Alpha Risk of Taguchi Method with L_{18} Array for NTB Type QCH by Simulation

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Abstract— **Taguchi method is a widely used approach for parameter design to achieve quality and yield improvements for many business applications. Nevertheless, there has been much discussion in literature about the invalidity of the statistical techniques adopted in this method. This research proposes an extension to ongoing research by investigating the alpha risk of Taguchi method with L_{18} ($2^1\times3^7$) array for the nominal-the-best (NTB) type quality characteristic (QCH) using simulation. It is assumed that all QCH values are normally distributed with the same mean and standard deviation. Then the null hypothesis, that all factors should be identified as insignificant, is true. Simulation results however, showed that the alpha risk is very high and hence Taguchi method may provide a misleading parameter design. This research, therefore, recommends relying on more efficient alternatives.**

Index Terms—**Alpha risk, Nominal-the-best, Simulation, Taguchi method.**

I. Introduction

Taguchi [1] considers three stages in product's or process's development: system design, parameter design, and tolerance design. In system design, the engineer uses scientific and engineering principles to determine the basic configuration. In the parameter design stage, the specific values for the system parameters are determined. Finally, tolerance design is used to determine the best tolerances for parameters.

In most literature review, the parameter design, or so-called Taguchi method [2], received the most attention. Parameter design is an off-line production technique for reducing variation and improving quality by using the product array. In parameter design, Taguchi focuses on determining the effects of the control factors on the robustness of the product's function. Instead of assuming that the variance of the response remains constant, it capitalizes on the change in variance and looks for opportunities to reduce the variance by changing the levels of the control factors. In Taguchi method, orthogonal arrays (OAs) are employed to optimize the amount of information obtained from a limited number of experiments. The signal-to-noise (S/N) ratio is then used as a quality measure to decide optimal factor levels. Analysis of variance (ANOVA) for S/N ratio follows to determine significant factor effects. In ANOVA, Taguchi obtains an approximate estimate of error variance by pooling-up technique [3]. Then, he adopts F value of four to decide significant factor effects. According to Taguchi, the application of the above procedure provides a robust design. Taguchi method has been adopted for parameter design in many business applications [4-5].

Nevertheless, the statistical techniques of Taguchi method have been the subject of debate and much discussion in different platforms. For example, Leon *et al.* [6] introduced the concept of performance measure independent of adjustment as a replacement for S/N ratio. Box [7] used sampling experiments with random numbers to illustrate the bias produced by pooling. Tsui [8] mentioned that Taguchi's analysis approach of modelling the S/N ratio leads to non-optimal factor settings due to unnecessary biased effect estimates. Ben-Gal [9] suggested the use of data compression measures combined with S/N ratio to assess noise factor effects.

Failure to select the best conditions for process or product parameters is a costly mistake in today's highly competitive markets. Li and Al-Refaie [10] investigated the alpha risk of Taguchi method, or the probability of identifying insignificant factors as significant, with L_{16} array for the larger-the-better type quality characteristic (QCH) using simulation. The L_{16} array contains 15 two-level factors. Occasionally, there is interest in using an OA that has some factors at two levels and some factors at three levels. The most-widely used mixed-levels OA is the L_{18} ($2^1\times3^7$) array [11]. To extend the above research for another QCH type, the research investigates the alpha risk of Taguchi method with L_{18} ($2^1\times3^7$) array for the nominal-the-best (NTB) type QCH using simulation. Further, Dabade *et al*. [12] employed Taguchi method using QCH values instead of S/N ratio. Furthermore, Sun *et al*. [13] tested factor's significance at 5 % significance level instead of four. In these regards, the alpha risk of Taguchi method will be also investigated at 5 % significance level and for QCH. The remainder of this paper is organized as follows. Section II outlines research methodology. Section III provides analysis and discussion of alpha risk. Section IV summarizes conclusions.

II. Methodology

It is assumed that QCH, x, is normally distributed with mean and standard deviation of μ and σ, respectively. Let y be a standardized random variable of x calculated as $(x-\mu)/\sigma$; or $y \sim$ NID(0, 1). The L_{18} ($2^1\times3^7$) array is shown in Table 1. This array has 18 rows (experiments) and nine columns, including a hidden column I which contains A×B interaction. Column A has two levels, whereas columns B to I are assigned each at three levels. All y values will be generated from NID(0, 1). Consequently, the null hypothesis, H_o, that all the nine factors are insignificant, is true. The alternative

Manuscript received March 6, 2008. This work was supported by the Department of Industrial Engineering and Systems Management in Feng Chia University.

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hypothesis, H_1, will be that at least one factor is identified as significant. Typically, the alpha risk is calculated as the probability of rejecting H_o given that H_o is true.

Let k represents the number of pooled-up columns into error term and α_k denotes alpha risk. The L_{18} ($2^1 \times 3^7$) has 17 total degrees of freedom; one degree of freedom for column A, whereas two degrees of freedom associated with each of the eight three-level columns. If each column is assigned to a factor, no degrees of freedom will be left for error term. In order to test factor's significance, the sum of squares for the bottom five columns; or about half the degrees of freedom of L_{18} ($2^1 \times 3^7$) array as suggested by Taguchi, can be pooled-up to obtain an approximate estimate of error term. Consequently, at most five columns of L_{18} ($2^1 \times 3^7$) array will be pooled-up as error term as illustrated in Table 2. For example, when one column is pooled-up into error term; i.e., k equals one, the error sum of squares (SS_E) is obtained as follows:

a. If the smallest sum of squares (SS) corresponds to column A, the SS_E is equal to the SS_A. Then, one degree of freedom is associated with error term (df_e). The MS_E is equal to SS_E. The mean square (MS) contributed by each of three-level factors is obtained from SS divided by two.
b. If the smallest SS corresponds to a three-level factor, the SS_E is equal to the smallest SS, whereas df_e is equal to two.

The SS_E is obtained when two to five columns are pooled-up in a similar manner. The methodology adopted to estimate the alpha risk of Taguchi method is outlined in the following steps:

Step 1: Start the first simulation cycle by generating two replicates, y_1 and y_2, from NID(0, 1) for each standardized QCH, y_i, in each row i; i = 1, ... , 18.

Step 2: Let $\bar{y}_i$ be the average of y_1 and y_2 values and s_i^2 denotes the variance. Calculate the S/N ratio, η_i, using

$$\eta_i = \log_{10}\left(\frac{\bar{y}_i}{s_i}\right)^2 \qquad i = 1, \ldots, 18 \tag{1}$$

where $\bar{y}_i$ is calculated as

$$\bar{y}_i = (1/2)\sum_{r=1}^{2} y_{ir} \qquad i = 1, \ldots, 18 \tag{2}$$

and s_i^2 is given by

$$s_i^2 = \sum_{r=1}^{2} (y_{ir} - \bar{y}_i)^2 \qquad i = 1, \ldots, 18 \tag{3}$$

Step 3: Let l represents the number of factors identified as significant and p (k, l) denotes the probability of identifying l factors as significant when k columns are pooled-up. Let $\bar{p}$ (k, l) represents the average of p (k, l) values, while s_p is the standard deviation for several simulation cycles. Conduct ANOVA by calculating the SS contributed by each factor. Then, pool-up one column into error term as shown in Table 2. Obtain the F ratio for each remaining factor as MS divided by MS_E, and then compare it with four. If the F ratio for a factor is greater than four, that factor is identified as significant. Otherwise, it is identified as insignificant. Perform simulation for several cycles each of large enough runs to ensure that s_p is very small relative to α_k. Estimate the $\bar{p}$ (1, l) values then calculate α_1 using Eq. (4).

$$\alpha_1 = \sum_{l=1}^{8} \bar{p}(1,\ l) \tag{4}$$

The probability of identifying correctly all the (9-k) factors as insignificant, $\bar{p}$ (1, 0), is equal to (1-α_1). Hence, the s_p of α_1 is equal to the s_p of $\bar{p}$ (1, 0).

Step 4: By similar simulation, repeat steps 1 to 3 to estimate the α_k for k equals two to five. Generally, when k columns are pooled-up, the SS_E is calculated as the sum of the k smallest SSs, while df_e is sum of the degrees of freedom associated with the k pooled-up columns. Obtain MS_E as SS_E by df_e. Calculate the F ratio associated with each of the (9-k) remaining factors as MS divided by MS_E. Then, test factor's significance at four. Estimate the $\bar{p}$ (k, l) values by similar simulation for k equals two to five. Finally, calculate α_k using Eq. (5).

$$\alpha_k = \sum_{l=1}^{(9-k)} \bar{p}(k,\ l) \qquad k = 2, \ldots, 5 \tag{5}$$

Step 5: Repeat steps 1 to 4 by similar simulation to estimate the alpha risk at 5 % significance level instead of four, as illustrated in Table 2. For example, when one column in pooled-up into error term, factor's significance is tested at 5 % significance level as follows:

a. If column A is pooled-up, the F ratio for each of the eight remaining three-level factors is compared with $F_{0.05,2,1}$ of 199.50.
b. If a three-level column is pooled-up, then the F ratio for the column A is compared with $F_{0.05,1,2}$ of 18.51, whereas the F ratio for each of the eight remaining three-level factors is compared with $F_{0.05,2,2}$ of 19.00.

Step 6: Repeat the above procedure by similar simulation while $\bar{y}_i$ is used instead of S/N ratio in step 2.

III. Analysis and Discussion

Simulation is conducted for ten cycles each of 10000 runs. The alpha risk is then estimated for S/N ratio and $\bar{y}_i$ at both F criteria for all k values.

A. The Alpha Risk at Four Using S/N Ratio

This part corresponds to steps 1 to 4. S/N ratio is used as a quality measure. Then, ANOVA for S/N ratio is conducted at four. The alpha values at four are estimated for one to five pooled-up columns by simulation. Table 3 displays the $\bar{p}$ (k, l) and α_k at four for all k values.

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Table 1. The orthogonal array L_{18} ($2^{1\times}3^7$).

Exp. (i)	**Column***								Standardized QCH			S/N ratio (η_i)
	A	B	C	D	E	F	G	H	Replicates	$\overline{y}_i$	s_i^2	
1	1	1	1	1	1	1	1	1	y_{11}, y_{12}	$\overline{y}_1$	s_1^2	η_1
2	1	1	2	2	2	2	2	2	y_{21}, y_{22}	$\overline{y}_2$	s_2^2	η_2
3	1	1	3	3	3	3	3	3	y_{31}, y_{32}	$\overline{y}_3$	s_3^2	η_3
4	1	2	1	1	2	2	3	3	y_{41}, y_{42}	$\overline{y}_4$	s_4^2	η_4
5	1	2	2	2	3	3	1	1	y_{51}, y_{52}	$\overline{y}_5$	s_5^2	η_5
6	1	2	3	3	1	1	2	2	y_{61}, y_{62}	$\overline{y}_6$	s_6^2	η_6
7	1	3	1	2	1	3	2	3	y_{71}, y_{72}	$\overline{y}_7$	s_7^2	η_7
8	1	3	2	3	2	1	3	1	y_{81}, y_{82}	$\overline{y}_8$	s_8^2	η_8
9	1	3	3	1	3	2	1	2	y_{91}, y_{92}	$\overline{y}_9$	s_9^2	η_9
10	2	1	1	3	3	2	2	1	$y_{10,1}, y_{10,2}$	$\overline{y}_{10}$	s_{10}^2	η_{10}
11	2	1	2	1	1	3	3	2	$y_{11,1}, y_{11,2}$	$\overline{y}_{11}$	s_{11}^2	η_{11}
12	2	1	3	2	2	1	1	3	$y_{12,1}, y_{12,2}$	$\overline{y}_{12}$	s_{12}^2	η_{12}
13	2	2	1	2	3	1	3	2	$y_{13,1}, y_{13,2}$	$\overline{y}_{13}$	s_{13}^2	η_{13}
14	2	2	2	3	1	2	1	3	$y_{14,1}, y_{14,2}$	$\overline{y}_{14}$	s_{14}^2	η_{14}
15	2	2	3	1	2	3	2	1	$y_{15,1}, y_{15,2}$	$\overline{y}_{15}$	s_{15}^2	η_{15}
16	2	3	1	3	2	3	1	2	$y_{16,1}, y_{16,2}$	$\overline{y}_{16}$	s_{16}^2	η_{16}
17	2	3	2	1	3	1	2	3	$y_{17,1}, y_{17,2}$	$\overline{y}_{17}$	s_{17}^2	η_{17}
18	2	3	3	2	1	2	3	1	$y_{18,2}, y_{18,2}$	$\overline{y}_{18}$	s_{18}^2	η_{18}

* A × B Interaction is estimated in a hidden column (I).

Table 2. Illustration of pooling-up technique and F test.

k value	SS_E	Pooled-up columns	df_e	F test	F value	
					Taguchi	5 % significance level
k = 1	The smallest SS	Column A	1	Eight remaining 3-level factors	4	$F_{0.05,2,1}$ = 199.50
		Three-level column	2	Column A	4	$F_{0.05,1,2}$ = 18.51
				Seven remaining 3-level factors	4	$F_{0.05,2,2}$ = 19.00
k = 2	The sum of two smallest SSs	Column A & one three-level column	3	Seven remaining 3-level factors	4	$F_{0.05,2,3}$ = 9.55
		Two three-level columns	4	Column A	4	$F_{0.05,1,4}$ = 7.71
				Six remaining 3-level factors	4	$F_{0.05,2,4}$ = 6.94
k = 3	The sum of three smallest SSs	Column A & two three-level columns	5	Six remaining 3-level factors	4	$F_{0.05,2,5}$ = 5.79
		Three three-level columns	6	Column A	4	$F_{0.05,1,6}$ = 5.99
				Five remaining 3-level factors	4	$F_{0.05,2,6}$ = 5.14
k = 4	The sum of four smallest SSs	Column A & three three-level columns	7	Five remaining 3-level factors	4	$F_{0.05,2,7}$ = 4.74
		Four three-level columns	8	Column A	4	$F_{0.05,1,8}$ = 5.32
				Four remaining 3-level l factors	4	$F_{0.05,2,8}$ = 4.46
k = 5	The sum of five smallest SSs	Column A & four three-level columns	9	Four remaining 3-level factors	4	$F_{0.05,2,9}$ = 4.26
		Five three-level columns	10	Column A	4	$F_{0.05,1,10}$ = 4.70
				Three remaining 3-level l factors	4	$F_{0.05,2,10}$ = 4.10

From Table 3, the following results are obtained:

1. The ratio of s_p relative to α_k is very small and considered negligible for all k values. Consequently, simulation for ten cycles each of 10000 runs is good enough to obtain accurate estimates of the alpha mistake.

2. The α_k is very high for all k values. Note that the α_k slightly decreases as k value increases. Nevertheless, the smallest α_k (= 0.82766), which corresponds to α_5, is still unacceptable. As a result, Taguchi method using S/N ratio at four is concluded a risky approach for parameter design for all k values.

3. Let $\bar{p}_{max}(k, l)$ be the largest $\bar{p}(k, l)$ for k pooled-up columns. In Table 3, the $\bar{p}_{max}(k, l)$ for one pooled-up column corresponds to the probability, $\bar{p}(1, 8)$, of identifying all the eight remaining factors as significant. Whereas, the $\bar{p}_{max}(k, l)$ for two to five pooled-up columns corresponds to identifying as significant all the remaining (k, 7-k) factors. Mathematically,

$$\bar{p}_{max}(k, l) = \bar{p}(k, 7-k) \quad k = 2, \ldots, 5 \tag{6}$$

In other words, when k columns are pooled-up into error term then factor's significance is tested at four, Taguchi method using S/N ratio tends to misidentify most of the remaining factors as significant.

Table 3. The $\bar{p}(k, l)$ and α_k at four.

l value	Pooling-up				
	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$
$l = 0$	0.01579	0.02028	0.04274	0.08684	0.17234
$l = 1$	0.02383	0.04416	0.09113	0.16359	0.26217
$l = 2$	0.03712	0.07520	0.14186	0.22141	**0.27766**
$l = 3$	0.05419	0.11270	0.19167	**0.23500**	0.19485
$l = 4$	0.07826	0.15826	**0.21412**	0.19269	0.09298
$l = 5$	0.11157	**0.21406**	0.19789	0.10047	
$l = 6$	0.15074	0.19524	0.12059		
$l = 7$	0.20878	0.18010			
$l = 8$	**0.31972**				
α_k	0.98421	0.97972	0.95726	0.91316	0.82766
s_p	0.00309	0.00395	0.00504	0.00447	0.00346
$s_p/\alpha_k \times 100$ %	0.31	0.40	0.53	0.49	0.42

B. The Alpha Risk at 5 % Significance Level Using S/N Ratio

In this part, ANOVA is conducted at 5 % significance level instead of four. In step 5, the alpha risk is estimated by similar simulation for all k values. The results are displayed in Table 4, where it is noted that:

1. The α_k is very high for all k values. Note that the smallest α_k (= 0.57454), which corresponds to α_1, because the $F_{0.05,2,1}$, $F_{0.05,1,2}$, and $F_{0.05,2,2}$ values in Table 2 are much larger than four. As a result, the probability of identifying correctly as insignificant increases, and hence the α_k decreases. Despite that, the α_1 is still unacceptable. As a result, Taguchi method at 5 % significance level still provides a misleading parameter design for all k values.

2. Observing the $\bar{p}_{max}(k, l)$ values, it is noted that when one and two columns are pooled-up, the $\bar{p}_{max}(k, l)$ corresponds to the probability, $\bar{p}(k, 0)$, of identifying correctly as insignificant all the (9-k) remaining factors. However, when three to five columns are pooled-up, the $\bar{p}_{max}(k, l)$ corresponds to identifying as significant all the remaining (k, 6-k) factors, or

$$\bar{p}_{max}(k, l) = \bar{p}(k, 6-k) \quad k = 2, \ldots, 5 \tag{7}$$

Compares the above result with alpha risk at four, it is noted that Taguchi method tends to identify as significant less number of factors at 5 % significance level.

3. Comparing the α_k at the same k value, it is clear that the α_k at 5 % significance level is smaller than the α_k at four for all k values. The reason is that all the values of 5 % significance level in Table 2 are larger than four.

Table 4. The $\bar{p}(k, l)$ and α_k at 5 % significance level.

l value	Pooling-up				
	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$
$l = 0$	**0.42546**	**0.17252**	0.13140	0.15294	0.21112
$l = 1$	0.11364	0.14718	0.16920	0.21207	**0.27817**
$l = 2$	0.08613	0.14384	0.18325	**0.22899**	0.25762
$l = 3$	0.07311	0.14034	**0.18440**	0.20271	0.17875
$l = 4$	0.06524	0.13350	0.16083	0.14191	0.07434
$l = 5$	0.06089	0.11506	0.11504	0.06138	
$l = 6$	0.05771	0.09046	0.05588		
$l = 7$	0.05609	0.05710			
$l = 8$	0.06173				
α_k	0.57454	0.87748	0.86860	0.84706	0.79016
s_p	0.00213	0.00425	0.00378	0.00268	0.00412
$s_p/\alpha_k \times 100$ %	0.37	0.48	0.44	0.32	0.52

C. The Alpha Risk for A standardized QCH

Step 6 is conducted using a standardized QCH instead of S/N ratio in step 2. The $\bar{p}(k, l)$ and α_k values are estimated at both F criteria by similar simulation and shown in Table 5. It is noted that the α_k is very high at both F criteria for all k values. Comparing the $\bar{p}(k, l)$ and α_k values between S/N ratio and a standardized QCH at the same F and k values, it is obvious that the $\bar{p}(k, l)$ and α_k are almost the same for both quality measures for all k values. The main conclusion made is that Taguchi method using a standardized QCH is still risky for parameter design at both F criteria for all k values. Accordingly, the use of S/N ratio unnecessary complicates the data analysis in parameter design.

To verify the robustness of alpha risk to increasing the number of replicates for a standardized QCH, four replicates are generated from NID(0, 1) for each row. S/N ratio is then calculated using Eq. (1). ANOVA for S/N ratio is then conducted at both F criteria for all k values. The $\bar{p}(k, l)$ and α_k values are estimated at both F criteria by similar simulation for all k values and displayed in Table 6. Clearly, at the same F and k values, the α_k with four QCH replicates is almost the same as the α_k with two replicates listed in Tables 3 and 4. Consequently, the alpha risk is concluded insensitive to increasing the number of QCH replicates.

Table 5. $\overline{p}$ (k, l) and α_k values at both F criteria using a standardized QCH.

l value	**four**					**5 % significance level**				
	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$
$l = 0$	0.00973	0.01119	0.02622	0.05915	0.16757	0.39930	0.13469	0.09835	0.11257	0.21152
$l = 1$	0.01933	0.0351	0.07542	0.14999	0.26022	0.11507	0.14527	0.15592	0.20214	0.27738
$l = 2$	0.03285	0.06521	0.13465	0.21875	**0.27124**	0.08931	0.13855	0.18926	**0.23743**	**0.25733**
$l = 3$	0.05186	0.10732	0.18621	**0.24802**	0.20721	0.07441	0.13576	**0.19330**	0.21965	0.17883
$l = 4$	0.07214	0.15456	**0.22333**	0.21122	0.09376	0.06952	0.12742	0.17340	0.15853	0.07494
$l = 5$	0.10874	**0.22778**	0.21729	0.11287		0.06392	0.12626	0.12828	0.06968	
$l = 6$	0.15378	0.20111	0.13688			0.06146	0.10061	0.06149		
$l = 7$	0.21531	0.19773				0.06163	0.06144			
$l = 8$	**0.33626**					0.06538				
α_k	0.99027	0.98881	0.97378	0.94085	0.83243	0.60070	0.86531	0.90165	0.88743	0.78848

Table 6. The alpha risk at both F criteria using S/N ratio with four QCH replicates.

l value	**four**					**5 % significance level**				
	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$
$l = 0$	0.01340	0.01855	0.03743	0.07879	0.16825	**0.43546**	**0.16700**	0.12604	0.14537	0.21055
$l = 1$	0.02328	0.04129	0.08621	0.15980	0.26126	0.10920	0.14703	0.16650	0.20979	**0.27766**
$l = 2$	0.03551	0.07343	0.13944	0.21991	**0.27069**	0.08150	0.14348	0.18220	**0.22829**	0.25738
$l = 3$	0.05361	0.11082	0.18582	**0.23583**	0.20612	0.06940	0.14061	**0.18380**	0.20544	0.17897
$l = 4$	0.07861	0.15356	**0.21621**	0.19839	0.09368	0. 06368	0.13288	0.16237	0.14706	0.07544
$l = 5$	0.10768	**0.21864**	0.20386	0.10728		0.06012	0.11611	0.12064	0.06405	
$l = 6$	0.14865	0.19540	0.13103			0.05910	0.09370	0.0584		
$l = 7$	0.21121	0.18831				0.05750	0.05919			
$l = 8$	**0.32805**					0.06407				
α_k	0.98660	0.98145	0.96257	0.92121	0.83175	0.56454	0.83300	0.87396	0.85463	0.78945

IV. CONCLUSIONS

One may ask 'does it matter if some insignificant factor effects are pronounced significant using the Taguchi method?'. It is sometimes argued that for identifying the combination of best factor levels it is of no importance whether or not a factor effect is statistically significant. However, if we are to use statistics to catalyze the creativity of engineers and scientists they should know what factors to reason about. Trying to argue why insignificant factor effects have an effect will merely confuse and lead a process/product engineer astray. One interesting aspect of the Taguchi method is that it has been quite successful despite its shortcomings. Apparently any reasonable systematic experimentation, however flawed, may convey important information on how to design a new product or process and on how to improve existing products and processes. It is our belief that the Taguchi strategy is sound and should be included in any quality improvement attempts. However, the Taguchi method is inefficient to carry out his strategy into practice. This research recommends the use of simpler and more modern data analytic methods for parameter design.

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