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Development of an Optimal Maintenance Policy for Perkins Electrical Generating Sets Using Markov Chain Predictive Model

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Abstract

The study aimed at developing an optimal maintenance policy for 800kVA Perkins electrical generating sets (gen-sets) using Markovian predictive model. The 800kVA Perkins gen-set used by the Michael Okpara University of Agriculture, Umudike (MOUAU) was employed as a case study. To derive the solution for the analysis, the Markovian predictive model utilized sought answer to such questions as, "At what rate should the generator be maintained; and at what condition would it be after maintenance?" Theoretical data derived from the system were compiled, tested and thereafter simulated. Results of the analysis gave a value of 10 weeks and 2 days as the optimal operation policy period for 800kVA gen-sets; meaning that the system should be regularly maintained at the end of this period. In conclusion, appropriate models for enhancing the performance of the MOUAU's main gen-set have been developed in this study. In particular, the models are for determining the effective maintenance policy for an electrical gen-set so as to ensure that the system lasts long in service. Hopefully, results from the study will assist maintenance engineers and plant operators in improving the performance of their gen-sets through preventive rather than reactive maintenance. Consequently, it is recommended that the engineers and plant operators of the 800kVA Perkins gen-set at MUOAU and any other institution should adopt the developed models in the plant maintenance practices. It is also recommended that the maintenance policy developed from the study be integrated with the automated generator condition assessment models.

Keywords: Optimal maintenance policy, management system, Markovian predictive model, theoretical data, generating set

Nomenclature

K	Failure frequency per year
n	Number of states or the condition rating of the engine for an activity (or efficiency at 95% significant level of confidence)
$n_{optimal}$	Optimal policy value
N	Number of years projected for the engine to generate power or shelf-life of the engine (yrs)
P	Probability or transition matrix
Q_n	State vector time at step n (used to output results generated from "P" matrix when ran on the Matlab interface)
r	Initial state vector
t_c	Average duration of one corrective maintenance (hrs)
t_{cm}	Total corrective maintenance (hrs)
t_i	Average duration of one inspection or average time for an engine inspection (hrs)
t_m	Average duration of one maintenance (hrs)
T_n	Total downtime (hrs) caused by the generator for each activity (task) in a given state (n)
t_{pm}	Preventive (repair) maintenance (hrs)
t_r	average duration of one preventive maintenance (hrs)
λ	Transition rate
λ_{ij}	Rate of transition from one state to the other
λ_n	Failure rate occurrence per year

1. Introduction

In view of the rapid development around the globe, power demand has increased drastically during the past decade (Giftson and Rajan 2013). The advances in computer and information technology having created a strong trend in the world today also necessitated the integration of various operation facilities into large scale systems. As a result of this integration, the productivity and efficiency of these systems have been significantly improved. On the other hand, the integration as Giftson and Rajan (2013) suggested, has also created a strong functional dependency between the components of the system. Failure of any one of these components as they stated could destabilize the entire system and hence cause significant financial loses and serious safety problems.

To meet this demand, the development of power system technology has become increasingly important in order to maintain a reliable and economic electric power supply. One major concern of such development is the optimization of power plant maintenance scheduling. Since maintenance is aimed at extending the life-time of power generating facilities or to improve its performance in the mean time the next failure for which repair cost may be significant, an effective maintenance policy would reduce the frequency of service interruptions and their consequences (Giftson and Rajan 2013). In other words, an effective maintenance scheduling is very important for a power system to operate economically and with high reliability. Therefore, it is the focus of this work to resolve maintenance decision problems and establish an optimal maintenance policy for an electrical generating system with an economic dependency. This was done using MOUAU, 800kVA Perkins gen-set in-situ at the University as case study. In this direction, an opportunistic maintenance policy generally applicable to the economic dependency problem was proposed for developing optimal maintenance schedule.

Although, effective maintenance policy development has become the major challenge and primary concern for today's system managers, many maintenance-scheduling methods had been proposed using conventional mathematical programming methods or heuristic techniques. Heuristic approaches provide the most primitive solution based on trial-and-error approaches (Giftson and Rajan 2013). These techniques may not generally lead to the global optimality for a complex problem; that is, the procedure tends to fall into a local minimum if a starting point is not carefully chosen. Heuristic methods were used earlier in solving maintenance scheduling problems for centralized power systems because of their simplicity and flexibility. Mathematical optimization-based techniques such as integer programming (Dopazo and Merrill 1975), dynamic programming (Yamayee *et al*.1983; Zurn and Quintana 1975) and branch-and-bound (Egan *et al*.1976) were proposed to solve maintenance scheduling problems. For small problems, these methods give an exact optimal solution. However, as the size of the problem increases, the size of the solution space increased greatly and hence, the running time of these algorithms. These approaches tend to suffer from an excessive computational time with the increase of variables. To overcome this difficulty, modern techniques such as simulated annealing (Cerny 1985; Kirkpatrick *et al*.1983), stochastic evolution (Saab and Rao 1991), genetic algorithms (Goldberg 1989) and Tabu search (Rajan and Mohan 2004) were utilized as alternatives where the problem size precludes traditional techniques. These techniques are completely distinct from classical programming and trial-and-error heuristic methods.

Maintenance as Dhillon (2002) defined is all actions appropriate for retaining an item or part or equipment in place, or restoring it to a given working condition. Hence, maintenance more specifically is used to repair broken equipments, preserve equipment conditions and prevent their failure, which ultimately reduces production loss and downtime as well as the environmental and the associated safety hazards. Effective and optimum maintenance has been the subject of research both in academia and in industry for a long time. Despite this abundance, the optimization of decision variables in maintenance planning like preventive maintenance frequency or spare parts inventory policy, is usually not discussed in textbooks nor included as a capability of the software packages. Nonetheless, it has been extensively studied in academic research, for which many models were discussed and summarized by Wang and Pham (2006) and various review papers (Wang 2002a and Wang 2002b). Most of the models were deterministic models obtained by making use of simplified assumptions, which allowed the use of mathematical programming techniques to solve.

The most common optimization criterion is minimum cost and the constraints are requirements on system reliability measures: availability, average uptime or downtime. More complex maintenance models that considered simultaneously many decision variables like preventive maintenance (PM) time interval, labor workforce size, resources allocation were usually solved by genetic algorithm (GA) (Saranga 2004; Shum and Gong 2006), while

Monte Carlo simulation is usually used to estimate reliability parameters in the model. Tan and Kramer (1997) utilized both Monte Carlo simulation and GA. However, none of the preventive maintenance planning models considered constraints on resources available in process plants, which include labour and materials (spare parts). For example, the maintenance work force, which is usually limited, cannot perform scheduled PM tasks for some equipment at scheduled PM time because of the need to repair other failed equipments. Such dynamic situations cannot be handled by deterministic maintenance planning models or were not considered in published maintenance planning models that use Monte Carlo simulation tools. To ameliorate all the aforementioned shortcomings, a new maintenance model based on the use of Monte Carlo simulation was developed in this research paper. The model incorporated three practical issues that were not considered in previous works as: different failure modes of equipment, ranking of equipment according to the consequences of failure, and labour and material resource constraints. The maintenance model, which was developed by Nguyen *et al*. (2008) was integrated in this work with a GA optimization to optimize the PM frequency.

2.0 Material and methods

To execute the work, the following assumptions were made that:
i) the gen-set performs as in its initial design and manufacturing conditions.
ii) maintenance is carried out at the end of every inspection of the system.
iii) every failed components of the system is repaired or replaced.
iv) the rotating parts of the system on the gen set must be properly timed; and
v) replacement parts must be in serviceable condition and replaced with genuine spares.

2.1 Condition Assessment Scale

Presented in Table 1 is the physical assessment of the conditions of the gen-set and its ratings as adapted from Wang (2002a) with some other modifications by the present researchers. The generator from the table was assumed to be in different states as time went on. The condition of the generator was also described by the rate of damages done in percentage (%) during the running of the engine.

Table 1: Physical assessment of the conditions of the generating set and its ratings

Condition rating of the gen set	Condition/state description of the gen set	Extent of damage of the engine at different states (%)
1	Excellent	0-10
2	Very good*	11-20
3	Good	21-30
4	Very fair*	31-40
5	Fair	41-55
6	Poor	56-70
7	Very poor*	71-85
8	Failed	>85

Source: Wang (2002a); and '*'modified by the present researchers.

Table 2: Downtime maintenance due to various faults on the generator

Task	Total downtime, T_n (hr)
Battery failure	5.40
Leakages	5.50
Connectors	5.65
Air cleaner	5.70
Radiator flush	5.80
Fan tension	6.25
Filters	6.10
Noise	8.91

Also, the downtime maintenance employed at MOUAU due to various faults (tasks) developed on the gen-set is as shown in Table 2.

2.2 Description of the Machine State and Formulation of the Markovian Chain Predictive Model

$x_1,\ x_2, x_3, \dots, etc$ is a stochastic process representing a collection of condition ratings of a gen-set based on a three-year inspection data. At any time t, the condition of a generating set can be described in exactly one of a finite number of mutually exclusive and exhaustive categories or states. Eight states, associated with the condition ratings 1 to 8 presented in Table 1, with 1 being the optimal generator condition, and 8 corresponding to critical (worst) generator condition were used. Consequently, the state diagram describing the states of the gen-set and the efficiencies which represented the stated problem as a Markov chain is presented in Fig.1.

Fig.1: State diagram for the efficiencies of the gen-set

A stochastic process is said to be a Markov chain, if it has the Markovian property (i.e., the conditional probability of any future event, given any past event and the present state where: $X_t = i$, is independent of the past event and depends only upon the present state). This property can be expressed as represented in Eqn 1.

$$\text{P}\ (X_{t+1}= i_{t+1}\ |\ X_t = i_t,\ X_{t-1}= i_{t+1}, \dots, X_1= i_1,\ X_0 = i_0) = \text{P}\ (X_{t+1}= i_{t+1} |\ X_t = i_t) \qquad (1)$$

In order to reduce the complexity of the analysis, the future condition of generators was assumed to depend only on the present state, and independent of the past condition. It was further assumed that for all states, i and j, and all $t, P(X_{t+1} = i_{t+1}|X_t = i_t)$ were independent of t. The probability P_{ij} represented in Eqn 2 thus, indicate that the generator condition was in a state i at time t, and will remain in a state j at time, $t + 1$ without changing (i.e., it would remain stationary) over time (unless rehabilitation was performed, or other external factors did change). Hence, P_{ij} represents otherwise the probability of the process going from state i to j. This stationary assumption is expressed by Eqn 2 as:

$$P\ (X_{t+1} = \text{j}\ |\ X_t = i) = P_{ij} \qquad (2)$$

The transition probabilities are commonly displayed as an "$m \times m$" matrix called the transition probability matrix, P (Wang 2002a). The term transition is used when the system moves from state i during one period to state j during the next period. Accordingly, the probabilities, P_{ij}'s, are referred to as the transition probabilities. Hence, eight states (Table 1) associated with the eight possible conditions of the generators were established. To simplify the computation, it was assumed that the generator deteriorated by one state in one transition period. Thus, the transition probability matrix P becomes Eqn 3:

$$\begin{array}{ll} \textbf{To State} & \begin{array}{cccccccc} \quad 1 & \quad\ 2 & \quad\ 3 & \quad\ 4 & \quad\ 5 & \quad\ 6 & \quad\ 7 & \quad\ 8 \end{array} \\ \textbf{From} & \\ \textbf{P} = & \begin{bmatrix} P(11) & P(12) & P(13) & P(14) & P(15) & P(16) & P(17) & P(18) \\ P(21) & P(22) & P(23) & P(24) & P(25) & P(26) & P(27) & P(28) \\ P(31) & P(32) & P(33) & P(34) & P(35) & P(36) & P(37) & P(38) \\ P(41) & P(42) & P(43) & P(44) & P(45) & P(46) & P(47) & P(48) \\ P(51) & P(52) & P(53) & P(54) & P(55) & P(56) & P(57) & P(58) \\ P(61) & P(62) & P(63) & P(64) & P(65) & P(66) & P(67) & P(68) \\ P(71) & P(72) & P(73) & P(74) & P(75) & P(76) & P(77) & P(78) \\ P(81) & P(82) & P(83) & P(84) & P(85) & P(86) & P(87) & P(88) \end{bmatrix} \end{array} \qquad (3)$$

where $\quad \sum P\ ij = 1 \qquad (3b)$

Eqn 3b indicates that the sum of each row probability must be equal to 1.

Based on the assumptions made, the transition rate (λ) of the probability matrix P, otherwise the rate of transition from one state to the other, λ_{ij} given in Eqn 4 were developed using Eqns 5-6h following the state diagram for the efficiencies of the gen-set as established in Fig.1.

$$P = \begin{bmatrix} \lambda_{11} & \lambda_{12} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \lambda_{22} & \lambda_{23} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \lambda_{33} & \lambda_{34} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \lambda_{44} & \lambda_{45} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \lambda_{55} & \lambda_{56} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \lambda_{66} & \lambda_{67} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \lambda_{77} & \lambda_{78} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \lambda_{88} \end{bmatrix} \quad (4)$$

$$\lambda_{ij} = \frac{T_n - N\,(t_i)}{t_m} \quad (5)$$

$$\lambda_{11} + \lambda_{12} = 1;\ \text{and}\ \lambda_{11} = 1 - \lambda_{12} \quad (6)$$

Similarly:

$\lambda_{22} + \lambda_{23} = 1$; and $\lambda_{22} = 1 - \lambda_{23}$ (6b)
$\lambda_{33} + \lambda_{34} = 1$; and $\lambda_{33} = 1 - \lambda_{34}$ (6c)
$\lambda_{44} + \lambda_{45} = 1$; and $\lambda_{44} = 1 - \lambda_{45}$ (6d)
$\lambda_{55} + \lambda_{56} = 1$; and $\lambda_{55} = 1 - \lambda_{56}$ (6e)
$\lambda_{66} + \lambda_{67} = 1$; and $\lambda_{66} = 1 - \lambda_{67}$ (6f)
$\lambda_{77} + \lambda_{78} = 1$; and $\lambda_{77} = 1 - \lambda_{78}$; and (6g)
$\lambda_{88} = 1$ (6h)

where λ_{11} to λ_{88} and λ_{12} to λ_{78} respectively represent the rates of retention of the system or the efficiencies of the gen-set at each state, and the corresponding losses due to the system.

2.3 Determination of Transition Rate (λ)

The field data collected on the 800kVA MOUAU gen-set maintenance history from the generator Unit maintenance Catalogue for a period of one year and three months (15months) revealed that the device usually breaks down from time to time. To reduce the number of breakdowns, nth inspections were made *'Nth'* times a year, after which, preventive maintenance was carried out. The field data as collected for the preventive and the corrective maintenances carried out on the gen-set for various faults developed (Table 2) are shown in Tables 3.

Table 3: Maintenance data (hrs) for MOUAU 800kVA generator set in the years 2014 and 2015

Month	Preventive maintenance (t_{pm})	Corrective maintenance (t_{cm})
Feb. 2014	4.00	0.00
Mar. 2014	5.00	0.30
April 2014	0.50	0.45
May 2014	13.00	3.80
June 2014	9.00	1.30
July 2014	8.00	1.30
Aug. 2014	12.00	2.20
Sept. 2014	12.00	3.20
Oct. 2014	14.00	4.60
Nov. 2014	7.00	0.60
Dec. 2014	8.00	1.10
Jan. 2015	5.00	0.45
Feb. 2015	9.00	0.55
Mar. 2015	10.00	2.55
April 2015	7.00	3.00
Total	123.5	25.40

Consequently, the total downtime T_n (hrs) caused by the generator for each activity or task in a given state n as presented in Table 2, and the minimum time t_m taken for one maintenance of the system (hrs) are evaluated using the Eqns 7 and 7b respectively.

$$T_n = t_m(\lambda_{ij}) + t_i(N) \quad (7)$$

and

$$t_m = t_r + t_c \quad (7b)$$

According to the views of Experts (CAT™ 2014) in the service line, if an average time taken for an engine inspection t_i, being 8mins or 0.133hrs as obtained from the MOUAU gen-set Unit (which also was taken to be the average duration of one inspection) can be attained, the number of years projected for the engine to generate power, otherwise, the shelf-life of the engine N, could extend to 40years. Hence, the average durations of one preventive (repair), t_r and one corrective, t_c maintenances (hrs) are respectively given as:

$$t_r = \frac{t_{pm} - (t_i \; x \; N)}{N} \qquad (7c)$$

and

$$t_c = \frac{t_{cm}}{N} \qquad (7d)$$

Moreso, from the state vector time at step n, Q_n (used to output the results generated from "P" matrix when ran on the Matlab interface), the failure frequency per year, K and the failure rate occurrence per year, λ_n respectively, the optimal value for the policy, $n_{optimal}$ presented in Eqn 7h was estimated using Eqns 7e-7g.

$$Q_n = rp^n \qquad (7e)$$

$$K = \frac{n}{\lambda+1} = \frac{t_r}{t_c} \qquad (7f)$$

$$\lambda_n = \frac{n}{K+1} \qquad (7g)$$

$$n_{optimal} = \left(\frac{Kt_r}{t_i}\right)^n \qquad (7h)$$

3.0 Results and Discussions

The parametric results for the values of the transition matrix, P obtained using Eqns 5-6h (where: λ_{11} = 0.9777, λ_{22} = 0.9532, λ_{33} = 0.9081, λ_{44} = 0.8941, λ_{55} = 0.8663, λ_{66} = 0.7409; and λ_{77} = 0.7827 respectively) are presented in Eqn 8. The state vectors as reconciled with the Table 1 and the transition matrix of Eqn 8 show that 0.977 represented the state vector of the condition or state of the gen-set that is excellent, followed by 0.9532 as very good, and 0.9081 as good, in that order, upto…1.0000 as failed. To predict the future condition of the generator from the probability of failure, the calculated results (Eqn 8) obtained from the Markov models (Eqns 3 and 4) being representative of the efficiencies of the gen-set in Fig.1, were simulated using the Matlab program (Eqns 9-9g) and subsequently analysed, employing the Markovian matrix model presented in Eqn 10.

$$P = \begin{bmatrix} 0.9777 & 0.0223 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.9532 & 0.0468 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.9081 & 0.0919 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.8941 & 0.1059 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.8663 & 0.1337 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.7409 & 0.2591 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.7827 & 0.2173 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1.0000 \end{bmatrix} \qquad (8)$$

E = (S0*P)P^2 (9)
F = (S0P^2*P^3)P^3 (9b)
G = (S0P^2*P^3)P^7 (9c)
H = (S0P^2*P^3)P^12 (9d)
I = (S0P^2*P^3)P^18 (9e)
J = (S0P^2*P^3)P^25 (9f)
K = (S0P^2*P^3)P^33 (9g)

$$V = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \qquad (10)$$

The Eqns 9-9g are of the Markovian process since they are probabilistic and not stochastic. The calculated values of Eqn 8 conforming to such process, when in-putted into the MATLAB interface utilizing the program and ran, gave rise to the state vector time at step n.

The prediction utilized the argument shown in Eqn (11), which indicated that, at the initial state (SO), the system is unity (i.e. perfect or excellent). Thus, the resulting probability matrix, P (Eqn 8) when executed using the predicted results from the Matlab program (Eqn 10), gave the state vector time at step n (Q_n), presented in Eqn 12.

$$SO = [1 \;\; 0 \;\; 0 \;\; 0 \;\; 0 \;\; 0 \;\; 0 \;\; 0] \tag{11}$$

$$Q_n = \begin{bmatrix} 0.9777 & 0.0223 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 \\ 0.9346 & 0.0613 & 0.0040 & 0.0001 & 0.0000 & 0.0000 & 0.0000 & 0.0000 \\ 0.8734 & 0.1075 & 0.0168 & 0.0021 & 0.0002 & 0.0000 & 0.0000 & 0.0000 \\ 0.9346 & 0.1507 & 0.0397 & 0.0095 & 0.0017 & 0.0003 & 0.0000 & 0.0000 \\ 0.7130 & 0.1829 & 0.0689 & 0.0251 & 0.0074 & 0.0019 & 0.0006 & 0.0003 \\ 0.6228 & 0.1995 & 0.0975 & 0.0481 & 0.0196 & 0.0068 & 0.0031 & 0.0025 \\ 0.5318 & 0.2002 & 0.1185 & 0.0734 & 0.0380 & 0.0163 & 0.0093 & 0.0125 \\ 0.4440 & 0.1877 & 0.1278 & 0.0938 & 0.0581 & 0.0288 & 0.0192 & 0.0405 \end{bmatrix} \tag{12}$$

Based on the Markov predictive model (Wang 2002b), the optimal maintenance policy for such a generating set can always be described “when the system hits state i, and recovers itself back to state j”. In this regard, Eqns 8 and 10 as representatives of Eqn 3 indicate that at an excellent state stage $(V_{ij} = V_{11})$ of Eqn 10, the system was in its perfect condition without deterioration. However, if not maintained at any interval but allowed to hit stage 3 $(V_{ij} = V_{33})$, the system deration is inevitable, otherwise, it would be restored to a state in good condition $(V_{ij} = V_{42} = V_{ij} = V_{22})$. This thus, enabled the system performance to be predicted with Q_n (Eqn 12), which was the state vector time at step n.

Also, the maintenance strategy chart results of the 800kVA generator for the period of 15 months are shown in Fig.2. From the figure, it was evident that the maintenance strategy taken for maintaining the generator was high with preventive maintenance duration of 14hrs in the month of October 2014. Similarly, due to this nature of the maintenance strategy adopted, the corresponding corrective maintenance was also high (about 5.30hrs) for the same month. Consequently, the greatest downtime observed (Fig.3) was caused by noise with a total downtime of about 9hrs, while the least task was the battery fault with a total downtime value of about 5 to 6 (5.40) hrs.

Invoking the values of t_{pm} = 123.5hrs and t_{cm} = 25.40hrs from Table 3, and those of t_r = 2.9545hrs and t_c = 0.6350hrs obtained from Eqns 7c-7d respectively, the value of t_m was evaluated as 3.5895hrs applying Eqns 7-7b. Based on Assumption 1, and for a 95% of the time before transiting to the succeeding condition state, the optimal value for the policy, $n_{optimal}$ was estimated from Eqn 7h as 10.17 weeks, utilizing the values of K = 4.6528, λ_n = 0.0885 from Eqns 7f-7g respectively, and $t_i = 0.133$, employing the n factor of 0.5 at 95% significant level of confidence. Hence, the system performance (Q_n) from Eqns 7e and 12 as predicted, has an optimal value of 10.17 weeks. Consequently, with Q_n = 10.17 weeks, which represents the optimal maintenance policy value for the system under review, the generator should be maintained every 10 weeks and 2 days (outmost, every 11 weeks).

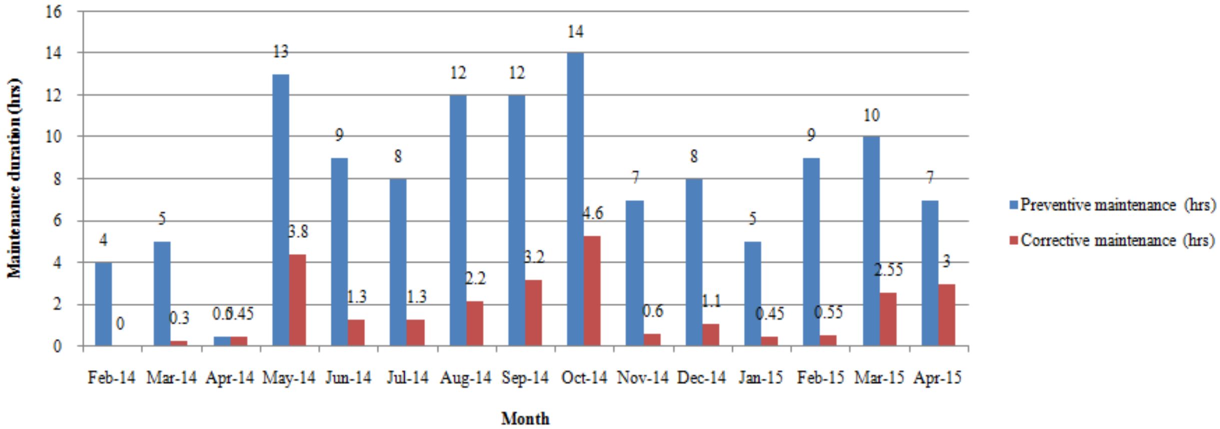

Fig.2: Maintenance strategy chart result on the 800kVA generator set for the period of 15months

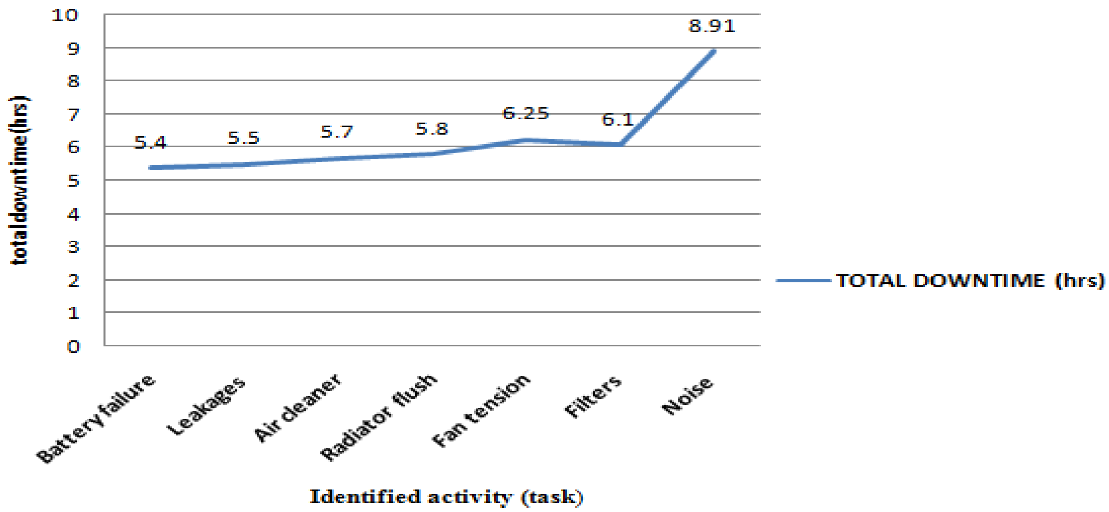

Fig.3: Total downtime chart result due to various faults (identified activity) from the generator

4.0. Conclusion

The use of Markov chain models for developing an optimal maintenance policy for electrical generating sets under break down conditions was presented. It was demonstrated that the magnitude of uncertainty had significant impact in the selection of maintenance policies, which is necessary for rational decision making in this field. The optimal maintenance period of 10.17 weeks obtained indicates that for every 10 to 11 weeks of using a Perkins Electrical Generating set, maintenance should be carried out on the system.

Although this research focused on the method under the context of a generating system, it can also be easily extended to other fields of generating components. In this direction, suggestions for future work focusing on integrating the maintenance policy with automated generator condition assessment models, as well as the management systems are proffered. To fully optimize the usefulness of the optimal maintenance policy on generators, it is recommended that extension should be made to other generator types like the Caterpillar, Cummins, Damen engines, etc. Overall, optimal maintenance policy if gainfully implemented will assist maintenance engineers and plant operators improve the performance of the gen-set, and make more accurate predictions of the condition of generating sets. This would be a good step towards preventive rather than the reactive maintenance.

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