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PERFORMANCE ANALYSIS OF LOG-TYPE LIFETIME DISTRIBUTION BASED ON INFINITE FAILURE NHPP SOFTWARE RELIABILITY MODEL

HYO JEONG BAE

Professor, Department of Drone and GIS Engineering, Namseoul University, 91 Daehak-ro, Seonghwan-eup, Seobuk-gu, Cheonan-si, Chungnam, Korea (31020)
E-mail: baehj@nsu.ac.kr

ABSTRACT

This study analyzes the performance of an infinite-failure NHPP software reliability model based on logarithmic time transformation by applying a Log-Type lifetime distribution, which is effective for complex reliability analysis as it can represent various types of failure occurrences. Software failure time data are employed, and the model parameters are estimated using the MLE approach. The proposed models are evaluated using multiple criteria, including goodness-of-fit measures such as MSE and R^2, predictive performance assessed via m(t), failure occurrence intensity characterized by λ(t), and reliability measured by $\hat{R}(\tau)$. The analysis results indicate that the Log-Poisson model outperforms the competing models. Consequently, this study systematically extends and validates the reliability performance of Log-Type distribution families that have not been sufficiently examined in previous studies, and the findings are expected to provide useful baseline information for early-stage software failure rate analysis.
Keywords: *Infinite-failure, Log-Linear, Log-Poisson, Log-Power, Log-Type, NHPP.*

1. INTRODUCTION

As artificial intelligence (AI) advances rapidly, improving the reliability of software systems has become increasingly important. In particular, AI-based software exhibits more complex failure timing and behavior than conventional software due to its strong dependence on data, thereby underscoring the need for systematic reliability testing. These emerging characteristics expose the limitations of traditional software reliability analysis methods, necessitating the development of more flexible and robust probabilistic models. For these reasons, NHPP (Non-Homogeneous Poisson Process)-based models have been widely adopted in software reliability studies because they can effectively represent time-varying failure occurrence rates. However, most existing NHPP models rely primarily on specific lifetime distributions, such as the exponential and Weibull distributions, which limits their ability to adequately capture the nonlinear characteristics of actual software failure processes. Consequently, current NHPP-based software reliability research has not sufficiently incorporated logarithmic or other nonlinear failure distributions, and related studies remain relatively scarce [1]. On this basis, Yang [2] analyzed the reliability performance characteristics of software systems using an NHPP-based exponential-type reliability model. Subsequently, Kim [3] extended this line of research by adopting a modified exponential distribution, through which key attributes influencing reliability performance were newly identified and examined. Furthermore, Xiao and Dohi [4] evaluated the attributes of Weibull-type models by applying an NHPP-based reliability model combined with the Weibull distribution and provided a comprehensive performance evaluation. Following these previous studies, Yoo [5] analyzed the reliability properties of NHPP-based models through various extensions of Weibull-type distributions, while Park [6] examined model performance by incorporating the classical Weibull distribution into an infinite-failure NHPP reliability framework. In contrast, Yang [7] demonstrated that, unlike traditional NHPP studies, log-type distributions are capable of capturing diverse failure occurrence patterns, thereby providing a more precise representation of complex software reliability behavior. In this context, Yang and Kim [8] reinterpreted the characteristics of NHPP-based software reliability growth models by leveraging intensity functions derived from log-type distributions.

Accordingly, the present study extends conventional Log-Type lifetime distributions to an infinite-failure NHPP software reliability framework and evaluates the resulting models using multiple performance criteria. Moreover, the study focuses on developing effective optimization procedures and identifying the best-performing model among the candidate frameworks.

2. RELATED RESEARCH

2.1.1 NHPP model

An NHPP-based software reliability model is a stochastic framework that represents software failure occurrences during operation as a non-homogeneous Poisson process, enabling quantitative assessment of failure trends over time and the prediction of future failures. Define N(t) as the total number of failures up to time t, where m(t) and λ(t) correspond to the mean value and intensity functions. Then, N(t) is modeled as a Poisson distribution governed by the parameter m(t), as expressed below.

$$P\{N(t) = n\} = \frac{[m(t)]^n \cdot e^{-m(t)}}{n!} \quad (1)$$

In reliability modeling, m(t) denotes the mean cumulative number of failures, while λ(t) defines the time-dependent failure intensity at a specific time instant. Consequently, the relationship between these two functions is given as follows.

$$m(t) = \int_0^t \lambda(s)ds \quad (2)$$

$$\frac{dm(t)}{dt} = \lambda(t) \quad (3)$$

2.1.2 Infinite Failure NHPP Software Reliability Model

To reflect realistic operational conditions, this study is conducted using an infinite-failure NHPP model. The infinite-failure assumption postulates that the number of latent defects in software is unbounded and that failures cannot be completely eliminated, thereby allowing new defects to emerge continuously. Consequently, the infinite-failure-based model shows that it is very efficient for software systems characterized by substantial size and structural complexity.

For the purpose of analyzing the reliability characteristics of the proposed model, F(t) and f(t) are defined as the cumulative distribution function and the corresponding probability density function, respectively. Accordingly, the functions governing the reliability performance of the infinite-failure NHPP model are derived as follows [9].

$$m(\mathrm{t}) = -\ln(1 - \mathrm{F(t)}) \quad (4)$$

$$\lambda(\mathrm{t}) = \frac{f(t)}{(1 - F(t))} \quad (5)$$

Based on these definitions, the likelihood function of NHPP model is formulated as presented below.

$$L_{NHPP}(\Theta|\underline{x}) = \left(\prod_{i=1}^{n} \lambda(x_i)\right) exp[-m(x_n)] \quad (6)$$

2.2 Infinite Failure NHPP Log-Linear Model

The NHPP Log-Linear model is an infinite-failure-based framework in which the mean value function, representing predictive capability, exhibits a linear relationship with the logarithm of time. In this model, the failure occurrence rate increases rapidly during the initial phase and gradually decreases as time progresses. Owing to its simple and transparent structure, the model can be effectively applied even with limited data and enables rapid parameter estimation. Consequently, it is well suited for reliability assessment under constrained conditions and for evaluating learning effects in software testing.

Based on the foregoing derivations, the reliability performance functions of the model are analytically derived and defined as follows [10].

$$m(t) = \frac{e^{\alpha}\left(e^{\beta t} - 1\right)}{\beta} \quad (7)$$

$$\lambda(t) = \exp(\alpha + \beta t) \quad (8)$$

Note that $-\infty < \alpha < \infty,\ \beta > 0$

When substituted into Equation (6), the likelihood function is as in Equation (9).

$$L_{NHPP}(\Theta|\underline{x}) = \left(\prod_{i=1}^{n} e^{\alpha+\beta t}\right) exp\left[-\frac{e^{\alpha}\left(e^{\beta t} - 1\right)}{\beta}\right] \quad (9)$$

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Thus, the maximum likelihood estimators $\hat{\alpha}_{MLE}$ and $\hat{\beta}_{MLE}$ can be calculated as follows.

$$\sum_{i=1}^{n} x_i + \frac{n}{\hat{\beta}} - \frac{n\,x_n}{1-\,e^{-\hat{\beta}\,x_n}} = 0 \quad (10)$$

$$e^{\hat{\alpha}} - \frac{n\,\hat{\beta}}{e^{\hat{\beta}\,x_n}-1} = 0 \quad (11)$$

2.3 Infinite Failure NHPP Log-Poisson Model

The NHPP Log-Poisson model, also referred to as the Log-Poisson execution-time model, is commonly known as the Musa–Okumoto model and represents an infinite-failure framework based on the logarithmic characteristics of execution time. In this model, inter-failure times are assumed to follow a log-type distribution, resulting in a failure intensity that gradually decreases according to a logarithmic function. These characteristics make the model well suited for reliability analysis of large-scale systems, in which failures occur frequently during the initial phase and decrease progressively over time.

Accordingly, the reliability performance functions of the model are analytically derived and defined as follows [11].

$$\text{m(t)} = \frac{1}{\theta} ln(\lambda_0 \theta t + 1) \quad (12)$$

$$\lambda\text{(t)} = \frac{\lambda_0}{\lambda_0 \theta t + 1} \quad (13)$$

By substituting the above expression into Equation (6), the corresponding likelihood function is obtained as follows.

$$L_{NHPP}(\Theta|\underline{x}) = \left(\prod_{i=1}^{n} \frac{\lambda_0}{\lambda_0 \theta t + 1}\right) exp\left[-\frac{1}{\theta}\, ln(\lambda_0 \theta t + 1)\right] \quad (14)$$

Therefore, applying a logarithmic transformation to both sides of the equation and simplifying the expression yields the log-likelihood function for the model, which is presented in Equation (15).

$$\text{ln}L_{NHPP}(\Theta|\underline{x}) = nln\lambda_0 - ln\sum_{i=1}^{n}(\lambda_0 \theta\, x_i + 1) - \frac{1}{\theta} ln(\lambda_0 \theta x_n + 1) \quad (15)$$

Consequently, by applying the bisection method to these equations, the maximum likelihood estimators of this model's parameters, $\hat{\theta}_{MLE}$ and $\hat{b}_{MLE}$, can be determined as follows.

$$\hat{\theta}_{MLE} = \frac{1}{n}\text{ln}(\hat{\emptyset}\; x_n + 1\,) \quad (16)$$

$$\widehat{\lambda_0}_{MLE} = \frac{\hat{\emptyset}}{\hat{\theta}_{MLE}} \quad (17)$$

Note that $\hat{\emptyset}$ $(= \widehat{\lambda_0}_{MLE} \times \hat{\theta}_{MLE})$ becomes the root of the following Equation (18).

Specifically, the parameter ϕ is estimated by solving the following equation using the bisection method.

$$\frac{\partial \text{ln} L_{NHPP}(\emptyset|\underline{x})}{\partial \emptyset} = \frac{n}{\emptyset} - \sum_{i=1}^{n} \frac{x_i}{\emptyset x_i\, + 1} - \frac{n\, x_n}{(\emptyset x_n\, + 1)\, \text{ln}(\emptyset x_n\, + 1)} = 0 \quad (18)$$

2.4 Infinite Failure NHPP Log-Power Model

The NHPP Log-Power model is an infinite-failure model that incorporates both logarithmic and power-law characteristics of failure occurrence times. In this model, the failure intensity decreases in a nonlinear shape, enabling a flexible representation of various failure reduction patterns.

These characteristics make the model suitable for complex, large-scale systems, as it can capture both the rapid failure reduction in the initial phase and the gradual failure reduction in the stabilization phase. Accordingly, the reliability performance functions of the model are analytically derived and defined as follows [12].

$$\text{m(t)} = \text{a}\; ln^{b}(1{+}\text{t}) \quad (19)$$

$$\lambda\text{(t)} = \frac{ab\; ln^{b-1}(1+t)}{1+t} \quad (20)$$

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By inserting Equations (19) and (20) into Equation (6) and applying a logarithmic transformation, the corresponding log-likelihood function is derived as follows.

$$\ln L_{NHPP}(a,b|\underline{x}) = n\,ln a + n\,ln b$$
$$-(b-1)ln\left[\sum_{i=1}^{n}\ln(1+x_i)\right] - \sum_{i=1}^{n}\ln(1+x_i)$$
$$-\,\mathrm{a}\,ln^{b}(1+x_n) \quad (21)$$

Accordingly, the maximum likelihood estimators $\hat{a}_{MLE}$ and $\hat{b}_{MLE}$ can be calculated as follows by Equations (22) and (23), respectively.

$$\frac{\partial \ln L_{NHPP}(a,b|\underline{x})}{\partial a} = \frac{n}{\hat{a}} - ln^{b}(1+x_n) = 0 \quad (22)$$

$$\frac{\partial \ln L_{NHPP}(a,b|\underline{x})}{\partial b} = \frac{n}{\hat{b}} - ln\left[\sum_{i=1}^{n}\ln(1+x_i)\right]$$
$$-\,\mathrm{a}\,ln^{b}(1+x_n)\; ln[\ln(1+x_n)] = 0 \quad (23)$$

3. RELIABILITY PERFORMANCE ANALYSIS

This study assessed the proposed model's reliability performance based on failure time data irregularly recorded under normal operating conditions of desktop computer system software. The failure time data used in this work included a total of 30 failures over approximately 187.35 hours of observation time, and detailed information is provided in Table 1 [13].

The suitability of the collected data for reliability analysis was evaluated using the Laplace trend test, and the corresponding results are presented in Figure 1. Generally, if the Laplace trend test statistic lies between −2 and 2, it is interpreted as evidence that the data contain no significant trend or systematic deviation, indicating stable operation and suitability for analytical evaluation.

Table 1: Software Failure Time.

Failure number	Failure time (hours)	Failure time (hours)$\times 10^{-2}$
1	4.79	0.0479
2	7.45	0.0745
3	10.22	0.1022
4	15.76	0.1576
5	26.10	0.261
6	35.59	0.3559
7	42.52	0.4252
8	48.49	0.4849
9	49.66	0.4966
10	51.36	0.5136
11	52.53	0.5253
12	65.27	0.6527
13	69.96	0.6996
14	81.70	0.817
15	88.63	0.8863
16	107.71	1.0771
17	109.06	1.0906
18	111.83	1.1183
19	117.79	1.1779
20	125.36	1.2536
21	129.73	1.2973
22	152.03	1.5203
23	156.40	1.564
24	159.80	1.598
25	163.85	1.6385
26	169.60	1.696
27	172.37	1.7237
28	176.00	1.76
29	181.22	1.8122
30	187.35	1.8735

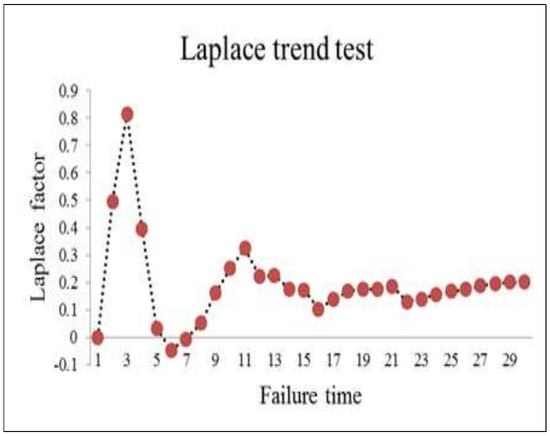

Figure 1: Analysis Results by Laplace Trend Test.

Figure 1 shows that all trend test statistics fall within the interval (−2, 2), indicating that no statistically significant anomalies are present in the dataset. Consequently, the failure time data presented in Table 1 are considered appropriate for subsequent reliability analysis.

In this study, parameter estimation was conducted by numerically transforming the original failure time data to ensure convergence, followed by the application of MLE.

Table 2: Parameter Estimation by MLE.

NHPP Model	MLE (Maximum Likelihood Estimation)	
Log-Linear	$\hat{\alpha} = 2.7721$	$\hat{\beta} = 0.0014$
Log-Poisson	$\hat{\theta} = 0.0047$	$\widehat{\lambda_0} = 17.1984$
Log-Power	$\hat{a} = 20.3058$	$\hat{b} = 1.4775$

Furthermore, the resulting nonlinear equations were solved using the bisection method, a standard numerical analysis technique [14]. The estimated parameter values are summarized in Table 2.

3.1. Efficient Model Identification

In this study, model effectiveness was evaluated using two key performance metrics: MSE and R². First, MSE was used to assess model accuracy. MSE is defined as the average of the squared differences between the model's predicted values and the actual observed values, and it serves as a key indicator of model performance, as expressed below.

$$MSE = \frac{\sum_{i=1}^{n} \left(m(x_i) - \hat{m}(x_i)\right)^2}{n-k} \tag{24}$$

Note that n stands for the recorded faults, whereas k indicates the parameter count.

Second, R² was used to select the most appropriate model based on predictive ability. R² is commonly referred to as the coefficient of determination and is an indicator that quantifies the explanatory power of a model, with values between 0 and 1.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(m(x_i) - \hat{m}(x_i)\right)^2}{\sum_{i=1}^{n} \left(m(x_i) - \sum_{j=1}^{n} m(x_j)/n\right)^2} \tag{25}$$

Note that $\hat{m}(x_i)$ corresponds to the accumulated failure counts up to time x_i, as derived from m(t).

Accordingly, R² is defined in Equation (25), where a higher R² value indicates a better model fit. Consequently, models with higher R² values are considered more appropriate for selection.

Model efficiency can be determined by using MSE as a selection criterion. Thus, a smaller MSE value indicates higher accuracy and greater reliability in efficient model selection.

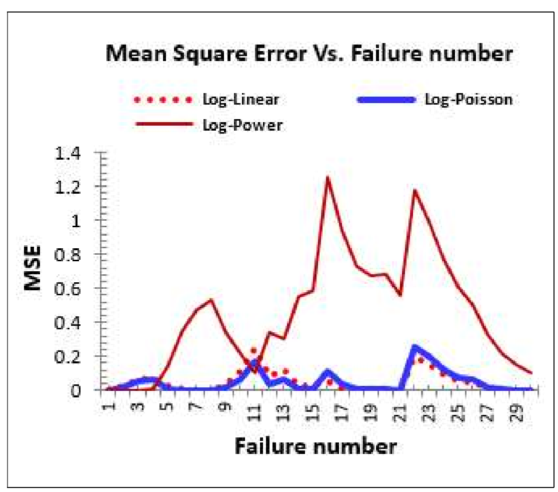

Figure 2: Efficiency Analysis by MSE.

Figure 2 graphically presents the results of the MSE analysis with respect to the number of failures. These results indicate that the Log-Poisson model maintains the lowest error levels across the entire failure range, demonstrating superior predictive performance relative to the other models. Additionally, the Log-Linear model exhibits consistently low MSE values over the same range, indicating its effectiveness.

Table 3 presents the results of a detailed comparison and analysis of the changes in MSE values for each number of failures. These values served as criteria for determining the most efficient model in this work.

Table 3: MSE Analysis.

Failure number	Log-Linear	Log-Poisson	Log-Power
1	0.00195	0.00112	0.00582
2	0.02334	0.01864	0.00086
3	0.06659	0.05576	0.00023
4	0.07816	0.06097	0.00545
5	0.02432	0.01112	0.13686
6	0.00336	0.00004	0.35089
7	0.00141	0.00128	0.47061
8	0.00211	0.00115	0.53244
9	0.03979	0.01402	0.34246
10	0.11359	0.06467	0.21184
11	0.24072	0.16549	0.09918
12	0.08659	0.04022	0.33731
13	0.11653	0.06003	0.30301
14	0.03068	0.00555	0.54787
15	0.02385	0.00278	0.58281
16	0.05475	0.11067	1.25611
17	0.00737	0.03387	0.93801
18	0.00037	0.00603	0.72958
19	0.00077	0.00434	0.67651
20	0.00015	0.01018	0.68432
21	0.00196	0.00165	0.55823
22	0.19535	0.25228	1.17384
23	0.14851	0.19321	0.98391
24	0.08962	0.12147	0.77023
25	0.05431	0.07613	0.60272
26	0.04764	0.06331	0.50354
27	0.01281	0.02007	0.33475
28	0.00116	0.00314	0.21591
29	0.00001	0.00023	0.14585
30	0.00000	0.00000	0.09934

Generally, a model is regarded as efficient if it satisfies the criteria of a relatively low MSE value and an R^2 value of 0.8 or higher.

Table 4 indicates that the Log-Poisson model achieves the lowest MSE and the highest R^2, thereby demonstrating superior predictive performance and goodness of fit [15].

Table 4: Efficient Model Selection.

Type	NHPP Model	R^2	MSE
Log-type lifetime distribution	Log-Linear	0.9953	1.46787
	Log-Poisson	0.9955	1.39955
	Log-Power	0.9568	13.6005

3.2. Mean Value Function (m(t))

In an NHPP framework, the function m(t) quantifies the expected aggregate failures that have occurred from the start of testing up to time t. Furthermore, m(t) serves as an indicator that predicts potential future failures, allowing users to estimate the number of failures that may occur during software operation. Consequently, it plays a crucial role as a fundamental attribute function for assessing reliability performance.

Table 5 presents a detailed comparison of the equations used to derive m(t) in this study.

Table 5: Equations for calculating m(t).

Type	NHPP Model	m(t)
Log-type lifetime distribution	Log-Linear	$\frac{e^{\alpha}\left(e^{\beta t}-1\right)}{\beta}$
	Log-Poisson	$\frac{1}{\theta}ln(\lambda_0\theta t+1)$
	Log-Power	a $ln^b(1+t)$

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Figure 3 examines the performance characteristics of the m(t) function by presenting simulation results that evaluate its predictive accuracy relative to the true values. The results indicate that the Log-Poisson model achieves the smallest estimation error compared with the true values, thereby demonstrating superior performance among the considered models [16].

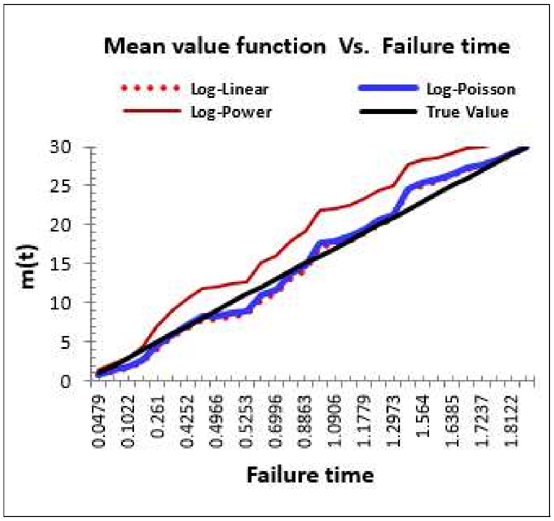

Figure 3: Performance Analysis by $m(t)$.

3.3. Intensity Function (λ(t))

In an NHPP framework, λ(t) denotes the expected failure intensity per unit time at time *t*. Accordingly, when considered together with m(t), λ(t) serves as a fundamental indicator for evaluating reliability performance by characterizing the instantaneous failure behavior at a given time point.

Table 6 presents a detailed comparison of the equations used to derive λ(t) in this study.

Table 6: Equations for calculating λ(t).

Type	NHPP Model	λ(t)
Log-type lifetime distribution	Log-Linear	$\exp(\alpha + \beta t)$
	Log-Poisson	$\frac{\lambda_0}{\lambda_0 \theta t + 1}$
	Log-Power	$\frac{ab\, ln^{b-1}(1+t)}{1+t}$

Figure 4 illustrates the simulation outcomes derived from the λ(t) function, which characterizes the instantaneous failure intensity over the entire observation period.

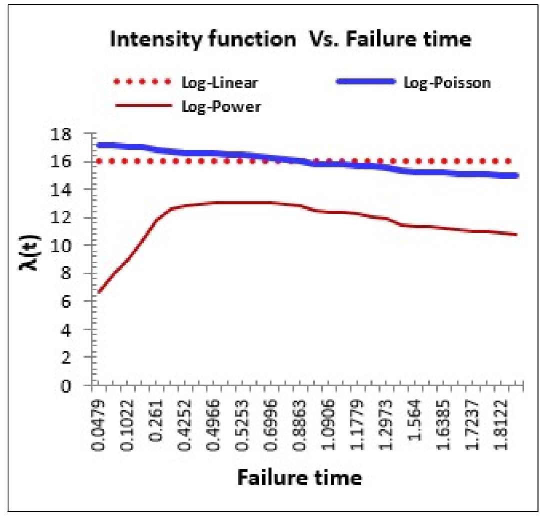

Figure 4: Performance Analysis by $\lambda(t)$.

The simulation results indicate that the Log-Power model exhibits a failure rate pattern that closely resembles actual physical failure mechanisms. Specifically, the failure rate is initially low, increases significantly over time, and subsequently decreases gradually as failures are repaired. These findings suggest that the model demonstrates a high degree of goodness of fit. In contrast, the Log-Linear model shows a high initial failure rate that does not decrease even after failure correction, indicating relatively poor performance in terms of model fit.

This study aims to systematically analyze time-dependent software failure patterns through λ(t) analysis, thereby supporting early-stage testing activities. Consequently, if the m(t) and λ(t) functions discussed above are effectively utilized, the reliability of the proposed models can be accurately evaluated, and unnecessary testing efforts in the early development phase can be reduced [17].

Table 7 presents a detailed comparison and analysis of the test results at the overall failure point, based on m(t) and λ(t), which are key functions determining the reliability property of the proposed models. Accordingly, this work aims to identify the optimal reliability model using the test data summarized in Table 7.

Table 7: Analysis of Performance Attribute Functions.

Failure Time (hours) $\times 10^{-2}$	Performance Attribute Functions					
	$m(t)$			$\lambda(t)$		
	Log-Linear	Log-Poisson	Log-Power	Log-Linear	Log-Poisson	Log-Power
0.0479	0.76605	0.8222	1.40372	15.99325	17.13192	6.63464
0.0745	1.19147	1.27743	2.15579	15.99385	17.09523	7.94146
0.1022	1.63451	1.75044	2.91942	15.99447	17.05718	8.94805
0.1576	2.52064	2.69331	4.39073	15.99571	16.98161	10.35291
0.261	4.17472	4.44198	6.95757	15.99802	16.84231	11.84044
0.3559	5.69303	6.03433	9.13451	16.00015	16.71647	12.54034
0.4252	6.8019	7.18964	10.63001	16.00171	16.62575	12.82636
0.4849	7.75724	8.17988	11.86114	16.00304	16.54839	12.97202
0.4966	7.94447	8.37341	12.09661	16.00331	16.53331	12.99199
0.5136	8.21653	8.65429	12.43548	16.00368	16.51145	13.01667
0.5253	8.40378	8.84739	12.6665	16.00394	16.49644	13.03085
0.6527	10.44286	10.9387	15.07322	16.00681	16.33475	13.06799
0.6996	11.19361	11.70342	15.91275	16.00785	16.27602	13.04056
0.817	13.07308	13.60568	17.91669	16.01048	16.13084	12.90878
0.8863	14.18266	14.72061	19.03967	16.01203	16.04636	12.80077
1.0771	17.23817	17.7604	21.93051	16.01631	15.81825	12.43663
1.0906	17.45439	17.97384	22.12487	16.016618	15.80236	12.40849
1.1183	17.89806	18.41111	22.51978	16.01723	15.76985	12.35013
1.1779	18.85273	19.34892	23.35224	16.01857	15.70034	12.22217
1.2536	20.0654	20.53412	24.37734	16.02027	15.61294	12.05643
1.2973	20.76551	21.21531	24.95354	16.02125	15.56293	11.95976
1.5203	24.33881	24.65779	27.73302	16.02625	15.31263	11.46538
1.564	25.03917	25.3259	28.24876	16.02723	15.26452	11.36956
1.598	25.58411	25.84426	28.64399	16.02801	15.2273	11.29546
1.6385	26.23326	26.46007	29.10808	16.02891	15.18319	11.20776
1.696	27.15496	27.33131	29.75488	16.03019	15.12102	11.08444
1.7237	27.59901	27.74975	30.06156	16.03082	15.09124	11.02556
1.76	28.18094	28.29686	30.45876	16.03163	15.05241	10.94896
1.8122	29.01782	29.08115	31.02089	16.03281	14.99691	10.83997
1.8735	30.00068	29.99847	31.66784	16.03418	14.93225	10.71381

3.4. Reliability Function ($\hat{R}(\tau)$)

The reliability function $\hat{R}(\tau)$ is a fundamental performance metric that represents the probability that a system operates without failure up to a specified mission time. That is, by jointly considering the model's key performance functions, namely m(t) and λ(t), the reliability of the proposed model can be quantitatively assessed. Thus, this study assigns a specific mission time to the proposed reliability model and analyzes its reliability performance over the corresponding period.

Consequently, reliability is defined under the condition that failures are allowed during the initial test interval (0, x_n), where $x_n = 187.35 \times 10^{-2}$. The probability of failure-free operation is then evaluated over the subsequent reliability interval (x_n, $x_n + \tau$), where τ denotes the mission time. Accordingly, the reliability function reflecting this definition is expressed as follows [18].

$$\hat{R}(\tau|x_n) = exp[-\{m(x_n + \tau) - m(x_n)\}] \qquad (26)$$

As illustrated in Figure 5, an analysis of the reliability variation with respect to the mission time (145H$\times 10^{-1}$) indicates that all proposed models exhibit an overall decreasing trend in reliability as the mission time increases. However, the Log-Power model maintains comparatively higher reliability values throughout the mission duration, leading to its assessment as the most effective model among those considered.

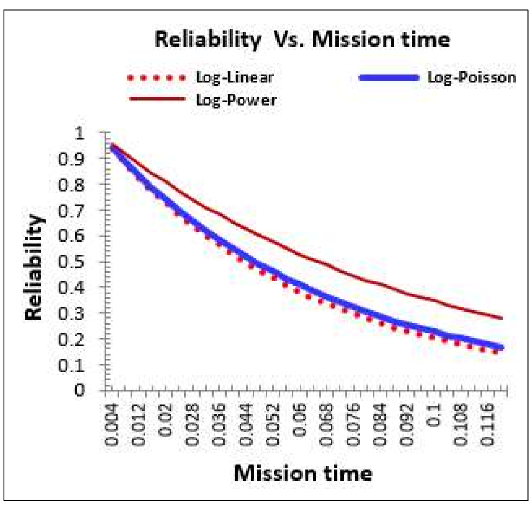

Figure 5: Reliability Analysis by $\hat{R}(\tau)$.

The reliability function $\hat{R}(\tau)$ takes values within the interval [0, 1], where larger values correspond to higher levels of system reliability. From this perspective, the Log-Power model demonstrates superior efficiency in reliability performance.
Table 8 presents the results of the analysis of reliability trend fluctuations over the mission time.

Table 8: $\hat{R}(\tau)$ Analysis.

Mission Time (hours) $\times 10^{-1}$	$\hat{R}(\tau)$		
	Log-Linear	Log-Poisson	Log-Power
0.1	0.93787	0.94202	0.95806
0.5	0.87961	0.88743	0.91791
1	0.82496	0.83601	0.87948
1.5	0.77371	0.78758	0.84268
2	0.72564	0.74197	0.80745
2.5	0.68056	0.69902	0.77372
3	0.63828	0.65856	0.74141
3.5	0.59863	0.62045	0.71049
4	0.56144	0.58456	0.68087
4.5	0.52656	0.55076	0.65251
5	0.49384	0.51892	0.62535
5.5	0.46316	0.48892	0.59934
6	0.43439	0.46067	0.57443
6.5	0.40741	0.43406	0.55057
7	0.38209	0.40899	0.52772
7.5	0.35835	0.38538	0.50584
8	0.33608	0.36313	0.48488
8.5	0.31521	0.34218	0.46481
9	0.29562	0.32244	0.44557
9.5	0.27725	0.30384	0.42715
10	0.26003	0.28632	0.40951
10.5	0.24387	0.26982	0.39259
11	0.22872	0.25427	0.37641
11.5	0.21451	0.23962	0.36088
12	0.20118	0.22582	0.34601
12.5	0.18868	0.21282	0.33177
13	0.17696	0.20057	0.31812
13.5	0.16596	0.18902	0.30505
14	0.15565	0.17815	0.29252
14.5	0.14598	0.16791	0.28051

3.5. Reliability Performance Assessment

The present study assesses the adequacy of software reliability models by integrating efficiency indices (MSE, R^2) with the analytical results of key performance-determining functions, including m(t), λ(t), and $\hat{R}(\tau)$. Based on these criteria, the relative performance of the proposed models was comparatively assessed [19].

The performance indices derived from the analysis are comprehensively summarized in Table 9. As shown in the results, the Log-Poisson model demonstrates superior performance compared with the other models.

Table 9: Performance Assessment.

NHPP Model	Efficiency		Performance		
	MSE	R^2	m(t)	λ(t)	$\hat{R}(\tau)$
Log-Linear	Good	Best	Best	Worst	Good
Log-Poisson	Best	Best	Best	Good	Good
Log-Power	Worst	Best	Bad	Best	Best

Consequently, the analyzed data serve as a valuable basis for informing design decisions in the initial development step and can also function as effective test data throughout the preparation stage.

4. CONCLUSION

If developers effectively utilize failure time data collected during the early stages, they can design reliability prediction models capable of forecasting failures in advance. Accordingly, failure time data accumulated during software operation can enhance product reliability and ultimately contribute to improvements in overall software quality. On this basis, this study applies a Log-Type lifetime distribution to an infinite-failure-based NHPP reliability model to comparatively evaluate its performance and to further analyze its properties.

The results of this study are summarized as follows. First, based on an analysis of the efficiency criteria used to evaluate model performance (MSE, R^2), the Log-Poisson model demonstrates the highest level of goodness of fit.
Second, the assessment of the model performance properties (m(t) and λ(t)) indicates that the Log-Poisson model is the most efficient, exhibiting high predictive accuracy with respect to the true values and a comparatively lower failure occurrence rate.

Third, the prediction of future reliability ($\hat{R}(\tau)$) indicates that although all proposed models exhibit an overall decreasing trend in reliability over time, the Log-Power model consistently maintains the highest reliability, thereby demonstrating its superiority.

In conclusion, the Log-Poisson model demonstrates superior performance compared with the other evaluated models. Accordingly, this study not only proposes an optimal approach for analyzing reliability-related attribute data required by developers in the early stages, but also provides the resulting data derived from the proposed approach. Furthermore, future research should focus on identifying models optimized for specific domains within the software industry and subsequently conducting more in-depth studies of the reliability performance attributes of the selected models.

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REFERENCES:

[1] T. J. Yang, “Performance Analysis on the Reliability Attributes of NHPP Software Reliability Model Applying Exponential and Inverse-Exponential Lifetime Distribution”, *Journal of Theoretical and Applied Information Technology,* Vol. 100, No. 22, 2022, pp. 6645-6656.

[2] T. J. Yang, “Comparative Analysis on the Reliability Performance of NHPP Software Reliability Model Applying Exponential-type Lifetime Distribution”, *International Journal of Performance Engineering,* Vol. 18, No. 10, 2022, pp. 679-689.

[3] H. C. Kim, “A Study on the Comparative Evaluation of Software Reliability Model Applying Modified Exponential Distribution”, *International Journal of Engineering Research and Tech.,* Vol. 13, No. 5, 2020, pp. 867-872.

[4] X. Xiao and T. Dohi, “On the Role of Weibull-type Distributions in NHPP-based Software Reliability Modeling”, *International Journal of Performability Engineering,* Vol. 9, No. 2, 2013,

pp. 123-132.

[5] T. H. Yoo, "A Performance Valuation for NHPP Software Reliability Model Depend on Weibull-type Distribution", International *Journal of Pure and Applied Mathematics,* Vol. 118, No, 19, 2018, pp. 1021-1033.

[6] S. K. Park, "Performance Evaluation of Weibull type Lifetime Distribution Based on Infinite Failure NHPP Software Reliability Model", *Journal of Theoretical and Applied Information Technology,* Vol. 103, No. 22, 2025, pp. 9293 9303.

[7] T. J. Yang, "Comparative Study on the Performance Evaluation of Infinite Failure NHPP Software Reliability Model with Log-Type Distribution Property", *ARPN Journal of Engineering and Applied Sciences,* Vol. 17, No. 11, 2022, pp. 1209-1218.

[8] T. J. Yang and H. C. Kim, "Comparative Software Infinite NHPP Reliability Growth Model Based on the Intensity Function of Log-Linear and Log-Power Forms", *Smart Computing Review,* Vol. 4, No. 6, 2014, pp. 451-458.

[9] T. H. Yoo, "The Infinite NHPP Software Reliability Model Based on Monotonic Intensity Function", *Indian Journal of Science and Technology,* Vol. 8, No, 14, 2015, pp. 1-7.

[10] S. K. Park, "Performance Evaluation of Weibull-Type Lifetime Distributions Based on Infinite Failure NHPP Software Reliability Model", *Journal of Theoretical and Applied Information Technology,* Vol. 103, No. 22, 2025, pp. 9293-9303.

[11] H. C. Kim, "The Comparative Study for Statistical Process Control of Software Reliability Model Based on Finite and Infinite NHPP Using Rayleigh Distribution", *International Journal of Soft Computing,* Vol. 11, No. 3, 2016, pp. 165-171.

[12] T. J. Yang, "Performance Evaluation of NHPP Software Reliability Model Applying Gamma Family Lifetime Distribution", *ARPN Journal of Engineering and Applied Science,* Vol. 18, No. 10, 2023, pp. 1171-1180.

[13] Y. Hayakawa, G. Telfar, "Mixed Poisson-type Processes with Application in Software Reliability", *Mathematical and Computer Modelling,* Vol. 31, 2000, pp. 151-156.

[14] H. C. Kim, "The Comparative Study for Statistical Process Control for Software Reliability Property Utilizing Inverse Rayleigh and Rayleigh Distribution", *Journal of Engineering and Applied Sciences,* Vol. 13, No. 1, 2018, pp. 2500-2504.

[15] T. J. Yang, "A Study on the Reliability Performance Analysis of Finite Failure NHPP Software Reliability Model Based on Weibull Life Distribution", *International Journal of Engineering Research and Technology,* Vol. 12, No. 11, 2019, pp. 1890-1896.

[16] T. H. Park, "A Comparative Analysis on the Performance Attributes of a Software Development Cost Model Based on Weibull Lifetime Distribution", *Journal of Theoretical and Applied Information Technology,* Vol. 101, No. 13, 2023, pp. 5229-5239.

[17] H. J. Bae, "Performance Assessment of NHPP Software Reliability Models Applying PARETO-type Lifetime Distribution Properties", *Journal of Theoretical and Applied Information Technology,* Vol. 103, No. 7, 2025, pp. 2857-2867.

[18] Y. C. Ra, "A Comparative Analysis on the Performance of Finite Failure NHPP Software Reliability Model Based on Rayleigh-type Lifetime Distribution", *Journal of Theoretical and Applied Information Technology,* Vol. 99 , No. 24, 2021, pp. 6162-6172.

[19] S. K. Park, "Comparative Analysis on the Reliability Attributes of Finite Failure NHPP Software Reliability Model with Exponential Distribution Characteristics", *Journal of Theoretical and Applied Information Technology,* Vol. 100, No. 18, 2022, pp. 5220-5231.