On Condition Maintenance Model for Complex Electromechanical Equipments Based on Remaining Useful Life and Wiener Process

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Abstract. Aiming at the problem of condition based maintenance modeling for complex electromechanical equipment, a condition based maintenance model based on residual life prediction and improved Wiener process is proposed; first of all, for the degradation process character of complex electromechanical equipment, this paper proposes a residual life prediction model based on random coefficient Wiener process; To estimate the parameters of degradation process, a prior distribution construction method based on state data is proposed; And the posterior distribution and estimation of degradation process parameters are constructed by Bayes theory, and the remaining life prediction of equipment in operation is realized. Secondly, the decision model of condition based maintenance is established by balancing the reliability and economy targets with the information of remaining life; And the immune particle swarm optimization algorithm is used to solve the model. The case study shows that the residual life prediction model proposed in this paper has higher prediction accuracy and lower prediction uncertainty, the condition based maintenance decision-making model is more practical, has higher operational reliability and economy, and the convergence accuracy of the model solving algorithm is higher.

1. Introduction

With the extensive application of complex electromechanical equipment as a control and actuator in aviation, aerospace and weaponry, higher requirements are placed on its reliability and safety. At the same time, due to its technical complexity, it requires higher technical and economic investment in maintenance and repair. The traditional regular maintenance inevitably causes safety risks and waste of inputs due to "under-maintenance" or "over-maintenance". The contradiction between availability and economy has become increasingly prominent, and it has been unable to meet the maintenance needs of complex electromechanical equipment.

"Health Management" aims to maintain health and maintain equipment in a healthy state [1]. It is a key link and core technology in the Prognostic and Health Management (PHM) architecture. Event-led reactive repairs (after-the-fact repairs) and time-related preventive repairs (regular repairs) are replaced by state-based repairs, ie, On Condition Maintenance (OCM). Depending OCM, accurate parts can be accurately repaired at the right time, effectively improving product availability and reducing maintenance costs.

Under the demand traction and technology promotion, the model of condition-based maintenance decision-making has become a focus issue and hot research direction of PHM technology in the application process of complex electromechanical field [2-9].
From the perspective of equipment degradation process, the method of modeling decision-making is classified. The most commonly used are: proportional hazard model, impact model, delay time model, stochastic process model. Proportional hazards model (PHM) is an empirical model based on mathematical statistics theory\(^\text{[2]}\), which can better describe the internal relationship between system life cycle and related covariates, and determine the impact of each covariate on system risk. It is widely used in reliability and other fields\(^\text{[3]}\). On the basis of this, it aims at the common problems of a batch of equipment, and lacks effective means for the decision-making of condition based maintenance of a single independently operated equipment.

Shock Model (SM) is a typical model in reliability theory engineering\(^\text{[4]}\). Based on the physical damage mechanism, the life, reliability and failure characteristics of the impact equipment are studied. It is widely used in dynamic systems and power grid systems. SM is more realistic from the mechanism of equipment failure, but it is too targeted, and requires a clear understanding of the failure mechanism of the equipment, and the model analysis and solution are more complicated\(^\text{[5]}\).

The Delay Time Model (DTM) is a maintenance inspection model proposed by A.H.Christ\(^\text{[6]}\). It divides the equipment degradation process into two stages through two time points: “initial defect time” and “fault delay time”. DTM provides a viable basic model for functional detection problems, but it lacks an effective mathematical analysis foundation and usually needs to be used with other models.

The above maintenance decision model mostly uses the statistical reliability theory, taking the working time as the decision variable, ignoring the difference between the actual operation of the specific equipment and the utilization of the degradation process performance data. The model is relatively rough. With the development of the theory of maintenance and the support technology, the theory and method of modeling the maintenance decision using the actual operating state of the equipment are widely used. It is basically to establish a model that conforms to the process of equipment degradation, and then establish a condition-based maintenance decision model based on the actual state of the equipment and the maintenance work content.

Due to the randomness of the degradation process of complex equipment, the modeling of condition based maintenance decision-making based on stochastic process has become a hot research direction, such as the modeling of condition based maintenance decision-making based on gamma process\(^\text{[7]}\), Markov chain\(^\text{[8]}\). For complex mechanical and electrical equipment, due to its complex fault mechanism, random dynamic changes of load and operating environment, its degradation degree also has random dynamics, which is reflected in the degradation data with random non-monotonicity, and the adoption of monotonic models such as gamma process and Markov chain has certain limitations. Wiener process is a non-monotonic process, which is suitable for the modeling of non-monotonic degradation process\(^\text{[9]}\).

Therefore, this paper will use the degenerative process model of the Wiener process, combined with the state data of the equipment in operation and the remaining life information, to carry out modeling research on the condition of maintenance maintenance of complex electromechanical equipment.

2. Modeling the remaining life of the equipment in operation

2.1. Basic model of remaining life

Using a stochastic process to model the degradation process, the device life defined by the first time\(^\text{[10]}\) is

\[
T = \inf\{t : X(t) \geq l \mid X(0) < l\}
\]

Where \(X(t)\) is the amount of degradation of the device at time \(t\), and \(l\) is the failure threshold.

Remaining Useful Life (RUL) refers to the length of working time when the equipment is not repaired, from the moment it is detected to the time when the equipment fails. Assuming that the time when the device is running to the current state is \(\tau\), and the device is still not invalid, that is, the amount of degradation \(X(\tau)\leq l\), the remaining life \(TR\) of the device is defined according to equation (1).
\[ T_R = \inf \{ t : X(t + \tau) \geq I \big| X(\tau) < I \} \]  

(2)

2.2. Degradation process modeling based on random coefficient Wiener process

The degradation process obeying the unary Wiener process can be expressed as:

\[ X(t) = \mu t + \sigma B(t) \]  

(3)

Where X(t) is the amount of degradation of the device at time t, B(t)~N(0, t) is the standard Brownian motion, and \( \mu \) and \( \sigma \) are the drift parameter and the diffusion parameter, respectively.

In the past, the Wiener process-based residual life prediction modeling multi-hypothesis process parameters \( \mu \) and \( \sigma \) are constant, which neglects the degradation difference between different equipments of different devices and different degradation stages of the same equipment. It is assumed that the process parameters \( \mu \) and \( \sigma \) are random variables. Let \( \theta = \sigma^2 \), since \( \theta > 0 \), \( \theta^{-1} > 0 \), assuming that \( \theta^{-1} \) obeys the Gamma distribution (all gamma distributions are in the first quadrant) [11], the \( \theta \) distribution function can be expressed as:

\[ f(\theta) = \frac{\beta^\alpha}{\Gamma(\alpha)} \theta^{-\alpha} \exp(-\beta/\theta) \]  

(4)

Suppose that under the condition that the parameter \( \theta \) is known, the parameter \( \mu \) obeys the Gaussian distribution of variance and \( \theta \), that is, \( \mu \sim N(\varphi, \gamma \theta) \), then

\[ f(\mu|\theta) = \frac{1}{\sqrt{2\pi\gamma \theta}} \exp\left(-\frac{(\mu - \varphi)^2}{2\gamma \theta}\right) \]  

(5)

The joint probability density function of the parameters \( \mu, \theta \) can be expressed as

\[ f(\mu, \theta) = f(\theta) \cdot f(\mu|\theta) \]

\[ = \frac{\beta^\alpha}{\Gamma(\alpha)} \theta^{-\alpha} \exp(-\beta/\theta) \cdot \frac{1}{\sqrt{2\pi\gamma \theta}} \exp\left(-\frac{(\mu - \varphi)^2}{2\gamma \theta}\right) \]  

(6)

In addition, the first time distribution of the unary Wiener process obeys the inverse Gaussian distribution [13], after determining the current degradation amount \( x_t \) and the estimated values of the parameters \( \mu, \theta \), the remaining life of the device defined by the equation (2) can be expressed as:

\[ f_{x_t}(t) = \frac{1-x_t}{\sqrt{2\pi \hat{\theta}}} \exp\left(-\frac{(\hat{\mu}t - l + x_t)^2}{2\hat{\theta} t}\right) \]  

(7)

The expectation of remaining life is:

\[ EL_R = E\left[f_{x_t}(t)\right] = \frac{l-x_t}{\hat{\mu}} \]  

(8)

2.3. Process parameter pre-test distribution structure based on state data

For the estimation of the degradation process parameters \( \mu, \theta \), the traditional method is to use all the degraded data on the entire degradation trajectory of other similar equipment to infer, but in actual conditions, the parameter distribution of the equipment in different health states often has different shape parameters or scales parameters [14]. Therefore, in order to improve the accuracy of the parameter \( \mu, \theta \) statistical inference and the degree of fitting with the actual population distribution, this paper conducts a parameter estimation based on state data, which essentially considers the degraded process parameters as another stochastic process, which depends on the parameter is the health status of the device. A
The schematic diagram of the pre-test distribution structure of the degradation process parameters based on the state data is shown in Figure 1.

![Schematic diagram of the pre-test distribution structure of the degradation process parameters based on the state data](image)

Figure 1. Schematic diagram of operation based on state data parameter estimation

It mainly includes the following steps: ① Constructing a health state assessment model by using other types of equipment degradation data; ② Using the given equipment degradation data to evaluate the current health state of the equipment, and obtaining the current health state of the equipment; ③ Combining the health status of the in-service device, extracting the degradation data belonging to the health state in the historical degradation data of other devices of the same type; ④ Maximum likelihood estimation of degraded process parameters using extracted historical state data and likelihood functions of similar devices.

Steps 1 and 2 pertain to the assessment of the health status of the device. For details, refer to related content in the existing research in [15], and details are not described here. Suppose that the degradation data of n similar devices are obtained, and the health status of the equipment in operation is evaluated as Λ, and the degradation data of the deterioration data of n similar devices is extracted. The time interval of the degradation data monitoring is the same. Assuming that the number of degradation data of the i-th device belongs to the health state is mi, the amount of degradation Δxi[j](Δxi[j] = xi[j]- xi(j-1)) between the time ti(j-1) and the tij of the device i can be obtained. According to the nature of the Wiener process:

$$\Delta x_i \sim N(\mu_i \Delta t, \theta_i \Delta t)$$

(9)

The likelihood function is established by the degradation data of the i-th device belonging to the health state:

$$L(\mu, \theta) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\theta_i \pi \Delta t}} \exp \left( -\frac{(\Delta x_i - \mu_i \Delta t)^2}{2\theta_i \Delta t} \right)$$

(10)

The partial derivatives of μi and θi in equation (10) are obtained, and the maximum likelihood estimation of the degradation process parameters μi, θi of the i-th device in the healthy state can be obtained. The degradation parameters of the respective devices under the state Λ are sequentially estimated by the state degradation data of the n devices, and the n estimated values of the degradation process parameters μ, θ in the state are obtained, and the estimated values are taken as samples and substituted into the equations (4) and (5), the distribution parameters of μ and θ are estimated, and the estimated values of α, β, φ, and γ can be obtained and substituted into equation (6) to obtain pre-test distribution of μ, θ.
2.4. Parameter statistical inference based on Bayes update
The pre-test distribution of the degradation parameters $\mu$, $\theta$ is obtained from the historical state data of the same type of equipment. This distribution is actually a "prior" inference of the overall distribution of the equipment in a healthy state. In the case of obtaining the current data of the equipment in operation, the Bayesian theory can be used to further infer the unknown parameters $\mu$, $\theta$. Assuming that there are a total of $m$ degradation data in the state in which the equipment is in a healthy state, and the amount of degradation between time $t_{j-1}$ and $t_j$ is $\Delta x_j$ ($\Delta x_j = x_j - x_{j-1}$), the amount of degradation is used to establish the following Function:

$$
f(\Delta x_1, \Delta x_2, \ldots, \Delta x_{m-1}|\mu, \theta) = \prod_{j=1}^{m-1} \frac{1}{\sqrt{2\pi \theta \Delta}} \exp \left( -\frac{(\Delta x_j - \mu \Delta)^2}{2\theta \Delta} \right)$$

According to Bayes theory and equation (6), the post-test distribution of $\mu$, $\theta$ is expressed as:

$$
f(\mu, \theta|\Delta x_1, \Delta x_2, \ldots, \Delta x_{m-1}) \propto f(\Delta x_1, \Delta x_2, \ldots, \Delta x_{m-1}|\mu, \theta) \cdot f(\mu|\Delta x_1, \Delta x_2, \ldots, \Delta x_{m-1}) \cdot f(\theta|\Delta x_1, \Delta x_2, \ldots, \Delta x_{m-1})
$$

$$
= \theta^{\frac{1}{2}} \exp \left( -\frac{(\mu - \hat{\mu})^2}{2\hat{\theta}} \right) \cdot \theta^{\frac{1}{2}} \exp \left( -\frac{(\theta - \hat{\theta})^2}{2\hat{\theta}} \right)
$$

Among them:

$$
\hat{\alpha} = \hat{\alpha} + \frac{1}{2}, \quad \hat{\beta} = \hat{\beta} + \frac{(\Delta x_1 - \Delta \hat{\phi})^2}{2\Delta (1 + \hat{\beta} \Delta)}
$$

$$
\hat{\phi} = \frac{\phi}{1 + \hat{\phi} \Delta}, \quad \hat{\gamma} = \frac{\gamma + \hat{\phi} \Delta}{1 + \hat{\phi} \Delta}
$$

Through the iteration of equation (14), the post-test distribution of $\mu$ and $\theta$ is obtained, and then the edge probability density $f(\mu|\Delta x_1, \Delta x_2, \ldots, \Delta x_{m-1})$ and $f(\theta|\Delta x_1, \Delta x_2, \ldots, \Delta x_{m-1})$. According to the squared loss function, the optimal estimator of the parameter (Bayes estimator) is the posterior distribution expectation, and the statistical inference value of the parameter is obtained:

$$
\hat{\mu} = \int \mu f(\mu|\Delta x_1, \Delta x_2, \ldots, \Delta x_{m-1}) d\mu
$$

$$
\hat{\theta} = \int \theta f(\theta|\Delta x_1, \Delta x_2, \ldots, \Delta x_{m-1}) d\theta
$$

The estimated values of the current degradation amount $X_\tau$ and $\mu$, $\theta$ are substituted into equations (7) and (8), and the current remaining lifetime probability density and remaining life expectancy of the in-service device are obtained.
3. Conditional maintenance decision modeling

3.1. Analysis of decision objectives and decision variables

Traditional research adopts a single target method such as safety, or economy, or availability. In view of the prominent role of complex electromechanical equipment and the serious consequences of failure, the objectives of this paper include improving operational reliability (availability) and Economic.

For the two-objective decision problem, the usual processing scheme includes two types: One is to fix one of the targets and then to optimize the other; the other is to transform one of the targets into a quantity related to the other, that is, to convert the two-objective optimization problem into a single-objective optimization problem. For the task-oriented maintenance decision-making problem [16], according to different task requirements, select a certain target to set different fixed values; while the second option is more general and general. Therefore, this paper adopts the second scheme to model. The main method is to convert the operational reliability into the fault loss (punishment) index, convert it into the cost, and optimize the minimum cost.

\[ \lambda = \frac{ELR}{L} \]

status data and remaining life information

Initial stage of operation, \( \lambda \) becomes smaller

Late operation, \( \lambda \) becomes smaller

Figure 2. Schematic diagram of the balance between economic goals and availability goals

However, the fixed fault loss is not practical. For this reason, as shown in Figure 2, the adjustment parameter \( \lambda \) is introduced to adjust the fault loss by using the ratio of the remaining life of the equipment to the life of a given equipment. In the initial stage of equipment operation, the remaining life of the equipment is large, \( \lambda \) is small, the operational reliability index is less restrictive, and the model mainly focuses on economy; as the equipment runs time, the remaining life of the equipment is getting smaller and smaller. The adjustment parameter \( \lambda \) is large, and the failure loss (punishment) is continuously increased, and the operational reliability target is gradually emphasized. Thereby, the purpose of balancing operational reliability and economy is achieved.

Depending on the content of the maintenance activity, the maintenance decision includes maintenance project decisions and inspection interval decisions. Maintenance items include no maintenance measures, preventive maintenance, and repair repairs. The three states can be broken down into two state thresholds: the latent fault state threshold \( l_p \) and the functional fault state threshold \( l \) (\( l_p < l \)). The functional fault state threshold \( l \) is the failure threshold in equation (1), generally given by the manufacturer; and the potential fault state threshold \( l_p \) is the variable that needs to be decided. The larger the \( l_p \) value, the larger the preventive maintenance cycle and the smaller the economic input, but the more prone to functional failure, the worse the operational reliability; the smaller the \( l_p \) value, the easier the fault state is detected and the higher the operational reliability. However, preventive maintenance is frequent and economic investment is large. Similarly, the larger the detection interval time \( T \), the lower the detection cost, but the probability of fault leakage is increased, and the operational reliability is reduced. The smaller the \( T \), the more the device status information can be obtained, and the probability of missing the fault is reduced, but inevitably increase monitoring costs. Therefore, the potential fault state threshold \( l_p \) and the detection interval time \( T \) are taken as the decision variables of the model.

3.2. Modeling assumptions and parameter descriptions

In order to facilitate the maintenance decision modeling, the model needs to be defined and parameterized. The modeling assumptions and parameters are as follows:

- Assuming that the device degradation process is a Wiener process, the degradation amount of the device is \( X(t) \);
Failure to take maintenance measures in the maintenance content does not change the deterioration trend of the equipment; preventive maintenance and repair maintenance restore the equipment as it is;

- The equipment test is complete and can detect the potential fault completely; the functional fault can be known without detection, and the repair repair should be carried out immediately; the first supervision time is $T_1$, which is the known amount; the interval between the $(j-1)$ and $j$-th detection is $T_j$;
- $\Phi_t(x)$ represents the probability distribution of the amount of degradation $X(t)$ at time $t$, i.e. $\Phi_t(x) = \mathbb{P}\{X(t) \leq x\}$, and the probability density is $\phi_t(x) = \frac{d\Phi_t(x)}{dx}$;
- $L$ represents the given life of the equipment (generally given by the manufacturer), and $ELR(t)$ is used to indicate the remaining life expectancy of the equipment at time $t$; the adjustment parameter $\lambda = 1 - ELR(t)$;
- $\lambda_{lp}$ represents the potential failure threshold, and $l$ represents the functional failure threshold;
- $P_f(t_{i-1}, t_i)$ indicates the probability of a functional failure between detection intervals $(t_{i-1}, t_i)$, and $P_R(t_i)$ indicates the probability of finding a potential failure at the $i$-th detection;
- $C_p$ is the cost of preventive maintenance, $C_f$ is the cost of repair repair, $C_i$ is the cost of each test, $C_m$ is the maximum fault loss (punishment).

3.3. Modeling of condition-based maintenance decision based on residual life information

Assume that after the $n$-times of the equipment has been tested, the amount of degradation still does not reach the preventive maintenance threshold $l_p$, and establish a general model for maintenance-oriented maintenance decisions:

$$
\min C(l_p, T) = EC / EL \\
\text{s.t.} \quad 0 < l_p < l \\
0 < T < EL_A(t)
$$

The expected cost (loss) $EC$ in the life cycle of the equipment is as shown in equation (18), including the previous inspection cost $NC_i$, the subsequent expected inspection cost $EC'_i$, the subsequent expected preventive maintenance cost $EC'_p$, and the subsequent expected repair maintenance cost $EC'_f$. And subsequent expected failure loss $EC'_m$.

$$
EC = NC_i + EC'_i + EC'_p + EC'_f + EC'_m
$$

Among them

- $NC_i = nC_i$
- $EC'_i = \sum_{i=n+1}^{\infty} (i-1)C_i P_f(t_{i-1}, t_i) + \sum_{i=1}^{\infty} iC_i P_R(t_i)$
- $EC'_p = \sum_{i=n+1}^{\infty} C_i P_p(t_i)$
- $EC'_f = \sum_{i=n+1}^{\infty} C_i P_R(t_{i-1}, t_i)$
- $EC'_m = \sum_{i=n+1}^{\infty} 2C_i P_f(t_{i-1}, t_i)$

Under the premise that the device degradation process obeys the Wiener process, use $\triangle X_i = X(t_i) - X(t_{i-1})$ to indicate the degradation of the device between detection intervals $(t_{i-1}, t_i)$. Incremental, the
probability of functional failure $P_f$ (ti-1, ti) and the probability of potential failure $P_p$ (ti) can be expressed as

$$P_f(t_{i-1}, t_i) = P\left(X(t_{i-1}) < l_p, X(t_i) > l\right)$$

$$= P\left(X(t_{i-1}) < l_p, X(t_i) > \Delta X_i > l - X(t_{i-1})\right)$$

$$= \int_{l_p}^{\infty} \varphi_{t_{i-1}}(x)(1 - \Phi_{t_i}(l - x))dx$$

(19)

$$P_p(t_i) = P\left(X(t_{i-1}) < l_p, l_p < X(t_i) < l\right)$$

$$= P\left(X(t_{i-1}) < l_p, X(t_{i}) - X(t_{i-1}) < \Delta X_i < l - X(t_{i-1})\right)$$

$$= \int_{l_p}^{l} \varphi_{t_{i-1}}(x)\left(\Phi_{t_i}(l - x) - \Phi_{t_i}(l_p - x)\right)dx$$

(20)

For the Wiener process, the expression [17] of $\varphi(t)$ is

$$\varphi_t(x) = \frac{x}{\sigma\sqrt{2\pi t}} \exp\left(-\frac{(x - \mu)^2}{2\sigma^2 t}\right)$$

(21)

Among them, the parameters $\mu$ and $\sigma$ are estimated values obtained by the state-based parameter estimation method according to equations (15) and (16). The desired cost $EC$ during the life cycle of the device is thus determined.

The desired length $EL$ over the life of the device can be expressed as:

$$EL = \sum_{i=1}^{n} T_i + EL_{\text{ul}}$$

(22)

The first addition indicates the current running time of the equipment in operation; the second addition indicates the remaining life expected of the equipment in operation. The collated formulas (18) and (22) are substituted into equation (17), and the decision-making model based on life information is obtained with $l_p$ and $T$ as the decision variables and $C(l_p, T)$ as the decision target.

3.4. Model optimization based on immune particle swarm optimization

The decision-making model of condition-based maintenance is a multi-variable and multi-constraint model, which has high complexity and non-linearity, so it is difficult to solve it by traditional methods. Particle Swarm Optimization algorithm (PSO), as an intelligent group algorithm, has great advantages in solving problems such as nonlinear continuous and combinatorial optimization. However, it is easy to fall into the local extreme point and cannot reach the global optimal solution. If the inertia coefficient and the maximum speed are set too large, the particle swarm will skip the global optimal solution, so that the algorithm cannot effectively converge; in the case of convergence, all particles are affected by the “social” cognitive part and will fly in the same direction, which makes the particle group lose diversity and reduce the convergence speed and accuracy.

This paper draws on the literature [18], introduces the immune mechanism into the particle swarm algorithm, and uses the immune immune antibody memory mechanism and self-regulation mechanism to improve the performance of the PSO algorithm. The flow chart of the immune PSO (Immune PSO, IPSO) algorithm is shown in Figure 3.

It should be noted that each particle composition is a potential fault threshold and a state monitoring time. The fitness function $F$ is expressed as $1/C(l_p, T)$; the termination condition is that the difference between two adjacent generations $F$ is less than a given threshold $\varepsilon$. 

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4. Instance verification

The Dynamically Tuned Gyroscope (DTG) is a high-speed rotating precision inertial sensor widely used in systems such as flight control, navigation and attitude. As a platform sensing measurement reference device, random drift error is the main factor determining its measurement accuracy. A certain type of DTG is selected as the research object, the random drift coefficient of sensitive axis direction of DTG is selected as the key parameter of life prediction, and nine random drift data of the whole degradation process of DTG are selected for the study of degradation process and condition based maintenance decision-making modeling. The monitoring data in each DTG degradation process is shown in Figure 4.

From the data curve, it can be found that the amount of DTG drift degradation has obvious nonlinear and non-monotonic characteristics. Therefore, it is more reasonable to use Wiener process modeling. According to the relevant technical indicators, the drift failure threshold \( l = 0.6[^\circ/\text{h}] \), and the DTG factory-set life \( L = 100 \text{ [h]} \). Other expenses are: \( C_i = 200 \text{ [¥]} \), \( C_p = 1500 \text{ [¥]} \), \( C_f = 3000 \text{ [¥]} \), \( C_m = 8000 \text{ [¥]} \).

One DTG is selected as the verification object. On the degraded trajectory, 10 points are taken in order for life prediction, and the other 8 DTG data are used as the prior knowledge of predictive learning. Without loss of generality, the DTG numbered S952 is used as the verification object, and its lifetime is 99.8 hours. The amount of drift degradation during the degradation process is shown by the red curve in Figure 4 (the fourth curve from the left to the threshold).
4.1. Validation of the remaining life prediction model of the in-service equipment

A prediction model of the improved Wiener process based on state data and Bayes updating the degradation process parameters (i.e., the model established in this paper, denoted as M1), and a prediction model of the Wiener process based on the estimation of the degradation process parameters based on all degraded data (denoted as M2) and the prediction model of the constant coefficient Wiener process (i.e., the Wiener process obeying the fixed degradation parameters, denoted as M3) is compared to verify the validity of the proposed model. The remaining life predictions are performed on the 10 degraded points selected by the DTG of the number S952 by using the three models. The prediction result data is shown in Table 1.

Table 1. S952 dynamic gyro life prediction results

| Serial number | Working hours[h] | Actual remaining life[h] | Drift degradation [°/h] | predicted value[h] | relative error [%] |
|---------------|-----------------|--------------------------|-------------------------|-------------------|-------------------|
|               |                 |                          |                         | M1    | M2    | M3    | M1    | M2    | M3    |
| 1             | 3               | 96.8                     | 0.0183                  | 92.3   | 90.7  | 107.3 | 4.92  | 6.66  | 10.87 |
| 2             | 12              | 87.8                     | 0.0679                  | 82.7   | 81.9  | 98.1  | 5.74  | 7.08  | 11.81 |
| 3             | 18              | 81.8                     | 0.1088                  | 78.2   | 76.9  | 90.6  | 4.38  | 6.24  | 10.79 |
| 4             | 27              | 72.8                     | 0.1479                  | 69.9   | 69.1  | 83.4  | 3.86  | 5.31  | 14.58 |
| 5             | 36              | 63.8                     | 0.2277                  | 60.8   | 59.7  | 71.3  | 4.64  | 6.76  | 11.79 |
| 6             | 42              | 57.8                     | 0.2471                  | 59.9   | 54.48 | 65.1  | 3.65  | 6.13  | 12.65 |
| 7             | 57              | 42.8                     | 0.3461                  | 44.3   | 40.1  | 49.5  | 3.71  | 6.70  | 15.86 |
| 8             | 66              | 33.8                     | 0.4136                  | 32.4   | 30.4  | 41.2  | 3.92  | 10.97 | 22.01 |
| 9             | 75              | 24.8                     | 0.489                   | 23.9   | 21.4  | 19.4  | 3.63  | 15.73 | 21.75 |
| 10            | 87              | 12.8                     | 0.5379                  | 13.2   | 11.5  | 9.82  | 3.88  | 10.68 | 23.23 |

By analyzing Table 1, it is not difficult to find that the proposed model can obtain better prediction results at each prediction point, and the prediction accuracy is higher than the other two models.

The remaining life probability density curve, the life expectancy curve and the actual life curve predicted by the three models at the 10 prediction points are obtained as shown in Figure 5 to Figure 7.
By analyzing the above prediction curves, it can be found that the model M1 proposed in this paper has a tighter probability density curve at each prediction point, that is, the prediction has the best certainty, and the model M2 is not as good as the model M1 in the certainty of the prediction. However, it is better than the model M3. This is because the model M3 uses fixed degradation parameters, which increases the scale factor of the probability density curve with time and increases the uncertainty of the prediction.

4.2. On-line maintenance decision model and optimization verification

Based on the remaining life prediction, this paper will use the monitoring data and remaining life information of the equipment in operation, and use the residual life based maintenance maintenance decision model established in this paper to model the fault threshold \( \lambda \) and the detection interval time \( T \). Finally, the model is solved by the immune particle swarm optimization algorithm (IPSO) and the standard particle swarm optimization algorithm (PSO), and the convergence curves of \( \lambda \) and \( T \) and fitness function \( F \) are obtained as shown in Figure 8 and Figure 9.

It can be seen from the analysis of Figure 8 and Figure 9 that this paper introduces the fault penalty adjustment parameter \( \lambda \) through the remaining life, which has a greater tolerance to faults in the initial stage of equipment operation. Therefore, both \( \lambda \) and \( T \) are larger; The remaining life is continuously reduced, and the penalty for the failure is gradually increased. Both \( \lambda \) and \( T \) become smaller. The expected cost per unit time \( C(\lambda, T) \) obtained by IPSO and PSO is 40.32 [¥/h] and 46.91 [¥/h],
respectively. It can be seen that the convergence precision of IPSO is higher. Using the modeling method of [19], the fixed $lp$ is $0.463[^{°}/h]$ and the fixed $T$ is $12.56$ [h], and the final $C(lp, T)$ is $52.83$ [¥/h]. It can be seen that the model proposed in this paper is more practical, and has a lower cost rate on the basis of reliable operation.

Figure 8. Shows the convergence curves of $lp$, $T$ and $F$ by IPSO

Figure 9. Shows the convergence curves of $lp$, $T$ and $F$ by PSO

5. Conclusions

In this paper, based on the situation of maintenance decision of complex electromechanical equipment, a decision-making model based on residual life information and Wiener process is proposed. Firstly, the residual life prediction model based on the random coefficient Wiener process is established. According to the characteristics of the complex electromechanical equipment degradation process, the degraded process parameters are regarded as random variables, in order to better fit the degradation process parameter curve and make the device healthy. On the basis of health assessment of equipment, the prior distribution of process parameters is constructed by using the historical state data of similar equipment, and the posterior distribution and Bayes estimation of degradation process parameters are constructed by using Bayes statistics to integrate the historical state information of other equipment and the state information of equipment in operation, so as to predict the remaining life of equipment. Secondly, the Wiener process-based maintenance decision model is constructed by using the remaining life information of the equipment in operation, and the remaining life information is used to balance the operational reliability and economic goals. The potential failure threshold and the state monitoring interval are used as decision variables to life cycle. The lowest unit cost rate is the optimization goal, the decision model is established, and the improved immune particle swarm optimization algorithm is used to solve and optimize the model. Finally, the case study of the DTG shows that the residual life prediction model proposed in this paper has higher prediction accuracy and lower prediction uncertainty; the decision-making model of situation based maintenance is closer to reality, has higher reliability and economy, and the immune particle swarm optimization algorithm has higher convergence accuracy.
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