Literature Survey

PREDICTING THE ENERGY OUTPUT OF WIND TURBINE BASED ON WEATHER CONDITION

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1. Improvement of wind power prediction from meteorological characterization with machine learning models - Renewable Energy, Volume 183, 2022

Link : https://www.sciencedirect.com/science/article/pii/S0960148121014919

Abstract

This work uses a decision tree machine learning model to assess the effectiveness of hub-height wind speed, rotor-equivalent wind speed, and lapse rate as variables in power prediction. Atmospheric data is used to train regression trees and correlate the power outputs to wind profiles and meteorological characteristics to be able to predict power responses according to physical patterns. The decision tree model was trained for four vertical wind profile classifications to showcase the need for multiple calculations of wind speed at various levels of the rotor layer. Results indicate that when compared to traditional power curve methods, the decision tree combining rotor-equivalent wind speed and lapse rate improves prediction accuracy by 22% for the given data-set, while also proving to be the most effective method in power prediction for all classified vertical wind profile types. Models incorporating lapse rate into predictions performed better than those without it, showing the importance of considering atmospheric criteria in wind power prediction analyses.

Methods

Decision tree

Highlights

- Regression decision tree models used to improve wind power prediction.
- Correlate the power outputs to wind pro_les and meteorological charac-teristics.
- Machine learning models outperform the traditional turbine power curve approach.
- Decision tree with rotor equivalent wind speed and lapse rate improves predictions.

Drawbacks

- Ensure we have instrumentation installed at the new wind project site with the ability to gather atmospheric data and wind data at various heights for the length of the turbine.
- Develop the training model further with more points and turbine powers so that we can generalize the model to alternative locations.
- Drawbacks of predictor variable REWS
- There have been scenarios where the REWS method provides marginal to no improvement based on atmospheric conditions, turbine design, site location, etc.
- The usefulness of REWS depends on turbine dimension and wind shear regime, where if the ratio of turbine rotor diameter to hub-height is below 1.8 and the wind shear is constantly between −0.5 and 0.4, the REWS method may not be necessary
- This method does demonstrate the susceptibility of the turbine power curve by atmospheric conditions and the usefulness of measuring wind speed across the rotor layer as opposed to at a single instance, such as HHWS.
- Power prediction methods, such as the TPC and REWS, only utilize wind speed as a factor for prediction, without considering the surrounding atmospheric criteria. Studies have shown that variations in atmospheric conditions, such as temperature, atmospheric stability, wind shear, wind direction, and turbulence intensity can be factors in over or underestimation of turbine power output

2. Deep Learning-Based Prediction of Wind Power for Multi-turbines in a Wind Farm - Frontiers in Energy Research, 2021

Link: https://www.frontiersin.org/articles/10.3389/fenrg.2021.723775/full

Abstract

The prediction of wind power plays an indispensable role in maintaining the stability of the entire power grid. In this paper, a deep learning approach is proposed for the power prediction of multiple wind turbines. Starting from the time series of wind power, it is a two-stage modeling strategy, in which a deep neural network combines spatiotemporal correlation to simultaneously predict the power of multiple wind turbines. Specifically, the network is a joint model composed of Long Short-Term Memory Network (LSTM) and Convolutional Neural Network (CNN). Herein, the LSTM captures the temporal dependence of the historical power sequence, while the CNN extracts the spatial features among the data, thereby achieving the power prediction for multiple wind turbines. The proposed approach is validated by using the wind power data from an offshore wind farm in China, and the results in comparison with other approaches shows the high prediction preciseness achieved by the proposed approach.

Methods

Long Short-Term Memory Network (LSTM) - Convolutional Neural Network (CNN) joint model, Support Vector Machine (SVM), gradient-based training

Highlights

- The wind power of multiple wind turbines is predicted in this study, unlike predicting the total power of the wind farm or a single wind turbine in most studies.
- This study makes use of temporal correlation and spatial correlation (i.e., Spatiotemporal correlation) in a wind farm which could be helpful for multi-location wind power prediction using the joint LSTM-CNN model.
- Specifically, LSTM captures the temporal dependence between the wind power data of each single wind turbine, and CNN extracts the spatial correlation between the wind power data of multiple wind turbines.
- The corresponding output values of each turbine are put into a two-dimensional matrix according to the location of the wind turbines.

Drawbacks

- In the model, the length of the sliding window to obtain the input sequence (i.e., α) directly affects the effect of LSTM on the temporal correlation extraction of historical sequence data. So, a large number of experimental tests is needed to determine the value of α.
- The number of LSTM models is set as the same as the quantity of the selected wind turbines. This causes slowness in computation when scaling.
- CNN and SVM perform poorly. The reason is that, when facing the problem of power prediction of multiple wind turbines, the CNN can effectively capture the spatial features of the data, but it does not take the temporal correlation into account. Similarly, the LSTM has excellent performance when facing timing prediction problems, but ignores the spatial features. Since the SVM only uses the global spatial and temporal information in the data, its prediction preciseness is noticeably lower than the three counterparts.

3. Forecasting of Wind Turbine Output Power Using Machine learning - 10th International Conference on Advanced Computer Information Technologies, Deggendorf, Germany, 2020

Link:

https://www.researchgate.net/publication/341219336_Forecasting_of_Wind_Turbine_Output_Power_Using_Machine_learning

Abstract

Most of the countries around the world are facing huge environmental impact, and the most promising solution to mitigate these is the use of renewable energy, especially wind power. Though, the use of offshore wind energy is rapidly increasing to meet the elevating electricity demand.The researchers and policymakers have become aware of the importance of providing near accurate predictions of output power. Wind energy is tied to variabilities of weather patterns, especially wind speed, which are irregular in climates with erratic weather conditions. In this paper, the output power of the wind turbines is predicted using the random forest regressor algorithm.The SCADA data is collected for two years from a wind farm located in France. The wind direction, wind speed and outdoor temperature are used as input parameters to predict output power. The model is tested for two different capacity factors. The estimated mean absolute errors for the proposed model in this study were 3.6% and 7.3% for 0.4 and 0.2 capacity factors, respectively. The proposed model in this study offers an efficient method to predict the output power of a wind turbine with preferably low error.

Methods

Random Forest Regressor Algorithm

Highlights

- The elimination of variability of the wind is not possible, but by using machine learning, the outputs are typically a model that can address future issues of the same kind.
- This model has a low over-fitting tendency, simple and is fast to train.
- The model uses a design parameter called capacity factor which is used to evaluate the performance of a wind farm using real and rated values.
- The Mean Squared Error (MSE) and Mean Absolute Error (MAE) are calculated to evaluate the performance of the model.

Drawbacks

- The problem of missing data could have been solved using different imputation methods.
- The intermittency of wind speed introduces challenges in prediction, so this model did not pay too much attention to the variance of wind power supply due to it, when wind penetration went relatively low.
- The estimated mean absolute error for the proposed model for the capacity factor is nominal but could be minimized.

4. Wind power forecasting based on daily wind speed data using machine learning algorithms - Energy Conversion and Management, Volume 198, 2019

Link: https://www.sciencedirect.com/science/article/pii/S0196890419308052

Abstract

Wind energy is a significant and eligible source that has the potential for producing energy in a continuous and sustainable manner among renewable energy sources. However, wind energy has several challenges, such as initial investment costs, the stationary property of wind plants, and the difficulty in finding wind-efficient energy areas. In this study, long-term wind power forecasting was performed based on daily wind speed data using five machine learning algorithms. We proposed a method based on machine learning algorithms to forecast wind power values efficiently. We conducted several case studies to reveal performances of machine learning algorithms. The results showed that machine learning algorithms could be used for forecasting long-term wind power values with respect to historical wind speed data. Furthermore, the results showed that machine learning-based models could be applied to a location different from model-trained locations. This study demonstrated that machine learning algorithms could be successfully used before the establishment of wind plants in an unknown geographical location whether it is logical by using the model of a base location.

Methods

Random Forest, support vector machines,Regression model, k means clustering and deep learning

Highlights

- In this paper Long-term wind power forecasting is being performed using different machine learning algorithms.
- When Wind power was being forecast for a different region, The results seem to show that using the training set and using the generated model with the training data could be used for other locations that have different wind characteristics.
- When wind power forecasting is based on only daily mean wind speed,it seems that machine learning algorithms could build reliable wind power models using only wind speed values even if there are no standard deviations to forecast long-term wind power values of a location.

Drawbacks

- However, using wind energy is challenging due to its initial investment costs, the requirement of careful analyses before establishing a wind plant, the distance of wind-efficient areas to the national grids, and its environmentally disruptive effects.

5. An Aggregative Machine Learning Approach for Output Power Prediction of Wind Turbines - IEEE TPEC, 2018

Link: https://ieeexplore.ieee.org/abstract/document/8312085

Abstract

Accurately forecasting power output of renewable sources is a necessity in operation of today's grid in order to achieve optimal energy utilization and carbon-free ecosystem. This study devises a stable, effective and accurate model for day ahead prediction of wind turbine power output through use of an aggregative approach. The method involves two types of Artificial Neural Network (Radial Basis and Conventional Feedforward Networks), Adaptive Neuro-Fuzzy Inference System (ANFIS) and Support Vector Machine (SVM) techniques. It is targeted at comparing the prediction models for their individual performances and finally coming upon an aggregative approach which outperforms the individual models through a strategic combination of them. Three techniques of combining (Simple Averaging, Regression and Outperformance) were tested. Though the individual models showed satisfactory performance by themselves, the combination techniques were able to outperform the individual models. Regression technique of combining was seen to be the most effective of all. The predicted output power through this technique was seen to greatly fit with the measured data with an NMSE of 1.03% for the test year. The combination techniques have also demonstrated more stable performance than the individual models while tested with the extreme cases of windy and less windy weeks.

Methods

Adaptive Neuro-Fuzzy Inference System (ANFIS), Radial Basis and Conventional Feedforward Networks (RBNN), Prediction, Back Propagation Neural Network(BPNN) and Support Vector Machine (SVM), Aggregating Ensemble Of Approaches

Highlights

- In this they have used soft computing approaches in predicting the power output from a wind turbine by using a strategic approach of combining the forecasts from individual models.

- The aggregative approach seems to exhibit better accuracy and also seems to show stable performances under extreme cases of windy and less windy periods.
- Though the individual models performed with a satisfactory forecast performance, the addition of the combining step seems to resolve the difficulty to identify a single best forecast model
- The aggregative approach seems to have alleviated issues of state-dependent performance of individual models and their systematic errors.

Drawbacks

- Lower performance of radial basis network when the 'power output of the previous hour' is added to the input matrix suggesting lower effectiveness of the approach in time series forecasting. Hence the paper has avoided the 'power output of the previous hour' for the radial basis NN
- SVM regression is seen to deteriorate in terms of prediction accuracy when more input parameters than wind speed are considered.Hence the paper only uses wind speed for the SVM model.

6. Machine learning ensembles for wind power prediction - Renewable Energy, Volume 89, 2015

Link: https://www.sciencedirect.com/science/article/pii/S0960148115304894

Abstract

We first analyze homogeneous ensemble regressors that make use of a single base algorithm and compare decision trees to k-nearest neighbors and support vector regression. As the next step, we construct heterogeneous ensembles that make use of multiple base algorithms and benefit from a gain of diversity among the weak predictors. In the experimental evaluation, we show that a combination of decision trees and support vector regression outperforms state-of-the-art predictors (improvements of up to 37% compared to support vector regression) as well as homogeneous ensembles while requiring a shorter runtime (speed-ups from 1.60× to 8.78×). Furthermore, we show the heterogeneous ensemble prediction can be improved when using high-dimensional patterns by increasing the number of past steps considered and hereby the spatio-temporal information available by the measurements of the nearby turbines. The experiments are based on a large wind time series data set from simulations and real measurements.

Methods

Decision tree, Regression, K-nearest neighbors, Support vector machines, Ensemble machine learning

Highlights

- Use of heterogeneous machine learning ensembles for wind power prediction.
- A combination of decision trees and SVR outperforms state-of-the-art predictors.
- The prediction is improved by using high-dimensional spatio-temporal patterns.

Drawbacks

- Ensemble methods require less tuning and expert domain knowledge.
- Investing more computation time.
- There exist more sophisticated ensemble approaches like AdaBoost or Stacked Generalization, but, as we want to give a proof of concept with the possibility of heterogeneity, we limit ourselves here to bagging.
- Only if the data is diverse in nature the ensemble technique would be advantageous.
- We decided to implement a relatively simple bagging approach with weighting, which has some advantages. While the implementation is straight-forward and offers a moderate computational cost, we consider the approach sufficient for a proof of concept, which is also shown in the experimental evaluation.
- Because there are no computational dependencies between the ensemble members, the problem is embarrassingly parallel. To give an easy and fair comparison, in our experiments we only employ only one CPU core for the runtime measurements.
- With increasing number of features, the data become more and more challenging for the employed regression algorithms: First, the computational time is often dependent on the dimensionality of the data. Second, the prediction accuracy can get worse.

7. Using machine learning to predict wind turbine power output - IOPScience, 2013

Link: https://iopscience.iop.org/article/10.1088/1748-9326/8/2/024009/meta

Abstract

Wind turbine power output is known to be a strong function of wind speed, but is also affected by turbulence and shear. In this work, new aerostructural simulations of a generic 1.5 MW turbine are used to rank atmospheric influences on power output. Most significant is the hub height wind speed, followed by hub height turbulence intensity and then wind speed shear across the rotor disk. For a randomly selected atmospheric condition, the accuracy of the

regression tree power predictions is three times higher than that from the traditional power curve methodology. The regression tree method can also be applied to turbine test data and used to predict turbine performance at a new site. No new data are required in comparison to the data that are usually collected for a wind resource assessment.

Methods

Regression Tree, Machine Learning

Highlights

Such an approach could significantly reduce bias in power predictions that arise because of the different turbulence and shear at the new site, compared to the test site.

Drawbacks

- Although this method has been demonstrated using simulated inflow and turbine response data, the method could be used to generate turbine performance models from turbine power testing data.
- Changes of wind direction with height, non-uniform shear, and the state of the turbine were not considered here but may impact turbine deployment sites, and their effect should be investigated using field data.