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TAGUCHI METHODS FOR QUALITY ENGINEERING

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Abstract

Designing products and processes so that they are insensitive to variation in conditions is known as 'quality engineering'. This concept was introduced by the Japanese Taguchi, who made absolutely clear that in order to limit variation of the quality characteristics - and thus to achieve constant high quality - against as low costs as possible, quality must be designed into products and processes. One way to do so efficiently, is making engineers/designers to use experimental design techniques, in which noise factors play an important role. Taguchi developed quality engineering methods for engineers, which rely heavily on statistics. And though it can be argued that the statistics of Taguchi's methods is not always most efficient, we think that the methods are nonetheless very important. We think that they are able to bridge the gap between engineering and statistical experimental design methods, and that they therefore contribute considerably to the very valuable concept of quality engineering.

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1. INTRODUCTION

Quality engineering is a subject which has come increasingly popular in recent years. It is thanks to the Japanese Genichi Taguchi that the discussion on this subject, and on what quality ought to mean, has received fresh impetus (e.g. Taguchi, 1986).

Although Taguchi's ideas were generally welcomed, his methods for realising the so-called "off-line quality control" (the "Taguchi methods") were received with varying degrees of enthusiasm. Technicians have recognised them as a useful body of tools in the design and also in the solution of problems. On the other hand, statisticians were full of praise for Taguchi's emphasis on the use of experimental design, but showed no understanding for the manner in which the selection of experimental design and analytical methods have been arrived at. The danger that criticism of one aspect would lead to the whole package being rejected, proved not to be imaginary. This was partly the result of Taguchi's inability to make it sufficiently clear that his methods form a coherent package as tools for engineers, in which experimental design is a means of solving problems.

A deluge of publications has now made clear what Taguchi aims to achieve with his methods (e.g. Barker, 1986; Basso et.al., 1986; Gunter, 1987; Kackar, 1985, 1986; Pignatiello, 1988). And in the American Supplier Institute (ASI) he has found an organisation which is succeeding in making his intentions clear. This paper, based on Trip (1989), contains a brief summary of Taguchi's philosophy and methodology. It will be concluded with a discussion on how within Philips the concept and methods of quality engineering are introduced and implemented.

2. QUALITY ENGINEERING

The design of quality in products and processes is the idea at the heart of Taguchi's Methods for quality engineering. Two fundamental concepts can be derived from Taguchi's basic idea:

1. Quality is not a matter of meeting specifications, but of attaining a target value. In accordance with this principle, departures from the target value are to be considered as losses, which means incurring costs.
2. If high quality is to be achieved in systems, it is an economical necessity that quality is designed in advance in the system. Inspection is not economically justified, because quality is not improved by this.

The designing of quality is a three-stage procedure:

* system design (conformance to functional characteristics),
* parameter design (conformance to the target value),
* tolerance design (determination of permissible variation).

System and parameter design offer the best possibilities to limit loss of quality, while the achievement of high quality in the tolerance design phase is associated with higher costs.

It is upon the above-mentioned basic rules, which appear simple and indeed obvious, that Taguchi's conceptual framework and methodology for implementation are based.

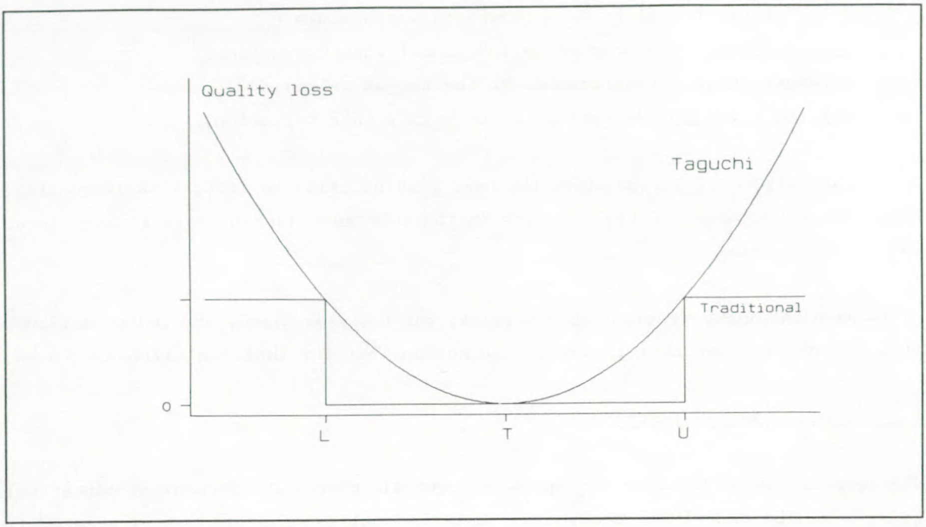
2.1 The quality/loss function

The quality/loss function occupies a central place in Taguchi's conceptual framework. The underlying thought is that the quality of a product is related to the losses which it causes to the customer. By expressly relating quality to losses for the customer, it is also clear that meeting specifications is an old-fashioned quality concept. The point is that the target value is to be met - every departure from the target value involves loss. One must bear in mind that specifications are in general rather random limits which reflect that, on account of all kinds of variations, the target value is not always attainable.

The quality/loss function for a 'nominal the best' target value is shown in the next figure. Due to the fact that it is practically impossible (and a waste of energy) to determine the exact loss function, a simple parabola is selected to approximate the relation between the quality of a product and its incurred loss.

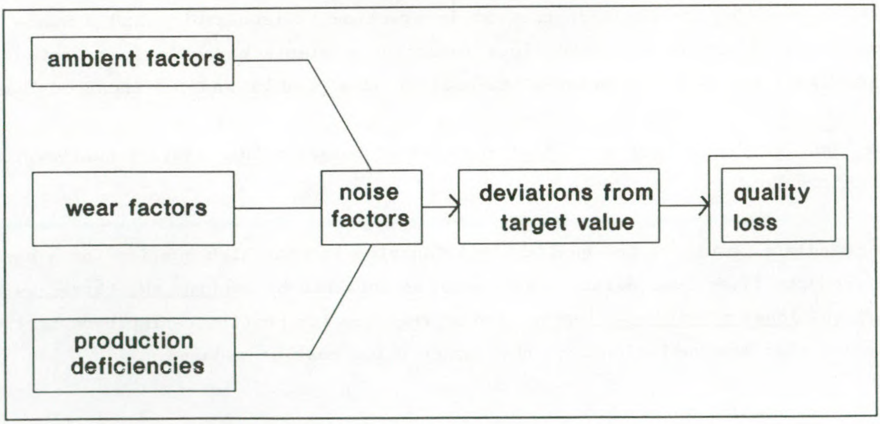
For 'smaller the better' or 'larger the better' target values similar quality/loss functions hold.

An immediate result of the quality/loss function is that high quality for a batch of products (i.e. low quality losses) can be obtained by meeting the target value with the least possible variation. And a programme for continuous improvement thus implies that the variation from the target value must be reduced.



2.2. Noise factors

Products and processes will, for all kinds of reasons, not always meet the target value. The causative influences (or noise factors) can be divided into three categories (see figure).



By ambient factors is meant such matters as temperature, humidity and the person of the user, i.e. factors which can influence the quality during the operational phase of the product or process (think, for example, of influence of such factors when starting a motorcar). By wear factors is meant, for example, characteristics or materials which vary through time. Finally, production deficiencies will result in products which have been made under the same specifications nevertheless being subject to variation.

Quality engineering thus means that a product or process must be designed such that it is robust in relation to each of the above-mentioned categories of noise factors: the functional properties must be insensitive to variations in the noise factors. In order to realise this, Taguchi has extended the familiar design phases (system design and tolerance design) to include the parameter design phase.

2.3. Design phases

The total design phase of a product or process consists of three steps:

1. system design
2. parameter design
3. tolerance design

In system design, scientific and technical knowledge is applied to design a prototype which meets the functional specifications. This provides a provisional setting of the product or process parameters.

In the parameter design phase, the setting of the parameters is optimised, in the sense that the variation of the quality characteristics (as a result of the variation of all kinds of noise factors) is minimal in relation to the target values. In other words, parameter design is a matter of finding the setting at which the loss of quality is smallest.

Finally, tolerance design is concerned with determining how much variation around the nominal setting of the parameters is permissible. In this phase, it becomes clear which parameters must be monitored during manufacturing ('on-line quality control') in order to be sure of the desired results of the quality characteristics. It will be clear that tolerance design can reduce quality losses only at the cost of greater expenses (for process monitoring or more expensive material and equipment).

The Taguchi methods are primarily concerned with parameter design although some guidelines for tolerance design are given as well.

3. EXPERIMENTAL DESIGN

Statistical experimental design is the main tool to realise parameter design and tolerance design (Taguchi, 1987). However, these methods are used differently from what statisticians are used to. They are expressly intended as an everyday tool for engineers, i.e. people who are not skilled statisticians.

The (technical and scientifical) knowledge of engineers is always the starting point for an experiment. For a good experiment it is absolutely necessary that all people involved make their knowledge explicit. Taguchi stresses this point and firmly believes that engineers know what they are working on. A brainstorming session among those involved should reveal:

- quality characteristics;
- factors (controllable and noise);
- the approximate effect of controllable factors;
- important interactions between controllable factors.

With the results of this group-activity, an experimental design is to be set up.

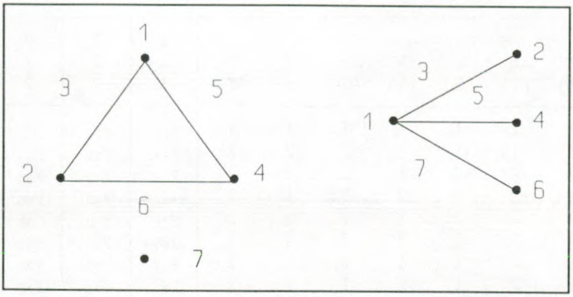
To improve the general level of experimentation efficiency, Taguchi is convinced that engineers should be able to do it all by themselves. For this reason, he has selected only a few of all existing experimental designs. This set of flexible, easy to use experimental layouts is called 'orthogonal arrays' (Taguchi and Konishi, 1987). An example of a very popular array is shown below: the so-called L_8 orthogonal array.

trial number	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	1	1	1	1	1	1	1
2	1	1	1	2	2	2	2
3	1	2	2	1	1	2	2
4	1	2	2	2	2	1	1
5	2	1	2	1	2	1	2
6	2	1	2	2	1	2	1
7	2	2	1	1	2	2	1
8	2	2	1	2	1	1	2

L_8 (2^7) orthogonal array to investigate at most 7 factors at 2 levels in 8 trials (factors are assigned to columns, the 1's and 2's indicating the appropriate level).

In fact, this design stems from a 2^3 full factorial, but it has the flexibility to be used as a 2^{4-1} fractional factorial, or even as a Plackett-Burman design (or 2^{7-4}) to investigate seven factors in eight trials (Montgomery, 1984). The key is that factors (and interactions) may be assigned to columns of an orthogonal array. The L_8 array could e.g. also be used to investigate 6 factors and 1 specified interaction (assuming that all other interactions can be ignored).

To assist in assigning the interaction to the right column, Taguchi developed the so-called 'linear graph'. In the next figure the two generic linear graphs belonging to the L_8 orthogonal array are shown.



Both figures tell e.g. that if the interaction of the two factors assigned to columns 1 and 2 is to be investigated, then it will show up in column 3 (and therefore no factor should be assigned to this column). A more general procedure, based on 'interaction graphs' is described by Kacker and Tsui (1990).

4. PARAMETER DESIGN

The purpose of parameter design is to find settings of the controllable product or process parameters, whereby the loss of quality is smallest. For a 'nominal the best' target value, this means that the influence of noise factors should be as small as possible and that the target value should be met.

Controllable factors and noise factors thus are treated differently. Controllable factors are factors that can be set easily, while noise factors cannot be controlled, or only with high costs. Because noise factors cause variation, and because they are expensive to control, their influence should be limited. And

Taguchi suggests to do this by selecting proper settings of the easy to control controllable factors. In fact, Taguchi doubts the classical assumption of analysis of variance, that the variation is the same in the whole experimental region. On the contrast, his methods aim at selecting regions where variation is minimal.

4.1. Experimental layout

The consequence of this approach is that interactions between controllable factors and noise factors should be investigated. This is given expression in the structure of the experiment. Each experiment consists of the controllable factor design (or 'inner array') and the noise factors design (or 'outer array'): see e.g. the layout below.

								1	1	2	2	M
trial	A	B	C	D	E	F	G	1	2	1	2	N
number	(1)	(2)	(3)	(4)	(5)	(6)	(7)	1	2	2	1	O
1	1	1	1	1	1	1	1	y_{11}	y_{12}	y_{13}	y_{14}	
2	1	1	1	2	2	2	2	y_{21}	y_{22}	y_{23}	y_{24}	
3	1	2	2	1	1	2	2	y_{31}	y_{32}	y_{33}	y_{34}	
4	1	2	2	2	2	1	1	y_{41}	y_{42}	y_{43}	y_{44}	
5	2	1	2	1	2	1	2	y_{51}	y_{52}	y_{53}	y_{54}	
6	2	1	2	2	1	2	1	y_{61}	y_{62}	y_{63}	y_{64}	
7	2	2	1	1	2	2	1	y_{71}	y_{72}	y_{73}	y_{74}	
8	2	2	1	2	1	1	2	y_{81}	y_{82}	y_{83}	y_{84}	

Controllable factors design ("inner array")   Noise factors design ("outer array")

The factors A through G are controllable, and they will be varied according to an L_8 orthogonal array. The factors M, N and O are noise factors, varying according to an L_4 orthogonal array. The combination of the two arrays says that each selected combination of settings of controllable factors is repeated in four different circumstances, according to the levels of the noise factors. The obtained measurements are denoted by y_{ij}, $(i = 1,\ldots,8;\ j = 1,\ldots,4)$.

There is of course a certain contradiction in wanting to incorporate a noise factor: after all, such a factor is by definition hardly, if at all, controllable. This is, however, usually possible for the purpose of an experiment, e.g. operators are in general noise factors (it is impossible to limit variation through the use of one operator only), but for the experiment it is possible to select two levels.

4.2. Analysis

In analyzing the results of an experiment a distinction is made between the three cases of the target value:

a. the smaller, the better;

b. the larger, the better;

c. nominal is best.

Each case demands its own analysis, with a signal-to-noise ratio deduced from the quality/loss function, and related to traditional signal-to-noise ratio's from the telecommunication world (where Taguchi originates from).

For cases a. and b. the analysis methods are identical. Firstly, all measurements belonging to a certain combination of levels of controllable factors are summarized in the signal-to-noise ratio. Secondly, the effects of the factors on this signal-to-noise ratio are calculated. Finally, a distinction is made between important and not important factors. Only the exact definition of the signal-to-noise ratio differs. For the above layout, the four measurements $y_{i1}, \ldots, y_{i4}$ are summarized into (Taguchi, 1986):

- the smaller, the better: $S/N_i = -10 \log (\sum_j y_{ij}^2/4)$
- the larger, the better : $S/N_i = -10 \log (\sum_j (1/y_{ij}^2)/4)$

The expression between brackets is the mean squared deviation, which is proportional to the quality loss. S/N thus expresses the quality loss on a logarithmic scale, and is larger as the loss (and the logarithm of it) is smaller; the signal becomes larger in relation to the noise (see also Maghsoodloo, 1990).

For case c. ('nominal is best'), the measurements are summarized in the average and the signal-to-noise ratio, one relating to the level (the average) and one relating to the variation (the signal-to-noise ratio). The type of measurements determines which definition of the signal-to-noise ratio should be taken. When absolute deviations are meaningful, the signal-to-noise ratio relates to the standard deviation, and when relative deviations (compared to the mean) make more sense, the signal-to-noise ratio relates to the coefficient of variation (see Kackar, 1985). Subsequently the effects of the factors on both statistics are analyzed separately. Finally the factors are classified according to their influence on level and on variation:

Controllable factor		influence on the variation	
		much	little
influence on the level	much	control factor	signal factor
	little	control factor	cost factor

To minimize the quality loss, firstly settings of controllable factors which are classified as control factors are chosen such that variation is minimal. Then settings of signal factors are chosen such that the target is met. Finally, settings of cost factors are chosen such that the costs are as low as possible. Note that, in contrast to current practice, attention is first given to the variation and only then to the level.

4.3. Example

An injection moulding process is to be optimized with respect to the quality characteristic shrinkage (a percentage). The shrinkage ought to be small, but even more important, it should be as constant as possible for several different conditions.

There are seven controllable factors:

- A: cycle time;
- B: mould temperature;
- C: cavity thickness;
- D: holding pressure;
- E: injection speed;
- F: holding time;
- G: gate size.

All factors were assumed to have an approximate linear effect, so two levels were selected for each factor. Moreover, all interactions were assumed to be negligible. The controllable factors design is an L_8 orthogonal array.

Three important noise factors were selected:

- M: percentage regrind;
- N: moisture content;
- O: ambient temperature.

All noise factors were set at two levels. The noise factors design is an L_4 orthogonal array.

The complete design has the layout of section 4.1; the results are shown in the next table.

trial number	A (1)	B (2)	C (3)	D (4)	E (5)	F (6)	G (7)	M 1 N 1 O 1	1 2 2	2 1 2	2 2 1
1	1	1	1	1	1	1	1	2.2	2.1	2.3	2.3
2	1	1	1	2	2	2	2	0.3	2.5	2.7	0.3
3	1	2	2	1	1	2	2	0.5	3.1	0.4	2.8
4	1	2	2	2	2	1	1	2.0	1.9	1.8	2.0
5	2	1	2	1	2	1	2	3.0	3.1	3.0	3.0
6	2	1	2	2	1	2	1	2.1	4.2	1.0	3.1
7	2	2	1	1	2	2	1	4.0	1.9	4.6	2.2
8	2	2	1	2	1	1	2	2.0	1.9	1.9	1.8

The problem is formulated as a 'nominal the best' case, because the shrinkage should be as constant as possible. The target value is not yet defined, however, except that it is preferred to be small. For the analysis, the average of the four measurements of each line, and the signal-to-noise ratio must be calculated. In this situation a relative measure of spread is preferred, and then Taguchi recommends the following signal-to-noise ratio:

$$S/N = 10\,{}^{10}\log\,(\bar{y}/s^2 - 1/n)$$

$$\text{where } \bar{y} = n^{-1}\,\Sigma y_j$$

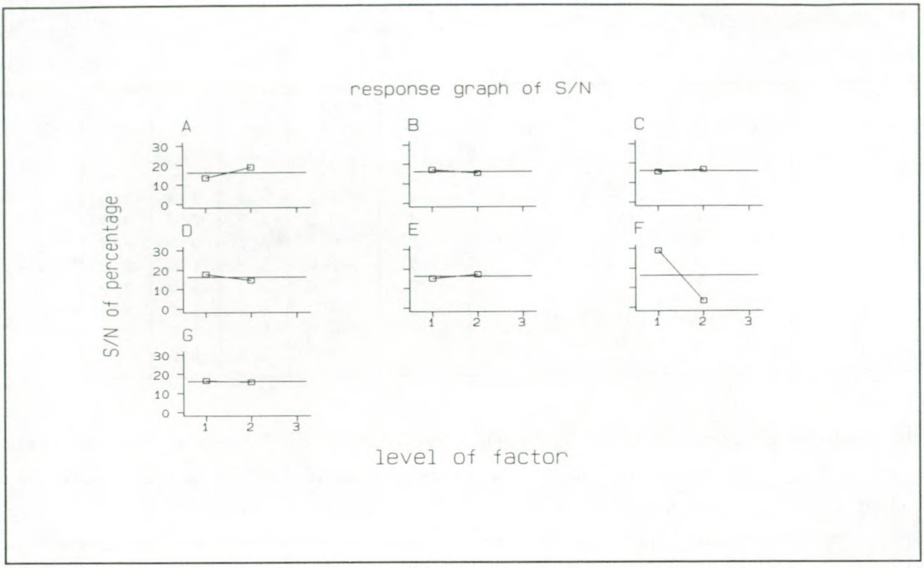
$$\text{and } s^2 = \Sigma(y_j - \bar{y})^2 \,/\, (n-1)$$

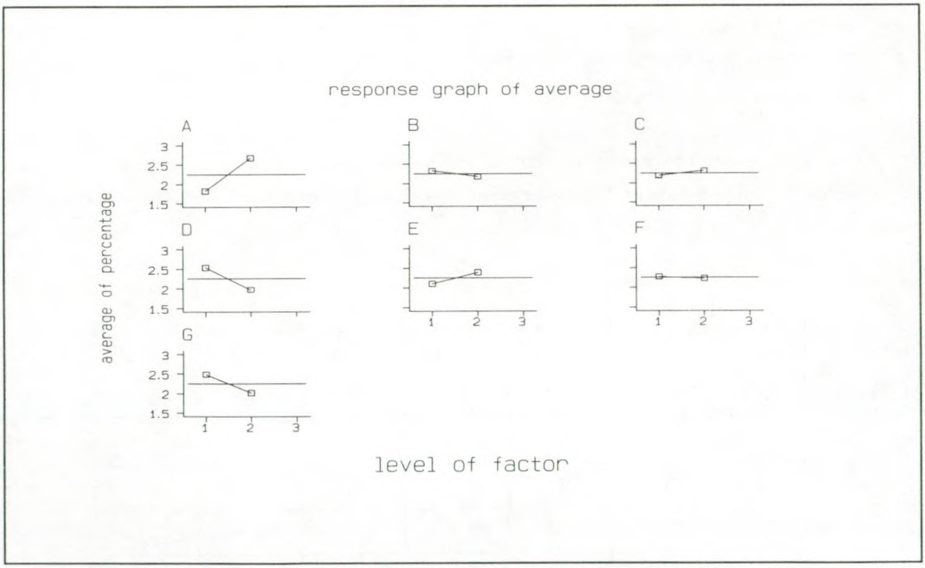
Now the signal-to-noise ratio and the average are considered as responses and they are analyzed. In the tables below (response tables) the effects of the factors are shown.

S/N	A	B	C	D	E	F	G
level 1	13.4	17.0	15.4	17.7	15.1	29.1	16.5
level 2	18.9	15.3	16.9	14.6	17.2	3.2	15.8

average	A	B	C	D	E	F	G
level 1	1.8	2.3	2.2	2.5	2.1	2.3	2.5
level 2	2.7	2.2	2.3	2.0	2.4	2.2	2.0

For interpretation, response graphs are recommended (see pictures below).


response graph of S/N
A
B
C
D
E
F
G
S/N of percentage
30
20
10
0
1
2
3
level of factor


response graph of average
A
B
C
D
E
F
G
average of percentage
3
2.5
2
1.5
1
2
3
level of factor

Classification of factors is a subjective affair, especially when no reference is made to experimental error. Nonetheless, based on the response graphs an attempt is made. And it is clear that for the variability (or S/N) factor F is most important (of all controllable factors included), followed by factor A. The decision to classify these factors as important for variability, and all others as unimportant is completely arbitrary, however, and subject to discussion. The same holds true when A, D and G are classified as important for the level.

The result is the following table

<table>
<tr><td colspan="2" rowspan="2">Controllable factors</td><td colspan="2">influence on variation</td></tr>
<tr><td>much</td><td>little</td></tr>
<tr><td rowspan="2">influence on level</td><td>much</td><td>A</td><td>D,G</td></tr>
<tr><td>little</td><td>F</td><td>B,C,E</td></tr>
</table>

With this table in mind, factors A and F (control factors) are set to minimize variation: A_2 and F_1 are chosen. Then factors D and G (signal factors) are set to minimize percentage shrinkage: D_2 and G_2 are chosen. Finally, factors B, C and E (cost factors) are set such that costs will be minimal.

4.4. Check

An experiment cannot be considered as finished, unless a confirmation experiment is performed. For several reasons it is of the utmost importance to check the interpretation of the analysis.

1. Since the experiments are highly fractioned there is a big chance that the recommended setting was not actually included in the experiment. It therefore should prove its ability to really be realistic.
2. The analysis gives rise to a 'paper champion' which by nature may well be (a little) optimistic. Moreover, a lot of assumptions have been made concerning factors, levels and interactions, and they will be reflected in the prediction of the results of the paper champion. If the prediction differs 'a lot' from the results of the confirmation experiment, then it must be suspected that the qualitative knowledge related to the problem is insufficient..
3. Before recommending the paper champion it should be checked that the results are really better than they were at the outset.

In general, predictions will be based upon the assumption of additive models. The reader may want to check that for the above example the average percentage shrinkage of the paper champion is 2.18, and that the signal-to-noise ratio is 29.9 (amounting to a standard deviation of 0.07).
This prediction can be compared with the results of trial 8 of the experiment (average = 1.90; signal-to-noise ratio = 27.3; standard deviation = 0.08).

The confirmation experiment can be expanded to an experiment comprising more runs, and it can serve then as the basis for tolerance design.

5. TOLERANCE DESIGN

In parameter design, the optimum combination of levels of controllable factors is selected. When the effect of noise has not been sufficiently reduced, then it becomes necessary to restrict the variation of the major noise factors to within narrower ranges - even if the costs will be increased. Tolerance design is the process of identifying the major noise factors and the permissible variation.

To obtain this knowledge, more experimentation is necessary. The influence of noise factors on the quality characteristic(s), in the neighbourhood of the optimum setting, must be quantified. It is important to note that a completely new experiment is performed, and that factors are classified accordingly. For example, it may have been found in parameter design that the optimal temperature of an oven is 750° C. However, there exists no single oven which can be set so that the temperature is precisely 750° C - there will always be some variation around the desired value. Now, for tolerance design, the temperature may be considered as a noise factor, if it is suspected that temperature variation has quite a large contribution to variation of the quality characteristic(s).

The general procedure for tolerance design is to select all suspected important factors causing variation, and then performing a three-level experiment. If a factor is distributed with mean μ and standard deviation σ, then the levels are chosen as follows (see also D'Errico and Zaino, 1988)

$$\begin{cases} \text{level } 1 = \mu - \sqrt{3/2}\,\sigma \\ \text{level } 2 = \mu \\ \text{level } 3 = \mu + \sqrt{3/2}\,\sigma \end{cases}$$

Now, the relative influence of the factors is comparable and an analysis of variance will reveal the factors that are most important to control.

Tolerance design, as contrasted with parameter design, may require the use of expensive components, materials and procedures, with small variability. It is therefore necessary to calculate whether the reduction in variability is worth the additional cost in each situation. The quality/loss function is to be employed for this.

6. DISCUSSION

Within the statistical world discussion have flared up as to the correctness of the statistics of Taguchi. Comments are made about the choice of experimental design and underlying models (Hunter, 1985), and about the signal-to-noise ratio concept (Box, 1988; León et al., 1987). Alternative analysis methods are proposed (Nair and Prebigon, 1986; Vining and Myers, 1990) and some authors even warn strongly for using Taguchi's methods (Tribus and Szonyi, 1989). Taguchi's supporters sometimes defend themselves convulsively, thereby creating a false contradiction between Taguchi's methods and traditional experimental design.

In our opinion, however, it is not a question of either Taguchi or experimental design. Rather, it is the problem to be solved which ought to dictate the method. Taguchi's methodology is developed for robust design, and it is also suitable for the rapid determination of a good setting. But for building (quantitative) models and learning to comprehend the mechanisms which underlie a phenomenon, Taguchi's methodology is found wanting, and e.g. response surface methodology is appointed (Box and Draper, 1987).

It should be kept in mind that Taguchi's methods are not primarily intended to be most efficient statistical methods. Their aim, especially parameter design, is to be a means for robust design and quality engineering. And we are absolutely convinced that certainly the concept is really valuable, and even necessary for companies like Philips - facing strong Japanese competition. Statisticians may have some doubts about the efficiency of the methods, but then, they are intended to be used by engineers (designers) and not professional statisticians. And as a tool for engineers, the methods dispense with all sophistications of statistics. The user unfamiliar with the material is led through the jungle of statistical methods, over a safe and broad road without alleyways. If modifications and improvements of the methods are suggested, it is important to consider that ordinary engineers, not knowing much about statistics, are the users.

Based on our conviction that Philips will benefit maximally if engineers are familiar with experimental design methods, we use the Taguchi framework as an important vehicle to reach this goal. Except for half-day seminars, to create awareness among managers and potential users, we organize four-day workshops for project teams that apply the Taguchi methods on a problem of their own. Our experience so far is that nearly all participants of the workshops are enthusiastic about the methods and the ideas behind them. Most of them also see many opportunities of applying the methods fruitfully. But even then, it remains difficult to have these well designed experiments actually performed. To convince management that it is better, and in the end also cheaper, to invest now in a well designed experiment is a major effort in many cases.

Another experience is that experimenters often shy away from the consequence of including noise factors, because this would mean that the originally small experiment based on controllable factors with only a few interactions, becomes at least twice as large. But because this interferes with the principles of quality engineering, we tend to deal with this extensively.

It is our policy to maximize the chances that during the workshop designed experiments are really performed. For this reason we offer follow-up support, to help convince management, to assist with the analysis, and also to stimulate the setup of new experiments. Unfamiliarity with statistical computations might be another drawback for using Taguchi methods. Easy to use software might overcome this, but unfortunately we were not aware of some package fulfilling our needs appropriately. Therefore we developed own software (Taguchi.Kit) to be used with STATA (a CRC trademark), a recommended statistical software package within Philips (Wanders and Trip, 1989)

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