Reliability Prediction of the Electronic Products

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Abstract - **The electronic products' (EP's) technical condition forecasting requires that a future efficiency evaluation should be done using the diagnostic results from past moments of time. The paper analyzes an application of one of the most topical prediction methods of the reliability – the pattern recognition method. It is developed a system of principles and criteria of determining the relationship of a specified electronic product with one of the preliminary identified product classes.**

Index Terms - **Information parameters of reliability prediction, Reliability forecasting**

I. THEORY

The EP's condition forecasting need comes from the fact, that these products are subjects of outer influence in the process of handling and exploitation. This influence results in a components' technical condition change and eventually leads not only to a components failure, but to a failure of the systems, built of these components. The failure consequences for a technical system can be exclusively dangerous, that's why preventing from failures using EP's technical condition forecasting takes a significant part in system reliability bettering. Using the forecasting methods the future EP's efficiency for a defined time interval can be evaluated, the exploitation time can be defined and the technical test time can be decreased.

Coit [1] and Johnson and Gullo [2] analyzed system reliability forecasting prioritization strategy and prediction methodology. Gedam and Beaudet [3] accomplished Monte Carlo simulation using "Excel" spreadsheet for forecasting reliability of a complex system. Mok and Ten [4] considered a review of plastic-encapsulated-microcircuit reliability prediction method.

The pattern recognition method is to be the most perspective one for the EP's reliability parameters forecast. Two approaches are used in the pattern recognition: *probability* and *determined*. In the probability approach the solution is based on the supposal that the pattern distribution in the general combination is granted, and these distributions coincide with the theoretical distributions. For the determined approach the general combination distribution is accepted to be the same as the distribution in the training extract.

As this paper about electronic components, it is reasonable to formally define what is understood by a component or part. The two words may be used interchangeably. We will use the definition proposed by ESA: a component is a product that performs an electronic, electrical or electromechanical function and consists of one or more elements so joined together that they cannot normally be disassembled without destruction.

In all field failure reports a significant number of no-defect-found (NDF) are recorded on components returned for laboratory testing. The percentage may very from 10-80%, illustrating one of the difficulties in obtaining reliable field failure data in the first place. The expression no-faults-found or no-failures-found (NFF), no-trouble-found (NTF), could-not-duplicate (CND), or retest O.K. are used variously with NDF for these situations. The pie-charts address only the components with verified failures. Some of the results reported a group of 'unidentified' failures [5].

It seems that the distribution between intrinsic and extrinsic failures is fairly even for integrated circuit. Both classes of failure should therefore be considered in any attempt to improve the field reliability of the components. However, it is also necessary to realize that the field studies did not indicate whether the recorded failures belonged to the early failure period, the useful life period, or the long-term wearout. Whilst most of the long-term wearout failures very likely are intrinsic, present day evidence strongly suggests that the majority of the early and useful life period failures in fact are extrinsic.

It is important to mention that hazard rate curves normally demonstrate the intrinsic reliability of the components, that is the reliability or lifetimes associated with intrinsic failures. They show the failure patterns that evolve under a constant set of operating and environmental conditions, such as would be used in a lifetest. The components used in such lifetests have not at this point been subjected to the destructive or damaging events associated with higher levels of assembly and handling.

Very briefly, the early life period often exhibits a fairly high hazard rate. Sometimes the hazard rate shows one or more humps before it finally attains a low, decreasing pattern [6]. Sometimes the early life hazard rate decreases continuously from the very beginning In either case, the underlying cause is the existence of comparatively large built-in defects that quickly grow in size until a failure (usually a short or open circuit) occurs [7]. The term intrinsic infant mortality failures are used to describe these early life failures.

The early life period can under normal operating conditions vary from tens of hours to many thousands of hours.

When in a population of like components, the early life failure have surfaced, the failure pattern enters its low hazard rate period the useful life period. In effect, the intrinsic hazard rate can be zero in this period. If failures do occur, the cause is quite often that there is a tail of early life failures ('residual' failures) caused by defects of an 'intermediate' size. Additionally, failures in the later part of the useful life period will very likely be caused by an early tail of the long-term wearout distribution.

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The duration of the useful life period is normally very long for electronic components working under field conditions. One possible criterion for determining the extent of the period is to define it as the 1% percentile lifetime (or some other percentile) after any infant mortality type failures have been eliminated. Another possible criterion is to determine it as the lifetime corresponding to a certain hazard rate value (popularly called a FIT-rate) in the first tail of the wearout distribution. The value of 10 FIT has on occasion been used as a criterion. Useful life periods well above 50 years would not be unusual (beds on results of accelerated lifetimes). However, new technologies with extremely small geometries may possibly have useful life periods of less than ten years.

Although hazard rate curves normally are associated with the intrinsic reliability of components, it is quite feasible to have similar plots for the composite reliability, in other words 'the end results', which is the combination of the intrinsic and extrinsic failures. In order to generate a plot of extrinsic reliability we would need to keep track of a sample of like components being used in a certain system. They would all go through the same handling and assembly procedures and be installed in the same end-use environments. Most components in the sample would come through unscathed, whilst some might have been subjected to electrical overstress, been dropped on the workbench or on the factory floor, been overheated through careless use of a soldering iron, or received some other form of stress that can have weakened them. It is very likely that these weakened components will give rise to an extra number of early failures. These additional early life failures are called extrinsic infant mortality failures, as they have been born by circumstances extrinsic to the components [8].

The purpose of the reliability prediction is to separate all the elements, characterizing with high infant mortality failures (faint elements)from reliability(strong) elements

II. PROBLEMS OF THE RELIABLE PREDICTION BY THE ELECTRONIC PRODUCTS

The successive application of the pattern recognition method strongly depends on the proper choice of information parameters. The outgoing combination of characteristics often is too big, but for an effective method application a small number of important characteristics enabling the dividing of one pattern from another is to be used. That's why choosing information parameters is a important deal, on which the pattern recognition method realization depends.

In the forecast algorithm based on the pattern recognition method using the information obtained in the $t_0,t_1,t_2,...,t_i,...,t_n$ time moments a reliability level forecast in the time moments $t_{n+1},t_{n+2},...,t_{n+i},...,t_{n+m}$ is done.

The succession of actions is the following: the initial parameters of the components from the general combination are measured; the training extract is chosen from the component combination; the extracted components are reliability tested in the time interval t_{n+m}; the actual no-failure time t_f is determined for every component from the training extract; the components are devised by classes depending on the t_f and t_{n+m} ratio: class $R^{(1)}$, gathering the components for which $t_f \geq t_{n+m}$; class $R^{(2)}$ gathering the components for which $t_f < t_{n+m}$.

The solution rule chosen is based on the initial parameters measured in the t_0=0 moment evaluation, and the results from the the test (the information for the parameters in the $t_1,t_2,...,t_i,...,t_n$ moments) . Basing on the solution rule, the timing is forecast for every component from the combination and the component is classified to class $R^{(1)}$ or class $R^{(2)}$. After the individual forecast, extracts from the general combination from class $R^{(1)}$ and class $R^{(2)}$ are being tested. The solution rule can be corrected basing on the results of the last test. Regarding a more precise forecasting an information for the parameters in intermediate moments of time is added to the information for the parameters in the initial moment of time. In addition, priory data from the component exploitation in real conditions can be used applying Bayes methods.

The theory of recognition must supply solutions for the following subjects: decreasing the number of information parameters and thus decreasing the expenses for "burn-in", without increasing the failure probability in determining of the present and future EP's conditions; determining level of discretization of information parameters and the kind of their approximation, which places new requirements to the measurement (for decreasing the price or increasing the accuracy); extraction from the information parameters of new, less and more informative parameters; choice of corresponding diagnosis procedure, ensuring the best system operation possible; burn-in of the diagnosis procedure basing on the data from the training extract, on expert data, on literature data or from similar objects; choice of forecasting algorithms, which mostly correspond to the inner structure of the problem.

For a good dividing of the classes, and for avoiding mistakes which can be done while deciding the class of the component, the pattern recognition methods take use of a powerful mathematical set of methods. Unfortunately the subjects of procedure optimization are not fully researched yet.

III AN INFORMATION PARAMETERS OF THE METHOD FOR RELIABLE PREDICTION BY THE ELECTRONIC PRODUCTS

In the present article a method for optimization of the number of information parameters in EP's reliability forecasting based on the pattern recognition method , is developed and layed out. Regarding this a sample EP multitude $G=\{\tilde{O}_1,\tilde{O}_2,\ldots \tilde{O}_j,\ldots \tilde{O}_m\}$ is taken observed on the out of the production process. The condition of every component X_j from this multitude is described by a set of parameters $x_1^{\,1},x_2^{\,1},\ldots,x_i^{\,1},\ldots, x_h^{\,1}$; $x_1^{\,2},x_2^{\,2},\ldots,x_\mu^{\,2},\ldots,x_p^{\,2}$; $x_1^{\,n},x_2^{\,n},\ldots,x_b^{\,n},\ldots,x_f^{\,n}$, where n is the number of the parameter groups, and h, p, f – the number of parameters in the groups. The number of the components corresponding to the desired reliability level is r and these components build the $R^{(1)}$ class, and the rest (m-r) components do not meet the requirements of the desired reliability level. These components build the $R^{(2)}$ class. We look for an algorithm allowing classifying with a desired accuracy A of the outgoing from production components with a minimum information parameters number. This is an important problem when developing the diagnosis algorithms and it is successive solution is a premise for a significant decrease of calculation difficulties when keeping the recognition quality.

In the sample multitude G the sub-multitude $R^{(1)}=\{X_1,\ldots,X_\alpha,\ldots,X_r\}$ and the sub-multitude $R^{(2)}=\{X_{r+1},\ldots,X_\beta,\ldots,X_m\}$ are contained. Components from the sub-multitude $R^{(1)}$ are X_α, $\alpha \le r$, and elements of the multitude $R^{(2)}$ are X_β, $r < \beta \le m$. The division of the multitude G in the two sub-multitudes listed is done according to the criteria B(X) expressing the set of technical requirements to the information parameters. The criteria B(X) can be assigned according to the technical conditions. It can be assigned by intuitive manner – on the base of priory data and results and can express the opinion of a specialists group. It can be assigned and after making the necessary tests with a fixed duration and test conditions. In practice the use of Bayes's method for combining priory and posteriori information is appropriate.

The correlation between the $y_1^{\,1},\ldots y_k^{\,i},\ldots y_f^{\,n}$ parameters and B(X) criteria is expressed with the grouping symbol for the sub-multitudes in a multitude given:

$$B(X) = \operatorname{sign} G\{X\}=\operatorname{sign}\sum \xi_k^{\,i} y_k^{\,i} - \eta\ , \qquad (1)$$

Where: $\xi_k^{\,i}$ is the corresponding to $y_k^{\,i}$ weighting coefficient, which expresses the information importance of the parameters' group when recognizing every failure from the no-failure conditions class, and η is the classifying threshold chosen.

The level of non-conformity Ψ between to left and right part of (2) when decreasing the number of parameters' groups must not exceed an accuracy A, with which the ready Eps have to be classified, i.e. $\Psi \le A$.

The iteration procedure for minimizing the number of information parameter groups ends when reaching the limit condition when the upper inequality is yet true. Every iteration cycle differs from the past one with the fact that the number of information parameters groups decreases by one.

In the second particular problem a further information parameters number minimization is done while regarding the kind of the statistical law by which the values of these parameters are distributed. The multitude of possible values of every parameter is divided by l number of sub-multitudes (levels of quantization). The accuracy of this way expressed information parameter is determined by the number of levels of quantization. For the different information parameters a different level quantization number can be chosen.

When decreasing the number of the information parameters a so called principle of dynamic component arrangement in the sample multitude. For every particular parameter weighted coefficients can be formed, which appropriate would be determined by the level of fulfillment of independence and normality hypothesis. Using the algorithm an optimal solution rule can be derived according to the Ψ criteria:

$$\Psi=\sum_{\alpha=1}^{r}\left[1-\operatorname{sign}\left(\sum \xi_{k\alpha}{}^{i} y_{k\alpha}{}^{i}-\eta\right)\right]+\sum_{\beta=r+1}^{m}\operatorname{sign}\left(\sum \xi_{k\beta}{}^{i} y_{k\beta}{}^{i}-\eta\right). \qquad (2)$$

We should find such $\xi_1 \div \xi_m$ and η, for which function (2) has a minimum. The choice of the threshold is such, so all the elements, from a sub-multitude should be classified correctly, i.e. non-of the elements of the one sub-multitude, f.e. $R^{(2)}$ should not be among the elements of the other sub-multitude, in this case $R^{(1)}$. In this way the "user's risk" can be moved to zero. In the reverse way the "user's risk" can be moved to zero if non of the elements from the sub-multitude $R^{(1)}$ is not among the elements from $R^{(2)}$. For optimizing of the industrial production of Eps a significant importance has the possibility of regulating the levels of the two "risks" upper pointed. In the choice of weighted coefficient, for every next tuning step the angle of displacement of the hyperplane dividing the two patterns decreases.

The obtained with this algorithm results strongly coincide with the basic hyperplane. For achieving of this coincidence with the basic hyperplane is enough to work with the elements from the one sub-multitude $R^{(1)}$ or $R^{(2)}$. In the first case, part of the elements $X_\beta \in R^{(2)}$ may be classified incorrectly ("null-risk" for the user), and in the second case part of the elements $X_\beta \in R^{(1)}$ may be classified incorrectly ("null-risk" for the user). The experiments made with this algorithm show good combination of the high coincidence speed with the necessary accuracy of the obtained solution.

IV. CONCLUSIONS

During the last few years the reliability of integrated circuits and other semiconductors has improved significantly chiefly because the markets supplied by component manufacturers have demanded a greater degree of assurance that the products they use demonstrate a longer and more effective life. The percentage of dead on arrival supplies received has become less and the pressures on goods inwards testing procedures have, to some extent, been reduced. Nevertheless, screening, including burn-in, or rescreening of devices supplied as 'high rel' components remain an important discipline in the manufacture of electronic assemblies.

Early failures, also known as 'infant mortalities', and the concern for extended life in components, therefore, continue to exercise the minds of those companies whose products are required to provide, in use, long mean time between failures with extended operation in the field. The reliability of components and the constant availability of the assemblies they drive have an obvious effect upon the status and ranking of the assembly manufacturer as well as his reputation and, in cases of massive failure, the very existence of the company could be threatened.

Some real tests of semiconductor components and a reliability forecast with the examined algorithm have been made, and as a result the function between the authenticity level of the prognosis P_k and the number the information parameters and the time for the burn-in (Fig. 1).

The results of the tests made lead to the following conclusions:

- The application of the developed algorithm strongly decreases the duration of the burn-in. In the limit condition this duration can be move to zero whit taking some risk from the producer's side and no risk from the user's side – the probability for appropriate components classification even in one-time parameter measurement cantons 14 % risk for the producer and null risk for the customer.

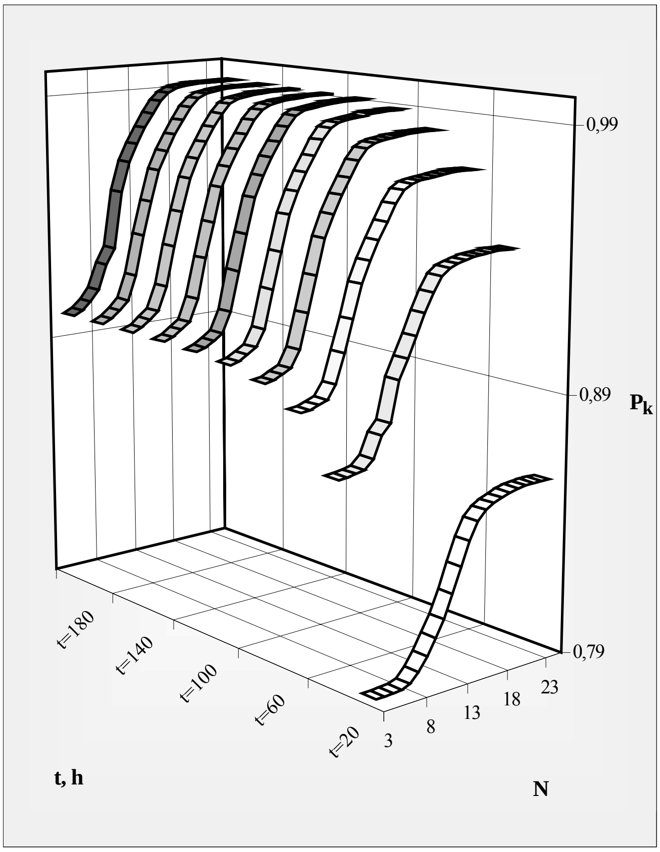

Fig.1 The prediction authenticity level in function of the number of information parameters and the time for the burn-in

- The developed algorithm gives a possibility for evaluation of the importance of the information parameters. Basing on this evaluation a reasonable choice of information parameters for different EPs types can be made without additional expenses.

All the measured parameters influence on the accuracy of the prognosis. The influence level of the different parameters is different

- The developed algorithm applied in the EPs reliability forecast gives opposability for sorting the elements not only in to classes – "faint" and "strong", but to a bigger number of classes. Every of the so classified elements is characterized with a definite value of the mathematical expectation for the mean time-to-failure, therefore it characterizes with a definite value of mathematical expectation for the rest reliability parameters $\{\lambda(t), P(t), Q(t)\}$.

The authenticity of the obtained function is confirmed from the exploitation test made to a big number of elements mounted in Multiplexer Telephone Systems УТС 100.

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