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Original Article

Parametric optimization in WEDM machining process for OHNS steel and its experimental validation

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Abstract

Wire electric discharge machining (WEDM) has become a key unconventional technology, as it offers a perfect solution for manufacturing machine-made components such as oil hardened nickel (non-shrinking) steel (OHNS) stainless steel and full forms which are not feasible with traditional machining techniques. Few scholars have tried to model this method due to an outdated number of operation variables and answers. In this paper, we will take the readings from the following parameters in WEDM including dielectric conductivity pulse width, time between pulses, maximum feed rate, servo control mean reference voltage, short pulse time, wire feed rate, wire mechanical tension, injection pressure on a distinct procedure responses including MRR and SR. In this various optimization and relation finding methods are shown. The cutting of OHNS steel using a wire electro-discharge machining method with copper electrodes was studied in this article. During this project L36 orthogonal array supporting the in the tests, Taguchi laboratory architecture was used. The analysis of variance is accustomed to evaluate data to find the right answer parameter conditions. The most machining parameters are performance measurements for dielectric conductivity (DC), pulse width (PW), time between pulses (TBW), maximum feed rate (MFR), servo control mean reference voltage (SCMRV), short pulse time (SPT), wire feed rate (WFR), wire mechanical tension (WMT), material removed rate (MRR), and surface roughness (SR) have been chosen to calculate the parameters. The use of response tables and graphs to determine the best parameter levels is common within the WEDM process.

Keywords: WEDM, OHNS steel, MRR, SR, Taguchi, ANOVA

1. Introduction

During the last decade, WEDM has grown in importance as unconventional machining is commonly used in aircraft, industrial, and other tool and die corporations. In applications such as marine, space, and others. The WEDM protocol is used to machine super alloys with corrosion-resistant, toughness, and temperature, as well as strong durability, hardness, and temperature super alloys. It must determine the best process parameters to obtain the best possible results to take care of better quality and process protection, as well as cost and time management in the production process. WEDM's key responses are material removal intensity, kerf thickness, and surface roughness. The optimum configuration of process parameters can be a critical factor in improving the materials' machinability. The supply of machining data from manufacturers, engineering data books, and machine tool operators' knowledge is not very empirical, lowering efficiency even further. To increase efficiency in these cases, the best machining parameters must be chosen and implemented. This research's aim of experiments is to establish the ideal quantity of process parameters for maximizing the consistency of OHNS steel work pieces using Taguchi's orthogonal array design and variance analysis.

2. Literature Review

A research analysis was carried out with the aim of figuring out the best cutting position with a suitable wire offset configuration (Sarkar, Mitra, & Bhattacharyya, 2005).

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In order to predict the reaction parameters, such as CS, SF, and deviation of dimensions, the process was modelled using an additive model. For each machining criterion, the main influencing factors are identified (Kumar & Singh, 2010). In the dielectric medium, an additive powder influences the behavior of sparking and aids in the improvement of surface properties. The results show a 73 percent increase in micro hardness and no microcracks on the machined wall. The transport of manganese carbide is made up of manganese and carbon from the plasma tube. X-ray diffraction analysis of machined materials demonstrates this. The powder can melt due to the plasma channel's high temperature (Lakshmikanth, Murali, Arunkumar, & Santhanakrishnan, 2013). Analysis of the results leads to conclude that pulse on time influences more on both MRR and surface roughness. In order to get better performance measures, factors at level A3 B1 C3 can be set for maximization of MRR. Similarly, the factors at levels A1 B3 C3 are recommended for minimization of Ra. For tungsten carbide, the experiments for the WEDM method have been completed successfully, and realistic results have been collected. Experimental findings can be used in industry to determine the best parameter combination for achieving the desired SR and MRR for the products (Lal, Kumar, Khan, & Siddiquee, 2014). The L27 orthogonal array on hybrid metal matrix composite was used in the experiments. The effects of process variables like Pon, PC, and drum speed were investigated. The best process parameter environment Taguchi-based grey relational analysis was used to evaluate the highest performing machined characteristics. The research was presented in the American Chemical and Engineering Press Journal (Saini, Zahid a. Khan, 2013). AMMCs are next-generation manufacturing materials that outperform non-reinforced alloys in terms of physical and mechanical properties (Patel, Patel, & Patel, 2014). In a straight turning operation, CS is the most important factor that influences SR. For turning operations, On MRR, the FR and DOC are the most effective. GRA provides a stronger surface finish at low speeds, low feed volumes, and deep cuts. The aim of this research is to see how process variables influence SF and MRR. The construction of experiment (COE) with complete factorial configuration was used to create 27 specimens on AISI D2 Steel in this study. At low speeds, low feed rates, and high depths of cut, grey relational analysis provides a better surface finish. (Saini *et al.*, 2016). WEDM is a unique machining technique for complex type systems and components made of hard materials like composites and HSS. 316L stainless steel is widely used in weldments because of its resistance to carbide precipitation caused by welding. Stainless steel 316L's outstanding properties, such as compatibility and visible physical, mechanical, and biological efficiency, have led to expanded use in a variety of industries. Grey relational analysis (GRA), ANOVA along with Taguchi method was used to optimize the cutting speed (CS) and surface roughness (SR), simultaneously. (Kausar *et al.*, 2015). WEDM (wire electrical discharge machining) is another unconventional machining technique that is often used. In the presence of a dielectric solvent, WEDM uses specifically regulated sparks that occur when a very thin wire comes into contact with a work piece. During machining, it has been found that current has the greatest impact and the other metrics have a lesser impact. The aim of this research is to see how different WEDM parameters affect the surface roughness of EN36 alloy steel. (Barge & Shejkar, 2017). RSM is used to optimize FR, SS, and load are all drilling parameters to consider. On a VMC machine, the experiments were run. The temperature of the drill tool bit is measured during the drilling process. Effects of machining parameters were investigated in WEDM. The L 27 orthogonal sequence studies were carried out using the Taguchi technique. The optimal mixture ranges of machining parameters for MRR and SR is determined. Answer analysis using the signal to noise (S/N) ratio determines the parameters that have the greatest effect on the response (Prakash, Juliyana, Moorthy, & Karthik, 2017). In a multi-process micro EDM computer, an experimental study was carried out. Dies, molds, precision manufacturing, and contour cutting all use the WEDM process, which is an extremely dynamic, time-varying, and stochastic method (Rawbawale, 2017). It's particularly common in the aerospace and medical fields. Using CNC WEDm, the complex form can be created with a high level of precision and finish on the surface. The instrument is a 0.25 mm diameter brass thread, and the dielectric is pure water. For making intricate features on electrically conductive materials, WEDM has become one of the most commonly used machining techniques. AA7075 are widely used in industries such as aerospace and maritime (Ramanan & Dhas J, 2017). Manufacturing criteria such as DC, Pon, and Poff have been investigated as a function of MRR and SR machined surface integrity. EDM is a metalworking method that removes material from a conductive work piece using electrical corrosion (Vani, Arun, Reddy, & Madduleti, 2018). The aim of this project is to determine the best Wire-EDM parameters for machining Inconel 718. The aerospace industry uses the In Connel material extensively, both in airframes and engine parts. Connel has excellent biocompatibility, particularly when direct contact with tissue or bone is necessary. Cutting speed, feed, and cut depth were the process parameters (Krishna & Kumar, 2017). SR was chosen as a success criterion. Experiments were carried out using a L9 orthogonal array based on the Taguchi system. Cutting speed was discovered to be the most influential process parameter on surface roughness (Kumar & Packiaraj, 2012). The aim of this study is to see how drilling parameters like cutting speed (5, 6.5, and 8 m/min), feed (0.15, 0.20, and 0.25 mm/rev), and drill tool diameter (10, 12, 15 mm) affect surface roughness. The aim of designing linear regression equations is to find a connection between the selected drilling parameters and the drilled hole quality characteristics (Kalavathi & Bhuyan, 2018). Machining is used to cut conductive metals at any hardness, as well as materials that are tough or impossible to cut using conventional techniques. The results of the WEDM method parameters were investigated using the Taguchi technique (Nehadabed, Sapit, & Kariemshather, 2019). The present paper focuses on electric discharge machines made of titanium alloy wire. The study conveys the big six criteria, and the Minitab 18 is used to build the pilot plan. The test results support the advanced RSM-validity models and suitability.

3. Materials and Methods

In applications where alloy steels aren't suitable, OHNS Steel is used and is not able to be used to give plenty of wear resistance, stiffness, resilience, and strength. Reflect the mechanical and chemical composition characteristics of

OHNS steel used in the manufacture of various aircraft parts. Number of a sample of five OHNS steel plates of 10 mm.

3.1 Experiment setup

The CNC WEDM will be used in this process. The following is how the experiment is set up: WEDM main instrument is brass wire with a diameter of 0.25mm. Wire, which has a tensile strength of 900-1000 MPa and a hardness of 52-62 HRC, can be used as an electrode to cut the workpiece. For these tests, the workpiece dimensions were held at 860*550*40mm.

This phase of the research is solely for the purpose of determining the surface quality of a substance based on input parameters obtained from a device connected to a system. The main goal of using the Taguchi approach in WEDM is to assess surface roughness and minimize it. In this present work we have taken 6 control Parmenter of DC, PW, TPW, MFR, SCMRV, SPT, WFR, WMT, IP Ref Table 2. In this process we are using Minitab 2019. This experiment is observed on the S/N ratio which is converted by given data.

3.2 Experimental setup

In this experiment we are using the CNC WEDM machine as illustrated in Figure 1. In this experiment, a half-hard wire with a diameter of 0.250mm was used. This experiment has been judged on basic parameters like MRR and SR. The resulting relation calculates the mean.

The mean cutting speed (MCS) is calculated as the length of movement divided by the machine time. Working time of the machine is retrieved from the device connected to the machine. The relationship is used to measure MRR.MRR stands for Mean Cutting Speed multiplied by Material Thickness (mm) multiplied by Cut Distance(mm) To measure the width of the cut in the experiment, we are using a profile projector that has the least count of 0.001. As shown in Figure 2, cutting of material 10 mm has been made by WEDM into the workpiece. Following this, we used the profile projector to measure the width of the cut at various locations to determine the width of the cut.

The spark gap is measure by using the following
Width of cut = wire diameter + (2*Spark gap)

WEDM is shown in Figure 1. This research paper focuses on how we use the Taguchi design process for experiments. For this experiment, the L36 (2^1*3^8) was chosen. The dielectric conductive has two stages in this design phase, while all eight parameters have three stages. The method parameters are mentioned below in Table 2.

Figure 1. WEDM machine

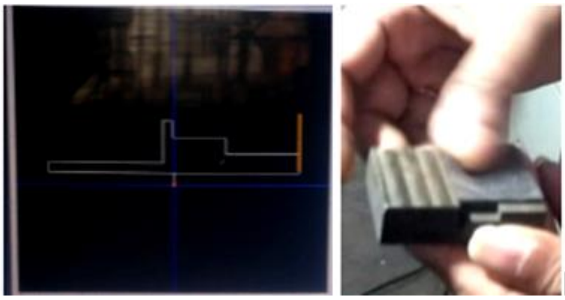

Figure 2. 10 mm straight cutting workpiece

Table 1. OHNS STEEL's composition

Element	C	Si	Mn	P	S	Cr	W
Content (%)	0.85-1.00	0.15-0.35	1.00-1.20	0.03 Max	0.03 Max	0.50-0.70	0.50-0.70

Table 2. Parameters of the process and their values at various stages

Symbol	Parameters	Stage 1	Stage 2	Stage 3
DC	Dielectric conductivity	10	14	
PW	Pulse width	0.6	0.8	1.2
TBW	Time between pulses	5	13	21
MFR	Maximum feed rate	2	12	22
SCMRV	Servo control mean reference voltage	20	40	60
SPT	Short pulse time	0.2	0.4	0.6
WFR	Wire feed rate	4	8	12
WMT	Wire mechanical tension	0.5	1.5	2.5
IP	Injection Pressure	2	3	4
	Workpiece Height	10.1 mm		
	Machining voltage	80 volts		
	Ignition pulse current	8 units (1/2A)		

3.3 Step of Taguchi methodology

We used eight simple steps to put this method into action.
Step l: Determine the highest levels of efficiency, facet results, as well as mode of failure.
Step 2: Identify the sources of the noise, monitor the conditions, and determine the output characteristics.
Step 3: Determine the performance that needs to be improved.
Step 4: Determine the value of management variables.
Step 5: To test, choose an orthogonal array matrices experiment.
Step 6: Carry out the test of the matrix
Step 7: As a starting point, analyse the data using the optimal amounts and performance.
Step 8: Carry out the verification experiment and plan the next steps.

4. Results and Discussion

MRR and SR have been used in this process to analyze what effect has been seen in the process parameter. In this process, we have used the L36, a mixed orthogonal array, as depicted in (Table 3). Each trial has been repeated once. As a result, 36 experimental runs were terminated in an erratic manner in order to reduce the effect of noise on the experiment as much as possible at all times. A loss of performance has been illustrated in this Taguchi approach to calculating the deviation between the experimental and hence the target price of a performance characteristic. As we can see, the loss function is a transformer in SN Ratio. In this process, we have 3 characteristics like, but we have used smaller ones better. Here we have the desired objective to enlarge MRR and SR as shown in Table 4 and Table 5. Using that reading, we have to make the SN ratio a graph. The significance effect was investigated using level average reaction review of experimental results and the analysis of that data on every input parameter of the machine of Table 2, and then the values were plotted in graph form. The experiment of MRR obtained by the machine is shown in Figure 4. The experiment of SR obtained by the machine is shown in Figure 5. From Figure 3, we have shown that the material removal rate in the graph forms how it increases and decreases in PW and SPT. As we showed in Figure 3, this is because the MRR increases as the discharge energy rises with PW and SPT. The number of discharges within a given timeframe decreases as the time between pulses increases, resulting in a lower MRR.

Table 3. Trial table L 36

Sr no	DC (mho)	PW (μs)	TBP (μs)	SCMRV (volts)	SPT (μs)	WFR (m/min)	WMT (Deca Newton)	IP (bars)	MFR (micron/min.)	MRR	SR
1	10	0.6	5	20	0.2	4	0.5	2	2	156.7	156.7
2	10	0.8	13	40	0.4	8	1.5	3	12	158.3	2.54
3	10	1.2	21	60	0.6	12	2.5	4	22	161.4	2.89
4	10	0.6	5	20	0.2	8	1.5	3	12	163.1	3.12
5	10	0.8	13	40	0.4	12	2.5	4	22	162.8	2.9
6	10	1.2	21	60	0.6	4	0.5	2	2	169.1	3.29
7	10	0.6	5	40	0.6	4	1.5	4	22	165.3	3.15
8	10	0.8	13	60	0.2	8	2.5	2	2	165.1	3.13
9	10	1.2	21	20	0.4	12	0.5	3	12	151.9	2.15
10	10	0.6	5	60	0.4	4	2.5	3	22	160.4	2.81
11	10	0.8	13	20	0.6	8	0.5	4	2	159.1	2.8
12	10	1.2	21	40	0.2	12	1.5	2	12	161.7	2.86
13	10	0.6	13	60	0.2	12	1.5	2	22	163.8	3.08
14	10	0.8	21	20	0.4	4	2.5	3	2	162.6	2.98
15	10	1.2	5	40	0.6	8	0.5	4	12	155.4	2.32
16	10	0.6	13	60	0.4	4	0.5	4	12	159.3	2.6
17	10	0.8	21	20	0.6	8	1.5	2	22	161.2	2.96
18	10	1.2	5	40	0.2	12	2.5	3	2	166.3	3.3
19	14	0.6	13	20	0.6	12	2.5	2	12	169.8	3.32
20	14	0.8	21	40	0.2	4	0.5	3	22	167.3	3.31
21	14	1.2	5	60	0.4	8	1.5	4	2	163.2	3.13
22	14	0.6	13	40	0.6	12	0.5	3	2	157.8	2.55
23	14	0.8	21	60	0.2	4	1.5	4	12	151.5	2.1
24	14	1.2	5	20	0.4	8	2.5	2	22	156.4	2.38
25	14	0.6	21	40	0.2	8	2.5	4	2	156.7	2.37
26	14	0.8	5	60	0.4	12	0.5	2	12	158.6	2.54
27	14	1.2	13	20	0.6	4	1.5	3	22	163.8	3.08
28	14	0.6	21	40	0.4	8	0.5	2	22	162.6	2.98
29	14	0.8	5	60	0.6	12	1.5	3	2	155.4	2.32
30	14	1.2	13	20	0.2	4	2.5	4	12	159.3	2.6
31	14	0.6	21	60	0.6	8	2.5	3	12	161.2	2.96
32	14	0.8	5	20	0.2	12	0.5	4	22	166.3	3.3
33	14	1.2	13	40	0.4	4	1.5	2	2	169.8	3.32
34	14	0.6	21	20	0.4	12	1.5	4	2	167.3	3.31
35	14	0.8	5	40	0.6	4	2.5	2	12	163.2	3.13
36	14	1.2	13	60	0.2	8	0.5	3	22	163.8	3.08

Table 4. MRR's ANOVA findings (Data gathered from experiment.)

Source	DF	Seq SS	Adj SS	Adj MS	F	P
DC	1	3.063	3.063	3.063	0.1	0.752
PW	2	7.691	7.691	3.845	0.13	0.88
TBP	2	23.629	23.629	11.814	0.4	0.678
SCMRV	2	8.987	8.987	4.494	0.15	0.861
SPT	2	4.501	4.501	2.25	0.08	0.927
WFR	2	22.469	22.469	11.234	0.38	0.691
WMT	2	15.894	15.894	7.947	0.27	0.769
IP	2	45.107	45.107	22.554	0.76	0.483
MFR	2	85.136	85.136	42.568	1.43	0.265
Residual Error	18	535.694	535.694	29.761		
Total	35	752.17				

Table 5. ANOVA results for SR (Data gathered from experiment.)

Source	DF	Seq SS	Adj SS	Adj MS	F	P
DC	1	0.0078	0.0078	0.007803	0.04	0.847
PW	2	0.01591	0.01591	0.007953	0.04	0.962
TBP	2	0.05741	0.05741	0.028703	0.14	0.87
SCMRV	2	0.02676	0.02676	0.013378	0.07	0.937
SPT	2	0.06277	0.06277	0.031386	0.15	0.859
WFR	2	0.04311	0.04311	0.021553	0.11	0.901
WMT	2	0.14036	0.14036	0.070178	0.34	0.714
IP	2	0.15141	0.15141	0.075703	0.37	0.696
MFR	2	0.59894	0.59894	0.299469	1.46	0.257
Residual Error	18	3.68032	3.68032	0.204462		
Total	35	4.78476				

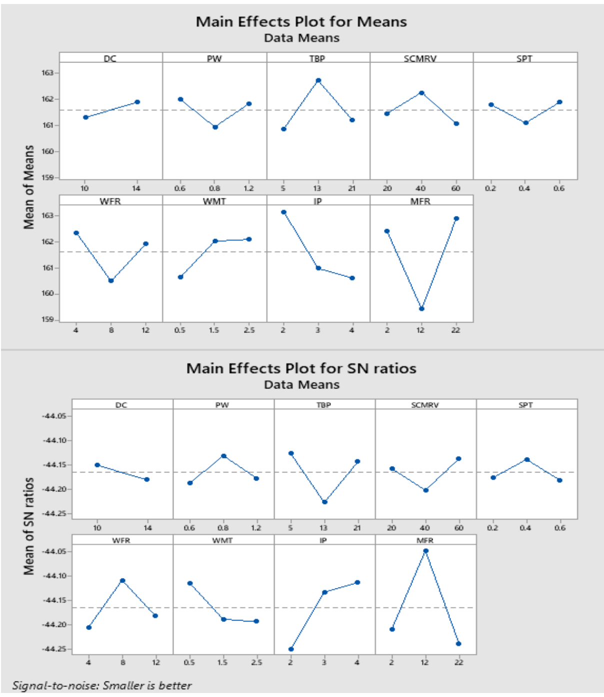

Figure 3. MRR as a function of process parameters (a) Data gathered from experiment. and (b) S/N ratio

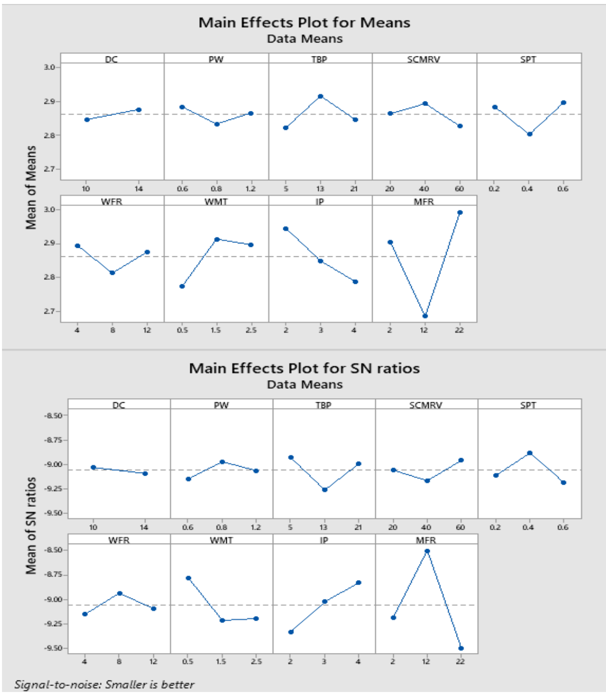

Figure 4. SR as a function of process parameters (a) Data gathered from experiment. and (b) S/N ratio

The effect of the eight control factors can be seen in the graph below which we have taken for Table 3 on surface roughness. As shown in Table 3, we have calculated the mean value of the surface roughness. This experiment results in a level of Figure 4 that shows the optimal cutting parameters as well as the relative effects of each parameter.

As seen in Figure 4, the present SN ratio for surface roughness. If the current rises, the discharge energy rises with it’s shown in the Ref SPT graph of SN ratio, we have seen that the increased discharge current spark cycle will last longer and this leads to cutting speed and discharge current are also high. As a product of these kinds of outcomes, we can assume that surface finishing will be good and improve in MRR. Therefore, the result shows that a small spark time is good for a better surface finish. TBP delay time impact voltage from Ref Figure 4 graph, which we have given in the middle electrode. Wait time is reduced as it increases the quantity of discharges in a given period of time and ends up in a decrease in void voltage. As a result, discharge current will increase for a comparable power input, and the amount of energy discharged would rise, resulting in an increase in surface roughness. We should keep the delay time low to get a better result in surface finishing. Ref Figure 4 of IP as the injection pressure is fewer waste particles are not completely separated, and this has an effect on the wire's temperature. Convective heat transfer occurs at lower injection pressures, commonly medium, resulting in a high temperature for the wire. However, in order to regulate wire tension and MRR, the wire temperature must be kept below a certain level. This would have an effect on the surface finish.

4.1. Selection of optimum levels

In this topic, we are going to see the ANOVA technique which we have used to identify the parameters which are given in the following Table 2 and this also helps quantify the effect of characteristics of success. The results MRR is see in Table 4 and SR are seen in Tables 5, respectively, while Table 7 shows the other answer Table 7 depicts the various types of characteristics that are responsible for this mechanism at each stage. The delta statistics in the table compare the impact's relative magnitude. The statistics of delta are the highest minus the lowest average of each variable. The delta values, which are defined using Minitab 19, are used to build the tables. This demonstrates the critical factor that caused error.

Form Table 3 Residual Error:18 Form Table 4 Residual Error: 18 Tables 7 and 9 display the delta value for the 1st that more significant for MRR which is MFR.1th that more significant for SR which is MFR. MRR is influenced by PW, SCMRV.TBP, WFR, WMS, DC, MFR, IP

4.2 Validation of experiment

In this section, take the parameter input for Table 2 and MRR form Table 2 and for this reference, we will use Minitab 19 to obtain the predicate value for the machine reading Table 3.

Table 6. Confidence limits (CI) and (PI) Prediction limits of MRR

Setting	Predicted fits	Confidence limits	Prediction limits
levels	Fit	95% CI	95% PI
level 1	163.477	(155.1, 170.8)	(148, 176)
level 2	159.952	(151, 168)	(143, 173)
level 3	163.234	(155, 171)	(148, 175)

Table 8. Confidence limits (CI) and (PI) Prediction limits of SG

Setting	Predicted fits	Confidence limits	Prediction limits
levels	Fit	95% CI	95% PI
level 1	2.99212	(2.221, 3.493)	(*, 3.785)
level 2	2.72586	(1.64181, 3.30445)	(*, 3.62589)
level 3	2.88891	(2.02320, 3.41820)	(*, 3.72113)

Table 10. Confidence limits (CI) and (PI) Prediction limits of and Actual value of MRR

Setting	Predicted fits	Confidence limits	Prediction limits
levels	Fit	95% CI	95% PI
level 1	163.477	(155.1, 170.8)	(148, 176)
level 2	159.952	(151, 168)	(143, 173)
level 3	163.234	(155, 171)	(148, 175)
	162.221	153.7, 169.93	146.33,174.66

Table 7. Data gathered from experiment for MRR.

Level	DC	PW	TBP	SCMRV	SPT	WFR	WMT	IP	MFR
1	161.3	162	160.9	161.5	161.8	162.4	160.7	163.2	162.4
2	161.9	161	162.7	162.3	161.1	160.5	162	161	159.4
3		161.8	161.2	161.1	161.9	161.9	162.1	160.6	162.9
Delta	0.6	1	1.9	1.2	0.8	1.8	1.4	2.5	3.5
Rank	9	7	3	6	8	4	5	2	1

Table 9. Data gathered from experiment for SR.

Level	DC	PW	TBP	SCMRV	SPT	WFR	WMT	IP	MFR
1	2.847	2.885	2.822	2.864	2.885	2.895	2.774	2.947	2.906
2	2.877	2.834	2.917	2.894	2.803	2.814	2.914	2.85	2.687
3		2.867	2.847	2.828	2.898	2.877	2.898	2.789	2.993
Delta	0.029	0.051	0.094	0.067	0.094	0.081	0.14	0.157	0.307
Rank	9	8	5	7	4	6	3	2	1

Regression Equation:
(MRR^λ-1)/(λ×g^(λ-1)) = 40.642 - 0.335 DC_10 + 0.335 DC_14 + 0.36 P W_0.6 - 0.66 P W_0.8+ 0.30 P W_1.2- 0.78 TBP_5 + 1.10 TBP_13 - 0.32 TBP_21- 0.11 SCMRV_20 + 0.66 SCMRV_40 - 0.54 SCMRV_60 + 0.21 SPT_0.2- 0.50 SPT_0.4 + 0.29 SPT_0.6 + 0.81 WFR_4 - 1.18 WFR_8 + 0.37 WFR_12- 0.90 WMT_0.5 + 0.46 WMT_1.5 + 0.44 WMT_2.5 + 1.59 IP_2 - 0.63 IP_3- 0.97 IP_4 + 0.87 MFR_2 - 2.10 MFR_12 + 1.22 MFR_22
($\lambda = 4$, g = 161.532 is the geometric mean of MRR)

Where all MRR value data is taken from Table 2. We have taken the readings of each parameter and the number of level settings in this process, and we have three settings because we have three levels of reading 95 % Confidence limits (CI) and (PI).

Therefore, the 95 % of confidence and prediction limits all confirmation in MRR.

In this section, take the parameter input for Table 2 and SR form Table 2 and for this reference, we will use Minitab 19 to obtain the predicate value for the machine reading Table 4.

Regression Equation:
(SR^λ-1)/(λ×g^(λ-1)) = 0.9754 - 0.0249 DC_10 + 0.0249 DC_14 + 0.015 P W_0.6 - 0.027 P W_0.8+ 0.012 P W_1.2 - 0.033 TBP_5 + 0.039 TBP_13 - 0.006 TBP_21+ 0.008 SCMRV_20 + 0.031 SCMRV_40 - 0.039 SCMRV_60 + 0.034 SPT_0.2- 0.062 SPT_0.4 + 0.028 SPT_0.6 + 0.039 WFR_4 - 0.062 WFR_8+ 0.023 WFR_12 - 0.079 WMT_0.5 + 0.056 WMT_1.5 + 0.023 WMT_2.5+ 0.081 IP_2 - 0.013 IP_3 - 0.069 IP_4 + 0.052 MFR_2 - 0.166 MFR_12+ 0.114 MFR_22
($\lambda = 3$, g = 2.83743 is the geometric mean of SR)

Where all SR value data is taken from Table 2. We took the reading of each parameter and the number of level settings in this process because we have three levels of reading, 95 % Confidence limits (CI) and Prediction limits (PI).

Therefore, the 95 % of confidence and prediction limits all confirmation in SR.

4.3 Confirmation experiment

Three validation tests were carried out when the operation variables were at their optimum rate to verify the outcomes obtained MRR and SR for both of the response characteristics. The characteristics' average values were calculated and compared to the expected value.

Actual value is the average of all the level 3 of MRR.

5. Conclusions

In this study, the response parameters MRR and SR are examined by altering the machining settings on OHNS work piece. Bass wire of 0.25 mm diameter was utilized as an electrode in WEDM. The performance characteristics of Dielectric conductivity Pulse width, Time between pulses, Maximum feed rate, Servo control mean reference voltage, short pulse time, Wire feed rate, Wire mechanical, Tension, Injection Pressure were investigated. The following conclusions are reached from the experimental results.

By using the angle of variance in relation to experimental readings and providing the ideal setting (Dielectric conductivity 14 Pulse width 0.8, Time between pulses 13, Maximum feed rate 12, Servo control mean reference voltage 40, Short pulse time 0.4, Wire feed rate 8, Wire mechanical 1.5, wire Tension 0.5, Injection Pressure 3) as show in Table 11 and Table 12.

In both MRR and SR, the maximal influence of parameters was calculated in ANOVA (Analysis of variance). Due to this, we can find the residual error of MRR and SR which is 18 %.

Table 11. Confidence limits (CI) and (PI) Prediction limits of and Actual value of SR

Response	Fit	95% CI	95% PI
SR	3.38244	(2.65224, 4.31369)	(2.21970, 5.15427)

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