

Real-time Equipment Health Evaluation and Dynamic Preventive Maintenance

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Abstract –With the great advancement of sensor and information technology, the semiconductor equipment data is now available to process engineers in real time. However, the volume of data collected and quickly accumulated is often so large that the data is rarely analyzed and put to use effectively. In this paper, we propose an integrated approach that utilizes multivariate statistical techniques to combine various equipment data items into a single equipment health index. We then use this index to determine appropriate time points for equipment preventive maintenance (PM).

Index Terms – Real-time equipment monitoring, Multivariate analysis, Condition-based PM

INTRODUCTION

Fig. 1 shows a typical real-time equipment monitoring scheme referred to as a “bull’s eye” or “simultaneous monitoring” scheme [1-4]. Values of various machine data items are displayed simultaneously on a monitoring board. The board consists of 3 concentric circular regions with different colors: green for SAFE, yellow for WARNING, and red for DANGEROUS. The distance of the observation points from the board center represents the deviation from the target setting. The distribution of data points provides an easy reading of the equipment’s current operating condition. When the points are concentrated around the center, it indicates a good overall health. In contrast, when data points are scattered over a wide area, it indicates a worrisome situation. Thus, the engineers can easily read the equipment status by examining the distribution of the data points.

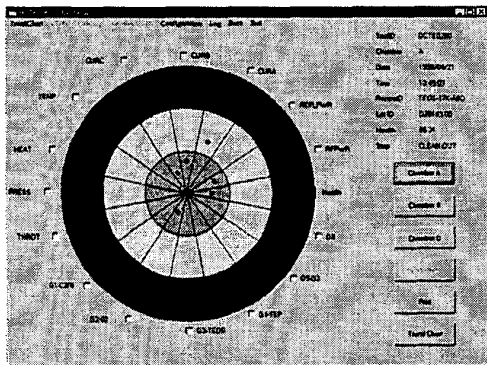


Fig. 1 Equipment Simultaneous Monitoring Scheme

Similarly, an overall equipment health index can be calculated by the distribution pattern of the data points. Using the very same idea of process capability indices (PCI) [5], we propose an integrated index called *Machine Capability Index* (MCI) and then translate the index value into an equipment

health score in a range of [0, 100]. In this way, engineers can easily interpret the equipment’s health condition by reading health score. The real-time equipment health evaluation can also serve as the basis for determining an appropriate time to perform machine preventive maintenance (PM). [6]

MCI AND EQUIPMENT HEALTH SCORE

Eq. (1) shows a generic formula for the multivariate PCI:

$$C_p = \frac{\text{volume of specification region}}{\text{volume containing 99.73\% of observed data}} \quad (1)$$

Calculation of MCI basically follows the same method used in calculating the multivariate PCI. Fig. 2 shows a bivariate case on how this index is calculated.

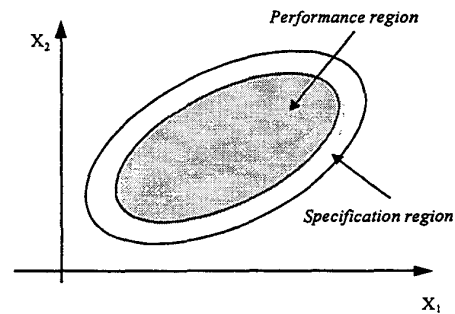


Fig. 2 Equipment performance vs. specifications

Based on a widely accepted assessment criterion, a process with $PCI \geq 2$ is regarded as a very capable process while a process with $PCI < 1.33$ is said to be a poor process. We develop a mapping function (Fig. 3) that translates $MCI = 1.33$ to a health score around 70 and $MCI = 2$ to 95.

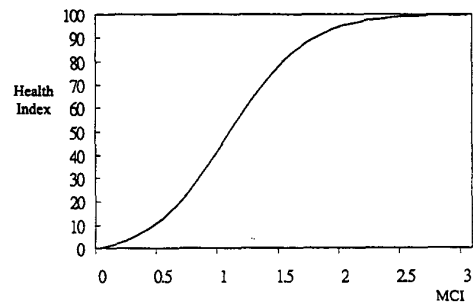


Fig. 3 MCI to health score mapping function

In this way, engineers can easily understand what the health score represents in terms of the machine capability. The real-time equipment health evaluation can also serve as the basis for determining an appropriate time to perform machine preventive maintenance (PM). In the following section, we first construct a stochastic prognosis model to characterize and prognosticate the declining machine health.

EQUIPMENT HEALTH PROGNOSIS MODEL

Since the equipment health score fluctuates over time, it can be viewed as a stochastic process: $H = (H_t : t \geq 0)$. The value of H is available at each time point with specified sampling interval. If $H_t = i$, then the process is said to be in state i at time t . We suppose that when the process is in state i , there is a fixed probability $P_{i,j}$ that the health index will be becoming in state j at the next time point. Such a stochastic process is known as a *Markov chain*. For a Markov chain, the conditional distribution of any future state H_{t+1} given the earlier states H_0, H_1, \dots, H_{t-1} becomes

$$\begin{aligned} P(H_{t+1} = j | H_t = i, H_{t-1} = i_{t-1}, \dots, H_1 = i_1, H_0 = i_0) \\ = P(H_{t+1} = j | H_t = i) = P_{i,j} \end{aligned}$$

We first establish a condition-based prognosis model based on Markov chain theories. Let Φ denote the matrix of one-step transition probabilities $P_{i,j}$:

$$\Phi = \begin{matrix} & \begin{matrix} F & 1 & 2 & \dots & n-1 \end{matrix} \\ \begin{matrix} F \\ 1 \\ 2 \\ \vdots \\ n-1 \end{matrix} & \begin{bmatrix} P_{F,F} & P_{F,1} & P_{F,2} & \dots & P_{F,n-1} \\ P_{1,F} & P_{1,1} & P_{1,2} & \dots & \\ \vdots & & & \ddots & \vdots \\ & & & & P_{n-2,n-1} \\ P_{n-1,F} & P_{n-1,1} & P_{n-1,2} & \dots & P_{n-1,n-1} \end{bmatrix} \end{matrix} \quad (3-1)$$

where H has n states ($S = \{F, 1, 2, \dots, n-1\}$) and $\sum_{j=F}^{n-1} P_{i,j} = 1$.

$P_{i,j}$ is the probability that H transits to state j given its current state is at i . If a machine is down, H will be no longer available hence the failure state F is reached, which is also known as an absorbing state:

$$S_n = F, P_{FF} = 1, P_{F,j} = 0, \text{ for } j = F, 1, 2, \dots, n-1$$

However the value of health index is continuous in the interval of $[0,100]$, but the number of states is finite. To simplify the problem, we should discretize the continuous interval $[0,100]$ into a finite number of segments. For example, take $[95,100]$ as the first state, $[90,95]$ as the second state... etc. The more the number of states, the better the sensitivity of the model. But the model of large state space size needs much more historical data for model estimation.

In Markov chain theories, the two-step transition probability can be obtained by taking a square of Φ . For instance, the (i,j) th entry of Φ^2 is the probability to be at state j after two periods of time, given the current state at i . Recursively, we can calculate the probability for the condition of the equipment to be at certain state after any number of time periods.

To further interpret the matrix Φ , each row, say row i , of Φ represents a state probability distribution given the current state at i . This conditional probability distribution will be likely to form a bell shape. For example, in the beginning of operation, H is most likely to be at a good-condition state, say state i , and remain at state i at the next available time point. H , however, is less likely to move to other states. Thus, $P_{i,i}$ is likely to be the highest probability among $P_{i,j}$'s (see Fig. 4).

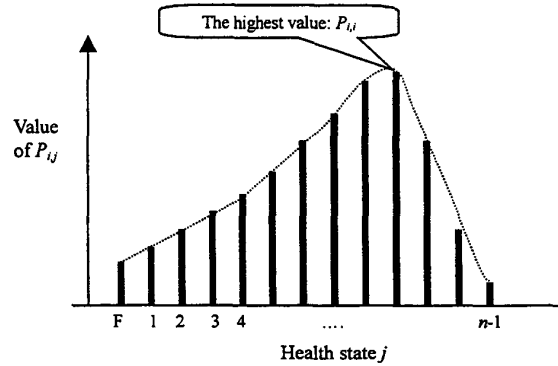


Fig. 4 Bell shape of conditional state transition probability

It is also natural to see that $H=90$ has a larger possibility to become 80 than to become 70. This leads to a probability distribution with a bell shape as illustrated in Fig. 4.

One of the most important properties of the above proposed prognosis model is the bell-shape probability distribution presented by entries in the same row of Φ . But as the machine grows older the health index H tends to worsen due to the deterioration of equipment; i.e., the probability of becoming better will decrease and that of becoming worse will increase. Let a larger value of state be corresponding to a higher health score. We can then observe that each row of matrix Φ , i.e. the conditional probability distribution, should act like a moving wave, as shown in Fig. 5, as the equipment ages.

The moving wave effect is the result of the machine's deterioration over its run time. The longer the machine's run time, the worse the machine's health tendency. We make a modification to the Markovian prognosis model to describe this aging effect, namely age-dependent prognosis model.

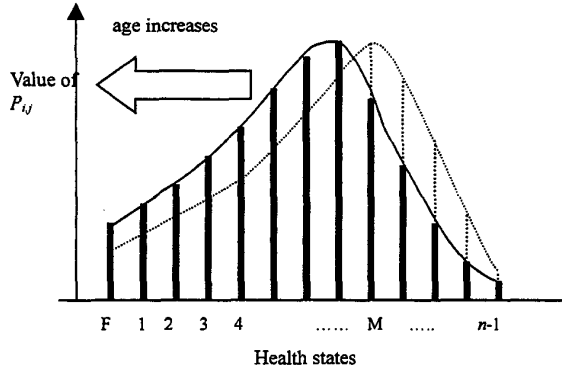


Fig. 5 Wave-moving conditional probability distribution for an aging machine

Let's observe the wave motion in Fig. 5. When the machine ages, the machine's health is more likely to become worse; that is, the probability for the machine's health to become worse increases while the probability for the machine's health to become better decreases. According to this fact, let $P_{i,M}$ be $\max\{P_{i,j}, j = F, 1, 2, \dots, n-1\}$. Also, denote the left-hand-side and right-hand-side cumulative probabilities as $P_i^L = \sum_{j=F}^{M-1} P_{i,j}$ and $P_i^R = \sum_{j=M}^{n-1} P_{i,j}$, respectively.

Then $P_i^R = 1 - P_i^L$ since $\sum_{j=1}^n P_{i,j} = 1$. As shown in Fig. 5, when the machine becomes older, P_i^L increases while P_i^R decreases. That is, $P_i^L(t) \leq P_i^L(t + \Delta)$ and $P_i^R(t) \geq P_i^R(t + \Delta)$ where $P_i^L(t)$ and $P_i^R(t)$ denote the cumulative probabilities at time t . We define an aging factor $\delta \in (0,1)$ as

$$\delta = \frac{P_i^L(t + \Delta) - P_i^L(t)}{P_i^L(t)}$$

Further assume that the amount of increase or decrease in $P_{i,j}$ is proportional to the fraction $P_{i,j}$ takes in P_i^L or P_i^R . We can now derive an age-dependent model to describe the wave-moving conditional probability distribution. Given current time t , the transition probability at the next available time $t + \Delta$ is,

$$P_{i,j}(t + \Delta) = P_{i,j}(t) + \frac{P_{i,j}(t) \cdot P_i^L(t) \cdot \delta}{P_i^L(t)} = P_{i,j}(t) \cdot (1 + \delta) \text{ for } j < M \text{ and}$$

$$P_{i,j}(t + \Delta) = P_{i,j}(t) - \frac{P_{i,j}(t) \cdot P_i^L(t) \cdot \delta}{P_i^R(t)} = P_{i,j}(t) \cdot \left(1 - \frac{P_i^L(t)}{P_i^R(t)} \delta\right) \text{ for } j \geq M.$$

This function is derived from the principle that $P_{i,j}$ decreases for $j \geq M$ and increases for $j < M$. δ can be viewed as an aging factor and also should be estimated from historical equipment data. The above equations are developed to describe the wave-moving phenomenon and ensure that $\sum P_{i,j}$ remain equal to 1. By transforming the values of the entries in Φ over the machine's aging course, the prognosis model that previous section mentioned is able to take the equipment age into account. An age-dependent prognosis model is therefore established.

DYNAMIC PM SCHEME

When minimizing the cost, we often take the long-term average of total maintenance cost as the objective cost function to be minimized. The main maintenance cost of the equipment comes from the preventive maintenance and the breakdown repair. The cost of a failure repair is usually much higher than that of performing a PM. Sufficient PM's can reduce the possibility of equipment breakdown but increase the PM cost. Therefore, a trade-off exists between the PM cost and the failure cost. A metric to evaluate the efficiency of a PM policy is the expected maintenance cost per unit time. First, recall the age-dependent transition probability matrix in the prognosis model:

$$\Phi(m) = \begin{matrix} & F & 1 & 2 & \dots & n-1 \\ \begin{matrix} F \\ 1 \\ 2 \\ \vdots \\ n-1 \end{matrix} & \begin{bmatrix} P_{F,F}(m) & P_{F,1}(m) & P_{F,2}(m) & \dots & P_{F,n-1}(m) \\ P_{1,F}(m) & P_{1,1}(m) & P_{1,2}(m) & \dots & \vdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \vdots & \vdots & P_{n-2,n-1}(m) \\ P_{n-1,F}(m) & P_{n-1,1}(m) & P_{n-1,2}(m) & \dots & P_{n-1,n-1}(m) \end{bmatrix} \end{matrix}$$

where m is the age index. Suppose the equipment data is acquired at scheduled sampling time $\Delta, 2\Delta, 3\Delta, \dots, m\Delta, \dots$, where Δ is a constant time interval. At these specific time points, a PM decision (to perform a PM or do nothing) is also made. Since the health state transition probabilities are age-dependent, $\Phi(m+1)$ can be only calculated from $\Phi(m)$ using the age-dependent model presented in the previous section.

Notice that our transition probability matrix is time dependent and is therefore a nonstationary Markov chain. That is, the equipment's health will have a higher possibility to become worse when it becomes older. In other words, the matrix $\Phi(m)$ changes over the machine's age. This has been fully discussed in previous sections.

For a stationary Markov chain, the n -step transition probabilities can be obtained from n powers of one-step transition probability matrix, i.e. $\Phi^{(n)}$. But in our age-dependent prognosis model, the n -step transition probabilities are different at different observation point. At any given period m , the n -step transition probabilities are calculated from the product of the current transition probability matrix $\Phi(m)$ and the subsequent $n-1$ matrices as in (2).

$$\Phi^{(n)}(m) = \Phi(m) \cdot \Phi(m+1) \cdots \Phi(m+n-1) \quad (2)$$

We can now determine the expected cost per unit time, denoted by μ . Given a health index state s at the m th period, the expected cost per unit time is expressed in (3) if we decide to perform a PM after k periods (i.e. PM at $(m+k)$) as shown in Fig. 6.

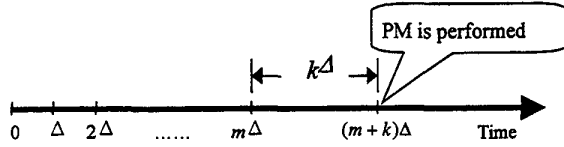


Fig. 6 Illustration of PM location on time axis

$$E(\mu(m, k) | s) = \frac{\text{expected cost per cycle}}{\text{expected cycle time}} \quad (3)$$

$$= \frac{C + K \cdot \Pr\{k\Delta > T(m) | s\}}{E[\min(k\Delta, T(m)) | s]}$$

where C is the cost of performing a PM, K is the additional payment for a breakdown repair, i.e., the cost of a breakdown repair is $C+K$. $T(m)$ is the Time To Failure (TTF) from the current time period m . $\Pr\{k\Delta > T(m) | s\}$ is the probability that the equipment breaks down before the PM at period k is performed given the current state is s . A maintenance cycle is terminated by either the PM or the equipment breakdown. Therefore, the numerator in (3) represents the expected cost per cycle and the denominator $E[\min(k\Delta, T(m)) | s]$ denotes the expected cycle length. Our objective is then to find an optimal k at any given period m that minimizes $E(\mu(m, k) | s)$.

The score of the health index reflects the condition of the equipment's health. In order to determine when the machine needs a PM given a real-time score of the health index, we should find a threshold for the health index scores. When the observed score exceeds this threshold, a decision is made to perform a PM at the next available time.

Suppose that

- The current time is $m\Delta$ (i.e. the machine age = $m\Delta$)
- The current state is s (i.e. the health index is corresponding to state s)
- A planned PM is schedule to perform after k periods of time (i.e. PM at time $(m+k)\Delta$)

The expected cost per unit time is $E[\mu(m, k) | s]$ which is calculated from (3).

Given the time point $m\Delta$ and the health index state s , there exists $k^*(s, m)$ that minimizes $E[\mu(m, k) | s]$.

$$E(\mu(m, k^*) | s) = \min_k E(\mu(m, k) | s) \quad (4)$$

Since we want to minimize the expected cost per unit time, a minimum cost PM decision is therefore: *If the minimum cost appears at $k^*(s, m) > 1$, it implies that to plan a PM at $k^*(s, m) > 1$ will attain a less average cost. Then, we should not perform a PM at next decision making time. If the*

minimum cost appears at $k^(s, m) = 1$, we should perform a PM right away.* This rule will be used to construct a dynamic PM policy.

A PM alarm boundary is formed by the least tolerable values of the health index over the equipment's age. Fig. 7 shows a typical PM alarm boundary in a dotted line and a sample path of the equipment health in a solid line. Once the health goes below the alarm boundary, a PM should be performed.

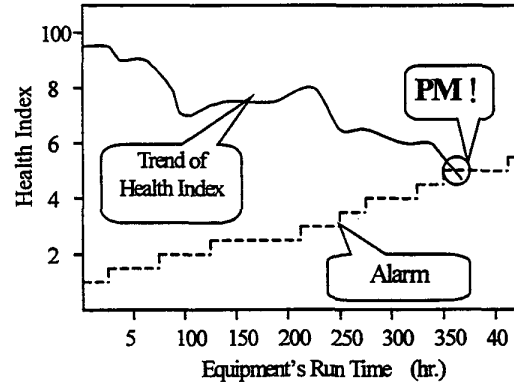


Fig. 7 Dynamic PM policy by equipment health

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