IE Interfaces
Vol. 12, No. 1, pp. 158-165, March 1999.

Practical Application of Reliability Growth in Automotive New Product Cycle

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자동차 개발에 있어서 신뢰팽장이론의 적용방법

정 원

One solution to the estimation of product reliability during the development phase is to measure reliability improvement over time and compare this improvement to previous product development progress. This paper presents the reliability growth theory and applies it to some subsystems of vehicles during their design, development and prototype testing. The data presented illustrates explicitly the prediction of the reliability growth in the product development cycle. The application of these techniques is a part of the product assurance function that plays an important role in product reliability improvement

1. Introduction

Customer satisfaction is definitely essential to survive in today's globally dynamic competition, and the ultimate proof of a product design is acceptance by the customer. As a result of the open marketplace, only those companies that listen to what the customer wants and provide high-quality and reliable products, which meet customer expectations, over the product useful life period with minimum cost in a timely fashion will eventually survive. To assure the quality and reliability expected by the customer is a particularly important aspect of motor vehicle development. Accurate analysis of the behavior of the product to be replaced and the goals established for the new product provide a first basis. Since reliability and life of a product are high-ranking development goals, applied techniques of reliability engineering play an important part.

The automotive new product cycle is often characterized as an evolutionary process[8]. The knowledge gained from past product performance coupled with changing environmental, consumer and business demands establishes the requirements for future product designs. These requirements eventually take the form of specific product performance, cost and durability objectives through a long period of concept planning, reviews, cost trade-off and engineering analysis. Generally, about one year prior to a new product introduction, physical prototype models are manufactured and placed on development tests. The purpose of these development tests are to evaluate the product design, uncover the weak points and provide a means to evaluate design correction. During this development testing phase, design management is continually assessing the performance of the product against program objectives. Such characteristics as gradeability, acceleration, fuel economy, cooling, handling, etc. are generally easily measured and monitored. The design manager can directly compare these measurements to stated objectives.

This paper provides a practical application of reliability growth theory to automotive development from the specification of reliability goals to prediction, verification and analysis. Implementation of this kind of testing will provide very useful information on concept selection, product/process reliability, and cost effectiveness without too much time, money and engineering effort being spent on the development of failure suspect parts. Recent experience with the testing of automotive components has led to a practical method for efficiently organizing, initiating, and monitoring a reliability growth test process under a competitive automobile environment.

2. Reliability Growth Modeling

2.1 The Growth Program

A reliability growth program is one which utilizes all development testing to find reliability problems. Testing may include functional testing, environmental testing, safety testing, performance testing, as well as mobility testing. In this way reliability improvement becomes integral and visible part of the development process and follows a strategy of a constant striving to make the system better.

The basic process in which reliability is improved is the same as in testing and improving any measurable characteristic, consisting of test, detect failures, redesign and retest. However, the growth process must be managed in order to be successful. Important factors in a successful growth process are that data are collected upon which actions can be taken, how that information is used, who the information is available to, and how to plan for reliability improvement. This requires coordination and cooperation of management as well as testers, data collectors and evaluators. <Figure 1> describes the reliability growth test process as it has been applied to automotive components under development.

At the start of a development program a reliability growth plan should be established to provide a measure of system performance that meets customer expectations, and should include the test conditions under which these objectives have to be met. These test conditions should be based on the knowledge of customer usage and environment for a specific component, system or vehicle. Generally automotive development cycle involves the following development stages[3].

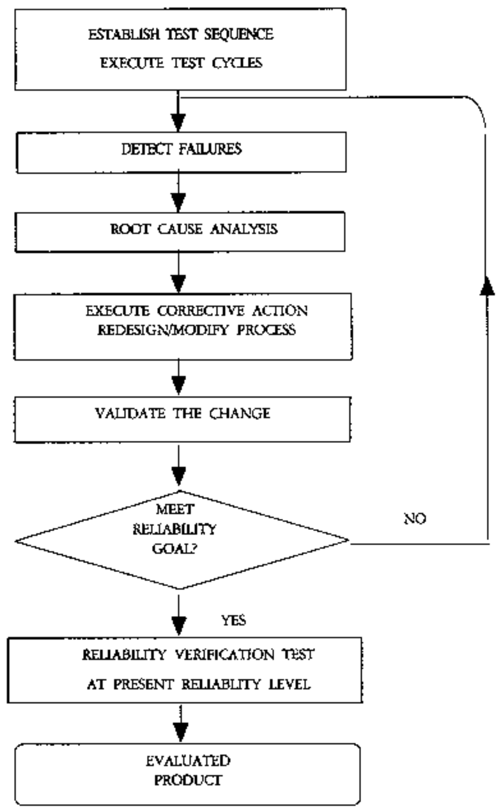

Figure 1. Reliability growth test process.

- Pre-Prototype - This phase involved the design and reliability testing of chassis, powertrain, and the body structure. A relatively small sample of vehicles was tested.
- Prototype - The intent of this activity is to assemble and test production intent vehicles and systems for development and design validation. Although primarily an engineering activities, the materials management, manufacturing, assembly, and quality assurance disciplines were involved.
- Pre-Pilot - This is primarily a manufacturing and engineering activity and provides the opportunity for early detection and correction of problems. Parts and vehicles built during pre-pilot will be used for engineering validation and durability testing of vehicles built with production parts.
- Pilot - The intent of pilot phase is that preceeding activities have been completed and are in place, and that parts conform to all specifications, so that the remaining effort is to validate the manufacturing and assembly production processes. Any vehicle built during this period meeting assembly specifications is saleable.

<Figure 2> shows a discrete reliability growth

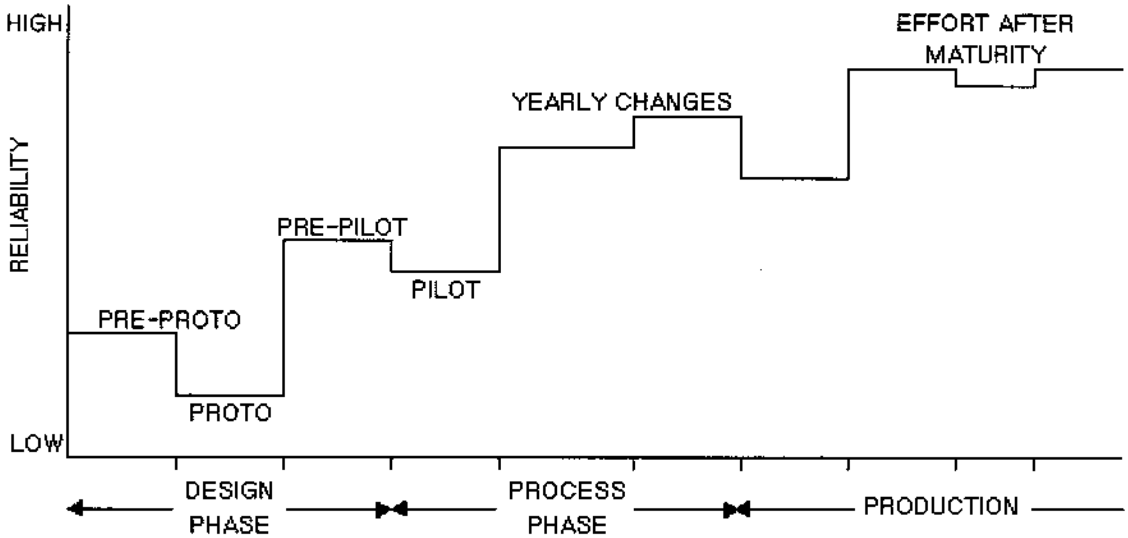

Figure 2. Growth pattern in the development and production.

pattern for each development phase. Problems are identified in one stage, and corrective action implemented prior to the next stage, typical of a TAAF(Test Analyze and Fix) process.

2.2 The Growth Model

The most commonly accepted pattern for reliability growth was first reported by J. T. Duane [7] in 1962. In his paper Duane discussed his observations on failure data for a number of systems during development testing. He observed that the cumulative failure rate versus cumulative operating time fell close to a straight line when plotted on log-log paper. The mathematical model is defined by

$$\log \rho_c(t) = \log \lambda - \alpha \log t$$
$$\rho_c(t) = \lambda t^{-\alpha} \tag{1}$$

where

$\rho_c(t)$ = cumulative failure rate at time t
λ = constant
α = growth rate
t = total test time

In this model, the failure times would be followed by the exponential distribution and the cumulative MTBF(Mean Time Between Failure) would be

$$M_c(t) = [\rho_c(t)]^{-1} = \frac{1}{\lambda} t^{\alpha}, \quad t > 0. \tag{2}$$

Therefore, we can rewrite this as

$$\log M_c(t) = \log \frac{1}{\lambda} + \alpha \log t \tag{3}$$

For an interpretation of these plots, let $D(t)$ denote the number of failures by time t, $t > 0$. Then, the observed cumulative failure rate $\rho_c(t)$ at time t is equal to $\rho_c(t) = D(t)/t$. Hence, from Eq.(1), $D(t) = \lambda t^{1-\alpha}$.

The instantaneous failure rate, $\rho_i(t)$, of the system is the change per unit time of $D(t)$. That is,

$$\begin{aligned} \rho_i(t) &= dD(t)/dt \\ &= \lambda(1-\alpha)t^{-\alpha} \end{aligned} \tag{4}$$

and the instantaneous MTBF would be

$$M_i(t) = \frac{1}{\lambda(1-\alpha)} t^{\alpha}, \quad t > 0. \tag{5}$$

From Eq. (2) & (5), the relationship between instantaneous and cumulative MTBF is given by

$$M_i(t) = \frac{1}{(1-\alpha)} M_c(t) \tag{6}$$

Crow[4] considered the same mean value properties as the Duane postulate but formulated a probabilistic model for reliability growth as an NHPP(NonHomogeneous Poisson Process).

The properties of NHPP satisfy all the conditions for a Poisson process except that the mean rate

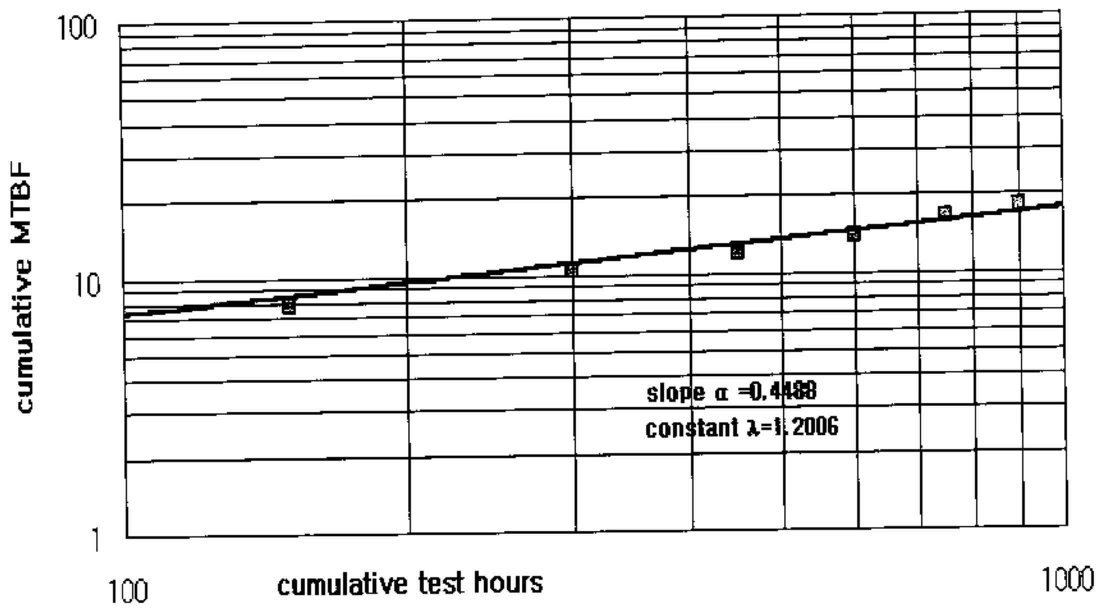

Figure 3. Prototype test growth trend.

varies with time. The NHPP has been used widely as a model for a system subject to improvement [1, 9].

If we let $D(s,t) = D(t) - D(s)$ be the expected number of failures over the time interval $[s, t]$, $t \geq s \geq 0$, <Figure 3>, then we would expect $D(s, t)$ to be

$$\begin{aligned} D(s,t) &= \int_s^t \rho_i(t)dt \\ &= \lambda t^{1-\alpha} - \lambda s^{1-\alpha} \end{aligned} \quad (7)$$

Under the NHPP assumption, the probability that exactly m units will fail in any interval [s, t] has a Poisson distribution with mean $D(s, t)$. That is, for all $t \geq s \geq 0$

$$P_r\{X=m\} = \frac{[D(s,t)]^m e^{-D(s,t)}}{m!} \quad (8)$$

where X is the number of failures in $[s, t]$

3. Data Analysis

3.1 Prototype Test Data Analysis

The number of prototype vehicles placed on test is a design program-management decision based on available resources, magnitude of design change, and engineering budget limitations.

Whenever product failures or nonconforming conditions are experienced during the test, they are investigated and documented by the test engineer. These incidents reports are then sent to the responsible design engineers who must answer them as to the corrective action being taken in design. The design engineer then forwards the corrective action description back to the test engineer who closes out the report. It should be noted that whenever significant failures occur, the test engineer contacts the design engineer immediately and together they investigate the problem and its cause. The test report in that case is simply for documentation.

The first step in the application of the Duane growth model procedure is the determination of cumulative failure rate. <Table 1> is constructed using a simulated prototype test data. For this analysis, a random generating function for Duane model is developed, and presented in appendix. The prototype cumulative MTBF data log-log plot is shown in <Figure 3> The next task is to fit a straight line to the plotted data.

Crow[5] suggests the ML (maximum likelihood) estimates of α and λ.

Let T be fixed and suppose $n \geq 1$ failures were observed during $(0, T)$ at times $0 < x_1 < x_2 < \cdots < T$.

The ML estimates in this case is

$$\hat{\alpha} = 1 - n / \sum_{i=1}^{n} \log(T/x_i) \quad (9)$$

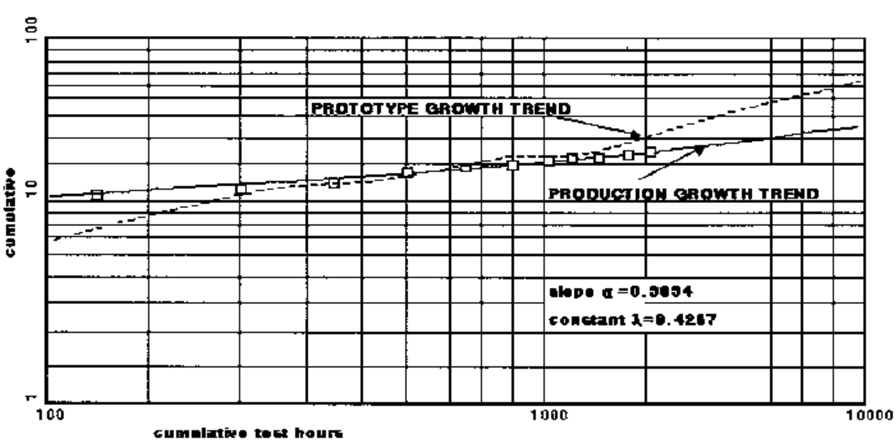

Figure 4. Production test growth trend.

$$\hat{\lambda} = n/T^{1-\hat{\alpha}} \tag{10}$$

The foregoing analysis results in the following quantities for the line of best fit for the prototype data $\hat{\lambda}=1.2006$ and $\hat{\alpha}=0.4488$. A plot is shown in <figure 3>. Thus, the reliability growth model for the prototype test and development program is $M_c(t)=\frac{1}{\lambda}t^{\alpha}=0.8329t^{0.4488}$.

Table 1. Prototype test statistics

Time Period(hrs)	Observed failures	Cumulative failures	Cumulative failure rate	Cumulative MTBF
0 - 150	19	19	0.1267	7.84945
150 - 300	8	27	0.0900	11.1111
300 - 450	7	34	0.0756	13.2345
450 - 600	4	38	0.0633	15.7903
600 - 750	6	44	0.0587	17.0445
750 - 900	7	51	0.567	17.6460

This growth rate model is displayed in <Figure 3>. The estimate of the current MTBF at the end of the test program (900 hrs.) using Eq.(5) is $M_i(900)=32.0005$ test hours. It is clear from <Figure 3> that the MTBF increases signifying improvement in reliability.

3.2 Production Test Data Analysis

During production phase the vehicles are produced in assembly plants where production will occur. The parts are off production tools. Welding, fixturing, trim, fastening, painting, etc. are some of the areas where differences exists compares to the proto and pre-pilot vehicles. New operations, if not done carefully, could introduce new failure modes that may cause the vehicle reliability to go down. The design reliability of the vehicle should not change during this phase, unless it is affected by the build process. In order to measure the overall reliability in this phase, we have to make the assessment in a different manner than used in the design phase.

<Table 2> displays a simulated data for the production test statistics. Cumulative test statistics were plotted on log-log paper using the same procedure followed for the prototype analysis. This plot is shown in Figure 4. The ML estimates was used to determine the line of best fit to the plotted data. The resulting reliability growth rate model for the production design phase is $M_c(t)=2.3436t^{0.3034}$.

Using these statistics and Eq. (4) the current failure rate estimate at the end of a one year production design test phase (2,100hrs.) is $M_i(2,100)=34.2654$ test hours. The current MTBF with test hours can be converted to customers usage operating period in kilometers. If we consider the situation that the test was accelerated, the current MTBF of 34.2654 hours in the test would be 5959.20 km operating period[2].

Thus, reliability growth model reflects continued reliability growth during the production design phase but at a slower rate. Note that the rates are compared by considering the slopes(0.4488 versus 0.3034). Also the model has determined that the final production design MTBF (34.2654) is improved over the final prototype MTBF (32.0005).

3.3 Reliability Objective and Sample Size

The setting of reliability objectives requires a comprehensive study of performance, test procedure, economics, resources, trade-off and many more factors. Assuming for this analysis the manager wants a 10 percent improvement in MTBF over his past experience, the resulting objective for the development program would be

$$MTBF_{objective} = (1.10)\, MTBF_{experience}$$

Thus, the MTBF objective is 37.6919 hours as compared to 34.2654 hours. The objective failure rate is then 0.02653.

For the planning of reliability and life time tests, the manager must also determine the maximum number of vehicles to be committed to testing in order to achieve his objective. For 37.6919 hours of current MTBF objective, from Eq. (6), cumulative MTBF would be 26.2562 hours. Recalling the straight line relationship of the Eq.(3):

$$\log M_c(t) = \log \frac{1}{\lambda} + \alpha \log t$$

$$\log 26.2562 = \log \frac{1}{0.4267} + 0.3034 \log t$$

$$t = 2875.0827$$

Assume 920 test hours per vehicle and the same growth rate as experienced in the maximum number of vehicles to commit to testing is four.

3.4 Goodness-of-Fit Test

Practically it is desirable to test the compatibility of a model and data by a statistical goodness-of-fit-test. One of the many goodness-of- fit tests for the exponential distribution can be used to assess the adequacy of the NHPP process. In fact, any of the following tests could be applied after the appropriate modification is made [10, 12].

- Anderson-Darling A2 Test
- Watson's U2 Test
- Kuiper's V Test
- Stephens's W* Test
- Shapiro-Wilk W Test

Crow[6] adapted a parametric Cramer-von Mises goodness-of-fit test for the multiple system NHPP model. This goodness-fit test is appropriate whenever the start times for each system is 0 and the failure data are complete over the continuous interval [0, t] with no gaps in the data. Although not as powerful as the Cramer-von Mises test, the Chi-squared test [6,11] can be applied under more general circumstances, regardless of the values of the starting times. It is particularly suited for the cases discussed in the vehicle development examples. This Chi-squared test uses the fact that the expected number of failures for a system over its testing time (t_1, t_2) is estimated by

$$D(t_1, t_2) = \hat{\lambda} t_2^{(1-\hat{\alpha})} - \hat{\lambda} t_1^{(1-\hat{\alpha})} \tag{11}$$

where $\hat{\lambda}$ and $\hat{\alpha}$ are the ML estimates given by equations (9) and (10).

If we illustrate this test for the situation of Table 1, the cumulative expected number of failures over the test interval t is $D(t) = \lambda t^{1-\alpha}$. For example, the expected number of failures over the test interval is estimated by

$$\hat{D}(t) = \hat{\lambda}\, 900^{1-\hat{\alpha}} = (1.2006)\, 900^{(1-0.4488)}$$

$$= 51.024$$

where $\hat{\lambda}$ and $\hat{\alpha}$ are given in prototype test data analysis. To assess the statistical significance we compute the chi-square statistic

$$\chi^2 = \sum_{i=1}^{k} \frac{[N(s_i, t_i) - D(s_i, t_i)]^2}{D(s_i, t_i)} \tag{12}$$

where k is the total number of intervals. The random variable χ^2 is approximately Chi-squared distributed with k-2 degrees of freedom. In this example, $\chi^2 =$ 1.9000, $k = 6$, and the critical value at the 10 percent significance level for df = 4 is 7.779.

3.5 Confidence Intervals on Growth Rate

Confidence intervals for the growth rate are now developed based on the following two different test situations, depending on how the data are recorded.

<u>Recording failure times</u>

First consider the test situation where failure times $t_1, t_2, \ldots, t_n$ are observed. In this case the quantity $2n(1-\alpha)/(1-\hat{\alpha})$ is Chi-square distributed with 2(n-1) degrees of freedom. Thus, an appropriate probability statement for a size 100(1- r) % is

$$P[\chi^2_{2(n-1),r/2} \le \frac{2n(1-\alpha)}{(1-\hat{\alpha})} \le \chi^2_{2(n-1),1-r/2}] = 1-r \quad (13)$$

which can be algebraically changed to

$$\alpha_U = 1 - \frac{(1-\hat{\alpha})\chi^2_{2(n-1),r/2}}{2n} \quad (14)$$

and

$$\alpha_L = 1 - \frac{(1-\hat{\alpha})\chi^2_{2(n-1),1-r/2}}{2n} \quad (15)$$

where $\chi^2_{\nu,\gamma}$ is the $100\times\gamma\%$ point of the chi-square distribution with ν degrees of freedom. It is often important to test the hypothesis $H_0: \alpha=\alpha_0$ versus $H_1: \alpha \ne \alpha_0$. Based on the result that a $2n(1-\alpha)/(1-\hat{\alpha})$ has Chi-square distribution with 2(n - 1) degrees of freedom, a size 100(1 - r) % test for testing any particular value of α can be constructed. The rule is to reject $CH_0: \alpha=\alpha_0$ if either $\hat{\alpha} < 1-2n(1-\alpha_0)/\chi^2_{2(n-1),r/2}$ or $\hat{\alpha} > 1-2n(1-\alpha_0)/\chi^2_{2(n-1),1-r/2}$.

Counting Failures Over a Time Interval

Let us assume that in a test situation we count the number of failures that occur over an interval of test time T. This situation could arise in practice in different ways. For example, we might have n test stands where we replace items as they fail and discontinue the test at a predetermined time. Or we might derive vehicles over a 40,000km test schedule and elect to count failures rather than failure intervals.

In the above situation where we have observed n failures over an interval of test time T, the 100 (1 - r)% two-sided confidence interval is

$$\alpha_U = 1 - \frac{(1-\hat{\alpha})\chi^2_{2n,1-r/2}}{2n} \quad (16)$$

and

$$\alpha_L = 1 - \frac{(1-\hat{\alpha})\chi^2_{2n,1-r/2}}{2n} \quad (17)$$

For the data in prototype test data, $\hat{\alpha}$ = .4488 and α_U = .5693, α_L = .3160 are 90% confidence bounds on α. A size 100(1 - r) % test of $H_0: \alpha=\alpha_0$ versus $H_1: \alpha \ne \alpha_0$ is to reject if either $\hat{\alpha} < 1-2n(1-\alpha_0)/\chi^2_{2n,1-r/2}$ or $\hat{\alpha} > 1-2n(1-\alpha_0)/\chi^2_{2n,r/2}$.

4. Conclusion

In this paper we provided an overview of practical application of reliability growth theory to the vehicle development from the specification of reliability goals to prediction, verification and analysis. The presented analysis could be applied to successfully demonstrating the relationship between failure detection and corrective action, and the achievement of higher reliability designs. Examples and procedures specifically illustrating these methods were given for practical situations. In addition to maximum likelihood methods, goodness-of-fit tests and confidence interval procedures were discussed and illustrated by numerical examples. Specification of reliability growth and useful life and the application of the most important methods of prediction and analysis are also discussed with the aid of examples.

Table 2. Production test statistics

Time Period(hrs)	Observed failures	Cumulative failures	Cumulative failure rate	Cumulative MTBF
0 - 150	14	14	0.0933	10.7181
150 - 300	10	24	0.0800	12.5000
300 - 450	8	32	0.0711	14.0647
450 - 600	5	37	0.0617	16.2075
600 - 750	7	44	0.0587	17.0358
750 - 900	2	46	0.0511	19.5695
900 - 1050	5	51	0.0486	20.5761
1050 - 1200	3	54	0.0450	22.2222
1200 - 1500	13	67	0.0447	22.3714
1500 - 1800	12	79	0.0439	22.7790
1800 - 2100	9	88	0.0419	23.8663

The selection of the growth model should be based on the type of process the development program follows. According to our survey on reliability growth models[9], the Modified Duane model fits the application. We believe that these principle of reliability growth analysis are common to any vehicle development program.

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정 원

한양대학교 산업공학과를 졸업하고 미국 Wayne State University에서 석사 및 박사학위를 취득하였으며, Trenton State College에서 조교수로 근무하였다.
현재 : 대구대학교 산업공학과 부교수
관심분야 : 생산정보시스템, 품질 및 신뢰성 공학 등

Appendix : Random Generating Function of the Duane Model

Assuming a constant rate between successive failure times, the probability of non-failure during a time interval is:

$$F = e^{\Delta T \gamma} \tag{18}$$

By using the inverse-transform method to generate ΔT, we get

$$\Delta T = \frac{1}{\gamma} \ln(U) \tag{19}$$

where U is a set of successive random numbers $(0 < U < 1)$. From Eq.(4) the instantaneous failure rate of the Duane model is given by

$$\rho_i(T) = \lambda(1-\alpha) T^{-\alpha} \tag{20}$$

If we replace γ with $\rho_i(T)$, the time between failures can be generated using the following equation

$$\Delta T = -\frac{\alpha T}{\lambda(1-\alpha)} \ln(U) \tag{21}$$

T is the cumulative time of the successive time between failures. Let $\lambda(1-\alpha) = \rho_i(0)$ where $\rho_i(0)$ is the instantaneous failure rate at the beginning of the test ($\log T = 0$, $i.e.\ T = 1$), then we can rewrite Eq. (21) as

$$\Delta T = -\frac{1}{\rho_i(0)} T^{\alpha} \ln(U). \tag{22}$$