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Multi- Criteria Optimization of PMEDM Process Parameters for MRR, SR and TWR Using TOPSIS Method

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***Abstract*—*Multi-objective optimization in PMEDM remains a very complex problem, so it continues to cause the attention of many research. In this paper, the authors presented the results of each specific optimization and simultaneous 4 quality characteristics of electrical discharge machining using titanium powder mixed in the dielectric fluid (PMEDM). The methods is used to optimize the Taguchi method and TOPSIS. The process parameters are used to investigates: workpiece material, tool material, polarity, pulse-on time, intensity of discharge, pulse-off time, powder concentration. This approach proved successful method for improving the processing efficiency of the study subjects*.

***Keywords*—** *MRR, SR, TWR, PMEDM, Taguchi, TOPSIS*.

I. INTRODUCTION

The research results of PMEDM methods showed promise as ways to improve productivity and quality in EDM. Suitable powder is mixed in the dielectric fluid in EDM, which can lead to increased MRR, TWR and SR is reduced. Many types of powder materials have been used, such as Al, Si, SiC, W, WC, Cu, and MoS_2 [1]. They are mixed into dielectric fluid to improve the material removal rate (MRR), surface roughness (SR), and electrode wear ratio (EWR) in EDM [2]. The Taguchi method has been widely used to solve optimization problems in this field [3]. However, the Taguchi method only solves singl-characteristic response optimization problem. Recently, the Taguchi method has been combined with several other methods, such as grey relational analysis (GRA), TOPSIS, particle swarm optimization (PSO), and fuzzy logic [4]. This has contributed to improving the efficiency of the optimization problem in PMEDM.

Recent research has shown that Taguchi combined with several other methods, such as GRA, TOPSIS, and PSO, can optimize multiple quality characteristics in EDM, and results have been good. Taguchi-GRA has been used to simultaneously optimize MRR, EWR, and OC expenditures in micro-EDM of CP Ti [5]. Current, frequency, and pulse width were used in the study; current hass the greatest influence, and pulse width has the smallest effect. SR and kerf width have been optimized simultaneously in WEDM using Taguchi–GRA [6]. The results have shown that ton is the most influential process parameter on wire feed, tof, and gap voltage, respectively, and it reduced the effect to SR and keft width. In addition, the surface topography of H11 steel was significantly improved [7]. Indicators including MRR, TWR, EWR, and SR in PMEDM were optimized simultaneously by TOPSIS and GRA. The results showed that both methods in combination are a solution for multi-objective optimization in this field. Surface quality at optimum conditions has also been analyzed and evaluated, and the results have shown that the surface quality improved. The optimum results for performance, surface quality, and machining precision of AISI-304 in micro-EDM have been identified by the TOPSIS method [8]. Quality criteria, including MRR, TWR, overcut, taper angle, and circularity at entry and exit points have been optimized simultaneously. The optimal results were good, and have been verified by experiment. The TOPSIS method has been used to optimize multiple targets in both traditional machining (milling, turning, drilling, grinding), non-traditional machining (EDM, abrasive jet machining, micromachining) and many other areas [9]. TOPSIS algorithms can simultaneously optimize a large number of quality characteristics, and its optimal results are better than other methods, such as Taguchi and GRA.

The research results show the effectiveness of combining the Taguchi and TOPSIS methods for optimizing multiple targets in PMEDM. This study presents the results of simultaneous optimization of the MRR, SR, and TWR indicators in PMEDM using Ti powder. The materials used in the machining process are die steels. The Taguchi–TOPSIS method, seven process parameters, and three kinds of interactions between them were studied.

II. EXPERIMENTAL PROCEDURE

2.1. Experimental Equipments

Electrical discharge machining AG40L (Sodick, Inc. USA). The tank is made of CT3 steel with size 330x180x320 and motor shafts fitted with stirring (100 rev / min) to titanium powder are mixed in the dielectric fluid (oil HD-1) during the experiment. The workpice materials are SKD61, SKD11 and SKT4 mould steel and it is the common type used been selected to be studied. Sample size 45x30x10mm. Cu, Gr is the two materials most commonly used and are very much interested in research. Electrode is shaped circular cylinder and it has a diameter size ϕ23mm. Size of the particle size of titanium powder is 45μm were selected to mixed in dielectric fluid. Measuring the mass of the embryo before and after processing with electronic scales AJ 203 (Shinko Denshi Co. LTD - Japan), the largest mass of balance is 200g, the accuracy of the balance is 0.001g. Surface roughness (Ra, Rz, ...) were measured using a strain gauge transducer type contact SJ-301 (MITUTOYO - JAPAN).

In the current study main effects and interaction effect of the input parameters are considered as shown in Table 1. In

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the field of PMEDM, researchers have studied the effect of powder size, worrkpiece material, electrode material, current, pulse on time, pulse off time. In this study, apart from main factors the interaction terms were considered namely workpiece material x electrode material (AXB), workpiece material x powder concentration (AxG), and electrode material x powder concentration (BxG). Taguchi's orthogonal array's is used for designing the experiments. In this study seven main factors are considered out of which two factors are at two levels each having one dof. Five main factors have three levels with each having two dof. Thus the total sum of dof including main factors and interaction terms is 20. Therefore based on the 20 dof, L_{27} orthogonal array suits the present requirement as it has 26 dof. The remaining 6 dof is assigned to random error. L_{27}orthogonal array has 13 columns, and each column has 2 dof together. Coefficient A is assigned to the column 1, B in column 2, G in column 5, C in column 9, in column D 10, E in column 12, F in column 13 as shown in Table 2. The experimental results of three output responses, (MRR), (SR), and (TWR), are shown in Table 2.

TABLE 1. Input process parameters

No	Factors	Symbols	Level		
			Level 1	**Level 2**	**Level 3**
1	Workpiece material	A	SKD61	SKD11	SKT4
2	Tool material	B	Cu	Cu*	Gr
3	Polarity	C	-	+	-*
4	Pulse-on time (μs)	D	5	10	20
5	Current (A)	E	8	4	6
6	Pulse-off time (μs)	F	38	57	85
7	Powder concentrationTi(g/l)	G	0	10	20

TABLE 2. Results of experiments

Exp. No	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**MRR (mm^3/ min)**	**TWR (mm^3/ min)**	**SR (μm)**
1	SKD61	Cu	-	5	8	38	0	10.487	1.95	3.35
2	SKD61	Cu	+	10	4	57	10	8.169	2.011	3.21
3	SKD61	Cu	-[a]	20	6	85	20	3.152	1.495	2.56
4	SKD61	Cu[a]	+	10	6	85	0	10.239	4.426	3.55
5	SKD61	Cu[a]	-[a]	20	8	38	10	14.304	4.364	3.61
6	SKD61	Cu[a]	-	5	4	57	20	0.089	0.054	1.45
7	SKD61	Gr	-[a]	20	4	57	0	37.466	11.499	4.78
8	SKD61	Gr	-	5	6	85	10	23.575	9.935	3.24
9	SKD61	Gr	+	10	8	38	20	38.843	19.626	4.35
10	SKD11	Cu	+	20	4	85	0	18.882	2.01	4.16
11	SKD11	Cu	-[a]	5	6	38	10	3.857	1.179	2.05
12	SKD11	Cu	-	10	8	57	20	14.496	3.56	3.2
13	SKD11	Cu[a]	-[a]	5	8	57	0	10.608	2.25	3.35
14	SKD11	Cu[a]	-	10	4	85	10	0.32	0.132	2.04
15	SKD11	Cu[a]	+	20	6	38	20	23.577	1.495	4.57
16	SKD11	Gr	-	10	6	38	0	23.885	7.439	4.57
17	SKD11	Gr	+	20	8	57	10	59.669	14.073	4.45
18	SKD11	Gr	-[a]	5	4	85	20	17.159	5.491	2.74
19	SKT4	Cu	-[a]	10	6	57	0	1.252	0.587	2.55
20	SKT4	Cu	-	20	8	85	10	20.745	5.078	4.31
21	SKT4	Cu	+	5	4	38	20	4.374	2.902	2.46
22	SKT4	Cu[a]	-	20	4	38	0	0.198	0.277	2.26
23	SKT4	Cu[a]	+	5	6	57	10	6.782	4.715	2.89
24	SKT4	Cu[a]	-[a]	10	8	85	20	19.682	4.413	3.5
25	SKT4	Gr	+	5	8	85	0	10.649	4.537	3.23
26	SKT4	Gr	-[a]	10	4	38	10	25.97	9.041	3.24
27	SKT4	Gr	-	20	6	57	20	54.36	14.581	5.65

[a] *- Dummy treated*

2.2. TOPSIS method

The steps involved in TOPSIS are described below [10]:

Step1: The decision matrix is set to rank in matrix format as follows:

$$X=\begin{bmatrix} x_{11} & x_{12} & . & x_{1j} & x_{1n} \\ x_{21} & x_{22} & . & x_{2j} & x_{2n} \\ . & . & . & . & . \\ x_{i1} & x_{i2} & . & x_{ij} & x_{in} \\ . & . & . & . & . \\ x_{m1} & x_{m2} & . & x_{mj} & x_{mn} \end{bmatrix} \quad (1)$$

x_{ij} is the value of the optimal characteristics, where: i = 1− m is the number of results of each characteristic, and j = 1 − n is the number of characteristics to be optimized.

Step 2: Determine the normalized decision matrix with the normalized value x_{ij}' as follows:

$$x_{ij}' = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}}$$

$$X'=\begin{bmatrix} x_{11}' & x_{12}' & . & x_{1j}' & x_{1n}' \\ x_{21}' & x_{22}' & . & x_{2j}' & x_{2n}' \\ . & . & . & . & . \\ x_{i1}' & x_{i2}' & . & x_{ij}' & x_{in}' \\ . & . & . & . & . \\ x_{m1}' & x_{m2}' & . & x_{mj}' & x_{mn}' \end{bmatrix} \quad (2)$$

Step 3: The weight of the characteristics (W_j) is assigned to the normalized decision matrix as follows:

$$Y = w_j . x_{ij}'$$

$$Y=\begin{bmatrix} y_{11} & y_{12} & . & y_{1j} & y_{1n} \\ y_{21} & y_{22} & . & y_{2j} & y_{2n} \\ . & . & . & . & . \\ y_{i1} & y_{i2} & . & y_{ij} & y_{in} \\ . & . & . & . & . \\ y_{m1} & y_{m2} & . & y_{mj} & y_{mn} \end{bmatrix} \quad (3)$$

Step 4: Identify the positive ideal solutions and negative ideal solutions as follows:

Positive ideal solution:

$$A^{+} = \left\{ \left(\max_{i} y_{ij} \middle| \in J \right), \left(\min_{i} y_{ij} \middle| j \in J' \right) \middle| i = 1,2,...,m \right\} \text{ (Best criteria)}$$

$$A^{+} = \left\{ y_1^{+}, y_2^{+}, ,..., y_j^{+}, ..., y_n^{+} \right\} \quad (4)$$

Negative ideal solution:

$$A^{-} = \left\{ \left(\min_{i} y_{ij} \middle| \in J \right), \left(\max_{i} y_{ij} \middle| j \in J' \right) \middle| i = 1,2,...,m \right\} \text{(Worst criteria)}$$

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$$A^{-}=\left\{y_1^{-},y_2^{-},,...,y_j^{-},...,y_n^{-}\right\} \quad (5)$$

Where: J is associated with the positive criteria and J ′ is associated with the negative criteria.

Step 5: The n-dimensional Euclidean distance is used to calculate separation measures. Each alternative solution is separated from the ideal solution as follows:

Separation from positive ideal solution:

$$S_i^{+}=\sqrt{\sum_{j=1}^{n}\left(y_{\mathrm{ij}}-y_j^{+}\right)^2} \quad (6)$$

Separation from negative ideal solution:

$$S_i^{-}=\sqrt{\sum_{j=1}^{n}\left(y_{\mathrm{ij}}-y_j^{-}\right)^2} \qquad i = 1, 2, \ldots, m \quad (7)$$

Step 6: The relative solution to the ideal solution will be calculated by the value of C *. C* is defined as:

$$C_i^{*}=\frac{S_i^{-}}{S_i^{+}+S_i^{-}}, \quad i=1,2,...,m; 0\le C_i^{*}\le 1 \quad (8)$$

Step 7: Ranking is based on the following principle: The value of the calculated value is closer to the relative value, it will correspond to the number of its order is reduced. The value of relative closeness with the serial number of the lower ranking will provide a good performance of A_i instead.

III. RESULTS AND DISCUSSION

Step1–The decision matrix: The indicators selected for optimization in PMEDM, the assigned quality characteristics, are as follows: x_{MRR} with MRR, x_{SR} with SR, and x_{TWR} with TWR.

$$X=\begin{bmatrix} \mathrm{MRR}_1 & \mathrm{SR}_1 & \mathrm{HV}_1 \\ \mathrm{MRR}_2 & \mathrm{SR}_2 & \mathrm{HV}_2 \\ . & . & . \\ . & . & . \\ . & . & . \\ \mathrm{MRR}_{27} & \mathrm{SR}_{27} & \mathrm{HV}_{27} \end{bmatrix}$$

Step 2–The normalized decision matrix: In the course of data analysis, the normalized values are determined. This involves adjusting the values measured on different scales to a notionally common scale, and determining the normalized matrix, as shown in Eq. 5. The normalized values are showed in Table 3.

Step 3–The weighted normalized decision matrix: Based on the impact on machining yield, a priority weight has been assigned to each response. Here, the weights have been assigned to each performance characteristics, the weight of the performance characteristics are determined by experiment, and the weights used are W_{MRR} = 0.3 for MRR, W_{SR} = 0.6 for SR, W_{TWR} = 0.1 for TWR.

TABLE 3. Normalized data

Exp. No	A	B	C	D	E	F	G	Vector normalization		
								x_{i1}	x_{i2}	x_{i3}
1	SKD61	Cu	-	5	8	38	0	0.1017	0.0596	0.1962
2	SKD61	Cu	+	10	4	57	10	0.0792	0.0615	0.1880
3	SKD61	Cu	-[a]	20	6	85	20	0.0306	0.0457	0.1499
4	SKD61	Cu[a]	+	10	6	85	0	0.0993	0.1353	0.2079
5	SKD61	Cu[a]	-[a]	20	8	38	10	0.1387	0.1334	0.2114
6	SKD61	Cu[a]	-	5	4	57	20	0.0009	0.0017	0.0849
7	SKD61	Gr	-[a]	20	4	57	0	0.3633	0.3514	0.2799
8	SKD61	Gr	-	5	6	85	10	0.2286	0.3036	0.1897
9	SKD61	Gr	+	10	8	38	20	0.3766	0.5998	0.2548
10	SKD11	Cu	+	20	4	85	0	0.1831	0.0614	0.2436
11	SKD11	Cu	-[a]	5	6	38	10	0.0374	0.0360	0.1201
12	SKD11	Cu	-	10	8	57	20	0.1405	0.1088	0.1874
13	SKD11	Cu[a]	-[a]	5	8	57	0	0.1029	0.0688	0.1962
14	SKD11	Cu[a]	-	10	4	85	10	0.0031	0.0040	0.1195
15	SKD11	Cu[a]	+	20	6	38	20	0.2286	0.0457	0.2676
16	SKD11	Gr	-	10	6	38	0	0.2316	0.2273	0.2676
17	SKD11	Gr	+	20	8	57	10	0.5785	0.4301	0.2606
18	SKD11	Gr	-[a]	5	4	85	20	0.1664	0.1678	0.1605
19	SKT4	Cu	-[a]	10	6	57	0	0.0121	0.0179	0.1493
20	SKT4	Cu	-	20	8	85	10	0.2011	0.1552	0.2524
21	SKT4	Cu	+	5	4	38	20	0.0424	0.0887	0.1441
22	SKT4	Cu[a]	-	20	4	38	0	0.0019	0.0085	0.1324
23	SKT4	Cu[a]	+	5	6	57	10	0.0658	0.1441	0.1692
24	SKT4	Cu[a]	-[a]	10	8	85	20	0.1908	0.1349	0.2050
25	SKT4	Gr	+	5	8	85	0	0.1032	0.1387	0.1892
26	SKT4	Gr	-[a]	10	4	38	10	0.2518	0.2763	0.1897
27	SKT4	Gr	-	20	6	57	20	0.5271	0.4456	0.3309

[a] - *Dummy treated*

Step 4–The positive ideal solutions and negative ideal solutions: As higher MRR is desirable (*as it corresponds to Higher-is-Better, HB criterion*), the maximum value among the recorded values is considered as the positive ideal solution, and the minimum value is referred as a negative ideal solution. For the rest of the responses, like SR and TWR, lower values are desirable (*as they correspond to Lower-is-Better, LB criterion*). Hence, the minimum of the recorded values is regarded as positive ideal solution, and the maximum value represents the negative ideal solution. The positive ideal solution and negative ideal solution are determined and shown in Table 4.

TABLE 4. Positive ideal solution and negative ideal solution.

Characteristics / Criteria	MRR	TWR	SR
A+	0,1736	0,0002	0,051
A-	0,0003	0,060	0,199

Step 5–The separation measures: The separation distance is measured for both positive ideal solution and negative ideal solution using Eqs. 6 and 7, and shown in Table 5.

Step 6–The relative closeness to the ideal solution: The relative closeness index is calculated using Eq. 8, and shown in Table 5.

Step 7–Ranking: The results clearly show that the 17th run is getting the first rank and good performance of the alternative A_i (Table 5 and Figure 1).

TABLE 5. TOPSIS values using vector normalization

Exp. No	y_{i1}	y_{i2}	y_{i3}	S_i^+	S_i^-	C_i^*	Rank
1	0.031	0.006	0.118	0.1580	0.1018	0.392	23
2	0.024	0.006	0.113	0.1622	0.1039	0.391	16
3	0.009	0.005	0.090	0.1690	0.1222	0.420	11
4	0.030	0.014	0.125	0.1622	0.0921	0.362	25
5	0.042	0.013	0.127	0.1528	0.0950	0.383	9
6	0.000	0.000	0.051	0.1733	0.1592	0.479	5
7	0.109	0.035	0.168	0.1382	0.1156	0.456	21
8	0.069	0.030	0.114	0.1261	0.1128	0.472	2
9	0.113	0.060	0.153	0.1328	0.1216	0.478	12
10	0.055	0.006	0.146	0.1522	0.0929	0.379	27
11	0.011	0.004	0.072	0.1637	0.1389	0.459	3
12	0.042	0.011	0.112	0.1455	0.1076	0.425	7
13	0.031	0.007	0.118	0.1577	0.1014	0.391	22
14	0.001	0.000	0.072	0.1739	0.1401	0.446	8
15	0.069	0.005	0.161	0.1519	0.0958	0.387	19
16	0.069	0.023	0.161	0.1528	0.0873	0.363	26
17	0.174	0.043	0.156	0.1138	0.1792	0.612	1
18	0.050	0.017	0.096	0.1327	0.1216	0.478	10
19	0.004	0.002	0.090	0.1743	0.1235	0.415	14
20	0.060	0.016	0.151	0.1522	0.0883	0.367	20
21	0.013	0.009	0.086	0.1649	0.1238	0.429	13
22	0.001	0.001	0.079	0.1753	0.1330	0.431	15
23	0.020	0.014	0.102	0.1626	0.1089	0.401	17
24	0.057	0.013	0.123	0.1375	0.1054	0.434	18
25	0.031	0.014	0.113	0.1563	0.1015	0.394	24
26	0.076	0.028	0.114	0.1197	0.1178	0.496	4
27	0.158	0.045	0.199	0.1549	0.1586	0.506	6

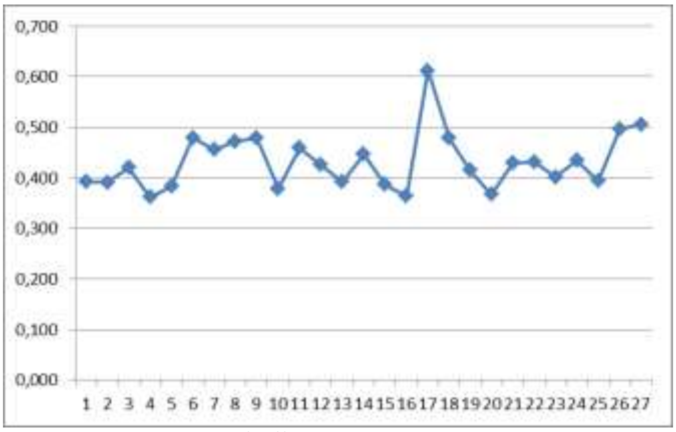

Fig. 1. Rankings of different multi criteria decision making

IV. CONCLUSIONS

Already using TOPSIS - Taguchi to optimize individual quality indicators of machining process refined by PMEDM (MRR, TWR, R_a). When the TOPSIS method is combined with the Taguchi method, we obtain: a number of optimized process parameters, reduced cost and time of the experiment, and the multi-objective optimization problem is solved simply. The results of multi-criteria optimization in PMEDM using powder Ti show that 17th running receives the 1st rank. Hence, the corresponding input parameters such as SKD11 workpiece material, Gr electrode material, positive electrode polarity, ton = 20 μs, I= 6 A, tof = 57 μs, and powder concentration of 10 g/l were found to be the optimum combination.

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