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# New Algorithm to Address Confounding Problems in Taguchi Parameter Design – A Practical Study

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## Abstract

It is essential to operate all manufacturing processes at optimum levels to stay competitive in the global environment. Optimum prediction in manufacturing process involves lot of experimentation as it involves time and cost. Taguchi Parameter Design (PDE) is a design where optimum prediction is achieved in lesser experimental runs subject to the condition that there is no confounding effect. Confounding effect is a drawback of Taguchi PDE due to which many Taguchi experiments fail in confirmation tests at desired confidence level. RABAL Algorithm is 12 step structured approach, which uses Orthogonality concept and linear graph for Factors and Interaction allocation and uses certain rules based on statistical concepts by which the accurate result of Taguhi parameter design experiment is ensured. Sleeve synchronizer 1&2 hard turning is a bottleneck operation in a gear manufacturing line taken for research optimized for better cycle time using Taguchi PDE and RABAL algorithm. Feed rate in first and second cut is observed as significant factors at 95% confidence level and Optimal parametric setting is identified. Accuracy of results is confirmed through confirmation tests. RABAL Algorithm can be used along with Taguchi PDE to minimize the confounding effects there by accuracy of experimental results are improved and results are achieved right first time.

**Keywords:** Confounding Effect, Hard Turning, RABAL Algorithm, Sleeve Synchronizer 1&2, Taguchi Parameter Design

## 1. Introduction

The Indian manufacturing sector is undergoing rapid changes in the recent past. Multinational companies, individually or with partnership, have put up their facilities to start manufacturing activities in India. Ancillary industries to support these manufacturers are also grown in tandem. In the past few years, requirements and expectations in the manufacturing sector have greatly increased. It calls for lot of intricate processes with higher quality levels. At the same time, there is intense competition between market participants in terms of quality, cost and delivery.

So it is essential to operate the process with optimal setting values for better quality and productivity and optimum parameter settings have to be identified with minimal experimental runs and with highest accuracy.

Considering the Basic production resources, the application of experiment design techniques becomes extremely efficient for carrying out these experiments with the highest efficiency pursuing the economical and time constraints as well as interpreting the results accurately[1].

## 2. Taguchi Parameter Design Experiment (PDE)

Taguchi Parameter Design is an engineering method for process and product design which focuses on minimizing

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variation and minimizing sensitivity towards noise. In Taguchi methodology, factors that affect the process quality are divided in to control factors and Noise factors, Control factors are set by the manufacturer (which are easily adjustable) and are important in determining product characteristic Quality[2,3]. Noise factors are the factors which can't be controlled by experimenter like climatic condition. Optimum selection of control parameters will ensure that the effect of noise factors in product characteristic will be minimal. Taguchi method used orthogonal arrays to study the entire process parameter space with minimal number of experimental runs[4]. The value of loss function is further transformed in to signal to Noise ratio. There are three types of quality characteristics used in the Analysis of S/N ratio i.e., Nominal the best, lower the better and Larger the better. The S/N ratio for each level of process parameters is computed based on S/N Analysis. Regardless of the category of Quality characteristic, a larger S/N ratio corresponds to optimal level of process parameters i.e., better quality characteristic[5].

With Orthogonal Arrays/Taguchi Methods, the approach to design of experiments, the philosophy towards interaction effects is different. Unless an interaction effect is explicitly identified a-priori and assigned to column in the orthogonal array, it is assumed to be negligible. Thus, unless assumed otherwise, interactions at all levels are assumed to be negligible. Taguchi encourages users to select variables that do not interact with one another. Interaction is rarely discussed and utilized by researchers in optimization using Taguchi parameter design[6-13]. If available interaction between the factors is neglected for experimentation, then there is a possible case of confounding, Dr. Taguchi incorporated additional power in the use of orthogonal arrays for testing design through linear graph. Linear graphs are used for assigning factors to the correct columns in order to study interactions between the factors while also revealing the effects of the individual factors. Although it is not possible to study all interactions as can be done with the full factorial test, likely interactions and its impact can be analyzed. Please find below the normal steps in Taguchi methodology[13-15] and most of the researchers using taguchi methodology as a separate tool for Optimisation or using taguchi method in combination with some other statistical methods like grey relational analysis for multi objective optimization[16-23].

### 2.1 7 Step Taguchi Methodology

Select Quality Characteristics

↓

Select Control & Noise factors

↓

Select Orthogonal Array

↓

Conduct Experiments

↓

Analyze Results

↓

Conduct Confirmation Experiment

↓

Conclusion

## 3. RABAL Algorithm

RABAL algorithm is structured 12 step approach, which ensures the appropriate factor selection in orthogonal array and which ensures minimal or no confounding effects and assures minimum possible experimental runs. RABAL Algorithm suggests 3 rules for optimum process parameter selection so that the errors in finding optimum will be minimized and which optimum prediction in Right first time.

### 3.1 12 Step Structured Methodology

**Step 1:** List the total number of control factors involved (A), Important control factors need to be studied (B), Total number of non important factors (C) and number of interaction between the factors for the study (D).

**Case 1: If C is less than or equal to D.**

**Step 2:** Express the number of control factors (A) and number of Interactions (D) in the form of linear graph, which is known as Experiment Linear Graph (ELG).

**Step 3:** Compute total Degrees of Freedom which is the summation of Degrees of freedom of control factors and Degrees of freedom of Interactions.

**Step 4:** Select minimum number of experiments required, which should be greater than Total degrees of freedom and based on these data nearest orthogonal array will be selected.

**Step 5:** Select the Standard Linear Graph (SLG) most relevant to Experiment Linear graph (ELG).

**Step 6:** Standard Linear Graph will be modified so that it will exactly match the Experiment Linear Graph.

**Step 7:** Allocate the column of Layout to factors and Interactions.

**Step 8:** Derive Actual Experimental Design, In Interactions Column assign the number of non important factors (C).

**Step 9:** Experimentation based on Randomization, Replication and Local control and Analyse results.

**Step 10:** If Factors are Significant and interactions are not significant then Optimum selection will be easy.

**Step 11:** If Any of the interaction is significant then small experimentation based on RABAL theory to ensure either interaction is significant or any of the non important factors (C) are significant.

**Step 12:** For Optimum selection will be based on three important rules.

**Rule 1:** Factor is not significant and also not interacting significantly with any other factors, any of the levels can be chosen.

**Rule 2:** If a Factor is significant, but not significantly interacting with any other factors the level with higher signal to noise ratio will be selected as optimum value.

**Rule 3:** Whether the factor is significant or not but it is interacting significantly with any other factors then the levels of interacting factors must be decided by taking them together from the interaction table. Levels of interacting factors should not be selected independent of each other.

**Case 2: If C is greater than D.**

**Step 2:** Express the number of control factors (A), Balance non important Factors (C-D) (Total control factors would be A + C – D) and number of Interactions (D) in the form of linear graph, which is known as Experiment Linear Graph (ELG).

**Step 3:** Compute total Degrees of Freedom which is the summation of Degrees of freedom of control factors (important and not important) and Degrees of freedom of Interactions.

**Step 4:** Select minimum number of experiments required, which should be greater than Total degrees of freedom and based on these data nearest orthogonal array will be selected.

**Step 5:** Select the Standard Linear Graph (SLG) most relevant to Experiment Linear graph (ELG).

**Step 6:** Standard Linear Graph will be modified so that it will exactly match the Experiment Linear Graph

**Step 7:** Allocate the column of Layout to factors (both important (B) and non important (C-D)) and Interactions.

**Step 8:** Derive Actual Experimental Design, In Interactions Column assign the number of non important factors (other factors than C - D).

**Step 9:** Experimentation based on Randomization, Replication and Local control and Analyse results.

**Step 10:** If Factors are Significant and interactions are not significant then Optimum selection will be easy.

**Step 11:** If any of the interaction is significant then small experimentation based on RABAL theory to ensure either interaction is significant or any of the non important factors (C) are significant.

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## 4. Sleeve Hard Turning Experiment

Sleeve Synchronizer 1&2 is a part used in Automobile manual transmissions, having critical manufacturing operations such as forging, Broaching, Spline rolling, vchamfering, Key way milling, hobbing, deburring, shaving, Carburising, Induction hardening and Hardturning. Main purpose of Sleeve synchronizer 1&2 is to power shifting of 2nd gear and first gear in Manual transmission. If the Sleeve 1&2 synchronizer is shifted backward by shift lever and fork, the 1st gear is engaged to the output shaft through the Hub. When the Sleeve 1&2 synchronizer is shifted forward by shift lever and fork, the 2nd gear is engaged to the output shaft. This research attempts to reduce the cycle time of Hardturning operation which is bottleneck operation.

## 5. Experimental Setup and Procedure

WIA Hard turning Lathe is used for conducting Experiments. 5.0 mm Plunge type CBN insert grade TSG 5.00-0.2-HDTB 650 is used for machining (0.2 mm nose radius).

Cycle time is recorded using a stop watch.

Component is clamped on its Inner diameter as shown in the and its face is clamped using hydraulic operated finger jaws. Totally Sleeve synchronizer 1&2 undergoes Two different cut cycles which is denoted using different colors and sequence is represented as 1 & 2 in Figure 1.

## 6. Solving the Problem using RABAL Algorithm

**Step 1:** List the total number of control factors involved (A), Important control factors need to be studied (B), Total number of non important factors (C) and number of interaction between the factors for the study (D).

Total Control Factors involved:

- 1st Face cut Feed (a) (Important).
- 1st Face cut Speed (b) (Not Important).
- 1st Face cut Depth of cut (c) (Not Important).
- 2nd face cut Feed (d)(Important).

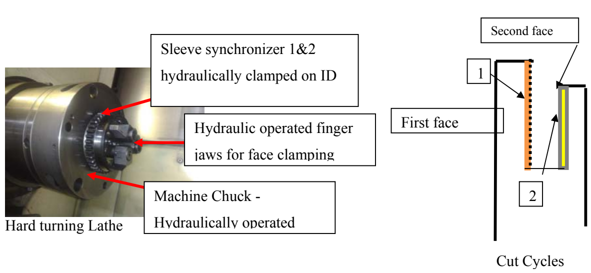



**Figure 1.** Experimental Set up Sleeve Synchronizer Clamped condition.

**Interaction Effects** – a x c is the required interaction effect to be studied.

**Case 2: If C is greater than D (Yes (C =2) is greater than (D = 1).**

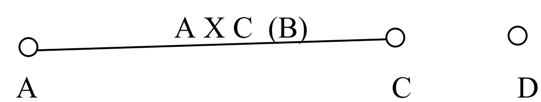
**Step 2:** Express the number of control factors (A), Balance non important Factors (C-D) (Total control factors would be A + C – D) and number of Interactions (D) in the form of linear graph, which is known as Experiment Linear Graph (ELG) and select the number of levels for the factors for the experimentation based on linearity and non linearity constraints.

### 6.1 Control Factors and their Levels

**Table 1.** Process parameters selection with levels

| No | Parameters selected for study | | Level 1 | Level 2 | Level 3 |
|---|---|---|---|---|---|
| 1 | First Face cut feed (m/min) | A | 0.13 | 0.15 | 0.17 |
| 2 | First face cut speed (rpm) | B | 130 | 150 | 170 |
| 3 | First Face cut Depth of cut (mm) | C | 0.08 | 0.1 | 0.12 |
| 4 | Second Face cut feed (m/min) | D | 0.12 | 0.14 | 0.16 |

Experiment Linear graph would be



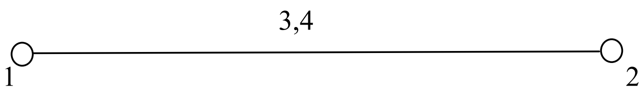

**Step 3:** Compute total Degrees of Freedom which is the summation of Degrees of freedom of control factors (important and not important) and Degrees of freedom of Interactions.

Factors Degrees of Freedom = 2 factors (2 X (3 – 1) = 4
Interaction Degrees of freedom = (3-1) X (3-1) = 4
Total Degrees of Freedom would be 8.

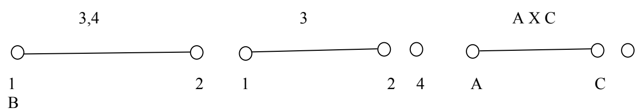
**Step 4:** Select minimum number of experiments required, which should be greater than Total degrees of freedom and based on these data nearest orthogonal array will be selected.

Total degrees of freedom are 8 so minimum no of experiments is atleast greater than 0ne which is equal to 9. So minimum number of experiments is nine based on that $L_9 3^4$ orthogonal array is selected for the study.

**Step 5:** Select the Standard Linear Graph (SLG) most relevant to Experiment Linear graph (ELG).




**Step 6:** Standard Linear Graph will be modified so that it will exactly match the Experiment Linear Graph.




**Step 7:** Allocate the column of Layout to factors (both (B) and (C-D)) and Interactions).

## 6.2 Standard Orthogonal array for L9 OA

**Table 2.** L9 Standard Orthogonal Array

| | A | C | AXC | B |
|---|---|---|---|---|
| Exp No | 1 | 2 | 3 | 4 |
| 1 | 1 | 1 | 1 | 1 |
| 2 | 1 | 2 | 2 | 2 |
| 3 | 1 | 3 | 3 | 3 |
| 4 | 2 | 1 | 2 | 3 |
| 5 | 2 | 2 | 3 | 1 |
| 6 | 2 | 3 | 1 | 2 |
| 7 | 3 | 1 | 3 | 2 |
| 8 | 3 | 2 | 1 | 3 |
| 9 | 3 | 3 | 2 | 1 |

**Step 8:** In Interactions Column assign the number of non important factors (other than C-D).

## 6.3 Factors and Interaction allocation in L9 OA

**Table 3.** Factors and Interaction allocation in L9 OA

| | A | C | AXC (D) | AXC (B) |
|---|---|---|---|---|
| Exp No | 1 | 2 | 3 | 4 |
| 1 | 1 | 1 | 1 | 1 |
| 2 | 1 | 2 | 2 | 2 |
| 3 | 1 | 3 | 3 | 3 |
| 4 | 2 | 1 | 2 | 3 |
| 5 | 2 | 2 | 3 | 1 |
| 6 | 2 | 3 | 1 | 2 |
| 7 | 3 | 1 | 3 | 2 |
| 8 | 3 | 2 | 1 | 3 |
| 9 | 3 | 3 | 2 | 1 |

**Step 9:** Experimentation based on Randomization, Replication and Local control and Analyse results.

## 6.4 Factor with Levels and Experimental Results

**Table 4.** Factor with levels and Experimental results

| | A | C | AXC (B) | AXC (D) | | | |
|---|---|---|---|---|---|---|---|
| Exp No | 1st Feed | 1st DOC | 1st Speed | 2nd Feed | C time 1 | C Time 2 | C Time 3 |
| 1 | 0.13 | 0.08 | 130 | 0.12 | 21 | 21 | 21 |
| 2 | 0.13 | 0.10 | 150 | 0.14 | 20 | 20 | 20 |
| 3 | 0.13 | 0.12 | 170 | 0.16 | 19 | 19 | 19 |
| 4 | 0.15 | 0.08 | 150 | 0.16 | 18 | 18 | 18 |
| 5 | 0.15 | 0.10 | 170 | 0.12 | 20 | 20 | 20 |
| 6 | 0.15 | 0.12 | 130 | 0.14 | 19 | 19 | 19 |
| 7 | 0.17 | 0.08 | 170 | 0.14 | 18 | 18 | 18 |
| 8 | 0.17 | 0.10 | 130 | 0.16 | 17 | 17 | 17 |
| 9 | 0.17 | 0.12 | 150 | 0.12 | 19 | 19 | 19 |

**Step 10:** If Factors are Significant and interactions are not significant then Optimum selection will be easy.

After doing Detailed Taguchi Analysis, it shows that Factor A is a critical factor and A x C (D) is also critical factor.

**Step 11:** If Any of the interaction is significant then small experimentation based on RABAL theory to ensure either interaction is significant or any of the non important factors (C) are significant.

Here interaction is not significant as AXC (B) is not significant as well as there is no possible relation between A and D.

**Step 12:** For Optimum selection will be based on three important rules.

**Rule 1:** Factor is not significant and also not interacting significantly with any other factors, any of the levels can be chosen.

**Rule 2:** If a Factor is significant, but not significantly interacting with any other factors the level with higher signal to noise ratio will be selected as optimum value.

**Rule 3:** Whether the factor is significant or not but it is interacting significantly with any other factors then the levels of interacting factors must be decided by taking them together from the interaction table. Levels of interacting factors should not be selected independent of each other.

Based on the above said 3 rules significant factors would be A and D and optimum would be at 3rd level which is further confirmed through confirmation trials.

## 7. Conclusion

Optimum selection for the hard turning experiments is carried out and ANOVA analysis is carried out and significant at 95% confidence level.

**Table 5.** Confirmation test results

| No | Parameters selected for study | | Level 1 | |
|---|---|---|---|---|
| 1 | First Face cut feed(m/min) | A | 0.17 | Significant |
| 2 | First face cut speed (rpm) | B | 150 | |
| 3 | First Face cut Depth of cut (mm) | C | 0.1 | |
| 4 | Second Face cut feed (m/min) | D | 0.16 | Significant |

From the above said experiment it is proved that RABAL algorithm is a useful tool and it can be use along with Taguchi method to reduce confounding issues. Researchers may further use the RABAL algorithm for multi objective function problems in Taguchi method.

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