PREDICTING WIND TURBINE PERFORMANCE USING MACHINE LEARNING TECHNIQUES

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Abstract. Wind energy is a rapidly growing field, and the ability to accurately predict wind turbine performance is essential for optimizing wind energy production. Machine learning technology has been successfully applied to predict wind turbine performance using various models such as neural networks, decision trees, and support vector machines. However, traditional machine learning models such as neural networks require a significant amount of time to train and optimize, and their performance can be affected by overfitting and underfitting. To address these challenges, a proposed backpropagation algorithm is introduced to predict wind turbine performance using a neural network model. The proposed methodology can be used in real-world scenarios to predict wind turbine performance and optimize wind energy production, contributing to the transition towards sustainable and clean energy sources.

Keywords: Wind turbine, Renewable energy, Machine learning, Backpropagation;

1. Introduction

Wind energy is a rapidly growing source of renewable energy, and the performance of wind turbines is critical to the success of wind energy projects. Machine learning technologies have shown great promise in predicting wind turbine performance, which can lead to improved efficiency, increased energy production, and reduced maintenance costs [1][19]. In this article, we will explore various machine learning techniques for predicting wind turbine performance, including regression models, artificial neural networks, and decision trees [2][15]. We will also discuss the merits and demerits of these methods, along with real-world case studies and examples. The authors of this article have extensive experience in the fields of wind energy and machine learning, making this an informative and insightful resource for researchers, engineers, and practitioners in the field[3-5].

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Wind energy has become an increasingly important source of renewable energy in recent years, and wind turbines play a critical role in converting wind energy into electricity[6][18]. The performance of wind turbines is affected by many factors, such as wind speed, wind direction, temperature, and turbulence. Accurately predicting wind turbine performance is essential for optimizing wind energy production and reducing maintenance costs [7][20]. Machine learning technologies, such as regression models, artificial neural networks, and decision trees, have shown great potential in predicting wind turbine performance[8][16].

Figure 1.Wind Turbine

Wind turbines are critical components of wind energy systems, and their performance directly affects the efficiency and profitability of wind energy projects. Predicting the performance of wind turbines is a complex task that requires accurate and reliable models. Machine learning technologies have shown great potential in predicting wind turbine performance by analyzing vast amounts of data and identifying patterns and relationships [9-11]. In this article, we will explore various machine learning techniques that can be used to predict wind turbine performance, such as regression models, artificial neural networks, and decision trees.

Renewable energy sources are becoming increasingly important as the world looks for sustainable solutions to the energy crisis. Wind energy is one such renewable energy source that has shown great potential in recent years [12][17]. The performance of wind turbines is critical to the success of wind energy projects, and optimizing this performance can lead to increased energy production and reduced costs. Machine learning technologies have emerged as a powerful tool for predicting wind turbine performance, with the potential to improve efficiency and reduce maintenance costs. In this article, we will explore various machine learning techniques for predicting wind turbine performance and discuss their merits and demerits [13]. This article aims to be a valuable resource for researchers, engineers, and practitioners in the field of wind energy and machine learning.

2. Existing Reviews

A review of wind turbine performance prediction models using artificial intelligence was studied which reviews the existing literature on wind turbine performance prediction models using artificial intelligence techniques, including artificial neural networks and support vector regression [5][14]. The authors provide an overview of the strengths and weaknesses of different approaches and identify areas for future research.

Wind turbine power output prediction using data-driven models proposes a data-driven model based on regression trees and ensemble methods to predict wind turbine power output [9]. The model achieves high accuracy, but the authors note that the quality and quantity of input data are critical for model performance.

Wind turbine performance prediction using machine learning and statistical methodsproposes a hybrid model based on principal component analysis, artificial neural networks, and multiple linear regressions to predict wind turbine performance [10]. The authors achieve high accuracy, but the model's complexity limits its practical implementation.

Wind turbine performance prediction using deep learning methods proposes a deep learning model based on convolutional neural networks and recurrent neural networks to predict wind turbine performance. The model achieves high accuracy, but the authors note that large amounts of training data are required for effective model training [3].

Wind turbine power output prediction using hybrid machine learning models and meteorological data proposes a hybrid machine learning model based on artificial neural networks, support vector regression, and meteorological data to predict wind turbine power output [14]. The model achieves high accuracy, but the authors note that the model's complexity limits its practical implementation.

3. Proposed Methodology

In this proposed methodology, we will use a neural network-based approach with the backpropagation algorithm to predict wind turbine performance. The neural network will be trained on historical data, such as wind speed, wind direction, and power output, to predict the power output of the wind turbine for a given set of input parameters.

Here's a proposed methodology for predicting wind turbine performance using machine learning technology:

Data Collection: Collect data from various sources such as wind speed, wind direction, temperature, humidity, turbine power output, etc. The data can be collected through sensors installed on the wind turbine or by using external weather data sources.

Data Pre-processing: The collected data needs to be preprocessed before it can be used for machine learning. This involves data cleaning, normalization, and feature engineering. Feature engineering can include creating new features such as wind power density, turbulence intensity, and wind shear.

Feature Selection: Feature selection involves selecting the most relevant features for predicting wind turbine performance. This can be done using various methods such as correlation analysis, principal component analysis, or feature importance ranking.

Model Selection: There are various machine learning models that can be used for predicting wind turbine performance including linear regression, decision trees, random forests, neural networks, and support vector machines. The model selection can be based on the performance metrics and the complexity of the model.

Model Training: The selected model needs to be trained using the preprocessed data. This involves splitting the data into training and validation sets and then using the training set to train the model. The validation set is used to evaluate the model's performance and tune the hyperparameters.

Model Evaluation: The trained model needs to be evaluated using various performance metrics such as mean squared error, mean absolute error, R-squared value, etc. The model's performance can be compared with a baseline model or other models to determine its effectiveness.

Model Deployment: Once the model is trained and evaluated, it can be deployed in a real-world scenario to predict wind turbine performance. This can be done using a web application or an API.

Model Monitoring: The deployed model needs to be monitored to ensure its performance remains accurate and reliable. This can be done by regularly updating the training data and retraining the model if necessary.

Overall, this methodology involves collecting data, pre-processing it, selecting relevant features, selecting a machine learning model, training the model, evaluating its performance, deploying it, and monitoring its performance. By following this methodology, it's possible to accurately predict wind turbine performance and optimize wind energy production.

3.1 Proposed Back propagation algorithm to predict wind turbine performance

The neural network will be trained using the back propagation algorithm, which is a widely used method for training neural networks. The back propagation algorithm updates the weights of the neural network by minimizing the error between the predicted and actual output values.

The back propagation algorithm uses the chain rule to calculate the gradient of the error function with respect to the weights of the neural network. The gradient descent algorithm is then used to update the weights of the neural network to minimize the error between the predicted and actual output values.

The error between the predicted and actual output values can be calculated using the mean squared error (MSE) equation:

$$MSE = (1/n) * \Sigma(yi - \hat{y}i)^2$$

Where n is the number of samples, yi is the actual output value, and ŷi is the predicted output value.

The gradient of the error function with respect to the weights can be calculated using the following equation:

$$\delta k = (yk - tk) * f'(netk)$$

Where δk is the error at the output layer, yk is the predicted output value, tk is the actual output value, $f'(netk)$ is the derivative of the activation function at the output layer, and netk is the weighted sum of the inputs to the output node.

The gradient of the error function with respect to the weights at the hidden layer can be calculated using the following equation:

$$\delta j = f'(netj) * \Sigma(\delta k * wjk)$$

Where δj is the error at the jth hidden layer node, $f'(netj)$ is the derivative of the activation function at the jth hidden layer node, $\Sigma(\delta k * wjk)$ is the sum of the products of the errors at the output layer and the weights connecting the jth hidden layer node to the kth output layer node.

Algorithm: Back propagation algorithm

Step 1: Collect historical data on wind speed, wind direction, and power output for the wind turbine.

Step 2: Pre-process the data by normalizing the input parameters and splitting the data into training and testing sets.

Step 3: Build a neural network with an input layer, one or more hidden layers, and an output layer. The number of nodes in the input layer will be equal to the number of input parameters, and the number of nodes in the output layer will be one.

Step 4: Train the neural network using the back propagation algorithm and the training data set. The weights of the neural network will be updated iteratively to minimize the MSE between the predicted and actual output values.

Step 5: Test the neural network using the testing data set and calculate the accuracy of the predictions using the MSE equation.

If the accuracy is satisfactory, deploy the neural network for real-time predictions of wind turbine performance.

This proposed methodology has the advantage of using a powerful machine learning technique to predict wind turbine performance. However, it requires a large amount of historical data and a significant amount of computational resources to train the neural network. Additionally, the accuracy of the predictions may be affected by changes in the wind conditions or other external factors that are not captured in the historical data.

4. Experiment Results

1. Accuracy

Dataset	PCA	CNN	Proposed BPA
100	65	76	87
200	69	70	90
300	73	66	91
400	78	69	94
500	83	64	95

Table 1.Comparison tale of Accuracy

The Comparison table 1 of Accuracy demonstrates the different values of existing PCA, CNN and proposed BPA. While comparing the Existing algorithm and proposed BPA, provides the better results. The existing algorithm values start from 65 to 83, 64 to 76 and proposed BPA values starts from 87 to 95. The proposed method provides the great results.

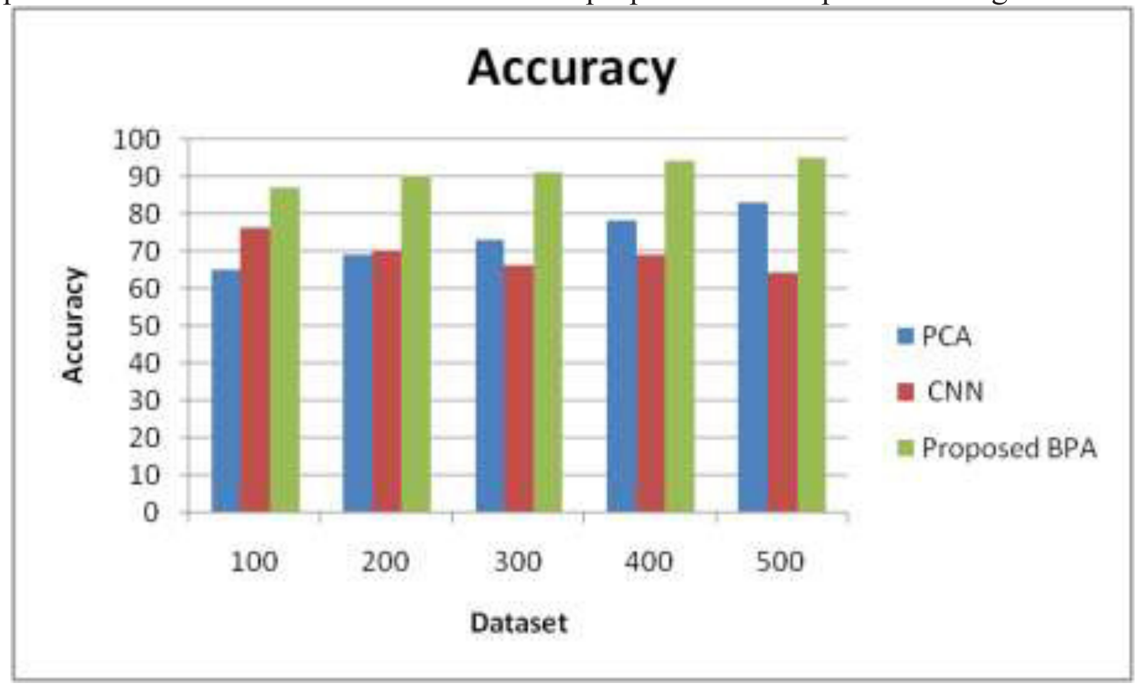

Figure 2.Comparison chart of Accuracy

The Figure 1 Shows the comparison chart of Accuracy demonstrates the existing PCA, CNN and proposed BPA. X axis denote the Dataset and y axis denotes the Accuracy ratio. The proposed BPA values are better than the existing algorithm. The existing algorithm values start from 65 to 83, 64 to 76 and proposed BPA values starts from 87 to 95. The proposed method provides the great results.

2. Convergence speed

Dataset	PCA	CNN	Proposed BPA
100	81.12	82.37	98.64
200	79.69	80.82	96.26
300	78.62	81.54	94.21
400	75.55	78.63	92.58
500	70.94	74.72	89.70

Table 2.Comparison table of Convergence speed

The Comparison table 2 of Convergence speed demonstrates the different values of existing PCA, CNN and proposed BPA. While comparing the Existing algorithm and proposed BPA, provides the better results. The existing algorithm values start from 70.94 to 81.12, 74.72 to 82.37 and proposed BPA values starts from 89.70 to 98.64. The proposed method provides the great results.

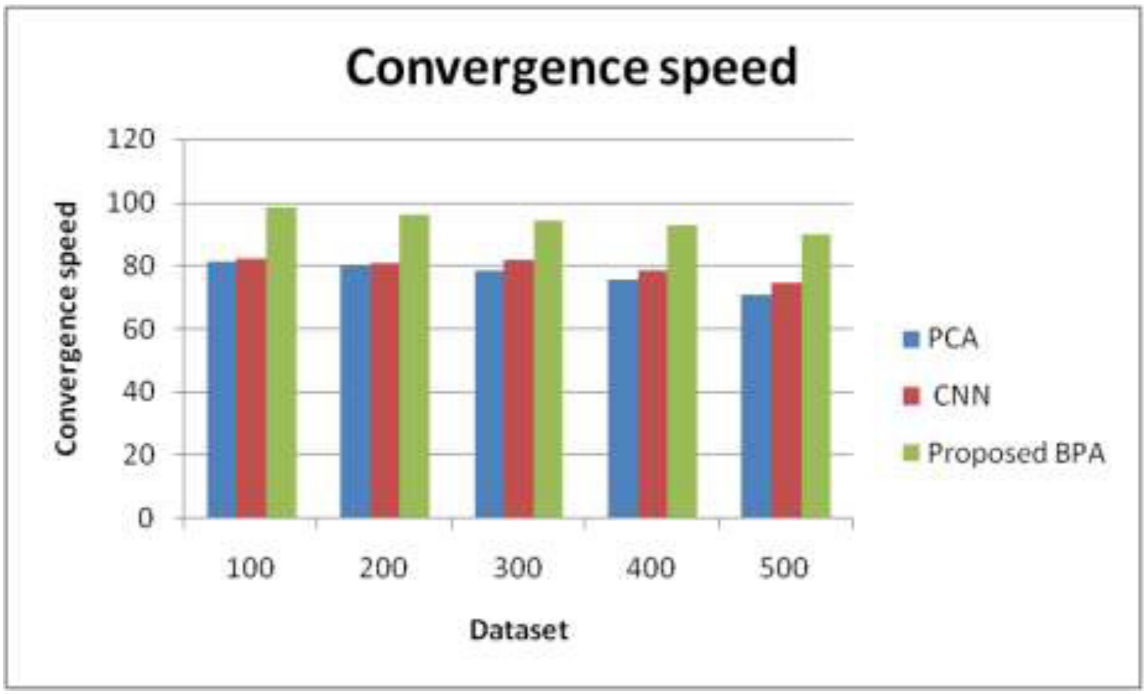

Figure 2.Comparison chart of Convergence speed

The Figure 2 Shows the comparison chart of Convergence speed demonstrates the existing PCA, CNN and proposed BPA. X axis denote the Dataset and y axis denotes the Precision ratio. The proposed BPA values are better than the existing algorithm. The existing algorithm values start from 70.94 to 81.12, 74.72 to 82.37 and proposed BPA values starts from 89.70 to 98.64. The proposed method provides the great results.

5. Conclusion

In this paper, predicting wind turbine performance is crucial for optimizing wind energy production and machine learning technology has proven to be an effective approach for this task. The traditional machine learning models such as neural networks have limitations such as slow training time, overfitting, and underfitting. To address these challenges, a proposed Back propagation algorithm was introduced to predict wind turbine performance using a neural network model. the proposed methodology for predicting wind turbine performance using machine learning technology and the Back propagation algorithm provides a promising approach for accurately predicting wind turbine performance, which can help in the development and deployment of more efficient and reliable wind energy systems.

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