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Research on preventive maintenance strategy of Coating Machine based on dynamic failure rate

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Highlights

- Combining physical degradation models with BP-LSTM deep learning models for predicting equipment failure moments.
- Dynamic failure rate thresholds are determined strictly based on historical equipment failure data and merit-seeking guidelines.
- GPSO is used to solve the dynamic equation seeking problem.
- Example of a preventive maintenance strategy realized for a coating machine.

Abstract

In this paper, a dynamic preventive maintenance strategy is proposed for the problem of high maintenance cost rate due to excessive maintenance caused by unreasonable maintenance threshold setting when complex electromechanical equipment maintenance strategy is formulated. Increasing failure rate factor and decreasing service age factor are introduced to describe the evolution rules of failure rate during the maintenance of the coating machine, and the BP-LSTM (BP-Long Short Term Memory Network, BP-LSTM) model is combined to predict the failure rate of the coating machine. A Dynamic preventive maintenance Model (DM) that relies on dynamic failure rate thresholds to classify the three preventive maintenance modes of minor, medium and major repairs is constructed. A dynamic preventive maintenance strategy optimization process based on Genetic-Particle Swarm Optimization (GPSO) algorithm with the lowest cost rate per unit time in service phase is built to solve the difficult problem of dynamic failure rate threshold finding. Based on the historical operating data of the coating machine, a case study of the dynamic preventive maintenance strategy of the coating machine was conducted to verify the effectiveness of the model and the developed maintenance strategy proposed in this paper. The results show that the maintenance strategy developed in this paper can ensure better economy and applicability.

Keywords
dynamic preventive maintenance model (DM); BP-LSTM; dynamic failure rate threshold; preventive maintenance strategy; Genetic-Particle Swarm Optimization (GPSO)

1. Introduction

With the increasing level of automation and leanness of the equipment, the need for stable and reliable operation of the equipment has put higher requests on the preventive maintenance strategy of the equipment. Traditional timed preventive maintenance strategies [22] or maintenance strategies with a given failure rate threshold [7] are prone to excessive maintenance, resulting in reduced equipment availability or high maintenance costs. Therefore, how to reasonably develop a preventive maintenance strategy, to improve the operational reliability and economy of the equipment system, to ensure the quality of equipment products and manufacturing and processing capabilities, has an important role.

In recent decades, maintenance strategies have been studied. Maintenance strategies have evolved from initial corrective maintenance, to preventive maintenance, and then to dynamic preventive maintenance [9]. Corrective maintenance refers to repair activities after equipment failure, with a delay. Preventive maintenance refers to maintenance activities carried out before equipment failure occurs, with the aim of preventing or reducing equipment failure and improving equipment reliability [37]. However, the current research on equipment failure prediction is not mature, which makes it difficult to develop correct maintenance strategies in advance and increases the maintenance cost of equipment. Therefore, reliability-centered

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preventive maintenance [23, 27, 29] and condition-based preventive maintenance [3, 28, 40] have become hot topics of research. However, most authors only consider the degradation characteristics of the physical model of the device, ignoring that the degradation has a certain stochastic nature, resulting in its limitations. Preventive maintenance for a given threshold gives us a new research direction. For example, Aafif Y [1] monitors the status of the gearbox by its temperature and cools it once the temperature reaches a predetermined threshold level. Zhang L [39] considered the reliability of a Multi-Component Repairable System (MCRS) performing preventive maintenance as soon as a given threshold value is reached. Bautista L [6] performs preventive replacement if the level of degradation of the degradation process exceeds a certain threshold when checking the work of the system. Although the above-mentioned ways of giving the threshold value can effectively reduce the frequency of equipment failure or reduce the maintenance cost, whether the threshold value is set reasonably needs further verification. Some authors have proposed dynamic preventive maintenance strategies. For example, Wu ZY [34] proposed a dynamic condition maintenance model based on an inverse Gaussian process and established a dynamic maintenance threshold function, which sets different thresholds at different degradation stages and can reduce the risk of early failure of the equipment while ensuring a lower expected cost ratio. Chen W [8] proposed a dynamic portfolio maintenance model for PV plants based on component correlation and availability. The state of the equipment and correlation set is predicted and its availability is determined. Alvarez C [4] proposed a stochastic dynamic planning model for condition-based maintenance applications. The optimal timing of inspection and preventive maintenance for each component of a non-redundant system was determined. However, most of the above studies only consider the state of the equipment and ignore the degradation characteristics of the failure rate of the equipment. Gong Q [13] proposed a dynamic preventive maintenance strategy for metro vehicle traction systems considering stages. The decreasing service life factor and the increasing failure rate factor are introduced, and a dynamic reliability model considering the effect of preventive maintenance on component failure rate is established. Although this literature considers the effect of maintenance on the failure rate, the enumeration method is computationally intensive and inefficient to solve when optimizing the maintenance strategy.

With the continuous development of deep learning algorithms, the application of deep learning in maintenance strategies is also increasing. Yousefi N [38] used deep reinforcement learning methods to provide a new dynamic maintenance model for degraded repairable systems subject to degradation and random shocks. Rodriguez MLR [30] proposed a new multi-intelligence approach to learn maintenance strategies executed by technicians under the uncertainty of multiple machine failures. Xin JY [35] proposed a new framework based on system reliability for multi-objective optimization of in-service asphalt pavement preventive maintenance (PM) management based on time-varying Limit State Functions (LSFs), combining the uncertainty in LSTM neural network predictions and the observed errors in International Roughness Index (IRI) measurements. The aforementioned literature uses deep learning algorithms to analyze the system, without considering the integration with physical models. When performing long-time prediction, the prediction results may deviate from the reality.

A dynamic preventive maintenance strategy with dynamic failure rate thresholds is proposed to solve the above problems. The main contributions of this paper are as follows.

(1) To improve the prediction accuracy of equipment failure moments, a failure prediction model combining a physical model of equipment degradation and a BP-LSTM deep learning model is proposed.

(2) A dynamic preventive maintenance strategy finding process based on Genetic-Particle Swarm Optimization (GPSO) algorithm is built, which improves the solution efficiency and solves the difficult problem of dynamic equation finding.

(3) The three preventive maintenance modes of minor, medium and major repairs are classified based on dynamic failure rate thresholds to make the dynamic preventive maintenance strategy more in line with the actual situation.

The rest of the paper is organized as follows. In Section 2, describe the dynamic preventive maintenance strategy; In Section 3, the GPSO algorithm is constructed to solve the dynamic preventive maintenance model; In Section 4, dynamic preventive maintenance strategy analysis is conducted; In Section 5, gives the conclusion.

2. Coating machine dynamic preventive maintenance strategy

As complex electromechanical equipment in the field of lithium battery positive and negative slurry coating, the coating machine consists mainly of four parts: the parent roll delivery system, the coating system, the heating drying system and the cooling system. Each system consists of a large collection of mechanical, pneumatic, electronic components. For example, the parent roll conveyor system is equipped with 2 3-inch convex bond inflation shaft, 5 kg magnetic powder brake controls roll tension, and the overall rack adopts EPC (Edge Position Control) hydraulic automatic deflection correction and pneumatic film mechanism. The coating machine is key equipment in the lithium battery production line, and its working reliability has an important impact on the uniformity of the slurry coating on the electrode surface, which directly affects the safe operation of lithium batteries. Therefore, it is important to establish an effective preventive maintenance strategy to ensure the stable and reliable operation of the coating machine.

2.1 Dynamic preventive maintenance modes for coating machine

Most traditional equipment maintenance models use fixed failure rate thresholds for maintenance strategy development. The selection of failure rate thresholds directly affects preventive maintenance programs, and the subjectivity of their settings can easily lead to over or under-maintenance of preventive maintenance. The dynamic preventive maintenance model is based on the dynamic failure rate threshold for maintenance strategy development, which is strictly determined according to the equipment's historical failure data and the merit-seeking criteria, effectively solving the above problems. To construct a dynamic preventive maintenance strategy for the coating machine, make the following assumptions:

(1) The initial failure rate of the coating machine is 0 [25].

(2) Preventive maintenance of the coating machine is divided into three maintenance modes based on failure rate thresholds: minor, medium, and major maintenance, as shown in Fig. 1. Assuming that the coating machine will fail at time $t_N, (N = 1, 2, \cdots, N.)$, when the failure rate of the coating machine is $\lambda(t)$, the maintenance model has the following definition:

Minor repair: When $\lambda(t) < \lambda_{med}$, the coating machine's failure rate does not reach the medium repair threshold λ_{med} at the moment, the coating machine undergoes a minor repair, as "repair as old", and the repair time is very short and negligible.

Medium repair: When $\lambda_{med} \leq \lambda(t) < \lambda_{maj}$, the coating machine's failure rate reaches the medium repair threshold λ_{med} at time t_N and does not reach the major repair threshold λ_{maj}, the coating machine undergoes a medium repair and the repair time is advanced $t_N{}'$. The medium repair does not "repair as new" the coating machine, but restores the coating machine to a better condition than it is now, the failure rate changes faster and the service life of the coating machine decreases after the repair. The repair time is fixed at σ.

Major repair: When $\lambda(t) \geq \lambda_{maj}$, the coating machine's failure rate at t_N is greater than or equal to the major repair threshold of λ_{maj}, the coating machine undergoes a major repair and the repair time is advanced to $t_N{}'$. The major repair makes the coating machine "repaired as new". The repair time is fixed at ρ.'

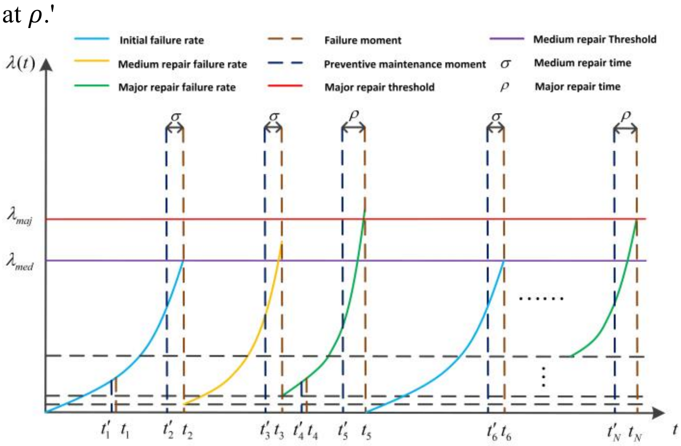


Fig. 1. Three maintenance modes of dynamic preventive maintenance strategy for coating machine.

In this strategy, minor, medium, and major repairs are performed before the moment of failure. For example, in Fig. 1, the coating machine failure occurs at the time t_1, t_4, corresponding to the failure rate $\lambda(t) < \lambda_{med}$, and the minor repair is advanced to t_1', t_4'; the coating machine failure occurs at the time t_2, t_3, t_6, corresponding to the failure rate $\lambda_{med} \leq \lambda(t) < \lambda_{maj}$, and the medium repair is advanced to t_2', t_3', t_6'; the coating machine failure occurs at the time t_5, t_N, corresponding to the failure rate $\lambda(t) \geq \lambda_{maj}$, and the minor repair is advanced to t_5', t_N'.

2.2 Coating machine failure rate evolution rules

Based on the usage process of the coating machine, a combination of a failure rate increment factor and a service age decrement factor is introduced in this section to describe the degradation process of the coating machine to more accurately portray the failure rate evolution rule of the coating machine.

(1) Failure rate evolution rule with failure rate increment factor

The failure rate of the coating machine after the ith preventive maintenance, according to reference [24], can be expressed as

$$\lambda_{i+1} = a_i \lambda(t) \quad (1)$$

Where $a_i > 1$ is the failure rate increment factor. Under this kind of rule, the failure rate of the coating machine will be brought back to 0 after each repair, but it will make the failure rate change faster, and the failure rate evolution rule is shown in Fig.2.

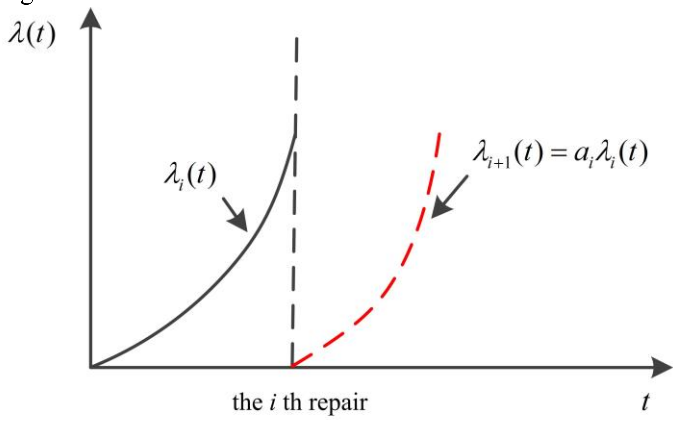


Fig. 2. Failure rate evolution rule with increasing failure rate factor.

The failure rate of the coating machine after the ith preventive maintenance, according to reference [18], can be expressed as

$$\lambda_{i+1} = \lambda_i(t + b_i T_i) \quad (2)$$

Where $0 < b_i < 1$ is the service age decrement factor and T_i is the last maintenance time interval. Under such a rule, the failure rate of the coating machine will become $\lambda_i(t + b_i T_i)$ after each repair. The rules of failure rate evolution are shown in Fig. 3.

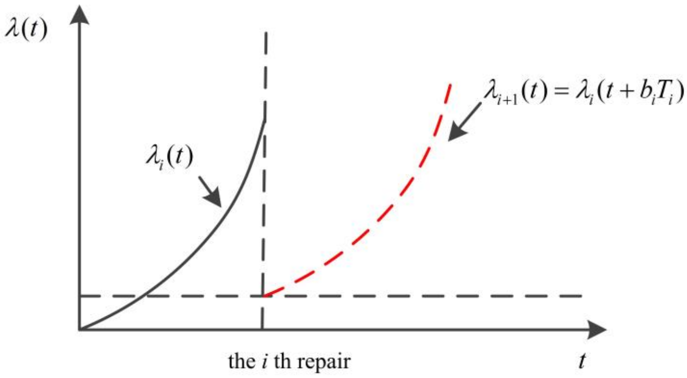


Fig. 3. Failure rate evolution rule with service age decrement factor.

(3) Description of the degradation process of the coating machine

The failure rate evolution rules under the failure rate increment factor and the failure rate evolution rules under the service age decrement factor are integrated to construct the failure rate evolution rules of the coating machine as shown in Fig. 4.

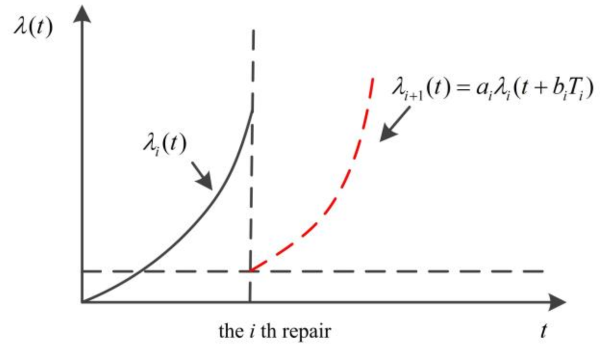


Fig. 4. Evolution rule of failure rate with two adjustment factors.

Fig. 4 shows that the failure rate of the coating machine increases and the service life decreases after the repair. The relationship between the failure rate of the coating machine before and after the repair can be expressed as

$$\lambda_{i+1} = a_i \lambda_i (t + b_i T_i) \tag{3}$$

Where $a_i > 1$ is the failure rate increment factor, $0 < b_i < 1$ is the service age decrement factor, and T_i is the last maintenance time interval. The values of a, b can be statistically derived from the maintenance records of the equipment. For calculation ease, assume $a_i \to a, b_i \to b$ that during the maintenance cycle, and then we can get the failure rate in the i th maintenance cycle as

$$\lambda_i = a\lambda_{i-1}(t + bT_{i-1}) = a^2\lambda_{i-2}(t + 2bT_{i-2}) = a^i\lambda_0(t + ibT_0) \tag{4}$$

Due to the two maintenance cycles before and after the coating machine $T_{i+1} \approx bT_i$. Therefore, the rule for the evolution of the failure rate of the coating machine is obtained as

$$\lambda_i(t) = a^i \lambda_0 (t + ibT_i) \tag{5}$$

2.3 Failure rate prediction method of coating machine based on BP-LSTM

The model for dynamic preventive maintenance uses failure rate prediction for maintenance strategy development. Combining the advantage of Long Short Term Memory Network (LSTM) with long time memory function in time series modeling problems [21] and the feature of BP neural network with extremely strong generalization ability [36], a BP-LSTM fault prediction model is proposed to predict the failure rate. The failure rate prediction framework based on BP-LSTM is shown in Fig. 5.

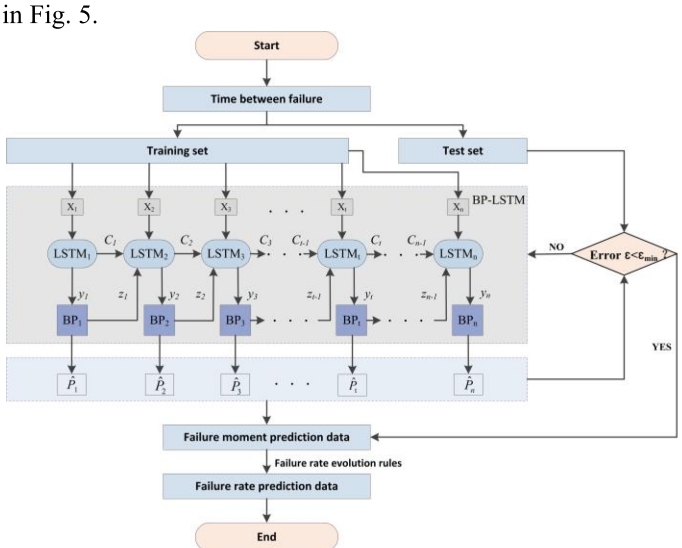


Fig. 5 Failure rate prediction framework based on BP-LSTM.

Based on the prediction framework in Fig. 5, the BP-LSTM failure rate prediction model is constructed in the following:

(1) The original fault data is analyzed to extract fault features and constitute the training set $X = \{x_1, x_2, \cdots, x_t, \cdots, x_n\}$, $t = \{1, \cdots, n\}$.

(2) Initialization of LSTM. Given the initial weight matrix, an initial weight matrix is a random number uniformly distributed between [0, 1]. Set a reasonable maximum number of iterations for training and a minimum error.

(3) Take the training set x_t as an example, input x_t into BP-LSTM$_t$, x_t first get the current output y_t by LSTM$_t$, the formula where y_t is calculated as follows:

$$y_t = \sigma(w_{xo}x_t + w_{ho}h_{t-1} + b_o) \otimes tanh\big(\sigma(w_{xi}x_t + w_{hi}h_{t-1} + b_i) \otimes tanh(w_{xc}x_t + w_{hc}h_{t-1} + b_c) + \sigma(w_{xf}x_t + w_{hf}h_{t-1} + b_f) \otimes C_{t-1}\big) \tag{6}$$

The current output y_t obtained from the LSTM$_t$ is then input to the BP neural network, reducing error with the current long-term state C_t to obtain the previous short-term state z_t of LSTM$_{t+1}$, $z_t = \sum_{j=1}^{n} \sigma\big(\sum_{i=1}^{l} w_{il} y_t + a_l\big) w_{lj} + b_j$. The output of input x_t through BP-LSTM$_t$ can be expressed as $\hat{p}_t$, $\hat{P}_t = BP - LSTM_t(x_t, C_{t-1}, z_{t-1})$.

Similarly, the output of the whole BP-LSTM model can be obtained as $\hat{P} = \{\hat{P}_1, \hat{P}_2, \cdots, \hat{P}_n\}$.

(4) The actual output of the BP-LSTM model and the test set is used to calculate the error, which is input into the model, and the weight and bias of the model are adjusted to make the error decrease continuously and achieve the optimization of the network. The error calculation formula is shown in Eq. (7).

$$\varepsilon = \frac{1}{N}(p_t - \hat{p}_t)^2 \tag{7}$$

In Eq. (7): p_t, $\hat{p}_t$is the true and predicted value of the fault; N is the number of data for test verification.

(5) Output the failure moment prediction data and combine with the failure rate evolution rules to get the failure rate prediction data.

(6) The model stops training when the number of training sessions or error values meet the requirements

2.4 Objective function construction for dynamic preventive maintenance model

The coating machine uses the lowest cost rate per unit of operating time as the goal when performing maintenance strategy development, assuming that the coating machine maintenance costs consist of downtime losses, labor costs, and maintenance material costs as follows:

(1) Downtime losses C_d

Refers to the loss of products that should be produced due to medium and major repairs, minor repairs are very short and downtime losses are not counted. Define the cost of downtime per unit of time as C_e, downtime for medium maintenance is σ, downtime for major maintenance is ρ, then the downtime losses can be determined by Eq. (8).

$$C_d = C_e\sigma + C_e\rho = C_e(\sigma + \rho) \tag{8}$$

(2) Labor costs C_r

Refers to the labor costs incurred in the process of medium and major repairs, and the labor costs are not counted for the very short time of minor repairs. Define the cost of labor per unit of time as C_{r0}, downtime for medium maintenance is σ, downtime for major maintenance is ρ, then the labor costs can be determined by Eq. (9).

$$C_r = C_{r0}\sigma + C_{r0}\rho = C_{r0}(\sigma + \rho) \quad (9)$$

(3) Maintenance material costs C_g

Refers to the cost of materials required in the course of minor, medium, and major repairs. Define the cost of materials required for a single minor repair as C_{gmin}, the cost of materials required for a single medium repair as C_{gmed}, the cost of materials required for a single major repair C_{gmaj}.

Based on the above definition of cost, assume that the cost of each minor repair of the coating machine is C_{min}, each medium repair of the coating machine is C_{med}, and each major repair of the coating machine is C_{maj}. We can identify three preventive maintenance mode costs as follows:

(1) Minor repair costs

The repair time for minor repairs is very short and negligible, so the cost of minor repairs only includes the cost of repair materials, not including downtime losses and labor costs, which is

$$C_{\min} = mC_{g\min} \quad (10)$$

In Eq. (10), m is the number of minor repairs.

(2) Medium repair costs

$$C_{med} = i\left(C_e\sigma + C_{r0}\sigma + C_{gmed}\right) \quad (11)$$

In Eq. (11), i is the number of medium repairs.

(3) Major repair costs

$$C_{maj} = k(C_e\rho + C_{r0}\rho + C_{gmaj}) \quad (12)$$

In Eq. (12), k is the number of major repairs.

In summary, we can obtain the total cost of maintenance as

$$\begin{aligned} C &= C_{min} + C_{\mathrm{med}} + C_{\mathrm{maj}} \\ &= mC_{g\min} + i\left(C_e\sigma + C_{r0}\sigma + C_{gmed}\right) + k\left(C_e\rho + C_{r0}\rho + C_{gmaj}\right) \end{aligned} \quad (13)$$

Therefore, the cost rate per unit of operation time in the forecast cycle is

$$EC = \frac{mC_{g\min} + i(C_e\sigma + C_{r0}\sigma + C_{gmed}) + k(C_e\rho + C_{r0}\rho + C_{gmaj})}{T - i\sigma - k\rho} \quad (14)$$

In Eq. (14), T is the whole forecast period.

As a result, we solve for the optimal failure rate threshold with the lowest cost rate per unit of operating time in the forecast cycle, and propose the objective function of the dynamic preventive maintenance model as follows:

$$\begin{cases} \min EC = \dfrac{mC_{gmin} + i(C_e\sigma + C_{r0}\sigma + C_{gmed}) + k(C_e\rho + C_{r0}\rho + C_{gmaj})}{T - i\sigma - k\rho} \\ \text{s.t.}\begin{Bmatrix} \lambda(t) < \lambda_{\mathrm{med}} \\ \lambda_{\mathrm{med}} \le \lambda(t) < \lambda_{\mathrm{maj}} \\ \lambda(t) \ge \lambda_{\mathrm{maj}} \end{Bmatrix} \end{cases} \quad (15)$$

In Eq. (15), $\lambda(t)$ is the failure rate corresponds to the predicted value at each failure moment, and the constraint $s.t.$ is used to determine the repair mode corresponding to each failure moment predicted by the BP-LSTM, and thus the number of failures corresponding to each repair mode. The design variables corresponding to the objective function are λ_{med}, λ_{maj}.

It is worth noting that Eq. (15) is a dynamic equation and it is very difficult to obtain its solution, so we need to solve the above equation with the help of an optimization algorithm.

3. Research on dynamic failure rate finding method

The dynamic preventive maintenance model is divided into three preventive maintenance modes of minor repair, medium repair, and major repair based on dynamic failure rate threshold. We solve for the optimal medium repair threshold and major repair threshold with the lowest cost rate per unit of operating time. The objective function of the model is a dynamic equation, and the optimization process may face the situation of falling into local optimum or difficult to get the global optimum. At present many researchers used and proposed modified algorithms or hybrid algorithms [10, 12, 32]. Therefore, this section combines the Particle Swarm Optimization (PSO) algorithm with better local search capability [16] and the Genetic Algorithm (GA) with better global search capability [26] to solve the problem of finding the dynamic failure rate threshold of the coating machine.

The Particle Swarm Optimization (PSO) algorithm evaluates the quality of each particle through the fitness function. Each iteration of particles will update their relative positions [11], simulate the birds flying foraging behavior, and collaborate collectively to find optimal solutions [15]. The traditional continuous optimality search rule [14] is as follows：

The information of *D*-dimensional spatial particles can be expressed as a position information Eq. (16) and velocity information Eq. (17).

$$x_i = (x_{i1}, x_{i2}, \cdots, x_{iD}) \quad (16)$$

$$v_i = (v_{i1}, v_{i2}, \cdots, v_{iD}) \quad (17)$$

Based on the individual optimal solution and the global optimal solution evolution, the velocity is updated as follows：

$$v_{id}^{k+1} = v_{id}^k + c_1 * rand_1^k * \left(pbest_{id}^k - x_{id}^k\right) + c_2 * rand_2^k * \left(gbest_d^k - x_{id}^k\right) \quad (18)$$

The position is updated as follows：

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1} \quad (19)$$

In Eq. (18) and Eq. (19), v_{id}^k—velocity of the *i* th particle in the *d* th dimension of the *k* th iteration; x_{id}^k—position of the *i* th particle in the *d* th dimension of the *k* th iteration; c_1, c_2—acceleration coefficient, generally $c_1 + c_2 \le 4$, usually $c_1 = c_2 = 2$; $rand_1, rand_2$—random number within [0,1]; $pbest_{id}^k$—the individual extremum of particle *i* in the *d* th dimension; $gbest_d^k$—global extreme value point.

To solve Eq. (15) by the PSO algorithm, we have to correspond it by the following method.

On the basis of the objective function, multiple particles are generated, each of which is composed of natural numbers of [1-N], then they can form a particle population.

(1) Position of the particle: corresponds to the medium repair threshold λ_{med} and major repair threshold λ_{maj}.

(2) Velocity of particles: previous studies have set the velocity taking space as 0 and 1, which is used to represent whether the next generation of particles has been shifted or not. However, the movement of particles by this way generates non-compliant particles and requires the particles to be processed again. For this reason, we abolished the concept of velocity in particle swarms.

(3) Particle adaptation: corresponding to the cost rate function *EC*, the smaller the value of the cost rate, the better its corresponding failure threshold.

GA also need to be improved when solving dynamic problems, where traditional crossover and variation operators may lead to non-compliant offspring chromosomes from otherwise compliant parent chromosomes. Therefore, to redesign the crossover and variation operators:

1) Crossover is a key step in the update and solution space of the GA. The traditional crossover operator may lead to misalignment of the solution space, for example, ABCDE and

BCAED cross over at the second point to produce ACCDE and BBAED.

To ensure the integrity of the genes, we use the preferential selection crossover method for crossover, and the preferential preservation of the crossover operator is shown in Fig. 6.

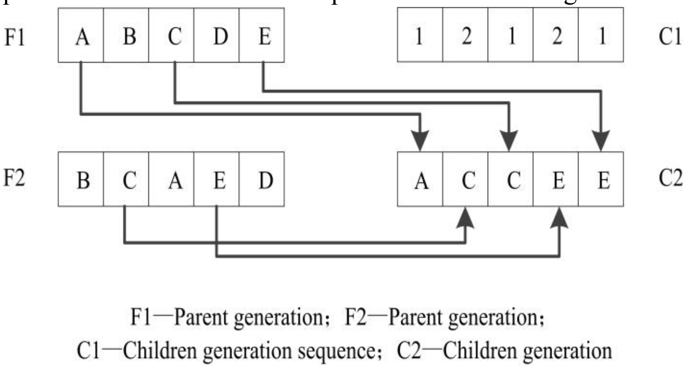


Fig. 6. Priority preservation crossover operator.

2) Variation operator. Unlike the traditional variation operator, the variation operator cannot simply select any two points for replacement, because the chromosome after the exchange may not satisfy the priority constraint, and the variation may be invalid after the compliance treatment as the same as before the variation. It is improved by taking any two points and arranging all the genes between them in reverse order, and then the probability of validity of the variation after the compliance treatment is higher.

Since once a relatively better particle is generated in the population of the PSO algorithm, the particles will all evolve toward that particle, and if the particle is not globally optimal and the direction of the global optimum is opposite to that of this particle, the particle will not be able to find the global optimal solution, making its local search ability stronger. When the solution quality is not required, the algorithm can efficiently find high-quality solutions, but not optimal solutions. Therefore, with the continuous iteration of the PSO algorithm, the population diversity is bound to decrease and it is easy to fall into the local optimum, thus obtaining a local optimal solution.

In addition, the dynamic equation numerical optimization search problem and its result has been constrained, which easily leads to the initial population itself is likely to have scattered around the local optimal solution, so that the global optimal solution cannot be found and thus the optimal failure rate threshold cannot be obtained. The crossover operator in GA generally determines the location of one or several crossover points at random and then swaps the genes of two chromosomes to select two new individuals. The variation operator generally randomly selects a position on a chromosome and randomly changes it within its variable range according to certain rules. GA can improve its global searchability by mutation, and combining GA with particle swarm algorithm can enhance the global search ability of PSO.

Therefore, the Genetic-Particle swarm Optimization (GPSO) algorithm is used to solve the dynamic preventive maintenance model in this paper. The solution flow is shown in Fig. 7.

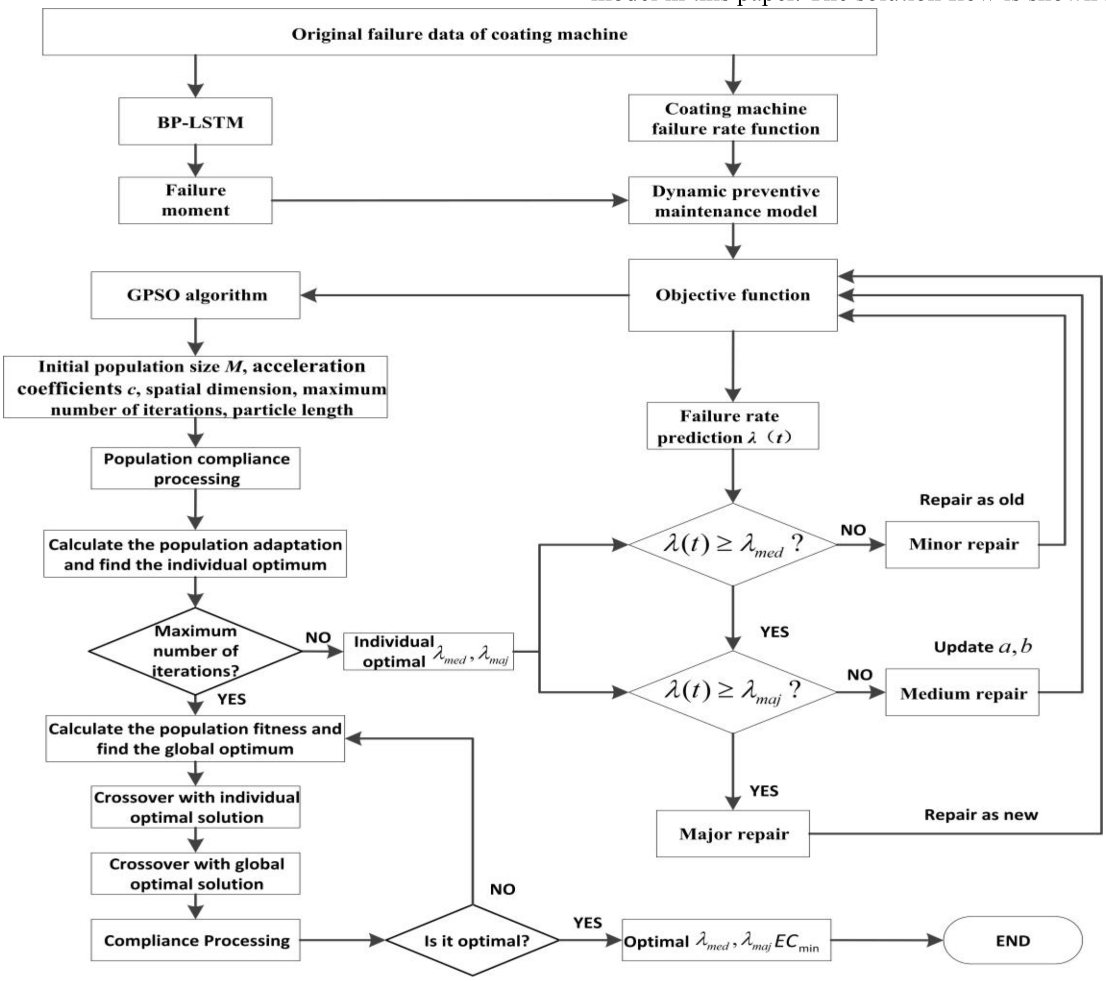


Fig. 7. Flow chart of dynamic preventive maintenance model solving based on GPSO algorithm.

4 Coating machine dynamic preventive maintenance strategy case study

4.1 Analysis of dynamic preventive maintenance strategy verification for coating machine

This paper verifies and analyzes the dynamic preventive maintenance strategy based on a total of 122 failure messages from two anode coating machines of a company's electrode production line for two years, 2017 and 2018.

4.1.1 Dynamic preventive maintenance strategy training analysis

Based on the coating machine failure information through data analysis to obtain the coating machine failure interval as shown in Schedule 1, the statistical analysis of Schedule 1 coating machine failure interval, it is known that the coating machine failure rate function conforms to the exponential Weibull distribution, based on the coating machine failure rate evolution rules, to obtain the final coating machine failure rate as shown in Eq. (20).

$$\lambda(t) = a^i \frac{0.7013\left(1-e^{-\left(\frac{t+ib\sigma}{1.179}\right)^{0.6297}}\right)^{0.313} e^{-\left(\frac{t+ib\sigma}{1.179}\right)^{0.6297}} \left(\frac{t+ib\sigma}{1.179}\right)^{-0.3703}}{1-\left(1-e^{-\left(\frac{t+ib\sigma}{1.179}\right)^{0.6297}}\right)^{1.313}} \quad (20)$$

In Eq. (20), a—failure rate increment factor, b—service age decrement factor.

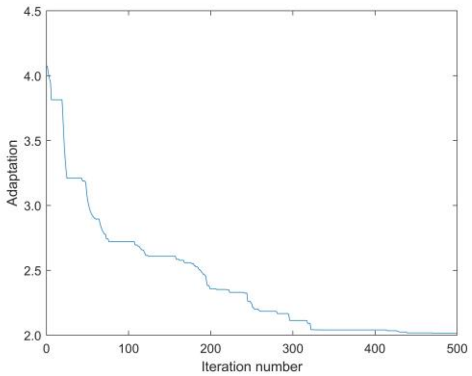
Given the coating machine maintenance parameters shown in Table 1, 122 coating machine failure intervals are input into the dynamic preventive maintenance model and the training results are as follows.

Table 1. Coating machine maintenance parameters

NO.	Parameters	Value	NO.	Parameters	Value
1	a	1.08	6	C_{r0} (10^4yuan/h)	0.001
2	b	0.95	7	C_{gmin} (10^4yuan/time)	0.003
3	σ/h	2	8	C_{gmed} (10^4yuan/time)	0.01
4	ρ/h	7	9	C_{gmaj} (10^4yuan/time)	0.03
5	C_e (10^4yuan/h)	0.8			

The parameters of the GPSO algorithm are set as follows: initial population $M = 40$, acceleration coefficients $c_1 = c_2 = 2$, spatial dimension 5, the maximum number of iterations is 100, particle length 0.1, and other parameters use system default values. The simulation solution of Eq. (15) is performed using MATLAB programming, and the algorithm training is shown in Fig. 8.

a). Algorithm training process



b). Primary population distribution

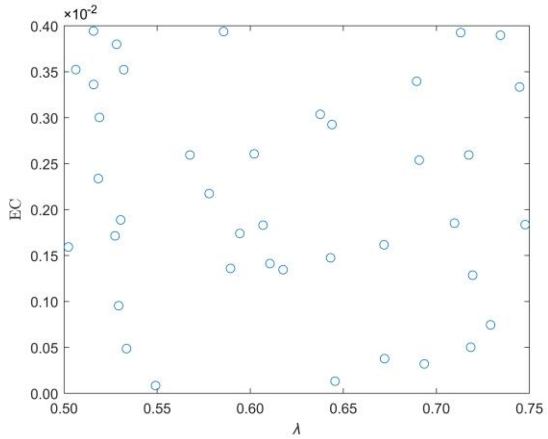


Fig. 8. GPSO Algorithm Training.

From Fig. 8a, it can be seen that the adaptation values gradually decrease with the number of iterations and the results tend to converge and the GPSO algorithm reaches the optimum at 450 iterations. The GPSO algorithm at 450 iterations is now used to analyze the coating machine, and Fig. 8b shows the stochastic primitive population obtained by MATLAB solution. The y axis in Fig. 8b represents the randomly generated failure threshold λ (the sum of the primitive population of the λ_{med} and λ_{maj}) and the x axis represents the corresponding cost rate EC. From Fig. 8, it can be seen that: the primary population is widely distributed in the $EC - \lambda$ plane, and only the local distribution is denser, which ensures the diversity of particles, and on the other hand, it also shows the effectiveness and rationality of the primary population. When the GPSO algorithm is solved at 450 iterations, the results of the dynamic preventive maintenance model are shown in Fig. 9; the globally optimal values are shown in Table 2.

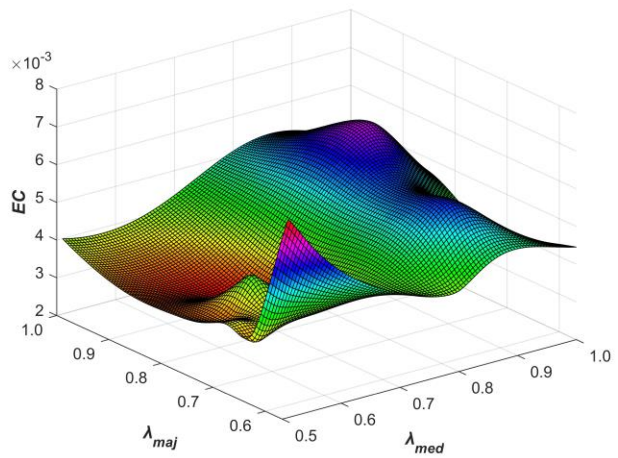


Fig. 9. Dynamic preventive maintenance model solution results

Table 2. Global optimal values of dynamic preventive maintenance model.

NO.	Parameters	Optimum value
1	λ_{med}	0.65
2	λ_{maj}	0.80
3	m	104
4	i	13
5	k	5
6	EC_{min}	0.00298

From Fig. 9, it can be seen that the cost rate varies with increasing or decreasing the medium and major repair thresholds, and the optimal value is given in Table 2. That is, the minimum cost rate of 0.0026 (10^4yuan/h) can be obtained for the coating machine at a medium repair threshold of $\lambda_{med} = 0.65$ and a major repair threshold of $\lambda_{maj} = 0.80$. The corresponding number of repair modes are minor repair $m = 104$, medium repair $i = 13$, and major repair $k = 5$.

4.1.2 Comparative analysis of model efficacy

(1) Comparison of dynamic preventive maintenance model and fixed threshold maintenance model

The dynamic preventive maintenance model develops maintenance strategies based on dynamic failure rate thresholds and verifies its effectiveness by comparing it with the fixed threshold maintenance model. The GPSO algorithm was used to solve the above model, and the specific comparison results are shown in Table 3.

Table 3. Comparison of dynamic preventive maintenance model and fixed threshold maintenance model

Model	λ_{med}	λ_{maj}	Number of minor repairs	Number of medium repairs	Number of major repairs	EC_{min} (10^4yuan/h)
Dynamic preventive maintenance model	0.65	0.80	104	13	5	0.00298
Fixed threshold maintenance model	0.65	0.75	104	11	7	0.00346
	0.65	0.70	104	6	12	0.00462
	0.60	0.80	97	20	5	0.00363
	0.55	0.80	85	32	5	0.00460

Table 3 lists the optimal maintenance strategies for the dynamic preventive maintenance model and the fixed threshold maintenance model. The comparison shows that the cost rate of the maintenance strategy developed by the dynamic preventive maintenance model is significantly lower than that developed by the fixed threshold maintenance model, which proves that the dynamic preventive maintenance model can better take into account the cost rate of the coating machine. It can also be found that when the medium repair threshold remains unchanged and the major repair threshold decreases, the number of medium repairs decreases, the number of major repairs increases slightly, and the cost rate increases significantly; when the major repair threshold remains unchanged and the medium repair threshold decreases, the number of minor repairs decreases, the number of medium repairs increases significantly, and the cost rate increases subsequently; that is, the impact of the major repair threshold on the cost rate is large, and the impact of the medium repair threshold on the cost rate is relatively small. Therefore, the optimal failure rate threshold must be found to ensure the lowest cost rate when developing a coating machine maintenance strategy. The dynamic preventive maintenance model follows a strict merit-seeking model to determine the optimal failure rate threshold, which is not affected by any subjective factors, ensuring the reasonableness of the failure rate threshold and proving the superiority of the dynamic preventive maintenance model.

(2) Comparison between dynamic preventive maintenance model and other maintenance models

To further verify the effectiveness and superiority of the dynamic preventive maintenance model (DM) in maintenance strategy formulation, the reliability-constrained maintenance model (RM) [5], the importance-constrained maintenance model (IM) [17], and the age-dependent replacement model (AM) [31] were used to compare with the dynamic preventive maintenance model. Based on the coating machine failure data, the above models were solved using the GPSO algorithm, and the results of the four models were obtained as shown in Table 4, and the cost rate comparison of the four models is shown in Fig. 10.

Table 4. Comparison of dynamic preventive maintenance model and other maintenance models.

	DM	RM	IM	AM
λ_{med}	0.65	—	—	—
λ_{maj}	0.80	—	—	—
R_{med}	—	0.75	—	—
R_{maj}	—	0.90	—	—
I_{med}	—	—	0.80	—
I_{maj}	—	—	0.90	—
A_{med}	—	—	—	10
A_{maj}	—	—	—	5
Number of minor repairs	104	100	109	98
Number of medium repairs	13	13	7	9
Number of major repairs	5	11	6	15

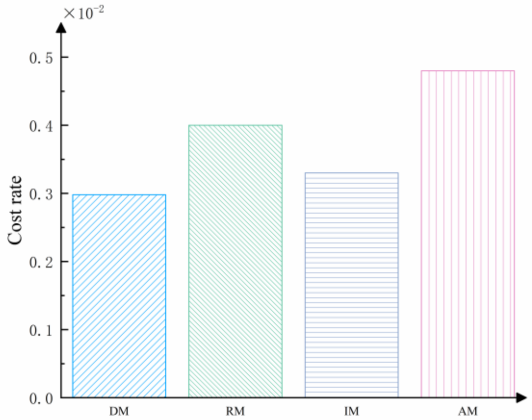


Fig. 10. Dynamic preventive maintenance model compared with other maintenance models cost rate.

Table 4 shows the optimal maintenance strategy for the dynamic preventive maintenance model and the other three maintenance models. Fig. 10 gives a comparison of the cost rates of the four maintenance strategies. The cost rate of the strategy developed by the dynamic preventive maintenance model is 0.00298 (10^4yuan/h), the cost rate of the strategy developed by the reliability-constrained maintenance model is 0.004 (10^4yuan/h), the cost rate of the strategy developed by the importance-constrained maintenance model is 0.0033 (10^4yuan/h), the cost rate of the strategy developed by the age-dependent replacement model is 0.0048 (10^4yuan/h). By comparison, the cost rate of the maintenance strategy developed by the dynamic preventive maintenance model is significantly lower than the maintenance strategies developed by the other three maintenance models. The maintenance strategy developed by the dynamic preventive maintenance model has 104 minor repairs, 13 medium repairs, and 5 major repairs. The number of major repairs is 6 times less than the reliability-constrained maintenance model, 1 times less than the importance-constrained maintenance model, and 10 times less than the age-dependent replacement model and the number of major repairs is the least. The obtained failure thresholds are the most reasonable and the best economy is achieved, which further proves the superiority of the dynamic preventive maintenance model.

4.1.3 Comparative analysis of the effectiveness of the optimization search algorithm

To verify the performance of the GPSO algorithm in solving the dynamic preventive maintenance model, four algorithms, Particle Swarm Optimization (PSO) algorithm [19], Genetic Algorithm (GA) [20], Ant Colony Optimization (ACO) algorithm [33], and Improved Artificial Bee Colony (IABC) algorithm [2], are used to compare with the GPSO algorithm in this paper. The dynamic preventive maintenance model was solved using each of the five algorithms to obtain the optimal adaptation comparison as shown in Fig. 11, the lowest cost rate comparison as shown in Fig. 12, and the comparison of the results of each algorithm as shown in Table 5.

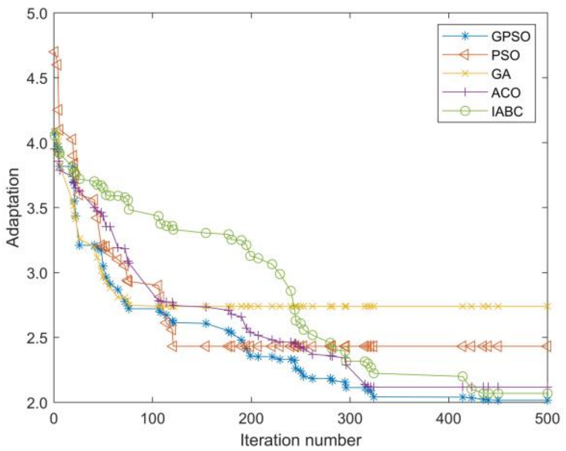


Fig. 11. Comparison of optimal adaptation of five algorithms.

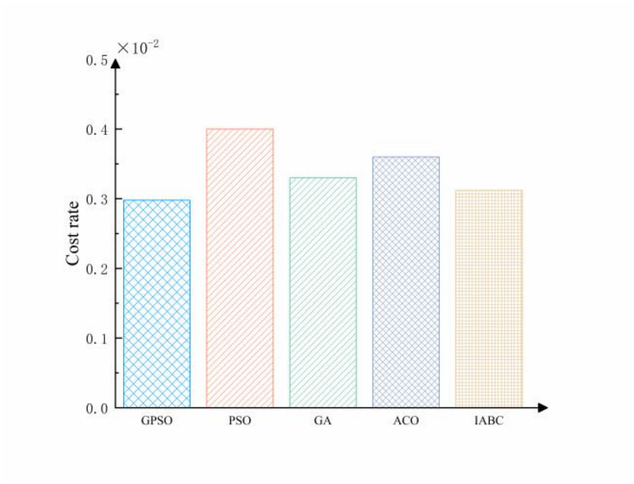


Fig. 12. Comparison of five algorithm cost rate.

Table 5. Comparison of the results of the five algorithms.

	λ_{med}	λ_{maj}	Iteration number	Adaptation	Number of minor repairs	Number of medium repairs	Number of major repairs	EC_{min} (10^4yuan/h)
GPSO	0.65	0.80	450	2.0165	104	13	5	0.00298
PSO	0.60	0.70	115	2.432	96	16	10	0.00400
GA	0.70	0.86	106	2.74	110	11	1	0.00330
ACO	0.67	0.69	320	2.118	106	7	9	0.00360
IABC	0.64	0.78	435	2.069	103	15	4	0.00312

From Fig. 11, Fig. 12 and Table 5, it can be seen that the cost rate of the dynamic preventive maintenance strategy with GPSO algorithm seeking is significantly lower than that of the four maintenance strategies with PSO algorithm, GA, ACO algorithm and IABC algorithm seeking with a cost rate of 0.00298 (10^4yuan/h). As the threshold of medium repair increases, the number of minor and medium repairs increases; as the threshold of major repairs decreases, the number of major repairs increases, and the number of major repairs has a significant effect on the cost rate. All five algorithms can obtain the optimal solution, but the GPSO algorithm obtains the lowest adaptation of the optimal solution as 2.0165 with better results. Although the GPSO algorithm has more iterations than the other four algorithms, it obtains more reasonable medium and major repair thresholds. In summary, the algorithm and model used in this paper are more effective and superior.

4.2 Prediction result analysis of coating machine based on BP-LSTM

Using the coating machine maintenance data in Table 1, a dynamic preventive maintenance model was used to develop a maintenance strategy for the coating machine over the future 6,500 hours of operation. The final maintenance strategy is shown in Fig. 13, the maintenance moments and their corresponding maintenance modes are shown in Table 6, and the optimal parameters of the maintenance strategy are shown in Table 7.

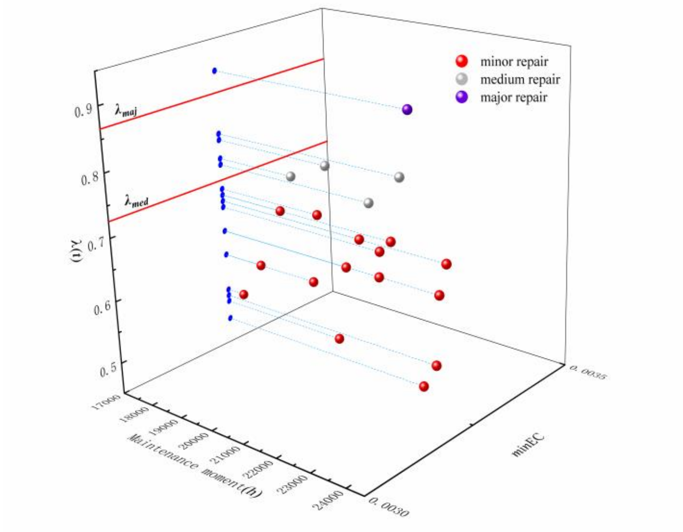


Fig. 13. Future 6500h maintenance strategy chart for coating machine.

Table 6. Maintenance moment and corresponding maintenance mode.

NO.	Maintenance moment	Maintenance mode	NO.	Maintenance moment	Maintenance mode
1	17543	minor repair	11	21745	medium repair
2	18213	minor repair	12	21998	minor repair
3	18962	minor repair	13	22031	minor repair
4	19363	medium repair	14	22364	minor repair
5	19955	minor repair	15	22651	medium repair
6	20153	minor repair	16	22913	major repair
7	20461	medium repair	17	23241	minor repair
8	20713	minor repair	18	23613	minor repair
9	21006	minor repair	19	23716	minor repair
10	21432	minor repair	20	23920	minor repair

Table 7. Optimal parameters for dynamic preventive maintenance strategy.

NO.	Parameter	Optimum value
1	λ_{med}	0.72
2	λ_{maj}	0.87
3	m	15
4	i	4
5	k	1
6	EC_{min}	0.00324

From Fig. 13, Table 6, and Table 7, it can be seen that during the future 6500h operation of the coating machine, the dynamic preventive maintenance strategy determines the optimal medium repair threshold of 0.72 and major repair threshold of 0.87 by prediction, and divides the maintenance schedule into 20 times based on the optimal threshold, including 15 times for minor repairs, 4 times for medium repairs and 1 time for major repair. The optimal cost rate of 0.00324 (10^4yuan/h) was obtained. Significantly, the number of minor repairs accounted for three-quarters of the total repairs, reflecting that the coating machine is in stable operation, but preventive maintenance with one major repair is predicted at 22913h, possibly due to functional failure caused by a vulnerable component running continuously for too long, and maintenance should be focused on.

4. Conclusions

In this paper, a dynamic preventive maintenance strategy is proposed for the problem of high maintenance cost rate due to excessive maintenance caused by unreasonable maintenance threshold setting when complex electromechanical equipment maintenance strategy is formulated, which provides valuable reference for the development of maintenance strategies. According to the effect of preventive maintenance on the equipment, the incremental failure rate factor and the decreasing service age factor are introduced to describe the changes of degradation characteristics during the operation of the equipment. The physical model of device degradation is combined with a BP-LSTM deep learning model to predict the failure rate of the device. A dynamic preventive maintenance model was constructed to classify the three preventive maintenance modes of minor, medium and major repairs based on the dynamic failure rate threshold. A dynamic preventive maintenance strategy for the coater was developed based on this model. A dynamic preventive maintenance strategy optimization process based on GPSO algorithm is established with the objective of minimizing the cost rate per unit time during the service phase given multiple cost types. The resulting optimal dynamic failure rate threshold reduces the risk of coater failure while ensuring the lowest cost rate. Since the dynamic preventive maintenance model is based on the original failure data and determines the optimal failure rate threshold according to a strict merit search model, it is not influenced by any subjective factors and ensures the reasonableness of the failure rate threshold. And three preventive maintenance modes corresponding to different types of failures are considered to make the dynamic preventive maintenance strategy more realistic. The analysis of the dynamic preventive maintenance strategy demonstrates its effectiveness, economy and applicability. The proposed maintenance strategy provides a new guiding direction for manufacturers.

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Acronyms

LSTM	Long Short-Term Memory	GPSO	Genetic-Particle Swarm Optimization
BP	Back Propagation	PSO	Particle Swarm Optimization
DM	Dynamic preventive maintenance Model	GA	Genetic Algorithm
RM	Reliability-constrained maintenance Model	ACO	Ant Colony Optimization
IM	Importance-constrained maintenance Model	IABC	Improved Artificial Bee Colony
AM	Age-dependent replacement Model		

Notations

λ_{med}	Medium repair threshold	λ_{maj}	Major repair threshold
N	Total number of repair	σ	Medium repair time
ρ	Major repair time	t_N	Failure moments predicted by BP-LSTM model
t_N'	The actual moment of performing maintenance	a	Failure rate increment factor
b	Service age decrement factor	m	Number of minor repairs
i	Number of medium repairs	k	Number of major repairs
C_{gmin}	Cost of materials required for a single minor repair	C_{gmed}	Cost of materials required for a single medium repair
C_{gmaj}	Cost of materials required for a single major repair	C_e	Cost of downtime per unit of time
C_{r0}	Cost of labor per unit of time		

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Schedule

Schedule 1. coating machine Time between failures

	NO.	TBF	NO.	TBF	NO.	TBF	NO.	TBF
TBJ001	1	13	21	947	41	2036	61	4779
	2	23	22	977	42	2110	62	4813
	3	37	23	1211	43	2250	63	4953
	4	76	24	1248	44	2531	64	5042
	5	81	25	1305	45	2630	65	5592
	6	94	26	1474	46	2645	66	5644
	7	106	27	1479	47	2723	67	5724
	8	119	28	1487	48	2903	68	5801
	9	136	29	1493	49	3005	69	6091
	10	558	30	1526	50	3051	70	6403
	11	628	31	1532	51	3111	71	6521
	12	651	32	1589	52	3150	72	6667
	13	661	33	1607	53	3188	73	6691
	14	692	34	1642	54	3204	74	6754
	15	793	35	1665	55	3397	75	6780
	16	818	36	1704	56	3564	76	7148
	17	824	37	1717	57	3948	77	7161
	18	832	38	1810	58	4113	78	7737
	19	887	39	1851	59	4171	79	7844
	20	939	40	2032	60	4619		
TBJ002	1	22	12	1500	23	2355	34	5719
	2	67	13	1798	24	2553	35	5811
	3	79	14	1953	25	2901	36	6412

	NO.	TBF	NO.	TBF	NO.	TBF	NO.	TBF
TBJ001	1	13	21	947	41	2036	61	4779
	2	23	22	977	42	2110	62	4813
	3	37	23	1211	43	2250	63	4953
	4	76	24	1248	44	2531	64	5042
	5	81	25	1305	45	2630	65	5592
	6	94	26	1474	46	2645	66	5644
	7	106	27	1479	47	2723	67	5724
	8	119	28	1487	48	2903	68	5801
	9	136	29	1493	49	3005	69	6091
	10	558	30	1526	50	3051	70	6403
	11	628	31	1532	51	3111	71	6521
	12	651	32	1589	52	3150	72	6667
	13	661	33	1607	53	3188	73	6691
	14	692	34	1642	54	3204	74	6754
	15	793	35	1665	55	3397	75	6780
	16	818	36	1704	56	3564	76	7148
	17	824	37	1717	57	3948	77	7161
	18	832	38	1810	58	4113	78	7737
	19	887	39	1851	59	4171	79	7844
	20	939	40	2032	60	4619		
	4	630	15	1965	26	3319	37	6434
	5	683	16	1989	27	4093	38	6456
	6	870	17	2051	28	4169	39	6623
	7	923	18	2057	29	4622	40	6737
	8	938	19	2063	30	4749	41	7823
	9	953	20	2226	31	4905	42	8049
	10	960	21	2299	32	4986	43	8633
	11	1237	22	2332	33	5406		