Predicting Wind Turbine Scheduling Maintenance Using Artificial Neural Network for Preventing Blade Breakage: Case Study Baron Techno-Park

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Abstract

One of the main issues that Baron Techno-Park (hybrid power plant) are facing is the practices of finding a suitable maintenance strategy. The operation and maintenance (O&M) of wind turbines is heavily affected by weather conditions, particularly wind conditions. Blade failures, such as blade breakages, can lead to catastrophic consequences. The causes of blade breakages in Baron Techno-Park are due to unpredictable high wind speed from different directions. A technique that this research proposes to implement a maintenance strategy to create an efficient O&M and prevent the breakage of the wind turbine blades, is using the Artificial Neural Network (ANN). ANN performance is satisfactory with the wind speed error of 30.25 % and wind direction error of 13.74 %. Also, R2 has the highest prediction of 0.998. It analyses the survival wind speed of 60 m/s which is specified in the wind turbine specification. In addition, it analyses the prediction results. It is safe to say that during the month of July 2021, it is not necessary for a maintenance schedule.

Keywords: Maintenance Strategy, Blade Breakages, Wind Turbine, Artificial Neural Network, Prediction.

INTRODUCTION

One of the main issue that Baron Techno-Park (hybrid power plant) is facing are the practices of finding a suitable maintenance strategy. It is very important for implementation, especially for the wind turbines in the facility. The operation and maintenance (O&M) of wind turbines are heavily affected by weather conditions, particularly wind conditions. As a result, it can keep these assets operating as efficiently and safely as possible. Having an effective O&M will surely benefit the operators and owners from the environment and economics perspective [1].

Rotor blades are one of the major components of wind turbines, besides drive train, generator bearing, and gearbox that have a high frequency of failure that increases due to aging. Blade failures, such as blade breakages, can lead to catastrophic consequences [2]. The causes of blade breakages in Baron Techno-Park are due to unpredictable high wind speed from different directions.

A technique that this research proposes to implement a maintenance strategy to create an efficient O&M and also prevent the breakage of the wind turbine blades, is using the Artificial Neural Network (ANN). ANN is the most widely used forecasting technique, because of its high accuracy and generalization ability [3]. Using the ANN can help predict future events such as wind speed and wind direction which is the main concern for the blades' breakage.

Previous research on wind turbine maintenance has been done by many researchers with different kinds of techniques to solve different kinds of wind turbine maintenance problems, such examples have been done by [4]. On condition-based maintenance strategy of wind turbine using the Monte Carlo Simulation (MCS). On condition, the maintenance is a maintenance strategy that deals with equipment failures that are divided into random failures and wear-out failures. Random failures refer to the service life of the equipment that occurs unpredictably during the lifetime of the equipment. Wear-out failures refer to reduced reliability of the equipment due to wear, fatigue, and deterioration, which the failure rate increases with the increase of time. The on-condition maintenance has a cost that can be calculated relevance to time and due to the randomness of wind power equipment failures, the MCS helps deal with the problems by optimizing the maintenance cost of On-condition maintenance. The results show that as the increased time the maintenance cost decrease, but regardless of that when it hits a breaking point of 17 days then the cost of the maintenance increases due to the factor of the breakdown maintenance cost (when the equipment begins to fail). Therefore, it is relevant that the maintenance occurs below 17 days before the breakage of the equipment [4].

Another maintenance strategy research has been done by [5]. It deals with the cost-effective maintenance plan for multiple defect types in wind turbine blades. This research is basically about the use of the reliability parameters calculated from field data for multiple defect groups. Afterward, it will then be formulated into multiple maintenance plans and then consolidate into a single cost-effective maintenance plan. At the same time trying to achieve the optimal availability/reliability of the product. The method they used is to implement the preventive maintenance through the visualization of the Weibull distribution for a master maintenance plan that is reliable and has optimum maintenance cost [5].

Lastly from all the previous maintenance strategy research, with using different techniques to solve the maintenance problems in a wind turbine. Therefore, this research will aim to achieve on using the ANN for predicting wind speed and wind direction pattern to set scheduling maintenance to prevent a blade breakage from happing in Baron Techno-Park.

ARTIFICIAL NEURAL NETWORK METHOD

ANN is a mathematical model based on the biological workings of a brain (nervous system). The structure of ANN consists of three layers, which are the input layer, hidden layer, and output layer. Each layer is connected by a series of nodes and weights. To calculate the network input between the layers, the activation functions are applied such as the sigmoid transfer function and the tangent sigmoid transfer function. This research is considering using the Cascade Forward Networks (CFN). The advantage of CFN is that accommodates the non-linear relationship between the input and output, also by not eliminating the linear relationship between the two layers. The disadvantage of using the CFN is that the network weight to be estimated will increase as much as the neurons in the input layers [6], [7]. Such a problem is not a significant problem if the results obtained are satisfactory. Many factors also play the role of having satisfactory results such as the ANN settings and data observation. Overall the CFN can help predict data that consists of time series prediction, which this research is doing. Figure 1 shows the visualization of the CFN, with X as the input data, Z as the hidden layer, and because of this research goal is to predict the wind speed and wind direction, it consists of two outputs which are represented by Y.

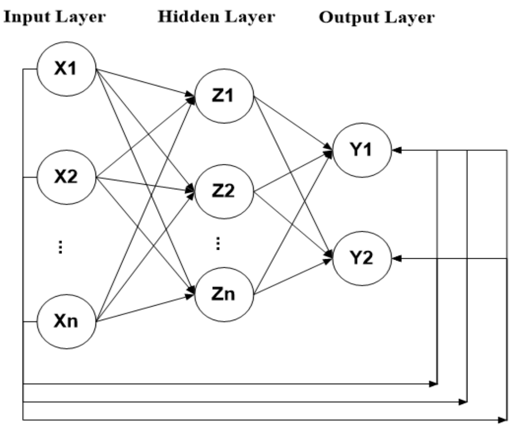

Figure 1. Artificial Neural Network Structure (Cascade Forward Network)

Data Correlation

The data that was obtained by Baron Techno-Park goes through the process of data acquisition, meaning that the data gathered from the sensors is sorted into a meteorology database (weather pattern database). The data is the data of July from the year 2015-2020. As of the month of July is the transition of the rainy season to the dry season. The meteorology database then goes to the process of data correlation that will find the variable correlation between the input and output for the ANN to predict. Using the Rstudio© program, the data correlation can be visualized into a graph that is seen in figure 2. The variable that has a high correlation with the input data is chosen. High correlation is the correlation value above 0.6 or below -0.6. The input data wind speed and wind direction (wind speed and wind direction at the high of 10 meters) is highlighted by the orange circle. The variables that have a high correlation with the input variables are wind speed 1, wind direction 1, wind gust, wind speed 2, wind direction 2, and wind direction 3.

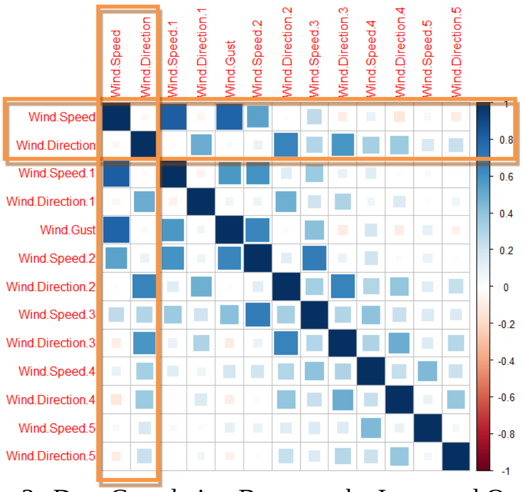

Figure 2. Data Correlation Between the Input and Output variables

The high correlation data chosen is then inputted into the ANN to be processed for prediction. The ANN settings used are by default. It means that the training algorithms are set to be using the Levenberg-Marquardt and the ANN node structure is set to 1-10-1 and the percentage of training, evaluation, and testing are at 70%, 15%, and 15%, respectively.

ANN Evaluation

After the data process through the ANN, the results will be evaluated using a statistical formula. Such a formula has been stated by previous research [8] that shows how to determine a statistical formula to evaluate the performance of the ANN results. The research finds that over the years the most popular formula to be used is the Mean Absolute Percentage Error (MAPE), noted that the data are taken from the year 1982 until 2007. According to the research, it is found that the best evaluation method is not to see the trend that other researchers are taking but to see the classification category of the evaluation formula and to see whether the problem in this research falls into that category. Based on the analysis of the structure of numerous performances, this research proposes a framework of metrics: primary metrics, extended metrics. Composite metrics, and hybrid sets of metrics. Therefore, the research identifies three main components for the primary metrics: method of determining point distance, method of normalization, method of aggregation of point distances over a data set. For each component, implementation options have been identified and their properties described. However, this research proposes another new primary metrics typology design around the key components. A new generic mathematical formula for primary performance metrics has been proposed which implies sequential, determining the point distance between the actual and predicted values, normalizing it, and then aggregating results over a complete data set. Using the method proposed by [8], the research finds the absolute error for the ANN performance with using predicted and real data. The formula used according to the metrics proposes:

- Determining the point distance using absolute error,
- Normalizing it with the Fractional Absolute Error (FAE),
- The aggregation has chosen the mean.

The formula for the Fractional Absolute Error:

$$FAE = \frac{1}{n}\sum_{i}^{n}\frac{2|e_i|}{R_i + P_i} \tag{1}$$

As e_i is the point distance $|R_i - P_i|$, R_i is real data and P_i is the predicted data. Then, n is the number of data points and i as the index of the data vector. FAE is the best formula to use because it takes in mean values, similar to the output results of the ANN which takes in the mean regression of the real data.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(R_i - P_i)^2}{\sum_{i=1}^{n}(R_i - \bar{R}_\iota)^2} \tag{2}$$

The coefficient of the determination (R^2) represents forecast values and measured values at x and y axis. It is also a common use for evaluating ANN performance. The range value is between 0 and 1. If the forecasted values are closer to 1, it means that the coefficient of the determination values has a higher prediction. In this case for wind speed and wind direction prediction [9].

RESULTS & ANALYSIS

As explained previously that the meteorology data was taken from the year 2015-2020, this research will try and predict the for the month of July (2015-2020) and will compare the results with the month of July 2021 and see whether the prediction predicted using the five-year data is valid and has high accuracy in predicting the month of July 2021.

Observing figure 3 and figure 4, there is a slight difference in wind speed compared with the predicted (July 2015-2020) data and the real data (July 2020). However, the wind direction is consistent facing south-east, which corresponds with the topology of the area that the Indian Ocean is facing south of Baron Techno-Pak. Wind direction only offers the efficiency of the turbine and slightly increases the damage to the turbine, but dependently the wind speed affects more on the damage to the blades. Analyzing figure 5, where the top histogram plot is July 2015-2020, and the bottom is July 2021. It shows that the ANN manages to predict wind speed above 5.7 m/s similarly with the real data, but it fails to predict below that.

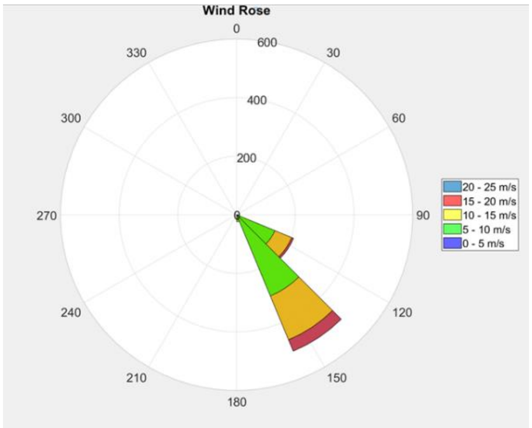

Figure 3. Wind Rose July 2015-2020 (Prediction)

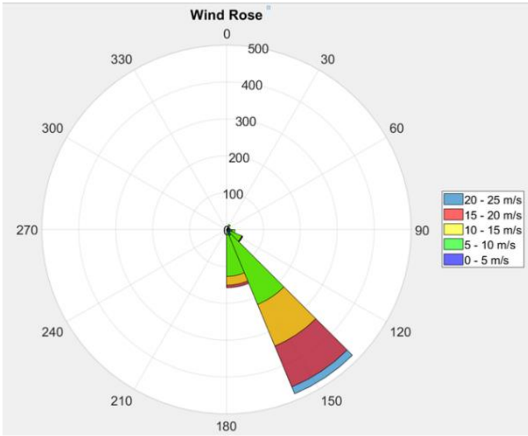

Figure 4. Wind Rose July 2021 (Real Data)

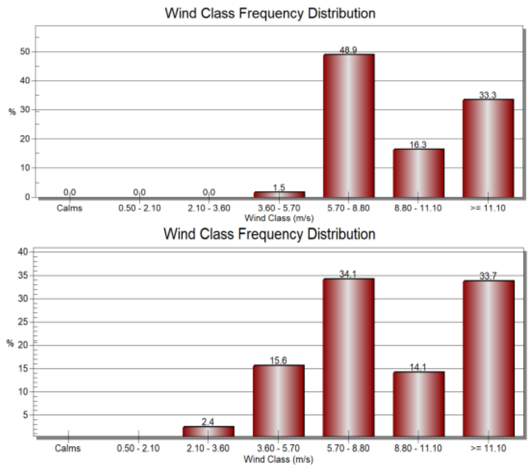

Figure 5. Histogram Wind Speed for July 2015-2020 and July 2021

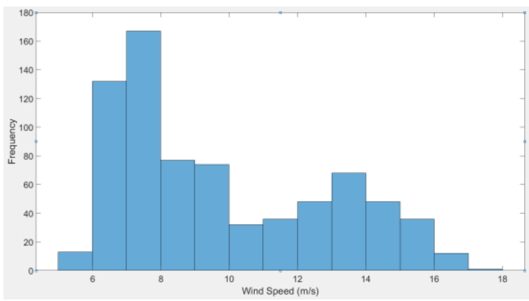

Figure 6. Histogram Wind Speed for July 2015-2020 (Prediction)

The performance of the ANN can be seen in table 1. Which is evaluated with the formula FAE and R^2

Tabel 1. ANN Performance Evaluation

Inputs	FAE	R^2
Wind Speed	30.25 %	0.998
Wind Direction	13.74 %	0.998

Wind turbine specification is taken from Baron Techno-Park and observing the wind speed specification for the turbine which specify [10]:

Tabel 2. ANN Performance Evaluation

Wind Speed	
Cut-in	2.5 m/s
Rated	17 m/s
Survival	60 m/s

Analyzing table 2 above, it shows that the survival rating for the wind speed is 60 m/s. It means that in such extreme weather the blades can withstand wind below 60 m/s without breaking. Looking at figure 5 and figure 6, it shows wind up to 5.7 m/s – 8.8 m/s is the most frequent wind speed during July and the maximum wind speed only reaches up to 18 m/s. therefore for this research analysis, it concludes that during the month of July with wind speed relatively coming from the south-east and wind speed predicted highest frequency 5.7 m/s - 8.8 m/s and maximum wind speed not above 18 m/s. it is safe to say no maintenance schedules are needed for the month of July 2021, because no blade specifications are violated through the prediction of the ANN.

CONCLUSION

This research concludes that the ANN predicted wind direction most frequent during the month of July is to the south-east, with most frequent up to 5.7 m/s -8.8 m/s and maximum wind speed not above 18 m/s.

ANN performance is satisfactory with the wind speed error of 30.25 % and wind direction error of 13.74 %. Also, R^2 has the highest prediction of 0.998.

It analyses the survival wind speed of 60 m/s which is specified in the wind turbine specification. It also analyses the prediction results. It is safe to say that during the month of July 2021, it is not necessary for a maintenance schedule.

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