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Influence of Input Factors on Surface Roughness and Material Removal Speed when Wire-EDM a Hardened SKD11 Steel Curve Profile

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Abstract: The goal of this research is to identify the best set of process machining parameters for wire-EDM (Electrical Discharge Machining) cutting of hardened SKD11 steel when machining a curve profile. The multi-objective function includes reducing surface roughness and increasing MRR (Material Removal Rate). The optimization process is prepared by using Taguchi method coupled Grey Relational Analysis. The obtained results revealed that T_{off} has the greatest influence on the average grey value (48.30%), followed by the influence of WF (Wire Feed, 15.99%), VM (Cutting Voltage, 9.33%), SV (Server Voltage, 5.05%), T_{on} (Pulse on Time, 1.81%), while SPD (Cutting Speed) has a negligible effect (0.89%). Moreover, using the optimal set of machining parameters generates in surface roughness of 1.25399 μm and MRR of 26.5562 mm^2/min. The verification experiment and Anderson-Darling method demonstrate the validity of the proposed model, which can be utilized for estimating surface roughness and MRR.

Key words: Wire Electrical Discharge Machining, wire-EDM, surface roughness, Material Removal Speed, SKD11.

1. Introduction

Non-traditional machining processes can meet the requirements of quality of products. EDM (Electrical Discharge Machining) process, a non-conventional machining operation, has been widely utilized for years so far [1-3]. The machining quality given by EDM can be improved by optimizing cutting parameters which have crucial impact on surface integration. Cutting voltage, pulse on time, pulse off time, server voltage, wire feed, and cutting speed are all important parameters that affect machining quality. Thanks to mathematical tools, the optimum process factors meeting several goals can be chosen, e.g. augmenting MRR (Material Removal Rate), and reducing the roughness of surface [4-6]. Typically, to get more than two objectives or multiple ones, the combination between Grey relational analysis and Taguchi method should be used [7-10].

There have been researchers applying the mentioned approach for finding the optimum set of machining parameters when EDM conducting of steel. Kolahan F. et al. [3] used Taguchi method coupled to Grey Relational Analysis (GRA) to optimize the EDM process parameters for AISI 2312 (40CrMnMoS86) hot worked steel alloy. The goals of this study are to reduce tool wear rate and augment MRR. It is shown that the peak current has the strongest influence on the both tool wear rate and MRR. The coupling between Taguchi method and GRA is also presented in the study of Chiang K.T. et al. [11] and Huo J. et al. [12] for predicting tool material performance and minimize surface roughness of hot pressed ZrB2 and hardened SKD11 during EDM, respectively. In order to increase MRR and reduce electrode wear rate, Xie et al. [13] operated the EDM process of Ti-6Al-4V alloy. It was revealed that applying the optimized machining parameters generates the small electrode wear ratio and

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high MRR. Tran et al. [14] executed the multi-objective optimization process of EDM hardened 90CrSi steel where there is the fact that the current has the strongest influence (32.63%), and the pulse off time has the smallest effects (1.04%) on the grey grade value. Moreover, the validation of experiments exhibits the reality of the study as an efficient method to predict surface roughness and MRR.

A multiple optimization process of Wire-EDM hardened SKD11 steel will be presented in this study in which reducing the surface roughness and increasing Material Removal Speed (MRS) are simultaneously considered. There are six process parameters selected (cutting voltage, pulse on time, pulse off time, server voltage, wire feed, cutting speed) to conduct the optimization for EDM process. GRA coupled with Taguchi technique and Analysis of Variance viz. Minitab@19 is applied to determine the optimum process parameters.

2. Experimental Work

2.1 Design of Experiments

In this study, six process parameters selected are considered as input parameters presented in Table 1. Except for the cutting speed that used two investigated levels, the remains are conducted by three levels. The experimental matrix is designed based on the survey levels of the variables and using Taguchi experimental planning method with design L18 (2^1 + 3^5). The Minitab@19 is used to design the experimental matrix. The order of declaring experimental variables is shown in Fig. 1. The experimental matrix and the results of surface roughness measurement and removal rate are described in Table 2. The workpiece material was SKD11 steel and the Wire-EDM machine used in the experiment was described in Fig. 2.

2.2 Multi-objective Optimization

The signal to noise (*S*/*N*) ratio for every test is able to be calculated using the assumption that "the smaller the better" for surface roughness:

$$S/N = -10log_{10}(\frac{1}{n}\sum_{i=1}^{n} y_i^2) \qquad (1)$$

In the case of MRS, however, "the larger the better" [15]:

$$SN = -10log_{10}(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^2}) \qquad (2)$$

Table 1 Input parameters and the investigated levels.

No.	Input parameters	Notation	Unit	Levels		
				1	2	3
1	Cutting voltage	VM	V	6	9	12
2	Pulse on time	T_{on}	μs	6	9	12
3	Pulse off time	T_{off}	μs	8	12	16
4	Server voltage	SV	V	24	29	34
5	Wire feed	WF	mm/min	8	10	12
6	Cutting speed	SPD	m/min	2	4	-

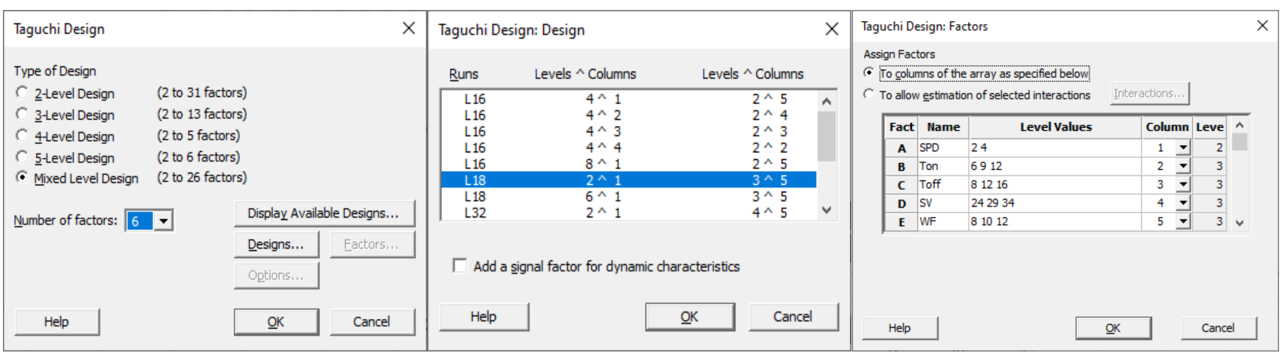

Fig. 1 Procedure for declaring input parameter in Minitab@19.

Table 2 Experimental matrix and output results.

Exp. No.	Input parameters						Mean of Ra (μm)	Mean of MRS (mm^2/min)
	VM	T_{on}	T_{off}	SV	WF	SPD		
1	6	6	8	24	8	2	1.4230	8.1310
2	9	6	12	29	10	2	1.3487	27.9737
3	12	6	16	34	12	2	1.4580	33.0520
4	9	9	8	24	10	2	1.5803	15.0477
5	12	9	12	29	12	2	1.6000	30.6887
6	6	9	16	34	8	2	1.5121	32.0623
7	12	12	8	29	8	2	1.6730	26.0733
8	6	12	12	34	10	2	1.6544	41.1867
9	9	12	16	24	12	2	1.4677	26.0730
10	9	6	8	34	12	4	1.6651	11.4643
11	12	6	12	24	8	4	1.5757	20.9563
12	6	6	16	29	10	4	1.3374	28.6173
13	6	9	8	29	12	4	1.5240	23.0500
14	9	9	12	34	8	4	1.7039	38.7530
15	12	9	16	24	10	4	1.4253	27.9260
16	12	12	8	34	10	4	1.7730	30.1433
17	6	12	12	24	12	4	1.6279	38.8440
18	9	12	16	29	8	4	1.6383	26.3060

Fig. 2 Wire-EDM machine used in the experiment.

where n is the total number of tests and y_i is the data that was detected. Z_{ij} ($0 \leq Z_{ij} \leq 1$) can be used to calculate the normalized grey relation values for both surface roughness and MRR:

$$Z_{ij} = \frac{SN_{ij} - \min(SN_{ij}, j = 1,2,..k)}{\max\left(SN_{ij}, j = 1,2,..n\right) - \min(SN_{ij}, j = 1,2,..n)} \quad (3)$$

Table 3 displays the S/N ratio and the normalized grey relation values. To express the relationship between reference and experimental normalized data, the grey relation coefficient, $\gamma(i)$, is calculated as follows:

$$\gamma(i) = \frac{\Delta min + \xi \cdot \Delta max}{\Delta_j(k) + \xi \cdot \Delta max} \quad (4)$$

Table 3 *S*/*N* ratio values, normalized *S*/*N* ratio values and the absolute value.

No.	Input parameters						Ra (μm)		MRS (mm^2/min)	
	VM	T_{on}	T_{off}	SV	WF	SPD	Mean	*S*/*N*	Mean	*S*/*N*
1	6	6	8	24	8	2	1.4230	-3.0641	8.1310	18.2009
2	9	6	12	29	10	2	1.3487	-2.5981	27.9737	28.9349
3	12	6	16	34	12	2	1.4580	-3.2752	33.0520	30.3838
4	9	9	8	24	10	2	1.5803	-3.9750	15.0477	23.5491
5	12	9	12	29	12	2	1.6000	-4.0824	30.6887	29.7389
6	6	9	16	34	8	2	1.5121	-3.5917	32.0623	30.1193
7	12	12	8	29	8	2	1.6730	-4.4699	26.0733	28.3226
8	6	12	12	34	10	2	1.6544	-4.3731	41.1867	32.2949
9	9	12	16	24	12	2	1.4677	-3.3326	26.0730	28.3237
10	9	6	8	34	12	4	1.6651	-4.4286	11.4643	21.1856
11	12	6	12	24	8	4	1.5757	-3.9493	20.9563	26.425
12	6	6	16	29	10	4	1.3374	-2.5256	28.6173	29.1319
13	6	9	8	29	12	4	1.5240	-3.6597	23.0500	27.2526
14	9	9	12	34	8	4	1.7039	-4.6289	38.7530	31.7637
15	12	9	16	24	10	4	1.4253	-3.0783	27.9260	28.9199
16	12	12	8	34	10	4	1.7730	-4.9742	30.1433	29.5834
17	6	12	12	24	12	4	1.6279	-4.2326	38.8440	31.7862
18	9	12	16	29	8	4	1.6383	-4.2881	26.3060	28.3996

Table 4 Grey relational coefficient and grey grade values.

Exp. No.	*S*/*N*		Zi		Δ_i (*k*)		Gray relational values y_i		$\overline{y_i}$
	Ra	MRS	Ra	MRS	Ra	MRS	Ra	MRS	
			Reference value						
			1.000	1.000					
1	-3.0641	18.2009	0.780	0.000	0.220	1.000	0.695	0.333	0.514
2	-2.5981	28.9349	0.970	0.762	0.030	0.238	0.944	0.677	0.811
3	-3.2752	30.3838	0.694	0.864	0.306	0.136	0.620	0.787	0.703
4	-3.9750	23.5491	0.408	0.379	0.592	0.621	0.458	0.446	0.452
5	-4.0824	29.7389	0.364	0.819	0.636	0.181	0.440	0.734	0.587
6	-3.5917	30.1193	0.565	0.846	0.435	0.154	0.535	0.764	0.649
7	-4.4699	28.3226	0.206	0.718	0.794	0.282	0.386	0.640	0.513
8	-4.3731	32.2949	0.245	1.000	0.755	0.000	0.399	1.000	0.699
9	-3.3326	28.3237	0.670	0.718	0.330	0.282	0.603	0.640	0.621
10	-4.4286	21.1856	0.223	0.212	0.777	0.788	0.391	0.388	0.390
11	-3.9493	26.425	0.419	0.584	0.581	0.416	0.462	0.546	0.504
12	-2.5256	29.1319	1.000	0.776	0.000	0.224	1.000	0.690	0.845
13	-3.6597	27.2526	0.537	0.642	0.463	0.358	0.519	0.583	0.551
14	-4.6289	31.7637	0.141	0.962	0.859	0.038	0.368	0.930	0.649
15	-3.0783	28.9199	0.774	0.761	0.226	0.239	0.689	0.676	0.683
16	-4.9742	29.5834	0.000	0.808	1.000	0.192	0.333	0.722	0.528
17	-4.2326	31.7862	0.303	0.964	0.697	0.036	0.418	0.933	0.675
18	-4.2881	28.3996	0.280	0.724	0.720	0.276	0.410	0.644	0.527

where:

$\Delta_j(k)$ is the deviation of reference data.

$\Delta_j(k) = \left\|Z_0(k) - Z_j(k)\right\|$ and Z0(k) is the reference data or best data.

+) $\Delta\min = \min_{\forall j \in i} \min_{\forall k} \left\|Z_0(k) - Z_j(k)\right\|$ minimum value of $\Delta_j(k)$.

+) $\Delta\max = \max_{\forall j \in i} \max_{\forall k} \|Z_0(k) - Z_j(k)\|$ maximum value of $\Delta_j(k)$.

+) ξ is distinguishing or identification coefficient and its value varies from 0 to 1. We select its value of 0.5 herein.

Determining the gray relational grade:

$$\overline{\gamma_j} = \frac{1}{k}\sum_{i=1}^{m} \gamma_{ij} \qquad (5)$$

From this equation, the average value of grey relation interactions was discovered in the third step; k is the number of objectives optimized.

3. Results and Analysis

To balance the output responses, the average values of grey should be the higher the better. Now the initial problem with multi-objective function becomes the equivalent one with single objective where the average grey value is the unique variable.

The Taguchi method is used to evaluate the influence of the process parameters on the average gray relation values. With the purpose that the average gray relation value is as large as possible, the S/N value of $\overline{y_i}$ is calculated according to Eq. (2). Table 5 displays the calculated results demonstrating the impact of the input parameters on the average gray relation values analyzed using the ANOVA (Analysis of Variance) method.

From the results of the analysis of the influence of the parameters on the average gray relation values in Table 5, it shows that: T_{off} has the greatest influence on $\bar{y_i}$ (48.30%), followed by the influence of WF (15.99%), VM (9.33%), SV (5.05%), T_{on} (1.81%), while SPD has a negligible effect on $\bar{y_i}$ (0.89%).

The influence order of the parameters on the gray relation values obtained by ANOVA analysis is described in Table 6.

It was found from Table 6 that the influence order of input parameters is T_{off}, WF, VM, SV, T_{on} and SPD. The specific effects of input parameters through the levels are shown in Fig. 2.

The results in Fig. 3 show that when SPD increases from 2 to 4 m/min, $\bar{y}$ decreases; for T_{on}, when T_{on} increases from 6 µs to 9 µs; however, $\bar{y}$ decreases slightly when T_{on} increases from 9 µs to 12 µs,; T_{off}

Table 5 The influence of the parameters on the gray relation values, $\overline{y_i}$.

Source	DF	Seq SS	Adj SS	Adj MS	F	P	C (%)
SPD	1	0.002190	0.002190	0.002190	0.29	0.611	0.89
T_{on}	2	0.004440	0.004440	0.002220	0.29	0.757	1.81
T_{off}	2	0.118602	0.118602	0.059301	7.77	0.022	48.30
SV	2	0.012400	0.012400	0.006200	0.81	0.487	5.05
WF	2	0.039259	0.039259	0.019630	2.57	0.156	15.99
VM	2	0.022909	0.022909	0.011455	1.50	0.296	9.33
Residual error	6	0.045769	0.045769	0.007628			18.64
Total	17	0.245569					

Table 6 Influence order of the input parameters on $\bar{y_i}$.

Level	SPD	T_{on}	T_{off}	SV	WF	VM
1	0.6166	0.6278	0.4912	0.5748	0.5593	0.6556
2	0.5946	0.5952	0.6542	0.6389	0.6696	0.5749
3	-	0.5939	0.6714	0.6031	0.5879	0.5863
Delta	0.0221	0.0339	0.1802	0.0641	0.1102	0.0807
Rank	6	5	1	4	2	3
				Average gray relation value of 0.606		

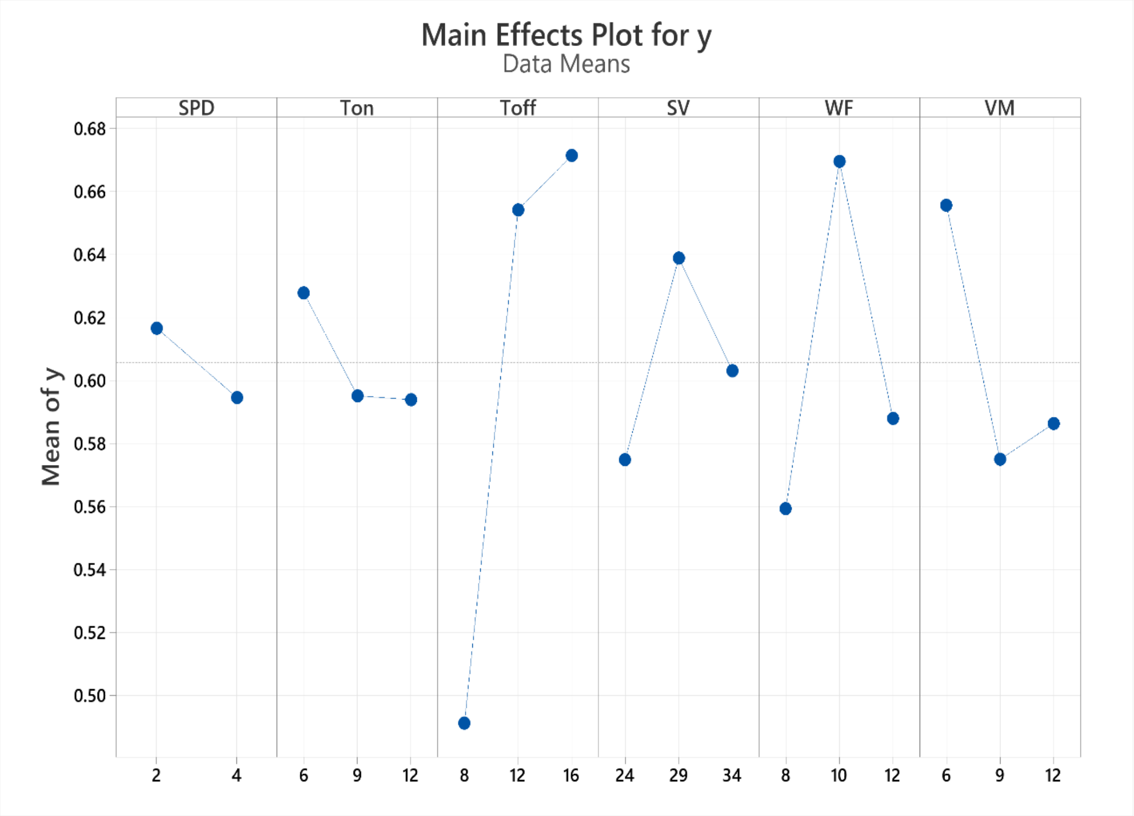

Fig. 3 The influence of input parameters on the value of $\bar{y}$.

parameter has a positive influence on , when increasing from 8 μs to 16 μs it makes a strong increase; for the SV parameter, when SV increases from 24 to 29 V, $\bar{y}$ increases, when it continues to increase SV from 29 V to 34 V, $\bar{y}$ decreases. It was noted that WF has the same effect as SV. When it increases from 8 mm/min to 10 mm/min, $\bar{y}$ increases. However, if WF increase from 10 to 12 mm/min, $\bar{y}$ decreases. For the effect of VM: when VM increases from 6 V to 9 V, $\bar{y}$ reduces; if continues to increase VM from 9 to 12 V, it causes a slight increase of $\bar{y}$. In the Taguchi method, to determine the optimal set of machining parameters, it is necessary to consider the influence of the input parameters on the *S*/*N* ratio. As analyzed above, the parameter set with the highest value of $\bar{y}$ for each input parameter is the most reasonable set of parameters. The larger the target the better, the larger the *S*/*N* value, which also means the smaller the noise effect. The influence of input parameters on the *S*/*N* value is shown in Fig. 4.

The general direction of the impact of every input variable on the *S*/*N* value and the multi-objective optimal variables set is determined by the results in Fig. 4, as shown in Table 7.

Based on the obtained optimal process factors, it is possible to find the results of the objective functions using Minitab 19 software as shown in Table 8.

From the results of predictive analysis, it shows that using the optimal set of process parameters, it will result in surface roughness Ra of 1.25399 μm and MRS of 26.5562 mm^2/min.

To evaluate the model fit, it is based on the error distribution graphs shown in Fig. 5. The errors of the experimental points corresponding to the blue points on the histogram are close to the normal distribution line (red solid line) in the normal distribution error distribution chart. This demonstrates that the deviation level is very low. A histogram revealing the frequency of errors reveals that errors near 0 occur frequently. The final two graphs depict the random distribution of experimental errors, indicating that the built model is heavily influenced by the input parameters chosen and is unaffected by the order of the experiments.

The suitability of the experimental model confirmed by the Anderson-Darling method in Fig. 6 reveals that the data corresponding to the experimental indications (blue dots) are in the region bounded by two limit lines, e.g. upper and lower with a standard deviation of 95%, and the p value of 0.613 is $\geq$ 0.05, meaning that the applied experimental model is appropriate.

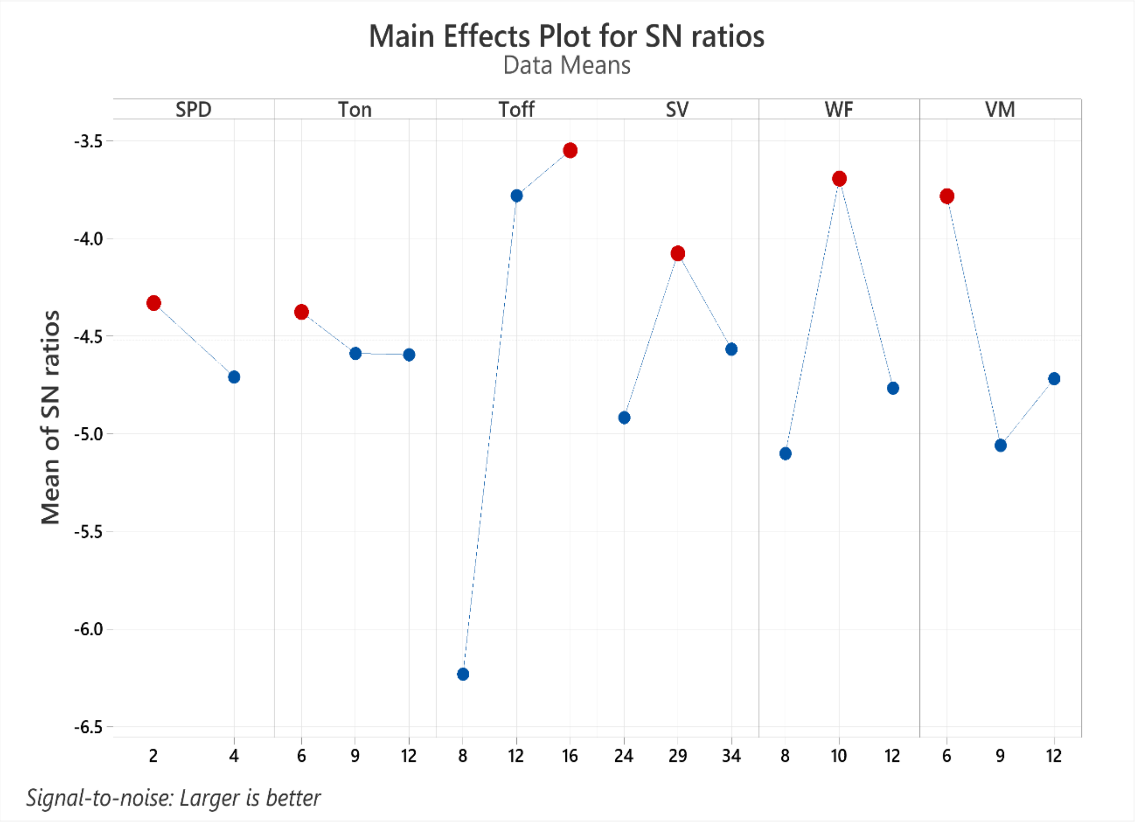

Fig. 4 Effect of parameters on the *S*/*N* value of $\bar{y}$.

Table 7 Optimum set of process parameters.

No.	Input parameters	Denotation	Unit	Optimal level	Optimal value
1	Cutting speed	SPD	m/min	1	2
2	Pulse on time	T_{on}	µs	1	6
3	Pulse off time	T_{off}	µs	3	16
4	Cutting voltage	VM	V	1	6
5	Server voltage	SV	V	2	29
6	Wire feed	WF	mm/min	2	10

Table 8 Results of predictive analysis of Ra and MRS values corresponding to the optimal set of process parameters.

Output	*S*/*N* ratio	Mean	St. Dev.	Ln(St. Dev.)
Ra	-2.10939	1.25399	0.0014646	-6.19419
MRS	28.0955	26.5562	0.0663960	-2.09219

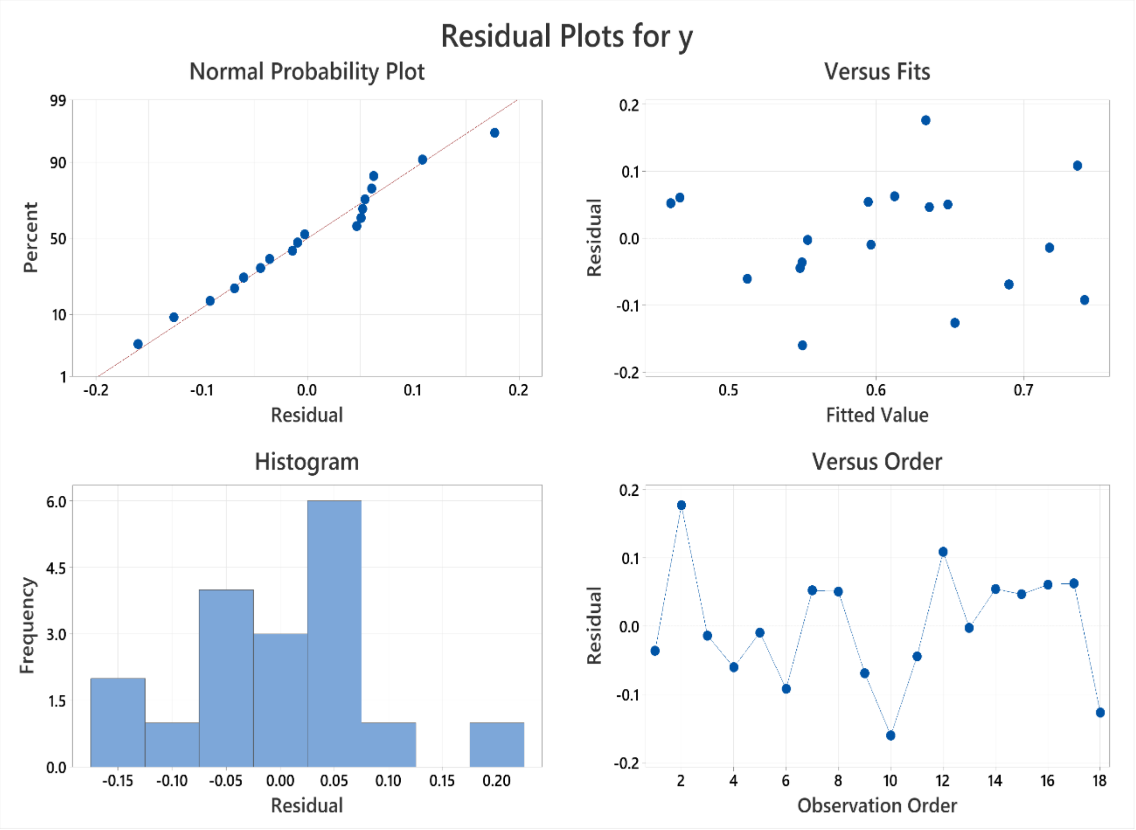

Fig. 5 Error evaluation distribution charts.

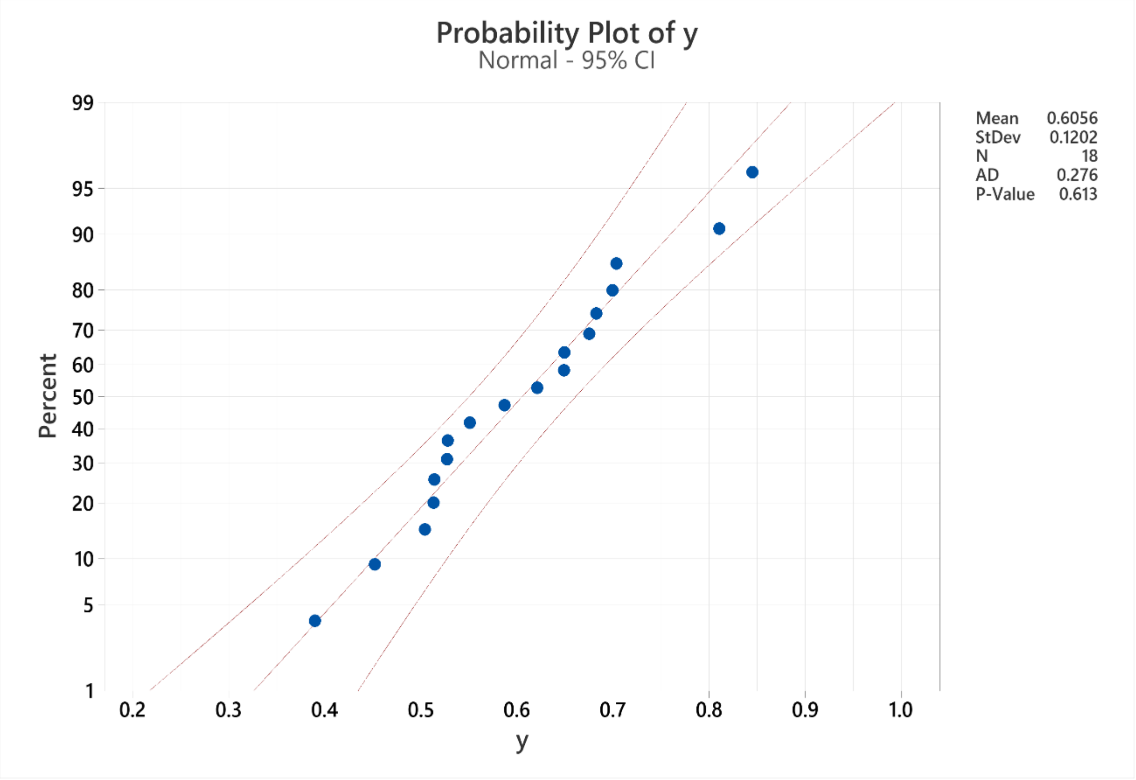

Fig. 6 Probability graph of the fit of the experimental model for $\overline{y}$.

4. Conclusions

This article shows the multi-objective function optimization when considering curve profile of EDM process of hardened SKD11 steel. Six process parameters are chosen as the input for the multi-objective functions. The Taguchi technique is accompanied to GRA to minimize the surfaces' roughness and maximize the MRR. The following conclusions can be made:

Pulse off time shows the most impact on the grey grade value (48.30%), followed by the influence of WF (15.99%), VM (9.33%), SV (5.05%), Ton (1.81%), while SPD has a little effect (0.89%).

The utilization of the optimal set of process parameters results in reduction of surface roughness of 1.25399 μm and MRS of 26.5562 mm^2/min.

The validation experiment and the Anderson-Darling method prove the robustness of the proposed optimization process, which can be regarded as an effective method to estimate the surface roughness and MRR when conducting EDM on hardened SKD11 steel curve profiles.

Acknowledgment

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