An improved method for evaluating the preventive maintenance quality of buses

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***Abstract*—This paper proposes an improved method to evaluate the quality of preventive maintenance. This method evaluates the quality of preventive maintenance by comparing the pseudo-failure rate and the actual failure rate after the maintenance point. When using the weighting method to establish the power-law model to fit the failure data before the maintenance point, we focus on its prediction effect. When the normal function weight and the negative exponential function weight are used to estimate the model parameters, it is found that the model with negative exponential function weight has better predictive ability. To improve the accuracy of the prediction, the parameters of the negative exponential weight function are optimized. When using the power-law model to model the failure data after maintenance, we pay attention to the fitting effect. In the subsequent case study, we used two methods to evaluate the quality of preventive maintenance of a fleet of 26 buses, and the results show that the improved method is more reasonable.**

Keywords- power-law model; negative exponential function; pseudo-failure rate; maintenance quality evaluation

I. INTRODUCTION

In order to maintain good technical condition and ensure safe operation, the automobile transportation enterprises implement the vehicle preventive maintenance system and regularly prevent and maintenance the operating vehicles (e.g., see [1]). Generally speaking, the preventive maintenance of the vehicle will reduce the failure rate. However, the failure rates of some vehicles after maintenance have not decreased significantly, and even some failure rates are higher than before. It is necessary to evaluate the quality of preventive maintenance in the vehicle maintenance department ([2]). Some researchers have studied the issue of maintenance quality evaluation.

In the aspect of maintenance quality evaluation, Wang et al ([2]) proposed a method for evaluating the quality of maintenance of weapons and equipment. The authors use the analytic hierarchy process to fuse the indicators of maintenance quality evaluation into a quality index to evaluate the quality of maintenance. In the aspect of failure data modeling, Attardi L et al([2]) proposes A new two-parameter Engelhardt-Bain process (2-EBP) model to describe the failure mode of a complex repairable system. The model can be regarded as a dynamic power-law process, and the model parameter system changes with age. In addition, some researchers analyze failure data for fleet health management and fleet maintenance quality assessment. These methods include using least squares to model the failure data and the change point method. It should be pointed out that Jiang([8]) uses a weighted least squares method to fit the observed data to the power-law model and the fitted model is then used to optimize the overhaul decisions for the population and individual systems, respectively. Based on the above research, Jiang et al([9]) fit the failure observations before and after maintenance to the power-law model using a least squares method, and evaluated the quality of preventive maintenance by comparing the failure rates before and after maintenance.

Among these existing methods for evaluating the quality of maintenance, it is common to fit the failure data before and after the maintenance point to a model, and then compare the failure rate within the same length of time before and after the maintenance point. If the failure rate before maintenance is greater than the failure rate after maintenance, the quality of preventive maintenance is considered to be good. Otherwise, the quality of preventive maintenance is poor. This maintenance quality is evaluated by comparing the failure rates in different time intervals (although they are adjacent), and the failure rates in different time intervals are generally not the same. Considering the factor of failure rate change caused over time, this paper proposes a method to compare the two failure rates in the same time interval to evaluate the quality of preventive maintenance. The former is the pseudo failure rate, which is the predicted failure rate based on the failure data before maintenance, and the latter is the actual failure rate after maintenance. Therefore, the comparison failure rate eliminates the difference caused by time, and can objectively evaluate the preventive maintenance effect.

The paper is organized as follows. The existing method is introduced in Section 2. The proposed method of maintenance quality evaluation is presented in Section 3 and illustrated in Section 4. The paper is concluded in Section 5

II. THE EXISTING METHOD

In the literature 8, Jiang proposed a method for fitting the

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failure point process to a power rate model by using weighted least squares method. The main process is as follows.

A. Empirical Mean Cumulative Function (MCF)

Assume there are N groups of nominally identical and independent systems; the failure data for each system can be described as:

$$\{t_{i1} \le t_{i2} \le \cdots \le t_{im_i} \le T_i, 1 \le i \le N\}\ . \qquad (1)$$

Here T_i is censored time if $T_i > t_{im_i}$; otherwise, it is a failure time.

To generalize the problem, consider a failure point process ($t_i, i = 1,2,\ldots$). For a given time t , the number of cumulative failures over ($0, t$), $N(t)$, is a discrete random variable. Let $M(t)$ be the mathematical expectation of $N(t)$ .For a certain system, the empirical MCF is given by

$$M(t_{ij}) = [M^*(t_{i,j-1}) + M^*(t_{i,j})]/2 \qquad (2)$$

where $M^*(t_{i0}) = 0$, $M^*(t_{ij}) = M^*(t_{i,j-1}) + I_j$, and $I_j = 1$ $[= 0]$ for a failure [censoring] observation. For more details about the empirical MCF, see literature 7 and 10.

B. The Power-law Model

To fit the empirical MCF, the appropriate model is the power-law model. Its expression is

$$M(t) = (t/\eta)^{\beta}, \quad \eta, \beta > 0\ . \qquad (3)$$

The corresponding failure intensity function is given by

$$m(t) = \beta M(t)/t\ . \qquad (4)$$

C. The Weighted Least Squares Method

In order to emphasize the importance of data at different times, the weight function $w(t) (0 < w(t) \le 1)$ was introduced. The model parameters are obtained by the weighted least squares estimation method can by minimizing the following equation([6])

$$SSE_w = \sum_{j=1}^{m_i} w(t_j)[(M(t_j, \eta, \beta) - M_e(t_j)]^2 \qquad (5)$$

where $M(t_j, \eta, \beta)$ is the power-law model while $M_e(t_j)$ is the empirical MCF.

In the literature 8, the author uses the following weight function:

$$w(t) = \exp[-\frac{(t-\mu)^2}{2\sigma^2}] = \sqrt{2\pi}\sigma\phi(t; \mu, \sigma), 0 < t \le \mu \qquad (6)$$

where $\phi(.)$ is the normal pdf. Let μ be a given value, and σ is obtained by solving the equation:

$$\sum_{j=1}^{m_i} w(t_j) = n_w \qquad (7)$$

Here n_w is a suitable constant, generally taking 2.5.

D. Application

In the literature 9, the authors fit the failure data of two adjacent preventive maintenance cycles (τ_{i-1}, τ_i) and (τ_i, τ_{i+1}) to the power-law model, and then compare the failure rates of 30 days(According to relevant regulations, the guarantee period for the quality of vehicle secondary maintenance is 5000 km or 30 days, therefore we take Δt as 30(days)) before and after the maintenance point to evaluate the quality of maintenance.

From Figure 1, as seen, the failure data between (τ_{i-1}, τ_i) are fitted into a power-law model as below

$$M_i(t) = \alpha_i t^{\beta_i}\ . \qquad (8)$$

The failure data between (τ_i, τ_{i+1}) are fitted into another power-law model as below

$$M_{i+1}(t) = \alpha_{i+1}(t - \tau_i)^{\beta_{i+1}}\ . \qquad (9)$$

The failure intensities during $(\tau_i - \Delta t, \tau_i)$ and $(\tau_i, \tau_i + \Delta t)$ are derived as

$$m_i(\tau_i) = \alpha_i[\tau_i^{\beta_i} - (\tau_i - \Delta t)^{\beta_i}]/\Delta t\ , \qquad (10)$$

and

$$m_i(\tau_{i+1}) = \alpha_{i+1}\Delta t^{\beta_{i+1}-1}\ . \qquad (11)$$

Use the difference

$$\Delta m_i(\tau_i) = m_i(\tau_i) - m_i(\tau_{i+1}) \qquad (12)$$

to evaluate the effect of preventive maintenance. A larger $\Delta m_i(\tau_i)$ indicates a good effect of preventive maintenance. Sometimes $\Delta m_i(\tau_i)/m_i(\tau_i)$ is used to indicate the relative effect of preventive maintenance.

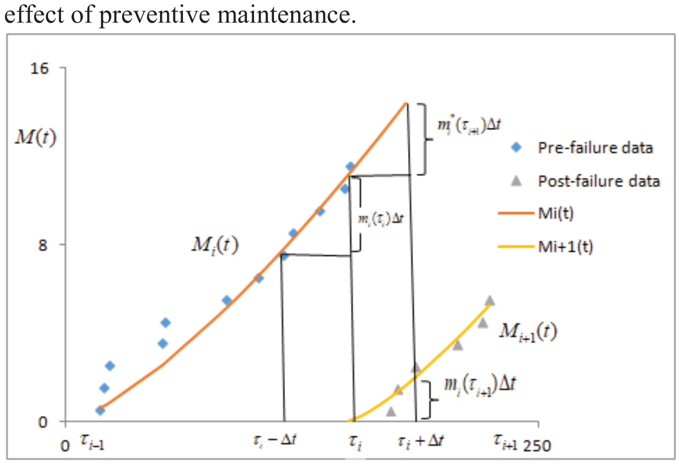

Figure 1 Empirical MCF scatter plot and power-law models fitted by different methods

III. PROPOSED METHOD

A. The Main Idea

In section 2.D, maintenance quality evaluation is performed by comparing the failure rates in different time intervals (although they are adjacent). In fact, the failure rates in different time intervals are generally not the same. We propose a method to compare the two failure rates in the same time interval to evaluate the quality of maintenance. The former is the pseudo failure rate, which is based on the per-maintenance failure data to predict the maintenance failure rate, and the latter is the actual failure rate after maintenance, This comparison of the failure rate excludes the difference caused by time, and can objectively evaluate the preventive maintenance effect. To achieve a more accurate prediction of pseudo failure rate, two problems must be solved. One is the choice of the weight function, and the other is the optimization of the weight function parameters.

B. Choice of Weight Function

As can be seen in Figure 1, for the per-maintenance data, we establish a power-law model to focus on its predictive ability. To avoid over-fitting, it is not necessary to assign too large weight to the data near the maintenance point, and a suitable weight can be it is. By comparing the normal weight function with the negative exponential weight function, it can be found that both weight functions can give greater weight to the data near the maintenance point, but in fact, the weight obtained by the negative exponential function is relatively balanced. Through calculation, we find that using the negative weight function has better predictive ability in the case of the same weight sum, so we use the following negative exponential weight function

$$w(t) = e^{-|t-\mu|/\sigma} \tag{13}$$

Where μ is given value, generally the maintenance point, while σ is obtained by solving the equation:

$$\sum_{j=1}^{m_i} w(t_j) = n_w \tag{14}$$

Here, the selection of n_w has a great influence on the parameter σ, which affects the distribution of weights. Generally, it can be better trained according to the failure data.

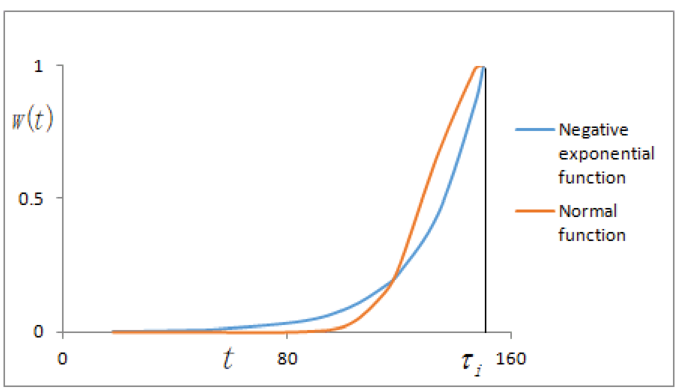

Figure 2 Two weight function graphs

Figure 2 shows the curves of the normal weight function and the negative exponential weight function.

IV. ILLUSTRATIONS

In this section, we evaluate the quality of preventive maintenance based on the failure time data of a fleet before and after secondary maintenance.

A. Data

The data shown in Table 1 come from the maintenance database of a public transportation company in Changsha City. We selected 26 vehicles of the same model to study the quality of their maintenance. They were put into use at the same time and were running on the same line. We extracted information on the failure time and maintenance time of these vehicles before and after the secondary maintenance from the failure and maintenance records of these vehicles from September 1, 2006 to December 31, 2009.

Table I shows the secondary maintenance and failure time data for the two vehicles numbered 1 and 3.

TABLE I MAINTENANCE AND FAILURE TIMES (IN DAYS) DATA OF TWO VEHICLES

i	Maintenance and failure time data								
1	1	5	16	27	31	49	77	90	93
	99	103	113	118	124*	146	162	165	171
	173	186	200	201	203	216	230		
3	3	10	17	23	29	35	43	55	76
	77	140	150	177	178	179	187	191	193
	195	197*	199	205	206	208	214	216	225
	229	230	240	241	242	265	268	272	273
	276	283	293	299	306	307	309		

Data marked with * for maintenance time, the rest for failure time

B. Modeling

We use the power-law model to fit the failure data before and after the maintenance. For the data before the maintenance, we focus on the prediction ability. For the failure data after the maintenance, we focus on the fitting effect. The specific practices are as follows:

- For each vehicle's per-maintenance failure data, We fit the data from the repair point 30 days ago to a power law model by weighted least squares method, and use the data within 30 days before the maintenance to evaluate the model. The predictive power of the model is evaluated by calculating the magnitude of the sum of the squares of the differences between the predicted values of the fitted model and the actual empirical MCF values. The results show that the negative exponential weight function has better prediction effect than the normal weight function. For the failure time data after maintenance, we use the normal weight to fit the power-law model to ensure its better fitting effect..
- When using the negative exponential weight function to fit the data before maintenance, an appropriate n_w (equation 14) can achieve the best prediction effect. When we train the model with 18 vehicles with more data before maintenance, the result shows that the best n_w from 14 vehicles fell into interval [1.5, 3]. In this interval, the model obtained by selecting n_w is relatively robust, for which we choose n_w as 2 (most of the best n_w around 2).

C. Maintenance Quality Evaluation

In this part we use different methods to evaluate the quality of preventive maintenance. In the first method, we take $n_w = 2.5$ and use the normal weight function to fit the data before and after maintenance point to the power-law model, and then according to the difference Δm (that is $m_i(\tau_i) - m_i(\tau_{i+1})$ as shown in figure1) of the failure rate within 30 days before and after the maintenance point to evaluate the quality of preventive maintenance. In the second method, we take $n_w = 2$, use the negative exponential weight function to weight the data before the maintenance point to the power-law model, and use the fitted model to calculate the failure time data within 30 days after maintenance; the method of modeling the failure data after the maintenance point is the same as the first method. After the actual failure rate is obtained, the quality of preventive maintenance is evaluated according to the difference $\Delta^* m$ (that is $m^*(\tau_{i+1}) - m(\tau_{i+1})$ as shown in figure1) between the two failure rates within 30 days after maintenance. $\Delta m / m(\tau)$ and $\Delta^* m / m^*(\tau)$ are relative failure rates, respectively. Thus, we obtain a quantitative evaluation of the maintenance effect of each vehicle, as shown in Table II.

TABLE II PREVENTIVE MAINTENANCE QUALITY EVALUATED BY TWO METHODS

i	Δm	$\Delta m / m(\tau)$	$\Delta^* m$	$\Delta^* m / m^*(\tau)$
1	0.1048	0.1328	0.662	0.725
2	0.1033	0.1254	0.860	0.886
3	0.0625	0.3111	0.166	0.482
4	0.2444	0.5311	0.775	0.883
5	-0.0056	-0.0215	-0.037	-0.156
6	0.0772	0.1095	0.428	0.511
7	0.0744	0.2455	0.506	0.779
8	0.0525	0.0686	0.493	0.562
9	0.0339	0.1167	0.199	0.466
10	0.1159	0.1830	0.511	0.647
11	0.0133	0.2825	0.080	0.748
12	0.1441	0.2518	0.687	0.807
13	-0.0335	-0.0356	-0.971	-1.091
14	0.0598	0.6898	0.315	0.847
15	0.1349	0.0632	0.539	0.354
16	-0.2489	-0.3098	-2.004	-1.850
17	-0.1035	-0.1212	-2.866	-3.639
18	0.0560	0.0803	0.232	0.438
19	0.0002	-0.0028	0.005	-0.059
20	0.1344	0.2415	0.802	0.783
21	0.0563	0.0732	0.497	0.525
22	0.0035	-0.0087	0.025	-0.057
23	-0.1333	-0.1469	-1.031	-1.066
24	0.1169	0.1477	0.297	0.948
25	0.0292	0.0267	0.186	0.144
26	0.0862	0.0976	0.742	0.773

From Table2, we can see that the average value of $\Delta^* m$ obtained by Method 2 is 12.04%, which is higher than the average value of Δm (4.53%) obtained by Method 1, indicating that the preventive maintenance reduces the failure rate by 12.04%. According to Method 1, five of the 26 vehicles have negative Δm, indicating that the results of the five vehicles are even worse after maintenance; According to Method 2, seven of the 26 vehicles have negative $\Delta^* m$, indicating that seven vehicles are even worse after maintenance. Through analysis of the reasons, the maintenance time for vehicle 13, 14,16,17,20, and 26 are 125, 119, 98,121,110,105 days respectively, and the maintenance times are significantly advanced. From the failure time data, the failure numbers of these vehicles before maintenance are high, indicating that the technical conditions of these vehicles are deteriorated. After maintenance, the failure rates of the four vehicles of 5, 13, 16, and 17 have not been effectively reduced, and further investigation is needed.

In addition, the absolute value of $\Delta^* m$ of each vehicle obtained from method 2 is generally greater than the absolute value of Δm, which indicates that method 2 has better discrimination. The Δm of the No. 3 vehicle is 0.0625, while $\Delta^* m$ =0.166. As can be seen from Figure 3, according to the change trend of the failure rate before maintenance, if the preventive maintenance activity is not taken, the failure rate after the maintenance point will be higher, obviously greater than the failure rate after maintenance, so method 2 is more reasonable than method 1.

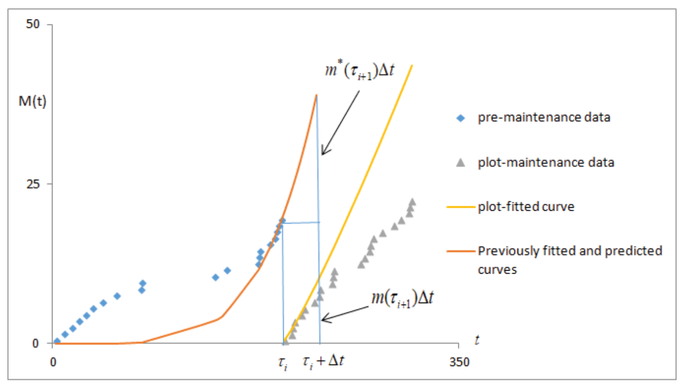

Figure 3 Pseudo failure rate and actual rate of the 3rd vehicle

V. CONCLUSION

In this paper we present an existing method for evaluating the quality of preventive maintenance. Using the normal function as the weight function, the failure data before and after the maintenance are fitted to the power-law model by weighted least squares method, and then the quality of the maintenance is evaluated by comparing the failure rate before and after the maintenance.

We propose a new method for evaluating the quality of maintenance by comparing the pseudo-failure rate after the maintenance point with the actual failure rate after maintenance. In order to estimate the pseudo-failure rate more accurately, we use a negative exponential weight function and optimize the parameters of the weight function.

Subsequent research includes a more comprehensive evaluation of maintenance quality from more aspects and from different perspectives, such as considering the type of failure, maintenance costs, and maintenance time, and so on.

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