Adaptive Clustering for Distribution Parameter Estimation in Technical Diagnostics

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Abstract: A novel approach has been introduced to estimate the parameters of exponential and DN distributions during the rejection testing of electronic devices, accompanied by a detailed procedure for its implementation. This innovative method enhances noise immunity and minimizes the error associated with the rejection process through the application of a clustering technique involving wavelet transform. The effectiveness of the method has been verified using resistors, employing criteria such as noise level and stability. The substantial improvement in noise immunity and the reduction in rejection procedure errors are achieved by incorporating an adaptive clustering method coupled with wavelet transform. Notably, in clustering with a signal-to-noise ratio by amplitude of 1.17, the relative error in determining the minimum of the test function was reduced to 8.32%. These promising outcomes substantiate the recommendation of the developed method for the automated selection of resistors, particularly those designated for long-term operational equipment with critical applications. The presented method thus contributes significantly to enhancing the reliability and accuracy of electronic device testing and selection processes.

1 INTRODUCTION

Automated Systems for Technical Diagnostics (ASTD) in the production of electronic components (EC) are utilized to address various tasks, including the assessment of reliability parameters. Given the current state of electronics characterized by increased multifunctionality and miniaturization of EC, information in such systems is presented as multidimensional arrays of correlated parameters. The application of ASTD for evaluating reliability parameters of complex EC is indispensable.

During EC production, it is often necessary to select more reliable components, requiring the choice of a reliability assessment model and estimation of its parameters. In cases where the impact of sudden failures needs evaluation, the assessment often involves a single parameter – the failure intensity of the exponential distribution λ. The accuracy of reliability parameter estimation is enhanced by employing two-parameter distributions, such as the two-parameter DN-distribution [1-4].

The duration of accelerated tests is significantly shorter than the actual durability of EC. Due to the high reliability of EC, these tests are conducted until failure occurs in a small portion of the sample, resulting in substantial error. The source of this error is the high variance of the distribution DN parameter estimates, further exacerbated by the noisy reliability data (objective and subjective errors in collection and recording).

In such studies, for instance, during accelerated tests of complex EC for durability, it was revealed that the failure intensity has a bimodal nature (the first peak characterizes failures of anomalous complex EC, and the second – failures of the main part of the sample); meanwhile, the mean time to failure for these groups may differ by four orders of magnitude [5]. In such situations, when screening potentially unreliable EC, it is necessary to enhance robustness and reduce the error in separating the batch of EC into two groups.

The state of EC during screening is described by the values of their parameters, which vary from object to object and over time during testing. When there are many correlated parameters, automated approaches are applied for EC separation, implemented using one of the pattern recognition methods – statistical classification. Such classification consists of two stages: clustering and classification. Clustering methods are used to group EC into clusters with common properties and varying degrees of monotonic dependence of controlled parameters on operating time. Assessing the rate of change of cluster parameters is possible using an adaptive approach, where initial cluster center parameters are determined from the analysis at a previous time.

EC is divided into clusters based on the compactness of parameters through quality functional optimization. The optimization method is chosen considering the properties of this quality functional, which may not be explicitly known and may possess a multi-extremal, noisy surface due to screening being performed on small samples. Clustering methods based on gradient search do not provide sufficient robustness under these conditions. It is proposed to apply adaptive clustering using wavelet transformation (WT), allowing for low-error clustering in the presence of high data noise and small sample sizes [6].

2 PROBLEM STATEMENT

The purpose of this work is to develop a method for determining the parameters of the exponential and *DN* distributions for reliability estimation of a batch of electronic components (ECs) to improve noise immunity and reduce the error of automated rejection in ASTD using adaptive clustering with the use of wavelet transform (WP) and the procedure for implementing this method.

3 CHALLENGES IN SCREENING WITHIN ASTD

The creation and use of information technologies and automated systems for technical diagnostics in the production of electronic products are largely determined by both the capabilities of obtaining and processing the information necessary for diagnostics, as well as the availability of methodological foundations that allow making decisions based on this information. ASTD in electronics are used to solve various problems, including the estimation of reliability parameters. Since the current state of electronics is characterized by an increase in the multifunctionality and miniaturization of electronic components (ECs), the information in such systems is presented in a complex form, in the form of multidimensional arrays of correlated parameters. The use of ASTD for complex ECs has no alternative. In the course of their operation, ASTD use procedures for the formation and processing of information that allow making a decision about the degree of compliance of the object's parameters with the requirements of normative technical documentation and, if necessary, to form the corresponding control actions during production. It is for this reason that reducing the error of the decisions made in ASTD, especially in the case of selecting reliable ECs, especially for applications where the cost of an incorrect decision is high, is a rather important task.

The scope of application of such systems for the selection of reliable ECs is limited by a complex of contradictions. On the one hand, the growth of the quality characteristics of information formation and display systems of ASTD is due to the high cost of their hardware (testing systems, precision mechanics, and optics). On the other hand, the rapid improvement of the element base and assembly technologies is the reason for the growth of the number of organizations focused on small-scale, pilot production, and prototype production, for which the use of such ASTD is limited for economic reasons. The reduction of the product life cycle in electronics requires reducing the time for control and diagnostic operations when selecting reliable ECs, which necessitates conducting such operations on small data samples, increasing their noise; the noise of data in ASTD also grows due to interference in communication channels, uneven temperature changes of the object or sensors, etc., and the decision-making procedures in ASTD based on gradient iterative algorithms of successive approximation are characterized by low noise immunity. In connection with the growth of the complexity of electronic equipment to ensure the safety systems of various industries, the requirements for its reliability are growing. On the other hand, the diagnostic decision-making procedures developed on the basis of noise-resistant iterative algorithms of successive approximation are characterized by high error. In addition, there are no methodological foundations that allow, on the basis of existing methods for choosing reliability distributions and estimating their parameters, to increase the degree of automation of the selection of reliable ECs.

Most often, in the case when it is necessary to estimate the reliability in the absence of running-in failures or when the aging phenomena are assumed to be insignificant, the reliability of ECs and devices based on them is estimated using the exponential distribution. This approach simplifies the processing of experimental results, which is essential in cases where, for technical, economic reasons, or due to lack of time, it is impossible to conduct tests for complete samples of large volumes. For this distribution, the probability of failure-free operation over the given interval $(t,\ t+\tau)$ does not depend on the time of previous operation t, but only on the interval τ. That is, if it is known that the EC is in working order, then its future state does not depend on the past. This model takes into account, mainly, sudden failures of a random nature, while failures that occur as a result of irreversible physicochemical changes in the parameters of the EC do not obey the exponential law. Therefore, the use of the exponential failure model in the experimental evaluation and prediction of the reliability of ECs makes this estimate approximate and leads to significant errors. The exponential distribution has one parameter – the failure intensity λ, which does not change over time. The assumption of the constancy of λ over time increases the error of reliability forecasts compared to two-parameter distributions. Therefore, it is recommended to use the exponential distribution to conduct a relative reliability assessment at the stage of conceptual design, when it is necessary to evaluate the reliability of various options, and on the basis of their analysis, choose the element base.[3]

To identify and remove ECs with actual and potential failures from a finished batch before delivery to the customer, rejection tests are carried out at the final control. To assess the compliance of the selected ECs with the customer's requirements, their reliability parameters are usually evaluated in the process of accelerated censored tests. In the course of such tests, during the analysis of degradation processes leading to EC failures, it was revealed that they have a random nature, and the change of these processes has both monotonic and non-monotonic character. For example, complex ECs, such as integrated circuits (ICs), are simultaneously exposed to the influence of many factors. These factors, uncorrelated and correlated with each other, form the overall process of IC degradation. The parameters of degradation processes, exceeding which certain values can cause a failure of an IC component, have different physical nature: accumulation of dislocations, plastic and elastic deformations, fatigue mechanical destruction, electrochemical corrosion, generation and movement of charges on the surface of a semiconductor crystal, etc. [1, 3].

A comparative analysis of probabilistic-physical distributions that take into account the physical processes leading to failure is presented in [3]. Based on this analysis, the calculated reliability estimates of such complex ECs as ICs, based on the results of accelerated tests, have an error of no more than 10%, if the two-parameter diffusion DN distribution is used as a failure model, corresponding to a non-monotonic Markov process [1, 4]. In the case when it is not possible to establish the prevailing degradation processes leading to failures, it is also recommended to use this distribution for objects consisting of ECs [4].

4 ESTIMATION OF DISTRIBUTION PARAMETERS

The task of estimating distribution parameters in the reliability assessment of electronic components (EC) is as follows. Suppose there are N objects (EC), each characterized by a set of k parameters. Vector $x_j(t) = \left(x_j^1(t), x_j^2(t), \dots, x_j^k(t)\right)$ characterizes the state of the j-th object at time t. This means that the mutual arrangement of the set of points $x_1(t), \dots, x_N(t)$ in the k-dimensional parameter space X reflects the real classification (grouping by parameters over time) of the studied objects. To identify this structure, the cluster analysis with WT [6] is used.

Using this method, at the time of rejection t_1, the separation of n points in the X space into 2 classes (clusters) is performed. The concept of the cluster center $a_i(t),\ \ i = 1, \dots, r$ is introduced.

At time t_2, each point $x_j(t_2)$ is classified into one of the classes obtained at the first step. Then, the values of the cluster centers $a_i(t_2),\ \ i = 1, \dots, r$ are recalculated and the distances between the points $x_j(t_2)$ and the new centers $i = 1, \dots, r; j = 1, \dots, n$ are calculated. This procedure is performed for all m time points.

At the next stage, the failure intensity λ is estimated for each of the two groups [4]. The equivalent device hours (EDH) are calculated for each cluster of ECs. The failure intensity is defined as $\lambda = \frac{r}{EDH}$. Here, r is the number of ECs that failed during the test time.

Then, the parameters of the DN-distribution are estimated for each of the two groups [4, 8]:

$$F(t) = DN(t; \mu, \nu) = \Phi\left(\frac{t-\mu}{\nu\sqrt{\mu t}}\right) + \\ + \exp(2\nu^{-2})\, \Phi\left(-\frac{t+\mu}{\nu\sqrt{\mu t}}\right)$$

where μ is the scale parameter, which coincides with the expected value of the random variable t; ν is the shape parameter, which is equal to the coefficient of variation of the distribution of the variable t.

The proposed method was tested on a sample of resistors [7]. The noise level and the expected value of the resistance change in the groups were used as predictive parameters. The data from the first control (after 24 hours of operation in the loaded mode) were divided into two clusters using adaptive clustering: the first cluster included groups from 1 to 8, and the second cluster included group 9, based on the noise level [8, 9].

The calculated failure intensities were $\lambda_1 = 0{,}35\times10^{-5}$ hour^{-1} in the absence of rejection, $\lambda_2 = 0{,}19\times10^{-5}$ hour^{-1} for resistors of the first cluster, and $\lambda_3 = 0{,}19\times10^{-5}$ hour^{-1} for resistors of the second cluster.

Furthermore, the coefficients of variation of the diagnostic parameter, the expected value of the resistance change, were calculated for the first, second cluster, and the entire sample of resistors without rejection, using the formula.

$$\nu_j = \frac{\sqrt{n}}{\sum_{i=1}^{n}\Delta x_{ji}}\sqrt{\sum_{i=1}^{n}\left(\Delta x_{ji} - \frac{1}{n}\sum_{i=1}^{n}\Delta x_{ji}\right)^2},$$

where $\Delta x_{ji} = x_{ji+1} - x_{ji}$, index j corresponds to the cluster number j=1,2 or j=3 for the entire sample of resistors; index i corresponds to the time point (operating time) $t_i = (i = 1, 2, \dots, n)$.

The intervals between measurements $\Delta t = t_{i+1} - t_i$ were taken to be non-uniform (the expected value of the resistance change was determined after 24, 168, 1000, 5000, and 10000 hours after the start of measurements) [8]. Further, according to the methodology [4], taking into account that the values of ν_j were ν_1=1.38, ν_2=1.43, and ν_3=1.55, the scale parameters are estimated by solving the equation.

$$F_j(t_i, \mu_{ji}, \nu_i) = \widetilde{F_j}(t_i), \tag{1}$$

where $\widetilde{F_j}(t_i) = \frac{i}{N}$, $(i = 1, \dots, r)$; i - failure number in the corresponding cluster $(i = 1, \dots, r)$; t_i – is operating time of the i-th failed resistor, since the exact time of failure is not available [8], the right boundary of the time interval during which it failed was considered as the moment of failure in the calculations.

The average estimate of the parameter $\overline{\mu_J}$ for each of the three groups of resistors was determined as

$$\overline{\mu_J} = \frac{1}{r}\sum_{i=1}^{r}\overline{\mu_{J\iota}},$$

where $\overline{\mu_{J\iota}}$ - results of solving (1) at $(i = 1, \dots, r)$.

As a result, the calculated values of the average operating time to failure using the DN distribution were 4,8 years in the absence of rejection, 7,5 years for the resistors of the first cluster, and about 2 years for the resistors of the second cluster.

5 CONCLUSIONS

A method has been developed for determining the parameters of the exponential and DN distributions for the rejection testing of electronic components (ECs) and a procedure for implementing this method. The method was tested on the example of rejecting resistors based on noise level and stability. The improvement in noise immunity and the reduction of the error of the rejection procedure is achieved by applying the method of adaptive clustering with the use of the VP (the relative error in determining the minimum of the test function during clustering with the signal-to-noise ratio by amplitude of 1.17 was 8.32% [6, 10]). This result allows us to recommend the developed method for the automated selection of ECs intended for long-term operating equipment, especially of responsible purpose.

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