Critical Equipment Identification Approach for Condition-Based Maintenance Planning in a Beverage Plant

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Abstract
A critical equipment identification approach for condition-based maintenance (CBM) planning in the beverage plant is presented. In this study, critical equipment in a beverage industry was identified for effective condition based maintenance planning. The approach involves multiplying four generic factors namely; probability of failure, losses in in-process materials, mean-time-to-repair (MTTR) and mean cost of repairs. The score for the probability of failure was estimated as a function of cumulative failure rate (CFR) of respective plant equipment. Four grades of equipment failure probability were used: very low probability of failure, low probability of failure, medium probability of failure and high probability of failure. MTTR was determined from the identified probability distribution described by the repair data of the reference equipment. Losses in in-process materials were computed from a comparison of the total throughput and the lost brews. The results show that the Dust aspirator, Weighing bin, Mash filter and Chain conveyors with average criticality index of 0.2712, 0.2199, 0.1350 and 0.1563 respectively, are the most critical equipment in a beverage plant. This implies that planning and control of maintenance on the identified critical equipment based on condition monitoring will help improve the production efficiency in the brewing process.
Keywords: Critical equipment, Condition based maintenance, Cumulative failure rate, Mean time to repair, Mean cost of repairs

1. INTRODUCTION

Many processing equipment in a typical beverage plant suffer increasing wear with usage, age or both and are subject to random failures from this deterioration. Mash filters, screw conveyors, bucket elevators, combi-cleaners, suction blowers, weighing bin, dust aspirators, hammer mill, centrifugal pumps, gear boxes, dosing pumps, plate heat exchangers, bag slitter, rotary sluice, air dryer e.t.c. are all components of a beverage (brewing process) plant and illustrate such wearing items. These components can possess various physical deterioration processes such as crack initiation and propagation, cumulative tear and wear, corrosion, fatigue, creep e.t.c. The failure or deterioration of these components might incur high costs in the form of production losses and delays. It could also threaten productivity and pose reasonable safety hazards to the system and personnel (e.g. if the elasticity of a driving belt component drops below the elastic limit). When the deterioration index of any component is sufficiently established or when any of its control parameters can be measured in terms of another parameter that strongly correlates the component state (e.g. vibration, noise, temperature, erosion/corrosion index) at any given time, it is a good choice to base the maintenance on the components condition rather than its age. However, where there are sufficiently multiple components that make up a system's production process and where some components exhibit a superior mission critical character in the production process, it is more appropriate to base the condition monitoring primarily on the identified critical equipment. A secondary maintenance category (e.g. preventive, corrective, overhaul etc) can later be applied to the rest of the equipment. Condition based maintenance (CBM) has been described as a means of maintaining and improving the quality of the elements involved in a production process continuously and cost-effectively through detecting and controlling the deviations in the condition of equipment involved in the production process (Damilare and Olasunkanmi, 2010). It is decided by production costs, working environment and product quality. The need to carry out maintenance actions based on CBM towards avoiding failure and its negative effects had been treated in the past (Castanier et al., 2005). Successful implementation of condition monitoring demands a condition monitoring system (CMS), described as a tool for establishing the state of health (condition) in which the components in a system are (Hameed et al., 2009). Condition based maintenance of multi-component systems through identification of ''mission critical'' equipment can save a lot of productive time for a brewing plant. Many firms are realizing a need for proper maintenance policy that matches specific production facilities and systems. Industrial plants, machines and equipment are becoming technologically more advanced and at the same time more complex and difficult to control. Therefore, the importance of the maintenance function has been greater than before, due to its new role in maintaining and improving availability, performance efficiency, on-time deliveries, safety requirements and overall plant productivity (Tahboub, 2011). Modern engineering systems are designed to ensure successful operation throughout the anticipated service life, in compliance with given safety requirements related to the risk posed to the personnel, the public and the environment. Unfortunately, the threat of deteriorating processes is always present, so that it is necessary to install proper maintenance measures to control the development of deterioration and ensure the performance of the system throughout its service life (Fatemeh and Sha'ri, 2011). Critical equipment identification for CBM is highly indispensable in the beverage plant where there are differential equipment maintenance intensities. Every beverage plant has several processing units with many components and the system can keep on running irrespective of idling of some component (e.g. branding component). Other components in a brewing house plant includes: Mash Filter, Chain Conveyors, Combi-Cleaner, Suction Blower, Dust Aspirators, Screw Conveyors, Motors, Valves Hammer Mill, Pumps, Gear Boxes, Air dryer, Shell and Tube heat Exchanger, Rotary Sluice, Bag Slitter and Plate Heat Exchanger. As a result of excessive use, temperature, wear, misalignment, vibration e.t.c., Of course, these equipment tends to malfunction and exhibits discrepancies in their working conditions which gradually lead to higher operating cost and other negative returns to the enterprise. In developed countries, instantaneous maintenance may be possible on critical equipment due to the fact that there is availability of very reliable maintenance equipment/tools, spare parts and appropriate maintenance personnel. This has made set up time to be minimal and sometimes assumed to be negligible. The reverse is the case in some developing countries such as Nigeria, where the maintenance function (effective running and maintenance of processing equipment) is still difficult to execute. Some companies still depend on foreign expertise in the maintenance of complex and sophisticated systems and spare parts could take several months to procure for (Kareem and Jewo, 2011). In view of this fact, critical equipment needs to be identified in which condition based maintenance will be centered on for early detection of faults and for possible cost reduction. Critical equipment is equipment whose failure will lead to wanton loss in production output where as Condition based maintenance (CBM) is a management philosophy that posits repair or replacement decisions on the current or future condition of assets (Samhouri, 2009). The main objective of this study is to identify critical equipment in a beverage industry in which condition based maintenance will be applied for early detection of faults. The methodology adopted in this study included: collection of failure data from the beverage and analysis of collected data to aid criticality of equipment identification.

2. Data Collection

Secondary data was collected for this study. The system data for the period 2009 to 2014 were sourced from a standard beverage plant in Nigeria on absolute confidentiality. There was a basic assumption that the data is correct and should be trusted, since it lacked means of verification due to prevailing company policy. Oral interviews were organized to elicit the opinion of the personnel in charge of the equipment in event of grey areas and necessary clarifications made. Accordingly following data presented in table 1 were deemed necessary to fully identify the critical equipment in the brewery plant.

- Total number of failures for seventeen equipment
- Mean cost of repairs
- Total brews lost and total throughput (brews) over the period
- Total maintenance time

Table 1: Collected Data (2009-20014)

S/N	Equipment	Total failures (unit time)	Total maintenance time (minutes)	Total brews lost	Total throughput	Mean cost of repairs (unit time)
1	Mash filter	30	1499	96	348	0.8
2	Chain conveyors	5	1562	12	60	0.6
3	Screw conveyors	2	986	8	24	0.6
4	Bucket elevator	1	322	2	12	0.6
5	Combi cleaner	2	1860	14	24	0.9
6	Suction blower	3	788	4	36	0.5
7	Weighing bin	11	2004	16	108	0.8
8	Dust aspirators	4	1623	11	48	0.7
9	Hammer mill	2	1662	14	24	0.9
10	Centrifugal pumps	10	1280	8	96	0.8
11	Gear boxes	14	1026	6	132	0.6
12	Dosing pumps	12	1131	9	108	0.5
13	Plate heat exchanger	1	528	4	12	0.8
14	Bag slitter	3	1736	3	36	0.2
15	Rotary sluice	4	410	2	36	0.5
16	Shell and tube heat exchanger	1	184	2	12	0.8
17	Air dryer	1	986	0	12	0.4

3. Methodology and Analysis

There are many independent variables that affect the likelihood of machine failure. From maintenance point of view, the following four factors represent the most generic variables which can affect the breakdown of the plant:

- Probability of Failure of Equipment (p_f)
- Losses in In-Process Materials Due to Failure of Equipment (l_p)
- Mean Time to Repair (T_m)
- Mean Cost of Repairs (R_c)

The score for the probability of failure was estimated as a function of cumulative failure rate (CFR) of equipment. Equipment with CFR of 0 to 3 was given a score of zero and therefore has very low probability of failure. Equipment with CFR of 3 to 6 was given a score of 0.25, and therefore has a low probability of failure. Equipment with medium probability of failure has a score of 0.5, with CFR of 6 to 12. Likewise, the equipment is deemed to posses a high probability of failure if it has a score of 0.75 and a CFR of 12 to 24. The range limit and probability score is presented in Table 2.

Table 2: Range Limit and Probability Score of Equipment

Lower Range Limit	Upper Range Limit	Class of Range	Score
0	3	Very low (VL)	0
3	6	Low (L)	0.25
6	12	Medium (M)	0.50
12	24	High (H)	0.75

The loss in in-process materials due to failure of equipment is calculated from the following relationship:

$$L_p = \frac{total\ brews\ lost}{total\ brews\ to\ be\ produced} \times 100\% \qquad (1)$$

The mean time to repair is computed with the use of information from the characteristics of the repair distributions and statistical analysis of the repair data. The approach to computing the mean time to repair is similar to what obtains in literature (Ebeling, 1997). Accordingly, following steps were followed to identify the candidate distribution from where the repair data came from:

- Construction of Bar chart of the repair times
- Computation of descriptive statistics
- Analysis of the empirical failure rate
- Properties of the theoretical distribution
- Construction of probability Plots
- Computation of the parameters of the distribution
- Maximum likelihood estimation for computed parameters
- Determination of the confidence limit for the parameters
- Determination of the mean time to repair from most fitting theoretical distribution

The descriptive statistics helps to either identify a candidate distribution or to eliminate some distribution. For example, "if the repair times came from a symmetrical or nearly symmetrical distribution such as the Normal or a Weibull, then the sample mean and median times to repair will be approximately equal. If the mean is considerably larger than the median, then the data are skewed to the right and the exponential, lognormal or Weibull will provide a better fit. The mean time to repair, standard deviation and empirical hazard rate can be empirically determined from the following dependence" (Ebeling, 1997):

$$\text{MTTR} = \sum_{i=1}^{n} \frac{t_i}{n} \qquad (2)$$

$$s^2 = \sum_{i=1}^{n} \frac{{t_i}^2 - nMTTR^2}{n-1} \qquad (3)$$

$$R(t_i) = 1 - \frac{i}{n} \qquad (4)$$

$$f(t_i) = \frac{1}{(t_{i+1} - t_i) - (n + 1 - i)} \qquad (5)$$

$$\lambda(t_i) = \frac{f(t_i)}{R(t_i)} \qquad (6)$$

Where MTTR is the mean time to failure, s, is the standard deviation, $R(t_i)$ is the reliability function, $f(t_i)$ is the probability density function and $\lambda(t_i)$ is the hazard rate function.

From the empirical hazard rate graph, it is possible to determine whether the hazard rate is decreasing, increasing, or constant. A constant failure rate will further support the use of the exponential distribution and a decreasing failure rate will support the use of the Weibull distribution. An increasing failure rate may be modeled by a Weibull, a Normal or a lognormal distribution. A probability plot may be necessary to obtain initial estimates of the candidate distribution parameters. For a Weibull probability plot, the vertical axis is given as $InIn\left[\frac{1}{1-f(t)}\right]$ where $f(t) = \frac{i-0.3}{n+0.4}$ and the horizontal axis is given as $\ln(t_i)$. Also, for a lognormal probability plot the vertical axis is given as $z_i = \phi^{-1}(f(t_i))$ and the horizontal axis is given as $\ln(t_i)$, where z_i is the standardized normal variate obtained from table of standardize normal probabilities. There are standard mathematical models for computing the maximum likelihood values for various distribution parameters. For the lognormal distribution, the maximum likelihood estimates of the mean, $\bar{t}^1$, and variance, S, are given by (Gerald and Shapiro, 1967):

$$\bar{t}^1 = \frac{1}{n}\sum_{i=1}^{n} t_i^1 \tag{7}$$

Where $t_i^1 = \ln t_i$

$$S^{1^2} = \frac{1}{n-1}\sum_{i=1}^{n}(t_i^1 - \bar{t}^1)^2 \tag{8}$$

A complicated mathematical analysis is involved in determining the maximum likelihood estimates for the Weibull distribution parameters. The shape parameter β is given by (Ebeling, 1997):

$$g(\hat{\beta}) = \frac{\sum_{i=1}^{r} t_i^{\hat{\beta}} \ln t_i + (n-r)t_s^{\hat{\hat{\beta}}} \ln t_s}{\sum_{i=1}^{r} t_i^{\hat{\beta}} + (n-r)t_s^{\hat{\beta}}} - \frac{1}{\hat{\beta}} - \frac{1}{r}\sum_{i=1}^{r} \ln t_i \tag{9}$$

Where n is the number of repair times, r is the number of failures, t_i is the ith repair time, $t_s = 1$ for a complete ungrouped data, also, for complete ungrouped data, $n = r$

The Newton-Raphson numerical method is often used to solve equation (9) for β iteratively using the fact that:

$$\hat{\beta}_{j+1} = \hat{\beta}_j - \frac{g(\hat{\beta}_j)}{g^1(\hat{\beta}_j)} \tag{10}$$

Where $g^1(\hat{\beta})_j = \frac{dg(\hat{\beta})}{d\hat{\beta}}$

The characteristic life or scale parameter of the distribution is obtained from:

$$\hat{\theta} = \left[\frac{1}{r}\left[\sum_{i=1}^{r} t_i^{\hat{\beta}} + (n-r)t_s^{\hat{\beta}}\right]\right]^{\frac{1}{(\hat{\beta})}} \tag{11}$$

Location parameter estimation may be computed for distributions whose probability plot describes a curve rather than a straight line. For Weibull and Lognormal distributions, the location parameter estimates, $\widehat{t_0}$, used in previous works (Crowder et al., 1991) is valid.

$$\widehat{t_0} = \frac{t_1 t_n - t_j^2}{t_1 + t_n - 2t_j} \tag{12}$$

Where j =$[np]$, n is the sample size, and p represents an empirically determined percentile with $p = 0.50$ for the Lognormal distribution. In the case of Weibull distribution, $p = 0.8829n^{-0.3437}$

The mean times to repair for the Weibull and Lognormal distributions are defined in Lewis (1987):

$$MTTR = \theta\Gamma\left[1 + \frac{1}{\beta}\right] \tag{14}$$

Where $\Gamma(x)$ refers to the Gamma function and is obtained from table of Gamma functions

$$MTTR = e^{\left(\bar{t}^1 + \frac{S^{1^2}}{2}\right)} \tag{15}$$

If the distribution demands a location parameter, equation (12) may be used to calculate the location parameter. The result is then added to the MTTR. Once the mean time to repair has been established, a confidence interval is determined to get the precision with which the maximum likelihood estimator estimates the distribution parameters. The confidence limit of the mean time to repair for a 90% confidence interval is computed for this study.

$$MTTR = MTTR \pm t_{\frac{\alpha}{2}}, n-1\frac{S}{\sqrt{n}} \tag{16}$$

Where $\alpha = 0.1$ is obtained from $100(1 - \alpha) = 90$, $t_{\frac{\alpha}{2}}$ is given in table of values for the students t distribution based on $n-1$ degrees of freedom. Interested readers can refer to Ebeling (1997) for a sample of the table.

Another factor that determines the criticality of equipment is the mean cost of repair. Equipment that experiences increase in the cost of repair requires more attention in order to avoid failures. Hence, these category of equipment are labeled ''mission critical''. In order to determine the criticality of the equipment, the scores of all factors discussed earlier were translated to give numerical values. The results are presented in Table 3. The cumulative score of criticality and the classes of criticality are computed and presented in Table 4. A graph of cumulative score of criticality against cumulative number of equipment is plotted as shown in Figure 1. Figure 2 shows a graph of Mean Time to Repair versus Maintenance time.

TABLE 3: Probability of Equipment Failure, Mean Time to Repair and Score after Analysis

S/N	Equipment	Probability of Failure	Score(S)	Losses in In-Process Material	Mean Time to Repair (hrs)	Mean Cost of Repair	Total Score
1	Mash filter	H	0.75	0.2759	0.8155	0.8	0.1350
2	Chain conveyors	L	0.25	0.2000	5.2100	0.6	0.1563
3	Screw conveyors	VL	0	0.3333	8.2167	0.6	0
4	Bucket elevator	VL	0	0.1667	5.3667	0.6	0
5	Combi cleaner	VL	0	0.5833	15.5000	0.9	0
6	Suction blower	VL	0	0.1111	4.3778	0.5	0
7	Weighing bin	M	0.50	0.1481	3.7117	0.8	0.2199
8	Dust aspirators	L	0.25	0.2292	6.7625	0.7	0.2712
9	Hammer mill	VL	0	0.5833	13.85	0.9	0
10	Centrifugal pumps	M	0.25	0.0833	2.135	0.8	0.0356
11	Gear boxes	H	0.75	0.0455	1.2217	0.6	0.0250
12	Dosing pumps	H	0.75	0.0833	1.328	0.5	0.0415
13	Plate heat exchanger	VL	0	0.3333	8.8000	0.8	0
14	Bag slitter	VL	0	0.0833	9.6444	0.2	0
15	Rotary sluice	L	0.25	0.0556	1.7083	0.5	0.0119
16	Shell and tube heat exchanger	VL	0	0.1667	3.0667	0.8	0
17	Air dryer	VL	0	0	16.4333	0.4	0

TABLE 4: Cumulative Scores and Criticality of Equipment

S/N	Equipment	Criticality	Total Score of Criticality	Cumulative Score of Criticality	Cumulative Score %	Cumulative No. of Equipment
1	Dust Aspirator	Critical	0.2712	0.2712	30.25	5
2	Weighing bin	Do	0.2199	0.4911	54.78	10
3	Chain conveyors	Do	0.1563	0.6474	72.22	15
4	Mash filter	Do	0.1350	0.7824	87.28	20
5	Dosing pumps	Semi critical	0.0415	0.8239	91.91	25
6	Centrifugal pumps	Do	0.0356	0.8595	95.88	30
7	Gear boxes	Do	0.0250	0.8845	98.67	35
8	Rotary sluice	Non Critical	0.0119	0.8964	100	40
9	Hammer mill	Do	0	0.8964	100	45
10	Bag slitter	Do	0	0.8964	100	50
11	Suction Blower	Do	0	0.8964	100	55
12	Bucket Elevator	Do	0	0.8964	100	60
13	Plate heat exchanger	Do	0	0.8964	100	65
14	Bag slitter	Do	0	0.8964	100	70
15	Combi cleaner	Do	0	0.8964	100	75
16	Shell and tube heat exchanger	Do	0	0.8964	100	80
17	Air dryer	Do	0	0.8964	100	85

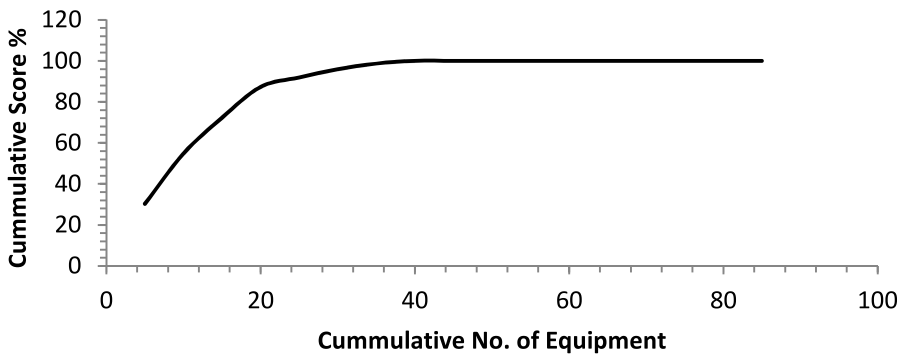

Fig.1: Graph of Cumulative Score of Criticality Vs Cumulative Number of Equipment

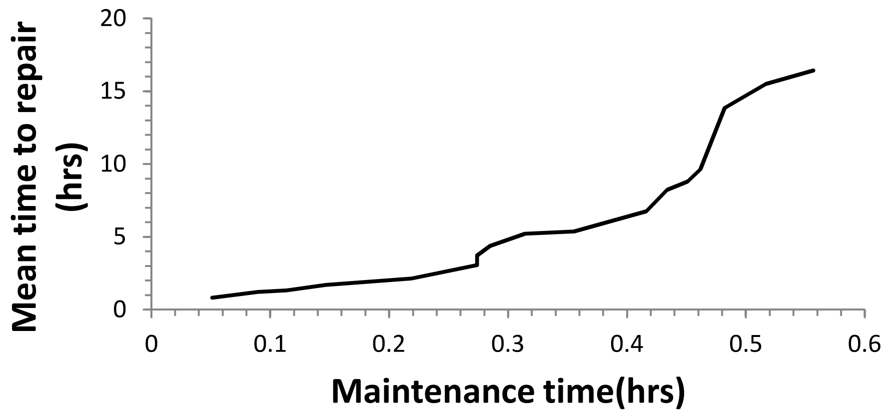

Figure 2: Graph of Mean Time to Repair versus Maintenance Time

4. Discussion

This study has provided a strategy for identifying critical equipment for a beverage plant for performance of

condition based maintenance. The results obtained in Table 4 shows that the Dust Aspirators, Weighing Bin, Chain Conveyors and Mash filter posses the highest criticality index. Hence condition based maintenance should be planned for the equipment first. The information revealed by this study is a good background for process equipment ranking, in terms of their mission criticality. From table 4, the Dosing Pumps, Centrifugal Pumps and Gear boxes were identified as semi critical and may be considered for condition based maintenance after the first set of components earlier identified. Identification of critical equipment is very important in goods-production-intensive industries because its failure usually results in wanton loss in in-process materials, delay in meeting customer demands which may ultimately result in loss of customer goodwill, thereby causing productivity losses for the industry. The critical, semi critical and non critical equipment were further illustrated graphically in figure 1. From figure 2, it can also be seen that the lower the maintenance time, the lower the mean time to repair and therefore the lower the production loss. Since the mean time to repair becomes reduced, the criticality and the equipment downtime are also reduced. Therefore, the maintenance team of the brew house should work assiduously towards reducing the time taken to carry out maintenance on failing or failed equipment. As a result of this reality, future research work aimed at optimizing maintenance time of materials and goods processing systems is hereby recommended. This is essentially important as maintenance time is usually neglected in maintenance modeling.
Other equipment in the brewery should not be completely left out as stated earlier. Alternative maintenance practices should be designed for other equipment.

5. Conclusion

This study has achieved its cleavage of presenting a critical equipment identification approach for condition-based maintenance (CBM) planning in the beverage plant. In this study, critical equipment in an example beverage plant was identified for effective condition based maintenance planning. The approach used involves multiplying four factors considered to affect identification of critical equipment most. They include Probability of failure, losses in in-process material, mean-time-to-repair and mean cost of repairs. The study revealed that the lower the maintenance time, the lower the mean time to repair and production losses. The results also show that if the mean time to repair becomes reduced, the criticality and the equipment downtime shrink. From the results of the study, we recommend optimization of the maintenance time (mean time to repair) for process equipment in brewery plants as a future research effort.

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