◆ Research Papers

Proactive Maintenance Framework of Manufacturing Equipment through Performance-based Reliability

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ABSTRACT

Manufacturing today is becoming increasingly competitive. If a company is to exist and successfully compete, it must pay very careful attention to production management, total quality assurance and total proactive maintenance issues. Overall machine performance, repair efficiency, system level utilization, productivity and quality of output need to be optimized as possible. To accomplish that objective, the behavior of manufacturing equipment and systems need to be monitored and measured continuously if it is possible. Then early warning of possible failure should be generated and proacted on that type of the situation to improve overall operation performance of manufacturing environment.

In this paper, Proactive maintenance framework using performance-based reliability structure as enabler technology is proposed. Its paradigm enables one to maximize system through-put and product quality as well as resources in the performance domain. In the case of inadequate knowledge of the failure mechanics, this empirical modeling concept along with performance degradation knowledge can serve as an important product and process improvement tool. The real-time framework extension to proposed framework uses on-line performance information and is capable of projecting the remaining useful period.

1. Introduction

Over the last few decades the customers have been demanding a wider variety of products and services for higher quality, reliability, innovation and low cost. To be reactive to the voice of customer, Manufacturing today is becoming increasingly competitive. If a company is to exist and successfully compete, It must pay very careful attention to production management, total quality assurance and total proactive maintenance issues. Production processes have been squeezed for the last dollar per hour, for one more component per shift.

The production equipment itself is one of the few remaining areas in plant operation where significant gains can be made. Therefore, Accurate real-time knowledge relating to the equipment and its operation are vital to efficient plant operation and productivity improvement. Overall machine performance, repair efficiency, system level utilization, productivity and quality of output need to be optimized as possible. To accomplish that objective, The behavior of manufacturing equipment and systems need to be monitored and

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measured continuously if it is possible. Then early warning of possible failure should be generated and proacted on that type of the situation to improve overall operation performance of manufacturing environment.

Figure 1 shows the conventional machine performance monitoring system paradigm which includes sensing, process fault detection and diagnostics. Typically, the sensing parameters are outputs from such as sensors, actuators, and time. In many manufacturing systems, performance parameters are like the cutting forces, accelerometer, torque, temperature, spindle motor current, acoustic signals, actual cutting time and so on. Measurable input performance parameter and out performance parameter are used to determine the states of equipments and systems as shown in figure 2. Monitoring the operation of a complex piece of machinery and monitored values of performance parameter provide us an accurate characterization of the current system state and reasonable managerial data for maintenance action, in which provides an accurate failure point in time and the remaining useful life.

Maintenance is a major cost driver in commercial and military industry. Currently, maintenance of large systems is often performed on a time-based schedule. The two traditional maintenance approaches: 1) run until mechanical failure occurs, then repair; and 2) schedule maintenance and inspection based on probabilistic failure models. Industry and military are looking for more economical methods of maintenance and for techniques to keep machines in operation longer. Performance-based reliability structure enabled by true prognostic capability, that is, the ability to predict remaining useful life, offers a valuable solution. This will be accomplished by continuously monitoring equipment conditions and performing maintenance actions only when objective evidence of a fault exists.

In this paper, Performance-based reliability structure that enables one to utilize on-line performance information from equipment and determine an accurate characterization of the current system state and reasonable managerial data for maintenance action, in which provides an accurate failure point in time and the remaining useful life. Furthermore, the real-time extension to performance-based reliability structure is capable of projecting the remaining useful period. With such performance-based modeling and implementation methodology, we can accomplish a significant savings in life cycle maintenance costs, improved system reliability, and increased safety.

2. Performance Monitoring and Failure Prediction

Industries has identified that the top maintenance priority is the development of the capability of accurately predicting remaining useful life of a critical component or system without reducing its operational time. This will require continuous monitoring to maximize availability of machines and predict the exact time of failure. [1,3] The prediction depends on fundamentally different dominant failure modes that encountered from systems. A successful failure prediction requires knowledge in: 1) detection and identification of failures, 2) failure prediction methodology, 3) direct sensing and analysis, 4) real-time diagnosis, and 5) sensors and signal processing technology.

In realistic operational environments, the following have to be accomplished: 1) advanced, intelligent, self-calibrating sensors; 2) a complete tool set for digital signal processing of sensor data and multi-sensor fusion techniques to combine information from multiple sensors; 3) test beds and models to observe and track the evolution of mechanical failure phenomena such as wear, crack growth, fatigue, etc; 4) a fundamental theoretical framework and practical models for predicting accurately the evolution of failure phenomena; and 5) new hybrid methods for automated reasoning that incorporate the features of fuzzy logic, rule-based systems, neural networks, and decision-level fusion. [5]

From the work need to done above, its crucial part is to develop a common baseline models and modeling concept based on performance measure from systems or machinery. A fundamental theoretical framework and practical models for predicting accurately the evolution of failure phenomena should be based on reliability, maintainability, and availability concept.

Product/process failure involves a change in a performance measure (some measure of system quality) from a satisfactory level to an unacceptable level. "Unacceptable" may be numerically smaller or larger than the initial performance measurement. Conceptually, we can always find (perhaps from a life test) or postulate (perhaps from theoretical analyses) a deterministic or probabilistic relationship to explain typical or expected performance. In any situation, the measured performance, value at any specific time would not be deterministic. Fluctuation from this relationship would occur more or less. This could be modeled by letting performance value be a random variable at any specific time. The location and/or scale parameter of the distribution of performance value would gradually drift in time according to some empirical relationship established from performance data. Such behavior is quite common in electronics, electro-mechanical and mechanical devices.

Failure phenomena are modeled by empirical relationships as the result of distinct performance degradation with regard to physical performance, on a continuous scale when the critical performance plane is placed at a given level. Associated with variation of the performance, at any specific time will be a measure of the system's susceptibility to failure as a function of current and past performance measurements.

Our main concern is to develop theoretical framework that use on-line real-time performance information, in turn, that provides an accurate failure point in time and the remaining useful life. With shown figure 1, 2 performance-based reliability measure provide the state of system performance as numerical scale of 0 to 1.

Different products have different intended uses, resulting in different critical physical performance measures. When dealing with reliabilities, a corresponding appropriate definition of failure, in terms of physical performance, needs to be defined clearly. Physical performance is the integral performance measure of the integrity of a designed part, component, product, subsystem or system. Performance is affected by many variables as well as the product usage level. Many devices experience deterioration over time and finally fail when they reach a predetermined performance level or performance plane. Product performance characteristics are related to product applications as well as consumer expectations. In many cases, product specifications provide insight as to the expected performance level. Product performance is often measured in terms of both life and physical properties. A feature of physical performance is that it is potentially measurable

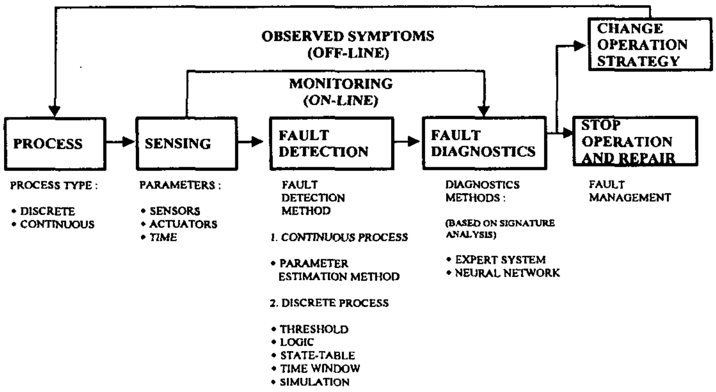

Figure 1. The Conventional Fault Monitoring, Detection and Diagnostic process [5]

and can be monitored continuously over time. Once we are to set some level tolerable performance-base reliability such as 0.95, Monitoring system combined with performance-based reliability structure will notify us the exact failure point. Then, the maintenance action should be followed right before predicted failure point in time. Also, warning system could be placed, Operator may get attention for failure diagnostics.

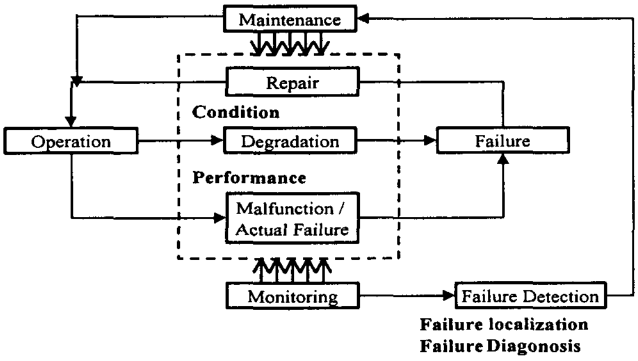

Figure 2. Machine Performance States; Operation, Degradation and Failure

3. Performance-based Reliability

Figures 3, 4 and 5 depict conceptual performance curves. Figure 3 shows a performance "curve," actually a volume, between two curves defined by the worst and best performances observed across the time and load dimensions.

Figure 4 shows a single slice (taken out at one level of the load) out of the performance volume of Figure 3. This slice shows individual performance curves for each of 8 devices (e.g., drill bits) tested or monitored. These curves show performance dropping off as a function of time (e.g., number of holes drilled), at a given load (the slice taken).

A performance plane is drawn at a low performance level in Figure 4. The points at which these performance curves pass through this plane are equivalent to failure times (life times) that would be recorded in a classical reliability study. The classical practice has been to take these failure times and fit them to parametric models, such as a Weibull model, and then use this model as a reliability predictor. From a conceptual standpoint, the use of contemporary covariate models can extend this plane back across the load dimension. Thus, one can think of the current practice of reliability assessment and analysis as a subset of the concepts shown in Figures 3 and 4. In order to add further detail to this hypothetical illustration, one can think about passing a plane in a vertical direction through a point on the time axis. This intersection is shown in Figure 5. In Figure 5, the vertical plane represents a censoring plane. Placement of the censoring plane at a preselected point in time would be known as a Type I or time censoring concept in classical reliability work. If this same plane were passed through the jth ordered

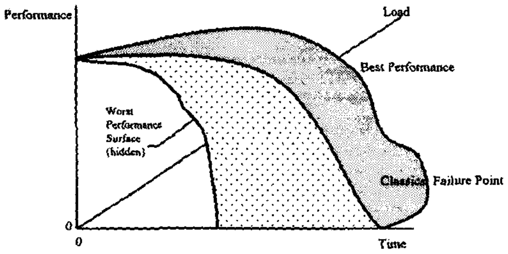

Figure 3. Performance-based Reliability Concept

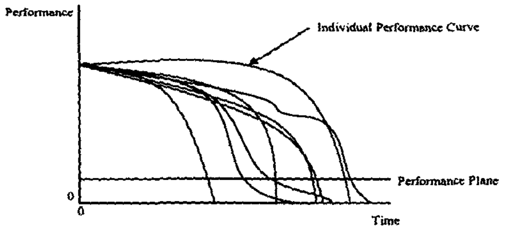

Figure 4. Individual Performance Reliability Curves for a Given Load Level with a Performance Plane Superimposed

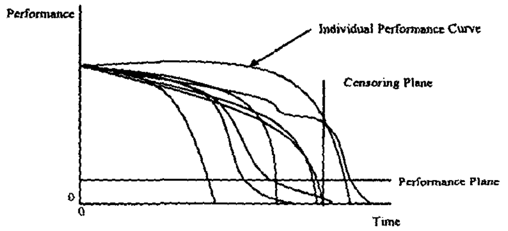

Figure 5. Individual Performance Reliability Curves for a Given Load Level with a Censoring Plane Superimposed

failure time, it could be referred to as a Type II or failure censoring concept. In relation to a drilling example, we are concerned with developing the conditional probability (reliability), as stated by equation (1), that the performance will be above the performance plane for the amount of time stated, under a given set of operating conditions.[2]

NOTATION

t : time or cycles

m_t : the performance measure at any point in time t

m_0 : the initial value of product performance at the beginning

m_f : some lower (or upper) limiting value considered to be a failure

u_{m_t} : the mean value of m_t at time t

G_m(t) : the rate of approach of m_t to the performance plane and the rate of descent/ascent below/above the performance plane once m_t passes through the performance plane

A : the total area under the curve of G_m(t)

$X_1, \cdots, X_{n-1}$: multiple load variables

$\beta_0, \beta_1, \cdots, \beta_n$: regression coefficients

P.C.L. : the performance critical limit

O.C.P. : a vector of operating conditions

E.C.P. : a vector of environmental conditions

T : a random variable that represents time to failure

gau() : Gauss/Normal distribution

Performance-based reliability utilizes performance information which is very product specific. When an appropriate definition of failure, in terms of performance, is given, performance reliability is defined as "the conditional probability that the performance measures of a component, device, equipment, product, subsystem, or system is less (or greater) than a performance critical limit (which represents an appropriate definition of failure in terms of physical performance), given operating and environmental conditions, for a specified period of time or cycles." It can be summarized as

$$\begin{aligned} P(\text{Performance} > (<)\ \text{P.C.L.} \mid \text{O.C.P}=(O_1, O_2, \cdots, O_k\ ),\\ \text{E.C.P}=(E_1, E_2, \cdots, E_k\ ,\ ), T>t) \qquad (1) \end{aligned}$$

Once an empirical performance function is fit from past or current performance data, the fitted performance function traces the central tendency measure of performance over time.

The location information from the performance function represents the best available estimate for performance until significant new evidence is presented (from real-time monitoring) that suggests that performance is not on track. Dispersion may be assumed to be constant, σ^2, over time, but may also vary over time. If the dispersion is changingover time and/or with explanatory variables, a relationship function must be developed that can give the best available estimate of dispersion over time and explanatory variables.

As we can see in Figure 6, the conceptual performance function $m_t(t;\ X_1, X_2, \cdots, X_k)$, which may contain explanatory variables, traces the mean performance at time t. At every instant of time, t, we assume that some distribution of the performance measure about the m_t value exists. We expect that device performance will follow this distribution, until evidence to the contrary is presented. Furthermore from simple statistical process control, if the performance of an individual device is within $u_{m_t} \pm b\sigma$, where b is a constant (usually 3), then the performance may be assumed to be on track. Otherwise, we may assume that the performance process has shifted and devise a new performance function m't using the last few points as a trend projection for future expected performance.

The probability that the device will fail at time t, given the operating conditions, is represented by the shaded areas (relative to the m_t curve) in Figure 6. Assuming that performance location and dispersion dimensions can be fitted and modeled, some parametric form for the f(m_t) is useful in order to quantitatively develop failure probabilities. At this point in the development of the performance reliability model, we will assume that the performance distribution function, f(m_t), can be approximated by the normal distribution. Of course, this assumption would need to be verified empirically in any specific application. However, the previously developed concepts and relationships will hold regardless of the distributional form chosen. Therefore,

$$\Pr(m_t \leq m_f) = \mathrm{P(F,t)} = \mathrm{gau}\{(m_f - u_{m_t})/\sigma)\} \qquad t \geq 0 \quad (2)$$

The performance reliability function is given by:

$$\mathrm{R(t)} = 1 - \mathrm{F(t)}$$

$$= 1 - \int_0^t \frac{G_m(t)}{\int_0^\infty G_m(t)dt} dz \qquad (3)$$

'here

$$G_m(t) = \mathrm{gau}\{(m_f - u_{m_t})/\sigma)\} \qquad m_t > m_f$$

$$G_m(t) = 0.5 \qquad m_t = m_f$$

$$G_m(t) = \mathrm{gau}\{(-m_f - u_{m_t})/\sigma)\} \qquad m_t < m_f$$

re 6 shows the empirical performance C.D.F. and reliability function for a nce function. The conditional reliability for a future Δt period, given survival to 't+Δt|t) is given by:

$$R(t+\triangle t \mid t) = \frac{R(t+\triangle t \mid t)}{R(t)}$$

$$\frac{R(t+\triangle t \mid t)}{R(t)} = \frac{1-\int_0^{t+\triangle t} \frac{Gm(z)}{\int_0^{\infty} Gm(u)du}\,dz}{1-\int_0^{t} \frac{Gm(z)}{\int_0^{\infty} Gm(u)du}\,dz} \tag{4}$$

where

$G_m(t)$ = gau{(m_f - u_{m_t})/ σ)} $m_t > m_f$

$G_m(t)$ = 0.5 $m_t = m_f$

$G_m(t)$ = gau{($-m_f$ - u_{m_t})/ σ)} $m_t < m_f$

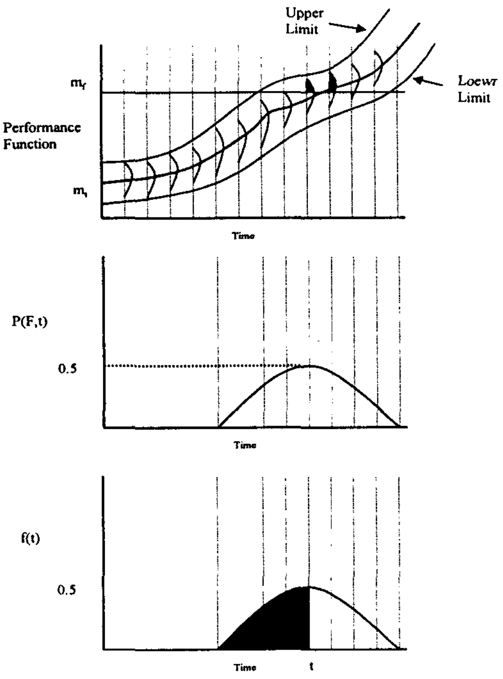

Figure 6. Relationship between Performance and Failure Distribution

4. Maintenance Framework Through Performance-based Reliability

In order to use performance-based reliability structure, It is need to establish performance relationships based on physical failure phenomenons. We can establish general typical (standard) performance models using regression type function. Usually, performance models can be extended into the simultaneous, multiple, stress dimension. The first-order general performance model would be

$$m_t = \beta_0 + \beta_1 X_1 + \cdots + \beta_1 X_{n-1} + \beta_n t, \tag{5}$$

where $X_1, \cdots, X_{n-1}$ are multiple load variables

This performance functions represent some degree of success of manufacturing equipment. They can be use the trace the performance of facilities any given time, t. The trend of up direction or down direction explains degradation is in progress. Using such recent acquired performance data, performance function will be updated in real-time. For some degradation processes, the degradation rate itself could be a function of a stress variable, s. Thus, there could be a dependence between the degradation rates and stress variables such as temperature, voltage, velocity, strain and so forth. In such cases, many well established physical process models may be applicable to the degradation rate (slope).

The Arrhenius and the Eyring models are often used when temperature is the stress variable. The Coffin-Manson model is used for solder cracking under thermal cycling. The inverse power law is sometimes used to model voltage as a stress variable for electronics and dielectrics. Also, the power law is used in Taylor's tool performance model for wear of machine tools as a function of cutting velocity. When both temperature and voltage must be considered, the Arrhenius reaction model and the inverse power law model can be combined to form a combined model. [4]

Performance-based reliability is a measure of a performance level under the given conditions when the failure performance level is predefined in the performance domain. Degradation slope in the performance function at time t make us predict the remaining time to next arrival to the failure plane.

To extend to maintenance procedure, One must determine the two level of performance value. The one is the failure level, The other is warning level of performance. They are determined from field experience and level of quality factors. Then, the remaining useful life to next warning and failure level will be generated. All maintenance action is delayed until a monitoring system alerts the operator that it is time to conduct a particular maintenance action. At the end of useful life time in point, a signal to stop the whole system will be initiate to prevent catastrophic failure.

5. Conclusion

Failures in manufacturing systems follow a particular performance track that may be predictable within a multi-dimensional state-space sufficiently far in the future to be useful to the operator as well as the maintainer. This make us predict remaining useful life of equipment in service reliability and accurately, if you are able to sense the performance parameters within the framework of continuous monitoring. This lead us to detect the failure evolution at some time before the operator is alerted to warning and failure level of performance value. In doing this, we establish the performance function and the acceptable level uncertainty in the time by using performance-based reliability. A lower risk of application (where the prediction will be less difficult) will likely drive a higher precision because the operator will desire to get as much life as possible out of the equipment. In higher risk application (where the prediction will likely be more difficult), the precision required will probably not be as high because the operator will be likely to try to push the component to its limit.

References

[1] Blanchard,B.S., Verma, D., Peterson,E., Maintainability, John Wiley, 1995.
[2] Lewis,E.E., Introduction to Reliability Engineering, 2nd Ed., John Wiely, 1996.
[3] Moubray, J., Reliability-centered Maintenance, Butterworth-Heinemann, 1997.
[4] Nelson, Wayne, "Applied Life Data Analysis", Wiley, 1982
[5] Williams, J.H., Condition-based Maintenance and Machine Diagnostics, Chapman & Hall 1994.