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THREE-GRADE PREVENTIVE MAINTENANCE DECISION MAKING*

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A complex repairable system generally adopts multi-grade preventive maintenance. The optimization of maintenance decision making is usually regarded as a complex mathematical problem. This study proposes a three-grade preventive maintenance optimization method for complex repairable system based on field failure data. Specifically, all failures are classified into three categories: minor, moderate and major failures according to two factors, the downtime and repair cost. Different failure categories are introduced to optimize different grades preventive maintenance. Cumulative failure numbers of three categories are used as condition variables to represent the failure intensity. The relations between the condition variables and operating time can be represented by a random failure point process model to the setup of maintenance decision making optimization models. An empirical case is used to illustrate the effectiveness of the proposed method. Based on the field failure data, an optimal period (or optimal cumulative failure number) of a certain grade preventive maintenance is determined, which can support maintenance decision-making.

Key words: complex repairable system, preventive maintenance, decision making, field failure data.

1. INTRODUCTION

Complex repairable systems are widely used in construction machinery, transport vehicles, elevators, etc. To ensure a complex repairable system operating safely and reliably, preventive maintenance (PM for short) is required [1, 2]. According to the different contents of maintenance task, PM activities are usually grouped into simple preventive maintenance and preventive replacement [2–4]. However, managers are normally very conservative in PM decision making and implementation because of the expensive cost of PM. Therefore, the system may lack enough maintenance and cause serious potential risks [5]. In addition, since the system has been affected by actual operating environment and maintenance activities, there is a significant difference between the field reliability and design reliability [6, 7]. Besides, the manufacturers usually recommend PM system according to the design reliability, which easily lead to inaccurate or non-optimal PM. In other words, if managers blindly use the PM system recommended by the manufacturer, excessive or insufficient maintenance could be caused. Therefore, it is very meaningful to optimize PM based on the field failure data.

A complex repairable system often comprises a number of subsystems, and the reliability of each subsystem is usually different [8]. Therefore, the operating system should be interrupted many times to perform PM, and during the PM optimization, an optimal period of each PM should be obtained. To ensure the working process of system be stable and controllable, the whole system should be performed multi-grade PM. Therefore, it becomes a complex mathematical problem on how to determine the optimal grades, the task of each grade as well as PM periods. These issues have been paid lots of attention by many researchers.

Nakamura et al. [9] applied the dimensional reduction method to solve the problem in which a few available data are used together with other factors relating to the failures of pumps owned by Kyushu Electric Power Company. The whole distribution of period of failure using available actual data is extrapolated to the distribution of the mean time to failure. Then, the most suitable maintenance interval for

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each pump is determined. The result shows that the total maintenance times for the next 10 years of operation of the pump system is reduced from 115 to 87.

Muthukumaran et al. [10] reported a PM program model of transport vehicles implemented by the software MASSTRAM. In this model, a vehicle fleet is regarded as a system. Each vehicle in the fleet is regarded as a subsystem subjected time-based PM. Subsystem failure rate is assumed as a function of their mileage. The maintenance policy determines the subsystems minimum preventive replacement mileage. Then let other preventive replacement mileage be integer multiples of the minimum preventive replacement mileage. The actual preventive replacement work has been better carried out with the Muthukumaran model. Literature [11] regarded the type-I PM of construction mechanical system as time-based PM, and the period is T0. The subsystems are arranged into six groups in an ascending order of life. The PM period of nth group is n times T0. The type-I PM is mainly subjected to the life time T0 subsystems. The life time 2T0 subsystems are checked simultaneously. The type-II PM is subjected to the life time T0 and 3T0 subsystems. The life time 4T0 and 5T0 subsystems are checked. The type-III PM is subjected to all subsystems. When checking the subsystems, if any subsystem is determined through the estimated operating state and remaining useful life that it can not operate to the upcoming PM, the repair, adjustment or replacement will be performed.

Literatures [10, 11] discussed the combinatorial optimization method, which reflected the ideology of the group maintenance [12–16] and opportunity maintenance [17–20]. For group maintenance, two typical policies have been developed: age-based group replacement policy [12, 13] and failure counting-based group replacement policy [14]. The age-based group replacement policy needs to arrange all subsystems into several groups in an ascending order of life. The maintenance policy determines the subsystems minimum preventive replacement period firstly. Then let the other subsystems preventive replacement periods be integer multiples of the minimum preventive replacement period. The subsystems will be performed corrective replacement upon failure between the last and the upcoming PM. Failure counting-based group replacement policy is on the basis of minimum repair number. Corrective replacement will be performed after a certain repair number. Literatures [15, 16] suggested considering the life as well as the minimum repair number. The recommended policy calls for a group replacement when the system is of certain age, or when certain failure numbers have occurred, whichever comes first. For the group maintenance, more attention has been paid to the multiple of grades rather than the relationship between subsystems and components. In addition, data completeness is required stringently to support the analysis and modelling.

When a mandatory maintenance action (e.g., failure of a component) is needed under opportunistic maintenance policy, one looks for other components for which PM actions can be carried out at the same time. The components for which PM action is carried out must meet certain technical and economical conditions. The “technical and economical conditions” can be a critical age [17–19], or hazard-rate level [20, 21], etc. However, the opportunity maintenance focuses on the preventive replacement, which is similar with the group maintenance. Data completeness is also required stringently as well as the calculations of life and remaining life. Meanwhile it is hard to find the optimal solutions of the model. For example, if the system contains n subsystems or components, the optimization model will contain 2n model parameters [17–19].

In recent years, many scholars have introduced the condition-based maintenance or multi-criteria decision making (MCDM for short) into the PM of complex repairable system. Literatures [22, 23] considered replacing oil according to oil quality. Literatures [24, 25] were about the monitor of system. Labib et al. [26, 27] proposed to implement the fixed rules and flexible strategies in repairable system. A hybrid of a rule-based approach and the analytic hierarchy process (AHP for short) technique was used to maintenance decision making. Literatures [28–30] focused on a single grade or some subsystems PM optimization. Literature [28] was about the engine overhaul decision making. Literatures [29] and [30] concerned about vehicle overhaul and some vehicle components PM optimization respectively. Literatures [31–34] applied the MCDM into software maintenance by classifying and predicting software defect. While literatures [35] proposed applying data mining and knowledge discovery to support decision making. Undoubtedly, condition-based maintenance is expensive, and more attention is paid to a certain grade of PM optimization rather than the global optimization.

This study attempts to establish a three-grade PM (type-I, type-II and type-III PM) optimization method based on field failure data. More specifically, the failure modes of subsystems or components in a system are different. The effects on the whole performance of system affected by different failure modes within a subsystem are also different. Therefore, all failures are classified into three categories: minor, moderate and major failures in terms of two factors, the downtime and repair cost. Assume a system adopts three-grade PM, and different grades PM can exclude different failure categories. We will optimize different grades PM on the basis of the corresponding failure categories. It is assumed that the PM includes preventive replacement and preventive repair. Cumulative failure number is regarded as condition random variable to represent the failure intensity of each category. The relation between the condition variable and operating time will be represented by a random failure point process model to the setup of maintenance decision making optimization models. An empirical case will be presented to illustrate the effectiveness of the proposed method. Based on the failure classification, the failure intensity of each category will be determined. The proposals of maintenance decision making of three-type PM will be given out finally.

2. PROPOSED OPTIMIZATION METHOD

The following indices and variables are used in the proposed method:

$J(\cdot)$ – cost rate

$E(.)$ – expectancy

α,β – model parameters of power law model

t_j – the j^{th} failure time

c_j, d_j – repair cost and downtime of the j^{th} failure

c^*, d^* – cost and downtime limit

T_1 – period of type-I PM

T_{1i}, T_{2i}, T_{3i} – the i^{th} failure time of minor, moderate and major failure

$N(T_{1i}), N(T_{2i}), N(T_{3i})$ – the cumulative minor, moderate and major failure numbers

N_{i1} – cumulative minor failure numbers upon the i^{th} moderate failure

M_{i1}, M_{i2} – cumulative minor and moderate failure numbers upon the i^{th} major failure

c_{r1}, c_{r2}, c_{r3} – average repair cost of minor, moderate and major failure

c_{p1}, c_{p2}, c_{p3} – average PM cost of type-I, type-II and type-III PM.

Consider a complex repairable system is subjected three-type of PM: type-I, type-II and type-III PM. Upon an operational failure, the system is restored by a corrective maintenance (CM for short). For illustrative purposes, the failure-repair process of a complex repairable system is shown in Fig. 1. The failure time, downtime and repair cost of the targeted system are recorded timely by the management information system. According to repair cost and downtime, all failures should be classified into three categories and the corresponding relations between the failure categories and PM types are shown in Fig. 1. The cumulative failure number of each category is regarded as optimization variable. For example, the minor failure is regarded as the optimization variable of type-I PM to the setup of maintenance decision optimization model. The details of the proposed method are described as follow.

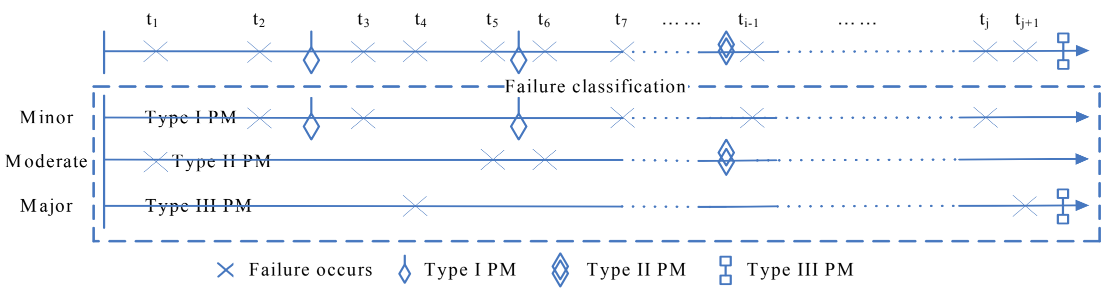

Fig. 1 – Failure-repair process and the ideology of the proposed method.

Assume c^* and d^* are the limit of repair cost and downtime respectively. We divide all failures into three categories according to (c^*, d^*), where the definitions of three failure categories are visually displayed in Fig. 2. c^* and d^* can be determined by piecewise-linear model [36, 37]:

$$y(t_i)=\begin{cases} a_1 t_i + b_1 & 0 \le t_i \le t^* \\ a_2 t_i + b_2 & t_i \ge t^* \end{cases} = \begin{cases} \max(a_1 t_i + b_1, a_2 t_i + b_2) & \text{Convex increasing} \\ \min(a_1 t_i + b_1, a_2 t_i + b_2) & \text{Concave decreasing} \end{cases}. \quad (1)$$

Taking the observed value c_i for example, the parameters a_1, b_1, a_2, b_2 can be estimated by minimizing the sum of squared errors (SSE for short) denoted as:

$$\text{SSE} = \sum_{i=1} \left[c_i - y(t_i)\right]^2 . \quad (2)$$

The Solver of Microsoft Excel can be used to find the parameters where SSE achieves its minimum. Once the parameters are estimated, the c^* can be obtained by:

$$c^* = a_1 \frac{a_2 - a_1}{b_1 - b_2} + b_1 . \quad (3)$$

Similarly, the d^* can be obtained in the same way. The fitting result of the piecewise-linear model is shown in Fig. 3. It can be seen from Fig. 3 that the fitted piecewise-linear model is very close to the observed value. Therefore, c^* (or d^*) obtained from this method is rational.

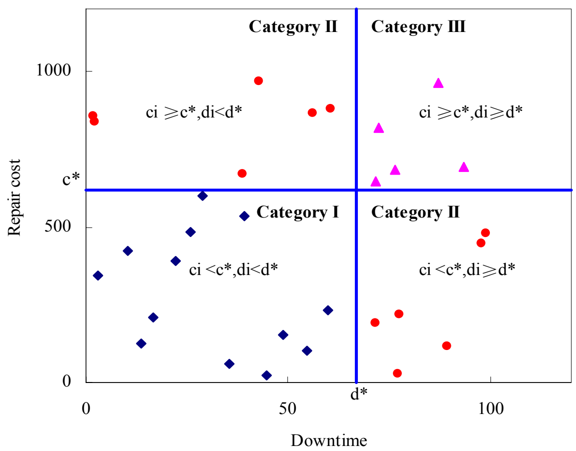

Fig. 2 – Failure classification.

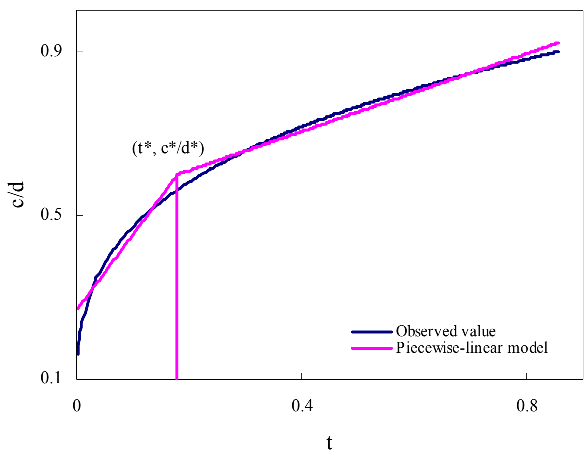

Fig. 3 –Fitting result of piecewise-linear model.

When the failure classification is completed, the failure time of each failure category, and cumulative minor, moderate (or minor) failure numbers upon the occurrence of major (or moderate) failure can be obtained, as shown in Table 1.

Table 1

Data list after failure classification

T_{3i}	$N(T_{3i})$	M_{i1}	M_{i2}	T_{2i}	$N(T_{2i})$	N_{i1}	T_{1i}	$N(T_{1i})$
2006.9.15	1	18	7	2006.9.7	1	3	2006.9.1	1
2007.3.26	2	26	7	2006.9.9	2	5	2006.9.2	2
…	…	…	…	…	…	…	…	…
PL Parameters	α_3, β_3	α_{31}, β_{31}	α_{32}, β_{32}	—	α_2, β_2	α_{21}, β_{21}	—	α_1, β_1

Due to the impact of operating conditions, environment and maintenance, the time between failures is not independent and identically distributed. Thus, the random failure point process model is the appropriate model [38]. The power law model (PL, see [38]) is applied to model the cumulative failure numbers as shown in Table 1. Taking the major failure for example, the PL model is given by:

$$E\left[N(T_{3i})\right] = \alpha_3 T_{3i}^{\beta_3} . \quad (4)$$

The parameters can be estimated by minimizing SSE. Then the maintenance decision making optimization models will be given out based on the abovementioned preparations.

More generally, the type-I PM mainly contains inspection, lubrication and cleaning. But other types PM are performed to prevent hidden problems happening. Therefore, type-I PM is usually considered as time-based PM while type-II and type-III PM are regarded as condition-based PM. In the following, maintenance optimization models for three-type PM will be established and illustrated respectively.

For type-I PM, the maintenance cost in a type-I PM period generally includes repair cost and PM cost. Thus, the cost rate of a type-I PM period can be defined as:

$$J\left(T_1\right)=\left(\alpha_1 T_1^{\beta_1}\cdot c_{r1}+\alpha_2 T_1^{\beta_2}\cdot c_{r2}+\alpha_3 T_1^{\beta_3}\cdot c_{r3}+c_{p1}\right)\Big/T_1\,, \tag{5}$$

where $\alpha_1 T_1^{\beta_1}\cdot c_{r1},\alpha_2 T_1^{\beta_2}\cdot c_{r2},\alpha_3 T_1^{\beta_3}\cdot c_{r3}$ are the three categories failure repair cost within T_1. The optimal value of T_1 is determined by minimizing the cost rate given by equation (5).

For type-II and type-III PM, the following failure counting policy is used to perform optimization [39]. This policy can be extended to the case under following considerations: The system is subjected type-II (or type-III) PM at the $(m+1)^{\text{st}}$ (or $(k+1)^{\text{st}}$) failure after the system has been repaired for m (or k) times. The optimal m (or k) can be determined by minimizing $J(m)$ (or $J(k)$) given by:

$$J\left(m\right)=\left(\alpha_{21}m^{\beta_{21}}\cdot c_{r1}+\alpha_{23}m^{\beta_{23}}\cdot c_{r3}+mc_{r2}+c_p\right)\Big/T_2\;,\;J\left(k\right)=\left(\alpha_{31}k^{\beta_{31}}\cdot c_{r1}+\alpha_{32}k^{\beta_{32}}\cdot c_{r2}+kc_{r3}+c_p'\right)\Big/T\;. \tag{6}$$

where $c_p=c_{p1}\left(T_2/T_1\right)+c_{p2}$, $c_p'=c_{p3}+c_{p1}T/T_1+c_{p2}\alpha_{32}k^{\beta_{32}}/m$, $T_2=\left(m/\alpha_2\right)^{1/\beta_2}$ and $T=\left(k/\alpha_3\right)^{1/\beta_3}$. $c_{p1}\left(T_2/T_1\right)$ is the cost of type-I PM between the last and upcoming type-II PM. $c_{p1}\left(T/T_1\right)$ and $c_{p2}\alpha_{32}k^{\beta_{32}}/m$ are the cost of type-I PM and type-II PM between the last and upcoming type-III PM respectively. $\alpha_{21},\beta_{21},\alpha_{23},\beta_{23}$ are the reciprocals of $\alpha_{12},\beta_{12},\alpha_{32},\beta_{32}$ respectively.

In the following, an empirical case study is presented to illustrate the effectiveness of the proposed method based on real-world data.

3. CASE STUDY

A bus company runs 48 bus routes with more than one thousand buses. In order to maintain the operational reliability and safety, the bus is usually subjected to three-type of PM:

– Type-I PM focuses on cleaning, lubrication and fastening with an interval of about twice per month;

– Type-II PM focuses on inspection, adjustment the brake system and cleaning of filters with an interval of about three times per year;

– Type-III PM overhauls the bus with an interval of about once per 3-4 years when the bus is new, 1.5 years after the first type-III PM occurred. Type-III PM mainly focuses on engine overhaul, including the disintegration of the engine, cleaning, inspection of the parts, and replacing the cylinder sleeve, piston pins and piston rings etc.

Upon an operational failure, the bus is restored by a corrective repair, which can be deemed as a minimal repair though certain opportunistic maintenance actions may be combined. Management information system records the failure information, such as failure time, repair cost and downtime.

To illustrate the effectiveness of the proposed method, we collected a fleet of 22 buses (with the same model) operational data from September 1, 2006 to December 31, 2009, including failure time, repair cost, downtime, and PM cost of type-I, type-II and type-III PM. For simplicity, parts of failure observations are displayed as examples in Table 2. The fleet has been subjected 54 times type-I PM with an average interval of 23 days and 9 times type-II PM with an average interval of 153 days in duration of 1217 days. Only one bus has been performed type-III PM by the time that the observation ends. The average PM costs of three-type PM are displayed in the last row of Table 2.

Apply piecewise-linear model to approximate the repair cost and downtime, then we get $c^* = 424.20$ RMB and $d^* = 87.90$ minutes respectively. According to Fig. 2, we divide all failures into three categories, minor, moderate and major failures, which are corresponding to 2 242, 703 and 144 times respectively, and the average repair costs are 57.00 RMB, 547.90 RMB and 1 190.00 RMB respectively.

After failure classification, we summarize the failure roots of three failure categories. It can be found that the proposed failure classification results are similar with the PM technical standard worked out by the bus company. In other words, the proposed classification method is effective.

When failure classification is completed, the data can be further sorted as shown in Table 1. Then, we apply the PL model to model the cumulative failure numbers shown in Table 1. The estimated model parameters are shown in Table 3.

Table 2

Filed failure data (totally 3089 data)

t_i	c_i	d_i
2006.09.01	388.90	35
……	……	……
……	……	……
Average value	213.13	75.75
c_{p1}=296.70	c_{p2}=1967.13	c_{p3}=9800.00

Table 3

Model parameters and optimization results

α_1	0.123	β_1	1.375	T_1
α_2	0.035	β_2	1.398	11 days
α_3	1.25×10^{-3}	β_3	1.643	m
α_{31}	33.574	β_{31}	0.832	83 times
α_{32}	13.829	β_{32}	0.788	k
α_{21}	1.851	β_{21}	1.076	114 times

Let c_{p1}, c_{p2}, c_{p3} equal the average value as shown in the last row of Table 2. According to equations (5, 6), the optimization results are displaced in the last two rows of Table 3. It can be seen from Table 3 that the optimal interval of type-I PM is 11 days. However, the average actual interval is 23 days, which is longer than the optimization result and the company technical standards (15 days). This result shows that the company has not paid enough attention to type-I PM. The task of type-I PM contains fastening, lubrication and cleaning, etc. Literatures [30, 40] pointed out that the lubrication and cleaning play a great impact on system reliability, therefore, it is recommended that the company should pay more attention to type-I PM.

For type-II PM, m = 83 means the bus fleet should be performed type-II PM every 84 times (4 times for single bus) moderate failure. Table 4 shows the proposed type-II PM time and the 10th time is predicted. According to Table 4, the interval between last and the upcoming type-II PM decreases with use age. In fact, the fleet is subjected time-based type-II PM, where the average period is 153 days. By comparing the results obtained from the proposed method with the actual execution time, we can find that the type-II PM has not been performed on appropriate time, which may bring unreasonable maintenance and economic losses.

Table 4

Type-II PM time

Order	1	2	3	4	5
Proposed time	2007-03-23	2007-08-21	2008-01-19	2008-05-28	2008-08-27
Interval time/days	—	151	151	130	91
Actual executed time	2006-11-23	2007-01-15	2007-06-15	2007-11-17	2008-05-05
Order	6	7	8	9	*10*
Proposed time	2008-12-12	2009-04-14	2009-07-16	2009-10-09	*2010-01-10*
Interval time/days	107	123	93	85	*93*
Actual executed time	2008-09-30	2009-02-25	2009-07-03	2009-09-28	2009-11-15

For type-III PM, k = 114 indicates that when the major failure of the bus fleet occurred 115 times (6th times for single bus), type-III PM should be performed. The 115th times major failure of the bus fleet occurred in May 2009. In other words, the bus fleet should be performed type-III PM in May 2009. In fact, only the 21st bus has been performed type-III PM by the time of May 2009. If applying this optimal result to the case under consideration, 16 buses should have been performed type-III PM before the observation ends, and other 6 buses should be performed type-III PM when the 6th major failure occurred. Table 5 shows these buses and their type-III PM time.

There are significant changes for the occurrence frequency of the major failure. Therefore, we attempt to use segmented PL model (more details about the segmented PL model see [41]) to model cumulative major failure numbers. The optimization result obtained by segmented PL model is 87 times, which means that the bus fleet should be performed type-III PM upon the 88th times (5th times for single bus) major failure. The results are displayed in Table 5. It can be seen from Table 5 that when the failure exist significant changes in the trend, the segmented model should be considered.

The results show the effectiveness of the proposed method. The optimal period of type-I PM, and the optimal cumulative failure numbers before type-II and type-III PM are determined. Based on the obtained results, we can make the following observations.

1) The classification results for all failures are very close to the technical standards of the company PM, indicating that this classification method is rational;

2) The company has not paid enough attention to type-I PM;

3) The type-II and type-III PM have not been performed on appropriate time. The proposed type-II and type-III PM time have been provided;

4) The existing significant changes of the occurrence frequency should be considered.

Table 5

Major failure number and type-III PM time

Bus	Major failure number	PL model	Segmented PL model	Bus	Major failure number	PL model	Segmented PL model
1	8	2008.12	2008.08	12	6	2009.03	2009.01
2	6	2009.09	2009.06	13	6	2009.09	2009.06
3	9	2008.09	2008.06	14	7	2008.11	2008.08
4	4	>2009.12	>2009.12	15	6	2009.06	2009.04
5	4	>2009.12	>2009.12	16	5	>2009.12	2009.08
6	4	>2009.12	>2009.12	17	5	>2009.12	2009.07
7	10	2009.02	2008.12	18	6	2009.06	2009.04
8	6	2009.12	2009.10	19	8	2008.10	2008.10
9	9	2008.12	2008.11	20	7	2009.06	2009.05
10	9	2009.01	2008.10	21	6	2009.12	2009.12
11	5	>2009.12	2009.10	22	8	2009.05	2009.05

4. CONCLUSIONS

We have proposed an optimization method of three-grade PM based on field failure data. The effectiveness of the proposed method has been illustrated by a case study. According to the results, this method has the following advantages:

1) The cumulative failure number is an important characterization of operational reliability, which can be used as variable to optimize the maintenance decision making to reflect the ideology of condition-based maintenance;

2) The proposed method is strongly flexibility. The downtime and repair cost can be replaced by other indexes. Even without records, failure classification can be performed by the qualitative analysis method, such as AHP. This method is still effective to other multi-grade PM optimization;

3) And taking the number of different severity failure as index for PM decision making, the opportunity of PM is easy to be grasped.

As future work, an interesting issue is to study the classification of failure using classification algorithms in Data Mining. In addition, we only consider the cost in the maintenance optimization model in the proposed method. Multiple criteria can be considered in the maintenance plan and the different MCDM methods can be introduced to the proposed method.

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