An Integrated Maintenance Scheduling of a Wind Energy System Minimizing Economic Losses

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Abstract. The world is faced with a continuous challenge of climate change and global warming as a result of excess carbon emission due to the traditional method of generating electricity from fossil fuels. As measures to curb this challenge, re-searchers explored into renewable energy resources which provide clean and hazard-free energy. Wind as one of the fast-evolving sources requires a lot of attention in generating and sustaining the wind system to ensure reliability and customer satisfaction. In this context, this paper develops a model that forecasts wind energy production by artificial neural network (ANN) method. An integrated model for optimizing the production and maintenance planning cost was developed to minimize economic as well as the production losses that satisfy random demand. Our developed algorithm also determines the minimal number of preventive maintenances to be performed on the turbine thereby evaluating the eco-nomic losses associated with the total production lifecycle.

1 Introduction

Climate change and global warming have become more apparent recently and poses serious challenge to man and the environment as indicated in a report submit-ted to the United Nations General Assembly by the World Commission on Environment and Development [1] indicated a serious diagnosis of the global situation and came up with the following main points; human activities pose serious threat on the earth's ability to support life, ecological and economic development are seen to be interwoven into a seamless network of causes and effects on local, regional and global scale and to achieve sustainable development. All countries must move quick-ly to restructure not only national and international policies but must also restructure their institutions.

In essence, world energy consumption contributes immensely to environmental deterioration, pollution and greenhouse gas emission. Similarly, the energy consumption index increases with increase in population and economic development. Energy and environmental problems are closely related, since it is nearly impossible to produce, transport, or consume energy without significant environmental impact. The environmental challenges related to energy production and consumption include air pollution, climate change, water pollution, thermal pollution, and solid waste disposal. Emission of air pollutants from fossil fuel combustion is the major cause of air pollution and the main contributor to the emission of greenhouse gases. Therefore, many researches are carried out in the field of renewable energy generation. Renewable energies such as solar, wind, tidal, ocean current and hydro are some of the main sources of energy/power generation. Wind energy is the focus of our study and is one of the promising and most harnessed sources of the renewable energies globally [2].

Due to the random nature of wind energy, it is important to effectively plan the production system to ensure continuity of energy production and stability. Therefore, this work proposes an optimization model for wind energy production by forecasting power production using artificial neural network (ANN). Also, a maintenance planning strategy is proposed to determine the optimal number of maintenances to be performed. The maintenance strategy is integrated with production to minimize eco-nomic losses on the wind energy system. The strategy adopted in our work, is a peri-odic strategy of perfect preventive maintenance with minimal repair. Perfect maintenance is applied during each preventive action, thus restoring the system to a new state (AGAN: as good as new). Whereas corrective maintenance with minimal repair (ABAO: as bad as old) is applied when failure occurs between two successive preventive maintenance sessions, without improving the failure rate.

Through our research and to the best of our knowledge, not many literatures considered joint integrated production and maintenance policy for wind turbine, this work therefore seeks to integrate wind power production into the maintenance strategy proposed in this work. It seeks to develop an optimal strategy that determines the number of maintenances to be performed, and the periodicity between successive maintenance that presents the minimal cost of maintenance. The strategy

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adopted is that a perfect maintenance action is performed during preventive maintenance with minimal repair at failure during production. A reliability assessment is also performed on the components, which is also considered as a constraint to improve the performance of the system. This work presents a novel maintenance strategy by integrating power production plan into the maintenance strategy taking into account the non-negligible time of preventive and corrective maintenances.

2 Wind energy production and maintenance modelling

This section deals with the problem formulation for both production and maintenance.

2.1. Wind production forecasting by ANN

ANN is an algorithm inspired from the arrangement of neurons in the human brain as shown in figure 1. The neurons from the input layer are connected to the hidden layer neurons via networks with some weights assigned from each of the input neurons to each of the hidden layer neurons. The hidden layer neurons are also connected to the output layer in the same manner as the input. The output layer is where prediction results are obtained.

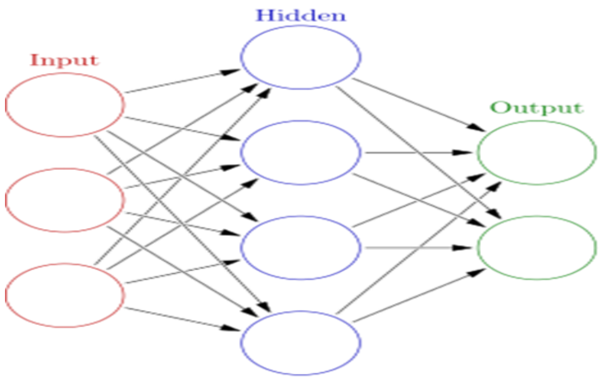

Fig. 1. Caption of the Figure 1. Below the figure.

Mathematically, ANN output estimation represented as [3].

$$k_{j,input} = \sum_{i=1}^{m} w_{i,j} x_i + b_{input}$$
$$k_{j,output} = f(k_{j,input}) \quad (1)$$
$$y_p = \sum_{j=1}^{n} k_{j,output} + b_{hidden}$$

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 h_j, b_{input} is the input layer bias, b_{hidden} is the hidden layer bias and y_p is the output of the model.

Inspired from the work of [4], the neural network algorithm is designed to have an input layer comprising 3 inputs; wind speed, humidity and temperature, a single hidden layer having 20 nodes and an output layer. The output layer is a single node output presenting the expected power generation.

2.2 Performance Analysis

This measure is used to validate the forecasted output value of the model. In this work we test our model based on the root mean square error (rMSE) expressed as follows:

$$rRMSE = \sqrt{\frac{\sum_{i=1}^{n} |y_t - y_p|^2}{y_t}} \quad (2)$$

where y_t is the true or measured output value, y_p is the predicted output value and n is the total number of data set

2.3 Storage and service rate modelling

During each production period, excess energy is stored in order to satisfy the service level at that period. Inspired from the work of [5], the amount stored is determined according to the power generation of wind turbines and the random demand expressed by a balanced storage equation expressed below:

$$S_k = S_{k-1} + P_k - D_k \quad (3)$$

S_k is the energy stored at period k, S_{k-1} is the stock at the previous production period (k-1) with P_k *and* D_k being the energy produced and the demand at period k. To ensure power security regardless of the wind fluctuations, a service level $S(k)$ is imposed for each period. This service level is determined according to probabilistic functions of electricity demand which helps in making the right decisions for storage policies during production planning. Service rate is the probability that the turbine does not break and must be greater than a minimum threshold (θ) as intended by the manager. This probability is often represented as [5]:

$$prob(S(k) \geq 0) \geq \theta \quad (4)$$

3 Maintenance planning modelling

Maintenance planning is an essential part of industrial management in determining the optimal maintenance strategy that allows the firm minimize its maintenance and production costs. To improve the life and performance of a machine or system, maintenance is performed either in the form of repairs, component replacement and mechanical servicing [6]. The ultimate aim of maintenance is twofold: firstly to ensure that the facility is able to operate as intended and secondly, to ensure that maintenance resources are optimized. An effective maintenance strategy is concerned with maximizing equipment uptime and performance while balancing the associated resources expended with the cost. Optimal maintenance strategy characterized by time and duration of PM sessions (makespan), have a great influence on operational cost, therefore, optimizing it to minimize the total cost while maximizing production and reliability becomes essential.

3.1. Maintenance planning optimization

The objective of maintenance optimization for wind turbines is to improve their reliability and minimize production and maintenance costs [19]. In this work, the novelty lies in the integration of losses incurred due to non-production time during maintenance. Therefore, the total production cost (C) is minimized constrained to power production, service rate and reliability constraint shown below:

$$\min C = \sum_{k=1}^{H} \left(C_{pk}.P_k + C_{sk}.S_k\right) + C_{post} \quad (5)$$

where

$$C_{post} = C_{sell} \times \frac{\sum_{k=1}^{H} P_k \times (\mu_c \times \varphi(N) + \mu_p \times N)}{H} \quad (6)$$

subject to

$$0 < P_k < P_{max}$$
$$(P(S(k) > 0) > \theta$$
$$R_{wt}(t) > R^*$$

C_{pk} is cost of production of 1 kW, C_{sk} is cost of storage of 1 kW, C_{post} is cost of loss of production, C_{sell} is cost of selling 1 kW, H is the production horizon, P_{max} is the maximum Power from the wind turbine, k is index referring to production period (k =1,2,..,H) and N is the number of maintenance sessions. $(\mu_c \times \varphi(N) + \mu_p \times N)$ represents the wind turbine unavailability time, $\varphi(N)$ is the average number of failures, μ_c *and* μ_p are the time of corrective and preventive maintenances respectively.

However, considering that failures may occur between PM schedules, minimal repairs should be adopted. Corrective measures can only be estimated by evaluating the turbine's average number of failures with the following relation [8]:

$$\varphi(N) = \sum_{k=0}^{N-1} \left[\int_{kT}^{(k+1).T} \lambda_{wt}(t)dt\right] + \int_{N.T}^{H.\Delta t} \lambda_{wt}(t)\, dt \quad (7)$$

$\lambda_{wt}(t)$ is the failure rate per production period expressed as a function of reliability expressed below:

$$\lambda_{wt}(t) = \frac{-\frac{dR_{wt}(t)}{dt}}{R_{wt}(t)} \quad (8)$$

The reader can refer to the reference for explanation of the turbine reliability modelling and the failure rate as well.

The priority of this work is to determine the minimal total production cost of the system taking into account the implication of shortage and loss of production costs. Loss of production cost is observed to be caused due to non-negligible time duration of preventive and corrective maintenance. Another goal is to determine the optimal number of preventive maintenance session (N*) and the optimal periodicity (T*) between two (2) successive PM times represented by the relationship below:

$$T^* = \frac{H}{N^*} \quad (9)$$

Failures can occur in between production periods in which case minimal repair should be performed to restore the system to its previous condition. In this condition, the system failure rate does not decrease, it rather remains unchanged. Therefore, when planning a PM session, substantial time and cost resources are allocated for corrective maintenance (CM) to take care of failure. In this regard, turbine failure rate and degradation factor are considered for planning maintenance by the following reliability estimations.

3.2. Reliability estimation

For simplicity, this work considers four (4) major components of the turbine whose reliability were investigated. The selection is based on the impact of failure on the components on the turbine identified by [9]. The components are: main bearing, main shaft, gearbox and generator related by the following reliability equation [8].

$$R_{wt}(t) = R_{mb}(t).R_{ms}(t).R_{gb}(t).R_{gen}(t) \quad (10)$$

R_{wt} is reliability of wind turbine, R_{mb} is reliability of main bearing, R_{ms} is reliability of main shaft, R_{gb} is reliability of the gearbox while R_{gen} is reliability of the generator. The reliabilities are modelled by Weibull function where η_i is component i's shape parameter and β_i is component i's scale parameter. The equations are explicitly presented as follows:

Bearings

The reliability of a wind turbine bearing is calculated as

$$R_{mb}(t) = e^{-\left(\frac{t}{\eta_{mb}}\right)^{\beta_{mb}}} \quad (11)$$

Main shaft

The reliability of the main shaft is calculated as

$$R_{ms}(t) = e^{-\left(\frac{t}{\eta_{ms}}\right)^{\beta_{ms}}} \quad (12)$$

Gearbox

The reliability of the gearbox is calculated based on the following 4 subcomponents; Intermediate shaft (IMS) bearing, High speed stage (HSS) bearing, keyways and gears. The reliability is stated as follows:

$$R_{gb}(t) = e^{-\left[\left(\frac{t}{\eta_{hss}}\right)^{\beta_{hss}} + \left(\frac{t}{\eta_{ims}}\right)^{\beta_{ims}} + \left(\frac{t}{keyway}\right)^{\beta_{keyway}} + \left(\frac{t}{\eta_{gear}}\right)^{\beta_{gear}}\right]} \quad (13)$$

Generator

The generator also encompasses 2 subcomponents; bearings and windings. Its reliability is the product of the subcomponents.

$$R_{gen}(t) = e^{-\left[\left(\frac{t}{\eta_b}\right)^{\beta_b} + \left(\frac{t}{\eta_{winding}}\right)^{\beta_{winding}}\right]} \quad (14)$$

Taking into account the impact of power production and the degradation variation on turbine, the remodelled integrated reliability equation is expressed

$$R_{wt}(t) = R_{mb}(t).R_{ms}(t).R_{gb}(t).R_{gen}(t).e^{-\left(\frac{P_k}{P_{max}}\right)} \quad (15)$$

3.3. Integrated production and maintenance resolution

This strategy is aimed at treating the production problem first where the obtained optimal solution is integrated into the maintenance problem. In our work, sequential method was defined as a successive optimisation of two events considering production plan as a constraint to optimise the maintenance plan. Determining the optimal maintenance plan requires an initial determination of power production. Accordingly, power production is highly influenced by machine failure rate. To achieve our desired objective, we first forecast power using the ANN technique explained section 3.1 to determine the expected power per period. We determine failure rate of the wind turbine as the first step of the maintenance plan. Subsequently, maintenance planning is followed with equations 6 under reliability, power and service rate constraints to determine the optimal number of preventive maintenances that yields minimal cost over the horizon. The maintenance algorithm is presented in figure 2 where number of maintenance actions (N*) and the periodicity (T*) are the decision variables.

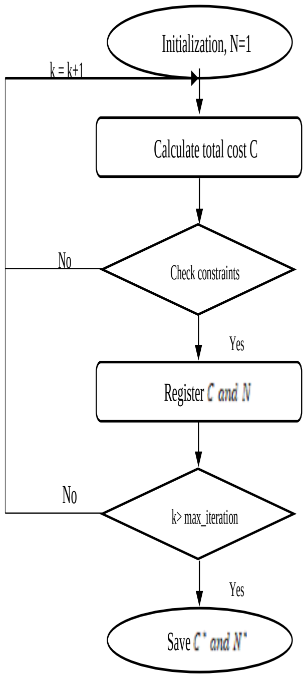

Fig. 2. Maintenance optimisation flow chart

4 Numerical simulations

Katsina wind farm data for the year 2020 was obtained and implemented in this model. Hummer H25-100kW wind turbine whose characteristics are presented on table 1 is used for this analysis, while table 2 provides the wind speed and load demand data of our selected case study. The cost of producing, storing and selling 1kW of energy (C_p, C_s and C_{sell}) are selected to be 12 NGN, 15 NGN, and 50 NGN respectively which must respect a service rate threshold of 80 %. Inspired from the work of [9], 90% reliability threshold was imposed for this illustration. All wind turbines considered in this work are assumed to have similar ratings, therefore, maintenance action is illustrated for one (1) wind turbine which can be applied to many as considered.

Table 1. Hummer H25-100kW wind turbine characteristics

Rated Power (kW)	Cut-in speed (m/s)	Rated speed (m/s)	Cut-out speed (m/s)	Rotor diameter (m)	Hub height (m)
100	2.5	10	20	25	50

The time for preventive and corrective maintenances are chosen to be 1.2 and 10 time- units respectively. Since the reliability of the components are modelled with Weibull function, scale and shape parameters are presented on table 3.

Table 2. Input parameter for Lambar Rimi

Period (k)	Wind speed (m/s)	Demand (kW)
1	5.4	48
2	3.9	42
3	4.5	50
4	5.7	74
5	4.3	70
6	4.9	60
7	4.5	67
8	4.3	69
9	3.5	51
10	3.6	52
11	3.3	42
12	4.7	35

Table 3. Turbine component's Weibull parameters

Component	Subcomponent	β_i	η_i
Main bearing	-	1.43	6389
Main shaft	-	1.09	3835
Gearbox	Gears	2.50	5715
	HSS bearing	1.52	7244
	IMS bearing	3.63	4694
	keyways	0.84	101790
Generator	Bearings	1.39	4956
	Windings	-	7158

4.1. Production and maintenance results

The production result obtained is presented on table 4 showing the power forecasted and stored per production period. The objective of our integrated policy is to determine the optimal number of maintenance (N*) at minimal cost and maximal reliability. For the maintenance, the optimal number of maintenance sessions (N*) to be performed is 2 at 29,341,461 NGN presented on figure 4. This means that maintenance should be performed twice at 6 months interval.

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Table 4. Optimal production plan using the ANN

Period (k)	Generated power (x10^5 W)	Stored power (x10^3 W)
1	1.2238	1.1758
2	1.1117	1.0691
3	1.5661	1.5161
4	1.5803	1.5063
5	1.4624	1.3924
6	1.5834	1.5174
7	1.3508	1.2838
8	1.0183	0.9493
9	1.2787	1.2277
10	5.2777	0.7208
11	6.5760	0.9156
12	1.4688	1.4338

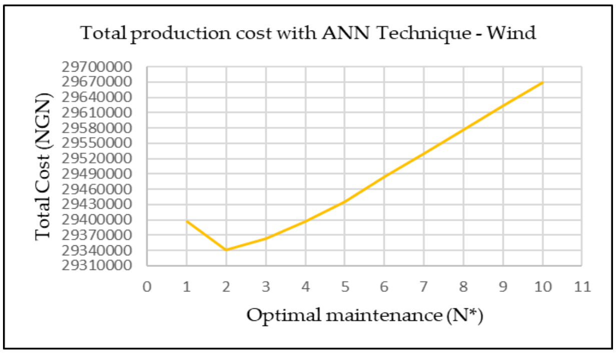

Fig. 3. Optimal economic maintenance plan

4.2. Sensitivity analysis: Influence of service rate

We decided to vary the service rate to 60%, 70% and 90% to understand its influence on the production cost. The result of this variation is presented on table 5.

Table 5. Influence of service rate on production cost

Service rate (%)	Cost (x10^6 NGN)
60	1.9617
70	2.5725
80	2.9145
90	3.1780

5 Conclusion

This work presented an integrated production and maintenance scheduling model based on power forecast by ANN. Production planning was performed by forecasting power production from ANN and was integrated with maintenance model to determine the optimal lifecycle cost for a wind energy power plant. The optimization algorithm was developed to determine the minimal integrated production cost which corresponds with the optimal number of PM actions (N*). The novelty of the work is that the problem takes into account the costs of loss of production due to non-negligible maintenance time subject to reliability constraints. Finally, from the algorithm, PM sessions are to be performed at an interval of 6 months on the system. A sensitivity analysis was performed to validate the algorithm by varying the service rate and reliability thresholds to understand their effect on the production costs. For further work, other techniques of the production will be considered under stricter constraints

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