JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p. 2464 - 2475
https://publishoa.com
ISSN: 1309-3452

Box–Behnken Design: Optimization and Prediction of TI-6AL-7NB

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ABSTRACT

Titanium's enhanced mechanical properties, corrosion resistance, and biocompatibility have expanded its usage in biomedical applications. Using the response surface approach, the present study optimizes the process parameters during the machining of titanium alloys: Ti-6Al-7Nb utilized in dental implantation by wire electrical discharge machining (WEDM) (RSM). WEDM parameters such as servo voltage, pulse-on time, pulse-off time, and wire feed rate were modified to determine their influence on the cut quality of Ti-6Al-7Nb utilizing surface roughness and material removal rate as response parameters.

I. INTRODUCTION

Titanium alloys are one of the most used materials for biocompatibility. Because of their high mechanical and corrosion resistance, titanium and titanium alloys have been used as implant materials [1]. Commercially in the early stage, pure titanium (CP-Ti) was the most commonly used in dental as biomaterial, despite its low strength, refining issues, and poor abrasion resistance. That's why long-term use of titanium in dental implants and detachable partial dentures is out of the question [4]. Ti-6Al-4V alloy, first designed as an aeronautical material, has been evaluated as a substitute for CP-Ti due to its good mechanical qualities and adequate corrosion resistance [5]; nevertheless, the cytotoxicity of elemental Vanadium remains debatable [6]. Consequently, several studies have demonstrated that the Vanadium and Aluminum ions produced by this ternary alloy might generate cytotoxic effects and neurological problems, respectively [7]. In addition, this alloy has transferred adequate strain to neighboring bones over time, resulting in bone resorption and, ultimately, implant loosening [8]. Vanadium-free β-alloys, particularly Ti-6Al-7Nb alloy [9], were also employed as implants due to their enhanced mechanical properties, corrosion resistance, and biocompatibility. It has been studied as a novel alloy for complete hip prosthesis, designed for orthopedic applications as a wrought material. Niobium was replaced with Vanadiums, as it has similarly sustained the transition in the binary system, which is essential for forming the two-phase structure. As a result, Niobium was chosen as the third component of the titanium, aluminum, and niobium alloy [10] to generate the desired microstructure. WEDM is an unconventional machining technique used to cut any conductive material. Elect thermal machining can generate intricate forms in a single setup while maintaining incredible precision and accuracy. During this process, the material will deteriorate by using successive sparks. Discharges occur between the workpiece and a moving wire electrode immersed in a fluid that acts as dielectric media.

A Computer Numerical Control is used to alter the mobility of the wire (CNC). Because it does not leave a blemish on the workpiece, wire electrical discharge machining (WEDM) is suitable for cutting both thin and thick components. Consequently, WEDM is recognized as a robust machining process and is widely utilized in numerous industries, including the tool and die, aircraft, automobile, and medical sectors [11]. Because WEDM is a complex stochastic process mechanism, even a slight variation in one of the process parameters can affect the responses, including material removal rate, kerf width, surface roughness, and other characteristics. Therefore, it is vital to pick the optimal process parameter combinations. Response Surface Methodology (RSM) [12] predominantly utilizes the statistical regression technique since it is practical, inexpensive, and relatively straightforward. It is required to construct experimental designs for many parameters to represent and evaluate each parameter's influence on the strategy function (or functions). George E. P. Box and Donald Behnken created the box-Behnken design (BBD) in 1990 [13], which requires three levels for each element, and has fewer total runs than Central Composite Design (CCD). Face-centered CCD is the most widely employed RSM in existing research [14]. The benefit of RSM is its ability to minimize prediction error and enhance estimates utilizing polynomial equations. RSM is used to build first and second-order polynomial equations. Typically, this polynomial model is referred to as a regression model. Equations 1 and 2 express the first and second-order models, respectively.

$$z = \beta_o + \sum_{u=i}^{k} \beta_u m_u + \delta \qquad 1$$

$$z = \beta_o + \sum_{u=i}^{k} \beta_u m_u + \sum_{u=1}^{k} \beta_{uu} {m_u}^2 + \sum_u \sum_v^k \beta_{uv} m_u m_v + \delta \qquad 2$$

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Volume 13, No. 3, 2022, p. 2464 - 2475
https://publishoa.com
ISSN: 1309-3452

In the above equation, $\beta_u, \beta_{uu}, \beta_{uv}$ are the linear, quadratic, and interaction terms' coefficients, respectively, where z is the response function. The terms m_u and m_v are independent variables. Most research employed quadratic equations to create models [15] because a polynomial or quadratic equation of the second order is adequate for the optimal zone, and the value is near the response region. Many research works are carried out on modeling, and optimization studies in machining have applied the response surface technique and forecasted the chip-tool contact temperature using RSM. Montgome [16] improved power consumption in their study using Taguchi and central composite design (CCD). They used the first-order model to determine the significant factors and the second-order model to illustrate the effect of the interaction between variables. Various studies [17] by scholars have used RSM regression models to predict responses from non-conventional approaches like neural networks. When four components at three levels are studied, they conclude RSM is the superior method for predicting and optimizing the effect of parameters compared to the Taguchi method. The RSM presents statistically planned experiments for concluding data. In RSM, the second-order model is the most commonly employed approximation polynomial model. Common second-order model structures include the 3k factorial, Boehlert, Box-Behnken, and CCD. The survey finds that the second-order model is the most commonly used approximating polynomial model in RSM; hence, the Box-Behnken is the optimal design for data optimization in the manufacture of dental implants. Box and Behnken created and developed the Box-Behnken Design [18]. The Box-Behnken design gives three evenly spaced levels (1, 0, +1) for each variable). The required number of experiments is based on the equation $x = 2l(l_1) + p$, where l is the number of variables and p is the number of points at the center. The design is shown as a cube; all points are located on a 2-radius sphere. In addition, this design has no points at the vertices of the zone formed by the top and lower bounds of each variable [19]. With 13 experimental points, the Box-Behnken design for three variables optimizes through experimentation.
Regarding the number of necessary runs, this design is more inexpensive and efficient than 3k designs with 27 trials. Therefore, this strategy is advantageous for avoiding tests conducted under severe conditions, which may provide undesirable findings. However, it is unhelpful in cases where we want to know the extreme reactions. The Box-Behnken design has been utilized to determine the appropriate experimental settings, optimizing many processes' performance.

II. MATERIALS

The performance characteristics for Ti-6Al-7Nb were evaluated utilizing wire cut EDM with a 10mm thickness and six distinct process settings. Brass wire with a wire diameter of 0.25mm was employed as the electrode. Distilled Water was used as a coolant. Proper selection of machining variables plays a significant role in material removal and surface finish. The RSM methodology was utilized in the present work, an effective technique for designing performance parameters. RSM was used to evaluate the optimum machining settings for minimal surface roughness and maximum material removal rate using six process variables, including peak current, pulse on time, the pulse of time, peak current pulse on time, and servo voltage. The selected three levels as shown in the table 1. According to the RSM quality designing concept for the BBD method, 52 experiments are selected and presented in the table 2. The extents of these process variables were chosen based on reviewing the relevant literature, machine capabilities, and preliminary testing. Experiments utilizing the one variable at a time method. Table 1 lists the stages of several processes of the parameters and their respective labels. Using a scanning probe microscope, the surface roughness was evaluated.

Table 1 Levels of process parameters

S.No	Symbols	Input factors	Level- I	Level - II	Level -III	Units
1	A	Pulse on Time (Ton)	114	118	122	µs
2	B	Pulse on Time (Toff)	42	48	54	µs
3	C	Peak current (IP)	140	180	220	Ampere
4	D	Servo voltage(SV)	45	55	65	Volt
5	E	Wire feed rate (WF)	5	8	12	m/min
6	F	Wire Tension(WT)	550	1000	1350	gram

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Volume 13, No. 3, 2022, p. 2464 - 2475
https://publishoa.com
ISSN: 1309-3452

Table 2: BBD with six parameters, as well as experimental MRR and SR

	Factor						**Response**	
Std	A:Ton µs	B:Toff µs	C:IP Ampere	D:SV Volt	E:WF m/min	F:WT gram	MRR mm^3/min	SR µm
1	118	59	210	55	6	550	0.588	2.98
2	118	47	210	55	12	550	1.024	3.29
3	118	59	210	55	6	1450	0.604	2.99
4	118	59	170	55	12	1000	0.547	2.81
5	118	53	210	55	9	1000	0.707	3.15
6	114	53	170	55	9	1450	0.437	3.01
7	118	53	250	45	9	1450	0.837	3.39
8	122	47	210	65	9	1000	1.012	3.5
9	122	53	170	55	9	550	0.842	3.27
10	114	59	210	65	9	1000	0.407	2.65
11	122	53	210	65	12	1000	0.822	3.32
12	118	59	250	55	12	1000	0.804	3.07
13	118	59	170	55	6	1000	0.553	2.79
14	118	53	250	45	9	550	0.841	3.34
15	118	47	170	55	6	1000	0.971	3.25
16	114	59	210	45	9	1000	0.492	2.82
17	122	59	210	65	9	1000	0.804	3.16
18	118	53	210	55	9	1000	0.668	3.15
19	118	59	210	55	12	550	0.601	3
20	114	53	250	55	9	1450	0.552	3.01
21	122	47	210	45	9	1000	1.292	3.78
22	118	53	210	55	9	1000	0.585	3.11
23	114	53	210	45	12	1000	0.533	2.85
24	118	53	250	65	9	1450	0.79	3.18
25	118	59	250	55	6	1000	0.811	3.06
26	118	53	210	55	9	1000	0.671	3.19
27	122	59	210	45	9	1000	1.007	3.41
28	118	47	250	55	6	1000	1.032	3.38
29	118	53	210	55	9	1000	0.67	3.15
30	122	53	250	55	9	1450	1.064	3.62
31	118	47	210	55	12	1450	0.974	3.32
32	118	53	170	65	9	550	0.556	2.97
33	114	47	210	65	9	1000	0.507	3.1

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34	114	53	250	55	9	550	0.547	2.98
35	114	53	170	55	9	550	0.418	2.99
36	118	59	210	55	12	1450	0.598	2.98
37	114	47	210	45	9	1000	0.87	3.2
38	118	53	170	45	9	550	0.647	3.28
39	114	53	210	65	12	1000	0.441	2.78
40	122	53	210	45	6	1000	1.087	3.43
41	118	47	250	55	12	1000	1.042	3.48
42	118	47	170	55	12	1000	0.966	3.25
43	122	53	250	55	9	550	1.152	3.72
44	122	53	210	65	6	1000	0.821	3.33
45	114	53	210	65	6	1000	0.432	2.73
46	118	53	210	55	9	1000	0.709	3.18
47	118	47	210	55	6	1450	0.993	3.35
48	122	53	210	45	12	1000	1.087	3.44
49	118	47	210	55	6	550	1.026	3.31
50	118	53	170	45	9	1450	0.637	3.21
51	114	53	210	45	6	1000	0.541	2.83
52	122	53	170	55	9	1450	0.835	3.25
53	118	53	250	65	9	550	0.785	3.19
54	118	53	170	65	9	1450	0.55	2.99

III. RESULTS

The actual observations, predicted values, and various calculated parameters for adequacy, response surface equations, and correlation coefficient values are presented in the proper sequence.
The variance analysis findings for the introduced models are displayed in Table 3. The corresponding P-value for the model is statistically significant.

Table 3: The effect of Process parameters on MRR

Source	**Sum of Squares**	**df**	**Mean Square**	**F-value**	**p-value**	
Model	2.57	27	0.0951	30.72	< 0.0001	significant
A-Ton	0.2182	1	0.2182	70.53	< 0.0001	
B-Toff	0.3666	1	0.3666	118.50	< 0.0001	
C-IP	5.217E-06	1	5.217E-06	0.0017	0.9676	
D-SV	0.0774	1	0.0774	25.00	< 0.0001	
E-WF	0.0008	1	0.0008	0.2503	0.6210	
F-WT	0.0008	1	0.0008	0.2640	0.6117	
AB	0.0000	1	0.0000	0.0091	0.9248	
AC	0.0109	1	0.0109	3.52	0.0721	

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ISSN: 1309-3452

AD	0.0083	1	0.0083	2.69	0.1130	
AE	0.0000	1	0.0000	0.0000	1.0000	
AF	0.0018	1	0.0018	0.5721	0.4562	
BC	0.0179	1	0.0179	5.77	0.0237	
BD	0.0158	1	0.0158	5.09	0.0327	
BE	6.250E-06	1	6.250E-06	0.0020	0.9645	
BF	0.0012	1	0.0012	0.3723	0.5470	
CD	0.0007	1	0.0007	0.2272	0.6376	
CE	0.0000	1	0.0000	0.0079	0.9298	
CF	0.0004	1	0.0004	0.1229	0.7287	
DE	0.0000	1	0.0000	0.0131	0.9098	
DF	0.0000	1	0.0000	0.0068	0.9348	
EF	0.0002	1	0.0002	0.0524	0.8208	
A^2	0.0064	1	0.0064	2.08	0.1616	
B^2	0.1157	1	0.1157	37.40	< 0.0001	
C^2	0.0154	1	0.0154	4.97	0.0347	
D^2	2.716E-06	1	2.716E-06	0.0009	0.9766	
E^2	0.0079	1	0.0079	2.55	0.1224	
F^2	0.0000	1	0.0000	0.0040	0.9500	
Residual	0.0804	26	0.0031			
Lack of Fit	0.0703	21	0.0033	1.66	0.3019	not significant
Pure Error	0.0101	5	0.0020			
Cor Total	2.65	53				

It also displays in table 4, the R^2-statistic value and the corrected R^2-statistic value. R^2-statistic is defined as the proportion of variance.

Table 4: R^2 values on MRR

Source	Std. Dev.	R^2	Adjusted R^2	Predicted R^2	PRESS	
Linear	0.0809	0.8838	0.8689	0.8484	0.4013	
2FI	0.0885	0.9053	0.8432	0.7292	0.7166	
Quadratic	**0.0556**	**0.9696**	**0.9380**	**0.8557**	**0.3821**	**Suggested**
Cubic	0.0454	0.9938	0.9588	0.3798	1.64	Aliased

The variance analysis findings for the introduced models are displayed in Table 5. The corresponding P-value for the model is statistically significant.

Table 5: The effect of Process parameters on SR

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	3.11	27	0.1152	49.64	< 0.0001	significant
A-Ton	0.1506	1	0.1506	64.88	< 0.0001	
B-Toff	0.1832	1	0.1832	78.95	< 0.0001	
C-IP	0.0073	1	0.0073	3.15	0.0876	
D-SV	0.0482	1	0.0482	20.75	0.0001	
E-WF	0.0036	1	0.0036	1.54	0.2264	
F-WT	4.870E-07	1	4.870E-07	0.0002	0.9886	
AB	0.0018	1	0.0018	0.7756	0.3865	
AC	0.0861	1	0.0861	37.11	< 0.0001	
AD	0.0060	1	0.0060	2.59	0.1197	
AE	0.0006	1	0.0006	0.2639	0.6118	
AF	0.0036	1	0.0036	1.56	0.2233	
BC	0.0036	1	0.0036	1.56	0.2233	
BD	0.0002	1	0.0002	0.0862	0.7714	
BE	6.250E-06	1	6.250E-06	0.0027	0.9590	
BF	0.0008	1	0.0008	0.3447	0.5622	
CD	0.0036	1	0.0036	1.56	0.2233	
CE	0.0010	1	0.0010	0.4363	0.5147	
CF	0.0000	1	0.0000	0.0108	0.9181	
DE	0.0000	1	0.0000	0.0054	0.9421	
DF	0.0001	1	0.0001	0.0485	0.8275	
EF	0.0002	1	0.0002	0.0862	0.7714	
A^2	0.0056	1	0.0056	2.41	0.1324	
B^2	0.0151	1	0.0151	6.51	0.0169	
C^2	0.0035	1	0.0035	1.49	0.2332	
D^2	0.0021	1	0.0021	0.8895	0.3543	
E^2	0.0585	1	0.0585	25.21	< 0.0001	
F^2	0.0123	1	0.0123	5.30	0.0296	
Residual	0.0603	26	0.0023			
Lack of Fit	0.0564	21	0.0027	3.40	0.0893	not significant
Pure Error	0.0040	5	0.0008			
Cor Total	3.17	53				

It also displays in table 6, the R^2-statistic value and the corrected R^2-statistic value. R^2-statistic is defined as the proportion of variance.

Table 6: R^2 values on SR

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https://publishoa.com
ISSN: 1309-3452

Source	Std. Dev.	R^2	Adjusted R^2	Predicted R^2	PRESS	
Linear	0.0766	0.9130	0.9019	0.8818	0.3747	
2FI	0.0725	0.9469	0.9121	0.8242	0.5575	
Quadratic	**0.0482**	**0.9810**	**0.9612**	**0.9053**	**0.3003**	**Suggested**
Cubic	0.0342	0.9970	0.9804	0.5612	1.39	Aliased

The fact that the Model F-value was calculated to be 30.72 indicates that the model is significant. A noise level of this magnitude would only have a 0.01 percent chance of producing an F-value of this magnitude.
P-values that are lower than 0.0500 denote the significance of the model terms. In this particular scenario, the relevant model terms are A, B, D, BC, BD, B^2, and C^2. When the model terms are insignificant, values greater than 0.1000 show this. Your model could be improved by using model reduction if it has many terms that are not significant (not counting those that are required to support hierarchy). The lack of Fit F-value is 1.66 suggests that it is not statistically significant compared to the pure error. There is a 30.19 percent probability that the F-value for lack of fit might be this high owing to noise. A lack of fit that is not large is considered good because we want the model to be accurate.
The ratio of the variability described by the model to the overall variability of the actual data serves as a measure of model fit. The closer R^2 is to 1, the better a model matches the experimental data. The calculated value of R^2 of 0.9696 for material removal rate indicates that the model explains about 96.9% of the variance. The calculated value of R^2 of 0.9612 for surface roughness indicates that the model explains about 96.1% of the variance. Hence the regression equation for MRR and SR is given in table 7.

Table 7: Equation for MRR &SR

MRR	=	SR	=
+31.84633		+3.29	
-0.314339	Ton	+0.1752	A
-0.416909	Toff	-0.2657	B
-0.046532	IP	+0.0507	C
+0.014606	SV	-0.0991	D
-0.061361	WF	+0.0285	E
+0.000803	WT	-0.0003	F
-0.000078	Ton * Toff	+0.0150	AB
+0.000230	Ton * IP	+0.1038	AC
-0.000570	Ton * SV	-0.0194	AD
+6.78141E-17	Ton * WF	-0.0102	AE
-8.26389E-06	Ton * WT	-0.0189	AF
+0.000197	Toff * IP	+0.0213	BC
+0.000740	Toff * SV	-0.0050	BD
+0.000035	Toff * WF	-0.0007	BE
+4.44444E-06	Toff * WT	-0.0089	BF
+0.000023	IP * SV	+0.0212	CD
+0.000015	IP * WF	+0.0131	CE
-2.70833E-07	IP * WT	+0.0011	CF
+0.000075	SV * WF	+0.0015	DE
+3.61111E-07	SV * WT	+0.0033	DF
-3.33333E-06	WF * WT	-0.0052	EF
+0.001562	Ton^2	+0.0233	A^2
+0.002946	$Toff^2$	+0.0383	B^2
+0.000024	IP^2	+0.0183	C^2
-5.13889E-06	SV^2	-0.0142	D^2
+0.003077	WF^2	-0.1027	E^2
-5.41838E-09	WT^2	+0.0273	F^2

The standard probability curve for the MRR and SR residuals is depicted in Figures 1 a and b respectively. The fact that the residuals are oriented around a straight line provides evidence that the model assumptions are correct and suggests that the errors follow a normal distribution.

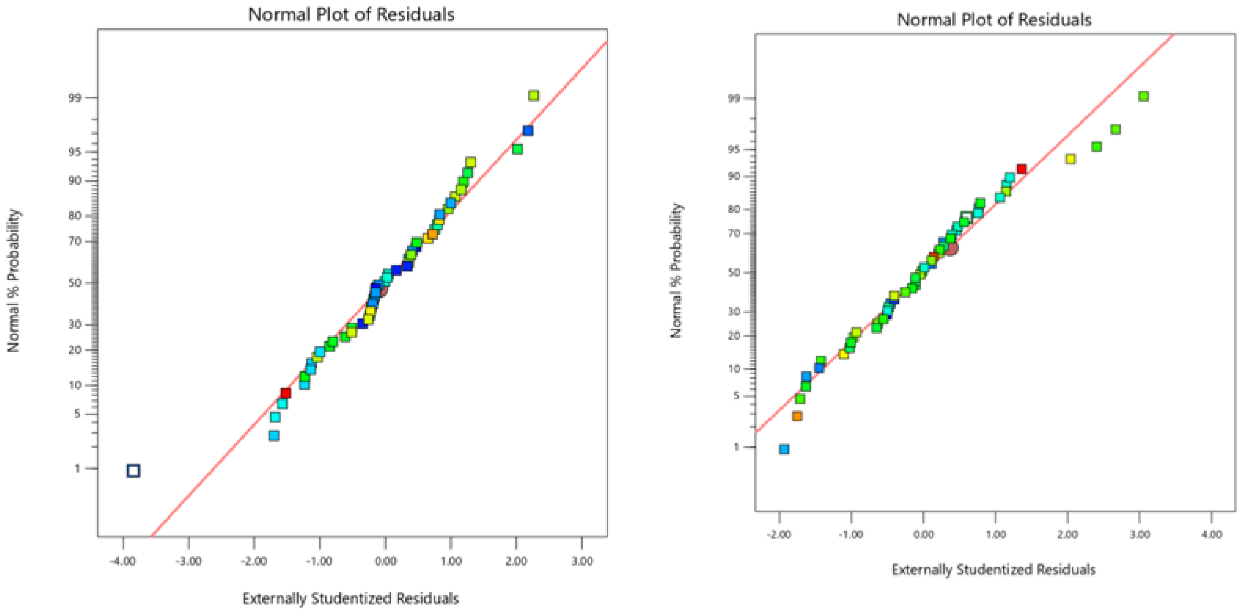

Fig 1: Normal plot of residuals for the MRR and SR

Figure 2 shows the curve that represents the MRR and SR residuals. The fact that the residuals are lower than the red straight line shows that the model assumptions are accurate and that the experimental runs are consistent with the residual.

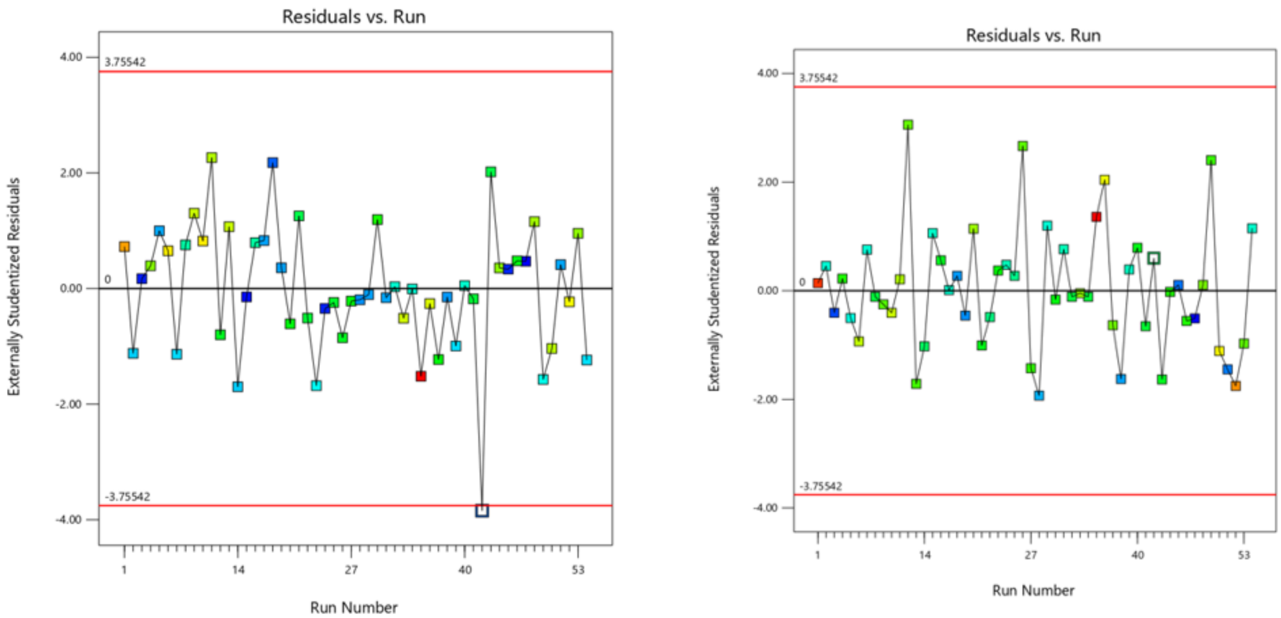

Fig 2: Residuals for the MRR and SR with Run

The response surface plot of the Ton and Toff parameter against surface roughness and material removal rate is displayed in Figure 3. The gradient for pulse-on time and pulse-off time improves from the lowest to the maximum levels when considering material removal rate and surface roughness. This suggests that an increase in either the pulse-on time or the pulse-off time will lead to a rise in both the surface roughness and the material is removal rate.

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Volume 13, No. 3, 2022, p. 2464 - 2475
https://publishoa.com
ISSN: 1309-3452

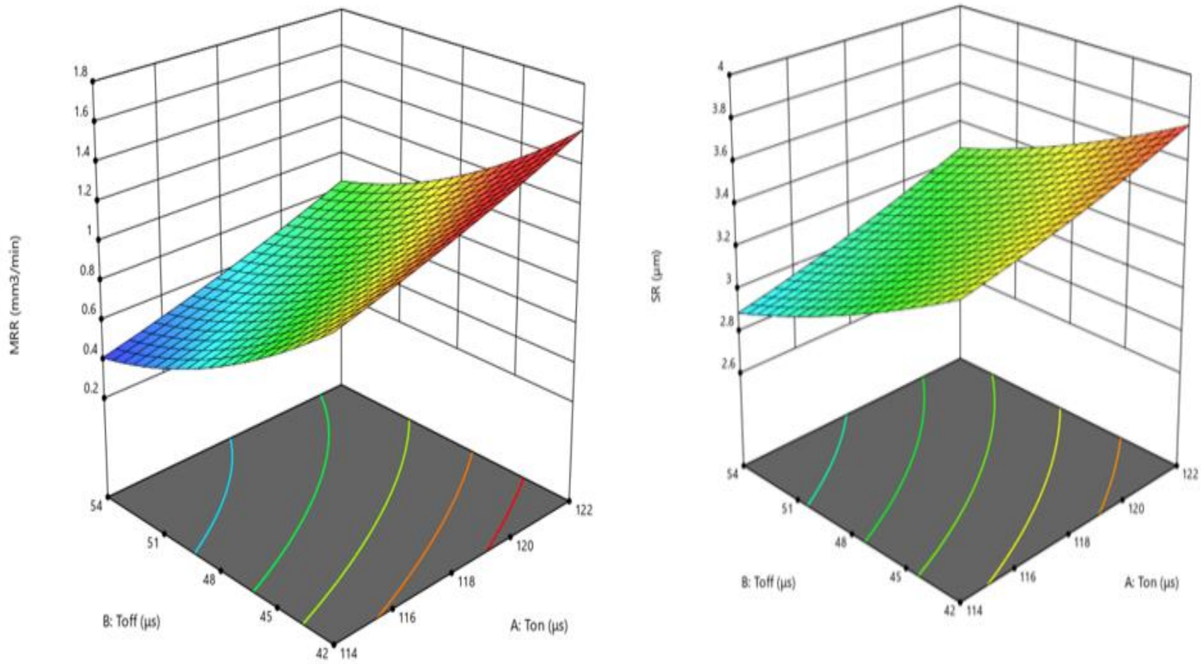

Fig 3: Response surface plot for the MRR and SR with T_{on} and T_{off}

Figure 4 compares the predicted values to the actual values obtained through experimentation. The difference between the predicted and actual values of the experiment is less than 0.1 for both MRR and SR, demonstrating that the model is dependable and can make accurate predictions.

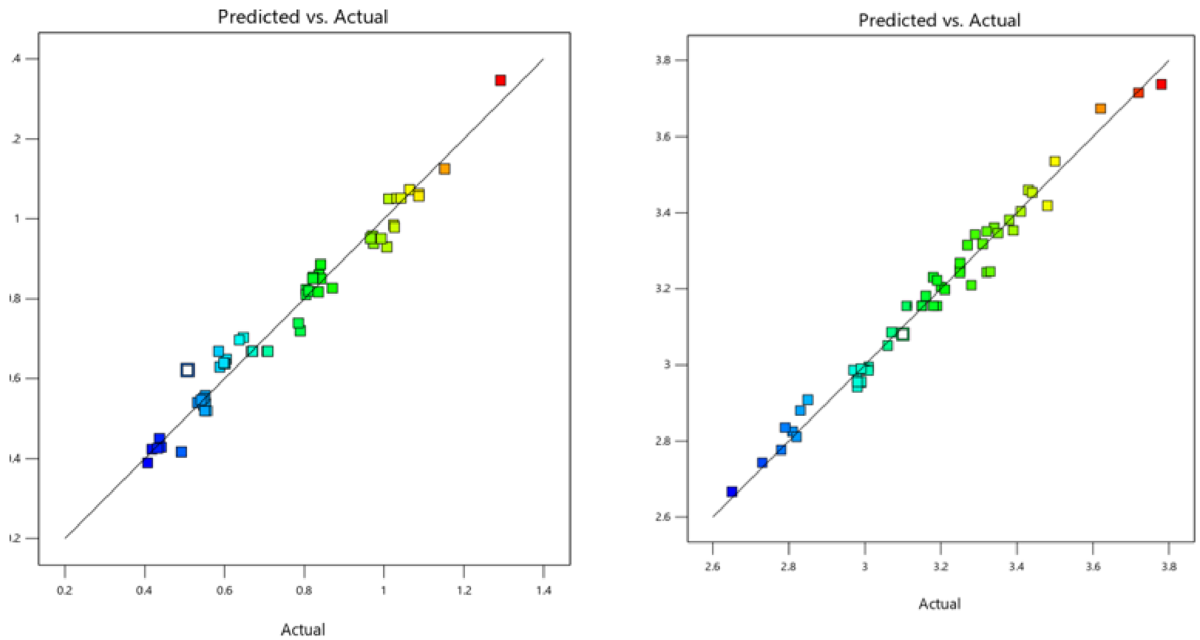

Fig: 4 Normal plot of residuals for material removal rate and Surface roughness

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https://publishoa.com
ISSN: 1309-3452

Run Order	Material Removal Rate		Surface Roughness	
	Actual Value	**Predicted Value**	**Actual Value**	**Predicted Value**
1	1.15	1.13	3.72	3.72
2	0.5880	0.6290	2.98	2.97
3	0.4320	0.4256	2.73	2.74
4	0.9660	0.9512	3.25	3.24
5	0.5560	0.5192	2.97	2.99
6	1.09	1.06	3.43	3.46
7	0.5980	0.6396	2.98	2.96
8	0.7070	0.6683	3.15	3.16
9	1.03	0.9787	3.31	3.32
10	1.09	1.06	3.44	3.45
11	1.01	0.9296	3.41	3.40
12	0.8210	0.8506	3.33	3.25
13	1.02	0.9847	3.29	3.34
14	0.5850	0.6683	3.11	3.16
15	0.4180	0.4234	2.99	2.96
16	0.7090	0.6683	3.18	3.16
17	0.5500	0.5192	2.99	2.99
18	0.4920	0.4170	2.82	2.81
19	0.5470	0.5336	2.81	2.82
20	0.8370	0.8597	3.39	3.35
21	0.7850	0.7392	3.19	3.22
22	0.8040	0.8231	3.07	3.09
23	0.6370	0.6967	3.21	3.20
24	0.4370	0.4499	3.01	2.99
25	0.8110	0.8200	3.06	3.05
26	0.8220	0.8534	3.32	3.24
27	0.8420	0.8501	3.27	3.31
28	0.5330	0.5403	2.85	2.91
29	0.5470	0.5509	2.98	2.94
30	0.8700	0.8264	3.20	3.21
31	0.5520	0.5579	3.01	2.99
32	0.6700	0.6683	3.15	3.16
33	1.03	1.05	3.38	3.38
34	0.6680	0.6683	3.15	3.16
35	1.29	1.35	3.78	3.74
36	1.04	1.05	3.48	3.42
37	0.8410	0.8857	3.34	3.36
38	0.5410	0.5464	2.83	2.88
39	0.6010	0.6376	3.00	2.99
40	0.6710	0.6683	3.19	3.16
41	0.8040	0.8107	3.16	3.18
42	0.5070	0.6213	*3.10*	*3.08*
43	0.7900	0.7197	3.18	3.23
44	0.9710	0.9577	3.25	3.25
45	0.4410	0.4284	2.78	2.78
46	0.8350	0.8171	3.25	3.27
47	0.4070	0.3894	2.65	2.67
48	0.9930	0.9507	3.35	3.35
49	0.6470	0.7032	3.28	3.21
50	1.01	1.05	3.50	3.54
51	0.5530	0.5375	2.79	2.84
52	1.06	1.07	3.62	3.67
53	0.9740	0.9388	3.32	3.35
54	0.6040	0.6490	2.99	2.95

IV. CONCLUSION

Using BBD of RSM, the influence of WEDM process parameters, namely Ton, Toff, WE, WT, SV, and IP, on MRR and SR responses was empirically examined in the current study. In addition, individual reaction and multi-objective/response optimizations were performed to determine the ideal WEDM process parameter settings for each process. Analysis of variance (ANOVA) was utilized to assess the importance of process parameters. From this investigation, the following inferences may be made:

1. The MRR is significantly impacted by the dynamic interaction between the pulse off time, denoted by Toff, and the peak current, denoted by Ip. In contrast, the SR is significantly impacted by the interactions between Ton and Toff and between Ton and Ip.
2. The duration of effort that the pulse on, pulse off, and the peak current significantly impact the material removal rate (MRR) and surface roughness (SR). Pulse on time is the factor that has the most significant impact on MRR and SR.
3. The MRR and SR rise when Ton and IP are both increased, but the MRR and SR fall when Toff is decreased.
4. The three-dimensional response surface and graphical representations provided by RSM may help observe and analyze the influence that changes in process parameters have on the responses.

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JOURNAL OF ALGEBRAIC STATISTICS
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ISSN: 1309-3452

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