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Application of Taguchi Methodology in Ceramics Processing

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***Abstract* – Partial Factorial experiments such as those proposed by Taguchi to apply in the optimization of production processes was successfully employed. Taguchi methodology of experimental design has been employed for the evaluation and optimization of ceramic processing. These experimental methods use a much smaller number of experiments than traditional full factorial experiments. Simplification as well as advantages and disadvantages of Taguchi methods will be discussed. In addition, an example study of the drying of slip-cast compacts, casting, firing, and testing of clay-based ceramic will be given as an explanatory example.**

***Keywords* – Taguchi, Partial Factorial Design, Optimization, Processing, Ceramics.**

I. Introduction

The traditional method of investigating, the effect of multifactor or multi-parameter response is to systematically vary each parameter while simultaneously holding all others constants. The method is very useful for exploring how a single parameter influences the response. However, it becomes time-intensive and costly when many parameters settings are investigated. For example, analysis of four-parameter system with three levels for each parameter requires 81 different experiments (3^4). Conducting every possible combination for a given set of parameters and levels is referred to as full factorial experiment. In one considers that each experiment should be performed a number of times to verify that the results are reproducible, it is seen that hundreds of experiments may be needed to fully investigate this relatively simple system [1& 2].

The alternative strategy is known as partial factorial experimental programs, that dramatically decrease the required number of experiments [9]. This results in a significant reduction in the volume of information that is available and hence a reduction in the overall amount that is learned about the system. However, carefully designed experimental programs still yield very valuable data from a rather limited set of experiments [4].

Although a variety of different types of partial factorial experiments are employed in industry, Taguchi methods are rarely used. We use Taguchi method of experimental design because it is quite simple to use, it employs a minimum number of experiments, and it implicitly includes techniques to examine and decrease the variability of the system. The major disadvantage of the method is that it does not handle interactions between the parameters in a simple way. This paper only contains a brief explanation of the method along with some experimental results, so the reader is directed to references and the bibliography for further details [5].

II. Taguchi Method of Experimental Design

The Taguchi method of experimental design allows the minimum number of experiments to be performed to determine the effects of 3 - 8 independent variables on a response. It is very efficient method that uses a polynomial of the highest possible degree in the parameter space to describe how each parameter affects the response. In addition, the method meshes very well with Taguchi's loss function, which associates a cost with the response being away from the optimal value regardless of whether the error is due to the process being out of specification or there being uncontrolled variability. However, as with all lightly efficient methods, there are a number of problems with this technique that can result in erroneous results, particularly if a high degree of precision is required [5-8].

The first of these problems is that Taguchi method ignores interactions between different parameters. This is the result of the assumption that the response is a linear combination of the effects due to each parameter. This is shown in equation 1;

$$y_{pred} = \bar{y} + eff(a_i) + eff(b_i) + \ldots\ldots eff(c_i) \tag{1}$$

Where y_{pred} is the predicted response, $\bar{y}$ is the average response of the system, and $eff(a_i)$ is the effect of parameter a at the i^{th} level.

These neglected interactions can be divided into synergistic interactions, which result a large response than the linear combinations, and anti-synergistic interactions, which result in a lower response. Both cause problems in applying the Taguchi method, but anti-synergistic interactions are more problematic.

The second problem is that Taguchi method frequently determines as many arbitrary parameters as there are experimental data points. This results in there being zero-degree freedom in the system of equations that is used to calculate the parameter effects. The response surface then describes the response at the combination of values of the independent variables that were examined, but it may not describe the response at other combinations. This effect can be decreased by including dummy parameters that add experimental conditions without increasing the number or arbitrary parameters that have to be determined. This increases the number of degrees of freedom in the system and hence includes some aspects of regression analysis to smooth out the effect of erroneous data points.

A third objection to Taguchi method is that the experiments are normally performed in the order in which they are listed in the experimental condition matrix, without randomization. This is done because the variables that are the most difficult to change and /or control are arranged in this matrix so that they change infrequently. This can result in systematic errors if any of the independent variables or the response - measuring apparatus drift over time. This is normally accounted for by running calibration experiments at various points in the experimental program to detect these changes. Most practitioners of the Taguchi method believe that these systematic errors are smaller than the errors introduced by frequent changes of the experimental conditions that randomization entails.

As a result of these problems, the Taguchi method is best suited to screening experiments or fine - tuning of systems where there are few, if any, interactions. In these cases, the method is very efficient and very powerful. When the Taguchi signal-to-noise function is used to analyze the data, it is possible to obtain much more information about the variability of the system and how to control this variability than can be obtained by any other method that uses the same number of experimental conditions.

III. Orthogonal Arrays

Orthogonal arrays are used in the Taguchi method of experimental analysis to ensure that a set of experimental parameters is selected that covers the experimental space as uniformly as possible. In addition, the orthogonal array ensures that the effect of each parameter is taken into account the same number of times (in most cases) and that each of the parameters is pairwise orthogonal to the others. This pairwise orthogonality prevents particular interactions (synergistic or anti-synergistic) from dominating the results [9].

A slight complication is that orthogonal arrays only exist for a select number of test conditions. This does tend to limit the usefulness of this method to particular numbers of parameters and levels. It is possible to use dummy arguments to supplement the parameters and/or levels present, thereby allowing arbitrary quantities of either to be examined while maintaining balanced interactions among the parameters. However, there are two disadvantages involved with the use of dummy arguments. The first is that more experiments must be performed than dictated by the degree of freedom of the system. The second is that the set of experiments may be more sensitive to the effects of some parameters than the others, due to the arrangement of the dummy arguments. The number of parameters and levels included in some of the more common orthogonal arrays are given in Table 1, where it is readily seen that there is a dramatic decrease in the number or required experiments from the full factorial experimental procedure [10 & 11].

Table 1. Nomenclature of Orthogonal Arrays [1].

Name	Parameters	Levels	Combination Possible	Required Trials
L_4	3	2	8	4
L_8	7	2	128	8
L_9	4	3	81	9
L_{12}	11	2	2048	12
L_{16}	15	2	32768	16
L'_{16}	5	4	1024	16
L_{18}	7/1	3/2	4374	18

IV. Signal / Noise Function

The signal-to-noise (S/N) is frequently used to combine optimization of the response with reduction of the variability due to noise. The term S/N originated in the area of electronic circuit design where it was desirable to maximize the output of an amplifier for a given power input while minimizing the amount of noise introduced into the signal. A result of the electronic origin of the S/N is that the values are normally converted to decibels (dB) via a logarithmic transformation, which results in the extreme cases being converted to more manageable numbers. However, the concept is applicable to any system where an optimal response is desired with a minimum of variability [8].

V. Loss Function

Taguchi introduced the concept of a loss function that assigns a cost to any response other than the optimal response, as opposed to the traditional approach of only assigning a cost if the process is out of tolerance and the part must be scrapped or reworked. The Taguchi loss function, L(y), is given by [9-11];

$$L(y) = K(y - T)^2 \tag{2}$$

Where y is the measured response, T is the target value, and K is the cost of deviation from the target, which is normally dictated by the cost to scrap a part when the tolerance limits are exceeded, as shown in Figure 1. In fact, the Taguchi loss function actually assigns a higher cost to a part that is out of tolerance than the cost to scrap it, since a process that has produced one out-of-tolerance part is likely to produce others.

The Taguchi loss function can be used to extend the concept of signal-to-noise ratio to cases where the optimal response is not necessarily the maximum response. This is done by applying a logarithmic transformation to the loss function. Since we are normally interested in quantifying a process based upon the performance of a number of parts rather than one part, the transformation is applied to the average Taguchi loss function for a series of nominally identical parts. A bit of algebraic manipulation results in the Taguchi signal-to-noise function, η, being given by equations 3-6 depending on whether the optimal response is a maximum, a minimum, or a target value. In all cases it is optimal to maximize η.

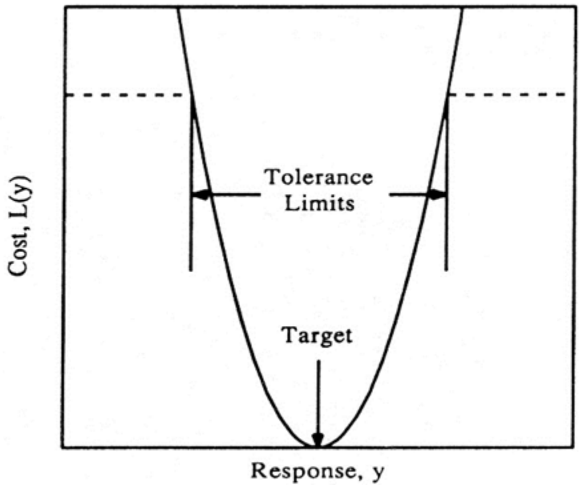

Fig. 1. Taguchi Loss Function [1].

1. The optimal response being a maximum is referred to as the more-is-better (MB) case, which is appropriate for the fracture strength of a structural material. The Taguchi signal - to - noise ratio is:

$$\eta_{MB} = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^{\,2}}\right) \tag{3}$$

2. When the optimal response is minimum, such as the number of defects in glaze, we have the less - is - better (LB) case, where the Taguchi signal -to-noise function is;

$$\eta_{LB} = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n}y_i^{\,2}\right) \tag{4}$$

3. The final case is when a particular target value of the response, such as the thickness of a coatings, is desired, which is known as nominal-is-better (NB). There is normally some parameter or scaling factor, such as coatings time, that can be adjusted to force the mean to the target. If the variance is dependent of this scaling factor, the Taguchi signal-to-noise function is;

$$\eta_{MB,1} = -10\log_{10} Sy^2 \tag{5}$$

Where S_y is the sample variance, if the variance also depends upon the scaling factor, the Taguchi signal-to-noise function is;

$$\eta_{MB,2} = 10\log_{10}\frac{Sy^2}{\bar{y}^2} \qquad (6)$$

Where: $\bar{y}$ is the mean response of the experimental run.

VI. Experimental Approach

The utility of Taguchi method will be illustrated using a ceramic processing study. A series of clay bodies composed of various fractions of goldart and redart clay. Green bodies were slip cast in acrylic moulds on plaster to yield bend bars that were 10 × 15 ×10 mm after drying. These were then fired in air at temperatures ranging from 1050 to 1200 °C with a holding time of 0-20 hours. The bend bars were then broken in four-point bending to determine the fracture strength, and the density of one portion of each bar was measured using Archimedes' method. The possible experimental parameters are summarized in Table 2. However, any combination of four parameters could be used [12-15].

Four of those parameters, which are highlighted in Table 2 were selected at three different levels using the Taguchi method and an L_9 orthogonal array. Once the four variable parameters were selected, a single value of each of the other fixed parameters was selected [16].

Table 2. Possible Parameters to Study.

Parameter	Levels
Composition (fraction of low-fine clay)	**0 – 100%**
Grog (fraction of dry total)	0-40%
Grog size	0.1 -1 mm
Solution pH	**3 - 11**
Dispersant Concentration	0 – 5 vol%
Dispersant Type	NH_3-PAA, NH_3-PMAA
Firing Temperature	1000 – 1200 °C
Firing Time	**0 – 20 hours**
Ramp rate	**1 – 20 °C/min**

The objective of this study was to demonstrate how changing the processing of clay body affects the properties, so the parameters were chosen to cover a fairly broad range and have reasonably strong and hopefully relatively equal effects on the properties. The L_9 orthogonal array is shown in Table 3 with the actual values of variable parameters.

The objective of this study was to maximize the strength and minimize the density of the material while increasing the reproducibility of the process. As a result, the less-is-better Taguchi signal-to-noise ratio was used for the density and the more-is-better was used for the strength. The specific strength could have been computed and used as the response to be optimized. A summary of the experimental results is given in Table 4 with the best value of each of the four types of response highlighted. It is readily seen that the strongest samples were among the most dense, and that the sample with the lowest density was the weakest.

Table 3. The L9 Orthogonal Array, Parameters and Levels.

Expt. #	A Goldart %	B Slip pH	C Hold time (h)	D Ramp rate °C/min
1	50	7	1	2
2	50	9	3	8
3	50	11	9	12
4	70	7	3	12
5	70	9	9	2
6	70	11	1	8
7	90	7	9	8
8	90	9	1	12
9	90	11	3	2

The results were used to determine the effect of each of the parameters on both of the measured responses. This process is demonstrated for the calculation of the effect of parameter C (hold time) at level 2 (3h), known as c_2 on the strength.

Table 4. Summary of the Experimental Results.

Exp.	#	Strength		#	Density	
		Mean (MPa)	η_{MB}		Mean (g/cm^3)	η_{LB}
1	8	21.46 ± 2.83	27.04	7	2.21 ± 0.08	- 6.52
2	6	24.01± 2.69	27.14	6	2.71 ± 0.19	-6.75
3	8	24.09 ± 6.99	28.12	7	2.50 ± 0.15	-7.98
4	8	26.49 ± 4.12	29.12	7	2.72 ± 0.05	-7.12
5	8	22.00 ± 4.84	25.62	7	2.81 ± 0.04	-6.77
6	6	7.52 ± 0.63	16.82	7	1.48 ± 0.04	-5.29
7	8	19.78 ± 3.07	24.87	7	2.11 ± 0.07	-6.48
8	8	5.34 ± 1.89	9.86	7	1.68 ± 0.06	-4.53
9	6	12.83 ± 2.64	22.13	7	2.02 ± 0.03	-6.12
Mean		17.27 ± 3.8	22.6	Mean	2.10 ± 0.08	-6.40

$$c_2 = \frac{y_2 + y_4 + y_9}{3} - \bar{y}$$
$$= \frac{24.01 + 26.49 + 12.38}{3} - 17.27 = 3.69$$

Where y_2, y_4 and y_9 are the responses for the experiments where C was set to level 2. This process extends to all four different responses and each of the 12 parameter effects subjected to the constraint that effects of a given parameter must sum to zero.

The effects of different parameters on the strength and η_{MB} for the strength are show in Figure 2. It is readily that composition and hold time had the largest effect on the strength with the ramp rate having the smallest effect. It is possible to use this information to predict the combination of parameter levels that will result in the highest strength by taking the level with the largest positive effect for each of the parameters. The predicted maximum strength should be obtained for a sample made of 50% goldart clay at pH 7 that was fired for 3 hours using a ramp rate of 2°C/min, although a ramp rate of 12°C/min is predicted to give nearly the same strength. This experimental condition is known as $a_1b_1c_2d_1$, and it was not conducted so a confirming experiment must be performed.

Examination of the plot for η_{MB} for the strength shows that the effects on this response are very similar to those for the actual value of strength, except for parameter D, the ramp rate. In this case the fast ramp rate, 12 °C/min resulted in a significantly lower η_{MB} than a ramp rate of 2°C/min. As a result, the ramp rate should be set to 2°C/min rather than 12°C/min, even though both levels are predicted to result in nearly the same strength.

The effect of the parameters on the density and η_{LB} for the density are shown in Figure 3. In this case the composition and firing time have the largest effect with the minimum density predicted to occur for the experimental condition $a_3b_2c_1d_2$, which was not performed. It is always desirable to maximize the signal-to-noise ratio η since the formation accounts for the direction in which the response is to be driven. As such the experimental condition $a_3b_2c_1d_2$ is predicted to optimize η_{LB} as the density.

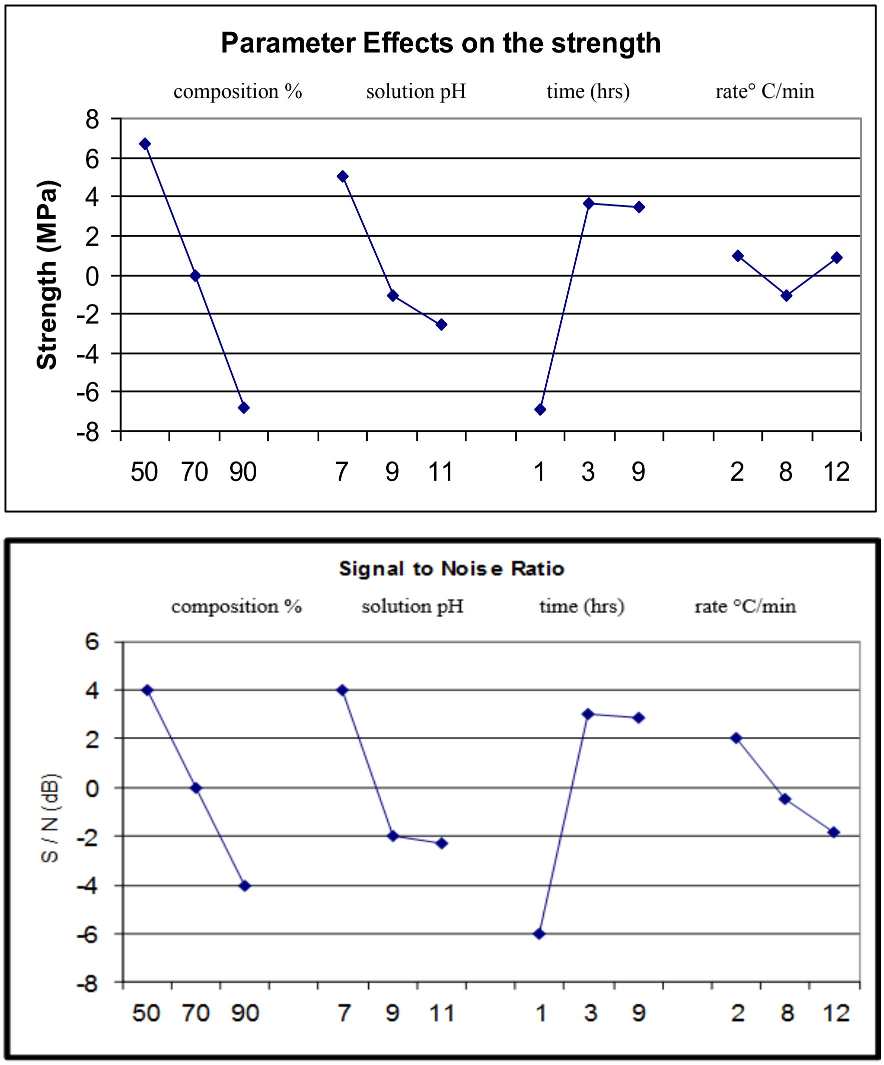

Fig. 2. The parameter effects on the strength (top) and η_{MB} (bottom) for the sintered clay body.

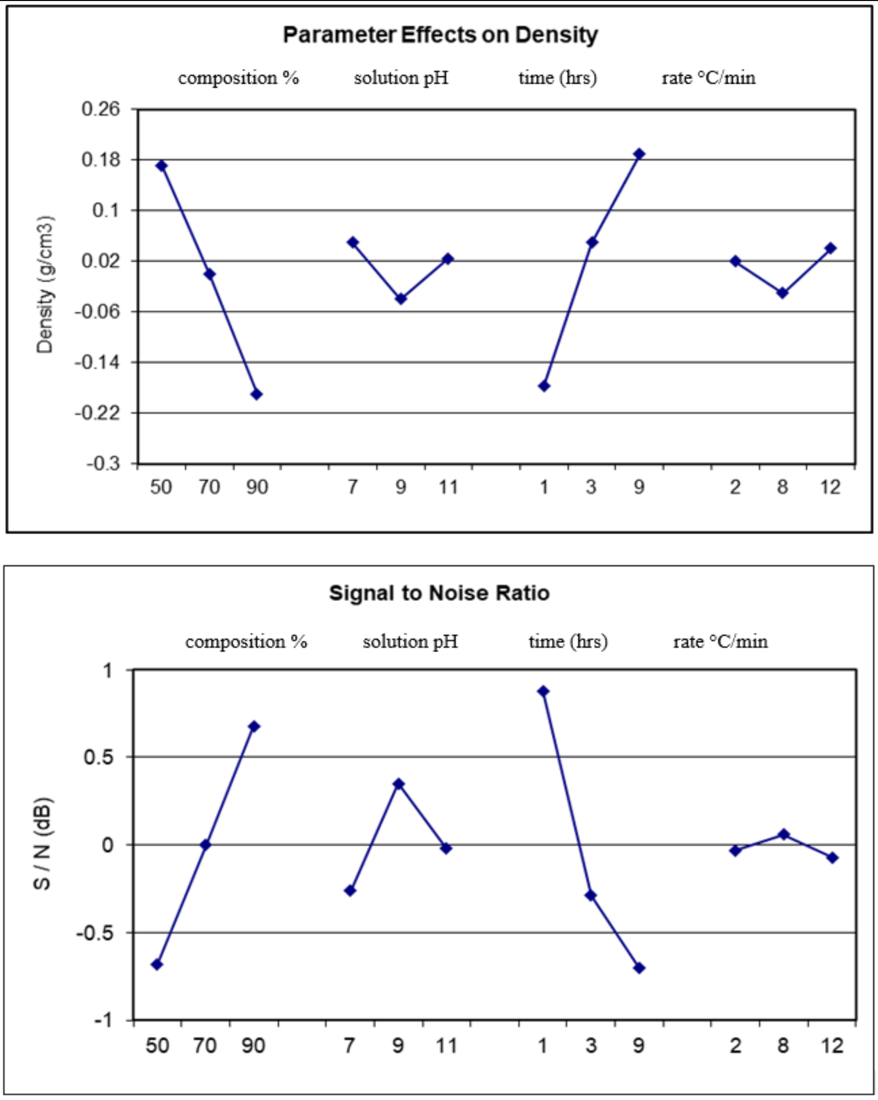

Fig. 3. The parameter effects on the density (top) and η_{LB} (bottom) for the sintered clay body.

As stated above, it is necessary to perform confirming experiments to determine if the predicted optimal experimental condition is really the optimal experimental condition. In complicated system such as this clay product, there are frequently interactions between the parameters that modify the results from those that are predicted from simple addition of the parameter effects. The presence of these interactions in this system can be verified by calculating the predicted minimum strength, which is negative; a clearly impossible situation. In addition, the smaller effects are often at the level of noise, and as such their contribution is not significant. Further information on quantifying the significance of the effects can be found in references such as Phadke [4] and Ross [5]. It is also good to perform confirming experiments for the second and possibly third-best predicted experimental conditions in case the interaction effects make one of these the best condition.

The results of the confirming experiments are shown in Table 5, where it is seen that there is relatively poor argument between the predicted and the measured responses. This result is not really unexpected based upon the complexity of the system that was studied and what is known about interactions between the various parameters. However, it is seen that responses for the experimental conditions that were predicted to give optimal results were among the best responses in most cases, indicating that the parameter interactions are not extremely severe.

Table 5. Confirming Experiments and Results.

Measured Property	Experimental Condition	Measured Response	Predicted Response
Maximum strength (MPa)			
Predicted maximum	$a_1b_1c_2d_1$	21.93	32.34
Second choice	$a_1b_1c_3d_1$	24.90	32.05
Actual maximum	$a_2b_1c_2d_3$	26.42	--------
Minimum density (g/cm)^3			
Predicted minimum	$a_3b_2c_1d_2$	1.80	1.57
Second choice	$a_3b_2c_1d_2$	N/A	------
Actual minimum	$a_3b_2c_1d_3$	1.68	--------

VII. Conclusions

Partial factorial experiments are much more efficient than full factorial experiments for exploring the effects of a number of parameters on one or more experimental responses. The Taguchi method is one of the most efficient and easiest methods to use. This is a consequence of the assumed additivity of the parameter effects and the fact that interactions between the parameters are ignored. The fact that the Taguchi method ignores parameter interactions means that it is not the optimal method for investigation where strong parameter interactions are present and high-precision results are necessary. However, it works very well for screening experiments and it is particularly useful as an introduction to partial factorial experimentation, since the calculations are simple and easily understood. In addition to being very easy to use, one of the great advantages of Taguchi method is that it implicitly includes reduction of system variability via the various formulations of the signal-to-noise function can be optimized.

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