COMPARATIVE STUDY ON THE PERFORMANCE EVALUATION OF INFINITE FAILURE NHPP SOFTWARE RELIABILITY MODEL WITH LOG-TYPE DISTRIBUTION PROPERTY

Tae-Jin Yang
Department of Electronic Engineering, Namseoul University, Daehak-ro, Seonghwan-eup, Seobuk-gu, Cheonan-city, Chungnam, Korea
E-Mail: solomon645@nsu.ac.kr

ABSTRACT

In this study, the performance of software reliability is evaluated by applying the Log-type (Log-Poisson, Log-Power, Log-Logistic) distributions to the infinite fault NHPP model. For this study, a research solution was developed by an analysis algorithm using software failure time data. Also, maximum likelihood estimation (MLE) was applied to solve the parameter values, and the nonlinear equation was calculated using the binary method. As a result, first, in the strength function analysis, the Log-Logistic model was evaluated as an efficient model because the failure rate showed the greatest decrease as the failure time passed. Second, in the mean value function analysis, the proposed models showed either underestimation or overestimation in estimating the true value, but the Log-Logistic model was effective as it showed the smallest error estimation along with the Log-Poisson model. Third, in the future mission reliability analysis, the Log-Logistic model was evaluated to show a higher reliability trend than other models whose reliability gradually decreased as the mission time passed. In conclusion, by analyzing these evaluation results, it can be seen that the Log-Logistic model is an efficient model with the best performance among the proposed models. Through this study, the reliability performance of the Log-Type distribution model was newly compared and evaluated, and it was able to help software developers to find the optimal software reliability model.

Keywords: infinite failure, log-logistic, log-poisson, log-power, log-type distribution, NHPP, software reliability.

1. INTRODUCTION

In the era of the 4th industrial revolution based on digital convergence technology, the most important thing is to develop reliable software that can accurately process convergence data that can be applied to various industrial fields without failure. In the process of developing such high-quality software, the important topic is research on software reliability. For this reason, many software developers are still researching and investing in finding ways to improve software stability. In particular, to evaluate the performance of reliability that determines the quality of software, many studies on reliability properties using the strength function and mean value function of the NHPP (Non-homogeneous Poisson process) model have been proposed [1]. Concerning the NHPP reliability model, Xiao and Dohi [2] studied the efficiency of the Weibull type distribution through the performance analysis of software reliability. Ma, and Wu, Zhang [3] explained the one factor of software reliability demonstration testing result, Nagaraju and Wandji [4] proposed the improved algorithm for NHPP software growth models. Also, Kim [5] evaluated the statistical process of software reliability with the infinite failure NHPP model using the Rayleigh distribution. Kim and Shin [6] presented the comparative result of infinite failure NHPP software reliability model based on exponential and inverse exponential distribution, and Yang [7] proposed the study result on reliability attributes of software reliability model based on Type-2 Gumbel and Erlang life distribution. Also, Yang [8] analyzed the attributes on the cost and release time of the software development model based on Exponential-type distribution.

Therefore, in this study, the reliability performance of the proposed model was newly analyzed and evaluated by applying the log-type distribution widely used in the software reliability test field to the infinite failure NHPP reliability model. Also, the optimal reliability model was presented through these analysis results.

2. RELATED RESEARCH

2.1 Infinite Failure NHPP Software Reliability Model

2.1.1 NHPP model

The NHPP model is a stochastic distribution model in which the number of occurrences N(t) at time t follows a Poisson distribution with parameters. Mainly, it is useful for modeling permutations in which the number of mutually independent events occurs steadily over time.
In the NHPP model, N(t) refers to the accumulated number of software flaws detected up to the test time t, and m(t) refers to the expected value at which flaws can occur. Therefore, the NHPP model is as follows:

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

$Note.\ n=0,1,2,\cdots\infty.$

Therefore, the NHPP model contains property about mean value m(t) and intensity pattern λ(t) as below.

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

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

2.1.2 NHPP Software reliability model

We will use the NHPP software reliability model with software failure time based on the NHPP model to analyze the attributes of software development costs. The time-domain NHPP model is divided into a finite failure which means that no more failures occur when repairing a failure, and an infinite failure in which failures can continue to occur even when repairing a failure.

In this study, we will analyze based on the infinite failure cases. In the infinite failure NHPP model, if f(t) is a probability density function and F(t) is a cumulative distribution function, then the average value function $m(\mathrm{t})$ and the intensity function $\lambda(t)$ are as follows [9].

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

$$\lambda(\mathrm{t}) = \mathrm{m(t)}' = \frac{f(t)}{[1 - F(t)]} = h(t) \quad (5)$$

Considering Equations (4) and (5), the likelihood function of the infinite-failure NHPP model is derived as follows.

2.2 Infinite Failure NHPP: Log-Poisson Model

The Log-Poisson execution time model is an infinite failure software model introduced by Musa and Goel-Okumoto in the reliability field.

When the Log-Poisson distribution is applied to the infinite failure NHPP reliability model as shown in Equations (4) and (5), it is as follows.

$$\mathrm{m(t|\theta}, \lambda_0) = \frac{1}{\theta}\ln(\lambda_0 \theta t + 1) \quad (7)$$

$$\lambda(\mathrm{t|\theta}, \lambda_0) = \frac{\lambda_0}{\lambda_0 \theta t + 1} \quad (8)$$

Note that $\theta > 0,\ \mathrm{b} > 0$.

After substituting Equations (7) and (8) into Equation (6), if taking the logarithm of both sides, then the log-likelihood function can be solved as follows:

$$\ln L_{NHPP}(\theta, \lambda_0 | \underline{x}) =$$

$$n ln\lambda_0 - ln\sum_{k=1}^{n}(\lambda_0 \theta x_i + 1) - \frac{1}{\theta}\ln(\lambda_0 \theta x_n + 1) \quad (9)$$

Therefore, the maximum likelihood estimator $\hat{\theta}_{MLE}$ and $\widehat{\lambda_0}_{MLE}$ and in the following Equations (10) and (11) can be estimated by a numerical method.

$$\hat{\theta}_{MLE} = \frac{1}{n}\ln(\widehat{\emptyset}\ x_n + 1\ ) \quad (10)$$

$$\widehat{\lambda_0}_{MLE} = \frac{\widehat{\emptyset}}{\hat{\theta}_{MLE}} \quad (11)$$

Note that $\widehat{\emptyset}\ (= \widehat{\lambda_0}_{MLE} \times \hat{\theta}_{MLE})$ becomes the root of the following Equation (12).

That is, to obtain the value $\emptyset$, it can be solved using the following equation by the bisection method.

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

$$- \frac{n\ x_n}{(\emptyset x_n + 1)\ln(\emptyset x_n + 1)} = 0 \quad (12)$$

2.3 Infinite Failure NHPP: Log-Power Model

The Log-Power model is an infinite fault software reliability model developed by Xie and Homg and is widely used in the field of reliability tests because of its distribution property. When the Log-Power distribution is applied to the infinite failure NHPP reliability model as shown in Equations (4) and (5), it is as follows.

$$\mathrm{m(t)} = a ln^b(1{+}\mathrm{t}) \quad (13)$$

$$\lambda(\mathrm{t}) = \frac{abln^{b-1}(1+t)}{1+t} \quad (14)$$

Note that a and b are scale parameters and shape parameters, respectively.

After substituting Equations (13) and (14) into Equation (6), if taking the logarithm of both sides, then the log-likelihood function can be solved as follows.

$$\ln L_{NHPP}(a, b | \underline{x}) = nlna + nlnb$$

$$-(b-1)ln\left[\sum_{i=1}^{n}\ln(1+x_i)\right] - \sum_{i=1}^{n}\ln(1+x_i)$$

$$- a ln^b(1+x_n) \quad (15)$$

Therefore, when Equation (15) is partially differentiated from parameters a and b, the maximum likelihood estimator $\hat{a}_{MLE}$ and $\hat{b}_{MLE}$ satisfy the following equation.

$$\frac{\partial \ln L_{NHPP}(a,b|\underline{x})}{\partial a} = \frac{n}{\hat{a}} - ln^{b}(1+x_n) = 0 \tag{16}$$

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

$$- \, a ln^{b}(1+x_n)\ ln[\ln(1+x_n)] = 0 \tag{17}$$

Note that $\underline{x} = (x_{1,}\, x_{2,},\ x_3 \cdots x_n)$.

2.4 Infinite Failure NHPP: Log-Logistic Model

In NHPP models, the failure rate per unit of residual defects is generally constant or has a monotonically increasing and monotonically decreasing trend. But, the Log-Logistic distribution is widely used in the field of reliability testing and evaluation because the failure rate (hazard function) per unit increases and then decreases.

Here, the probability density function f(t) and the cumulative distribution function F(t) considering the shape parameter (k) of the log-logistic distribution can be defined as follows [10].

$$\mathrm{f}(\mathrm{t}|\tau,\mathrm{k}) = \frac{\tau k(\tau t)^{k-1}}{[1+(\tau t)^{k}]^2} \tag{18}$$

$$\mathrm{F}(\mathrm{t}|\tau,\mathrm{k}) = \frac{(\tau t)^{k}}{[1+(\tau t)^{k}]} \tag{19}$$

Note that $\tau > 0,\ k > 0$

When the Log-Logistic distribution is applied to the infinite failure NHPP reliability model as shown in Equations (4) and (5), it is as follows.

$$\mathrm{m}(\mathrm{t}|\tau,\mathrm{k}) = \ln[(1+(\tau t)^{k}] \tag{20}$$

$$\lambda(\mathrm{t}|\tau,\mathrm{k}) = \frac{\tau k(\tau t)^{k-1}}{[1+(\tau t)^{k}]} = \frac{\tau^{k} k(t)^{k-1}}{[1+(\tau t)^{k}]} \tag{21}$$

Note that $\theta > 0,\ \tau, k > 0$.

After substituting Equations (20) and (21) into Equation (6), if taking the logarithm of both sides, then the log-likelihood function at shape parameter k=1 can be solved as follows.

$$\ln L_{NHPP}(\tau,k|\underline{x}) = knln\tau + nlnk + (k-1)\sum_{i=1}^{n} lnx_i$$

$$-\sum_{i=1}^{n}\ln[1+(\tau x_i)^{k}] - ln[1+(\tau x_n)^{k}] \tag{22}$$

Therefore, the maximum likelihood estimator $\hat{\tau}_{MLE}$ and $\hat{k}_{MLE}$ in the following Equations (23) and (24) can be solved by the bisection method.

$$\frac{\partial \ln L_{NHPP}(\Theta|\underline{x})}{\partial \tau} =$$

$$\frac{n}{\hat{\tau}} - \sum_{i=1}^{n}\frac{x_i}{1+(\hat{\tau}x_i)} - \frac{x_n}{1+(\hat{\tau}x_n)} = 0 \tag{23}$$

$$\frac{\partial \ln L_{NHPP}(\tau,\mathrm{k}|\underline{x})}{\partial k} = nln\tau + n - \sum_{i=1}^{n} lnx_i$$

$$-\sum_{i=1}^{n}\frac{\tau x_i(ln\tau x_i)}{1+(\hat{\tau}x_i)} - \frac{\tau x_n(ln\tau x_n)}{1+(\hat{\tau}x_n)} = 0 \tag{24}$$

Note that $x = (x_{1,}\, x_{2,},\ x_3 \cdots x_n)$.

3. SOLUTIONS BY THE ANALYSIS ALGORITHM USING SOFTWARE FAILURE TIME DATA

In this study, we will compare and evaluate the reliability performance of the proposed model using the analysis algorithm (steps 1-5) presented above.

Step 1: Analyzing the availability of the collected software failure data using Laplace trend test analysis.
Step 2: Computing the value of parameter using maximum likelihood estimation (MLE).
Step 3: Calculating the coefficient of determination (R^2) and mean square error (MSE) for efficient model selection.
Step 4: Evaluating the performance attributes ($m(t)$, $\lambda(t)$) and future reliability $(\hat{R}(\tau))$.
Step 5: Providing analysis information on the optimal model selection.

Table-1 shows the software failure time data used in this study [11]. This software failure time means the failure data that occurred 41 times during 1197.945 hours.

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Table-1. Software failure time data.

Failure Number	Failure Time (hours)	Failure Time (hours) $\times 10^{-2}$	Failure Number	Failure Time (hours)	Failure Time (hours) $\times 10^{-2}$
1	5.649	0.05649	21	131.829	1.31829
2	8.92	0.0892	22	141.712	1.41712
3	20.29	0.2029	23	164.212	1.64212
4	29.955	0.29955	24	342.85	3.4285
5	34.715	0.34715	25	356.144	3.56144
6	75.95	0.7595	26	399.144	3.99144
7	78.171	0.78171	27	446.494	4.46494
8	78.625	0.78625	28	476.644	4.76644
9	83.022	0.83022	29	497.144	4.97144
10	89.114	0.89114	30	497.661	4.97661
11	89.804	0.89804	31	591.161	5.91161
12	92.96	0.9296	32	665.644	6.65644
13	93.66	0.9366	33	686.444	6.86444
14	110.655	1.10655	34	765.944	7.65944
15	111.988	1.11988	35	772.977	7.72977
16	122.545	1.22545	36	774.944	7.74944
17	127.045	1.27045	37	791.561	7.91561
18	128.712	1.28712	38	815.978	8.15978
19	128.99	1.2899	39	837.145	8.37145
20	131.768	1.31768	40	861.945	8.61945
			41	1197.945	11.97945

The failure time data used in this paper means random failures caused by software design and analysis errors and insufficient testing during the normal operation of desktop applications. Therefore, in this study, the Laplace trend test was applied to determine the availability of the collected failure time data.

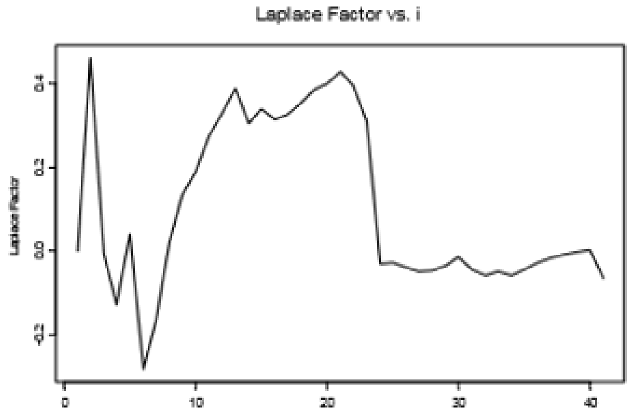

Figure-1. Estimation results of Laplace trend test.

If the analysis result of the Laplace trend test has existed between -2 and 2, the analyzed data is reliable because there are no extreme values.

Figure-1 shows that the estimated value of the Laplace factor exists between 0 and 2. Therefore, this data can be used because there are no extreme values [12].

In this study, the Maximum Likelihood Estimation (MLE) method was applied to obtain the parameter values of the proposed models.

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Table-2 shows the results of the nonlinear equation calculated using the bisection method.

Table-2. Parameter estimation value of the proposed models.

Type	NHPP Model	MLE (Maximum Likelihood Estimation)		Model Comparison	
				MSE	R^2
Log-Type Lifetime Distribution	Log-Poisson	$\hat{\theta} = 0.02003$	$\hat{\lambda} = 0.05306$	67.3997	0.88406
	Log-Power	$\hat{a} = 16.0583$	$\hat{b} = 0.47858$	119.1212	0.79510
	Log-Logistic	$\hat{k} = 1.0(Fixed)$	$\hat{\tau} = 0.52969$	95.9416	0.83497

The Mean Square Error (MSE) can be defined as an evaluation criterion for selecting an efficient model as follows.

$$MSE = \frac{\sum_{i=1}^{n}\left(m(x_i) - \hat{m}(x_i)\right)^2}{n-k} \tag{25}$$

Note that n is the number of observations and k is the number of parameters to be estimated.

When evaluating an efficient model using MSE, the smaller the value of the mean squared error, the more efficient the model [13].

The coefficient of determination (R^2) is a measuring value to the explanatory power of the difference between the target value and the observed value.

When evaluating an efficient model using R^2, the larger the value of the decision coefficient, the more efficient the model because the error is relatively small.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(m(x_i) - \hat{m}(x_i)\right)^2}{\sum_{i=1}^{n}\left(m(x_i) - \sum_{j=1}^{n} m(x_j)/n\right)^2} \tag{26}$$

As shown in Table-2, the Log-Poisson and Log-Logistic models are more efficient than the Log-Power model because the MSE value is smaller and the R^2 value is larger. Figure-2 shows the analysis result of the mean square error for the failure time that occurred 41 times during 1197.45 hours [14].

The calculating method of the mean value function that determines the software reliability performance is shown in Table-3. Also, Table-4 shows the trend to the estimated result value of the average value function m(t).

Table-3. Calculating methods of the mean value function m(t).

Type	NHPP model	$m(t)$ of Log-Type Distribution
Log-Type Distribution	Log-Poisson	$m(t) = \frac{1}{\theta}\ln(\lambda_0\theta t + 1)$
	Log-Power	$m(t) = a ln^b(1+t)$
	Log-Logistic	$m(t) = \ln[(1 + (\tau t)^k]$

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Table-4. Estimated result values of mean value function m(t).

Failure Number	Failure Time (hours)	Log-Type Distribution		
		Log-Poisson	**Log-Power**	**Log-Logistic**
1	5.649	0.298879024	10.94872463	8.79068539
2	8.92	0.471127578	13.26095158	11.079656
3	20.29	1.065282299	17.67452768	15.64416698
4	29.955	1.564838563	19.8377095	17.94108025
5	34.715	1.809044241	20.66436141	18.82571894
6	75.95	3.876001083	25.10047994	23.61680345
7	78.171	3.98493935	25.26492587	23.79545542
8	78.625	4.007178453	25.29797226	23.83136345
9	83.022	4.222053592	25.60861383	24.16901389
10	89.114	4.51824083	26.013148	24.6090036
11	89.804	4.551677453	26.05723149	24.65696935
12	92.86	4.699499123	26.24853255	24.86515822
13	93.66	4.738123715	26.29758286	24.91854912
14	110.655	5.551672529	27.25187681	25.95808759
15	111.988	5.614925884	27.32046494	26.03285745
16	122.545	6.113064596	27.83669586	26.59583182
17	127.045	6.323898264	28.0434585	26.82141881
18	128.712	6.401774962	28.11821308	26.90299307
19	128.99	6.414750387	28.13058611	26.91649556
20	131.768	6.544226395	28.25279396	27.04986947
21	131.829	6.547065697	28.25544864	27.05276692
22	141.712	7.004959625	28.67020735	27.50556066
23	164.212	8.032013977	29.51630465	28.42985705
24	342.85	15.51332123	33.75240633	33.06659603
25	356.144	16.02770238	33.97163637	33.30686526
26	399.144	17.65609867	34.6286606	34.02707526
27	446.494	19.38984215	35.27501173	34.73576294
28	476.644	20.46322718	35.65183805	35.14900541
29	497.144	21.18009599	35.89470527	35.41536981
30	497.661	21.19804266	35.90070024	35.42194504
31	591.161	24.34202308	36.89388794	36.51142329
32	665.644	26.71215095	37.57860777	37.26269388
33	686.444	27.35441382	37.7561727	37.457537
34	765.944	29.73578236	38.38862324	38.1515901
35	772.977	29.94108276	38.441379	38.20948853
36	774.944	29.99835073	38.45604803	38.22558762
37	791.561	30.47954031	38.57850671	38.35998638
38	815.978	31.1782901	38.75386679	38.55245011
39	837.145	31.77621895	38.90169568	38.71470234
40	861.945	32.46778255	39.07021968	38.89967422
41	1197.945	41.00022356	40.97072725	40.98601905

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In Figure-2, the mean squared error of the Log-Poisson model shows a trend of the smallest error with failure number, which is more efficient than the other models in terms of fitness [15].

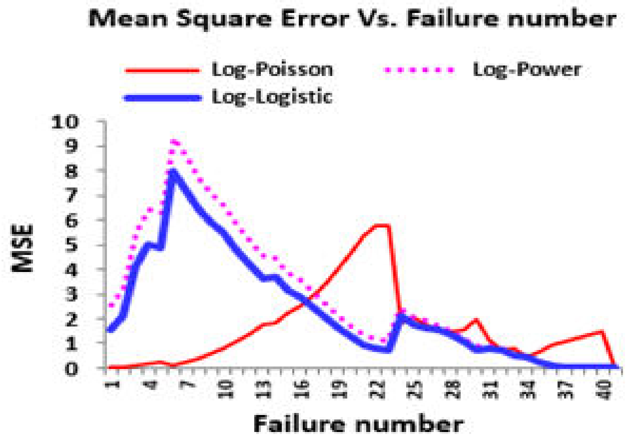

Figure-2. The analysis of Mean Square Error (MSE).

Figure-3 shows the analysis result of the intensity function (failure occurring rate per defect) concerning the failure time.

It can be seen that the Log-Logistic and Log-Power models are efficient because the intensity function representing the failure occurring rate decreased significantly as the failure time passed.

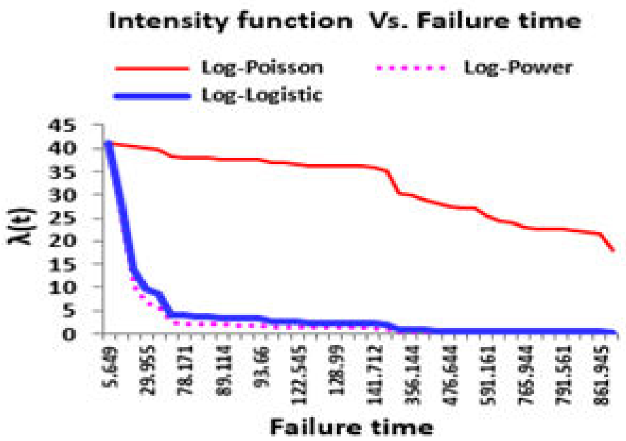

Figure-3. The analysis of Intensity Function $\lambda(t)$.

Figure-4 shows the analysis result of the mean value function (failure occurring expected value) concerning the failure time.

In this figure, all models show error values in the predictive ability of the real value, but the Log-Logistic model has the smallest error value among the proposed models.

Also, the Log-Logistic model is the most efficient than the other models because the error width is small.

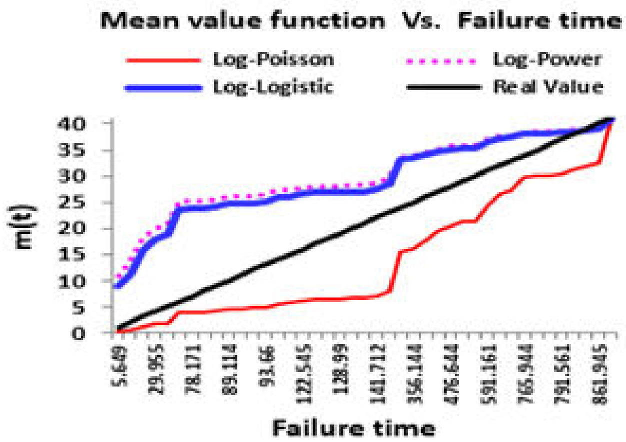

Figure-4. The analysis of Mean Value Function. $m(t)$

Where the future reliability $\hat{R}(t)$ is the probability that no software error will occur between the confidence intervals when testing at $t = x_n = 1197.945$. (where τ is the future mission time) [16].

$$\hat{R}(\tau|x_n) = e^{-\int_{x_n}^{x_n+\tau} \lambda(\tau)d\tau} = exp[-\{m(x_n+\tau) - (x_n)\}]$$

$$= exp[-\{m(1197.945+\tau) - m(1197.945)\}] \quad (27)$$

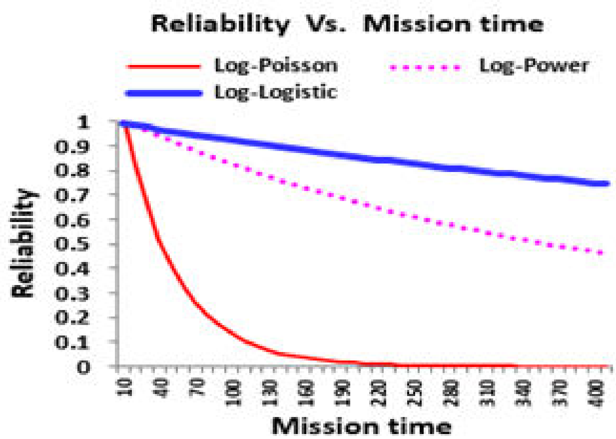

Figure-5. The analysis of Future Reliability $\hat{R}(t)$

Therefore, the larger the future reliability value, the better the reliability performance. Figure-5 shows that the Log-Logistic distribution model has higher reliability than other models whose future reliability decreases as the mission time passes [17]. That is, in terms of reliability, the Log-Logistic distribution model is further reliable than the other models because of the highest reliability.

Also, Table-5 shows the trend to the estimated result value of the future reliability $\hat{R}(t)$.

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Table-5. Estimated result values of future reliability $\hat{R}(t)$.

Failure Number	Mission Time (hours)	Log-Type Distribution		
		Log-Poisson	Log-Power	Log-Logistic
1	10	1.032031598	1.00659745	0.991734395
2	20	0.818508648	0.983926516	0.983604311
3	30	0.649858524	0.961958286	0.975606441
4	40	0.516505983	0.940665221	0.967737587
5	50	0.410949693	0.920021085	0.959994651
6	60	0.327306452	0.900000865	0.952374635
7	70	0.26095701	0.880580711	0.944874635
8	80	0.208270525	0.86173787	0.937491838
9	90	0.166389953	0.843450628	0.930223518
10	100	0.13306471	0.825698255	0.923067032
11	110	0.106520033	0.808460953	0.91601982
12	120	0.085354901	0.791719804	0.909079397
13	130	0.068462164	0.775456731	0.902243354
14	140	0.054965986	0.759654448	0.895509355
15	150	0.044172805	0.744296422	0.888875131
16	160	0.035532835	0.729366837	0.882338481
17	170	0.028609815	0.714850553	0.875897269
18	180	0.023057224	0.700733077	0.869549418
19	190	0.018599542	0.687000527	0.863292915
20	200	0.015017489	0.673639605	0.8571258
21	210	0.012136369	0.660637566	0.851046173
22	220	0.009816875	0.647982193	0.845052185
23	230	0.00794781	0.635661769	0.839142038
24	240	0.00644033	0.623665055	0.833313987
25	250	0.005223384	0.611981269	0.827566331
26	260	0.004240097	0.60060006	0.82189742
27	270	0.003444898	0.58951149	0.816305645
28	280	0.002801243	0.578706016	0.810789443
29	290	0.002279794	0.56817447	0.805347293
30	300	0.001856984	0.557908042	0.799977713
31	310	0.001513859	0.547898265	0.794679261
32	320	0.001235162	0.538136997	0.789450533
33	330	0.001008605	0.528616409	0.784290162
34	340	0.000824279	0.519328969	0.779196816
35	350	0.000674187	0.510267429	0.774169197
36	360	0.000551869	0.501424815	0.769206042
37	370	0.000452105	0.49279441	0.764306119
38	380	0.00037067	0.48436975	0.759468227
39	390	0.000304142	0.476144604	0.754691195
40	400	0.00024975	0.468112974	0.749973882
41	410	0.000205244	0.460269075	0.745315176

4. CONCLUSIONS

It is possible to efficiently improve the reliability performance by analyzing the performance after quantitatively modeling the occurrence of the failure in the software test or the software development process. In this study, the reliability performance of Log-Type distribution (Log-Poisson, Log-Power, Log-Logistic) was compared and evaluated based on the NHPP model under infinite failure conditions using software failure time data.

The results of this study are as follows:

First, in the strength function analysis, the Log-Logistic model was evaluated as an efficient model because the failure rate showed the greatest decrease as the failure time passed. Also, the mean square error (MSE) showed a relatively small trend along with the Log-Poisson model.

Second, in the mean value function analysis, the proposed models showed either underestimation or overestimation in estimating the true value, but the Log-Logistic model was effective as it showed the smallest error estimation.

Third, in the future mission reliability analysis, the Log-Logistic model was evaluated to show a higher reliability trend than other models whose reliability gradually decreased as the mission time passed. Thus, the Log-Logistic model has the best performance than other models because it has the highest reliability. That is, by analyzing these evaluation results, it can be seen that the Log-Logistic model is an efficient model with the best performance among the proposed log-type models.

As a result, this study was able to present analysis data that can be used as a basic design guide for software developers along with a new evaluation on the reliability performance of the Log-Type distribution model. Also, future tasks to find the most optimal model by applying the same type of software failure time data to more diverse distributions will be needed.

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