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A Design of Condition Monitoring System for Predictive Maintenance

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Abstract. Global competition to increase production output and to improve quality is spurring manufacturing companies to use condition monitoring and fault diagnostic systems for predictive maintenance. As monitoring, testing, and measuring techniques develop, predictive control of components and complete systems have become more practical and affordable. In this article, we will consider the computer based data acquisition system for condition monitoring and the condition parameter analysis techniques for fault detection and diagnostics in the machinery and briefly discuss reliability prediction and the limit value determination in condition monitoring.

Key Words : *predictive maintenance, codition monitoring, condition parameter, degradation data.*

1. INTRODUCTION

Recently there have been increasing demands for high reliability of operating process or manufacturing machines when they are running. Also catastrophic failures, availability, spare parts control, *etc.*, are becoming more and more vital and dominating factors in modern production plants. Acceptance of maintenance policies can be a worth-while investment in tackling such problems. Maintenance actions or policies can be classified as corrective maintenance, preventive maintenance and on-condition maintenance which is also called predictive maintenance (Chan *et al.*, 1997). Maintenance actions are dependent on many factors such as the failure rate of the machine, the cost associated with downtime, the cost of repair and the expected life of the machine. For example, a maintenance policy which requires no repairs, replacements or preventive maintenance until failure allows for maximum run-time between repairs. Although it allows for maximum run-time between repairs it is neither economical nor efficient as it may result in a catastrophic failure that requires extensive repair time and cost. Another widely used maintenance policy is to maintain the machine according to a predetermined schedule, whether a problem is apparent or not. Actual repair costs can be reduced in this manner, but production loss may increase if the machine is complex and requires days or even weeks to maintain. This preventive maintenance also may create machine problems where none existed before. Becker *et al.* (1998) cite a 1990 report from Electric Power Research Institute (EPRI) which states that one-third of the money spent on preventive maintenance in the electric power industry (which that year amounted to $ 60 billion) was wasted. Obviously, if a machine failure can be predicted and the machine can be taken off-line to make only the necessary repairs, a tremendous cost saving can be made. Predictive maintenance can also be done when failure modes for the machine can be identified and monitored for increased intensity and when the machine can be shut down at a fixed control limit before critical fault levels are reached.

The recent developments in sensors, chemical and physical non-destructive testing (NDT), and sophisticated measurement techniques have facilitated the continuous monitoring of the system performance. Today's advances are raising the bar toward machine prognostics, where failure modes and the remaining life of a system can be predicted. For industry and the military, the 21st century will bring about the age of prognostics and health-management systems (Becker *et al.*, 1998). Machine prognostics essentially involves taking data from sensors that are placed on the various parts of the system to record specific system condition, and feeding these data into a computer program so that potential system faults and failures can be identified, tracked, and predicted. The aim of prognostics is to stop disabling or fatal failures before they happen. The concept of prognostics goes beyond diagnostics, in which the sensed data are simply monitored for the occurrence of anomalies or failure that are then corrected. The prognostics process is analogous to the way physicians deal with medical problems. First the problem is detected; then a diagnosis is made about the failure mode and its severity. It is also important to predict the evolution of the failure in order to estimate the remaining useful life of the machine.

There are three main tasks to be fulfilled for predictive maintenance. The first task is to find the condition parameter which can describe the condition of the machine. A condition parameter could be any characteristic such as crack, corrosion, vibration *etc.*, that is directly or indirectly connected with an item of the system and its performance, and describes the condition of the item during the operating life.

The second task is to monitor the condition parameter with suitable equipments. The final task is to assess the current machine condition from the measured data and to determine to determine the symptom limit value, S_L, whose two components are the alarm value S_a and the breakdown value S_b. If a running machine reaches the alarm value it is an indication that it is experiencing an intensive wearing. Hence the type and advancement of the fault must be identified in order to prepare the maintenance procedure. If a machine reaches the breakdown value, S_b, the shutdown of a machine for maintenance becomes necessary.

In this article, leaving aside the choice of the condition parameter, we will consider the computer based data acquisition system for condition monitoring and briefly discuss reliability prediction and the limit value determination in condition monitoring.

2. DATA ACQUISITION SYSTEM

Modern computer technology permits a steady state dynamic data collection and analysis system. By interfacing data acquisition system with the computer, raw data can be converted into meaningful information regarding the present condition of the system and a schedule for the desired predictive maintenance. In this Section, we discuss the elements of the computer based data acquisition (DAQ) system. The most common DAQ systems use a desktop PC or laptop computer with a plug-in DAQ hardware, signal coditioner, and transducers as showen in Figure 1.

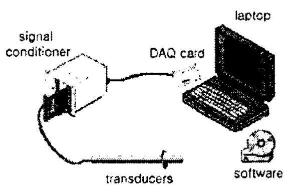

Figure 1. The Typical Data Acquisition System

Transducers

Transducers change physical phenomena into electrical signals. According to the concerned physical phenomena, there are many kind of transducers. For example, proximity transducers, velocity transducers and accelerometer convert the mechanical vibration to an electrical signal. Thermocouple changes the temperature into a voltage.

Signal Conditioner

Transducer output must often be conditioned to provide signals suitable for the DAQ hardware. The most common type of signal conditioning is amplification. Another common application for signal conditioning is filtering. Filtering removes unwanted noise from the signal that you are trying to measure. The others are isolation, excitation, and linearization *etc.*

Data Acquisition Hardware

The DAQ board or card digitizes incoming analog signal for software. There are some basic considerations of signal conversion. We will show three important cosiderations among them.

Resolution

When converting the analog value into a digital one, the number of bits in the analog to digital converter (ADC) affects the resolution of the result. The ADC divides the input signal values into steps, based on the number of bits and the instrument's full scale range. A 8 bit converter divides the analog range into $2^8 = 256$ steps.

Range

Range refers the minimum and maximum voltage levels that the ADC can span.

Sampling Rates

This shows how often conversions can take place. With a faster sampling rate, you can acquire more points in a given time. As you expect, this provides a better representation of the original signal.

Software

Software is needed to program for acquiring, analyzing, and presenting the information from DAQ hardward.

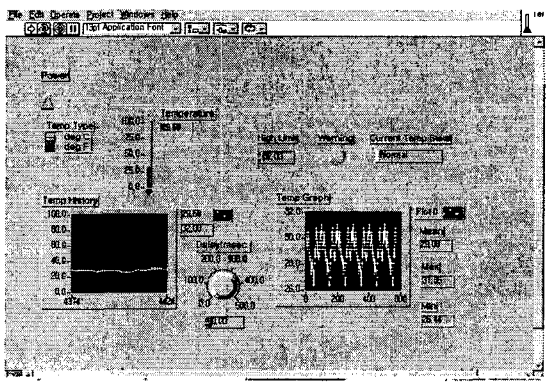

Figure 2. Window for Temperature Monitoring

Now, you can build a window for temperature monitoring as Figure 2. This window will obtain a volatage from a plug-in DAQ board inside the computer and convert the volatage into a Fahrenheil or Celsius temperature reading. Forthermore you can detect when a temperature is out of range and if the temperature exceeds the high limit, a warning indicator will turn on and a beep will sound.

3. INFORMATION FOR CONDITION MONITORING

As discussed above, condition monitoring requires observing a condition parameter with time. When the parameter's value degrades and reaches a predetermined limit, S_L, then a corrective action is taken accordingly. In this Section, we present three approaches for determining the limit values of typical condition parameter.

3.1 Reliability Estimation Based on Degradation Data

The limit value, S_L, can be determined by observing the changes in the condition parameter with time. The value of S_L can be corresponded to an acceptable reliability value of the system as described below.

It is assumed that the effect of the degradation phenomenon on the system performance or the condition parameter can be expressed by a random variable called degradation criterion. It is clear that units with the same age would have different degradation criterion levels. Figure 3 is a plot of the crack-length measurements versus time (in million cycles) from Bogdanoff and Kozin (1985). There are 21 degradation paths, one for each of 21 test units. From this plot, we can find that the degradation criterion is a time-dependent random variable that can follow different distributions at different distinct times.

In general, the degradation criterion, X, may follow a distribution which changes with time in the type of the distribution family and its parameters as shown in Figure 4. The solid curve represents the mean of the degradation criterion versus time and the areas under the density functions and above the threshold level line represent the failure probability at the corresponding times.

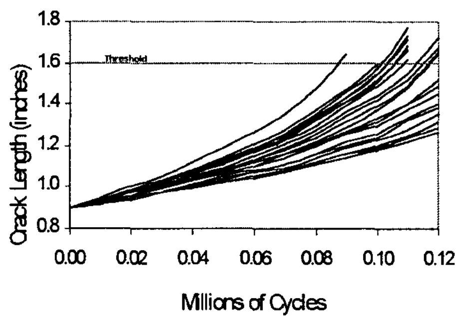

Figure 3. Fatigue-Crack-Growth Data from Bogdanoff and Kozin(1985)

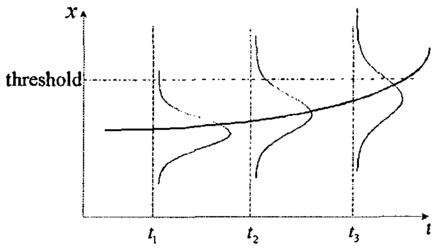

Figure 4. $f(x;t)$ versus t for MIDP

Eghbali and Elsayed (1997) develop a statistical approach based on degradation data. They assume the degradation criterion follows the same distribution family but its parameters may change with time. Furthermore, it is assumed that the degradation paths are monotonic functions of time; they are either Monotonically Increasing Degradation Paths (MIDP) or Monotonically Decreasing Degradation Paths (MDDP). They define:

X degradation criterion (random variable), $x \geq 0$

$f(x;t)$ probability density function (pdf) of the degradation criterion, X, at a given time t

$\lambda(x;t)$ failure rate function of $f(x;t)$, referred to as the *degradation failure rate function*

The corresponding degradation criterion distribution for this degradation model is a Weibull distribution with a time-dependent scale parameter.

$$f(x;t) = \frac{\gamma}{\theta(t)} x^{\gamma-1} \exp[\frac{-x^{\gamma}}{\theta(t)}], \quad t > 0$$

where $\theta(t) = b\exp(-at)$ is the scale parameter, x is the degradation criterion at which a failure occurs and a, b, γ are constants. The corresponding reliability function can then be determined as

$$R_x(t) = P(X > x; t) = \exp[\frac{-x^{\gamma}}{b\exp(-at)}].$$

Conversely, if the desired reliability at time t, $R_x(t)$ is given, the level of the degradation criterion, x, which is equivalent to the breakdown value, S_b, can be determined. Hence we use the above equation to determine S_b corresponding to $R_{S_b}(t)$.

Important studies that have used degradation data to assess reliability can be found in Gertsbackh and Kordonskiy (1969), Nelson (1981), Carey and Koenig (1991), Lu and Meeker (1993), Chick and Mendel (1996), Feinberg and Widom (1996), Lu *et al.* (1997), Meeker *et al.* (1998), and Ettouney and Elsayed (1999).

3.2 Determination of the Limit Values in Condition Monitoring

The last stage of condition monitoring is the inferences on the machine condition which is based on values of the condition parameter, S. One of them is to assess the symptom limit value, S_L. The knowledge of the limit values is of great importance for critical machines which run continuously with automatic monitoring and shutdown system. However in the most cases of diagnostic implementation, for large and expensive machinery in particular, it is difficult to perform active diagnostic experiments, which means establishing the S_L on the basis of the known machine condition. Hence the determination of S_L is possible only as the result of passive diagnostic experiments, where the values of S are observed on the group of running machines without knowledge of their condition.

Detailed description of condition inference techniques can be found in Cempel (1984, 1985, 1987, 1990). A simple solution for determining S_L is given by Dabrowski (1981). It is determined in the way its tail probability does not exceed a given small level, α ; Pr $(S > S_L) \leq \alpha$. Another possible way of determining S_L from passive experimental data is based on the Neyman-Pearson technique of the statistical decision theory. It minimizes the number of breakdowns at an assumed and allowed percent of needless repairs, A, by means of a proper choice of the breakdown symptom value, S_b. According to Cempel(1985), this condition of minimizing the breakdown number can be written as follows

$$A = P_g \int_{S_b}^{\infty} p(s)ds, \tag{3.1}$$

where $p(s)$ is the pdf of the condition parameter, S, and P_g is the probability of good machine condition.

Cempel (1987) treated observed symptoms as an outcome of Weibull type stochastic process and estimated S_b using Eq. (3.1). Additionally he defined the alarm symptom value, S_a, and estimated it using the following equation.

$$A = P_g \int_{S_a}^{S_b} p(s)ds.$$

Recently, in an attempt to develop a realistic approach to determine the maintenance policy, proportional hazards model (PHM) is used to schedule for maintenance. Performance of a system is influenced not only the operating time, but by other factors. These influencing factors include operating condition (*e.q.*, vibration levels, temperature, pressure, levels of metal particles in engine oil, humidity, dust) and operating history (*e.q.*, number of previous overhauls, time since last failure and maintenance). They are generally referred to as covariates or explanatory variables.

Given all the explanatory variables, PHM can be used to identify the explanatory factors of interest and to schedule for maintenance.

$$h(t, \mathbf{z}) = h_0(t)e^{\beta \mathbf{z}},$$

where $h(t, \mathbf{z})$ is the hazard function at time t for observations with covariate vector, $\mathbf{z}$, $h_0(t)$ is an unspecified baseline hazard function (*i.e.* the hazard function when all covariates are zero), and β is a vector of unknown regression coefficients. This model assumes that the covariates act multiplicatively on the hazard function, so that for different values of the explanatory variables the hazard functions at each time are proportional to each other. The use of the PHM in maintenance decision making is described in Jardine *et al.* (1989), Love and Geo (1991a, b) and Kobbacy *et al.* (1997).

4. VIBRATION MONOTORING

Most industrial machinery operate by means of motors and other rotating parts which will eventually cause faults. These faults may cause the machine to break down and degrade its performance. Generally, when a machine develops a fault, it gives a signal in various forms, *e.g.* changes in vibration, pressure, oil characteristics, etc. In rotating machinery such as gear boxes and bearings, vibration signal is commonly used for fault diagnostics. This is due the fact that when a machine or a structural component is in good condition, its vibration profile has a normal characteristic shape, and it changes as a fault begins to develop (Paya *et al.*, 1997).

4.1 Vibration Measurement

Vibration is a oscillating motion, exerted upon the machine at regular intervals related to the speed of rotation and causing the physical displacement of some portion of the machine in response to this force (Callaway, 1982). This motion produces a transducer volatage output that varies over time. For simple motion, when this volatage is plotted against time, a sinusoidal waveform is produced. The signal chrateristics of this waveform will provide the basic vibration measurement information concerning machinery condition. The vibration is defined and is measured by the following characteristics.

Amplitude

Vibration amplitude can be expressed as peak to peak or zero to peak and measured as displacement, velocity or acceleration.

Frequency

The smallest interval of time to complete a vibration cycle is a period. Vibration frequency is defined as the number of cycles completed in a unit of time , expressed in cycles per minute (cpm) or cycles per second (Hz).

Phase Angle

Phase angle is the fractional part of a period between a reference (zero vibration amplitude) and a particular time of interest (some vibration amplitude), it is measured in degrees using a circle as a complete period of vibration (360^o).

Form

The form of the vibration is an important means of presenting vibration for analysis. The three previously discussed charateristics have all been measurable quantities that can be displayed. Vibration form is the raw waveform displayed on an oscilloscope.

4.2 Vibration Analysis

Condition monitoring techniques based on vibration data analysis are classified into two types; the first, *analytic* methods, are suitable for diagnosis of specific faults while the second, *discriminant* methods, simply relate the general condition to a single number or series of numbers. Although *analytic* methods can yield considerable information, they require skilled interpretation of data and a large part of the success of these methods is due to the analyst. *Discriminant* methods require less skilled operators although this may lead to a reduction in the reliability of the techniques. You can refer these methods for more information in Jeong and Elsayed (2000).

5. SOUND RECOGNITION AND ACOUSTIC EMISSION

Sound recognition is used to detect a wide range of abnormal occurrences in manufacturing processes. The sound recognition system recognizes various operational sounds, including stationary and shock sounds, using a speech recognition technique; then compares them with the expected normal operational sounds (Takata and Ahn, 1987).

Acoustic emission (AE) is defined as the transient elastic energy spontaneously released from materials undergoing deformation, fracture or both. The released energy produces high-frequency acoustic signals. The strength of the signals depends on parameters such as the rate of deformation, the volume of the participating material and the magnitude of the applied stress. AE is used in many applications such as non-destructive evaluation and materials research.

The first known comprehensive investigation of AE was performed by Kaiser (1953). In fact, Kaiser characterized a basic irreversibility phenomenon which bears his name. In the Kaiser Effect, when a material is stressed to a given level and the stress removed, upon reapplication of stress there is no detectable emission at a fixed sensitivity level until previously applied stress levels have been exceeded. Advances in both materials science and electronics technology have contributed to bring AE to the forefront of new NDT methods. The signals can be detected by sensors often placed several feet away from the source of signal generation. There are presently many AE transducers and sensors that can be utilized for specific applications. You can refer the ananysis of AE data in Jeong and Elsayed (2000).

6. OTHER CONDITION PARAMETER MONITORINGS

There are other condition parameters that can be used for default analysis. One condition parameter measurement,whatever it serves you, is never enough to monitoring the condition of the machine. The good technique that increase the effectiveness of the condition parameter is to correlate the condition parameter with other machine characteristics, for example, vibration versus temperature, vibration versus oil condition, temperature versus oil condition, *etc.*

6.1 Temperature Monitoring

Elevation in component or equipment temperature is frequently an indication of potential problems. For example, most of the failures of electric motors are attributed to excessive heat which is generated by antifriction bearings. The bearing life is dependent on its maintenance schedule and their operating conditions. Similarly, hot spots, which are usually caused by excessive currents, in electric boards indicate that failure is imminent. Therefore, a measure of temperature variation can be effectively used in monitoring components and equipment for predictive maintenance purposes. In most electrical equipment, the limiting components are made from polymeric materials and they age because of thermal degradation. The rate at which they age can be calculated using the activation energy for the degradation process, which is obtained from accelerated ageing tests.

The effect of temperature on the device is generally modeled using the Arrhenius reaction rate equation given by

$$r = Ae^{-(E_a/kT)}, \tag{6.1}$$

where

$$\begin{aligned} r &= \text{the speed of reaction,} \\ A &= \text{an unknown nonthermal constant,} \\ E_a &= \text{the activation enerage (eV),} \\ k &= \text{the Boltzman Constant } (8.62310^{-5}\ \text{eV}/^{\circ}\text{K}), \\ T &= \text{the temperature in Kelvin.} \end{aligned}$$

Assuming that device life is proportional to the inverse reaction rate of the process, then Eq. (6.1) can be rewritten as

$$L = Ae^{+(E_a/kT)},$$

where L is the nominal life of the device. Using this Arrhenius model, the life distribution related to the monitored temperature can be estimated. Also, we can obtain the failure rate and temperature behaviour curve over time. From here we can determine the maintenance schedule as discussed in Section 3.

There are many transducers that respond to changes in temperature with varying electrical signals. The signal conditioning is required for these transducers.

6.2 Fluid Monitoring

Analysis of equipment fluids such as oil can reveal important information about the equipment wear and performance. It can also be used to predict the reliability and expected remaining life of parts of the equipment. Measuring oil quality is usually done with a complex chemical laboratory benchmark procedure that measures several parameters indicating oil degradation. These factors include the particle count, the types of particles, and total acid number. As the equipment operates, minute particles of metal are produced from the oil covered parts. The particles remain in suspension in the oil and are not removed by the oil filters due to their small size. The particle count will increase as equipment parts wear out. There are several methods that can identify the particle count and the types of particles in the oil.

A different approach to monitoring engine oil quality has been developed by an automotive industry where a mathematical model uses the engine's computers to infer the rate of oil degradation from data already being collected by various systems within the vehicle. Schwartz *et al.* (1987) found that oil temperature, vehicle mileage, engine revolutions, and changes in the physical and chemical properties of oil during use all provided an indication of oil degradation. Based on these measurements, they developed a mathematical model which relates oil life to oil temperature and either vehicle mileage or engine revolutions.

A combined approach of monitoring driving conditions and using sensors has also been taken by another automotive industry. They developed a passenger car maintenance system which calculates oil change intervals based on driver-specific data, and supplements that information with a sensor that continuously monitors oil level, oil temperature, and the dielectric number of the engine oil (DeGaspari, 1999).

Jardine *et al.* (1989) studied an interesting examination of the method of proportional hazards modelling (PHM) to determine whether or not PHM could improve on the accuracy of the oil-analyst/expert system in determining the risk of failure of a diesel engine.

6.3 Corrosion Monitoring

Corrosion is a degradation mechanism of many metallic components. Clearly, monitoring the rate of degradation, *i.e.*, the amount of corrosion, has a major impact on the preventive maintenance schedule and the availability of the system. There are many techniques for monitoring corrosion such as visual, ultrasonic thickness monitoring, electrochemical noise, impedance measurements, and thin layer activation.

Corrosion causes degradation in the system's performance and it becomes necessary to determine the time for the performance to degrade to a threshold value. Reliability prediction using the degradation data can be obtained accordingly as described in Ettouney and Elsayed (1999).

6.4 Other Diagnostic Methods

Components and systems can be monitored in order to perform maintenance and replacements by observing some of the critical characteristics using a variety of sensors or microsensors. For example, pneumatic and hydraulic systems can be monitored by observing pressure, density of the flow, rate of flow, and temperature change. Similarly, electrical components or systems can be monitored by observing the change in resistance, capacitance, volt, current, temperature, and magnetic field intensity. Mechanical components and systems can be monitored by measuring velocities, stress, angular movements, shock impulse, temperature, and force (Elsayed, 1996).

Recent technological advances in measurements and sensors resulted in observing characteristics that were difficult or impossible to observe, such as odor sensing. At this point of time silicon microsensors have been developed that are capable of mimicking the human sense of sight (e.g., a CCD), touch (e.g., a tactile sensor array), and hearing (e.g., silicon microphone). Sensors to mimic the human sense of smell to discriminate between different odor types or notes are at the early stage of development. Nevertheless, some commercial odor discriminating sensors are now available such as the Fox 2000 or Intelligent Nose (Alpha MOS, France).

The improvements in sensors' accuracy and the significant reduction in their cost have resulted in their use in a wide variety of applications. For example, most of the automobiles are now equipped with electronic diagnostic systems which provide signals indicating the times to service the engine, replace the oil filter, and check engine fluids.

Most importantly, the advances in microcomputers, microprocessors, and sensors can now offer significant benefits to the area of preventive maintenance and replacements. Many components, systems, and entire plants can now be continuously monitored for sources of disturbances and potential failures. Moreover, on-line measurements, analysis, and control of properties and characteristics, which have been traditionally performed off-line, result in monitoring of a wider range of components and systems than ever before.

CONCLUSIONS

This article presents different approaches for condition monitoring and fault diagnostics system for predictive maintenance. It describes methodologies for determining the limit value of the condition parameter (or criterion) which corresponds to a predetermined reliability level. It then provides details of the most commonly used condition parameters, starting with vibration, acoustic emission and concluding with feature extraction. Applicability of such condition parameters and advantages and disadvantages are also discussed.

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