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PREDICTION OF MACHINING PERFORMANCES IN POWDER MIXED ELECTRO-DISCHARGE MACHINING TO PROCESS SKD61 STEEL BY RESPONSE SURFACE METHODOLOGY

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Abstract. In electro-discharge machining (EDM) with mixing powder, it is called powder mixed electro-discharge machining (PMEDM), then machining performances- i.e. material removal rate(MRR) and tool wear rate (TWR) has great significance in evaluating the effectiveness and machining accuracy of the machining method. Therefore, in this study, response surface methodology (RSM) was utilized for estimating functions of process variables {comprising peak current (I_p), pulse on time (T_{on}), and powder concentration (C_p)} for the machining performances for processing SKD61 steel during EDM process with tungsten compound powder. Box-Behnken matrix was utilized for designing and conducting a series of empirical trials. Analysis of variance (ANOVA) was applied to evaluate the adequate of predictive models. The outcomes reveal that the predicted models of MRR and TWR have a high precision with R^2 values of MRR and TWR being 99.2% and 99.11%, respectively. The error comparison of the predictive and empirical values for the confirmed experiments is less than 5%, this once again consolidates that the developed models' accuracy. These development models can efficiently prognosticate the desired machining performances of the PMEDM method for processing SKD61 steel.

Keywords: EDM, PMEDM, tungsten compound powder, MRR; TWR.

1. INTRODUCTION

The electro-discharge machining (EDM) method emerges as a potential machining method for cut-difficult materials and ensures the execution of complex shapes [1,2]. This is possible because the EDM method works on the mechanism of spark discharge to erode the material [3]. However, since this is a thermal method for material removal, the defects left on the machined surface are significant [4]. In addition, another factor that should also be considered, is the low machining efficiency. This has hindered the quality of the product, and it has also increased the cost of the product. In recent years, powder-mixed electrical discharge solution has been of interest, it is called powder-mixed discharge machining (PMEDM). This method has overcome some of the disadvantages mentioned above. The aim of this solution is to improve the discharge channel, make the discharge channel more efficient, and simultaneously improve surface defects and the machining performances. The mechanism of powder-mixed EDM is depicted as shown in Fig. 1.

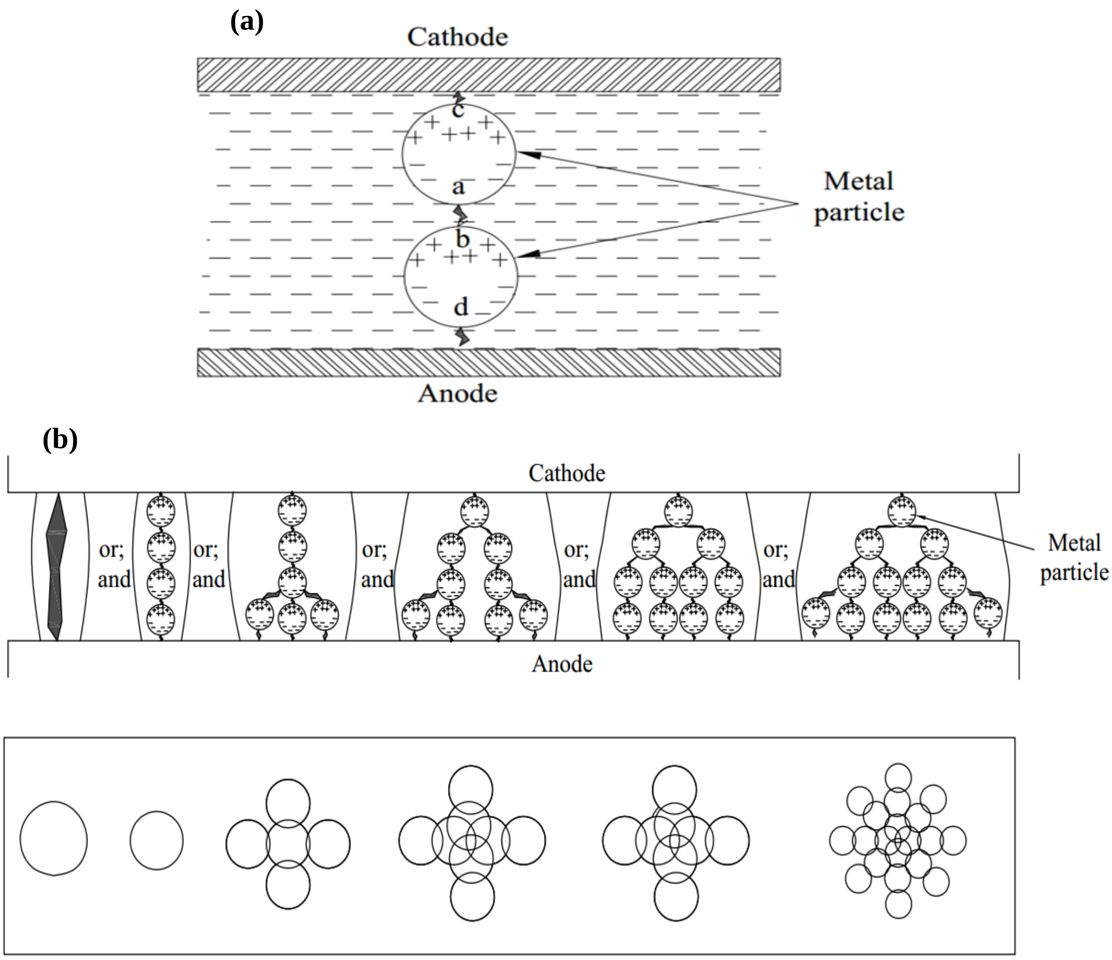

Figure 1. (a). The spark discharge is created by the conductive powder [19], (b). Proposing discharge process with the conductive powder in PMEDM.

Over the past four decades, many research works in PMEDM with different powders have been carried out. Working on the influence of powders (including C, Fe, Cu, and Al) on discharge properties, machining efficiency, and surface quality was firstly reported in 1981 by

Erden et al. [5]. Subsequently, numerous studies on different powders [1,4], such as Si, SiC, Gr, Mo, Cr, Ti, TiC, W, Al, Ni, and C have been reported on the impact on the machining properties and surface quality. The types of workpiece materials were studied, including SS304, Ti64, AISI D2 steel, AISI W1 steel, SKD61 steel, and AISI P20 steel, which are commonly used in industries.

In regard to SKD61 steel, although there are some studies on this material with different powders. For instance, surface attributes of SKD61 steel, including surface roughness and thickness of recast layer, were explored in condition EDM with added Al and surfactant powders [6]. The result revealed that the impact of Al and surfactant powders on surface roughness (SR) and thickness of recast layer be meaningful in improving. Another study about the SKD61 steel with Cr and Al added to various dielectrics was reported in [7]. This study has disclosed that these factors such as peak current, pulse on time, types of dielectric, grain size, and the ratio of Al and Cr powders, have influenced the material removal rate (MRR), the tool wear rate (TWR), SR, and microhardness (MH). Subsequently, the SKD61 steel with Mo powder added to dielectrics in rotation electrode states was explored about SR, infiltration of Mo element, formation of carbide phases, and MH [8]. The results showed that there was a favorable modification and improvement for the application in the surface manufacturing industry. Recently, The authors [9–11] considered the effect of tungsten carbide powder. These studies have reported relatively comprehensive surface properties with tungsten carbide powder such as SR, MH, micro-cracks, the change in chemical composition, and the formation of phase organization in surface layers, and have shown the positive and negative influence of this powder. However, these works have not considered the machining performances including MRR and TWR, and have not shown the multi-objective optimal parameter for the desire to maximize MRR and minimize TWR. But these are very necessary for the sector of industrial manufacturing.

Hence, this study focuses on developing the predicted models of materials removal rate and tool wear rate by utilizing the response surface method (RSM) for the machining of SKD61 steel by EDM process with adding tungsten compound powder. From the obtained prediction models, the impact of crucial process parameters on the machining performances can be analyzed and evaluated. Additionally, this helps technology and research people to make the appropriate choice for a specific application purpose in the manufacturing sector.

2. EXPERIMENTAL METHOD AND PROCEDURE

2.1. Materials and processes

As considered above, in the hot stamping die manufacturing industry, SKD61 tool steel is very popular. All SKD61 steel specimens (Fig.2b) were machined to acquire the dimensions of 45x19 mm (height x diameter). The compositional chemistry of SKD61 tool steel is to consist of 0.38C, 1V, 1Si, 0.4Mn, 1.25Mo, 5Cr, and balanced Fe (in % wt.) [12]. An EDM machine (CNC-460 EDM of Aristech brand) was taken on the role of implementing the trials, and using electrode copper (99%Cu) with reverse polarity as a tool, as shown Figs.2a and 2c. Tungsten compound powder (Code: WC-727-6; its titular chemistry component is 82.5W-11.9Co-5.56C- 0.02Fe-0.02 other composition (wt.%), and the particle size of smaller than 31μm) from Praxair Surface Technologies (Fig.2e) was mixed into the working oil tank which contained the oil EDM fluid 2 of Shell Company (Fig.2d).

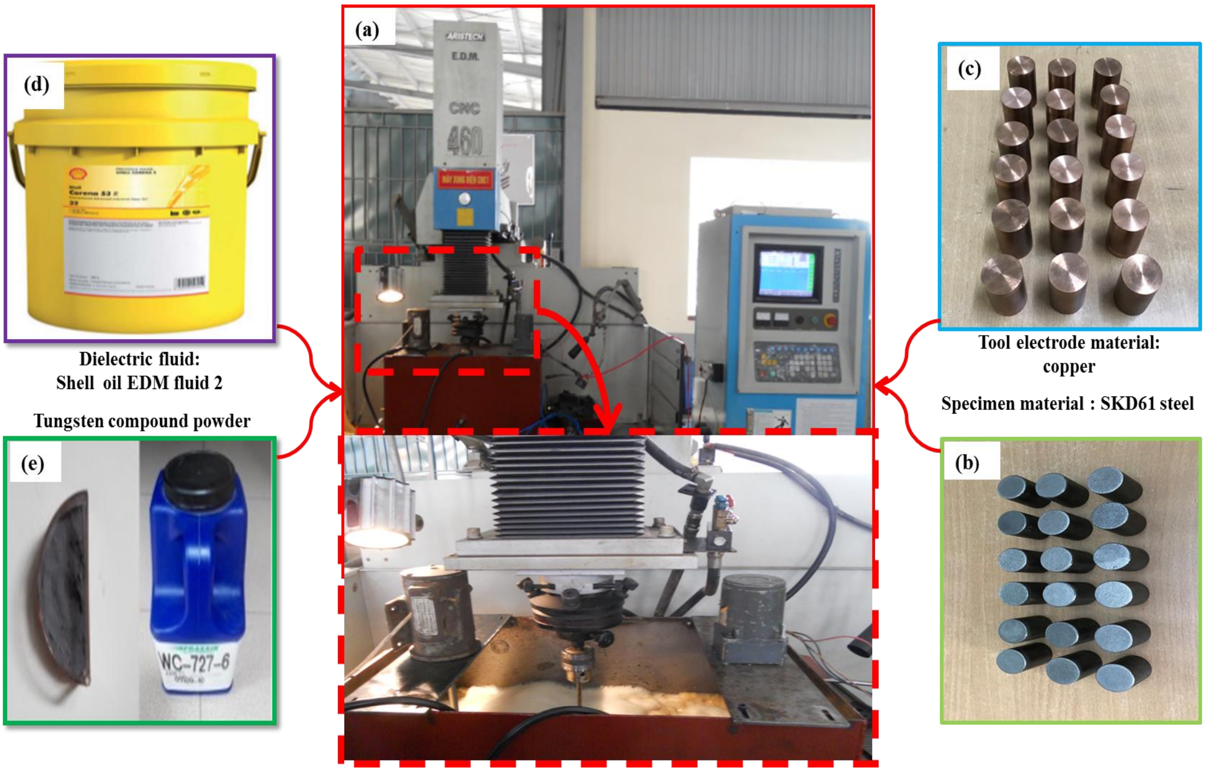

Figure 2. (a) EDM CNC-460 machine, (b) the specimen material, (c) the tool electrode material, (d) the dielectric liquid, and (e) the powder.

2.2. Empirical procedure

Criteria and basis for selection of technological parameters: In EDM process, for electrical parameters, based on the literature overview, the configuration of the controller settings of the electrical discharge machine, and through pilot experiments. The electrical parameters such as peak-current (I_p) and pulse-on time (T_{on}) have a potent influence on MRR and TWR [6,13,14]. Therefore, I_p and T_{on} were considered the prime effect on machining performances, while other variables of electrical parameters such as the current voltage, the pulse-off time, and the polarity of electrode were fixed with values of 120V, 50µs, and reverse polarity, respectively. Regarding the amount of powders (C_p), the pilot trials were handled to select based on electrical parameter levels and combined with the powder's thermal and electrical attributes. Hence, the essential process parameters, including I_p, T_{on}, and C_p, were played as the variables of the process for the experiment design, and the output attributes included MRR and TWR. To minimize the number of trials/test runs and to save the empirical cost, the strategy of empiric was established following the Box-Behnken in RSM. In compared with other empirical statistical methods, the capability of Box-Behnken is to ensure accurate models, and this methodology is the most preferable for three factors and levels [15]. The levels of the machining parameters are described in Table 1. The selection of the levels of I_p and T_{on} was grounded on the specifics of the CNC-460 EDM machine, according to prior works [6,10,16,17], and the pilot trials. The levels of C_p were based on pilot experiments and the powder's thermal and electrical attributes.

Table 1. Three levels of process parametric variables.

Process variables	Code	Levels		
		-1	0	+1
T_{on} (μs)	A	50	100	150
I_p (A)	B	5	7	9
C_p (g/l)	C	0	15	30

Table 2. Empirical matrix and acquired data.

Run	Process parameters			Output variables	
	I_p, A	T_{on}, μs	C_p, g/l	MRR, g/min	TWR, g/min
Empirical value for developing model					
1	9	50	15	0.003074	0.0009316
2	7	100	15	0.002195	0.0005951
3	5	150	15	0.002655	0.0003636
4	7	100	15	0.002185	0.0005951
5	9	100	30	0.003056	0.0008889
6	7	100	15	0.002215	0.0005911
7	7	100	15	0.002125	0.0005751
8	7	150	0	0.002164	0.0005019
9	7	100	15	0.002155	0.0005851
10	5	100	30	0.002109	0.0005633
11	7	50	0	0.001727	0.0004727
12	5	100	0	0.001919	0.0003478
13	7	150	30	0.002684	0.0005263
14	7	50	30	0.002000	0.0006842
15	5	50	15	0.001672	0.0004782
16	9	100	0	0.002852	0.0008434
17	9	150	15	0.003317	0.0009167
Empirical value for testing model accuracy					
18	5	50	30	0.001693	0.0006071
19	7	150	15	0.002512	0.0005618
20	7	100	30	0.002148	0.0006346
21	9	150	30	0.003264	0.0008486

2.3. Determination method of MRR, TWR, and micro-defects of surfaces

MRR&TWR: the weight of the electrode and specimen was performed by TE214S-Sartorius balance (the readability of 0.0001g). The processing time in Eqs (1) and (2) is the time to execute the mutating dimension of samples from 45mm down to 44.3mm.

MRR (g/min) in the PMEDM process is computed by Eq. (1)

$$\mathrm{MRR(g/min)} = \frac{W_1 - W_2}{\text{Processing time}} \tag{1}$$

where W_1 and W_2 are respectively the inceptive and finishing weight of the Workpiece (g).

TWR (g/min) in the PMEDM process is depicted by Eq. (2)

$$\mathrm{TWR(g/min)} = \frac{w_1 - w_2}{\text{Processing time}} \tag{2}$$

where w_1 and w_2 are respectively the initial and final weight of tool electrodes (g).

Micro-defects of surfaces: The surfaces of specimens processed by PMEDM and EDM were observed the micro-defects and photographed by scanning electron microscopy method (SEM) on HITACHI SU3800 machine.

Empirical matrix and acquired responses: the empiric matrix with the process variables and these response data are described in Table 2. They were used to develop the regression model for MRR and TWR. Additionally, four added runs (from 18 to 21) were utilized to appraise the correctness of the development models. At one technological mode, the sample and electrode were measured three times before and after machining, then the average value of the measurements was taken and the outcomes are indicated in Table 2.

3. RESULT AND DISCUSSION

3.1. Establishing the prediction models

To initiate the mathematical regression model of output attributes, including MRR, TWR. A regression model of quadratic form has been proposed, as defined by Eq. (3):

$$y = \alpha + \sum_{i=1}^{n} \alpha_i x_i + \sum_{i=1}^{n} \alpha_{ii} x_i^2 + \sum_{i<j} \sum_{j=2}^{n} \alpha_{ij} x_i x_j \tag{3}$$

where $\propto_0$, $\propto_i$, $\propto_{ii}$, and $\propto_{ij}$ are the coefficients of the prediction models; the variables of processes include x_i and x_j; the number of variables is n with n = 3; and the output attribute is y –i.e. MRR or TWR. In this investigation, the Design Expert 12 software conducted reckoning and establishing the coefficients, and the prediction models. The adequate predicted models about factual factors for MRR and TWR are depicted in equations. (4) and (5), respectively:

$$\mathrm{MRR} = 0.00394 + 1.101\times10^{-5} T_{on} - 0.001047 I_p + 1.599\times10^{-5} C_p - 1.851 T_{on} I_p + 8.246\times10^{-8} T_{on} C_p + 1.104\times10^{-7} I_p C_p + 3.2843 T_{on}^2 + 0.000105 I_p^2 - 5.039\times10^{-7} C_p^2 \tag{4}$$

$$\mathrm{TWR} = 0.00085 - 2.4004\times10^{-7} T_{on} - 0.00024 I_p + 2.387\times10^{-5} C_p + 2.4909 T_{on} I_p - 6.2349 T_{on} C_p - 1.4166 I_p C_p - 6.0701\times10^{-9} T_{on}^2 + 2.4849\times10^{-5} I_p^2 - 1.9316\times10^{-7} C_p^2 \tag{5}$$

3.2. Evaluation of the regression models

The analysis of variance (ANOVA) method was utilized to evaluate the accuracy of the development models. The outcomes of ANOVA for the prediction models of the material removal rate and the tool wear rate were described in Tables 3 and 4, respectively.

The MRR model (as indicated in eq. (4) and Table 3) was considered for appraising the adequacy via ANOVA analysis, which was with 95% of confidence and 5% of significance.

Table 3 is to correspond to the ANOVA results of MRR. The P-value corresponding to the terms of the model is less than 0.05 which indicates these terms of the model are significant. Accordingly, the terms (including A^2, B^2, C^2 AB, A, B, C) are meaningful for the RMR model. The development model has been confirmed by the precision/adequacy through coefficients, including "R^2", "R^2(adj)" and "R^2(pred)". In which, the R^2 values for MRR model is 0.992. This proves a good compromise between the empiric values and the predictive values. The "R^2(pred)"of MRR model is 0.8911, which is also a suitable agreement with the "R^2(adj)" (0.9817 for MRR). The Adeq. Precision measures the signal to noise ratio. A ratio greater than 4 is desirable. Therein, The Adeq. Precision of 31.07 indicates an adequate signal. This model can be used to navigate the design space.

Table 3. ANOVA for MRR model.

Source	**SS**	**MS**	**F-value**	**p-value**
Model	3.788E-06	4.209E-07	96.62	1.658E-06
A-T_{on}	3.788E-06	4.209E-07	96.62	1.658E-06
B-I_p	6.882E-07	6.882E-07	158.0	4.655E-06
C-C_p	1.945E-06	1.945E-06	446.4	1.338E-07
AB	1.762E-07	1.762E-07	40.45	0.0003816
AC	1.371E-07	1.371E-07	31.47	0.0008077
BC	1.530E-08	1.530E-08	3.512	0.1031
A^2	4.391E-11	4.391E-11	0.01008	0.9228
B^2	2.839E-08	2.839E-08	6.517	0.03795
C^2	7.497E-07	7.497E-07	172.1	3.487E-06
Lack of Fit	2.549E-08	8.497E-09	6.797	0.04758
"R^2" = 0.992, " R^2(adj)" = 0.9817, and "R^2(pred)" = 0.8911, Adeq. Precision=31.07				

Table 4. ANOVA for TWR model.

Source	**SS**	**MS**	**F-value**	**p-value**
Model	5.193E-07	5.770E-08	86.88	2.393E-06
A-T_{on}	8.336E-09	8.336E-09	12.55	0.009433
B-I_p	4.175E-07	4.175E-07	628.7	4.095E-08
C-C_p	3.085E-08	3.085E-08	46.45	0.0002496
AB	2.482E-09	2.482E-09	3.737	0.09448
AC	8.747E-09	8.747E-09	13.17	0.008409
BC	7.225E-09	7.225E-09	10.88	0.01315
A^2	9.696E-10	9.696E-10	1.460	0.2662
B^2	4.160E-08	4.160E-08	62.64	9.763E-05
C^2	3.035E-09	3.035E-09	4.569	0.06989
Lack of Fit	4.364E-09	1.455E-09	20.43	0.006893
"R^2" = 0.9911, " R^2(adj)" = 0.9797, and "R^2(pred)" = 0.8659, Adeq Precision=29.4				

For The TWR model (as depicted in eq. (5) and Table 4) was considered for evaluating the adequacy via ANOVA analysis, which was with 95% of confidence and 5% of significance. Table 4 is to correspond to the ANOVA results of TWR. The P-value corresponding to the terms of the model is less than 0.05 which indicates these terms of the model are significant. Accordingly, the terms (including B^2, AC, BC, A, B, C) are meaningful for the TWR model. The development model has been confirmed by the precision/adequacy through coefficients, including "R^{2}", "R^2(adj)" and "R^2(pred)". In which, the R^2 values for TWR model is 0.991. This proves a good compromise between the empiric values and the predictive values. The "R^2(pred)"of TWR model is 0.8659, which is also a suitable agreement with the "R^2(adj)" (0.9797 for TWR). The Adeq. Precision measures the signal to noise ratio. A ratio greater than 4 is desirable. Therein, The Adeq. Precision of 29.4 indicates an adequate signal. This model can be used to navigate the design space.

3.3. Influence analysis of process variables on MRR &TWR

Figs. 3a and b describe the perturbation of the material removal rate and the tool wear rate, respectively, as functions of coded units. In Fig. 3a, it is the primary influence plot of the variables on MRR. It is revealed that I_p and T_{on} express the same influence trend on MRR, While C_p increases to a certain level then it tends to decrease. A rasing of I_p, T_{on}, or C_p in the whole design space causes an increase in MRR. This signifies that the MRR is meliorated. Indeed, when the pulse on time, the peak current increases, and that brings out the energy of thermal in the discharge channel to be increased [9]. Moreover, due to the participation of the thermal and electrical conductive particles of the powder, the discharge area is widely opened [18]. It is these roots that boost the MRR. In Fig. 3b, it expresses the crucial impact of the variables on TWR. It is indicated that TWR increases with an augmentation in I_p or C_p in the whole design space. Meanwhile, the increase of T_{on} in the entire design space has reduced TWR.

The interplay impacts of input variables on the MRR are indicated in Fig. 4. It is also clear that the MRR augments with a rise in the peak current for all of the pulse on time (Fig. 4a) and for all of the powder concentration (Fig. 4b). In addition, the increase in the powder concentration also makes for an augment in the MRR for all of the peak current (Fig. 4b) and for all of the pulse on time (Fig. 4c), while the increase in the pulse on time also leads to an increase in the MRR for all of the peak current (Fig. 4a) and for all of the powder concentration (Fig. 4c). The MRR obtains the greatest value when the powder concentration, the pulse on time, and the peak current achieve the highest values.

The interplay impacts of parameter variables on the TWR are also indicated in Fig. 5. It is clearly observed that the TWR elevates with a rise in the peak current for all of the pulse on time (Fig. 5a) and for all of the powder concentrations (Fig. 5b). In addition, the increase in the powder concentration also makes for an augmentation in the TWR for all values of the peak current (Fig. 5b), while the increase in the pulse on time also results in a slight drop in the TWR for all of the peak current (Fig. 5a) and for all of the powder concentration (Fig. 5c). At the smallest value of the peak current, the pulse on time, and the powder concentration, the TWR obtains the minimizing value.

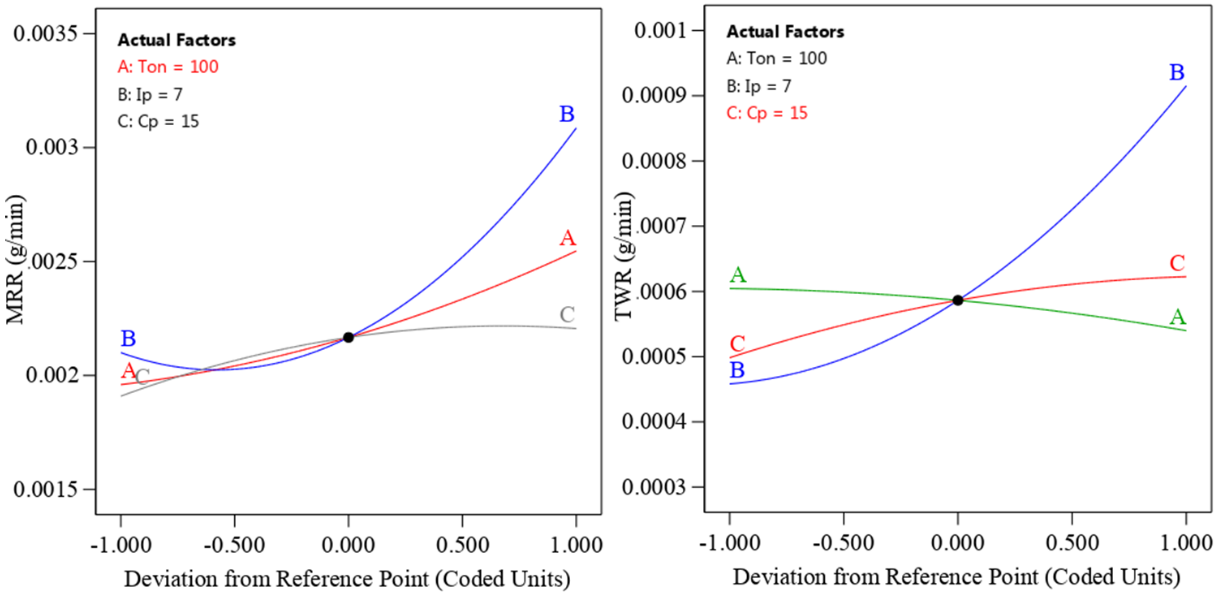

Figure 3. Primary influence of process variables on MRR&TWR.

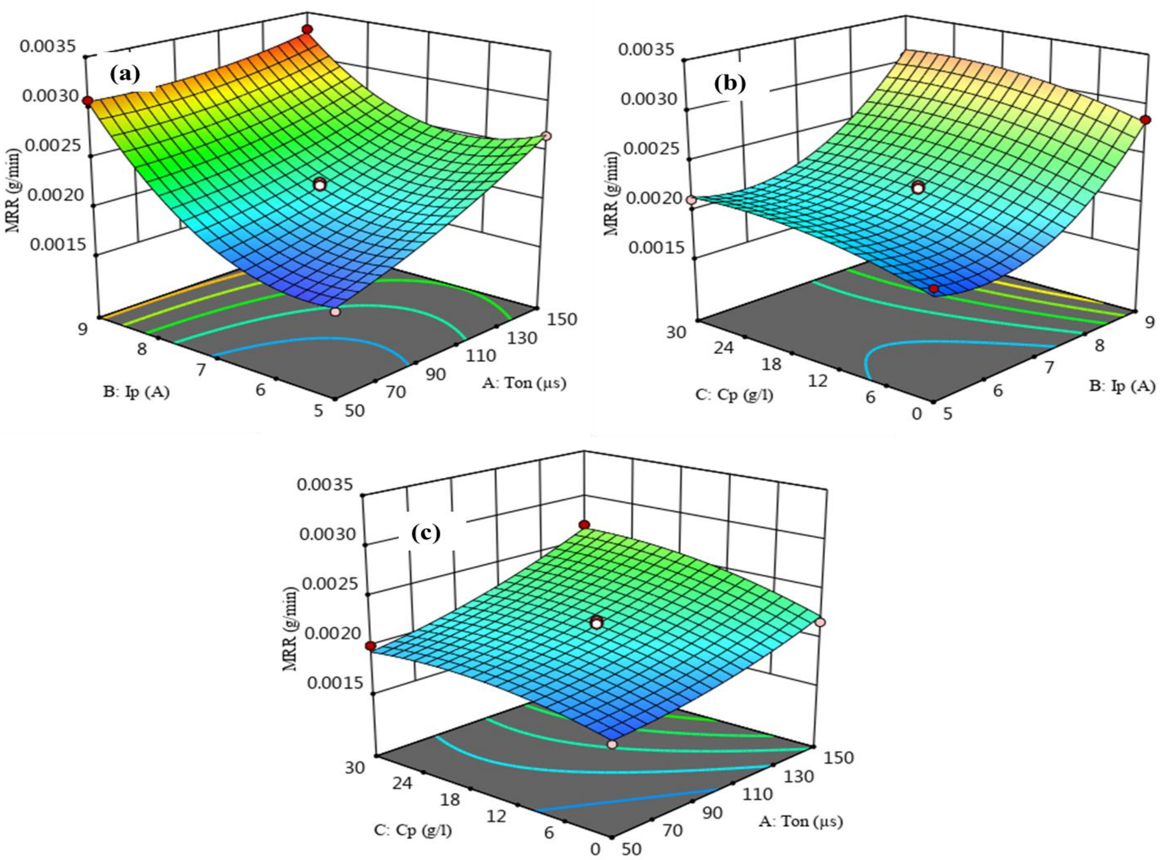

Figure 4. Interplay influence of input variables on MRR: (a) I_p and T_{on}, (b) I_p and C_p, and (c) C_p and T_{on}.

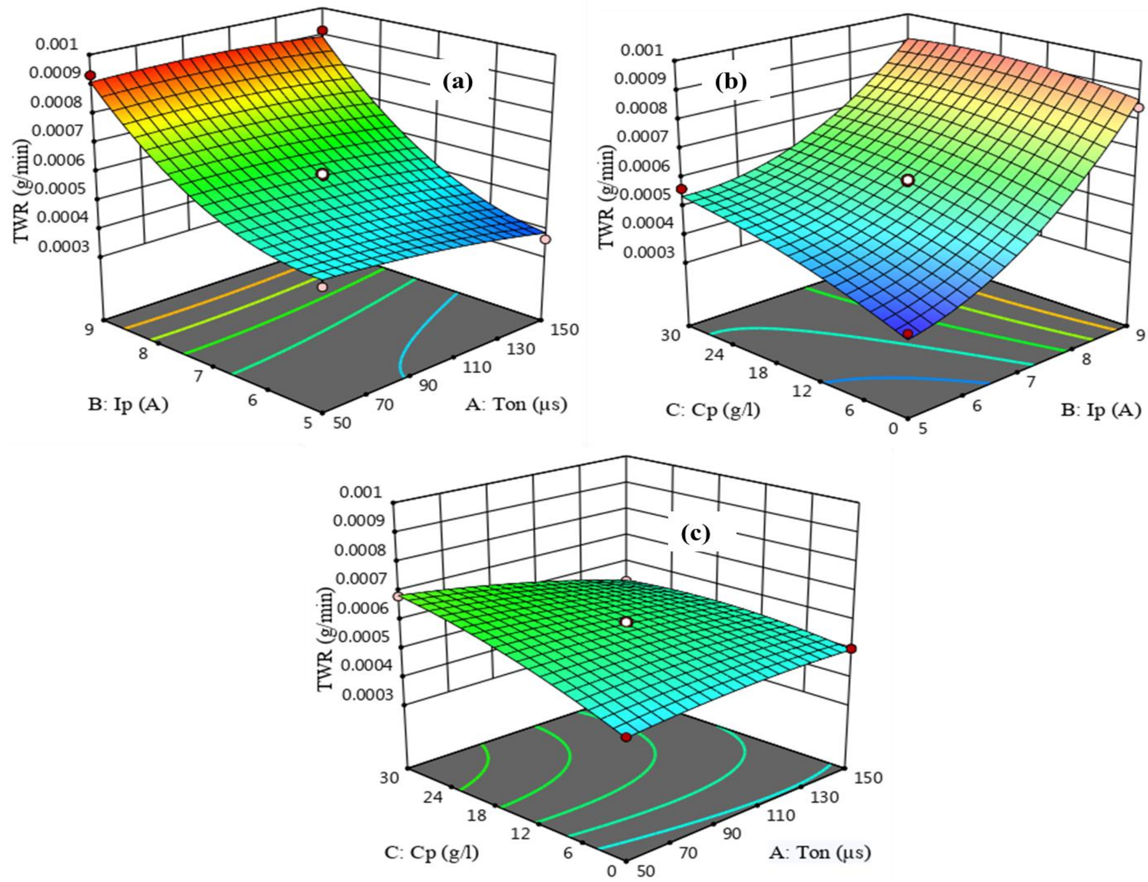

Figure 5. Interplay influence of input variables on TWR: (a) I_p and T_{on}, (b) I_p and C_p, and (c) C_p and T_{on}.

From the above-mentioned evaluation, it is clear that both I_p or/and T_{on} are increased, causing the discharge energy is increase and leading to an increase in MRR and TWR [19]. In addition, Adding the powder particles to the working liquid produces stratified discharge which makes for an increase in MRR and a decrease in TWR [20]. A combination of I_p and T_{on} leads to a low/ high density of the powder particles in the next discharge process. This has a positive/negative influence on the improvement in MRR and TWR.

3.4. Verification of the regression models

In this study, the experimental data from 18 to 21 (as indicated in Table 2) were performed to evaluate the precision of the propounded model. The experimental values and predicted values of the checkpoints are compared in Table 5. As a result, the percent deviations of MRR and TWR are in the ranges of 2.36% to 4.52%, and 1.08% to 3.88%, respectively. The small deviations exhibit that the proposed models are appropriate and can be utilized for predicting the attributes with good precision. Moreover, these developed models can be adopted to identify the optimal attributes.

Table 5. Comparison of empirical and predicted values.

No.	MRR, g/min			TWR, g/min		
	Exp. values	**Pred. values**	**Error (%)**	**Exp. values**	**Pred. values**	**Error (%)**
18	0.001623	0.0017	4.52	0.0006071	0.0006258	2.98
19	0.002512	0.0026	3.38	0.0005618	0.0005408	3.88
20	0.002148	0.0022	2.36	0.0006346	0.0006235	1.78
21	0.003264	0.0034	4.00	0.0008486	0.0008395	1.08
Error=Abs (Pred. values − Exp. values)/Pred. values× 100%						

3.5. Optimization of the machining performances

Foundation on the development models, the optimized variables of the process can be anticipated. In the PMEDM process, the machining performances are expected with the following criteria: the MRR is obtained at maximum, while the TWR is acquired at minimum. This guarantees reducing process time and enhancing dimensional precision in the manufacturing process. Hence, the issue of optimizing the machining performances was represented as follows:

Find x = [I_p, T_{on}, C_p] to minimize *TWR* and maximize *MRR*

Binding in conditions: $5 \leq I_p \leq 9$ (A), $50 \leq T_{on} \leq 150$ (µs), and $0 \leq C_p \leq 30$ (g/l).

This problem was resolved by applying the optimized module in the Design-Expert 12 software. The optimal results are obtained as follows: MRR_{max}=0.002756(g/min); TWR_{min}=0.0004152(g/min) at the process parameter set of I_p=5A, T_{on}=150µs, C_p= 26g/l.

The experimental values of responses at the optimal process parameters are depicted in Table 6. The error between the values of output variables according to the predictive and empirical models are within the tolerable assortment, with the maximum erratum is 3.12% of the output variable (MRR), and the minimum error is 2.57% of the output variable (TWR).

Table 6. Verification Experiments of the results at the optimal process parameters.

Machining performances	Optimal process variables	Pred. values	Exp. values	Error (%)
MRR, g/min	I_p=5A, T_{on}=150µs, C_p=26g/l	0.002756	0.00267	3.12
TWR, g/min		0.0004152	0.0004045	2.57
Error=Abs (Pred. values − Exp. values)/Pred. values× 100%				

The micro-defects (including the micro-cracks, the droplets, the voids) on the machined surface at the optimal technological modes were explored and compared to those at optimal technological modes without the powders, as indicated in Fig. 6. This proves that the micro-defects of machined surfaces by PMEDM (as shown in Fig. 6a) are better than those of machined surfaces by EDM (as depicted in Fig. 6b).

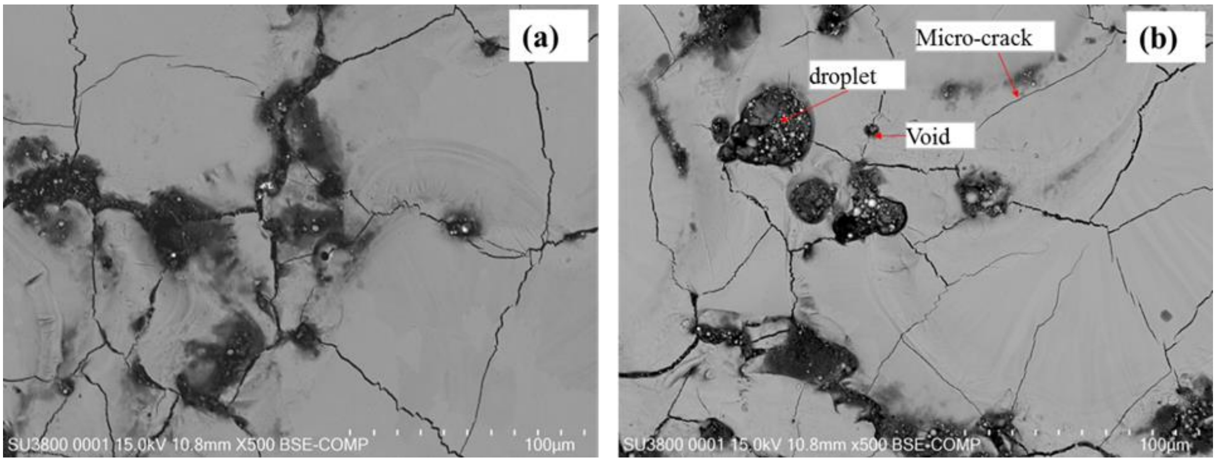

Figure 6**.** Micro-defects of the machined surface: (a) at optimal process parameters; (b) at optimal electrical parameters without powders.

4. CONCLUSION

This study's goal is to develop the predicted models for the machining performances (including MRR and TWR) in the EDM process with tungsten compound powder to process SKD61 steel. For this aim, The trial matrix follows the Box-Behnken method. The regress models were established by response surface methodology, and the precision of these models was evaluated by the ANOVA. The outcomes point out that the regress models have high precision and can be utilized to investigate the influences of process variables on the machining performances and to anticipate the desired MRR and TWR in the entire design space. From the development models, the optimal responses and process variables, comprising MRR_{max} of 0.002756(g/min), TWR of 0.0004152(g/min), peak current of 5(A), pulse on time of 150(μs), and powder concentration of 26(g/l) were found for machining SKD61 steel. Besides, the prediction of the machining performances of other metals can be utilized in the method of this study. In addition, the micro-defects of machined surfaces by PMEDM are better than those of machined surfaces by EDM. In future works, the surface features such as chemical composition, content, and distribution, thickness recast layer, surface topography, and percentage of micro-crack acreage on surfaces of PMEDM process with SKD61 steel will be investigated to verify their suitability for factual applications.

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