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On the planning of the scope of new technology testing

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Abstract. *This paper is a follow-up to [1]. It examines the matters of planning of the scope of highly dependable objects testing. The process of new technology development and manufacture involves determining its dependability indicators. The most objective method of identifying dependability characteristics of products is field testing. One of the widely used testing plans is the [N,U,T] plan. This plan that involves testing N nonreparable samples within the time interval between 0 and a certain T. It is assumed that during the tests k objects fail, while N-k objects successfully pass the tests. Thus, at the outcome of the experiment we have a mixed sample that includes k times to failure and N-k right censored observation. If the tested object is highly dependable it is quite possible that within the time period [0,T] failures will not happen, i.e. k will be equal to 0, therefore the probability of failure within this time period is extremely low and the number of tested objects is limited. Nevertheless even in this situation it would be desirable to be able to be in control of the accuracy of the estimation obtained during such experiments. It is clear that the accuracy of such estimation will depend not only on the number of tested objects N, but also on the experiment duration. For a fixed N, as the observation time T grows the estimation accuracy increases due to the increasing proportion of complete times, while the proportion of censored ones goes down. It should be noted that when we talk about identifying the dependability characteristics of complex and costly objects we cannot test large batches of finished products. Therefore the problem consists in defining testing duration and size of the product batch to be tested subject to specified requirements for the accuracy of estimation of dependability characteristics obtained as the result of the tests. The scope planning is based on the manufacturer's requirement to validate the lower bound of the probability of no failure* $\underline{P}_0$ *with a specified confidence level at a certain time point* t_0. **The aim** *of the paper is to identify the test scope of a batch of finished products N(T) under the condition of fulfilment of the manufacturer's requirement for compliance with the lower confidence bound of the probability of no failure with a specified confidence level 1 – . Three failure distributions are under examination: exponential distribution law, Weibull distribution and distribution with linear rate function. The considered types of distribution law enable the research of objects with decreasing, constant and increasing failure rate function.* **Methods.** *In this paper the authors deduce formulas for calculation of the scope of experiment for a number of experiment durations. The estimates are obtained using the maximum likelihood method and methods of researching asymptotic properties of estimates through the Fisher information quantity.* **Conclusions.** *The findings allow for a substantiated approach to planning the scope of highly dependable objects testing. It is shown that the longer is the experiment duration the fewer products must be supplied for testing. The dependence is non-linear, close to hyperbolic and is conditioned by both the input parameters and the parametrization of the failure rate function.*

Keywords*: test scope planning, experiment duration, probability of no-failure, failure rate, lower bound estimate of probability of no-failure, confidence level.*

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Introduction

The process of new technology development and manufacture involves determining its dependability indicators. The most objective method of identifying dependability characteristics of products is field testing. This paper examines the $[N,U,T]$ test plan. This plan that involves testing N nonreparable samples within the time interval between 0 and a certain T. It is assumed that during the tests k objects fail, while N-k objects successfully pass the tests. Thus, at the outcome of the experiment we have a mixed sample that includes k times to failure and N-k right censored observation. It is clear that the accuracy of the obtained estimate will depend not only on the number of tested objects N, but also on the experiment duration. For a fixed N, as the observation time T grows the estimate accuracy increases due to the increasing proportion of complete times, while the proportion of censored ones goes down. It should be noted that when we talk about identifying the dependability characteristics of complex and costly objects we cannot test large batches of finished products. Therefore the problem consists in defining testing duration and size of the product batch to be tested subject to specified requirements for the accuracy of estimation of dependability characteristics obtained as the result of the tests.

Problem definition

The experiment is conducted according to the plan $[N,U,T]$. This plan involves testing N samples within a given time interval between 0 and T with no replacement of failed products [2–4]. During the test k failures are observed. Let us designate the obtained operation times as $t_1, t_2, \ldots, t_k$. ν products successfully pass the tests $\nu = N–k$ (ν is the number of nonfailed samples with the operation time T). The nonfailed objects make up the sample of right censored operation times. Figure 1 shows the plan of the experiment.

Thus, sample no. 1 worked without failure up to the moment in time T. The second sample failed at the moment t_2, etc.

Let us assume that at a certain moment t_0 the lower confidence bound with a specified confidence level $1–\alpha_0$ for PNF $P(t_0)$ must not be lower than $\underline{P}_0$, i.e.

$$\Pr(P(t_0) \geq \underline{P}_0) \geq 1–\alpha_0. \tag{1}$$

It is obvious that it can be achieved by selecting the test scope $N(t_0)$ only in the case when the actual PNF in this point $P(t_0)$ is to the right of $\underline{P}_0$. Otherwise the problem is unsolvable.

It would be logical to assume that at a certain moment in time T ($T \geq t_0$) in order to ensure an equal accuracy of PNF estimation in point t_0 the required scope of finished products tests $N(T)$ is at least equal to that defined for point t_0. That is primarily due to the fact that the PNF is a non-increasing function. Let us designate the required test scopes as $N(t_0)$ and $N(T)$.

The aim of the paper is to identify the test scope of a batch of finished products $N(T)$ under the condition of fulfilment of the manufacturer's requirement for compliance with the lower confidence bound of the probability of no failure with a specified confidence level $1 – \alpha$. During the test we will identify the correlations between the test scopes of $N(T)$ and $N(t_0)$ provided that the requirements for the accuracy of the results for different test durations are equal. During the tests we will consider various parametrizations of the failure rate function $\lambda(t)$.

In the process of solving the problem we will be assuming that the failure rate function is defined by one of the formulas [1, 2]:

$$\lambda(t)=\lambda; \tag{2}$$

$$\lambda(t)=\lambda_1+\lambda_2 t; \tag{3}$$

$$\lambda(t)=\lambda_1 t^{\lambda_2}. \tag{4}$$

The formula (2) (the rate is constant) is typical to exponential distribution of time to failure, the formula (3) is typical to the distribution function with linear failure rate, while the function (4) is typical to the Weibull distribution law.

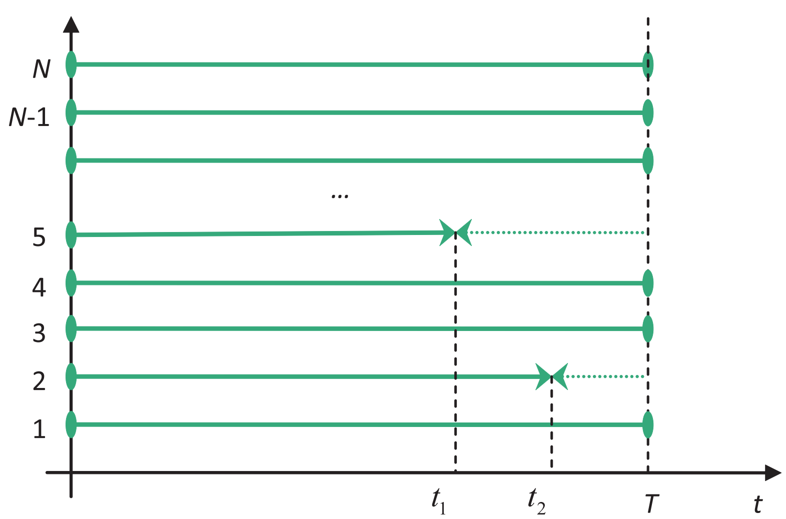

Figure 1. Plan of the experiment

In order to simplify the calculations, as in [1], let us transform the considered model as follows:

$$\lambda(t)=\lambda g(t) \tag{5}$$

where $g(t)=1$ corresponds with the exponential distribution,

$g(t)=a+bt$ corresponds with the distribution with a linear failure rate function, (6)

$g(t)=t^a$ corresponds with the Weibull distribution. (7)

The function $g(t)$ must meet two main conditions:

$$g(t)\geq 0,$$

while the integral function

$$G(t)=\int_0^t g(\tau)d\tau \to \infty \text{ if } t\to\infty.$$

We will assume that the coefficients a, b in (6), (7) are known, while the parameter λ is unknown and estimated by sample.

In the next section we will identify how the accuracy of this parameter's estimation depends on the duration T of the experiment and subsequently deduce the condition of its preservation under the chosen experiment plan.

Evaluation of parameter λ and identification of its accuracy

It is known [2] that the accuracy of an estimate obtained using the maximum likelihood method (MLM estimates) depends on the Fisher information quantity.

In the beginning, let us find the quantity of Fisher information contained in the initial statistics. The likelihood function that corresponds with the chosen plan of experiment $[N,U,T]$ will be as follows:

$$L(\vec{t};T;\lambda)=\prod_{i=1}^{k} f_{t_i}(t_i;\lambda)\prod_{j=1}^{\nu} P_{t_j}(T;\lambda)=$$
$$=\lambda^k\cdot\prod_{i=1}^{k} g(t_i)\cdot\exp\left(-\lambda\left(\sum_{i=1}^{k} G(t_i)+\nu G(T)\right)\right),$$

where $f_t(t,\lambda)=\lambda g(t)\exp(-\lambda G(t))$ is the distribution density of time to failure.

Log-likelihood function:

$$l(\vec{t};T;\lambda)=\ln L=k\ln\lambda+\sum_{i=1}^{k} g(t_i)-\lambda\left(\sum_{i=1}^{k} G(t_i)+\nu G(T)\right).$$

We identify the partial derivative.

$$\frac{\partial}{\partial\lambda}l(\vec{t};T;\lambda)=\frac{k}{\lambda}-\left(\sum_{i=1}^{k} G(t_i)+\nu G(T)\right). \tag{8}$$

Here $k=\sum_{i=1}^{N}\mathrm{I}\{t_i\leq T\}$ is a binomially distributed random value (r.v.):

$$Bin(N;F_t(T))=Bin\left(N;1-e^{-\lambda G(T)}\right). \tag{9}$$

The information quantity (dispersion of the right part of the equation (8) will be defined by the sum of three summands. Let us find each individually.

$$\operatorname{var}\left[\frac{k}{\lambda}\right]=\frac{NP_t(T)(1-P_t(T))}{\lambda^2}=\frac{Ne^{-\lambda G(T)}\left(1-e^{-\lambda G(T)}\right)}{\lambda^2}.$$

$$\operatorname{var}\left[\sum_{i=1}^{k} G(t_i)+\nu G(T)\right]=\operatorname{var}\left[\sum_{i=1}^{N} G(t_i\wedge T)\right]=$$
$$=\frac{N\left(1-2\lambda G(T)e^{-\lambda G(T)}-e^{-2\lambda G(T)}\right)}{\lambda^2}.$$

$$\operatorname{cov}\left[\frac{k}{\lambda};\sum_{i=1}^{N} G(t_i\wedge T)\right]=$$
$$=\frac{1}{\lambda}\operatorname{cov}\left[\sum_{i=1}^{N}\mathrm{I}\{G(t_i)\leq G(T)\};\sum_{i=1}^{N} G(t_i)\wedge G(T)\right]=$$
$$=\frac{1}{\lambda}\left[\sum_{i=1}^{N}\mathrm{E}\left(G(t_i\wedge T)\cdot\mathrm{I}\{t_i\leq T\}\right)-\mathrm{E}\left(G(t_i\wedge T)\right)\mathrm{EI}\{t_i\leq T\}\right]=$$
$$=\frac{N}{\lambda^2}\left(e^{-\lambda G(T)}-e^{-2\lambda G(T)}-\lambda G(T)e^{-\lambda G(T)}\right).$$

By adding the dispersions to covariations we identify the Fisher quantity:

$$\mathrm{I}(\vec{t};T;\lambda)=\frac{N}{\lambda^2}\left(1-e^{-\lambda G(T)}\right)=\frac{N}{\lambda^2}(1-P(T))=\frac{NF_t(T)}{\lambda^2}, \tag{10}$$

where $F_t(T)$ is the distribution function of time to failure.

Now, let us deduce the MLM estimate for λ:

$$\hat{\lambda}_T=\frac{k}{\sum_{i=1}^{N} G(t_i\wedge T)}. \tag{11}$$

The estimate is acquired by equalling the right side of the equation (8) to zero. It is known that the MLM estimate is asymptotically unbiased, consistent, asymptotically efficient and asymptotically normal. Thus,

$$\hat{\lambda}_T\overset{as}{\sim}Norm\left(\lambda;\frac{1}{\mathrm{I}(\vec{t};T;\lambda)}\right)=Norm\left(\lambda;\frac{\lambda^2}{NF_t(T)}\right). \tag{12}$$

In the next section we will research the Fisher information quantity.

Research of estimate $\hat{\lambda}_T$

Let us introduce the designation of the numerator of Fisher information quantity (10):

$$K(T)=NF_t(T). \tag{13}$$

Obviously $K(T)$ will also depend on the parameter λ, because it affects the distribution function $F_t(T)$, yet we are primarily interested in the dependence of the introduced indicator on time. In terms of significance, $K(T)$ will be the expectation of r.v. k that is equal to the average number of failures by the moment of time T distributed according to the law (9).

Due to the well-known asymptotic property of the distribution function

$$K(T) \underset{T\to\infty}{\to} N. \tag{14}$$

Obviously sooner or later all N samples will fail. In this case the estimate (11) will tend to the estimate based on the complete sample:

$$\hat{\lambda}_T = \frac{k}{\sum_{i=1}^{N} G(t_i \wedge T)} \underset{T\to\infty}{\to} \hat{\lambda}_\infty = \frac{N}{\sum_{i=1}^{N} G(t_i)}. \tag{15}$$

If the test scope N is a time-independent constant, then the function $K(T)$ and function $F_t(T)$ will be non-decreasing, while $K(0)=0$.

Let is consider the condition that will ensure the achievement of the required lower bound of the PNF in point t_0. Under the chosen PNF estimation method its lower confidence bound will be $\underline{P}_0$. This value is identified by calculating the upper bound of the parameter λ: $\underline{P}_0 = e^{-\bar{\lambda}_{t_0} G(t_0)}$, where $\bar{\lambda}_{t_0}$ is the upper bound of the parameter λ calculated as if the testing of samples ended at the moment t_0. This indicator will be identified through the solution of the equation

$$1-\alpha_0 = P\left(\hat{\lambda}_{t_0} < \bar{\lambda}_{t_0}\right) \approx \Phi\left(\frac{\bar{\lambda}_{t_0} - \lambda}{\lambda}\sqrt{K(t_0)}\right), \tag{16}$$

where $\Phi(x)$ is the standard normal law distribution function Norm(0,1). By solving the equation (16) we obtain:

$$\bar{\lambda}_{t_0} = \lambda\left(1 + \frac{u_{1-\alpha_0}}{\sqrt{K(t_0)}}\right).$$

If the test lasts to the moment in time T, the upper bound of the parameter will be identified through the solution of an equation similar to (16), where t_0 is replaced with T. The following formula is obtained:

$$\bar{\lambda}_T = \lambda\left(1 + \frac{u_{1-\alpha_0}}{\sqrt{K(T)}}\right), \tag{17}$$

where $u_{1-\alpha_0}$ is the quantile of the normal law Norm(0,1) of the level $1–\alpha_0$.

Estimate (17) will be used in the calculation of the lower bound of the PNF in point t_0. According to the stated aim of the research it is required to ensure the fulfilment of the condition according to which the lower bound of the PNF calculated with the confidence level $1–\alpha_0$ was not lower than $\underline{P}_0$ regardless of the duration of experimental observations. As the failure rate is one-to-one expressible through PNF, a similar condition can be formulated for the rate. Therefore, for the random positive moment of time T the following can be written:

$$\bar{\lambda}_T = \bar{\lambda}_{t_0}. \tag{18}$$

Thus, it is required to choose the size of the batch of products to be tested in such a way as to ensure the upper bound of failure rate $\bar{\lambda}_T$ did not depend of the observation time. In other words, the accuracy of estimation of the parameter λ at the moment of time t_0 must be equal to that at the moment T. That can be achieved if the Fisher information quantity is assumed to be constant. This condition will be written as $K(T)$=const.

Condition of preservation of accuracy of estimate λ

The error is estimated at the moments t_0 and T will be identical if the information quantities in those points are equal. We will achieve the equality of the information quantities by selecting the required test scope $N(T)$ and $N(t_0)$.

The condition of equality of information quantities for two random moments in time t_0 and T will be as follows:

$$\mathrm{I}(\vec{t};t_0;\lambda) = \mathrm{I}(\vec{t};T;\lambda). \tag{19}$$

This condition (19) will ensure an estimation accuracy of the unknown parameter λ based on the findings of experiment $(N(T),U,T)$ as if we estimated λ based on the findings of experiment $(N(t_0),U,t_0)$.

Out of (10), (14) and (19) follow the properties:

$$\frac{N(T)}{N(t_0)} = \frac{F(t_0)}{F(T)} \text{ or}$$

$$K(T) = Const = K(t_0) = Ek(t_0) = K(\infty) = N(\infty). \tag{20}$$

Thus, for any T the constant $K(T)$ will be equal to both the expected number of failures at the moment t_0 and the number of samples $N(\infty)$. In the following section let us identify the constant $N(\infty)$.

Solution of the problem

Formula (15) defines the estimation of parameter λ if $T\to\infty$. Let us define the asymptotic number of samples $N(\infty)$ based on the accurate distribution of estimate $\hat{\lambda}_\infty$. It is known [8] that r.v. $2\lambda G(t_i)$ will have the ch-square distribution with two degrees of freedom: $2\lambda G(t_i) \sim \chi^2_2$. Due to the independence of summands:

$$2\lambda \sum_{i=1}^{N} G(t_i) \sim \chi^2_{2N}. \tag{21}$$

Proposition (21) allows constructing a right-hand confidence interval for parameter λ.

$$\Pr\left(\hat{\lambda}_\infty \le \bar{\lambda}\right) = \Pr\left(2\lambda \sum_{i=1}^{N} G(t_i) \ge \frac{2\lambda N}{\bar{\lambda}}\right) = 1-\alpha_0.$$

Table 1. Asymptotic values for the number of test (α_0=0.05)

q_0	0,051	0,178	0,273	0,342	0,394	0,436	0,469	0,498	0,522	0,543
$N(\infty)$	1	2	3	4	5	6	7	8	9	10

Table 2. Values of $N(\infty)$ depending on α and $\underline{P}_0$.

α \ $\underline{P}_0$	0,1	0,2	0,3	0,4	0,5	0,6	0,7	0,8	0,9	0,95	0,99	0,999
0,01	5,08	6,54	7,81	8,98	10,09	11,16	12,19	13,19	14,16	14,64	15,02	15,11
0,02	4,10	5,25	6,26	7,18	8,06	8,90	9,71	10,50	11,27	11,65	11,95	12,01
0,03	3,53	4,52	5,37	6,16	6,90	7,61	8,30	8,97	9,62	9,94	10,19	10,25
0,04	3,14	4,01	4,75	5,44	6,09	6,72	7,32	7,90	8,47	8,75	8,97	9,02
0,05	2,84	3,62	4,28	4,90	5,48	6,04	6,57	7,09	7,60	7,85	8,04	8,09
0,06	2,60	3,30	3,91	4,46	4,99	5,49	5,97	6,44	6,90	7,12	7,30	7,34
0,07	2,40	3,04	3,59	4,10	4,58	5,03	5,47	5,90	6,31	6,52	6,68	6,72
0,08	2,23	2,82	3,32	3,79	4,23	4,64	5,05	5,44	5,82	6,00	6,15	6,18
0,09	2,08	2,62	3,09	3,52	3,92	4,31	4,68	5,04	5,39	5,56	5,69	5,72
0,1	1,95	2,45	2,89	3,28	3,65	4,01	4,35	4,69	5,01	5,17	5,29	5,32

Out of which we obtain a transcendent equation to find $N(\infty)$:

$$\frac{\chi^2_{\alpha_0}(2N)}{2N} = \frac{\lambda}{\underline{\lambda}} = \frac{\ln P_0}{\ln \underline{P}_0} = q_0, \tag{22}$$

where $\chi^2_{\alpha_0}(2N)$ is the quantile of ch-square distribution with $2N$ degrees of freedom of level α_0.

Table 1 shows an example of calculation of asymptotic values of $N(\infty)$ for various q_0.

We can use the asymptotic distribution of estimate (12) and by solving the equation (16) under N obtain the following results:

$$N(\infty) \approx \left(\frac{u_{1-\alpha_0} q_0}{1-q_0}\right)^2. \tag{23}$$

The analysis of (23) has shown that approximate calculation is very optimistic (see Figure 2) and the estimate of the required test scope turns out to be significantly conservative.

If the PNF P_0 in point t_0 is unknown, we can, as in [1], assume that:

$$P_0 = \frac{1+\underline{P}_0}{2}. \tag{24}$$

In fact, due to the significant asymmetry of the binomial distribution in case of highly dependable equipment the following inequation will be fulfilled: $P_0 > \frac{1+\underline{P}_0}{2}$. Therefore, $q_0 < \ln\frac{1+\underline{P}_0}{2} \Big/ \ln \underline{P}_0$ and the asymptotic value estimate $N(\infty)$ will be exaggerated, i.e. the estimate will be pessimistic.

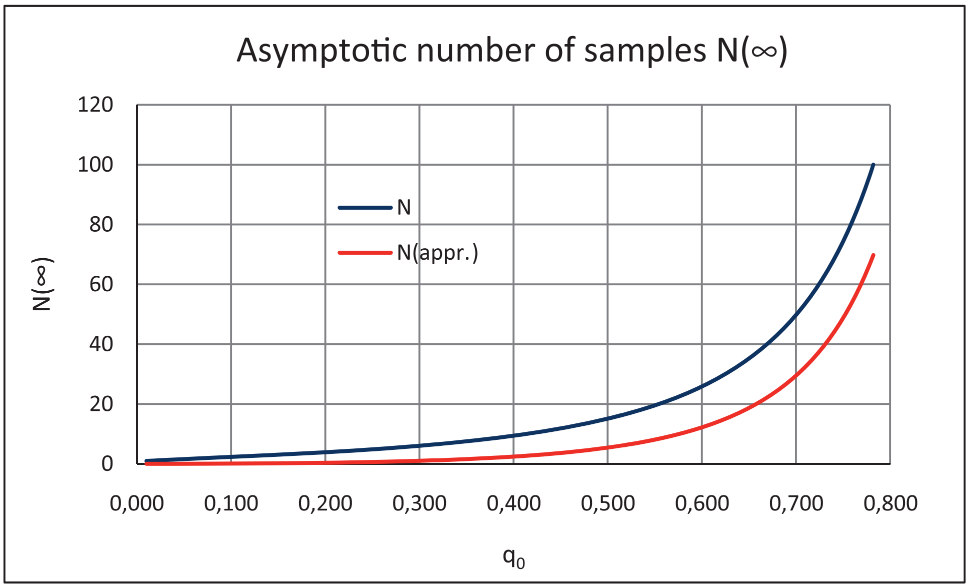

Figure 2. Exact and approximate values of $N(\infty)$

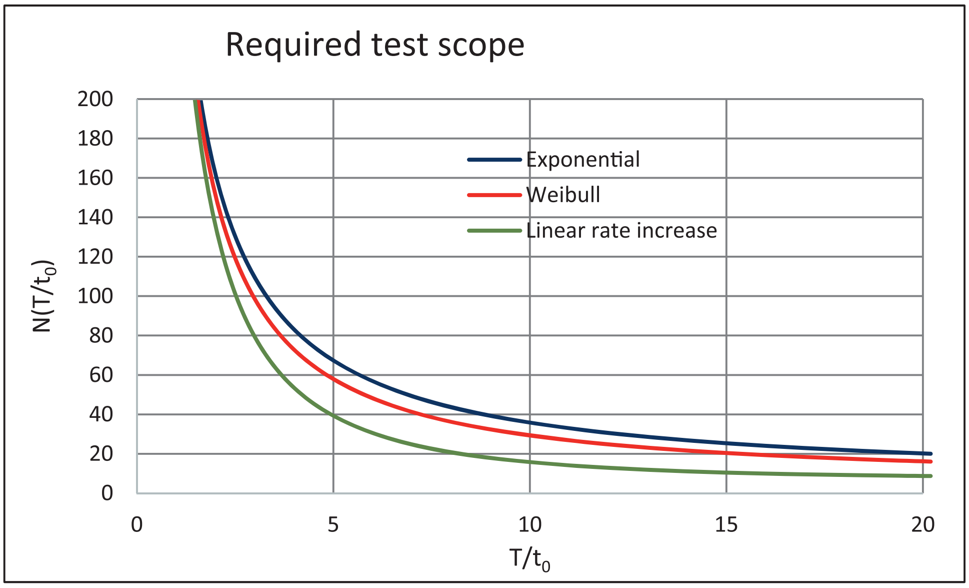

Figure 3. Dependence of the test scope on the time under different distribution models

Table 2 shows calculated values of $N(\infty)$ depending on the significance of α and lower bound of PNF $\underline{P}_0$.

In order to evaluate the test scope in random point t it remains to apply (20).

Out of (20) follows $N(T)=\frac{N(\infty)}{F(T)}$. As the true value of the parameter λ is unknown it can be evaluated based on the condition $\lambda=-\frac{\ln P_0}{G(t_0)}$. From which

$$N(T)=\frac{N(\infty)}{1-P_0^{G(T)/G(t_0)}}. \tag{25}$$

The time dependance in case of low $\lambda G(T)$ is almost hyperbolic under $G(T)$.

$$N(T)\approx\frac{N(\infty)}{\lambda G(T)}. \tag{26}$$

Fig. 3 shows the behavior of the required test scope (25) depending on T on the time scale T/t_0. The input parameters are as follows: $\underline{P}_0$=0.95; α_0=0.05, t_0=5, $N(\infty)$=7.85 (see Table 2). During the calculations the distribution parameters were chosen as follows: for the Weibull distribution the parameter a=1.1. For the model with linearly increasing rate function a=1; b=0.1.

It can be seen that models with an increasing rate function compared to those with a constant failure rate require a relatively smaller number of tests.

Conclusion

The obtained results allow for a substantiated approach to planning the scope of highly dependable objects testing. The input information is the manufacturer-supplied information on the requirement to confirm the lower bound of the product's PNF with given confidence level. The formulas obtained in the paper enabled the research of the dependence of the scope of testing from the experiment duration. It is shown that the longer is the experiment duration, the fewer products must be supplied for testing. The dependence is non-linear and conditioned by the parametrization of the failure rate function. New asymptotic results have been obtained that allow adequately assessing the number of tests for a given time period.

References

1. Antonov AV, Chepurko VA, Chekhovich VE, Ukraintsev VF. Regarding the planning of testing scope for new equipment samples. Dependability 2016;(3):3-7. DOI:10.21683/1729-2640-2016-16-3-3-7.

2. Antonov AV, Nikulin MS, Nikulin AM, Chepurko VA. Teoria nadiozhnosty. Statisticheskie modeli: Uchebnoie posobie [Dependability theory. Statistical models: A study guide]. Moscow: INFRA-M; 2015 [in Russian].

3. Gnedenko BV, Beliaev YuK, Soloviev AD. Matematicheskie metody v teorii nadiozhnosti [Mathematical methods in the dependability theory]. Moscow: Nauka; 1965 [in Russian].

4. Beliaev YuK, Bogatyrev VA, Bolotin VV et al. Ushakov IA, editor. Nadiozhnost tekhnicheskikh system: Spravochnik [Dependability of technical systems: Reference book]. Moscow: Radio i sviaz; 1985 [in Russian].

5. Antonov AV, Nikulin MS. Statisticheskie modeli v teorii nadiozhnosti; Ucheb. posobie [Statistical models in the dependability theory: A study guide]. Moscow: Abris; 2012 [in Russian].

6. Zarenin YuG, Stoyanova II. Opredelitelnye ispytania na nadiozhnost [Determinative dependability testing]. Moscow: Izdatelstvo standartov; 1978 [In Russian].

7. Cramer H. Matematicheskie metody statistiki [Mathematical methods of statistics]. Moscow: Mir; 1975 [In Russian].

8. Antonov AV. Sistemny analiz; Uchebnik dlia vuzov [System analysis. Textbook for higher educational institutions]. Moscow: Vysshaya Shkola; 2008 [in Russian].

9. David H. Poriadkovye statistiki [Order statistics]. Moscow: Nauka. Main office of physics and mathematics literature; 1979 [in Russian].

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