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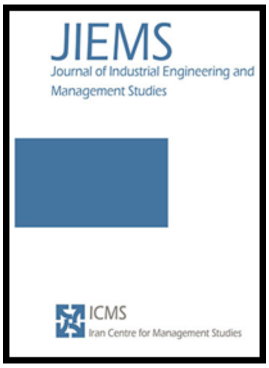

Failure data analysis for preventive maintenance scheduling of a bottling company production system

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Abstract
Equipment breakdown adds to the cost of production and considerably affect the overall equipment efficiency in automated lines due to unplanned downtime. Preventive maintenance with appropriate actions has been considered to enhance products quality, equipment reliability and minimize the probability of system brake down or failure. To this end, this study conducted a reliability status of nine packaging facilities, from the perspective of existing failure data of production system in the Nigerian multinational bottling plant. Failure data of the production system were stratified and analyzed to achieve the failure interval of each of the facilities and the sub-systems. Stratification of failure data resulted to an established input format that fitted the Pareto chart analysis, Weibull Distributions and Reliability/Failure Time analysis. The results showed that the facility with minimum value of reliability was filler machine. A standby filler system was therefore recommended in order to prevent unnecessary idleness of the other facilities especially when the production target is high. The study concluded that, analysis of downtime in a production/manufacturing system assisted in predicting the likely failure interval and hence a preventive maintenance scheduled was proposed.

Keywords*:* weibull distribution; downtime; reliability; stratification; failure data.

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1. Introduction

Automated plant line manufacturing systems are widely used in industries nowadays due to less use of raw materials and high production rate. However, total productive maintenance (TPM) involving Preventive Maintenance (PM) is a useful tool for improving manufacturing plant's productivity through the utilization of overall equipment efficiency (OEE) index (Battini et al., 2006). One of the factors that considerably affect OEE in automated lines is unplanned downtime. Usually, this problem occurs through a machine failure along the manufacturing lines and it leads to a loss in production minutes thereby reducing plant productiveness (Ab-Samat, et al., 2012). An approach on maintenance strategies is aimed at

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conserving the quality and market share of a product in any manufacturing or production environment. PM with appropriate actions has been considered to enhance products quality, equipment reliability and minimize the probability of system brake down or failure (Nwadinobi and Ezeaku, 2018). The method necessitates the maintenance managers to obtain adequate and proper information about running conditions of an equipment in order to take preventive measures before crises occur with the intention to sustain equipment availability (Adik and Bobade, 2018). Total Productive Maintenance (TPM) according to Gupta et al. (2012) is essentially for increasing the availability of an existing machinery and reducing the need for further capital investment. Wakjira, et al. (2012) were able to reduce downtime and increase the OEE of existing machineries by TPM execution in boiler plant in an Ethiopian malt manufacturing unit. In reviewing recent studies concerning downtime analysis of a manufacturing pants, it is noted that there is dearth of information on the reliability and downtime information on a packaging facilities of bottling company even though, studies have been performed through Weibull distribution and reliability/failure data analysis for construction, process, manufacturing and power industries. For this reason, the present study aims at investigating downtime and reliability of a bottling production system utilizing Pareto chart, Weibull and reliability/failure time analysis.

In a study conducted by Dibyojyoti and Thuleswar (2015), Pareto chart was employed to examine factors contributing to approximately eighty percent downtime. The study indicated equipment breakdown, minor stoppages, shift change, change over and utility failure as the principal factor. Out of these five major losses, equipment breakdown was further isolated. Yang et al. (2008) proposed a method for scheduling of maintenance operations in a manufacturing system using the continuous assessment and prediction of the level of performance degradation of manufacturing equipment, as well as the complex interaction between the production process and maintenance operations. In all cases that were studied, application of the newly proposed maintenance scheduling tool resulted in a noticeable increase in the cost-benefits, which indicates that the use of predictive information about equipment performance through the newly proposed maintenance scheduling method could result in significant gains obtained by optimal maintenance scheduling. One way to accelerate productivity is to augment the operational availability of existing machines (Tejas and Uday, 2017). Reliability of any equipment is a powerful segment of information to the maintenance engineers (Dibyojyoti and Thuleswar, 2015). Lai *et al.* (2006) validated the fact that Weibull models are used to describe various types of observed failures of systems and phenomena. They are widely used in reliability and survival analysis. Raju *et al* (2018) confirmed that one of the most extensively used statistical perspective for reliability estimation is a Weibull distribution. In their study a three-parameter Weibull distribution was embraced to examine the data sets of Load-Haul-Dumper (LHD) in underground mines using 'Isograph Reliability Workbench 13.0' software package. The parameters were evaluated using best fit distributions and Weibull likelihood plots. Percentage reliability of each individual subsystem of LHD was estimated. Fadeyi, *et al.* (2013) employed reliability model to address downtime in a sanitary towel manufacturing firm. They identified components of the production system responsible for downtime and applied reliability model to reduce downtime. Prombanpong *et al.* (2013) worked on downtime using a range of buffer capacities and then calculated improved line efficiency in an automobile transfer line. From the foregoing, besides the use of identified components responsible for downtime for evaluating reliability of a production line, analysis of unplanned downtime data of facilities/equipment in the production system has potential to prevent equipment breakdown and total shutdown of the whole production systems hence, reducing further capital investment. In this study, existing failure data were stratified to extract the unplanned downtime data (equipment breakdown time). Weibull distribution was adopted to analyze the reliability state of packaging facilities exercising extant failure data obtained from nine packaging facilities from the case study of a bottling company and verified using the goodness of fit test. The reliability status and likely failure interval of each facility were predicted and a preventive maintenance scheduled was proposed.

2. Methodology

2.1. Stratification of an existing failure data

The study utilized existing failure data collated over a period of six months for nine (9) facilities/equipment in the production system of a case bottling company. The facilities include: Filler, Empty bottle inspector, EBI, Labeler, Bottle Washer, Recrater, Repalletizer, Decrater, Pasteurizer and Depalletizer. Stratification of the existing failure data for the nine facilities was done by separating planned downtime from the unplanned (equipment breakdown time) downtime. The stratified data were simplified and resolved into input variables based on a predetermined set of criteria such as unplanned downtime events which were absorbed into censored and uncensored observations that fit into the STATISTICA software tool for Pareto chart and Weibull distribution failure time analysis. The unplanned downtime was then analyzed at the appropriate interval for preventive maintenance of each of the facility/equipment. Similar method was employed by Piqueras and Fernandez-Crehuet (2020) for the analysis of preventive maintenance of machineries.

2.2. Predicting the Likely Failure Interval of Each Facility

The stratified or grouped failure input data suitable for a descriptive and inferential statistic tool was used through the application of Pareto chart, Weibull distribution and reliability/failure time analysis as shown in Figure 1. The Weibull analysis and reliability/failure time analysis allowed the Weibull distribution to fit data sets (stratified input failure data) containing complete responses also known as failure times, counts (uncensored observations) and incomplete responses (censored observations).

The governing equations for the empirical approximation of the 3- parameter Weibull distribution analysis computed by STATISTICA software are used to describe the relationship between reliability R(t) and unreliability against Time to fail (t) and probability density function (PDF). These equations are described as follows;

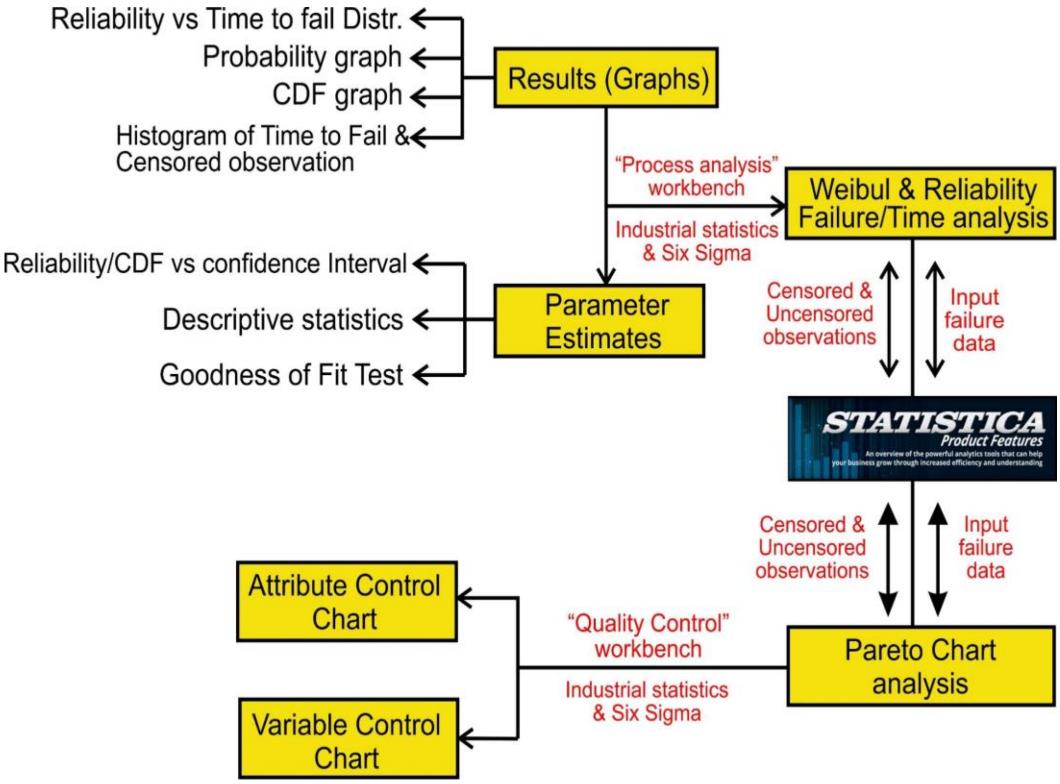

Figure 1. Flow chart for predicting the failure intervals using *STATISTICA* software model

Reliability R(t) vs Time to Fail: These equations were computed to determine the percentage occurrences where there is constant, decrease or increase in the variation of the observed variables (failure input data) utilized to determine the reliability state of systems and its components. Raju et al., (2018) described reliability as the probability of a machine or its components to perform its designated job over a stipulated period of time in acknowledged circumstances.

$$R(t) = e^{\frac{-(t-\gamma)^{\beta}}{n}} \tag{1}$$

where n = scale parameter, β = Slope/shape parameter, γ = Location parameter

Cumulative Distribution Function (CDF): Also known as unreliability. It was calculated to determine the uncertainties of systems and its components efficiency. According to Dibyojyoti and Thuleswar (2015) the expression in equation 1 attempts to finding out the CDF governing the failure rate of machines in order to better understand equipment failure. From the work of Raju et al., 2018, the empirical approximation of 3-parameter Weibull distribution was derived to identify the relations of Probability density function, CDF, hazard rate or failure rate and reliability. In order to derive these parameters, the unreliability factor can be taken as a linear quadratic model shown in equation (2). This may help to identify the co-ordinates of both x and y-axis to plot the Weibull likelihood plots. A 3-parameter Weibull distribution's unreliability or cumulative distribution function (CDF) parameter is shown in equation (2).

$$CDF = F(t) = 1 - e^{\frac{-(t-\gamma)^{\beta}}{n}} \tag{2}$$

where, n, β & γ are scale, shape and location parameters. The linear form of equation (2) can be written as

$$y = mx + C \tag{3}$$

$$F(t) = 1 - e^{\frac{-(t-\gamma)^{\beta}}{n}} \tag{4}$$

$$\text{In}\ [(1 - \text{F(t)}] = In\ e^{\frac{-(t-\gamma)^{\beta}}{n}} \tag{5}$$

$$\text{In}\ [-\text{In}(\frac{1}{c1} - \text{F(t)}] = \ \beta\ In^{\frac{-(t-\gamma)\ \cdot}{n}} \tag{6}$$

$$\text{In}\ [-\text{In}(\frac{1}{1-f(t)})] = \ \beta\ In(t-y) - \beta(n)^{\cdot} \tag{7}$$

$$\text{y} = \text{In}\ \left[\ \text{In}\left(\frac{1}{1-f(t)}\right)\right], x = \text{In(t} - \text{y)} \tag{8}$$

Thus, the CDF equation can be written as;

$$y = \beta x - \beta In(\eta) \tag{9}$$

This is now a linear equation, with an intercept of βln(η) and a slope of β. Co-ordinates of both x and y-axes of the Weibull probability plotting were derived. The x-axis is simply a logarithmic, since x=ln(t-γ). The y-axis is more complex and represented as;

$$\text{y} = \text{In}\ \left[\ \text{In}\left(\frac{1}{1-f(t)}\right)\right] \tag{10}$$

Probability Density Function PDF: This is a mathematical function described by Raju et al., (2018). It can be represented mathematically or on a plot where the x-axis represents time. The Probability function for the 3-parameter Weibull distribution is expressed as probability density function (PDF) curves and can be changed by the influence of either shape parameter, β, scale parameter, η and location parameter, γ variation.

$$f(t) = \frac{\beta}{\eta} = e^{\frac{(t-\gamma)^{\beta-1}}{n}} e^{\frac{-(t-\gamma)^{\beta}}{n}} \tag{11}$$

Where; the scale parameter (η) defines where the bulk of the distribution lies, the shape parameter (β) defines the shape of the distribution and the location parameter (γ) defines the location of the distribution in time.

The Confidence Interval for CDF/Reliability: This computes the values for reliability and CDF or unreliability with confidence interval of 95% for estimates of lower confidence limit (LCL) and upper confidence limit (UCL) for the complete failure times as expressed by equation 12 and 13.

$$LCL_X = \left(\frac{\frac{j}{n-f+1}}{F_{X-X,\ 2*(n-j+1),2*+(\frac{1}{n-j+1})}}\right) \tag{12}$$

$$UCL_X = \left(\frac{\frac{j}{(n-f+1)} * F_{X-X,2*(n-j+1)}}{1+(\frac{1}{n-j+1}) * \frac{F_{X,2*j,2*(n-j+1)}}{(n-j+1)})}\right) \tag{13}$$

Where;
LCL_x is the lower confidence limit (with x< 0.5) indicating unreliability.

UCL; is the upper confidence limit (with x>0.5) indicating reliability.
J; is the failure order.
N; is the total number of data points.
$F_{x,;}$ is the respective *F* distribution value for p=x, with degrees of freedom v1 and v2

2.3. Defining input variables (failure data) for Labeller machine and sub-system that will fit the Weibull distributions analysis

The failure input data in Table I was derived from an existing stratified failure data obtained for Labeller machine and its sub-systems in a spreadsheet format that is suitable for the Weibull and reliability/ failure time analysis using STATISTICA software tool. In Table 1, the first column identifies the respective five months (February, March April, May and June) in which a particular component or sub-system for Labeller machine failed. The values in the second column describes the total loading time or machine operational time in (hrs. and days) for each month respectively. Column with subject "defect" identifies failure constraint of Labeller machine components or sub-systems represented by failure codes denoted by letters. The column with subject “Count” signifies frequency of failure occurrence for each defect represented by letter codes. STATISTICA automatically computes the cumulative total of counts for all the five-months representing each category of defect.

Table 1. Input failure data for Labeller machine and sub- systems utilized to fit Pareto chart analysis and the Weibull distributions and reliability/failure time analysis.

Month	Time (Hrs)	Defect	Count
FIRST (Feb 2018)	672 (28days)	L_a	1
FIRST (Feb 2018)	672 (28days)	L_b	20
FIRST (Feb 2018)	672 (28days)	L_c	1
FIRST (Feb 2018)	672 (28days)	L_f	0
FIRST (Feb 2018)	672 (28days)	L_g	1
FIRST (Feb 2018)	672 (28days)	L_v	1
FIRST (Feb 2018)	672 (28days)	Others	2
SECOND (March 2018)	672 (28days)	L_a	3
SECOND (March 2018)	672 (28days)	L_b	1
SECOND (March 2018)	672 (28days)	L_c	3
SECOND (March 2018)	672 (28days)	L_f	0
SECOND (March 2018)	672 (28days)	L_g	0
SECOND (March 2018)	672 (28days)	L_v	7
SECOND (March 2018)	672 (28days)	Others	0
THIRD (April 2018)	672 (28days)	L_a	3
THIRD (April 2018)	672 (28days)	L_b	5
THIRD (April 2018)	672 (28days)	L_c	5
THIRD (April 2018)	672 (28days)	L_f	1
THIRD (April 2018)	672 (28days)	L_g	0
THIRD (April 2018)	672 (28days)	L_v	7
THIRD (April 2018)	672 (28days)	Others	2
FOURTH (May 2018)	672 (28days)	L_a	1
FOURTH (May 2018)	672 (28days)	L_b	10
FOURTH (May 2018)	672 (28days)	L_c	3
FOURTH (May 2018)	672 (28days)	L_f	1
FOURTH (May 2018)	672 (28days)	L_g	0
FOURTH (May 2018)	672 (28days)	L_v	2
FOURTH (May 2018)	672 (28days)	Others	1
Fifth Month (June 2018)	336 (14 days)	L_a	0
Fifth Month (June 2018)	336 (14 days)	L_b	4

Month	Time (Hrs)	Defect	Count
Fifth Month (June 2018)	336 (14 days)	L_c	0
Fifth Month (June 2018)	336 (14 days)	L_f	0
Fifth Month (June 2018)	336 (14 days)	L_g	0
Fifth Month (June 2018)	336 (14 days)	L_v	0
Fifth Month (June 2018)	336 (14 days)	Others	1

3. Results and discussion

3.1. Pareto chart analysis for nine packaging systems in the production line

A total of nine facilities were involve, in which downtime losses were recorded during the time of machine operation for one hundred and twenty-six- days (126days) with loading time of (3024 hours) for an existing failure data in the typical multinational bottling company. All downtime analysis (Pareto chart analysis, Weibull Distributions and Reliability/Failure Time Analysis) were carried out based on the above stated conditions after stratifying the failure data to fit the input (failure) data spreadsheet for the nine packaging systems that fitted the pareto chart analysis.
The consequence of Pareto chart analysis shown in Figure 2 identifies "Attribute control charts" that summarizes various aspects of quality and efficiency of all the nine facilities with evidence that can easily be understood to avoid the need for any expensive, precise devices and time-consuming measurement procedures. Facilities are arranged in the descending order of percentage downtime as follows: Filler, EBI, Labeler, Bottle Washer, Recrater, Repalletizer, Decrater, Pasteurizer and Depalletizer as shown in Figure 2.

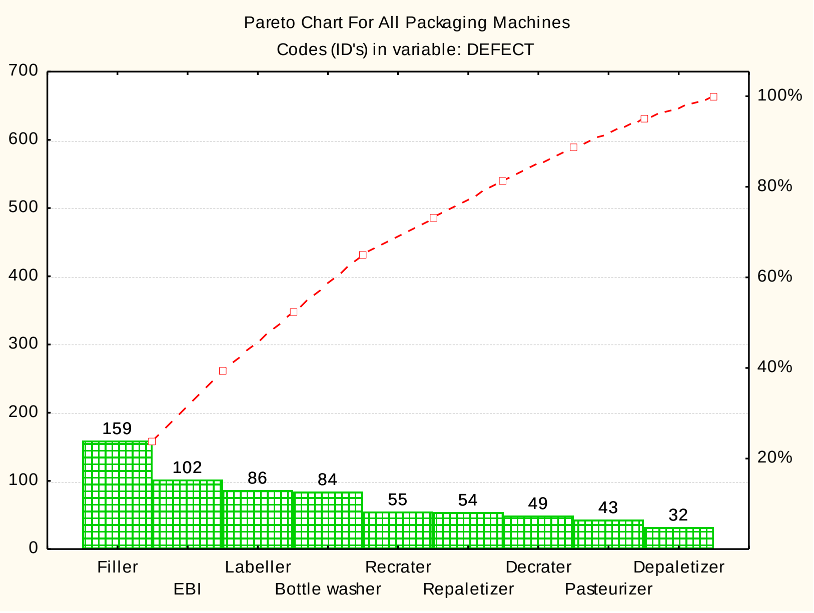

Figure 2. Pareto chart analysis for all (9) nine packaging Facilities

Pareto chart analysis shows that the histogram of nine (9) systems efficiency was at 100% as at the last maintenance practice, but as the facilities undergo continuous operation within a specified load time at 3024 hours, failure occurrences (denoted at the left vertical axis) disrupt the optimal efficacy of systems' operation. The critical point of systems effectiveness at 70% (expressed at the vertical right axis) identifies and distinguishes facilities with highest and lowest percentage of downtime. Filler, EBI, Labeller and bottle washer (BW) designates unreliability having the highest percentage of downtime while the remaining facilities or systems signifies reliability.

3.2. Pareto Chart Analysis for Labeller Machine and its Sub-Systems or Components

Figure 3 summarizes a graph for the chart of histogram by category and distinguishes the frequency of failure occurrence (counts) denoted by the left vertical axis against, each default for Labeller sub-systems. The subsystems are represented in failure codes denoted by the horizontal axis from the input variables (observed failure times). The highest percentage of downtime for defect in descending order is shown to be L_b, L_v, L_c, L_a, others are L_f and L_g respectively. From the previous maintenance practices conducted on Labeller machine, the contour lines of the Pareto chart identify efficiency to be 100% denoted by the right vertical axis. After some hours of operation with a specified loading time of 3024hrs, the critical point of systems reliability at (70%) identifies and distinguishes facilities with highest and lowest percentage of downtime. Defect with L_b, L_v, and L_c on the contour lines of the Pareto chart signifies the critical point of inefficiency or unreliability of Labeller sub-systems with defect L_b having the highest and potential increase of failure occurrence while the remaining defect identifies reliability of filler sub-systems.

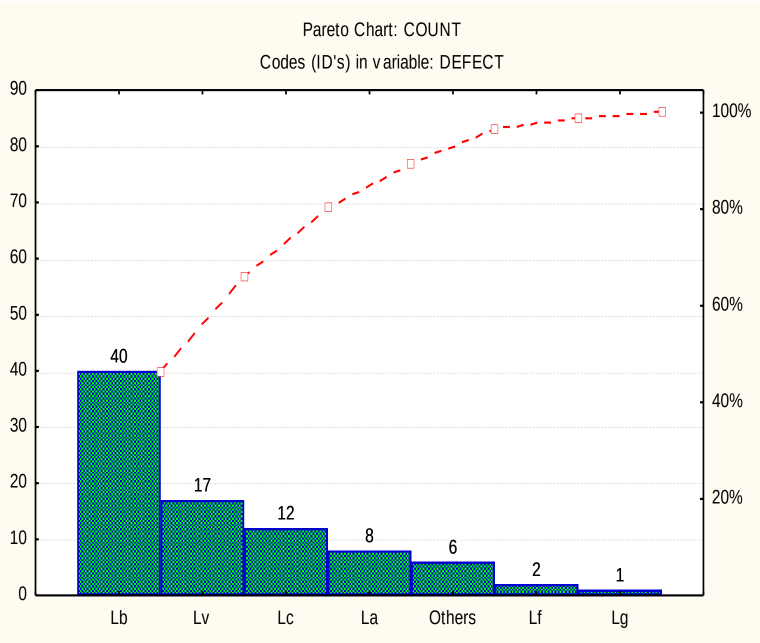

Figure 3. Pareto chart analysis for Labeller machine and its components or sub-systems

The chart shown in Figure 3 describes "Variable control" chart as it provides more persuasive evidence of quality problems than "attribute control" chart in Figure 1 which is essential to assist Engineers prioritize an effective preventive or predictive maintenance practice.

3.3. Weibull and reliability/failure time analysis for Labeller machine and sub-systems

Results of the analysis show various graph or plots for reliability function (R(t) and cumulative distribution function (CD(F(t) versus time to fail (hrs.); probability function; and histogram of failure times and censored times in which the input or failure data for Labeller machine and its components were utilized. In Figure 4, the reliability analysis for Labeller machine and its sub-systems with values signifying reliability R(t) on the vertical axis were plotted against Time-to-Fail (hrs.) on the horizontal axis. The most integral and crucial perspectives in adopting 3-

parameter Weibull and reliability failure/time analysis is based on the shape parameter or Weibull slope parameter (β) which is of special importance, as it identifies the reliability state of Labeller sub-system (i.e., the probability of Labeller sub-systems to consistently perform its designated function in acknowledged circumstances within a specified operating time (Raju et al., 2018). Comparing the Pareto chart analysis with the reliability/failure time analysis of Labeller sub-systems, a minimum reliability (R) scale of (0.7) was given by Nicolas and Rosemary (2006). Based on the reliability scale value, it is observed from Figure 4 that for:

- $R < 0.7$: Defect with L_b, L_v, and L_c identifies the "unreliability" state of Labeller sub-systems having a constant or potential increase in failure rate.
- $R > 0.7$ Defect with L_a, others, L_f and L_g identifies the "reliability" state of Labeller sub-systems which is prone to fail with respect to time.

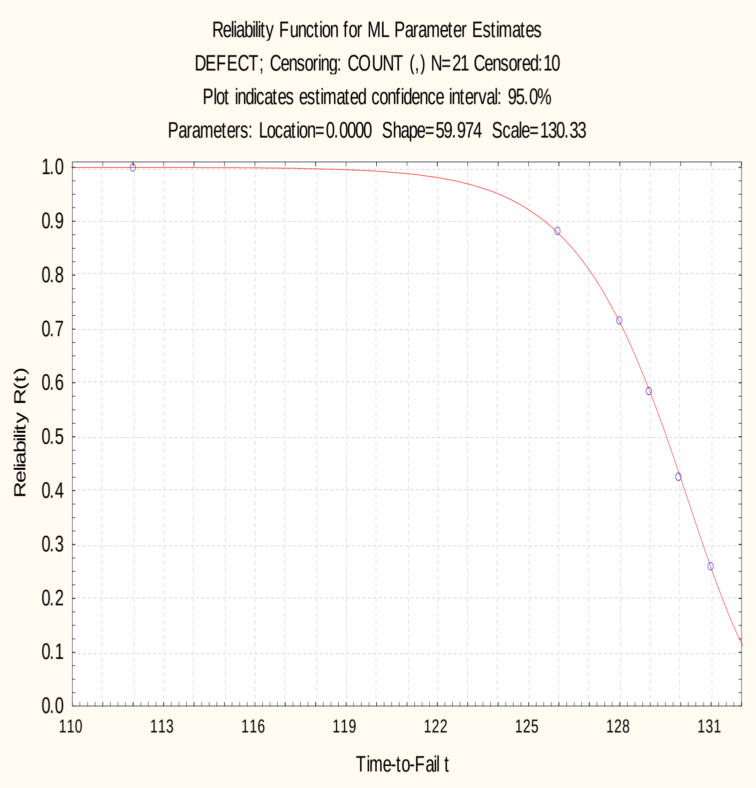

Figure 4. Reliability analysis (R(t) vs. Time to fail(t) for Labeller machine and sub-systems. Location =0.000; Shape=59.97; scale=130.33

Figure 5 shows the graph of probability function in which the values for (Time-to-Failure (t) minus Location) denoted in the horizontal axis is scaled logarithmically against the probability of the observed failure data which can be less than or equal to 1 as depicted by the vertical axis. In Figure 6, a plot of histogram with failure times and censored observation is displayed. The total number of observations (N) are denoted on the vertical axis against Time to fail (in hours) on the horizontal axis. The plot identifies the histogram of failures times (uncensored observations) in red colour and histogram of censored observation (incomplete failures) in blue colour.

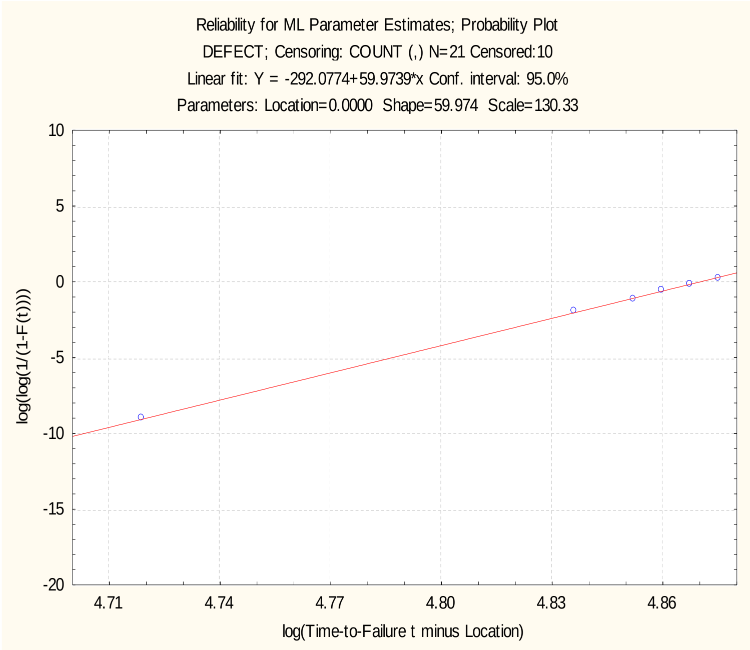

Figure 5. Probability Function (CDF) graph (F(t) vs. Time to fail(t) for Labeller machine and its components or sub-systems

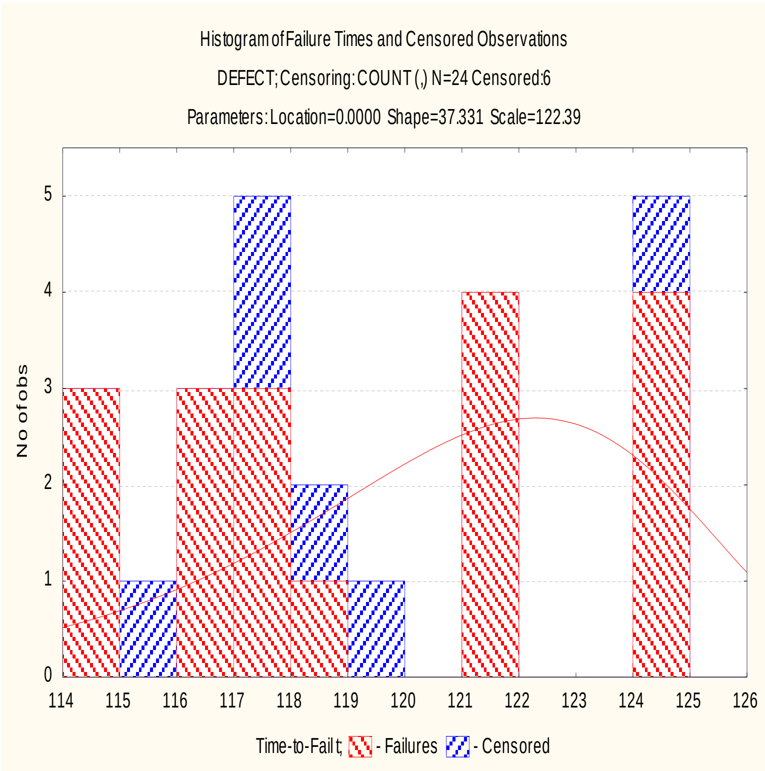

Figure 6. Histogram of failure times and censored observation for Labeller machine

3.4. Interpretation of parameter estimates obtained from Weibull distributions and reliability/failure time analysis for Labeller machine and sub-system

Several spreadsheets (Tables) consisting of value estimates for the 3-parameter Weibull distribution and reliability/time analysis using the STATISTICA model showed results obtained for reliability (R(t) vs cumulative distribution function F(t), confidence intervals or

minimum and maximum likelihood parameters, descriptive statistics and goodness of fit test. The various spreadsheets obtained from the analysis are shown and interpreted in Tables 2, 3 and 4.
Table 2 shows a spreadsheet result for the parameter estimates for reliability R(t), CDF and confidence intervals. The values are computed to fit the Weibull distribution analysis in a graphical format and are utilized to estimate the rate of failures in other to understand equipment efficiency. The first column points out values of censored data (C*) while the remaining values signify uncensored (complete failures). The values in the second column represents time to fail (t) in hours for each defect denoted by the vertical axis in the reliability and cumulative distribution function graphs. Therefore, the minimum value at 112 hours (4 days, 16 hours) recognizes the “critical” unreliability state of Labeller sub-systems. The column with subject "expected cumulative distribution" implies the values of complete responses of the observed failure times ciphered by STATISTICA.

Table 2. Parameter estimates for the reliability R(t) values and confidence intervals for Labeller machine and sub-systems

*Censor Case	Time to Fail	Expected Cum Dist.	-95.0% CDF LCL	+95.0% CDF UCL	Reliability	-95.0% REL. LCL	+95.0% REL. UCL	Log of T-Location
14	112.0000	0.000113	0.000001	0.011035	0.999887	0.988965	0.999999	4.718499
35*	112.0000							
28*	112.0000							
29	126.0000	0.123462	0.044188	0.319020	0.876538	0.680980	0.955812	4.836282
22*	126.0000							
1*	126.0000							
9*	127.0000							
31	128.0000	0.287417	0.152724	0.499854	0.712583	0.500146	0.847276	4.852030
3*	128.0000							
4	129.0000	0.417485	0.253892	0.631048	0.582515	0.368952	0.746108	4.859812
11	129.0000	0.417485	0.253892	0.631048	0.582515	0.368952	0.746108	4.859812
32	129.0000	0.417485	0.253892	0.631048	0.582515	0.368952	0.746108	4.859812
25*	129.0000							
18*	129.0000							
26	130.0000	0.576292	0.376918	0.789590	0.423708	0.210410	0.623082	4.867534
19	130.0000	0.576292	0.376918	0.789590	0.423708	0.210410	0.623082	4.867534
33	130.0000	0.576292	0.376918	0.789590	0.423708	0.210410	0.623082	4.867534
12	130.0000	0.576292	0.376918	0.789590	0.423708	0.210410	0.623082	4.867534
5*	130.0000							
34	131.0000	0.743257	0.501126	0.929947	0.256743	0.070053	0.498874	4.875197
6*	131.0000							

Table 2 further shows the values for the cumulative function CDF obtained at the confidence interval of 95% for values of lower confidence limit (CDF-LCL) and upper confidence limit (CDF-UCL) for the complete failures. Similarly, STATISTICA computes the reliability function with 95% confidence level for values at lower confidence limit (RF-LCL) and upper confidence limit (RF-UCL). It was observed that CDF ranges from 0.01 to 0.92 for all the censored cases. CDF increases with increasing time to fail indicating an increasing probability of failure with respect to time. Table 2 further shows that the reliability of the labelling machine and its components decreases with increasing time to fail.
Table 3 summarizes the goodness of fit test for estimates of the three-parameter Weibull distribution and Reliability/Time Analysis for Labeller machine. Hollander-Proschan Test shows P value of significance ($p = 0.96428$) for complete and censored data sets that compares the theoretical reliability function involving some computations from the model. The test sometimes indicates a poor fit when the data are heavily censored. Mann-Scheuer-Fertig test shows the p value of significance to be ($p < 0.05$), which allows the null hypothesis for the

values to follow the Weibull distribution with the estimated parameters. The test has reasonably good power which is applied to censored data (Dodson, 1994). It is observed from Table 3 that Neither the Hollander-Proschan nor the Mann-Scheuer-Fertig test statistic is significant, further recognizes the unreliability state of Labeller machine and its sub-systems.

Table 3. Descriptive statistics for the Weibull and reliability analysis for Labeller machine

Test	Test Value	P
Hollander-Proschan	-0.249299	p=.80313
Mann-Scheuer-Fertig	0.360166	p>.25

4. Conclusion

The study examined the downtime information and analyze the failure data of nine machine utilizing the Pareto chart, Weibull and reliability/failure time analysis to predict the likely failure intervals for all the nine facilities. Continuous operation of the facilities for a specified load time of 3024 hours was observed to disrupt the optimal efficiency of the systems operation. It was found that the lowest level of reliability was associated with Filler, EBI, Labeler, Bottle Washer, Recrater, Repalletizer, Decrater, Pasteurizer and Depalletizer in the declining order. Therefore, due to the critical unreliability of Filler machine, installation of a *standby* Filler system is recommended in situations where production target is high. The minimum value of reliability/time to fail at 112hours (4days, 16hours) for eight packaging facilities such as Empty Bottle Inspector (EBI), Labeller, Bottle Washer, Pasteurizer, Repalletizer, Recrater, Decrater and Depalletizer machine was utilized as a benchmark to establish an improved PM schedule for all the nine facilities including Filler which had the highest percentage of downtime with minimum reliability/time to fail (t) value at 115 hours (4 days, 19 hours). Results of several options for graph plots and value estimates for the three-parameter Weibull distribution to the observed failure assisted in understanding the reliability state of facilities and sub-systems under investigation which assists in scheduling a preventive maintenance plan to limit downtime to the planned downtime and increase productivity of the OEE and strengthen the customer satisfaction.

References

Ab-Samat, H., Jeikumar, L. N., Basri, E. I., Harun, N. A., and Kamaruddin S., (2012). "Effective preventive maintenance scheduling: a case study", In: *Proceedings of the 2012 International Conference on Industrial Engineering and Operation Management*, Istanbul, Turkey, pp. 1249-1257.

Adik, P., and Bobade, S., (2018). "Analysis of losses due to breakdown of equipment in construction", *International Research Journal of Engineering and Technology (IRJET)*, Vol. 5, No. 6, pp.1831-1836.

Battini D., Manzini, R., Persona, A., and Regattieri, A., (2006). TPM approach and new buffer design paradigm in plant layout, Chicago.

Bose, D., Ghosh, G., Mandal, K., Sau, S.P., and Kunar, S., "Measurement & evaluation of reliability, availability & maintainability of a diesel locomotive engine", *International Journal of Scientific and Research Publications*, Vol. 3, No. 9.

Dhillon, B. S., and Liu, Y., (2006). "Human error in maintenance", *Journal of Quality in Maintenance Engineering*, Vol. 12, pp. 21-36.

Dibyojyoti, D., and Thuleswar, N., (2015). "Breakdown and Reliability Analysis in a Process Industry", *International Journal of Engineering Trends and Technology (IJETT)*, Vol. 28, No. 3.

Dodson, B., (1994). Weibull and reliability time analysis, ISBN-10 087389295X. ISBN- 13.978-0873892957.Best Sellers Rank 659410.

Fadeyi, J. A., Oguoma, O. N., and Ogbonnaya, E. A., (2013). "Sanitary towel production plant optimization using reliability model", *Nigerian Journal of Technology*, Vol. 32, pp. 101-108.

Gupta, Amit K., Garg, R. K., (2012). "OEE improvement by TPM implementation: A case study", *International journal of it, Engineering and Applied Sciences Research (IJIEASR)*, Vol. 1, No.1.

Raju J. B., Govinda, R. M., Govinda, C. H., and Murthy, S. N., (2018). Reliability analysis and failure rate evaluation of load haul dump machines using Weibull distribution, Dept, of Mining Engineering, NITK surathkal 575025, India. 24th June 2018

Senra P., Lopes I., and Oliveira, J. A., (2017). "Supporting maintenance scheduling: a case study", 27th international conference of flexible automation and intelligent manufacturing, FAIM 2017, 27-30 June, 2017, Modena, Italy. *Procedia Manufacturing*, Vol. 11, pp. 2123-2130.

Shagluf, A., Longstaff, A. P., and Fletcher S., (2014). "Maintenance strategies to reduce downtime due to machine Positional errors", In: *Maintenance Performance Measurement and Management Conference Coimbra*, Portugal.

Tejas, and Uday (2017). Machine operational availability improvement by implementing effective preventive maintenance strategies, Department of Mechanical Engineering, Walchand College of Engineering, Sangli, Maharashtra, India - 416415.

Lai, C.D., Murthy, and D. Xie, M., (2006). Weibull Distributions and Their Applications. Springer Handbook of Engineering Statistics VL, Chapter 3.

Mirzai, M., Gholami, A., Aminifar, F., (2006). "Failure Analysis and Reliability calculation for power transformers", *Journal of Electrical Systems.*

Nicolas, and Rosemary (2006). SPSS for Psychologist: A guide to data analysis using SPSS, third edition.

Nwadinobi, C. P., and Ezeaku, I. I., (2018). "Review of maintenance scheduling and optimization models", *International Journal of Scientific Research in Mechanical and Material Engineering*, Vol. 2, No. 5, pp. 23-35.

Piqueras, R., and Fernandez-Crehuet (2020). "Data analysis for the preventive maintenance of machinery", *Studies in Engineering and Technology*, Vol. 7, No. 1, pp 1-8.

Prombanpong, S., Kaewyu, J., Thanadulthaveedech, N., and Matwangsang, M., (2013). "A buffer design for mitigation downtime effect in an automated transfer line", *International Journal of Innovation, Management and Technology*, Vol. 4, No. 155.

Wakjira, Melesse, W., Singh, A.P., (2012). "Total productive maintenance: A case study in manufacturing industry", *Global Journal of Researches in Industrial Engineering*, Vol. 12, No. 1.

Yang, Z., Djurdjanovic, D., and Ni, J., (2008). "Maintenance scheduling in manufacturing system based on predicted machine degradation", *Journal of Intelligent Manufacturing*, Vol. 19, pp. 87-98.

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