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Development of process technology in wire-cut operation for improving machining quality

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Abstract *Many of the quality problems have their origin either in the product design or process design. The statistical design of experiments is a scientific method for optimization of design parameters. This paper highlights an application of improving process design in the metal cutting operation by the wire-cut EDM (electro discharge machining) process on a hi-tech Japax Machine. An experiment was conducted on nine process parameters as per the* L_{16} (2^{15}) *orthogonal array layout. The responses considered were precision in machined dimensions and surface roughness. The data were then analyzed for mean and signal-to-noise ratio. All the nine factors turned out to be significant in at least one of the analyses and the best operating conditions were found considering the results of different analyses. Implementation of the results showed that the dimensional variability* ($\pm 3\sigma$) *is reduced from* ± 0.015 *to* ± 0.007 *and the surface roughness from 4 μm to 2 μm. Other benefits were increased tool life by over 10% and a total elimination of rework. This exercise saved the company about US$25 000 annually.*

Introduction

An electric machine manufacturing plant was having problems with the quality of cutting tools, namely dies and punches made in the plant. Dies and punches are used to cut slots and blanks in the stator and rotor stamping made from electrical lamination sheets at the press shop. Stamping machining quality depends greatly on the quality of cutting tools. The parameters that decide the quality of cutting tools are hardness, dimensional precision and surface roughness. The application of these tools calls for manufacture within a very close tolerance, with a low surface roughness. A hi-tech machine tool, CNC Japax from Japan, was procured by the Company for this purpose. In this machine, metal is cut by wire using the electro discharge machining (EDM) process. However, the intended purpose of high-precision machining was not achieved. Hence, a study was conducted on optimization of process conditions.

The then existing situation can be summarized as follows:

- Dimensional variability was not achieved within two-thirds of tolerance. The dimensions at different points within a piece also varied. Surface roughness was around 4 μm. This resulted in rework of cutting tools, causing an average loss of 45 hours per set, costing Rs 4000 (about US$160). Annual production was about 110 sets of tools.
- The dimensional accuracy and surface finish of these tools achieved after rework were not up to standard, resulting in lower tool life.

Table 1. *Factors and levels for the experiment*

Factor	Level 1	Level 2	Level 3
A Cutting speed, first cut (mm/min)	0.8*	1.0	—
B Cutting speed, second	2.0[a]	2.5	0
C Wire tension (g)	$T - \Delta T$	T [a]	—
D Wire Speed (m/min)	$S - \Delta S$	S [a]	$S + \Delta S$
E Peak current (A)	$P - \Delta P$	P [a]	$P + \Delta P$
F Resin (make)	1*	2	—
G Clear-cut motor position	ON	OFF[a]	—
H Pulse-off time (s)	4[a]	5	—
I Pulse-on time (s)	3[a]	4	—

[a] Existing level.

This analysis led to questions such as:

- Is the procured technology really capable of achieving the desired result (good surface finish and high-precision machining)?
- Is the problem created by a lack of control?
- If the technology is proven, has sufficient research been carried out to arrive at an optimum process standard?

Information from other users revealed that this technology was capable of meeting the quality requirement. It was found that controllability does not pose any problems in a computer numeric control machine. Thus the problem narrowed down to the critical examination of process conditions. A statistically designed plant-scale experiment was employed to accomplish this.

Planning of experimentation: experimental factors and levels

The instruction manual provided with the machine tool gave a broad range of process parameters. The user was expected to fix the operating levels of each process parameter, depending on the nature of the job and material (a flow chart explaining the process of machining is given in Appendix A). However, with the trial-and-error method used, it had not been possible to identify the optimum combination out of infinitely many possibilities. Nevertheless, the instruction manual was very useful for identifying the factors to be selected for experimentation, along with their respective ranges. Table 1 gives the factors and levels considered for the experiment.

Of the above nine factors in Table 1, two are qualitative in nature (i.e. F and G). They were tried at two levels as only two alternatives were possible. The remaining seven factors are quantitative in nature. Out of these three are considered at three levels, while four are considered at two levels for experimentation. Where the direction expected to give better result is known, the factor is tried at only two levels, i.e. the existing level and the level likely to give better result. Three levels are considered, one above and one below the existing level, in situations where the direction expected to give better result is not known.

Experimentation

Here, all the main effects and only one first-order interaction A × I are to be considered. Of course, other interactions, if present, get confounded with some of the main effects but they are not considered, for the following reasons.

First, the other interactions were not of any technical significance and, second experimentation in industry is costly and time consuming. Thus, quite often, a full factorial experiment is not feasible owing to these constraints.

Further, Taguchi (1988) advises experiments on main effects only. In his view, a main effect that is still significant relative to error variance, including interaction, can be regarded as a reliable effect, i.e. it has a consistent effect, even when the conditions of other factors differ. Stress is laid on such factors when experiment by orthogonal array is being undertaken. Since only reliable factorial effects will be obtained, the very high reliability of these factorial effects can be appreciated. However, when additivity to the main effect fails, i.e. when interaction exists, experimentation not considering the interaction may not work. Unfortunately, most often we have very little information regarding the presence or absence of an interaction. Therefore, the experiment is planned on the assumption that other interactions may not be present and main effects will show significance despite being confounded with the interaction.

In the light of the foregoing reasoning, the experiment is designed as an $L_{16}(2^{15})$ orthogonal array layout (16 trials). Using the idle column method (Taguchi, 1988), a full factorial experiment would have required no less than $2^6 \times 3^3 = 1728$ experimental trials. Table 2 gives the orthogonal array table for $L_{16}(2^{15})$ layout (Taguchi, 1962).

The linear graph technique invented by Taguchi (1988) is used to design the present experiment.

Orthogonal array

Orthogonal arrays can be traced back to Euler's Graeco-Latin squares. Their usage for the design of experiments was explored simultaneously in the USA and Japan during World War II.

Taguchi has tabulated 18 basic orthogonal arrays. Most of these arrays are also found in the work of Addelman, Box, Hunter and Hunter, Cochran and Cox, Plackett and Burman, etc. An array indicates the number of rows and columns it has, and also the number of levels in each of the columns. Thus, the array $L_8(2^7)$ has eight rows and seven two-level columns. The number of rows of an orthogonal array represents the number of experiments. In order for an array to be a viable choice, the number of rows must be at least equal to the degrees of freedom (df) required for estimating the effects of main effect and interaction of interest in the experiment. The number of columns of an array represents the maximum number of factors that can be studied. The array $L_8(2^7)$ is given in Table 3 for illustration. Table 4 shows in which column the interaction is confounded for every pair of columns of the L_8 array. Thus, it can be used to determine which columns should be kept empty in order to estimate a particular interaction.

The interaction table contains all the relevant information needed for assigning factors to columns of the orthogonal array, so that all main effects and desired interaction can be estimated without confounding. The interaction tables are generated directly from the linear algebraic relations that were used in creating the orthogonal arrays.

Table 2. *L_{16} (2^{15}) orthogonal array layout*

No.	Column 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2
3	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2
4	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1
5	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2
6	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1
7	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1
8	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2
9	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
10	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1
11	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1
12	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2
13	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1
14	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2
15	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2
16	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1
	Group 1	Group 2		Group 3				Group 4							

Table 3. *$L_8(2^7)$ array*

No.	Column 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
	Group 1	Group 2		Group 3			

Linear graph

The process of fitting an orthogonal array to a specific problem has been made easy by a graphical tool called the linear graph. Linear graphs represent the interaction information graphically and make it easy to assign factors and interactions to the various columns of an orthogonal array with the help of an interaction table Taguchi (1962).

In a linear graph, the columns of an orthogonal array are represented by nodes and lines. When two nodes are connected by a line, it means that the interaction of the two columns represented by the nodes is confounded with the column represented by the line. When two

Table 4. *Interaction table for L_8*

	1	2	3	4	5	6	7
1	(1)	3	2	5	4	7	6
2		(2)	1	6	7	4	5
3			(3)	7	6	5	4
4				(4)	1	2	3
5					(5)	3	2
6						(6)	1
7							(7)

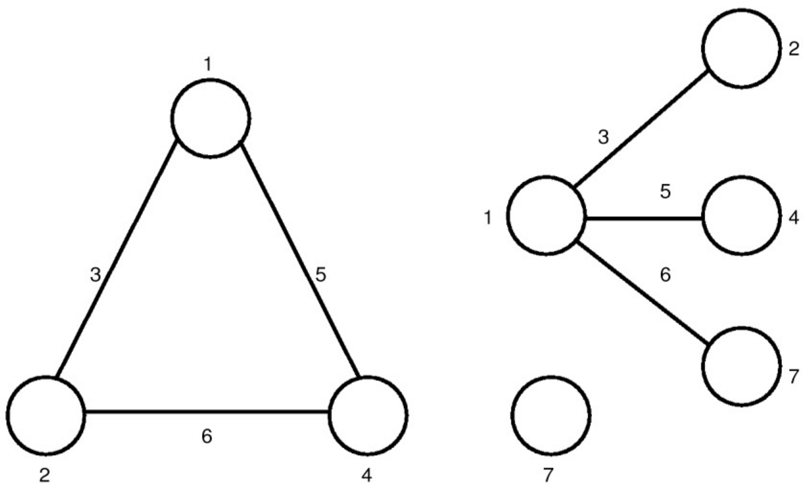

Figure 1. *Standard linear graph for $L_8(2^7)$ array.*

factor interactions are confounded, a linear graph will show only one of the interactions assigned to the column. The information regarding confounding of other interactions can be obtained from the interaction table. In a linear graph, each node and each line has a distinct column number associated with it. Further, every column of the array is represented in its linear graphs, creating a variety of different orthogonal arrays from the standard ones to fit real problem situations.

The two standard graphs associated with $L_8(2^7)$ are given in Fig. 1.

Linear graphs are useful for creating four-level and three-level columns in two-level orthogonal arrays. A four-level factor in a two-level orthogonal array is represented by two nodes and the line joining them. The assignment of a three-level factor in a two-level orthogonal array is done by first generating a four-level column by the multi-level technique (Taguchi, 1988), and then making one of the levels a dummy level. This assignment of three-level factors in a two-level orthogonal array consumes 3 df while only 2 df are required for estimating a three-level factor. To accommodate a large number of three-level factors in a two-level orthogonal array, Taguchi has suggested the use of the idle column method. Here, one column is kept idle and a three-level factor is represented by a node and line joining the idle column. In this way, a large number of three-level factors can be assigned in a two-level orthogonal array without losing df on the dummy level. The multi-level and dummy level technique is explained in Appendix B and the idle column method in Appendix C.

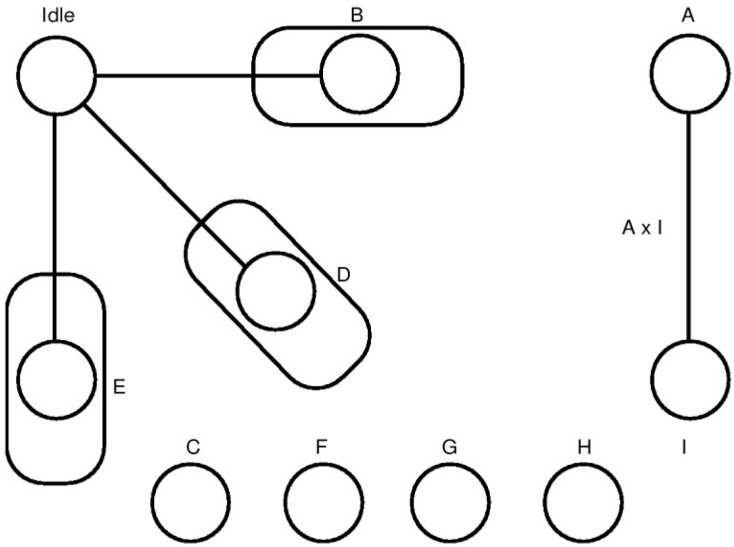

Figure 2. *Required linear graph.*

Selection of design layout using linear graphs

The steps in the selection of the layout are as follows:

(1) Express the information required in an experiment by way of linear graphs. In the graph, a main effect is represented by a node, and an interaction between two factors is represented by the line joining the nodes. This is termed the required linear graph.
(2) Compute the total df required to estimate all the factorial effects that are of interest. The minimum number of experimental runs will be the total df computed to estimate the effects plus one. Choose an orthogonal array nearest to the size of the experiment thus determined.
(3) Compare the standard linear graph (Taguchi, 1962) of the chosen array with the required linear graph obtained in step 1.
(4) Modify the selected standard linear graph by deleting edges joining a pair of nodes or by joining unconnected nodes as required so as to make the standard graph correspond to the required linear graph. Thus, each factorial effect on the required linear graph is made to correspond with each column number on the standard or modified linear graph respectively.
(5) Correspond each factor with the respective column of the standard orthogonal table.

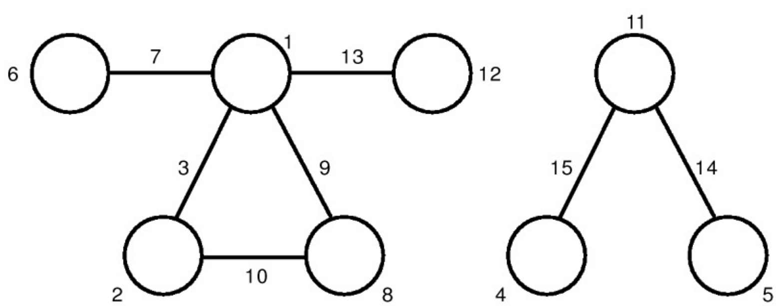

Figure 3. *Standard linear graph.*

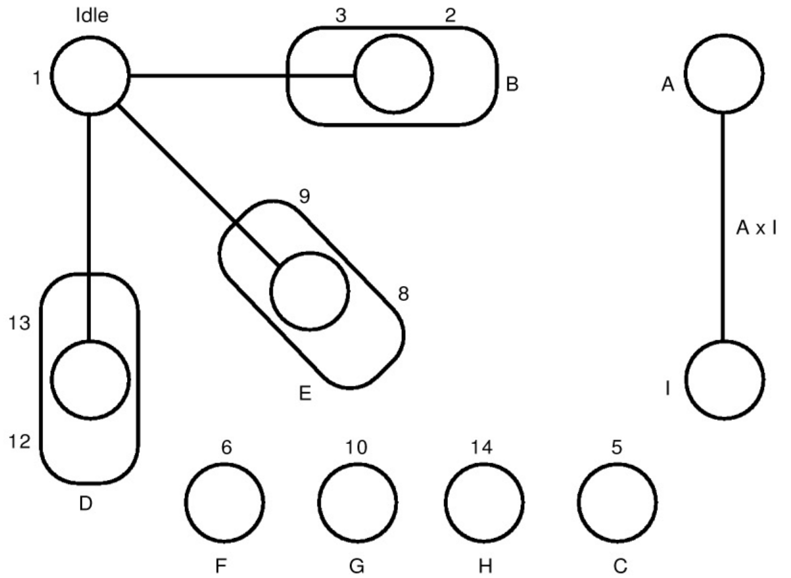

Figure 4. *Linear graph for experiment.*

The required linear graph using the idle column for the present case is given in Fig. 2. Total df required to estimate all main effects and one first-order interaction A × I is 13.

$$\text{Minimum no. of experimental runs} = 13 + 1 = 14$$
$$\text{Nearest orthogonal array} = L_{16}(2^{15})$$

Therefore, the experiment is designed as an L_{16} orthogonal array.

Consider the standard linear graph (Fig. 3) of L_{16}, which matches the required linear graph. By erasing lines 7, 10 and 14 in the standard graph, we get the linear graph for our experiment. The linear graph for the present experiment is given in Fig. 4.

The layout for the experiment is given in Table 5. Numbers in parentheses are the column numbers of the L_{16} orthogonal array table.

Quality requirement for cutting tools

Normally, the shapes of dies and punches used for slot cutting and blanking in an electrical lamination sheet are of the type given in Figs 5 and 6.

Here, the die and punch made for slot cutting and punch for blanking are single composite tools (made from a single block of material) while the die made for blanking is of the segmental type; that is, four segments of the tool are cut and assembled.

A good surface finish on dies and punches helps the cut piece to fall from the die easily. The dies and punches get damaged when a cut piece remains in the die instead of falling out—sometimes the die is broken. Hence, surface roughness is a critical parameter for increasing tool life.

The dimensional accuracy of the assembled tools depends upon the dimensional accuracy of the segments. Errors in segments get added up and have a cumulative effect on the assembled tool. For perfect alignment of the assembled tool and longer tool life, the segments should satisfy the following requirements:

- dimensions such as width and angle should be very close to the target;

Table 5. *Experiment layout*

No.	Idle (1)	B (2, 3)	A (4)	C (5)	F (6)	E (8, 9)	G (10)	I (11)	D (12, 13)	H (14)
1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	2	2	2	2	2
3	1	1	2	2	2	1	1	1	2	2
4	1	1	2	2	2	2	2	2	1	1
5	1	2	1	1	2	1	2	2	1	2
6	1	2	1	1	2	2	1	1	2	1
7	1	2	2	2	1	1	2	2	2	1
8	1	2	2	2	1	2	1	1	1	2
9	2	2[a]	1	2	1	1[a]	1	2	2[a]	1
10	2	2[a]	1	2	1	3	2	1	3	2
11	2	2[a]	2	1	2	1[a]	1	2	3	2
12	2	2[a]	2	1	2	3	2	1	2[a]	1
13	2	3	1	2	2	1[a]	2	1	2[a]	2
14	2	3	1	2	2	3	1	2	3	1
15	2	3	2	1	1	1[a]	2	1	3	1
16	2	3	2	1	1	3	1	2	2[a]	2

[a] Dummy level.

- variation in dimension from one point to another in the same segment should be minimal;
- surface roughness should be minimum and uniform from one point to another.

These requirements are common to other types of tools where the complete tool is manufactured as a single piece, as in the case of punches.

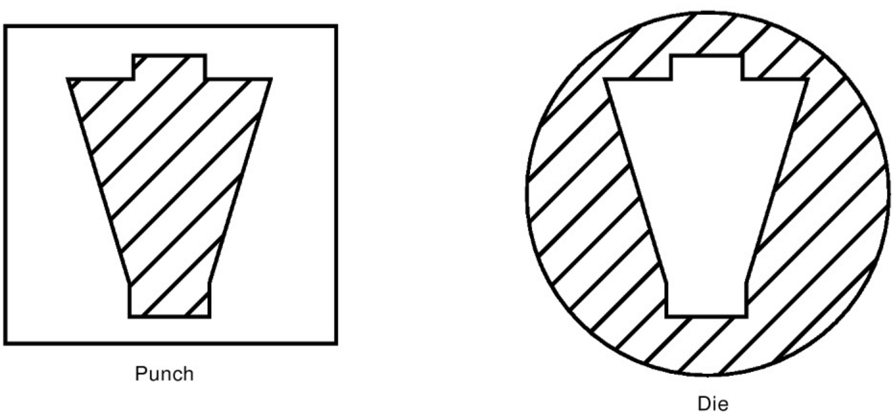

Figure 5. *Tools for slot cutting.*

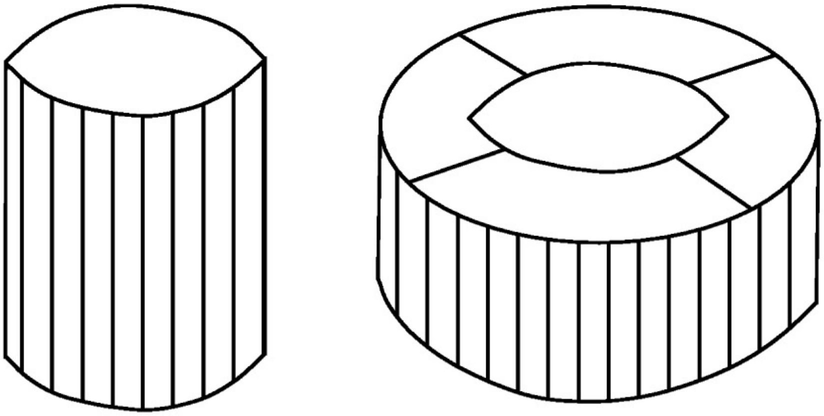

Figure 6. *Tools for blanking.*

Response

The following responses were considered:

- width in millimetres;
- angle between two sides in degrees;
- surface roughness in microns.

Conduct of the experiment

A 20-cm piece was cut for each experimental combination. Measurements at four different points were made on each pieced for width, angle and surface roughness (which are the responses considered). The data are given in Table 6.

Table 6. *Data on width, angle and surface roughness*

Exp. no.	Width[a] 1	2	3	4	Angle[b] 1	2	3	4	Surface roughness 1	2	3	4
1	298	329	346	345	276	69	−133	172	2.000	1.500	1.750	2.000
2	76	150	216	156	696	543	829	−96	3.750	2.875	3.250	2.625
3	245	274	90	251	1070	266	309	1026	3.500	2.250	2.750	3.125
4	252	−288	280	90	−311	−613	996	695	3.625	3.500	3.375	3.125
5	458	547	345	462	253	897	341	513	3.250	3.500	4.000	3.250
6	458	310	243	304	466	−942	−1842	−370	3.500	3.625	4.000	3.500
7	355	328	108	25	15	−175	−79	104	3.000	3.000	4.500	3.875
8	−18	159	−124	− 17	450	381	347	486	3.875	3.750	3.500	3.500
9	63	16	−197	−141	−259	−370	−510	−427	2.750	4.625	4.500	3.750
10	243	282	116	69	76	−689	−681	83	2.750	5.500	4.250	2.875
11	96	66	78	111	39	225	392	422	3.500	3.750	4.000	3.500
12	−12	170	09	185	−70	−753	172	145	3.625	3.875	3.500	3.375
13	239	−197	296	−155	−1198	278	440	−1037	2.875	3.250	3.125	3.000
14	239	164	234	120	28	267	390	150	3.625	2.750	3.125	3.500
15	175	277	139	185	400	126	307	420	3.750	2.875	3.000	2.875
16	219	305	52	216	215	−31	−523	−274	4.625	2.750	3.375	4.375

[a] Coded data = (actual data − 19.97) × 10 000.
[b] Coded data = (actual data − 89.95) × 10 000.

Analysis

Here we are interested in finding out the best operating condition that will give a uniform width of 20-mm and uniform angle of 90°. In other words, it is to minimize the variance while keeping the mean on target. The problem of minimizing the variance of width and angle while keeping the mean on target is a problem of constrained optimization. Taguchi has suggested the use of the signal-to-noise (S/N) ratio, where the problem can be converted into an unconstrained optimization (see Phadke, 1989). The property of unconstrained optimization is to minimize sensitivity to noise factors by maximizing the S/N ratio rather than minimising standard deviation and optimizing mean separately. An approach where we maximize the S/N ratio usually leads to a useful solution. Therefore, it was decided to carry out the analyses shown in Table 7 to arrive at the optimum combination.

The S/N ratio theory uses quadratic loss function as an objective function to find the best level of control factors. Taguchi (1988) has suggested the following S/N ratio for the 'nominal is better and smaller is better' type.

(1) S/N ratio—nominal is better

$$10 \log \frac{Sm - V_e}{nV_e} = 10 \log \left(\frac{\bar{Y}^2}{V_e} - \frac{1}{n} \right) \tag{1}$$

where

$$Sm = \left(\sum_{i=1}^{n} Y_i \right)^2 / n$$

$$V_e = \frac{1}{n-1} \sum_{i=1}^{n} (Y_i - \bar{Y})^2$$

(2) S/N ratio—lower is better

$$-10 \log \left(\sum_{i=1}^{n} Y_i^2 / n \right) \tag{2}$$

Mean S/N ratio for three responses are computed using the above formulae. The various sums of squares required for preparing ANOVA tables are obtained with the help of a computer program. Analysis of variance is carried out on mean response as well as on S/N ratio. The method of analysis is explained in detail in Taguchi (1988, Vol. 1, pp. 300–302). F-ratios are computed in each ANOVA and a test of significance is carried out.

Table 7. *List of analyses*

No.	Characteristic	Objective	Type of analysis
1	Width	Target of 20 mm with least variability	1 Analysis of mean 2 S/N ratio—nominal is better
2	Angle	Target of 90°C with least variability	1 Analysis of mean 2 S/N ratio–nominal is better
3	Surface roughness	Lower and consistent	1 Analysis of mean 2 S/N ratio—lower is better

Table 8. *Ratios of significant factors*

	Width		Angle		Surface roughness	
Factor	Mean	S/N ratio	Mean	S/N ratio	Mean	S/N ratio
A	4.62*					
Idle 1						
B_{1-2}					15.22**	9.54*
Idle 2						
B_{2-3}					4.99*	
C	15.25**	28.16**				
Idle 2						
D_{3-2}	4.64*	20.64**	5.97*			
Idle 1						
E_{1-2}	13.02**				6.26*	
Idle 2						
E_{3-1}	4.84*					
F				6.34*		
G		14.89**				
H			4.68*			
I				5.10*		
A × I			11.85**			
F-values						
5%	4.02	4.75	4.02	4.67	4.03	4.96
1%	7.12	9.38	7.12	9.07	7.17	10.04

*, ??; **, ??.

Results

The factor effects are tested against the error and significant factors are identified. The significant factors in different analyses are given in Table 8.

The process of discovering a scaling factor and the optimum levels for various control factors is a simple one. It consists of determining the effect of control on the S/N ratio (η) and mean (μ) and then classifying these factors as follows:

(1) Factors that have a significant effect on η. For these factors, we should pick the levels that maximize η.

(2) Factors that have a significant effect on μ but practically no effect on η. Any one of these factors can serve as a scaling factor. We use one such factor to adjust the mean on target.

(3) Factors that have no effect on η and no effect on μ. These are neutral factors and we can choose their best levels from other considerations such as ease of operation or cost.

The average responses for different levels of significant factors in the analyses for width, angle and surface roughness are given in Table 9.

Table 9 helps us to arrive at the best level of significant factors by comparing their average response. For example, when we consider the mean width response, A_1 is better than

Table 9. *Average responses of significant factors*

Factor/ level	Width		Angle		Surface roughness	
	Mean	S/N ratio	Mean	S/N ratio	Mean	S/N ratio
A_1	19.990					
A_2	19.983					
Idle 1						
B_1					2.810	−8.81
B_2					3.601	−11.18
Idle 2						
B_2					3.761	
B_3					3.300	
C_1	19.993	70.81				
C_2	19.981	63.78				
D_3	19.986	71.86	89.962			
D_2	19.978	63.35	89.924			
Idle 1						
E_1	20.000				2.953	
E_2	19.984				3.461	
Idle 2						
E_1	19.977					
E_3	19.986					
F_1				74.00		
F_2				66.65		
G_1		69.85				
G_2		64.74				
H_1			89.945			
H_2			89.969			
I_1					3.207	
I_2					3.531	
A_1I_1			89.918			
A_1I_2			89.970			
A_2I_1			89.982			
A_2I_2			89.957			

A_2 (level closer to the target of 20 mm). Similarly, C_1 is better than C_2. When we compare the S/N ratios, the level with a higher S/N ratio is better (lower variance than the level with a lower S/N ratio). In comparing the results for surface roughness, the level with lower level of roughness is better than the higher level. In the width analysis, level E_1 is better under idle 1 while level E_3 is better under idle 2. Simple averages of E_1, E_2 and E_3 are 19.988, 19.984 and 19.986. The level of E_1 is closer to the target and is chosen as the best level.

The best levels of significant factors on η and μ based (from Table 9) on average responses are summarized in Table 10. This analysis reveals that there are five factors (B, C, D, F and G) which maximize the S/N ratio for width, angle and surface roughness. Keeping them at their best level will help to achieve more consistent quality product with respect to width, angle and surface roughness. The remaining four factors (A, E, H and I) can be used as scaling factors for adjusting means on targets for width (factors A and E) and angle (factors A, H and I).

Table 10. *Best levels of critical factors*

Response	Analysis particulars	Best level of critical factors
Width	Mean	A_1 C_1 E_1 D_3
	S/N ratio	C_1 G_1 D_3
Angle	Mean	H_2 D_3 A_2 I_1
	S/N ratio	F_1
Surface roughness	Mean	B_1 E_1 I_1
	S/N ratio	B_1

Table 11. *Expected responses for the two possible combinations*

Possible combinations	Width	Angle	Surface roughness
(1) $A_2B_1C_1D_3E_1F_1G_1H_2I_1$	20.0024	89.9993	2.235
(1) $A_1B_1C_1D_3E_1F_1G_1H_2I_1$	20.0090	89.9360	2.235
Target	20.0000	90.0000	Minimum

Optimum combination

An examination of the best level of significant factors in the above analyses reveals one area of conflict. The first level of factor A is found to be better for mean width and the second level of A is better for mean angle. Fortunately, there is more than one scaling factor for adjusting the width and angle dimension to the target. However, we have to choose the optimum combination among the two possibilities:

(1) A_2 B_1 C_1 D_3 E_1 F_1 G_1 H_2 I_1
(2) A_1 B_1 C_1 D_3 E_1 F_1 G_1 H_2 I_1

The expected results with regard to width, angle and surface roughness are estimated for two combinations. These are given in Table 11.

It can be seen from Table 11 that the expected responses for combination 1 are much closer to the target value than those for combination 2. Thus, the first combination was selected as an overall optimum combination.

All the factors considered for the experimentation influenced the quality of the wire-cutting EDM process in some way or other. The analysis of concurrent measures has helped in identifying the significance of five factors for minimizing the variance while keeping the mean on the target and lower surface roughness.

Confirmatory trial and implementation

A trial run was made with the optimum combination. The results of the trial run and a comparison with the previous situation are given in Table 12. As can be seen from the table, the variability has reduced from ± 0.015 to ± 0.007, against the requirement of ± 0.010, and surface roughness has improved from 4 μm to less than 2 μm. This improvement was considered by the technical persons as a big achievement for machining quality.

Table 12. *Comparative results*

No.	Characteristic	Observation	Mean $\hat{\mu}$	SD $\hat{\sigma}$	Limit $\hat{\mu} \pm 3\sigma$	Earlier variation
1	Width	(1) 19.9986				
		(2) 19.9988	20.0006	0.00223		
		(3) 20.0029			20.006 ± 0.0067	20.000 ± 0.015
		(4) 20.0020				
2	Angle	(1) 90.0039				
		(2) 89.9992	90.0002	0.00238		
		(3) 89.9990			90.0002 ± 0.0071	90.000 ± 0.015
		(4) 89.9987				
3	Surface roughness	(1) 2.000				
		(2) 1.750				
		(3) 2.000	1.9700	0.15730	1.97 ± 0.4700	4.0 ± 0.500
		(4) 2.125				

The optimum combination was then implemented on a permanent basis. Twenty-two tools were made with the process following the optimum combination. None of the tools needed to be reworked, whereas before every tool used to be reworked.

Conclusions

It has seen that a fractional factorial experiment using the orthogonal array layout has helped in finding a solution to the chronic problem of non-availability of process specifications for the wire-cut EDM process. The experimentation has been highly economic, as the results are achieved involving only 16 trials, whereas a full factorial experiment would have required 1728 trials.

As a result of the experimentation, apart from achieving values close to target in respect of width and angle dimensions, it has been possible to slash the variation within a piece ($\pm 3\sigma$) with respect to width and angle from 15 to 7 μm, while surface roughness recorded an improvement from 4 to 2 μm. Technologists were helped by knowing factors for adjusting the mean width and angle to the target.

To summarize, the experimentation has enabled the achievement of:

- values close to target for both width and angle dimensions;
- vastly improved consistency in the above;
- much lower surface roughness.

Benefits

The company lost no time in implementing the optimum combination secured in experimentation, with the following benefits accruing:

- rework was totally eliminated;
- tool life was improved by about 10% owing to improvement in surface roughnesss.

The estimated annual savings from elimination of rework and increase in tool life is expected to be around Rs 750 000 (about US$25 000).

References

PHADKE, M.S. (1989) *Quality Engineering Using Robust Design* (Englewood Cliffs, NJ, Prentice Hall).
TAGUCHI, G. (1962) *Tables of Orthogonal Arrays and Linear Graphs* (Tokyo, Maruzen).
TAGUCHI, G. (1988) *System of Experimental Design, Volumes 1 and 2* (New York, UNIPUB and American Supplier Institute).

Appendix A: Flow chart for machining operation

Figure 7 is a flow chart of the machining operation.

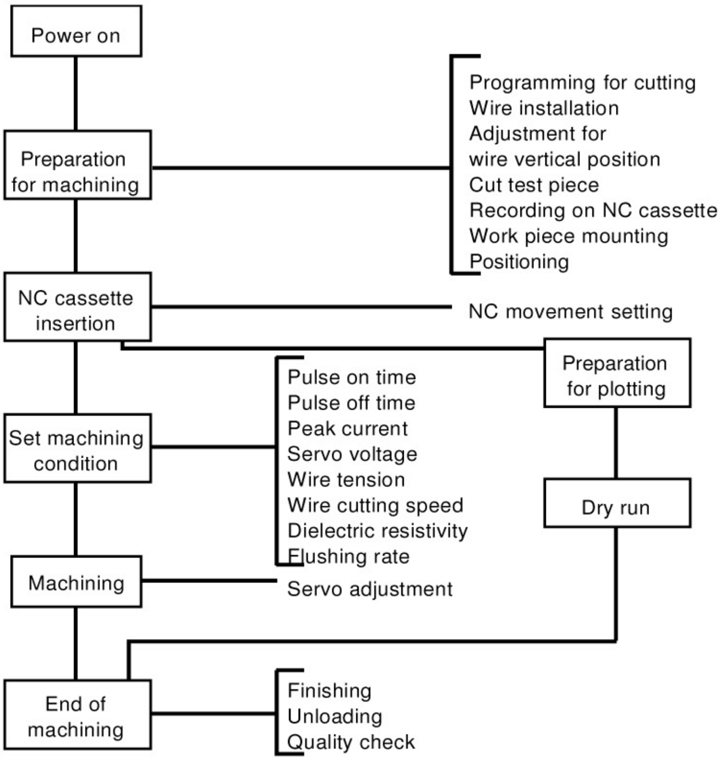

Figure 7. *Flow chart of machining operation.*

Appendix B: Multi-level and dummy-level techniques

Multi-level technique

This technique is useful for designing fractional experiments when the levels of different factors are not the same. For such an experiment, a multi-level arrangement is applied, with a four- or eight-level column arranged in two-level series orthogonal tables, or a nine- or twenty-seven-level column arranged in three-level series orthogonal tables.

Let us consider the problem of accommodating a four-level factor in the two-level orthogonal array series. In the linear graph, the representation of a four-level factor is made by the two nodes and the edge joining them. In other words, we use three columns of the array for a four-level factor. The two columns corresponding to the two nodes give four possible level combinations: (1, 1) (1, 2), (2, 1) and (2, 2). We use the following one-to-one corresponding levels of the four-level factor:

$$(1, 1) \to 1 \qquad (2, 1) \to 3$$

$$(1, 2) \to 2 \qquad (2, 2) \to 4$$

Table 13. *Assignment of 4×2^4 design in $L_8(2^7)$ using the multi-level technique*

Experiment no.	1	2	3	1 2 3	4	5	6	7
1	1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	2	2
3	1	2	2	2	1	1	2	2
4	1	2	2	2	2	2	1	1
5	2	1	2	3	1	2	1	2
6	2	1	2	3	2	1	2	1
7	2	2	1	4	1	2	2	1
8	2	2	1	4	2	1	1	2

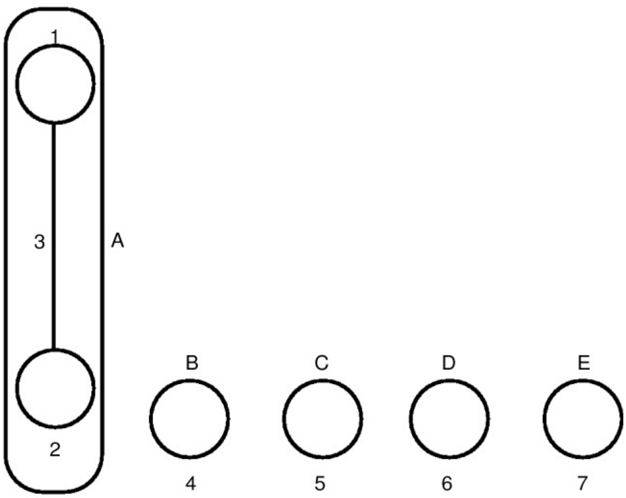

Figure 8. *Linear graph for 4×2^4 design.*

Assignment using the multi-level technique is now explained. Let us assume that A has four levels and B, C, D and E have two levels each. The assignment using linear graph is shown in Fig. 8. Table 13 gives the assignment to an orthogonal array.

Dummy-level technique

The dummy-level technique is especially useful for accommodating two-level factors in three-level orthogonal array series, or accommodating three-level factors in four-level orthogonal series.

In the above example, suppose factor A is at three levels. With the help of the multi-level technique, a four-level column (1, 2, 3) is generated. Since factor A consists of only three levels, the most important level of A is repeated whenever the symbol 4 appears in column (1, 2, 3). For example, if the first level of A is most important, then this level is replicated most often. For instance,

$$A_1 = A_2, \qquad A_2 = A_2, \qquad A_3 = A_3, \qquad A_4 = A_1$$

Table 14 shows the assignment of a 3×2^4 designing $L_8(2^7)$ layout using the dummy-level technique.

Table 14. *Assignment of 3×2^4 design in $L_8(2^7)$ using dummy level*

Experiment no.	A (1, 2, 3)	B	C	D	E
1	1	1	1	1	1
2	1	2	2	2	2
3	2	1	1	2	2
4	2	2	2	1	1
5	3	1	2	1	2
6	3	2	1	2	1
7	1[a]	1	2	2	1
8	1[a]	2	1	1	2

[a] Dummy level.

Appendix C: The idle column method

This method is used to accommodate three-level factors in two-level orthogonal series. Let A be a factor at two levels, A_1, A_2 and let B be a factor at three levels, B_1, B_2 and B_3. B is treated as a pseudo-factor at two levels. If it is assigned in a two-level series table, part of B forms B_1 and B_2 when A is A_1, and B_2 and B_3 when A is A_2.

In this way, we can compare B_1 and B_2 within A_1 and compare B_2 and B_3 within A_2. The column of $A \times B$ which is the interaction of factor A and pseudo-factor B in the orthogonal table must be erased. The distribution of the df is as follows:

Factorial effects	Degree of freedom
A	1
B_1, B_2 (within A_1)	1
B_2, B_3 (within A_2)	1
Total	3

Such a layout results in the confounding of the effect between B_1 and B_3 (or, precisely, half the effect between B_1 and B_3) with the effect between A_1 and A_2. However, the effect owing to factor A may be calculated after making corrections owing to effect of factor B. It is best, however, to avoid correction calculations as much

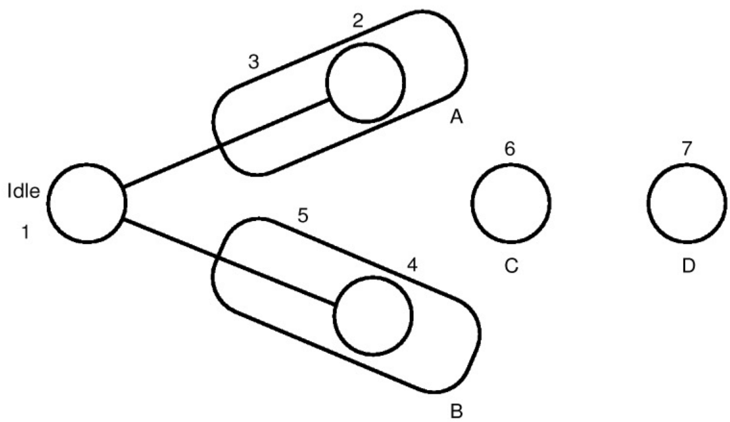

Figure 9. *Assignment by idle column.*

Table 15. *Assignment by idle column*

	Factor				
	Idle	A	B	C	D
No.	1	2, 3	4, 5	6	7
1	1	1	1	1	1
2	1	1	2	2	2
3	1	2	1	2	2
4	1	2	2	1	1
5	2	2	2	1	2
6	2	2	3	2	1
7	2	3	2	2	1
8	2	3	3	1	2

as possible. Therefore, as long as there are enough columns available, the column to which A corresponded is usually left without any factor corresponding to it, and we erase interactions with the empty column.

The empty column in this case is termed an 'idle column'. Only when there is a shortage of columns, a factor such as a block, which is useless even if obtained, is assigned to the idle column.

For assignment using the idle column method, let us assume that A and B both have three levels and C and D have two levels. Assignment by the idle column technique is as shown in Fig. 9. Table 15 obtained gives the assignment to an orthogonal array.