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Reliability analysis-based life cycle assessment of railway components using long-term maintenance data

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ABSTRACT

This study proposes a framework to evaluate the reliability of rail operation times and optimal maintenance intervals for sleepers and fasteners using a long-term maintenance database in South Korea. Additionally, the study investigates the effects of rail grinding and establishes optimal rail replacement intervals. It was found that the optimal maintenance interval of 2.04 and 2.36 months for fasteners and sleepers and optimal replacement interval of 89 months with griding interval of 10 months for rail would be recommended. It was also found that rail grinding reduces rail degradation rates and extends rail lifespan. In addition, reinforced concrete sleeper, concrete track bed (slab track), and straight rail track shows higher long-term durability than prestressed concrete sleeper, gravel ballast, and curved rail track. Overall, the proposed framework can provide data-driven cost-based optimization to determine the best maintenance strategies for long-term sustainable railway operation.

1. Introduction

The expansion of urban rail networks and increasing passenger demands have made ensuring the reliability and safety of metro rail systems a critical challenge. Rail system operations heavily depend on track maintenance practices and the condition of key components such as rails, sleepers, and fasteners. Inadequate maintenance can compromise vehicle-track interaction, increase operational loads, and raise the risk of failures, ultimately affecting passenger safety and comfort (Andrade and Teixeira, 2015; Bai et al., 2015; Soleimanmeigouni et al., 2018). To maintain high service quality while minimizing disruptions, metro operators need to implement data-driven maintenance strategies that ensure the timely replacement of degraded components (Guler, 2014; Liljenström et al., 2022; Prescott and Andrews, 2015; Sun et al., 2024). Consequently, reliability analysis and life cycle cost analysis (LCCA) have become essential tools for maintenance optimization, providing a comprehensive framework for evaluating asset management policies throughout the service life of track components (Berawi et al., 2010; Caetano and Teixeira, 2015; Patra et al., 2009; Sharma et al., 2018).

Due to cyclic loading and environmental factors, metro rail systems are subject to various forms of deterioration, including wear, rolling contact fatigue (RCF), and structural fatigue (Lee et al., 2024; Meier-Hirmer et al., 2009; Sadeghi and Askarinejad, 2010; M. Zhu et al., 2013). RCF-related defects, such as surface cracks, can lead to unexpected failures, while structural fatigue, particularly at welded joints, can result in fractures exacerbated by residual stresses from thermite welding (Gurubaran et al., 2017; Ringsberg, 2000; Zerbst et al., 2009). These degradation mechanisms necessitate the development of robust predictive models to anticipate failures and guide preventive maintenance activities (Quiroga and Schnieder, 2012; Yella et al., 2009). One of the most effective maintenance strategies to mitigate these degradation issues is rail grinding. This process removes surface irregularities, alleviates rolling contact fatigue (RCF), and restores the rail profile, reducing stress concentrations and extending rail lifespan (Li et al., 2024; Wang et al., 2022). Regular grinding also improves vehicle-track interaction, minimizes dynamic loads, and enhances operational safety, making it a crucial component of long-term maintenance planning. Moreover, railway tracks on ballast are susceptible to degradation due to cyclic loading and environmental effects, leading to loss of structural integrity and increased maintenance demands. Insufficient resistance of the ballast bed can result in excessive settlement and track misalignment, further contributing to long-term operational challenges (Dahlberg, 2001; Indraratna et al., 2010; Selig and Waters, 1994).

In recent years, advancements in machine learning and deep learning

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technologies have further enhanced predictive maintenance capabilities by enabling more accurate failure forecasting and operational efficiency in metro rail systems (Böhm, 2017; Fumeo et al., 2015; Nair et al., 2024; Thaduri et al., 2015). Such data-driven approaches provide deeper insights into degradation patterns over time, allowing to optimize maintenance schedules and extend the lifespan of critical infrastructure components (Ferreira and Murray, 1997; Lyngby et al., n.d.; Zhao et al., 2009). Additionally, the integration of reliability analysis with LCCA has been essential in identifying optimal maintenance intervals, effectively balancing preventive and corrective maintenance costs while maximizing operational efficiency (Famurewa et al., 2015; Patra et al., 2010). Additionally, studies are increasingly focusing on incorporating environmental impact assessments within LCCA, evaluating not only the economic aspects but also the ecological footprint of maintenance activities (Hansen and Pachl, 2014; Jardine et al., 2006; Vale et al., 2012). Such approaches are essential for achieving sustainable urban rail infrastructure that minimizes its environmental impact while optimizing life cycle costs (Åkerman, 2011; de Andrade and de Almeida, 2016; Grassie, 2005; Magel et al., 2005; Reddy et al., 2007).

Therefore, the main objective of this research is to develop a comprehensive maintenance strategy for metro rail infrastructure, leveraging reliability analysis and life cycle assessment based on long-term maintenance data. Weibull distribution models and Negative binominal model were applied to analyze rail life expectancy and to forecast failures in sleepers and fasteners. Kolmogorov-Smirnov (KS) goodness-of-fit tests (Massey Jr, 1951) were performed to validate the developed models and the optimized griding schedules was developed by adjusting the Weibull hazard rate. The developed models were used to discuss failure rates and degradation patterns over time and minimization of operational disruptions.

2. Database and modeling

2.1. Database

The database used in this study was obtained from the Seoul Metro operation, which spans 285.181 km with 2451-weekday train services. The network operates primarily underground, with some elevated sections and river crossings. The annual humidity in Seoul is approximately from 55 to 76% with a temperature ranging from -6 - 29 °C. We analyzed 20 years of metro rail replacement history data to understand the operational lifespan and utilization patterns of rail infrastructure. Fig. 1 illustrates the evaluation of operation time (represented as t_1, t_2, t_3, t_4, and t_5) at each rail segment, which is calculated from the difference between the installation and replacement dates. In addition, we also obtained 10 years of annual replacement data for critical track components such as fasteners and sleepers. This additional dataset enabled us to conduct a comprehensive reliability analysis on the rail, fasteners, and sleepers that frequently require maintenance in rail tracks due to their susceptibility to wear and failure.

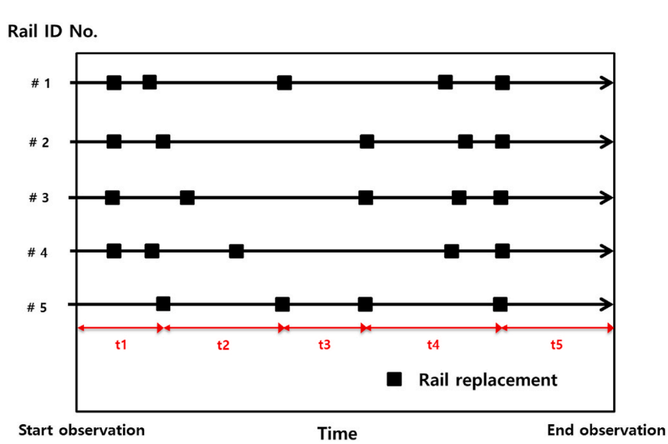


Fig. 1. Metro-rail replacement data.

2.2. Pre-process of maintenance data

We considered reliability as a function of operation times, making the number of usage months the key data for reliability analysis and the KS goodness-of-fit test (Patra et al., 2009). Rail replacements typically occur in 25 m intervals, reflecting the standard rail length. This results in varying numbers of replacements across a segment during each maintenance cycle. For example, a 750 m segment would require 30 replacements per maintenance. To account for these length-dependent numbers of replacements in each segment, we applied a preprocessing method that assigns weights to the number of rail replacements per segment. The length of the rail segment was multiplied by 10 before rounding off to generate data. For example, an extension value of 73.53 km with 6458 days of operation time would result in 735 data points with 6458 operation time for reliability analysis. After preprocessing the rail replacement data, the total number of data was 2,193,155. It can be noted that the unexpected events (e.g., extreme weather, accidents) and external conditions (e.g., temperature, traffic density) were not incorporated in the database used in this study.

2.3. Reliability modeling

We primarily employed the Weibull distribution for analyzing component life data, given its versatility in reliability engineering (Abernethy, 2006). The probability density function (PDF) of the Weibull distribution is expressed as:

$$f(t) = \frac{\beta}{t}\left(\frac{t}{\eta}\right)^{\beta} exp^{-\left(\frac{t}{\eta}\right)^{\beta}} \tag{1}$$

where t is the time to failure, β is the shape parameter, and η is the scale parameter. The shape parameter, β indicates the failure trend: $\beta > 1$ suggests an increasing failure rate (wear-out failure), $\beta = 1$ implies a constant failure rate, and $\beta < 1$ indicates a decreasing failure rate (early-life failure). The cumulative distribution function (CDF) of the Weibull distribution, which helps in assessing the probability of failure within a specific timeframe, is given by:

$$F(t) = 1 - exp^{\left(-\left(\frac{t}{\eta}\right)^{B}\right)} \tag{2}$$

The hazard function (h), which expresses the instantaneous failure rate at any given time, is defined as:

$$h(t) = \frac{\beta}{\eta^{\beta}} t^{\beta-1} \tag{3}$$

Eqs. (1)–(3) enable capturing the random nature of failure events of track components. Accordingly, Mean Time To Failure (MTTF) for Weibull distribution, an important metric in reliability analysis, can be determined by:

$$MTTF = \eta\Gamma\left(1 + \frac{1}{\beta}\right) \tag{4}$$

which Γ denotes the gamma function. For parameter estimation η and β, the maximum likelihood estimation (MLE) method is employed in this study. This ensures unbiased estimates, especially when dealing with larger datasets, enhancing the precision of reliability predictions (Meeker et al., 2022). The MLE equations for η and β can be expressed as:

$$\hat{a} = \frac{n}{n\, ln(T) - \Sigma_{i=1}^{N(T)}\, ln(t_i)} \tag{5}$$

$$\hat{b} = \frac{n}{T^{\hat{a}}} \quad (6)$$

where n is the sample size and t_i are the individual time-to-failure observations. Eqs. (5) and (6) ensures a robust statistical approach to modeling the expected behavior of rail components under operational stress.

In addition to Weibull-based modeling, we employed the Negative binomial model to evaluate the reliability of sleepers and fasteners, which exhibit irregular and clustered failure patterns. Unlike the Poisson process, which assumes a constant failure rate, the Negative binomial model accommodates overdispersion and variability for real-world maintenance data. The probability mass function (P) is defined as:

$$P(X = x_i) = \binom{x_i + r - 1}{x_i}(1-p)^r p^{x_i}, x_i = 0, 1, 2, \ldots \quad (7)$$

where μ represents the mean event rate and x_i is the number of observed failures. The mean and variance of this distribution are both equal to μ, reflecting the random nature of failures over time. In this study, the event rate μ and corresponding variance (V) are calculated as:

$$\mu = \frac{r(1-p)}{p} \quad (8)$$

$$V = \frac{r(1-p)}{p^2} \quad (9)$$

Using Eqs. (8) and (9), parameters were estimated based on the observed failure rates for sleepers and fasteners over the observation period. Using the Negative binomial model for sleepers and fasteners allowed us to capture the variability in failure rates for components subject to irregular stress patterns, while the Weibull model effectively represented the cumulative life expectancy of rails. With the parameters obtained from these models, we conducted an in-depth analysis of maintenance intervals and life cycle costs (LCC). This dual-model framework enabled a targeted investigation into cost-effective maintenance schedules, optimized according to the unique characteristics of each component. Note that spatial and temporal dependencies were not considered in this study because of the region-limited database and the variability of failure rates based on monthly failure counts (see Table 1).

2.4. Modeling of LCCA of sleeper and fastener

This study evaluates the suitability of a statistical model to characterize maintenance events for sleepers and fasteners in metro rail systems. Initially, a Poisson process model was tested, given its common application in modeling count data. However, the Poisson model failed to adequately fit the data in the Kolmogorov-Smirnov (K-S) goodness-of-fit test (data not shown here), contrary to the findings in previous studies (Denley, 2018). This discrepancy may be due to the unique nature of metro rail maintenance data, where maintenance activities are often clustered periodically, reflecting scheduled replacement practices rather than random occurrences. Such clustering is typical of rail maintenance operations, where large-scale replacements are often performed periodically rather than on an individual failure basis. Therefore, the subsequent analysis involved parameter estimation for the negative binomial model and validation using the K-S test. As shown in Table 2, a total of 40,879.54 sleepers and 58,386.3 fasteners were replaced for 10 years, with an average of 4087.95 sleepers and 5838.63 fasteners replaced per year.

Table 1
Reliability models used in this study for each track component.

Track component	Reliability model
Rail	Weibull distribution model
Fastener and sleeper	Negative binomial model

Table 2
Metro-rail maintenance data for sleeper and rail fastener from 2013 to 2022.

Year	Sleeper	Fastener
	Total replacement per year	Total replacement per year
2013	7310	7716
2014	6689	10611
2015	6254	9663
2016	5400	7681
2017	4340	5140
2018	3865	6620
2019	2269	3669
2020	2140	2269
2021	1357	3605
2022	1255	1411
Total	40879	58386
Average	4087	5838

To model the probability of observing k failures before r successes (with p as the probability of success), we estimated the parameters r and p for the negative binomial distribution from the sample mean ($\bar{x}$) and variance (s^2) as follows:

$$r = \frac{(\bar{x}^2)}{s^2 - \bar{x}} \quad (10)$$

$$p = \frac{(\bar{x}^2)}{s^2} \quad (11)$$

To further enhance the efficiency of the maintenance strategy, the **optimal maintenance interval (*I*)** for each component can be determined based on the average replacement rate using the following formula:

$$\lambda = r \cdot \frac{(1-p)}{p \cdot N_{total}} \quad (12)$$

$$I = \frac{12}{\lambda} \quad (13)$$

where λ is the average maintenance rate (events per year) and N_{total} is the total number of assets. This interval provides an estimate of the frequency at which maintenance tasks should ideally be scheduled to balance preventive and corrective maintenance activities effectively. In addition to this simple interval calculation, a more refined optimal interval (T) can be calculated by:

$$T = \sqrt{\frac{2 \cdot C_p}{C_c \cdot \lambda}} \quad (14)$$

where C_p and C_c are the preventive and corrective maintenance costs respectively. T incorporates both the cost of scheduled maintenance actions and the cost incurred by unexpected failures, providing a cost-minimizing balance. This allows for determining the most economical frequency of maintenance based on the trade-off between frequent preventive actions and the risk and expense of corrective repairs.

2.5. Modeling of grinding effect

To enhance safety and maintenance efficiency, this study investigated the model employs an adjusted Weibull hazard rate ($h(t, T_{pm})$) that accounts for the effects of periodic rail grinding (Coria et al., 2015):

$$h(t, Tpm) = \left(\frac{T_0}{T_{pm}}\right)^{\beta} \alpha\, \beta \left(\frac{t}{\alpha}\right)^{\beta-1} \quad (15)$$

where T_{pm} represents the rail grinding interval, T_0 represents the current standard grinding interval, and α and β are the Weibull scale and shape parameters, respectively. This adjustment allows for dynamic alterations to the hazard rate based on the actual maintenance performed, offering a more accurate depiction of rail degradation over time (Shang et al., 2020).

As shown in Fig. 2, the real hazard rate, $\lambda(t)$, is compared to the adjusted hazard rate $h(t, T_{pm})$, clearly illustrating the significant impact of maintenance activities such as rail grinding. The intervals where grinding occurs are marked by a temporary decrease in the hazard rate, followed by a gradual increase as the effects of grinding diminish over time. This refinement enables more precise risk assessments, thereby improving maintenance scheduling, potentially extending rail service life, and enhancing overall safety.

The expected cost rate per unit time ($C(t_p)$) in the age replacement model is formulated as:

$$C(t_p) = \frac{C_{p(r)}\, R(t_p) + C_{c(r)}\, F(t_p)}{t_p\, R(t_p) + M(t_p)\, F(t_p)} C(t_p) \tag{16}$$

where $C_{p(r)}$ is the preventive replacement cost for rail, $C_{c(r)}$ is the corrective replacement cost for rail, t_p is the preventive replacement interval, $R(t_p)$ is the reliability function, $F(t_p)$ is the cumulative distribution function, and $M(t_p)$ is the expected length of the failure cycle. This model is extended to include routine maintenance costs and incorporates discounting to calculate the total equivalent monthly cost (EMC_{total}), which is expressed as:

$$EMC_{total} = EMC_{in} + EMC_{EL} \tag{17}$$

where EMC_{in} presents the present value of recurrent replacement and maintenance monthly costs, and EMC_{EL} is the monthly equivalent cost of the initial investment. This extended model allows for the evaluation of rail degradation's impact on life cycle costs, optimization of preventive replacement intervals, and analysis of maintenance policies' effects on rail service life and costs.

3. Results

3.1. Weibull model

Table 3 present the results of KS test using seven distribution models for all. As seen in Table 3, the Weibull distribution showed the lowest D_n value ($D_n = 0.0888$) among seven distribution models, indicating that the Weibull well described observed operation time over remaining six distribution models. Note that the lower D_n value indicate the better fit of observed data for given distribution model ($D_n = \max|E_n(x) - S_n(x)|$ where $E_n(x)$ is empirical distribution function and $S_n(x)$ is theoretical cumulative distribution function under the null hypothesis).

Table 4 shows KS test results for operation time of all rail components, sleeper, ballast, and construction type of railway (tunnel or box)

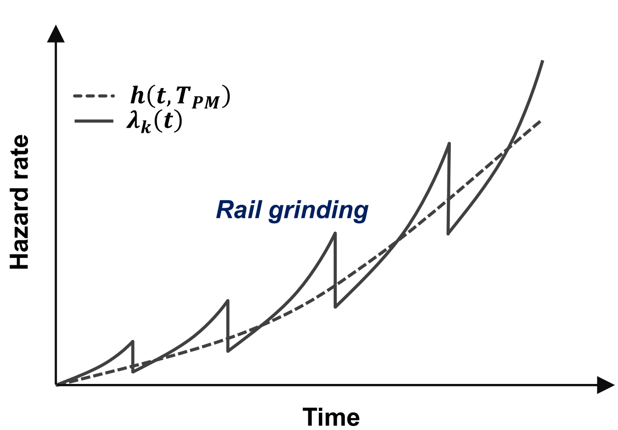


Fig. 2. Comparison of the hazard rate (λ_k) and adjusted hazard rate with rail grinding ($h(t, T_{pm})$) (after (Coria et al., 2015)).

Table 3
KS test results with various distribution model with all rail maintenance data.

Distribution model	D_n
Weibull	0.0888
Gamma	0.0892
Lognormal	0.0978
Logistic	0.116
Exponential	0.1514
Normal	0.1581
Rayleigh	0.1795

Table 4
KS test results for various conditions.

Conditions	Shape parameter	Scale parameter	D_n
All data	138.728	1.743	0.089
Straight	158.522	1.728	0.122
Curve	141	1.991	0.085
PC sleeper	135.423	1.548	0.261
RC sleeper	145.577	1.837	0.102
Gravel ballast	135.423	1.548	0.261
Concrete track bed	145.788	1.835	0.102
Tunnel	154.608	2.034	0.135
Box	139.662	1.763	0.081

using Weibull model. Overall, relatively low D_n value shown in Table 4 confirmed the validity of selecting Weibull model to describe the operation time of rail components. Relatively high D_n value of 0.261 for PC sleeper and gravel ballast indicate the need for using other distribution models to describe these components. Nevertheless, the $D_n < 0.14$ for rest of components or construction types of railway indicate that Weibull model can be a reasonable selection of describing the operation time in railway engineering. The fitted Weibull model shown in Fig. 3 for operation time for all rail components, straight rail only, and curved rail only also confirmed the applicability of Weibull model in modeling operation time of rail.

3.2. Negative binomial model for sleeper and fastener

To account for the clustered and periodic nature of maintenance events for sleepers and fasteners, a Negative binomial model was employed. This model was chosen due to its ability to accommodate over-dispersed count data, where variance exceeds the mean, and to reflect the inherent variability in maintenance practices. The suitability of the model was validated using the K-S test using negative binomial model at a 5% significance level, yielding p-values of 0.7583 for sleepers and 0.8963 for fasteners, indicating a good fit. These results confirm that the Negative binomial model effectively represents the data, capturing the variability in maintenance intervals more accurately than a Poisson model, which assumes events occur randomly and independently.

Unlike random Poisson-distributed failures, metro rail maintenance is often conducted periodically or in clusters, reflecting scheduled replacement practices rather than individual failure-based interventions. For example, sleepers and fasteners are typically replaced in large quantities during planned maintenance windows to ensure safety and efficiency. As summarized in Table 5, the analysis estimated monthly failure rates (λ) as 340.66 events/month for sleepers and 486.55 events/month for fasteners. The railway network comprises 734,538 sleepers and 2,788,879 fasteners with an average annual replacement rate of 4087.95 sleepers and 5838.63 fasteners indicates that the yearly replacement represents approximately 0.56% of the total sleeper inventory and 0.21% of the total fastener inventory. This implies that an even higher replacement rate of fasteners than sleepers can be anticipated for the metro railway system, highlighting the need for more frequent inspections, and predictive maintenance using real-time

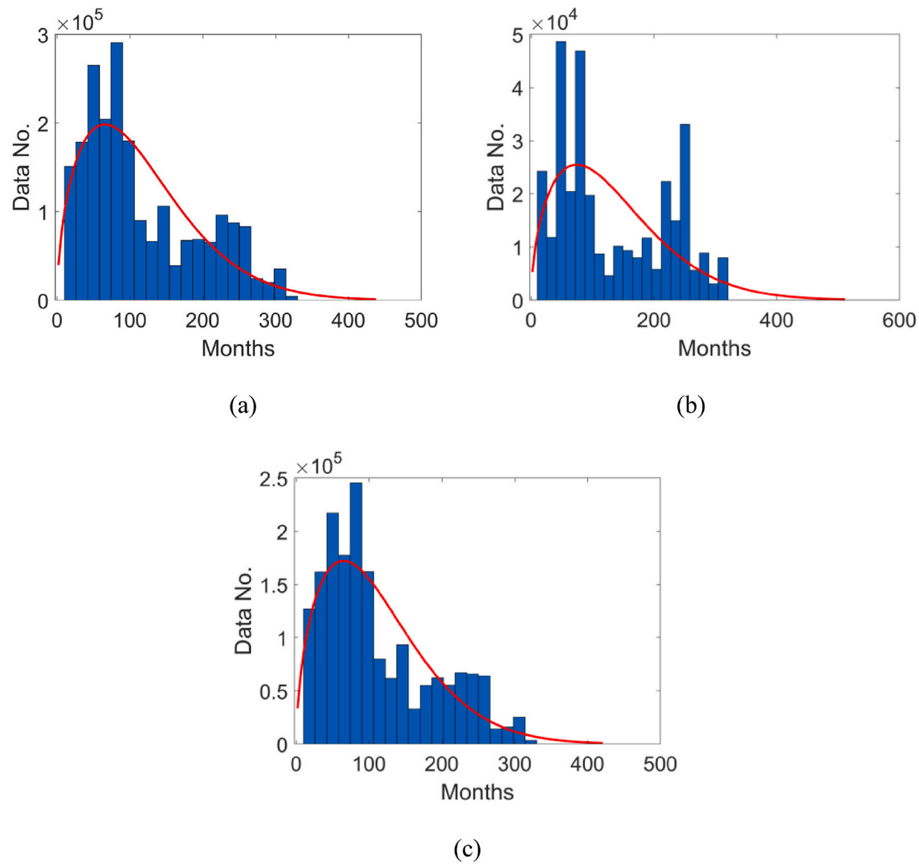


Fig. 3. Weibull modeling of operation times for all rail components ((a)), straight rail only ((b)), and curved rail only ((c)).

Table 5
Negative binomial parameter estimation and optimal maintenance intervals.

Component	Estimated r	Estimated p	Lambda (events/ month)	80% Threshold (CDF events/month)
Sleeper	3.651	0.011	340.66	475.33
Fastener	3.929	0.008	486.55	672.83

monitoring such as the track inspection vehicle. Figs. 4 and 5 display the Probability Density Function (PDF) and Cumulative Distribution Function (CDF) of the Negative binomial model for sleepers and fasteners. The 80% CDF thresholds (475.33 events per month for sleepers and 672.83 events per month for fasteners) can be suggested as decision points for initiating preventive maintenance before reaching critical failure levels.

4. Discussion

4.1. Optimal maintenance intervals of sleeper and fastener

On the contrary to theoretical background of refined optimal maintenance intervals, we further incorporate the economic considerations, the total life cycle cost analysis was calculated using preventive and corrective maintenance costs (C_{total}), along with cumulative failure probabilities of negative binomial model (F) for varying maintenance intervals (T_{pm}). Preventive maintenance costs (C_p) is inversely proportional to T_{pm}, while corrective maintenance cost (C_p) is directly

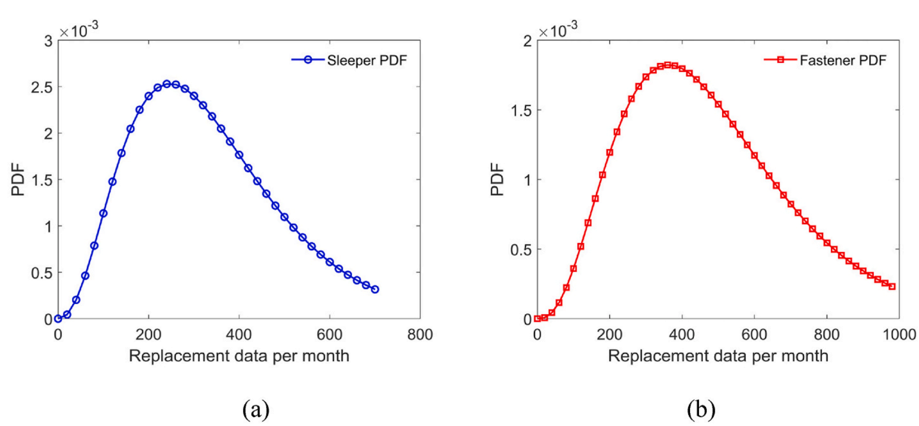


Fig. 4. Probability distribution of replacement per month based on negative binomial model for sleeper ((a)) and fastener ((b)).

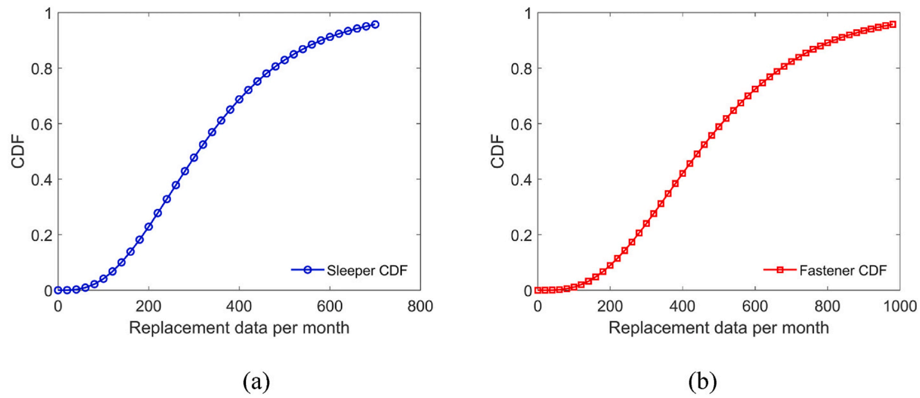


Fig. 5. Cumulative distribution of replacement per month based on negative binomial model for sleeper ((a)) and fastener ((b)).

proportional to F as shown below:

$$F = \sum (PDF \bullet T_{pm}) \tag{18}$$

$$C_{total} = \frac{C_p}{T_{pm}} + C_c \bullet F \tag{19}$$

As seen in Eq. (19), the C_{total} is calculated by integrating the failure probabilities derived from the negative binomial model (Eq. (18)). The optimal T_{pm} corresponding to the minimum C_{total} for sleepers and fasteners were evaluated using the bounded optimization function. In addition, T (Eq. (14)) was also introduced to incorporate economic considerations and failure rates.

For sleepers, T and T_{pm} were calculated as 2.62 and 2.36 months respectively whereas 1.90 and 2.04 months for fasteners were evaluated (Table 6 and Fig. 6). The C_{total} reflects these trade-offs, where the values for sleepers and fasteners were found to be \$33.95 and \$9.80, respectively, based on the refined and optimized intervals as shown in Fig. 6. The C_p and C_c in Table 6 were directly derived from these calculations to ensure consistency with the results. The preventive maintenance typically occurs every three months in South Korea, abovementioned T and T_{pm} values evaluated in this study imply that the shorter maintenance intervals would be required than current maintenance interval in practice to minimize C_{total} and reduce the chance of unexpected failure. The results shown in Fig. 6 indicate that the more frequent preventive maintenance does not always lead to the higher C_{total}, which implies that the data-driven analysis shown in this study can be applied to evaluate optimized T_{pm} for given maintenance database. Note that the preventive (C_p) and corrective (C_c) maintenance costs presented in Table 6 were estimated based on labor, material, and equipment expenses from railway authorities in South Korea.

4.2. MTTF analysis

Fig. 7 illustrates the evaluated MTTF values for various rail components and construction types calculated by Equation (4). As seen in Fig. 7, concrete track bed shows a higher MTTF of 122 months than gravel ballast (MTTF = 115 months), highlighting concrete track bed is more beneficial in maintenance frequency than gravel ballast. Similarly,

Table 6
Optimal Maintenance Intervals and optimal total cost for Sleepers and Fasteners.

Component	Preventive Cost (C_p)	Corrective Cost (C_c)	Refined Optimal Interval (T) (month)	Optimal T_{pm} (month)	Optimal C_{total}
Sleeper	\$40	\$150	2.62	2.36	\$33.95
Fastener	\$10	\$50	1.90	2.04	\$9.80

RC sleepers (MTTF = 121 months) outperform PC sleepers (MTTF = 115 months), which can be attributed to structural stability and load distribution of RC sleeper, particularly under high-stress track areas. It is notable that the type of construction also affects MTTF, where tunnels yield a longer MTTF of 128 months compared to box culverts (MTTF = 116 months), likely due to protection of rail by tunnel structure. In addition, the higher MTTF of 135 months for straight rails was evaluated than that of 115 months for curved rails, which is more or less intuitive because of high lateral forces applied to the curved rails. Overall, the results shown in Fig. 7 suggest the impact of rail geometry, material selection, and construction type in maintenance planning.

It can be noted that the calculated MTTF shown in Fig. 7 is based on consistent operational conditions, which may not be the case for real-world operational conditions. In addition, environmental factors such as extreme weather conditions and variations of traffic loads were not incorporated into the database, the MTTF values shown in Fig. 7 may not perfectly represent real-world operation conditions. Nevertheless, the framework for evaluating MTTF values shown in this study can be applied to assess the maintenance interval of railway components for given database.

4.3. Optimal preventive replacement interval of rail with considering of grinding and inspection

In this analysis, we calculate EMC_{total} for rail components (such as curved sections for RFC and tunnel sections for corrosion) by using Weibull distribution parameters that represent the failure behavior of these components. The parameters for the Weibull model are given as α_{corr}, β_{corr} for the corrective maintenance hazard rate, and α_{rcf}, β_{rcf} for the rolling contact fatigue (RCF) hazard rate. The key formulas used in this analysis include the hazard rate (h_{rate}), which combines the corrective maintenance hazard rate and the rolling contact fatigue hazard rate. This rate is calculated over a time period (t_p in months) and T_{pm} to represent the preventive maintenance interval.

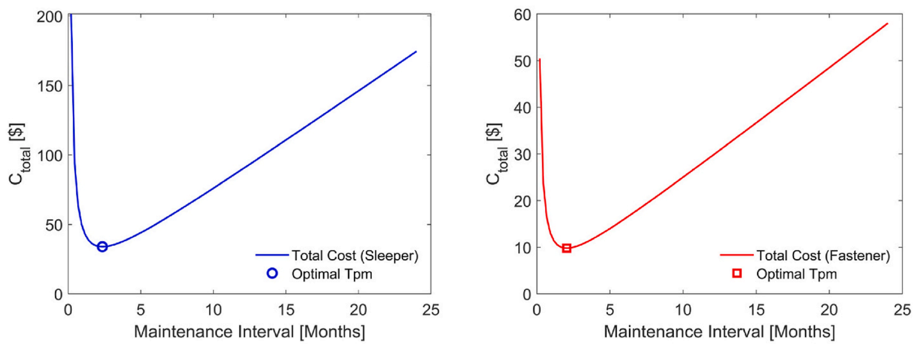
$$h_{rate} = \frac{\beta_{corr}}{\alpha_{corr}}\left(\frac{t_p}{\alpha_{corr}}\right)^{\beta_{corr}-1} + \left(\frac{T_{pm}}{T_0}\right)^{\beta_{rcf}}\frac{\beta_{rcf}}{\alpha_{rcf}}\left(\frac{t_p}{\alpha_{rcf}}\right)^{\beta_{rcf}-1} \tag{20}$$

The cumulative hazard function (H_{func}) is integrated over time to compute the reliability function (R), which represents the probability that a component survives without failure over t_p.

$$H_{func} = \left(\frac{t_p}{\alpha_{corr}}\right)^{\beta_{corr}} + \left(\frac{T_{pm}}{T_0}\right)^{\beta_{rcf}}\left(\frac{t_p}{\alpha_{rcf}}\right)^{\beta_{rcf}} \tag{21}$$

$$R = e^{-H_{func}} \tag{22}$$

The failure density function (f) is calculated using the hazard rate and reliability function, representing the instantaneous failure rate weighted by the probability of survival up to that time.



(a) (b)

Fig. 6. Total maintenance cost as a function of maintenance intervals for sleeper (a) and fastener (b).

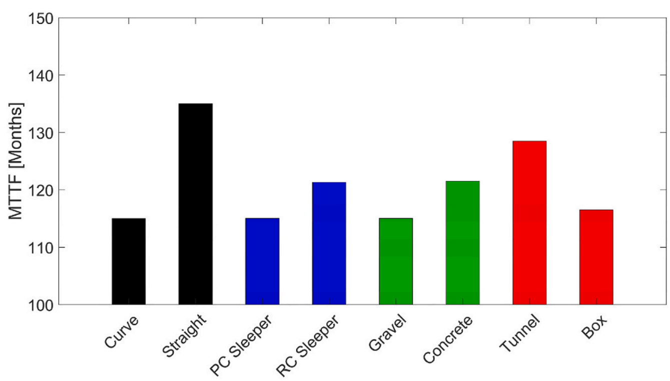


Fig. 7. Evaluated MTTF across various rail components and conditions.

$$f = h_{rate} \bullet R \tag{23}$$

The EMC_{total} calculation can be a sum of initial setup costs (EMC_{in}) and lifecycle costs (EMC_{EL}):

$$EMC_{total} = EMC_{in} + EMC_{EL} \tag{24}$$

$$EMC_{in} = C_{in} \cdot i \tag{25}$$

$$EMC_{EL} = PVm \cdot a_{EL} \tag{26}$$

where a_{EL} is an annuity factor for life expectancy (EL), and PV_m represents the present value of maintenance costs over time. Table 7 summarizes the parameters used in the calculation of EMC_{total} in this study. The optimal t_p is the optimal time interval where components are proactively replaced based on their remaining reliability. While T_{pm} determines the regular maintenance schedule, the t_p minimizes lifecycle costs by balancing preventive and corrective costs and aligning with reliability thresholds.

Fig. 8 illustrates calculated EMC_{total} (Fig. 8(a)) and cumulative EMC_{total} (Fig. 8(b)) at $T_{pm} = 4$, 6, 8, 10, 12, and 14 months. As seen in Fig. 8(a), calculated EMC_{total} decreases at relatively low t_p whereas increase in EMC_{total} was obtained at $t_p >$ optimal t_p for all values of T_{pm}. This indicate the presence of optimal t_p regardless of T_{pm} that provides minimum EMC_{total}. In addition, optimal t_p and corresponding EMC_{total} at varied T_{pm} shown in Table 8 suggests the increase in optimal EMC_{total} as T_{pm} increases from 8 to 14 months whereas similar EMC_{total} at $T_{pm} = 4$, 6, and 8 months was observed. This implies the presence of threshold T_{pm} where the decrease in T_{pm} does not lead to decrease in EMC_{total}. It can be suggested that $6 < T_{pm} < 8$ months can be recommended to minimize EMC_{total} for rail maintenance. The increase in $\mathrm{EMC_{total}}$ as T_{pm} increases from 8 to 14 months is due to the Weibull hazard rate effect, which accelerates rail degradation, increases failure probability ($F(t_p)$), and raises total corrective maintenance costs ($F(t_p) \bullet C_c$).

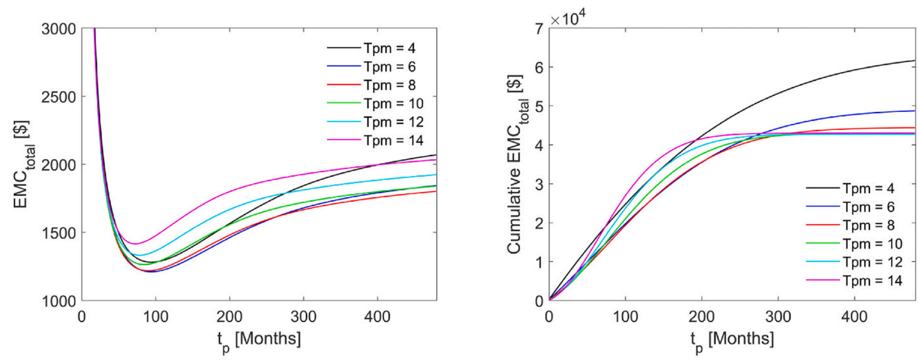
Table 7
Parameters used in reliability and maintenance cost analysis.

Parameter	Description	Value	Units
α_{corr}	Weibull shape parameter for corrective maintenance	154	–
β_{corr}	Weibull scale parameter for corrective maintenance	2.034	–
α_{rcf}	Weibull shape parameter for RCF	141	–
β_{rcf}	Weibull scale parameter for RCF	1.991	–
r	Annual interest rate	0.05	–
i	Monthly interest rate (compounded from annual rate)	$(1+r)^{1/12} - 1$	–
C_{in}	Initial maintenance cost	40000	USD
$C_{p(r)}$	Preventive maintenance cost	4000	USD
C_s	Spare parts cost	70000	USD
$C_{c(r)}$	Corrective maintenance cost	120000	USD
C_{pm}	Monthly preventive maintenance cost	2000	USD/month
C_{ui}	Inspection cost per unit	200	USD/unit
C_{vi}	Verification cost per unit	300	USD/unit
T_O	Reference period for maintenance	12	months
T_{ui}	Unit inspection interval	6	months
T_{vi}	Verification inspection interval	12	months
T_{pm}	Preventive maintenance intervals to analyze	4, 6, 8, 10, 12, 14	months
t_p	Time period for analysis	0–480	months

As seen in Fig. 8(b), T_{pm} values between 6 and 10 months exhibit the relatively stable cumulative cost growth over time at $t_p > 200$ months, whereas increase in cumulative EMC_{total} at $T_{pm} = 4$ months was obtained, which is likely attributed to the high frequency of preventive interventions. This high frequency of preventive intervention offsets the cost savings from reduced corrective maintenance. Therefore, it is more beneficial to select intermediate T_{pm} (e.g., $T_{pm} = 8$ months) which demonstrates a more stable cumulative EMC_{total} compared to $T_{pm} = 4$–6 months, reflecting reduced variability over time.

Apart from the consideration of EMC_{total} only, the results presented in Table 8 show that $T_{pm} = 8$ months may be the optimal choice of T_{pm} as relatively low optimal t_p with low EMC_{total} was obtained at $T_{pm} = 10$ months. Because the lower optimal t_p represents less frequent preventive replacements, 4 months longer optimal t_p for $T_{pm} = 10$ months than that for $T_{pm} = 8$ months may be more beneficial than approximately $8 higher EMC_{total} for $T_{pm} = 10$ months than that for $T_{pm} = 8$ months. Therefore, $t_p = 85$ months (corresponding to the optimal T_{pm} of 10 months) can be suggested for preventive replacement of rail.

The cumulative EMC_{total} shown in Fig. 8(b) also support the optimal $T_{pm} = 10$ months as it shows relatively low cumulative EMC_{total} at low t_p with converged cumulative EMC_{total} at high t_p. In practice, $T_{pm} = 12$ months has been selected in South Korea, which is more or less consistent with the optimal $T_{pm} = 10$ months obtained in this study.



(a) (b)

Fig. 8. EMC_{total} (a) and cumulative EMC_{total} (b) at T_{pm} = 4, 6, 8, 10, 12, and 14 months.

Table 8
Optimal EMC_{total} and corresponding optimal t_p under Varying T_{pm}.

T_{pm} (Months)	Optimal t_p (Month)	Optimal EMC_{total} ($)
4	95	1281.37
6	93	1210.81
8	89	1218.22
10	85	1263.94
12	79	1332.74
14	73	1416.86

Nevertheless, reducing 2 months of T_{pm} from 12 to 10 months can optimize life cycle costs and operational efficiency. Overall, the findings shown in Fig. 8 and Table 8 emphasize the importance of data-driven EMC-based optimization to determine the best preventive maintenance strategies for sustainable railway operation. The EMC_{total} as a function of α_{corr}, β_{corr}, α_{rcf}, and β_{rcf} shown in Fig. 9 indicate that the α_{corr} most significantly affects on EMC_{total} among the four parameters. The increased α_{corr} and α_{rcf} led to reduced EMC_{total} at relatively short intervals, whereas variations in β_{corr} and β_{rcf} show almost no impact on EMC_{total} as shown in Fig. 9.

It can be noted that the frameworks shown in this study can be applied to maintenance and cost databases in other regions to obtain maintenance schedules of railway system because this study used long-term 20-year maintenance data. It can be also noted that the including potential influencing factors such as environmental factors (e.g., extreme weather, geographical conditions, technology-dependent labor costs) can provide robust maintenance schedules using the proposed framework shown in this study. The developed framework shown in this study can also apply to obtain reliability-based maintenance optimization for other infrastructure systems such as highways or bridges (e.g., optimal maintenance intervals for structural fatigue in bridges).

5. Conclusions

This study developed a reliability-based life cycle assessment

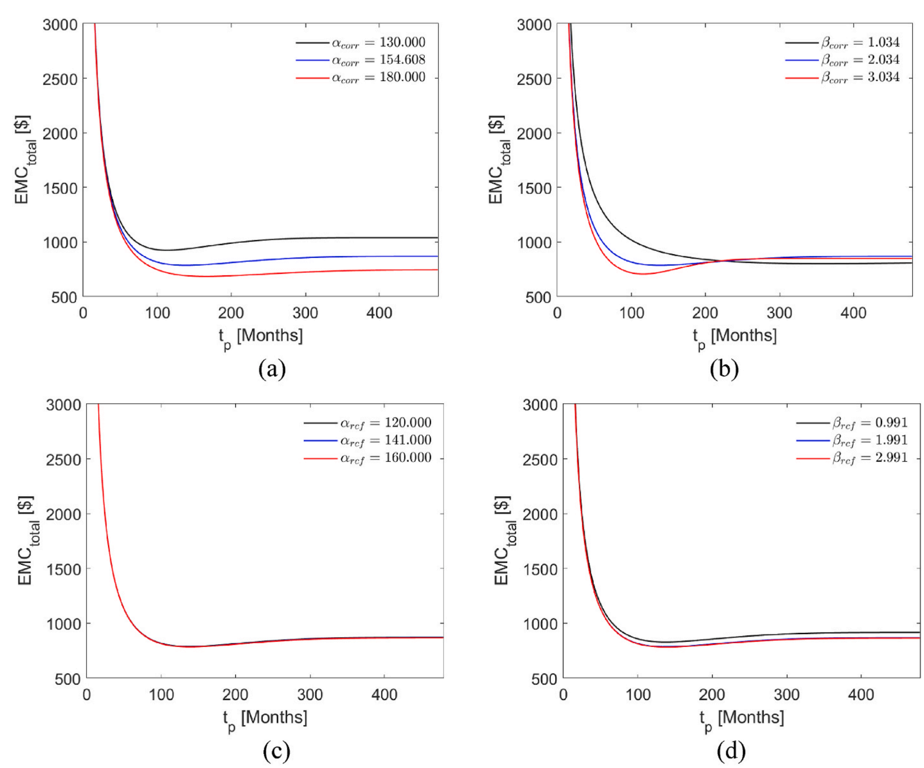


Fig. 9. Impact of on EMC_{total}: (a) α_{corr}, (b) β_{corr}, (c) α_{rcf}, (d) β_{rcf}.

framework for metro rail systems using the database in South Korea, particularly focusing on optimizing maintenance strategies using long-term data. Based on the reliability analysis and life cycle assessment, following conclusion can be drawn:

1. Higher MTTF values for concrete track bed, RC sleeper, and straight rail track than gravel ballast, PC sleeper, and curved rail track were obtained, which implies that the material of sleeper and ballast and the shape of rail track substantial affect the long-term durability of track system.
2. The Weibull model well described the distribution of operation times for rail, which yield the shape and scale parameter of 1.743 and 138.73 months for all parts of rail. Likewise, the Negative binomial model well described the distribution of operation times for sleepers and fasteners, which yields 80% cumulative failure thresholds of 475.33 events per month for sleepers and 672.83 events per month for fasteners.
3. The life cycle cost analysis provided optimal $T_{pm} = 2.04$ and 2.36 months with corresponding $C_{total} = \$9.80$ and 33.95 per unit were evaluated for fasteners and sleepers respectively. This implies that the shorter maintenance intervals would be required than the typical maintenance interval of 3 months in South Korea to minimize C_{total} and reduce the chance of unexpected failure.
4. The time for preventive replacements was evaluated as 93 months for rail at the optimal T_{pm} of 8 months. However, the optimal T_{pm} of 10 months can be recommended to achieve cost effectiveness and low optimal t_p of 89 months.
5. The proposed framework shown in this study can be further applied to multi-variable database such as integrating environmental impact or data from real-time monitoring sensor, which would provide reliable parameters (e.g., optimal T_{pm}, MTTF) for optimizing maintenance schedule of track system.

CRediT authorship contribution statement

Koochul Ji: Writing – original draft, Visualization, Investigation, Formal analysis, Data curation. **Ilyoon Choi:** Supervision, Funding acquisition. **Jongmuk Won:** Writing – review & editing, Supervision, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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