Establishments of Predictive Maintenance Control Limits

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Abstract

The strategic use of goal-based and aging limits enables proactive maintenance to be carried out at the highest level. Likewise, when rate-of-change and statistical limits are deployed, the benefits of early fault detection are achieved. The combination of these limit-setting strategies affords the broadest and most effective protection for the plant equipment. This paper will explains the importance of predictive maintenance control limits and clarify in sequence how mean time between failure (MTBF) is used to establish these limits.

Keywords
Predictive maintenance, MTBF, control limits, system failure

1. Introduction

There are many definitions of condition monitoring, including that in Kelly, 2000. The one following emphasizes that that condition monitoring is part of maintenance, not something done by experts from outside (Beebe, 2001): Condition monitoring, on or off-line, is a type of maintenance inspection where an operational asset is monitored and the data obtained analyzed to detect signs of degradation, diagnose cause of faults, and predict for how long it can be safely or economically run. Figure 1.1 shows the basic principle.

A suitable parameter is chosen that indicates internal condition of the plant item. For example, in rotating machinery, the vibration level is commonly used. Initial samples are used to establish by experience the repeatability band that is obtainable in the normal operating circumstances when the item is considered to be in good condition. Note that with new and overhauled equipment, there may be a change in measured values until the wearing-in period (infant mortality) has passed. Routine readings are taken at suitable intervals.

For most vibration monitoring, monthly is usual. For other monitoring, quarterly or even yearly is usual. Continuous monitoring may be appropriate for critical machinery. Methods for optimising inspection intervals have been developed (Sherwin and A1-Najjar, 1998). Issues such as access, size of plant and the convenience of setting up routes for data collection or testing may over-fide the theoretically ideal intervals.

When degradation eventually occurs, the parameter falls outside the repeatability band, and the frequency of readings is often increased to enable prediction of the time until the parameter corresponds to the condition where maintenance action is required.

The prediction of the remaining time to failure is the most inexact part of the process, but nevertheless is usually of sufficient accuracy to meet the needs of a business. Development continues to refine this stage, e.g. ISO/ DIS13381-1, Hansen et al, 1995.

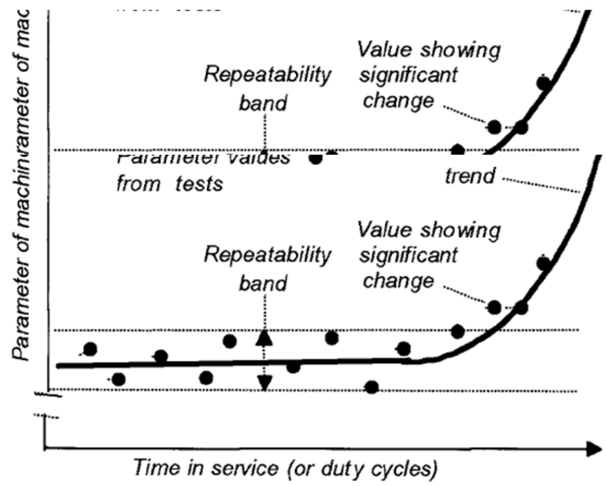

Figure 1.1 The principle of condition monitoring trending

Typically, sets of alert/alarm limits are established to monitor the overall condition of the machine being monitored in a predictive maintenance program to improve the reliability, availability and reduce the failure and failure rate; this paper will explain how these limits could be set and establishment.

Definitions

Availability is an ability of a component to be in state to perform a required function at a given instant of time or at any instant of time within a given to time interval, assuming that the external resources, if required, are provided.

Reliability is an ability of a component to perform a required function under given conditions for a given time interval.

Failure is a transition event that occurs when the delivered service deviates from the correct service state to an unwanted state.

Failure rate is the frequency with which an engineered system or component fails.

Literature Review

Designing control limits for condition monitoring is an important aspect of setting maintenance schedules and has been virtually ignored by researchers to date. a novel statistical process control tool, the Weighted Loss function CUSUM (WLC) chart was proposed for the detection of condition variation. The control limit was designed using baseline condition data, where the process was fitted by an autoregressive model and the residuals were used as the chart statistic.

The condition variation was reflected by the changes of mean and variance of the statistic's distribution against baseline condition, which can be detected by a single WLC chart. The approach was evaluated using a case study which showed that the chart can detect faulty conditions as well as their severity. The proposed approach has the advantage of requiring healthy baseline data only for the design of condition classifiers. It is applicable in numerous practical situations where data from faulty conditions are unavailable [1].

Condition monitoring involves fault diagnosis and condition prognosis. Few studies have focused the design of condition control limits – an important topic given that control limits initiate maintenance activities and trigger diagnostic tasks in automatic fault detection. Ideally, control limits should be established such that false alarms are not triggered under baseline conditions, whilst faults can be detected without delay. In practice, the 'red-line' is widely used as the control limit which comes from standards or application experience. Such control limits have drawbacks in that false alarms and miss alarms are difficult to control. Some work has been directed to the effort of determining the control limit dynamically with limited success [2-3].

The selection of parameters sensitive to condition is critical for condition monitoring. Based on the parameters, it is desirable to design mathematically derived control limits. The ideas from statistical process control, which aims to detect the mean shift and/or variance shift based on assumptions of the statistical distribution, have been utilized by condition monitoring applications in recent years. The control limit design for control charts provides a mathematically controllable approach to balance the Type I error (the probability of fault triggering under healthy conditions) and Type II error (the probability of a healthy condition being indicated when faults exist) [4-5].

A suitable statistic is required for control chart operation. The statistic is usually assumed to follow a certain probability distribution. The identically and independently distributed (iid) normal distribution is commonly adopted. Some time-domain features of vibration signals under healthy conditions follow normal distributions. However, these features are usually auto-correlated and do not meet the requirement of iid. At the same time, features in the frequency-domain and time-frequency domain are not used for statistical condition monitoring purposes [6].

Condition monitoring is an essential part of maintenance. The challenge is to find a cost effective method of obtaining the data required to make accurate decisions. The data obtained from the condition assessment was analyzed to determine thresholds, or engineering limits, that will enable systems to provide an alarm when critical values are reached. This reduces the level of experience required by the maintenance engineer and eliminates unnecessary input on a human level [7].

The Mathematical Approach

In the application of maintenance optimization, the failure distribution of the equipment must be specified before any maintenance strategy is carrying out. Wrong identification of failure distribution will affects the cost of maintenance and loss of production.

In the new approach only two steps are used for determining the best fit distribution and its parameters. The basic idea in the new approach determines the shape parameter β of weibull distribution. This parameter is calculated using the following equation

$$\beta = \frac{\sum_{i=1}^{n} x_i y_i - \bar{x}\sum_{i=1}^{n} y_i}{\sum_{i=1}^{n} x_i^2 - n\bar{x}^2} \tag{1}$$

This approach is to determine the value of reliability that need to be improve. The value can be decided based on the control chart. The control chart also can be used to monitor improvement in reliability for necessary action to be taken if the improved system is not reflecting the desired result.

The control chart must have upper control limit (UCL), central limit (CL) and lower control limit (LCL). Assuming false alarm probability α, which the control limits can be obtained from the following equations:

$$\text{UCL} = \left(\frac{1}{MTBF}\right)^{-1} \ln\left[\frac{2}{\alpha}\right] \tag{2}$$

$$\text{CL} = \left(\frac{1}{MTBF}\right)^{-1} \ln 2 \tag{3}$$

$$\text{LCL} = \left(\frac{1}{MTBF}\right)^{-1} \ln\left[\frac{1}{1-\alpha/2}\right] \tag{4}$$

These control limits can be utilized to monitor the reliability. After each failure, the time can be plotted on the chart. If the plotted points falls between the calculated control limits, it indicates that the process in the state of statistical control and no action is warranted. If the point falls above the UCL, it indicates that the process average, or the failure occurrence rate, may have decreased which results in an increased time between failures.

This is an important indication of possible process improvement. If it happens, the management should take action to find out the causes and maintain it. If the plotted point falls below the LCL, it indicates that the process average, or the failure occurrence rate, may have decreased which resulted in the decrease in failure time.

This means that the process may have deteriorated and thus actions should be taken to identify and remove them. In either case, the people involved can know when the reliability of the system is changed and a proper follow up can be made to improve the reliability. The control chart will also help the maintenance personals.

Case Study

In order to illustrate the control chart procedure described above, the following 96 simulated values shown in table 1 are introduced. These values from an exponential distribution with mean (MTBF) of 1000 cycles.

Table.1. Simulation of the Exponential Distribution for 96 Values

2100	2232	625	1852	299	559	54	660	562	69	91	541
427	50	571	306	412	9	1129	749	208	490	792	485
140	351	398	610	1463	1237	884	1985	2083	588	1640	363
315	631	353	853	767	418	855	726	4707	329	196	160
224	29	300	2892	2051	62	312	495	2622	832	555	963
2607	1136	405	263	723	967	1516	1731	1785	2278	163	
	1476	712	44	789	666	2894	116	1513	1112		338
	1072	2168	2707	788	67	1096	572	1013	225		269
	1406	644	181	19	1041						

By examining this data, one notices that they are "all over the place". The values range from 9 to 4707. Remember that the standard deviation of the exponential distribution is equal to its mean; in this case, 1000 cycles. One can also compute that the proportion of values larger than the mean 1000 is 30/96 = 0.3125.

More than 60% of the values are below the mean; this is one of the characteristics of the exponential distribution. In fact, note that for any device subject to exponential failures, there is a 0.632 probability of failure before the mean time to failure, or, equivalently, 63.2% of such devices will fail before the mean.

Using the shape parameter formula given in equation 2. The parameter is calculated as fallows.

$$\beta = \frac{(201.903 - 6.28 \times -34.4882)}{(2918.2410 - 96 \times 6.28^2)} = 1$$

Showing that the failure time follows exponential distribution. The Failure rate of this distrbution is calculated using the following formula

$\lambda = \frac{n}{\sum_{i=1}^{n} t_i}$ where n is the number of data and t_i is the time between failure, therfore

$$\frac{96}{98167} = 0.001$$

λ = f/cycal.

The control limits for α = 0.3 and MTBF=1000 cycles are calculated as follows

LCL= $\left(\frac{1}{1000}\right)^{-1} \ln\left[\frac{1}{1-0.3/2}\right]$ 62.4

CL= $\left(\frac{1}{1000}\right)^{-1} \ln 2$ 693.1

UCL= $\left(\frac{1}{1000}\right)^{-1} \ln\left[\frac{2}{0.3}\right]$ 1897.1

The simulated values shown in table 1 are plotted with respect to UCL and LCL. This polt is shown in figure 2. There are more than simulated values exceeding the upper limit and others below the lower control limit.

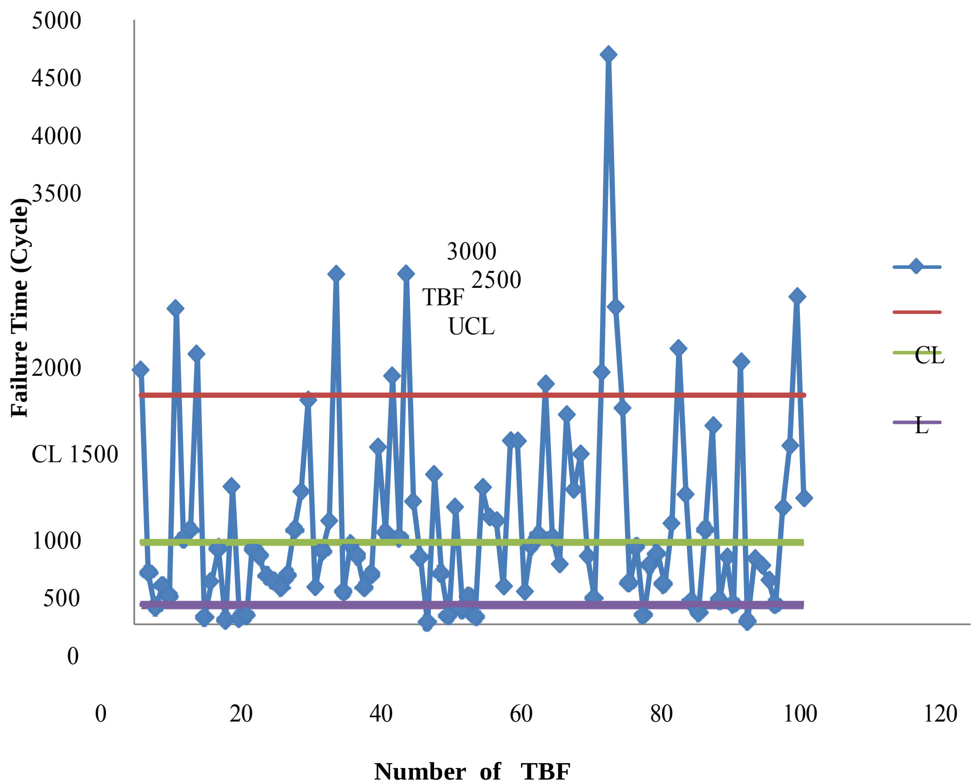

Figure 2: Control Limits of TBF

Results and Discussion

The control limits can be used to predict the machine failure based on the reliability. The time between failures can be utilized to establish the limits of the control chart. If the (time between failures) fall between the calculated control limits which ware 1897.1, 162.4 for upper and lower control limits respectively, it indicates that the process in the state of statistical control and no action is warranted. If the point falls above the UCL, it indicates that the process average, or the failure occurrence rate, may have decreased which results in an increased time between failures. This is an important indication of process improvement. If it happens, the management should take action to find out the causes and maintain them. If the plotted point falls below the LCL, it indicates that the process average, or the failure occurrence rate, may have increased which resulted in the decrease in time between failure.This means that the process may have deteriorated and thus actions should be taken to identify the causes and remove them. In either case, the people involved can know when the reliability of the system is changed and a proper follow up can be made to improve the reliability. The control chart will also help the maintenance personals.

Conclusion

Modeling predictive maintenance control limits is one of the main pulling factors that helps to achieve the predictive maintenance objectives. The new area of predictive maintenance focuses on the reliability of the device being monitored to be a predicting tool on the maintenance activities.

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Biography

Mariam Azraga is an Engineer in Industrial and Manufacturing System Engineering Department at Benghazi University, Benghazi, Libya. Recently she earned B.S. in Industrial and Manufacturing System Engineering from Benghazi University of Libya. Miss Mariam has done graduation projects with Assistance Prof. Dr Omar M. Elmabrouk in the area of maintenance planning, In the project, she studied the estimation of the control limits that are used in predictive maintenance strategy. She does not only used the quality control technique but also she used the reliability technique to estimate the limits. Her research interests include manufacturing, optimization, reliability, six sigma and lean. He is member of the national society of the industrial engineering at the I&MSE department, Benghazi University.

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