PREDICTING THE ENERGY OUTPUT OF WIND TURBINE BASED ON WEATHER CONDITION

INTRODUCTION:

Wind power is **a clean and renewable energy source**. Not only is wind an abundant and inexhaustible resource, but it also provides electricity without burning any fuel or polluting the air. Wind continues to be the largest source of renewable power in the United States, which helps reduce our reliance on fossil fuels. But, Wind power generation differs from conventional thermal generation due to the stochastic nature of wind. Thus wind power forecasting plays a key role in dealing with the challenges of balancing supply and demand in any electricity system, given the uncertainty associated with the wind farm power output. Accurate wind power forecasting reduces the need for additional balancing energy and reserve power to integrate wind power. For a wind farm that converts wind energy into electricity power, a real-time prediction system of the output power is significant. Before developing this real-time prediction system, we need to know the currently existing solutions, advantages and drawbacks of each solution. To know these, a literature survey is made.

LITERATURE SURVEY:

[1] FORECASTING OF WIND TURBINE OUTPUT POWER USING MACHINE LEARNING

In this paper, the output power of the wind turbines was predicted using the random forest regressor algorithm. The SCADA data was collected for two years from a wind farm located in France. The model was trained using the data from 2017. The wind direction, wind speed and outdoor temperature were used as input parameters to predict output power. Then, the model was 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 and 0.2 capacity factors, respectively.

Objective:

The main objective of this paper was to offer an efficient method to predict the output power of wind turbine with preferably low error.

Advantages:

- Real-Time data collected and used as a dataset.

- High accuracy.

Disadvantages:

Climate varies from year to year due to external factors like global warming, seasonal changes. Day to day weather and location are not taken as parameter for prediction.

[2] GREY PREDICTORS FOR HOURLY WIND SPEED AND POWER FORECASTING

This paper uses grey predictor models such as Traditional Grey Rolling Model GM(1,1), Improved Shifted Grey Model, Averaged Grey Model for fore-casting for 1 hour ahead average hourly wind speed. Forecasting using the traditional GM(1,1) model revealed an improvement over the persistent model. But, this model is characterized by the occurrence of some overshoots in the predicted time series. Such overshoots can result in predicting wind speed time series worse than that of the persistent model. To overcome the problem of overshoots occurrence, three modified versions of the GM(1,1) model were introduced. The adaptive alpha-based grey model and the improved Grey model achieved higher levels of improvement over the persistent model than the traditional GM(1,1) model. However, those models lack the good tracking characteristic for the actual wind speed time series of the traditional model. The averaged Grey model attained the highest level of wind speed forecasting and wind power prediction accuracy, compared with the persistent model and the other presented Grey models, while demonstrating a very good tracking feature and a reduction in the overshoot occurrence.

Advantages:

The averaged Grey model attained the highest level of wind speed forecasting and wind power prediction accuracy while demonstrating a very good tracking feature and a reduction in the overshoot occurrence.

Disadvantages:

Does not include problems due to line breakdown, power flow and power quality issues as parameters and generation-load prediction matching is not shown.

[3] USING MACHINE LEARNING TO PREDICT WIND TURBINE POWER OUTPUT

In this paper, new aero structural simulations of a generic 1.5 MW turbine were used to rank atmospheric influences on power output. Simulation data parameters were the hub height wind speed followed by hub height turbulence intensity and then wind speed shear across the rotor disk. These simulation data were used to train regression trees which was implemented in MATLAB and it predicted the turbine response for any combination of wind speed, turbulence intensity, and wind shear that might be expected at a turbine site. For a randomly selected atmospheric condition, the accuracy of the regression tree power predictions was 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. The predictions in this study used an ensemble of 100 regression trees. No new data are required in comparison to the data that are usually collected for a wind resource assessment.

Advantages:

Significantly reduce bias in power predictions that arise because of the different turbulence and shear at the new site, compared to the test site.

Disadvantages:

Implementing the method requires turbine manufacturers to create a turbine regression tree model from test site data.

[4] PREDICTING THE ENERGY OUTPUT OF WIND FARMS BASED ON WEATHER DATA: IMPORTANT VARIABLES AND THEIR CORRELATION

This paper proposed energy prediction in a computer science perspective based on weather data and analysed the important parameters as well as their correlation on the energy output. To deal with the interaction of the different parameters, symbolic regression was used based on the genetic programming tool DataModeler. Real-time prediction of energy production of the wind farm *Woolnorth* in Tasmania, Australia was made based on weather and energy and for the creation of models and prediction, authors associated the wind farm with the Australian weather station *ID091245*, located at Cape Grim, Tasmania as its data is available for free for a running observation time window of 72 h. Thus, the prediction gave an accuracy of up to 80% *R* on the training range and up to 85.5% on the unseen test data.

Advantages:

Real-time data has been used which gives more accurate prediction.

Disadvantages:

The models proposed produce less accuracy than some machine learning like random forest algorithm

[5] SHORT-TERM WIND POWER PREDICTION BASED ON EXTREME LEARNING MACHINE WITH ERROR CORRECTION

In this paper, a combined approach based on Extreme Learning Machine (ELM) and an error correction model was proposed to predict wind power in the short-term time scale.

Firstly, an ELM was utilized to forecast the short-term wind power. Then the ultra-short-term wind power forecasting was acquired based on processing the short-term forecasting error by persistence method. For short-term forecasting, the ELM did not perform well. The overall NRMSE (Normalized Root Mean Square Error) of forecasting results for 66 days is 21.09 %. For the ultra-short-term forecasting after error correction, most of forecasting errors lie in the interval of [−10 MW, 10 MW]. The error distribution was concentrated and almost unbiased. The overall NRMSE is 5.76 %.

The proposed model was then verified using the measured data in a wind farm located in the northern China for a period of about 15 months from 24 February 2014 to 31 May 2015. The 41072 non-consecutive data points before 02 March 2015 are used for training the ELM models whereas the consecutive time series of 66 days from 02 March 2015 to 31 May 2015 is used to verify the model's performances. The total installed capacity of the wind farm was 50 MW. The measured data are used for both training the ELM model and verifying the model. The time scale of collecting data is 15 min. The scatter of wind power versus wind speed of the wind farm was plotted in.

Advantages:

It is noted that the computation time was approximately proportional to the hidden nodes number. When the hidden nodes number was 3, the computation time is 1.5377 s, including the time for training model with 41072 data points and forecasting 6336 data points. That indicates a high computational efficiency for wind power forecasting, which can satisfy the practical needs.

Disadvantages:

The amount of data used to train the model was just a year's data and as climate varies from year to year, one year's data is not enough to get higher accuracy when this model is implementation and used for a number of years. Extreme Learning Machine (ELM) is not the best algorithm for using in large windfarm datasets though error correction models are used with ELM.

[6] FORECASTING WIND POWER GENERATION USING ARTIFICIAL NEURAL NETWORK:"PAWAN DANAWI"- A CASE STUDY FROM SRI LANKA

This paper develops artificial neural network (ANN) models to forecast wind power generation in "Pawan Danawi", a functioning wind farm in Sri Lanka. Monthly average power generation data (MW) from January 2015 to December 2019 (5 years, 60 data sets) were obtained from the wind farm authorities. Wind speed, wind direction, and ambient temperature of the area were used as the independent variable matrices of the developed ANN models, while the generated wind power was used as the dependent variable. ANN models were used because ANN reported suitable to forecast the wing power generation accurately outperforming other techniques such as support vector machine (SVM), neural network (NN), random forest (RF), and k-nearest neighbor (k-NN) and fuzzy logic techniques.

Then the models were tested with three training algorithms, namely, Levenberg-Marquardt (LM), Scaled Conjugate Gradient (SCG), and Bayesian Regularization (BR) training algorithms. In addition, the model was calibrated for five validation percentages (5% to 25% in 5% intervals) under each algorithm to identify the best training algorithm with the most suitable training and validation percentages. Mean squared error (MSE), coefficient of correlation (R), root mean squared error ratio (RSR), Nash number, and BIAS were used to evaluate the performance of the developed ANN models. Results revealed that all three training algorithms produce acceptable predictions for the power generation in the Pawan Danawi wind farm with $R>0.91$, MSE<0.22, and BIAS<1. LM and SCG algorithms have reached the optimum result in less time. Among them, the LM training algorithm at 70% of training and 5% of validation percentages produces the best forecasting results and also gives the lowest MSE at epoch 2.

Advantages:

- When considering the computational efficiency of the three algorithms, LM and SCG produce minimum MSE at relatively lesser epochs.
- Can work efficiently for similar environmental and climatic conditions (off shore) to identify the wind power potential of the area.
- According to the results, the error is negligible in most of the months and numerically less than 0.9 MW demonstrating the accuracy of the LM-based ANN model. As per the calculations, it exhibits an RSR of 0.524 and a Nash number of −0.723.

Disadvantages:

- Unlike the LM and SCG training algorithms, BR training algorithms show the best performance at 15% of validation percentage at epoch 922.
- However, the minimum MSE values of the BR algorithm are smaller than those of the other two algorithms only at a much higher epoch.
- In addition, there is a strong correlation between input parameters and power output at all five validation percentages in the BR algorithm. This can advantageous in some cases but in some might not.
- The model works best for off shore wind farms but it may not work best for onshore wind farms as the data values, climate obtained varies with on shore values.

[7] DEEP LEARNING – BASED PREDICTION OF WIND POWER FOR MULT-TURBINES IN A WIND FARM

In this paper, a deep learning approach was proposed for the power prediction of multiple wind turbines as the difficulty of conducting the temporal-spatial sequence prediction, such as “wind turbine power prediction” was to simultaneously extract the time dependence and spatial features hidden in the data. Therefore starting from the time series, after data preprocessing, the LSTM-CNN joint prediction model was proposed, which exploits a two-stage modeling strategy. Then, a deep neural network combines spatio temporal correlation to simultaneously predict the power of multiple wind turbines. Specifically, the network was a joint model composed of Long Short-Term Memory Network (LSTM) and Convolutional Neural Network (CNN). Herein, the LSTM captured the temporal dependence of the historical power sequence, while the CNN extracted the spatial features among the data, thereby achieving the power prediction for multiple wind turbines at different locations. Rectified Linear Unit (ReLU) is selected as the activation function of the convolutional layer which can improve the performance of CNN. The proposed approach was 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.

Advantages:

- The comparison results showed that the proposed joint method of CNN-LSTM has more excellent performance on predicting the wind power of multiple wind turbines within a wind farm with the regular layout than the existing prediction methods, such as LSTM, CNN, and SVM.
- On this basis, it can be used to perform accurate power scheduling.
- As CNN can extract the spatial features among the data, the power prediction for multiple wind turbines at different locations can be achieved.

Disadvantages:

- This paper just uses SCADA data of 34 wind turbines at Guishan offshore wind farm in China which was collected within 1 week of November 2019. This data is not enough to predict energy output from wind turbines for a longer run.

[8] A PREDICTION MODEL FOR WIND FARM POWER GENERATION BASED ON FUZZY MODELING

In this paper, based on the historical data of a wind farm, the application of a fuzzy model for wind power prediction is carried out. It has been found that wind power can be successfully predicted using a fuzzy model.

Advantages:

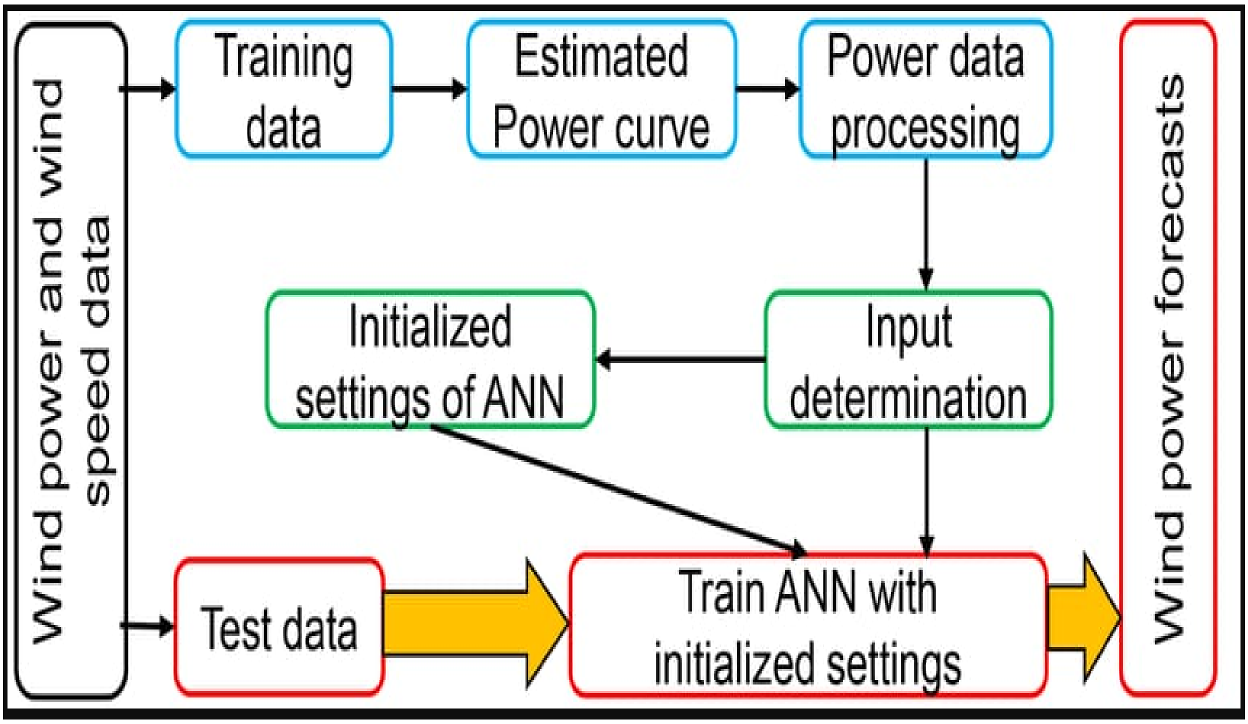
- The prediction by use of the fuzzy model has the smallest error when the period is 0.5 hour.

- The model not only maintains good prediction accuracy but also provides an interpretable model structure which contains several rules, from which it may also reveal a useful qualitative description of the prediction system.

Disadvantages:

- This model must be improved by considering effects of other factors like wind direction, humidity, etc as parameters.

Process flow : flow chart



CONCLUSION:

By referring above research papers and several existing apps, different algorithms for wind prediction are known and missing parameters found are:

1) Weather conditions based on atmospheric weather prediction such as wind speeds at different altitudes, humidity, temperature, pressure, etc.
2) Rotor Diameter
3) Height of the Wind Mill
4) Past history dataset for a considerable number of years and so on.

These parameters will be resolved in our project and we also use the best algorithms which gives the best accuracy with our dataset.