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ORIGINAL ARTICLE

Single-machine-based predictive maintenance model considering intelligent machinery prognostics

Wenzhu Liao · Ying Wang · Ershun Pan

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Abstract As an increasing number of manufacturers are beginning to realize the importance of maintaining throughput, many maintenance models have been developed to enable machines to achieve near-zero downtime. However, previous maintenance models usually ignore machine's deterioration process. Therefore, this paper develops a novel data-driven machinery prognostic approach for machine performance assessment and prediction. With this prognostic information, a predictive maintenance model is proposed for a repairable deteriorating machine. As machine performance can be assessed, once it reaches the maintenance threshold, a maintenance operation is performed to restore the machine. Moreover, an operational cost is introduced to meet real manufacturing process. In this predictive maintenance model, the optimal maintenance threshold and maintenance cycle number are obtained with the aim to minimize the long-term average cost. Finally, a case study is presented. The computational results show the efficiency of this proposed predictive maintenance model.

Keywords Predictive maintenance · Prognostics · Assessment · Prediction · Optimization

W. Liao (✉)
College of Mechanical Engineering, Chongqing University, Chongqing 400030, China
e-mail: liaowz@cqu.edu.cn

Y. Wang · E. Pan
School of Mechanical Engineering, Shanghai Jiao Tong University, Shanghai 200240, China

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1 Introduction

In manufacturing, machines suffer increasing wear with usage and age as deterioration process, which causes low reliability and high operational cost [1]. Machine failures usually make huge economic losses. Hence, maintenance management as an important part in manufacturing systems has been widely used to keep machines in good operation to decrease failures and reduce high operational cost and breakdown cost [2]. Many researchers have studied on a rich variety of maintenance models.

Since 1960s, the analysis and modeling of maintenance operations have aroused the interests from researchers. Barlow and Hunter first proposed a simple periodic replacement model considering minimal repair, in which minimal repair was performed immediately after machine failures to restore the machine to its prior state before failures [3]. Based on this time-based maintenance model, a lot of scheduled maintenance models that predetermine fixed time intervals to perform maintenance operations (i.e., machine's unavailable periods are known in advance) have been developed. For example, Khandelwal et al. studied an application of periodic maintenance model for a machine [4]. Then, Yak et al. used a periodic maintenance model to achieve the reliability requirements for a fault-tolerant computer system [5]. By comparing with failure-based maintenance models, scheduled maintenance models show that they are more positive and efficient [6]. However, how to decide maintenance interval is a crucial work [7, 8]. If the maintenance interval is too long, although it can decrease maintenance operations so as to reduce maintenance cost, machine reliability will be low and more failures will occur. This leads to higher breakdown cost. If the maintenance interval is too short, although the machine remains in good operation condition, maintenance cost will be much higher. Hence, neither too long nor too short maintenance interval is suitable for maintenance models due to economic loss [9]. If maintenance operations could be well planned according to machine's condition, much more resources would be saved. Machine's condition should thus be known ahead to help arrange flexible maintenance intervals for appropriate maintenance operations. Based on this scheme, preventive maintenance is studied for the optimization of those cases in which maintenance operation is controllable [10–12]. Although now there is some research on preventive maintenance models, most of them involved the use of common function distributions to describe machine degradation, which seems unpractical [13, 14].

Therefore, it becomes essential to develop good maintenance planning based on machine's real deterioration process. With the development of complex manufacturing process, condition-based maintenance which is a kind of maintenance programs that recommends maintenance operations based on machine's condition is being implemented [15]. Condition-based maintenance attempts to avoid unnecessary maintenance tasks by performing operations only when there is evidence of abnormal behaviors of the machine, which requires machine's condition information. In recent years, with the applications of embedded agent techniques and tether-free techniques [16], it is possible to monitor machine's condition information continuously. However, most of available condition-based maintenance research only set several machine's failed cases, then identify current machine's condition whether belonging to those cases. Obviously, this kind of condition-based maintenance ignores machine degradation, which conducts the research on predictive maintenance models with machinery prognostic information nowadays. Predictive maintenance is a positive and useful condition-based maintenance methodology that machine's condition can be estimated and predicted through continuous monitoring [17]. As machine's performance can be obtained, it is feasible for predictive maintenance to determine the required maintenance operations prior to any predicted failure, which can be proved to greatly improve the machine safety [18].

Through reviewing previous literature research about maintenance models, it can be found that maintenance models are greatly improved and developed. Comparing with the early failure-based maintenance models, time-based maintenance models show that they are more positive and efficient because this kind of scheduled maintenance models predetermine fixed maintenance time intervals to reduce machine breakdowns. However, as time-based maintenance models do not consider machine's condition which should be an important issue for performing maintenance operations, preventive maintenance models are developed in which machine's condition is known ahead and maintenance operations are controllable. Later, because most of preventive maintenance models used common function distributions to describe machine degradation, they cannot satisfy real manufacturing processes. Based on this scheme, condition-based maintenance which is a kind of maintenance programs that recommends maintenance operations based on machine's condition is being implemented. However, most of available condition-based maintenance models only set several machine's failed cases, which ignores machine deterioration process. Hence, in order to determine the required maintenance operations prior to any predicted failure, a positive and useful predictive maintenance methodology with machinery prognostic information is researched to estimate and predict machine's performance through continuous monitoring, which improves the machine safety greatly.

Thus, by comparing previous relevant maintenance research, this paper is devoted to propose a predictive maintenance model to arrange the maintenance scheduling for a repairable deteriorating machine with the aim to minimize the long-term average cost. By applying the developed novel data-driven machinery prognostic approach in this paper, machine's performance (i.e., machine's health index H) can be estimated and predicted. Whenever machine's health index reaches a maintenance threshold H_s, a predictive maintenance operation is performed to restore the machine. Once it is the Nth time for the machine to reach the maintenance threshold H_s, the machine should be replaced to be "as good as new." In this predictive maintenance model, the optimal machine's maintenance threshold H_s^* and predictive maintenance cycles number N^* are determined under the criterion of minimization of the long-term average cost in machine's residual life. Thus, in this paper, a predictive maintenance $\left(H_s^*, N^*\right)$ model with a data-driven machinery prognostic approach is proposed to search good maintenance scheduling for a repairable deteriorating machine. Moreover, in order to construct a more reasonable maintenance model, an operational cost is introduced to be variant according to machine's condition and its maintenance process.

The rest of this paper is structured as follows: Section 2 gives the development of this proposed predictive maintenance model. Section 3 describes the problem description of this study. Section 4 presents a novel data-driven machinery prognostic approach for machine performance assessment and prediction. Then, Section 5 provides the mathematical framework of predictive maintenance optimization model. In Section 6, a case study is demonstrated, and the computational results are discussed. Finally, Section 7 gives the conclusions and future work of this paper.

2 Development of this proposed predictive maintenance model

Comparing with the maintenance models available today, this study tries to develop a predictive maintenance model focused on the following parts in order to meet more practical situations:

1. In reality, machines suffer increasing wear with increased age and usage due to machine degradation, which causes low reliability [19]. In previous maintenance models, machine's deteriorating process is usually ignored. They just pre-design fixed maintenance intervals to perform maintenance operations, or compare current machine's condition with bad cases to decide whether maintenance operations are required. It is obvious that machine's condition and its deteriorating process should be known for arranging suitable maintenance operations. Hence, in order to meet practical situations, this study develops a machinery prognostic approach and considers machine's deterioration process to support maintenance planning. In this proposed predictive maintenance model, maintenance intervals can be well controllable, and the suitable maintenance threshold and maintenance cycles number can be solved with the aim of minimizing long-term average cost.
2. As this predictive maintenance model is studied with the aim of minimizing the long-term average cost, it is necessary to discuss related cost factors for the cost objective function [20]. Although researchers have provided many maintenance models considering a maintenance cost, few of them consider an operational cost. Generally, an operational cost is used to describe the cost occurred during the operating process [21, 22]. However, few researchers have focused on cost analysis about the operational cost and moreover defined it as an invariant value. In real manufacturing process, a machine becomes weak and hard to operate after a long time operation; hence, the operational cost should be higher. Once machine's condition gets worse, it may be not an economical way to perform maintenance operations only as the operational cost becomes extremely high [23, 24]. When involved in such situation, replacing the machine will be more economical and practical. Therefore, in order to well construct the predictive maintenance model, an operational cost is considered in this paper. Moreover, it is defined to be variant with usage and maintenance operations. By adding this operational cost, this predictive maintenance model could meet more practical situations.
3. For a repairable machine, maintenance operations can restore the machine. However, if the maintenance model is constructed without the limit of maintenance operations, one issue appears. The issue is if a maintenance cost is low enough, the maintenance cycles number N solved by academic cost objective function will be an infinite value, which is impossible in reality. In real manufacturing process, a machine cannot be performed by maintenance operations all along. That is to say, maintenance operations cannot be performed without any restriction because there will never be an infinite number of maintenance operations in finite time [25, 26]. Hence, in order to avoid the situation of "no replacement but infinite number of maintenance operations" caused by academic cost objective functions, this study has taken an upper bound of maintenance cycles number to be the restriction for cost objective function in proposed predictive maintenance model.

With these above-mentioned considerations, this study tries to develop a predictive maintenance model with machinery prognostic information for a repairable deteriorating machine to bridge the gaps between theory and practical situations.

3 Problem description

This paper studies a predictive maintenance model for a repairable deteriorating machine with its machinery prognostic information. In this study, machine's condition obtained from the original on-line collected data is used to estimate machine's health index (i.e., the initial input parameter about machine's condition in this predictive maintenance model is machine's health index H). It is supposed that once machine's health index reaches the maintenance threshold H_s, scheduled predictive maintenance operations should be performed. The predictive maintenance operations can reduce the increasing risk of machine failures and can be able to restore the machine to be "as good as new" (i.e., the machine is renewed). When it is the Nth time for the machine to reach the maintenance threshold H_s, the machine should be replaced. As shown in Fig. 1, H_0 ($0 \leq H_0 \leq 1$) is machine's initial health index at the beginning, H_{new} is machine's health index when machine's condition is "as good as new," and H_{fail} is machine's health index when machine's condition is bad. And i is the ordinal of predictive maintenance cycles, where $i \in \{1,2,\ldots,N\}$. It is clear that $T_i(i = 1, 2, \cdots, N)$ denotes each maintenance interval during the maintenance process.

The whole research structure of this study is presented in Fig. 2. Machine's original condition data is collected by monitoring tools and then used to estimate and predict machine's health index with proposed machinery prognostic approach. Based on the obtained prognostic information which is viewed as an inputting item for this proposed predictive maintenance model, the optimal maintenance threshold and maintenance cycle number are determined with the aim to minimize the long-term average cost.

4 Data-driven machinery prognostic approach

Nowadays, in prognostic and health management research, with the advancements in sensor and intelligent prognosis

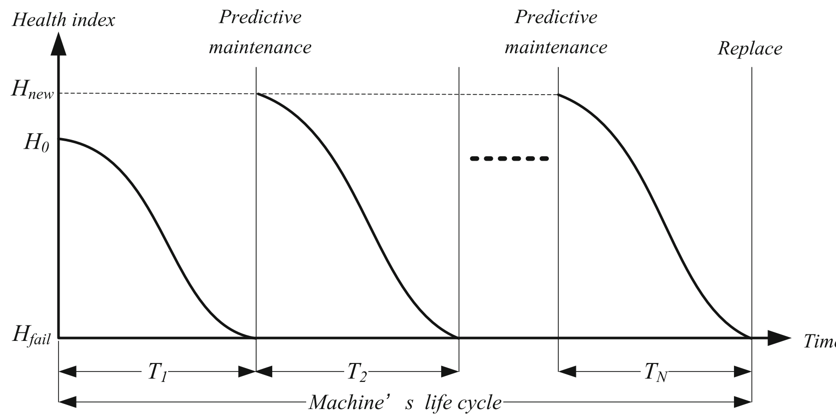


Fig. 1 Machine's deterioration process and its predictive maintenance cycles

technologies, machine's condition can be monitored and its degradation can be estimated [27–29]. Machinery prognostics that is the capability to provide early detection and isolation of the precursor and/or incipient fault condition to a machine failure condition has been applied to the field of predictive maintenance. Prognostics is to know before, to predict the future as a result of rational study and analysis of available pertinent data [30]. In manufacturing process, machine's current and future conditions obtained by machinery prognostic approach provide the important information for maintenance planning. The continuous assessment and prediction of a machine's performance can thus enable collaborative machine life cycle management, which conducts predictive maintenance to prevent unexpected machine failures and reduce unscheduled costly downtime [31–33]. Hence, it is vital to develop good machinery prognostic approach to accurately estimate machine's health condition and predict machine's deterioration process.

This section develops a data-driven machinery prognostic approach based on statistical pattern recognition and autoregressive and moving average model. By applying this approach, machine's health condition can be estimated and machine degradation can be predicted.

4.1 Machine performance assessment

This section develops a performance assessment method based on statistical pattern recognition to estimate machine's health condition. With the collected monitoring data, machine's health index can be obtained by this performance

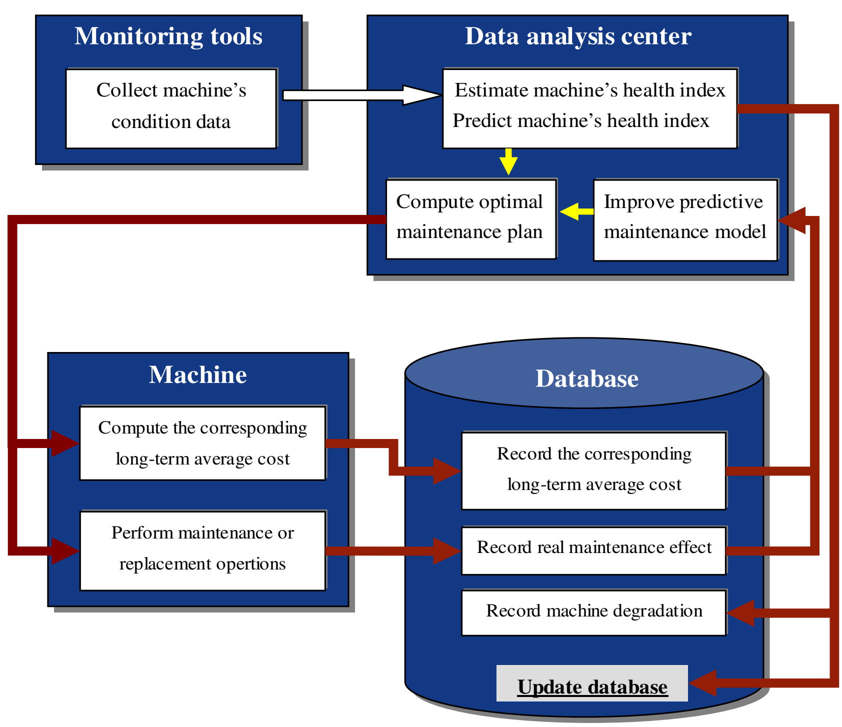


Fig. 2 The research structure of this predictive maintenance model

assessment method to describe machine's health condition, which provides the base for machine performance prediction.

First, because the collected monitoring data usually contain multidimensional data sets, feature extraction is applied to obtain dominant information. In this paper, principle component analysis is adopted for feature extraction and dimension reduction. The procedure is given as below:

Step 1: Normalize machine's collected condition monitoring data.
Step 2: Build correlation matrix.
Step 3: Compute the eigenvalues and eigenvector of correlation matrix.
Step 4: Compare the variance contribution and accumulation of eigenvalues.
Step 5: Obtain the dominant feature of machine's condition by selection criterion.

Then, the dominant feature is clustered by considering statistical pattern recognition. The main idea is: By designing a decision boundary, a given sample can be clustered into one certain pattern with the decision function. Given a set of patterns of machine's condition $\{\omega_1,\omega_2,\ldots,\omega_c\}$, c is the number of patterns. If $\mathbf{X}=(x_1,x_2,\ldots,x_d)^T$ is the feature vector for one certain machine's condition, for two patterns of machine's condition ω_1 and ω_2, $\mathbf{X}$ is clustered into ω_1 (e.g., $\mathbf{X} \in \omega_1$) with the following decision criterion.

$$l(\mathbf{X}) = \frac{p(\mathbf{X}|\omega_1)}{p(\mathbf{X}|\omega_2)} > \frac{p(\omega_2)}{p(\omega_1)} \tag{1}$$

where $l(\mathbf{X})$ is the likelihood function. With these recognized patterns of machine's condition, new sample can be recognized.

Finally, chi-square test is used to obtain machine's health index. Given a Gaussian distribution of multi-variables as $\vec{X} \sim \mathrm{MVN}(\vec{\mu}, K)$, after applying feature extraction and dimension reduction, it transforms to be $\widetilde{X} \sim \mathrm{MVN}(0, I_\mathrm{p})$. Thus, machine's health index $H(\vec{X})$ can be obtained by

$$H(\vec{X}) = 1 - F_{\chi_p^2}\left(s\sum_{i=1}^{p}\widetilde{x}_i^2\right) \tag{2}$$

where s is the sensitivity factor (usually to be 0.25).

4.2 Machine performance prediction

Based on the obtained machine's health index, autoregressive and moving average model is used to predict machine degradation. Given a general machine performance prediction model as

$$H_t - \sum_{i=1}^{p}\phi_i \cdot H_{t-i} = \varepsilon_t - \sum_{j=1}^{q}\theta_j \cdot \varepsilon_{t-j} \tag{3}$$

where $\{\varepsilon_t\}$ is the white noise, $\phi_1\phi_2\cdots\phi_p$ is the autoregressive coefficient, and $\theta_1\theta_2\cdots\theta_q$ is the moving average coefficient, p and q are the order, respectively. Equation 3 means machine's future health index H_t is influenced by machine's previous health index and the turbulence occurred during this interval.

Given a set of samples of machine's health index $\{H_1, H_2, \cdots, H_m\}$, where m is the length, the mathematical statements of machine performance prediction model are presented as follows:

Step 1: Estimate a regression factor δ and residual variance σ.

$$\widehat{\delta}(\partial_m) = \left(\widehat{\delta}_1, \widehat{\delta}_2, \cdots, \widehat{\delta}_{\partial_m}\right)^T = [\widehat{\gamma}(j-i)]^{-1}_{\partial_m\times\partial_m}[\widehat{\gamma}(i)]_{\partial_m\times 1} \tag{4}$$

$$\widehat{\sigma}^2_{\partial_m} = \widehat{\gamma}(0) - [\widehat{\gamma}(i)]^T_{\partial_m\times 1}[\widehat{\gamma}(j-i)]^{-1}_{\partial_m\times\partial_m}[\widehat{\gamma}(i)]^T_{\partial_m\times 1} \tag{5}$$

where $\widehat{\gamma}(K) = \frac{1}{m}\sum_{t=1}^{m-K} H_t H_{t+K}$ and ∂_m is a multiple of lg m.

Step 2: Obtain residual $\widehat{\varepsilon}_t$.

$$\widehat{\varepsilon}_t = H_t - \sum_{i=1}^{\partial_m}\widehat{\delta}_i H_{t-i} \tag{6}$$

Step 3: Estimate model parameters $\widehat{\beta}$ and $\widehat{\sigma}^2_{pq}$.

$$\begin{cases} \widehat{\beta} = \begin{pmatrix} \widehat{\phi} \\ \widehat{\theta} \end{pmatrix} = \begin{pmatrix} \left[\widehat{\gamma}^H(j-i)\right]_{p\times p} & \left[\widehat{\gamma}^{H\varepsilon}(j-i)\right]_{p\times q} \\ \left[\left[\widehat{\gamma}^{H\varepsilon}(j-i)\right]_{p\times q}\right]^T & \left[\widehat{\gamma}^{\varepsilon}(j-i)\right]_{q\times q} \end{pmatrix} \begin{pmatrix} \left[\gamma^H(K)\right]_{p\times 1} \\ \left[\gamma^{H\varepsilon}(K)\right]_{q\times 1} \end{pmatrix} \\ \widehat{\sigma}^2_{pq} = \widehat{\gamma}(0) - \begin{pmatrix} \widehat{\phi} \\ \widehat{\theta} \end{pmatrix}^T \begin{pmatrix} \left[\gamma^H(K)\right]_{p\times 1} \\ \left[\gamma^{H\varepsilon}(K)\right]_{q\times 1} \end{pmatrix} \end{cases} \tag{7}$$

where

$$\widehat{\gamma}^{H}(K) = \frac{1}{m-K}\sum_{t=1}^{m-K} H_t H_{t+K}, \quad K = 1,2,\cdots,p \tag{8}$$

$$\widehat{\gamma}^{\varepsilon}(K) = \frac{1}{m-\partial_m-K}\sum_{t=1}^{m-K} \varepsilon_t \varepsilon_{t+K}, \quad K = 1,2,\cdots,q \tag{9}$$

$$\widehat{\gamma}^{H\varepsilon}(K) = \frac{1}{m-\partial_m-K}\sum_{t=1}^{m-K} H_t \varepsilon_{t+K} \tag{10}$$

$$\widehat{\gamma}^{\varepsilon H}(K) = \widehat{\gamma}^{H\varepsilon}(-K) \tag{11}$$

Step 4: Estimate the order p and q.

SBC criterion is used to estimate the order [34], shown as

$$\text{Minimize} \quad \text{SBC} = \lg \widehat{\sigma}_{pq}^2 + \frac{(p+q+1)\lg(m-p)}{(m-p)} \tag{12}$$

5 Construction of this predictive maintenance model

In this section, the mathematical framework for predictive maintenance model with the aim of minimizing the long-term average cost is established to prove the structural characteristics of the optimum. First, some assumptions are given as follows:

1. An independent machine is studied.
2. A new machine is installed at the beginning.
3. The machine is repairable and deteriorates with increased usage and age.
4. Machine's condition can be monitored continuously and perfectly.
5. The time for maintenance operation is negligible.
6. The machine begins a new deteriorating process after maintenance operations.

In order to minimize the long-term average cost for the machine, the related cost factors in cost objective function must be well considered. As discussed in Section 2, an operational cost used to describe the cost during machine's operating process is considered. Moreover, it is viewed to be variant with usage and maintenance operations. In this paper, the operational cost is constructed by three parts: a fixed cost for operating, a relative variant cost for the frequency of maintenance operations, and a relative variant cost for time. Hence, this study defines the operational cost $C_o(i,t)$ changes according to i and t (i.e., $C_o(i,t)$ is relative with i and t, where i is maintenance cycles and t is time). $C_o(i,t)$ is constructed with three parts: c_{oo}, c_{vi}, and c_{vt}. c_{oo} represents the fixed cost for operating, c_{vi} represents the relative variant cost rate according to the maintenance cycles number, and c_{vt} represents the relative variant cost rate according to time. Generally, c_{vi} and c_{vt} could be deduced from machine's history maintenance data. Hence, the operational cost is constructed as:

$$C_o(i,t) = c_{oo} + c_{vi} \cdot i + c_{vt} \cdot t \tag{13}$$

With Eq. 13, it can be obtained that $\int_0^{T_i} C_o(i,t)\mathrm{d}t$ represents the operational cost for each predictive maintenance cycle.

In this predictive maintenance model, for machine's whole life cycle, there will be probable predictive maintenance cost, probable replacement cost, and probable operational cost. Generally, a maintenance cost C_{pm} is less than a replacement cost C_r (i.e., $C_{pm}<C_r$). Thus, the expected long-term average cost ETC for each predictive maintenance cycle can be inferred as:

$$\text{ETC}_i = \frac{\int_0^{T_i} C_o(i,t)\mathrm{d}t + C_{pm}}{T_i} \quad \text{for } 0 < i < N \tag{14}$$

where T_i is the ith maintenance interval. In this predictive maintenance model, T_i could be estimated by the proposed machinery prognostic approach given in Section 4.

For this predictive maintenance model, once it is the Nth time to reach maintenance threshold H_s, the machine is replaced. Hence, in the Nth maintenance cycle, replacement is scheduled. Thus, the expected long-term cost for the Nth maintenance cycle should be

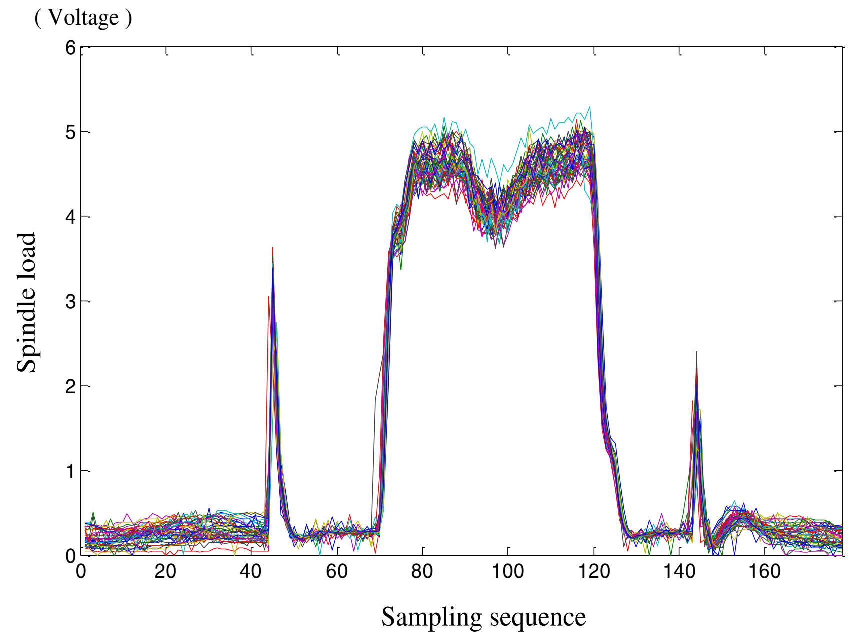
$$\text{ETC}_N = \frac{\int_0^{T_N} C_o(N,t)\mathrm{d}t + C_r}{T_N} \quad \text{for } i = N \tag{15}$$

Therefore, from the machine installation to replacement ($0<i\leq N$), the expected long-term average cost is:

$$\text{ETC} = \frac{\sum_{i=1}^{N-1} \text{ETC}_i \cdot T_i + \text{ETC}_N \cdot T_N}{\sum_{i=1}^{N} T_i} \quad \text{for } (0 < i \leq N) \tag{16}$$

With a given maintenance threshold in real situations, the entire optimization is implemented as a two-variable search, where the variable N is incremented. When the machine is available within a permitted operating region, the minimal ETC could be obtained by comparing all the local optimal results corresponding to different maintenance threshold H_s.

Fig. 3 Fifty sample sets for machine's good condition



The procedures of the search algorithm are outlined as follows:

Step 1: Fix the upper bound of maintenance cycle N_{up} according to the related maintenance data.

Step 2: Initialize C_{pm} beyond the N_{up}th predictive maintenance as a very larger number, say 10^7.

Step 3: Initialize ETC* as a very larger number, say 10^7 (ETC* is used to store the minimal ETC value).

Step 4: For the given maintenance threshold region $[H_1,H_2]$ where $H_1<H_2$, let $H_s=H_1$.

Step 5: Search N from one in step of one until ETC cannot be further reduced. For a given value of N:

Step 5.1: Calculate the value of $\{T_1,\ldots,T_N\}$ by Eqs. 3, 4, 5, 6, 7, 8, 9, 10, and 11.

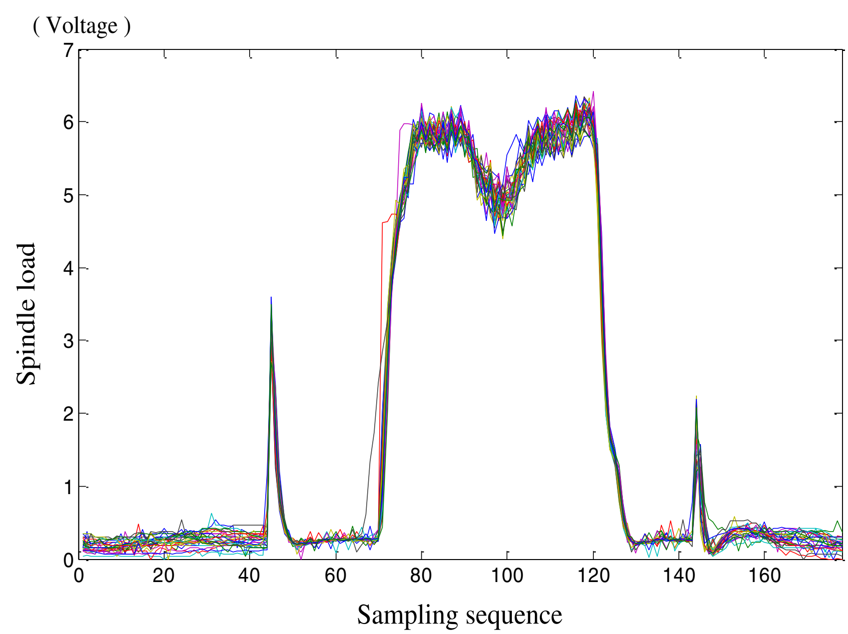
Step 5.2: Calculate ETC by Eq. 16.

Step 5.3: If the calculated ETC is smaller than the current ETC*, replace the current ETC* by the calculated ETC (i.e., ETC*=ETC). And the current value of N and $\{T_1,\ldots,T_N\}$ are stored as the local optimal result, $N^*=N$.

Step 6: Let $H_s=H_s+0.01$, if $H_s\leq H_2$, return to Step 5. Otherwise, stop.

Note that the traversal of machine's health index belonging to maintenance threshold region is spaced with unit

Fig. 4 Thirty sample sets for machine's bad condition



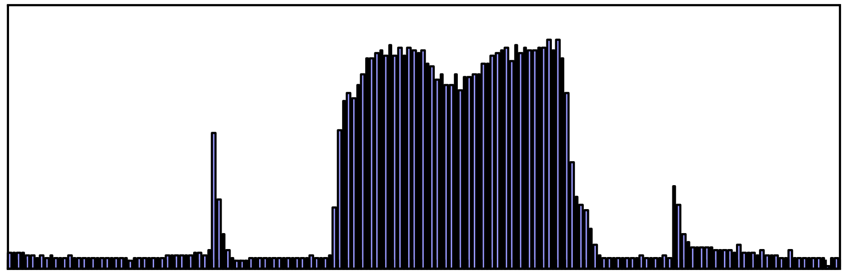


Fig. 5 A set of samples for testing

0.01, as such kind of precision of health index can well satisfy real maintenance processes. And it also simplifies computation. At the end of the entire search, the optimal ETC* can be identified. Then, the corresponding predictive maintenance plan (H_s^*,N^*) is determined.

6 A case study

In this study, a case about a drilling machine is researched to demonstrate the development and application. The drilling machine is performed maintenance operations to decrease its failures and keep health condition to remain its operating status. Although frequent maintenance operations can keep its operating status, high maintenance cost occurs. In order to balance the trade-offs between high health condition and low long-term average cost, a suitable predictive maintenance model is required. The original data of this drilling machine such as its condition data and cost factor can be collected by monitoring tools and deduced from history maintenance data.

6.1 Machine condition prognosis

In this example, a spindle load signal acquired from this drilling machine is used for machine performance assessment and prediction. First, 50 sets of samples of machine's perfect condition and 30 sets of samples of machine's failure condition are collected (see Figs. 3 and 4, the sampling interval is 135 s).

By training these samples, the patterns of "good" and "bad" machine conditions are recognized. Then, through applying the machine performance assessment method in Section 4.1, for a test set of samples (seen in Fig. 5), machine's corresponding health index is obtained to be H=0.6088.

Table 1 Parameters for machine's performance prediction model

Parameter	ϕ_1	ϕ_2	θ_1	θ_2
Estimation	−0.016127	0.086295	−0.836623	−0.105490
Schwarz criterion	−12.86193			

Then, 500 sets of samples of machine's condition during the operation process are collected, and the corresponding machine's health indexes are assessed. By applying the machine performance prediction method in Section 4.2, machine's performance prediction model is built. Its parameters are in Table 1.

Figure 6 shows the comparison between the actual health index and the predicted health index for these 500 sets of samples. It can be seen that the 85% of variances belong to [−2σ, +2σ] range, which satisfies T test or F test. Therefore, this performance prediction model is reasonable and effective.

Finally, assume machine's health index threshold is H_{fail}=0.20 for maintenance operations. By applying this machinery prognostic approach, it can be obtained that machine's residual life is 18.04 h. Through monitoring machine's real operation process, it is found that after 18.0 h, machine's health index reaches 0.20. By comparing the predicted results with the actual results (see Fig. 7), the computation error is 0.22%, which satisfies T test or F test. Thus, this developed data-driven machinery prognostic approach can well describe machine degradation.

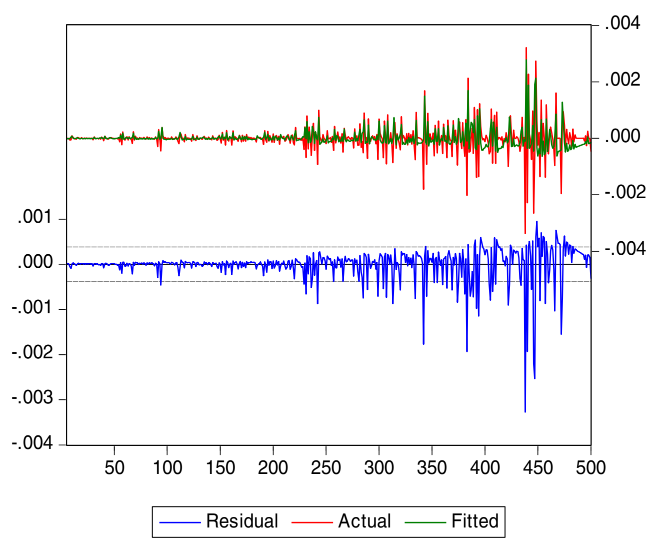


Fig. 6 Comparison between the actual data and the estimated data of the 500 sets of samples

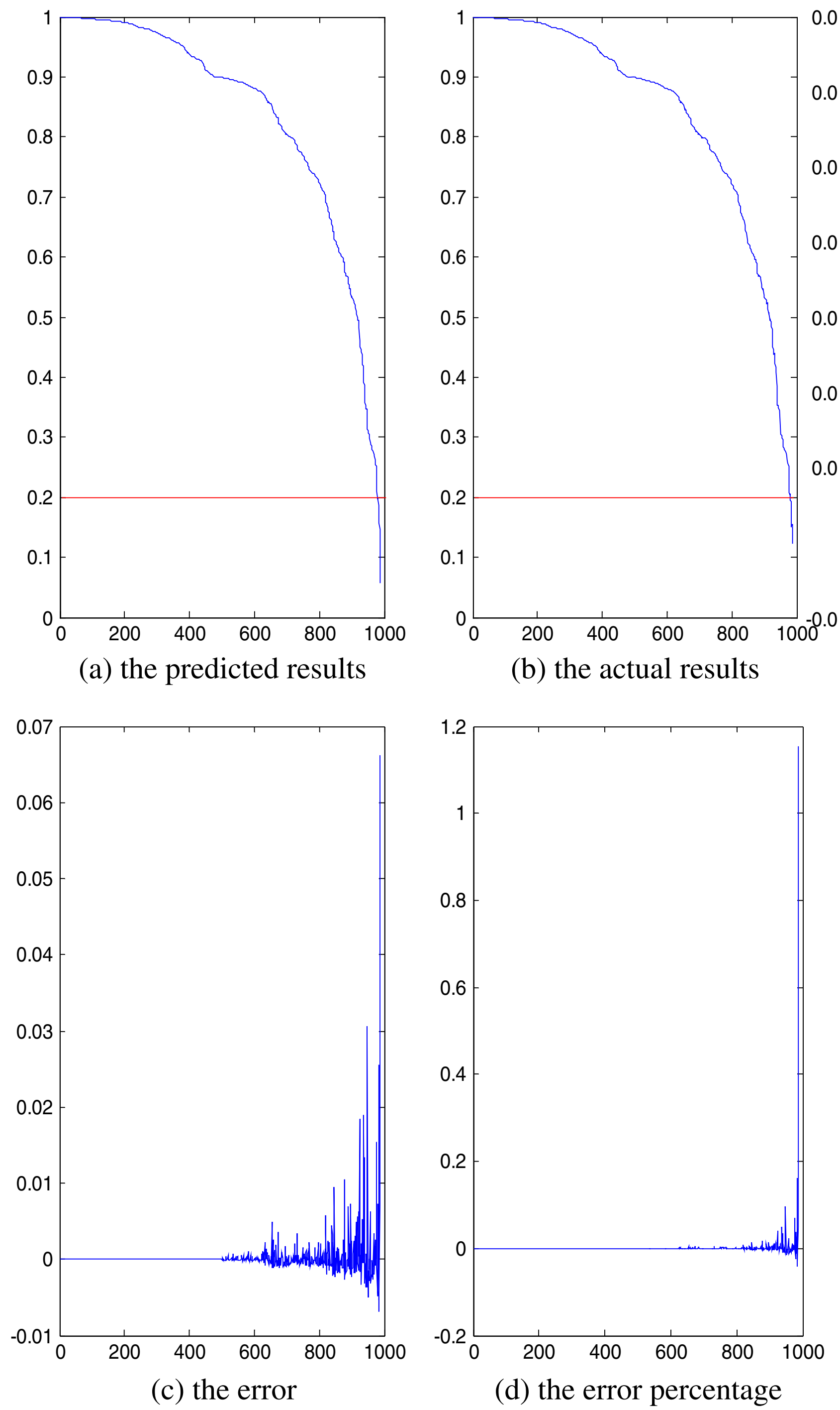


Fig. 7 Comparison between machine's predicted health index and the actual health index. **a** The predicted results, **b** the actual results, **c** the error, and **d** the error percentage

6.2 Maintenance arrangement

As the machinery prognostic information is obtained, this section uses it to construct predictive maintenance model. Meanwhile, because the machine cannot be performed only by maintenance operations all along, discussed in Section 2, in order to avoid the situation of "no replacement but infinite maintenance operations," the upper bound of predictive maintenance cycles number is restricted to be $N \leq 10$. Table 2 shows the related cost factors in this predictive maintenance model. Generally, these related cost factors are pre-designed. In real manufacturing, maintenance engineers

Table 2 The related cost factors in this example

C_{pm}	C_r	c_{oo}	c_{vi}	c_{vt}
500	5,000	4	1.2	0.05

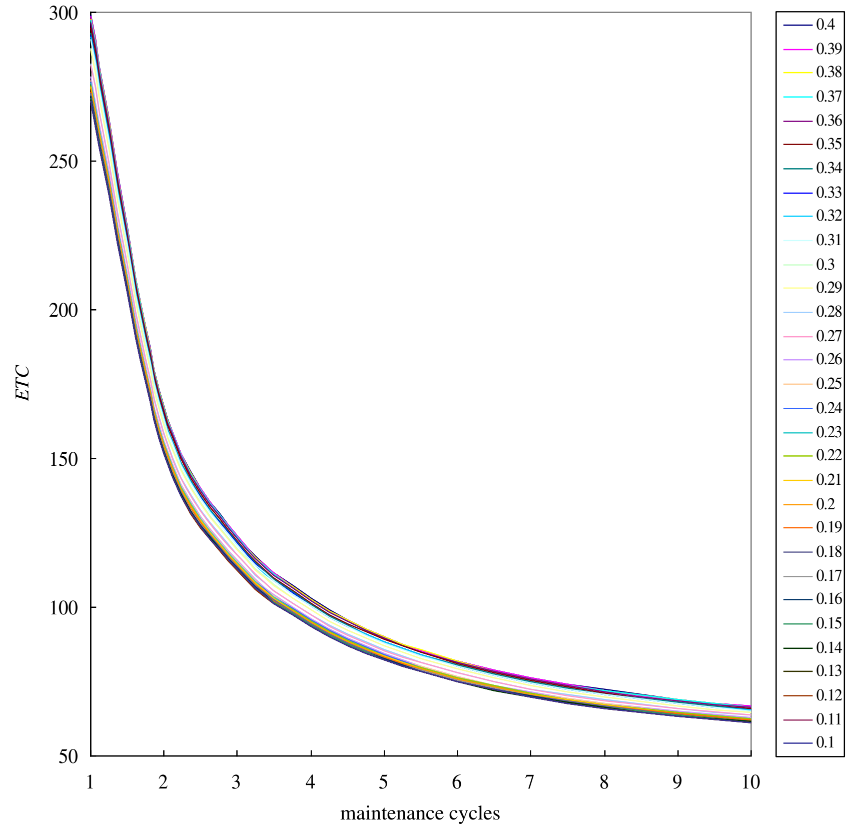


Fig. 8 Relationship between ETC and H_s and N

usually should be responsible for the design of these cost factors.

Let the searching range of the maintenance threshold be $H_s \in [0.10, 0.40)$ for computation simplification and resources saving. According to the procedures of the search algorithm about this predictive maintenance model presented in Section 5, the computational results with the aim to minimize the long-term average cost are obtained. Figure 8 illustrates the computational results of the predictive maintenance model for this drilling machine with the given maintenance threshold H_s. If one maintenance plan requires machine's maintenance threshold to be H_s=0.90, the optimal maintenance scheduling is obtained: Among machine's maintenance threshold region, there is a minimal long-term average cost ETC=61.337 under a predictive maintenance plan (0.13, 10). That is to say, there should be $N-1=9$ predictive maintenance cycles, and this machine should be replaced when it reaches the maintenance threshold H_s=0.13 at the 10th time.

From Table 3, the computational results could also prove that neither too small nor too large machine's maintenance threshold is suitable for maintenance arrangement with the aim to minimize the long-term average cost. It indicates that if this drilling machine requires smooth working, in order to minimize the long-term average cost, machine's maintenance threshold should be set to be 0.13 and the machine should run 10 predictive maintenance cycles. When it is the 10th time for this machine to reach the maintenance threshold, the machine should be replaced.

Table 3 Computational results of *ETC* values when N=10

H_s	0.39	0.38	0.37	0.36	0.35	0.34	0.33	0.32	0.31	0.3
ETC	66.704	66.583	66.462	66.342	65.985	65.633	65.516	65.400	65.285	64.715
H_s	0.29	0.28	0.27	0.26	0.25	0.24	0.23	0.22	0.21	0.2
ETC	64.602	63.719	63.611	62.865	62.656	62.552	62.448	62.345	62.243	62.140
H_s	0.19	0.18	0.17	0.16	0.15	0.14	0.13	0.12	0.11	0.1
ETC	61.937	61.836	61.735	61.635	61.535	61.436	61.337	61.347	61.357	61.367

Table 4 Computational results with the variation of C_{pm}

C_{pm}	ETC	H_s	N
100	42.289	0.13	10
200	47.051	0.13	10
300	51.813	0.13	10
400	56.575	0.13	10
1,000	85.146	0.13	10
1,500	108.956	0.13	10
2,000	132.765	0.13	10
3,000	180.385	0.13	10
4,000	227.992	0.13	9

6.3 Results discussion

In order to discuss the influences of the cost parameters, the computational results with the variation of maintenance cost C_{pm} and replacement cost C_r are shown in Tables 4 and 5, respectively. In Table 4, with the increase of maintenance cost C_{pm}, the corresponding ETC increases and the maintenance cycles number N decreases. Table 5 illustrates the variation of replacement cost. With the increase of replacement cost C_r, the corresponding ETC increases and the maintenance cycles number N increases. The computational results in Table 5 indicate that increasing C_r means relatively decreasing C_{pm}, which could be exactly in line with the computational results in Table 4.

During the maintenance period, when machine's maintenance threshold becomes lower, the maintenance interval gets longer, which brings high operational cost. In the other hand, when machine's maintenance threshold becomes higher, the maintenance interval gets shorter, which brings high maintenance cost. If one maintenance plan cannot balance the maintenance cost, the operational cost, and the replacement cost, the long-term average cost cannot be minimal. It is thus important to decide a suitable machine's maintenance threshold and maintenance cycles number to minimize the long-term average cost. In Fig. 8, it is obvious that if machine's maintenance threshold is larger than 0.13, frequent maintenance cost and replacement cost make the long-term average cost high. If machine's maintenance threshold is smaller than 0.13, high operational cost makes the long-term average cost high. It can be proved that the operational cost presented in this study can meet practical manufacturing situations.

In addition, in order to discuss the importance of an operational cost in this predictive maintenance model, a situation that "Do not consider the operational cost" is considered. Figure 9 illustrates the relationship between ETC and H_s. The optimal predictive maintenance plan $\left(H_s^*, N^*\right)$ without considering the operational cost is (0.10, 10), and the corresponding ETC is 50.264. For the situation of "Do not consider the operational cost," the maintenance arrangement is mostly decided by the cost rate C_r/C_{pm}, which does not consider the cost occurred and influenced in the maintenance process. Obviously, it is not practical. In this study, this proposed predictive maintenance model considers an operational cost to enrich the cost function for manufacturing requirements. Moreover, this predictive maintenance model further discusses the variant operational cost that can well describe machine's deterioration process. This proposed predictive maintenance model provides a good way for maintenance scheduling to minimize the long-term average cost.

According to the original maintenance plan, this drilling machine adopts periodic maintenance. Maintenance operation is performed every 18 h, and when this operation reaches the fifth time (i.e., after 90 h), this machine is replaced. The long-term average cost ETC obtained by this periodic maintenance is 85.828. It can be found that the value is much higher than that obtained by the proposed predictive maintenance model in this paper. Moreover, as this periodic maintenance model does not consider machine's deterioration process, it cannot assure machine's availability, which conducts huge losses due to the following machine's missing tasks. Therefore, the above computational results show that this predictive maintenance model decreases the maintenance interval and performs better than the original periodic maintenance model or age T models. Moreover, the obtained maintenance interval can help prepare those maintenance operations and achieve the goal of near-zero inventory for the spare parts.

7 Conclusion and future works

Nowadays, as an increasing importance of maintenance management in modern manufacturing process, machinery prognostic approaches that can well describe machine

Table 5 Computational results with the variation of C_r

C_r	ETC	H_s	N
1,000	39.507	0.13	7
2,000	45.464	0.13	10
3,000	50.755	0.13	10
4,000	56.046	0.13	10
6,000	66.628	0.13	10
7,000	71.919	0.13	10
8,000	77.210	0.13	10
9,000	82.501	0.13	10
10,000	87.792	0.13	10

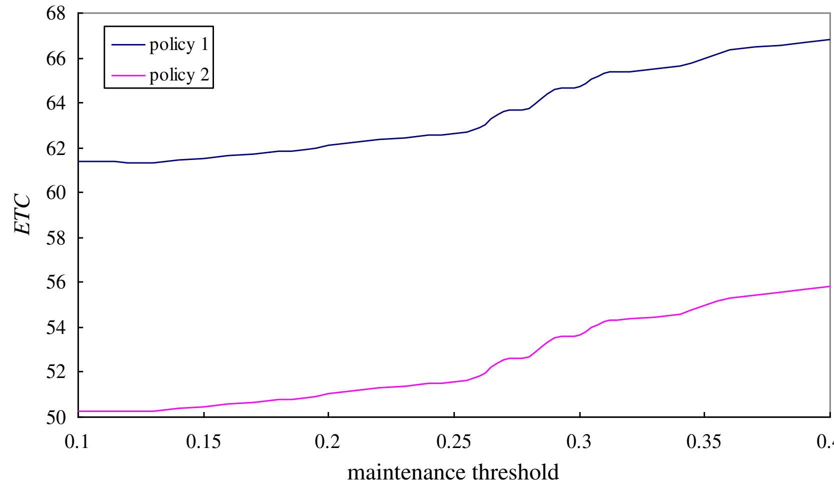


Fig. 9 Relationship between ETC and H_s obtained by policy 1 and policy 2. Note: Policy 1 is the proposed predictive maintenance policy in this study. Policy 2 is maintenance policy without considering operational cost

degradation should be researched to support predictive maintenance model construction. As many previous traditional maintenance models do not consider machine's deterioration process, this study is devoted to provide a predictive maintenance model for maintenance scheduling to minimize the long-term average cost of a repairable deteriorating machine. Through machine's condition data collected by intelligent monitoring tools, this paper develops a novel data-driven performance assessment and prediction approach to assess machine's health condition and predict machine's residual life, which greatly supports machinery prognostic research. Once machine's health index reaches the maintenance threshold, scheduled predictive maintenance operation is performed to restore the machine. In order to meet real manufacturing situations, a variant operational cost influenced by machine's condition and the maintenance process is considered to reasonably describe machine degradation. Through the case study about a drilling tool, this developed machinery prognostic approach and predictive maintenance model is verified and discussed. The computational results can well match machine's real degradation, which proves that this developed machine performance assessment and prediction approach is efficient and practical. Based on this prognostic approach, the proposed predictive maintenance model performs better than the original periodic maintenance model or age T models. Therefore, this predictive maintenance model can help reduce long-term average cost and prepare maintenance operations to achieve the goal of near-zero inventory for the spare parts.

However, there are still some research needed to be further discussed based on this predictive maintenance model. For example, although considering an operational cost can improve this predictive maintenance model, how to design those parameters for its influencing factors must be studied, especially for some complex maintenance processes.

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