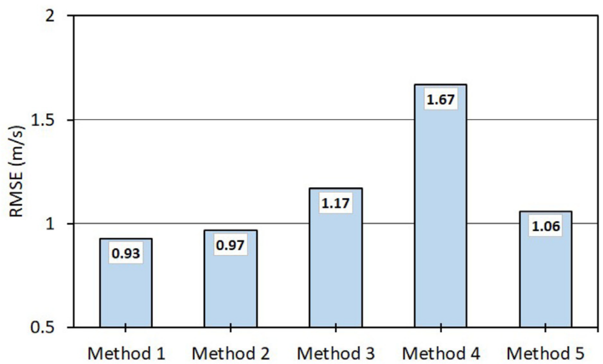
in Figure 15. All the models show comparable forecast performance, with the GBM regression models showing better results compared to the other two in all prediction scenarios. Except in Method 1, SVR models come second in prediction accuracy in all instances, while in Method 1, the KNN model slightly outperforms the SVR model at both the test locations. It is also observed that except in the instance of using the KNN model at location S1, Methods 1, 2, 5, 3 and 4 continue to emerge as methods in the increasing order of RMSE values as in the case of results



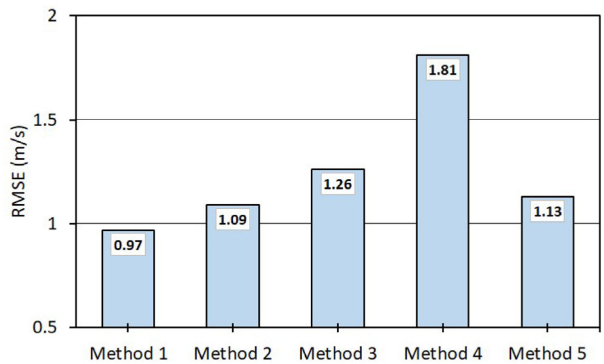
(a) Location S1



(b) Location S2



(c) Location S1



(d) Location S2

Fig. 14. Percentage of quarter-a-day predictions in the one year test period with RMSE values below different benchmarks in respect of the various methods for (a) Location S1 and (b) Location S2 and RMSE values of predictions with the different methods over the one year test period for (c) locations S1 and (d) location S2 based on SVR models.

Table 3. Slope of best fitting lines of RMSEs of segment (quarter-a-day) wise predictions over the one year test period generated by different methods based on SVR models.

Sl. No.	Method used	Slope of best fitting line
1	Method 1	0.00003
2	Method 2	0.00039
3	Method 3	0.00046
4	Method 4	0.00057
5	Method 5	0.00060

obtained with the SVR models. Methods 3 and 5 interchange the positions in this order at location S1 when the KNN model is employed.

7 Conclusion

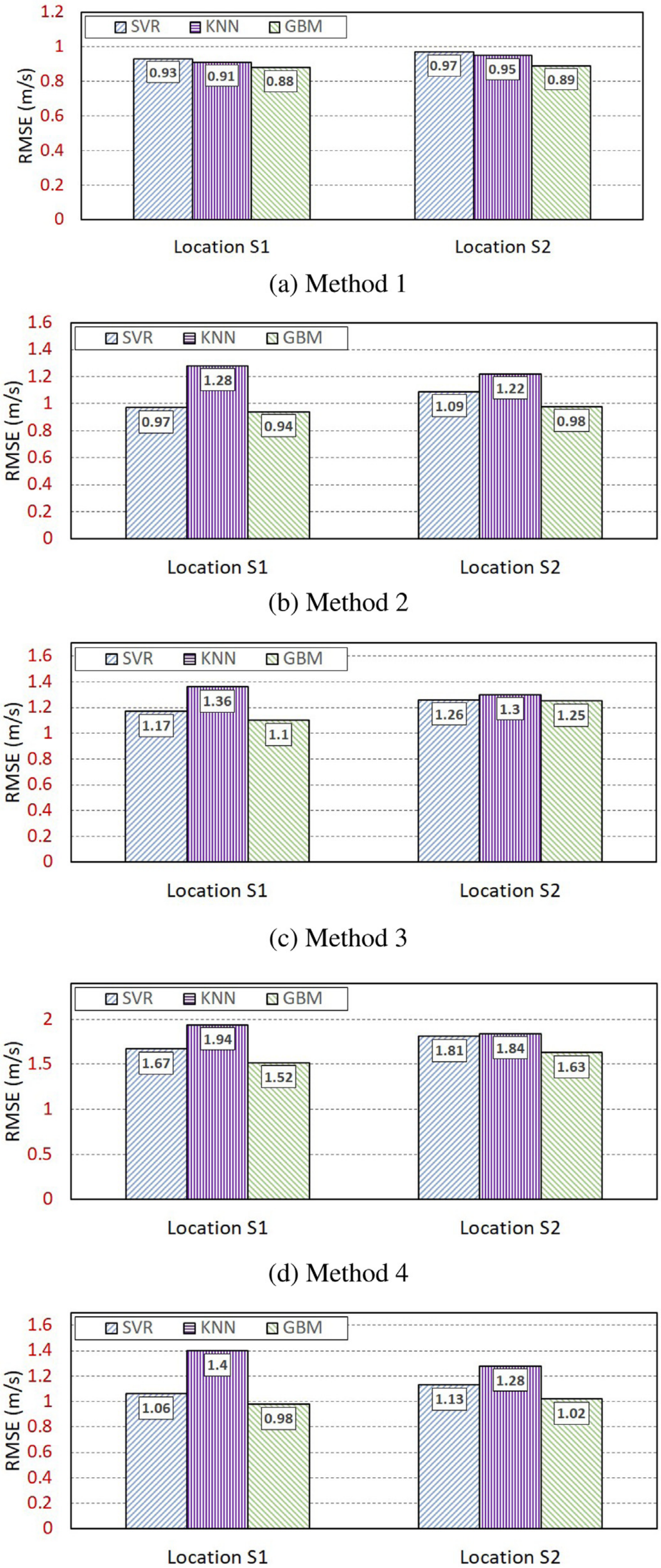
Wind speed forecasting at the hub heights of wind turbines is an important prerequisite for the proper planning and effective grid integration of wind electricity. This is usually achieved by employing computational predictive models and utilizing a vast amount of wind speed data measured by installing and retaining high-altitude wind measuring masts in the field. Tall wind mast structures reaching the hub heights of huge wind machines are difficult and expensive to erect and upkeep for long periods. This study explored alternative methods to obtain time ahead wind forecasts at a high altitude with accuracy levels acceptable to the wind energy industry, by employing low-height wind measuring mast structures that are easier to install and maintain. In the first phase, five distinct methods requiring different wind measuring physical arrangements in the field

Table 4. Listing of the various methods in the increasing order of model error, with brief descriptions of the practical advantages associated with such methods in the erection and upkeep of the physical systems for data collection for wind speed forecasting at the height of 80 m.

Sl. No.	Method	SVR model performance in RMSE (m/s)	Requirements/advantages/disadvantages with regard to setting up of the wind measuring mast system
1	Method 1	0.93	Erection and upkeep of a wind mast of 80 m height at the location of interest are necessary during the training period as well as the whole future testing period. Advantage: Highest forecast accuracy; Disadvantage: Most difficult mast system.
2	Method 2	0.97	The Establishment of an 80 m high wind mast at the location of interest is required during the training period of the first one year. Wind speed data are taken at 80 m and 50 m heights during this period for the training of the model. During the subsequent testing periods, a wind mast of 50 m height only needs to be retained.
3	Method 5	1.06	Erection and upkeep of an 80 m wind mast at one reference location within the geographical area of the wind regime are required only for the training period of an initial one year. Wind speed data are taken from this wind mast at 80 m and 50 m heights during this period for training the model. This trained model is employed at any other location of interest, where a wind mast of 50 m height only is needed to be erected and maintained.
4	Method 3	1.17	A wind mast of 50 m height only is required to be established and retained at a location of interest and wind data from anemometers fitted to it at 50 m and 20 m heights are collected, using which the time ahead wind speeds at the higher altitude are predicted.
5	Method 4	1.67	A wind mast of 50 m height is to be established and retained for the training period of the first one-year at the location of interest and wind data at 50 m and 20 m heights are to be collected from it during this period. In the subsequent testing periods, a shorter wind mast of 20 m height only needs to be retained. Advantage: Simplest mast system; Disadvantage: Lowest forecast accuracy.

were investigated using the SVR-based machine learning wind forecast models. While the conventional Method 1, trained and tested with size optimized data sets, yielded an RMSE of 0.93 m/s for one step (one hour) ahead predictions mapped along the one year forecast period, that value increased to 0.97 m/s, 1.17 m/s, 1.67 m/s and 1.06 m/s for the Methods 2, 3, 4 and 5 respectively, when employed at the location S1. Furthermore, the RMSE values of predictions over quarter-a-day time segments along the one-year forecast duration analyzed for the location S1 using Methods 1 to 5 revealed that 70.18%, 65.96%, 53.34%, 52% and 59.04%, respectively of such predictions had individual RMSE values less than 1 m/s. Analyses with data from the location S2 also produced similar results in terms of comparable accuracy levels and order of error variation in respect of the different methods, implying generality in the application. The different methods show comparable performance when employed with other machine learning models of KNN regression and GBM regression also. Though, in general, the individual Methods 2, 5, 3 and 4 show diminishing forecast accuracies in that order compared to the conventional approach in Method 1, the practical advantages gained in the installation and maintenance of the relatively simpler engineering structures of wind measuring mast systems in the field, as outlined in Table 4, make each of these newly proposed alternative methods useful and acceptable to the wind energy industry.

This study is constrained within three fixed altitudes of 80 m, 50 m and 20 m based on data availability. Investigations using different combinations of altitudes are suggested to understand the relative performance of the different methods in such cases. In Method 5, more studies by varying the distance between the reference and test locations are also suggested for optimizing the cross-location process. In addition to the presently employed



(a) Method 1

(b) Method 2

(c) Method 3

(d) Method 4

(e) Method 5

Fig. 15. Comparison of performance of the different methods when employing different machine learning models.

machine learning models, other models based on better-performing algorithms, including hybrid models also are likely to improve the forecast results.

Conflict of Interest

None

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None

Author contribution statement

All authors contributed equally to this work.

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References

1. Global Wind Energy Council. Gwec| global wind report 2021 (2021)
2. A.S. Darwish, R. Al-Dabbagh, Wind energy state of the art: present and future technology advancements, Renew. Energy Environ. Sustain. **5**, 7 (2020)
3. L. Nguyen, M. Metzger, Comparison of forecasting methods for vertical axis wind turbine applications in an urban/suburban area, J. Renew. Sustain. Energy **9**, 023302 (2017)
4. M. Lackner, A. Rogers, J. Manwell, Uncertainty analysis in wind resource assessment and wind energy production estimation, in *45th AIAA Aerospace Sciences Meeting and Exhibit* (2007) p. 1222
5. M.A. Lackner, A.L. Rogers, J.F. Manwell, Uncertainty analysis in mcp-based wind resource assessment and energy production estimation, J. Solar Energy Eng. **130**, 031006 (2008)
6. A. Costa, A. Crespo, J. Navarro, G. Lizcano, H. Madsen, E. Feitosa, A review on the young history of the wind power short-term prediction, Renew. Sustain. Energy Rev. **12**, 1725–1744 (2008)
7. A.M. Foley, P.G. Leahy, A. Marvuglia, E.J. McKeogh, Current methods and advances in forecasting of wind power generation, Renew. Energy **37**, 1–8 (2012)
8. I. Okumus, A. Dinler, Current status of wind energy forecasting and a hybrid method for hourly predictions, Energy Convers. Manag. **123**, 362–371 (2016)
9. R.C. Sreelekshmi, K. Asokan, K. Satheesh Kumar, Deterministic nature of the underlying dynamics of surface wind fluctuations, Ann. Geophys. **30**, 1503 (2012)
10. G.V. Drisya, D.C. Kiplangat, K. Asokan, K. Satheesh Kumar, Deterministic prediction of surface wind speed variations, Ann. Geophys. **32**, 1415–1425 (2014)
11. G.V. Drisya, K. Asokan, K. Satheesh Kumar, Diverse dynamical characteristics across the frequency spectrum of wind speed fluctuations, Renew. Energy **119**, 540–550 (2018)

12. A. Di Piazza, M.C. Di Piazza, G. Vitale, Solar and wind forecasting by narx neural networks, Renew. Energy Environ. Sustain. **1**, 39 (2016)
13. L. Fugon, J. Juban, G. Kariniotakis, Data mining for wind power forecasting, in *European Wind Energy Conference & Exhibition EWEC 2008*, EWEC (2008) 6 pages
14. Z.O. Olaofe, A 5-day wind speed & power forecasts using a layer recurrent neural network (lrnn), Sustain. Energy Technolog. Assess. **6**, 1–24 (2014)
15. S.R. Nandha Kishore, V. Vanitha, Wind speed forecasting for grid code compliance, J. Renew. Sustain. Energy **5**, 063125 (2013)
16. A. Lahouar, J. Ben Hadj Slama, Hour-ahead wind power forecast based on random forests, Renew. Energy **109**, 529–541 (2017)
17. A. Meng, J. Ge, H. Yin, S. Chen, Wind speed forecasting based on wavelet packet decomposition and artificial neural networks trained by crisscross optimization algorithm, Energy Convers. Manag. **114**, 75–88 (2016)
18. Q. Han, F. Meng, T. Hu, F. Chu, Non-parametric hybrid models for wind speed forecasting, Energy Convers. Manag. **148**, 554–568 (2017)
19. J. Wang, Y. Song, F. Liu, R. Hou, Analysis and application of forecasting models in wind power integration: a review of multi-step-ahead wind speed forecasting models, Renew. Sustain. Energy Rev. **60**, 960–981 (2016)
20. L. Xiao, J. Wang, Y. Dong, J. Wu, Combined forecasting models for wind energy forecasting: a case study in China, Renew. Sustain. Energy Rev. **44**, 271–288 (2015)
21. D.C. Kiplangat, K. Asokan, K. Satheesh Kumar, Improved week-ahead predictions of wind speed using simple linear models with wavelet decomposition, Renew. Energy **93**, 38–44 (2016)
22. H.S. Dhiman, D. Deb, J.M. Guerrero, Hybrid machine intelligent svr variants for wind forecasting and ramp events, Renew. Sustain. Energy Rev. **108**, 369–379 (2019)
23. D. Liu, D. Niu, H. Wang, L. Fan, Short-term wind speed forecasting using wavelet transform and support vector machines optimized by genetic algorithm, Renew. Energy **62**, 592–597 (2014)
24. N.S. Pearre, L.G. Swan, Statistical approach for improved wind speed forecasting for wind power production, Sustain. Energy Technolog. Assess. **27**, 180–191 (2018)
25. J. Browell, D.R. Drew, K. Philippopoulos, Improved very short term spatio temporal wind forecasting using atmospheric regimes, Wind Energy **0**, 1–12 (2017)
26. D. Kim, J. Hur, Short-term probabilistic forecasting of wind energy resources using the enhanced ensemble method, Energy **157**, 211–226 (2018)
27. H. do Nascimento Camelo, P. Sérgio Lucio, J. Bosco Verçosa Leal Junior, P. Cesar Marques de Carvalho, A hybrid model based on time series models and neural network for forecasting wind speed in the brazilian northeast region, Sustain. Energy Technolog. Assess. **28**, 65–72 (2018)
28. Z. Yang, J. Wang, A hybrid forecasting approach applied in wind speed forecasting based on a data processing strategy and an optimized artificial intelligence algorithm, Energy **160**, 87–100 (2018)
29. A. Khosravi, R.N.N. Koury, L. Machado, J.J.G. Pabon, Prediction of wind speed and wind direction using artificial neural network, support vector regression and adaptive neuro-fuzzy inference system, Sustain. Energy Technolog. Assess. **25**, 146–160 (2018)
30. M. Optis, J. Perr-Sauer, The importance of atmospheric turbulence and stability in machine-learning models of wind farm power production, Renew. Sustain. Energy Rev. **112**, 27–41 (2019)
31. N. Ahmed, A.L.C. Barczak, M.A. Rashid, T. Susnjak, Runtime prediction of big data jobs: performance comparison of machine learning algorithms and analytical models, J. Big Data **9**, 1–31 (2022)
32. P. Valsaraj, D.A. Thumba, K. Satheesh Kumar, Spatio-temporal independent applicability of one time trained machine learning wind forecast models: a promising case study from the wind energy perspective, Int. J. Sustain. Energy **0**, 1–19 (2022)
33. LLC Global Energy Concepts, Windpact turbine design scaling studies technical area 3-self-erecting tower and nacelle feasibility: March 2000-march 2001. Technical report, National Renewable Energy Lab., Golden, CO (US) (2001)
34. T.M. Mitchell, Artificial neural networks, Mach. Learn. **45**, 81–127 (1997)
35. F. Bañuelos-Ruedas, C. Angeles-Camacho, S. Rios-Marcuello, Methodologies used in the extrapolation of wind speed data at different heights and its impact in the wind energy resource assessment in a region, in *Wind Farm-Technical Regulations, Potential Estimation and Siting Assessment* (InTech, 2011)
36. A. Vasel-Be-Hagh, C.L. Archer, Wind farm hub height optimization, Appl. Energy **195**, 905–921 (2017)
37. G. Gualtieri, S. Secci, Comparing methods to calculate atmospheric stability-dependent wind speed profiles: a case study on coastal location, Renew. Energy **36**, 2189–2204 (2011)
38. J.O. Counihan, Adiabatic atmospheric boundary layers: a review and analysis of data from the period 1880-1972, Atmos. Environ. (1967) **9**, 871–905 (1975)
39. D.A. Spera, *Introduction to modern wind turbines* (ASME Press, New York, 1994)
40. J.D. Pneumatikos, An experimental test of the empirical formulae commonly used to represent wind speed profiles near the ground, Renew. Energy **1**, 623–628 (1991)
41. C. Herrero-Novoa, I.A. Pérez, M. Luisa Sánchez, M. Ángeles Garcia, N. Pardo, B. Fernández-Duque, Wind speed description and power density in northern spain, Energy **138**, 967–976 (2017)
42. D. Solyali, M. Altunç, S. Tolun, Z. Aslan, Wind resource assessment of northern cyprus, Renew. Sustain. Energy Rev. **55**, 180–187 (2016)
43. M.R. Patel, *Wind and solar power systems: design, analysis, and operation* (CRC Press, 2005)
44. M.R. Elkinton, A.L. Rogers, J.G. McGowan, An investigation of wind-shear models and experimental data trends for different terrains, Wind Eng. **30**, 341–350 (2006)
45. R.H. Kirchhoff, F.C. Kaminsky, Wind shear measurements and synoptic weather categories for siting large wind turbines, J. Wind Eng. Ind. Aerodyn. **15**, 287–297 (1983)
46. R. Istchenko, B. Turner, Extrapolation of wind profiles using indirect measures of stability, Wind Eng. **32**, 433–438 (2008)
47. R.J. Barthelmie, The effects of atmospheric stability on coastal wind climates, Meteorolog. Appl. **6**, 39–47 (1999)
48. P. Valsaraj, D. Alex Thumba, K. Asokan, K. Satheesh Kumar, Symbolic regression-based improved method for wind speed extrapolation from lower to higher altitudes for wind energy applications, Appl. Energy **260**, 114270 (2020)
49. M.L. Kubik, P.J. Coker, J.F. Barlow, C. Hunt, A study into the accuracy of using meteorological wind data to estimate

turbine generation output, Renew. Energy **51**, 153–158 (2013)
50. M. Kaltschmitt, W. Streicher, A. Wiese, *Renewable energy: technology, economics and environment* (Springer Science & Business Media, 2007)
51. J. Li, X. Wang, X. Bill Yu, Use of spatio-temporal calibrated wind shear model to improve accuracy of wind resource assessment, Appl. Energy **213**, 469–485 (2018)
52. S. Rehman, N.M. Al-Abbadi, Wind shear coefficients and their effect on energy production, Energy Convers. Manag. **46**, 2578–2591 (2005)
53. O.A. Jaramillo, M.A. Borja, Wind speed analysis in la ventosa, mexico: a bimodal probability distribution case, Renew. Energy **29**, 1613–1630 (2004)
54. R.N. Farrugia, The wind shear exponent in a mediterranean island climate, Renew. Energy **28**, 647–653 (2003)
55. D. Meyer, E. Dimitriadou, K. Hornik, A. Weingessel, F. Leisch, *e1071: Misc Functions of the Department of Statistics, Probability Theory Group (Formerly: E1071), TU Wien*, R package version 1. 6–8 (2017)
56. R.J. Stone, Improved statistical procedure for the evaluation of solar radiation estimation models, Solar Energy **51**, 289–291 (1993)
57. A.M. Fraser, H.L. Swinney, Using mutual information to find independent coordinates for strange attractors, Phys. Rev. A **33**, 1134–1140 (1986)

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