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# Reliability design of preventive maintenance scheduling for cumulative fatigue damage †

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## Abstract

As the cumulative running times of a locomotive truck increases, degradation such as fatigue, wear, and deterioration occur. Particularly the container train and uncovered freight train, their maintenance cost during their lifetime is three times more than the manufacturing cost. Generally, for the freight train, corrective maintenance to repair a bad part after a breakdown is not adapted; however, preventive maintenance that fixes a bad part before a breakdown is. Therefore, it is important and necessary to establish a system of optimal preventive maintenance and exact maintenance period. This study attempts to propose a preventive maintenance procedure that predicts a repair period using reliability function and instantaneous failure rate based on fatigue test and load history data. Additionally, this method is applied to the end beam of an uncovered freight train, which is the brake part, and its usefulness is examined and analyzed.

*Keywords*: Preventive maintenance; Cumulative fatigue damage; Miner's rule; Maximum likelihood estimator; Kaplan-Meier estimator

## 1. Introduction

The performance of locomotive truck frames decreases as the cumulative running time increases. Its causes are expected to be fatigue, wear, and deterioration. New inspection and repair methods are needed for their safety because freight trains require higher speed and longer running time. In the case of container and uncovered freight trains, the maintenance cost is about three times more than their manufacturing cost during their lifetime [1, 2]. Therefore, it is important to establish an optimal preventive maintenance schedule to minimize the total cost with the desired or specified levels of operational safety and reliability [3-5]. It can also maximize the availability of the components and optimize some other specified objectives.

According to the time of maintenance executed, maintenance is usually divided into two major categories: corrective maintenance (CM) and preventive maintenance (PM) [6-11]. The former corresponds to the actions that occur after the system breaks down, while the latter corresponds to the actions that take place while the system is operating. Most investigations on preventive maintenance have been limited by regular inspection time or components management. Since the performance test or endurance test of freight trains is achieved in proving railroad, its reliability estimation is very difficult to obtain.

Reliability estimation function can be predicted by probability density function, cumulative distribution function, or hazard rate function, which is a function of replacement time (or fatigue crack initiation time) based on the maintenance records. The preventive maintenance of freight trains is very useful because the demand prediction of their parts through reliabil-

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ity estimation allows the acquisition of spare items.

This study discusses the preventive maintenance method based on actual load history. Fatigue life is estimated by the probability distribution of life data from the durability analysis process. Furthermore, the reliability function and hazard rate function are evaluated by the Kaplan-Meier method [12-14]. Finally, this method is applied to the fatigue damage problem of the end beam which is a brake part of an uncovered freight train to examine the usefulness of preventive maintenance.

## 2. Cumulative Fatigue Damage Evaluation

### 2.1 Definition of cumulative fatigue damage

The end beam of a freight train is subjected to variable amplitude service loading. The measurements of the service stress (or strain) histories are required to obtain general information on service loading and to determine the fatigue life of the end beam. Signal processing uses cycle counting algorithms to extract stress-strain hysteresis loops quickly and accurately. In this study, the rainflow cycle counting [15-18] is used as a signal processing method for fatigue analysis.

Fig. 1 shows the procedure for the cycle counting method as demonstrated by Downing and Socie [15].

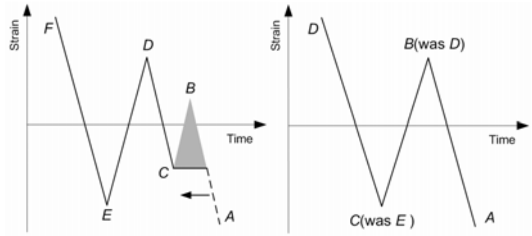
**[STEP1]** Consider the following sequence of peaks/ valleys. The notation uses point $A$ as the most recent data point, point $B$ as the previous point and so on (Fig. 1(a)).

**[STEP2]** A cycle is closed because the range from $A$ to $B$ is greater than the range from $B$ to $C$ and is represented by the range from $B$ to $C$.

Range $A$ to $B$ $>$ Range $B$ to $C$

**[STEP3]** Fig. 1 (b) shows a new cycle. Previously, the range from $A$ to $B$ is greater than that from $B$ to $C$; therefore, $B$ to $C$ is a cone cycle. This procedure is repeated until no more cycles are closed at this point.

The cumulative fatigue damage rule for the actual running environment is necessary for estimating the safety of railway vehicles. The extracted cycle produces stress amplitude $\sigma_a$ and mean stress. Cumulative damage $D$ and number of cycles to fractures $N$ are determined using the Palmgren-Miner rule [19, 20]




(a) (b)

Fig. 1. Rainflow cycle counting.

and histogram of the cycle ranges. For the infinite life design for very high mean stresses, the Buch mean stress correction is selected. Palmgren-Miner rule is expressed as follows. Failure is expected to occur if

$$D = \frac{n_1}{N_{f_1}} + \frac{n_1}{N_{f_1}} + \frac{n_1}{N_{f_1}} + \cdots = \sum_i \frac{n_i}{N_{f_i}} \geq 1 \tag{1}$$

where $n_i$ is the number of applied cycles and $N_{f_i}$ is the number of cycles to failure at a specified stress amplitude $\sigma_i$, respectively.

Since in many cases the Palmgren-Miner rule leads to non-conservative life predictions, the linear damage rule associated with the critical damage sum $D$, which is other than 1, has been proposed in many design codes for fatigue damage assessment of structures subjected to variable amplitude loading. In this study, the critical cumulative damage value of $D$ is 1 in Eq. (1).

### 2.2 Fatigue reliability assessment

Reliability assessment prevents products from premature failure. There are two parameter estimation methods for statistical data according to life distribution assumption: parametric distribution analysis and nonparametric analysis. In the case that fatigue life data is based on the Weibull distribution, shape parameter $m$ and scale parameter $\eta$ are determined by maximizing the loglikelihood function. This method is called maximum likelihood estimation [14, 21]. The maximum likelihood estimator is determined as follows:

$$\frac{\sum_{i=1}^{r} \ln t_i}{r} = \left( \frac{\sum_{i=1}^{n} \ln t_i^m \ln t_i}{\sum_{i=1}^{n} \ln t_i^m} \right) - \frac{1}{m} \tag{2}$$

$$\eta = \left( \frac{\sum_{i=1}^{n} \ln t_i^m}{r} \right)^{1/m} \tag{3}$$

where $r$ is the number of data observed. Reliability function, cumulative distribution function, and probability density function are defined to perform reliability estimation. Their functions for the Weibull probability distribution can be expressed as Eqs. (4) to (6), respectively.

$$R(t) = \exp\left[ \left( -\frac{t}{\eta} \right)^m \right] \tag{4}$$

$$F(t) = 1 - \exp\left[ \left( -\frac{t}{\eta} \right)^m \right] \tag{5}$$

$$f(t) = \frac{m}{\eta} \left( \frac{t}{\eta} \right)^{m-1} \exp\left[ \left( -\frac{t}{\eta} \right)^m \right] \tag{6}$$

Furthermore, the hazard rate function (instantaneous failure rate function) is the ratio of probability density function to reliability function. It is expressed as Eq. (7).

$$h(t) = \frac{m}{\eta} \left( \frac{t}{\eta} \right)^{m-1} \tag{7}$$

The Kaplan-Meier estimator [12, 14] for fatigue data with censored observations is used in this study. It is compared with the median that corresponds to more than 50% of the failure probability. The Kaplan-Meier estimator of hazard rate function and reliability function are expressed as Eqs. (8) and (9), respectively.

$$R(t) = \prod_{j \in t_j < t} \left( 1 - h_j(t) \right) = \prod_{j \in t_j < t} \left( 1 - \frac{d_j}{n_j} \right) \tag{8}$$

$$h_j(t) = \frac{d_j}{n_j} \tag{9}$$

where $n$ is the total number of units, $n_j$ and $d_j$ denote the number of subjects that survive just before time $t_j$ and the number of failure occurring at time $t_j$, respectively.

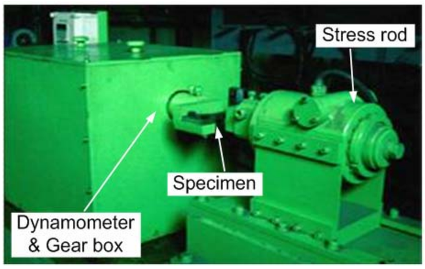



Fig. 2. Apparatus for Schenck-type bending fatigue testing.

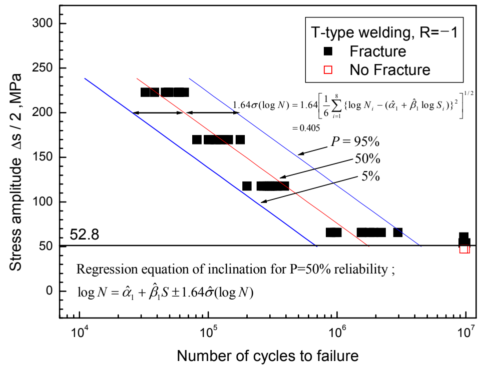



Fig. 3. P-S-N curve for SS400 steel.

## 3. Freight train preventive maintenance scheduling

### *3.1 P-S-N curve of SS400 steel*

The material of the end beam for an uncovered freight train is SS400 steel. Its fatigue test was performed by the Schenck-type twisting and bending fatigue testing machine under the maximum bending moment of 4 kg·m, frequency of 1,800 rpm, and stress ratio of -1 (Fig. 2). The static and dynamic test results of the T-type welded specimens are introduced in the references [2]. See references for further details. A P-S-N (probabilistic-stress-life) curve can be obtained from JSME S002.

Fig. 3 shows the P-S-N curve for SS400 steel. The relationship between stress amplitude and fatigue life is given in Eq. (10).

$$\log N = 6.728 - 0.0094\Delta s / 2 \pm 0.405 \tag{10}$$

The mean of the fatigue limit by the JSME statistical S-N testing method was 52.8 MPa.

### *3.2 Estimation of loading history*

It is very difficult to change the size of the end beam

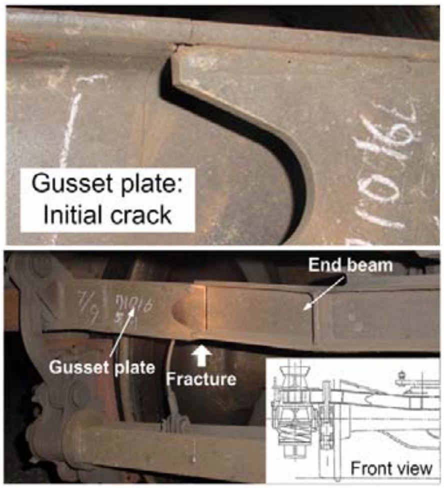



Fig. 4. Photograph of a fractured end beam.

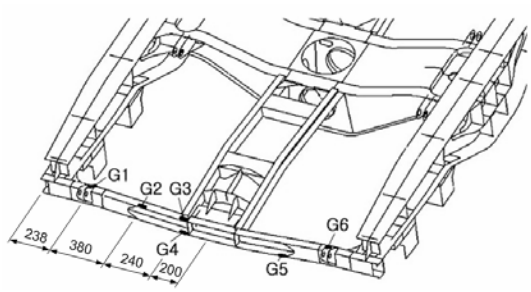



Fig. 5. Attachment location and number of strain gauges.

It is very difficult to change the size of the end beam because it is built into the lower part of the truck frame. Its structural redesign cannot be performed to prevent fatigue fracture in the viewpoint of safety and economy. Therefore, if the fatigue properties of the end beam are understood, planned preventive maintenance interval can be determined.

Fig. 4 shows the end beam supporting brake system and its fatigue failure site. Fatigue crack in the end beam was initiated at the welded gusset plate edge and was propagated in the vertical direction of running direction. The load history through the structure test of the truck frame was measured to predict fatigue damage. The load history in the running section included the start, acceleration, and brake sections. The running section was the place where fatigue failure of the end beam occurred.

Fig. 5 shows the attachment locations of the six strain gauges with a direction perpendicular to the fatigue crack. In this study, we assumed that the direction perpendicular to the crack propagation is the principal stress direction. A one axis strain gauge (KFG-5-128) was installed on the end beam before loading, and the test track was the Donghae-Jecheon section. The load history in the test track was measured at 16.7 m/s over 1,500 seconds from start to braking. Fig. 6 shows the results of the test series with the load history based on the six strain gauges. The distribution of the stress range at each location of strain gauges is listed in Table 1.

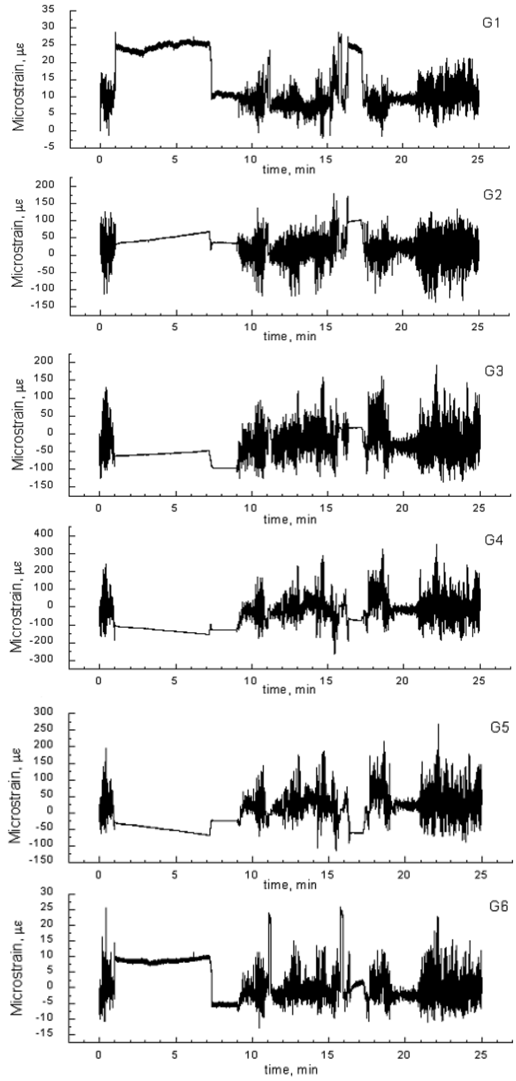



Fig. 6. Strain time-history in 1,500 seconds.

FE-safe [22], a commercial fatigue analysis program, was used to calculate the fatigue life of the end beam. Palmgren-Miner rule was used as the fatigue cumulative damage rule. The first counting data for the stress level was determined within the confidence

Table 1. Results of the strain gauge measurement.

| Stress (MPa) | G1 | G2 | G3 | G4 | G5 | G6 |
|---|---|---|---|---|---|---|
| Min. | 0.51 | 36.26 | 36.75 | 70.65 | 31.14 | 3.41 |
| Max. | 7.74 | 48.26 | 51.62 | 94.14 | 72.02 | 6.96 |
| Mean | 3.71 | 8.47 | 8.83 | 13.28 | 0.13 | 0.4 |

Table 2. Expected fatigue life and cumulative fatigue damage at each measured location.

| Location number | | Modified Palmgren-Miner rule | | |
|---|---|---|---|---|
| Mean stress correction | | Life | Damage | Year |
| G1 | None | Unlimited | 0 | Unlimited |
| G2 | | 983,700 | $1.02\times10^{-6}$ | 46.79 |
| G3 | | 360,400 | $2.77\times10^{-6}$ | 17.14 |
| G4 | | 209,800 | $4.77\times10^{-6}$ | 7.98 |
| G5 | | 5,146,000 | $1.94\times10^{-7}$ | 244.78 |
| G6 | | $170\times10^{6}$ | $5.88\times10^{-9}$ | 8,086 |
| G1 | Goodman | $23.2\times10^{6}$ | $4.31\times10^{-8}$ | 4,833 |
| G2 | | 35,350 | $2.83\times10^{-5}$ | 7.36 |
| G3 | | 36,550 | $2.74\times10^{-5}$ | 7.61 |
| G4 | | 14,010 | $7.14\times10^{-5}$ | 2.92 |
| G5 | | 50,780 | $1.97\times10^{-5}$ | 10.58 |
| G6 | | $11.5\times10^{6}$ | $8.69\times10^{-8}$ | 2,397 |

interval of the P-S-N curve by a correction method for the curve that considers stresses under fatigue limit.

Fig. 7 shows the cycle range-mean histogram located at G4. Fig. 8 shows the 2-dimension contour line of the fatigue damage for this case. It should be noted that although the high amplitude stress cycle has low frequency, fatigue damage is relatively large. When a freight train is broken, high amplitude stress cycle can occur. Therefore, the breaking load influences the fracture of the end beam.

The stress cycle with a mean stress correction produces a shorter fatigue life than the stress cycle with no mean stress correction. Table 2 shows the fatigue life and damage at all strain gauge locations using the modified Palmgren-Miner rules.

The stress cycles and fatigue damage at the G2 location were 35,350 cycles and $2.83\times10^{-5}$, respectively. Fatigue life at the location was expected to be 53,025,120 seconds because the stress history was measured during 1,500 seconds. If we suppose that the running speed of a freight train is 16.7 m/s to convert time life to cycle life, fatigue life corresponds to 883,750,000 m. Furthermore, if we consider that the design life of a freight train is 25 years ($3\times10^{9}$ m), its life expectancy is 7.36 years.

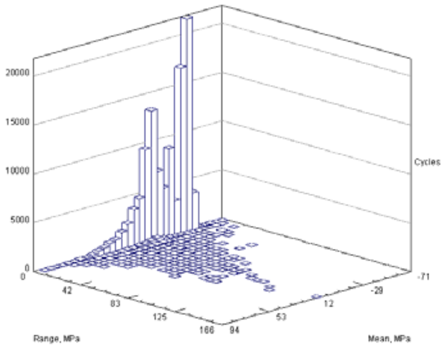



Fig. 7. Result of the rainflow cycle counting histogram.

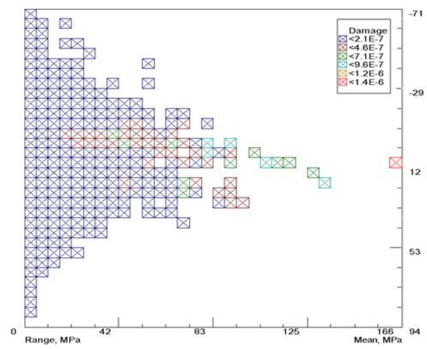
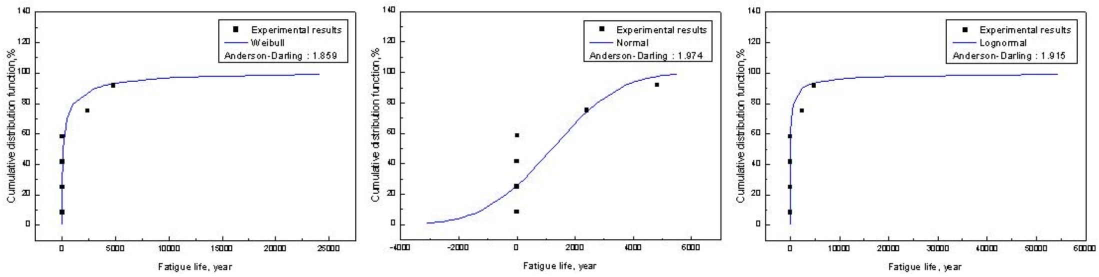



Fig. 8. Result of the rainflow cycle counting histogram.

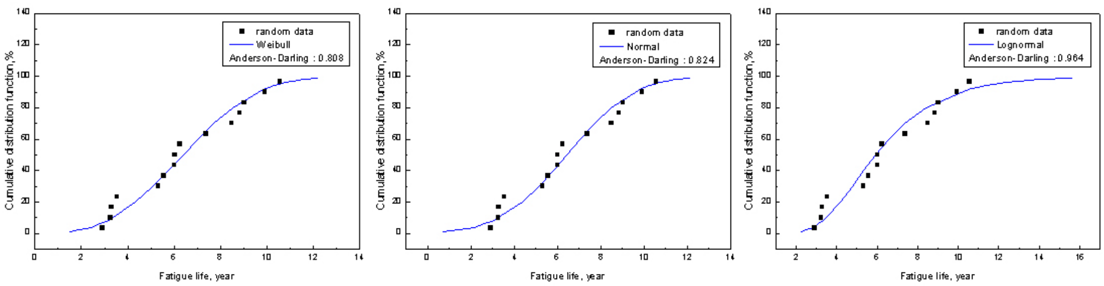
### *3.3 Reliability analysis*

Reliability estimation for life data was implemented using the statistical analysis software MINITAB R14 [23] to predict the probabilistic fatigue life of the end beam.

Fig. 9 shows the goodness-of-fit test of the life data. Weibull distribution, normal distribution, and log-normal distribution were used as the candidate statistical distributions of the life data [24, 25]. The Anderson-Darling value that evaluates the difference between test data and approximated data was selected as the test statistics. The locations of G1 and G6 had infinite fatigue life; therefore, they did not influence the fatigue life of the end beam. Random sample data were generated for four life data except those above two. The goodness-of-fit test and reliability analysis were performed for those. Fig. 9 (b) is the result of the goodness-of-fit test for random data. Among theses distributions, samples could be approximated by the Weibull distribution because the test statistics of the population parameter was 0.808.

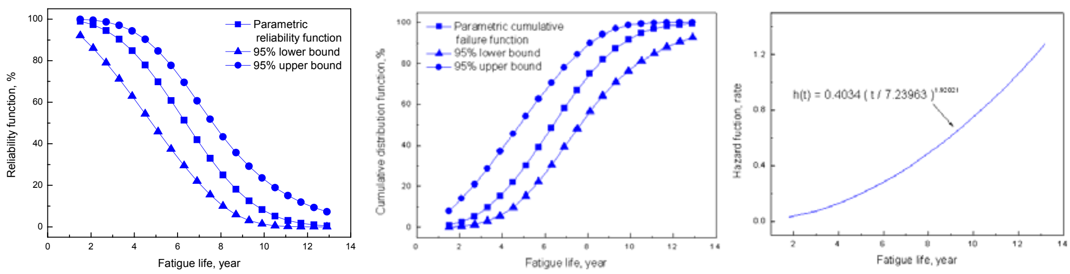



(a) Experiment data




(b) Random data

Fig. 9. Result of the goodness-of-fit test.




(a) PDF (b) CDF (c) HF

Fig. 10. Reliability analysis of fatigue life using parametric method.

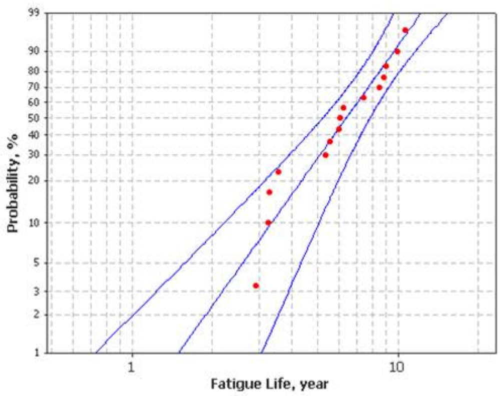



Fig. 11. Two-parameter Weibull plots of fatigue life data.

Fig. 10(a) shows the reliability function of the Weibull distribution with a 95% confidence interval.

Fig. 10(b) shows cumulative distribution function of the Weibull distribution with 95% confidence interval. Fig. 10(c) shows the hazard rate function that increases according to time. This expresses the increasing failure rate (IFR) due to system wear and fatigue. Fig. 11 shows the cumulative distribution function with a 95% confidence interval on the Weibull distribution probability paper. Since all data fell within the 95% confidence interval, life data could be approximated by the Weibull distribution. Its shape parameter and scale parameter were 2.92, 7.24, respectively, and its median was 6.386 years. Table 3

Table 3. Estimation of the two-parameter Weibull distribution.

| Item | Estimate | Standard error | 95% Normal confidence interval | |
|---|---|---|---|---|
| | | | Lower | Upper |
| Shape parameter | 2.92021 | 0.606582 | 1.94359 | 4.38757 |
| Scale parameter | 7.23963 | 0.675148 | 6.03026 | 8.69155 |
| Mean (MTTF) | 6.45737 | 0.622304 | 5.34594 | 7.79986 |
| Standard deviation | 2.40430 | 0.414068 | 1.71552 | 3.36963 |
| Median | 6.38570 | 0.667379 | 5.20293 | 7.83734 |
| First quartile | 4.72526 | 0.697779 | 3.53777 | 6.31136 |
| Third quartile | 8.09643 | 0.717753 | 6.80509 | 9.63281 |
| Interquartile range | 3.37117 | 0.588058 | 2.39496 | 4.74528 |

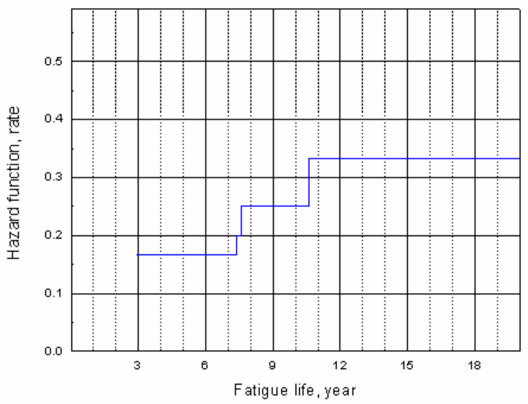



Fig. 12. Hazard function for fatigue life using Kaplan-Meier method.

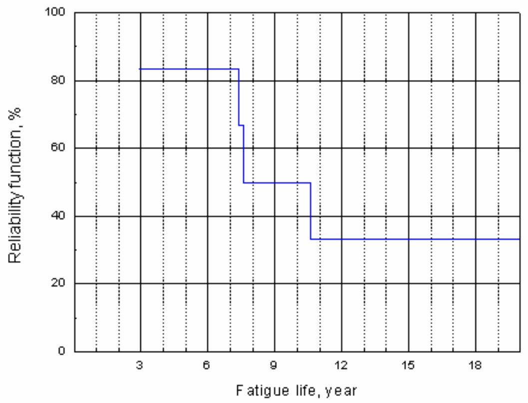



Fig. 13. Reliability function for fatigue life using Kaplan-Meier method.

Table 4. Percentile and hazard function for cumulative failure probability.

| Cumulative failure probability (%) | Percentile (year) | Hazard function |
|---|---|---|
| 1 | 1.49824 | 0.01685 |
| 2 | 1.90291 | 0.02939 |
| 3 | 2.19018 | 0.03964 |
| 4 | 2.42119 | 0.04871 |
| 5 | 2.61811 | 0.057 |
| 6 | 2.79179 | 0.06476 |
| 7 | 2.94845 | 0.07211 |
| 8 | 3.09205 | 0.07914 |
| 9 | 3.22525 | 0.08591 |
| 10 | 3.34997 | 0.09247 |

summarizes the statistical characteristics of the fatigue life of the end beam. Furthermore, the probability distribution of life data was estimated by the Kaplan-Meier method to compare the parametric method with the nonparametric method.

Fig. 12 and Fig. 13 show the hazard rate function and reliability function, respectively. Accordingly, as the hazard rate function increases, the reliability function decreases. Mean life was estimated to be more than $1\times10^3$ year due to the effect of the locations G1 and G6: however, the median was 7.61 years. Compared with the parametric method, this result showed a big difference in the mean but a small difference in the median (6.386 years).

### *3.4 Preventive maintenance periods*

Failure of the end beam influences the time schedule of freight trains and causes economic loss. Therefore, it is very important to achieve preventive maintenance before failure accidents.

Preventive maintenance of existing freight trains can be divided by 90-day inspections, 30-month inspections, and 60-month inspections. Important parts such as the end beam and others are considered to be part of the 30-month inspections.

Table 4 shows the percentile and hazard rate function of the cumulative hazard probability for the distribution. In Table 4, the percentile expressed in years is the fatigue life that corresponds to the cumulative failure probability. Table 4 presents the assurance period fewer than the 10% failure probability to estimate the assurance period or assurance expense. Random failure probability was very high due to the local life distribution of the end beam.

Therefore, the derating design is necessary to prevent failure during the random failure period. Furthermore, the middle inspection of the end beam should be performed within 1.5 years for planned preventive maintenance.

## 4. Conclusions

This study performed the reliability analysis of fatigue accumulation damage in a freight train using the damage summation method. The main results are as follows.

(1) The fatigue life for the end beam of a freight train is predicted at a variable amplitude loading with the modified Miner hypothesis of cumulative damage. The longer the running time of the end beam is, the higher the failure rate. Therefore, preventive maintenance is available if a specific failure rate is applied to the maintenance schedule.

(2) The shape, scale, and median parameters in the approximated Weibull distribution are 2.92, 7.24, and 6.386 years, respectively. The median above is similar to the median evaluated by the Kaplan-Meier method.

(3) Due to the different local life distributions of the end beam, random failure probability is very high. Therefore, middle inspection of the truck frame should be performed within 1.5 years (instantaneous failure rate of 1%) for planned preventive maintenance.

## Acknowledgment

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