International Journal of Advances in Engineering and Management (IJAEM)
Volume 3, Issue 11 Nov 2021, pp: 702-714 www.ijaem.net ISSN: 2395-5252

Minimizing Equipment Downtime by Adopting Basic Math Model to Improve Electric Power Production in Nigeria

T.D. Bestmann, A.O. Odukwe, J. C. Agwunwamba and K. Orima

1.Maintenance Department, Nigerian Agip Oil Company Ltd, Kwale-Delta State, Nigeria
2. Faculty of Engineering, University of Nigeria, Nsukka, Enugu State, Nigeria

Submitted: 10-11-2021 Revised: 21-11-2021 Accepted: 24-11-2021

ABSTRACT:
The math model proposed takes into consideration both equipment failure preventive and corrective maintenance rates, and can be used to predict system probability of being in failed state i.e. undergoing repairs, availability and mean time to failure.It represents a system that can either be operating normally, in degradation mode, or has failed completely. A good example of this type could be power generation plant, i.e. electricity production at full capacity, derated capacity or not at all. Corrective maintenance initiated from degradation and completely failed modes of the system to repair failed parts, i.e. higher failure and downtime rates. The model provide a framework that can be applied and used in a preventive maintenance scheduling andis not restricted to manufacturing or service systems; may equally be used to find optimal preventive and replacement schedules. It is expected that the presentation will put in proper focus and promote better understanding of maintenance practice in the power sector.

Keywords: mathematical model, adoption, power sector, performance improvement, failure prevention, maintenance activities

I. INTRODUCTION

Generating units are prone to failure due to mechanical, electrical, thermal stress and adverse working environmental conditions. Operations and Maintenance (O & M) are responsible for a large chunk or proportion of energy production cost. Reducing down the maintenance cost is the key to keep the power industry competitive. This is aimed at maximizing power output, minimizing outage time and optimizing maintenance activities in the electric power industry. In mathematical maintenance analysis it may be necessary to find solutions to a set of linear differential equations, particularly, when applying the Markov method[10]. Even though there are various methods for solving differential equations, the Laplace transform approach is probably the most effective technique for solving a set of linear differential equations. This piece of example demonstrates application of Laplace transform to solve Linear Differential Equation. Assume that the following two differential equations describe a repairable system as expressed [7].

$$\frac{dPo\,(t)}{dt} = -\lambda Po(t) + \mu Pi(t)(1)$$

$$\frac{dPi\,(t)}{dt} = -\mu Pi(t) + \lambda Po(t)(2)$$

Where, $dPi(t) =$ Probability that the system is in state i at time t,

For i = 0 (working normally), i = 1 (failed);

λ = system failure rate; and

μ = system repair rate.

At time t=0, $Po(0) = 1$ and $Pi(0) = 0$

It can be shown using Laplace transforms Equations (1) and (2) that the probability of the system operating normally, i.e.…, $Po(t)$, is given by the equation

$$f(t) = \frac{\mu}{\lambda+\mu} + \frac{\lambda}{\lambda+\mu} e^{-(\lambda+\mu)t}(3)$$

Taking Laplace transform of equation (3) and (4) yields

$$SPo(s) - Po(0) = -\lambda Po(S) + \mu Pi(S)(4)$$

$$SPi(s) - Pi(0) = -\mu Pi(S) + \lambda Po(s)(5)$$

Where, Pi(s) is the Laplace transform of the probability that the system is in state i= 0, 1. For given initial conditions Equations (4) and (5) becomes

$$SPo(s)-1=-\lambda Po(s) +\mu Pi(s) \quad (6)$$

$$SPi(s) =-\mu Pi(s) +\lambda Po(s)(7)$$

Rearranging equation (6) yields $Pi(s) = \frac{\lambda_{Po(s)}}{S+\mu}$ (8)
Substituting equation (7) into (8) produce
$Po(s) = \frac{(S+\mu)}{S(s+\lambda+\mu)}$(9)
Taking inverse Laplace transform of equation (9) results into
$Po(t) = \frac{\mu}{\lambda+\mu} + \frac{\lambda}{\lambda+\mu}e^{-(\lambda+\mu)t}$ (10)
For $f(t) = Po(t)$, equation (3) and (10) are identical. It means equation (3) denotes the probability of the system operating normally when its (i.e., system) failure and repair rates are given.

II. MODEL FOR SYSTEM PERFORMANCE IMPROVEMENT

By following the Laplace transform linear differential equation methodology demonstrated in section above systematically and meticulously in formulating a model, the basic consideration as objective functions is the plant availability and reliability based on assigning resources to both equipment failure preventive and corrective maintenance.

Hence, the entire life of a system can be considered as a series of life cycle. For this, the concept of the system life at the start of the cycle is defined; the system life is at its highest value, representing fully restored or as good as new condition. A series of random shocks cause deterioration and the system life value drops in discrete steps corresponding to the frequency and the magnitude of the shocks. Finally, the system suffers failure, at which the system life value drops to zero. The system is now restored completely; at this point, the second cycle starts [2].

It could appear that both the system life and the shock magnitude would need to be measured in the same units, if any relationship is to be developed. For convenience, a unit of life (CLU) as a common unit for both systems life and for shock magnitude is chosen. Further, the cycle is constrained to lie between (0CLU) and (1CLU), where (0CLU) represents failure of the system, and (1CLU) represents a fully restored state.

Notation:
Dt=system downtime (0 ≤Dt≤ 1);
Kt=annual system downtime cost (= Kt f (Dt));
Bt= system life at time t in units of cycle life (CLU) (0CLU) ≤ (CLU);
L (,) –life cdf of repaired system;
i -index for life cycles, ι = 1, 2, 3 …. ;
Sij – shock magnitude for j^{th} shock in the i^{th} cycle in unit of cyclic life, (OCLU) (ICUL);
Qx– mean number of shocks to accumulate a total magnitude of life at X;
Di-equipment downtime in the i^{th} cycle, Time interval between failure and start of next cycle;
Ti -total cycle time for the i^{th} cycle;
μ - mean shock rate (0 ≤∞≤);
∝ - Frequency of inspection (0 ≤∝≤∞);
P_{ois} - (K,μ, t) probability of K shocks arriving at μ in time interval (P,t);
ϑ(·) – Survivor functions of time until failure in the i^{th} cycle;
E {g(x)–Mathematical expectation of g(x) is any continuous function defined for all real (x) value.

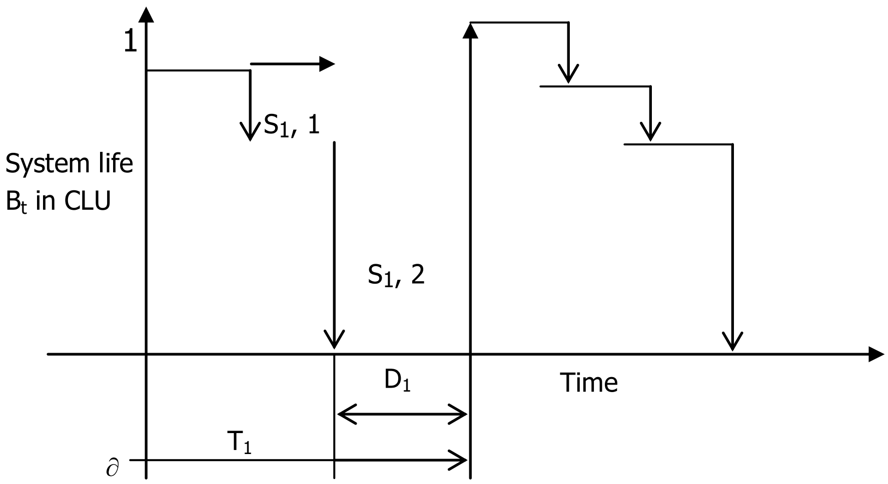
Assumptions:

- inspection is performed at a frequency of α independent of the shock failure process;
- shocks arrive randomly according to a Poisson process of rate μ; and
- system life is regenerative, and a new cycles starts after each repair, which restores the system to its original condition [4].

The Figure 1: Shows the behavior of a typical system subjected to shock. It begins operations with the system life having a value of (1CLU). A series of random shocks reduce this to a value of (0CLU), which represents failure. The system is repaired or restored to its original state of (1CLU) and it is repaired again.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 3, Issue 11 Nov 2021, pp: 702-714 www.ijaem.net ISSN: 2395-5252

Figure 1: Showing system life with random shocks



$D_t = \left[\frac{E\{D_i\}}{E\{T_1\}}\right]$(11)

Since the process is regenerative for all $t \geq 0$, it follows that;

$E\{T_1\} = E\{T_1\}$ and $E\{D_i\} = E\{D_i\}$ (12)

Hence;

$D_t = \left[\frac{E\{D_i\}}{E\{T_1\}}\right]$ (13)

Since $E\{D_i\} = \left[\int_0^\infty \Pr.\ \{D_1\} > t\right] \partial t$ (14)

In any given cycle, for the system to be still operational at time t, the cumulative shock magnitude as measured in units of cycle life (CLU) must be less than 1, meaning the system has failed. It follows that:

$\Pr[D_1 > t] = \Pr\{\text{cumulated shock magnitude} \geq 1$ (15)

The cumulative shock magnitude is a function of both the cumulative number of shocks and the magnitude of each shock.

Cumulative number of shocks = $\int_0^\infty P_{ois}(K, \mu, t)\, \partial t$ (16)

The magnitude of shocks is, in turn, a function of life cdf of a repaired system and the number of shocks to accumulate a total magnitude of at least x.

Hence, it can be shown that [7, 5]:

$\Pr\{D_1 > t\} =$
1−0∞PiosK, μ, t∂t. [0∞Qx Ldx+1 (17)

that is; $E\{D_1\} = 1 - \frac{\left[\int_0^\infty Q(x)\,(Ldx)+1\right]}{\mu}$(18)

since $E(T_1)$ = expectation of cycle time (19)

Hence, $m\,c\,t = \frac{\text{Mean number of inspectation episodes}}{\text{Frequency of inspection}}$--
(20)

Hence, $E\{T_1\} = \sum_0^\infty \Phi\, \frac{(i/\alpha)}{\alpha}$ (21)

$\mu\,.E\{T_1\} = \sum_{i=1}^\infty \Phi\, \frac{(i/\alpha)}{\alpha}$ (22)

Hence, using equation (22) downtime D_t can be expressed as follows [7].

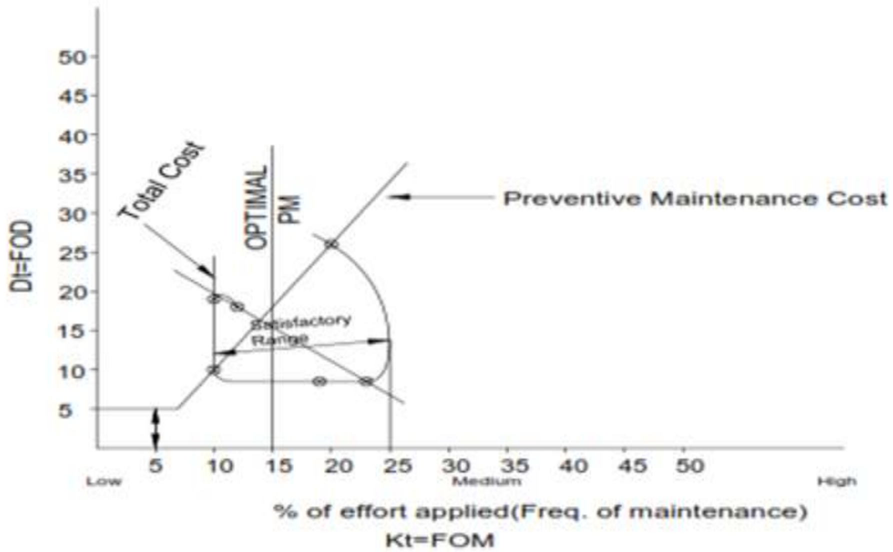
$D_t = 1 - \frac{[\Phi\{\sum_{i=1}^\infty Q(x)\, L(dx)+1\}]}{[\mu\,\{\sum_{i=1}^\infty \phi(i/\alpha)\}]}$(23)

The new model derived as shown in equation (23) is an improvement over the existing models. It is more realistic in that it captures the existing situation in the electric power industry. It has more advantages to use over otherexisting models because it tried to remove all limitations associated. These other models are basically useful to lowerfailure rate and grossly reduce downtime. The main feature of the hybrid model is as follows: The annual system downtime cost Kt is a function of the system downtime Dt, and at its simplest it could be a linear function of Dt *as illustrated in Figure* 2. It is either linear programming or linear optimization – a method of solving an optimization problem when the objective function is a linear function and the constraints are linear equations or linear inequalities. Dt has been expressed as, both function of frequency of inspection ∝ and mean rate of shocks μ. The model is available to be tested and inputs made and it does not involve too much enumeration. Assuming a gamma distribution for the shock magnitude involved, downtime Dt is treated as variable involving probability; thus reducing the failure due to usual subjective methodology of finding downtime. Generally, the average magnitude value of the shock and the

International Journal of Advances in Engineering and Management (IJAEM)
Volume 3, Issue 11 Nov 2021, pp: 702-714 www.ijaem.net ISSN: 2395-5252

annual frequency are well known to the operator. Also, the maximum equipment downtime cost that would be permissible, are also known. These can be used to determine the optimum frequency of inspection, [3, 6].

Figure 2: The impact of PM on revenue loses



2.1 Verification of the model

In the Tables 1 and 2 for verification of the model to ascertain its reliability by finding the maximum and minimum values of the given function called the objective function i.e. K_t= system annual downtime cost; and D_t = system downtime inspection rate values. For example, observing case study power plant facility over a period of time for 60 months and obtained the following data from analysis and imputing these carefully into equation (23) as it may apply for both D_t= FOD=193.6% and K_t = FOM= 7.5%. Having these basic values of Φ, Q(x), L, μ, i/α and i for both Kt and Dt then the following results in the tables 1 and 2 were obtained accordingly.

The model was tested with field data of operations from both Afam and Sapele power plants to verify its reliability. It is simply presented in a tabular format. The mark of minimum K_t value indicates TPM program i.e. opportunity to pro act rather than react. K_t Mark of maximum value indicates huge cost of operation which resonates between replacement, repair and breakdown costs; and a total deviation from TPM principles and underlying policies.

Table 1: System annual downtime cost K_t (FOM)

S/N	FOM	REPLACEMENT COST	REPAIR COST	BREAKDOWN COST	PREVENTIVE MAINT. COST
1	20	50m	40m	30m	10m
2	23	57m	46m	54m	11.5m
3	12	30m	24m	18m	6m
4	19	47m	38m	28m	9.5m
5	10	25m	20m	15m	5m
6	10	25m	20m	15m	5m
Total	94	-	-	-	-
K_t Value		37.2%	29%	25.4%	7.5%

Minimum K_t value using equation (23) as a function of the system annual downtime cost is 7.5% as indicated in Table 1. Hence, it is more appropriate to operate a preventive maintenance (PM) system which is a typical TPM program. Optimum (minimum) value of the objective function 7.5% is the product of the application of the model in equation (23). The Figure 3 show graphical representation of system annual downtime cost K_t (FOM)

Figure 2: System annual downtime cost Kt (FOM)

S/N	FOD	REPLACEMENT COST	REPAIR COST	BREAKDOWN COST	PREVENTIVE MAINT. COST
1	25.798	50m	40m	30m	10m
2	8.585	57m	46m	34m	11.5m
3	18.484	30m	24m	18m	6m
4	8.585	47m	38m	28m	9.5m
5	10.074	25m	20m	15m	5m
6	19.316	25m	20m	15m	5m
Total	90.842	-	-	-	-
D_t value		38.9%	48.4%	65%	193.6%

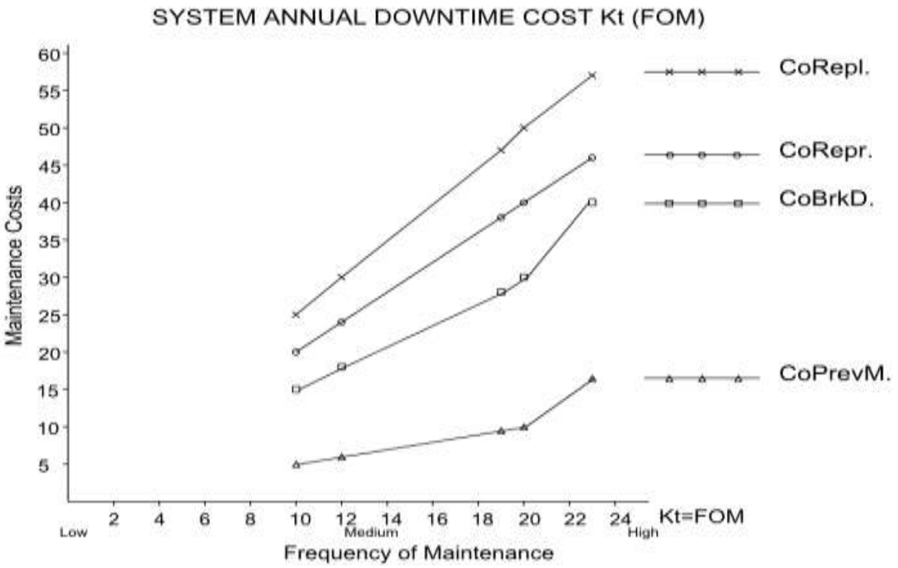
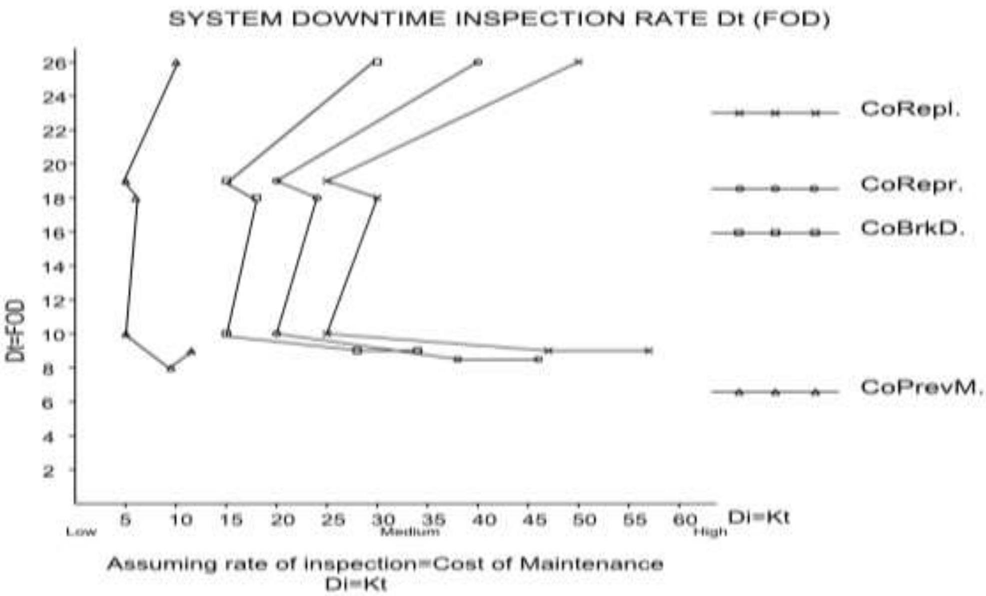


Figure 3: System Downtime inspection rate D_t (FOD)

Maximum Dt value using equation (23) as function of the equipment downtime inspection rate is 193.6% and expressing Dt as both function of frequency of inspection and mean time to repair (MTTR) indicated that PM action should be carried out thrice as much as other maintenance actions. Therefore, it is expected that PM actions can be 97% on monthly basis to forestall equipment down time or failure. Increased PM action-a typical TPM program raises equipment reliability and availability, hence increase in system productivity and performability.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 3, Issue 11 Nov 2021, pp: 702-714 www.ijaem.net ISSN: 2395-5252

Figure 4: Show graphical representation of system downtime inspection rate Dt (FOD).



III. MAINTENANCE CHARACTERISTICS AND VARIATION OF COST WITH THE BASIC MAINTENANCE PARAMETERS

Maintenance cost usually consists of indirect costs. Direct (visible) costs comprise factors such as direct labour, e.g. manpower, direct material, e.g. spare parts, and overheads, e.g. tools, transportation, training and methods. Indirect (invisible) costs are all the costs that may arise due to planned and unplanned maintenance actions, e.g. lost production costs.Implementing more effective maintenance approach brings benefits. Nothing, however mentions how to calculate or estimate the relevant life cycle cost factors, or required parameters. This is because the impact of the maintenance function can be found in many areas in the industry such as production, quality and logistics. When a breakdown occurs, it is often easy to show that a lack of maintenance was responsible. But when breakdowns do not occur, it is not easy to demonstrate that maintenance has prevented the big issue. It is easy to say that maintenance costs so much per year, but not what is the gain of that maintenance, and how it can be measured. Appreciating maintenance benefits which could result from implementation of a wise maintenance policy involves importantly appreciating all the various costs involved [7], [8] When greater percentage of time is spent on dealing with emergencies (i.e. firefighting) and lesser time spent on planning preventive maintenance, a high proportion of cost is always unavoidable. Emerging repairs means that high inventory level of replacement components, particularly critical parts, are to be carried out all the time. Also reactive maintenance has a negative impact on the production time.

Afam and Sapele power stations records or data of operation showed that with good maintenance policy, costs can be drastically reduced in the electric power industry. Plant availability could be increased, and so increase in profitability achieved. The costs of maintenance can be represented by the curves, shown in Figures 5 and 6. Increase in maintenance inspections, lubrication and fault diagnosis will produce drastic decrease in repair costs and other costs, thereby minimizing production downtime.

Table 3: Cost variation with basic maintenance parameters (FOM)

S/N	FoM	CoRepl	CoRepr	VoC_1	Co BrkD	VoC_2	Co PrevM	VoC_3
1	20	50m	40m	10m	30m	20m	10m	40m
2	23	57m	46m	5m	34m	17m	11.5m	39.5m
3	12	30m	24m	6m	18m	12m	6m	24m
4	19	47.5m	38m	9.5m	28m	19.5m	9.5m	38m
5	10	25m	20m	5m	15m	10m	5m	20m
6	10	25m	20m	5m	15m	10m	5m	20m

Table 4: Cost variation with basic maintenance parameters (FOD)

Breakdown occurs because there is no idea as to what causes the breakdown until the equipment actually breakdown. It is the consequence of failure that determines the resources needed for a particular policy. The consequences of failure have adverse effects on quality, reliability, availability, safety and operational cost; hence the idea is to build on preventive and predictive maintenance.

When equipment fails, there is a mean downtime designated BO. When equipment is scheduled for repair or replacement the mean downtime is designated B1x. In this mathematical model it is assumed that B_1x is always greater than Bo by 3 i.e. $\frac{Bo}{B1\,x} = 3$[1]. Therefore, if the mean downtime caused by equipment failure is three times as long as the mean downtime caused by scheduled equipment repair or replacement then $\frac{B1x}{Bo} = \frac{1}{3} = 0.333$

An appropriate probability distribution, usually the "Weibull" distribution can be used to define an optimum maintenance policy to model the failure mechanism of equipment knowing the times between failure (MTBF). The expression for the Weibull reliability function, R (t) = exp $(-t/\eta)^{\beta}$. Where R (t) = Probability that equipment will not fail during a time interval, η = scale parameter, β= shape parameter, these can be obtained graphically. The Weibull probability R (t) of obtaining two different times between failures (TBF) can be determined by establishing the relationship between the coefficients of variation of the failure distribution,

$\frac{\sigma}{MTBF}$, and the downtime ratio [$\frac{B1x}{Bo}$, B_1x <Bo] assumed, using the criteria,

if $\frac{\sigma}{MTBF} \geq \frac{Bix}{Bo}$[2]

[Plan I

i.e. carrying out preventive maintenance actions any time, that is To = ∞,

and $\frac{\sigma}{MTBF} < 1 - \frac{Bix}{Bo}$ [2]Plan II

i.e. restricted maintenance and must be calculated.

These criteria clearly define basic maintenance policies. In the first case, the optimal maintenance policy is to repair or replace component only at failure. In the second case, optimal maintenance policy is to build on preventive or predictive maintenance and effect repairs immediately at a time To, such that T (T_O) is a minimum or at failure.

A reasonable practical approximation can be obtained using the following equation as stated Y = Bo + B1x + µ, for normal underlying failure distribution, [1]. This model can apply specifically to equipment with wear-out failure mechanism that is equipment for which the conditional probability of failure with a given survival to time t1 increases continuously denoting instantaneous failure rate. The Weibull distribution is convenient for our purpose because of the instantaneous failure rate with respect to time; and its accurate failure analysis and risks prediction with any sample size. The Weibull and its guiding characteristics behavior indicates that; equipment with β = 1 (constant behavior) have a totally random failure mechanism independent of age; for equipment in this category, optimal policy is to repair or replace components only at failure. The Weibull distribution models the exponential distribution which is the useful life period, i.e. low constant failure rate. A value of β < 1 (decreasing behavior) typifies a startup or early failure of equipment period and the optimal policy is to carry out preventive and predictive maintenance on components only before failure. And the value of β > 1 (increasing behavior) shows end of life wear out or increasing failure rate. At β = 3, the Weibull distribution models the normal distribution, this is early wear out time. When β = 10, it is rapid wear-out occurring.

3.1 Constructing the Distribution for the Series

If Y = Bo + B1x + µ (24)

Then the mean of Y, denoted by m is

m = E(Y) = Bo + B1x (25)

The probability distribution of Y

Assuming normal errors µ is

International Journal of Advances in Engineering and Management (IJAEM)
Volume 3, Issue 11 Nov 2021, pp: 702-714 www.ijaem.net ISSN: 2395-5252

$$F(Y) = \frac{1}{\sqrt{2\pi\sigma}} \exp^{-½} - \frac{\{Y-m\}2}{\sigma 2} - \quad (26)$$

Now if the problem is to obtain estimates of Bo, B_1 and later σ², resorting to regression becomes remarkable available option; hence there are eight model cases as shown in Table (a) and the results are expressed as[9].

Case 1 when X = FOD, Y = CRPL

$$Y_1 = \frac{1}{\sqrt{2\pi(14.15)}} \exp^{-½} \frac{\{Y1-(40.16-0.00014\,FOD)\}}{199.94} \quad (27)$$

Case 2, when X = FOD, Y = CRP

$$Y_2 = \frac{1}{\sqrt{2\pi(12.55)}} \exp^{-½} \frac{\{Y2-(35.03-0.00024\,FOD)\}}{157.50} \quad (28)$$

Case 3, when X = FOD, Y3 = CBD

$$Y_3 = \frac{1}{\sqrt{2\pi(9.23)}} \exp^{-½} \frac{\{Y3-(25.71-0.00016\,FOD)\}}{85.19} \quad (29)$$

Case 4, when X = FOD, Y4 = CPM

$$Y_4 = \frac{1}{\sqrt{2\pi(3.14)}} \exp^{-½} \frac{\{Y4-(8.76-0.00006\,FOD)\}}{9.86} \quad (30)$$

Case 5, when X =FOM, Y5 = CRPL

$$Y_5 = \frac{1}{\sqrt{2\pi(2.3)}} \exp^{-½} \frac{\{Y5-(3.54-2.20\,FOM)\}}{5.29} \quad (31)$$

Case 6, when X = FOM, Y6 = CRP

$$Y_6 = \frac{1}{\sqrt{2\pi(3.3.E-15)}} \exp^{-½} \frac{\{Y6-(1.16E-16.00\,FOM)\}}{(3.30E-15)2} \quad (32)$$

Case 7, when X = FOM, Y7 = CBD

$$Y_7 = \frac{1}{\sqrt{2\pi(0.20)}} \exp^{-½} \frac{\{Y7-(0.35+1.47\,FOM)\}}{(0.04)} \quad (33)$$

Case 8, when X = FOM, Y8 = CPM

$$Y_8 = \frac{1}{\sqrt{2\pi(8.24E-16)}} \exp^{-½} \frac{\{Y8-(2.90E-15.50\,FOM)\}}{(8.24E-16)2} \quad (34)$$

Figure 5: Plot for the series CRPL, CRP, CBD and CPM (FOD)

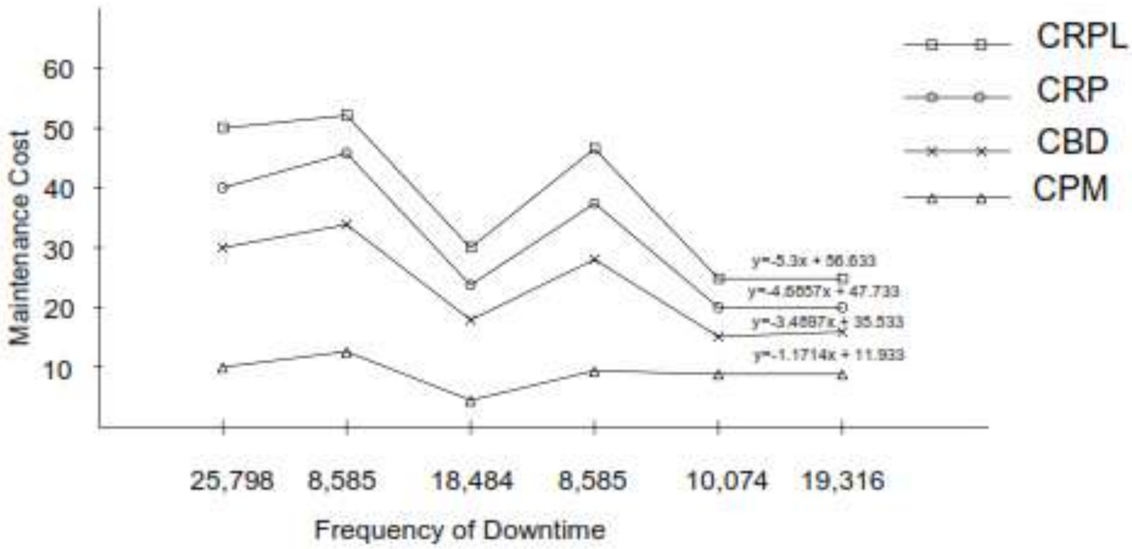
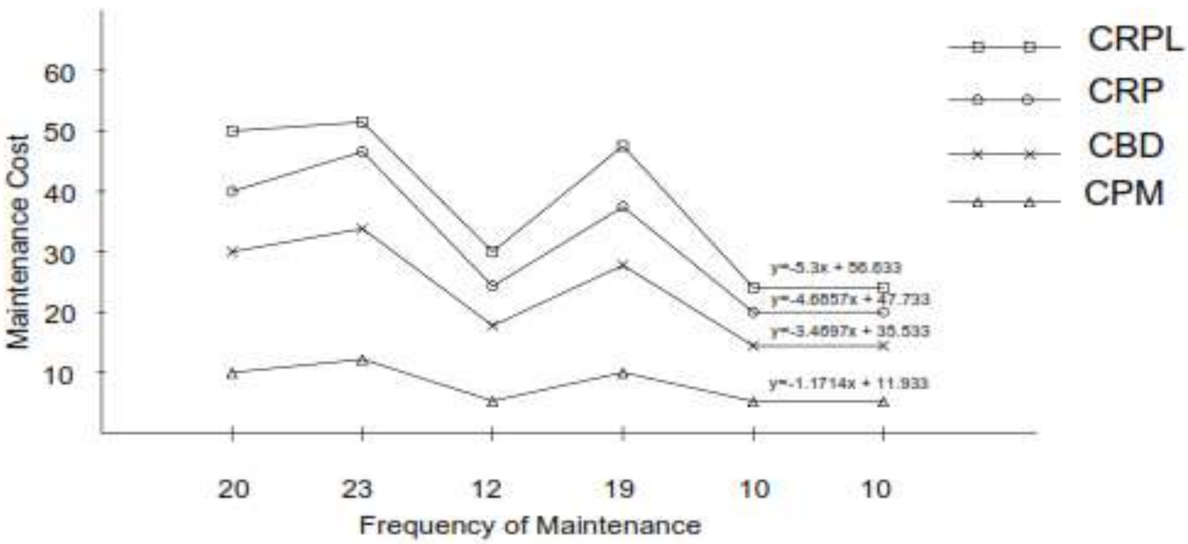


Figure 6: Plot for the series CRPL, CRP, CBD and CPM (FOM)



Poor R2 values of regression models U1, U2, U3 and U4 as shown in the models for statistical analysis for Figures 5 and 6 are a reflection of how the system is operated or loaded and an indication of small sample size due to large outage period of generating Turbine units. This is a report of statistical analysis for constructing probability distribution to obtain estimates of a given regression series requiring determination of probable values [9].

3.2 Models for Statistical Analysis of Maintenance Activities

Table a 1
$Y_1 = B_0 + B_1 FOD + U_1$
Dependent variable: CRPL
Method: Least Squares
Date: 08/28/15 Time: 09:44
Sample: 1 6 (Poor R^2 value = small sample size due to large unit outage period.)
Included observations: 6

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	40.15762	14.63146	2.744607	0.0517
FOD	-0.000137	0.000888	-0.154297	0.8848

R-squared	0.005917	Mean dependent var	38.08333
Adjusted R-squared	-0.242604	S.D. dependent var	12.69022
S.E. of regression	14.14606	Akaike info criterion	8.397951
Sum squared resid	800.4442	Schwarz criterion	8.328538
Log likelihood	-23.19385	F-statistic	0.023807
Durbin-Watson stat	1.433030	Prob(F-statistic)	0.884848

Table a 2
$Y_2 = B_0 + B_2 FOD + U_2$
Dependent Variable: CRP
Method: Least Squares
Date: 08/28/15 Time: 09:52
Sample: 1 6 (Poor R^2 value = small sample size due to large unit outage

period.)
Included observations: 6

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	35.02614	12.98294	2.697858	0.0542
FOD	-0.000244	0.000788	-0.309569	0.7723

R-squared	0.023398	Mean dependent var	31.33333
Adjusted R-squared	-0.220753	S.D. dependent var	11.36075
S.E. of regression	12.55223	Akaike info criterion	8.158875
Sum squared resid	630.2340	Schwarz criterion	8.089462
Log likelihood	-22.47663	F-statistic	0.095833
Durbin-Watson stat	1.328405	Prob(F-statistic)	0.772345

Table a 3
$Y_3=B_0 + B_3$ FOD $+ U_3$

Dependent Variable: CBD
Method: Least Squares
Date: 08/28/15 Time: 09:56
Sample: 16 (Poor R^2 value = small sample size due to large unit outage period.)
Included observations: 6

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	25.71190	9.550879	2.692098	0.0545
FOD	-0.000157	0.000580	-0.271049	0.7998

R-squared	0.018036	Mean dependent var	23.33333
Adjusted R-squared	-0.227455	S.D. dependent var	8.334667
S.E. of regression	9.234026	Akaike info criterion	7.544869
Sum squared resid	341.0690	Schwarz criterion	7.475455
Log likelihood	-20.63461	F-statistic	0.073467
Durbin-Watson stat	1.309791	Prob(F-statistic)	0.799766

Table a 4
$Y_4= B_0 + B_4$ FOD $+ U_4$

Dependent Variable: CPM
Method: Least Squares
Date: 08/28/15 Time: 09:59
Sample: 16 (Poor R^2 value = small sample size due to large unit outage period.)
Included observations: 6

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	8.756534	3.245736	2.697858	0.0542
FOD	-6.10E-05	0.000197	-0.309569	0.7723

R-squared	0.023398	Mean dependent var	7.833333
Adjusted R-squared	-0.220753	S.D. dependent var	2.840188
S.E. of regression	3.138058	Akaike info criterion	5.386287
Sum squared resid	39.38962	Schwarz criterion	5.316873
Log likelihood	-14.15886	F-statistic	0.095833
Durbin-Watson stat	1.328405	Prob(F-statistic)	0.772345

International Journal of Advances in Engineering and Management (IJAEM)
Volume 3, Issue 11 Nov 2021, pp: 702-714 www.ijaem.net ISSN: 2395-5252

Table a 5

$Y_5 = B_0 + B_5$ FOM + U_5

Dependent Variable: CRPL
Method: Least Squares
Date: 08/28/15 Time: 10:04
Sample: 1 6
Included observations: 6

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.545455	2.985772	1.187450	0.3007
FOM	2.204545	0.180928	12.18464	0.0003

R-squared	0.973765	Mean dependent var	38.08333
Adjusted R-squared	0.967206	S.D. dependent var	12.69022
S.E. of regression	2.298097	Akaike info criterion	4.763241
Sum squared resid	21.12500	Schwarz criterion	4.693828
Log likelihood	-12.28972	F-statistic	148.4655
Durbin-Watson stat	2.528926	Prob(F-statistic)	0.000260

Table a 6

$Y_6 = B_0 + B_6$ FOM + U_6

Dependent Variable: CRP
Method: Least Squares
Date: 08/28/15 Time: 10:08
Sample: 1 6
Included observations: 6

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.16E-14	4.28E-15	2.708580	0.0536
FOM	2.000000	2.60E-16	7.70E+15	0.0000

R-squared	1.000000	Mean dependent var	31.33333
Adjusted R-squared	1.000000	S.D. dependent var	11.36075
Log likelihood	2.298097	Akaike info criterion	4.763241
S.E. of regression	3.30E-15	Sum squared resid	4.35E-29
F-statistic	5.94E+31	Durbin-Watson stat	0.585034
Prob(F-statistic)	0.000000	Schwarz criterion	0.000345

Table a 7

$Y_7 = B_0 + B_7$ FOM + U_7

Dependent Variable: CBD
Method: Least Squares
Date: 08/28/15 Time: 10:10
Sample: 16
Included observations: 6

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.351240	0.257420	1.364461	0.2441
FOM	1.466942	0.015599	94.04180	0.0000

R-squared	0.999548	Mean dependent var	23.33333
Adjusted R-squared	0.999435	S.D. dependent var	8.334667
S.E. of regression	0.198132	Akaike info criterion	-0.138567
Sum squared resid	0.157025	Schwarz criterion	-0.207981
Log likelihood	2.415702	F-statistic	8843.860
Durbin-Watson stat	1.862114	Prob(F-statistic)	0.000000

International Journal of Advances in Engineering and Management (IJAEM)
Volume 3, Issue 11 Nov 2021, pp: 702-714 www.ijaem.net ISSN: 2395-5252

Table a 8

$Y_8=B_0 + B_8$ FOM $+U_8$

Dependent Variable: CPM
Method: Least Squares
Date: 08/28/15 Time: 10:11
Sample: 16
Included observations: 6

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.90E-15	1.07E-15	2.708580	0.0536
FOM	0.500000	6.49E-17	7.70E+15	0.0000
R-squared	1.000000	Mean dependent var		7.833333
Adjusted R-squared	1.000000	S.D. dependent var		2.840188
Log likelihood	-1724538	Akaike info criterion		-4.320332
S.E. of regression	8.24E-16	Sum squared resid		2.72E-30
F-statistic	5.94E+31	Durbin-Watson stat		0.585034
Prob(F-statistic)	0.000000	Schwarz	criterion	3.205612

IV. CONCLUSION

Engineering maintenance is an important sector of any economy. Each year the power industry in Nigeria spends million of amounts in naira on plant maintenance and operation, and in 2017 alone,the electricity regulatory commission in Nigeria budget request included $9 million for operation and maintenance for the power production industry. Furthermore, it is estimated that approximately 80% of the industry funds is spent to correct chronic failures of machines, systems, and people. The elimination of many of these chronic failures through effective maintenance can reduce the cost between 40 and 60%.

This study through math models ushers in a broader solution for equipment management—cradle-to-grave strategy to preserve equipment functions, avoid the consequences of failure, and ensure the productive capacity of equipment; which ordinarily cannot be achieved by simply following the traditional approach to maintenance,taking cognizance of the frequent issues of; human error, quality and safety, software maintenance, maintenance costing, reliability, and maintainability of equipment.

A maintenance optimization model with dual-objective potential, i.e. high failure/downtime rate and costs reduction is presented in this work to calculate the reliability, optimum inspection frequency to maximize profit, mean time to failure of a system subject to periodic maintenance, failed part replacement with a new and statistically identical one and periodic maintenance performance on the system at required period, starting at time zero. The model is based on the premise that facility/equipment under repair lead to zero output, thus less profit. Furthermore, if equipment is inspected too often, there is danger that it may be more costly due to factors such as loss of production, cost of materials, and wages than losses due to breakdowns.

REFERENCES

[1]. Barlow, R and Proschan, F (1996) “Mathematical theory of Reliability,” John Wiley and Sons, London

[2]. Barlow, R.E., Hunter, L.C. and Proschan, F. (1970) Optimum checking procedures, Journal of science for Industrial and applied math, Vol. 4 pp. 1078 -1095

[3]. Dekker, R. & scarf, P. (2004) On the impact of Optimization models in maintenance decision-making: the state of the art, Reliability Engineering & System safety 60(2), pp 111-119

[4]. Dhillon, B.S., Maintenance, in Reliability and Quality Control: Bibliography on General and Specialized Areas, Beta Publishers, Gloucester, Ontario, Canada, 1992, 287–302.

[5]. Kumar, U.D., New trends in aircraft reliability and maintenance measures, Journal of Quality in Maintenance Engineering, 5:4, 1999, 287–295.

[6]. Latino, C.J., Hidden Treasure: Eliminating Chronic Failures Can Cut Maintenance Costs up to 60%, Report, Reliability Center, Hopewell, Virginia, 1999.

[7]. Mathew, T. (2002) Maintenance Management math model: a new paradigm Aladon Ltd. Ashville, North Carolina

[8]. Niebel, B.W., Engineering Maintenance Management, Marcel Dekker, New York, 1994.
[9]. O'Connor, & Patrick, D.T. (2002) Practical Reliability Engineering, 4th edition, Wiley Chichester, Uk
[10]. Zweekhorst, A., Evolution of maintenance, Maintenance Technology, October 1996, 9–14.