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Proposing an Innovative Method for Predicting Optimum Wind Generator Output

Abstract: - Renewable energy sources offer environmental benefits and a more consistent supply, making them essential for integrating into energy fusions. Network operators have challenges with intermittent and stochastic power sources like wind power owing to their fluctuating production. This study presents an innovative method for predicting wind turbine power output, from any location in a vast region with high efficiency. To ensure a representative sample of geographical locations, the research region is divided into a grid and sampled accordingly. The ideal production times for each sub-area are discovered and utilized to anticipate electricity output. It uses the LSTM model to predict meteorological data and the linear model to approximate wind turbine power curves. The sub-area showed one-day wind speed, direction, and power projections clustering scores. Wind and directional predictions yielded RMSE (0.35m\sec, 7.9rad) and R2 (94%, 71%) scores.

Keywords: LSTM, RMSE, Energy Fusions, Turbine Power, wind power.

I. INTRODUCTION

Conventional energy depletion has spurred interest in renewable energy. According to the 2022 IEA assessment, gas, uranium, oil, and coal, will expire in 55, 65, 115, and 100 years. Respectively, which are immeasurable on a social measure. Meanwhile, the IEA predicts a 40% increase in global energy consumption by 2035 owing to industrialization and development programs. This means that nations with surplus output and self-usage will not be able to supply their needs using traditional generators. Exporting nations will struggle, raising energy import prices and decreasing energy imports in low-production countries. These conventional resources are less equally distributed than renewable energy sources, and climate change rules encourage to use of green energy.

In light of the unequal distribution of conventional resources, the development of these renewable forms of energy is necessary in the battle against climate change. The cultivation of already existent resources and the use of those resources need the formulation of new laws. The development of renewable energy sources and improvements in energy efficiency are becoming more important solutions to the difficulties that are caused by the production of energy. These topics include concerns about the economy, the environment, and the material world. As the Earth orbits the sun, the solar source is intermittent and fluctuates randomly, the available output power of the PV generator is therefore randomized. Like the wind, the wind turbines' output power changes randomly, but owing to a minimum beginning speed, it also varies intermittently. In conclusion, wind and PV generators' performance and power vary with time and place.

There are several approaches discussed here that may be used to deal with the sporadic and random unpredictability of these sources. To maintain a nearly constant output, it is possible to utilize several different generators, each of which produces something that complements the others. Another solution to the problem of intermittency is the use of energy storage, however, the production, operation, and recycling of this solution are expensive. In the context of globalization, interconnected countries have the potential to engage in the exchange of products and promote consumption when their production levels are high. Forecasting is considered to be the most suitable approach for addressing random fluctuations in output power due to its use of artificial intelligence techniques, which provide a comprehensive assessment of future power development.

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In certain geographically feasible areas, solar and wind energy resources can be developed and utilized in the coming years. When developing a suitable and adaptive forecast to combine these variable resources, it is necessary to take into account both the approach, that is being utilized and the surrounding environment. In addition, the findings of this research have led to the development of LSTM time series forecasting and wind turbine power curve approximation models. These models were used to forecast the speed and direction of the wind for 24 hrs, and the combination of the power curves of wind turbines and a forecasting model is known as LSTM. The results of this study will help to determine areas throughout a country that have the potential to house wind turbines and forecast how wind turbines will behave during various seasons and at different times of the year. In this work, a technique is described that can be used to estimate and determine the optimal production times of a wind source positioned at any place in a big geographical region. The results of the study are presented in the third portion, which is followed by a summary and conclusion in the fourth section.

II. METHODOLOGY

The wind turbines' behavior is hard to anticipate because of the influence that the elements have, like Satellites, meteorological stations, and numerical models measure geographic wind speeds. There are a wide variety of wind turbines, and the quantity of power they create is directly proportional to the wind speed at the location where the turbine is located. The kinetic energy of the wind is converted into mechanical and electrical energy by the wind turbine, which then results in the production of electricity. The output is presented in the form of a curve, which may be construed either as a generator or as a model, depending on the context. The great majority of wind turbines are controlled using a system known as the Pallabazzer.

2.1 WIND POWER VOLATILITY DUE TO WEATHER

Weather conditions because wind turbine output power to vary randomly. The study flowchart in Fig. 1 shows how to identify and manipulate key influencing factors to control variability. Wind turbines have multiple models, and their power output varies with wind speed. The output is displayed as a curve, which may represent a generator or a model. Most wind turbines operate using the Pallabazzer model. This involves using mechanical power on the wind turbine shaft, which is determined by factors such as wind speed, blade area, and power coefficient. To calculate the electrical power output of wind speed, the wind turbine, and direction are used, to determine optimal energy extraction by orienting the wind turbine blades. Wind power provides many environmental advantages, however, intermittency and possible effects on animals and landscapes are issues. Technology, site selection, and environmental management solve these problems. Wind power may reduce energy production and consumption's environmental effects when combined with other clean energy sources and a reliable energy storage system.

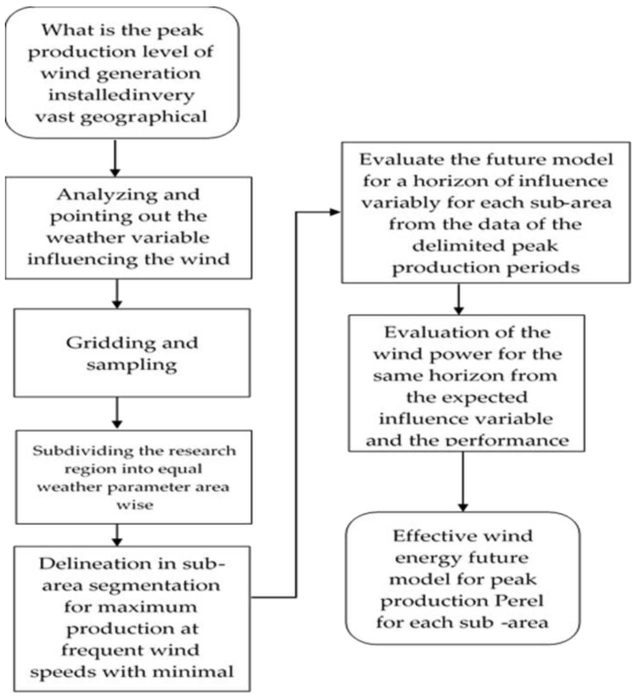

Figure 1 Flowchart for Proposed Research Method

2.2 GRIDDING AND SAMPLING

Geographic wind speeds are analysed through gridding and sampling via weather stations, satellites, and numerical weather models. This data is formatted for analysis, visualization, and modelling using gridding and sampling. There are many ways to generate wind speed data: For analysis or display, geographical wind speed data sampling requires picking data points or subsets of the gridded data. To concentrate on particular locations, periods, or characteristics in wind speed data, sampling methods are helpful Standard sampling methods are used in climate research, renewable energy planning, and weather forecasting

2.3 DELINEATION

In wind power, delineation refers to specifying sub-areas or characteristics. Professionals aim to enhance these vital areas in the complex field. Researchers, engineers, and politicians can tackle wind power sector challenges by dividing it into sub-areas. The data set Data Obtained from The Geostationary Operational Environmental Satellite (GOES) Operated by The NOAA NOAA uses satellites called GOES to monitor the weather, paying special attention to wind patterns. Data collected by GOES may be used to both monitor and forecast the wind speed.

Database: GOES NASA POWER LARC

Frequency of the Data:1 hour

Kinds of Data: V60M

V60M: Ground Wind speed at 60M

D500M: Ground Wind Direction at 60M

Period: from Jan 1, 2013 to Dec 31, 2022

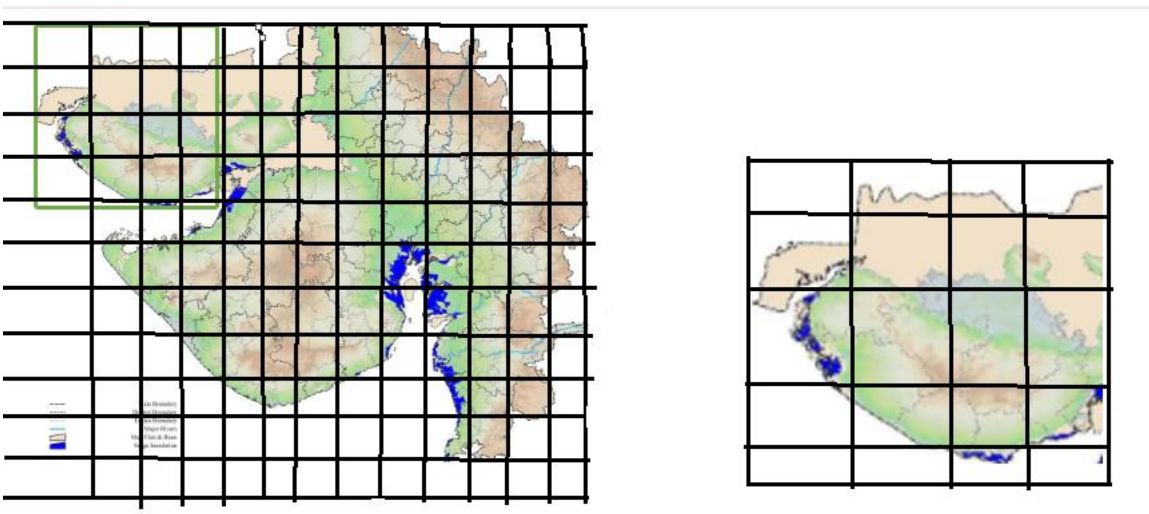

Figure 2 GRID AND SAMPLE MAP

2.4 PRE-PROCESSING SAMPLE DATA

Data, including the speed and direction of the wind, are gathered from NASA meteorologists for every sample. To get precise information, the data must be pre-processed once the gridding and sampling steps have been finished. This incorporates a wide variety of processing techniques.

2.5 DETECTING AND ELIMINATING OUTLIERS

The term abnormality refers to data points that deviate significantly from the mean, suggesting a deterministic process is influencing the data. Measurement errors or rare occurrences like fires or weather might be the root cause of these anomalies. Outlier detection is used in many applications. Representative and observable outliers are the simplest to spot in a dataset. This reveals exceptionally far-off numbers. Box plots show one-variable distributions. Median, lower, and higher quartiles form these graphs. Any extreme number that exceeds I times the interquartile range is an outlier. Mean, standard deviation, maximum, and minimum computations usually use I=1.5. Statistics provide speedy detection of data irregularities.

2.6 NEW DATASET VARIABLES

Improve model learning by adding variables to the data set. Meteorological data (wind speed, irradiance, temperature) need periodicity for analysis and forecasting. This research determines the series' highest frequencies using a quick Fourier transform. By methods 1 and 2 add variables by using this frequency.

$$X_{sin} = \mathrm{SIN}(T * (\frac{2*\pi}{T}))$$

$$X_{cos} = \mathrm{COS}(T * (\frac{2*\pi}{T}))$$

For f = 1, introduce X_{sin} andX_{cos}. T is the time for data collection. In addition, creates the direction of the wind understood by models. Angular direction of the wind. Models should know that 0° and 360° are the same. In addition, in light winds, the wind direction is useless. Therefore, link these variables. To generate two new variables (wind speed and direction) in Eqs. (3) and (4)

$$W_Y = w_s \sin(w_d)$$

$$W_X = w_s \cos(w_d)$$

$W_X$and $W_Y$are two original variables, w_s and w_d, individually, wind speed and direction at time T.

2.7 NORMALIZE AND STANDARDIZE DATA

During model training, it's important to scale variables with different orders of magnitude. Standardization or Minmax normalization are used. This study uses Eq. (5)'s Minmax normalization, which doesn't require knowledge of data distribution.

$$X_{NORM} = A + \frac{(X - MIN(X)(B - A)}{MAX(X) - MIN(X)}$$

X_{NORM} Denotes the usual variables, A and B are limits of original scale.

2.8 DATA SUB-DIVISION

The majority of the dataset (75%) is utilized for model training, while 25% is used for hyper parameter tuning and 15% is used for test. The purpose of the research is to optimize the power output of wind turbines and the production scheduling of wind turbines. Figure 3 below shows wind profiles for sub-areas of the research area which are either identical or similar to each other in terms of their wind patterns.

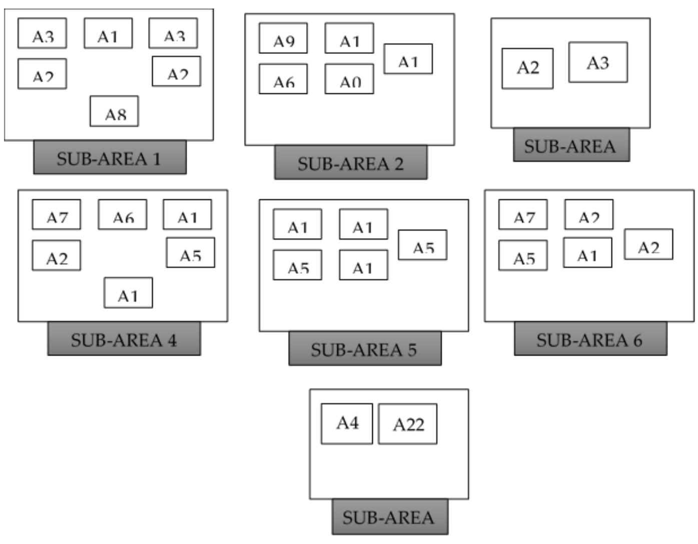

Figure 3 Division of Sub-Area

This indicates that samples that have the same climatological and/or hydrological properties are grouped. This method will cut down on the total number of research participants by employing recognized time series clustering methods. Research on the environment and renewable energy sources often groups wind speed measurements. It recognizes patterns and combines wind speed observations that are equivalent. There are a few different methods that may be used to cluster wind speed data. In this investigation, k-means clustering was used to analyse wind speed. The selection of the appropriate value for the clustering technique known as K-means is the step that is considered to be the most crucial. There are a few different routes that may be pursued to accurately determine the value of K. These methods include, for instance, the elbow technique and the silhouette score. Carry out several tests using a diverse range of K values to focus on the one that gives the most accurate picture of the underlying structure of your wind speed data. A statistical analytic technique called clustering is used to arrange unprocessed data into uniform silos. Data is organized into groups based on a shared feature within each cluster.

The sorting tool will employ predetermined criteria to assess how close elements are to one another. In this study, the grouping of the time sequence of the speed of the wind was accomplished by the use of the k-means approach. The K-means algorithm is a kind of unsupervised, non-hierarchical clustering method. The term "algorithm" refers to a set of step-by-step instructions or procedures that the algorithm facilitates the partitioning of the observations in the dataset into K separate clusters.   The same cluster will have comparable data. Furthermore, it is important to note that an observation may only be assigned to a single cluster at any one moment, and thus cannot simultaneously be a member of many distinct clusters. The exclusivity of membership is seen in a single cluster at a given moment. The aforementioned remark cannot be applied universally. The data points are assigned to two distinct clusters. The exclusivity of membership is seen in a single cluster at a given moment. The aforementioned remark cannot be applied universally. The data points are assigned to two distinct clusters. There is no clustering for the same dataset. The challenge is selecting K clusters that reveal intriguing data patterns. Most cluster numbers are chosen by computing the variance of K-means with various K values. Clusters. Varying distances between cluster centroids and cluster observations make up the variance. Therefore, strive to locate k clusters that reduce the gap between their geographic centres and what is seen in the same cluster. The cluster count indicates the number of wind profiles in the research region Grid space and study-area samples are optimized by clustering. Figure 4: Proposed optimization approach. Sample until increased clusters (wind profiles) end.

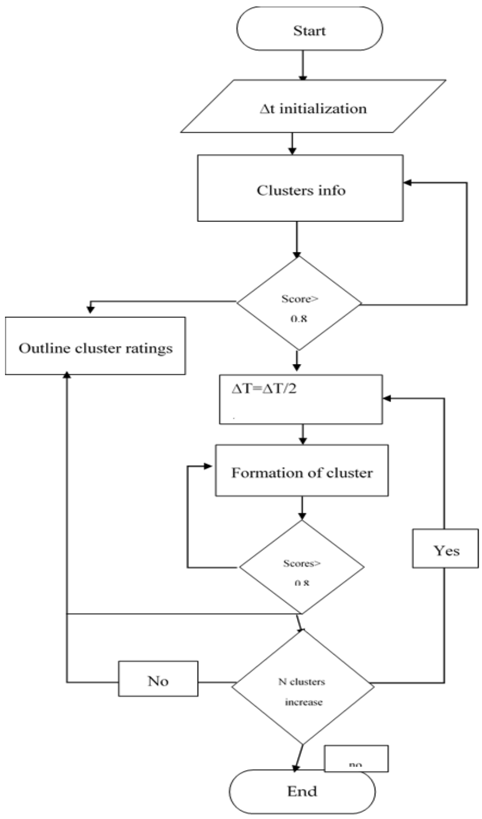

Figure 4 Optimization of Flow Chat for Grid Pitch and Cluster

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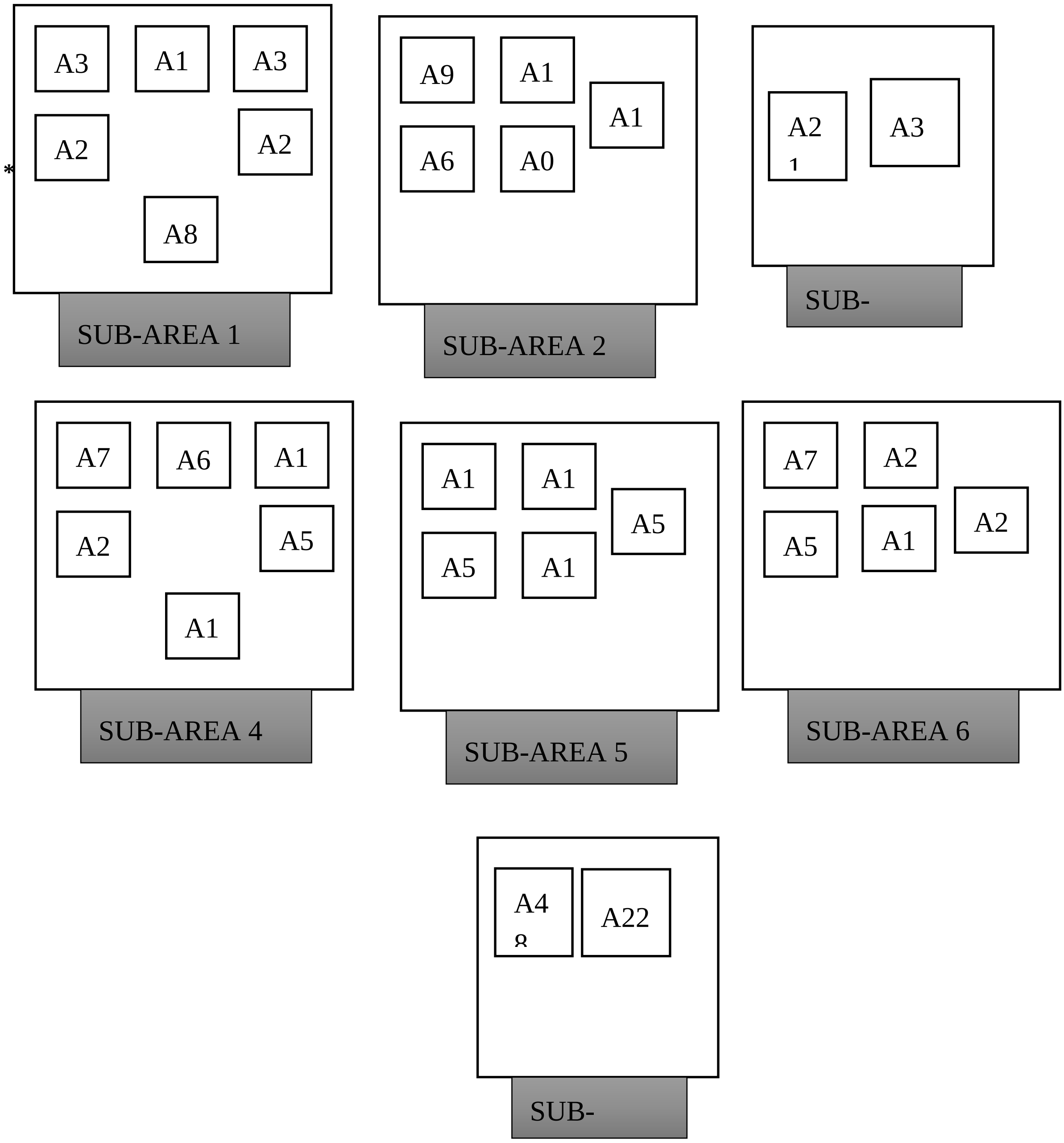

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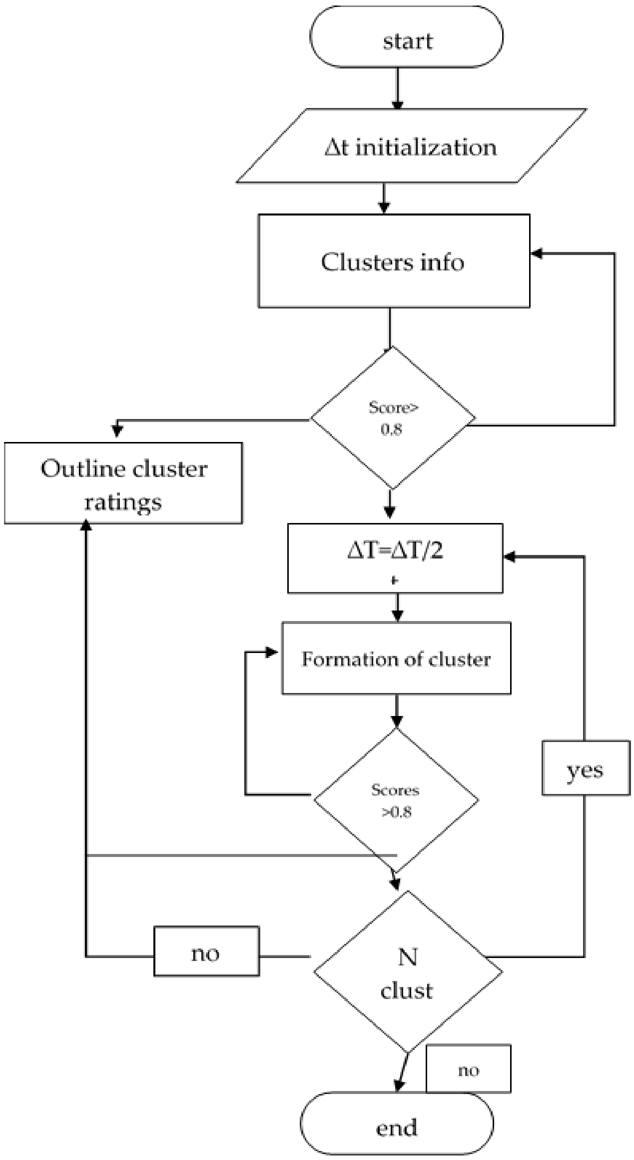


Figure 6 Optimization of Flow Chat for Grid Pitch and Cluster

2.8.1 SUBAREA CHARACTERIZATION

After the sub-areas have been formed it is important to determine the most suitable months for manufacturing wind turbines. Calculate the wind speeds for each of the sub-zones, bearing in mind that moderate to high variation is to be anticipated, and then proceed to the next step. Applying the Weibull distribution to control the position of wind turbine blades as well as the most typical wind speeds get your bearings with the help of wind roses

III. PREDICTING WIND POWER

Models for predicting the performance of wind turbines often use elements of both physics-based and statistical models, as well as machine learning methods. Precise estimations of energy output to improve the operation and maintenance of wind farms must be given. This will ensure that power generated by wind turbines is both efficient and dependable**.**

3.1 OPTIONAL FORECASTING METHODS

The wind power forecasting models are then trained using the data that was collected after the optimal production periods had been identified. Attempting to forecast times when wind turbines will not be operational is pointless. The literature lists numerous wind power forecasting methods. Figure. 5 shows the first method. This first method uses a time series forecasting model and power reading history to predict wind turbine power values. Simple design, but predicting model only applicable for installation where data were generated. Power measurement intervals must be lengthy for reliable forecasting. Time series forecasting and regression were used in a second method (Figure. 6). The time series forecasting model predicts wind speed, which the regression model links to wind turbine power values. Historical wind power and impact parameter data are needed for this. As with the previous model, the architecture is more sophisticated and the representation is only usable for the system it was built for and its surroundings indeed, meteorological characteristics depend on geography. A time sequence prediction model predicts future parameters and a Palla-bazer, linear, Chang wind power estimating model estimates wind turbine features such asas $v_{cut-off}$,v_{rated} and Prated in the final technique (Figure. 7).

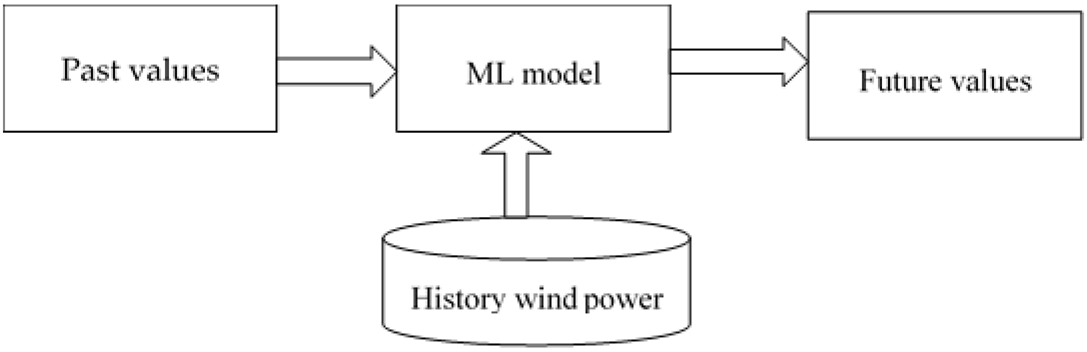


Figure 7 Forecasting model 1

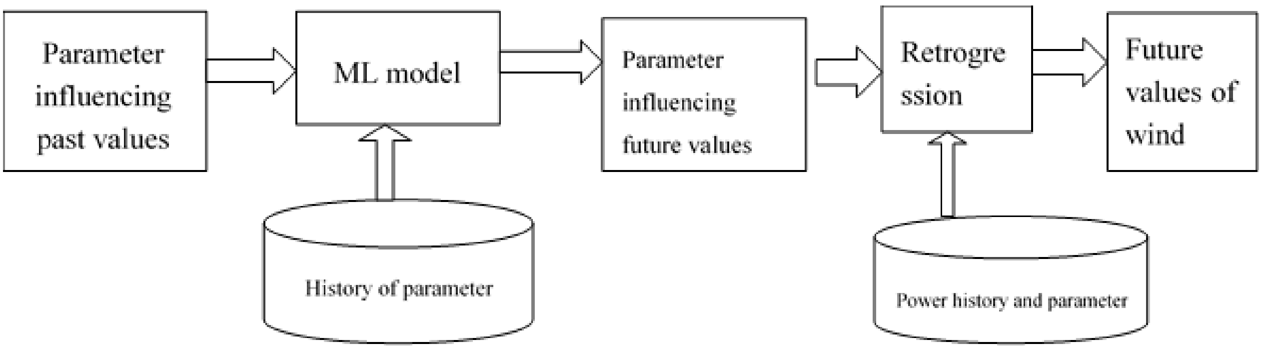


Figure 7 Forecasting model 2

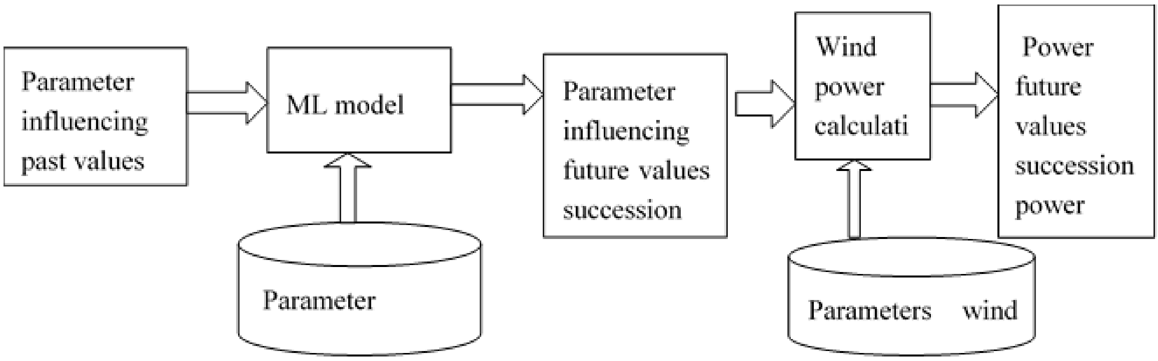


Figure 7 Forecasting model 3

Assigning the installation site and repeating the impact parameter prediction model to alter the power estimate model parameters may be used for different wind turbines. It's more fluid and adaptive without the system, but the process continues.

3.2 SELECTION OF FORECASTING MODEL

A forecasting model and wind speed time sequence are used to assess future power using the projected turbine's power curve model and speed. A thorough wind power and wind speed forecasting model survey. The classic neural network is improved by convolution. Designed for image processing, it encodes visual characteristics while lowering model configuration requirements. Besides input and output layers, CNNs include convolutional, pooling, and fully linked layers (Figure. 8) Assessment suggests that LSTM and CNN are the best basic wind speed forecasting models. Recurrent neural networks are improved using LSTM neural networks to tackle the vanish gradient problem. LSTM units consist of a dynamic memory c and gates of three – Input, Forget, and Output. The Forget Gate devalues knowledge that was helpful as of $t - 1$ but is now useless. The output Gate controls information transmission at t+1 using active memory C and the action function. Three gates govern information flow in LSTM cells, which store values at random intervals using memory vector C Figure. 9. The well-organised model of each wind profile (sub-area wind speediness changes) will be compared.

Use the typical power curve to estimate wind-generating power. A wind speed curve shows electricity production. Wind generator-specific. A literature-based power curve model or actual curves with an interpolation technique may be used to simulate wind turbines. Our next section presents three power curve modelling approaches and market-available small and medium power devices. Power curve parameters include:

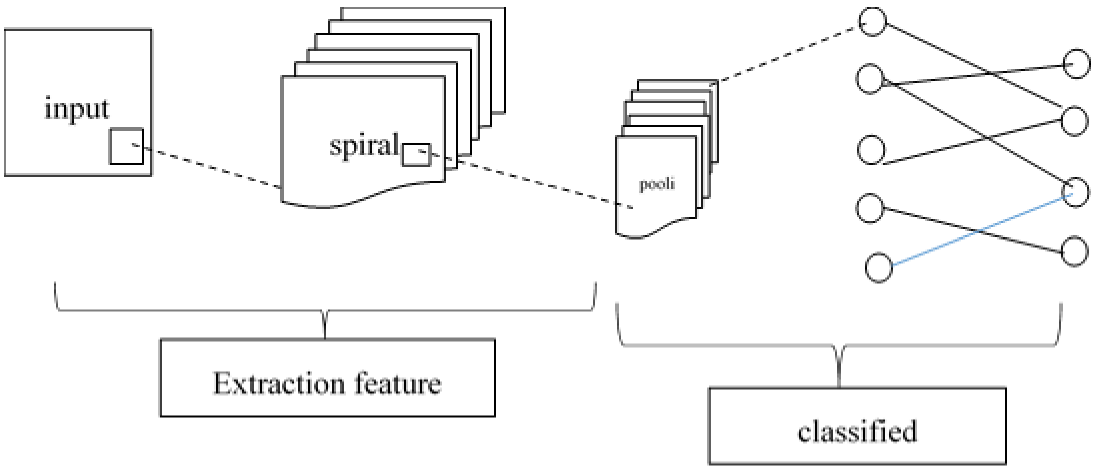


Figure 8 CNN models

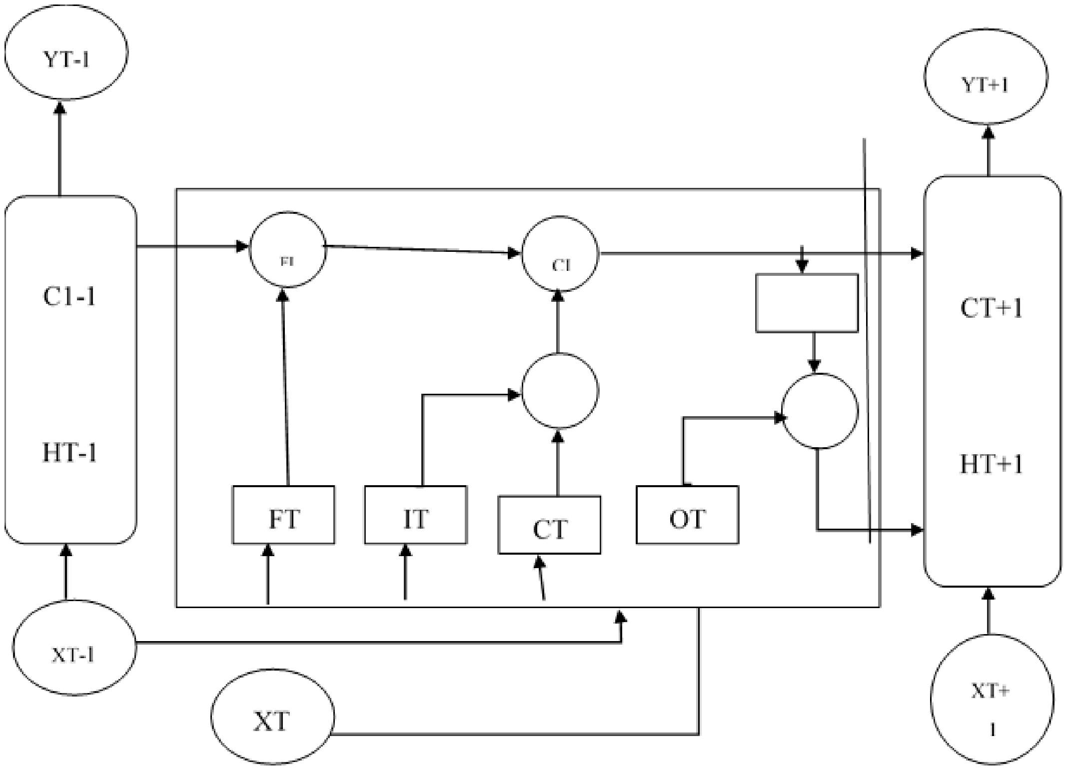


Figure 9 LSTM Unit Model

v_{cut-in} : The rate at which the electricity is activated.

v_{rated}: The pace at which the rated power is achieved.

$v_{cut-off}$: The rate at which the electricity is deactivated.

$p_{rated:}$Rated power

The linear form is a basic approach that assumes a linear relationship between the variables, implying that the power fluctuation between v_{cut} and v_{rated} is linear. Therefore, the diminished power curve is represented by three components.

$$P = \begin{cases} 0, V \leq V_{cut-in} \\ A + V_{cut-in} < V < \quad V_{cut-rated} \\ 1, V_{rated} < V < V_{cut-off} \end{cases}$$

The coefficients A and B are acquired or determined.

$$\begin{cases} A = \dfrac{V_{cut-in}}{V_{rated} - V_{cut-in}} \\ B = \dfrac{1}{V_{rated} - V_{cut-in}} \end{cases}$$

$$P = \left(\frac{V^2 - V_{cut-in}^2}{V_{rated}^2 - V_{cut-in}^2} \right)$$

Research findings indicate a tendency to overestimate the productivity of wind generators. However, despite this observed discrepancy, the use of this model remains prevalent in research about hybrid systems.

The Pallabazzer model also distinguishes itself from the linear model due to the non-linear nature of the curve between the engagement speed and the speed at which the nominal power is achieved. In this section, the diminished authority is articulated through:

$$P = A_1 V^3 + A_2 2 + A_3 V + A_4$$

$$P_{MEC} = \frac{1}{2} C_P A_R p_a V^3$$

3.3 OPTIMIZING FORECASTING HYPERPARAMETERS

Discovering which model parameters improve performance is crucial. To predict meteorological parameters, we used CNN and LSTM models. The hyper parameters of these two models and their optimization ranges are shown in Table 1. Input data sequence: 2–63 h, forecast sequence: 2–23 h. CNN operates with 20–200 filters and 20–900 units. Also, the LSTM network has 100–1000 units. 3 learning rates: 20–3, 20–4. Optimization occurs.

TABLE: 1 CNN &LSTM parameter

CNN parameter		LSTM parameter	
WIDTH INPUT	2 TO63 H		
WIDTH LABLE	2 TO 23 H		
FILTERS	20 TO 200	UNITES 20 TO 900	
UNITS	20 TO 900		
LEARNING -RATES	20-3 20-4	LEARNING -RATES	20-3 20-4

3.4 MODELS TRAINING

Meteorological data (wind speed and direction) and optimal hyper parameters are used to train the models. Tensor Flow is used to develop CNN and LSTM models during the training process in Python 3.

3.5 CLUSTERING EVALUATION

Selecting the proper measure is crucial for model evaluation. This research analyzes models using these measures. A determination's quality is indicate squared linear regressions. Fitting the model to the observed data with a value between 0 and 1. Simple linear equation

$$R^2 = 1 - \frac{\sum_{I=1}^{N} (Y_I - \widehat{Y_I})^2}{\sum_{I=1}^{N} (Y_I - \overline{Y})^2}$$

The average of the squares of the mistakes is the mean square error (MSE), which measures prediction model quality. Outliers and big mistakes are penalized. The formula for expressing it:

$$MSE = \frac{1}{N} \sum_{I=1}^{N} (Y_I - \widehat{Y}_I)^2$$

Yi is the real value, Y^i is the anticipated value, and n is the forecast size.

MSE may be reduced to the same unit as the quantity assessed using the root mean squared error (RMSE). This is the square root of MSE:

$$RMSE = \sqrt{\frac{1}{N} \sum_{I=1}^{N} (Y_I - \widehat{Y}_I)^2}$$

NRMSE, an extension of MSE, is used to assess wind speed prediction models in the literature. Divide square root error by series range. The Silhouette (start writing)

$$NRMSE = \frac{RMSE}{Y_{MAX} - Y_{MIN}} ouNRMSE = \frac{RMSE}{\overline{Y}}$$

The quality of a clustering may be measured by a statistic called the Silhouette score. It varies from 1 to 1:

If the coefficient is negative, the classification is inaccurate; if it is zero, the categorised element is either very near the cluster's decision border or is out on its own. Obtaining a positive coefficient indicates that the categorization is accurate.

The formula provides an equation for it.

$$S_{SIL} = \frac{B - A}{MAX(A, B)}$$

The variables "A" and "B" reflect the mean distance between a data point and its corresponding group and the normal distance between the data point and its adjacent cluster, respectively.

IV. RESULTS GRID SAMPLE

The gridding method and the changeable range of latitude (l) and longitude (L) are both shown in Figure 10. The latitudes of the samples ranged from 4.535 degrees to 22.6 degrees, while the longitudes ranged from 0.8 degrees to 5.065 degrees the step angle of 0.15 degrees provides the most accurate results for the grid. Keep in mind that the grid spacing that has the fewest clusters of meteorological parameter profiles, in this case wind speed, and is the best. There is a difference of 0.085 degrees between a test sample and a validation sample, but there is a difference of 0.25 degrees between two test examples or two validation samples. Validation samples assess cluster quality while test samples generate clusters. 2880 test and 2280 validation samples were collected.

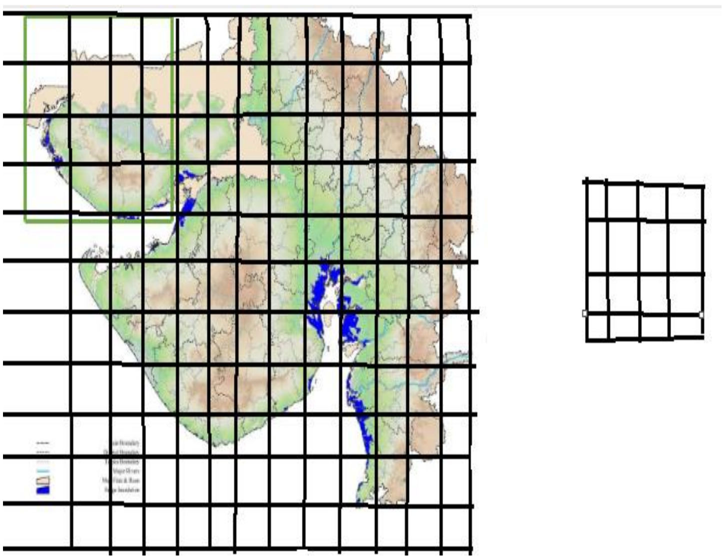


Figure 10: gridded map (study area)

4.1 PRESENTING DATA

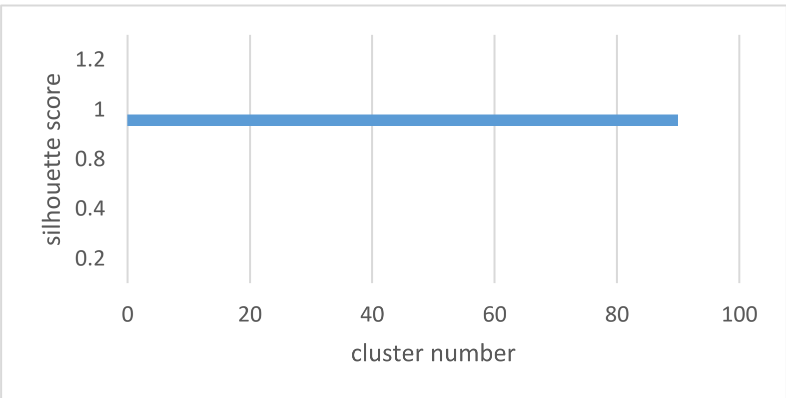


Figure 11: 90 clusters of silhouette score

There are no obvious irregularities to be found. When compared to the highest values, which vary from 6.89 to 16 meters per second, the mean values fall somewhere in the range of 4.45 to 6.36 meters per second. Because it is common knowledge that wind turbines need a minimum starting speed of 3 meters per second, the inclusion of this information makes it possible to continue the examination over the whole of the territory under consideration for the study. It is worth mentioning that there exists a range of standard deviations ranging from 2.18 to 3.3 m/s. The observed variances in statistics also indicate disparities among the various samples.

4.2.1 CLUSTER ANALYSIS

The clustering process will commence after researchers have determined that the data are usable and that the research would be beneficial to the whole study area. This area is used to aggregate the samples that were taken at consistent wind speeds over the whole study region. Every cluster denotes a smaller region that maintains a consistent wind speed. 90 groupings total. See Figure 11 for the 90 clusters' Silhouette scores. Silhouette scores are near 1 for 89 clusters, indicating complete resemblance. Silhouette score: 0 for cluster 90. Because this cluster has one sample, this value is generated. Wind speeds in clusters 90 and 56 for August 2020. Cluster 56 has flawlessly stacked curves. Cluster 90 has exactly one curve, confirming the Silhouette score of 0. For clarity, the samples' wind speed profiles are called Windspeed Latitude Longitude. Other cluster results are after setting up the clusters, validation samples show that the 90 clusters represent the full research region. Figure 12 displays the 1080 validation samples' Silhouette score. A silhouette scores all above our 0.9 criteria (range 0.96–1). Hence, the 90 detected profiles indicate wind speed changes over the research region. N

4.2.2 CHARACTERIZE EACH SUBAREA

The clustering process produces a total of ninety subzones. In each sub-area, the predominant wind directions are mapped out in preparation for the construction of wind turbines. As a result of the large number of sub-zones, only cluster 56, which was chosen at random, will be presented. Choose any sub-zone. The sub-area 56 wind increase is shown in Figure 13. This zone has southwest-blowing winds. This helps us find an appropriate blade orientation. The wind speed frequency histogram and Weibull distribution. The wind speed is 4.4 M/S. The most convincing wind speeds are 3.2–6.4 m/s. This speed range permits wind turbine installation. When would ideal production occur?

In sub-area 56, periodical wind speeds vary from 3.37 to 5.3 m/s and 1.55 to 2.3 m/s, as shown in Figure 14. To find the best manufacturing time, compare monthly wind speeds and standard deviations. This sub-area has an excellent manufacturing period from Sep. to Dec. since wind turbines start at 7.2 to 10 km/h.

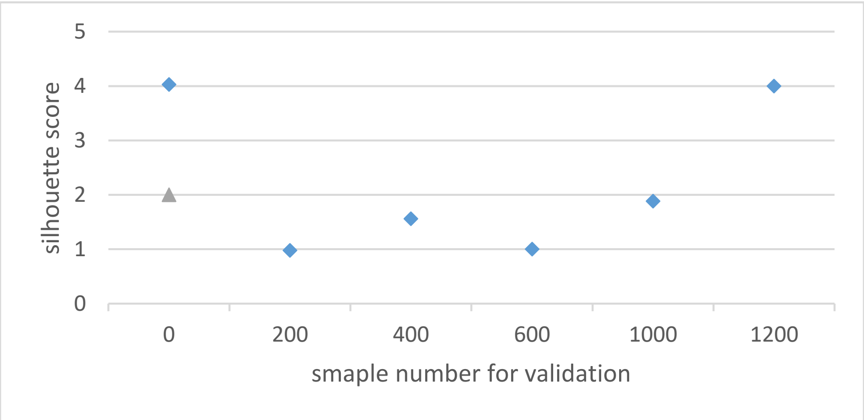


Figure 12: silhouette score for validation

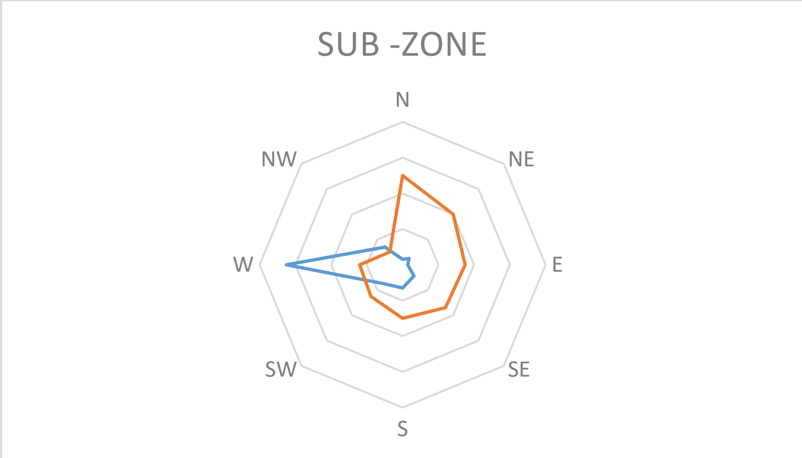


Figure 13: Sub Area 56 of Wind Rose

Once a year, day-by-day, half-day, third-day, and quarter-day attendance are noteworthy. After adding columns, Figure 14 displays the dataset. For wind speed and direction predictions for sub-area 56, Tables 2 and 3 show CNN and LSTM hyper parameter tuning results. Both models performed best with an 11-hour prediction using 17 hours of prior data. Therefore, we only offer 17_11 model results. For CNN w_x and w_y predictions, optimum (filters, units, and learning rate) parameters were (60, 690, 11–3) and (60, 200, 11–3).

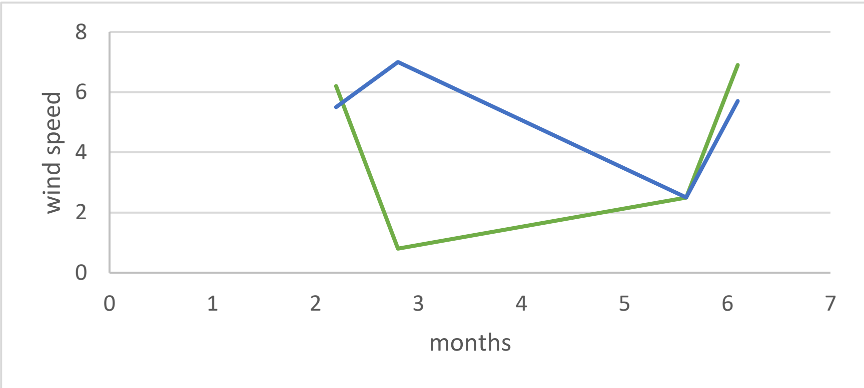


Figure 14: monthly average and standard deviation of winds for sub-area 56

The models are trained using meteorological data for each sub-area's best production times. To achieve this, translate wind speed and direction data while adding new variables using the speeds' predominant frequencies. Fast Fourier transform (FFT) of sub-area 56 wind speed is shown in Figures 15 and 16. Respectively. In the LSTM, optimum (units, learning speed) parameters for W x and W y forecast were (560, 11–3) and (150, 11–3). The LSTM model has the highest performance in predicting W x and W y, with R2 coefficients of determination (86%, 0.47 m/s) and RMSE (91%, 0.33 m/s). These sub-areas wind speed and direction prediction use the LSTM model respectively. For W X and W Y predictions, the LSTM found optimum (units, learning rate) parameters of (560, 10–3) and (260, 10–3). The highest-performing model for predicting W x and W y is the LSTM, with R2 coefficients of determination (86%, 0.47 m/s) and RMSE (91%, 0.33 m/s). Thus, these sub-areas wind speed and direction prediction use the LSTM model. The 11-hour forecasts of W x and W y on three randomly chosen test set pieces. These statistics show that anticipated trends are typically accurate. However, anticipated and real W x and W y differ. They reflect the goal and projected W x and W y, correspondingly. The outlook is favourable. Table 4 shows forecasted results. Wind speed and direction are calculated from W x and W y predictions. The forecasted wind speed and direction.

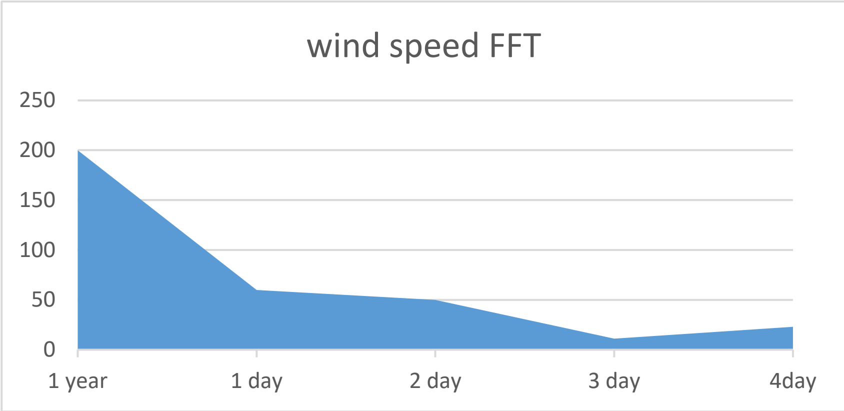
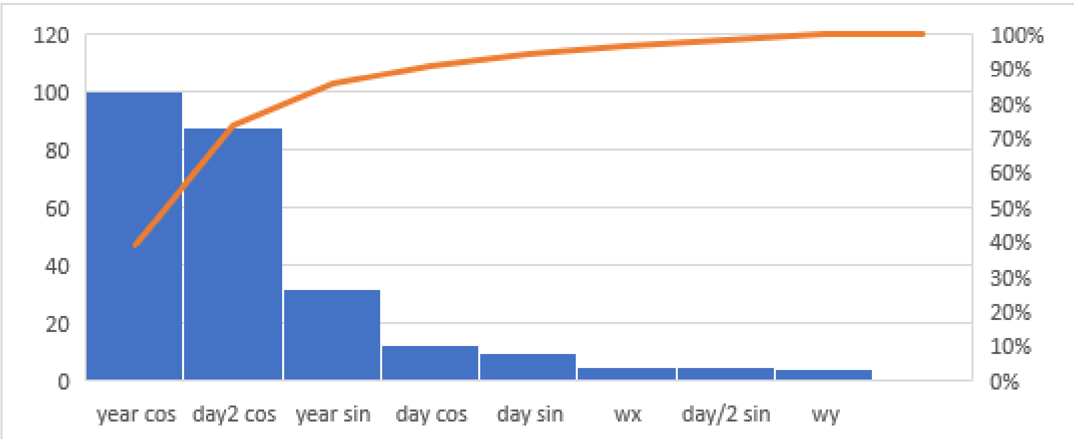


Figure 15: Wind Speed FFT

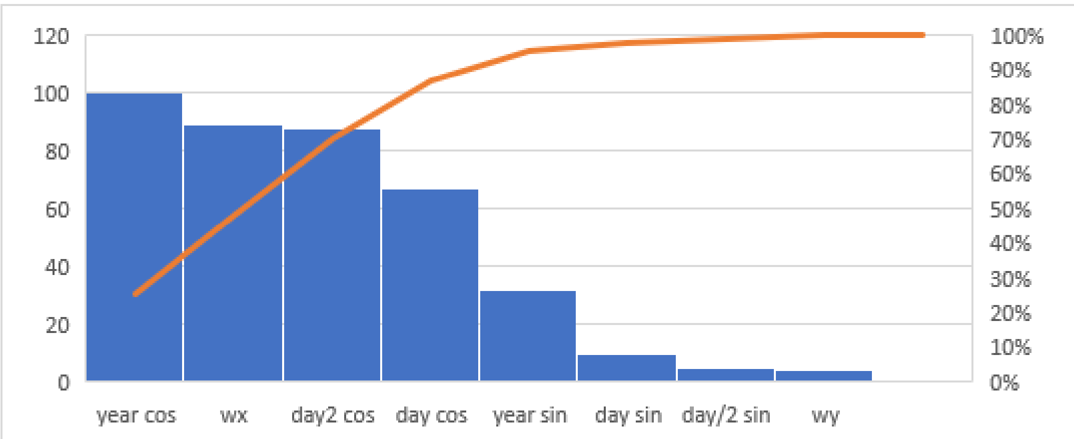
The challenging aspect of learning is attributed to the unpredictable fluctuations in wind speed.

The wind speed and direction values may be inferred from the forecasted values of. Therefore, we get the 12-hour prediction values for W x and W y. $\begin{cases} W_Y = W_S\, Sin(W_D) \\ W_Y = W_S\, cos(W_D) \end{cases} \Rightarrow \frac{W_Y}{W_X} = tanW_D \;\; and \; W_D = tan^{-1}(\frac{W_Y}{W_X})$

The forecast provides information on wind speed and direction for 11 hours.



(a)



(b)

Figure: 16 data set of the new variable

Table 2:w_x forecasting CNN and LSTMPresentation

CNN parameter		LSTM parameter	
WIDTH INPUT	17 h		
WIDTH LABLE	11 h		
FILTERS	60	UNITES	200
UNITS	690		
LEARNING -Rates	11-3	LEARNING -Rates	11-3

Table 3:w_y forecasting CNN as well as LSTM Presentation

CNN parameter		LSTM parameter	
WIDTH INPUT	15 h		
WIDTH LABLE	11 h		
FILTERS	60	UNITES	150
UNITS	690		
LEARNING -RATES	11-3	LEARNING -RATES	11-3

$$W_S = \frac{W_Y}{\sin(tan^{-1}\frac{W_Y}{W_X})}$$

A validation was conducted to assess the forecasting ability of the models using data from December 31, 2020, and January 1, 2021.

Figures 17, 18 and 19 provide the typical curves of the goal and projected values for W x and W y, individually. The forecast has a high level of accuracy. The wind speed and direction values are inferred from the forecasted variables W x and W y, which are expected to provide accurate estimations of the actual (goal) standards of wind speed and direction.

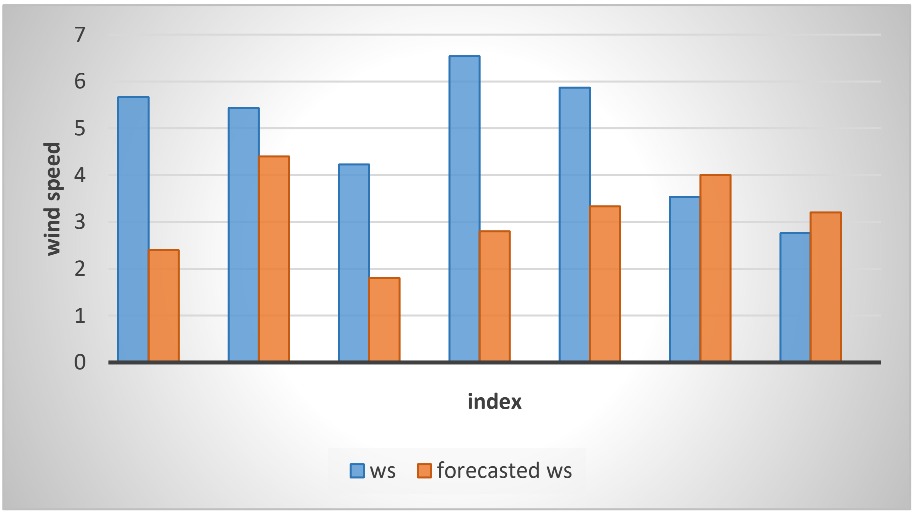


Figure 17: wind speed forecast

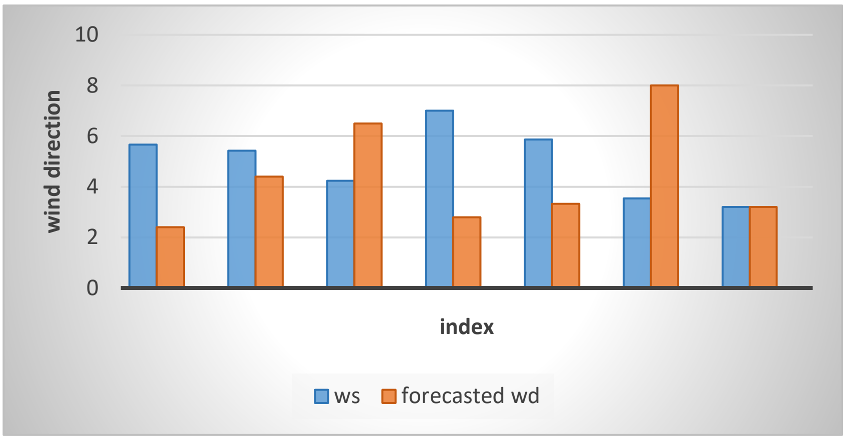


Figure 18: wind direction forecast

Table 4 shows forecasted results. The coefficients of determination for wind speed and direction are 93% and 70%, correspondingly, with square root errors of 0.35 m/s and 8.9 rad. The LSTM model can predict wind speed and direction medium term with these results. Forecasting with deep learning networks is usually short-term and has a Root Mean Square Error > 0.7 m/s. Forecast timeframes, datasets, and computers vary. This makes accuracy and computation time comparisons difficult. The LSTM model is more efficient even with a 12-hour horizon for most wind speed prediction models.

Table 4: Wind Direction and Wind Speed Forecasting

Forecasting wind speed	
RMSE	0.23M/S
R2	98%
Forecasting wind direction	
RMSE	70%

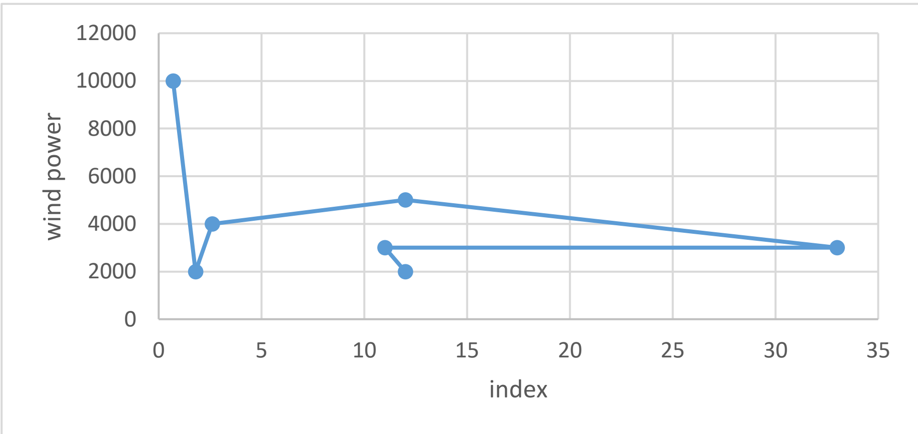


Figure 19: wind power estimated

V. CONCLUSION

The conclusion outlines the approaches and variables that were used. Intermittent production makes use of performance, wind turbines, photovoltaic power generation, and the randomization of photovoltaic energy. LSTM time series forecasting and wind turbine power curve approximation models were utilized in these studies. These models were able to predict the 24-hour wind direction and speed, as well as the output power of the wind generator. The large area of wind generators can be anticipated and determined with this tool. Predictions for wind speed, direction, and power was clustered. Forecasts for wind and direction have RMSE (0.35 m/sec, 7.9 rad) and R2 (94%, 71%). Generator power is random. Similar to the wind, wind turbine power swings randomly, but with a minimum beginning speed. Different locations affect wind and PV generator performance and power. After installing a generator, wind speed randomness must be used to estimate output power. This study utilized clustering and AI to determine optimal wind power production locations and periods. An LSTM and a wind turbine power curve approximation model were used in this research project to provide forecasts about the wind speed, direction, and output power over a period of 12 hours. Wind turbine impacts must be balanced using a comprehensive, multi-stakeholder strategy. Planning, community interaction, environmental preservation, and renewable energy promotion are needed. To maximize wind energy advantages, minimize the environmental and community consequences. With this information, a nation will be better able to identify places for wind turbines and predict their performance throughout the year.

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