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An Integrated Production/Maintenance Optimization Planning of a Stand-alone Wind Energy System for Rural Electrification

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Abstract. The renewable energy industry has gained so much attention due to the global importance attached to it. However, these sources are volatile in nature, hence, it is important to properly plan the production system to ensure continuity. This work focused on production and maintenance of wind energy system as a stand-alone system for rural electrification. The methodology for power production forecast in this work is optimization using machine learning technique; support vector regression (SVR) and estimation from theoretical technique. The production optimization is aimed to determine the optimal number of panels and batteries required to satisfy the random demand at minimal cost. In order to improve the system functionality and minimize failure, an integrated preventive maintenance model was developed to determine the optimal number of maintenances to be performed. Thus, scheduling optimal time to perform the preventive maintenance. The maintenance model is integrated with the power production rate to determine the maintenance cost. A numerical simulation was presented in order to test the developed algorithm using a case study in Katsina, Nigeria.

1 Introduction

The ever-growing demand owing to increasing world population inspired us to contemplate alternative sustainable energy sources. Thus, eliciting many research in the area of renewable energy especially solar and wind energy. The current renewable industry is categorized with strong competition to satisfy the needs of a client that is often demanding in terms of energy availability, and cost. However, due to the stochastic nature of the renewable source, appropriate planning must be carried out to ensure customers' needs are satisfied. The scope of this work is on the wind energy sector. Over the years, both offshore and onshore wind energy has received tremendous attention thereby causing annual increase in electricity generation from the wind as shown in figure 1. According to [1], a global installed capacity of 60.4 GW was injected in 2019, which marks the second largest year in history and close to the profuse year of 2015 (63.8 GW) thereby totaling the installed capacity to 651 GW in 2019. The increased injection of wind energy was forecasted by experts in [1] and is expected to rise to 355 GW by the end of 2024 (71 GW annually averagely).

In this study, a stand-alone wind energy development concept is established in terms of modelling and optimization. Stand-alone systems make isolated rural areas self-sufficient for basic needs such as cooking, pumping water and electricity in a cost effective and efficient manner without the need for central grid. Thus, the energy manager needs to efficiently optimize the number of components (wind turbines and batteries) required to satisfy the demand. In this work therefore, we developed a production model that minimizes the production cost by optimizing the number of wind turbines and batteries required for a rural settlement.

Furthermore, a renewable energy (wind in our case) plant is treated as a production industry. Therefore, it is important to perform maintenance on the system in order to improve its functionality to minimize failure and loss of customer's trust. In this context, we developed maintenance strategy integrated with the power production already stated earlier. To develop optimal joint production and maintenance planning, [2] presented an integrated model of preventive maintenance production and planning for multi-state systems. An integrated preventive maintenance strategy was developed by [3] which factors turbine degradation and spare part sourcing as the constraints in their work, with the aim of determining the optimal total cost related to production, maintenance and spare parts. [4] presented an integrated maintenance economic plan related to wind turbines 'energy production by minimizing the total costs of production and maintenance considering the production rate and the degree of deterioration of the turbine over the horizon.

Having studied the above works, we can say that the main objective of maintenance planning is to determine the optimal number of preventive maintenance sessions (N*) to be performed over a production horizon (H), taking into account the optimal production plan

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along with the costs associated with preventive and corrective maintenance.

2 Mathematical modelling

In this section, mathematical modelling problem for both production optimization and maintenance policy are formulated and presented as follows:

2.1. Production optimization problem

The mathematical modelling for optimizing the production system is implemented by minimizing the cost of the system subject to constraints as expressed below:

$$\min C_{system}\,(N_{wt}, C_b)$$

Subject to:

$$N_{wt} * P_{wt}(t) + V_b * SOC(t) \geq P_L(t)$$
$$AEC_{min} \leq AEC(t) \leq AEC_{max}$$
$$N_{wtm} \leq N_{wt}(t) \leq N_{wtM}$$

The total cost of the system (C_{system}) is then elaborated as

$$C_{system} = C_{cap} + C_{ope} \quad (1)$$

$$C_{cap} = \sum_{t=1}^{H} N_{wt}(t) * C_{wt} + C_b(t) * C_{bat} \quad (2)$$

$$C_{ope} = C_{t1} + C_{t2} + C_{t3} \quad (3)$$

C_{cap} is the capital cost of purchasing and installing the components and (C_{ope}) is the operational cost. The operational cost comprises of costs of production (C_{t1}), cost of storage (C_{t2}) and cost of shortage (C_{t3}) evaluated as follows:

$$C_{t1} = \sum_{t=1}^{H}\left(C_p \times \sum_{j=1}^{N_{wt}} P_k(t)\right) \quad (4)$$

$$C_{t2} = \left(C_s^{+} \times \Delta t \times \sum_{t=1}^{H}\left(SOC(t) \times 1_{SOC(t)>0}\right)\right) \quad (5)$$

$$C_{t3} = \left(C_s^{-} \times \Delta t \times \sum_{t=1}^{H}\left(SOC(t) \times 1_{SOC(t)<0}\right)\right) \quad (6)$$

Storage and shortage costs (C_{t2}) *and* (C_{t3}) are evaluated based on the condition of the battery's state of charge which will be later discussed. However, in the meantime, they are modelled as

$$1_{SOC(t)<0} = \begin{cases} 1 \text{ if } SOC(t)) < 0 \\ 0\ otherwise \end{cases} \quad \text{for storage}$$

and

$$1_{SOC(t)<0} = \begin{cases} 1 \text{ if } SOC(t)) < 0 \\ 0\ otherwise \end{cases} \quad \text{for shortage}$$

.

2.2 battery sizing

The battery storage sizing is formulated based on a battery's state of charge (SOC) at any time t which is expressed as follows:

$$SOC(t) = SOC(t-1) + \frac{P_G(t) - P_L(t)}{V_b . TC_b} \quad (7)$$

Given that

$$P_G(t) = \sum_{t=1}^{H} N_{wt} \times P_{wt}(t) \quad (8)$$

Where V_b *and* C_b are the battery voltage and capacity respectively, $P_G(t), P_L(t), P_{wt}(t), N_{wt}(t)$ *and* TC_b are defined as generated power, load demand power, wind turbine power, number of required turbines and the battery's total capacity correspondingly. To ensure good performance of the battery bank, [5] introduced cycle invariance criterion such that SOC at t returns to its initial state $SOC(t_0)$ at the end of each production period. This is mathematically articulated as

$$SOC(t) = SOC(t-1) \quad (9)$$

However, the total battery capacity TC_b is undetermined. Hence, we let $AEC(t)$ denote the available energy capacity of battery bank at t expressed as:

$$AEC(t) = AEC(t_0) + \sum_{t=1}^{H} \frac{P_b(t)}{V_b} \quad (10)$$

We assume that the initial condition $AEC(t_0) = 0$ which means the battery is empty at the initial condition. To avoid deep cycle, a suitable initial condition is proposed such that $AEC(t)$ at each period is characterized by the SOC

$$AEC(t) = SOC(t).C_b \quad (11)$$

In order to determine the total battery bank capacity TC_b over a finite time horizon (H), the TC_b must satisfy the following condition

$$TC_b \geq AEC_{max} - AEC_{min} \quad (12)$$

where

$$AEC_{max} = \max\left(AEC(t)\right) \textit{ and } AEC_{min} = \min\left(AEC(t)\right) \ni t = 1 \ldots H \quad (13)$$

On another hand, to improve the battery efficiency, energy flow in the battery must be limited within a certain range expressed as follows

$$TC_b \geq \frac{|P_b(t)|}{V_b} \qquad \ni t = 1 \ldots H \quad (14)$$

Each battery cycle is characterized by its depth of discharge (DOD) to minimize deep cycle. This means that the amount of capacity withdrawn from a battery is expressed as a percentage of its maximum capacity. Therefore, the allowable DOD must be taken into account in order to extend the working life of the battery. Accordingly, the TC_b is maximum of the combination of equation 12 and 13 expressed in the following form [6]:

$$TC_b = max\left((AEC_{max} - AEC_{min}), |P_b(t)|/V_b\right)/DOD \quad (15)$$

2.3 Power production

For the purpose of this study, we developed the production model based on SVR and theoretical formulation using the Weibull function. They are modelled as follows:

i. Support Vector regression (SVR)

A Support Vector (SV) is a nonlinear kernel-based machine learning technique used for regression as well as classification. It consists of creating or mapping training data into hyper-planes to vividly discriminate predictions from training data in the feature space shown in figure 1. It functions when it is being activated by an activation function known as 'kernel function'. A support vector regression output prediction is calculated in the following form:

$$f(x) = w\varphi(x) + b \quad (16)$$

where φ is the activation function, x is an input data point. w is a normal vector and b is a scalar. They are estimated by minimization of regularized risk function solved as follows [7].

$$\text{minimize } L_p = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{1}(\xi_i + \xi_i^*) \quad (17)$$

$$\text{Subject to} \quad \begin{cases} y_i - \varphi(x_i) - b \leq \epsilon + \xi_i \\ \varphi(x_i) + b - y_i \leq \epsilon + \xi_i \\ \xi_i,\ \xi_i^* \geq 0 \quad i = 1,2,\dots n \end{cases}$$

$\frac{1}{2}\|w\|^2$ represents the regularization term, y_i is the ith target and C is the error penalty factor used to control trade-offs between regularization term and empirical risk. ϵ is the deviation threshold of the function f, and ξ_i is the slack error that guarantees the solution by coping the in-feasible constraints and *n* is the number of elements in training data sample.

ii. Performance analysis

This analysis is used to validate the forecasted output of the SVR model. We adopted the root mean square error for this work. Thus expressed:

$$rRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}|y_t - y_p|^2}}{y_t} \quad (18)$$

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

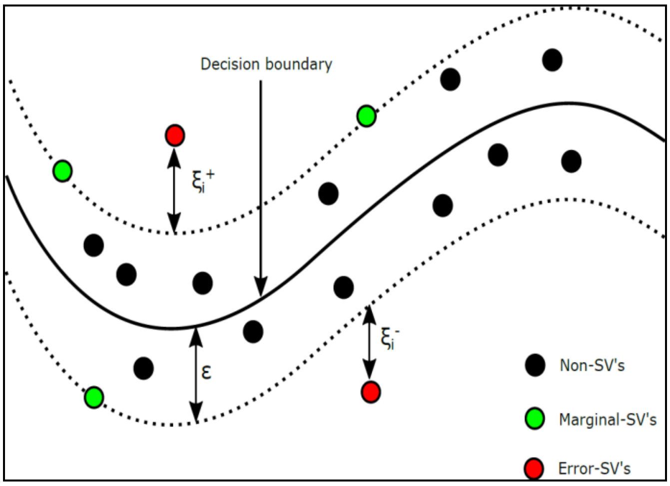

Fig. 1. Support Vector Regression.

iii. Theoretical Weibull modelling:

Estimating wind energy from a wind turbine is an essential aspect of theoretical wind energy management. It enables the manger to estimate the quantity of wind energy to be produced per period. Wind speed is often treated as a random variable characterized by Weibull distribution function expressed as follows:

$$f(v) = \frac{a}{c}\left(\frac{v}{c}\right)^{a-1} exp\left(-\left(\frac{v}{c}\right)^{a}\right) \quad (19)$$

where v is the wind speed (m/s), c and a are the Weibull scale and shape parameters. Different methods of calculating the two parameters of Weibull distribution of wind speed are available in literature [8]. From which the obtainable average wind power P_{wind} from a turbine is estimated by:

$$P_{wind}(v) = \begin{cases} P_r \dfrac{(v^a - v_{ci}^a)}{(v_{ci}^a - v_r^a)} & for\ v_{ci} \leq v \leq v_r \\ P_r & for\ v_r \leq v \leq v_{co} \\ 0 & Otherwise \end{cases} \quad (20)$$

where P_r is rated power of the turbine, υ_r is rated wind speed and υ_{ci} is the cut-in wind speed, υ_{co} is the cut-out wind speed respectively, a is Weibull shape parameter.

2.4 Maintenance planning problem formulation

The objective of this section is to determine the optimal period to perform preventive maintenance on a wind turbine defined by the optimal number of preventive maintenance sessions. The progression of a wind turbine failure rate during each production period is modelled as a function of time and production rate presented by the following relationship:

$$\Delta\lambda(t, P_k) = f(P_k).\lambda_n(t) \quad t \in [0, \Delta t] \quad (21)$$

Where the nominal failure rate ($\lambda_n(t)$) modelled with Weibull distribution as follows

$$\lambda_n(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \quad (22)$$

β and η being Weibull scale and shape parameters respectively. Our maintenance problem is therefore formulated taking into account the influence of the equipment degradation presented in the following form [9];

$$M_C(P_k, N) = C_{pm} \cdot N + C_{cm} \cdot \bar{Y}(P_k, N) \quad (23)$$

where $\bar{Y}(P_k, N)$ is average failure rate, and we can say that $N = \left\lfloor \frac{H}{T} \right\rfloor$.

As already stated, the maintenance strategy adopted in this work is perfect maintenance with minimal repair. Thus, evaluating the average number of failures between preventive maintenance intervals. It is a function of production rate (P_k) and N determined by calculating the integral of the function rate of the failure which must be a monotonically increasing function expressed as follows:

$$\bar{Y}(P_k, N) = \sum_{j=1}^{\frac{H/T}{\Delta t}} \left[\sum_{i=1}^{\frac{T}{\Delta t}} \int_0^{\Delta t} \frac{P_{i,T}}{P_{max}} . \lambda_n(t).dt + \sum_{i=2}^{\frac{T}{\Delta t}} \left(\frac{T}{\Delta t} - (i-1) \right) . \left(\frac{P_{i-1,T}}{P_{max}} . \lambda_n(\Delta t).\Delta t \right) \right]$$
$$+ \left(\sum_{i=\left\lfloor \frac{H/T}{\Delta t} \right\rfloor . T+1}^{H} \int_0^{\Delta t} \frac{P_i}{P_{max}} . \lambda_n(t).dt + \sum_{i=\left\lfloor \frac{H/T}{\Delta t} \right\rfloor . T+2}^{H} \left(H - \left\lfloor \frac{H}{\frac{T}{\Delta t}} \right\rfloor . T \right) \right.$$
$$\left. - \left(i - \left\lfloor \frac{H}{\frac{T}{\Delta t}} \right\rfloor . T - 1 \right) . \frac{P_i}{P_{max}} . \lambda_n(\Delta t).\Delta t \right)$$

2.5 Integrated production and maintenance algorithm

In order to determine the optimal number of preventive maintenance actions, we propose the following simple numerical procedure shown on fig 2. The algorithm calculates maintenance cost corresponding to N ∈ {1…}. N* is the optimal N with the lowest maintenance cost Mc*. From the beginning of the algorithm, for each N, the associated cost Mc is calculated. In two successive computations, Mc with minimal amount automatically becomes the optimal cost Mc* and is stored until a lesser cost is obtained. In that case, the new minimal cost automatically becomes the optimal. All the wind turbines are assumed to be identical with similar power ratings, thus expected to have same power output. Therefore, maintenance planning is considered for one (1) wind turbine.

3 Numerical analysis

This section is aimed at demonstrating the viability of our developed algorithm for Katsina wind farm in Nigeria as the case study. Katsina is the capital of Katsina state in the federal republic of Nigeria located at 13º01'N latitude and 07º41'E longitude. We consider the pilot 10 MW wind farm installed in Katsina having average monthly wind speed presented on table 1. The wind system is considered as a stand-alone wind/battery energy system supplying a remote area of Lambar Rimi community which has a monthly average load demand also shown on table 1.

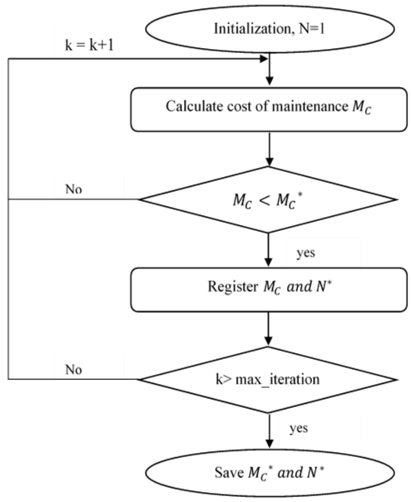

Fig. 2. Numerical procedure to determine optimal number of maintenances (N*).

Table 1. Input parameter for Lambar Rimi

Period (k)	Wind speed (m/s)	Load 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

It is estimated that the cost of energy production and storage from wind power plant is 15 NGN and 17 NGN respectively (NGN = Nigerian Naira). When load demand is unmet and energy has to be sourced from the grid, the cost of this shortage is obtained at 25 NGN. The cost of purchasing a Hummer H25-100kW turbine is 1,800,000 NGN. Table 2 presents the maintenance parameters.

Table 2. Maintenance planning data

β	η	Cpm (NGN)	Ccm (NGN)
1.5	5	50,000	300,000

3.1 Production result

Analysis of power production forecasting to show SVR model accuracy with rMSE is 3.42%. With this performance index, we can certainly say that our model fits well with the data.

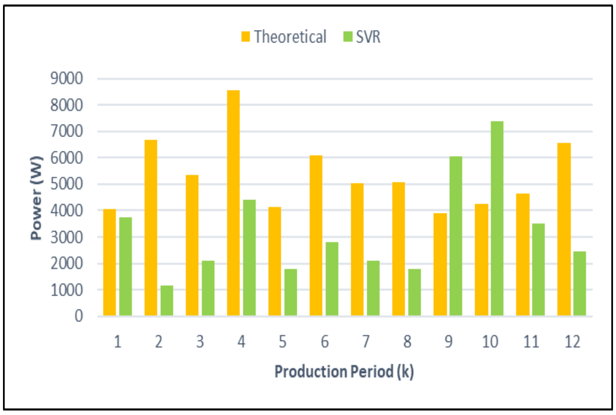

Fig. 3. Power available in the battery for the 2 models.

The optimal production plan for both theoretical and SVR methods as well as the quantity of power in the battery are presented on table 3.

Table 3. Optimal wind production plan

	Theoretical		SVR	
	Total cost = 45.2808 x10^7 (NGN)		Total cost = 42.3162 x10^7 (NGN)	
Period (k)	Number of wind turbines (wt)	Power generated (x10^6W)	Number of wind turbines (wt)	Power generated x10^5 (W)
1	4	3.770	3	2.300
2	3	1.160	2	1.730
3	4	2.110	2	1.880
4	5	4.390	3	2.760
5	3	1.770	2	1.840
6	3	2.810	3	2.110
7	4	2.110	3	2.030
8	3	1.770	2	1.990
9	3	0.608	2	1.490
10	3	0.742	2	1.570
11	3	0.354	2	1.460
12	4	2.450	3	2.180

From the tables of results, cost of production from the theoretical technique is seen to be higher than the SVR technique. This can be explained by the fact that the theoretical technique uses Weibull function which depends on random Weibull parameters for a wind turbine. With the SVR, it is a forecast from the real-life situation of the powerplant, hence providing a true solution.

3.2 maintenance planning result

The proposed optimal maintenance plan is presented on table 4 showing the optimal values for the maintenance costs as well as the number of PM sessions for SVM and theoretical techniques. From the table, it is seen that the optimal maintenance to be performed on the system is 2 to be performed every 6 months for both techniques. The theoretical technique presented the minimal cost of maintenance at 198,901 NGN while with the SVM, the cost is 207,316 NGN.

Table 4. Optimal number of preventive maintenances

Technique	N*	Cost (NGN)
SVM	2	207,316.00
Theoretical	2	198,901.00

3.3 sensitivity analysis

In this section, we seek to study the influence of the change of some parameters on the maintenance plan. We therefore study the variation in the values of the unit costs of preventive maintenance (Cpm) and corrective maintenance (Ccm) and their effect on the optimal number of preventive maintenance sessions to be carried out on the wind energy system. Here, we vary the difference between corrective maintenance costs and preventive maintenance costs by increasing the difference of corrective maintenance from NGN300,000 to NGN 500,000, NGN 700,000 and NGN 900,000 keeping the preventive maintenance cost at NGN50,000. The obtained result is shown on table 5.

Table 5. Optimal number of PM (N*) with varying cost of corrective maintenances:

Ccm (NGN)	Technique	N*	Cost (NGN)
500,000	SVM	3	266,600.00
	Theoretical	3	250,295.00
700,000	SVM	3	313,240.00
	Theoretical	3	290,413.00
900,000	SVM	3	359,880.00
	Theoretical	3	330,531.00

By varying the maintenance costs, the optimal number of actions to be performed are 3 for both SVM and the theoretical approach which are to be performed every 4 months. With further increase to NGN 700,000, it yields the same result. This means that the cost increases by reducing the effect of failure rate on the system. This can be said to be caused by the influence of Weibull parameters on the maintenance cost.

4 Conclusion

In this work, we developed methodology for optimizing a wind farm considering katsina in Nigeria as our case study. For each period over one-year horizon, the optimal number of wind turbines, the battery capacity required and the quantity of energy produced were obtained and the total production cost presented. Maintenance planning scheduling was also proposed to determine the optimal number of maintenance sessions to be performed and the optimal cost associated with it. The optimal wind energy plan obtained with the machine learning technique presented the least production cost. In this case, we can say Weibull parameters influence the cost estimation. For further work, a metaheuristic method of artificial intelligence will be applied to solve both production and maintenance problems.

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