The measured pressure sensitivity depends on input polarization of light and examined output polarization. It changes from 0,45rad/MPa*m to 4,2rad/MPa*m for two different fibers with change of input and output light polarization.

Measured temperature sensitivity depends on input polarization of light and examined output polarization too. It change from 3rad/K*m to 12 rad/K*m for two exemplary fibers. The change of K_T for different h indicates the existence of maximum. Its determination requires of further experimental investigations.

Probably the shape of dependence of K_T on h is caused by stress profile inside optical fiber in spite of small numerical aperture.

We hope that the planed experimental investigation of the analogous dependences in the dual core photonic crystal fibers may explain this problem.

1. *Woliński T.R. Polarimetric Optical Fibers and Sensors in Progress in Optics Vol.XL, ed. E.Wolf (2000), 1-75.*

2. *Friberg S.R., Silberberg Y., Oliver M.K., Andrejco M.J., Saifi M.A., W.Smith P. Ultrafast All-Optical Switching in a Dual-Core Fibre Nonlinear Coupler, Appl. Phys. Lett. 51, (1987), 1135-1137.*

3. *Gang-Ding Peng, T.Tjugiarto, P.L.Chu. Twin-core optical fiber with large core ellipticity, Appl. Opt. Vol.30, No6, (1991), 632-634.*

UDC 621.382

A.S.Andonova, N.G. Atanasova
FETT, Technical University of Sofia,
Sofia, Bulgaria

TESTING ALGORITHMS FOR SCREENING OF LARGE ELECTRONIC SYSTEMS

When a hardware system is screening, a problem is when to stop the test and accept the system. Based on this these, the paper describes and evaluates seven possible algorithms. Three of these algorithms as most promising are tested with simulated data. Different systems are simulated, and 50 Monte Carlo simulations made on each system. The stop times generated by the algorithm is compared with the known perfect stop time. Of the three algorithms two is selected as good. These two algorithms are then tested on real data. The algorithms are tested with three different levels of confidence. The number of correct and wrong stop decisions are counted. The conclusion is that the Weibull algorithm with 90% confidence level takes the right decision in every one of the cases.

1. Introduction

When performing a run-in or acceptance testing on a large hardware system, it is often a problem to decide when to stop testing [1,2]. If it is stop too early the system will be delivered to the customer with too many early failures. On the other hand testing is very expensive, and the test can delay the delivery.

For hardware screening exist the same problem. A stress screening process will in the beginning precipitate many early failures per hour, but the last failures take a lot longer to precipitate. In the IEC standard IEC 61163-1 “Reliability stress screening of repairable items produced in lots” [3], the problem is solved by accepting that a sample of the product is run for an extended screening period, in order to find the optimum duration of the screening process. This duration is expressed as a failure free period. The aim is to stop the screening process as soon as the curve of the accumulated failures per 100 items levels out i.e. the curve converges towards a straight line as can be seen in fig. 1.

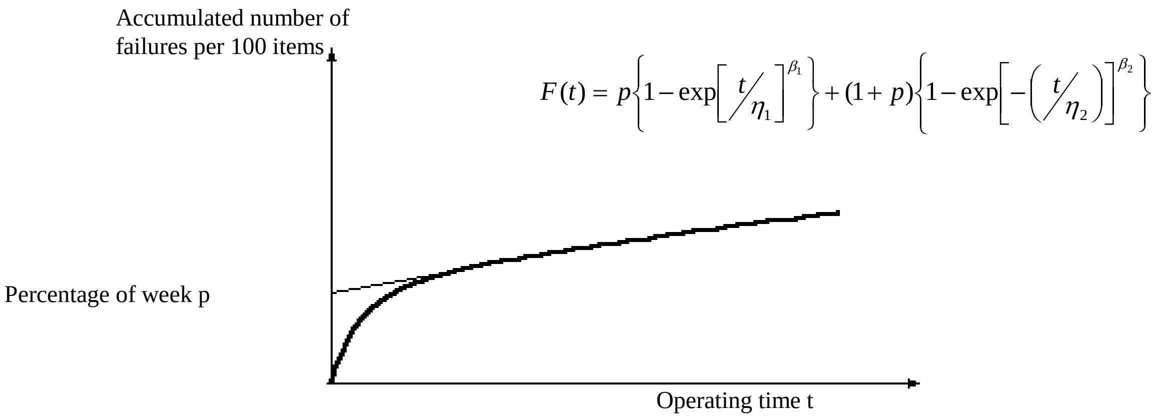

Fig. 1. Bimodal Weibull distribution

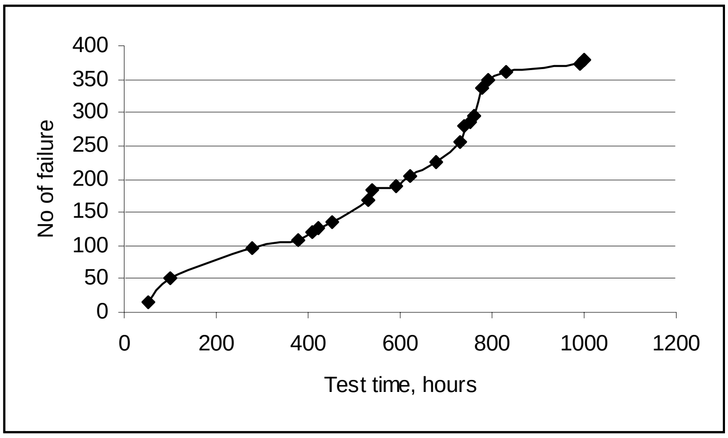

Fig. 2. M(t) curve for product 3 SW programme

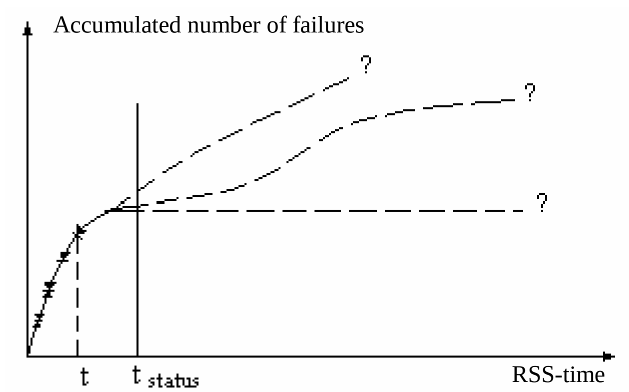

Fig. 3. How will the failure curve continue if the RSS is continued

The computation is based on the assumption that the failure development can be approximated by a bimodal distribution. The early failure parts of the bimodal distribution describe the time to failure for the weak (flawed) components by either an exponential distribution or a Weibull distribution. The strong (unflawed) population is also described either by an exponential or a Weibull distribution [5]. Since it is only need to remove the weak population it is only need to estimate the parameters of the weak population. It is can therefore assume that the strong population has a very long time to failure. But when it is not produce a large number of items, but only one or a few, it cannot make an extended test on a sample. It therefore has to take the decision during the screening process. As soon as it has not observed a failure for some time, it has to decide whether to continue the screening or stop it. Stochastic variances in the time between failures make this decision very difficult, as the curve over the accumulated failures as a function of time in practice often levels out temporarily as can be seen in fig.2.

The problem therefore is as illustrated in fig.3 to decide at the time A, after a failure free period of T_A to continue or to stop the test.

2. Possible Decision Algorithms

The aim was to find one or more algorithms that would allow a decision maker to decide at any time during the test or screening sequence whether to stop or continue screening. The algorithm should only require the information gathered from the start of the test/screening of a particular item until the decision point. We considered and tested the following possible decision algorithms:

1) Exponential distribution for estimating the parameters of the weak population

The simplest algorithm was to estimate the parameters of the weak population. If an exponential distribution of time between failures (TBF) is assumed we only need to estimate one parameter – lambda. This estimate can be updated for each new failure. Once the parameter for the distribution is updated, the time where certain percentages (for example 95%) of the weak population have failed can be computed. If this time has passed without a new failure, it can be assumed that 95% of the weak population has failed, and that maximum 5% early failures are left. This time therefore defines the failure free period that we need in order to decide when to stop the screening. When this failure free period has passed without any new failures, we stop the screening. If a new failure occur before the failure free period has expired, we update the estimate of lambda, and compute a new failure free period. The method is illustrated in tabl.1.Since the estimates of lambda vary much in the beginning, as we have only a few failures on which to base the estimate, we need to decide upon a minimum screening time, for example 168 hours (one week). We tested this decision algorithm.

Table 1

The Bimodal Method – Exponential distribution assumed

i	Test hours to failure, t_i	Estimated $1/\lambda$ (hours)	Stop time (hours)	Decision
1	3	3.0	13	t_i <168 h
2	38	20.5	94	t_i <168 h
3	42	27.7	127	t_i <168 h
4	5	33.3	153	t_i <168 h
5	70	40.6	186	t_i <168 h
6	127	55.0	253	t_i <168 h
7	167	71.0	326	t_i <168 h
8	247	93.0	428	Continue test
9	290	114.9	592	Continue test
10	1380	241.4	1111	Stop at 529 h
11	1554	360.7	1661	
12	1635	466.9	2150	
13	3422	694.2	3197	

2) Weibull distribution for estimating the parameters of the weak population

Choosing a two-parameter Weibull distribution to describe the weak population instead of the exponential distribution can modify the method described in *1*. The principle is the same, however. For each new failure a beta and eta is estimated for the weak population. Then we compute the time where the chosen percentage of the weak population has failed. This percentage can be for example 90%, 95% or 99% (see fig.4).

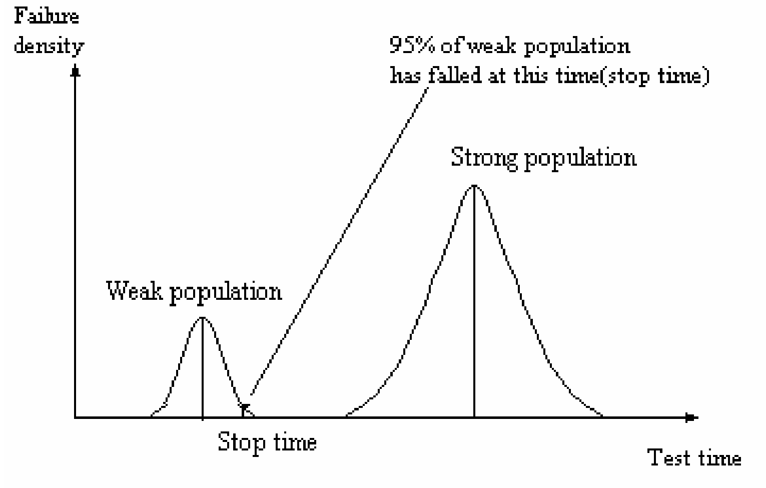

Fig. 4.Weak population

This time period defines the failure free period. If no failure has occurred for this number of hours, we stop the screening. If a failure occurs before this number of hours has passed, we update the estimate for beta and eta, and compute a new, updated failure free period. Also in this case we have to choose a minimum screening time to take care of the early fluctuations in the estimates. The method is illustrated in tab. 2.

Table 2

The Bimodal Method – Weibull distribution assumed

i	Test hours to failure, t_i	Estimated η_i (hours)	Estimated β_i	Stop time (hours)	Decision
1	3	2E96	202	2E96	t_i <168 h
2	38	17.0	.95	85	t_i <168 h
3	42	63.4	1.23	219	t_i <168 h
4	50	211.8	1.49	588	t_i <168 h
5	70	373.8	1.56	992	t_i <168 h
6	127	200.0	1.30	647	t_i <168 h
7	167	188.7	1.21	664	t_i <168 h
8	247	157.9	1.11	626	Continue test
9	290	169.3	1.08	700	Continue test
10	1380	42.7	.72	359	Stop at 529 h
11	1554	40.6	.66	404	
12	1635	45.0	.65	467	
13	3422	41.2	.61	513	

3) Graphical methods for M(t)-curve

It would be possible to plot the accumulated number of failure as a function of the screening time (see fig.2). When the curve levels out we should stop the screening. But the problem with this method is that it is very subjective. Further it is very difficult to judge if the curve has leveled out as illustrated in fig.3. The method was therefore rejected.

4) Graphical methods for Weibull curve

Just as with the M(t) plot described in *3* we could plot the accumulated percentage of failures as a function of the screening time on a Weibull probability paper. The problem here is that in order to compute the percentage of failures we need to know the total number of potential failures in the system. We can assume this number to be equal to the total number of components in the system. But since only a minor part of these can be expected to belong to the weak population the curve will be so small on the Weibull paper so that some scaling law will be needed. But since the method has the same disadvantages as method *3* it is also rejected.

5) Graphical methods for Weibull curve with confidence limits

In order to have objective decision criteria we could use the method shown on fig.5. As in *4* we draw a Weibull curve for the first failures observed. Like in method *4* above we use a scaling law to enlarge the relevant part of the curve. We then draw the 95% upper confidence limit (the so called Trumpet curve). In the example in fig.5 we have plotted 4 failures. We now continue screening waiting for failure no. 5. When failure no. 5 eventually occurs we know the y-ordinate where we will have to plot it (the accumulated percentage of failures equal to 5 failures). What we do not know yet it the time when failure no. 5 occurs. If however failure no. 5 occurs later than the 95% confidence limit we know that there is below 5% probability that failure no. 5 belongs to the weak population defined by the first 4 failures. We would therefore choose a stop time equal to the time from failure no.4 until the point where the y-ordinate for failure no. 5 intersects the 95% confidence curve.

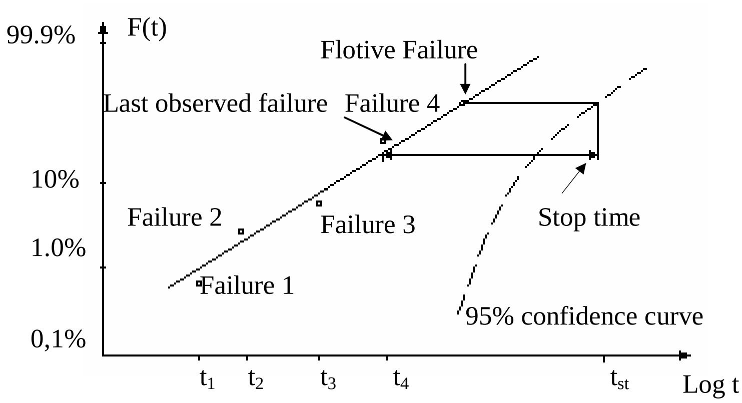

Fig. 5. The rank method

6) Markov-Chains

This method was used in [4]. It describes the probability of a weak component failing before the stop time being repaired by a "strong" component. The method operates with a transition matrix. For a single system, which can easily have up to 100 weak components, the method was deemed too complicated, even when using a computer program.

7) The Bayes method

This method was used in [4] to compute the probability that a failed component belongs to the weak population or to the strong population. The method therefore seemed very promising. But a test showed that the method resulted in a stop time that was too long (see fig.6). The reason can easily be seen if we

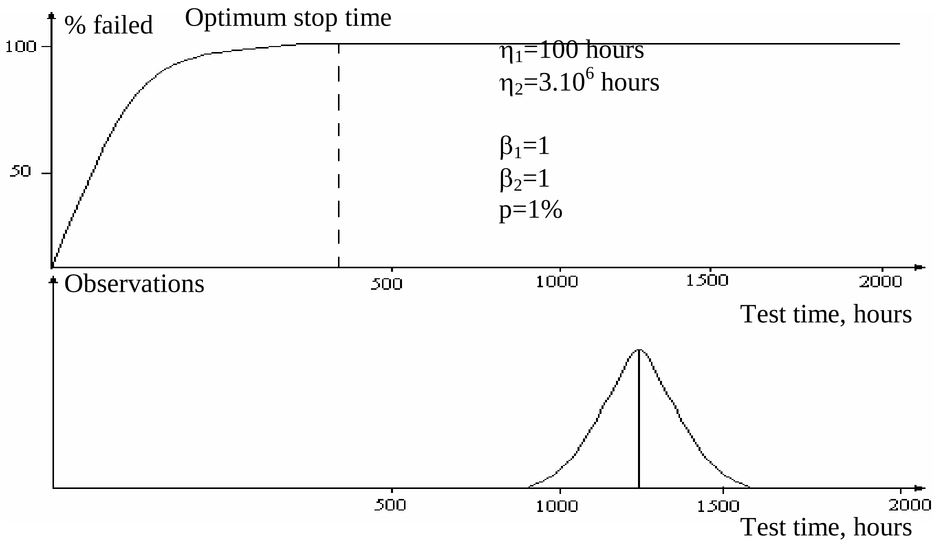

Fig. 6. Bayes' method

assume that we stop testing when the probability that a failure belongs to the weak population is 50%. In this case we stop screening at the point in the middle of the life time for the weak, and the strong population. Since the strong population usually has a very long life time, then half this time is also a very long time. To choose another percentage than 50% did not seem logical or promising. Therefore, the method was rejected.

The result was that of the proposed methods only method 1, 2 and 5 was selected for further testing.

3. Conclusions

In order to check the performance of the three selected algorithms and compare their efficiency we decided to run a simulation programme.

If the performance of the system were simulated, we would know the correct stop time. We simulate the system as a bimodal distribution consisting of a weak population and a strong population (see fig.4). Since we know the exact parameters of the weak population we can easily compute the time where 99% of the weak population have failed (see fig. 4). An example of such a bimodal distribution is shown on fig. 7. The correct stop time is shown with the vertical dotted line.

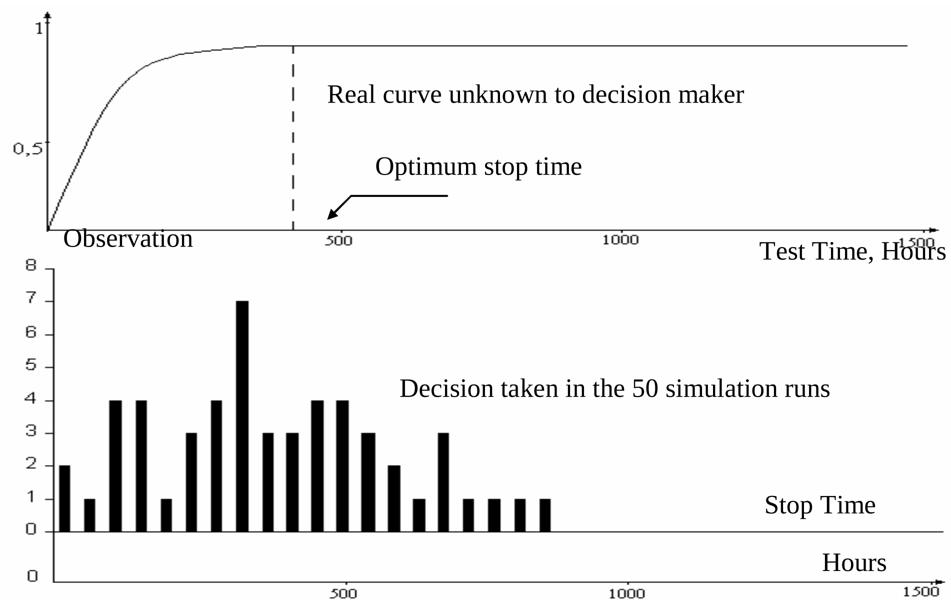

Fig. 7. An example of a bimodal distribution

But the decision-maker does not know the parameters of the distribution, but only the time to failure of the first failures in the sequence. Due to the stochastic character of the actual time to failures we have to create a number of sequences of failures in order to test the algorithms.

The procedure was therefore that a Monte Carlo program was used to create the time to failures for a sequence of failures based on the bimodal distributed system parameters. After each failure the decision algorithms were used to decide if the screening should stop or continue. The stop times of the algorithms then could be compared with ideal stop time as shown as the dotted line on fig.7.

Our conclusion is that the best algorithm is no. *1* the exponential distribution with *2* the Weibull distribution as the second best. Algorithm *5* Graphical Weibull with confidence limit is not useful.Based on these results the conclusion is that when we have very limited data it is more efficient to estimate one parameter (lambda) with a fair degree of confidence than to estimate two parameters (beta and eta) with a higher degree of uncertainty.

It was decided to test the two best algorithms on a large number of real data sets. We collected a large number of time to failures from testing of large hardware-software systems. The data was obtain from a Bulgarian companies. In this case it was found that the best algorithm is the Weibull algorithm with 90%

confidence. This algorithm is right in all cases, while we for 95% and ((% confidence level have a number of wrong decisions. We can also see that the exponential algorithm has a larger number of wrong decisions for all confidence levels.

1. *Quality and Reliability, Fairchild Semiconductor, 2002.*

2. *Andonova, N. Atanasova, Some Methods of Derivation for Electronic Products Test Target Requirement, Proceedings of the 32nd Int. Scientific Symposium of the Defense Research Agency, Bucharest, 12-13 April, 2001, pp. 109-113.*

3. *IEC 61163-1 Reliability Stress Screening – Part 1: Repairable items manufactured in lots, 1995-08.*

4. *Jensen F., Petersen N. Burn-In, An Engineering Approach to the design and Analysis of Burn-In procedures, John Wiley&Sons, London 1988 (in Bulgarian).*

5. *Atanasova N., Farkov G., Andonova A. Automatic estimation of the parameters of the distributions, Proceedings of the 7th International MTM Symposium, sept.,2003, pp-39-44.*

УДК 004.582

В.В. Григор'єв, Р.Т. Панчак
Національний університет “Львівська політехніка”,
кафедра електронних приладів, Львів, Україна

ПРОБЛЕМИ ДОКУМЕНТУВАННЯ РОЗРОБОК ПРИСТРОЇВ ЕЛЕКТРОННОЇ ТЕХНІКИ В СУЧАСНИХ САПР

Проаналізовано проблеми формування конструкторських документів для друкованих плат пристроїв електронної техніки в сучасних САПР та розглянуті шляхи їх вирішення.

The problems of formation of design documentacion for devices with PCB in modern CADs are analized, solutions are proposed.

Вступ

Результатом будь-якого процесу проектування є виготовлення конструкторської документації (КД) на виріб, що проектується [1–2]. Автоматизація розробки КД – це одна з галузей автоматизованого проектування, що найширше і ефективно використовується у практиці. Поясненням цього служить, з одного боку, висока трудомістість і рутинний характер розробки КД, а з іншого – можливість його формалізації і алгоритмізації .

Специфіка електронної техніки (ЕТ) полягає в поєднанні "механічної" (корпусів, панелей тощо) та "електронної" частини (друкованих плат, мікрозборок тощо) виробів. Для проектування "механічної" частини найчастіше використовуються системи автоматизованого проектування (САПР) AutoCAD та КОМПАС, "електронної" частини – OrCAD та ACCEL EDA (PCAD). Сьогодні все поширенішою стає думка, що проектування виробу ЕТ загалом повинно виконуватися в єдиному інформаційному просторі із застосуванням єдиних баз даних [3]. Крім цього, такі системи, як OrCAD, ACCEL EDA та PCAD, не забезпечують випуску потрібного комплекту конструкторської документації відповідно до вимог Єдиної системи конструкторської документації (ЄСКД), яка нині є чинною на території України, та Державним стандартам України.

З цієї позиції є актуальним аналіз наявних проблем документування розробок пристроїв ЕТ в сучасних САПР та способів їх вирішення. Проблеми документування розробок пристроїв електронної техніки розглянемо на прикладі друкованих плат (ДП).