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An AI-Ml Based Effective Innovative Proposed Method For Predicting Optimum Wind Generator For Energy Forecasting

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Abstract –
The integration of Artificial Intelligence (AI) and Machine Learning (ML) in wind energy forecasting represents a transformative approach to predicting wind behavior and optimizing wind energy systems. These advanced technologies provide a robust framework for enhancing the accuracy, reliability, and efficiency of wind energy forecasting, addressing many challenges of traditional methods. Wind energy forecasting involves predicting wind speed, direction, and power output from wind turbines over different time horizons. Accurate forecasts are critical for optimizing the operation of wind farms and Ensuring grid stability and smooth integration of wind energy into the power system there by reducing uncertainty and enhancing energy market efficiency. Conventional forecasting relies on Numerical Weather Prediction (NWP) models, which use mathematical equations to simulate atmospheric behavior

Keywords: *Numerical Weather Prediction (NWP), Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Long Short-Term Memory (LSTM), NOAA, NASA.*

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I. Introduction:

Introduction Renewable energy refers to energy that is generated from natural resources that are replenished over time and are considered sustainable and environmentally friendly. Unlike fossil fuels (such as coal, oil, and natural gas), which are finite and contribute to climate change, renewable energy sources are abundant, produce little to no greenhouse gas emissions, and can be harnessed for power generation continuously.

Types of Renewable Energy Sources:
1. Solar Energy:
How it works: Solar panels (photovoltaic cells) capture sunlight and convert it into electricity.
Benefits: Solar energy is abundant, widely available, and has no emissions during operation. It can be deployed in various settings, from small rooftop systems to large utility-scale solar farms.

2. Wind Energy:
How it works: It converts the kinetic energy of the wind into mechanical energy. Offshore and onshore wind farms are common.
Benefits: Wind energy is cost-effective, scalable, and produces no emissions. It can be harnessed both in large wind farms and smaller installations.

3. Hydropower (Water Energy):
How it works: Hydropower uses the energy of flowing or falling water to turn turbines, which generate electricity. It includes large-scale dams, as well as smaller "run-of-river" systems. 2 o
Benefits: Hydropower is highly efficient, can generate power consistently, and provides reliable energy storage through pumped storage systems.
Challenges: Environmental impact, including disruption of ecosystems and water resources, and the displacement of communities for large dams.

4. Geothermal Energy:
How it works: Geothermal energy taps into the Earth's internal heat. Hot water or steam from underground reservoirs is brought to the surface to drive turbines or provide direct heating. Benefits: Geothermal plants can provide continuous (baseload) energy and are highly efficient. It also has a low environmental impact compared to fossil fuels. Challenges: Geothermal energy is location-specific and only feasible in areas with significant geothermal activity, such as volcanic regions.

5. Biomass Energy:
How it works: Biomass energy involves burning organic materials (such as wood, agricultural waste, or dedicated energy crops) and generate electricity. It also includes biogas from the decomposition of organic matter.
Benefits: Biomass is carbon-neutral, as the CO2 released during combustion is offset by the carbon absorbed by the plants during growth.
Challenges: Biomass requires land and water, and burning biomass can release pollutants. Also, sourcing biomass sustainably is critical to avoid deforestation and other environmental impacts.

6. Ocean Energy (Tidal and Wave Energy):
How it works: Ocean energy includes two main forms: tidal energy (using the rise and fall of tides) and wave energy (using surface waves). Both are harnessed to generate electricity via turbines or other mechanical systems.
Benefits: Ocean energy has a huge potential due to the vast energy in ocean currents and waves. It's also a predictable source of energy (tides are highly regular).
Challenges: The technology for capturing ocean energy is still developing, and the impact on marine ecosystems and infrastructure costs are key challenges.

II. Literature Survey:

Renewable energy bases have rapidly expanding growth in the sector of power group as associated to the energy sources that are traditionally available and wind is one of them. The best possible way to estimate the wind power potential is expressed in watts per square meter (W/m2). The accuracy of an air conditioner may be anticipated with remarkable accuracy, despite the fact that it is not particularly exact due to its nature. Wind speed fluctuations damage wind-powered systems and also have an impact on stability owing to power outages, current fluctuations, and energy quality issues (Ray et al., 2006). This necessitates an understanding of how air works in an environment that employs air forecasting and wind forecasting methodologies. Wind speed estimates were part of a decades-long weather forecast used for navigation, flight control, and satellite launch, among other things. However, with the continuous usage of wind energy in global power generation, wind forecasting has recently gained traction. Installing a large number of wind turbine generators can reduce pollution, fossil fuel use, and overall energy generation costs dramatically. The amount of electricity generated by a wind power generating system at a certain wind farm is determined by the mean wind speed and standard deviation (Akdag and Ali,2009). Because annual mean wind speed variation is difficult to forecast, wind speed fluctuations over the course of a year can be well described using the probability density function (pdf).Wind power forecasting (Dodla, 2018) is critical for supply and demand in grid connected wind generating plants. Many accurate and dependable weather forecasting models use a range of modern methodologies. Many scholars have highlighted (Ramachandra & B.V., 2005) the current state of the art of innovation in wind energy forecasting models in recent updates. The electricity prediction is primarily dependent on short-term to second-by-second forecasting, intermediate duration of 2-7 days with long-term predictions with the help of various models and upto 2 days duration that also comes under short-term duration.

Wind forecast models are of two categories:
Numerical based model.
Statistical model.

In physical measurements, changing dynamics such as temp, wind speed, relative humidity, and pressure, as well as the requirement for bigger resources, numerical approaches use meteorological characteristics, geographical features, altitude, durability, and restrictions. Forecasting services are also available from other qualified firms. Statistical models (Chandel et al., 2014) use meteorological data to anticipate wind speed of wind in future and wind's output power, requiring a single step only to transform input variables to output power. Autoregressive (AR), Moving average (MA), integrated motion measurement model (ARIMA), Box Jenkins method, Kalman-filtering, and Artificial Neural Network (ANN) etc (A.M & Leahy, P.G., 2012). The Potential estimate of wind power usually depends on years-term meteorological measurements in the area of interest. In a comprehensive evaluation, In paper (Jung & Broadwater, 2014, 762-777) a precise technique was presented for assessing a region's wind resource and producing a wind map for the region. After finding acceptable windy places, (Aggarwal et al., 2014) conducted a preliminary assessment of Himachal Pradesh's wind potential, which was again acted on by the detailed assessment program.

Chang (Chang, 2011) studied six numerical approaches for calculating wind energy patterns and found that the WEPF technique is superior in estimating Weibull parameters. The importance of utilizing wind resources in Himachal Pradesh for energy generation and other purposes is stressed upon in (Aggarwal et al., 2014), but no big initiatives have yet been implemented. (WEPF) approach was utilized for the potential assessment of Himachal Pradesh. Various methods for the calculation of Weibull Parameters have been given in (Lars Lundberg et al., 2003) like the “Moment method”, “Maximum likelihood method”, “Modified maximum likelihood”, “Energy Estimation”, etc., for wind energy application in Iran's cities.

III. Proposal Of Innovative Method For Predicting Optimum Wind Generator Detailed Explanation:

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. Exporting nations will struggle, raising energy import prices and decreasing energy imports in low-production countries. These conventional resources are less equally distributed, and climate change rules encourage to use of green energy.

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 related 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 arrangement 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.

Wind Power Volatility: Due to 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 output fluctuates 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.

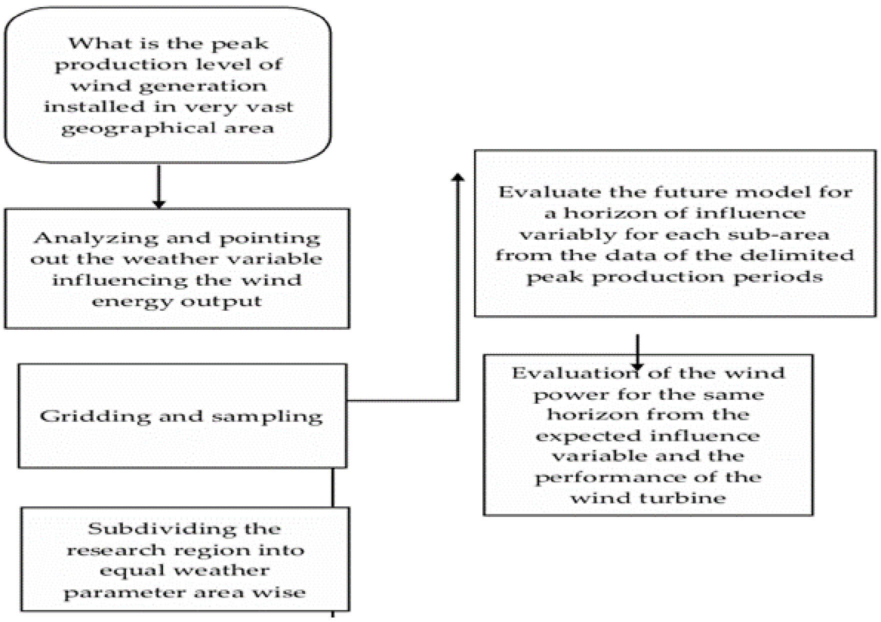

Figure 1: Flowchart for Proposed Research Method

Gridding and Sampling: Geographic wind speeds are analyzed 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

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 attained 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

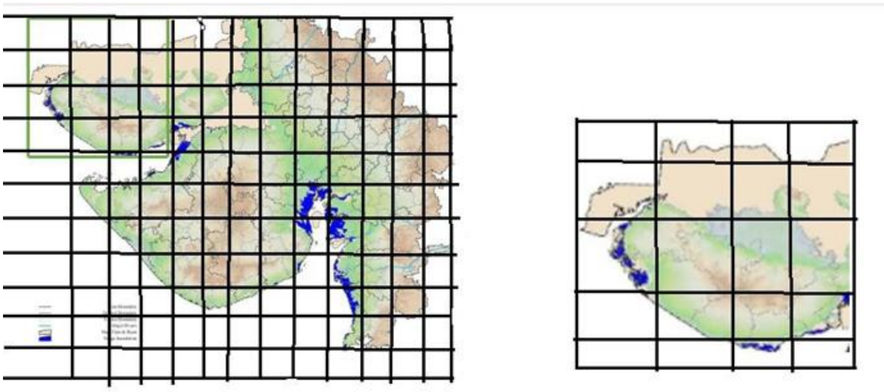

Figure 2. Grid and Sample Map

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 preprocessed once the gridding and sampling steps have been finished. This incorporates a wide variety of processing techniques.

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.

Data Sub-Division: The majority of the dataset (75%) is employed for training of the model, while 25% is used for “hyper parameter tuning” and 15% is employed for test. The purpose of the research is to optimize the power output of wind turbines and the production scheduling of wind turbines. Figure 3.5 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.

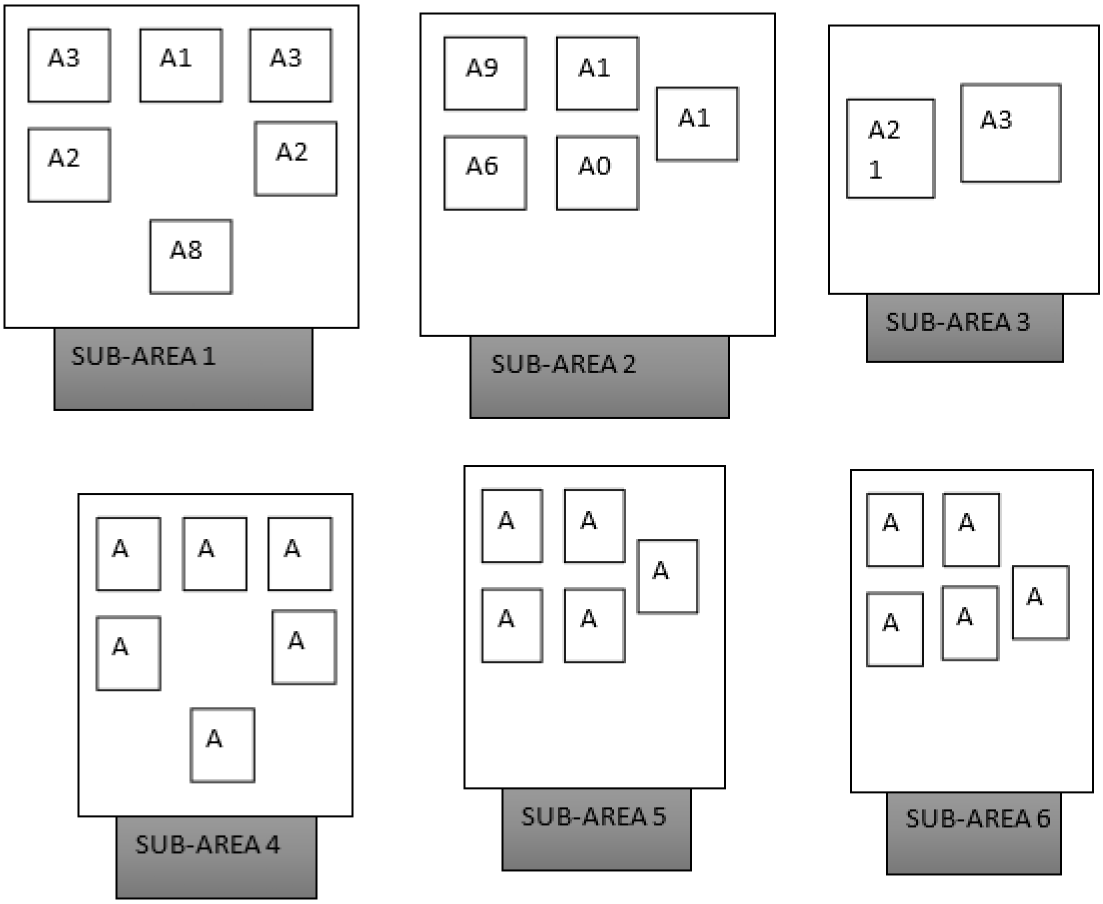

Figure 3. Division of Sub-Area

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 4 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.5). 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 as as $v_{\ cut-off}$, $_{rated}$ and Prated in the final technique (Figure. 6).

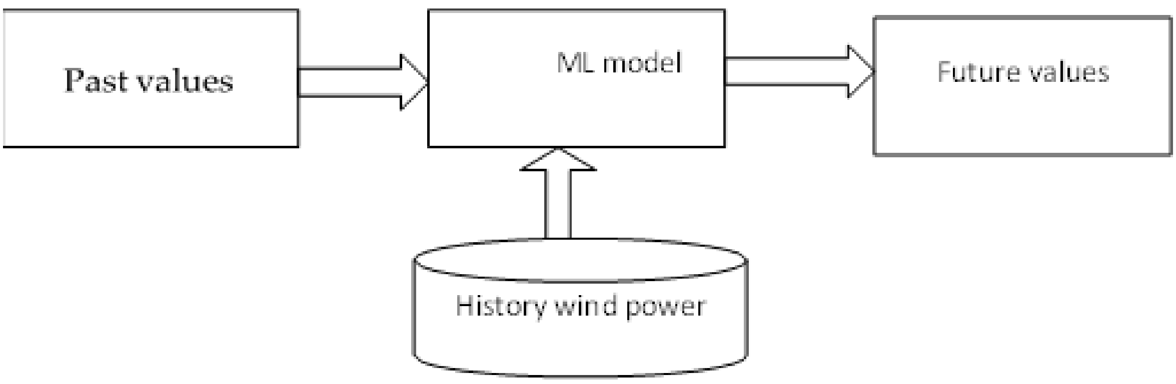

Figure 4. Forecasting model 1

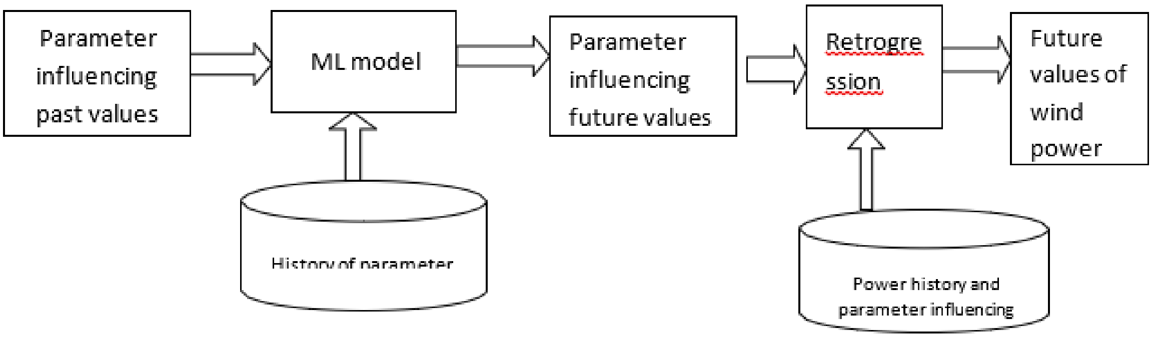

Figure 5 Forecasting model 2

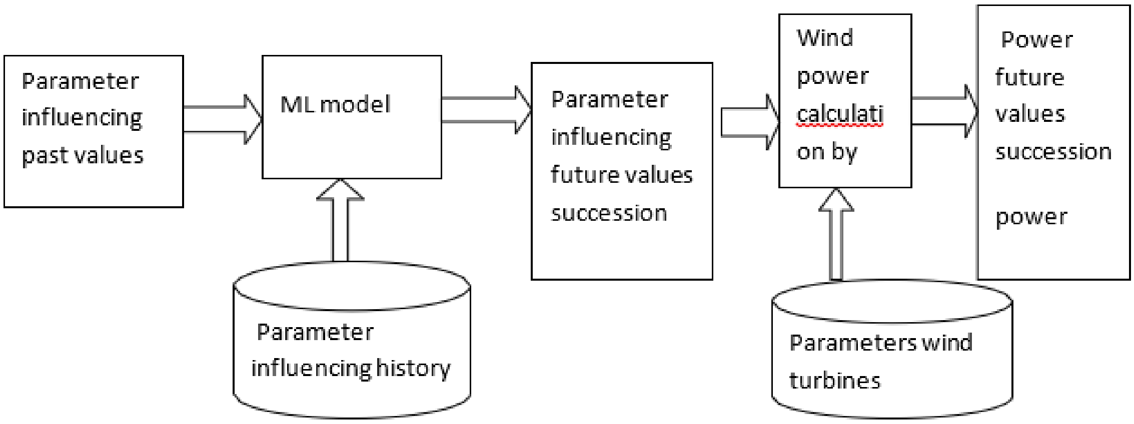

Figure 6 Forecasting model 3

IV. Conclusion And Future Work:

The proposed model has significantly fewer parameters and simpler parameters compared to the comparison model, reducing the risk of over fitting. It has the fastest convergence speed and performs multi-step forecasting directly, outperforming the Seq2Seq+attention method which performs it recursively. The study proposes the ideal model with the finest prediction result and fast speed, using the validation set's prediction effect as a benchmark. The model, which uses the Res-CNN net for the feature fusion, is greater than the TFT technique in multi-step prediction mechanisms and direct prediction mechanisms compared to the Seq2Seq+attention model.

The study proposes a solution to the wind power multi-step prediction issue using a multi-source information fusion and deep learning algorithmic. It suggests that utilizing time-varying information and static variable information for feature selection can increase forecasting model accuracy. Additionally, historical statistical data can be added for better prediction. The method also improves model generalization and feature engineering, making it faster and more accurate than recursive prediction

Res-CNN multi-source data fusion enhances model generalization and enhances forecasting capability. The direct prediction technique and self-attention mechanism exhibit effective multi-step prediction skills. It trains faster and predicts better than recursive prediction.

The study's numerical wind farm power forecasting experiment reveals that a deep learning prediction model outperforms Seq2Seq+attention, but the multi-step problem still has a significant time lag during strong gusts. The study also missed critical aspects like the division of working circumstances, which significantly impact data driven forecasting approaches.

The conclusion shows variables and methodologies. Performance, wind turbines, PV generating power, and randomizing PV energy are employed for intermittent production The models used in these studies are LSTM time series forecasting and wind turbine power curve approximation models. An LSTM forecasting model and awind turbine power curve model were able to predict the 24-hour wind direction and speed in addition to wind generator output power. 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 proves its practicality using artificial intelligence and clustering to find a good location, discover wind power production potential across a vast region, and determine the best production periods. This study predicts wind speed, direction, and output power over 12 h using an LSTM and wind turbine power curve approximation model. The data will help a country to choose wind turbine locations and estimate performance year-round.

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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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