2^k Factorial Experiments for Quality Improvement and Statistical Process Analysis Purposes

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Abstract: - This article presents some important aspects related to successful industrial experiment such as proper response definition, choice of factors and levels or experimental design selection. and discuss one factor of time experiments approach and factorial approach to experiments. The example of 2^k factorial design screening experiment is presented here. The overview of experimental results is recapitulated.

Key-Words: - quality, improvement, process, optimization, experiment, factor, response, design

1 Introduction

Experimentation is one of the most important methods in the quality movement. An industrial experiment is generally performed to increase the knowledge of a particular process. Experimentation is an empirical research method in which the researcher manipulates one or more factors (independent variables) in order to determine the effect of this manipulation on other response variables (dependent variables). Different treatments are administered to different groups of experimental samples or to the same subjects in different orders and performance on some response measure is observed and recorded.

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.

2 One factor of time experiments versus factorial experiments

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 factorial design that varies multiple factors at a time can reduce the number of runs and still offer enough information.

3 Proper response definition

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 industrial 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.

4 Choice of factors and levels

Experimental factors are 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.

5 Experimental design selection

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 total combination of all factors and their levels can become too large and daunting a task if every factor is changed one at a time. An alternative approach to one factor of a time approach is factorial design that can uncover interactions and is more efficient. The factorial design that varies multiple factors at a time can reduce the number of runs and still offer enough
information.

EXPERIMENTAL FACTORS SETTING				RESPONSE
A: Temperature [°C]	B: Resistance [Ω]	C: Burning time [s]	D: Burning voltage [V]	Yield [%]
25	5	60	9	43
85	5	60	9	64
25	15	60	9	46
85	15	60	9	62
25	5	420	9	67
85	5	420	9	52
25	15	420	9	78
85	15	420	9	61
25	5	60	15	38
85	5	60	15	89
25	15	60	15	42
85	15	60	15	92
25	5	420	15	71
85	5	420	15	82
25	15	420	15	66
85	15	420	15	93

Fig.1: The example of 2^k factorial design for burn-in process optimization of capacitors

6 Experimental design example

A special case of the factorial design is that where each of the k factors of interest has only two distinct levels, the high "+" and low "-" levels). The estimate of the effect for each factor is determined by subtracting the average "-" response for a factor from the average "+" response. These two levels may be variable, such as two values of temperature or humidity, or they may be attributive, such as two methods, or two types of material. Because the total number of factor-level combinations is the resultant of the number of levels of each factor, these two-level designs are known as 2k factorial designs (where k is the number of factors). The 2^k factorial design will have 2^k experimental runs.

These designs are efficient, producing maximum information with a minimum of experimental runs and are excellent for screening many factors in order to identify the vital few.

The example of 2^k factorial design for burn-in process optimization of capacitors is depicted in the figure 1. There are 16 experimental runs at prescribed levels of the factors to be applied to an experimental unit. In the last column there are the values of observed response.

7 Analysis of experimental results

In the phase of data analysis experimenter need to analyse the main and interaction effects. The main effect of a factor can be defined as the change in response produced by a change in the level of the factor. The interaction effect is the joined resultant of the change two or more factors. In a factor with two levels, the main effect is the average of all runs at the high level of the factor minus the average of all runs at the low level of the factor.

Tab.1: Estimated results of the effects

Main effects				Interaction effects										
A	B	C	D	AB	AC	BC	AD	BD	CD	ABC	ABD	ACD	BCD	ABCD
18	4,3	11,8	12,5	1	-17	2,3	17	-1	1	2,5	2,8	0,8	-2,5	1,8

For evaluation purpose of the statistical significance can be used normal probability plot of the effect estimates. For our experiment is the half-normal probability plot where are depicted absolute values of effects. This graph shows that statistically significant effects are the main effect A (temperature), C (burn-in time) and D (burn-in voltage) and these interaction effects: AD and AC.

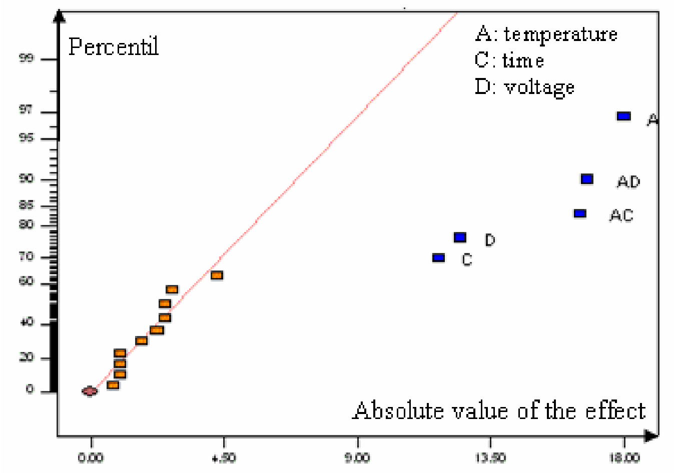

Fig.2: Half – normal probability plot

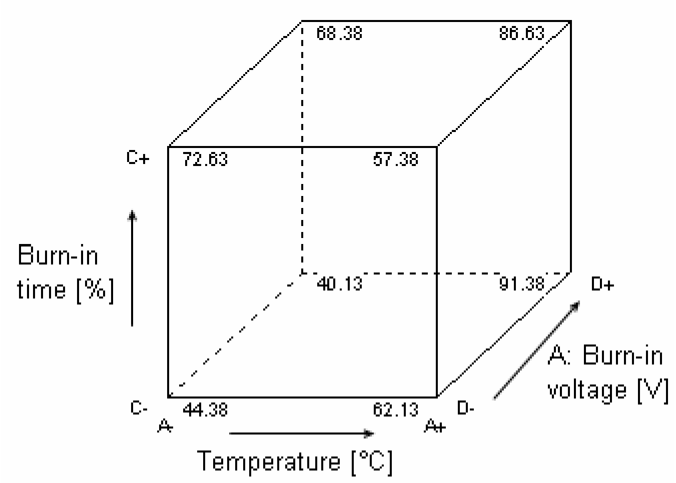

Fig. 3: Predicted yield (predicted values at the corners of the cube are expressed in percent)

At this moment we can fit a model and create various graph that are useful for quality improvement purposes. By using created empirical model we can to predict the values of yield. Example of the results by using fitted empirical model is given in the Fig. 3. These results are used to technological interpretation of the structure under investigation in the relation to research in the field of technological structure fabrication. Example of interaction graph related to this experimental situation is given at the Figure 4.

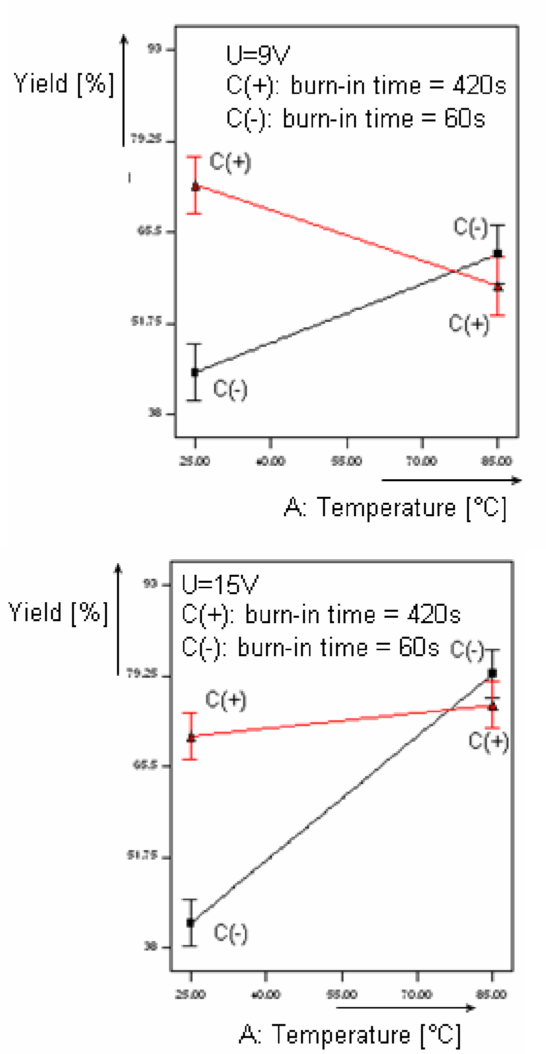

Fig. 4: Interactions graphs for burn-in process optimization experiment

5 Conclusion

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. We use the sequential experimental approach using information from the series of small pilot experiments, which provides approximate information. The 2^k factorial design provides the framework to design and analyze comparative experiments and setting of process or design variables which are most important in relation to quality requirements. This approach can be used for characterization, qualification, and testing in relation to quality improvement and statistical process analysis purposes.

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