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# Process and Operating Data based Method to Predict Remaining Useful Life of Equipment

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A B S T R A C T

*Reliability of components in equipment is critical to ensure overall equipment and system availability, safe operation and cost effectiveness. Reliability depends upon many factors such as design, material, operating conditions and maintenance strategies. To predict the condition of components, such as bearings, this paper presents how process data can be used to drive reliability. An algorithm based on statistical functions is developed to predict the expected bearing lifetime. Some of the critical operating parameters are considered, including: temperature, vibration, and lubrication. This prediction model also serves to develop actions such as adjustment to maintenance schedules to reduce the number of failures, and enhance overall plant reliability and availability by avoiding a component failure. To validate the model, three bearing case studies for gas compressors are used, and their results show that the proposed method is capable of predicting failures with good accuracy. The results have shown excellent correlation between model prediction and the real plant experience. Additionally, this approach is particularly useful for failure investigations and suggested inspection intervals. The suggested technique can be used for other components, such as mechanical seals.*



## 1. INTRODUCTION

Reliability of components in equipment is critical to ensure overall equipment and system availability, safe operation and cost effectiveness. A bearing is a fundamental mechanical component, which is used widely in the oil and gas industry. It is usually used to reduce rotational friction and support the load imposed on it in radial and axial directions. Thus, bearings can play a significant role in reliability for any mechanical system, and even a small defect in a bearing can cause serious failures. Bearing failure is one of the top causes of breakdown in rotating machinery [1]. It is necessary to predict bearing condition accurately, to decrease the maintenance cost, increase the reliability, and enhance the safety in a facility. Failure in equipment generally is more costly than its planned repair. Similarly, failure in a bearing can cause hydrocarbon leaks in oil a gas facilities and safety threats to personnel working in a facility.

Measuring bearing reliability based on monitoring operating parameters is a good tool, which depends on the normal process trends and their limitations [2] and [3]. Thus, this statement should cover all process trends, since each bearing has its specific operational cluster, depending upon its manufacturer defects and its operational life conditions. This reliability measurement should also be compared with the expected average process in a normal operating condition. This approach should consider the probability of failures in which process exceeds alert or alarm zones, in a historical context. Measure-bearing reliability can be estimated by using many factors, e.g., load, speed, oil temperature, vibration, and pressure limitations. It is difficult to predict the bearing reliability compared with its system limitation, without monitoring its process behavior. Plant process drives reliability; a good estimate of the residual life of operating machinery is always difficult, regardless of the technology deployed, which is currently easier than before due to the high utilization of IR 4.0 technologies. Such information is considered valuable in defining the corrective measures and criticality. When combined with all available conditional information, such as temperature, vibration, and lubrication quality comprise 80% of possible bearing failure reasons [4]. This paper will focus on these three main operational parameters to predict the condition of the bearing.

## 2. LITERATURE REVIEW

From a maintenance perspective, there are three major types of maintenance strategies: the predictive (improvement) maintenance, preventive maintenance, and corrective maintenance. Predictive maintenance is designed to reduce or eliminate the need for reactive maintenance, which comprises the actions required to take after failures happen. Preventive maintenance keeps equipment in good operating condition [5, 6].

The maintenance records and history are the main foundation for any reliability studies [7]. This foundation can lead to condition-based maintenance (CBM), which is the most traditional approach to estimating reliability and remaining useful life. CBM is dynamic preventive maintenance in practice, and able to analyze the distribution of the event data, such as replacement data and failure time historical data. The distribution functions, such as Weibull, Poisson, exponential, and normal distributions, have been utilized to analyze system reliability; but mainly Weibull distribution [1]. Their common point uses historical time to failure data, to estimate the reliability or mean-time-to-failure. Using this approximation, the manufacturers or engineers can make reasonable maintenance plans and schedule inspections [8, 9]. A method of predicting bearing failures based on the operating parameters is the concept of bearing diagnostics, which predicts and identifies the different types of failures or defects during operation. This approach was focused on the vibration and acoustic emission signals, which were established and modeled to predict the faults and identify failures, by using statistical features such as Root-Mean-Square (RMS) [10].

Another approach was focused on the quality of lubrication. Lubrication condition monitoring (LCM) is a good tool for an early warning system in machinery, as well as fault diagnosis and prognosis [11, 12]. One of the major problems in the bearing lubricating replacing programs is the consideration of the time parameter without checking the lubrication condition. It is a good strategy to perform time-based maintenance as an example once per week or month. After all, performing scheduled maintenance at regular periods is an old strategy, while performing scheduled maintenance based on conditions is more reliable.

## 3. BACKGROUND

The lubrication temperature can be affected by a number of factors: operating speed, shaft loading, type/amount of lubrication in bearing, equipment alignment, ambient temperature, and continuous or on–off services. Lubricant temperature should not exceed 230ºF. The oil oxidizes very fast if the oil temperature reaches 200ºF or more [13]. If the bearing runs under high temperature, the bearing material structure will be changed and its hardness will be decreased. The change of this structure will not return to its original state, even if the bearing temperature returns to normal conditions. This phenomenon is related to material elastic-plastic behavior [14]. The ambient temperature should be considered as a factor that influences the bearing material strength and its oil temperature

[15-17]. In general, lubrication analysis helps reliability and rotating equipment engineers to [18] identify problems before they become costly failures that result in unscheduled downtime and lost production. It helps in avoiding secondary damage, reduction in maintenance cost and increasing maintenance up-time. Therefore, it is a powerful and cost-effective predictive maintenance approach that provides useful insight about the condition of plant critical rotating equipment [19]. There is a specific system that was conducted by a railway company to monitor the equipment condition, which concluded that spending $1 for condition monitoring programs can recover $8-10 in avoided maintenance costs [18]. The full benefits can be obtained from analyzing oil, if samples are taken frequently and show a trend. This trend can lead the engineers to change the oil, or upgrade its specification to meet the operating requirements. In general, there are three functions of lubrication analysis: to assess mechanical wear condition, lubrication condition, and to check lubrication contamination. Lubrication oil can be contaminated due to a machine's operating environment, improper filling procedure, or through the mixing of different lubrication in the same machine.

In industry, analyzing lubrication is not the proper practice for small equipment. This is because lubrication analysis is costly if compared with replacement oil for healthy small equipment. There are many web-based lubrication frequency analysis programs available to monitor huge rotating equipment, especially equipment that has a bad maintenance record [19]. If any equipment item fails three times per year for the same reason, in reliability engineering that item will be defined as "bad actor" equipment. Since the lubrication analysis is very important, the daily visual inspection should be performed, while oil sampling should be taken if unusual conditions occur: abnormal vibration, temperature, pressure or noise, sudden oil color change, or foaming in the oil system sight glass (from daily inspection or excessive oil consumption). Some lubrication characteristics, e.g., color, appearance, odor, flash point, fire point, pour point, total acid number, total base number, viscosity, density, and specific gravity are listed by the American Society for Testing and Materials (ASTM) and International Organization for Standardization (IOS), as standard tests.

Recent studies on the oil and gas industry have determined that around 83% of rotating equipment failures are due to the mechanical seals (43%) and bearing (40%) problems. Other factors, such as coupling, hydraulic, and static joints, are responsible for just 17% of rotating equipment problems [4], as is shown in Fig. 1.

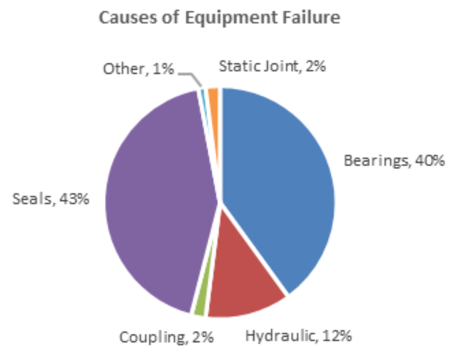


**Fig. 1.** Causes of Equipment Failures.

Fig. 2 shows that around 59% of bearing failures are mainly caused by bad lubrication quality, leading to increased oil temperature. In addition, 48% of the problems are due to the particle contamination and a further 11% are due to inadequate lubrication. Some 21% of the failures have been found to be from overloading, corrosion (materials), and misalignment — related to vibration — and are causing problems in bearing mechanism and reliability. And 20% is related to installation, disassembly, storage and other reasons [4].

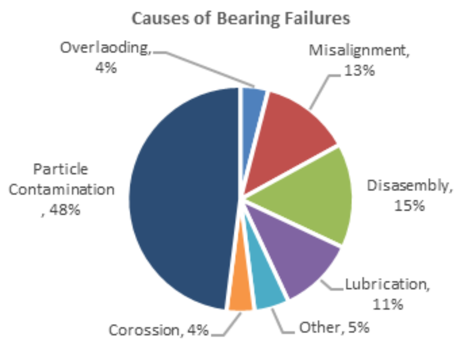


**Fig. 2.** Causes of Bearing Failures.

These findings conclude that 80% of bearing failure reasons are related to operating parameters (such as lubrication, temperature, and vibration) that may fail the equipment if their values reach system limitations. The failure probability and reliability, based on each item's parameters, can be monitored and calculated. Thus, the operating parameters (process) can drive reliability.

Most of the rolling bearing failures are due to fatigue problems, and depend on rating lifetime, while for journal (sleeve) bearing, only a small number of failures are caused by material fatigue. The journal bearing failures are caused by a condition that usually can be prevented. Generally, the causes of bearing failure typically can happen in circumstances such as harsh operating conditions, faulty storage, handling, and installation and poor lubrication.

The main reduction factor of journal lifetime bearings — additional to speed and loading — are the machined clearance, and the film thickness that directly depends on the condition of lubrication (fluid viscosity). Increasing lubricant temperature can reduce the film thickness. Small film thickness causes a bad lubrication condition. In general, clean lubricant is essential for bearings to have a long and reliable service life. Each bearing manufacturer recommends the expected bearing lifetime. But 40,000 hours is the minimum required/expected bearing lifetime for pumps and compressors in the oil and gas industry, regardless of bearing type [1].

## 4. PREDICTION MODEL

This section summarizes the predication model. Initially, the recommended bearing lifetime can be considered as the operational mean time to fail (MTTF) based on the operating parameters can be calculated [1] as the following formula Eq. 1:

$$MTTF_{AOP} = \int_{0}^{MTTF_{sug}} R_{OPsys}\, dt = R_{OPsys} * MTTF_{sug} \tag{1}$$

Where $MTTF_{AOP}$ Adjusted bearing lifetime based on operating parameters, *ROPsys* System reliability factor due to Operating parameters, $MTTF_{Sug}$ Expected lifetime for rolling or suggested lifetime for all types.

Since the bearing operating parameters are in series shape [20, 21], their relationship can be represented [1] in the following Eq. 2.

$$R_{OPSys} = \Pi R_i = R_{Temp} * R_{Vib} * R_{Lub} \tag{2}$$

Where $R_{Temp}$ reliability factor based on the bearing temperature, $R_{Vib}$ reliability factor based on the bearing vibration, $R_{Lub}$ reliability factor based on the bearing lubrication.

The reliability of the operating parameters system can be calculated using Eq. 3 [1, 20, 22].

$$R_{OPSys} = R_{Temp} * R_{Vib} * R_{Lub} = F_{Temp} * F_{Vib} * F_{Lub} \tag{3}$$

Where

$R_{Temp} = \left(1 - P(T > T_{system\ max})_{Temp}\right) = F(T < T_{system\ max})_{Temp}$

$R_{vib} = 1 - (P(V > V_{system\ max})_{V-Vibr} + P(V > V_{system\ max})_{H-Vibr} + (P(V > V_{system\ max})_{V-Vibr} \cap P(V > V_{system\ max})_{H-Vibr})) = F(V < V_{system\ max})_{vibr}$

$R_{Lub} = \left(1 - P(Vis > V_{issystem\ max})_{Visc}\right) * (1 - P(co > co_{system\ max})_{Color}) * (1 - P(Ap > Ap_{system\ max})_{Appear}) = F(Lub < Lub_{system\ max})_{Lub}$

The reliability of the operating parameters system can be calculated using Eq. 3 [1, 20, 22].

### 4.1 Data Collection

Generally, companies have an operational parameter monitoring system, which is called the Plant Information (PI) system. It can show all operational data in a single system that can be overviewed by plant area users. The PI system keeps critical data online, and this system functionality incorporates many features for gathering and analysing the data.

All the critical rotating equipment is connected to the PI system and can be monitored. The company's rotating equipment is in compliance with the international machinery equipment protection engineering standards. For example, the machinery will be shut down if an operating parameter gets to the specific point that is called the trip point, to avoid any equipment damage and catastrophic incident. For example, if very high bearing oil temperature or high bearing vibration is detected, the equipment protection system will take the proper action and will turn off the equipment. The lubrication condition history can be monitored through a special web-based program, and can show all lubrication test results.

### 4.2 Analysing Technique: Normal Distribution

The normal distributions will be used to analyze the historical data. This distribution can be utilized to find the probability value that will cause a trip of the equipment, based on operational parameters at critical points, such as high temperature, vibration, and lubrication quality, mainly viscosity [23]. Normal distribution is a typical technique, which is used to estimate percentage of errors for a set of data. Normal distribution is a continuous probability distribution that describes data that clusters around a mean or average. The graph of the associated probability density function is bell-shaped, with a peak at the mean, and is known as the Gaussian function or bell curve. It is the most important and widely used type of distribution probability in statistical analysis. There are two factors that distribute the normal distribution curve, the mean and standard deviation (SD). The mean will take a center position of the curve, while the SD controls the curve peak value. If the SD is large, the curve will be short and wide, while it will be tall and narrow if SD is small. The probability density function of normal distribution can be calculated mathematically by using the Eq. 4, [22, 24].

$$f(x) = \frac{1}{SD\sqrt{2*\pi}}\, exp[-\frac{(x-\overline{x})^2}{2*SD^2}] \tag{4}$$

Where *f(x)* probability density function, $SD$ standard deviation, $X$ variable value, $\bar{x}$ average of variable value

The standard deviation can be calculated using Eq. 5, called the population standard deviation for a high number of data [21].

$$SD = \sqrt{\frac{\sum(X-\bar{X})^2}{n-1}} \tag{5}$$

Where $SD$ simple standard deviation, n number of data points, $X$ variable value, $\bar{X}$ average of variable value or expected value.

In general, the failure probability in a normal distribution can be estimated by using Eq. 6:

$$F(z) = \Phi\left[\frac{x-\bar{X}}{SD}\right] \tag{6}$$

Where *F(z)* the probability of successful if $x$ activates, $x$ specific point, $\bar{X}$ average or expected value, $SD$ standard deviation data.

This distribution is a very important function in this project to find the probability in a specific condition, such as reaching the critical point that will shut down the equipment from the historical data.

## 5. CASE STUDY

For the case studies, three examples are considered in this paper. The first example is discussed in detail, while the other two examples are summarized in Table 1 of Section 6. This model covers three operating parameters: temperature, vibration, and lubrication quality. The operating temperature and vibration data for bearings were obtained from PI system. The lubrication condition data can be determined from the Oil Condition database.

### 5.1 Temperature

The bearing manufacturers recommend users operate the bearing at a normal operation temperature, which equals 140ºF [13]. Any changes from this value will affect bearing lifetime in the long or short-term weeks, [25]. Therefore, it has been assumed that, in the long term, the average temperature will be 140ºF. This value is used in the calculation of the standard deviation (Eq. 5). The protection system will shut down the compressors if the temperature reaches 250ºF and the alarm will start with 230ºF. The big changes in operation temperature should be considered and monitored. This is because the changes in operation temperature will affect any component's lifetime. In general, the probability of failure due to high temperature (temperature = 250ºF) from Eq. 4 and Eq. 6 after calculating the SD (standard deviation) from (Eq. 5) can be calculated. An example of the calculations is shown in the Appendix section of this paper.

It means the historical context for 256 temperature readings shows that the probability the compressor will be shut down due to high bearing temperature (temp= 250ºF) is 6.94% of total compressor operation, while its reliability will be 100-6.94=93.03%. From the reference data that is summarized in the Fig. 3, the temperature range and average trends show that there are no significant changes in operation temperature, and the maximum change is 3ºF a week. In this case, the average position has been considered.

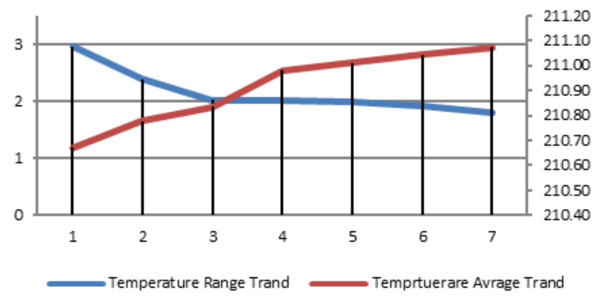


**Fig. 3.** Temperature Trend.

## 5.2 Vibration

The bearing manufacturers recommend operating the bearing within the lowest vibration values. This is because the excessive vibration means excessive force that causes a dramatic reduction in bearing life [26]. Any significant changes in vibration value will have an effect on bearing lifetime, long term or short term. These changes should be considered and monitored. The radial bearings in gas compressors should be protected by two sensors with 90° between them, to take the vibration value in x- and y-axes. The bearing vibration limitations are 0-2.5 mils (1 mil = 0.001") at speed 3600 rpm. The protection system will shut-down the compressors if vibration reaches 2.5 mils, and the alarm will start with 2 mils at any sensor. For this reason (any sensor can shut down the equipment = voting sensing system), the probability of tripping the compressor due to high vibration will be calculated [20] using Eq. 7.

$$P(X \cup Y \cup (X \cap Y)) = P(X) + P(Y) - P(X \cap Y) \quad (7)$$

Where, *P (x ∪ y)* probability if x or y activate, P (x ∩ y) probability if x and y activate, P(x) probability if x activates, P(y) probability if y activates.

$$P(X \cap Y) = P(X) * P(Y) \quad (8)$$

Where, *P (x ∩ y)* probability if x and y activate independent, *P(x)* probability if x activates, *P(y)* probability if y activates

In general, the probability of failure due to high vibration (vibration = 2.5 mils) from Eq. 6 (after calculating the SD using Eq. 5). An example of the calculations the expected value is $\bar{X} = 2.5$ and $n$=256 readings is shown in the Appendix section of this paper.

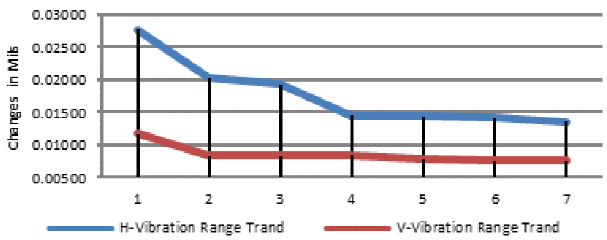


**Fig. 4.** Vibration Range Trend.

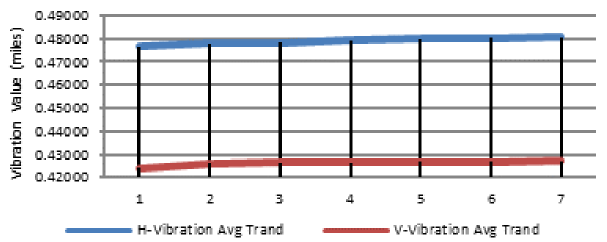


**Fig. 5.** Vibration Average Trend.

It means the historical data for 256 vibration readings shows that the probability the compressor will be shut down due to high bearing horizontal vibration (vib= 2.5) is 2E-5%, and its reliability will be 100-2E-5 =99.99998% of total compressor operation, while the probability it will be shut down due to high bearing vertical vibration (vib= 2.5) is 1.25E-6%, and its reliability will be 100-2E-5 =99.99999875% of total compressor operation. Eq. 7 and 8 can calculate the total probability of compressor failure due to high vibration in horizontal, vertical, or both axes, which resulted in 2.04E-7.

The results in the probability of compressor failure due to high vibration is very low, which is 0.0000204%, while the reliability affected by vibration is 99.9999796%. The range and average process trends are shown in the following charts in Fig. 4 and 5 that show the vibration values within its allowed range.

## 5.3 Lubrication Condition

It is a very important factor to predict bearing lifetime [11, 25, 27]. In general, three major tests can determine the lubrication quality.

The bearing manufacturers recommend operating the bearing within the lowest vibration values.

**Lubrication Viscosity Test**

It is a critical proportion of lubrication reliability [27]. Thus, it will be considered in bearing lifetime calculations. These are because the low viscosity will reduce the reliability and its lifetime. The best viscosity for turbine oil (that are used for these compressors) is 46 @ 40oC, while its limits are 38 and 56. In general, the probability of failure due high or high viscosity can be calculated using Eq. 5 and 6, the example of calculations are shown in Appendix.

Results shows that the historical data for 32 viscosity readings shows that the probability of compressor bearing lubricant quality will not have an effect on bearing lifetime, while its reliability will be 100-0=100%.

**Lubrication Oxidation and Color Test**

An oxidation test is a measure of a lubricant's ability to have oxidation stability, and is a very important factor for estimating the remaining useful lifetime. Its rate value depends on changes of temperature, the presence of contaminants such as water, and catalysts such as copper [18, 28]. This test is usually not conducted due to its high cost. The color test is an alternative that indicates lubrication oxidization quality. Thus, considering the color test as an operational condition factor, it will enhance the study to evaluate lubricant oxidation. The color limitations for turbine oil 46 are 0.5 and 6. It is very high number which indicates a short remaining lubricant life and oxidization. In general, the probability of failure due to high lubricant number can be calculated using Eq. 5 and 6, the example of calculations is shown in Appendix. Results shows that the historical data for 22 color readings shows that the probability of compressor bearing lubricant quality will affect the bearing lifetime is 10.33% of total compressor operation, while its reliability will be 89.67%.

**Lubrication Appearance Test:**

A sample is checked for clearance and brightness, or if it is hazy and cloudy, which indicates water contamination. The sample can also indicate if there are any suspended materials or if it is fumy. Thus, it will be used as a factor to estimate the lubricant's remaining useful lifetime. The test starts from a value of 1.1 and ends at 2.2. In general, the probability of failure due to high or high lubricant appearance can be calculated using Eq. 5 and 6. Example calculations are part of the Appendix of the paper. Results show that the historical data for 32 appearance readings highlight the probability that compressor bearing lubricant quality will affect the bearing lifetime at almost 0% of total compressor operation, while its reliability will be 100-0=100%.

## 6. RESULTS AND VALIDATION

Table 1 summarizes the three examples' solution, while the detail steps were done previously for the first example, which analyzed inboard hydrodynamic bearing equipped on a gas compressor, while examples 2 and 3 were performed on inboard and outboard bearings sequentially, which were equipped on the same gas compressor. In general, the system reliability will be calculated as per the equations Eq. 1, 2 and 3.

The total reliability of the system using Eq. 1 is 84.7%, whereas Eq. 2 is used to calculate MTTF based on operation parameters is 47.07 months. In this paper, an 80% correction factor is used, which resulted in 37.65 months. The results show that the bearing in example #1 will live for 37.65 months, based on its current process parameters, while the lifetime can be modified if any operational parameters are changed.

The results have shown excellent correlation with the real plant experience. The first bearing, which is equipped on an HP gas compressor, has no changes in its maintenance strategy and operating management. A bearing failure was experienced four months after the predicted time. The two bearings were monitored very well, and their maintenance strategy and operation management were changed, based on the changes in their operating parameters. Thus, they expected life to be extended significantly without experiencing any failure. The proposed model has shown excellent correlations with real field experience.

**Table 1.** Summary Findings and Results.

| Factor | | Case 1 | Case 2 | Case 3 |
|---|---|---|---|---|
| Capacity (SCFD) | | 6525 | 6525 | |
| Speed | | 5300 RPM | 5300 RPM | |
| Type of bearing | | Sleeve/Radial | Sleeve/Radial | |
| Suggested minimum lifetime | | 40,000 hours =55.55 Months | 40,000 hours =55.55 Months | |
| Inboard or Outboard bearing | | Inboard | Inboard | Outboard |
| Temperature effect | Best Value | 140°F | 140°F | 140°F |
| | Trip @ | 250°F | 250°F | 250°F |
| | Average | 214.14°F | 174.85°F | 174.32°F |
| | Reliability | 0.9306 | 0.9989 | 0.9990 |
| | MTTF (Months) | 51.692 | 55.490 | 55.496 |
| Vibration effect | Best Value | 0 | 0 | 0 |
| | Trip @ | 2.5 mils | 2.5 mils | 2.5 mils |
| | Reliability | 0.999999796 | 0.9995728 | 0.999996 |
| | MTTF (Months) | 55.5499 | 55.526 | 55.549 |
| Viscosity effect | Best Value | 46 | 46 | 46 |
| | Change @ | 38 OR 56 | 38 OR 56 | 38 OR 56 |
| | Average | 45.3187 | 45.565 | 45.5651 |
| | Reliability | 1 | 1 | 1 |
| | MTTF (Months) | 55.55 | 55.55 | 55.55 |
| Lubrication condition effect (appearance) | Best Value | 1.1 | 1.1 | 1.1 |
| | Change @ | 2.2 | 2.2 | 2.2 |
| | Average | 1.16 | 1.13 | 1.13 |
| | Reliability | 1 | 1 | 1 |
| | MTTF (Months) | 55.55 | 55.55 | 55.55 |
| Lubrication condition effect (color) | Best Value | 0.5 | 0.5 | 0.5 |
| | Change @ | 6 | 6 | 6 |
| | Average | 4.409 | 3.72 | 3.72 |
| | Reliability | 0.8967 | 0.89938 | 0.89938 |
| | MTTF (Months) | 49.8123 | 49.96 | 49.96 |
| Correction factors (total % of considered reasons) | | 80% | 80% | 80% |
| Expected bearing MTTF (Months) | | 37.0825 | 39.908 | 39.9295 |
| Action taken | | Nothing | Adjust its maintenance strategy and operation management | |
| Result (real failure) | | Failed with 4 Months | Exceeded Expected Life | |

## 7. CONCLUSION

To predict the condition of a component such as bearing, this paper presented and validated the proposed methodology. The paper shows how process data can be used to drive reliability and availability of the equipment in asset intensive facilities effectively. A methodology based on statistical functions is developed to predict the expected bearing lifetime of a bearing. Some of the critical operating parameters considered are temperature, vibration, and lubrication.

From the discussed three case studies, it is clearly proven that reliability can be driven by process (operating parameters). Integration between this models with maintenance history, will improve reliability prediction and investigation tools.

Thus, this model is highly recommended to be utilized for reliability engineers, and alert plant people to replace or maintain the bad actor bearings. The proposed methodology can be transformed into a software program to improve the efficiency of prediction with an opportunity to increase the number of parameters. This proposed methodology can be easily adopted for other components, such as mechanical seals and couplings, etc.

## APPENDIX

### Temperature (Section 5.1)

- From equation (Eq. 5), where the expected value is $\bar{X} = 140$ °F and n=256 readings: $SD = \sigma = \sqrt{\frac{\sum(X-\bar{X})^2}{n-1}} = \sqrt{\frac{\sum(T-140)^2}{255}} = \sqrt{\frac{1408721.93}{255}} = 74.32$
- From equation (Eq. 6), x= 250 °F and $\bar{X} = 140$ °F while $\sigma = 74.32$ to calculate (Z value) to find the probability of (Z) from tables or excel equations (NORMSDIST (Z)).
- $\mathrm{F(z)} = \Phi\left[\frac{\mathrm{x}-\bar{\mathrm{x}}}{\sigma}\right] = \Phi\left[\frac{250-140}{74.32}\right] = \Phi[1.48006] = 0.9303558$

### Vibration (Section 5.2)

- From equation (Eq. 5), where the expected value is $\bar{X} = 2.5$ and n=256 readings
  i. For Horizontal-Probe
  $$\mathrm{SD} = \sigma = \sqrt{\frac{\sum(Vib-\bar{X})^2}{n-1}} = \sqrt{\frac{\sum(Vib-0)^2}{255}} = \sqrt{\frac{62.12}{255}} = 0.493551$$
  ii. For Vertical-Probe
  $$\sigma = \sqrt{\frac{\sum(Vib-\bar{X})^2}{n-1}} = \sqrt{\frac{\sum(Vib-0)^2}{255}} = \sqrt{\frac{51.30}{255}} = 0.4485$$
- From equation (Eq. 6), x= 2.5 and $\bar{X} = 0$ while $\sigma = 0.49355$ for horizontal and $\sigma = 0.4485$ for vertical to calculate (Z value) to find the probability of (Z) from tables or excel equations (NORMSDIST (Z)).
  i. For Horizontal-Probe
  $$\mathrm{F(z)} = \Phi\left[\frac{\mathrm{x}-\bar{\mathrm{x}}}{\sigma}\right] = \Phi\left[\frac{2.5-0}{0.493551}\right] = \Phi[5.06533] = 0.9999998$$
  ii. For Vertical-Probe
  $$\mathrm{F(z)} = \Phi\left[\frac{\mathrm{x}-\bar{\mathrm{x}}}{\sigma}\right] = \Phi\left[\frac{2.5-0}{0.4485}\right] = \Phi[5.15464] = 0.99999998$$

The total probability of compressor failure due to high vibration in horizontal, vertical, or both axes.

$$\mathrm{P(X \cup Y \cup (X \cap Y)) = P(X) + P(Y) - P(X \cap Y) = (2E-7) + (1.25E-8) - ((2E-7) * (1.25E-8)) = 2.04E-7}$$

### Lubrication (Section 5.3)

### Lubrication Viscosity Test

- From equation (Eq. 5), where the expected value is $\bar{X} = 45.32875$ (process average) and n=32 readings:
  $$\mathrm{SD} = \sigma = \sqrt{\frac{\sum(X-\bar{X})^2}{n-1}} = \sqrt{\frac{\sum(X-45.33)^2}{31}} = \sqrt{\frac{7.0104}{31}} = 0.475535$$
- From equation (Eq. 6), x= 56 and $\bar{X} = 45.32875$ while $\sigma = 0.475535$ to calculate (Z value) to find the probability of (Z) from tables or excel equations (NORMSDIST (Z)).
  $$\mathrm{F(z)} = \Phi\left[\frac{\mathrm{x}-\bar{\mathrm{x}}}{\sigma}\right] = \Phi\left[\frac{56-45.31875}{0.475535}\right] = \Phi[22.467852] = 1$$

### Lubrication Oxidation and Color Test

- From equation (Eq. 5), where the expected value is $\bar{X} = 4.409$ (process average) and n=22 readings:
  $$\mathrm{SD} = \sigma = \sqrt{\frac{\sum(X-\bar{X})^2}{n-1}} = \sqrt{\frac{\sum(X-4.409)^2}{21}} = 1.2596$$
- From equation (Eq. 6), where x= 2.2 while $\sigma = 1.2596$ to calculate (Z value) to find the probability of (Z) from tables or excel equations (NORMSDIST (Z)).
  $$\mathrm{F(z)} = \Phi\left[\frac{\mathrm{x}-\bar{\mathrm{x}}}{\sigma}\right] = \Phi\left[\frac{6-4.4091}{1.2596}\right] = \Phi[1.263]$$

Results show that the probability — of compressor bearing lubricant quality will affect the bearing lifetime — is almost 10.33% of total compressor operation, while its reliability will be 89.6711%.

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