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Predictive maintenance policy based on process data

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ABSTRACT

For the 'under maintained' and 'over maintained' problems of traditional preventive maintenance, a new predictive maintenance policy is developed based on process data in this article to overcome these disadvantages. This predictive maintenance method utilizes results of probabilistic fault prediction, which reveals evolvement of the system's degradation for a gradually deteriorating system caused by incipient fault. Reliability is calculated through the fault probability deduced from the probabilistic fault prediction method, but not through prior failure rate function which is difficult to be obtained. Moreover, the deterioration mode of the system is determined by the change rate of the calculated reliability, and several predictive maintenance rules are introduced. The superiority of the proposed method is illustrated by applying it to the Tennessee Eastman process. Compared with traditional preventive maintenance strategies, the presented predictive maintenance strategy shows its adaptability and effectiveness to the gradually deteriorating system.

1. Introduction

The annual cost of maintenance has been reported to go up to 15% for manufacturing companies, 20%–30% for chemical industries [1], 40% for iron and steel industries [2]. Thus developing new maintenance technologies and arranging proper maintenance scheduling has become more and more important to enhance production and economic efficiency. Despite this economic factor, the maintenance of equipment always has a major impact on system reliability, availability and security.

The evolvement of maintenance technology has experienced three different types, i.e. corrective maintenance (CM), preventive maintenance (PvM) and predictive maintenance (PdM). CM, the earliest maintenance technology, means repairing a system only after a breakdown or an obvious fault. PvM means performing repair, service, or replacement for a component or system at a fixed period to prevent a breakdown. PdM decides whether or not to do system maintenance based on the condition of the system. CM and PvM are the traditional maintenance policies, which may cause low reliability or high maintenance cost. While PdM utilizes appropriate condition monitoring and maintenance management technologies, which can greatly increase the efficiency and profitability of industrial production [3]. Although PdM is an effective approach to promote system reliability, the implementation of this new PdM is not an easy task for uncertainties and less of fault data in practical processes.

Most of the present predictive maintenance approaches are based on a classical assumption, that is, the system failure can be explained by a stochastic deterioration process [4–7], which is consistent with many real failure processes, such as erosion [8], wear [9], and so on. They always supposed that the system state at time t can be summarized by a random aging variable X_t [5], which starts from 0, increases like a Gamma stochastic process until a predefined threshold. Then, maintenance rules can be developed according to system deterioration. However, this method suffers from the disadvantage that it is very difficult to find this aging variable X_t in real systems. Here, a new predictive maintenance policy is developed based on process variables, which can be obtained at a very low cost in modern industries. In many former references, reliability, the variable reflecting the system state in the present article, is calculated through a system failure function. However, it is very difficult and almost unreliable to obtain a real failure function for a complex industrial system. In this article, reliability can be deduced from the fault probability achieved by our former proposed probabilistic fault prediction method, which is much easier to realize. At last, the predictive maintenance can be implemented based on these real-time process variables.

The remainder of this paper is organized as follows. In Section 2, the idea of two different deterioration modes is introduced. Details of the PdM policy are explained in Section 3. In Section 4, several indexes are introduced to evaluate the maintenance performance.

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The effectiveness of the integrated method is illustrated by applying it to the Tennessee Eastman process in Section 5. Finally, Section 6 discusses the conclusions and some future research directions.

2. Mode of deterioration

In many references, the system is considered degrading stochastically subject to continuous accumulation of wear [10], drift, corrosion, and other influencing factors. In the earlier references, the deterioration is considered to be only one mode, which means that the component or system is degrading at almost the same speed with age increasing. While, Grall et al. proposed that the degradation can evolve according to two 'modes of deterioration' [10]. They supposed that the system state at any time can be perfectly denoted by a scalar aging variable X_t [6, 10, 11]. The system starts in a perfect working state at time $t=0(X_t=0)$, then the variable X_t increases as the system deteriorates according two different modes M_1 and M_2, which can be modeled by two stochastic processes under the same law but with different parameters [10].

The pioneer work has provided abundant theoretical bases for our following work. Based on this theory, we can suppose that the reliability of a component or system is deteriorated with age slowly. As shown in Fig. 1, the initial reliability is equal to 1 when the system is in a 'new' state. Then, the reliability keeps on a high level for a period when the component or system is in the normal stage. After that, it follows a deterioration stage, and at last, reaches its threshold. Also, the deterioration stage has two modes, M_1 and M_2. In the first deterioration mode, the system deteriorates slowly. While in the second deterioration mode, it deteriorates at a greater rate and falls into a failure state quickly.

The failure state in Fig. 1 does not mean that the system cannot be in operation, but means that its low reliability is unacceptable for economic and safety reasons. Different components and equipments should set different reliability thresholds for that larger threshold conforms to the area that requires high safety (e.g. aerospace equipment and aircraft), and smaller value corresponds to the area which requires low safety (e.g. some civil enterprises). The deterioration considered in this paper is a gradual process caused by incipient fault, but not sudden process caused by 'hard' fault.

Two problems here are (1) how to get the reliability through process data, which are easy to collect in modern industries; and (2) how to detect the mode change time t_{MC}. The concrete predictive maintenance policy is shown in the next section.

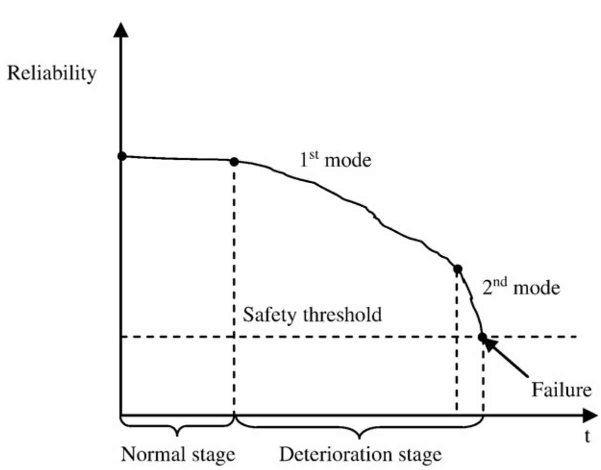

Fig. 1. Scheme of system deterioration.

3. Predictive maintenance

3.1. Review of probabilistic fault prediction

A probabilistic fault prediction method based on principle component analysis (PCA) and Bayesian Auto-regression (BAR) model, illustrated as Fig. 2, was presented in our pioneer work [12]. As shown in Fig. 2, the method has two stages, which are off-line modeling stage and on-line prediction stage, respectively. For the off-line modeling, PCA is performed to the historical normal process data to get system's monitoring index, i.e. the combined index.

A data set $X'(n\times m)$, composed of n samples of m variables, is firstly normalized to zero-mean and unit-variance matrix X. Then, X is decomposed as Eq. (1) by PCA.

$$X = TP^T + E = TP^T + \tilde{T}\tilde{P}^T \tag{1}$$

where $T\in R^{n\times l}$ and $P\in R^{m\times l}$ are the score and loading matrices, respectively; $\tilde{T}\in R^{n\times(m-l)}$ and $\tilde{P}\in R^{m\times(m-l)}$ are respectively a residual score matrix and a residual loading matrix; l is the number of principal components (PCs) retained in the PCA model; E is the residual matrix which can be further decomposed into the product of $\tilde{T}$ and $\tilde{P}$.

The combined index is given as Eq. (2) [13]:

$$CI = \frac{SPE(x_{new})}{\delta^2} + \frac{T^2(x_{new})}{\chi_l^2} = x_{new}^T\Phi x_{new} \tag{2}$$

where $x_{new}\in R^{1\times m}$ is a new sampling data; δ^2 and χ_l^2 are the control limits of the SPE and T^2 statistics, respectively; Φ is symmetric and positive definite, and it equals to

$$\Phi = \frac{P\Lambda^{-1}P^T}{\chi_l^2} + \frac{I-PP^T}{\delta^2} = \frac{P\Lambda^{-1}P^T}{\chi_l^2} + \frac{\tilde{P}\tilde{P}^T}{\delta^2} \tag{3}$$

where $\Lambda = T^TT/(n-1)$ are the principal eigenvalues, and I is an identity matrix.

After that, a sliding window cumulative sum (SW-CUSUM), which is shown in Eq. (4), was proposed to transform the combined index to a new index which shows more regularity.

$$C_t = \sum_{i=t-W}^{t} CI_i, t = W + 1, \cdots, n \tag{4}$$

where W is the window length.

Finally, the control limit of this transform index C_{CL} is deduced by kernel density estimation. For the on-line prediction, the transformed index is calculated as the same as that of the off-line modeling stage. BAR model is utilized to get the prediction density of the transformed index in future time. According to the control limit calculated at the modeling stage and the prediction density, the fault probability in the future time can be calculated.

$$p_F(t + k) = 1-p\left(\hat{C}(t + k)\leq C_{CL}\right) \tag{5}$$

where t is the current sampling time, k is the predictive step, $p_F(\cdot)$ is the fault probability, $\hat{C}(\cdot)$ is the samplings obeyed the prediction density distribution, $p(\hat{C}(t+k)\leq C_{CL})$ is the probability that the system in the normal state.