International Journal of Data and Network Science 2 (2018) 109–119

Contents lists available at GrowingScience

International Journal of Data and Network Science

homepage: www.GrowingScience.com/ijds

Multi-response optimization of process parameters for powder mixed electro-discharge machining according to the surface roughness and surface micro-hardness using Taguchi-TOPSIS

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C H R O N I C L E

Article history:
Received: June 1, 2018
Received in revised format: June 18, 2018
Accepted: September 14, 2018
Available online:
September 14, 2018

Keywords:
Taguchi
TOPSIS
EDM
PMEDM
S/N ratio
Titanium

A B S T R A C T

In this study, the efficiency of integration between Taguchi and TOPSIS in multi-response optimization of powder mixed electrical discharge machining (PMEDM) process was evaluated. The input parameters, such as workpiece and tool electrode material, polarity, pulse on time (ton), pulse off time (toff), Current (I) and powder concentration have been selected to optimize two responses; namely surface roughness (Ra) and surface hardness (HV). The results show that titanium powder mixed dielectric fluid improves multi-response optimization efficiency in PMEDM. In addition, machining conditions, such as tool electrode material, powder concentration, pulse on time, polarity, current density, A×G and B×G interactions play a very important role on S/N ratio of C* whereby powder concentration has the strongest influence. TOPSIS -Taguchi is a potential method for multi-response optimization in PMEDM. However, the optimal results using ANOVA analysis show that there is a necessity to have more studies in TOPSIS-Taguchi to improve the integration efficiency between two methods for optimizing multiple responses in PMEDM.

1. Introduction

Powder mixed electrical discharge machining (PMEDM) recently has shown its potential for concurrent improving material removal rate and surface quality. However, this method has a large amount of machining parameters and it still remains challenges, such as the uniformity of particles in dielectric fluid, particle trajectory in discharge gap, shape and physical properties of powder material, etc. It leads to many difficulties for optimizing PMEDM process, especially in multi-response optimization.

Taguchi has been widely applied to deal with responses affected by many parameters (Ahmed & Arora, 2017). However, Taguchi can only be an effective approach for optimizing process performance with a single quality response. Nowadays, TOPSIS-Taguchi integration is commonly used to solve multi-re-

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doi: 10.5267/j.ijdns.2018.9.001

sponse optimization problems in many technical fields, such as: information technology; electrical, electronic and mechanical engineering, etc. This combination can reduce experimental costs and increase optimization efficiency. TOPSIS is used for multi-response optimization in both traditional machining (milling, turning, drilling, grinding, etc.), non-traditional machining (EDM, water jet machining, etc.) and many other fields (Shukla et al. 2017; Mohapatraa & Sahooa, 2018). TOPSIS's algorithms allow to optimize a large number of responses with high quality of optimal results. In multi-response optimization, TOPSIS is a very simple method and easy to implement (Gadakh et al., 2012). Simultaneously, this method is also allowed to use both quantitative and qualitative input parameters. Therefore, it is a solution that can solve multi-response optimization problems more objectively. Many results of TOPSIS-Taguchi optimization method in EDM were shown. It can be used for optimizing material removal rate, electrode wear and surface roughness responses in PMEDM (Tripathy & Tripathy, 2017). Material removal rate (MRR), surface roughness and fractal dimension are also responses to optimize when machining AISI D2 tool steel (Prabhu & Vinayagam, 2016; Zerti et al., 2018). The results showed that voltage has the strongest effect (≈42.42 %) and pulse on time has the smallest effect (≈11.13%). Seven multiple responses in electrical discharge machining have been optimized using TOPSIS-Taguchi with a significant increase in machining efficiency (Manivannan & Kumar, 2017; Khanna et al., 2015; Manivannan & Kumar, 2016). Besides, many other methods have also been used as Artificial neural network, Response surface methodology, and Taguchi's combination with other methods (GRA, MOORA-PCA, VIKOR, multiple response signal-to-noise, weighted signal-to-noise,...) for multi-target optimization in EDM (Tirumala et al., 2018; Munmun & Kalipad, 2017; Bhaumik & Maity, 2017; Nayaka et al., 2017; Munmun & Kalipada, 2017; Dey & Chakraborty, 2015). However, Taguchi-TOPSIS and Taguchi-GRA are the most commonly used (Kumar et al., 2018; Zerti et al., 2018; Mohapatraa et al., 2017). Dastagiri et al. (2016) have shown that TOPSIS-Taguchi is more effective than Taguchi-GRA in multi-response optimization of PMEDM.

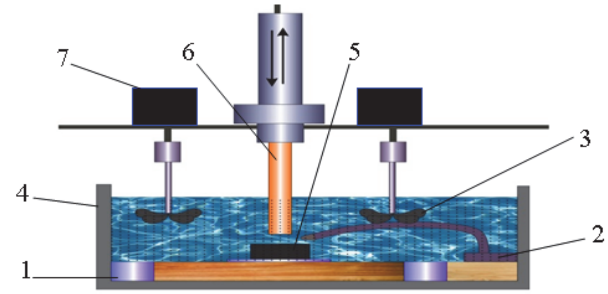
In this study, the authors have made the optimization of process parameters in PMEDM using titanium powder for die steels, surface quality after PMEDM has been evaluated by the two indicators SR and HV. In addition, the topography and composition of the chemical elements on the surface of the workpiece at optimum conditions are also analyzed.

2 Materials

In this study, a CNC high precision EDM machine (Sodick, Inc. USA) was used to perform the experiments. An external circulation system is shown in Fig. 1. Two stirrers rotate in opposite directions at a speed of 200 rpm to prevent the deposition of titanium powder at the bottom of the tank during the experiment. Dielectric fluid is pumped at a flow of 600 l/h to discharge gap. In order to prevent the debris entering the machining area, magnets are used to attract them.

This study utilised (45 × 27 × 10) mm^3 samples, 23 mm tool electrode diameter with 35 mm length. Dielectric fluid is HD-1 oil which widely used for EDM machine in Vietnam recently. Titanium powder (45 µm size) was mixed with the dielectric fluid in different concentrations. Experimental parameters are given in Table 1.

After machining, the samples were cleaned and later dry. Surface roughness (R_a) was measured using a profilometer (Mitutoyo Surftest SJ-301 - Japan) in a 5 mm measured length. Microhardness tester (model Indenta Met 1106) from Buehler, USA was used to measure microhardness of the surface. A 0.005 HV measuring range for measuring the specimen surface in a perpendicular using 50 g penetration load. SEM images were captured by a scanning electron microscope (model Jeol 6490 Jed 2300, Japan). And chemical composition of EDMed surface was analyzed with the use of an energy-dispersive X-ray spectroscopy (model PDA 7000, Switzerland). The measured repetition on each sampe is three and average results were calculated.



1- Magnets 2- Pump 3- Stirrer 4- Machining tank 5 -Workpiece
6- Electrode 7- Motor

Fig 1. Schematic line diagram

Table 1
Investigated parameters

No.	Investigated parameters	Symbol	Level			DOF
			Level 1	Level 2	Level 3	
1	Workpiece material	A	SKD61	SKD11	SKT4	2
2	Tool electrode material	B	Cu	Cu[a]	Gr	1
3	Polarity	C	-	+	-[a]	1
4	Pulse on time (μs)	D	5	10	20	2
5	Current density (A)	E	8	4	6	2
6	Pulse off time (μs)	F	38	57	85	2
7	Titanium powder concentration (g/l)	G	0	10	20	2
8	Interaction between workpiece material and tool electrode material	A×B	-	-	-	2
9	Interaction between workpiece material and powder concentration	A×G	-	-	-	4
10	Interaction between tool electrode material and powder concentration	B×G	-	-	-	2
11	Total					20

([a] - *Dummy treated)*

3. Methods

Experimental design methodology: Taguchi method is used to design the experiments. The advantage of this method is a minimum number of the experiments but a maximum amount of input parameters. In addition, the input parameters are both quantitative and qualitative. Based on orthogonal matrices, an experimental matrix is designed and the identification of the experimental matrix is very simple. A kind of the experimental matrix is selected. It bases on the number of input parameters, pairs of interactions between the parameters and the degree of freedom (DOF) of the parameters. In this study, seven input parameters and three pairs of these interactions are studied (Tab. 1). So, Taguchi matrix L27 is used: values A, B, C, D, E, F and G are assigned to column 1, 2, 9, 10, 12, 13 and 5, respectively. The experimental results of surface roughness R_a and surface hardness HV are shown in Table 2. The Taguchi method uses the signal-to-noise (S/N) ratio to optimize the results, and S/N ratio is determined by the Eq. (1):

$$(S/N)_{HB} = -10\log(MSD_{HB}) \quad (1)$$

where:

$MSD_{HB} = \frac{1}{r}\sum_{i=1}^{r}\left(\frac{1}{y_i^2}\right)$: Average squared deviation

r: Number of tests in an experiment (number of repetitions)
y_i: Experimental values

Table 2
Experimental results

Exp.	A	B	C	D	E	F	G	R_a (μm)	Hardness (HV)
1	SKD61	Cu	-	5	8	38	0	3.35	506.7
2	SKD61	Cu	+	10	4	57	10	3.21	658.96
3	SKD61	Cu	-[a]	20	6	85	20	2.56	581.6
4	SKD61	Cu[a]	+	10	6	85	0	3.55	496.68
5	SKD61	Cu[a]	-[a]	20	8	38	10	3.61	828.92
6	SKD61	Cu[a]	-	5	4	57	20	1.45	629.84
7	SKD61	Gr	-[a]	20	4	57	0	4.78	544.58
8	SKD61	Gr	-	5	6	85	10	3.24	748.42
9	SKD61	Gr	+	10	8	38	20	4.35	626.18
10	SKD11	Cu	+	20	4	85	0	4.16	509.72
11	SKD11	Cu	-[a]	5	6	38	10	2.05	679.54
12	SKD11	Cu	-	10	8	57	20	3.20	664.2
13	SKD11	Cu[a]	-[a]	5	8	57	0	3.35	546.02
14	SKD11	Cu[a]	-	10	4	85	10	2.04	679.2
15	SKD11	Cu[a]	+	20	6	38	20	4.57	655.18
16	SKD11	Gr	-	10	6	38	0	4.57	469.82
17	SKD11	Gr	+	20	8	57	10	4.45	907.64
18	SKD11	Gr	-[a]	5	4	85	20	2.74	683.52
19	SKT4	Cu	-[a]	10	6	57	0	2.55	530.72
20	SKT4	Cu	-	20	8	85	10	4.31	624.58
21	SKT4	Cu	+	5	4	38	20	2.46	631.68
22	SKT4	Cu[a]	-	20	4	38	0	2.26	468.04
23	SKT4	Cu[a]	+	5	6	57	10	2.89	544.38
24	SKT4	Cu[a]	-[a]	10	8	85	20	3.50	613.84
25	SKT4	Gr	+	5	8	85	0	3.23	445.44
26	SKT4	Gr	-[a]	10	4	38	10	3.24	681.22
27	SKT4	Gr	-	20	6	57	20	5.65	832.66

Multi-response optimization methodology: TOPSIS is a very popular method and provides a more realistic approach used in multi-response optimization. This method can pick out the best response (the most ideally response) from the positive responses and the worst response (the most negative response) from the negative responses. The steps taken in the TOPSIS method are described as follows:

Step 1: Arranging the selected responses in matrix form:

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

where:
$x_{11}, x_{12}, \dots x_{1n}$ - Selected responses
$x_{11}, x_{21}, \dots x_{m1}$ - Values of the first response at different levels
n - Amount of the selected responses
m - Amount of the values from one response

Step 2: Standardizing the matrix, convert the responses to non-dimensional form to make comparisons between response values. The standardized matrix is established through standardized values x'_{ij} ($0 \le x'_{ij} \le 1$):

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

$$X' = \begin{bmatrix} x'_{11} & x'_{12} & . & x'_{1j} & x'_{1n} \\ x'_{21} & x'_{22} & . & x'_{2j} & x'_{2n} \\ . & . & . & . & . \\ x'_{i1} & x'_{i2} & . & x'_{ij} & x'_{in} \\ . & . & . & . & . \\ x'_{m1} & x'_{m2} & . & x'_{mj} & x'_{mn} \end{bmatrix} \tag{3}$$

Step 3: Assigning weights of the selected responses to the standardized matrix defined as follows:

$$Y = w_j . x'_{ij}$$

$$Y = \begin{bmatrix} y_{11} & y_{12} & . & y_{1j} & y_{1n} \\ y_{21} & y_{22} & . & y_{2j} & y_{2n} \\ . & . & . & . & . \\ y_{i1} & y_{i2} & . & y_{ij} & y_{in} \\ . & . & . & . & . \\ y_{m1} & y_{m2} & . & y_{mj} & y_{mn} \end{bmatrix} \tag{4}$$

W_j- Weight of the responses

Y - Standardized matrix of the assigned responses

Step 4: Determining the best solution and the worst solution:
The best solution:

$$A^{+} = \left\{ \left(\max_i y_{ij} \middle| \in J \right), \left(\min_i y_{ij} \middle| j \in J' \middle| i = 1,2,...,m \right) \right\}$$ (the best response)

$$A^{+} = \left\{ y_1^{+}, y_2^{+}, ,..., y_j^{+}, ..., y_n^{+} \right\} \tag{5}$$

The worst solution:

$$A^{-} = \left\{ \left(\min_i y_{ij} \middle| \in J \right), \left(\max_i y_{ij} \middle| j \in J' \middle| i = 1,2,...,m \right) \right\}$$ (the worst response)

$$A^{-} = \left\{ y_1^{-}, y_2^{-}, ,..., y_j^{-}, ..., y_n^{-} \right\} \tag{6}$$

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

y_j^{+} - the best value of x_j

y_j^{-} - the worst value of x_j

Step 5: The individual distances are calculated using Euclidean distance with n dimensions. Each distance comes from the following ideal problem:
Separation from positive ideal solution:

$$S_i^+ = \sqrt{\sum_{j=1}^{n}\left(y_{\mathrm{ij}} - y_j^+\right)^2}\text{ , for i = 1, 2, …, m} \tag{7}$$

Separation from negative ideal solution:

$$S_i^- = \sqrt{\sum_{j=1}^{n}\left(y_{\mathrm{ij}} - y_j^-\right)^2}\text{ , for i = 1, 2, …, m} \tag{8}$$

Step 6: The nearest distance to the ideal value is calculated. The nearest distance of the alternative value A_i with respect to A^+ is defined as follows:

$$C_i^* = \frac{S_i^-}{S_i^+ + S_i^-}, \quad i = 1, 2, ..., m; 0 \le C_i^* \le 1 \tag{9}$$

Step 7: The arrangement is done by values close to C^*. The higher C^* value provides a better quality of A_i solution.

4. Results

Optimization results using TOPSIS-Taguchi:

Step 1: Arranging the selected responses in matrix form by Eq. (10).

$$x = \begin{bmatrix} R_{a11} & HV_{12} \\ R_{a21} & HV_{22} \\ . & . \\ . & . \\ . & . \\ R_{a271} & HV_{272} \end{bmatrix} \tag{10}$$

Step 2: Standardizing the matrix. The conversion values are determined by Eq. (3). The result is shown in Table 3.

Step 3: Determining the values of y_{11} and y_{12}. Based on experiences, the weight of the Ra and HV responses is chosen: $W_{Ra} = 0.4$ and $W_{HV} = 0.6$ and response values are given in Table 5 by Eq. (4).

Step 4: Determining the best solution and the worst solution: From Eq. (5) and Eq. (6), the best solution and the worst solution are determined. HV is described: the higher the better, while R_a is described: the smaller the better. So, the smallest value is the best solution and the biggest value is the worst solution. The results are shown in Table 4.

Step 5: Determining the values of S_i^+ and S_i^- [Table 5] based on Eq. (7) and Eq. (8).

Step 6: Determine the value of C_i^* [Table 5] based on Eq. (9).

Step 7: Arranging the C^* value in the order shown in Table 5. The results shown that: Experiment 6 provides the best surface quality.

Table 3
Standardized data

Exp.	A	B	C	D	E	F	G	Conversion Vector X_{Rai1}	X_{HVi2}
1	SKD61	Cu	-	5	8	38	0	0.183	0.154
2	SKD61	Cu	+	10	4	57	10	0.176	0.201
3	SKD61	Cu	-[a]	20	6	85	20	0.140	0.177
4	SKD61	Cu[a]	+	10	6	85	0	0.194	0.151
5	SKD61	Cu[a]	-[a]	20	8	38	10	0.198	0.252
6	SKD61	Cu[a]	-	5	4	57	20	0.079	0.192
7	SKD61	Gr	-[a]	20	4	57	0	0.262	0.166
8	SKD61	Gr	-	5	6	85	10	0.177	0.228
9	SKD61	Gr	+	10	8	38	20	0.238	0.191
10	SKD11	Cu	+	20	4	85	0	0.228	0.155
11	SKD11	Cu	-[a]	5	6	38	10	0.112	0.207
12	SKD11	Cu	-	10	8	57	20	0.175	0.202
13	SKD11	Cu[a]	-[a]	5	8	57	0	0.183	0.166
14	SKD11	Cu[a]	-	10	4	85	10	0.112	0.207
15	SKD11	Cu[a]	+	20	6	38	20	0.250	0.199
16	SKD11	Gr	-	10	6	38	0	0.250	0.143
17	SKD11	Gr	+	20	8	57	10	0.243	0.276
18	SKD11	Gr	-[a]	5	4	85	20	0.150	0.208
19	SKT4	Cu	-[a]	10	6	57	0	0.140	0.162
20	SKT4	Cu	-	20	8	85	10	0.236	0.190
21	SKT4	Cu	+	5	4	38	20	0.135	0.192
22	SKT4	Cu[a]	-	20	4	38	0	0.124	0.142
23	SKT4	Cu[a]	+	5	6	57	10	0.158	0.166
24	SKT4	Cu[a]	-[a]	10	8	85	20	0.192	0.187
25	SKT4	Gr	+	5	8	85	0	0.177	0.136
26	SKT4	Gr	-[a]	10	4	38	10	0.177	0.207
27	SKT4	Gr	-	20	6	57	20	0.309	0.253

Table 4
The best solution and the worst solution

	R_a	HV
A+	0.0317	0.1105
A-	0.1237	0.0542

Optimal results based on S/N ratio: The study utilized a Taguchi's experimental matrix to investigate seven parameters at a third level. There must be 3^7 experiments to determine exactly the optimal conditions under the traditional method. However, in the Taguchi's experimental matrix, there are only 27 experiments. It is possible to get an optimal value in the rest of the experiments. Therefore, it need to base on the S/N ratio in Taguchi's analysis to find the optimal combination. A higher S/N ratio of C^* leads to have a better result. The S/N value of C^* is calculated by Eq. (2) and shown in Table 2. The results showed that: electrode material (F = 28.8), pulse on time (F = 13.58), powder concentration (F = 22.47), A×G (F = 7.58) and B×G (F = 5.14) strongly influence on the S/N ratio of C^* (Table 4). Parameters, such as: workpiece material, polarity, pulse off time, current density and A×B, are negligible effect on the S/N ratio of C^*. Powder concentration has the strongest influence and workpiece material has the weakest influence. Fig. 2 and Fig. 3 show the influence of machining conditions and some pairs of interactions between them on the S/N ratio of C^*. The optimal value can be achieved when using: SKT4 workpiece material, copper electrode, negative electrode, I = 4 A, t_{on} = 5 µs, t_{of} = 57 µs, and 10 g/l powder concentration. The optimal values of the responses are determined by Eq. (11).

$$(SR, HV)_{optimal} = B_1 + D_1 + G_2 + B_1 \times G_2 + A_2 \times G_2 - 4 \times \bar{T} \tag{11}$$

Table 5
The conversion value calculated from step 3 to step 7

Exp.	x_{Rai1}	x_{HVi2}	y_{i1}	y_{i2}	S_i^+	S_i^-	C_i^*	Ranking	S/N
1	0.183	0.154	0.07332	0.09255	0.045	0.214	0.825	18	-1.67
2	0.176	0.201	0.07026	0.12036	0.040	0.295	0.881	11	-1.10
3	0.140	0.177	0.05603	0.10623	0.025	0.289	0.921	5	-0.71
4	0.194	0.151	0.07770	0.09072	0.050	0.199	0.799	20	-1.95
5	0.198	0.252	0.07901	0.15141	0.063	0.380	0.859	14	-1.32
6	0.079	0.192	0.03174	0.11504	0.005	0.370	0.988	**1**	-0.10
7	0.262	0.166	0.10462	0.09947	0.074	0.175	0.703	26	-3.06
8	0.177	0.228	0.07091	0.13670	0.047	0.344	0.879	13	-1.12
9	0.238	0.191	0.09521	0.11437	0.064	0.236	0.788	22	-2.07
10	0.228	0.155	0.09105	0.09310	0.062	0.176	0.740	25	-2.62
11	0.112	0.207	0.04487	0.12412	0.019	0.359	0.950	3	-0.45
12	0.175	0.202	0.07004	0.12132	0.040	0.298	0.882	10	-1.09
13	0.183	0.166	0.07332	0.09973	0.043	0.232	0.844	16	-1.47
14	0.112	0.207	0.04465	0.12406	0.019	0.359	0.951	2	-0.44
15	0.250	0.199	0.10003	0.11967	0.069	0.249	0.783	23	-2.12
16	0.250	0.143	0.10003	0.08581	0.073	0.137	0.654	27	-3.69
17	0.243	0.276	0.09740	0.16578	0.086	0.413	0.828	17	-1.64
18	0.150	0.208	0.05997	0.12485	0.032	0.328	0.912	6	-0.80
19	0.140	0.162	0.05581	0.09694	0.028	0.268	0.907	7	-0.85
20	0.236	0.190	0.09433	0.11408	0.063	0.236	0.790	21	-2.05
21	0.135	0.192	0.05384	0.11538	0.023	0.316	0.933	4	-0.60
22	0.124	0.142	0.04947	0.08549	0.031	0.265	0.896	8	-0.95
23	0.158	0.166	0.06325	0.09943	0.033	0.255	0.884	9	-1.07
24	0.192	0.187	0.07661	0.11212	0.045	0.259	0.852	15	-1.39
25	0.177	0.136	0.07070	0.08136	0.049	0.197	0.802	19	-1.92
26	0.177	0.207	0.07091	0.12443	0.042	0.306	0.880	12	-1.11
27	0.309	0.253	0.12366	0.15209	0.101	0.354	0.778	24	-2.18

Table 4
ANOVA of the S/N ratio of C^*

Source	DOF	SS	V	F	P	Contribution
A	2	0.2680	0.2777	1.21	0.363	6
B	1	3.2324	3.2324	28.08	0.002	3
C	1	0.6058	0.6058	5.26	0.062	5
D	2	3.1275	3.1275	13.58	0.006	2
E	2	0.9704	0.9704	4.21	0.072	4
F	2	0.1176	0.1176	0.51	0.624	7
G	2	4.1915	5.1751	22.47	0.002	1
A×B	2	0.1365	0.1365	0.59	0.582	-
A×G	4	3.4904	3.4904	7.58	0.016	-
B×G	2	1.1837	1.1837	5.14	0.050	-
Error	6	0.6908	0.6908	-	-	-
Total	26	18.0146	-	-	-	-

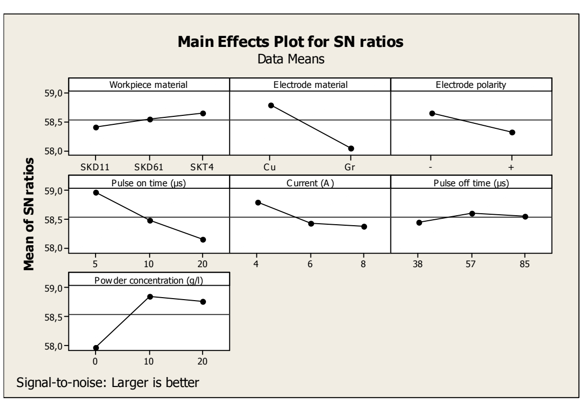


Fig. 2. Influence of machining conditions on the S/N ratio of C^*

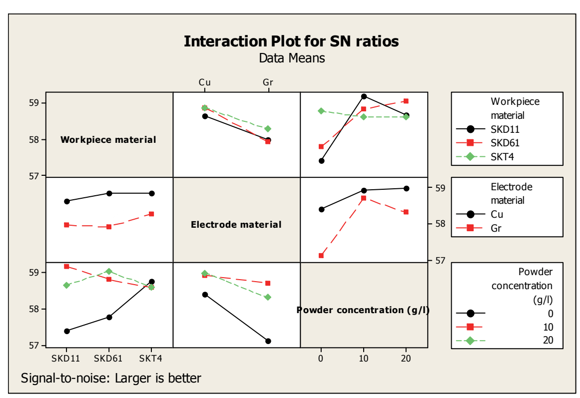


Fig. 3. Influence of interactive pairs on the S/N ratio of C^*

5. Discussion

The optimal results of TOPSIS-Taguchi and ANOVA analysis in Table 5 show that optimal values (Ra = 1.45 µm and HV = 649,5 HV) can be achieved for SKD61 when using negative polarity of tool electrode, t_{on} = 5 µs, I = 4 A, t_{off} = 57 µs at 20 g/l powder concentration. The result shows that: compared to surface hardness of SKD61 steel (≈ 506.5 HV), the hardness of EDMed surface at the optimal parameter is significantly increased (≈ 28.2 %) due to the presence of titanium on the workpiece surface (Fig. 4). Simultaneously, topography of EDMed surface at the optimal condition is characterized by small and uniform craters (Fig. 5) which facilitate for storing lubricant on the surface. Both surface hardness and topography enhance the working ability of the mold surface. The optimal results using TOPSIS-Taguchi have been greatly improved (R_a decreases 5.29 % and surface hardness increases 34.6 %) than the optimal results based on the S/N ratio. However, the set of machining parameters and the optimum values of these two methods are different, especially the difference in the level of optimal powder concentration which is the most important parameter of PMEDM. It has caused many difficulties in determining optimal conditions.

Table 5
Comparison of optimization results using TOPSIS-Taguchi and ANOVA analysis

Response	Taguchi-TOPSIS Machining parameters	Result	ANOVA Machining parameters	Result	Difference (%)
R_a (µm)	SKD61, Cu (-), t_{on} = 5 µs, I = 4A, t_{off} = 57 µs, 20 g/l	1.45	SKT4, Cu (-), t_{on}= 5 µs, I = 4 A, t_{off} = 57 µs, 10 g/l	1.37	-5.29
HV(HV)		629.84		847.79	34.60

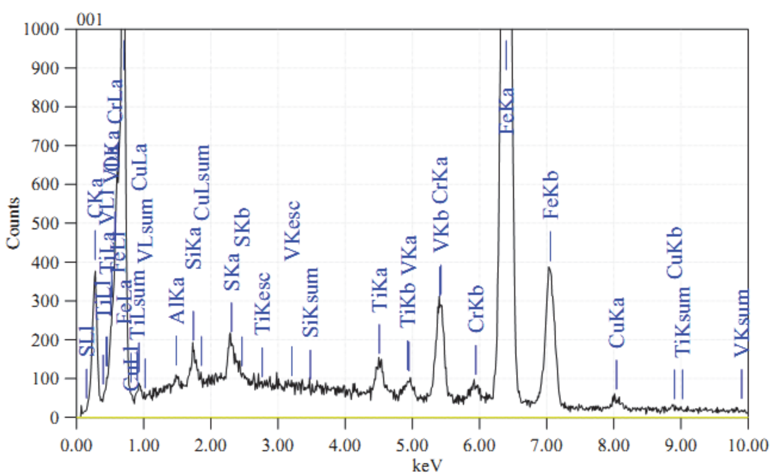
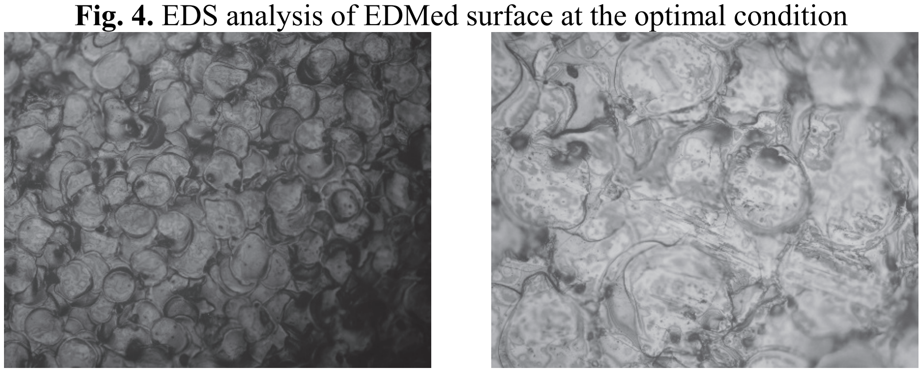


Fig. 4. EDS analysis of EDMed surface at the optimal condition



a) Magnification 200X *b) Magnification 500X*

Fig. 5. SEM image of EDMed surface at the optimal condition

6. Conclusions

The study has evaluated the suitability of Topsis-Taguchi for multi-response optimization in machining mold materials (SKD61, SKD 11 and SKT4) using titanium powder mixed electrical discharge machining. It can be revealed that the machining parameters such as powder concentration, tool electrode material, pulse on time, A×G and B×G interactions play an important role to the S/N ratio of C^*, whereby the powder concentration has the strongest influence. Surface roughness R_a = 1.45 μm and microhardness 629.84 HV are optimal results using Topsis-Taguchi with parameters to be as follows: SKD61 workpiece material, copper electrode, negative polarity, t_{on} = 5 μs, I = 4 A, t_{off} = 57 μs and 20 g/l powder concentration. However, other optimal results (2.34 μm R_a and 904,96 HV microhardness) are predicted by ANOVA analysis using other parameters, including: SKT4 workpiece material, copper electrode, negative polarity, t_{on} = 5 μs, I = 4 A, t_{off} = 57 μs and 10 g/l powder concentration.

TOPSIS, with a simple calculating method integrated with Taguchi, can be used to optimize a large number of the responses thereby minimizing the number of the experiments. It leads to reduction of material costs and processing time. However, there are some differences between the optimal results of C* using Topsis-Taguchi and using ANOVA analysis. Therefore, there is a need to have more future works to enhance the suitability of Topsis and Taguchi for multi-response optimization in PMEDM.

Acknowledgement

This research is funded by Vietnam National Foundation for Science and Technology Development (NAFOSTED) under grant number 107.01-2017.303.

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