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Performance Evaluation of Stochastic Model of a Paper Machine Having Three Types of Faults

Veena Rani
Research Scholar
Dept.of Mathematics
Baba Mastnath University
Rohtak,Haryana,India

Pooja Bhatia
Associate Professor
Dept. of Mathematics,
Baba Mastnath University
Rohtak, Haryana,India

Abstract: Aim of present paper is to evaluate the performance of a paper machine installed in a paper mill of Northern Haryana namely Sri Jagdumbe Paper Mills Ltd. located at Sirsa (Haryana) using stochastic modeling of a single unit considering three types of faults i.e. minor, major faults and power failure during operation of the machine. Minor/major faults are repairable as well as non repairable and for the purpose of calculations in this paper, it is assumed that there is facility of single repairman for inspection, repair and replacement etc. Considering all these aspects and using the real data collected from the mill, various measures of system effectiveness such as MTSF, Reliability, Availability and Busy period etc. are derived by using Semi-Markov process and Regenerative Point technique. The performance of the machine is evaluated using numerical results and graphs derived thereof. From the graphs so obtained, we get cut-off points of profit for different values of rates of minor, major faults/ revenue of availability/ costs etc., which will helpful for management team of Paper Mill to make the paper machine more yielding.

Keywords: availability; MTSF; performance; reliability; Regenerative Point technique.

1. INTRODUCTION:

Paper has several uses in different form in almost all the fields, therefore, paper industry has its own importance and it plays a vital role in the economic as well as social growth of a country. In the present scenario of competitive market, improvement in performance of the machines with minimum operating cost is the main objective of each industry. In the present paper, real data relating to a paper machine, installed in **Sri Jagdumbe Paper Mlls Ltd. Sirsa,** has been collected personally by visiting the said mill premises from time to time and a stochastic model is developed considering its various types of faults using Semi-Markov Process and Regenerative Point Technique. The paper machine is a single unit complex system with various sub systems wherein different faults occur during operation. The faults are categorised as minor and major faults on the basis of down time and cost which are repairable as well as non-repairable. Since the machine is operative round the clock, therefore, power failures/ degradation are also considered as faults. It is observed that on occurrence of a minor fault, machine partially stopped and we get the product with reduced capacity, whereas in case of major fault, operation of the machine is completely stopped. Further, in case of power failures/ degradation, the machine stops temporarily i.e. for few minutes. There is a single repairman who visits the machine immediately whenever needed. Firstly, he inspects the machine for fault finding and observes whether the fault is repairable or non-repairable. In case of repairable fault, the defective part is repaired whereas in case of non-repairable fault, the defective part of the machine is replaced. For numerical calculations, inspection rates, repair rates and replacement rates are assumed to follow Exponential Distributions. On the basis of so collected real data, by using Semi-Markov Process and Regenerative Point Technique, various measures of system effectiveness such as MTSF, Reliability, Availability (with full and reduced capacity) and Busy Period of repairman are obtained. Finally, numerical calculations and graphs drawn on the basis thereof have been used for evaluation of performance of the machine which is useful for smooth and better functioning of the industry.

So many Researchers and Scientists are trying to improve the performance of industries using various reliability techniques. **Branson and Shah (1971)** discussed a system with exponential failure and arbitrary repair distributions while adopting Semi-Markov Process. **Nakagawa (1976)** considered the replacement of the unit at a certain level of damage whereas. **Goel et al. (1986)** obtained the reliability analysis of a system with preventive maintenance. **Kumar et al. (1989)** analysed the reliability and availability behaviour of subsystems of paper industry by using probabilistic approach. **Gupta et al. (2005)** worked on the system reliability and availability in butter oil processing plant by using Markov Process and R-K method. **Kumar and Bhatia (2011)** discussed reliability and cost analysis of a one unit centrifuge system with single repairman and Inspection. **Malik et al.(2012)** analysed a stochastic model of a repairable system of a non-identical units with priority for operation and repair subject to weather conditions. **Bhatia and Kumar (2013)** studied Performance and Profit Evaluations of a Stochastic Model on Centrifuge System Working in Thermal Power Plant Considering Neglected Faults**. Sharma and Vishwakarma (2014)** applied Markov Process in performance analysis of feeding system of sugar industry. **Renu and Bhatia (2017)** dealt with reliability analysis for removing shortcomings using stochastic processes and applied for maintenance in industries. A few of the Researchers have worked for real data of paper machine. **Rajaprasad (2018)** investigated the reliability, availability and maintainability (RAM) characteristics of a paper machine from a paper mill.

For the purpose of performance evaluation, a stochastic model is developed by using Regenerative Point Technique and following measures of system effectiveness are obtained:

- Transition Probabilities
- Mean Sojourn Time
- Mean Time to System Failure (MTSF)
- Reliability
- Availability with full/reduced capacity
- Busy Period of Service man (Inspection, Repair, Replacement time)
- Power Degradation Period
- Performance Analysis (Profit)

2. ASSUMPTIONS:

- The system consists of a single unit,
- The system is as good as new after each repair and replacement.
- The Service man reaches the system in negligible time.
- A single Service man facility is provided to the system for inspection, repair and replacement of the components.
- Time distributions of various faults i.e. minor/major/ power failure are Exponential distribution and other time distributions are general.
- A minor fault leads to degradation/ failure whereas a major fault leads to complete failure.
- Due to power failure/degradation the machine stops temporarily for few minutes.

3. NOTATIONS:

O: Operative Unit.

$\lambda_1/\lambda_2/\lambda_3$: Rate of minor faults/ major faults/ power failure.

a/b: Probability that a minor fault to be repairable/ non- repairable.

x/y: Probability that a major fault to be repairable/ non- repairable.

$i_1(t)/I_1(t)$: pdf/cdf of rate of inspection of a minor fault w.r.t. time.

$i_2(t)/I_2(t)$: pdf/cdf of rate of inspection of a major fault w.r.t. time.

$g_1(t)/G_1(t)$: pdf/cdf of repair rate of minor faults w.r.t. time.

$g_2(t)/G_2(t)$: pdf/cdf of repair rate of major faults w.r.t. time.

$h_1(t)/H_1(t)$: pdf/cdf of replacement rate of minor faults w.r.t. time.

$h_2(t)/H_2(t)$: pdf/cdf of replacement rate of major faults w.r.t. time.

$k_1(t)/K_1(t)$: pdf/cdf of rate of power degradation/ failure w.r.t. time.

Ⓒ/Ⓢ: Laplace convolution/ Laplace stieltjes convolution.

*/**: Laplace transformation/ Laplace stieltjes transformation.

$q_{ij}(t)/Q_{ij}(t)$: pdf/cdf for the transition of the system from one regenerative state S_i to another regenerative state S_j or to a failed state S_j.

4. MODEL DESCRIPTION:

Different states of the system model according to Semi Markov process and Regenerative Point Technique are as follows:

State 0: Initial operative state.

State 1: Operative unit partially failed due to some minor faults.

State 2: Unit completely failed due to some major faults.

State 3: Unit temporarily failed due to power degradation/ failure.

State 4: After inspection unit undergoes for repair of minor fault and system is operative.

State 5: After inspection unit undergoes for removal of minor fault by replacement of components/ parts and system is operative.

State 6: After inspection unit undergoes for repair of major fault and system is operative.

State 7: After inspection unit undergoes for removal of major fault by replacement of components/ parts and system is operative.

Here, state 0 is operative state with full capacity whereas 1,4 and 5 are operative states with reduced capacity, state 3 is temporarily failed and states 2,6 and 7 are failed states.

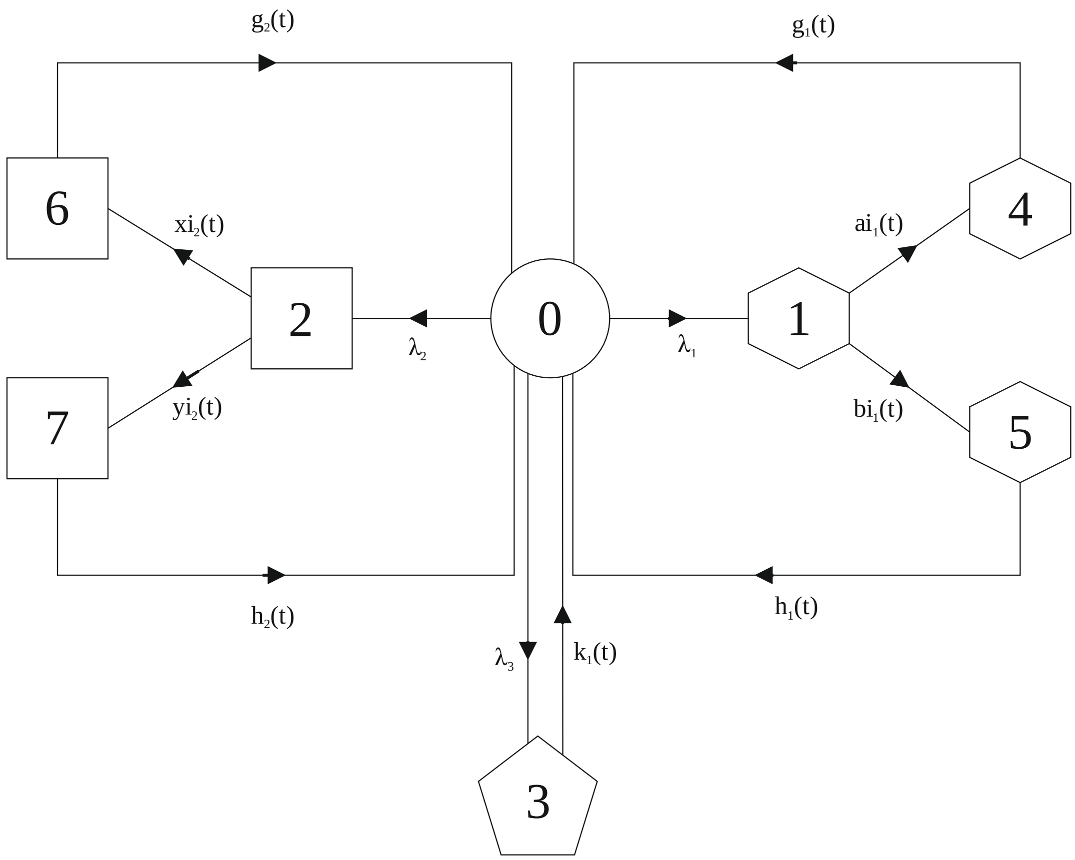

Figure.1. Model

○ Operative State □ Failed State ⬡ Degraded State ⬠ Temporary/short Failed State

5. RELIABILITY INDICATORS:

5.1 Transition Probabilities:

By simple probabilistic arguments, we can find transition probabilities given by:

$$p_{ij} = \lim_{s\to 0} Q_{ij}^{**}(s) \quad \text{where,} \quad Q_{ij}^{**}(s) = \int_0^\infty e^{-st} dQ_{ij}(t)dt$$

$$p_{01} = \frac{\lambda_1}{\lambda_1+\lambda_2+\lambda_3} \qquad p_{02} = \frac{\lambda_2}{\lambda_1+\lambda_2+\lambda_3}$$

$$p_{03} = \frac{\lambda_3}{\lambda_1+\lambda_2+\lambda_3} \qquad p_{14} = \mathbf{a}\, i_1^*(0) = \mathbf{a}$$

$$p_{15} = \mathbf{b}\, i_1^*(0) = \mathbf{b} \qquad p_{26} = xi_2^*(0) = \mathbf{x}$$

$$p_{27} = yi_2^*(0) = \mathbf{y} \qquad p_{30} = k_1^*(0) = 1$$

$$p_{40} = g_1^*(0) = 1 \qquad p_{50} = h_1^*(0) = 1$$

$$p_{60} = g_2^*(0) = 1 \qquad p_{70} = h_2^*(0) = 1$$

It is simple to verify that

$$p_{01} + p_{02} + p_{03} = 1, \;\; p_{14} + p_{15} = \mathbf{a}+\mathbf{b} = 1,$$

$$p_{26} + p_{27} = \mathbf{x}+\mathbf{y} = 1, \; p_{30} = p_{40} = p_{50} = p_{60} = p_{70} = 1$$

5.2 Means Sojourn Time:

The unconditional mean time taken by the system to transit from any regenerative state S_i into state S_j when time is counted from epoch of entrance is given by:

$$m_{ij} = \int_0^\infty t dQ_{ij}(t) = -Q_{ij}^{*\prime}(0)$$

Thus, $m_{01} = \frac{\lambda_1}{(\lambda_1+\lambda_2+\lambda_3)^2}$ $m_{02} = \frac{\lambda_2}{(\lambda_1+\lambda_2+\lambda_3)^2}$

$m_{03} = \frac{\lambda_3}{(\lambda_1+\lambda_2+\lambda_3)^2}$

$m_{14} = -\mathbf{a}\, i_1^{*\prime}(0)$ $m_{15} = -\mathbf{b}\, i_1^{*\prime}(0)$ $m_{26} = -\ x i_2^{*\prime}(0)$

$m_{27} = -\ y i_2^{*\prime}(0)$ $m_{30} = -\ k_1^{*\prime}(0)$ $m_{40} = -\ g_1^{*\prime}(0)$

$m_{50} = -\ h_1^{*\prime}(0)$ $m_{60} = -\ g_2^{*\prime}(0)$ $m_{70} = -\ h_2^{*\prime}(0)$

Also, Mean Sojourn Time in state S_i is given by:

$\mu_i = \int_0^\infty P(T > t)dt$

$\mu_0 = \frac{1}{\lambda_1+\lambda_2+\lambda_3}$ $\mu_1 = -\ i_1^{*\prime}(0)$ $\mu_2 = -\ i_2^{*\prime}(0)$

$\mu_3 = -\ k_1^{*\prime}(0)$ $\mu_4 = -\ g_1^{*\prime}(0)$ $\mu_5 = -\ h_1^{*\prime}(0)$

$\mu_6 = -\ g_2^{*\prime}(0)$ $\mu_7 = -\ h_2^{*\prime}(0)$

Thus, we see that

$m_{01} + m_{02} + m_{03} = \mu_0$, $m_{14} + m_{15} = \mu_1$, $m_{26} + m_{27} = \mu_2$

$m_{30} = \mu_3$, $m_{40} = \mu_4$, $m_{50} = \mu_5$, $m_{60} = \mu_6$, $m_{70} = \mu_7$

5.3 Measures of System Effectiveness:

Using probabilistic arguments for regenerative processes, various recursive relations are obtained and are solved to find different measures of system effectiveness, which are as follows:

Mean time to system failure (MTSF) = $\frac{N_1}{D_1}$,

Where, $N_1 = \mu_0 + \mu_1 p_{01} + \mu_4 p_{14} p_{01} + \mu_5 p_{15} p_{01}$

and $D_1 = p_{02} + p_{03}$.

Availability per unit time with full capacity (A_0) = $\frac{N_2}{D_2}$,

Availability per unit time with reduced capacity (RA_0) = $\frac{N_3}{D_2}$,

Busy period of service man (inspection time) $B_0^I = \frac{N_4}{D_2}$,

Busy period of service man (repair time) (B_0^R)= $\frac{N_5}{D_2}$,

Busy period of service man (replacement time) (B_0^{Rp})= $\frac{N_6}{D_2}$,

Expected Power Degradation Period due to power failure/degradation (D_0)= $\frac{N_7}{D_2}$,

Where,

$N_2 = \mu_0$; $N_3 = \mu_1 p_{01} + \mu_4 p_{14} p_{01} + \mu_5 p_{15} p_{01}$; $N_4 = \mu_1 p_{01} + \mu_2 p_{02}$;

$N_5 = \mu_4 p_{01} p_{14} + \mu_6 p_{02} p_{26}$; $N_6 = \mu_5 p_{01} p_{15} + \mu_7 p_{02} p_{27}$; $N_7 = \mu_3 p_{03}$

and

$D_2 = \mu_0 + \mu_1 p_{01} + \mu_2 p_{02} + \mu_3 p_{03} + \mu_4 p_{14} p_{01} + \mu_5 p_{15} p_{01} + \mu_6 p_{02} p_{26} + \mu_7 p_{27} p_{02}$

5.4 Performance (Profit) Analysis:

The performance of the system in the form of profit (P_0) can be figured as follows:

$P_0 = C_0 A_0 + C_1 RA_0 - C_2 B_0^I - C_3 B_0^R - C_4 B_0^{Rp} - C_5 D_0 - C_6$

Where,

C_0 = Revenue per unit availability with full capacity of the system;

C_1 = Revenue per unit availability with reduced capacity of the system;

C_2= Cost per unit time of inspection;

C_3 = Cost per unit time of repair;

C_4 = Cost per unit time of replacement;

C_5 = Cost per unit time of power degradation;

C_6 = Miscellaneous cost.

5.5 Numerical Study and Graphical Analysis:

Giving some particular values to the parameters and considering

$k_1(t) = \alpha_1 e^{-\alpha_1(t)}$, $h_1(t) = \gamma_1 e^{-\gamma_1(t)}$, $h_2(t) = \gamma_2 e^{-\gamma_2(t)}$,

$g_1(t) = \beta_1 e^{-\beta_1(t)}$, $i_1(t) = \eta_1 e^{-\eta_1(t)}$, $g_2(t) = \beta_2 e^{-\beta_2 t)}$,

$i_2(t) = \eta_2 e^{-\eta_2(t)}$,

We get $p_{01} = \frac{\lambda_1}{\lambda_1+\lambda_2+\lambda_3}$, $p_{02} = \frac{\lambda_2}{\lambda_1+\lambda_2+\lambda_3}$,

$p_{03} = \frac{\lambda_3}{\lambda_1+\lambda_2+\lambda_3}$, $p_{14} =$ **a**, $p_{15} =$ **b**

$p_{26} = x$, $p_{27} = y$, $p_{30} = 1$, $p_{40} = 1$, $p_{50} = 1$, $p_{60} = 1$, $p_{70} = 1$;

and $\mu_0 = \frac{1}{\lambda_1+\lambda_2+\lambda_3}$, $\mu_1 = \frac{1}{\eta_1}$, $\mu_2 = \frac{1}{\eta_2}$, $\mu_3 = \frac{1}{\alpha_1}$,

$\mu_4 = \frac{1}{\beta_1}$, $\mu_5 = \frac{1}{\gamma_1}$, $\mu_6 = \frac{1}{\beta_2}$, $\mu_7 = \frac{1}{\gamma_2}$.

For the above particular cases, taking values from the collected data and assuming the values

$\lambda_1 = 0.012$, $\lambda_2 = 0.007$, $\lambda_3 = 0.003$, $\alpha_1 = 4.5$, $\beta_1 = 4.71$, $\beta_2 = 0.82$, $\gamma_1 = 3.25$, $\gamma_2 = 0.53$, $\eta_1 = 0.9$, $\eta_2 = 0.7$, **a** = 0.8, **b** = 0.2, x=0.33, y=0.67.

We obtained the following values for the measures of system effectiveness:

Mean Time to System Failure (MTSF) (T_0) = 101.357

Availability per unit time with full capacity (A_0) = 0.9635

Availability per unit time with reduced capacity (RA_0) = 0.0155

Busy period of Repairman (Inspection time) (B_0^I) = 0.0225

Busy period of Repairman (Repair time) (B_0^R) = 0.0046

Busy period of Repairman (Replacement time) (B_0^{Rp}) = 0.0092

Power degradation per unit time = 0.00064

Using above numerical values, various graphs are drawn for MTSF(T_0), Availability with full/ reduced capacity (R_0/AR_0) and profit(P_0) of the system for different values of rates of minor faults, major faults as well as rate of power degradation (λ_1, λ_2, λ_3), different inspection rates(η_1,η_2), different costs (C_0, C_6) etc.

Following has been interpreted and concluded from the graphs so formed:

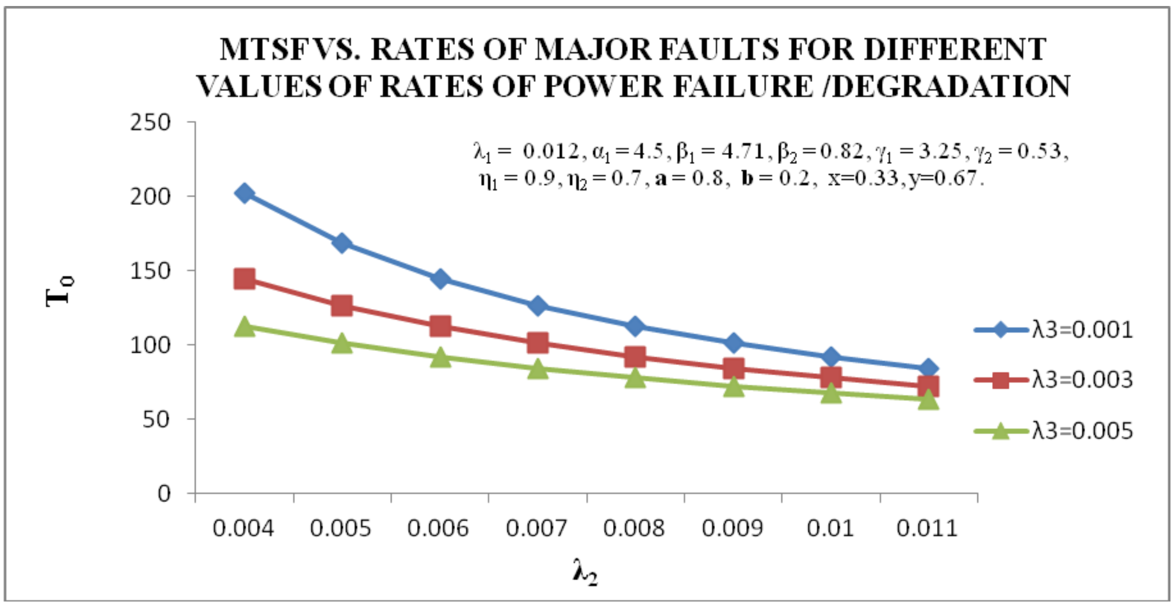

Figure.2.

Fig.2 gives the graph between MTSF (T_0) and the rate of major faults (λ_2) for different values of rate of power degradation (λ_3). The graph shows that the MTSF decreases with the increase in the values of rate of major faults and it has lower value for higher values of rate of power degradation.

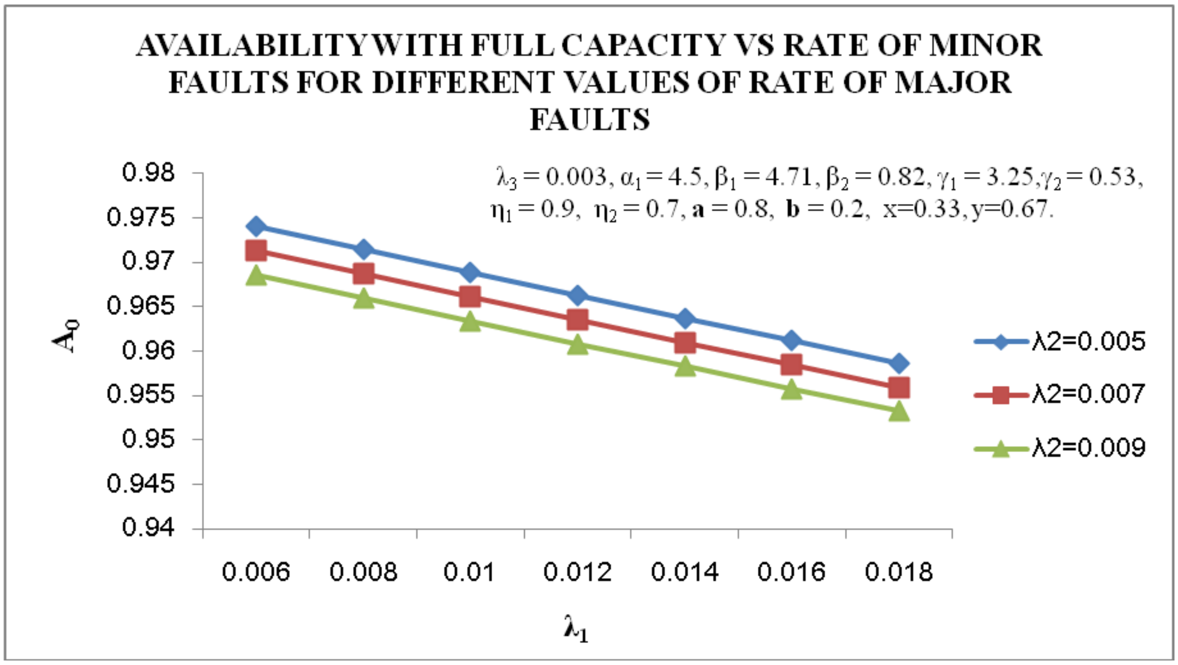

Figure.3.

Fig. 3 is the graph between availability with full capacity (A_0) and the rate of minor faults (λ_1) for different values of rate of major faults (λ_2). It reveals that availability with full capacity decreases with the increase in the value of rate of minor faults and it has lower values for higher values of rate of major faults.

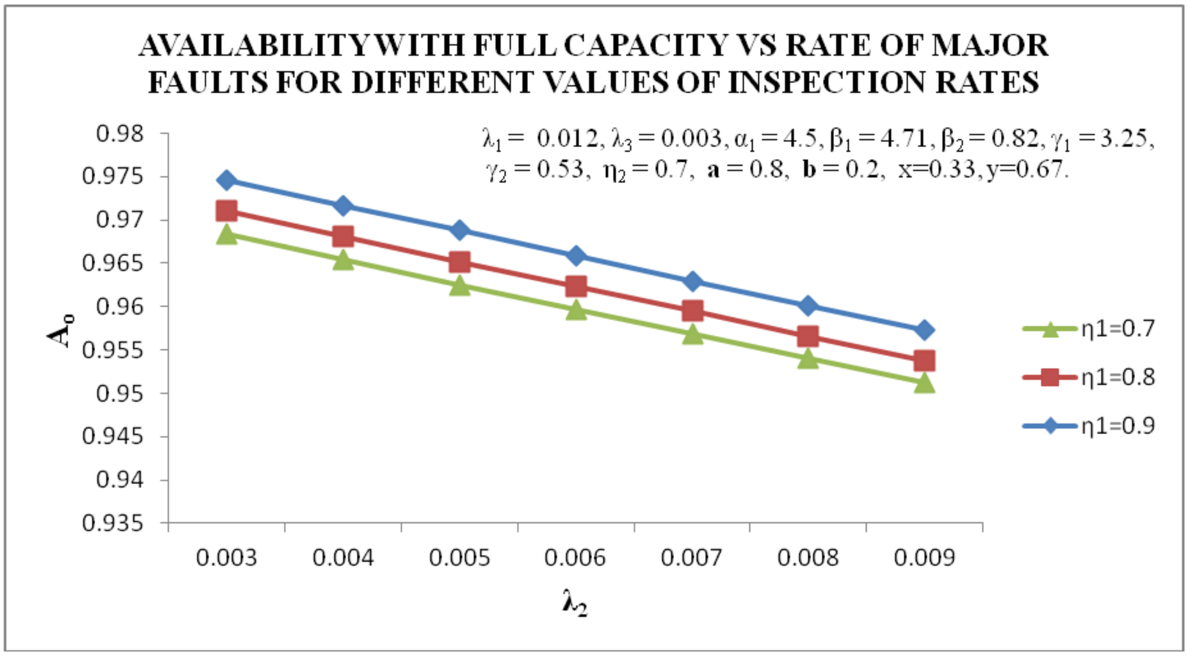

Figure.4.

Fig.4 presents the graph between availability with full capacity (A_0) and rate of major faults (λ_2) for different values of inspection rates (η_1). It can be concluded from the graph that the availability with full capacity decreases with the increase in the value of rate of major faults and it has lower value for lower inspection rate.

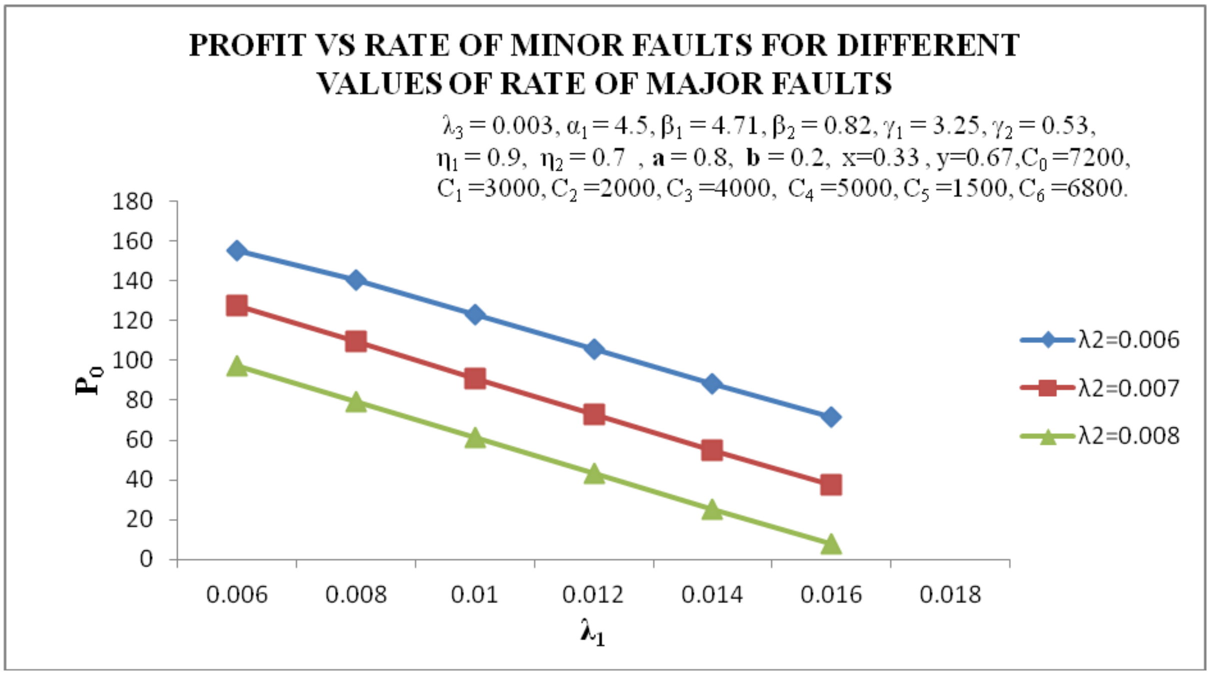

Figure.5.

In graph at Fig.5 relation has been shown between profit (P_0) and rate of minor faults (λ_1) for different values of rate of major faults (λ_2). It reveals that the profit decreases with the increase in the value of rate of minor faults and also it is shown that it has lower values for higher values of rate of major faults.

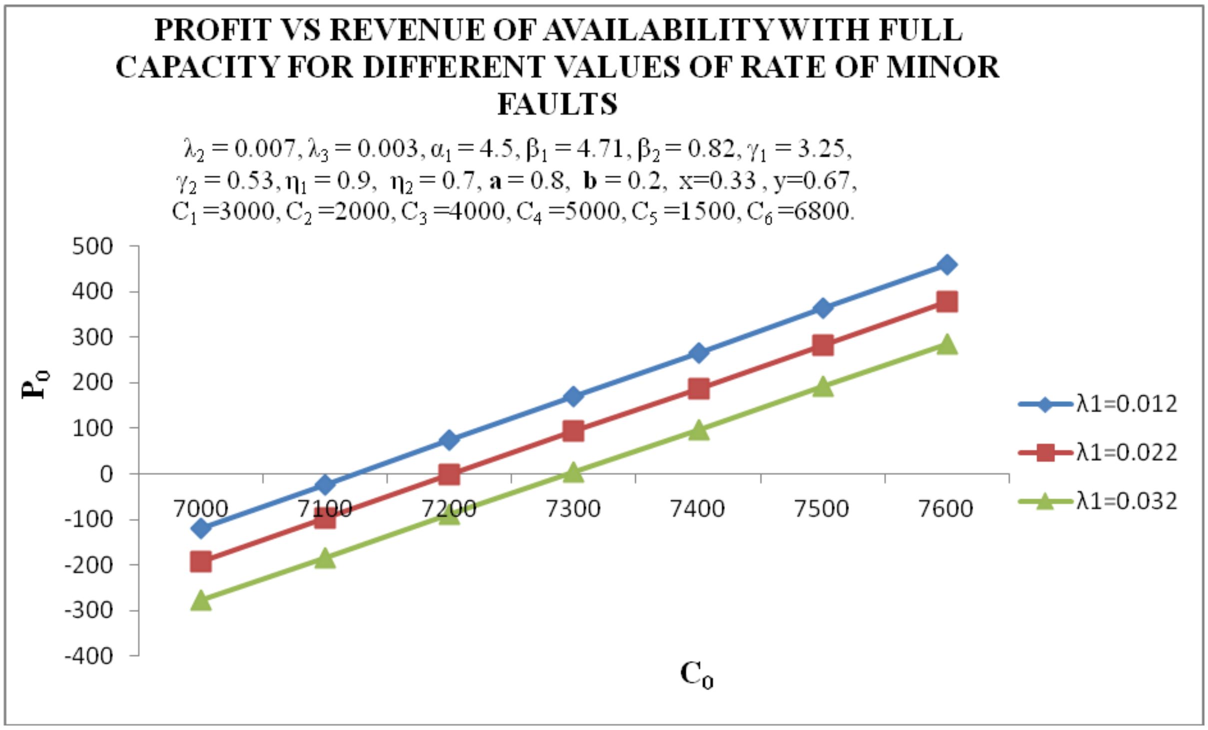

Figure.6.

Graph at Fig.6 is between profit (P_0) and the revenue of availability with full capacity (C_0) for different values of rate of minor faults (λ_1).

From the graph, we have concluded as follows:

1. The profit increases with the increase in the revenue of availability with full capacity and it has lower values for higher values of rate of minor faults.
2. For λ_1 = 0.012, the profit is negative or zero or positive according as C_0 is less than or equal or greater than Rs.7123.8. Thus, the machine will give profit for this when C_0 is greater than Rs.7123.8.
3. For λ_1 = 0.022, the profit is negative or zero or positive according as C_0 is less than or equal or greater than Rs.7202.3. Thus, the machine will give profit for this when C_0 is greater than Rs.7202.3.
4. For λ_1 = 0.032, the profit is negative or zero or positive according as C_0 is less than or equal or greater than Rs.7295.4. Thus, the machine will give profit for this when C_0 is greater than Rs.7295.4.

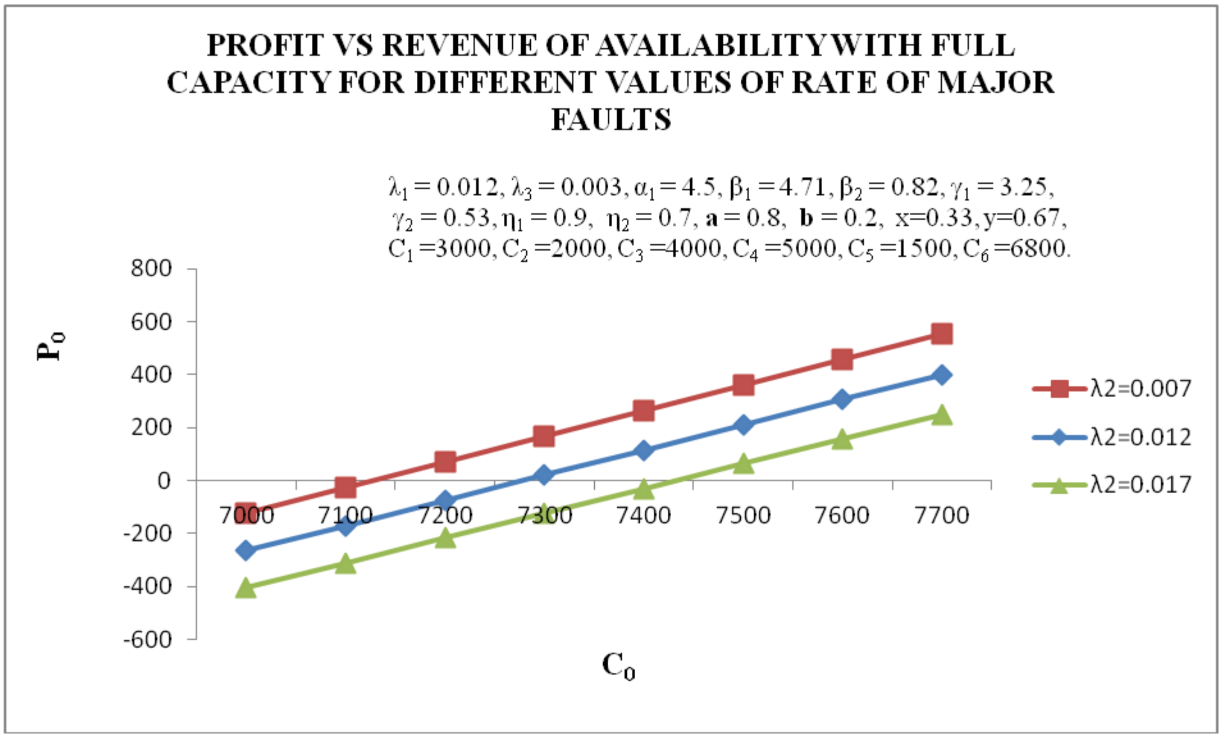

Figure.7.

Fig.7 shows the graph between profit (P_0) and the revenue of availability with full capacity (C_0) for different values of rate of major faults (λ_2).

We have concluded from the graph as follows:

i) The profit increases with the increase in the revenue of availability with full capacity and it has lower values for higher values of rate of major faults.

ii) For λ_2 = 0.007, the profit is negative or zero or positive according as C_0 is less than or equal or greater than Rs.7123.8. Thus, the machine will give profit for this when C_0 is greater than Rs.7123.8.

iii) For λ_1 = 0.012, the profit is negative or zero or positive according as C_0 is less than or equal or greater than Rs.7277.6. Thus, the machine will give profit for this when C_0 is greater than Rs.7277.6.

iv) For λ_1 = 0.017, the profit is negative or zero or positive according as C_0 is less than or equal or greater than Rs.7431. Thus, the machine will give profit for this when C_0 is greater than Rs.7431.

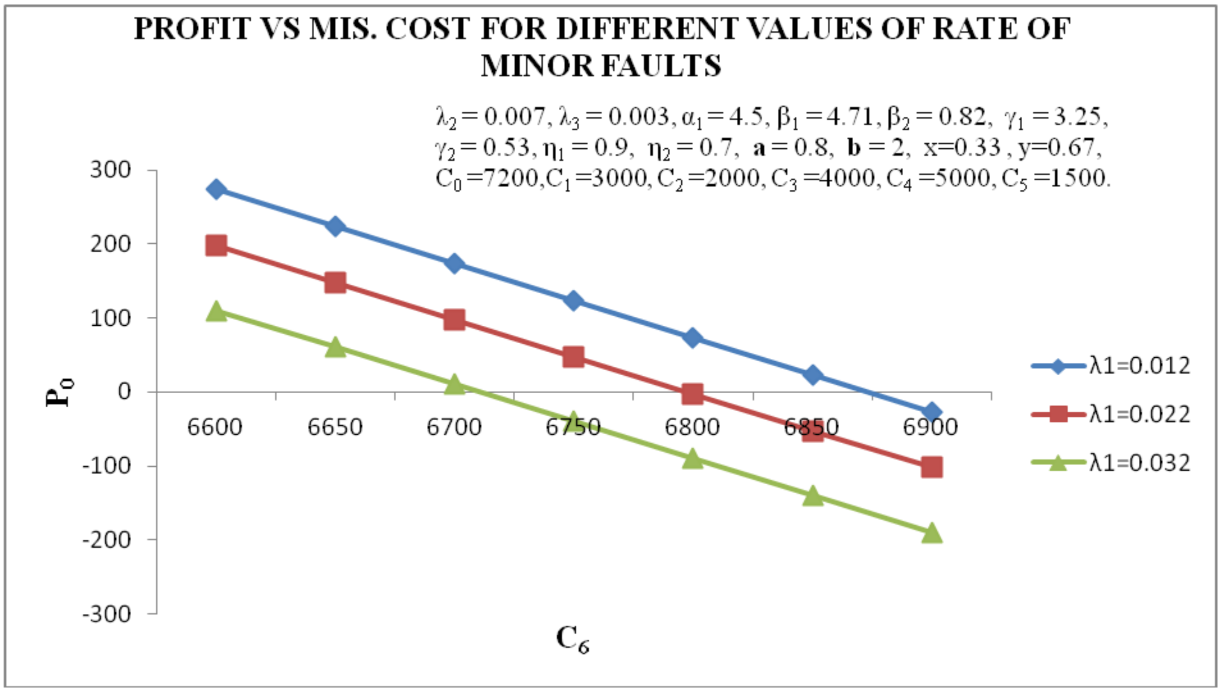

Figure.8.

Fig.8 is the graph between profit (P_0) and miscellaneous cost (C_6) for different values of rate of minor faults (λ_1).

The conclusions of the graph are as follows:

I. The profit decreases with the increase in the miscellaneous cost and it has lower values for higher values of rate of minor faults.

II. For λ_1 = 0.012, the profit is negative or zero or positive according as C_6 is greater than or equal or less than Rs.6873.4. Thus, the machine will give profit for this when C_6 is less than Rs.6873.4.

III. For λ_1 = 0.022, the profit is negative or zero or positive according as C_6 is greater than or equal or less than Rs.6797.7. Thus, the machine will give profit for this when C_6 is less than Rs.6797.7.

IV. For λ_1 = 0.032, the profit is negative or zero or positive according as C_6 is greater than or equal or less than Rs.6710.3. Thus, the machine will give profit for this when C_0 is less than Rs.6710.3.

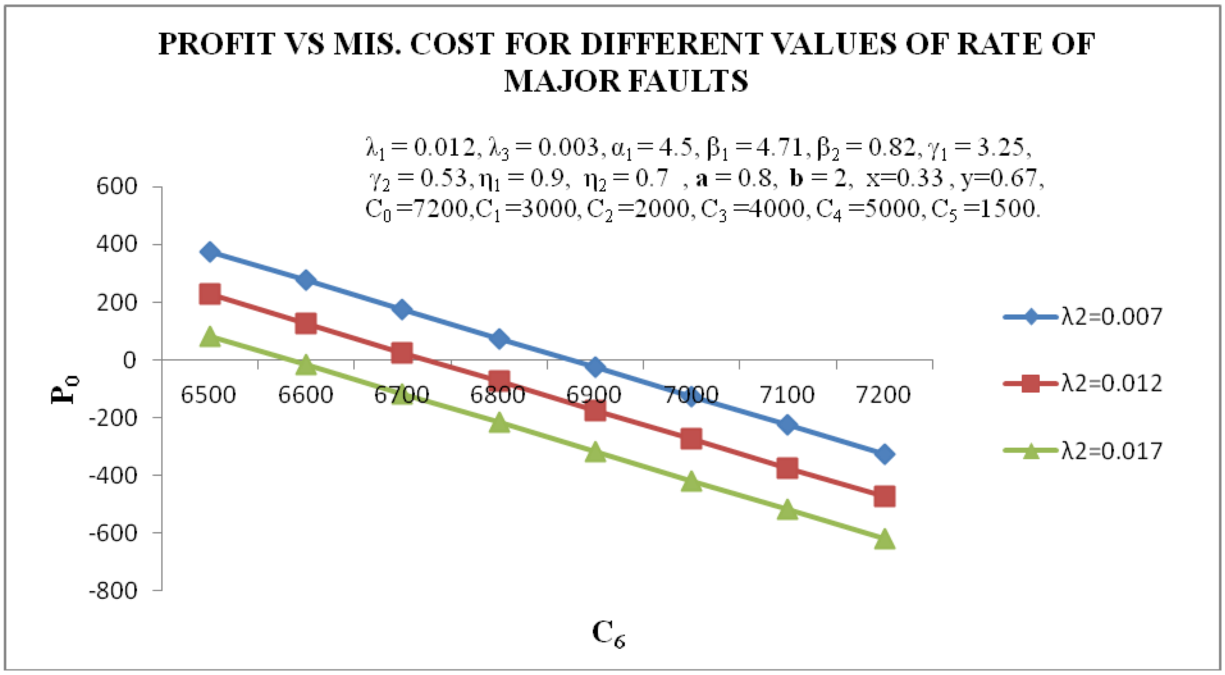

Figure.9.

Fig.9 gives the graph between profit (P_0) and the miscellaneous cost (C_6) for different values of rate of major faults (λ_2).

Following are conclusions of the graph:

a. The profit decreases with the increase in the miscellaneous cost and it has lower values for higher values of rate of major faults.

b. For $\lambda_2 = 0.007$, the profit is negative or zero or positive according as C_6 is greater than or equal or less than Rs.6873.4. Thus, the machine will give profit for this when C_6 is less than Rs.6873.4.

c. For $\lambda_2 = 0.012$, the profit is negative or zero or positive according as C_6 is greater than or equal or less than Rs.6726.2. Thus, the machine will give profit for this when C_6 is less than Rs.6726.2.

d. For $\lambda_2 = 0.032$, the profit is negative or zero or positive according as C_6 is greater than or equal or less than Rs.6583.1. Thus, the machine will give profit for this when C_6 is less than Rs.6583.1.

6. CONCLUSION:

From analysis of the graphs above, we conclude that mean time to system failure, availability and the profit per unit time of the paper machine decreases with the increase in the values of the rate of minor as well as major faults. Further, we obtained cut off points of profit for different values of rates of minor/major faults, for revenue of availability/costs etc. We derived that, for particular value of rate of minor/major fault what should be the greater value of revenue of availability or lower value of miscellaneous costs to get positive profit. On the basis of these values, various suggestions can be given to the management team of the Paper Mill to make the paper machine profitable.

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Solar Radiation as Alternative Power Supply for Electricity Generation in Nigeria

Ogbaka, D.T.[1]
[1]Department of Pure and Applied Physics, Faculty of Science. Adamawa State University, Mubi. Adamawa State, Nigeria

Aminu C. M.[2]
[2]Department of Electrical and Electronics Engineering Technology, Gombe State Polytechnic, Bajoga, Nigeria

Umar S.B[2]
[2]Department of Electrical and Electronics Engineering Technology, Gombe State Polytechnic, Bajoga, Nigeria

ABSTRACT: In this study, the Angstrom-Prescott regression equation which has been used to estimate the monthly average daily solar radiation on a horizontal surface was used. The values of the regression coefficients a and b as 0.34 and 0.42 were determine. The statistical error estimations such as RMSE and MBE used to test the correlation between the measured global solar radiation and the calculated global solar radiation. The RMSE was found to be 0.05 as low as expected and the MBE was also found to be 0.015. Global radiations obtained in this study are higher with mean value of 23.60 MJm^{-2} and the measured value 23.48 MJm^{-2} which shows the presence of high global solar energy potential in Maiduguri, Nigeria. The global solar radiation intensity predicted in this study can also be utilized in design, analysis and performance estimation of solar energy systems, which is gaining significant attention in Nigeria and the world at large.

Keyword: *Global Solar Radiation, Sunshine Hours, Regression Constants, Electricity.*

INTRODUCTION

Energy is a vital and important necessity for all earthly processes. The socio-economic activities of modern society revolved around the hub of energy availability. The 1973 oil crises, chaos caused by the Arab oil embargo, in western countries brought a sudden global realization to use renewable energy resources such as solar energy, hydropower, wind energy, wave energy, biomass and biofuels (Animalu and Adekola, 2002). This campaign for using renewable energy resources is becoming stronger today because of the finite nature of fossil fuel energy resources as well as the greenhouse gases emission which many scientists believe cause global warming. (Nwoke *et al.*, 2008). Effective applications of renewable energy resources to augment energy supply from fossil fuel energy resources (using cleaner for fossil fuel technologies) will enhance availability of energy with minimum environmental effect.

Solar energy can be defined as the energy obtains from the sun, which is electro magnetic in nature covering all wavelength of the sun (Ilenikhena, *et al.*, 2008). The sun is about 1.4 x 10^{14} m in diameter emits its energy at the rate of about 3.8 x 10^{23} Js^{-1} of solar energy of which about 1.7 x 10^{14} Js^{-1} reaches the earth, warming the ground , ocean ,atmosphere and drilling the photosynthesis process that maintain the biological life . Most of the solar radiation is confined within the wavelength of 3.8 and 0.7nm. Solar energy occupies one of the most important places as many among the various possible alternative energy sources it is the only option left to be developed and utilized. It is an inexhaustible source, potentially capable of meeting a significant portion of the world future energy needs with a minimum of adverse environment consequences. The availability of solar energy has to be considered. The region with greater solar insolation on the earth's surface lies between latitude 20° - 30° N and south of the equator (Ilenikhena and Mordi, 2005). Therefore, the availability of solar energy over the earth surface is not uniform (Eze, 2004). It has been confirmed that Nigeria receives 9.12 x 10s MWm^{-2} of energy per day from the sun. And if solar energy appliance with 5% efficiency is used to only 1% of the country surface area then 2.45 x 106 nJs^{-1} and electrical energy is equivalent to 4.66 million barrels of oil per day (Oparaku, 2007).

In Nigeria, the availability of a reliable power supply is still very minimal because the major source of electricity in the country is the hydropower, which is usually restricted to the generation of shaft power from falling water. The main hydropower station constructed across river Niger at Kainji is designed and managed by the different Power Distribution Companies in Nigeria to deliver the required energy for the expanding Nigeria industry. But these companies have been noted for unreliable power supply characterized by low voltage and incessant power cuts often without warning or even apologies to consumers (Ileoje, 1997).

This is the major reason among many others prompted the emergence of study. This erratic nature of electric power supply has caused the economy to fall, unless it is supplemented. The way out of this lies in the use of renewable source of energy for power generation, as they contain enormous, largely untapped and sustained opportunity for meeting the energy need as they are environmentally friendly as they do not contribute harmful and toxic emission to it. The solar energy is one of the cleanest and most environmentally sources of energy capable of generating a high amount of electricity. The aim of this study is to assess solar radiation as an alternative energy for electricity generation in Maiduguri.

MATERIALS AND METHOD

Maiduguri is the capital city of Borno state and one of the largest cities of Nigeria, situated in north eastern part of the country. The latitude of Maiduguri is 11.85° N, longitude is 13.08°E with altitude of 354m. The following parameters were collected from the Archives of Nigerian meteorological Agency, National Weather Forecasting and Climate Research Centre Abuja for the period of ten years, from two thousand and one to two thousand and ten (2001-2010). Mainly daily global solar radiation and Sunshine hour.

The Angstrom- Prescott regression equation which has been used to estimate the monthly average daily solar radiation on a horizontal surface in Nigeria or other places is given as (Angstrom, 1924; Prescott, 1940):

$$\frac{\bar{H}_m}{\bar{H}_o} = \left[a + b\frac{\bar{S}}{\bar{S}_o}\right] \qquad (1)$$

$\bar{H}_m$ is daily mean values of global radiation (MJm^{-2}day^{-1}), $\bar{S}_o$ the daily average value of day length, and 'a' and 'b' values are known as Angstrom constants and they are empirical. $\bar{H}_o$ is daily mean values of extraterrestrial radiation (MJm^{-2}day^{-1}), calculated using equation (2) as described by (Neuwirth, 1980; Duffie, and Beckman, 1991).

$$\bar{H}_o = \frac{24\times 3{,}600}{\pi} I_{sc} E_o \left[\cos(\varphi)\cos(\delta)\sin(\omega_s) + \frac{\pi\omega_s}{180}\sin(\varphi)\sin(\delta)\right] \qquad (2)$$

$$I_{sc} = \frac{1{,}367\times 3{,}600}{1{,}000{,}000}\, MJm^{-2}day^{-1} \qquad (3)$$

I_s the solar constant, The units in kWhm^{-2}day^{-1}

E_o represents the eccentricity correction, and described using Eq. (3.4) in Eq. 3.2

$$E_o = 1 + 0.033\cos\frac{360 n_d}{365} \qquad (4)$$

n_d is the day number of the year /Julian day (1 Jan, n_d = 1 and 31st December, n_d = 365), φ is the latitude of the site, δ the solar declination and, ω_s, the mean sunset hour angle for the given month. The solar declination (δ) and the mean sunset hour angle (ω_s) can be calculated:

$$\delta = 23.45 \sin 360\frac{284+n_d}{265} \qquad (5)$$

$$\omega_s = \cos^{-1}(-\tan\varphi\tan\delta) \qquad (6)$$

For a given day, the maximum possible values of day length can be computed by using Cooper's formula (Cooper, 1969):

$$\bar{S}_o = \frac{2}{15}\cos^{-1}(-\tan\varphi\tan\delta) \qquad (7)$$

Tiwari and Sangeeta (1997), computed regression coefficient *a* and *b* from the calculated monthly average global solar radiation has been obtained from the relationship given as:

$$a = -0.110 + 0.235\cos\varphi + 0.323\left(\frac{\bar{S}}{\bar{S}_o}\right) \qquad (8)$$

$$b = 1.449 - 0.553\cos\varphi - 0.694\left(\frac{\bar{S}}{\bar{S}_o}\right) \qquad (9)$$

The performance of the models was evaluated on the basis of the following statistical error tests: Root Mean Square Error (RMSE) and Mean Bias Error (MBE). It is recommended that a zero value for MBE is ideal while a low RMSE and low MPE are desirable (Nguyen and Pryor, 1997):

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}\left(H_{i,m} - H_{i,c}\right)^2\right]^{\frac{1}{2}} \qquad (10)$$

$$MBE = \frac{1}{n}\sum_{i=1}^{n}\left(H_{i,m} - H_{i,c}\right) \qquad (11)$$

Where $H_{i,m}$ is the ith measured value, $H_{i,c}$ is the ith calculated value of solar radiation and N is the total number of observations.

RESULTS AND DISCUSSION

Table 1 shows the values of measured monthly mean daily sunshine hours $\bar{S}$, day length $\bar{S}_o$, global solar radiation on a horizontal surface $\bar{H}_m$, extraterrestrial solar radiation on a horizontal surface $\bar{H}_o$, as well as the clearness index K_T.

Table 1: Meteorological parameters for Maiduguri from (2001-2010).

Months	$\bar{S}$ (hr)	$\bar{S}_o$ (hr)	$\bar{S}/\bar{S}_o$	$\bar{H}_m$	$\bar{H}_o$	$(\bar{H}_m/\bar{H}_o)$
Jan.	9.0	11.51	0.78	17.3	32.3	0.54
Feb.	9.7	11.76	0.73	21.5	34.7	0.62
Mar.	8.1	12.09	0.76	28.4	36.9	0.77
Apr.	8.3	12.40	0.75	26.8	37.9	0.71
May	8.9	12.63	0.71	28.1	37.4	0.75
Jun.	8.4	12.67	0.66	25.3	36.7	0.69
Jul.	6.6	12.51	0.53	24.2	36.8	0.66
Aug.	6.3	12.23	0.52	21.5	37.4	0.57
Sep.	7.5	11.89	0.63	23.4	37.1	0.63
Oct.	8.7	11.59	0.75	28.3	35.3	0.80
Nov.	10.0	11.40	0.88	24.8	32.7	0.76

Dec.	10.3	11.37	0.91	20.0	31.42	0.64

Table 2: Measured and calculated values of Solar Radiation for Maiduguri.

Months	$\bar{S}$	$\bar{S}_o$	$\bar{H}_m$	$\bar{H}_o$	$\bar{H}_e$
Jan.	9.0	11.51	17.3	32.32	21.32
Feb.	9.7	11.76	21.5	34.71	23.61
Mar.	8.1	12.09	28.4	36.99	26.58
Apr.	8.3	12.40	26.8	37.91	24.96
May	8.9	12.63	28.1	37.37	27.54
Jun.	8.4	12.67	25.3	36.74	23.43
Jul.	6.6	12.51	24.2	36.89	23.54
Aug.	6.3	12.23	21.5	37.46	19.62
Sep.	7.5	11.89	23.4	37.16	20.23
Oct.	8.7	11.59	28.3	35.35	26.75
Nov.	10.0	11.40	24.8	32.79	23.97
Dec.	10.3	11.37	20.0	31.42	22.40

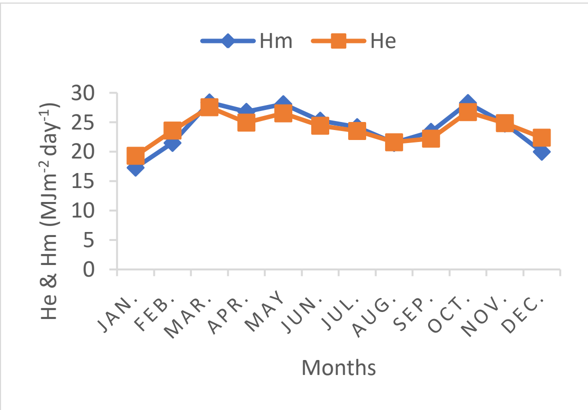

Fig. 1. Clearness index and Sunshine hours.

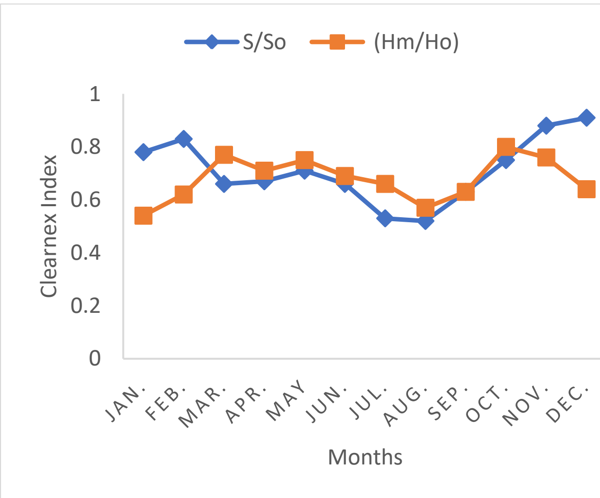

Fig. 2: Comparison between measured and predicted Solar Radiation

From Table 2, it is observed that the monthly global solar radiation is not uniform throughout the period of study. Peak solar radiation is observed in the months of March, April and May to be 26.58 MJm^{-2}day^{-1}, 24.96 MJm^{-2}day^{-1}, and 27.54 MJm^{-2}day^{-1}. On the other hand, the months of August and September recorded least amount of solar radiation average values of 19.62 MJm^{-2}day^{-1} and 20.23 MJm^{-2}day^{-1} respectively. This is as a result of the peak period of the cloud cover in Maiduguri due to the rainy season. In general, higher value of solar radiation is obtained in dry season than wet season. The relationship between the relative sunshine duration ($\frac{S}{S_o}$), and clear sky index (K_T) or ($\frac{H_m}{H_o}$) for Yola are presented in Figure 1 which shows the variation of the clearness index, a measure of the attenuation of the extraterrestrial global radiation in passing through the turbulent atmosphere before reaching the ground surface. Figure 2 shows the variation of the measured and predicted solar radiation during the year. From the regression analysis the following correlation was found to adequately fit the radiation data presented in Table 1, the values of the regression coefficients a and b as 0.34 and 0.42.

The statistical error estimations such as RMSE and MBE used to test the correlation between the measured global solar radiation and the calculated global solar radiation. The RMSE was found to be 0.05 as low as expected and the MBE was also found to be 0.015. Global radiations obtained in this study are higher with mean value of 23.60 MJm^{-2} and the measured value 23.48 MJm^{-2} which shows the presence of high global solar energy potential in Maiduguri, Nigeria. According to Offiong, (2003) reports that an average solar radiation for Nigeria per month needs to be as high as 20 MJm^{-2} depending on the time of the year which required for which is within the threshold for which Photovoltaic cell can be used to generate electricity. In line with world concern about the economic importance of global solar radiation as an alternative renewable energy, the models for estimating monthly global solar radiation of Maiduguri, Nigeria have been developed to be:

$$\frac{\bar{H}_m}{\bar{H}_o} = 0.34 + 0.42\frac{\bar{S}}{\bar{S}_o} \qquad (12)$$

The estimated global solar radiation data and its correlation will provide a useful source of information to designers of renewable energy, air conditioning systems and other solar energy related systems.

CONCLUSION

The Angstrom model developed in this study can also be applied to other cities to predict global solar radiation. The result of this study shows that there is greater availability of solar radiation in Maiduguri and also solar energy devices will function successfully throughout the year in the area, hence there is a good global solar radiation potential in Maiduguri location with bright prospects for solar energy utilization. The global solar radiation intensity predicted in this study can also be utilized in design, analysis and performance estimation of solar energy systems, which is gaining significant attention in Nigeria and the world at large.

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Estimate of Global Solar Radiation Using Artificial Neural Network Based on Meteorological Parameters in Yola

*Ogbaka D.T, Department of Pure and Applied Physics, Faculty of Science. Adamawa State University, Mubi. Adamawa State, Nigeria.

Abdullahi G., Department of Electrical and Electronic, School of Engineering and Engineering Technology, Federal Polytechnic, Mubi, Adamawa State, Nigeria.

Augustine B., Department of Pure and Applied Physics, Faculty of Science. Adamawa State University, Mubi. Adamawa State, Nigeria.

Tashara S. Department of Computer Science, Modibbo Adama University of Technology Yola, Adamawa State Nigeria.

ABSTRACT: Artificial neural networks have been used widely in many application areas. Artificial Neural Networks (ANNs) are currently accepted as an alternative technology offering a way to tackle complex and ill-defined problems. Despite the great importance of Global Solar Radiation (GSR), the number of radiation stations are very less when compared to the stations that collect regular meteorological data like air temperature and humidity. The main objective of this paper is to study the feasibility of an Artificial Neural Network (ANN) based method to estimate and predict GSR based on metrological parameters. It is very encouraging to observe a very close agreement between the ANN and the measured values. The Root Mean Square Error values, which are is the measure of accuracy of a particular model or correlation use. For the present analysis, it was found to be lowest for ANN model value (4.74). The Mean Bias Error value has the lowest under estimation with a value of -1.029, which fall within the expected and acceptable range A low value of MPE is expected, ANN model was observed to have a Mean Percentage Error value of (- 2.345). The result of this study proves that ANN can be used to predict global solar radiation potential in Yola, Nigeria using meteorological data.

Keywords: Artificial Neural Networks, Back Propagation, Global Solar Radiation, Meteorological

INTRODUCTION

For the improvement of quality of life of human being as well as economic and social development, energy is an essential factor. Solar energy reaches to the earth for the every year is 160 times the world's proven fossil fuel reserves, it is expected that the recent worldwide research and development on solar energy will help to reduce the energy crisis of the world (Kartini *et al.,* 2015; Medugu *et al.,* 2013). Solar radiation data are a fundamental input for solar energy utilization such as photovoltaic and solar thermal system design. For optimization and performance evaluation of solar technology for any particular location, the solar radiation data should be easily and readily available (Gana *et al.,* 2014). Solar radiation at the earth's surface is essential for the development and utilization of solar energy. It is needed for designing collectors for solar heaters and other photovoltaic equipment that depend on solar energy. Incoming solar radiation has a significant role in hydrological and crop growth modelling. For instance, it is a key input for estimating potential evapotranspiration which play a major role in the design of water supply storage reservoirs and irrigation systems. In spite of the importance of global solar radiation data, its measurements are not frequently available especially in developing countries (Allen, 1997).

An accurate knowledge of solar radiation distribution at a particular geographical location is of vital importance for the development of many solar energy devices. Unfortunately, for many developing countries solar radiation measurements are not easily available due to the shortage of measurement equipment's (Okundamiya and Nzeako, 2010). It is therefore important to consider methods of estimating the solar radiation using Artificial neural networks on the readily available meteorological parameters.

Artificial neural networks have applications in various fields of aerospace, defence, automotive, mathematics, engineering, medicine, economics, meteorology, psychology, neurology, and many others. They have also been used in weather and market trends forecasting, in the prediction of mineral exploration sites, in electrical and thermal load prediction, in adaptive and robotic control and many others2. Neural networks are used for process control because they can build predictive models of the process from multidimensional data routinely collected from sensors. Several researchers have demonstrated that they can be more reliable at predicting energy consumption in a building than other traditional statistical approach because of their ability to model non-linear patterns (Anstett and Kreider, 1992; Stevenson, 1994).

Artificial neural networks are composed of simple elements operating in parallel. The most popular learning algorithms are the back-propagation and its variants5. The Back-Propagation (BP) algorithm is one of the most powerful learning algorithms in neural networks. It tries to improve the performance of the neural network by reducing the total error by changing the weights along its gradient. The training of all patterns of a training data set is called an epoch. The training set has to be a representative collection of input-output examples.

When building the neural network model the process has to be identified with respect to the input and output variables that characterise the process. The inputs include measurements of the physical dimensions, measurements of the variables specific to the environment and equipment and controlled variables modified by the operator. Three types of networks used most commonly in ANN applications are feed forward networks, competitive networks and recurrent associative memory networks. A practical description of ANN methods with sample applications was presented in Hagan, Demuth and Beale (1997).

Many of the building energy systems are exactly the types of problems and issues for which the artificial neural network (ANN) approach appear to be most applicable. Neural networks have the potential for making better, quicker and more practical predictions than any of the traditional methods. The performance of a building energy system depends on the environmental conditions such as solar radiation and wind speed, the direction, strength and duration of which are highly variable. Many of the building energy systems are exactly the types of problems and issues for which the artificial neural network (ANN) approach appear to be most applicable. In these computational models attempts are made to simulate the powerful cognitive and sensory functions of the human brain and to use this capability to represent and manipulate knowledge in the form of patterns. Based on these patterns neural networks model input- output functional relationships and can make predictions about other combinations of unseen inputs. Neural networks have the potential for making better, quicker and more practical predictions than any of the traditional methods (Kreider and Wan, 1991).

MATERIALS AND METHOD

Yola, the capital of Adamawa State, comprising of Yola North and Yola South Local Government Areas, is located between Longitudes 12° 12'E, 12° 33'E of the Prime Meridian and between Latitudes 09° 12'N, 09° 19'N of the Equator. It is situated in the Benue Valley area of the state with a mean elevation 186 m.a.s.l. The area falls within the Tropical Wet and Dry/ West African Savanna Climate zone of Nigeria, with pronounced dry season in the low-sun months and wet season in the high-sun months. It is characterized by an average range of sunshine hours of 5.5 hours per day in August to 9.7 hours per day from the months of January through March. On balance, there are 2,954 sunshine hours annually and approximately 8.1 sunlight hours per day. Its Temperature characteristic is high all year round due to high solar radiation effect. However, seasonal changes usually occur such that there is a gradual increase in temperature from January to April when the seasonal maxima is recorded. Then a distinct gradual decline is recorded from the onset of rains in April/May due to cloud effects. This temperature characteristic continuous until October when a slight increase is experienced at the cessation of rains before the arrival of cold dry continental winds (harmattan) conditions (Adebayo, 1999). Thus, the study area is characterized by a mean temperature of 27.9 °C with a mean monthly range of 6.5 °C. The warmest mean maximum/ high temperature of the area is 39 °C in March & April, while the coolest mean minimum/ low temperature is 16 °C in December (Yola Climate Report, 2012).

The Angstrom- Prescott regression equation which has been used to estimate the monthly average daily solar radiation on a horizontal surface in Nigeria or other places is given as:

$$\frac{H_m}{H_o} = \left[a + b\frac{S}{S_o}\right] \quad (1)$$

H_m is daily mean values of global radiation ($MJm^{-2}day^{-1}$), S_o the daily average value of day length, and 'a' and 'b' values are known as Angstrom constants and they are empirical. H_o is daily mean values of extraterrestrial radiation ($MJm^{-2}day^{-1}$), calculated using equation (2) as described by Prescott, (1940).

$$H_o = \frac{24\times3{,}600}{\pi} I_{sc}E_o\left[\cos(\varphi)\cos(\delta)\sin(\omega_s) + \frac{\pi\omega_s}{180}\sin(\varphi)\sin(\delta)\right] \quad (2)$$

$$I_{sc} = \frac{1{,}367\times3{,}600}{1{,}000{,}000} MJm^{-2}day^{-1} \quad (3)$$

I_s the solar constant, The units in $kWhm^{-2}day^{-1}$

E_o represents the eccentricity correction, and described using Eq. (3.4) in Eq. 3.2

$$E_o = 1 + 0.033\cos\frac{360n_d}{365} \quad (4)$$

n_d is the day number of the year /Julian day (1 Jan, n_d = 1 and 31st December, n_d = 365), φ is the latitude of the site, δ the solar declination and, ω_s, the mean sunset hour angle for the given month. The solar declination (δ) and the mean sunset hour angle (ω_s) can be calculated as suggested by Duffie and Beckman, (1991):

$$\delta = 23.45\sin 360\frac{284+n_d}{265} \quad (5)$$

$$\omega_s = \cos^{-1}(-\tan\varphi\tan\delta) \quad (6)$$

For a given day, the maximum possible sunshine duration (monthly values of day length, (S_o) can be computed by using Cooper's formula (1969):

$$S_o = \frac{2}{15}\cos^{-1}(-\tan\varphi\tan\delta) \quad (7)$$

For a given day, the maximum possible sunshine duration (monthly values of day length, (N) can be computed by using (Duffie and Beckman, 1991):

$$N = \frac{2}{15}\omega_s \quad (7)$$

Falayi (2011), developed a model containing relative humidity, rainfall, cloud cover and temperature for Sokoto, which is Model 1.

$$\frac{H_m}{H_o} = -4.03308 + 0.0740\,(T_{max} - T_{min}) + 0.01075\,(RH) - 0.00065\,(RF) + 9.008\,(CC) \quad (8)$$

He also developed for Maiduguri, considered as Model 2 for this work:

$$\frac{H_m}{H_o} = 0.22093 + 0.02179\,(T_{max} - T_{min}) + 0.21792\,(RH) - 0.7561\,(RF) - 0.0008\,(CC) \quad (9)$$

Bristow and Campbell Model

Bristow and Campbell (1984) developed a simple model for daily global solar radiation with a different structure in which H is an exponential function of ΔT in 1984:

$$\frac{H_m}{H_o} = a\left[1 - e^{(-b\Delta T^{c})}\right] \quad (10)$$

Application of Artificial Neural Network

Artificial neural networks have been used widely in many application areas. Most applications use a feed-forward neural network with the back-propagation training algorithm. There are numerous variants of the classical back-propagation algorithm and other training algorithms (Haykin, 1999). All these training algorithms assume a fixed ANN architecture and during training, they change the weights to obtain a satisfactory mapping of the data. The main advantage of the feed-forward neural networks is that they do not require a user-specified problem solving algorithm (as is the case with classic programming) but instead they “learn” from examples, much like human beings. Another advantage is that they possess inherent generalization ability. This means that they can identify and respond to patterns which are similar but not identical to the ones with which they have been trained. On the other hand, the development of a feed-forward ANN-model also poses certain problems, the most important being that there is no prior guarantee that the model will perform well for the problem at hand (Benghanem *et al.*, 2009).

A feed-forward back-propagation neural network was used in this study. A typical neural network consists of an input, a hidden, and output layer. Other components include a neuron, weight, and connections or transfer function as shown in Fig. 1 and Fig. 2.

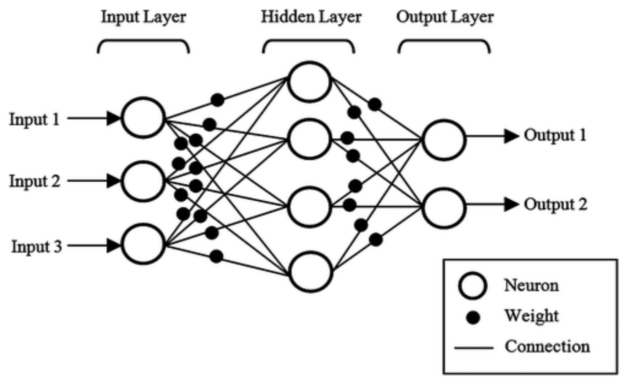

Fig. 1: A typical neural network for filtration

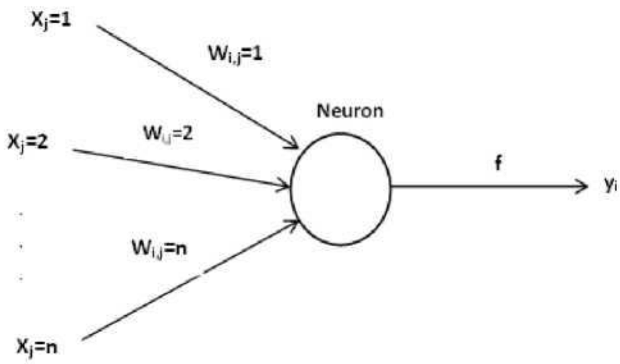

Fig. 2: Feed forward neural network

The values of X_1; X_2, X_n are inputs and Wi, W_2, W_n are weights. Each input is multiplied by the relevant weight. Obtaining products and bias are summarized. By applying activation function to the result of summary, the output of neuron is obtained. There are three steps in solving an ANN problem which are 1) training 2) generalization and 3) learning. Training is a process that network learns to recognize present pattern from input data set together with the desired pattern of activities for the output units. Generalization or testing evaluates network ability in order to extract a feasible solution when the inputs are unknown to network and are not trained to network. We determine how closely the actual output of the network matches the desired output in new situations. In the learning process the values of interconnection weights are adjusted so that the network produces a better approximation of the desired output. The disadvantage is that its operation can be unpredictable, because the network finds out by itself how to solve the problem.

The most common neural network model is the Multilayer Perceptron (Sharda and Patil, 1990). This type of neural network is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data, so that the model can then be used to produce the output when the desired output is
unknown.

Figure 1 shows the block diagram of a single hidden layer multiplayer perceptron (MLP). The inputs are fed into the input layer and get multiplied by interconnection weights as they are passed from the input layer to the hidden layer. Within the hidden layer, they get summed then processed by a nonlinear function (usually the hyperbolic tangent). If more than a single hidden layer exists then, as the processed data leaves the first hidden layer, again it gets multiplied by interconnection weights, then summed and processed by the second hidden layer and so on. Finally the data is multiplied by interconnection weights then processed one last time within the output layer to produce the neural network output. To perform any task, a set of experiments of an input output mapping is needed to train the neural network. These data are one of the most important factors to obtain reliable results from any trained ANN. Thus, the training sample data have to be fairly large to contain all the required information and must include a wide variety of data from different experimental conditions and process parameters.

In the present study, feed-forward, back-propagation, multilayer perceptron artificial neural network models are developed and trained separately by using Levenberg- Marquardt (LM) training algorithm and Gradient descent back propagation (GD) algorithm on ‘Neural Network Toolbox’ in MATLAB 9.7 version , to predict the average global solar radiation using meteorological data from 2014 – 2018 for Yola. The aim of this study is to investigate the feasibility of using ANN to model the non-linear relationship between solar radiation and other easily measurable important meteorological parameters. The predicted solar radiation values from the model can be used easily for design and assessment of renewable energy application systems.

Design of the Artificial Neural Network Model

Multi-layer feed-forward back-propagation network with different architecture were designed using the ‘Neural Network Toolbox in MATLAB 9.7 version. The network consist of three layers: input layer, hidden layer and output layer. There are two input parameters for the models 1 and 2 and three input parameters for the model 3 and one output parameter average global solar radiation for all the three models. Two different algorithms (LM and GD method) with single and double hidden layer topologies were used and the number of neurons was also varied to enhance the generalization capability of the network. No transfer function was used for input layer, hyperbolic tangent sigmoid transfer function for hidden layer and linear transfer function (purelin) for output layer.

Selecting the number of neurons for the hidden layer is a complicated problem. So far, no mathematically justifiable method is available for determining the hidden elements. Too many network nodes will increase the training time of the network and weaken the generalization and forecasting ability of the network. The number of the hidden elements is obtained by trial and error. Training is started with a minimum number of elements, the number of these elements is constantly increased and re-training of the ANN is continued until satisfactory training is achieved. The number of the hidden elements used for satisfactory training is considered as the optimal number.

Statistical Analysis

The performance of the models was evaluated on the basis of the following statistical error tests: the mean percentage error (MPE), root mean square error (RMSE) and mean bias error (MBE). These tests are the ones that are applied most commonly in comparing the models of solar radiation estimations. It is recommended that a zero value for MBE is ideal while a low RMSE and low MPE are desirable (Igbal, 1983; Akpabio *et al.*, 2004; Chen, 2011).

Mean percentage error: The Mean percentage error is defined as:

$$MPE\ (\%) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{(H_{i,m}-H_{i,c})}{H_{i,m}}\right)\times 100 \qquad (11)$$

Where $H_{i,m}$ is the ith measured value, $H_{i,c}$ is the ith calculated value of solar radiation and N is the total number of observations.

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}\left(H_{i,m}-H_{i,c}\right)^2\right]^{\frac{1}{2}} \qquad (12)$$

$$MBE = \frac{1}{n}\sum_{i=1}^{n}\left(H_{i,m}-H_{i,c}\right) \qquad (13)$$

According to Medugu and Yakubu (2011), regression coefficient *a* and *b* from the calculated monthly average global solar radiation has been obtained from the relationship given as:

$$a = -0.110+0.235\cos\varphi+0.323\left(\frac{n}{N}\right) \qquad (14)$$

$$b = 1.449 - 0.553\cos\varphi - 0.694\left(\frac{n}{N}\right) \qquad (15)$$

To compute estimated values of the monthly average daily global radiation H_{cal}, the values of computed *a* and *b* from equations (14) and (15) were used. where a = 0.293 and b = 0.537.

RESULTS AND DISCUSSIONS

Table 1 below gives the average computed values for the period of five years.

Table 1: Monthly Daily Average Meteorological data for Yola

Months	RH (%)	RF (mm)	T_{max} (^oC)	T_{min} (^oC)	$\frac{n}{N}$	H_m
Jan.	33.4	0.00	35.1	19.7	0.79	19.9
Feb.	30.2	0.00	39.6	22.2	0.64	21.3
Mar.	27.7	0.00	42.8	26.3	0.61	22.5
Apri.	49.5	44.9	38.9	29.5	0.65	20.4
May	68.7	98.7	34.6	27.1	0.52	19.7
Jun.	88.3	150.4	32.9	25.9	0.53	18.1
Jul	89.5	160.9	31.6	24.7	0.58	17.6
Aug.	96.2	203.2	32.3	24.3	0.44	15.8
Sept.	94.8	167.8	34.5	24.7	0.54	17.6
Oct.	78.5	87.4	35.8	24.5	0.68	20.3
Nov.	65.2	34.98	38.6	23.9	0.44	22.9
Dec.	53.5	0.00	36.5	21.8	0.53	18.4

Table 2: Monthly average daily global solar radiation for Yola.

Months	$\frac{n}{N}$	H_m	H_o	$\frac{H_m}{H_o}$
Jan.	0.79	19.9	35.8	0.55
Feb.	0.64	21.3	37.7	0.56
Mar.	0.61	22.5	39.8	0.56
Apri.	0.65	20.4	40.9	0.49
May	0.52	19.7	39.3	0.50

Jun.	0.53	18.1	38.4	0.47
Jul	0.58	17.6	37.5	0.46
Aug.	0.44	15.8	36.3	0.43
Sept.	0.54	17.6	39.5	0.44
Oct.	0.68	20.3	38.2	0.53
Nov.	0.44	22.9	33.7	0.67
Dec.	0.53	18.4	32.5	0.56

Table 3: Monthly average daily global solar radiation for the three models and ANN

Months	H_m	Model 1	Model 2	Model 3	
Jan.	19.7	20.5	18.3	18.0	
Feb.	21.5	20.4	19.2	19.3	
Mar.	22.3	22.7	22.4	22.7	
Apri.	20.4	22.3	24.8	23.9	19.7
May	19.6	20.3	26.3	23.3	19.01
Jun.	18.4	19.7	23.8	22.5	17.8
Jul	16.6	17.5	19.3	17.9	16.1
Aug.	15.5	16.9	19.7	17.3	14.88
Sept.	17.8	30.9	20.9	19.8	16.9
Oct.	19.8	19.2	21.5	21.5	18[illegible]
Nov.	21.6	21.4	20.3	18.5	20[illegible]
Dec.	20.3	20.7	18.9	17.2	19[illegible]

All numerical values are in units of $(MJm^{-2}day^{-1})$

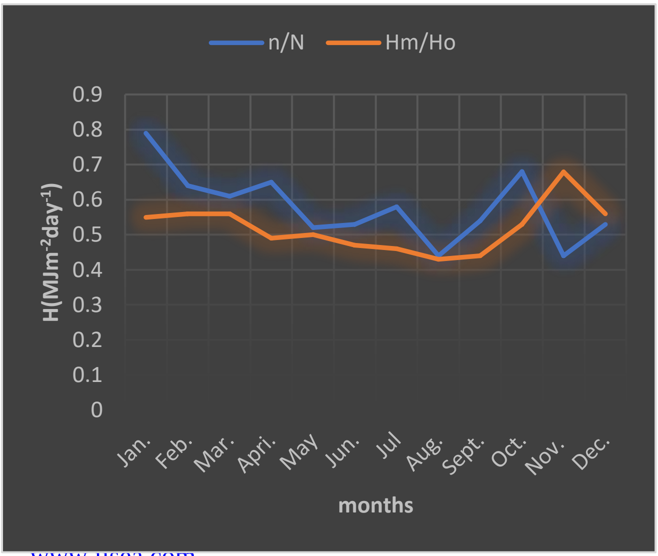

Figure 3: Relationship between the clearness index and relative sunshine duration in Yola.

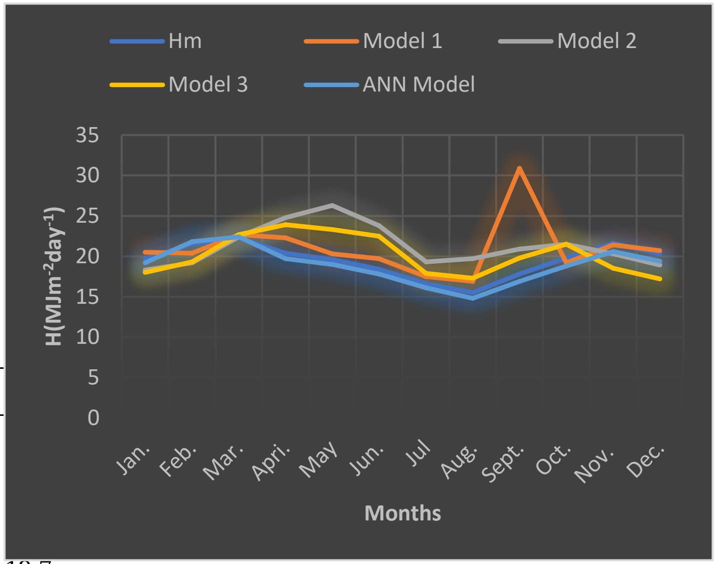

Figure 4: Estimated value of monthly average daily global solar radiation and measured value

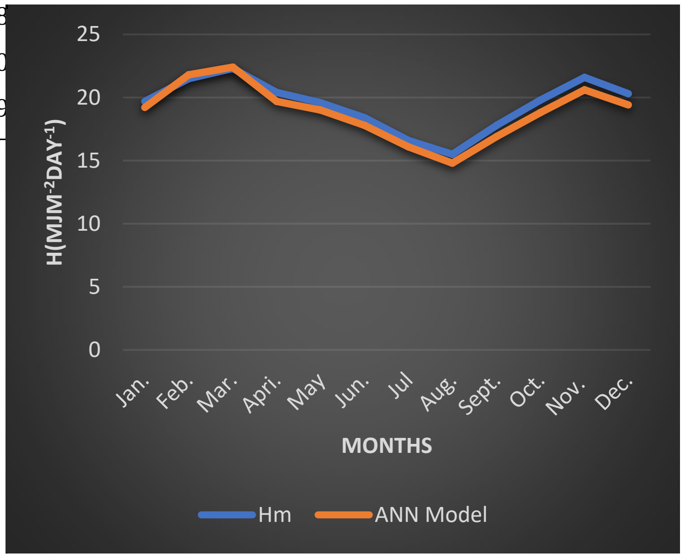

Figure 5: Estimated value of monthly average daily global solar radiation (Model 1) and measured values.

Table 4: *RMSE*, *MBE*, and *MPE* computed in the comparison between measured and estimated monthly average daily solar radiation

Models	Statistical Analysis Methods		
	RMSE	*MBE*	*MPE (%)*
Model 1	6.72	0.42	- 1.194
Model 2	10.39	2.39	0.378
Model 3	9.83	1.76	2.256
ANN Model	4.74	-1.029	- 2.345

The best predicted versus measured irradiation values for ANN model was presented in Figure 5 and the values were presented in Table 3. In Table 2 and figure 3, the value of clearness Index, K_T = 0.519 correspond to the lowest value of $\frac{n}{N}$ = 0.44 and H_m = 15.8 ($\mathrm{MJm^{-2}day^{-1}}$) in the month of August indicate poor sky conditions. These conditions correspond to the wet or rainy season (June – September) observed in Yola during which is much cloud cover. The monthly average daily solar radiation estimated through model 1 and model 4 for Yola are given in Table 3, along with the measured values. It is very encouraging to observe a very fine agreement between the ANN and the measured values. Figure 2 indicates that ANN model is the most suitable for the estimation of monthly average daily global solar radiation for Yola. Shown in table 4 are the statistical test results. The RMSE values, which are is the measure of accuracy of a particular model or correlation use. For the present analysis, it was found to be lowest for ANN model value (4.74) as shown in table 4. The MBE values obtained from the models are positive in some cases and negative in others, which shows that these models vary between under and over estimate of global solar radiation. However, model has the lowest under estimation with a value of -1.029, which is expected and acceptable. A low value of MPE is expected, ANN model was observed to have an MPE value of (- 2.345).

The global solar radiation can be adequately estimated using different proposed models using daily recorded meteorological variables of maximum and minimum temperature difference, relative humidity, cloud cover and rainfall. In order to obtain some accurate solar radiation estimations, it requires accurate mathematical modelling of all the climatological parameters. From figure 3, there is high proportion of cloudy days, relative to low solar energy with low temperature in the wet season while low cloudy day with high solar energy and high temperature in dry season across the latitudes. It was observed that the ANN models which gives good results when considering statistical indicators, RMSE, MBE, and MPE. It is found that the new model can be used for estimating daily values of global solar radiation with a higher accuracy and has good adaptability to highly variable weather conditions. The estimated value of global solar radiation reveals that solar radiation can be efficiently used to compensate for energy inadequacy.

CONCLUSION

This study has been proposed the model of ANN to predict monthly average daily global solar irradiation in horizontal surface in Yola, Nigeria as area of study. This study proves that ANN can be used predicting of global solar irradiation potential in Yola, Nigeria by using meteorological data. In view of the worldwide concern about the economic importance of global solar radiation as an alternative renewable energy, the monthly global solar radiation using relative humidity, sunshine hour, cloud cover, rainfall, maxi maximum temperature have been employed in this study to estimate global solar radiation for Yola, Adamawa State, Nigeria. This model will provide useful information for designers and engineers of solar energy and other renewable energy devices in Yola and environs. From the results when considering statistical indicators that are MBE, RMSE and MPE. This study plan can be introduced neural network technique for modeling the global solar irradiation in Yola.

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