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PRIORITY DISPATCH SCHEDULING IN AN AUTOMOBILE REPAIR AND MAINTENANCE WORKSHOP

AKINYEMI OLASUNKANMI O.*, KOYEJO OYEBOLA T.

Department of Mechanical Engineering, Olabisi Onabanjo University
(Ibogun Campus), PMB 5026, Ifo Post Office, Nigeria
*Corresponding Author: sukiyomakie@yahoo.com

Abstract

This research work applied a simulation model in determining the optimal number of artisans to employ to carry out routine checks on vehicles on a waiting line. The waiting line under consideration is that of an automobile repair and maintenance workshop in South- Western Nigeria. The data collection was based on arrival pattern of vehicles and service pattern of artisans in the maintenance workshop. A discrete distribution was assumed for both the inter–arrival and service time patterns. An optimal number of 7 servers serving one queue were obtained as against 4 servers and 1 queue in the system in use. There was also a savings in cost of ₦2.45 Million per month when compared to the system in use. The results of this research work will be significant and important for decision making.

Keywords: Scheduling, Priority dispatch, Maintenance, Performance measures.

1. Introduction

In an automobile industry, preventive maintenance is generally carried out on a daily basis so as to reduce the probability of vehicle breakdown performance degradation. This type of maintenance often involves physical inspection, oil changes, oil gauging, cleaning of contact set and plugs, tightening of loose bolts and nuts, wheel alignment and balancing, checking the lightening system, batteries and horns. Prior examination and monitoring of these parts can present vehicle breakdown and it has a great influence on the efficiency of daily fleet operations than other forms of maintenance [1].

Scheduling is defined as the allocation of resources to job overtime. Scheduling is an important tool in manufacturing and engineering industries. In the automobile

Nomenclatures

C_d	The downtime cost of a vehicle waiting in the system
$C(j)$	Total cost of system operation per unit time
C_L	The cost per unit time of an artisan
D_{ij}	Delay in queue of i^{th} vehicle on server j. It is the time a vehicle arrives at the workshop and is delayed before being served
DP_i	Departure time of i^{th} vehicle on j^{th} server
d(j)	Average delay in queue of vehicle on sever j (j=1, 2, 3, ..., m)
I_i	Inter-arrival time of i^{th} vehicle in the system
m	Total numbers of servers in the system
n	Total numbers of vehicles in the system
SIT_j	Sever idle time
S_i	Service time of i^{th} vehicle in the system
T_i	Time of arrival of i^{th} vehicle in the system
U_i	Utilization of server j
$U(m)$	Average utilization of servers j=1, 2, 3, ..., m
W_i	Waiting time of i^{th} vehicle in the system
$W(n)$	Average waiting time of vehicle in the system
Greek Symbols	
λ	The arrival of vehicles per unit time
δ	Point statistic estimator

industry, the purpose of scheduling is to minimize the completion time of jobs, mean flow time, lateness of jobs and processing cost. Scheduling process can also be used in traffic, home construction, facility maintenance, hospitals, courts and sport league.

Various authors have developed models in analyzing preventive maintenance operations for fleet maintenance problems. Oluleye and Anyaeche [2] used Markov model to analyze the preventive maintenance operation for a fleet of trucks. In their work, they assumed that state transition probabilities can be determined from past histories of trucks and logical expectation of the fleet operators. A number of authors have also used simulation to evaluate the performance of dispatching rules. Ramasesh [3], Rajendran and Holthaus [4] presented excellent state-of-the-art surveys of dispatching rules in a dynamic workshop. They evaluated the performance of a variety of dispatching rules with respect to some common performance measure such as variance of flow time, minimum and maximum flow time, mean tardiness, maximum tardiness and variance tardiness to mention a few. These rules are classified into 5 categories; rules involving process time, rules involving due dates, simple rules involving neither process time nor due dates, rules involving workshop conditions, and rules involving two or more of the first four categories.

In general, it has been noted that process time based perform better under tight load conditions, while due date based rules perform better under light load condition. Holthaus [5] presented a simulation – based analysis of dispatching rules for scheduling in workshop with machine breakdown with respect to flow time and due date based objectives, the relative performance well-known and the new dispatch rules proposed were evaluated for different setting of the model parameter. Until very recently the problem of scheduling in the presence of real-time events, termed dynamic scheduling and priority dispatch scheduling has been largely neglected.

In this work, effort is put on predictive-reactive scheduling (ordering and preparation of raw materials and planning for tools, set-up activities, etc.). Predictive scheduling enables better co-ordination by properly planning the timing of the workshop activities to increase workmanship and minimize completion time. Most times there are problems in scheduling due to some real-time events, the size of the problem (determined by the number of jobs, designated as n) and the number of the machines (designated as m). In an automobile repair/maintenance workshop, we have a case of a single machine problem, where the technicians represent single machine.

In this study, there are different kinds of problems a single machine encounters in real time events. This includes; sick leave, weather, traffic conditions thereby overstretching some of the technicians in a case where the numbers of technicians are few. Uncertainties due to exact scale of work often unknown before a technician arrives at his work bay do overstretches and varying technicians skill level (light duty and heavy duty).Furthermore other problems notable on the floor of workshop includes; last minute request which might have a higher priority, customer's cancelling their appointment dates and re-scheduling and sometimes, occasionally where the manager changes job schedule to suit business objectives. The main objective is for the vehicles to be processed on time by the right man-right time-right place-right cost.

2. Problem Formulation

2.1. System description

The Automobile Maintenance Company used as the case study is a limited liability company situated in the South Western part of Nigeria. The jobs are classified according to the distance covered, i.e., 5,000 km, 10,000 km, 15,000 km and 20,000 km. The 5,000 km maintenance services involves changing of oil and oil filter, the 10,000 km involves changing of oil, oil filter and adjusting of hand brake, what is done in the 5,000 km service is repeated in the 15,000 km service because they are in the same series only that the brake is checked for wear due to bad roads and reckless driving, the 20,000 km service is known as the comprehensive service where the oil and oil filter are changed, the plugs are changed if they are not platinum (which can last for 100,000 km or three years whichever comes first), changing of fuel filter, brake pads, air filter, topping of brake and gear oil, gauging of tyres, wheel alignment, checking battery. During these operations the artisans are timed, from the time they collect the parts to the time they return the car keys to the workshop manager.

2.2. Method of data collection

In a dynamic job shop, automobile for processing arrives at different points of times with certain specified inter-arrival times. The jobs may require a certain number of operations to be performed in a particular sequence on specified machines. The scheduling rule makes use of the attributes of the job such as operation times, due date, number of the operations and the like. This work is focused on the allotment of jobs to machines (in this case artisans), to improve the performance of the job shop by making use of inter-arrival times, due date settings and processing times.

The basic data required are the release date, processing time and due dates of each job. Real life data was collected using the company's standard work orders as follows:

- **Release date**

The release time is the earliest time at which the processing of each job can begin and it is sometimes called the ready time or release date. It is the time each job arrives at the shop. Therefore, the date the work order was brought was used as the release date of the job. We assumed that scheduling starts from the 1^{st} day of the month, so if a work order was brought on 12^{th} of January, the release date is 12. Therefore, release dates have values ranging between 1 and 31 inclusive depending on the month of the year.

- **Due date**

The due date is the latest time by which each job is due to be delivered to the customer. The date the work order is required was used to compute the due date. For example, if the work order is required on the 20^{th} of February, then the due date will be 31 days in January plus 20 days in February, which gives 51 days. In simulation studies of hypothetical job–shops the need for a due date procedure is twofold. First, due dates represent delivery commitments by the workshop, actual performance can be evaluated in light of the given due dates. Most simulation studies have considered due date related performance measures such as average tardiness or the distribution of the job lateness. The second need for the due date procedure in simulation studies stems from the fact that many scheduling rules are related to the jobs due dates. For example, the EDD (early due date) or the S/OPN (slack time per remaining operation) scheduling rules exploit due date information in order to reduce the chance of late deliveries [6].

- **Processing time**

The processing time is the amount of time unit required by each job to be processed on the machine. The processing time of each work order will be collected in the maintenance shop floor. In this work, processing time is determined when the artisan starts and ends the job.

3. Performance Measures

The expressions of performance measures used for this research work are stated below:

$$I_i = T_i - T_{i-1} \tag{1}$$

$$DP_{ij} = T_i + S_i \tag{2}$$

$$d(j) = \sum_{i=1}^{n} D_{ij} / n \tag{3}$$

$$W_i = D_{ij} + S_i \tag{4}$$

$$W(n) = \sum_{i=1}^{n} W_i / n \tag{5}$$

$$U(m) = \sum_{j=1}^{m} U_j / \text{Total number of servers} \tag{6}$$

$$\%SIT = \sum_{i=1}^{m} (SIT)_j / \text{Departure time of last vehicle} \times 100 \tag{7}$$

$$\%U = 100 - \left(\sum_{i=1}^{m} (SIT)_j / \text{Departure time of last vehicle} \right) \times 100 \tag{8}$$

Assumptions

- A machine can process only one job at a time and all machines are assumed to be the same.
- A job, once taken up for processing, should be completed before another job can be taken up, i.e., job pre-emption is not allowed.
- An operation on any job cannot be performed until all previous operations on the job are completed.
- There are no break downs (artisans are always available for processing times).
- There are no other limiting resources such as labor and material.
- There are no vehicles in the system initially.
- Service is based on First- in-First-Out.

3.1. Data analysis

Data were collected for the month of April 2009 in an automobile maintenance workshop. The service time in this data was grouped into different class width in the range 10, 15, 25, 35 and 50 respectively; a bar chart was drawn for each of these ranges as shown in Figs. 1 to 5 while Fig. 6 represented the bar chart for the inter arrival times. The smoothest looking bar chart was picked to determine the probability distribution of the data.

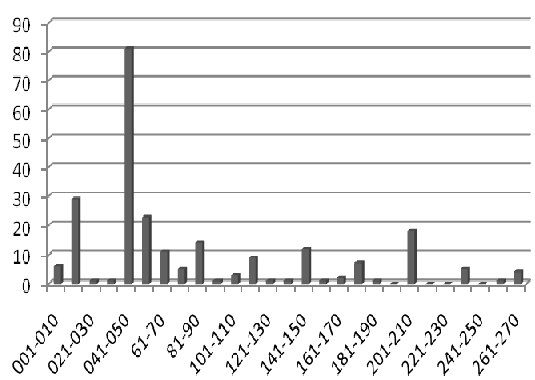

Fig. 1. Bar Charts of the Service Time Data for the Range of 10.

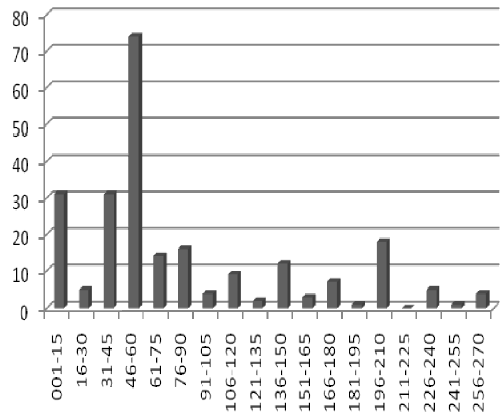

Fig. 2. Bar Charts of the Service Time Data for the Range of 15.

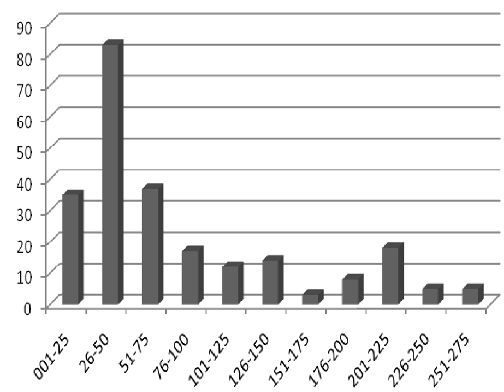

Fig. 3. Bar Charts of the Service Time Data for the Range of 25.

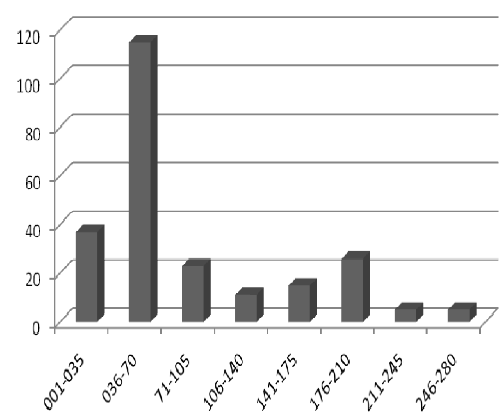

Fig. 4. Bar Charts of the Service Time Data for the Range of 35.

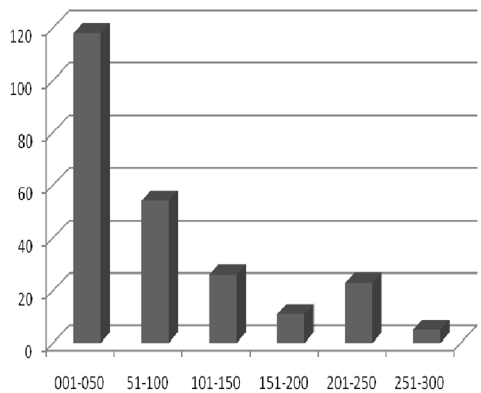

Fig. 5. Bar Charts of the Service Time Data for the Range of 50.

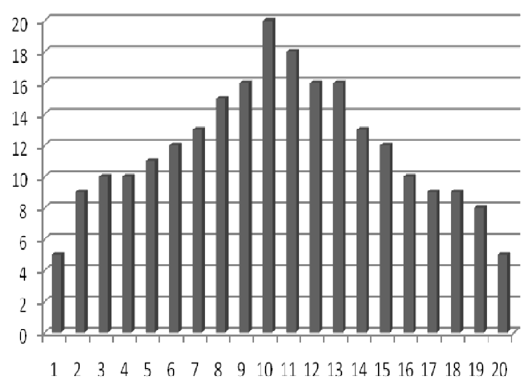

Fig. 6. Bar Chart of Inter-Arrival Time Data in Table 1.

According to these bar charts, range 50 appears to be the smoothest and its shape resembles that of a Poisson mass function. This graph is a discrete distribution graph, where $\delta = \frac{\sqrt{\operatorname{var}(x)}}{E(x)}$ is a point statistic estimator to affirm the likely probability distribution of data collected.

The Point statistics is calculated using the formula

$$\delta = \frac{\sqrt{\operatorname{var}}}{\bar{x}} \tag{9}$$

The result $\frac{\sqrt{\operatorname{var}}}{\bar{x}} < 1$ might suggest a binomial distribution, near 1 suggests a Poisson distribution while $\frac{\sqrt{\operatorname{var}}}{\bar{x}} > 1$ would be characteristic of negative binomial or geometric (a special of negative binomial). From the data obtained, the probability distribution for the service time and inter-arrival time is calculated with the formula above using Tables 1 and 2.

Table 1. Service Time of the Vehicles in the System.

Interval	x	f	$f.x$	$(x-\bar{x})$	$(x-\bar{x})^2$	$f\cdot(x-\bar{x})$
1 – 50	25.5	118	3009	-54.01	2917.0801	344215.4518
51 – 100	75.5	54	4077	-4.01	16.0801	868.3254
101 150	125.5	26	3263	45.99	2115.0801	54992.0826
151-200	175.5	11	1930.5	95.99	9214.0801	101354.8811
201-250	225.5	23	5186.5	145.99	21313.0801	490200.8423
251-300	275.5	5	1377.5	195.99	38412.0801	192060.4005
		∑=237	∑=18843.5			∑=1183691.984

Mean : $\bar{x} = \dfrac{\sum fx}{\sum f} = \dfrac{18843.5}{237} = 79.51$

Standard deviation: $\sqrt{\dfrac{\sum f(x-\bar{x})^2}{\sum f}} = \sqrt{\dfrac{1183691.984}{237}} = 70.67$

Point Statistic estimator for likely Probability distribution

$\delta = \dfrac{\sqrt{\text{var}}}{\bar{x}} = \dfrac{70.67}{79.51} = 0.89$

This value is near 1 which suggests that the probability distribution for the service time is a poisson distribution.

Table 2. Inter-arrival Time of the Vehicles in the System.

Interval	x	f	fx	$(x-\bar{x})$	$(x-\bar{x})^2$	$f\cdot(x-\bar{x})$
-0.5 – 1.5	1	5	5	-9.39	88.1721	440.8605
1.5 – 2.5	2	9	18	-8.39	70.3921	633.5289
2.5 - 3.5	3	10	30	-7.39	54.6121	546.121
3.5 – 4.5	4	10	40	-6.39	40.8321	408.321
4.5 – 5.5	5	11	55	-5.39	29.0521	319.5731
5.5 – 6.5	6	12	72	-4.39	19.2721	231.2652
6.5 – 7.5	7	13	91	-3.39	11.4921	149.3973
7.5 – 8.5	8	15	120	-2.39	5.7121	85.6815
8.5 – 9.5	9	16	144	-1.39	1.9321	30.9136
9.5 – 10 5	10	20	200	-0.39	0.1521	3.042
10.5 – 11.5	11	18	198	0.61	0.3721	6.6978
11.5 – 12.5	12	16	192	1.61	2.5921	41.4736
12.5 – 13.5	13	16	208	2.61	6.8121	108.9936
13.5 – 14.5	14	13	182	3.61	13.0321	169.4173
14.5 – 15.5	15	12	180	4.61	21.2521	255.0252
15.5 – 16.5	16	10	160	5.61	31.4721	314.721
16.5 – 17.5	17	9	153	6.61	43.6921	393.2289
17.5 – 18.5	18	9	162	7.61	57.9121	521.2089
18.5 – 19.5	19	8	152	8.61	74.1321	593.0568
19.5 - ∞	20	5	100	9.61	92.3521	461.7605
		∑=237	∑=2462			∑=5714.2877

Mean : $\bar{x} = \frac{\sum fx}{\sum f} = \frac{2462}{237} = 10.39$

Standard deviation: $\sqrt{\frac{\sum f(x-\bar{x})^2}{\sum f}} = \sqrt{\frac{5714.2877}{237}} = 4.91$

Point Statistic estimator for likely Probability distribution

$$\delta = \frac{\sqrt{\text{var}}}{\bar{x}} = \frac{4.91}{10.39} = 0.47$$

When $\delta < 1$ this suggests that the probability distribution for the inter-arrival time is a binomial distribution.

Table 3. Performance measures for Servers (1, 2, 3 and 4) and System.

Server (j)	Utilization (%)	Average Delay Time(d_j) (mins)	Average Waiting Time (W_n) (mins)
1	89.71	1. 118	
2	74.19	1.127	
3	87.76	1.025	
4	79.54	1.089	
	$U(m)$ = 82.8	$d(j)$ = 4.359	88. 61

Table 4. Summary of Results.

Variable	Range (min)	Mean(x) (min)	Standard Deviation (s)	Distribution
Inter-arrival Time	1 -20	10.39	4.91	Binomial
Service Time	10 - 240	79.51	70. 67	Poisson

3.2. Goodness-of-fit-test

After we have hypothesized a distribution form for our data, we must examine whether the fitted distribution is in agreement with our observed data $X_1, X_2 \ldots X_n$ (Table 5). The question we are really asking is this: is it possible to have obtained our observed data by sampling from the fitted distribution? If F is the distribution function of the fitted, this question can be addressed by a hypothesis test with a null hypothesis [7]. This is called Goodness-of-fit-test, since it tests how well the fitted distribution "fits" the observed data. The oldest goodness of fit hypothesis is the Chi – square test, the chi square statistic is

$$\chi^2 = \frac{(N_j - nP_j)^2}{nP_j} \tag{10}$$

where: N_j is the number of X_i's in the j^{th} interval (a_{j-1}, a_j)

$$P_j = \int \hat{f}(x)dx$$

nP_j is the expected number of X_i's that would fall in the j^{th} if h_o were true.

and H_o is null hypotheses (observed differences).

Table 5. Chi-square Test for Inter-arrival Time.

Interval	*j*	Interval	N_j	nP_j	$\frac{(N_j - nP_j)^2}{nP_j}$
-0.5 – 1.5	1	1	5	11.85	3.96
1.5 – 2.5	2	2	9	11.85	0. 6854
2.5 – 3.5	3	3	10	11.85	0.2888
3.5 – 4.5	4	4	10	11.85	0.2888
4.5 – 5.5	5	5	11	11.85	0.06097
5.5 – 6.5	6	6	12	11.85	0.001899
6.5 – 7.5	7	7	13	11.85	0.1116
7.5 – 8.5	8	8	15	11.85	0.8373
8.5 – 9.5	9	9	16	11.85	1.4534
9.5 – 10.5	10	10	20	11.85	5. 6053
10.5 – 11.5	11	11	18	11.85	3.1918
11.5 – 12.5	12	12	16	11.85	1.4534
12.5 – 13.5	13	13	16	11.85	1.4534
13.5 – 14.5	14	14	13	11.85	0.1116
14.5 – 15.5	15	15	12	11.85	0.001899
15.5 – 16.5	16	16	10	11.85	0.2888
16.5 – 17.5	17	17	9	11.85	0. 6854
17.5 – 18.5	18	18	9	11.85	0. 6854
18.5 – 19.5	19	19	8	11.85	1.251
19.5 - ∞	20	20	5	11.85	3.96
					χ^2 **= 26.376**

where

$k = 20$ and $P_j = 1/k, = 1/20 = 0.05$
$nP_j = 237 \times 0.05 = 11.85$

$V = K - 1, = 20 - 1 = 19$

For 19 degree of freedom

For $V = 19$, $\chi^2_{19,0.9} = 27.204 > 26.376$, we cannot reject H_o at the $\alpha = 0.10$ level. Thus, this test gives us no reason to believe that the data is not fitted well by a binomial (10.39) distribution.

4. Results and Discussion

Table 3 shows the performance measure of the servers (artisans) and the system under study. The simulation procedure for queues proposed earlier was used in ascertaining the inter-arrival and service time distribution of the vehicles arriving at the workshop. Mean values of 10.39 and 79.51 minutes were obtained for the inter-arrival and service times respectively from the simulation experiment (Table

4). However , by adapting a discrete distribution to fit the requirement of the problem and using the mean values together with the inter-arrival and service time ranges. Performance measures were determined for the four policies mentioned earlier (Table 7). This was done using QSB+ software developed by Chang and Sullivan.

Each policy (0, 1, 2, 3, 4, 5) as shown in Table 6 has been presented along with three measures of performance, i.e., average delay in queue, average waiting time and average server utilization (Table 7). It can be seen from the simulation result that policy 3 gives the least average delay time of 0.01 minutes (0.6 seconds) as against an average delay of 7.40 minutes in the system in use. This represents a savings of 7.39 minutes. The least average waiting time of 4.59 minutes for policy 3 is much less to that of 15.53 minutes in the actual system even though the other policies showed considerably less average waiting time to that of the actual system. Thus, all policies are better than that of the actual system in terms of average waiting time.

Table 6. Proposed Preventive Maintenance Policies.

Policy	No. of Servers	No. of Queues
0	4	1
1	4	3
2	6	2
3	7	1
4	4	2
5	7	2

Table 7. Simulation Results.

Measure Policy	Average delay $d(j)$ (min)	Average waiting time, $W(n)$ (min)	Average server utilization, U(m) (%)
0	7.40	15.53	90.21
1	0.79	10.29	83.25
2	0.03	6.05	78.54
3	0.01	4.59	66.57
4	0.67	8.78	83.25
5	0.03	6.31	66.57

The server utilization of 66.57% was the lowest compared to the other 5 policies. This implies that some of the artisans in policies 3 & 5 are 66.57% utilized. They could however devote their idle time to other maintenance activities in the workshop. Policy 3 uses a total number of 7 servers serving 1 queue while Policy 5 uses 7 servers and 2 queues. There is difference in timeliness as seen in average delay time and average waiting time (see Table 7). Similarly, Policies 1 and 4 uses 4 servers and 3 queues and 2 queues respectively. The difference in timeliness show that Policy 4 is more sub-optimal than Policy 1. In all, Policy 3 gave an optimal number of artisans in timeliness. It is also obvious from the results obtained that as the number of server increases, the average delay time, average waiting time and average utilization of the artisans decrease.

By incorporating cost elements into the simulation model, Aloba et al. [1] stated that the total cost of a system operation per unit time is given as:

$$C(j) = jC_L + W(n)\,\lambda\, C_d \tag{11}$$

From the company's record, each artisan is paid an hourly rate of ₦625.00. This translates to ₦10.42 per minute. Thus C_L= ₦10.42. also, since drivers are paid ₦25,000 per month on the average and there are 20 working days in a month, each day comprising of 9 hours, then ₦25,000 per month translates to ₦2.31 per minute, i.e., C_d = ₦2.31

The arrival rate may be expressed as

$$\lambda = \frac{\sum_{i=1}^{n} I_i}{n} \tag{12}$$

From Table 1, $\lambda = \frac{2463}{237}$ = 10.39 per minute.

Substituting values of j, C_L, $W(n)$, λ and C_d into Eq. (9) for each policy of the simulation result, the results are presented in Table 8. From the result below, it is obvious that as the number of servers increase, the cost of operation of the system decreases.

According to Tables 8 and 9; Policy 3 gives the lowest cost of the system operation of ₦ 183.10 per unit time. The savings in cost per unit time is ₦231.314 when compared to the original system, i.e., policy 0. It is reasonable to emphasize that since the average delay has been reduced considerably to an average of 0.01 minute, policy 3 still provides the optimal number of artisans with a total savings in cost of ₦2.45Million per month.

Table 8. Total Cost of System Operation per Unit Time for Policies 0, 1, 2 and 3.

Policy	j	C_L (₦)	$W(n)$ (min)	λ (per min)	C_d (₦)	$C(j)$ (₦)
0	4	10.42	15.53	10.39	2.31	414.41
1	4	10.42	10.29	10.39	2.31	288.65
2	6	10.42	6.05	10.39	2.31	207.73
3	7	10.42	4.59	10.39	2.31	183.10
4	4	10.42	8.78	10.39	2.31	252.41
5	7	10.42	6.31	10.39	2.31	224.39

Table 9. Gains per Month with Respect to Total Waiting Time of Customers in the System.

Policy	C_j (₦)	$C_o - C_{j(0,1,2,3)}$ (₦)	Gain/month (₦) Million
0	414.41	0	0
1	288.65	125.76	1.33
2	207.73	206.68	2.19
3	183.10	231.31	2.45
4	252.41	162.00	1.72
5	224.39	190.02	2.01

Any attempt at reducing the delay time will imply more servers being employed while the cost of the system operation will increase. There is no significant change in the average utilization of artisan (Policies 3 and 5) at this point since the service time for the vehicles will remain the same.

5. Conclusions

A simulation model to determine the optimal number of artisans to carry out maintenance and repair work on all vehicles arriving at the maintenance workshop was presented. A total number of 7 servers and 1 queue (Policy 3) will be both adequate and economical for the maintenance workshop. This is based on the fact that the average delay time of the vehicles is minimized. Also this policy gave the least cost of the system operation with a savings in cost of ₦2.45Millon per month. The model used adapted a discrete distribution for the vehicles inter-arrival and service time even though the actual distributions of these variables were both binomial and Poisson respectively. The justification in the use of the discrete distribution was due to the nature of inter-arrival and service time data. Application of the equations derived was based on reliable data gathering over a time period for specified number of vehicles. These data were used in modeling the system. Adequate record keeping will therefore enhance accurate model building.

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