ISSN 2229-5518

A Review of Traditional Design of Experiment and Taguchi Robust Parameter Design

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Abstract— Different design of experiment (DOE) methods and Taguchi orthogonal arrays are reviewed in this paper. The former includes traditional DOE approaches, namely, (a) single-factor experiment, (b) several factors one at a time, (c) several factors all at the same time, and (d) full factorial design. The traditional ANOVA and the Taguchi signal-to-noise ratio (SNR) are also discussed. In addition, this paper reviews traditional and Taguchi loss functions. A comparison is conducted on the traditional DOE and loss function versus Taguchi orthogonal arrays and the Taguchi loss function. ANOVA and SNR are also compared and summarized. This paper concludes that Taguchi orthogonal arrays, loss function analysis, and SNR are more efficient and accurate than traditional methods.

Index Terms— Taguchi Orthogonal Arrays; Taguchi Loss Function; Signal to Noise Ratio; Factorial ANOVA, One-factor Experiments, Several Factors One at a Time.

1 Traditional Design of Experiment

DESIGN of experiment (DOE) was first proposed by [1] and is commonly used by many researchers and engineers to find the effects of input parameters on output parameters [2]. The following types of DOE conventionally proposed by [1] exist.

1.1 One-factor Experiments

This DOE type selects only one input factor considered most essential by a researcher among others, with other factors assigned a constant value, that is, they are ignored. The selected factor is tested under two different conditions to see its effects on only one output factor such as product performance [3]. An example of the DOE is tabulated in Table 1.

TABLE 1
ONE FACTOR AT A TIME EXPERIMENT

Trial	Factor level	Test result	Test average
1	A_1	100	Y_1
2	A_2	200	Y_2

Table 1 shows only one factor, which is A with two levels of parameter setting. If there is any change in output factor Y, then factor A has a significant effect on the output factor Y. If no difference exists between Y1 and Y2, then other factors would be tested [3].

1.2 Several Factors One at a Time

This DOE method tests few factors simultaneously. For example, if there are four factors A, B, C, and D with two levels each, then the DOE procedure shown in Table 2 is performed.

TABLE 2
SEVERAL FACTORS ONE AT A TIME STRATEGY

Trial	Factors				Test result	Test average
	A	B	C	D		
1	1	1	1	1	100	Y_1
2	2	1	1	1	200	Y_2
3	1	2	1	1	300	Y_3
4	1	1	2	1	400	Y_4
5	1	1	1	2	500	Y_5

For the first trial run, all the factors are set to level one. For the second trial run, factor A is set to level two, while other factors remain as level 1. Furthermore, in the third trial run, factor B is set to level two, while other factors are set to level one. In the fourth trial run, factor C is set to level two. In the last trial run, factor D is configured to level two, while all other factors remain as level one. This is the traditional scientific approach to experimentation, but the combination effect with any two or more factors cannot be determined [3], such as when factors A and B are in level two while factors C and D are in level one.

1.3 Several Factors All at the Same Time

TABLE 3
SEVERAL FACTORS ALL AT THE SAME TIME STRATEGY

Trial	Factors				Test result	Test average
	A	B	C	D		
1	1	1	1	1	100	Y_1
2	2	2	2	2	200	Y_2

The "several factors all at the same time" experiment strategy uses several trial runs with the same factor level setting. As tabulated in Table 3, all the factors in the first trial run are set to level one. In the second trial run, all the factors are fixed to level two with the expectation of changes in the output factors from Y1 to Y2 [3]. Considered this a poor experimental strategy that has no scientific basis.

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1.4 Full Factorial Design

The full factorial experiment is a better test strategy that provides a certain experimental level setting; thus, it is more organized than the previous experiment strategies. As tabulated in Table 4, better level arrangement is executed to ensure that all kinds of potential level combinations are covered. In the first run, two input factors are set to level one. The second trial run uses the combination of factor A with level one and factor B with level two setting. In the third trial run, the factor A is set to level two and factor B is set to level one. In the final trial run, both input factors are set to level two. Generally, this type of DOE considers all the possible factor level combinations, which requires nk number of experimental trial runs, where n is the number of factor levels, and k is the number of factors. This strategy is good for investigating a few factors, but when several factors are inspect simultaneously, a very large trial run is required to complete the experiments [2], [3]. Therefore, an efficient test strategy was designed as discussed in the following section to resolve those problem.

TABLE 4
FULL FACTORIAL EXPERIMENT

Trial	Factors and factor levels		
	A	B	Respond
1	1	1	**
2	1	2	**
3	2	1	**
4	2	2	**

2 TAGUCHI ORTHOGONAL ARRAYS

The traditional DOE uses trial-and-error methods to verify and validate the theories that may be advanced to explain some observed phenomenon [3]. However, those strategies are not accurate or meaningless. Even though the full factorial design has an organized arrangement, it is not efficient and requires large trial runs to figure out the optimization setting [4]. To solve this issue, Genechi Taguchi formalized the fractional factorial DOE method into OAs, which can reduce the number of required experiment trial runs significantly [2].

OAs are basically a systematic factors versus level arrangement to ensure that all the possible combinations of levels for all the factors are tested with as few experimental runs as possible. Taguchi's OA is derived as La (bc), where the L indicates that the experimental designs are associated with Latin square designs, a is the number of trial runs, b is the number of levels, and c is the number of factors [2]. Taguchi's OA experimental design enables the experiment to be conducted more efficiently compared with the traditional full factorial DOE [2].

Table 4 tabulates the comparison between the Taguchi's OA DOE versus the traditional full factorial DOE.

TABLE 4
COMPARISON BETWEEN TAGUCHI'S OA DOE VERSUS FULL FACTORIAL DOE

OAs	Number of factors	Level of factors	Number of experiments for OA	Number of experiments for full factorial
L4(2^3)	3	2	4	8
L8(2^7)	7	2	8	128
L9(3^4)	4	3	9	81
L12(2^{11})	11	2	12	2048
L16(2^{15})	15	2	16	32768
L16(4^5)	5	4	16	1024
L18(2^1*3^7)	1, 7	2, 3	18	4374

Table 5 shows a significant efficiency improvement from full factorial DOE to Taguchi's OA DOE, with OA having 8 trial runs, whereas full factorial DOE required 8 runs for L4(23). L8(27) required only 8 trial runs for OA compared with full factorial DOE, which required 128 runs. The full factorial DOE for L9(34) required 81 runs to complete the experiment, whereas OA required only 9 runs. L12(211) and L16(215) required 12 and 16 runs for OA compared with 2048 and 32768 runs, respectively, for full factorial DOE. The full factorial DOE for L16(45) required 1024 experiment runs, whereas the Taguchi OA was completed in 16 runs. For L18(21*37), the Taguchi OA was completed in 18 runs, whereas full factorial DOE required 4374 runs. This comparison concluded that the Taguchi OA is more efficient than the traditional full factorial DOE [5]. The Taguchi OA improves not only the DOE efficiency but also the analysis accuracy where the variations around the target are minimized [5], as shown in Figure 1.

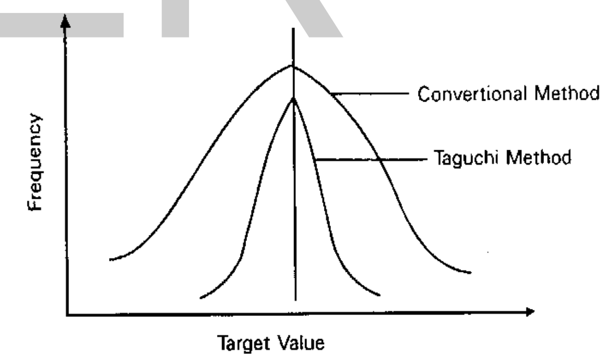

Fig. 1. Comparison of traditional method versus the taguchi method

Taguchi DOE produces a more accurate result because it utilizes both average and variation of data as part of its analysis unlike the traditional DOE, which uses only the average values of the response data [2]. To achieve this accuracy, Taguchi designed the Signal to Noise Ratio (SNR) method.

The traditional variability measurement method evaluates noise as the output value, which includes repeatability, reproducibility, and stability [6]. It determines only several specific and individual functions or symptomatic failures by calculating the average factor effect, but it does not capture the variability of results within a trial condition [7], [8]. However, measuring only the noise is not the best way to measure. The error within a certain range needs to be determined in real time. Therefore, the SNR approach was developed to measure the input to output relationship. This method takes into account not only the noise but also the factors that affect the output value. The output elements include sensitivity, slope, and variability, which are combined into a single index, namely, the actuator performance robustness against usage noise conditions [7].

3 Signal to Noise Ratio (SNR)

SNR was proposed by [9] as the measurement tool for robustness to produce a robust process or product. The concept is that the design must be optimized for robustness before any kind of compensation after failure is considered, with the compensation approach being the conventional whack-a-mole way to fire-fighting failure with the expectation that the product can function according to the manufacturer's specification after compensation [9]. The whack-a-mole approach is inefficient and costly, which may also result in customer dissatisfaction. SNR is used to measure robustness to see how well the product or process responds to noise; a high ratio corresponds to greater product quality and process performance [9].

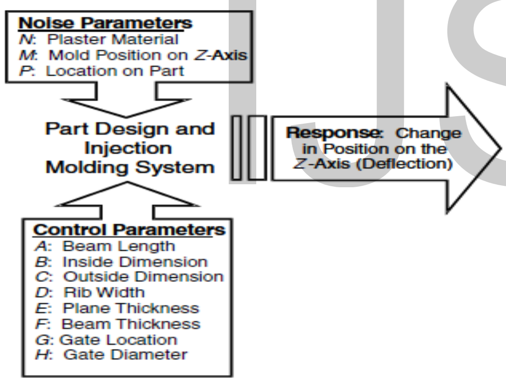

Fig. 2. P-diagram for static system

The SNR measurement approach identifies the best design parameter setting that will produce the optimum output so that robustness can be achieved with the minimum cost. Two system designs are used for SNR analysis, namely, the static system and the dynamic system. Static systems have a desired output, which has a fixed target value, dynamic systems have a target value that depends on the input signal [10]. The static system can measure by using approaches. namely, "the smaller the better", "the larger the better", and "the nominal the best", which are translated from the Taguchi loss function analysis [6]. The P-diagram example for the static and dynamic systems are shown in Figures 2 and 3, respectively.

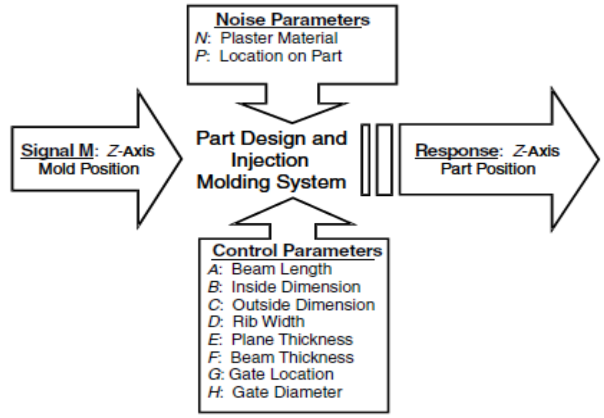

Fig. 3. P-diagram for dynamic system

The advantage of Taguchi SNR over ANOVA is that it can produce the information of optimization parameter setting (η) and the parameter sensitivity slope (β) [9]. This information makes the optimization process easier. The example for η and β are shown in Figures 4 and 5, respectively.

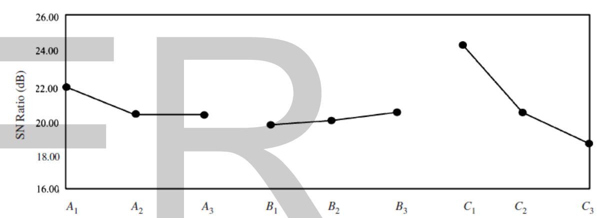

Fig. 4. SNR factorial effect graph

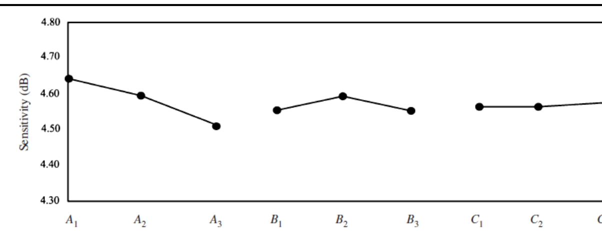

Fig. 5. Sensitivity graph

As shown in Figure 4, the SNR factorial effect graph provides the optimum and worst parameter settings where 3 control factors exist, namely, A, B, and C. The optimum parameter setting shown in the graph is A1, B3, and C1, while the worst parameter setting is A3, B1, and C3. In addition, the sensitivity graph shows which parameter is most and least sensitive to the product or process, as shown in Figure 5. Factor A has the most sensitive factor, while factor C is the least sensitive factor. The sensitivity graph has a similar function as ANOVA, but it cannot conclude if the factors have a significant effect or not. Therefore the SNR needs to be executed together with ANOVA, where ANOVA is used for preliminary analysis to determine which factor has a significant effect on the process or product and the identified factors are then used for SNR optimization analysis [11].

4 Taguchi Loss Function

The traditional way to measure product quality is to ensure that the product conforms to the manufacturer's specifications. However, [6] have a different view about product quality. According to them, quality should not only fulfil the manufacturers' specification, but the loss in dollars to society should be also considered from the perspective of inefficiency of the product quality performance.

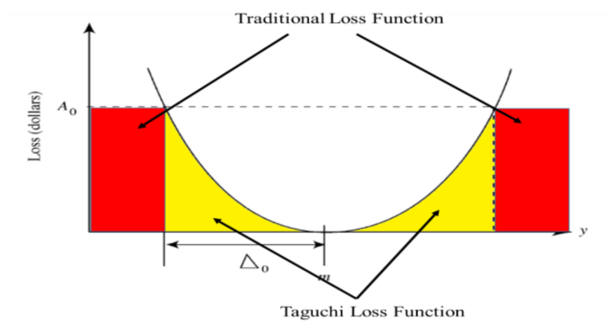

Fig. 6. Taguchi and traditional loss function

In Figure 6, the traditional loss functions are in the red area, while the Taguchi loss functions are in the yellow area. Taguchi believed that when the product does not perform according to the target value, then even though the performance almost meets the manufacturer's specification, the functionality variation still causes loss to society [6]. In addition, if the manufacturer's specifications are too loose, then the product quality itself is questionable. A simple example is shown in Figure 7.

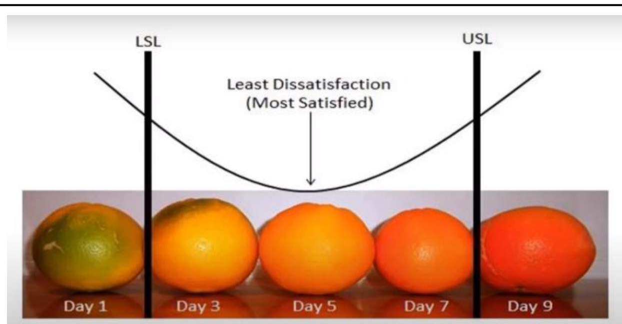

Fig. 7. Taguchi loss function example

As shown in Figure 7, the orange has the most satisfying taste on day 5. The orange on day 1 is not ready to eat. The orange on day 3 is acceptable to eat, but it does not taste as good as the orange on day 5. If one waits until day 7, the taste is slightly unsatisfying because it is past the ideal day but it is still between the specification limit, and if one eats the orange on day 9, the taste is highly unsatisfactory because it exceeds the control limit [12]. Three types of Taguchi loss functions exist, namely, the nominal the better, the smaller the better, and the larger the better, as explained in the following section.

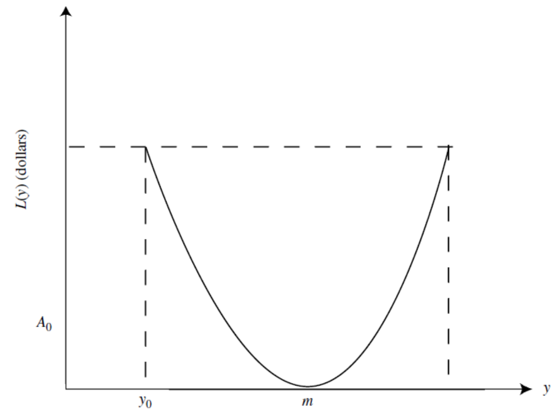

Fig. 8. Taguchi loss function – the nominal the better

As shown in Figure 8, the-nominal-the-better loss function has a finite target point to achieve, which is m at the middle, and the upper and lower specification limits are set on both sides of the target [6]. Equation 1 is used to calculate the loss function (L).

$$L = k(MSD), \quad (1)$$

where the L is the loss function, k is the proportionality constant, and MSD is the mean-squared deviation.

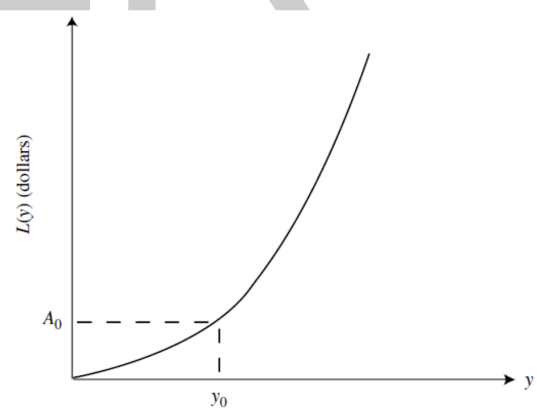

Fig. 9. Taguchi loss function: the smaller the better

For the-smaller-the-better loss function, if the product quality or process performance has a small value, then the loss will reduce. As shown in Figure 9, when the product quality (y) value increases, then the loss (A) also increases relatively [6]. Equation 2 is used to calculate the loss function (L) for the smaller the better.

$$L = ky^2, \quad (2)$$

where the L is the loss function, k is the proportionality constant, and y is the product quality value.

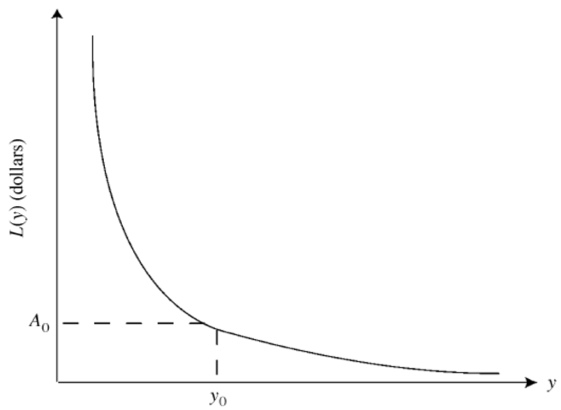

Fig. 10. Taguchi Loss Function – the larger the better

The larger-the-better loss function as shown in Figure 10. If the product or process quality value (y) is higher, then the loss (A) will decrease [6]. Equation 3 is used to calculate the larger-the-better loss function.

$$L = k\,(1/y^2), \qquad (3)$$

where the L is the loss function, k is the proportionality constant, and y is the product quality value.

5 Comparison Summary

In summary, Taguchi is a more efficient way than the traditional DOE method. As shown in Table 5, the Taguchi DOE requires fewer experiment trial runs than the traditional DOE, which requires a large number of trial runs when the number of factors increases. The traditional statistic method determines only several specific and individual functions or symptomatic failures by calculating the average factor effect, but it does not capture the variability of results within a trial condition unlike the Taguchi SNR, which measures the input-to-output relationship to include the effect of both noise and factors on the output value as the single index. Taguchi SNR is the measurement method of product or process robustness to ensure the optimization of the parameter that produces the optimum output of either the product quality or process performance, thereby reducing the overall inefficiency [9], unlike the traditional statistic, which does not identify the best parameter settings [13]. Finally the Taguchi loss function analysis, which takes into account the loss due to the deviation from the target quality value instead of only considering loss when the quality value is out of the specification, is a more accurate approach because many satisfaction levels exist, as explained in Figure 7, namely very satisfied, slightly dissatisfied, and very dissatisfied. If the product quality specification determined by the manufacturer is too loose, then even though the quality is still between the specifications, consumers will still be dissatisfied. Taguchi is a better method for optimization research because of those three reasons. The Taguchi and the traditional approaches are compared in Table 6.

TABLE 6
COMPARISON BETWEEN TAGUCHI AND TRADITIONAL DOE VERSUS FULL FACTORIAL DOE

Trial Run / DOE methods	Large experiment runs	Low experiment runs
Full factorial	√	
Taguchi OAs		√
Function / Statistic	**Significant effect**	**Parameter optimization**
ANOVA	√	
SNR		√
Function / Statistic	**Functionality deviation loss**	**Out-of-specification loss**
Traditional loss function		√
Taguchi loss function	√	√

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