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PERFORMANCE LOSS MODELLING OF A SERIES PRODUCTION LINE A NIGERIAN CASE STUDY

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ABSTRACT

For manufacturers to remain productive in a very competitive global environment, the high-level production challenges must be addressed and yield across the entire production line must be high and continuous. In this work, we modelled the performance losses of a series production line that are often ignored by literature because of their little duration in terms of failure classification. Developing a model to this effect would assist in evaluating the impact of minor losses on the line performance and also as a measurement index for determining the effectiveness of maintenance strategies on loss eradications. The result shows that the performance losses follow a non-homogeneous Poisson process. For easy evaluation of the proportion of downtime resulting from minor stops, the mean arrival rate was utilised. The cumulative downtime from minor stops is more than that of the breakdown which has received much attention. From the model, the proportion of downtime which accounts for about 6.25 per cent of the available time could be used as a maintenance performance indicator.

KEYWORDS: Performance losses; reliability; minor stops, Poisson process.

INTRODUCTION

A series production system consists of set of machines with similar or distinct functions but linked in series by conveyors with a goal of transforming the input material to the required output with the right quantity and quality over a period to meet customers' demands and retaining the needed confidence to keep customer satisfaction (Ascher and Feingold, 1984). In Nigeria, most practitioners focus on reducing breakdowns by adopting different corrective and preventive maintenance strategies but this has not yielded up to expectations hence the need for this study to understand the dynamics of the production environment proffer solution this underperformance of manufacturing industries in Nigeria.

Generally, in a non-parametric model of production systems, the transition of input from one machine to another is defined by a probabilistic failure rate which is cumulatively used in calculating the reliability of the equipment (Fiondella et al., 2015). In a typical production system linked by moving conveyor, there exist certain minor stops that do not require repair or major intervention on the machine but are tantamount in defining the output of the production line are often ignored in failure data capturing. These minor stops include jams along the conveyors, at the machine infeed, in the machine and at the machine discharge mostly not as a result of the machine functional failure but either due to the nature of the inputs, the links and other unforeseen circumstances. For a production system with very long conveyor lanes, the minor stops are a major source of speed loss, underperformance and the overall unreliability of the system. For the production system understudy, any stop that is not as a result of a component failure, functional failure, not external to the entire production system but less than 5 minutes is a minor stop. Loss modelling has not received much attention as most literature focus on critical failures that may lead to long downtime(Lin et al., 2013).

LITERATURE REVIEW

Maintenance is a continuous process and demands continuous improvement in order to achieve the desired efficiency and effectiveness at a minimal cost (EMC Corporation, 2015) and decision making in maintenance has to be augmented to instantly understand and efficiently act focusing on what can be known and must be known in order to enable the maintenance decision makers to take appropriate actions (Santos et al., 2015).

Two improvement approaches are widely adopted in maintenance namely; Total productive management and Reliability centred maintenance (Singh et al., 2013). Total production maintenance (TPM), has risen in popularity in the 1990s and is based upon much sound engineering practice. TPM is a continuous improvement approach (Chan et al., 2017a) aimed at the total eradication of losses in all process (Brah and Chong, 2004). The losses targeted by the TPM methodology include breakdown, setup and adjustment, idling and stoppage, reduced speed and defects in the process (Ahuja and Kumar, 2009). But again, in the absence of maintenance modelling, a TPM search for improvement cannot stop when the best is attained, because the state of `best' is unknown. Any such search for improvement needs to be guided by modelling if the inefficient consumption of resourcing in a situation of diminishing returns is to be avoided.

Reliability centred maintenance (RCM), has also become very popular over the past decades and has some comparable features to the delay time concept. RCM focused on improved design and technology based on the systematic assessment of the system maintenance needs (Chan et al., 2017b) derived from a holistic understanding of the functionality and the different failure mode and effect analysis (FMEA) associated with that system (Siddiqui and Ben-Daya, 2009). However, RCM is a procedure, not a modelling methodology, and is, therefore, subject to the same criticism as TPM. All the above “fashions” have two common features. Firstly they are prescriptive in that they propose procedures allegedly leading to improvement, and secondly, there is a lack of any underpinning scientific concept, testing, verification or validation (Christer, 1999).

Information technology started its impact in the 1980s with the development of computer-based maintenance information systems. The belief was that instant access to past data would solve problems (Karim et al., 2016). With relatively few exceptions, one observed that after a while such systems even when kept updated, were seldom accessed for data and perhaps not surprisingly, ultimately degraded. It is argued here that without skills in data analysis and the concept of maintenance modelling, computer-based maintenance information systems cannot aid the manager with his key decision problems (Christer, 1999).

One of the strengths of modelling is that it both identifies and quantifies the nature of the problem to be addressed (Christer et al., 2000). Having a performance model for the process by which losses and failures arise, a maintenance model for decision-making may be constructed (Christer et al., 2000). Attention is focused upon the maintenance engineering decisions of what to do, as opposed to the logistical decisions of how to do it (Christer, 1999).

In spite of the hundreds of literature and models being developed, its usage in the industry is very thin. This is due to the fact that only a few works of literature make use of actual maintenance scenarios. And of these few, only a percentile use case data and a very minute of these ones understudy post-study validation (Christer, 1999) and this trend, unfortunately, had continued.

In this work, we modelled the performance loss of a series production line that is often ignored by literature because of their little duration in terms of failure classification. In the long run, the accumulation of these minor stops has shown to be even more critical than the actual breakdown occurrence hence the need for it to taken seriously. Developing a model to this effect would assist in evaluating the impact of minor losses on the line performance and also as a measurement index for determining the effectiveness of maintenance strategies on loss eradications.

Importance of performance loss modelling

The conventional use of preventive and corrective intervention data will not be able to answer most of the questions in maintenance management decision as existing model assumes that the machines will always be at its optimal level once it is available or after repair and maintenance had taken place. But in reality, the machine follows a continuous number of touches even after restoration had taken place in order to have retained its availability. By loss modelling, we are to answer questions relating to;

i. Reduction in machine availability
ii. Reduction in line productivity
iii. The reliability state of the system
iv. Maintenance indicator and maintenance quality.

Delay time concept for performance losses

The arrival and inter-arrival of performance loss in a series production system can be modelled using the delay time concept introduce by Christer. Assuming time t is the time lapse from when a delay was noticed and rectified until when its reoccurs. Subjective estimate of the probability density function $f(t)$ of the arrival of delays could be obtained, which in turn enables the construction of models to illustrate the relationship between manned production period T and consequence variables such as the expected downtime per unit time or the expected operating cost per unit time.

For any defect, the following questions come up;

i. The frequency of delays (λ)
ii. Delay time(t).
iii. The probability distribution delays $f(t)$.

Assumptions for performance delay time concept

1. Defects are independent of each other
2. The model needs to be modified if dependency occur or according to the nature of the dependence
3. Defects resulting in delays $(t \leq 5mins)$ are dealt with immediately as assists while other are referred to as breakdown or preventive repairs.

As the production period T increases, the probability of arrival of delays $P(k\ events\ in\ interval\ t)$ also increases. From the estimate of function $p(k; \lambda)$, consequence variables of concerns maybe calculated.

Modelling performance losses

This continuous assist resulting from minor stoppages and adjustment which are referred to as performance loss or delay events had been observed to follow a Poisson distribution and the Poisson probability mass function is

$$p(k; \lambda) = \frac{e^{-\lambda}\lambda^{\kappa}}{\kappa!} \qquad (1)$$

Where λ is the shape parameter which indicates the average number of delays in the given time interval.

The Poisson cumulative probability function is

$$F(k; \lambda) = \sum_{i=0}^{k} \frac{e^{-\lambda}\lambda^{i}}{i!} \qquad (2)$$

Since the arrival rate of stops varies as a function of time, the inter-arrival rate of minor stops follows a non-homogeneous Poisson process. The non-homogeneous Poisson process is a generalisation of the homogeneous Poisson process. NHPP is defined as a counting process $[N(t), t > 0]$ which has independent incremental property. The expected number of delays in time $(0, t)$ is

$$m(t) \sim N(t) = \int_0^t \lambda(t)dt < \infty \qquad (3)$$

$N(t)$ is the number of arrivals in the time interval $(0, t)$.

When given the rate r for a delay to occur, then $\lambda = rt$ with r in unit of $\frac{1}{time}$ the probability of k delay events in interval of t is

$$P(k\ events\ in\ interval\ t) = \frac{e^{-(rt)}(rt)^{\kappa}}{\kappa!} \quad (4)$$

The probability of having n arrivals in the interval $(t,,t+x)$ can be expressed as

$$Prob(N(t+x) - N(t) = n) = \frac{[m(t+x)-m(t)]^{n} - e^{-[m(t+x)-m(t)]}}{n!} \quad (5)$$

Generally, for a non-homogeneous Poisson process with right continuous arrival rate $\lambda(t)$ bounded away from zero, the distribution of $N(t,x)$ satisfies

$$\Pr(N(t,x) = \mathrm{n}) = \frac{[m(t,x)^{n} - e^{-[m(t,x)]}}{n!} \quad (6)$$

Where

$$m(t) = \int_0^t \lambda(t)dt \quad (7)$$

From statistical theory, if the number of arrivals in a given period of time occurs randomly and independently from other arrivals and follows a Poisson distribution with mean λ, the inter-arrival time distribution follows an exponential probability with mean $\alpha = \frac{1}{\lambda}$

The probability density distribution of an exponential function is

$$f(t) = \alpha e^{-\alpha t} \quad (8)$$

The cumulative density function is

$$CDF = F(t) = \int_0^T f(t)dt \quad (9)$$

$$= \int_0^T \alpha e^{-\alpha t}dt \quad (10)$$

$$F(t) = 1 - e^{-\alpha t} \quad (11)$$

The probability of getting at least k number of delay events in a day is expressed as

$$Prob(N(t) > k) = P(m) = \sum_k^{\infty} \frac{e^{-\lambda}\lambda^{\kappa}}{\kappa!} \quad (12)$$

$$Prob(N(t) > k) = 1 - [Prob(N(t) > k) + Prob(N(t) = 0)] \quad (13)$$

$$1 - \left\{\sum_{n=1}^{k} \frac{e^{-\lambda}\lambda^{n}}{n!} + \frac{e^{-\lambda}\lambda^{0}}{0!}\right\} \quad (14)$$

The resulting downtime due to delay stops is

$$D(m) = \frac{[\alpha \times T \times d_m \times P(m)]}{T} \quad (15)$$

Where $\alpha = 1/\lambda$ is mean time between delays, d_m is the duration of delay, T is the production period and $P(m)$ is the probability of delay events

Case study

In this study, a packaging line of a beverage company was understudied for a period of one year. By definition, packaging is the process of putting beer/malt into a package. The packaging line consists of a number of machines linked together by conveyor for the purpose of transferring the products into a container with proper decoration.

Packaging Line Layout with Machines (V curve)

Line layout and speed control are the keys to good line performance based on optimum efficiencies and manning levels. The figure below shows a packaging line layout with machines in a V-Curve. The curve is used to represent to conveyors linking the machines.

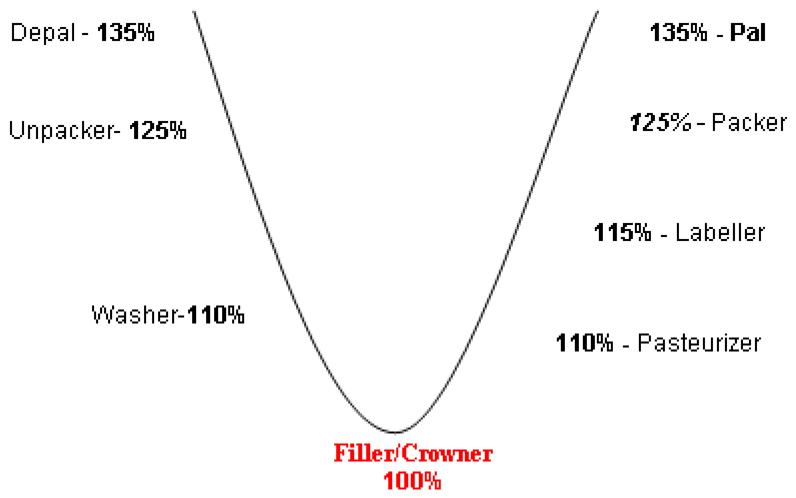


Figure 1: Line Layout (V-Curve)

From the curve, the speed relationship is such that the filler is ascribed the value of 100% when running at its Nominal speed. It is the reference for all other machines in the Packaging hall. The washer must run at a higher speed than the Filler in order to continually supply the filler with bottles, so it runs at 110% of the Nominal speed of Filler. The Unpacker runs at a higher speed of 125%. The Pasteurizer, Labeller, Packer and Palletizer also run at a higher speed of 110%, 115%, 125% 135% of the Nominal speed of the filler, respectively, in order to ensure that all filled and crowned bottles are carried away as soon as they are filled.

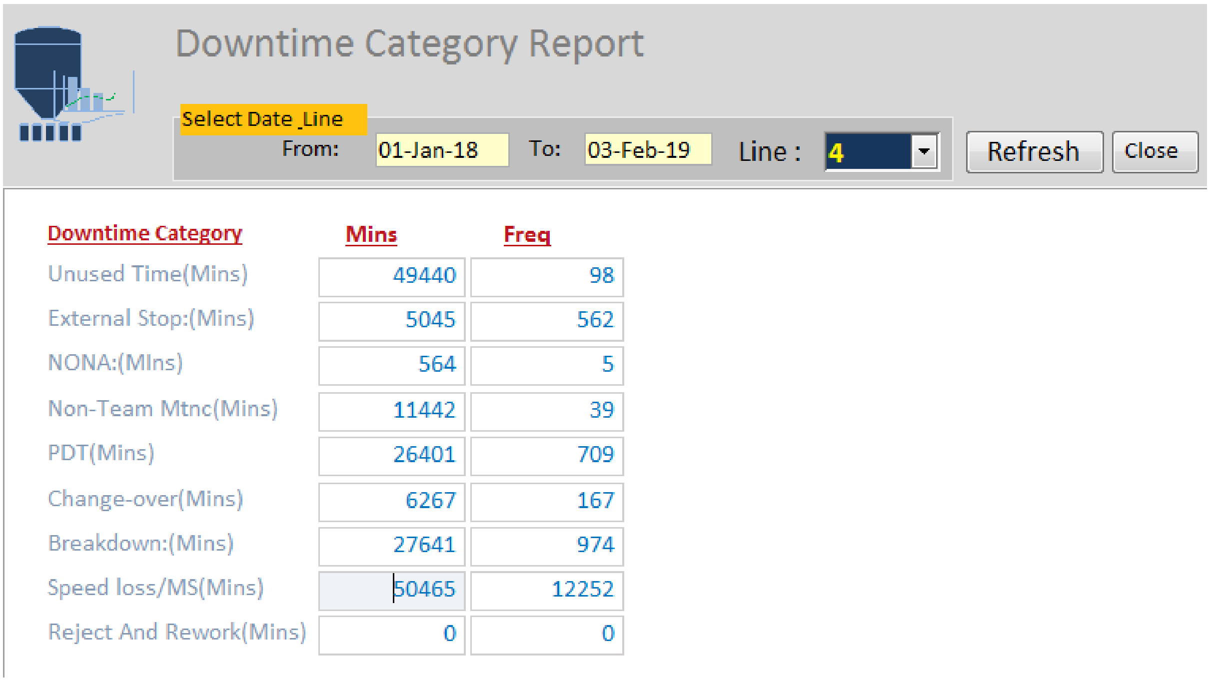
Breakdown definition

For packaging Line Operating Performance Indicator (OPI) measurement, all machines are considered as one, thus stoppages of the line are exclusively measured at the lowest point of the line V graph, where manning is available. The filler is, therefore, the designated point of measurement for line OPI as shown in figure 1. For the time measurements at the filler with an automatic reporting system, a classification into breakdown or speed losses is required, otherwise, incorrect data is used for both breakdown as well as speed losses.

Breakdown is defined as the Stop of a machine/system for more than 5 minutes as a result of mechanical, electrical / instrumentation failure of components, subassemblies or machinery and/ or control system. Stops related to adjustments, but not related to recent changeover are included as breakdowns is exclusively for the registration of failure of equipment and components. By this definition, any stop that is less than 5 minutes is regarded as minor stop or performance loss.

Breakdown/ Minor stop Data Capturing

Line data software is a line management software for line data collection. The data recorded include the line OPI, speed losses and breakdown information. Breakdown/stoppage data are collected and recorded at the nominal machine i.e. the filler.



Downtime Category Report

Select Date _Line

From: 01-Jan-18 To: 03-Feb-19 Line : 4 Refresh Close

Downtime Category	Mins	Freq
Unused Time(Mins)	49440	98
External Stop:(Mins)	5045	562
NONA:(MIns)	564	5
Non-Team Mtnc(Mins)	11442	39
PDT(Mins)	26401	709
Change-over(Mins)	6267	167
Breakdown:(Mins)	27641	974
Speed loss/MS(Mins)	50465	12252
Reject And Rework(Mins)	0	0

Figure 2: Downtime Data Capture.

From figure 2 above speed loss which is defined as minor stops contribute 50465 minutes which is almost twice compared to breakdown contributing 27641 minutes. The average duration of minor stops is about 4.1 minutes.

Performance Loss (minor stop) Deployment

Minor stop data from 1st of January 2018 to 3rd of February 2019 based on frequency and duration per day is shown in table 1.

Table 1: Minor stop data from 1st of January 2018 to 3rd of February 2019.

n	f_x	P	n	f_x	P	n	f_x	P	n	f_x	P	n	f_x	P
1	14	54	41	48	172	81	24	110	121	34	138	161	76	276
2	21	88	42	40	160	82	28	74	122	17	58	162	28	124
3	16	52	43	38	194	83	35	138	123	21	188	163	23	120
4	23	100	44	42	256	84	37	152	124	61	158	164	22	48
5	29	86	45	81	182	85	10	62	125	40	125	165	5	72
6	32	100	46	32	146	86	23	134	126	37	196	166	10	32
7	38	142	47	31	132	87	11	73	127	22	82	167	64	145
8	24	65	48	66	246	88	23	106	128	45	90	168	74	155
9	39	136	49	83	134	89	41	136	129	59	358	169	75	171
10	8	82	50	75	174	90	32	128	130	60	250	170	10	76
11	43	132	51	26	149	91	29	216	131	23	105	171	39	124
12	56	174	52	34	146	92	34	132	132	42	202	172	11	42
13	52	176	53	35	119	93	24	130	133	35	175	173	20	80
14	2	10	54	52	106	94	76	176	134	71	325	174	19	71
15	28	198	55	9	54	95	56	61	135	50	149	175	39	92
16	61	304	56	26	80	96	22	102	136	35	140	176	77	142
17	29	208	57	37	94	97	43	162	137	59	110	177	85	166
18	12	102	58	42	140	98	24	150	138	33	160	178	46	126
19	37	106	59	28	174	99	43	140	139	14	90	179	26	74
20	44	190	60	40	131	100	62	118	140	37	222	180	26	76
21	33	222	61	26	72	101	22	66	141	17	146	181	31	104
22	34	175	62	41	134	102	38	79	142	16	52	182	80	152
23	24	188	63	38	206	103	32	94	143	34	92	183	12	44
24	29	338	64	29	106	104	60	82	144	111	212	184	63	179
25	24	340	65	20	68	105	12	58	145	95	154	185	56	136
26	86	266	66	30	102	106	4	14	146	60	103	186	22	104
27	26	100	67	34	159	107	47	260	147	31	72	187	7	48
28	40	163	68	22	96	108	151	249	148	26	94	188	17	72
29	51	166	69	17	66	109	212	278	149	30	261	189	3	20
30	33	272	70	26	91	110	47	60	150	52	271	190	53	180
31	72	260	71	4	16	111	69	184	151	13	32	191	38	212
32	31	172	72	15	80	112	121	345	152	36	104	192	30	114
33	56	272	73	19	116	113	14	170	153	38	96	193	8	40
34	56	146	74	52	182	114	28	52	154	62	110	194	38	208
35	37	140	75	19	116	115	14	132	155	37	96	195	36	234

36	33	130	76	25	172	116	69	192	156	5	8	196	22	274
37	47	138	77	23	152	117	62	307	157	10	32	197	46	234
38	69	204	78	43	212	118	44	119	158	40	104	198	36	274
39	31	132	79	36	143	119	57	126	159	18	42	199	52	175
40	29	108	80	28	56	120	55	110	160	67	209	200	34	258

n	f_x	P	n	f_x	P	n	f_x	P	n	f_x	P
201	28	406	241	13	75	281	29	128	321	33	140
202	41	262	242	18	106	282	29	216	322	15	66
203	56	247	243	16	56	283	18	230	323	45	98
204	20	106	244	38	244	284	12	56	324	21	70
205	11	106	245	13	64	285	38	224	325	34	118
206	24	167	246	15	118	286	26	289	326	39	92
207	24	122	247	50	240	287	20	243	327	44	102
208	59	162	248	33	256	288	34	243	328	39	142
209	72	196	249	39	333	289	24	290	329	8	22
210	31	118	250	43	512	290	35	440	330	32	70
211	53	212	251	35	420	291	22	106	331	78	260
212	56	184	252	4	40	292	21	56	332	32	124
213	32	130	253	47	218	293	33	87	333	43	122
214	39	218	254	27	102	294	39	178	334	47	98
215	33	170	255	38	154	295	34	230	335	41	148
216	27	128	256	36	254	296	40	232	336	14	36
217	29	146	257	30	350	297	28	102	337	28	54
218	44	252	258	34	363	298	28	133			
219	34	206	259	77	272	299	27	204			
220	23	122	260	26	164	300	34	134			
221	15	98	261	28	122	301	25	88			
222	15	108	262	18	92	302	24	182			
223	52	322	263	59	176	303	73	182			
224	13	112	264	19	104	304	45	243			
225	33	68	265	82	330	305	72	262			
226	35	102	266	24	210	306	49	215			
227	12	54	267	33	328	307	27	142			
228	52	210	268	21	384	308	37	162			
229	36	120	269	51	200	309	49	268			
230	29	98	270	19	88	310	12	28			
231	28	108	271	4	12	311	15	34			
232	9	20	272	26	146	312	19	54			
233	22	54	273	41	252	313	24	70			
234	49	80	274	37	223	314	18	60			
235	15	94	275	28	104	315	35	146			
236	40	132	276	41	222	316	43	167			
237	56	156	277	23	368	317	39	116			
238	50	109	278	35	148	318	56	129			
239	2	4	279	45	198	319	35	144			
240	12	54	280	22	80	320	44	166			

The frequency of daily distribution of minor stops per production day is shown in figure 3.

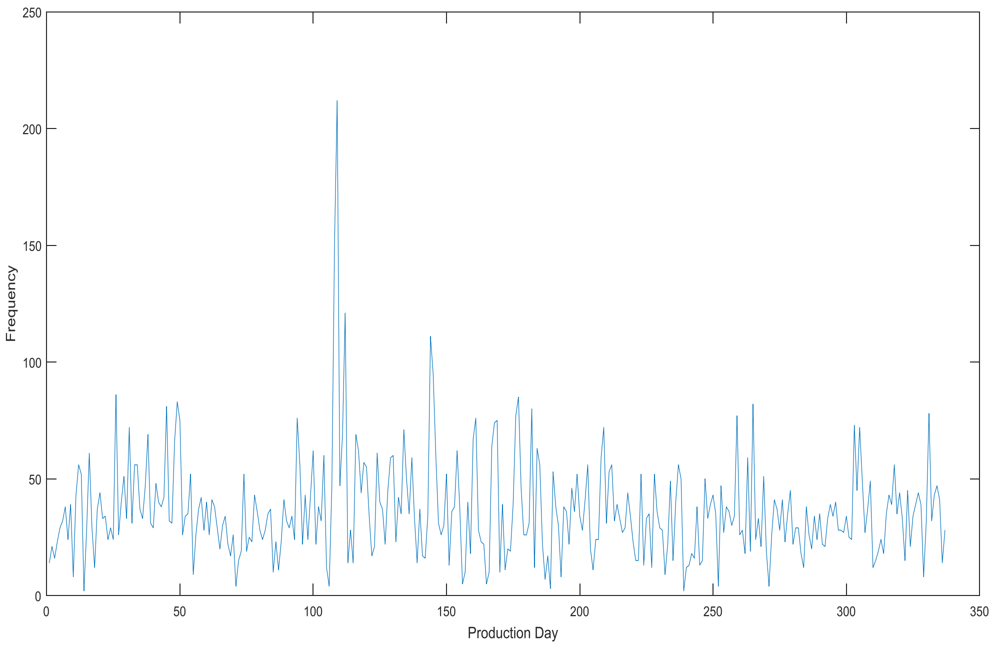


Figure 3: Frequency of Minor stops per Production day.

By plotting the density function using MATLAB, the resulting graph is shown in figure 4.

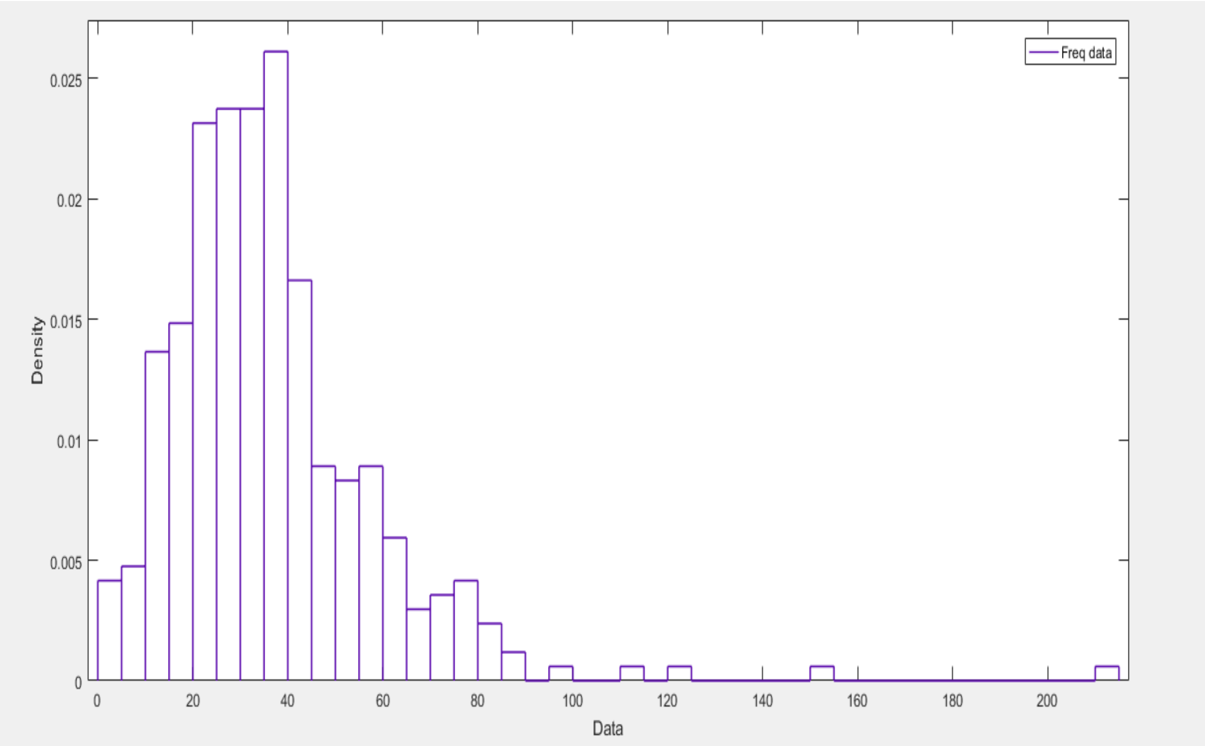


Figure 4: The density distribution of the delay stops.

Based on the parameters obtained from the density function, the plot was fitted to various theoretical distribution and the fit was found to follow a Poisson process as shown in figure 5.

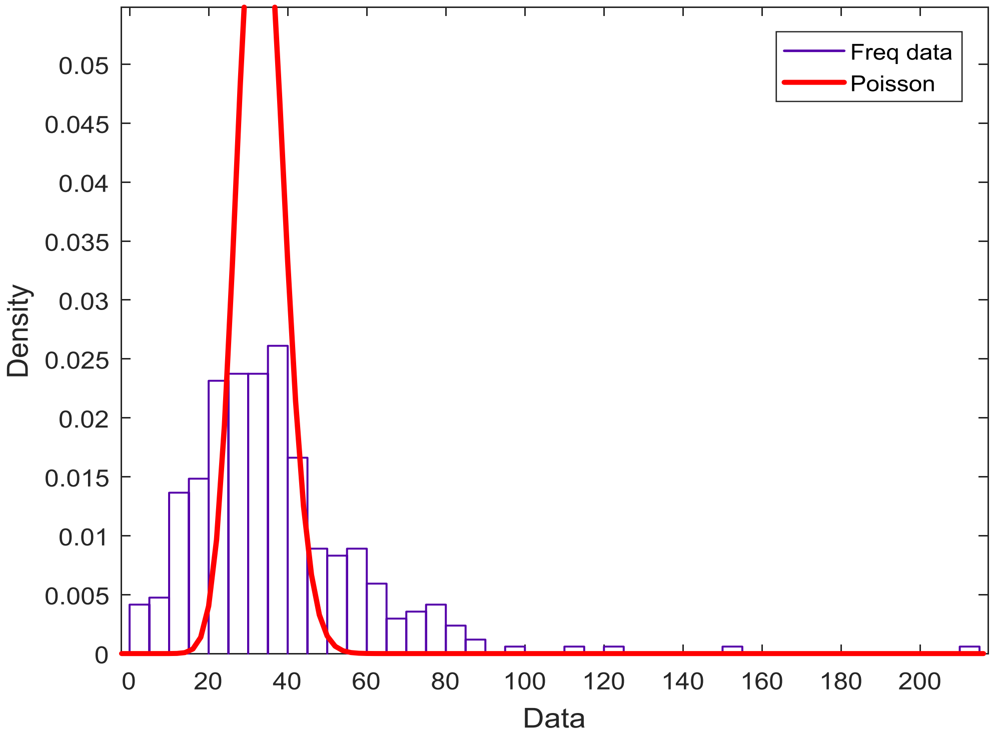


Figure 5: Fitting the distribution to a Poisson distribution.

Using MATLAB to check the parameter fit of the distribution.

The Data could be tuned to remove outliers using the upper and lower limits.

$Quartile\ 1 = 0.25(N + 1)\text{th ordered point}$

$Quartile\ 3 = 0.75(N + 1)\text{th ordered point}$

$Interquartile\ range = Quartile\ 3 - Quartile\ 1$

$Upper\ limit\ = Quartile\ 3 + (1.5 \times\ Interquartile\ range)$

$Lower\ limit\ = Quartile\ 1 - (1.5 \times\ Interquartile\ range)$

Table 2: the parameters estimations.

Distribution:	**Poisson**
Log-likelihood	-2842.44
Domain	$0 \leq y \leq \infty$
Mean	36.3561
Variance	36.3561
Lambda λ	36.3561
Standard error	0.328453

Table 3: When the data was tuned by removing outliers, the parameters estimations.

Distribution:	**Poisson**
Log-likelihood	-2091.46
Domain	$0 \leq y \leq \infty$
Mean	33.2741
Variance	33.2741
Lambda λ	33.2741
Standard error	0.321959

Testing the null hypothesis using Chi-square Goodness of fit test

The chi-square goodness-of-fit test determines if a data sample comes from a specified probability distribution, with parameters estimated from the data. The test groups the data into bins, calculating the observed and expected counts for those bins, and computing the chi-square test statistic using

$$x^2 = \sum_{i=1}^{N} \frac{(O_i - E_i)^2}{E_i} \qquad (16)$$

Where O_i are the observed counts and E_i are the expected counts based on the hypothesized distribution. The test statistic has an approximate chi-square distribution when the counts are sufficiently large. Test the null hypothesis that the data in x comes from a population with a Poisson distribution using MATLAB.

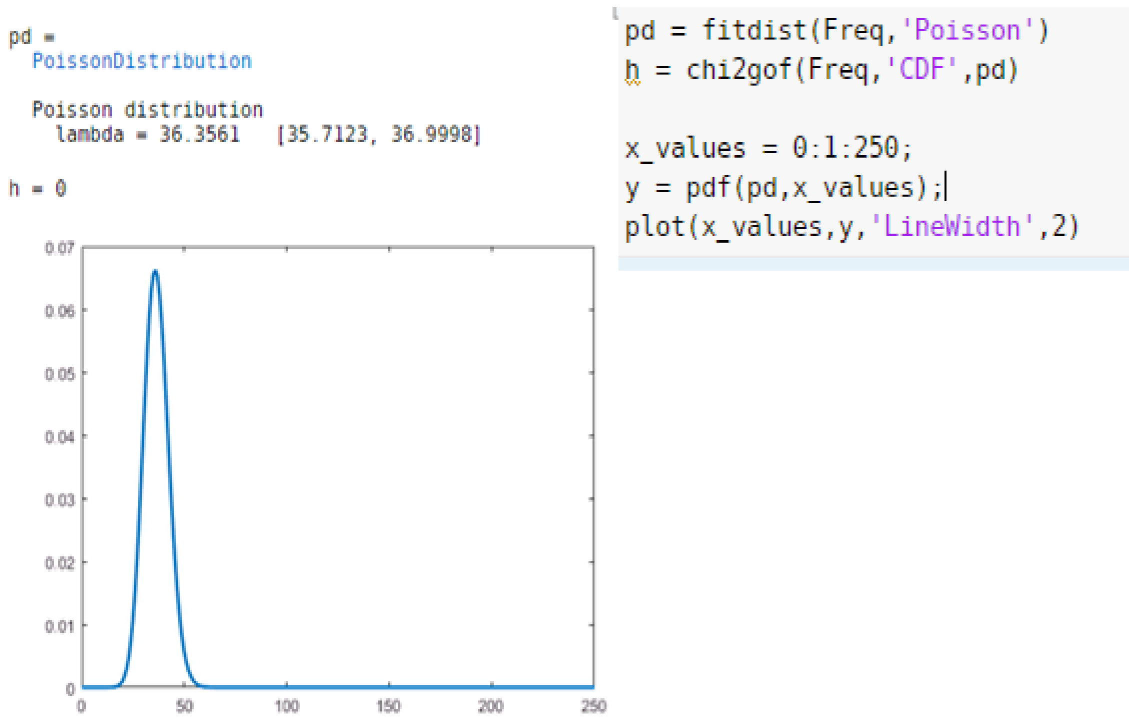


Figure 6: Chi-Square Goodness of Fit Test.

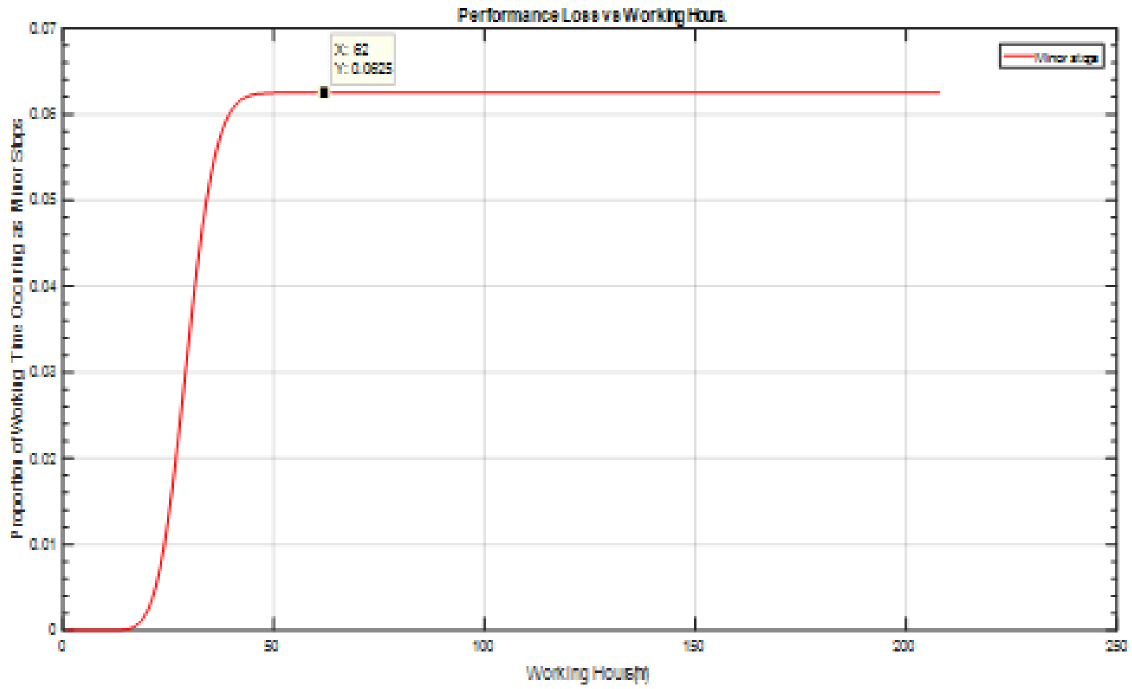


Figure 7: Proportion of delays to production time.

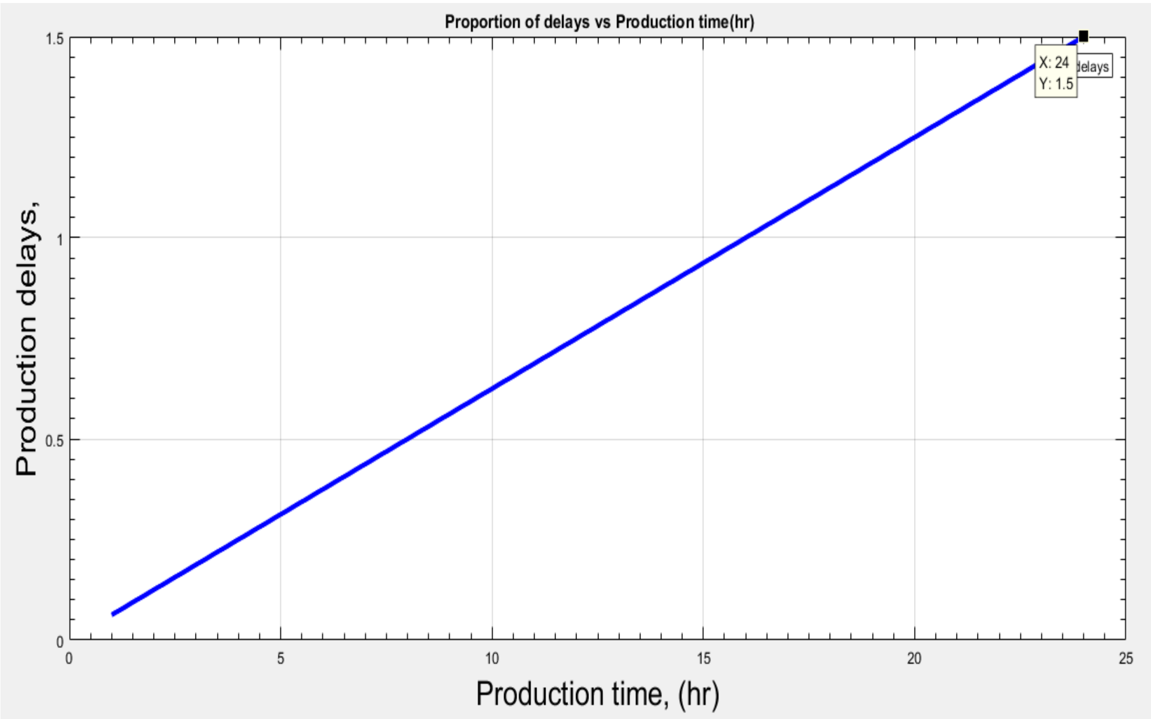


Figure 8: Linear relation between delays and production time.

DISCUSSION OF RESULT

Using minor stops data captured in table 1, figure 3 supports the non-homogenous arrival rate stoppages. Figure 4 shows the distribution of the data. From figure 5, the data was found to fit well with the Poisson distributions. Table 2 & 3 show the Poison distribution parameters with and without outliers respectively. To verify the distribution, figure 6 shows the result from the chi-square goodness-of-fit test using MATLAB. The returned value of h = 0 indicates that Chi-square Goodness of fit test fails to reject the null hypothesis at the default 5% significance level thus the distribution fits in as Poison process. From the analysis, as shown in figure 7, a proportion of 6.25 per cent of the production time is lost due to delays resulting from just minor stops and this has a linear relation with the production time as shown in figure 8.

The questions are how much of manned hour is the management of a production plant willing to scarify to such unproductivity as there are other major time losses such as breakdown downtime and inspection repairs?. The duration of delays has a major impact on the proportion of manned production time that is lost. The delay time could be reduced by assigning a versatile technician to restore delays as fast as possible or rather equipping the operators with the right technicality to clear such stops. The onus on the maintenance team to try as much as possible to reduce the possible causes of these delays to the minimum, therefore, reducing the arrival rates and thus the total proportion of production time that is lost to minor delays.

CONCLUSION

While long breakdown has been known to contribute to high maintenance cost, the result from this study shows that performance losses which are often ignored because of their negligible duration are a major factor in terms of machine productivity. By modelling the delays experienced over a period of one year, it has been identified that they follow a non-homogeneous Poisson process. For easy evaluation of the proportion of downtime resulting from minor stops, the mean arrival rate was utilised. The cumulative downtime from minor stops is more than that of the breakdown that has received much attention. From the model, the proportion of downtime which accounts for about 6.25 per cent of the available time could be used as maintenance integrity indicator. By this, while adequate preventive maintenance strategy is important, efforts should be channelled in loss eradications. The model could as serve as a reference for maintenance management decision making by defining a threshold of minor stops required to trigger an intervention. This loss modelling could also find application in determining the state reliability of a production line.

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