Technological Process Optimisation and Process Characterisation in Relation to the Quality Assessment

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Abstract: - In order to optimise and characterize technological processes for quality planning, evaluation and development purposes must be used proper methodology. Methodology for designed experiment and uncertainty can be one possible way to do this. Variation and effect of various technological factors in relation to the material structures stability, consistency and overall performance in the relation to the important aspects related to the observation and analysis of the influence more than one variable at a time on the response of interest.

Key-Words: - multi-vari analysis, variation, optimization, experiment, factor, response, design

1 Problem introduction, important aspects of burn-in process of electronic devices

The reliability of electronic devices constitutes an important aspect of quality control. Most of the electronic devices show a decreasing failure rate in the early life and an increasing failure rate in later life. One of the fundamental concepts in reliability is the "Bathtub" curve, as illustrated in Figure 1. The Figure 1 shows that the theoretical life characteristic curve has three distinct periods. The initial early failure period is sometimes called the infant-mortality or the burn-in or the debugging period. The initial decreasing failure rate is due to early failure of substandard products. Failure mechanisms during the infant mortality may arise from random defects built into the product during the manufacturing process. Manufacturing defects, latent material defects, poor assembly methods, and poor quality assurance can contribute to a high initial failure rate. The early failures in this region could be eliminated by a 100% "burn-in" (for components and parts) or by initial "debugging" (of a complex system).

Once the infant mortality is removed from the population, the useful life period (so called steady-state region) is reached with a relatively lower failure rate. Failures are random and relatively constant in time and have very low failure rate during the useful life.

Finally, as products age they reach a wear out phase characterised by an increasing failure rate. The final stage is wear out, the parts begin to wear out and fail at some relatively higher failure rate.

Screening and burn-in of products are often performed to weed out infant mortality before use or delivery. The term "screening" mean the use of some environmental stress as a screen for reducing infant mortality defects. Burn-in is an effective means for screening out defects contributing to infant-mortality. For the producer is the purpose of this testing (1) weed out defective or unsatisfactory product and (2) eliminate “infant mortality” before delivery to the customer. Burn-in process of electronic devices combines electrical stresses with temperature for a given period of time. In practice, the underlying mechanisms of the burn-in process are frequently so complicated that an empirical approach is necessary.

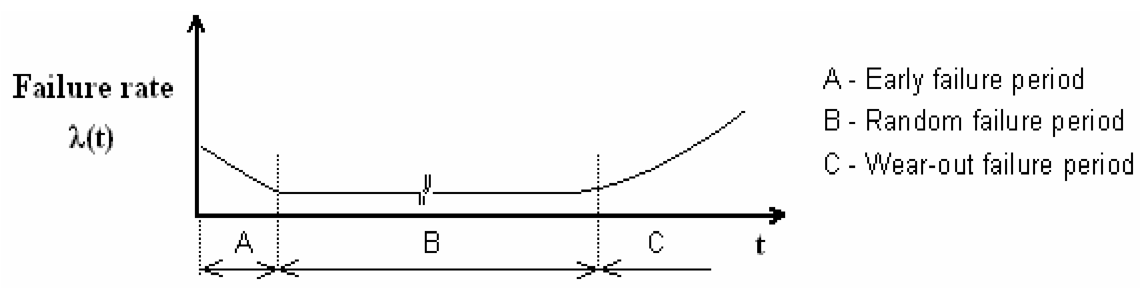

Fig.1: Typical "Bathtub" Curve showing the relationship between failure rate and device lifetime

Burn-in is the process of exercising of electronic devices to accelerated test. This is the process of operating devices under accelerated voltage, temperature, or load in order to screen out infant mortality failures. The understanding of the burn-in procedure is very important question related to planning and controlling of burn-in process in production of electronic devices. In practice, the underlying mechanisms of the burn-in process are frequently so complicated that an empirical approach is necessary.

The traditional probabilistic approach is to a large degree replaced by empirical study approaches constructed on designed reliability testing experiments. The methodological approach is based on manipulation of factors (independent variables) in order to determine the effect of this manipulation on other response variables (dependent variables). The problem studied in this paper is sequential experimental determining the burn-in process conditions for obtaining optimum results.

2 Some aspects of causality evaluation and basic terms

Experimental methods are used in research and development as well as in industrial settings for various purposes: determination of the effect(s) on some behaviour (the dependent variable) while controlling other relevant factors, examination of a hypothesized causal relationship between independent and dependent variables, observation of the effect of the treatments on the experimental units by measuring one or more response variables, translation of the different research hypotheses into a set of treatment conditions, reach "cause and effect" conclusions about the effect, evaluation of the statistical significance of an effect that a particular factor exerts on the dependent variable of interest, observation whether cause and effect relationships are present, settings of the technological factors in order to make the output that meet certain quality requirements.

Discovering key relationships between inputs and outputs is for quality control and improvement very important. Tools such as Cause and Effect diagram (also known as a "Ishikawa Diagram" or "Fishbone"), Cause and Effect Matrix, correlation analysis or Design of Experiments give advice in discovering causal relationships.

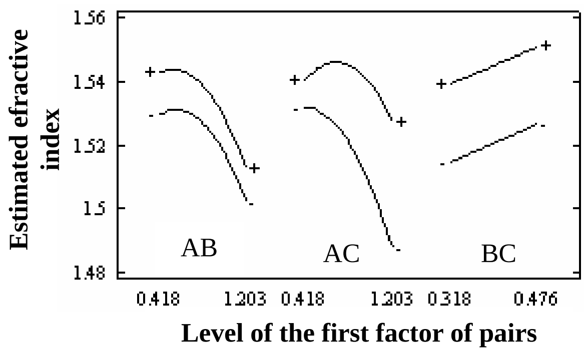

Fig.2: Graph showing the Interaction effect of particular experimental factors

An experiment is a study in which the investigator manipulates one or more variable to determine its effect on the response variable(s). The former variables are call "independent variables"; or "factors"; the latter are call "dependent variables" or "dependent measures". Graphical illustration of this type of problem is at the Figure 3. An experiment consists of testing combinations of different values (termed levels) of factors thought likely to influence the characteristic (so called response) of interest.

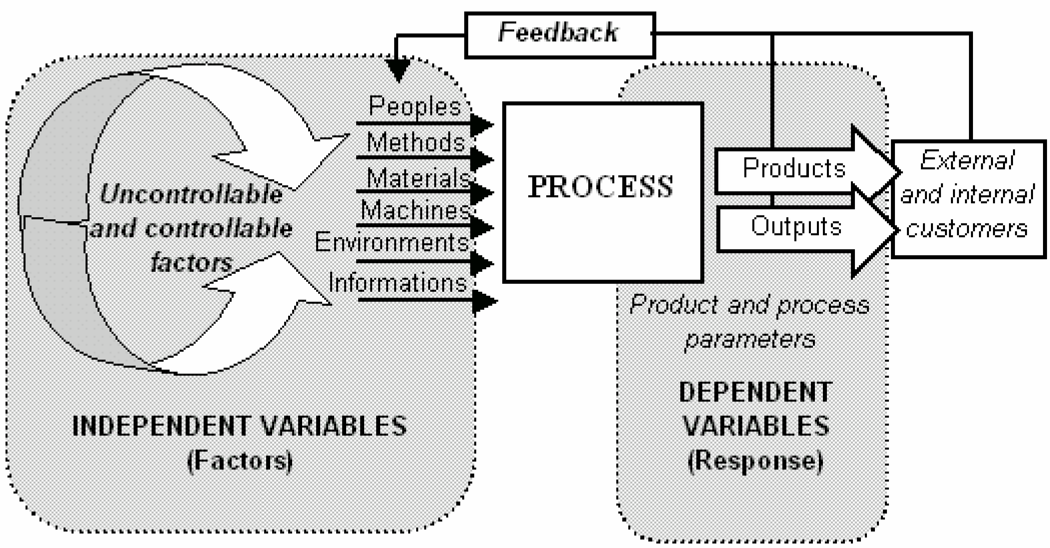

Fig.3: Graphical illustration of process variables and process output variables. Independent variables describe input parameters and dependent variables describe the output variables.

The change in the average response as a factor is varied is called the main effect of that factor. If the input factors are not independent, their interaction may also be considered. The interaction among factors refers to that the average effect of one factor depends on the level of another factor.
The interaction plot depicted in the Fig. 2 shows the estimated refractive index as a function of pairs of factors. In each plot, one factor is varied from its low level to its high level. On one line, the second factor is held at its low level. On the other line, the second factor is held at its high level. All other factors besides the two involved in the interaction are held constant at their central values. From another point of view we can say that input factors or factors within a process can be correlated with output parameters. These parameters are often important to the customer. They are so called critical to quality parameters, i.e. attributes most important to the customer. Key process input variables for processes must be understand in order to manage them in order to achieve given quality and reliability goals.
Critical to Quality characteristics related to output of a process that are important to the customer are sometimes call Key Process Output Variables (KPOV).
Critical to Quality characteristics represent the product or service characteristics defined by the customer (internal or external). They are the key measurable characteristics of a product or process whose specification limits or performance standard must be met to satisfy the voice of the customers. Specification limits set the requirements for judging acceptability of a particular characteristic.
Critical to quality characteristics are typically categorize under Quality or Reliability, Time, and Cost. These characteristics of product or service are usually determined from a qualitative (external or internal) customer statement and then translated into quantitative specification. The appropriate specification can allow comparison of actual result of KPOV against target or specification.

3 Uncertainty of measurement results related to the quantification of the factor values and responses

The uncertainty of measurement is the basic parameter that characterises quality of result of measurement. General, the basic requirements to expression of uncertainty in measurement are given by normative documents and standards. International standard ČSN EN ISO/IEC 17 025 “General requirements for the competence of testing and calibration laboratories” in paragraph 5.10.3 requires to test report includes “statement on the estimated uncertainty of measurement (where applicable)” and in paragraph 5.4.6 simultaneously say that calibration and testing laboratories shall have and shall apply procedures for estimating uncertainty of measurement.

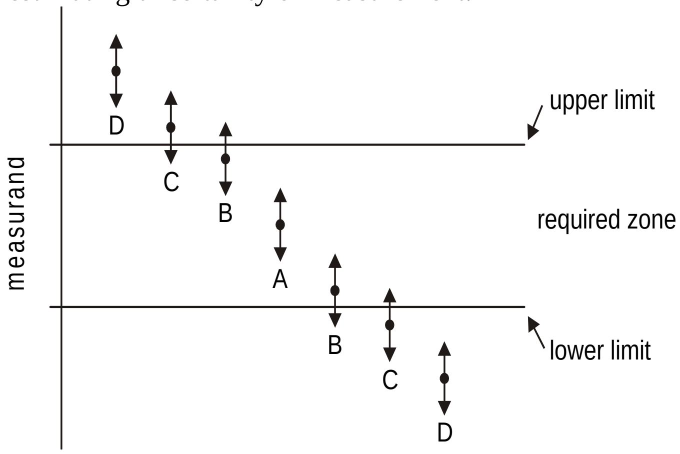

Fig.4: Uncertainty of measurement as important aspect for experimental evaluation of causality

In certain cases the nature of the test method may preclude rigorous, metrologically and statistically valid, calculation of uncertainty of measurement. In these cases the laboratory shall at least attempt to identify all the components of uncertainty and make a reasonable estimation, and ensure that the form of reporting of the result does not give a wrong impression of the uncertainty. Reasonable estimation shall be based on knowledge of the performance of the method and on the measurement scope.
Expression of uncertainty of measurement is directed also by requirements of European Accreditation of Laboratories (EAL). The basic documents are EAL-R2 “Methodology of expression of uncertainty in calibration laboratories” (for calibration laboratories) and EAL-G23 “Expression of uncertainty in quantitative testing” (for calibration and testing laboratories).
The formal definition of the term “uncertainty of measurement” is as follows:
“Parameter, associated with the result of a measurement that characterizes the dispersion of the values that could reasonably attributed to the measurand.”
The basic types of uncertainty:
(1) Type A: Type A evaluation of uncertainty is based on method of evaluation uncertainty by the statistical analysis of series of observation.
(2) Type B: Type B evaluation of uncertainty is based on method of evaluation of uncertainty by means other then the statistical analysis of series of observations.
Combined standard uncertainty is standard uncertainty of the result of measurement when the result is obtained from the values of a number of other quantities. It is the estimated standard deviation associated with the result and is equal to the positive square root of the combined

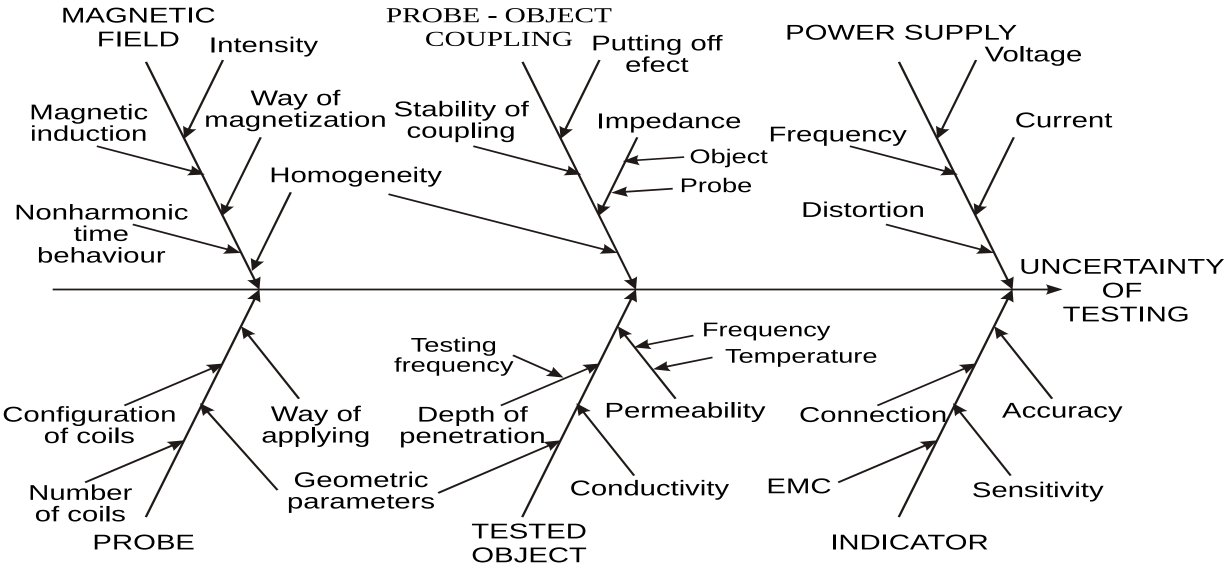

Fig.5: Example of sources of uncertainty in electromagnetic non-destructive testing

variance obtained from all variance and covariance components. Combine standard uncertainty is denoted $u_c(y)$.

Expanded uncertainty is quantity defining an interval about the result of a measurement that may be expected to encompass a large fraction of the distribution of values that could reasonably be attributed to the measurand. Expanded uncertainty is denoted U(y).

Uncertainty of measurement is inseparable part of measurement results and its importance is obvious from figure 1 where only result signposted A is correct, because this estimate of measurand and its uncertainty are fully in required zone. All other results (sign posted B, C, D) are not satisfied.

4 Methodology for evaluation of uncertainty of measurement

Overall uncertainty of measurement is expressed by specific mathematic methodology from single components of uncertainty. Evaluating of single sources of uncertainty in single partial steps is example of modular access to evaluation of uncertainty components. It is suitable to proceed from modular access in design of way for their evaluation and expression.

In particular measurement, it is necessary to proceed from actual methods of measurement for evaluation of uncertainties, because the single sources of uncertainty that participate on overall uncertainty result from this methodology. The mathematical methodology for evaluating and expressing of uncertainty is universal and in practice it must be particularised for current technical condition to conform to actual necessities of particular assignment. This methodology can be generally summarized to following steps:

4.1 Analysis of input conditions

The first step of measurement predicates in choosing appropriate method of measurement and appropriate measurement devices. It should be done by analysis of input conditions and input requirements. It is seasonable to approximately estimate possible sources of uncertainty because it could be important factor for choosing of measurement method. Measurement can be modelled mathematically to the degree imposed by the required accuracy of the measurement.

4.2 Mathematical model of measurement

Usually, a measurand Y is not measured directly, but is determined from N other quantities Xi through a functional relationship f by following equation:

$$Y = f(X_1, X_2, ..., X_N).$$

The functional relationship f is given by chosen measurement method and expressed the way by which the measurand is obtained from input quantities X_i. The mathematical model of the measurement that transforms the set of repeated observations into the measurement result is of critical importance because, in addition to the observation, it generally includes various influence quantities that are inexactly known. This lack of knowledge contributes to the uncertainty of the measurement result, as do the variations of the repeated observations and any uncertainty associated with the mathematical model itself.

Because the mathematical model may be incomplete, all relevant quantities should be varied to the fullest practicable extent so that the evaluation of uncertainty can be based as much as possible on observed data. The mathematical model should always be revised when observed data, including the result of independent determination of the same measurand, demonstrate that the model is incomplete. A well-designed experiment can greatly facilitate reliable evaluations of uncertainty and is an important part of the art of measurement.

4.3 Identification of all sources of uncertainty

When estimating the uncertainty of measurement, all uncertainty components, which are importance in the given situation, shall be taken into account using appropriate methods of analysis. In practice, there are many possible sources of uncertainty in a measurement, for example following:

• incomplete definition of the measurand,
• imperfect realization of the definition of the measurand,
• nonrepresentative sampling,
• inadequate knowledge of the effects of environmental conditions on the measurand,
• imperfect measurement of environmental conditions,
• personal bias in reading,
• finite instrument resolution,
• or inexact values of measurement standards or reference materials.

The possible sources of uncertainty result from mathematical model of measurement. It is necessary to identify all significant sources of uncertainty and it is also necessary not to "double-count" uncertainty components. Practically, the sources are not necessarily independent, and so some of sources may contribute to other sources. Good way for identification of sources of uncertainty and finding possible correlations is using Ishikawa charts.

As example, there is shown Ishikawa chart of sources of uncertainty in electromagnetic non-destructive testing in figure 2. It may be seen that any quantities can be components of uncertainty in more sources. Of course, in practise these possible sources would be reduced for a few really important sources by using method and other uncertainty components could be neglected.

4.4 Evaluation of input standard uncertainties

As it was written, input uncertainties are grouped into two categories (Type A and Type B evaluation). Both types of evaluation are based on probability distribution and the uncertainty components resulting from either type are quantified by variances or standard deviations. While Type A standard uncertainty is obtained from a probability density function derived from an observed frequency distribution, Type B standard uncertainty is obtained from an assumed probability density function based on the degree of belief.

When an input quantity X_i is estimated from n independent repeated observations (Type A), standard uncertainty associated with arithmetic mean is given by experimental standard deviation of the mean $\bar{x}$, thus:

$$u(\bar{x}) = \sqrt{\frac{1}{n(n-1)} \cdot \sum_{i=1}^{n} (x_i - \bar{x})^2}$$

When the input quantity X_i is not estimated from repeated observations, the associated estimated variance or the standard deviation is evaluated by scientific judgement based on all of the available information on the possible variability of X_i. In these cases, the standard uncertainty u(xi) is given by square root of variance of appropriated probability distribution to input quantity X_i. It often may be possible to estimate only bound (upper and lower limits) for X_i without knowledge about probability distribution. Then it may be assumed trapezoidal probability distribution with half-width and top of width or its extreme cases – rectangular or triangular probability distribution. Then the standard uncertainty is given by:

$$u(x_i) = \sqrt{\frac{a^2(1+\beta^2)}{6}} \,.$$

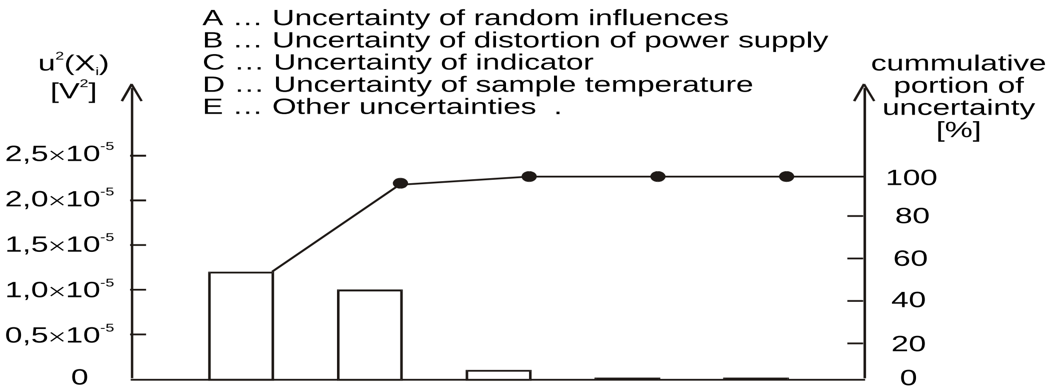

Fig.6: Example of Pareto analysis of uncertainty components

For β = 1 the trapezoidal probability distribution passes to rectangular probability distribution, for β = 0 the trapezoidal probability distribution passes to triangular probability distribution.
In practice, the input standard uncertainties must be evaluated for all significant sources of uncertainty by one of this way of evaluation. Then it is possible to express overall uncertainty of result of measurement.

4.5 Expressing of overall uncertainty

The final step in expressing of uncertainty is given by combining the standard uncertainties to one parameter that characterizes overall uncertainty of result of measurement. This parameter is known as combined standard uncertainty and is denoted $u_c(y)$. The combined standard uncertainty is given by:

$$u_c(y)=\sqrt{\sum_{i=1}^{N}\left(\frac{\partial f}{\partial x_i}\right)^2 u^2(x_i)+2\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\frac{\partial f}{\partial x_i}\cdot\frac{\partial f}{\partial x_j}\cdot u(x_i)\cdot u(x_j)\cdot r(x_i,x_j)}$$

where $r(x_i,x_j)$ is correlation coefficient that characterizes the degree of correlation between x_i and x_j.
When input quantities are uncorrelated, equation is reduced to:

$$u_c(y)=\sqrt{\sum_{i=1}^{N}\left(\frac{\partial f}{\partial x_i}\right)^2 u^2(x_i)}\ .$$

These equations are termed as “law of propagation of uncertainty”. The partial derivatives often call sensitivity coefficients; describe how the output estimate y varies with changes in the values of the input estimates x_i. By expressing of sensitive coefficients and single members of law of propagation of uncertainty it is possible to analyse single uncertainty components, find the dominant uncertainty component and (when it is required or useful) try to eliminate or reduced it. It is helpful to use any statistical methods, for example Pareto analysis as is shown on figure 3. There is performed Pareto analysis of uncertainty components in practical non-destructive testing of material properties realised by measurement of higher harmonics component of voltage induced in coil to that the controlled material is inserted.
The importance of expressing of uncertainties in measurement was unambiguously supported by experiments namely not only in a relation to results of measurements, but also in a relation to choose of measurement methodology. Quantification of components of entry uncertainty enables to delimit exactly the percent part of particular share in total uncertainty of measurements. On the basis of this knowledge it is possible to option the most acceptable method and to optimise the methodology of testing.
Although the combined standard uncertainty can be used to express the uncertainty of a measurement result, in some cases it is often necessary to give a measure of uncertainty that defines an interval about the measurement result that may be expected to encompass a large fraction of the distribution of values that could reasonably be attributed to the measurand. This additional measure of uncertainty is termed expanded uncertainty. The expanded uncertainty, denoted by symbol U(y), is obtained by multiplying $u_c(y)$ by a coverage factor, denoted by symbol k:

$$U(y)=k\cdot u_c(y)\ .$$

The result of a measurement is then conveniently expressed as Y = y ± U(y), which is interpreted to mean that the best estimate of the value attributable to the measurand Y is y, and that y - Y to y + U is an interval that may be expected to encompass a large fraction of the distribution of values that could reasonably be attributed to Y.
The value of the coverage factor is chosen on the basis of the required level of confidence to be associated with the interval defined by U(y). Typically, k is in the range 2 to 3. When the normal distribution applies and $u_c(y)$ has negligible uncertainty, $U(y)=2\cdot u_c(y)$ defines an interval having a level of confidence of approximately 95 percent, and $U(y)=3\cdot u_c(y)$ defines an interval having a level of confidence greater than 99 percent.

2 Observation and analysis of more than one variable at a time

The traditional technique to experimentation is based on changing only one factor at a time whilst holding the remaining factors constant. This method however doesn’t provide data on interactions of factors and it isn’t cost effective. There is no way to account for the effect of joint variation of factors and it usually isn’t possible to hold all other variables constant and a large number of runs are required.
The overall combination of all factors and their levels can grow to be too large and daunting a task if each factor is changed one at a time. An alternative approach called factorial design can uncover interactions and is more efficient than the approach of one factor at a time approach. The design of experiments enables to plan an experiment that simultaneously alters a number of variables in an experimental system to see how they affect and interact to affect responses. The statistical design of experiments enables to plan an experiment that simultaneously alters a number of experimental variables to evaluate how they affect response parameters. The

factorial design that varies multiple factors at a time can reduce the number of runs and still offer enough information. Factorial Designs are form of DOE where one or more trials are making with each combination of levels for the factors. This approach provides the way to the analysis of the effects of multiply technological factors on the response. To dampen the effect of systematic changes, the trials should ideally be conducted in a random order, known as randomization, and replicated.

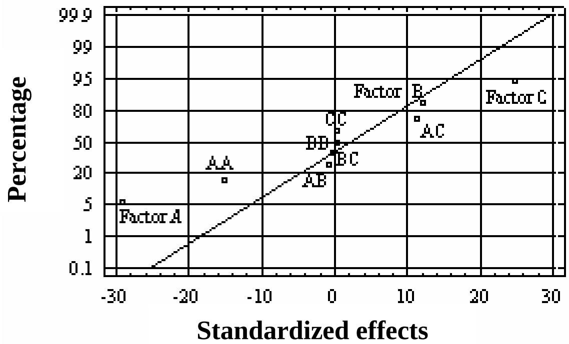

Fig.7: Example of normal probability plot for separation of the real effects from those which are caused by noise

A full factorial experiment combines the levels of each factor with each of the levels of all the remaining factors. The full factorial design has the advantage of being able to estimate interactions between factors. However, full factorial designs become very large as the number of factors and levels increases.

It is possible to investigate the main effects of the factors and their more important interactions in a fraction of the number of runs required for the full factorial experiment. These fractional factorials experiments are useful because they require much fewer runs, although they do not allow the separation of main effects from high-order interactions.

One of the strengths of the factorial experiment is that it allows the study of several factors at once, rather than only one factor at a time. DOE, in contrast to the one factor method, advocates the changing of many factors simultaneously in a systematic way.

The normal probability plot can be used to separate the real effects from those which are just noise. It is particularly useful when there are few or no degrees of freedom to estimate the experimental error.

The plot is scaled in such a way that the effects which are not real will fall approximately along a straight line, while the real signals will fall off the line. The noise effects behave like they come from a normal distribution centered at zero. If there are adequate degrees of freedom to estimate the experimental error, the analysis of variance (ANOVA) techniques can be used to determine significant factors.

A response surface is a surface that represents predicted responses to variations in factors in the region of interest. The region of interest is the set of runs, in which combinations of vital continuous factor levels are included, that are perform in order to predict investigated response. A mathematical statement of the relations among variables can be express as an empirical model. The most common empirical models fit to the experimental data take polynomial form.

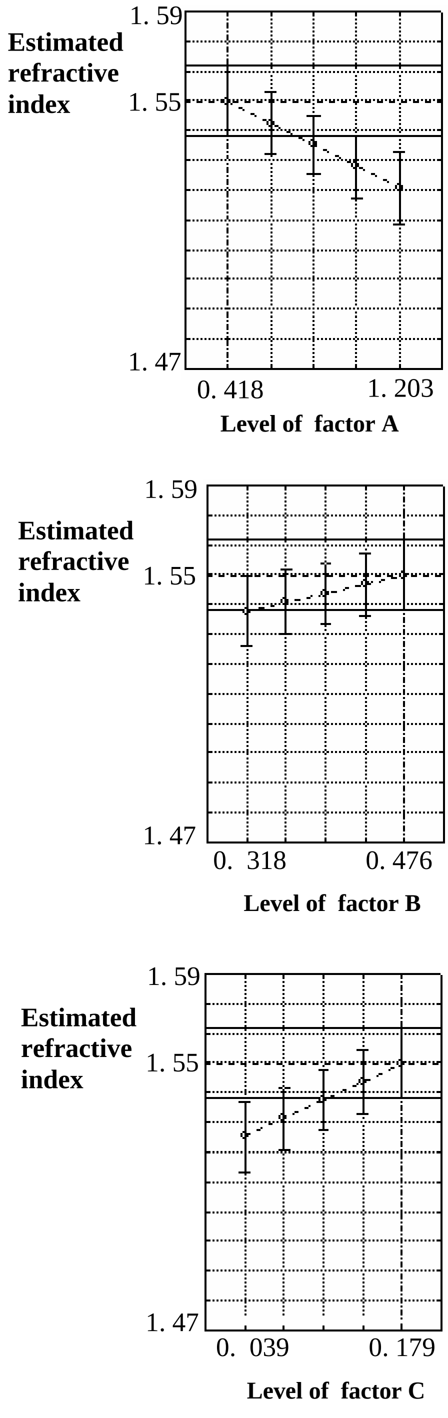

Fig.8: Estimated values of response (refractive index) for various values of experimental factors

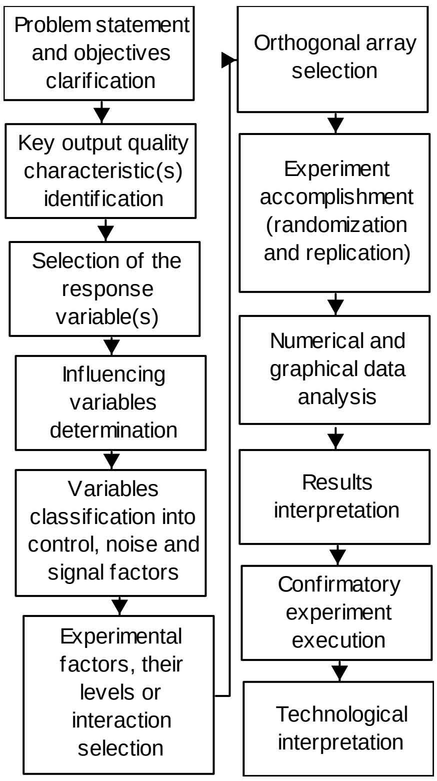

Fig.9: Overview of steps for the design of experiments by Taguchi methodology

3 Response surface description and response surface methodology

Response surface methodology helps to quantify the relationships between one or more measured responses and the vital continuous factors.

The response is a dependent variable of interest in an experiment whose changes we wish to study. It is a characteristic of an experimental unit measured after treatment and analyzed to address the objectives of the experiment. In most experimental situations, several responses are usually of interest, and their selection is related to the purpose of the study. In the context of industrial experiment are the responses related to the quality characteristics of a product which are most critical to customers.

Identifying quantifiable responses is very important steps of an experiment execution. Responses must be measured by capable measurement system that consistently produces reliable results.

Attribute data (pass/fail, good/bad) are for design of experiment purposes inefficient. These data ask for a large number of experimental units and leads to experimental plans that are time and resources consuming. One way to solve it is to define the numerical rating scale (e.g. 1-very bad to 3-okay to 7-very good) by providing benchmarks in the form of defective units or pictures and train about three people to use the scale. To evaluate the response, each trained people should independently rate each experimental unit after the experimental treatment. Then the response should be the average rating for each experimental unit, but it can be also evaluate the standard deviation of the ratings as a second response.

Response Surface Methodology approximates the response values Y in the form of polynomial function of independent variables x_i, x_j:

$$Y = \alpha_0 + \sum_{i=1}^{n} \alpha_i x_i + \sum_{i=1}^{n} \alpha_{ii} x_i^2 + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \alpha_{ij} x_i x_j$$

The symbol n is the number of independent variables and a_0, a_i, a_{ii} , a_{ij} are model coefficients.

Response surface methodology is use to determine the optimum combination of factors setting that yield a desired response and describe the response near the optimum or to determine how a specific response is affected by changes in the level of the factors over the specified levels of interest. The eventual objective of RSM is to gain understanding of the physical mechanism of a system.

4 Study of the microelectronic structure in the relation to the study of burn-in process influence

In this part is presented the example presents the simultaneous study of the effects that three vital continuous factors (concretely temperature, time and voltage) have on the microelectronic structure (concretely electrical parameters stability coefficient), see Figure 2.

FACTOR LEVEL	FACTOR		
	Temperature [°C]	Time [min]	Voltage [V]
High (+)	200	40	20
Center (0)	150	30	15
Low (-)	100	20	10

Fig.10: Experimental factors and their levels in the study of the influence of the burn-in process

RUN	FACTORS IN CODED UNITS			FACTORS IN ORIGINAL UNITS			RESPONSE Stability coefficient
	A	B	C	Temperature [°C]	Time [min]	Voltage [V]	[-]
1	1	0	-1	200	30	10	0,91
2	1	-1	0	200	20	15	1,13
3	-1	0	-1	100	30	10	0,5
4	1	1	0	200	40	15	1,42
5	0	1	-1	150	40	10	0,83
6	1	0	1	200	30	20	1,38
7	0	-1	-1	150	20	10	0,71
8	0	-1	1	150	20	20	0,99
9	0	1	1	150	40	20	1,36
10	-1	0	1	100	30	20	0,73
11	-1	-1	0	100	20	15	0,59
12	-1	1	0	100	40	15	0,95
13	0	0	0	150	30	15	0,77
14	0	0	0	150	30	15	0,72
15	0	0	0	150	30	15	0,81

Fig.11: Description of Box Behnken experimental design for two level full factorial design 2^3 with center points

Experimental factors are generally explanatory variables that might influence the response variable. These are the possible causes of variation that affect the response. Factors may be variable (continuous - thickness, pressure, voltage) or they may be attribute (discrete, categorical - production method, type of material).
Factors can be divided into control and noise factors. Control factors are those factors that can be deliberately manipulated during the experiment; these are during experiment changed across the experimental plan from run to run. Noise (lurking, nuisance) factors are background variables that are difficult, inconvenient or too expensive to control in actual experimental situation. Noise factors include time, day, ambient temperature, humidity, air flow or test conditions.
Unfortunately these uncontrolled variables can be a major cause for variability in the responses. The effect of background variables can contaminate primary variable effects unless they are properly handled by randomization, replication and blocking.
Determination of the important control factors that can affect the responses and selection levels or settings for each of these factors during the experiment can be done by various ways. Cause and effect diagram, flowcharts, brainstorming or brain writing are useful tools for this.
At various treatments are control factor setting at various levels. The levels need to be in an operational range of the product or process. The number of levels depends on the experimental factors, nature of the experimental design and whether or not the selected factor is variable or attribute. The cost of experimentation can grow significantly if too many factors and/or levels of factors are selected. If important factors are left out of the experiment, then the results may be inadequate.
The experimental plan for the presented example is depicted in the Figure 3. This can be used for study the effects of three experimental factors in 15 runs. According the experimental plan each factor was varied at high (+), central point (0) and low (-) levels according the experimental design as sum up in Figure 2. Center points serve to test for the presence of curvature, and give information about quadratic effects.
There is a simple underlying geometric structure to all factorial experimentation. For presented example, a three-factor experiment can be represent as a cube in which each corner represents one trial, see Figure 4.

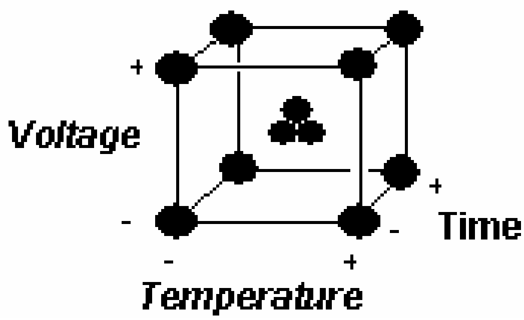

Fig.12: Visual representation of the geometric structure for two level full factorial design $2^3$with center points

From the fitted regression model was create the response plot. The response plot shows a plot of the effects for two of the factors on the response. Example of the response plot is in the Figure 5.

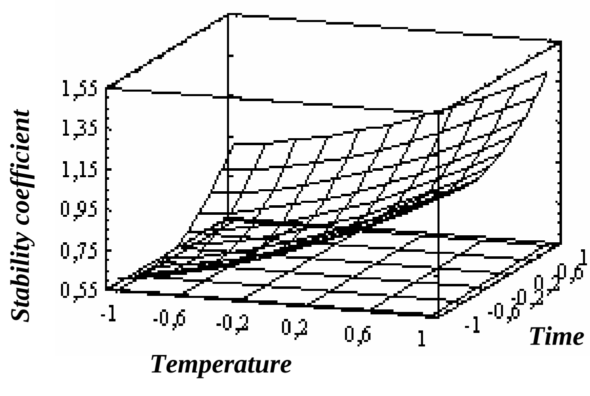

Fig. 13. Estimated response surface for tantalum capacitor structure stability evaluation

5 Conclusion

The understanding of the burn-in procedure is very important question in the electronic industry related to planning and controlling production burn-in of devices. This paper deals with the problem how to follow the factors influencing the burn-in procedure using design of experiments. The design of experiments using sound statistically oriented thinking is an important aspect of the solution of the optimization of the technological process to achieve required reliability.

In our research we need to study multiple sources of variation related to the modification of microelectronics structures, technological process factor settings and burn-in process. We can say that one of the most important problems in industrial research is the discovery of the optimum conditions of technological process. In some cases it is possible to calculate the optimum conditions on theoretical grounds, much more often, however, only an empirical approach is possible.

It is unwise to design too comprehensive an experiment at the start of a study. The idea of using information from the early parts of a series of observations to design the later work is termed the sequential approach to the discovery of the optimum conditions of technological process.

This paper describes some aspects of experimental cause and effect evaluation and presents some results of burn-in process sequential experimental evaluation. The used methodology consists of appropriate experimental plan that yields the most information from predetermined model with the least number of experiment runs. Empirical model coefficients and approximate models in the reference points obtained from the experimental data are created based on a multivariate regression analysis of each investigated response.When the region of experimentation is a long way from the top of the optimum a slope may be a good approximation. This approach can be used for characterization, qualification, and testing in relation to quality improvement and statistical process analysis purposes.

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