

Multi-objective Optimization of PMEDM Process for Maximum Material Removal Speed and Minimum Electrode Wear Rate When Machining SKD11 Steel

Anh Tuan Nguyen¹, Thi Tam Do², Thu Quy Le³, Ngoc Huy Thinh Tran⁴, Hoang Anh Le⁵, Ngoc Giang Tran², Ngoc Pi Vu², and Xuan Tu Hoang^{2(\boxtimes)}

¹ University of Economics – Technology for Industries, Ha Noi, Vietnam ² Thai Nguyen University of Technology, Thai Nguyen, Vietnam hxt_dhktcn@tnut.edu.vn

³ National Research Institute of Mechanical Engineering, Ha Noi, Vietnam
⁴ Nguyen Tat Thanh University, Ho Chi Minh City, Vietnam

⁵ Vinh Long University of Technology Education, Vinh Long, Vietnam

Abstract. This paper presents the results of a multi-objective optimization study when powder-mixed electrical discharge machining (PMEDM) of cylindrically shaped parts made of SKD11 steel to achieve the maximum removal speed (MRS), and minimum electrode wear rate (EWR). To carry out this study, an experiment was conducted with six input parameters, including the powder concentration, the powder size, the pulse on time, the pulse off time, the current, and the servo voltage. Besides, the Taguchi method combined with the gray relation analysis (GRA) method was used to design experiment, and analyze experimental results. The impact of the input parameters on the MRS and the EWR was analyzed. In addition, optimal input parameters to get the maximum MRS, and the minimum EWR simultaneously were found.

Keywords: PMEDM \cdot EDM \cdot Multi-objective optimization \cdot Cylindrically shaped parts \cdot SKD11

1 Introduction

Electrical discharge machining (EDM) is a machining method where the workpiece material removal is accomplished by sparks generated continuously between the electrode and the workpiece, which are separated by a dielectric. EDM is very suitable for processing complex parts or recessed cavities, such as stamping dies, forgings or castings, etc. Besides, this type of processing also has several disadvantages, such as the quality of the machined surface is not high, the electrodes usually wear out quickly, etc. In order to limit these disadvantages, a metal powder was mixed into the dielectric liquid, and so the EDM process became the PMEDM process.

Up to now, research on PMEDM has always been a topic of interest to researchers. Many studies on the PMEDM process have been carried out. Studies on this type of machining have been conducted to improve the machined surface quality [1–4], increase the material removal rate [1, 4–10], the machining time [11], or reduce the electrode wear rate [7, 8, 12]. Many studies have been done on PMEDM with mixing different metal powders into the dielectric liquid such as SiC [3–5, 9–11, 13], Al [1, 14], Al2O3 [15], W [8, 12], Cr [2], or Ti [5, 16, 17]. Besides, PMEDM with different machining materials has received much attention such as SKD11 [16, 17], AISI D2 die steel [5], 90CrSi [9–11], Ti-6Al-4V [13, 18], EN8 steel [2], Inconel 718 [14, 15], etc. Electrode materials are also the subject of many studies, such as copper [3, 4, 8], graphite [5, 19], and brass [20]. Recently, there has been some research on machining cylindrically shaped parts [3, 4, 9–11].

This work deals with a study to simultaneously optimize two single-objective functions, maximum MRS and minimum EWR, when processing cylindrically shaped parts of SKD11 steel using the PMEDM process. In the study, an experiment was carried out with the use of the Taguchi method combined with the gray relation analysis (GRA) method to design the experiment and analyze the experimental results. The influence of the input process parameters on the above objective functions was investigated. Furthermore, optimal input parameters to achieve the mentioned two objectives simultaneously have been proposed.

2 Experimental Setup

In this study, an experiment was carried out to solve the multi-objective optimization problem with two objectives performed simultaneously, including the maximum MRS and the minimum EWR, an experiment was performed. Six input process parameters were selected to evaluate their effects on MRS and EWR. These factors and their levels for the experiment are given in Table 1. Figure 1 shows the experimental setup. In this experiment, a Sodick A30 EDM machine, SKD11 steel samples, copper electrodes, and SiC powder for mixing in the dielectric fluid were used.

No	Parameters	Code	Unit	Level					
				1	2	3	4	5	6
1	Powder concentration	Cp	g/l	0	2	3	4	5	6
2	Powder size	Sp	nm	100	500	1000	-	-	-
3	Pulse on time	Ton	μs	10	20	30	-	-	-
4	Pulse off time	Toff	μs	10	20	30	-	-	-
5	Peak current	IP	A	4	8	12	-	-	-
6	Servo voltage	SV	V	3	5	7	-	-	_

Table 1. Input factors and their levels



Fig. 1. Experimental setup

The Taguchi method with the design L18 (3^4) with the support of the Minitab R19 software was used to create the experimental plan. Table 2 presents the plan of the experiment and the average values of the measured results of the MRS and the EWR.

Exp. No.	Input factors						Mean of MRS (g/h)	Mean of EWR (mg/min)
	Cp	Sp	Ton	$T_{\rm off}$	IP	SV		
1	0	100	10	10	4	3	9.8773	13.5333
2	0	500	20	20	8	5	16.0979	99.8345
3	0	1000	30	30	12	7	49.6445	29.6923
4	2	100	10	20	8	7	6.7254	35.9337
5	2	500	20	30	12	3	15.8857	85.4975
6	2	1000	30	10	4	5	41.9831	16.9221
7	3	100	20	10	12	5	32.4869	55.6941
8	3	500	30	20	4	7	12.4249	11.3585
9	3	1000	10	30	8	3	11.8259	10.2848
10	4	100	30	30	8	5	28.2703	24.1109
11	4	500	10	10	12	7	8.1986	10.4982
12	4	1000	20	20	4	3	5.2888	18.9691
13	5	100	20	30	4	7	5.3288	15.2504
14	5	500	30	10	8	3	15.1998	64.6147
15	5	1000	10	20	12	5	7.3727	24.7060
16	6	100	30	20	12	3	30.8676	67.6757
17	6	500	10	30	4	5	5.6500	10.7152
18	6	1000	20	10	8	7	5.2931	32.8711

Table 2. Experimental plan and the mean of MRS and EWR

626 A. T. Nguyen et al.

In this study, it is necessary to conduct multi-objective optimization or simultaneous optimization of two objectives, which are the maximum material removal rate and the minimum electrode wear. To do that, the Taguchi method combined with the GRA method was used.

The S/N indexes of MRS and EWR can be calculated by: For maximum MRS:

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

For minimum EWR:

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

Table 3 shows the calculated S/N indexes of the two objectives.

No.	Inp	ut facto	ors				MRS (g/	h)	EWR (mg/min)		
	Cp	Sp	T_{on}	$T_{\rm off}$	IP	SV	Mean	S/N	Mean	S/N	
1	0	100	10	10	4	3	9.8773	19.8928	13.5333	-22.6281	
2	0	500	20	20	8	5	16.0979	24.1354	99.8345	-39.9856	
3	0	1000	30	30	12	7	49.6445	33.9174	29.6923	-29.4529	
4	2	100	10	20	8	7	6.7254	16.5544	35.9337	-31.1100	
5	2	500	20	30	12	3	15.8857	24.0201	85.4975	-38.6391	
6	2	1000	30	10	4	5	41.9831	32.4615	16.9221	-24.5691	
7	3	100	20	10	12	5	32.4869	30.2342	55.6941	-34.9162	
8	3	500	30	20	4	7	12.4249	21.8858	11.3585	-21.1064	
9	3	1000	10	30	8	3	11.8259	21.4567	10.2848	-20.2439	
10	4	100	30	30	8	5	28.2703	29.0266	24.1109	-27.6443	
11	4	500	10	10	12	7	8.1986	18.2748	10.4982	-20.4223	
12	4	1000	20	20	4	3	5.2888	14.4672	18.9691	-25.5609	
13	5	100	20	30	4	7	5.3288	14.5327	15.2504	-23.6656	
14	5	500	30	10	8	3	15.1998	23.6368	64.6147	-36.2066	
15	5	1000	10	20	12	5	7.3727	17.3525	24.7060	-27.8560	
16	6	100	30	20	12	3	30.8676	29.7901	67.6757	-36.6087	
17	6	500	10	30	4	5	5.6500	15.0409	10.7152	-20.6000	
18	6	1000	20	10	8	7	5.2931	14.4741	32.8711	-30.3363	

Table 3. The calculated S/N value of MRS and EWR

To implement the GRA, the S/N values need to be transformed to dimensionless quantities or need to normalize the data. In this case, the S/N indexes are normalized in the range $(0\div1)$ and by $Z_i\ (0\le Z_i\le 1)$ which is calculated by the following Equation:

$$Z_{i} = \frac{S/N_{i} - \min(S/N_{i}, i = 1, 2, ..., n)}{\max(S/N_{i}, i = 1, 2, ..., n) - \min(S/N_{i}, i = 1, 2, ..., n)}$$
(3)

In which, n is the number of experiments; n = 18. The gray relation (GR) coefficient $y_i(k)$ is determined by:

$$y_i(k) = \frac{\Delta_{\min}(k) + \zeta \cdot \Delta_{\max}(k)}{\Delta_i(k) + \zeta \cdot \Delta_{\max}(k)}$$
(4)

In which, i = 1, 2,..., n; n = 18 is the experimental number; k = 2 is the single objective number; $\Delta i(k) = ||ZO(k) - Zi(k)||$, is the absolute value of the difference between $Z_0(k)$ (reference value ZO(k) = 1) and $Z_i(k)$. (Z-value of the *i*th experiment of the *k*th target); $\Delta \min(k)$ is the minimum value of i(k); max(k) is the maximum value of i (k); ζ is the discriminant coefficient; $0 \le \zeta \le 1$; For a experimental study, we can chose $\zeta = 0.5$.

The GR degree can be determined through the average GR value of the output objectives:

$$\overline{y_i} = \frac{1}{k} \sum_{j=0}^{k} y_{ij}(k) \tag{5}$$

Where, k is the single objective number; y_{ij} is the GR value of the j^{ih} output objectives in the i^{ih} experiment.

The results of the calculated GR value y_i and the mean GR value of the experiments are listed in Table 4.

No	S/N		Zi		Δ_i (k)		GR value yi		\overline{y}_l
	Ra	EWR	Ra	EWR					
			Reference value		MRS	EWR	MRS	EWR	
			1.000	1.000	1				
1	-5.9226	-22.6281	0.4271	0.8792	0.721	0.121	0.409	0.805	0.636
2	-7.9305	-39.9856	0.2228	0.0000	0.503	1.000	0.499	0.333	0.362
3	-10.1206	-29.4529	0.0000	0.5335	0.000	0.466	1.000	0.517	0.425
4	-6.0635	-31.1100	0.4128	0.4496	0.893	0.550	0.359	0.476	0.468
5	-7.0309	-38.6391	0.3144	0.0682	0.509	0.932	0.496	0.349	0.385
6	-1.8672	-24.5691	0.8398	0.7809	0.075	0.219	0.870	0.695	0.726
7	-7.2817	-34.9162	0.2889	0.2568	0.189	0.743	0.725	0.402	0.408
8	-1.0345	-21.1064	0.9245	0.9563	0.619	0.044	0.447	0.920	0.894
9	-6.8051	-20.2439	0.3373	1.0000	0.641	0.000	0.438	1.000	0.715
10	-7.6264	-27.6443	0.2538	0.6251	0.251	0.375	0.665	0.572	0.486
11	-5.3302	-20.4223	0.4874	0.9910	0.804	0.009	0.383	0.982	0.738
12	-0.2925	-25.5609	1.0000	0.7307	1.000	0.269	0.333	0.650	0.825
13	-5.4196	-23.6656	0.4783	0.8267	0.997	0.173	0.334	0.743	0.616
14	-7.4181	-36.2066	0.2750	0.1914	0.529	0.809	0.486	0.382	0.395
15	-1.7023	-27.8560	0.8566	0.6144	0.852	0.386	0.370	0.565	0.671
16	-9.1074	-36.6087	0.1031	0.1711	0.212	0.829	0.702	0.376	0.367
17	-1.8846	-20.6000	0.8380	0.9820	0.971	0.018	0.340	0.965	0.860
18	-8.2363	-30.3363	0.1917	0.4888	1.000	0.511	0.333	0.494	0.438

Table 4. S/N, S/N Z_i, Δ_i (k) and GR value \overline{y}_l

3 Results and Analysis

To ensure harmony between output targets, the average GR value should be as high as possible. In this case, the multi-objective optimization problem becomes a single-objective optimization problem with the average GR as the output. To solve this problem, the Taguchi method is used to evaluate the influence of the input PMEDM parameters on the average GR value. The S/N value of was calculated according to Eq. 2 to get the mean GR as large as possible. The analysis of variance (ANOVA) for S/N ratios are given in Table 5.

Source	DF	Seq SS	Adj SS	Adj MS	F	Р	C (%)
Ср	5	14.002	14.002	2.8004	1.27	0.495	21.91
Sp	2	2.247	2.247	1.1234	0.51	0.662	3.52
Ton	2	19.317	19.317	9.6586	4.38	0.186	30.23
Toff	2	9.726	9.726	4.8629	2.21	0.312	15.22
lp	2	12.359	12.359	6.1797	2.81	0.263	19.34
SV	2	1.836	1.836	0.9181	0.42	0.706	2.87
Residual Error	2	4.406	4.406	2.2028			6.90
Total	17	63.893					

Table 5. Analysis of variance for S/N ratios of \overline{y}_i .

From Table 5, it can be seen that the influence of the parameters on the average GR value is as follows: T_{on} has the greatest influence (30.23%); followed by the influence of C_p (21.91%), IP (19.34%), and T_{off} (15.22%). The other two parameters with negligible influence are S_p (3.52%), and SV (2.87%). This result is also shown in Fig. 2. This result is also described in Fig. 2.



Fig. 2. Effect of input factors on $\overline{y_i}$ (%)

The influence of the input parameters on the GR value through ANOVA analysis is evaluated in order as shown in Table 6. Table 6 shows the order of input parameters ranked according to their influence on y as T_{on} , Cp, IP, T_{off} , Sp, and SV, respectively.

Larger is be	etter									
Level	Ср	Sp	Ton	Toff	lp	sv				
1	-4.783	-5.303	-4.734	-4.943	-4.17	-5.579				
2	-5.732	-5.448	-6.549	-6.108	-6.192	-4.869				
3	-3.717	-4.637	-4.105	-4.337	-5.026	-4.940				
4	-4.551									
5	-6.416									
6	-5.577									
Delta	2.699	0.811	2.444	1.771	2.022	0.710				
Rank	1	5	2	4	3	6				
	Average gray relation value: 0.567									

Table 6. Influence order of input parameters on S/N.

The graph of the influence of the parameters on y is shown in Fig. 3. Theoretically, the value of each input parameter for which the value of the S/N ratio of \overline{y} is the largest will be the optimal value of that parameter. Therefore, from Fig. 3, it is easy to determine the optimal values of the input parameters for the multi-objective function (see Table 7).



Fig. 3. Influence of input factors on the S/N ratios of \overline{y}

Figure 4 depicts error distribution histograms. These graphs allow evaluating the appropriateness of the experimental model. From Fig. 4, the following observations can be drawn: On the normal error distribution chart (Fig. 4a), the points representing the errors of the experiments (the blue points) are close to the line. normally distributed (the solid red line). It shows that the error level is very small. The graph of error occurrence frequency or the Histogram (Fig. 4c) shows that errors near 0 (-0.05 to 0.05) appear with high frequency. The remaining two graphs (Fig. 4b and d) show that the experimental errors are distributed quite randomly. It shows that the built model is highly influenced by the input parameters and is not affected by the order of experiments.

Parameter	Code	Unit	Level	Value
Powder concentration	C_p	g/l	3	3
Powder size	Sp	nm	3	1000
Pulse on time	Ton	μs	3	30
Pulse off time	T_{off}	μs	3	30
Peak current	IP	Α	1	4
Servo voltage	SV	V	2	5

Table 7. Optimum input factors



Fig. 4. Residual plots for \overline{y}

Figure 5 depicts the fit of the experimental model. This graph was constructed by using the Anderson-Darling method. From the graph, it can be seen that the experimental points (the blue dots) are all within the limit region defined by two upper and lower limit lines with a standard deviation of 95%. In addition, the P-value of 0.236 is much larger than the value of $\alpha = 0.05$, indicating that the experimental model is suitable.



Fig. 5. Probability plot for \overline{y}

4 Conclusions

In this paper, the results of a multi-objective optimization problem when PMEDM cylindrically shaped parts made from SKD11 tool steel have been presented. This multi-objective problem consists of two single-objective functions, including the maximum MRS and the minimum EWR. To solve this problem, an experiment was conducted. The Taguchi method combined with the GRA method was used to design the experiment and analyze the experimental results. From the results of the experiment, the effect of six input process parameters including the powder size, the powder concentration, the pulse time, the pulse off time, the current, and the servo voltage on the multi-target function was evaluated. It was reported that the order of influence of the input parameters on the multi-objective function is T_{on} (30.23%), C_p (21.91%), IP (19.34%), T (15.22%), Sp (3.52%), and SV (2.87%). In addition, optimal input parameters to simultaneously optimize two single objective functions (the MRS and the EWR) have been proposed. The optimal parameters are $C_p = 3$ (g/l), Sp = 1000 (nm), $T_{on} = 30$ (µs), $T_{off} = 30$ (µs), IP = 4 (A), and SV = 5 (V).

Acknowledgment. This work was supported by Thai Nguyen University of Technology.

References

- 1. Jabbaripour, B., et al.: Investigating surface roughness, material removal rate and corrosion resistance in PMEDM of γ -TiAl intermetallic. J. Manuf. Process. **15**(1), 56–68 (2013)
- Ojha, K., Garg, R., Singh, K.: Effect of chromium powder suspended dielectric on surface roughness in PMEDM process. Tribol. Mater. Surf. Interfaces 5(4), 165–171 (2011)
- 3. Tran, T.-H., et al.: Electrical discharge machining with SiC powder-mixed dielectric: an effective application in the machining process of hardened 90CrSi steel. Machines **8**(3), 36 (2020)
- Hong, T.T., et al.: Multi-response Optimization in PMSEDM process using Taguchi-Grey method. In: Sattler, K.-U., Nguyen, D.C., Vu, N.P., Long, B.T., Puta, H. (eds.) ICERA 2020. LNNS, vol. 178, pp. 594–606. Springer, Cham (2021). https://doi.org/10.1007/978-3-030-64719-3_65
- Al-Khazraji, A., Amin, S.A., Ali, S.M.: The effect of SiC powder mixing electrical discharge machining on white layer thickness, heat flux and fatigue life of AISI D2 die steel. Eng. Sci. Technol. Int. J. 19(3), 1400–1415 (2016)
- Kansal, H., Singh, S., Kumar, P.: Technology and research developments in powder mixed electric discharge machining (PMEDM). J. Mater. Process. Technol. 184(1–3), 32–41 (2007)
- Kung, K.-Y., Horng, J.-T., Chiang, K.-T.: Material removal rate and electrode wear ratio study on the powder mixed electrical discharge machining of cobalt-bonded tungsten carbide. Int. J. Adv. Manuf. Technol. 40(1–2), 95–104 (2009)
- Kumar, N., Ahsan, R.: Study of PMEDM efficiency on EN-31 steel using tungsten powder in dielectric fluid. Int. J. Emerg. Technol. Eng. Res. 5(5), 17–24 (2017)
- 9. Nguyen, M.C., et al.: Influence of input factors on material removal rate in PMEDM cylindrical shaped parts with silicon carbide powder suspended dielectric. In: Key Engineering Materials. Trans Tech Publ. (2020)
- Hong, T.T., et al.: Optimization of PMEDM parameters for improving MMR in machining 90CrSi steel – a Taguchi approach. In: Sattler, K.-U., Nguyen, D.C., Vu, N.P., Long, B.T., Puta, H. (eds.) Advances in Engineering Research and Application: Proceedings of the International Conference on Engineering Research and Applications, ICERA 2020, pp. 648– 657. Springer International Publishing, Cham (2021). https://doi.org/10.1007/978-3-030-64719-3_71
- Hong, T.T., et al.: Effect of process parameters on machining time in PMEDM cylindrical shaped parts with silicon carbide powder suspended dielectric. In: Materials Science Forum. Trans Tech Publ. (2021)
- Singh, B., Kumar, J., Kumar, S.: Investigation of the tool wear rate in tungsten powdermixed electric discharge machining of AA6061/10% SiCp composite. Mater. Manuf. Process. 31(4), 456–466 (2016)
- 13. Yaşar, H., Ekmekci, B.: Ti-6Al-4V surfaces in SiC powder mixed electrical discharge machining. In: Advanced Materials Research. Trans Tech Publ. (2014)
- Patel, S., Thesiya, D., Rajurkar, A.: Effect of aluminium powder concentration on powder mixed electric discharge machining (PMEDM) of inconel-718. J. Mach. Form. Technol. 8 (1/2), 29 (2016)
- Patel, S., Thesiya, D., Rajurkar, A.: Aluminium powder mixed rotary electric discharge machining (PMEDM) on Inconel 718. Aust. J. Mech. Eng. 16(1), 21–30 (2018)
- Long, B.T., Phan, N.H., Cuong, N., Jatti, V.S.: Optimization of PMEDM process parameter for maximizing material removal rate by Taguchi's method. Int. J. Adv. Manuf. Technol. 87 (5–8), 1929–1939 (2016). https://doi.org/10.1007/s00170-016-8586-4

- Huu, P.-N.: Study of the effects of process parameters on tool wear rate in powder mixed electrical discharge machining by Taguchi method. Sci. Technol. Dev. J. 20(K7), 55–60 (2017)
- Rouniyar, A.K., Shandilya, P.: Multi-objective optimization using Taguchi and grey relational analysis on machining of Ti-6Al-4V alloy by powder mixed EDM process. Mater. Today Proc. 5(11), 23779–23788 (2018)
- 19. Ibrahim, A.N., Amin, S.A., Ali, S.M.: Effect of SiC powder mixing (PMEDM) on surface residual stresses using copper and graphite electrodes (2015)
- Bhattacharya, A., Batish, A., Kumar, N.: Surface characterization and material migration during surface modification of die steels with silicon, graphite and tungsten powder in EDM process. J. Mech. Sci. Technol. 27(1), 133–140 (2013)