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Zhisheng ZHANG
Wenke GAO
Yifan ZHOU
Zhiqiang ZHANG

RELIABILITY MODELING AND MAINTENANCE OPTIMIZATION OF THE DIESEL SYSTEM IN LOCOMOTIVES

MODELOWANIE NIEZAWODNOŚCI I OPTYMALIZACJA UTRZYMANIA RUCHU UKŁADU SAMOCZYNNEGO ZAPŁONU W LOKOMOTYWACH

Engine system is a prone-fault part in diesel locomotive and its malfunctions always occur regularly in different seasons in practice. However, the current maintenance policy in China has not attached deserving importance to seasonal influence, which is considered as one of the main causes for over/under-maintenance. To assess the current maintenance, in this study a double-fold Weibull competing risk model for summer and winter is developed using the real failure data (2008-2011) of locomotives from Urumqi Railway Bureau. Meanwhile, a new approach, termed as Approximately Combined Parameter Method (ACPM), is proposed to combine the initially estimated parameters into different folds, which can avoid a subjective determination of the model's parameters fold. After that, the combined parameters are used as initial values for maximum likelihood estimate (MLE) to achieve an accurate model. Necessary optimizations are introduced based on the chosen models. Results show that the maintenance period differs a lot between winter and summer, and the optimized maintenance can increase the availability and decrease cost more than the existing policy

Keywords: *diesel engine of locomotive, multiple Weibull competing risk model, maintenance optimization, approximately combined parameter method(ACPM).*

Układ silnikowy stanowi podatną na uszkodzenia część lokomotywy spalinowej, a w praktyce jego awarie występują zawsze regularnie w zależności od pory roku. Pomimo tego, obecna polityka obsługowa w Chinach nie przywiązuje wystarczającej wagi do wpływu pór roku, co uważa się za główną przyczynę nadmiernych lub niedostatecznych działań obsługowych. Aby ocenić bieżące działania obsługowe, w niniejszym artykule opracowano model zagrożeń konkurujących dla lata i zimy, oparty na połączeniu dwóch rozkładów Weibulla, wykorzystujący rzeczywiste dane o uszkodzeniach (2009–2011) lokomotyw używanych przez Agencję Kolejową Urumqui. Jednocześnie zaproponowano nowe podejście, o nazwie Approximately Combined Parameter Method (Metoda Przybliżonego Łączenia Parametrów, ACPM), które polega na łączeniu wstępnie obliczonych parametrów w różne wielokrotności, co pozwala na uniknięcie subiektywnego wyznaczania liczby parametrów modelu. W celu otrzymania dokładnego modelu, połączone parametry wykorzystuje się jako wstępne wartości w estymacji metodą największej wiarygodności. Konieczne optymalizacje wprowadza się na podstawie wybranych modeli. Wyniki pokazują, że letni okres obsługowy różni się zasadniczo od zimowego, a zoptymalizowana obsługa może zwiększyć gotowość systemu i zmniejszyć koszty utrzymania ruchu w większym stopniu niż dotychczasowa polityka obsługowa.

Słowa kluczowe: *lokomotywowy silnik Diesla, model konkurujących zagrożeń oparty na wielokrotnym rozkładzie Weibulla, optymalizacja utrzymania ruchu, metoda przybliżonego łączenia parametrów (ACPM).*

1. Introduction

The diesel engine system of locomotives must satisfy stringent reliability and availability requirements. Statistics shows that the system accounts for about 60% malfunctions and over 60% maintenance costs of diesel locomotives in China. Investigations indicate that some of them are caused by over/under-maintenance. The current maintenance policy of keeping periodical and condition-based maintenance under scheduled preventive maintenance is regarded as one of the major causes for over/under-maintenance. Therefore, optimizing the current maintenance policy is a must for enhancing the reliability and availability of diesel locomotives and their components.

So far, various approaches have been developed to improve the maintenance strategy for diesel locomotives, apart from improving the function of components. Some of them focus on condition-based maintenance, in these strategies, the maintenance duration or some aided decision are made through collecting actual technical state of key components based on monitoring [1, 3] or detecting information [1, 10]. Though potential failures of certain key components may be detected in time by this mode, it has not gained wide application to most of Chinese diesel locomotives as only a small number of components can be checked. Only few of them determine maintenance according to some parameters of key components. Lingaitis [8] et al. propose a method to determine the maintenance data using the state of fuel consumption of diesel locomotives, while the fuel consumption of diesel locomotive is easily influenced by some unpredictable rand factors, such as state of railway and traction weight and outside condition and so forth. Wei Di [14] employed a physical model by calculating the accumulative damage degrees of main generator according to plenty of operation records, and then determine their major maintenance period, and yet the physical model is restricted more because of the complexity of its failure mechanism. Little exists in the literatures to optimize common maintenance period of diesel locomotives based on the real failure data. In additional, The influence of environmental condition on the reliability of electromechanical equipments can not be ignored [11, 15]. Experience shows that malfunctions of the diesel engine system in locomotives always occur irregularly in different seasons in practice, which obviously influence the reliability of diesel engine system. While the current maintenance policy in China does not attach deserving importance to the seasonal influence, and there is no research to investigate the severity of seasonal influence on the diesel engine system. Therefore, it is necessary to develop a model considering the seasonal condition to assess and optimize the maintenance for diesel locomotives.

Weibull Model is widely used in reliability modeling of electromechanical equipments and in maintenance optimization [2, 4, 12]. As a typical electromechanical equipment, diesel engine system is suitable for Weibull model. Dan Ling et al. [7] proposed a method using Nonlinear Least Squares (NLS) theory and quasi-Newton method to estimate the parameters of mixture Weibull model. Chanseok Park [13] used EM method to estimate parameters of incomplete data in Competing Risk model. Furthermore, graphic approach and MLE are commonly used to estimate parameters because numerical solution can not yield a close form solution in general [9]. R.J proposed a method to estimate initial parameters of Double [6] and n-fold [5] Weibull Competing Risk Model in reference [5, 6]. D. Bocchetti et al. [2] developed a reliability model for cylinder liners of marine diesel engines using the method. However, there are two points that should be noted in modeling of Weibull Competing Risk Model: a) the fold number, which may turn out to be multiple, should not be determined beforehand by observation; b) the termination of the algorithm is subjective when the author estimates the parameters of multifold Competing Risk Model. While there is no literature to further study or to develop a beneficial algorithm for computer programming.

In view of the above, as an example of DF4B diesel locomotive, two main parts are introduced in this paper. One is the process of modeling. In this part, two double-fold Weibull Competing Risk models for winter and summer are respectively developed using the real failure data of Korla Locomotive Sect of Urumqi Railway Bureau, to estimate the reliability and optimization of diesel engine maintenance. The influence of seasonal variables on reliability is firstly considered in modeling, and a new method named ACPM is proposed, which can combine the initially estimated parameters into different folds, prevent the fold of parameters from being subjectively determined, and facilitate computer programming, at the same time, which can offer several models for making a choice. To select the best model among all that we obtain, the Bayesian Information Criterion (BIC) evaluation is employed as a criterion in this paper. For the selected models, the running mileage of locomotives is divided into three phrases serving as references for optimization. Another is the process of the maintenance optimization. In this part, the maintenance optimization based on availability and cost respectively as well as on both is explored. Results show that the maintenance period differs a lot between winter and summer. In additional, the effect of preventive maintenance (PM) cost and minimal repair cost on maintenance period in cost-oriented optimization is discussed in detail.

The rest of the paper is organized as follows: Section 2 introduces the process of building a reliability model of a diesel engine system. Maintenance optimization and discussion of the results come in section 3. A brief summary is given in the last section.

Symbols:

$F(t)$	Function of system failure rate
$f(t)$	Function of system failure rate density
$R_w(t)$	Function of reliability in winter
$R_s(t)$	Function of reliability in summer
$r_w(t)$	Function of failure rate in winter
$r_s(t)$	Function of failure rate in summer
C_p	PM action cost
C_f	Minimal repair cost
T_p	Time for PM action
T_f	Time for minimal repair

2. Reliability Model of Diesel Engine System

2.1. Failure Analysis of Diesel Engine System

China has many series diesel locomotives with a total of 11041, DF4B that is produced in 1980s or earlier is one of them, and that is about 4300 amount for about 40% in the whole diesel locomotives in China. Because of the large demand of locomotives in China, DF4B diesel locomotives may still serve on main or branch railway line for a long period. In the daily operation, the maintenance cost and malfunctions become outstanding problems bothered railway enterprises. Therefore, in this paper, DF4B diesel locomotives are taken as an example to investigate their reliability and maintenance policy.

For diesel locomotives, fewer failures occur in the body of engine, cylinders, pistons, crankshafts or transmission gears in a maintenance interval of diesel engine system, and most of them are caused by fuel and lubricating oil system, cooling system, supercharger, inletting or exhausting system in daily operation. Statistics of DF4B diesel engine system shows that malfunctions of the fuel and lubricating oil system take up about 43% in the whole account. Among the fault-prone components are fuel pumps and pipelines, fuel injection pumps, injectors, combined regulators, fuel supply gears, fuel supply levers, oil pumps, etc. Failures resulting from cooling systems composed of high/low-temperature cooling devices account for 32% or so. Another 14% is taken by those from turbochargers, inletting and exhausting systems, key components that demand costly maintenance and are prone to damage like burnt bearings, broken blades and over-large inletting gaps. Common malfunctions are shown as turbocharger bearings burned, blades damaged and over large on inletting gaps. Other uncommon malfunctions account for around 11%, most of which are caused by mechanical wear or unexpected break.

2.2. Data Preprocessing

To reveal seasonal influences on the diesel engine system, the failure data are divided into the groups of winter and summer based on the local climates as seen in Tables 1 and 2, which include the annual faults statistics (2008-2011) of DF4B diesel locomotives from Urumqi Railway Bureau, and which are complete failure data, covering repair time, running mileage after repair, failed components and reasons.

Assume that the failure data follow the Weibull distribution, and their initial reliability can be attained from the Median Rank Estimates as Eq. (1). Then switch each ti into versus initial reliability R(ti) utilizing the Weibull Conversion as Eq. (2) and plot a Weibull Probability Plot (WPP), as shown in Fig. 1, from which it can be seen that the distribution curve are befitting with the Weibull competing risk model.

Table 1. Failure Data in Summer

Failure data	PM interval	Failure data	PM interval	Failure data	PM interval	Failure data	PM interval	Failure data	PM interval
8276	31689	5593	35875	12543	44676	22399	34420	29793	
5667	37973	5996	39418	13063	39338	19008	39462	35403	39875
27933	42973	6218	36954	13748	32261	24323		7617	
4032	44921	15600		7458	39543	17434	37747	30991	
21420		7015	30750	14244		24490		21162	45699
2904	31852	14892		6966	37598	24798	40858	4930	
21162		8168	38476	16592		35403		31956	42359
3318	46006	8426	40352	7919	38974	25412	40233	32006	38403
22985		24566		18877		25526	39552	31915	
3355	36420	8647	38403	236	40373	26500	35875	32234	37419
3738	38577	10207	42489	8559		3209	40373	32844	38465
4375	46286	23219		25793		27923		29270	
30990		10907	35858	19840	40142	19056		34005	42013
212	31480	11450	41868	20751	46467	28025	39875	26031	
4877		11947	39315	34363		34865		34676	42675
5442	36116	12022		10528	35465	28177	37849	19528	46265
30025		21207	46418	21891		1478	38250	1867	
4797	35190	32046		28673	36964	28704		28633	31168
4431	34461	35556	39705	19696	36220	39909	46467	42627	46474
29997		36635	40586	4799		40687	46555	37149	
460	37722	400	40286	32937	34670	375	36714		
28832		23425							

Table 2. Failure Data in Winter

Failure data	PM interval	Failure data	PM interval	Failure data	PM interval	Failure data	PM interval	Failure data	PM interval
2471		38001	38517	8029	39620	6996	37557	7392	41955
8865	38780	31355	38398	8865	41383	24414		37410	
22436		7771	40463	36981		26700	36560	26460	41024
41012	42522	1496		10976	41189	27831	37367	4711	45413
8956	38054	15447	44282	11137	31026	28665	40373	44848	
37042	41735	32582	40572	4330	37828	28811	41733	3024	41755
9961	38324	26861	40853	11743		41746	42546	7015	
32582		31658	39272	16335	40466	31129	36164	3601	39711
220	44274	29452	35332	18622	38154	31398	39418	3879	38452
21657	36276	28835	38951	19300	39418	31472	42675	11138	
33400	38861	6680	40601	19683	41489	32358	39902	5023	36560
2829	33794	3056	37577	22074	40150	32784	40373	2224	36714
29290	38517	375	40606	22985	37722	9211	37330	7051	41295
30284		6514		33817	36165	34199	37537	23681	
33970	36815								

Median Rank Estimates of Initial Reliability $R(t_i) = 1 - \frac{i - 0.3}{n + 0.4}$ (1)

Weibull Conversion $\begin{cases} x = \ln t_i \\ y = \ln(-\ln R(t_i)) \end{cases}$ (2)

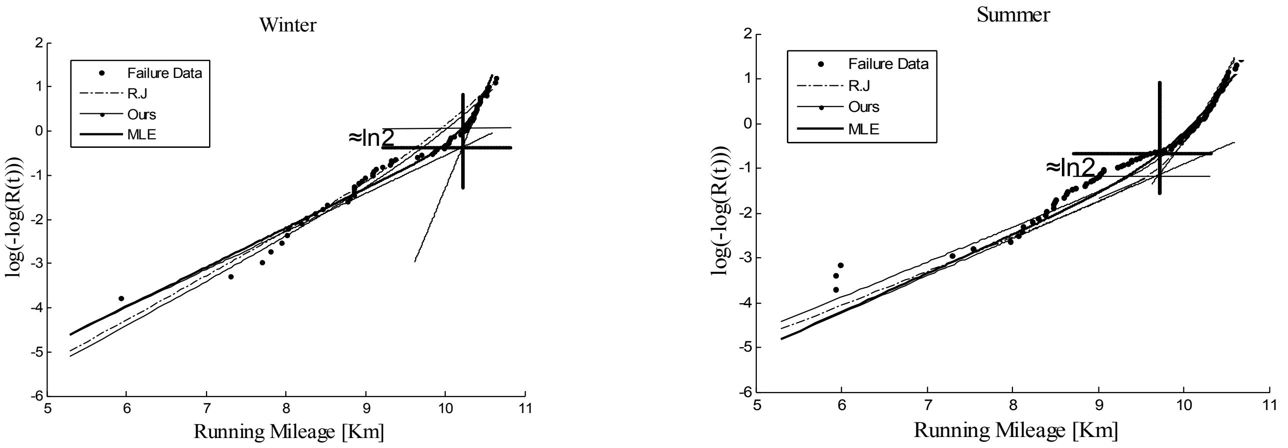

Fig. 1 WPP

2.3. Initial Parameter Estimation

Parameter estimation is important but usually difficult as methods like the maximum likelihood estimation cannot yield a close form solution in general. The numerical calculation and iteration method are needed. There are different methods which can be applied to model parameter estimation. Among them, the graphical approach such as the WPP method and MLE are of the common use. Jiang et al. have separately introduced methods to estimate parameters in Dual and Multiple Weibull competing risk model in literatures [5, 6]. The method can apply to large sample data, and can be regarded as an efficacious separation method often applying in engineering.

However, the terminal condition of the sub-sample separate algorithms that R.J proposed is judged personally, which may cause uncertainty of folds of estimated parameters, ensuring no optimal model and complicating computer programming. In this study, we set the termination using two approximately parallel lines, viz., the left asymptote of residual-data-fitted curve and the whole residual-data-fitted line. Let ka be the left asymptote slope of residual-data fitted curve, and kl be the slope of the residual-data fitted line, and let the algorithms end when $k_l \approx k_a$. Though it is still an approximate condition, among the estimated parameters several group *β*s are close when residual data is close to a straight line, and the distance among *β*s in the next section.

Applying the proposed terminal condition to separate sub-samples under the Matlab 7.0 step by step, the initial model of the diesel engine system is 3-fold and 5-fold for winter and summer respectively, as shown in Tables 3 and 4.

2.4. Approximately Combined Parameters

Further study is needed for accurate estimation as the initial models have been obtained by approximate means. As mentioned in the previous section, k_l is more close to k_a when the residual data distribute in a nearly straight line. In this study, the Hierarchical Clustering Method [16] is employed to approximately combine the initially separated parameters into different folds, from which a valid model is detected. This method is termed as approximately combined parameters (ACPM), the detailed procedure is illustrated in Fig. 2.

Let β_1 、⋯、β_n , denote the shape parameter, and η_1 、⋯、η_n denote the scale parameter, which are determined by sub-sample separation in the initial estimating process. Let $d_i = \beta_{i+1} - \beta_i$, and D_k is a distance matrix composed of d_i. The whole data is drafted to be divided into N ($N \le n$) categories, the sorting procedure is shown in Figure 2. Where the threshold value δ_0 is determined by the allowable error ς, and when $\min(t_i)^{\beta_i - \bar{\beta}} \le \varsigma$, assume approximately that $\beta_i \approx \bar{\beta}$,

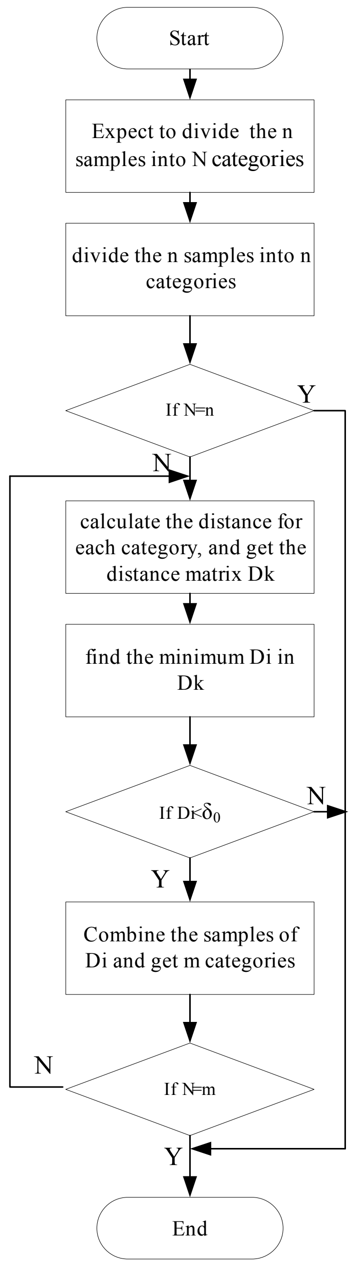

Fig. 2. Approximate Combine of Parameters

Table 3. Model Parameters of Diesel Engine System for Winter

β	η	BIC	Fold	Remark
0.9822 0.9931 2.2444	89980 56328 34289	1535.4	3	Initially estimated parameters
0.8794 1.0446 2.5826	92979 56327 34289	1462.9	3	Initially estimated parameters used as initial values for MLE
0.98765 2.2444	34732 34289	1526.9	2	ACPM
0.8745 5.9318	35199 34289	1356.3	2	Initially estimated parameters used as initial values for MLE
1.4065	1542	1523.8	1	See P.S.
1.1005	22911	1421.4	1	One-fold parameters used as initial values for MLE

Table 4. Model Parameters of Diesel Engine System for Summer

β	η	BIC	Fold	Remark
0.69483 0.76736 0.79204 0.86951 4.347	346010 140120 320010 337960 26499	1831.3	5	Initially estimated parameters
0.69611 0.82003 0.9791 1.1033 3.0132	140430 333070 319510 338230 26519	1849.4	5	Initially estimated parameters used as initial values for MLE
0.69483 0.7797 0.86951 4.347	346010 76278 337960 26499	1821.7	4	ACPM
0.95018 0.71451 1.238 3.0268	333070 76363 338230 26519	1814.9	4	Initially estimated parameters used as initial values for MLE
0.75141 0.86951 4.347	49296 337960 26499	1811.1	3	ACPM
0.7655 7.8098 4.9915	49175 338232 31075	1857.4	3	Initially estimated parameters used as initial values for MLE
0.78093 4.347	30692 26499	1799.9	2	ACPM
0. 86 3.1032	30239 26519	1794.1	2	Initially estimated parameters used as initial values for MLE
1.4941	219.7	1831.3	1	See P.S.
1.0529	22982	1807.1	1	One-fold parameters used as initial values for MLE

P.S. When parameters are combined as one-fold, the error is too large to be acceptable, which does not meet the requirement of ACPM algorithm, for the sake, we apply parameters that fit the original failure data in a straight line are chosen.

calculate η by Eq. (3) after the combination. Let $\beta_i - \bar{\beta} = \delta_0$ in the program.

From $$\sum(\frac{t}{\eta_i})^{\beta_i} = \sum\frac{t^{\bar{\beta}_j} t^{\beta_i - \bar{\beta}_j}}{\eta_i^{\beta_i}} \approx t^{\bar{\beta}_j}\sum\frac{1}{\eta_i^{\beta_i}}$$

We have $$\bar{\eta}_j = (\sum \eta_i^{-\beta_i})^{-\bar{\beta}_j^{-1}} \quad (3)$$

and $$\sum(\frac{t}{\eta_i})^{\beta_i} \approx (\frac{t}{\eta_j})^{\bar{\beta}_j} \quad (4)$$

The ACPM combine the estimated parameters into expected categories are indicated in Tables 3 and 4. Both the initially estimated and the approximately combined parameters are used as initial values for MLE to obtain the accurately estimated parameters, which are given in the two tables as well. The choosing of reasonable models is introduced in the next section.

2.5. BIC Evaluation of Models

Based on the ACPM and MLE, BIC is usually utilized to evaluate all the models for bigger sample size. The BIC evaluation of each model is calculated by Eq. (5), where N is the number of failure data, L is the Maximum Likelihood Function Value of Estimation Model, and k is the number of Parameters. All the BIC evaluation values are indicated in Tables 3 and 4, among them the smallest one is considered as the desirable model marked in different color.

$$BIC(k) = -2\ln L + k\ln N \tag{5}$$

As indicated by Tables 3 and 4 that ACPM is better than initially estimated model according to the BIC value. Fig. 1 shows the initially estimated model and the double-fold model for MLE and ACPM. According to the selected model that the intersection point (x_I, y_I) between the left asymptote and the right asymptote meet $R(x_I)\text{-}y_I \approx \ln 2$. Therefore, the selected model for winter and summer is denoted as function (6) and (7) respectively.

$$R_w(t) = \exp(-(t/35199)^{0.8754} - (t/34289)^{5.9318}) \tag{6}$$

$$R_s(t) = \exp(-(t/30239)^{0.86} - (t/26519)^{3.1032}) \tag{7}$$

2.6. Model Test

χ^2 test is a regular method to test a model when parameters are already known. In this case, according to the rang of sample, take $1\times4000, 2\times4000, \cdots, 10\times4000$ to divide the number axis into 11 disjoint intervals, using accumulated running mileage of locomotives as observation samples, and assume that the number of occurrences of observation samples in the different interval obey the multinomial distribution. Then we can construct Pearson Statistics as Eq. (8), and take the significance level α=0.05 to test the two models.

$$\hat{\chi}^2 = \sum_{i=1}^{11} \frac{(n_i - np_i)^2}{np_i} \tag{8}$$

Where $\hat{\chi}^2$ is the statistics of χ^2 test, n_i is the sample number within the i^{th} interval, and p_i is the accumulated probability of the given model within the i^{th} interval. Set the hypothesis as

H_0: $F_w(t) = 1 - \exp(-(t/35199)^{0.8754} - (t/34289)^{5.9318})$

and H_1: $F_w(t) \neq 1 - \exp(-(t/35199)^{0.8754} - (t/34289)^{5.9318})$

Get χ^2 test value in winter is: $\hat{\chi}^2 = 6.1959 < \hat{\chi}^2_{0.05}(10) = 18.3$. Then receive H_0 and reject H_1.

Similarly, the $\chi2$ test value in summer is: $\hat{\chi}^2 = 10.95 < \hat{\chi}^2_{0.05}(10) = 18.3$, and also receive H_0 and reject H_1. It is thus verified that both the winter and summer models are feasible.

2.7. Analysis of Reliability Models

With Eqs. (6) and (7) as valid reliability models of diesel engine system for winter and summer, and their reliability distribution is illustrated in Fig. 3. Some analysis is introduced as following based on reliability functions and hazard rate functions.

As revealed by the plot, both the cumulative distribution curves keep the decreasing trend, which, however, still differs from what we expected. They were expected to decline more slowly at the beginning than in the middle, while it is reasonable according to the actual state of locomotives. It can be mainly attributed to the professional maintainability of local employees. For example, according to our statistics, in a preventively replace action to a low-temperature water pump, an incorrect assembling of the pump body caused the fracture of a pump shaft after running 1,867 km. Most malfunctions like this

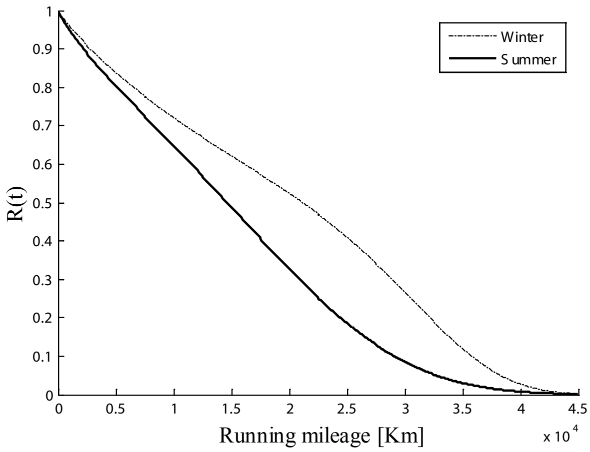

Fig. 3. Distribution of R (t) in Winter and Summer

example, which are caused by some incorrectly assembled or over maintained components, are main reasons that caused the reliability distribution curve quickly decreasing at the beginning, which does coincide with the authors' actual working experience and practice in repairing locomotives in this region. The current maintenance policy, briefly mentioned at the first section, is the main cause for the low reliability. Another typical example from our statistics is as follows: a a supply cam of the fifth cylinder was stripped off by severe wear-out due to insufficient maintenance, which ended in an engine failure after running over 3,216 km. Let us assume that the fault could be avoided if the maintenance action could be made in time, just to verify it can be found that it is inadvisable to extend the maintenance interval.

Let $r_w(t)$ and $r_s(t)$, separately denote the hazard rate of winter and summer, which relate to the reliability functions (6) and (7), and can get $r_w(t)$ and $r_s(t)$ as

$$r_w(t) = \frac{f_w(t)}{R_w(t)} = 2.49\times10^{-5}(t/35199)^{-0.1246} + 1.73\times10^{-4}(t/34289)^{4.9318} \tag{9}$$

$$r_s(t) = \frac{f_s(t)}{R_s(t)} = 2.84\times10^{-5}(t/30239)^{-0.14} + 1.17\times10^{-4}(t/26519)^{2.1032} \tag{10}$$

Two hazard rates are "bathtub-shaped" curves, by which we can crudely determine the maintenance interval. According to the monotonicity that the whole process can be clearly divided into three phases, which are marked as A, B(B' for winter) and C(C' for winter). As shown in fig. 4.

The phase A, about 0.2×10^4 km, is a running-in period after repairing. Our statistics reveals that the components which cause the

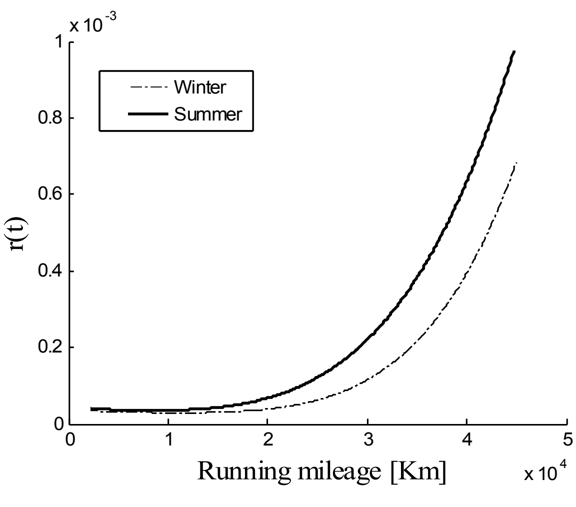

Fig. 4 Curves of Failure Rate Functions

engine failed more in summer than in winter are cooling pipelines of high/low-temperature system, and lubricating oil systems. The $B(B')$ phase stays about within 1.8×10^4 km in summer and 2.8×10^4 km in winter, which is termed as incidental period, whose failure rate goes close to a constant. The $C(C')$ phase is the worsening period, during which the failure rate goes up rapidly with the increase of the accumulated running mileage, this tendency being more distinct in summer than in winter.

The environment condition is known to be a main cause for higher failure rate in summer than in winter. From the failure rate value, we can see that diesel engine system fails great often in summer than in winter, mainly due to the summer temperature of over 40ºC that tends to make cooling systems operate under high load, unable to meet the cooling need of the entire locomotive in DF4B, and further cause the capability of lubricating oil becoming poor, and hence lead to wearing in worse in the incidental period. In contrast, it differs a lot in winter when low temperature (usually at −20 ºC) relieves the load of cooling systems by a great deal.

Therefore, judging by the hazard rate, it can be crudely regard that the maintenance interval in summer should be within 1.8×10^4 km, and in winter within 2.8×10^4 km. The current maintenance regulation say that the maintenance period does not less than 2.3×10^4 km, which may cause insufficient maintenance in summer and over maintenance in winter.

3. Maintenance Optimization

Based on the reliability models we got, and considered the requirements of railway enterprises, we comprehensively consider the effect of availability and economy to develop a maintenance policy. After that, the optimal intervals of PM period can be determined.

3.1. Optimization Based on Cost

To minimize the maintenance cost for the diesel engine system, the cost structure of the PM period is worth studying. Let C_f be the minimal repairing cost during the PM period, and $C_p(C_f>C_p)$ be the cost of preventively replacing components for maintenance. For a maintenance period, the expected cost E[C] and the expect cycle time E[T] can be calculated as follows[4]:

$$E[T]=\int_0^T tf(t)dt+T\int_T^\infty f(t)dt=\int_0^T R(t)dt \tag{11}$$

$$E[C]=C_f\int_0^T f(t)dt+C_p\int_T^\infty f(t)dt=C_fF(T)+C_pR(t) \tag{12}$$

The minimization of maintenance cost rate in a PM period can be represented as Eq. (13), where the numerator is equal to the expected total cost and the denominator equal to the expected total time.

$$\min:Z(T)=\frac{E[C]}{E[T]}=\frac{C_fF(T)+C_pR(T)}{\int_0^T R(t)dt} \tag{13}$$

Suppose that $r=\dfrac{C_f}{C_p}$

and then $\min:Z(T)=\dfrac{E[C]}{E[T]}=C_p\dfrac{\rho(1-R(T))+R(T)}{\int_0^T R(t)dt}$

Substitute the reliability functions of both seasons for $R(T)$; as $\dfrac{dZ(T)}{dT}=0$, we get

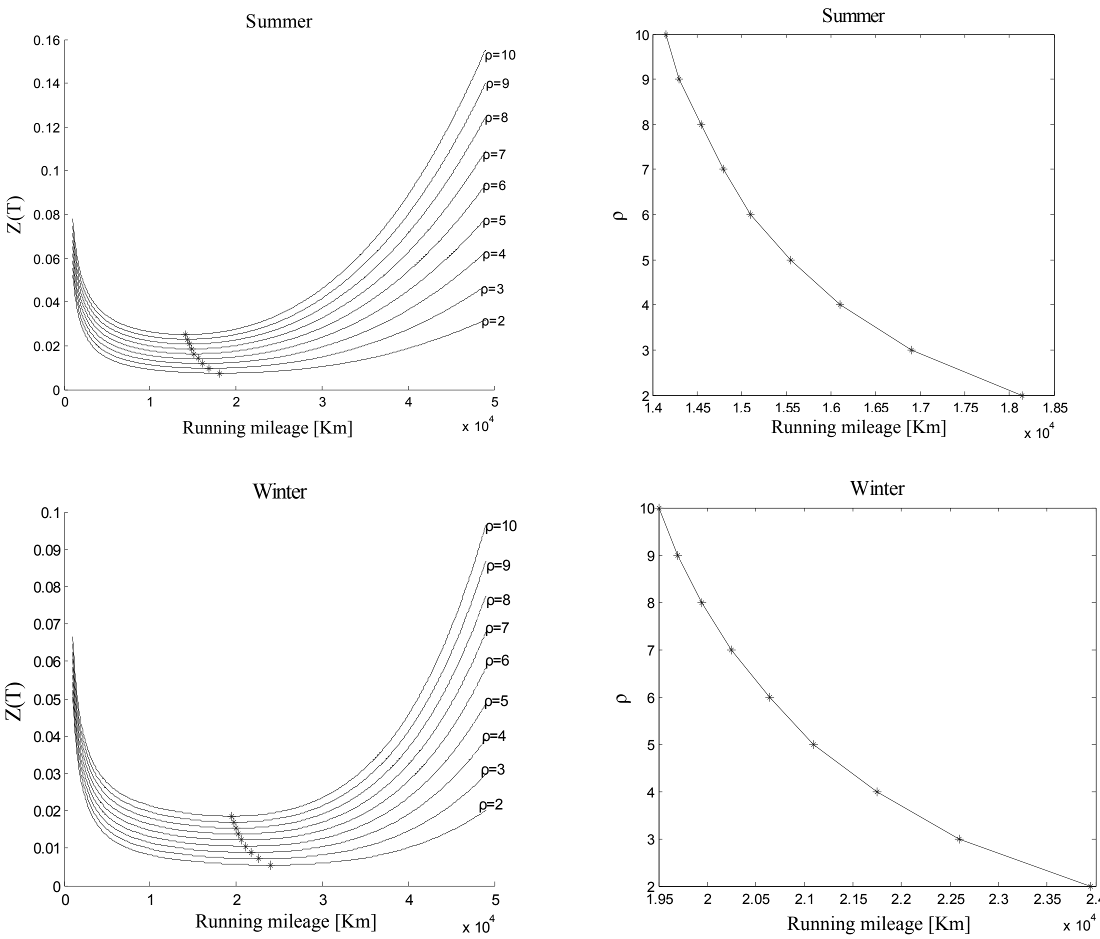

Fig. 5 ρ-(Z(T))

$$\left.\begin{aligned}&r(T)\int_0^T R(t)dt+R(T)=\frac{\rho}{\rho\text{-}1}\\&\rho>1\end{aligned}\right\}\tag{14}$$

As indicated by (14), the limit of its right side is close to a constant when ρ is infinite, and the maintenance period T can be viewed as a constant when ρ is large enough. According to the history records, ρ is between 2 and 8. Herein, we set ρ=8, and then we get T_s=1.43×104km and T_w=1.97×10⁴ km by Eq. (14), which are within the incidental period, and indicates apparently that there is a great gap between in summer and winter.

The optimization model based on maintenance cost is shown as (13), in which C_p and C_f are only relative to components. Based on the practice that ρ is between 2 and 8, we set ρ=2,3,…,8, and get the relationship curves for ρ and Z(T) as shown in Fig. 5.

Fig. 5 demonstrates tha ρ is approximately proportional to *minZ*(*T*). The striking variation of ideal maintenance period appears upon 1<ρ≤10. As in practice ρ is between 2 and 8, the expected maintenance period in summer is about 1.41~1.85×10^4 km, and that in winter is about 1.9~2.4×10^4 km. Fitting ρ and minZ(T) yields

$$E_w[C_\rho]=C_p(-4.6\rho+183)E_w(T_\rho)\times10^{-3}\tag{15}$$

$$E_s[C_\rho]=C_p(-5.16\rho+241)E_s(T_\rho)\times10^{-3}\tag{16}$$

Eqs. (15) and (16) can be considered as approximate experience formulas to determine the expected cost and the corresponding best maintenance period time.

3.2. Optimization Based on Availability

To maximize the efficiency of the diesel engine system, availability is also regarded as an index to optimize the maintenance period for maximum efficiency of the diesel engine system. Let T_f be the time for minimal repairing during the PM period, and T_p be the time for preventively replacing components in maintenance period. In this case, as the lifetime of diesel engine system is represented by the accumulated running mileage of locomotives, for description of the availability of diesel engines we need to convert T_p and T_f into corresponding equivalent kilometer t_p and t_f on the basis of the fact that locomotives finish transport assignment of 300 km every 8 hours. According to the maintenance regulations of railway enterprises, in general the maintenance assignment has to be finished within specified time. Therefore, letting T_p = 2 and T_f = 4 yields

thus $t_f=\frac{300}{8}\times T_f=\frac{300}{8}\times4=150(Km)$

and $t_p=\frac{300}{8}\times T_p=\frac{300}{8}\times2=75(Km)$

Let A be the availability and T the operation period. The maximum of E[A] is obtained as follows:

$$\max\text{: }E[A]=\frac{\int_0^T R(t)dt}{\int_0^T R(t)dt+T_pR(T)+T_fF(T)}\tag{17}$$

Set $0<T_p<T_f<T$.

Substitute reliability functions $R(T)$ for summer and winter into equation (17), and according to $\frac{dE[A]}{dT}=0$, we get

$$\begin{cases}r(T)\int_0^T R(t)dt+R(T)=\frac{T_f}{T_f-T_p}\\0<T_p<T_f<T<50000\end{cases}\tag{18}$$

Solving Eq. (18) obtains T_s = 2.27×10⁴ km and T_w = 2.83×10⁴ km, both of which are longer than the optimization based on cost but run into worsening period. Therefore, it is unreasonable to optimize the maintenance period just by single factor.

3.3. Optimization Based on both Availability and Cost

For the purpose of obtaining the optimal period based on the fact of railway that centers availability of locomotives and considers the maintenance cost, and thus we take both the efficiency and the economy into consideration. Let $\frac{E(A)}{E(A)^*}$ represent the value function of availability of diesel engine system, $E(A)^*$ is the versus max(E(A)) in optimization based on availability. Let $\frac{Z(T)}{Z(T)^*}$ represent the value function of relative maintenance cost rate of diesel engines, $Z(T)^*$ is the *min*(*Z*(*T*)) in optimization based on maintenance cost. The final optimization model based on both availability and cost[15] can be shown as:

$$\min: ETC=-w_1\frac{E(A)}{E(A)^*}+w_2\frac{Z(T)}{Z(T)^*}\tag{19}$$

Where w_1 and w_2 are weighted values relative to decision-making tendency, and $w_1\ge0, w_2\ge0, w_1+w_2=1$.

$$ETC=-w_1\frac{\int_0^T R(t)dt}{E(A)^*(\int_0^T R(t)dt+T_pR(T)+T_fF(T))}+w_2C_p\frac{\mathrm{r}\,(1-R(T))+R(T)}{Z(T)^*\int_0^T R(t)dt}\tag{20}$$

Considering that railway enterprises usually pay more attention to availability than to maintenance cost, so we adopt the optimization strategy that centers availability and also considers cost, set w_1=0.7, w_2=0.3, C_p=1000, and ρ=8. That $Z_w(T)^*=0.017$, $Z_s(T)^*=0.023$, $E(A)_w{}^*=0.993$, and $E(A)_s{}^*=0.990$ are known according to formula (10) and (13).

As $\frac{dETC}{dT}=0$ we have

$$\begin{cases}-0.7\frac{75(r(T)\int_0^T R(t)dt+R(T))\text{-}150}{E(A)^*(\int_0^T R(t)dt+75R(T)+150F(T))^2}+0.3\times500\frac{7(r(T)\int_0^T R(t)dt+R(T))-8}{Z(T)^*(\int_0^T R(t)dt)^2}=0\\0<T<50000\end{cases}\tag{21}$$

Thus, T_s = 1.575×10⁴ km, and T_w = 2.125×10⁴ km. The result indicates that the optimized maintenance period determined by addressing both availability and cost is within the incidental period and relative to w_1 and w_2. When w_1 = 0, the optimization is based on maintenance cost; when w_2 = 0, it is on availability. Both the values are relative to decision tendency.

3.4. Analysis of Optimization Results

According to the optimized results that the maintenance interval exist great gap between winter and summer, and the current maintenance period may cause insufficient maintenance in summer. The optimization result based on cost shows that the expected maintenance period in summer is 1.43×10⁴ km, and that in winter is 1.97×10⁴ km, both of them are within incidental period. Although the performance of diesel engine systems is stable in this period, the availability of locomotives is in a low. While the optimization result based on availability indicates that the maintenance period in summer is 2.27×10⁴ km, and that in winter is 2.83×10⁴ km, both of which are longer than the optimization result based on cost. While the result turns into worsening period, and the risk is increased. Therefore, it is thus clear that it is irrational to determine the maintenance period by only one factor. The third optimization result that centers the availability and considers the cost goes in accordance with the actual case. The decision tendency is determined by the weighted values. Taking into account the practice of railway enterprises, we set w_1=0.7, w_2=0.3, and get the optimal period in summer as 1.575×10⁴ km and that in winter as 2.125×10⁴ km, both of them are within incidental period.

Moreover, from the other side that the feasibility can be indicated from the comparison of maintenance cost and availability calculated by the formula (22) to (24) using the statistics, see table 1 and 2.

$$C_{real} = N_m C_f + N_p C_p \tag{22}$$

$$C_{op} = (C_f \int_0^T f(t)dt + C_p) N_p \tag{23}$$

$$E[A]_{real} = \frac{\sum_{i=1}^{N} t_i}{\sum_{i=1}^{N} t_i + N_m T_f + N_p T_p} \tag{24}$$

Where $E[A]$real and C_{real} and C_{op} separately denote the real availability and maintenance cost of the our statistics and the optimized maintenance cost, the optimized availability can be known by Eq. (18). N_m and N_p separately denote the whole times of minimum repair and preventive maintenance. The calculated results can be seen as Table 5.

As revealed by the above analysis, the maintenance period differs a lot between summer and winter, and the optimized results can improve the current maintenance period (≧2.3×10⁴ km) which maybe obviously decrease the locomotive's availability and increase maintenance cost, especially in summer. Meanwhile, it also indicates that the policy of extending the maintenance intervals adopted by certain railway enterprises is definitely undesirable.

Diesel locomotive is a complex electromechanical equipment, although malfunctions in diesel engine systems take up nearly 60% of those in the whole locomotive and the maintenance cost is also the majority, comprehensively analyzing maintenance period of diesel locomotives should consider diesel engine systems, running gears, electric apparatuses and brakes, and yet the maintenance period should not less than the results we got. Therefore, the result in this paper can be regarded as a reference to some railway enterprises.

Table 5. Comparison between real and optimized maintenance cost/availability

Items	Cost		Availability	
	Winter	Summer	Winter	Summer
Real result	¥625000	¥915000	0.9934	0.9921
Optimized result	¥533490	¥883910	0.9998	0.9997
Improved result	¥91510	¥31090	0.0065	0.0076

4. Conclusions

In the present study, the proposed double-fold competing risk models for winter and summer have been shown to give a good fit to the real data on diesel engines of locomotives of Urumqi Railway Bureau, and the optimized results indicate:

a) The maintenance period have great gap between winter and summer, railway enterprise should adopt different maintenance period in different season to avoid over maintenance.

b) The optimized maintenance can increase the availability and decrease cost more than the existing policy and can be regarded as a reference for Urumqi Railway Bureau and aroused their interest.

c) Obtained reliability models of diesel engine system can be used in grouped maintenance and performance improvement in diesel locomotives.

However, the diesel engine system is a complex electromechanical equipment, whose operating capability are influenced by many factors like outside environment, maintenance level of employee, operating level of engineer, track condition and so on. Therefore, further research on the topic is needed to address these factors using more accurate models than the ones proposed herein. Furthermore, this paper has also proposed a new method termed as ACPM for estimating multiple Weibull Competing Risk model parameters, which can get an objective fold and corresponding parameters rather than determined the fold in advance, at the same time, the method is easy to computer programming.

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Reference

1. Albarbar, A., F. Gub, and A.D. Ball, Diesel engine fuel injection monitoring using acoustic measurements and independent component analysis. Measurement 2010; 43(10): 1376–1386.
2. Bocchetti, D., et al., A competing risk model for the reliability of cylinder liners in marine Dieselengines. Reliability Engineering and System Safety 2009; 94(1): 1299–1307.
3. Fry, K.N. and BSc. Diesel locomotive a reliability improvement by system monitoring. Proc IMechE: Part F. 1995: 1-10.
4. J. Huang, C.R. Miller, and O.G. Okogbaa. Optimal Preventive-Replacement Intervals for the Weibull Life Distribution: Solutions & Applications. 1995 IEEE Proceedings Annual Reliability and Maintainability Symposium. Washington, DC, 1995: 370-373.
5. Jiang, R. and D.N.P. Murthy, Study of n-Fold Weibull Competing Risk Model. Mathematical and Computer Modelling 2003; 38(11): 1259–1273.
6. Jiang, R. and D.N.P. Murthy, Reliability modeling involving two Weibull distributions. Reliability Engineering and System Safety 1995; 47(3): 187–198.
7. Ling, D., H.-Z. Huang, and Y. Liu, A Method for Parameter Estimation of Mixed Weibull Distribution. IEEE Trans on reliability 2009; 1-4244-2509-9/09: 129–133.
8. Lingaitis, L.P., et al., Prediction Methodology of Durability of Locomotives Diesel Engines. Eksploatacja i Niezawodnosc – Maintenance and Reliability 2012; 14 (2): 154–159.
9. M. Sarhan, A., David C. Hamilton, and B. Smith, Statistical analysis of competing risks models. Reliability Engineering and System Safety

2010; 95(9): 953–962.
10. Martinez, V. M., et al., Results and benefits of an oil analysis programme for railway locomotive diesel engines. Insight 2003; 45(6): 402–406.
11. Martorell, S., A. Sanchez, and V. Serradell, Age-dependent reliability model considering effects of maintenance and working conditions. Reliability Engineering and System Safety 1999; 64(1): 19–31.
12. Mazhar, M. I. and H.K. S. Kara, Remaining life estimation of used components in consumer products: Life cycle data analysis by Weibull and artificial neural networks. Journal of Operations Management 2007; 25(6): 1184–1193.
13. Park, C., Parameter Estimation of Incomplete Data in Competing Risks Using the EM Algorithm. IEEE Transactions on Reliability 2005; 54(2): 282–290.
14. Wei, D. I., Repair Period of Diesel Locomotives Based on Accumulative Damage Degree. China Railway Science 2009; 30(6): 104–107.(in Chinese).
15. Xia, T., et al., Optimal CBPM policy considering maintenance effects and environmental condition. Int J Adv Manuf Technol 2011; 56(9): 1181–1193.
16. Xu, R. and D. Wunsch, Survey of Clustering Algorithms. IEEE Transactions on Neural Networks 2005; 16(3): 645-678.

Prof. Zhisheng ZHANG, Ph.D.
Wenke GAO, Ph.D. Candidate
Yifan ZHOU, Ph.D.
School of Mechanical Engineering, Southeast University, Nanjing
China, 211189
E-mail: oldbc@seu.edu.cn; gaowk_best@163.com; yfzhou1981@163.com

Zhiqiang ZHANG, Eng.
Locomotive Sect of Urumqi Railway Bureau, Korla
China, 841000
E-mail: xj_zqzhang@163.com