

Development of a Taguchi-based framework for optimizing two quality characteristics in Wire-EDM operations

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Abstract

A framework based on Taguchi parameter design was developed and successfully demonstrated to optimize two quality characteristics- surface roughness and angular accuracy in Wire Electrical Discharge Machining (W-EDM) process. An orthogonal array (OA) L_9 was used in the Taguchi experiment design for four controllable factors, each with three levels. With one non-controllable factor investigated, 18 experiments were conducted in the Taguchi-based experiment setting, compared to 3^4 (=81) parameter combination as required by a traditional DOE setting. Conducted for the two response variables, Taguchi experiments from the case study gave the optimal combination of pulse on time at $9\mu\text{s}$ (A_1), feed rate at 35 in/min (B_2), voltage at 8v (C_2), and wire tension at 165g (D_3) for surface roughness optimization, and pulse on time at $13\mu\text{s}$ (A_3), feed rate at 35 in/min (B_2), voltage at 8v (C_2), and wire tension at 160g (D_2) for angular accuracy optimization. This optimal parameter setting combination was verified through a confirmation run that confirms the optimal quality responses of $126.1\mu\text{m}$ for surface roughness and 0.024° for angular accuracy. This research ultimately showed the dual output variable improvement and the framework established itself as a means to solve similar problems in other machining applications. The developed framework can serve as guidance for researchers to obtain multi-variable optimal setting in a systematic way.

Keywords: WEDM· Taguchi method · Surface roughness · Angular accuracy

I. Introduction

As a non-traditional machining process, Wire Electrical Discharge Machining (W-EDM) erodes materials from a work piece by producing sparks between the work piece and the tool electrode. The process occurs in a dielectric liquid bath of deionized water. W-EDM has been widely used in advanced manufacturing processes for molds and die in fields such as aerospace, automotive, and surgical components. W-EDM machines are able to produce

complex 2D and 3D shapes. During W-EDM process, spark erosion frequently occurs, which can create more than one thousand sparks per second between the wire (Anode) and the work piece (Cathode). These sparks jump from the wire to the work piece and erode metal at temperatures in the range of $8000 - 12000^\circ$ [1] as shown in Fig 1[3]. The nature of W-EDM processes requires that both the work piece material and the wire be conductive.

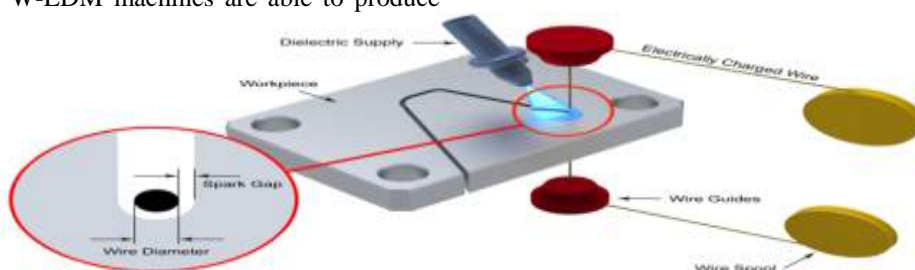


Fig.1 Principle of W-EDM [3]

Compared to traditional machining processes, W-EDM machines are capable of holding to closer tolerances and better surface finishes. Some W-EDM machines are extremely accurate allowing them to hold up to $\pm 0.0001''$ and producing a surface finish (R_a) of around $0.037 \mu\text{m}$ [4]. The advantages from W-EDM process have made it a reasonable alternative to other subtractive machining processes. One major advantage lies in the fact that there is little contact force between the workpiece and the wire, and hence

it can machine weak or thin work pieces without causing much deflection as in traditional machining processes. Additionally a W-EDM machine has several parameters including: pulse on time (a.k.a. the duration of time) which is the length of time that the wire releases sparks, wire feed rate or the speed in which the wire is fed through the work piece, wire tension or the axial forces exerted on wire, and voltage- the electrical charge passing from the wire to the work piece. These parameters significantly

influence quality of parts made by W-EDM process [5].

Since W-EDM is widely used in many manufacturing applications, many researchers have optimized machining parameters to improve quality and reduce production costs. Taguchi method is a very useful technique used to achieve higher quality

and reduce product cost [2]. Taguchi method has been used to study the performance of W-EDM to improve the output variable characteristics such as surface roughness, dimension accuracy, material removal rate (MRR). Table 1 shows the summary of related research using Taguchi method to improve and optimize the performance of W-EDM.

Table 1 Summary of the researches

No	Author/Year	Parameters	Performance Measures	Remark	Technique Used
1	Harpreet et al./ (2012)[6]	pulse on/ pulse off time	MRR	It was discovered that with an increase in pulse on time the MRR decreased, and inversely with an increase in pulse off time MRR increased.	Taguchi Methodology
2	Parveen Kumar et al/(2013) [7]	Pulse on time, pulse of time, wire speed rate, wire tension	MRR, Wire Rate, Surface Roughness	The result was found that the pulse on time and the wire speed rate are the most significant parameters.	Taguchi Methodology
3	Atul Kumar(2012)[8]	voltage, feed rate, pulse on time, pulse off time, wire feed, servo voltage, wire tension, flushing pressure	MRR, Surface Roughness	It was found that pulse on time and voltage have the most significant effect on MRR and surface roughness.	Taguchi Methodology
4	G.Lakshmikanth(2014)[9]	pulse on time, pulse off time, wire feed	MRR, Surface Roughness	In an investigation of the effect of pulse on time, pulse off time, and wire feed, the factor of pulse on time had the most significant effect on MRR and surface roughness.	Taguchi Methodology
5	Alpesh M. Patel et al/(2013)[10]	wire feed, wire tension, discharge current, discharge voltage	Electrode Wear Rate (EWR), MRR	The study demonstrated that discharge current, discharge voltage, and wire tension greatly influence EWR and MRR.	Taguchi Methodology
6	Sameh S. Habib (2014)[11]	pulse on time, pulse off time, discharge current, voltage	MRR, Surface Roughness, Gapsize	The study found that the pulse on time has the most significant influence on MRR, surface roughness, and gap size	Taguchi Methodology
7	Lokeswara Rao(2013)[12]	pulse on time, pulse off time, peak current, wire tension, servo voltage, servo feed	MRR, Surface Roughness	The study found the optimum cutting parameters for WEDM, the minimum surface roughness, and the maximum MRR.	Taguchi Methodology

8	Jasvinder Pal et al/(2014)[13]	pulse on time, pulse off time, peak current wire feed, servo voltage	Surface Roughness	It was found that the pulse on time, pulse off time, and servo voltage have a significant effect on surface roughness.	Taguchi Methodology
9	Jaganathan P al/(2012)[14]	applied voltage, discharge current, pulse width, pulse interval	MRR, Surface Roughness	It was found that factors like applied voltage, pulse width, and speed have played a significant role on MRR and surface roughness.	Taguchi Methodology
10	K.Hari al/(2014)[15]	pulse on time, pulse off time, servo voltage, wire feed, peak current, servo feed	MRR, Surface Roughness	It was found that pulse on time, pulse off time, and peak current are the most significant parameters that affect the MRR and surface roughness.	Taguchi Methodology

As seen from the literature review in Table 1, some studies show that while optimizing output variables by changing input parameters, two output variables can be improved individually, but not simultaneously. This would significantly hinder the application of Taguchi method in industry setting for process improvement when two output variables need to be optimized simultaneously. The objective of this research is to design an overarching framework by which dual output variable improvement can be accomplished using one parameter level setting. For the purpose of this research, Taguchi method is used to determine the optimal parameters for surface roughness and angular accuracy of workpieces machined by W-EDM machines. The subsequent sections will present the methodology and a case study with experimental verification used to show its efficacy

II. Methodology

In this research Taguchi method and Signal-to-Noise (S/N) ratio are used for comparative analysis of parameters' effect on response variables. Two response variables are tested for W-EDM process optimization. As shown in Fig 2, the following steps outline the procedure of experimentation in a systematic way to find the optimum results.

Step 1: The first step in this procedure is to select the machining operation that will be used in experiment. Once the machining operation is selected, measurable output variables should be identified as well. Measurable output variables (OV in Fig. 2) are those variables chosen to meet the needs from industry, such as dimensional accuracy, angular accuracy, surface roughness, material removal rate, and electrode wire rate, etc.

Step 2: After choosing measurable output variables, the next step involves running a baseline experiment for analysis. The baseline experiment produces initial

results of each output variable as a starting point for optimization. From the baseline analysis, an initial understanding of the machine capability with respect to the output variables is established. The baseline experiment result is then used as a gauge to compare with the result from Taguchi method to verify the improvement.

Step 3: Select proper controllable factors and noise factor. Proper selection of controllable factors is vital to product quality. In order to understand those factors affecting the process, a fishbone diagram is used to identify the possible causes of a problem.

Step 4: Taguchi Parameter Design and Orthogonal Array (OA) Matrix. Taguchi method has three segments: system design, parameter design, and tolerance design [17]. In this study, Taguchi parameter design is used to determine the optimal levels for the controllable system parameters. In Taguchi parameter design there are two types of factors that can affect product quality - controllable factors and noise factors. A factor is considered controllable if it is easily manipulated and has a significant impact on product quality. In W-EDM process, pulse on time, wire tension, and voltage are examples of controllable factors. A noise factor may have a negative effect on product quality, but cannot be controlled; temperature, vibration, or humidity are typical examples of noise factors in the application of Taguchi method [17]. Taguchi parameter design has been proved to be a reliable way to evaluate and implement improvements on product and process [18]. Moreover Taguchi method uses OA in its experiment design [5]. The advantage of using OA is the ability to study a large number of variables with a smaller number of experiments [8], and therefore the experiment can be conducted in a much more economical way compared to traditional Design of Experiment practices.

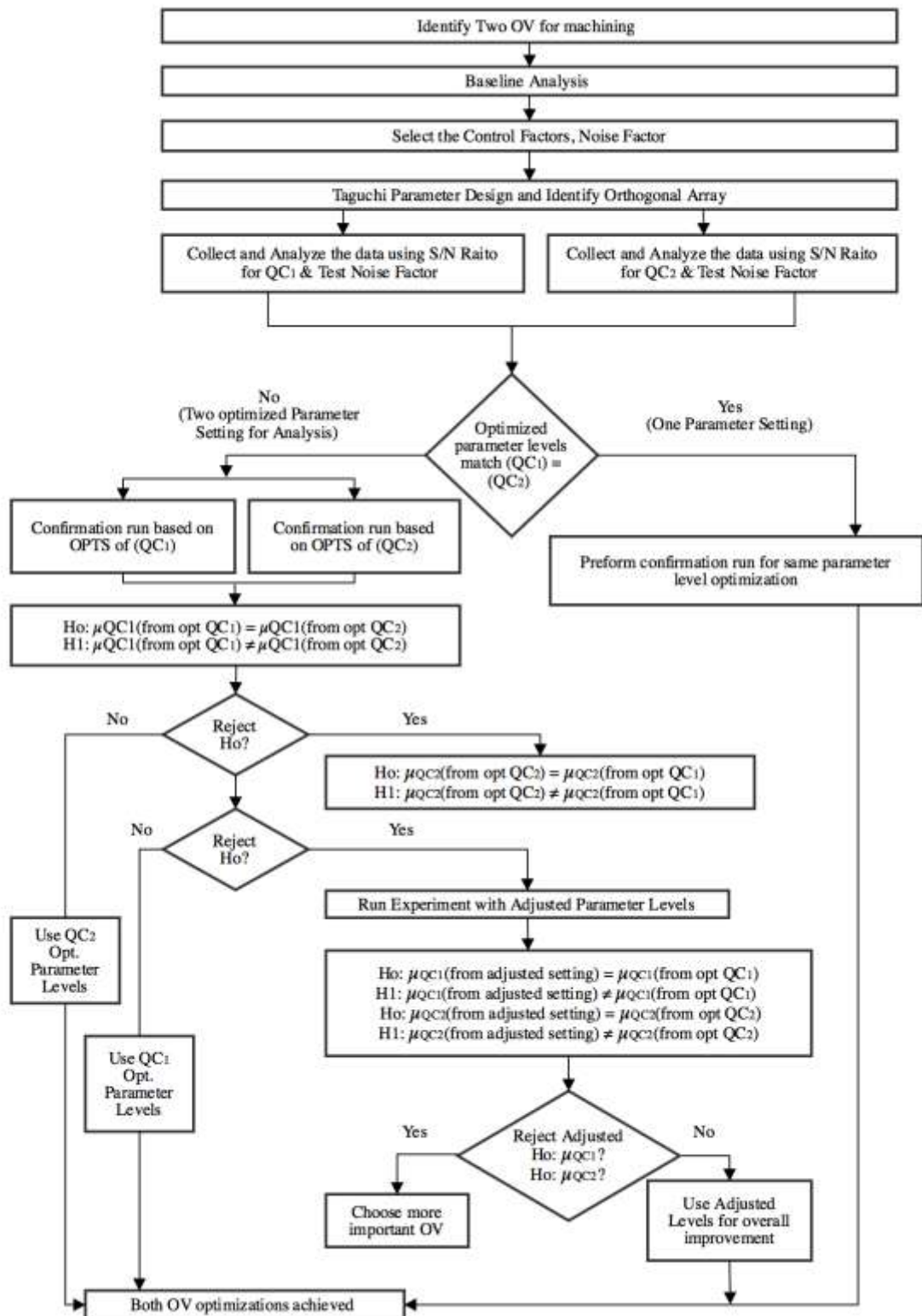


Fig. 2 Methodology framework for two output variables using Taguchi method

Step 5: After the required OA matrix is determined, machining experiment can be performed and data can be collected from the machined workpieces through measurement using appropriate measurement

instruments. Once the data is collected, S/N ratio is calculated to analyze the measurement data. S/N ratio is able to determine which controllable factors have more impact on the quality characteristics of the

product. There are three possible situations where S/N ratio can be calculated depending on the quality characteristic to be optimized.

$$\text{Smaller the better } \frac{S}{N} = -10 \log \left(\frac{1}{n} \sum_{i=1}^n y_i^2 \right) \quad (1)$$

$$\text{Nominal the better } \frac{S}{N} = 10 \log \left(\frac{\frac{1}{n} \sum_{i=1}^n y_i^2}{S_y^2} \right) \quad (2)$$

$$\text{Larger the better } \frac{S}{N} = -10 \log \left(\frac{1}{n} \sum_{i=1}^n \frac{1}{y_i} \right) \quad (3)$$

Where y_i^2 is the result of the observed value, and n is the number of times the experiment is repeated. In this research S/N ratio is defined as *Smaller the better* for optimizing both quality characteristics.

Followed by the data collection and analysis, a T-test for 99% confidence is used to find out if the noise factor significantly affects the quality characteristics.

$$H_0: \mu_{\text{LEVEL1 of NOISE FACTOR}} = \mu_{\text{LEVEL2 of NOISE FACTOR}}$$

$$H_1: \mu_{\text{LEVEL1 of NOISE FACTOR}} \neq \mu_{\text{LEVEL2 of NOISE FACTOR}}$$

Where $\mu_{\text{LEVEL1 of NOISE FACTOR}}$ is the mean collected from level one of the noise factor and $\mu_{\text{LEVEL2 of NOISE FACTOR}}$ is the mean collected from level two of the noise factor.

Step 6: After analyzing the data, the optimal parameter settings will either be identical or not. If the optimal parameter settings are identical, then one confirmation run is performed. In this situation, the confirmation run is an additional set of experiments performed to validate that improvement for both first quality characteristic (QC₁) and second quality characteristic (QC₂) are achieved. However, if the optimal parameter level settings are not identical, then two confirmation runs are needed. Each confirmation run uses its own parameter level setting to test both output variables of QC₁ and QC₂. Even though there are two confirmation runs performed on varying parameter levels, only one parameter level setting is needed eventually for both output variables improvement.

Step 7: If the outcome does not lead to an optimized parameter setting for the two quality characteristics, then further tests are needed. Using the results from each of the confirmation runs for QC₁ and QC₂, two separate hypotheses are proposed to test whether or not a single optimized parameter level setting is possible.

The first hypothesis test is executed to see if QC₁ mean using optimized parameter level settings for QC₁ will be significantly different from QC₁ mean from running the machining operation using the optimized level settings for QC₂.

$$H_0: \mu_{\text{QC1 (from opt Q1)}} = \mu_{\text{QC1 (from opt QC2)}}$$

$$H_1: \mu_{\text{QC1 (from opt Q1)}} \neq \mu_{\text{QC1 (from opt QC2)}}$$

Where $\mu_{\text{QC1 (from opt Q1)}}$ is the QC₁ mean from running experiments using the optimized parameter level settings for QC₁, and $\mu_{\text{QC1 (from opt QC2)}}$ is the QC₁ mean from running experiments using the optimized parameter level settings for QC₂.

Similarly, the second hypothesis test is conducted to see if QC₂ mean using optimized parameter level

settings for QC₂ will be significantly different from the QC₂ mean from running the experiment using the optimized level settings for QC₁.

$$H_0: \mu_{\text{QC2 (from opt QC2)}} = \mu_{\text{QC2 (from opt QC1)}}$$

$$H_1: \mu_{\text{QC2 (from opt QC2)}} \neq \mu_{\text{QC2 (from opt QC1)}}$$

Where $\mu_{\text{QC2 (from opt QC2)}}$ is the QC₂ mean from running experiments using the optimized parameter level settings for QC₂, and $\mu_{\text{QC2 (from opt Q1)}}$ is the QC₂ mean from running experiments using the optimized parameter level settings for QC₁.

From the hypothesis test, there are two possible outcomes. The first outcome is that the null hypothesis is not rejected. This is possible in three different ways. The first is that both null hypotheses are not rejected and the second and third are that we fail to reject one of the two null hypotheses. In case of the first outcome where the null hypothesis is not rejected, one confirmation run is enough to improve both output variables. The second outcome is that both null hypotheses are rejected. In that situation, additional testing must be performed as follows.

From the previous stage of the framework if both null hypotheses are rejected, an adjustment confirmation run will be performed. The parameter level settings that are not identical are first adjusted to a value between the two non-identical parameter values. The experiment is then performed and two final hypotheses are tested. The first hypothesis test is done to see if QC₁ mean from the optimized parameter level settings for QC₁ will be significantly different from the QC₁ mean obtained from the adjusted parameter level settings.

$$H_0: \mu_{\text{QC1 (from adjusted setting)}} = \mu_{\text{QC1 (from opt QC1)}}$$

$$H_1: \mu_{\text{QC1 (from adjusted setting)}} \neq \mu_{\text{QC1 (from opt QC1)}}$$

Where $\mu_{\text{QC1 (from adjusted setting)}}$ is the QC₁ mean from the adjusted parameter level settings, and $\mu_{\text{QC1 (from opt Q1)}}$ is the QC₁ mean from the optimized parameter level settings for QC₁.

The second hypothesis test is conducted to see if QC₂ mean from the optimized parameter level settings for QC₂ will be significantly different from the QC₂ mean obtained from the adjusted parameter level settings.

$$H_0: \mu_{\text{QC2 (from adjusted setting)}} = \mu_{\text{QC2 (from opt QC2)}}$$

$$H_1: \mu_{\text{QC2 (from adjusted setting)}} \neq \mu_{\text{QC2 (from opt QC2)}}$$

Where $\mu_{\text{QC2 (from adjusted setting)}}$ is the QC₂ mean from the adjusted parameter level settings and $\mu_{\text{QC2 (from opt QC2)}}$ is the QC₂ mean from the optimized parameter level settings for QC₂.

Ideally if both output variables are expected for optimization, one prefers to see that neither of the two null hypotheses is rejected. In this case the output from the adjusted parameter level settings is not significantly different from the output from the optimized parameter settings for each quality characteristic. However if one of the null hypotheses is rejected, then simultaneous improvement for both output variables was technically not possible with a

single parameter level setting. When this happens, there are two options for the user. One is to select the parameter level settings based on the more important quality characteristic from the two under investigation. However in reality the practitioner of this methodology may inquire into the difference of the output from the adjusted parameter level settings and the output from the baseline study for both QC₁ and QC₂. If there turns out to be a considerable improvement for both QC₁ and QC₂ by using the adjusted parameter settings, then the second option is to continue to use the adjusted parameter settings for both QC₁ and QC₂, for they both can still be improved although not optimized.

III. Case Study

The experiment was carried out on a Sodick VZ 300LW-EDM machine. The wire used in this experiment is made of brass with a diameter of 0.25mm, and the work piece material is 1080 steel sheet with a thickness of 0.175". Dimensions of the work piece are shown in Fig 3.

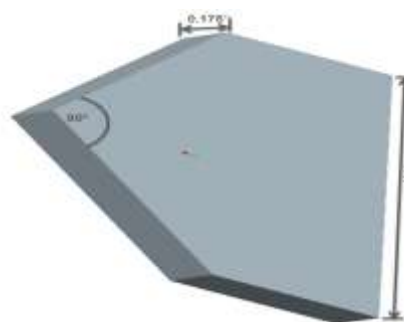


Fig. 3 Work piece dimension

3.1 Selection of output variables

In this research surface roughness and angular accuracy were selected as response variables. A Mitutoyo SJ-301 profilometer was used for measuring surface roughness and a Mitutoyo RV507 CMM machine was used for angular accuracy measurement.

3.2 Baseline analysis

The baseline run in this study was conducted using the default parameter level setting for the W-EDM operation. The parameter levels are: pulse on time at 12µs, wire feed rate at 35 units, voltage of 9v, and wire tension of 160 gram. These settings produced the following results as shown in Table 2.

Table 2 Baseline results

Run	1	2	3	4	5	6	7	8	9	10	Average
Surface Roughness Ra µin	147.9	141.7	136.1.9	144.2	140.2	138.9	145.7	139.1	140.9	142.6	142.4
Angular Accuracy θ°	0.0958	0.0637	0.0872	0.0781	0.0692	0.0725	0.0713	0.0961	0.0734	0.1018	0.082

3.3 Controllable factor and noise factor selection

The cause and effect diagram (fishbone diagram) outlined possible significant factors that could affect the machine conditions and lead to products with inferior quality. Fig. 4 displays the cause and effect diagram. With the cause and effect analysis, four machining parameters (pulse on time, wire feed rate, voltage, and wire tension) were selected in this

research as controllable factors. The selection of these four controllable factors are based upon the previous literatures summarized in Table-1 and their correlation to the output variables of this research. Vibration was selected as noise factor in this research since it most accurately represents an uncontrollable factor as seen in the machine shop environment.

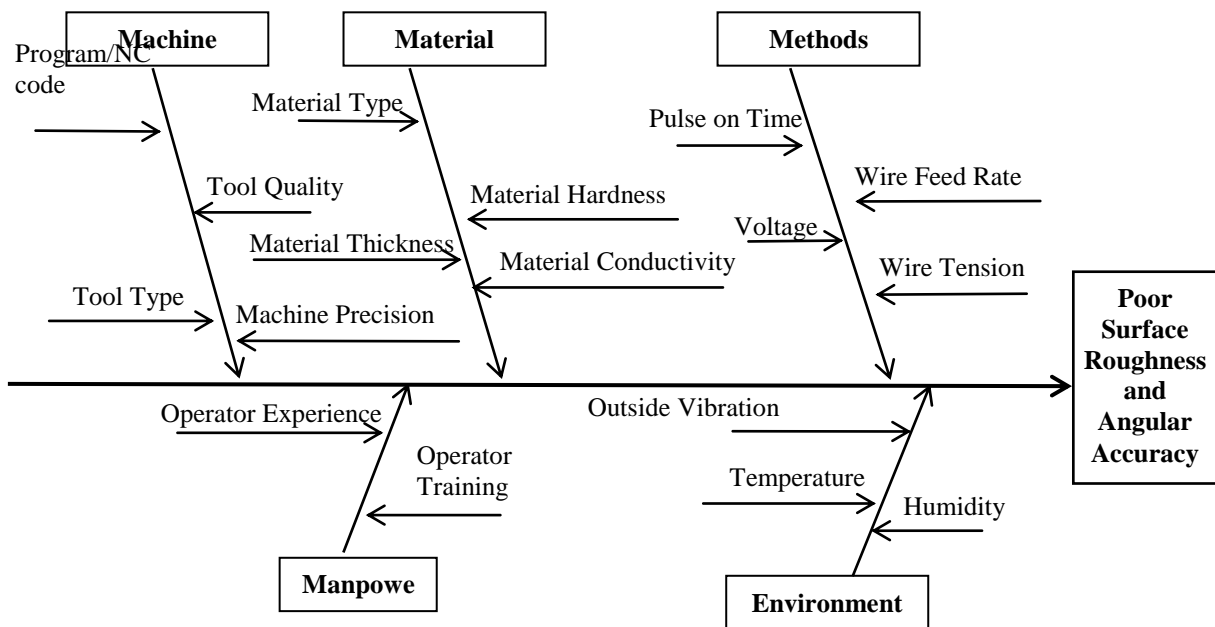


Fig. 4 Cause and effect diagram for poor surface roughness and angular accuracy

3.4 Designing OA matrix experiment

The next step is to implement Taguchi parameter design and OA matrix experiment for the controllable factors and noise factor. Taguchi experiment is used in this research for a reduced cost incurred in the experimentation compared to traditional experiment design. Taguchi experiment involves four

controllable factors including pulse on time, feed rate, voltage, and wire tension, each of which has three accompanying levels. Table 3 shows the Taguchi parameters design where vibration is considered as the noise factor for its uncontrollable effect on product quality.

Table 3 Taguchi parameters design

P	---	Symbol	Level- 1	Level- 2	Level-3
A	Pulse on time	T On(μ s)	9	11	13
R	Feed Rate	FR(in/min)	30	35	40
A	Voltage	V(volt)	7	8	9
M	Wire Tension	WT(gram)	155	160	165
E	Noise Factors	Vibration	V	on	Off
T	Response Variables	dimensional of angles			
E		surface roughness			
R					
S					

Selection of OA is based on the number of controllable factors (4 controllable factors in this research) and their levels (3 levels for each controllable factor). In this research the OA will be a L_9 table by which nine experiments will be done to study four controllable factors at three different levels for adequate experimental analysis. Table 4 shows the experiment design using an OA L_9 table.

Table 4 Experiments designed using OA L9

Exp. No.	Control Factors				Noise Factor	
	T on	FR	V	WT	Vibration	Vibration
1	1	1	1	1	ON	OFF
2	1	2	2	2	ON	OFF
3	1	3	3	3	ON	OFF
4	2	1	2	3	ON	OFF
5	2	2	3	1	ON	OFF
6	2	3	1	2	ON	OFF
7	3	1	3	2	ON	OFF
8	3	2	1	3	ON	OFF
9	3	3	2	1	ON	OFF

IV. Results and Discussion

Subsequent to the Taguchi-based experiment implementation, an analysis was done to reveal the effect of the pulse on time, wire feed rate, voltage, and wire tension on the quality characteristics of surface roughness and angle accuracy. The experiments were conducted using the L₉OA matrix. Tables 5 and 6 show the experimental results for surface roughness and angular accuracy, respectively.

The average value (Y-bar) and S/N ratio were calculated at different levels for the response characteristics. S/N ratio of smaller the better was computed using equation (1) for both surface roughness and angle accuracy. The angle accuracy value was calculated by measuring the angle first, then subtracting it from 90 degree to show the absolute angular deviation.

Table 5 Experiment results for surface roughness

Exp. No.	Control Factors				Noise Factor		Y-bar	S/N Ratio
	T on	FR	V	WT	V on	V off		
1	1	1	1	1	124.5	123.9	124.2	-41.88
2	1	2	2	2	122.6	120.2	121.4	-41.68
3	1	3	3	3	123.7	122.5	123.1	-41.81
4	2	1	2	3	128.6	124.3	126.45	-42.04
5	2	2	3	1	132.8	130.1	131.45	-42.38
6	2	3	1	2	137.2	135.9	136.55	-42.71
7	3	1	3	2	139.1	140.8	139.95	-42.92
8	3	2	1	3	134.2	137.9	136.05	-42.67
9	3	3	2	1	145.6	138.3	141.95	-43.05

Table 6 Experiment results for angle accuracy

Exp. No.	Control Factors				Noise Factor		Y-bar	S/N Ratio
	T on	FR	V	WT	V on	V off		
1	1	1	1	1	0.2366	0.2458	0.2412	12.35
2	1	2	2	2	0.1275	0.1259	0.1267	17.94
3	1	3	3	3	0.2721	0.2546	0.26335	11.58
4	2	1	2	3	0.1211	0.1312	0.12615	17.98
5	2	2	3	1	0.1446	0.1261	0.13535	17.35
6	2	3	1	2	0.1107	0.1013	0.106	19.49
7	3	1	3	2	0.0855	0.0174	0.05145	24.19
8	3	2	1	3	0.1382	0.0644	0.1013	19.35
9	3	3	2	1	0.0447	0.096	0.07035	22.51

4.1 Data analysis for surface roughness

Tables 7 and 8 show the responses of mean and S/N ratio of surface roughness. From the collected data, pulse on time is the most significant factor in affecting surface roughness while voltage and wire tension are shown to be less significant factors. It can

be observed that surface roughness increases with an increase in pulse on time, and surface roughness decreases with an increase in wire tension. Also surface roughness is higher with the first level of voltage and the third level of wire feed rate but decreases when using the middle two levels. Fig.5

shows that the optimal parameter settings for surface roughness are first level of pulse on time (A₁), second

level of wire feed rate (B₂), second level of voltage (C₂), and third level of wire tension (D₃).

Table 7 Response table of mean for surface roughness $r_{a \mu \min}$

Level	A (T on)	B (FR)	C (V)	D (WT)
1	122.9	130.2	132.3	132.5
2	131.5	129.6	129.9	132.6
3	139.3	133.9	131.5	128.5

Table 8 Response table of signal to noise (S/N) ratio for surface roughness

Level	A (T on)	B (FR)	C (V)	D (WT)
1	-41.79	-42.28	-42.42	-42.43
2	-42.37	-42.25	-42.26	-42.44
3	-42.88	-42.52	-42.37	-42.17

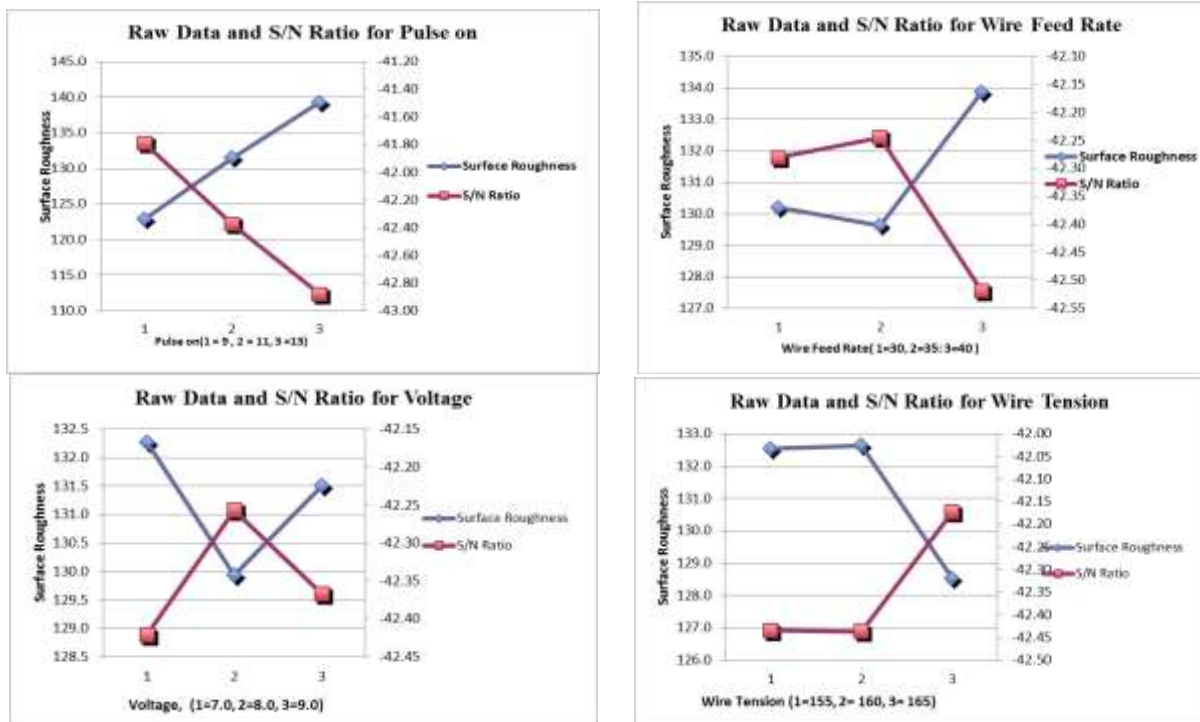


Fig. 5 Effects of controllable parameters on surface roughness and S/N ratio

After the optimization was completed, the effect of noise factor on W-EDM process was also studied by using a T-test to determine if vibration is significant to surface roughness.

$$H_0: \mu_{Ra \text{ (vibration On)}} = \mu_{Ra \text{ (vibration Off)}}$$

$$H_1: \mu_{Ra \text{ (vibration On)}} \neq \mu_{Ra \text{ (vibration Off)}}$$

Where $\mu_{Ra \text{ (vibration On)}}$ is the mean of vibration-on values and $\mu_{Ra \text{ (vibration Off)}}$ is the mean of vibration-off values obtained from Table 5.

By using equation,

$$t = \frac{\bar{\mu}_{Ra \text{ (vibration On)}} - \bar{\mu}_{Ra \text{ (vibration Off)}}}{\sqrt{\frac{S_{Ra \text{ (vibration On)}}^2 + S_{Ra \text{ (vibration Off)}}^2}{n_1 + n_2}}}$$

The t-value for surface roughness is 0.430 which is smaller than t critical value of 2.92 (with alpha = 0.01, degree of freedom = 16). Therefore the null hypothesis is not rejected, which means the vibration does not affect surface roughness.

4.2 Data analysis for angular accuracy

Tables 9 and 10 show the responses of mean and S/N ratio of angular accuracy. From the collected data, pulse on time and wire tension are the most significant factors affecting angular accuracy, while voltage and feed rate are shown to be less significant. It can be observed that angular accuracy decreases with an increase in pulse on time, and angular accuracy is the best with the middle level of wire tension. When observing the results of feed rate and

voltage, the middle two levels give the lowest deviation from the nominal 90-degree. Fig.6 shows that the optimal parameter settings are third level of

pulse on time (A₃), second level of wire feed rate (B₂), second level of voltage (C₂), and second level of wire tension (D₂).

Table 9 Response table of mean for angular accuracy θ°

Level	A (T on)	B (FR)	C (V)	D (WT)
1	0.210	0.140	0.150	0.149
2	0.123	0.121	0.108	0.095
3	0.074	0.147	0.150	0.164

Table 10 Response table of S/N ratio for angular accuracy

Level	A (T on)	B (FR)	C (V)	D (WT)
1	13.96	18.17	17.06	17.40
2	18.27	18.21	19.48	20.54
3	22.02	17.86	17.71	16.30

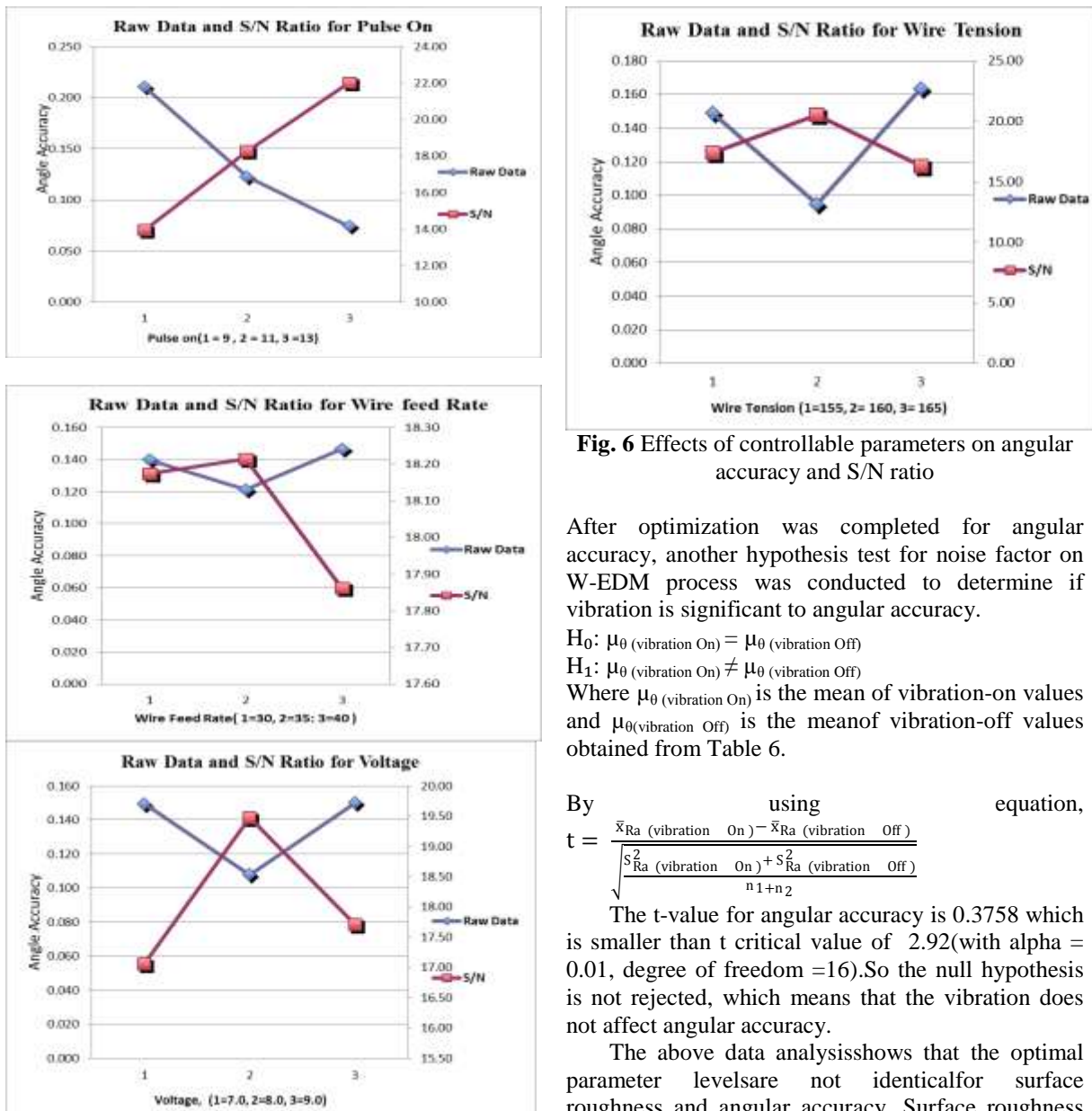


Fig. 6 Effects of controllable parameters on angular accuracy and S/N ratio

After optimization was completed for angular accuracy, another hypothesis test for noise factor on W-EDM process was conducted to determine if vibration is significant to angular accuracy.

$$H_0: \mu_{\theta} (\text{vibration On}) = \mu_{\theta} (\text{vibration Off})$$

$$H_1: \mu_{\theta} (\text{vibration On}) \neq \mu_{\theta} (\text{vibration Off})$$

Where $\mu_{\theta} (\text{vibration On})$ is the mean of vibration-on values and $\mu_{\theta} (\text{vibration Off})$ is the mean of vibration-off values obtained from Table 6.

By using equation,

$$t = \frac{\bar{x}_{Ra} (\text{vibration On}) - \bar{x}_{Ra} (\text{vibration Off})}{\sqrt{\frac{S_{Ra}^2 (\text{vibration On}) + S_{Ra}^2 (\text{vibration Off})}{n_1 + n_2}}}$$

The t-value for angular accuracy is 0.3758 which is smaller than t critical value of 2.92 (with alpha = 0.01, degree of freedom = 16). So the null hypothesis is not rejected, which means that the vibration does not affect angular accuracy.

The above data analysis shows that the optimal parameter levels are not identical for surface roughness and angular accuracy. Surface roughness

has levels of A_1 , B_2 , C_2 , and D_3 , while angular accuracy has levels of A_3 , B_2 , C_2 , and D_2 . Hence two confirmation runs are needed for each quality characteristic on their own optimal parameter level settings.

V. Confirmation runs

Confirmation run is an additional set of experiments performed using the optimal parameter

values as determined from the Taguchi experiments. For this research confirmation runs are used to validate that improvements for both surface roughness and angular accuracy can be accomplished. Tables 11 and 12 show the outcomes of confirmation runs for both surface roughness and angular accuracy quality characteristics.

Table 11 Confirmation run for surface roughness and confidence interval

Run	1	2	3	4	5	6	7	8	9	10
Surface										
Roughness	112.3	113.4	115.9	116.7	115.2	108.9	113.5	118.7	112.6	117.9
Ra μin										
Mean =	114.51		Standard Deviation =			2.954		Upper CI = 117.545		
T-value (99%) =	± 3.250		N = 10			Lower CI = 111.475				

Table 12 Confirmation run for angular accuracy and confidence interval

Run	1	2	3	4	5	6	7	8	9	10
Angular										
Accuracy θ°	0.0082	0.011	0.007	0.0084	0.0079	0.012	0.0091	0.0098	0.0095	0.0067
Mean =	0.00896		Standard Deviation =			0.0017		Upper CI = 0.01069		
T-value (99%) =	± 3.250		N = 10			Lower CI = 0.00723				

Based on the optimal setting (A_1 , B_2 , C_2 , and D_3) for surface roughness, the predicted optimal value for surface roughness is given as:

$$\text{Predicted Ra} = \mu A_1 + \mu B_2 + \mu C_2 + \mu D_3 - 3 * Y\text{-Avg} = 117.30 \mu\text{in}$$

Based on the optimal setting (A_3 , B_2 , C_2 , and D_2) for angular accuracy, the predicted optimal value for angular accuracy is given as:

$$\text{Predicted } \theta = \mu A_3 + \mu B_2 + \mu C_2 + \mu D_2 - 3 * Y\text{-Avg} = 0.00935^\circ$$

The letters with a number subscript in the above two representations denote the optimal parameter selections, and Y-Avg is the average of all response data. Through comparing the predicted values and the results from confirmation runs, it can be shown that both confirmation runs actually rendered more improvement than what was expected, and the predicted values fell between the upper and lower bounds. The mean of surface roughness from confirmation run is 114.51 μin , which is less than the predicted 117.30 μin , and the mean of angular accuracy from confirmation run is 0.00896 $^\circ$, less than the predicted 0.00935 $^\circ$.

Given the results from confirmation runs, a final T-test for 99% confidence interval was conducted to confirm the expected level of experimental repeatability. For surface roughness, it can be expected with 99% confidence that a part cut on a W-EDM machine will have surface roughness values between 111.475 μin and 117.545 μin . Likewise, an angle feature cut using a W-EDM machine will be

within the deviation range of 0.00723 $^\circ$ to 0.01069 $^\circ$ at 99% confidence.

VI. Merging two quality characteristics into one optimal parameter setting

The case study shows non-identical parameter settings for the two quality characteristics. The optimal parameter for surface roughness is A_1 , B_2 , C_2 , and D_3 and that for angular accuracy is A_3 , B_2 , C_2 , and D_2 . In order to optimize both quality characteristics simultaneously, it is necessary to reach one optimal parameter setting that can optimize both surface roughness and angular accuracy at the same time.

In this research a T-test was used to determine if there is a significant difference in mean between the surface roughness produced by the optimal parameter levels for surface roughness itself and the surface roughness produced by the optimal parameter levels for angular accuracy.

$$H_0: \mu_{\text{Ra (from opt Ra)}} = \mu_{\text{Ra (from opt } \theta)}$$

$$H_1: \mu_{\text{Ra (from opt Ra)}} \neq \mu_{\text{Ra (from opt } \theta)}$$

Where $\mu_{\text{Ra (from opt Ra)}}$ is the mean of surface roughness from the experiments using the optimized parameter level setting for surface roughness, and $\mu_{\text{Ra from opt } (\theta)}$ is the mean of surface roughness from experiments using the optimized parameter level setting for angular accuracy.

Table 13 shows both the surface roughness data from the optimized parameter level for surface roughness

itself and the data from the optimized parameter level for angular accuracy (θ).

$$\text{By using equation, } t = \frac{\bar{x}_{Ra}(\text{from opt Ra}) - \bar{x}_{Ra}(\text{from opt } \theta)}{\sqrt{\frac{s_{Ra}^2(\text{from opt Ra}) + s_{Ra}^2(\text{from opt } \theta)}{n_1 + n_2}}}$$

The t-value is -16.05 which falls outside of t-critical value ± 2.898 (with $\alpha=0.01$ degree of freedom=18). Thus the null hypothesis is rejected. The conclusion is that the non-identical parameter setting does affect surface roughness.

Table 13 T-test comparing of two data (surface vs. angular) for Ra

No.	(Ra) from opt Surface Roughness	(Ra) from opt Angular accuracy
1	112.3	133.6
2	113.4	141.1
3	115.9	145.6
4	116.7	134.7
5	115.2	138.6
6	108.9	139.7
7	113.5	135.2
8	118.7	137.9
9	112.6	135.6
10	117.9	138.2
Average	114.51	138.02
Standard Deviation	2.95	3.57
SE Mean	1.46	
T-value	-16.05	
Degree of Freedom	17	
T- alpha value .01	± 2.898	

Table 14 T-test comparing of two data (surface vs. angular) for θ

No.	(θ) from opt Angular accuracy	(θ) from opt Surface Roughness
1	0.0082	0.0514
2	0.011	0.044
3	0.007	0.0925
4	0.0084	0.067
5	0.0079	0.0566
6	0.012	0.0426
7	0.0091	0.0866
8	0.0098	0.0372
9	0.0095	0.0361
10	0.0067	0.0964
Average	0.00896	.0610

Standard Deviation	0.00168	0.0232
SE Mean	0.00737	
T-value	-7.067	
Degree of Freedom	9	
T- alpha value .01	± 3.250	

Similarly T-test was also used to determine if there is a significant difference between the mean of angular accuracy produced by the optimized parameter levels for angular accuracy itself and the mean of angular accuracy produced by the optimized parameter level for surface roughness.

$$H_0: \mu_{\theta(\text{from opt } \theta)} = \mu_{\theta(\text{from opt Ra})}$$

$$H_1: \mu_{\theta(\text{from opt } \theta)} \neq \mu_{\theta(\text{from opt Ra})}$$

Where $\mu_{\theta(\text{from opt } \theta)}$ is the mean of angular accuracy from the experiments using the optimized parameter level for angular accuracy, and $\mu_{\theta(\text{from opt Ra})}$ is the mean of angular accuracy from the experiments using the optimized parameter level for surface roughness.

Table 14 shows both the angular accuracy data from the optimized parameter level for angular accuracy and the data from the optimized parameter level for surface roughness.

$$\text{By using equation, } t = \frac{\bar{x}_{\theta(\text{from opt } \theta)} - \bar{x}_{\theta(\text{from opt Ra})}}{\sqrt{\frac{s_{\theta}^2(\text{from opt } \theta) + s_{\theta}^2(\text{from opt Ra})}{n_1 + n_2}}}$$

The t-value is -7.067 which falls outside of t-critical value ± 3.250 (with $\alpha=0.01$ degree of freedom=18), and therefore the null hypothesis is rejected. The conclusion is that the non-identical parameter setting does affect angular accuracy.

Since both null hypotheses were rejected with the above two T-tests, the optimal parameter settings for surface roughness and angular accuracy need to be adjusted into one optimal setting. With surface roughness optimal levels of $A_1, B_2, C_2,$ and D_3 and angular accuracy optimal levels of $A_3, B_2, C_2,$ and D_2 , the adjusted optimal levels are made at the middle points of each individual parameter. Hence the adjusted optimal levels in this case study are $A_2, B_2, C_2,$ and $D_{2.5}$. A final run was conducted using the adjusted parameter level setting. Table 15 shows the data collected from the final run with the measurement of the surface roughness and angular accuracy under the newly adjusted parameter settings of $A_2, B_2, C_2,$ and $D_{2.5}$. This data was then further compared in another T-test to the data collected from the confirmation runs made using each separate optimized parameter level setting.

Table 15 Final runs with adjusted parameter for surface roughness and angular accuracy

Run	1	2	3	4	5	6	7	8	9	10	Average
Surface Roughness μ_{Ra}	123.6	118.9	124.7	125.6	117.2	123.1	124	119.3	121.9	119.1	121.7
Angular Accuracy θ°	0.042	0.023	0.030	0.036	0.031	0.048	0.050	0.029	0.046	0.048	0.0388
	3	4	6	5	7	7	3	1	7	3	

A T-test was used to determine if there is a significant difference between the mean of surface roughness (Ra) from the adjusted parameter levels and the mean of surface roughness (Ra) from the optimized parameter levels for surface roughness.

Ho: $\mu_{Ra(\text{from adjusted setting})} = \mu_{Ra(\text{from opt Ra})}$

H1: $\mu_{Ra(\text{from adjusted setting})} \neq \mu_{Ra(\text{from opt Ra})}$

Where $\mu_{Ra(\text{from adjusted setting})}$ is the mean of surface roughness (Ra) from the adjusted parameter level setting, and $\mu_{Ra(\text{from opt Ra})}$ is the mean of surface roughness (Ra) from the optimized parameter level setting for surface roughness. Table 16 shows the surface roughness (Ra) from the adjusted parameter level and the surface roughness (Ra) from the optimized parameter level for surface roughness.

By using equation,

$$t = \frac{\bar{x}_{Ra(\text{from adjusted setting})} - \bar{x}_{Ra(\text{from opt Ra})}}{\sqrt{\frac{S_{Ra(\text{from adjusted setting})}^2 + S_{Ra(\text{from opt Ra})}^2}{n_1 + n_2}}}$$

The t-value is -5.52 which falls outside of t-critical value +/-3.250 (with alpha=0.01 degree of freedom=18), therefore the null hypothesis is rejected. This result means that the adjustment of parameter levels does affect surface roughness.

Table 16 T-test comparing of two data (surface vs. adjusted) for Ra

No.	(Ra) from Surface Roughness	(Ra) from opt Adjusted Parameter
1	112.3	123.6
2	113.4	118.9
3	115.9	124.7
4	116.7	125.6
5	115.2	117.2
6	108.9	123.1
7	113.5	124
8	118.7	119.3
9	112.6	121.9
10	117.9	119.1
Average	114.51	121.74
Standard Deviation	2.95	2.90
SE Mean	1.31	
T-value	-5.52	
Degree of Freedom	9	

Freedom

T- alpha value .01 ±3.250

Table 17 T-test comparing of two data (angular vs. adjusted) for θ

No.	(θ) from Angular accuracy	(θ) from opt Adjusted Parameter
1	0.0082	0.0423
2	0.011	0.0234
3	0.007	0.0306
4	0.0084	0.0365
5	0.0079	0.0317
6	0.012	0.0487
7	0.0091	0.0503
8	0.0098	0.0291
9	0.0095	0.0467
10	0.0067	0.0483
Average	0.00896	0.0388
Standard Deviation	0.00168	0.0097
SE Mean	0.0031	
T-value	-9.56	
Degree of Freedom	10	
T- alpha value .01	±3.169	

T-test was also used to determine if there is a significant difference in mean value between the angular accuracy (θ) collected from the adjusted parameter level and the angular accuracy (θ) collected from the optimized level for angular accuracy.

Ho: $\mu_{\theta(\text{from adjusted setting})} = \mu_{\theta(\text{from opt } \theta)}$

H1: $\mu_{\theta(\text{from adjusted setting})} \neq \mu_{\theta(\text{from opt } \theta)}$

Where $\mu_{\theta(\text{from adjusted setting})}$ is the mean of angular accuracy (θ) from the adjusted parameter level setting, and $\mu_{\theta(\text{from opt } \theta)}$ is the mean of angular accuracy (θ) from the optimized level setting for angular accuracy. Table 17 shows the angular accuracy (θ) from the adjusted parameter level and the angular accuracy (θ) from the optimized level for angular accuracy.

By using equation,

$$t = \frac{\bar{x}_{\theta}(\text{from adjusted setting}) - \bar{x}_{\mu\theta}(\text{from opt } \theta)}{\sqrt{\frac{S_{\theta}^2(\text{from adjusted setting}) + S_{\mu\theta}^2(\text{from opt } \theta)}{n_1 + n_2}}}$$

The t-value is -9.56 which falls outside of t-critical value ± 3.169 (with $\alpha=0.01$ degree of freedom=18), and the null hypothesis is rejected. Consequently the adjustment of parameter levels affects angular accuracy.

The finding of T-test shows that for both surface roughness and angular accuracy the null hypotheses are rejected. With both null hypotheses rejected, it is concluded that a single optimized parameter level setting could not be used for optimizing both output variables at the same time. In this situation, one optimized parameter level setting, either for surface roughness or angular accuracy, should be chosen depending on which quality characteristic is more important to the user. Alternatively the user could compare the outputs from the adjusted parameter level setting with the outputs from baseline study. If there is considerable improvement for both quality characteristics from the responses of baseline study, it is still worthy of using the adjusted parameter level setting.

VII. Conclusion

This research presents a framework based on Taguchi parameter design to optimize two quality characteristics- surface roughness and angular accuracy in Wire Electrical Discharge Machining (W-EDM) process. Four factors were investigated as controllable factors including pulse on time, wire feed rate, voltage, and wire tension, while one factor-vibration is considered as noise factor. The analysis of experimental results concludes that pulse on time is the most significant factor that impacts both surface roughness and angle accuracy. Wire tension is secondary significant to angle accuracy but was shown to have less influence on surface roughness. Voltage was shown to have some effect on the output variables while wire feed rate had little or no effect.

From the initial baseline study, the output variables of surface roughness and angular accuracy were found to have average values of $142.4\mu\text{in}$ and 0.082° . By using Taguchi method with a L_9 table experiment design, the optimized parameter level setting for each individual quality characteristic was found. The confirmation run conducted for surface roughness had an average value of $114.51\mu\text{in}$ while the confirmation run conducted for angular accuracy had an average value of 0.00896° . The difference in optimal parameter level setting for these two output variables lead to the adjustment of parameter levels into one setting for further data analysis. Hence two more runs of experiments were performed for each output variable using the adjusted parameter setting.

Data analysis shows that the surface roughness value was found to be $121.7\mu\text{in}$, and the angular accuracy value was found to be 0.0388° under the adjusted parameter setting. Although the adjusted parameter setting did not yield the same results compared to the optimized parameter setting for each output variables, overall improvement was still observed. As future work, the authors plan to apply this methodology to study the effect of other machining conditions such as different wire type and work piece material on other quality characteristics such as material removal rate (MRR) and electrode wear ratio (EWR).

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