Comparative Analysis of Wind Power Production Planning Based on Artificial Neural Network and Theoretical Approach

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Abstract
The need for cleaner energy together with the abundant availability of wind has made the wind one of the important sources of renewable energies. The stochastic nature of wind causes high uncertainty of the wind energy instigating the wind energy managers to carefully forecast expected power to ensure its availability and customer satisfaction at affordable price. Aback-up was provided by attaching battery storage system to supply energy deficit. To determine optimal production and maintenance cost, we have developed preventive maintenance (PM) models based on artificial neural network (ANN) and Theoretical method for power generation taking into account the production and storage costs as well as the maintenance cost. The ANN model provided an optimal solution by providing minimal cost of production and maintenance costs.

Keywords
Artificial Neural Network, Service rate, Mean demand, Production, Preventive maintenance.

Nomenclature

H	Number of production periods;
Δt	Duration of each production period
k	Index referring to a production period number where k =1,2,..,H;
D_k	Random demand for period k;
μ_k^d	Mean of the Gaussian demand;
σd	Variance of the Gaussian demand;
M_k	Number of wind turbines during period k
P_k	Global production level during period k
P_{jk}	Energy produced by wind turbine j during period k
S_k	Energy stored at the end of each period k;
M_k	Upper boundary of wind turbines machines;
m_k	Lower boundary of wind turbines machines;
υ_{in}	Cut in wind speed;
υ_{out}	Cut out wind speed;
υ_r	Rated wind speed;
υ	Wind speed;
a	Wind shape parameters;
c	Wind scale parameters;
P_{max}	Maximum Power of the wind turbine;
P_r	Rated Power of the wind turbine;
Θ	Service level rate
$a1/a2$	Optimal net stock coefficients
Cp	Cost of production of 1 kW
Cs	Cost of storage of 1 kW

1. Introduction

Wind power presently plays an important role in electricity generation industry. This is due to the need for cleaner energy together with the abundant availability of wind as one of the sources of renewable energies. As of 2019, the global installed capacity of wind energy is about 651 GW and estimated to be up to 1TW by 2024 (*Global Wind Energy Council Report*, 2019). Wind by its nature is random and uncertain, therefore, wind power generation has to be carefully planned with the possibility of providing back-up to reduce power supply shortage. Additionally, low controllability of wind power due to uncertainty raises the problem of instability of the power system. An effective way of reducing this shortage, and increasing wind electricity penetration into the electricity grid is by forecasting. Additionally, forecasting provides safe, power stability and boosts economic benefits and enhances production planning associated with wind energy generation (Zhang et al., 2019). Therefore, intelligent and accurate power forecasting tools are required to improve the accuracy of stable power predictions and decrease operational costs. Many wind forecasting techniques have been identified (Zhao et al., 2016), which are mainly classified into numerical weather forecasting (NWP), statistical methods, and hybrid methods (Han et al., 2015).

Long-time prediction horizon is best evaluated with NWP which yields more accurate results (Khan et al., 2019). Statistical methods are used to predict the correlation among various features of historical wind data with the help of explanatory variables. These require only wind data for forecasting, and thus, these tools are of particular interest for different types of engineering applications. The prediction accuracy of statistical methods decreases in long forecasting horizons. A new WP strategy for short-term forecast model was developed by (Shao & Deng, 2016) in combination with data fusion technique. The authors optimized the model by presenting four dimensionality reduction fusion method to improve the computational efficiency and enhance the forecast accuracy. The authors used real data from a wind farm in Jiangsu province in China for the experimental evaluation and to verify the significance of their model.

Artificial Neural Network (ANN) and Support Vector Regression (SVR) are some of the most widely used statistical methods having variety of applications such as in weather forecasts, asset prices, and economic forecasts (Marugán et al., 2018). The ANN is a machine learning algorithm that learns from sample data fed into it and uses what it learnt to make predictions. More interestingly, its weighting factors can be adjusted to reduce future errors between the predictions and the actual results, which facilitates its extensive application in prediction. Even though ANN is exceedingly accurate in predicting wind energy generation, many researchers are still working for further improvements in the accuracy of ANN. It is believed that optimizing the input of quality data into the ANN algorithm provides a highly accurate output of the predictions.

A novel bidirectional method of forecasting wind energy by backward forecasting for short time (1-6hrs) was proposed by (Zhao et al., 2016). In their work, a predefined threshold was set such that the difference between forward and backward forecasting is gauged against. An integrated Neural Network and Markov chain model was established for very short term wind speed forecast (2.5 seconds) was developed by (Kani & Riahy, 2008). The mean absolute percentage error and the maximum prediction errors obtained with that model showed improvement as against the ANN model developed. To further strengthen the efficiency of ANN in prediction, a day ahead wind power forecasting model was developed by (Jiang et al., 2017) for Jiangsu Province in China. It is a hybrid model comprising of ARMA and boosting algorithm where multi-step ahead 6 to 24 hrs forecast was found to be more accurate against the ARMA model. Boosting algorithm is a technique of combining weak classifiers, to form highly accurate combined classifiers. Moustris et al., (2016) proposed 3 ANN models for 8 hrs ahead forecast of wind power considering the mean hourly, maximum hourly and minimum hourly wind speed for a period of 12 days. Even though the three models showed good performance, the mean hourly model outperformed the rest and the authors concluded that the mean hourly wind speed is most suitable for wind energy forecast. Feedforward Neural Network for day-ahead production of average daily wind energy production forecast was proposed by (Dumitru & Gligor, 2017). The author varied the number of neurons and obtained the best prediction with 15 neurons. Peiris et al., (2021) proposed ANN models to forecast wind power from a Wind Farm in Sri Lanka considering wind speed, wind direction and ambient temperature. The models were trained and tested based on Levenberg-Marquardt (LM), Scaled Conjugate Gradient (SCG), and Bayesian Regularization (BR) algorithms at 5% from 10 to 25% validation for each algorithm where the LM algorithm produced the best prediction.

Maintenance scheduling and planning integrated with turbine power production has become important in planning wind energy maintenance in order that the turbine performs its intended function and reaches end of the horizon. Different types of maintenance planning and scheduling were studied by many researchers with different objectives. There are different bases of maintenance classification such as reliability-based, condition based, preventive and corrective maintenance. In most cases, a combination of 2 or 3 of the types are considered to improve the system performance. A preventive maintenance (PM) is a time-based planned maintenance action intended to be performed periodically at specified times to minimize failure, while corrective maintenance is performed at any time a system fails. in the work of (Wang et al., 2020), a preventive maintenance strategy was developed to determine the optimal strategy that maximises system availability by performing imperfect PM using a probability distribution method. To determine optimal periodicity of PM, (Duarte et al., 2006) developed algorithms to determine the increasing hazard rate of a series components system. a cost function considering preventive and corrective maintenance was defined to calculate the optimal time interval between PM actions and minimize maintenance cost. An integrated wind energy production and maintenance plan based on Weibull distribution approach was developed by (Hajej et al., 2015) where optimal cost of energy generation and storage were determined.

Most of the literature reviewed concentrated on the production without much attention to the maintenance costs, this paper therefore seeks to evaluate the optimal cost of power production and that of maintenance by comparing the power generation cost and maintenance cost based on theoretical Weibull distribution and Artificial Intelligence (AI) ANN.

2. Mathematical Model

In order to satisfy customers' random demand, this work considers a finite horizon composed of wind turbines and storage system. The type of lay-out considered is that of a typical industrial system where the problem deals with power generation and storage cost optimization. To achieve this, the following model was developed and the solution was approached using two different methods; the theoretical and artificial intelligent (AI) methods.

$$\min_{C_P, C_S} C = \sum_{k=1}^{H}\left(C_S \times \left(\overline{S} - a_1 - a_2\mu_k^d\right)^2\right) + \sigma_d^2(1+a_2)^2 \times \frac{H}{2}(H+1) + a_d^2 \times \sigma_d^2 \times \frac{H}{2}(H-1) + \sum_{k=1}^{H-1} C_p \times \left(\sum_{j=1}^{M_k} P_{jk}\right)^2 \quad (1)$$

Subject to

1) The number of machines operating within the production period.

$$m \leq M_k \leq M$$

2) The quantity of energy to be stored at that period

$$S_k = S_{k-1} + P_k - D_k$$

3) The service rate is satisfied

$$prob(S_k \geq 0) \geq \theta$$

2.1. Theoretical Approach of Wind Power Modelling

Wind energy is highly volatile and depends on wind velocity which is random. Therefore, generating wind energy is a hard task necessitating wind turbine functionality and wind availability. Considering the random nature of the wind, a Weibull distribution is proposed for energy generation. The equation for a given wind turbine i during production period j is given as:

$$f(v) = \frac{a}{c}\left(\frac{v}{c}\right)^{a-1} . exp\left[-\left(\frac{v}{c}\right)^a\right] \quad (2)$$

a and c are defined as $c = \frac{v_{mean}}{\Gamma\left(1+\frac{1}{a}\right)}$

and $a = \left({}^{\sigma}/_{v_{mean}}\right)^{-1.086}$

where Γ is gamma function and σ is the standard deviation of the wind speed data.

Therefore, the maximum Power output P_{wt} (kW/m^2) from wind turbine generator is calculated using the following equation

$$P_w = \begin{cases} P_r \left(\frac{v^a - v_{in}^a}{v_{in}^a - v_r^a}\right) & v_{in} < v < v_r \\ P_r & v_r < v < v_{out} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Where P_r is the rated power, V_{in}, V_{out} and V_r are the cut-in, cut-out and rated speed of the wind turbine respectively. The power from the turbine will be calculated thus:

$$P_{jk} = \int_0^\infty \left(P_w(v).f(v)\right).d(v) \tag{4}$$

$$P_{jk}(t) = \int_{v_{in}}^{v_r} (A+B).f(v).d(v) + P_r \int_{v_r}^{v_{out}} f(v).d(v) \tag{5}$$

Where

$$A = \frac{P_r.v_{in}^a}{(v_r^a - v_{out}^a)}, \qquad B = \frac{P_r.v^a}{(v_r^c - v_{out}^a)}$$

The global energy produced during period k is therefore expressed as

$$P_k = \sum_{i=1}^{Mj} P_{jk} \tag{6}$$

2.2. ANN

The ANN is an architectural network that was inspired by the functions of the human brain neurons. It generally consists of 3 main layers with some sub layers as; the input layer, the hidden layer (which can consist of many sub layers depending on the programmer) and an output layer. Figure 1 shows a simple representation of a typical ANN (Sa'ad et al., 2020).

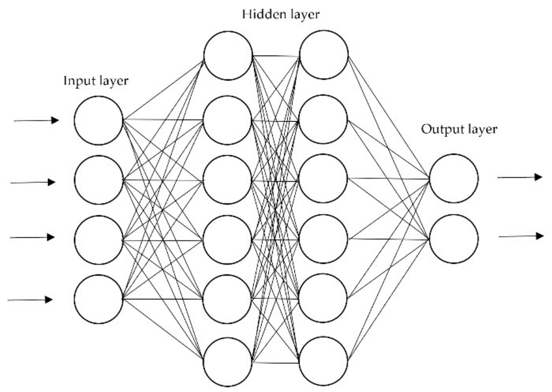

Fig 1: A schematic representation of a typical ANN

In an ANN, various parameters and hyper parameters affect the performance of the model in which the output is mostly dependent on these parameters. Some of these parameters are weights, biases, learning rate, batch size etc. with each node in the network having some weight assigned to it. A weighted sum of the inputs and the bias is calculated using a transfer function. The general equation for the ANN is given as

$$k_{j,input} = \sum_{i=1}^{m} w_{i,j} x_i + b_{input} \tag{8}$$
$$k_{j,output} = f\left(k_{j,input}\right) \tag{9}$$
$$y_p = \sum_{j=1}^{n} k_{j,output} + b_{hidden} \tag{10}$$

Where:

- f is the activation function of the model
- x_i is the ith input node
- $k_{j,input}$ is the input of the jth hidden node
- $k_{j,output}$ is the output of the jth hidden node
- $w_{i,j}$ is the weight assigned to the ith input node that is mapped to the jth hidden node
- b_{input} is the input layer bias
- b_{hidden} is the hidden layer bias

- y_p is the output of the model

It is worth mentioning that ANN works with four activation functions: linear, sigmoid, hyperbolic tangent and rectified linear unit and for the purpose of this work, we worked with sigmoid function. In our work, we considered wind speed, wind temperature and humidity as the input variables while the power output is y_p.

3 Maintenance Scheduling Optimization

In this section, we seek to determine the optimal maintenance plan by obtaining the minimum maintenance cost possible for the system. This optimal plan is characterized by determining the optimal number of preventive maintenance (N*) and the optimal periodicity T* that yields the optimal cost. The relationship between the number of PM and periodicity is given as (Faker et al., 2021)

$$T^* = \frac{H}{N^*} \tag{11}$$

It is imperative that while planning PM, corrective maintenance should be considered since there is the probability of unexpected break down at any time. For this, the corrective maintenance selected consists of minimal repair which restores the system to its previous condition before failure. This therefore takes into account the failure rate and the wind turbine degradation factor. Hence, this maintenance plan is dependent on the production planning as well with the failure rate equation given as

$$\bar{Y}(P_k, \mathrm{N}) = \sum_{i=0}^{N-1} \left[\sum_{k=In(i\times \mathrm{T})+1}^{In((i+1)\times \mathrm{T})} \int_0^{\Delta t} \lambda_k(t)\ dt\right] + \sum_{k=N\times T+1}^{H\Delta t} \int_0^{\Delta t} \lambda_k(t)\, dt \tag{12}$$

where $\bar{Y}(P_k, \mathrm{N})$ is the average failure rate during each period k and for each number of PM actions (N). The maintenance cost therefore, is modelled in the following equation

$$M_C(P_k, N) = C_{pm} \cdot N + C_{Cm} \cdot \bar{Y}(P_k, N) \tag{13}$$

Where M_c is the maintenance cost, C_{pm} is the cost of preventive maintenance, N is the number of PM actions while C_{cm} is the corrective maintenance cost.

4 Numerical Example

To illustrate the validity of our algorithm, we developed a numerical example based on chosen arbitrary values. The wind turbine used for this illustration is an E-20 HAWT with its characteristics presented in table 1. A 20v, 100Ah battery was considered for the storage while the production data is presented in table 2. Weibull scale and shape parameters are assumed to be 5 and 3 respectively. The number of wind turbines taken for this study are between a minimum of 3 and maximum of 6. It is also assumed that all the wind turbines operational characteristics are identical, therefore, they have similar rated power (P_r) and maximum power output (P_{max}). The demand is assumed to be random with a standard deviation of 1.1 and mean of 50.

Table 1: Wind Turbine Characteristics

Parameter	value
Max Power (kW)	20
Rated Power (kW)	18
Cut-in speed (m/s)	2
Rated speed (m/s)	9
Cut-out speed (m/s)	30
Hub height (m)	15
Rotor Diameter (m)	9.8

Table 2: Production Parameters

Parameter	Value
H (months)	12
Δt (months)	1
cp (cu/kW)	2
cs (cu/kW)	3
Minimum service level (%)	90

Table 3: Maintenance Parameters

Parameter	Value
β	2
η	10
C_{cm}(cu)	10000
C_{pm} (cu)	500

Since we assumed that all wind turbines are identical and to simplify our work, the maintenance strategy was built for one (1) turbine and the strategy was applied to all other turbines depending on the number selected for a particular period.

5 Results and Discussion

Simulation of the modelled algorithm was successfully performed and the following results were obtained. Table 4 presents the optimal production plan for each period over the horizon via ANN with a total cost of 45,730.14 cu, while result of the theoretical method is presented on table 4 presents with a value of 46,932.08 cu. For each period, the optimal number of wind turbines (M_k) enough to satisfy the demand, the power generated (Pk) and the excess energy stored (S_k) during each period. Using machine learning method saves about 2.6% of production cost which is because of the power forecasting done by ANN which minimized the model error and presented a good performance fit for the data.

Table 4: Optimal values for ANN

Total Cost	45,730.14 cu		
Periods	M_k	P_k x 10^5(kW)	S_k (kW)
1	3	0.681	7.781
2	5	0.482	4.781
3	5	0.769	12.527
4	3	0.839	12.354
5	5	0.861	27.210
6	5	1.179	36.664
7	3	1.473	51.889
8	3	1.318	48.889
9	5	1.051	57.669
10	3	0.850	75.812
11	4	0.619	72.812
12	3	0.485	69.812

Table 5: Optimal Vales for theoretical approach

Total Cost	46,932.08 cu		
Periods	M_k	P_k x 10^5(kW)	S_k (kW)
1	3	4.342	8..461
2	4	5.919	14.057
3	3	4.761	19.653
4	5	4.069	30.979
5	4	4.929	42.171
6	3	4.773	36.575
7	3	5.159	47.766
8	5	6.891	64.689
9	5	4.966	56.228
10	4	3.209	70.284
11	4	3.063	81.611
12	5	6.022	90.072

Figure 2 presents the optimal maintenance cost as well as the optimal number of preventive maintenance actions (N*) by the theoretical approach. From the figure, N* is found to be 4, this means that total of 4 preventive maintenances should be performed on the system to achieve a minimal cost of 3953.91 cu. In figure 3, the optimal maintenance cost obtained from ANN method is presented and the N* is found to be 2 with an optimal cost of 1866.15 cu. In this case, less preventive maintenance is to be performed on the system at lesser price as well. The advantage of using the AI method out weights the theoretical method thereby presenting a much less value that was well forecasted.

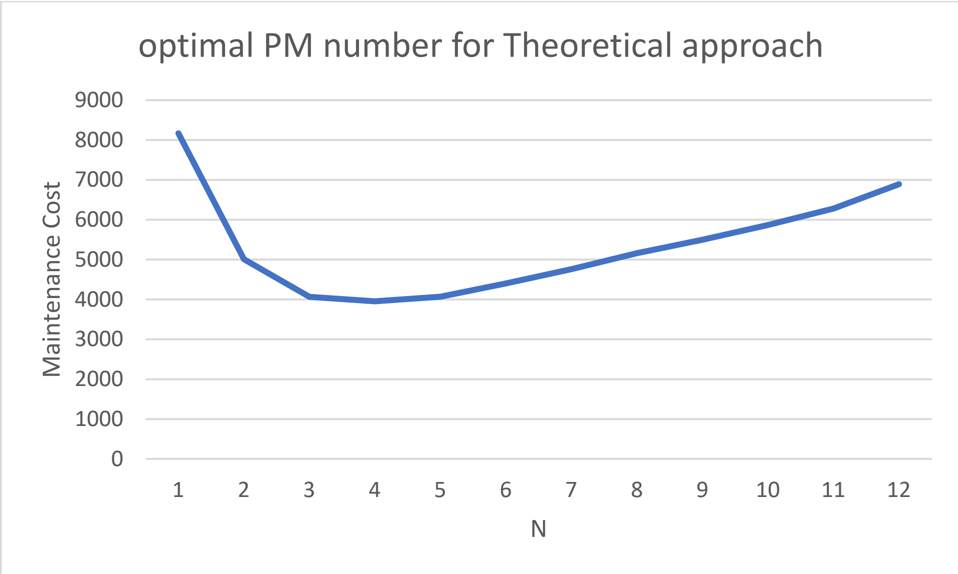

Figure 2: Theoretical maintenance cost optimization

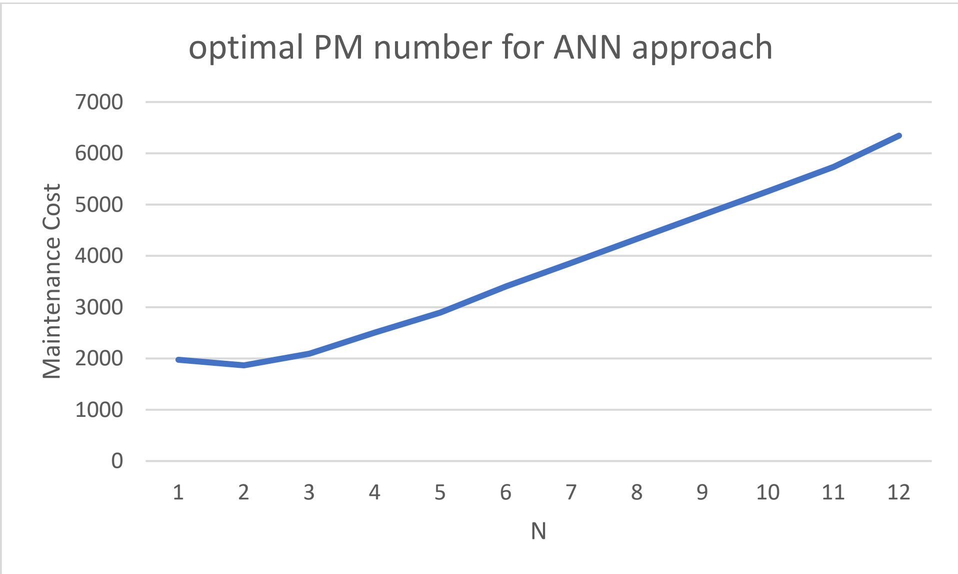

Figure 3: ANN maintenance cost optimization

6 Conclusion

This paper presented maintenance scheduling models derived by theoretical and ANN methods for wind energy implemented in MATLAB 2021b version. The aim of each of the models was to forecast and also optimize the cost benefit of performing preventive maintenance as well as to determine optimal number of preventive maintenance actions to be performed on the system that yields the optimal cost. The method employed was an integrated method by first determining the power generation from the turbine during each production period, then subsequent maintenance planning was scheduled factoring the periodic power result as well as storage requirement for the period. After successful maintenance planning was carried out, we then performed a cost evaluation to determine the optimal number of preventive maintenance. The results obtained from the two (2) methods were presented and compared. ANN model appeared to be the model with better maintenance economic benefit than the theoretical method by yielding less cost at minimal number of maintenance as well. In conclusion, power generation forecasting by AI helps in avoiding over or under production of energy thereby subsequently minimizing the maintenance cost as well. As an extension of this work, operational condition and the impact of the climate on the turbine will be considered on the models.

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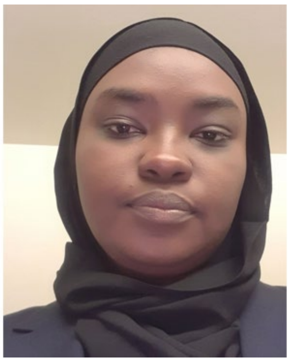
Authors' Biography



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