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SHORT-TERM WIND POWER PREDICTION IMPLEMENTING THE GRADIENT BOOST ALGORITHM IN PARTICLE SWARM OPTIMIZATION-EXTREME LEARNING MACHINE MODEL

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Abstract —As wind power output increases internationally, accurate wind power assesses are fundamental to maximizing the use of wind power and defend a safe and reliable electricity grid. We suggest a novel strategy that combines a gradient boosting algorithm with a limit learning machine optimized using particle swarm optimization (PSO-ELM), taking into account the inherent unpredictability and variability of wind power as well as the limitations of existing forecasting models. We first refine the ELM starting thresholds and input weights before building the PSO-ELM prediction model. A Gradient Boost technique is then used to generate a large number of PSO-ELM weak predictors. The input weights and thresholds of each weak predictor, which each includes a unique hidden layer node, are optimized using the PSO technique. The results from each weak predictor are combined and weighed to get the final forecast result using a robust wind power forecast model. We use measured data from Turkish wind turbines to verify the efficacy of our suggested strategy. We may evaluate the Gradient-PSO-ELM model's accuracy and dependability in predicting wind power output under real-world circumstances by contrasting the forecasts it produces with the actual measured data.. The findings demonstrate that the Gradient-PSO-ELM wind power prediction model has improved generalizability and accuracy.
Keywords -Gradient Boost Algorithm, Extreme Learning Machines, Optimization Algorithm, Wind power prediction

I. INTRODUCTION

The most advanced power production technology at the present in terms of business models for renewable energy is wind power [1]. The Asia-Pacific area now has the biggest wind power capacity in the world, at over 347 GW [2]. However, it is challenging to run the power system steadily and securely due to wind power's unpredictable nature. Therefore, accurate wind power projections are crucial to lowering grid transmission costs and increasing system effectiveness. In order to calculate maintenance plans, medium-term forecasts are time-bound in weeks or months, but long-term forecasts with yearly timeliness are utilized for wind and annual power planning. The accuracy requirements of these two forecasting techniques are not stable, and there is little research on the subject.

Short-term predictions are three-day wind power projections that are made in advance. The ultra-short-term forecast also mentions the approaching 10-4 hours of wind energy production [3]. These are essential topics for the wind energy sector because they can help with rotational reserve optimization and cost-effective load distribution. Recent years have seen a lot of interest in time series forecasting for wind power generating systems. [4] Long short-term memory (LSTM) neural networks, which process historical wind power data using k-means clustering to generate a big training set and then anticipate future wind power, were proposed by Sharma and Singh in Zhou et al. The wind force time series was divided into several subsequences's using wavelet techniques [5]. To anticipate wind energy, use [6]. Before employing LSTM to foretell and fuse subsequences, Lin and Luis [7] processed historical power series using the VMD technique. The wavelet decomposition method should be used to process the wind power time series, and the SVM should be used to estimate the wind energy on the last day of the week, according to Wang et al.'s proposal [8].

The most common technique for estimating short-term wind power is given in [9], and they are based on statistical and physical models. physical model-based methods for predicting wind speed integrate the real latitude, height, and terrain of wind farms [10]. In the end, an Ns Vs V fitting curve achieves this. This prognostic method is more complex to use, needs more processing, and is vulnerable to erroneous starting data [11]. In order to estimate wind power, a statistical model-based method creates a model from the training samples and then combines it with the training model. based on fresh input measurements [12]. Because it may be applied to issues with ambiguous internal processes and non-linear correlations are developed between inputs and outputs, this model offers a wider range of applications in the field of wind power forecasting [13]. Recently, several scientists have concentrated their efforts on creating statistical models for forecasting wind generation. Support vector machines (SVM) and neural networks are two methods that have demonstrated successful prediction [14]. Particle swarm optimization was represented by Ning and Liu [15] to enhance the SVM penalty coefficients and kernel parameters for Wind Energy. In order to provide predictions using SVM methods, we built an ideal SVM model utilizing historical data as training samples. Li and Mao [16] offer a technique for conducting wind power forecasting based on numerical weather forecasts by interfacing a BP neural network with two days' worth of historical climate and wind data. The technique forecasts the next four hours of ultra-short-term wind energy production. Wang et al.'s [17] method of empirical mode decomposition and feeding the generated signal components into a BP neural network was suggested for reconstructing the wind speed time series. It has newly examined in wind power forecasting and has advantages such as rapid training speed and strong generalization skills [18]. The erratic character of the ELM input parameters inevitably has an influence on forecast accuracy. Several studies change the input parameters using various developed techniques to improve ELM's capacity to predict outcomes. The initial input weights and thresholds of the ELM were optimized using the artificial fish shoal methodology by Zhai and Ma [20] and the salp swarm approach by Tan et al. [14]. Kings. [19] The ELM input weights

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were improved using a genetic algorithm. These optimization strategies have helped the models' prediction accuracy to some extent, but occasionally the models may encounter local maxima and have overfitting issues that limit their capacity to generalize [14]. Schapiro and Freund [21] created the collaborative learning strategy known as gradient boost. We attempt to obtain and modify the weights of all the training samples by repeatedly iteratively experienced the model. To enhance the overall model performance, weak predictors are generated at each iteration and then weighted to merge them into strong predictors.

Gradient algorithms may be employed with a variety of learning strategies. Gradient neural networks and BP neural networks were combined by Xiang et al. According to Xiang and Zhu [22] and Wen and Yu [23], the gradient boosting technique enhances the model's generalizability and avoids learning algorithms from unintentionally training in local optima. A gradient algorithm and a limit learning machine are combined to create the gradient boosted-PSO-ELM wind power prediction model. Particle swarm optimization is used to identified the ideal weights and thresholds for the model inputs. Then, as a weak predictor, the PSO-ELM model is employed. For each weak predictor, the number of hidden layer nodes is set using the validated interval. Then, we integrate them using the Gradient Boost approach to produce a reliable predictor of wind power, which will further improve the model's prediction precision and generalizability. Finally, real data is used to train the suggested model. The forecast results are contrasted with those of the existing model to see if the suggested wind power forecasting model has enhanced performance. A Gradient-PSO-ELM wind power prediction model is put out in Section II, along with information on the ELM, particle swarm optimization, and Gradient joint learning algorithms. The output forecast results of the Gradient-PSO-ELM wind power forecast model, which is trained in Section III, are compared with those of different contemporary mainstream models, using both smaller and larger samples as input.

II. Wind Forecasting Approach with AI

The major barriers to increasing wind power in the grid are uncertainty and fluctuation in wind speed. Therefore, anticipating wind energy generation accurately is challenging and can significantly affect how well the power system functions. Additionally, establishing unit commitments, scheduling maintenance, and maximizing profits for power dealers all depend on wind power estimates. Cost-effective operating and maintenance techniques for wind turbines are benefited by recent improvements in reliable and precise wind forecasting techniques. This paper thoroughly covers the state-of-the-art methodologies for wind power forecasting, covering physical, statistical (time series and artificial neural networks), and hybrid approaches, as well as the variables affecting precision and computation time in predictive modeling projects.

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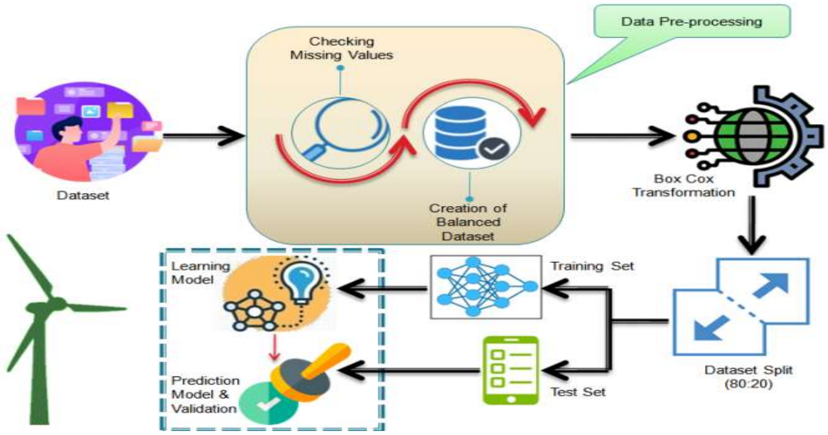

Fig. 1 Block Diagram of Wind Energy Forecasting with AI

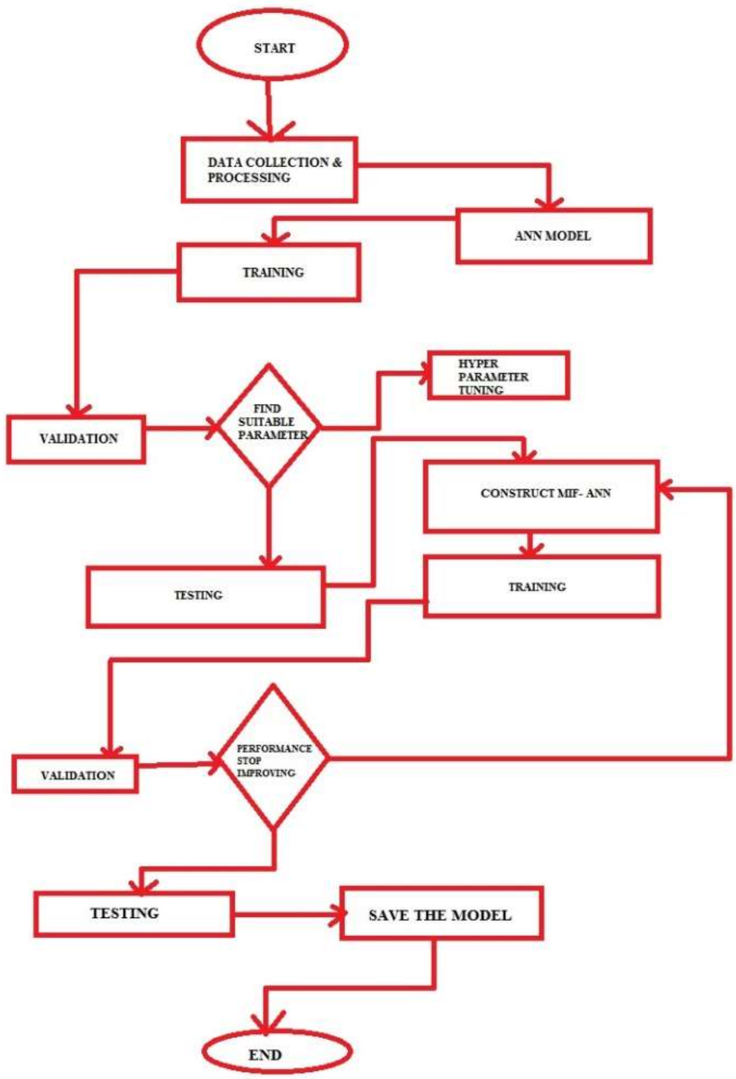

Fig. 2 Flowchart process using Artificial Intelligence

A dataset is a collection of various sorts of digitally stored data. Every machine learning algorithm needs enormous data. A dataset is a collection of unprocessed data gathered throughout the study process, typically in the form of numerical data. Numerous institutions, including government agencies, academic institutions, and research centres, make their data publicly accessible online for use by other researchers.

Unstructured data must be transformed through a process called data preparation in order for machine learning algorithms to utilize it. This is the first and most crucial stage in creating a machine learning model. Finding structured and clean data for machine learning applications is not always achievable.

An AI model or machine learning algorithm is taught how to make wise decisions using training data, which is labeled data. If you're trying to create a model of a self-driving car, for instance, your training data contains pictures and videos that have been labeled to denote vehicles, traffic signs, and people.

Therefore, a training set is a collection of pairs of intended output patterns and related input patterns. The network's weights should be adjusted the following time to reduce the inaccuracy. Once the inaccuracy is sufficiently modest, adjust the training.

After machine learning software has been taught on an initial training data set, it is evaluated using a secondary (or tertiary) data set known as a test set. Create a test training dataset with the information that will be used to objectively assess the final model.

Table 1.Forecasting Time Approach

Time Measurement	Application	Reference
Very distant in advance (more than one week)	Optimized wind farm design for a reorganized electrical market	30 days out 1 year out
Long-term (a week or more in advance)	Decisions about unit commitment-Maintenance planning to obtain the lowestpossible operational cost	72-hour notice
Medium-term (up to 24 hours in advance)	operational safety in the power market for the day ahead	six hours ahead A day ahead
short-term (between 30 minutes and 6 hours in advance)	Decisions about loadaugmentation or reduction in economic load dispatch planning - Controlling the power reserve	1 hour before 3 hours before hand 5 hours before hand
Very near (a few seconds to 30 minutes in the future)	Voltage regulation activities for grid stability	10 seconds-ahead

III. *Fundamental Theories*

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A. Extreme learning System s-based wind energy prediction technique

It highlights the drawbacks of traditional-SLFNs, including their slow learning rate and susceptibility towards local extremism.Faster training rates and more potent nonlinear fitting skills are produced by the absence of iterative adjustments needed during training.

The next part uses the example of wind forecasting with wind speed and direction to describe a limit learning machine-based wind forecasting approach. Given M training samples for wind farms (x_trainj, t_trainj, j 1, 2,... M). Out of these, t_trainj signifies the output data for the training samples corresponding to the wind data, and x_train j denotes the input data for the training samples comprising the observed wind speed and direction data. Take into account a network with ReLU activation function and L hidden layer neurons.

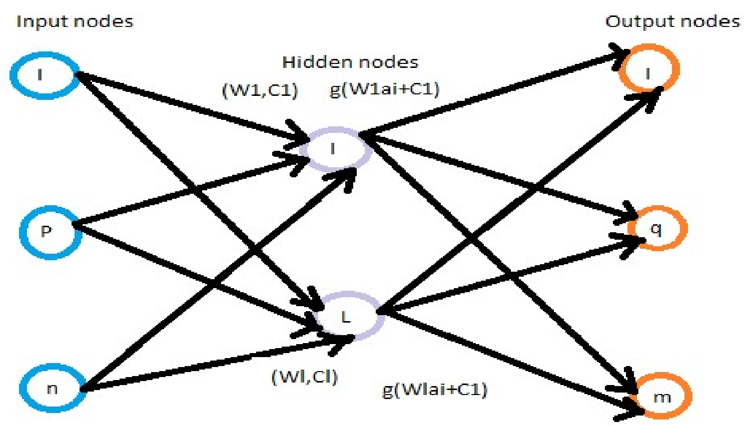

Fig. 3 Schematic Diagram of Extreme Learning machines

$$g(x) = x, x > 0 \qquad (1)$$

$$g(W1, x_{train}m + b1) \qquad (2)$$

Final square equation is

$$\boldsymbol{\beta = H + T}$$

By using the training sample data on H along with the knowledge of wind speed and direction, the short term forecast value for wind force may be derived using this method

B. Particle Swarm-Based Parameter Optimization Of Extreme Learning Technique

The essential idea behind particle swarm techniques is to initialize the finest clarification to an optimization problem as a particle, each of which has a starting velocity, location, and fitness value. Throughout each optimization iteration, each particle alters its location and speed in line with its unique flying experience and the aggregate flying experience of the group. A fitness value is further employed to evaluate the present location. The utmost individual optimum Pbest and

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global optimum Gbest are put together by computing the individual and global optimums [25]. These are a few of this strategy's traits.

$$V^{K+1} - V^{K} + V^{K+1}$$

Step 1: Set the target error, inertia factor, acceleration factors c1 and c2, and the maximum number of repetitions K to their initial values.

Step 2: Replace the position information with Gbest if the population's ideal location is smaller than it was prior to the update. Similar to this, replace the position information with Gbest if a specific particle's optimal position is smaller than Pbest before the update. When updating, replace location data with Pbest. Pbest is identical in every other way.

Step 3: The iteration ends when either K is reached. On the other hand, Gbest asserts that the particle information is equivalent to the ELM model's ideal pairing of i and bi.

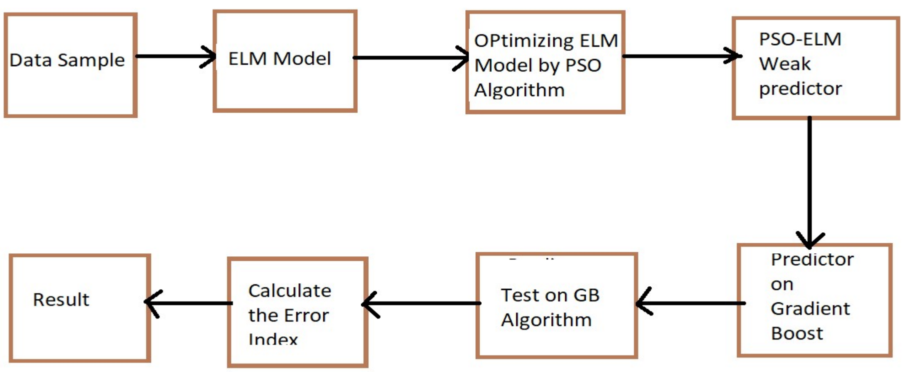

Fig. 4 Diagrammatic representation of PSO

C. Gradient Boost-PSO-ELM-Wind power prediction model

Gradient boosting is an set learning technique that include a number of weak learners, frequently decision trees, to raise prediction performance.

In order to reduce the total prediction error, the basic idea behind gradient boosting is to iteratively fit a new model to the residual error of an older model.

Let's have a look at a regression scenario where we wish to forecast wind energy generation. Finding a solid model F(x) that, given an input x and a training dataset that includes the label for the associated wind farm, y, can correctly predict y is the objective.

$$hi(x) = \frac{-\partial L(y, F(-x))}{\partial F - (X)}$$

The Excessive Learning Machine feed-forward neural network contains one hidden layer. In ELM, the output weights are analytically determined in a single step without additional iterations,

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whilst the hidden layer weights and biases are selected at random.

ELMs may be trained more quickly than traditional neural networks due to their unique features.

The representation of given input vector x

$$F(x) = \in \beta . g(Wi . x + bi)$$

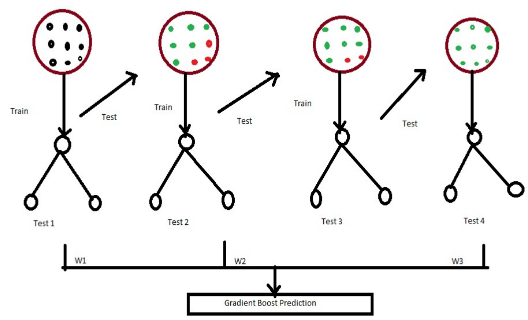

Fig. 5 Schematic representation of Gradient Boost

IV. Result Analysis

The work makes use of a public dataset on wind energy published by Kaggle as well as the Gradient Boost model.

This dataset comes from a Texas, Turkey, and SCADA system for wind turbines. For every 12 months in 2022, the SCADA system will collect data on absolute wind direction, mean wind speed (m/s) and active power (kW). There are 9555 valid data sets in all. Ten minutes pass between measurements.

Table 2. The sample data set of Wind Turbine

Sample	**Wind speed**	**Wind Pressure**	**Wind Gust**
1	18mph	26.23 in	29mph
2	14mph	26.37 in	26mph
3	20mph	26.77 in	28mph
4	7mph	26.91 in	25mph
5	13mph	26.81 in	27mph

D. Model Performance Evaluation

The predictability and performance of the ensemble learning models and neural networks used in this article are compared using relative mean biased error -RMBE,mean biased error -MBE,squared error -MSE, root mean squared error -RMSE, mean absolute percentage error-MAPE, mean absolute error -MAE and coefficient of determination -R2. The equation is:

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$$Ermbe = \frac{(Tpredict - Ttest)}{Tpredict}$$

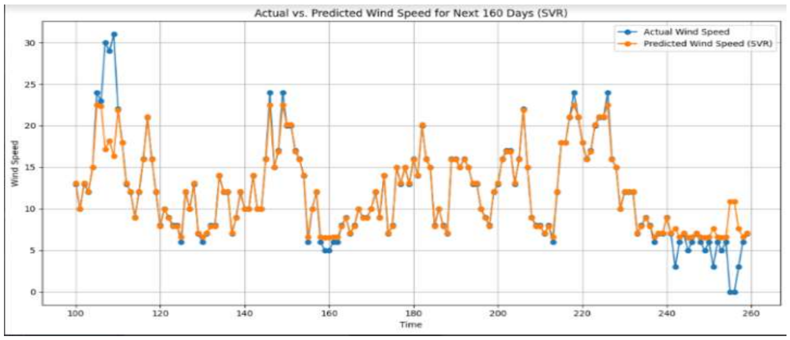

Fig. 6 Actual Vs Wind speed for Next 160 Days (SVR)

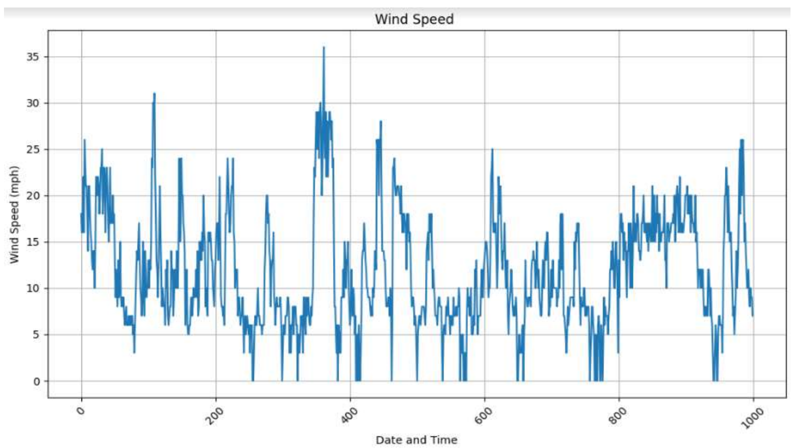

Fig. 7 Wind speed Vs Time with 1000 instances

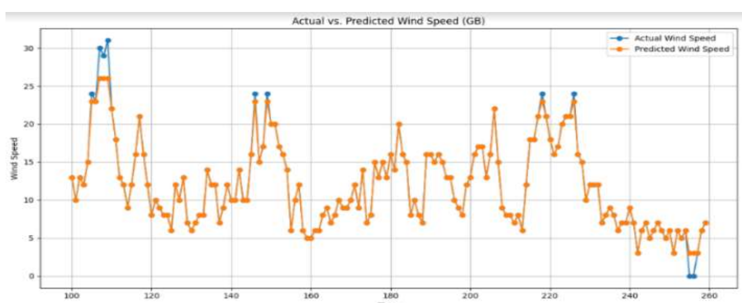

Fig. 8 Real Vs Forecast wind speed with Gradient Boost

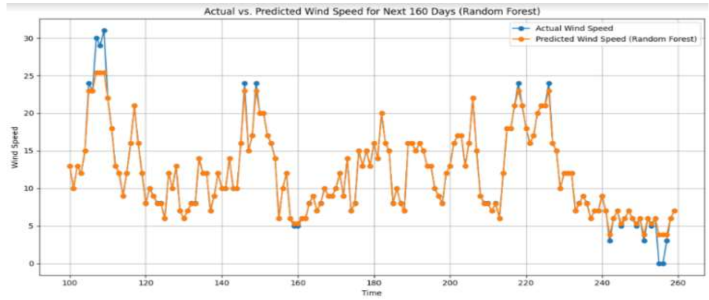

Fig. 9 Real Vs Forecasted wind speed with Random Forest

V. Conclusion

In a research that forecasts short-term wind power using a dataset containing 9600 data points, the gradient boost approach overcomes the Particle Swarm Optimization Extreme Learning Machine (PSO-ELM) model. By contrasting the PSO-ELM model's performance with that of other prediction models and techniques, it is shown how well it works with the gradient boosting approach. The data analysis findings show that the Gradient Boosting approach frequently outperforms other models and algorithms in terms of prediction accuracy. Lower MAE and RMSE values indicated a better match to the real wind power data.

The correlation coefficient (R) for the gradient boost method was also high, indicating a significant connection between the projected and actual values of wind speed. As a result, we demonstrate how the PSO-ELM model, coupled with a study of various models and slope lift calculations, is utilized to accurately predict the angle of the 9600 rise by adopting the gradient power of the transient wind power.

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