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Data-driven decision support methodology for enhancing production machine availability

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Abstract

Unscheduled preventive maintenance negatively impacts product quality and increases production time due to downtime and emergency shutdowns, raising production costs. We propose a decision support methodology to enhance equipment availability by analyzing historical time to repair (TTR) data using statistical analysis in Minitab. This study analyzed TTR data from seven machines (Filler, Mixer, Blowmould, Labeller, Variopac, Palletizer, and Conveyor) on a production line for 2022. The analysis included both parametric and non-parametric methods, with results presented graphically to summarize statistics like cumulative repair time probability (CRTPR1) and the hazard rate. Using least squares probability fitting, we found that five machines followed an exponential distribution, while the Palletizer and Mixer exhibited log-normal distributions. All machines had about a 63% probability of completing repairs within the meantime to repair (MTTR), except the Palletizer and Mixer, which showed less than 1% probability.

Keywords: Availability; Cumulative Repair Probability; Time to Repair (TTR); Parametric Analysis; Non-Parametric Analysis

1. Introduction

Unplanned downtime significantly impacts product quality by extending production times due to machine breakdowns and emergency shutdowns. Additionally, it leads to higher repair costs and production losses associated with major machine failures. These challenges are common in many manufacturing firms. One effective strategy to mitigate the consequences of these failures is to enhance machine availability [1]. With the increasing trend of automation and digitalization in production industries, ensuring a reliable operational process has become a critical challenge. To achieve a dependable production process, both in the short and long term, it is essential to establish a resilient operation that improves availability and productivity while maximizing production rates and minimizing unexpected shutdowns [2,3]. Given the current complexities in the beverage industry, the automation revolution is poised to pave the way for sustainable production, providing a framework for human-machine interaction and collaboration to create more value through the smart digitalization of production processes [4,5].

The ultimate objective of any system is to perform a specific intended function, often referred to as its mission. The overall capability of a system to accomplish its mission is described as system effectiveness. For consumer products, system effectiveness correlates with customer satisfaction, which is linked to the overall concept of quality [6].

It is important to note that reliability and maintainability methodologies and philosophies apply throughout the life cycle of a system. Reliability and maintainability are major attributes that determine system effectiveness. Reliability is defined as the probability that a system will satisfactorily perform its intended function for its expected lifespan under specified operating conditions [8]. In contrast, maintainability is characterized by a repair-time probability distribution,

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defining the probability that a failed system or component will be restored to a specified condition within a designated timeframe when maintenance is carried out according to prescribed procedures [9].

The first step in improving equipment availability involves systematically collecting and analyzing relevant data using appropriate statistical techniques. This study focuses on the equipment time to repair (TTR) data collected during the operational year of 2022 for a production line within the industry. Each machine's TTR is analyzed using both parametric and non-parametric methods, generating summary statistics, cumulative repair time probability (CRTPR1), the standard error of CRTPR1, a 95% confidence interval limit for cumulative repair probability (CLCRT), and the hazard rate value.

This research addresses a gap by focusing on decision support methodologies for improving equipment availability through the analysis of historical time to repair data using statistical analysis within a Minitab software environment. To the best of my knowledge, this methodology has not been applied to the food and beverage industry in Nigeria, thereby bridging a critical gap in this area.

The aim of this study is to develop a decision support methodology for improving equipment availability by analyzing historical time to repair data through statistical analysis in a Minitab software environment. To achieve this aim, the following objectives will be pursued:

- Acquire the necessary historical data on the time to repair (TTR) of the production equipment from management.
- Conduct a distribution-free statistical analysis of the acquired data.
- Ascertain the nature of the distribution for the TTR.
- Obtain a suitable maintainability function for the equipment.

2. Materials and Methods

The secondary data analysis was gathered from the Nigerian Bottling Company, commonly referred to as NBC. The company began production in 1953 at the basement facilities of the Mainland Hotel, which is owned by the Leventis Group, initially producing Coke under a license from the Coca-Cola Company. NBC operates 11 bottling plants across Nigeria and has 35 production lines, with the Abuja plant being one of the major facilities in the country.

The Abuja plant features four production lines, consisting of two PET (Polyethylene Terephthalate) lines and two RGB (Returnable Glass Bottle) lines. This project focuses specifically on the operations of the PET bottling lines, where each line operates within a closed-loop system, with all machines interconnected.

The PET line is divided into two units as seen on the schematic diagram of the system in Figure 1:

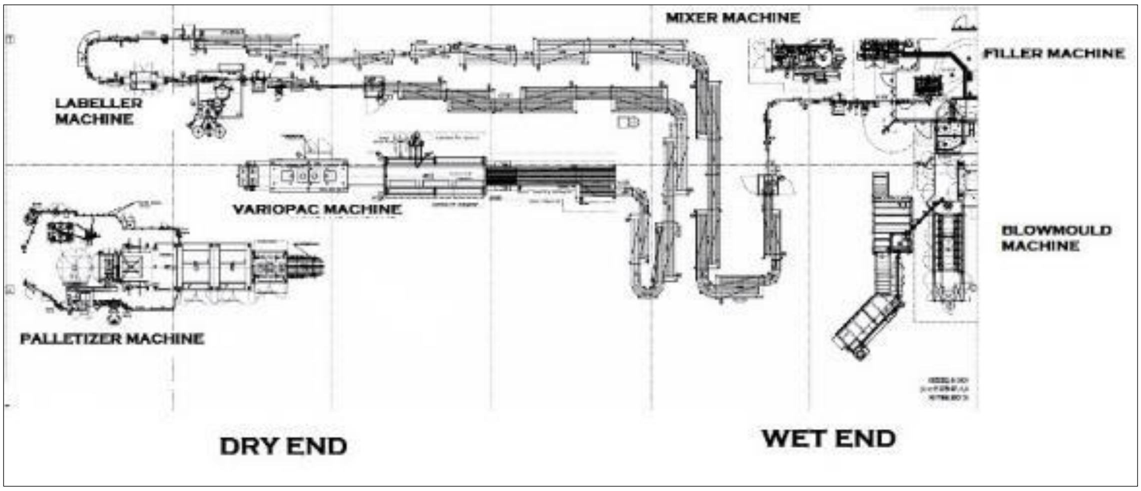


Figure 1 Schematic Diagram of the System

- WET END Unit comprises of the following Machines: a. Blowmould (BM) Machine b. Filler Machine(FL) c. Mixer Machine (MX)

- DRY END Unit comprises of the following Machines: a. Labeller Machine (LB) b. Variopac Machine (VP) c. Palletizer Machine (PZ)

2.1. System configuration

The system's configuration, which details how its components interact, is set up in a sequential arrangement. The conveyor acts as the communication medium between each consecutive component in the system. In this context, the conveyor serves as the transportation unit. The operational processes begin at the wet end and finish at the dry end of the system. A schematic diagram illustrating the system is shown in Figure 2.

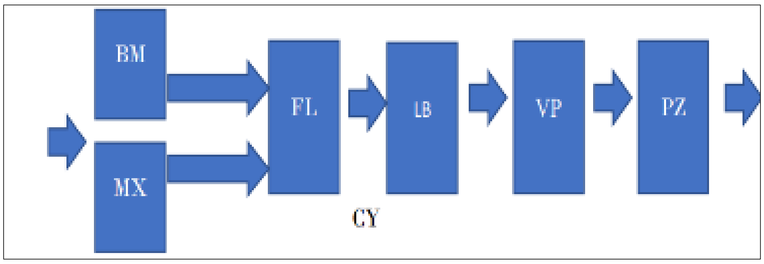


Figure 2 Block Diagram of the System Where, BM = Blowmould; MX = Mixer; FL = Filler; LB = Labeller; VP = Variopac and PZ = Palletizer

2.2. Data presentation

Table 1 Time to Repair Each Machine

S/N	FILLER TTR (min)	BLOWER TTR (min)	LABELLER TTR (min)	VARIOPAC TTR (min)	PALLETIZER TTR (min)	MIXER TTR (min)	CONVEYOR TTR (min)
1	28.0	240.0	48.0	25.0	12.0	39.0	49.0
2	22.0	40.0	60.0	13.0	29.0	10.0	59.0
3	25.0	29.0	40.0	10.0	15.0	14.0	46.0
4	131.0	34.0	153.0	29.0	5.0	25.0	7.0
5	41.0	42.0	285.0	19.0	91.0	42.0	55.0
6	35.0	12.0	40.0	25.0	10.0	15.0	10.0
7	27.0	17.0	17.0	148.0	28.0	29.0	30.0
8	20.0	20.0	22.0	60.0	42.0	90.0	20.0
9	18.0	29.0	20.0	56.0	58.0	60.0	18.0
10	9.0	39.0	28.0	118.0	20.0	100.0	16.0
11	25.0	28.0	150.0	50.0	26.0	45.0	23.0
12	55.0	38.0	20.0	30.0	32.0	70.0	20.0
13	35.0	26.0	40.0	70.0	23.0	12.0	43.0
14	27.0	15.0	180.0	33.0	28.0	61.0	179.0
15	18.0	30.0	220.0	20.0	12.0	98.0	28.0
16	35.0	145.0	30.0	45.0	26.0	15.0	14.0
17	15.0	125.0	60.0	55.0	15.0	20.0	20.0
18	25.0	21.0	130.0	28.0	40.0	5.0	90.0
19	10.0	25.0	119.0	300.0	11.0	14.0	70.0

20	25.0	180.0	156.0	40.0	22.0	10.0	10.0
21	19.0	15.0	17.0	27.0	15.0	18.0	14.0
22	27.0	15.0	25.0	38.0	35.0	11.0	40.0
23	15.0	29.0	4.0	17.0	59.0	20.0	19.0
24	38.0	65.0	25.0	36.0	420.0	26.0	15.0
25	3.0	14.0	35.0	20.0	60.0	20.0	21.0
26	10.0	29.0	20.0	109.0	42.0	7.0	21.0
27	13.0	11.0	22.0	20.0	72.0	15.0	25.0
28	75.0	25.0	105.0	25.0	25.0	25.0	14.0
29	24.0	22.0	360.0	22.0	26.0	18.0	39.0
30	152.0	22.0	60.0	13.0	14.0	63.0	35.0
31	15.0	29.0	40.0	24.0	20.0	105.0	35.0
32	13.0	20.0	72.0	20.0	7.0	60.0	44.0
33	35.0	25.0	311.0	60.0	38.0	15.0	42.0
34	3.0	6.0	60.0	70.0	15.0	35.0	21.0
35	17.0	27.0	46.0	100.0	35.0	3.0	150.0
36	25.0	29.0	88.0	10.0	12.0	29.0	20.0
37	10.0	23.0	131.0	100.0	52.0	15.0	97.0
38	59.0	29.0	16.0	35.0	51.0	55.0	35.0
39	30.0	30.0	30.0	28.0	36.0	25.0	50.0
40	14.0	30.0	20.0	21.0	100.0	40.0	114.0
41	17.0	20.0	75.0	195.0	38.0	15.0	28.0
42	45.0	3.0	239.0	35.0	30.0	29.0	14.0
43	26.0	58.0	60.0	10.0	40.0	10.0	13.0
44	34.0	18.0	35.0	165.0	26.0	18.0	35.0
45	209.0	32.0	28.0	120.0	15.0	17.0	19.0
46	28.0	29.0	120.0	3.0	7.0	55.0	75.0
47	10.0	26.0	60.0	25.0	30.0	15.0	9.0
48	13.0	110.0	100.0	45.0	12.0	60.0	30.0
49	23.0	30.0	10.0	67.0	15.0	60.0	15.0
50	21.0	44.0	25.0	211.0	18.0	15.0	48.0

The secondary data collected relates to the operational year of 2022, accurately reflecting the actual operating environment. It is important to clarify that this article does not provide a complete quantitative assessment of the developed equipment at every stage of its life cycle. Instead, it focuses on analyzing field data gathered from the customer usage environment. To derive our findings, we employed two fundamental analytical techniques: nonparametric and parametric analysis.

2.2.1. Nonparametric analysis techniques

The following text outlines a method of statistical analysis that does not require specific distribution assumptions for accurate evaluation. Therefore, these methods are commonly known as distribution-free analyses [10]. The main goal of this approach is to derive key statistics directly from the repair times, which includes summary statistics [11]. Cumulative Repair Time Probability (CRTP), the standard error of the CRTP, and the 95% confidence interval limits of the CRTP utilizing the Kaplan-Meier Method Model in MINITAB.

Considering ungrouped complete data, let n represent the ordered repair times denoted as t1, t2, ..., tn, where t1 ≤ t2 ≤ ... ≤ tn. For each time point ti, the number of units repaired up to that point is given by n − i. Accordingly, potential estimates for the functions of interest may be derived from the cumulative failure distribution [12].

$$\text{Cumulative failure distribution, } \hat{F}(t_i) = 1 - \hat{R}(t_i) = 1 - \frac{n-i}{n} \quad \ldots\ldots\ldots(1)$$

An improved estimate is obtained by using the mean plotting position, which is shown below:

$$\hat{F}(t_i) = \frac{i}{n+1} \quad \ldots\ldots\ldots\ldots (2)$$

While the most widely used is the median plotting position (median rank), given as:

$$\hat{F}(t_i) = \frac{i-0.3}{n+0.4} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

where $i = 1, 2, \ldots, n$.

An estimate of the probability density function may be obtained using equation (1)

$$\hat{f}(t) = \frac{\hat{R}(t_{i+1}) - \hat{R}(t_i)}{t_{i+1} - t_i}$$
$$= \frac{1}{(t_{i+1}-t_i)(n+1)} \quad for \quad t_i < t < t_{i+1} \quad \ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Therefore, the hazard rate is

$$\hat{\lambda}(t) = \frac{\hat{f}(t)}{\hat{R}(t)} = \frac{1}{(t_{i+1}-t_i)(n+1-i)} \quad for \quad t_i < t < t_{i+1} \quad \ldots\ldots\ldots\ldots(5)$$

An estimate of the mean time to repair (MTTR) is obtained directly from the sample mean:

$$\hat{MTTR} = \sum_{i=1}^{n} \frac{t_i}{n} \quad \ldots\ldots\ldots\ldots (6)$$

and an estimate of the variance of the failure distribution may be obtained from the sample variance:

$$s^2 = \sum_{i=1}^{n} \frac{(t_i - \hat{MTTR})^2}{n-1}$$
$$= \frac{\sum_{i=1}^{n} t_i^2 - n\hat{MTTR}^2}{n-1} \quad \ldots\ldots\ldots\ldots (7)$$

If the sample of n failure times is large, an approximate 100(1-ά) percent confidence interval for the underlying MTTR may be obtained [12] using

$$\hat{MTTR} \pm \boldsymbol{t_{\alpha/2,n-1}} \frac{s}{\sqrt{n}} \quad \ldots\ldots\ldots\ldots\ldots\ldots(8)$$

2.2.2. Parametric analysis technique

(Identifying Repair distribution); The objective of this analysis is to fit a theoretical distribution to a random sample of repair times. By "fit," we refer to the process of conducting a statistical test to either accept or reject the hypothesis that the observed repair times are derived from a specified distribution [13]. Our findings indicate that five machines conform to an Exponential distribution, while two machines align with a Lognormal distribution, as determined by the established rule of thumb for identifying candidate distributions.

2.2.3. Procedure for Identifying Candidate Distribution:

The following steps outline the process for identifying a candidate distribution:

Calculate summary statistics

Identify a candidate distribution through a process of elimination utilizing the following guidelines:

- If the sample mean and median are approximately equal, it suggests that the data originates from a symmetric or near-symmetric distribution, such as the Normal distribution or Weibull distribution with a shape parameter between 3 and 4.
- If the mean is significantly greater than the median, an exponential distribution may be appropriate, provided that the sample mean is approximately equal to the standard deviation. Otherwise,
- A Lognormal distribution or Weibull distribution may offer a more suitable fit.
    - Analyze the machine repair time data.
    - Employ the theoretical properties of the identified distributions.
    - Perform a probability plot. The nature of the transformation will be contingent upon the characteristics of the distribution as described above [12].

2.2.4. Probability plots

Probability plots provide an informal method of evaluating the fit of a set of data to a distribution. If we plot the points $(t_i, \hat{F}(t_i)), i = 1, 2, \ldots, n$, on appropriate graph paper, a proper fit to the distribution would graph as an approximate straight line.

The primary approach to probability plots is to fit a linear regression (least squares) line of the form:

$$y = a + bx \qquad \text{.........(9)}$$

To a set of transformed data. Where

$$b = \frac{n\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2} \qquad \text{...........} \qquad (10)$$

$$a = \bar{y} - b\bar{x} \qquad \text{..............} \qquad (11)$$

and the coefficient of correlation, r is:

$$r = \frac{n\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i y_i}{\sqrt{\{[n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2][n\sum_{i=1}^{n} y_i^2 - (\sum_{i=1}^{n} y_i)^2]\}}} \qquad \text{........} \quad (12)$$

2.2.5. Exponential plots

The cumulative distribution function for the exponential distribution is $F(t) = 1 - e^{-\lambda t}$. Taking the natural logarithm of both sides and transforming [12,13] we obtain:

$$ln\left[\frac{1}{1-F(t)}\right] = \lambda t \qquad \text{.....................} \qquad (13)$$

Comparing equation 13 with the linear equation model shown in equation 10.

$$\text{Therefore, } y \equiv ln\left[\frac{1}{1-F(t)}\right]\ ;\ a \equiv 0;\quad b \equiv \lambda;\ \ and\ x \equiv t \qquad \text{............ (14)}$$

$$\text{Hence, plot} \left(t_i, \quad ln\left[\frac{1}{1-F(t_i)}\right]\right)$$

Weibull plots

From the Weibull cumulative density function, $F(t) = 1 - e^{-(t/\theta)^{\beta}}$. Taking logarithms and transforming we obtain:

$$ln ln\left[\frac{1}{1-F(t)}\right] = -\beta\, ln\, \theta + \beta\, ln\, t \qquad (15)$$

Comparing equation 15 with the linear equation model shown in equation 10.

$$\text{Therefore, } y \equiv ln ln\left[\frac{1}{1-F(t)}\right]\ ;\ a \equiv -\beta\, ln\, \theta\ ;\ \ b \equiv \beta;\ and\ x \equiv ln\, t \qquad (16)$$

$$\text{Hence, plot}\left(ln\, t_i\,,\ \rightleftarrows ln ln\left[\frac{1}{1-\hat{F}(t_i)}\right]\right)$$

Lognormal Plots

From the Weibull cumulative density function, $F(t) = \Phi\left(\frac{1}{s} Ln \frac{t}{t_{med}}\right) = \Phi(Z)$. Taking appropriate transformation, we obtain:

$$Z = \Phi^{-1}[F(t)] = \frac{1}{s} Lnt - \frac{1}{s} Lnt_{med} \qquad \ldots\ldots\ldots\ldots \qquad (17)$$

The shape parameter, *s,* is the reciprocal of the slope of the fitted line, and t_{med}, the median, is obtained from the Y intercept of the fitted line. That is, $\hat{s} = \frac{1}{b}$ and $\hat{t}_{med} = \exp(-\hat{s}a)$ [12].

The test of model adequacy shall be carried out by checking the computed values of the coefficient of correlation, coefficient of determination and the adjusted coefficient of determination

a) Coefficient of Correlation, r: It measures the strength and the direction of a linear relationship between two variables (x and y) with possible values between -1 and 1. The computing formula is presented in equation (12). [14]

b) Coefficient of Determination, r2 : is the proportion of the variation in the dependent variable that is predictable from the independent variable(s). It is computed by the taking the square of the coefficient of correlation

c) Adjusted Coefficient of Determination, $'\,\boldsymbol{rr22}$: adjusts the value of r 2 to account for the number of independent variables in the model in order to avoid overestimating the impact of adding independent variables to the model. In the case of two variables model, it the same value as the r2 [14, 15].

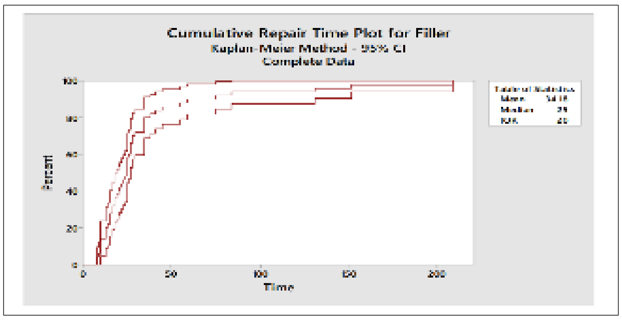
3. Results

The time to repair (TTR) data obtained will be presented and analyzed using the parametric analysis technique and non-parametric analysis technique.

3.1. Parametric Analysis Technique

3.1.1. Analysis of the Filler

The historical repair times data of the filler would be represented in an ascending order of magnitude and the following would be computed: a) an estimate of the cumulative repair – time distribution, and b) a 95 percent interval for the MTTR which is presented in Figure 3



Characteristics of Variables (Filler)			
		95% Normal CI	
MTTR	Standard Error	Lower	Upper
34.18	5.31572	23.7614	44.5986
Median =	25		
IQR =	20	Q1 = 15	Q3 = 35

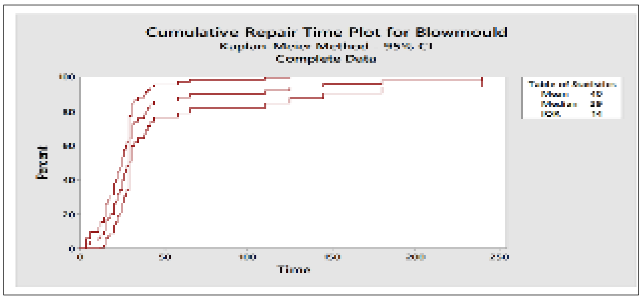
a) cumulative repair – time distribution plot **b) Characteristics of Filler Variables**

Figure 3 Parametric Analysis of Filler

Where, IQR = Interquartile Range; Q1 = Lower (First) Quartile; Q3 = Upper (Third) Quartile, and CI = Confidence Interval

3.2. Analysis of the Blowmould

The historical repair times data of the Blowmould would be represented in an ascending order of magnitude and the following would be computed: a) an estimate of the cumulative repair – time distribution, and b) a 95 percent interval for the MTTR. presented in Figure 4.



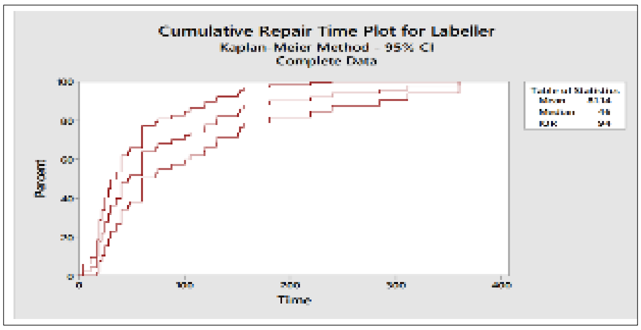
Characteristics of Variables (BlowMould)			
		95% Normal CI	
MTTR	Standard Error	Lower	Upper
40	6.28519	27.6812	52.3188
Median =	29		
IQR =	14	Q1 = 20	Q3 = 34

a)The cumulative repair – time distribution plot **b) Characteristics of Blowmould Variables**

Figure 4 Parametric Analysis of Blowmould

3.2.1. Analysis of the Labeller

The historical repair times data of the Labeller would be represented in an ascending order of magnitude and the following would be computed: a) an estimate of the cumulative repair – time distribution, and b) a 95 percent interval for the MTTR presented in Figure 5



Characteristics of Variables (Labeller)			
		95% Normal CI	
MTTR	Standard Error	Lower	Upper
81.14	11.6472	58.312	103.968
Median =	46		
IQR =	94	Q1 = 25	Q3 = 119

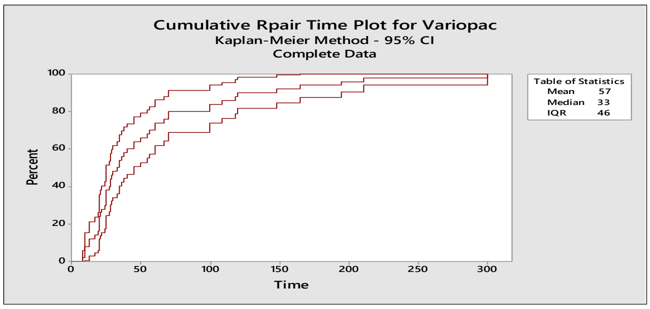
a) cumulative repair – time distribution plot **b) Characteristics of Labeller Variables**

Figure 5 Parametric Analysis of Labeller

3.2.2. Analysis of the Variopac

The historical repair times data of the Variopac would be represented in an ascending order of magnitude and the following would be computed: a) an estimate of the cumulative repair – time

distribution, and b) a 95 percent interval for the MTTR. Presented in figure 6 is the cumulative density and hazard rate plot.



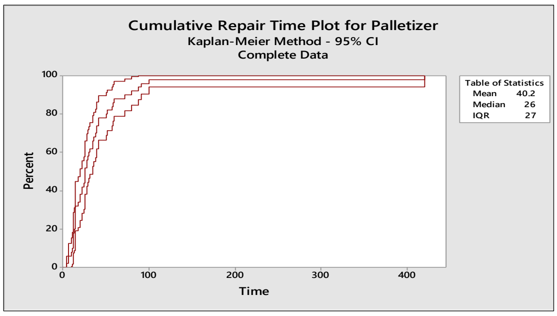
Characteristics of Variables (Variopac)			
		95% Normal CI	
MTTR	Standard Error	Lower	Upper
57	8.3909	40.554	73.446
Median =	33		
IQR =	46	Q1 = 21	Q3 = 67

a) cumulative repair – time distribution plot **b) Characteristics of Variopac Variables**

Figure 6 Parametric Analysis of Variopac

3.2.3. Analysis of the Palletizer

The historical repair times data of the Palletizer would be represented in an ascending order of magnitude and the following would be computed: a) an estimate of the cumulative repair – time distribution, and b) a 95 percent interval for the MTTR. Presented in figure 7 is the cumulative density and hazard rate plot.



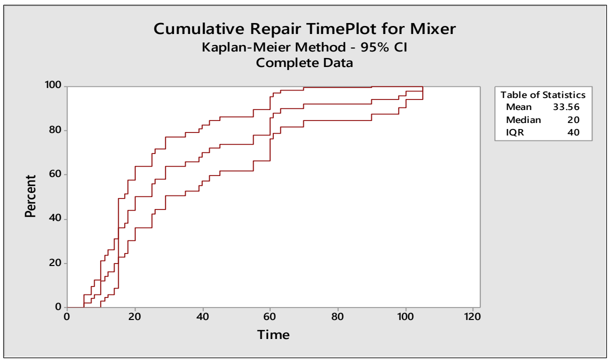
Characteristics of Variables (Palletizer)			
		95% Normal CI	
MTTR	Standard Error	Lower	Upper
40.2	8.4065	23.724	56.677
Median =	26		
IQR =	27	Q1 = 15	Q3 = 42

a) cumulative repair – time distribution plot **b) Characteristics of Palletizer Variables**

Figure 7 Parametric Analysis of Palletizer

3.2.4. Analysis of the Mixer

The historical repair times data of the Mixer would be represented in an ascending order of magnitude and the following would be computed: a) an estimate of the cumulative repair – time distribution, and b) a 95 percent interval for the MTTR presented in figure 8



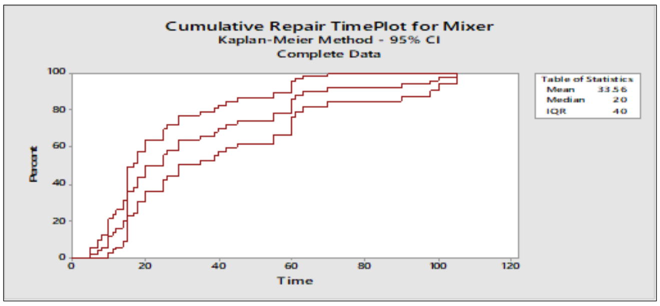
Characteristics of Variables (Mixer)			
		95% Normal CI	
MTTR	Standard Error	Lower	Upper
33.56	3.7264	26.256	40.864
Median =	20		
IQR =	40	Q1 = 15	Q3 = 55

a) cumulative repair – time distribution plot **b) Characteristics of Mixer Variables**

Figure 8 Parametric Analysis of Mixer

3.3. Analysis of the Conveyor

The historical repair times data of the Conveyor would be represented in an ascending order of magnitude and the following would be computed: a) an estimate of the cumulative repair – time distribution, and b) a 95 percent interval for the MTTR presented in figure 9



Characteristics of Variables (Conveyor)			
		95% Normal CI	
MTTR	Standard Error	Lower	Upper
38.88	4.9432	29.192	48.568
Median =	28		
IQR =	28	Q1 = 18	Q3 = 46

a) cumulative repair – time distribution plot **b) Characteristics of Mixer Variables**

Figure 9 Parametric Analysis of Conveyor

3.4. Non-parametric analysis technique (Computing Probability of MTTR)

In this section, the repair probability of the MTTR shall be computed for each of the machine using their respective repair cumulative distribution function [17] as presented in table 3.1

3.4.1. Filler:

The probability of computing the repair of the Filler machine within the MTTR is computed using the function presented in equation 2.12

$$\text{Prob. (MTTR = 43.25)} = 1 - \exp(-\lambda_r \times MTTR) = 1 - \exp(-0.018200 \times 43.25) = 0.5448 \text{ or } 54.48\%$$

Table 2 Summary of the Parametric Analysis

S/N	Machine	Repair Distribution	Parameter(s)
1	Filler	Exponential	λr= 0.018200
2	Blowmould	Exponential	λr= 0.019268
3	Labeller	Exponential	λr= 0.011239
4	Variopac	Exponential	λr = 0.011239

5	Palletizer	Lognormal	Sp = 0.85 & t_{med} = 27.49 min
6	Mixer	Lognormal	Sp = 0.79 & t_{med} = 24.91 min
7	Conveyor	Exponential	λr = 0.026221

Where, λ_r = repair rate, S_p = shape parameter and t_{med} = median repair time

3.4.2. Blowmould

The probability of computing the repair of the Blowmould machine within the MTTR is computed using the function presented in equation 2.12

$$\text{Prob. (MTTR = 51.90)} = 1 - \exp(-\lambda_r \times MTTR) = 1 - \exp(-0.019268 \times 51.90) = 0.6321 \text{ or } 63.21\%$$

3.4.3. Labeller:

The probability of computing the repair of the labelling machine within the MTTR is computed using the function presented in equation 2.12

$$\text{Prob. (MTTR = 89.00)} = 1 - \exp(-\lambda_r \times MTTR) = 1 - \exp(-0.011239 \times 89) = 0.6322 \text{ or } 63.22\%$$

3.4.4. Variopac:

The probability of computing the repair of the labelling machine within the MTTR is computed using the function presented in equation 2.12

$$\text{Prob. (MTTR = 64.67)} = 1 - \exp(-\lambda_r \times MTTR) = 1 - \exp(-0.015463 \times 64.67) = 0.6321 \text{ or } 63.21\%$$

3.4.5. Palletizer

The probability of computing the repair of the Palletizing machine within the MTTR is computed using the function presented in equation 2.16

$$\text{Prob. } (t_{med} = 27.49) = \phi\left(\frac{1}{S_p} ln \frac{1}{t_{med}}\right) = \phi\left(\frac{1}{0.85} ln \frac{1}{27.49}\right) = \phi(-3.8986) = 0.00005 \text{ or } 0.005\%$$

3.4.6. Mixer:

The probability of computing the repair of the Mixing machine within the MTTR is computed using the function presented in equation 2.16

$$\text{Prob. } (t_{med} = 24.91) = \phi\left(\frac{1}{S_p} ln \frac{1}{t_{med}}\right) = \phi\left(\frac{1}{0.79} ln \frac{1}{24.91}\right) = \phi(-4.0699) = 0.00003 \text{ or } 0.003\%$$

Table 3 Summary of the Non- Parametric Analysis

S/N	MACHINE	Probability of repair
1	Filler	54.48%
2	Blowmould	63.21%
3	Labeller	63.22%
4	Variopac	63.22%
5	Palletizer	0.005%
6	Mixer	0.03%
7	Converyor	63.21%

3.4.7. Conveyor

The probability of computing the repair of the conveying machine within the MTTR (see value in section 4.3.7) is computed using the function presented in equation 2.12

$$\text{Prob. (MTTR = 38.14)} = 1 - \exp(-\lambda_r \times MTTR) = 1 - \exp(-0.026221 \times 38.14) = 0.6321 \text{ or } 63.21\%$$

4. Discussion

4.1. Discussion of Filler machine

The analysis of the time to repair (TTR) data of the filler machine shows that the equipment as an average time to repair value of 34.98 minutes and a median time to repair value of 25 minutes. Also, the interquartile range (IQR) is 20 minutes in value.

On the other hand, in doing a probability plots through the least squares fitting procedure for the Filler TTR data, it is observed that exponential distribution best describes the repair time function of the equipment. The parameter of the distribution is 0.0182, with the least square correlation coefficient having a value of 0.93008. This is high value of the correlation coefficients shows that there is a strong linear fit of the exponential function to the data, thus supporting the hypothesis that the data came from exponential distribution. The estimated MTTR is 54.6 minutes, with a probability of 54.48%.

4.2. Discussion of Blowmould machine

The analysis of the time to repair (TTR) data of the Blowmould machine shows that the equipment as an average time to repair value of 40 minutes and a median time to repair value of 29 minutes. Also, the interquartile range (IQR) is 14 minutes in value.

On the other hand, in doing a probability plots through the least squares fitting procedure for the Filler TTR data, it is observed that exponential distribution best describes the repair time function of the equipment. The parameter of the distribution is 0.0193, with the least square correlation coefficient having a value of 0.91658. This is high value of the correlation coefficients shows that there is a strong linear fit of the exponential function to the data, thus supporting the hypothesis that the data came from exponential distribution. The estimated MTTR is 51.9 minutes, with a probability of 63.21%.

4.3. Discussion of Labelling machine

The analysis of the time to repair (TTR) data of the labelling machine shows that the equipment as an average time to repair value of 81.14 minutes and a median time to repair value of 46 minutes. Also, the interquartile range (IQR) is 94 minutes in value.

On the other hand, in doing a probability plots through the least squares fitting procedure for the Labeller TTR data, it is observed that exponential distribution best describes the repair time function of the equipment. The parameter of the distribution is 0.01124, with the least square correlation coefficient having a value of 0.99070. This is high value of the correlation coefficients shows that there is a strong linear fit of the exponential function to the data, thus supporting the hypothesis that the data came from exponential distribution. The estimated MTTR is 89.00 minutes, with a probability of 63.22%.

4.4. Discussion of Variopac machine

The analysis of the time to repair (TTR) data of the Variopac machine shows that the equipment as an average time to repair value of 57 minutes and a median time to repair value of 33 minutes. Also, the interquartile range (IQR) is 46 minutes in value.

On the other hand, in doing a probability plots through the least squares fitting procedure for the Variopac TTR data, it is observed that exponential distribution best describes the repair time function of the equipment. The parameter of the distribution is 0.0154, with the least square correlation coefficient having a value of 0.98202. This is high value of the correlation coefficients shows that there is a strong linear fit of the exponential function to the data, thus supporting the hypothesis that the data came from exponential distribution. The estimated MTTR is 64.67 minutes, with a probability of 63.21%.

4.5. Discussion of Palletizer machine

The analysis of the time to repair (TTR) data of the Palletizer machine shows that the equipment as an average time to repair value of 40.2 minutes and a median time to repair value of 26 minutes. Also, the interquartile range (IQR) is 27 minutes in value.

On the other hand, in doing a probability plots through the least squares fitting procedure for the Palletizer TTR data, it is observed that lognormal distribution best describes the repair time function of the equipment. The distribution has a shape parameter of 0.85 and median time to repair value of 27.49 minutes, with the least square correlation coefficient having a value of 0.97980. This is high value of the correlation coefficients shows that there is a strong linear fit of the lognormal function to the data, thus supporting the hypothesis that the data came from lognormal distribution. The estimated median time to repair, tmed is 27.49 minutes, with a very low probability of 0.005%.

4.6. Discussion of Mixer machine

The analysis of the time to repair (TTR) data of the Mixer machine shows that the equipment as an average time to repair value of 33.56 minutes and a median time to repair value of 20 minutes. Also, the interquartile range (IQR) is 40 minutes in value.

On the other hand, in doing a probability plots through the least squares fitting procedure for the Palletizer TTR data, it is observed that lognormal distribution best describes the repair time function of the equipment. The distribution has a shape parameter of 0.79 and median time to repair value of 24.27 minutes, with the least square correlation coefficient having a value of 0.98454. This is high value of the correlation coefficients shows that there is a strong linear fit of the lognormal function to the data, thus supporting the hypothesis that the data came from lognormal distribution. The estimated median time to repair, t_{med} is 24.91 minutes, with a very low probability of 0.003%.

4.7. Discussion of Conveyor machine

The analysis of the time to repair (TTR) data of the conveyor machine shows that the equipment as an average time to repair value of 38.88 minutes and a median time to repair value of 28 minutes. Also, the interquartile range (IQR) is 28 minutes in value.

On the other hand, in doing a probability plots through the least squares fitting procedure for the Conveyor TTR data, it is observed that exponential distribution best describes the repair time function of the equipment. The parameter of the distribution is 0.0262, with the least square correlation coefficient having a value of 0.98099. This is high value of the correlation coefficients shows that there is a strong linear fit of the exponential function to the data, thus supporting the hypothesis that the data came from exponential distribution. The estimated MTTR is 38.14 minutes, with a probability of 63.21%.

5. Conclusion

In this study, maintainability theory was applied in an industrial context and more specifically on a soft drink production system and the time to repair cumulative distribution was evaluated on the basis of the data obtained [18]. The methodology used was implemented in a Microsoft excel and Minitab software environment because of the tedious nature of the computations required. To this purpose, we have considered a system of seven components of which there were five components whose repair times were exponential [19] (that is, the Filler; Blowmould; Labeller; Variopac and conveyor) and two components that has Log -normal distributions [19,20] (that is, the Palletizer and Mixer). In the computed probability of repair being completed within the mean time to repair, MTTR value of each machine all have returned an approximate 63% with the exception of Palletizer and Mixer that has extremely low probability (that is, below 1%) value at the MTTR.

These are the recommendations in this study:

- It is suggested that further studies for the extension of this work should be carried out by using a more robust sample size data and also doing an in-depth analysis to check if other distributions can also fit to the data and comparing results obtained.
- It is suggested that high attentions should be given to the Palletizer and Mixer in preventive maintenances program in other to sustain their reliability and to avoid them being a bottle neck during production operations.
- This study has contributed to knowledge in the following:

- A suitable repair distribution has been obtained for each of the machines.
- The machines that create a bottle neck for the line system has been identified.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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