# Multi-Attribute Optimization of the WEDM Process for Surface Characteristics and Productivity

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Abstract: Wire-cut electrical discharge machining (WEDM) process is a proficient operation for the precise manufacturing of complex profiles of difficult-to-cut materials. The purpose of the current paper is to determine optimal processing inputs, including the WEDM current (*CU*), WEDM voltage (*DV*), pulse duration (*Ton*), and the speed of the wire electrode (*WS*) to decrease the depth of the recast layer (*DL*) as well as the root mean square roughness (*RMSR*) and enhance the cutting speed (*CS*) of the WEDM operation. The radius basis function (*RBF*) approach is employed to develop the predictive models of technical responses. The non-dominated sorting particle swarm optimization (NSPSO) is applied to obtain the optimal values of processing inputs and WEDM performances measured. The findings revealed that the proposed *RBF* models significantly contribute to the accurate prediction for the WEDM outputs. The optimal values of the *CU*, *Ton*, *DV*, and *WS* are 5.0 A, 6.0 µs, 33.0 V, and 4 m/min, respectively. The optimized values of the *RMSR* and *DL* are decreased by 60.98% and 15.55%, respectively, while the *CS* is enhanced by 8.90%. This work can be listed as an alternative solution for improving the surface characteristics and productivity of the WEDM process.

Keywords: cutting speed; optimization; parameters; root mean square roughness; the depth of the cast layer; WEDM

## **1 INTRODUCTION**

The wire-cut electrical discharge machining (WEDM) is a proficient operation, which is widely applied in the precise manufacturing of complex profiles of difficult-tocut materials. Unfortunately, the various drawbacks, including the holes, cracks, craters, and high roughness are produced on the machined surface. Consequently, the selection of the proper factors to improve the machining performances of the WEDM process is an important demand.

Enhancing technical outputs for different WEDM operations have been attracted by former investigators. An attempt has been conducted to enhance the material removal rate (MRR) and decrease the average surface roughness (Ra) for the WEDM operation of Inconel 706 [1]. The finding revealed that the pulse on duration (*POD*) of 105 µs, the pulse of duration (POF) of 27 µs, discharge voltage (DV) of 32 V, and the wire feed (WF) of 4 m/min were optimal values. The impacts of the POD, POF, and applied current (AC) on the MRR, Ra, and kerf width (KW) of the 5754 aluminium alloy was explored by Shihab [2]. The author emphasized that POD was found to be the most significant in the responses measured. The response surface method (RSM) and heat transfer search algorithm (HTSA) were applied to select the optimal values of the *POD*, *POF*, and *AC* for the WEDM of the NiTi alloy [3]. The obtained results indicated that the optimal outcomes of the MRR, hardness (MH), and Ra were 1.49 mm<sup>3</sup>/s, 462.52 HVN, and 0.11  $\mu$ m, respectively. A neuron network (NN) and wolf pack algorithm (WPA) were used to optimize the POD, AC, water pressure (WP), and feed rate (FR) for minimizing the total machining time  $(T_{\rm P})$ , manufacturing costs ( $C_P$ ), and Ra [4]. The analysed outcomes revealed that the optimal values of the  $T_P$ ,  $C_P$ , and Ra were 164.18 min, 239.542 RMB, and 1.02 µm, respectively. Muralidharan et al. used the RSM and desirability approach (DA) to obtain the minimal values of the POD, POF, DV, and the weight ratio  $(W_t)$  for the WEDM of the aluminium matrix. The optimal outcomes of the MRR and Ra were 0.077 g/min and 3.62 µm, respectively.

proper factors, which were satisfied with the optimization requirements. The Taguchi approach was used in conjunction with the NN to develop the model of the MRR, *Ra*, *KW*, and cutting speed (*CS*) for the WEDM of the Ti-48Al alloy [7]. The accuracy of the developed models was confirmed using a set of experimental data. The authors stated that the 5-6-6-4 structure of the networks could provide the highest precision for prediction accuracy. Nawaz et al. found the optimal solutions of the POD, POF, AC, and WS to improve the MRR and decrease the KW as well as Ra for a high-speed WEDM operation [8]. The obtained outcomes presented that the AC was found to be the most affecting parameter on the MRR and Ra, while the POD is the most significant on the KW. The magneticassisted WEDM was applied to enhance the MRR, Ra, and the depth of the recast layer (DL) [9]. The non-dominated neighbour immune algorithm (NNIA) was used to find optimal outcomes. The results indicated that the improvements in the MRR, Ra, and DL were 22.37%, 44.59%, and 15.07%, respectively. The reused wire technology was applied to decrease the Ra of the WEDM of Ti6Al4V alloy [10]. The author stated that the Ra was decreased by 2.65% with the aid of the new operation. The empirical models of the CA, Ra, and KW were developed in terms of the POD, POF, DV, WP, wire kind (WK), and wire tension (TW) for the WEDM of the hardened alloy [11]. The finding revealed that the POD is the most significant inputs, followed by the WK and POF, respectively. Similarly, the RSM was applied to develop the predictive models of the CS, Ra, and spark gap (SG) of the WEDM of the Al/SiCp-MMC material [12]. The results generated by the DA indicated that the POD of 0.75 µs, the *POF* of 16  $\mu$ s, the *DV* of 35 V, the *AC* of 120 A, the *TW* of 1200 g, and the WF of 10 m/min were listed as the optimal solutions. The grey relation analysis (GRA) was applied to select the optimal parameters, including the POD, POF, WF, doping (DP), and  $W_t$  for the magnesium matrix composite [13]. The optimal values of the MRR and Ra

The Kriging models were applied to render the predictive models of the cutting area rate (CAR), kerf width

(*KW*), and *Ra* in terms of the *POD*, *POF*, *AC*, and *DV* [6]. The feasible solutions obtained could be used to determine

were 14.9 mm<sup>3</sup>/min and 2.04  $\mu$ m. The regression models of the cutting velocity (*CV*) and *Ra* were proposed for the WEDM aluminum composite [14]. The optimum findings of the *CV* and *Ra* were 8.12 mm/min and 1.25  $\mu$ m, respectively with the aid of the *DA*. The WEDM characteristics of the 16MnCr5 Alloy, including the *MRR* and *Ra*, were investigated by Saini et al. [15]. The author stated that the *POD* was the highest contributing factor for the technical responses.

In machining processes, surface quality is one of the important customized requirements. most The achievement of the desired surface quality is an urgent demand for the functionality of the machined part. The surface roughness value is a major indication of surface quality. The performances and production costs of the machined parts are strongly influenced by surface roughness, which influences the electrical as well as thermal conductivity, holding lubricant, friction, and geometric tolerances. A lower roughness leads to a reduction in the frictional coefficient, wear, corrosion, and adhesion [16, 17]. Therefore, a decrease in surface roughness (Ra and/or RMSR) is necessary to achieve an eco-friendly machining process.

In this work, a parameter-based optimization of the WEDM operation for SS 304 has been considered to minimize the *RMSR* as well as the *DL* and enhance the *CS*. The *RBF* correlations were employed to depict the relations between the processing inputs and the measured parameters. An evolutionary algorithm namely NSPSO was applied to identify the global solution. The obtained result can be considered as an alternative solution to enhance surface properties and productivity for the WEDM operation. Moreover, the designed optimization method can become a useful approach for different machining operations to identify optimal outcomes.

### 2 OPTIMIZATION APPROACH 2.1 Optimization Responses

In the current paper, three WEDM performances measured, including the *RMSR*, *DL*, and *CS*, are improved with the aid of the optimization approach. The *RMSR* values are directly measured on the machined specimens.

The value of the DL (µm) value is calculated as:

$$DL = \frac{1}{20} \sum_{i=1}^{20} DL_i$$
 (1)

The cutting speed (mm/min) is computed as:

$$CS = \frac{L_{\rm m}}{t_{\rm m}} \tag{2}$$

where  $L_{\rm m}$  - the machining length (mm),  $T_{\rm m}$  - the machining time (min).

Table 1	WEDM pro	ocessing	inpu	its

Parameters	Unit	Level -1	Level 0	Level +1
WEDM Current	Α	4.0	7.0	10.0
Pulse duration	μs	1.0	4.0	7.0
WEDM voltage	V	30.0	60.0	90.0
Wire speed	m/min	3.0	5.0	7.0

In this work, key processing inputs considered are the WEDM current, WEDM voltage, pulse duration, and wire feed. Tab. 1 lists the lower and upper levels of each factor. The highest and lowest ranges are tested with the aid of the WEDM experiments to ensure machining capabilities.

## 2.2 Optimization Procedure

Fig. 1 presents an applied method for determining optimum factors. The proposed approach contains three primary steps.



- The WEDM experiments are performed to collect the required data [18].

- The predictive correlations of the *RMSR*, *DL*, and *CS* are constructed in terms of the processing inputs using the radius basis function approach.

The *RBF* method is an alternative method to generate the interpolative model, which can be effectively employed to describe the non-linear data with wide levels. The radial units are employed in conjunction with the linear ones to present the experimental data. *RBF* correlations show higher precision than the traditional models, such as response surface method or linear regression [19, 20]. The *RBF* model at the design point (*x*) can be presented as:

$$F(x) = \sum_{i=1}^{n} \lambda_i \phi((x - x_i) + bx + c$$
(3)

where  $\gamma$  - the positive constant,  $\lambda_i$ , b, and c - the correlated factors.

These factors are calculated as:

$$\begin{bmatrix} \phi & P \\ P^{\mathrm{T}} & 0 \end{bmatrix} \begin{bmatrix} \lambda \\ a \end{bmatrix} = \begin{bmatrix} G \\ 0 \end{bmatrix}$$
(4)

The *RBF* forms can be expressed as:

$$\varphi(r) = r \tag{6}$$

Step 3: The NSPSO is employed to identify the optimal values of processing inputs and WEDM performances. The NSPSO is an effective optimization

algorithm, which combines advantages of the Non-sorted dominated genetic algorithm (NSGA) and particle swarm optimization (PSO). The reliable solutions will be produced with the support of the NSPSO. The detail of the NSPSO is exhibited in the works of [21]. The operating procedure of the NSPSO is depicted in Fig. 2.



# 3 WEDM EXPERIMENTS AND MEASUREMENTS

All WEDM trials are conducted on the machine namely MTL-SFL70 to produce the machined specimens, as shown in Fig. 3. The machining path is directly programmed in the numerical controller of the machine. The dimensions of each workpiece are the length of 230 mm, the width of 90 mm, and the thickness of 8 mm. The electrode wire using molybdenum material is employed for all experiments. After each trial, a new wire is changed to

guarantee the machining precision. The machined length for each specimen is 30 mm. The machined program is stopped when the desired length is completed. The machined specimen is cut from the workpiece to measure the WEDM performances. Moreover, each specimen is cleaned and polished to serve the measuring operation.

The roughness values are obtained with the aid of a portable machine labeled Mitutoyo SJ-301. Microscopy entitled Carl Zeiss 37081 is applied to investigate the value of the depth of the recast layer.

## 4 RESULTS AND DISCUSSIONS 4.1 Investigate the Model Adequacy

The obtained data of the experimental WEDM operation are presented in Tab. 2. The representative values of the depth of the recast layer at different machining conditions are depicted in Fig. 4. The representative profiles of measured *RMSR* at different machining conditions are shown in Fig. 5.

To evaluate the model adequacy, the coefficient of determination is assessed. The  $R^2$  - values of the *RMSR*, *DL*, and *CS* are 0.9924, 0.9874, and 0.9902, respectively, showing the acceptable agreement between predictive and actual data. The data are evenly distributed on the straight, presenting that the developed models are highly satisfactory, as shown in Fig. 6.

## 4.2 Analysis of the Factor Effects

The influences of the process parameters on the *RMSR* values are depicted in Fig. 7. In the WEDM process, a low roughness is a desirable indicator.

Fig. 7a revealed that higher roughness values are produced with an increased CU and/or DV. When the low CU and/or DV are applied, the discharge energy is lower, which causes a low intensity of the WEDM spark. Less material is processed and vaporized. Moreover, the electrical spark is evenly distributed on the WEDM surface at the low CU and/or DV, which generates a smoother surface and the *RMSR* value is decreased. A WEDM surface with small dimensions of the craters, cracks, and holes is observed.



Figure 3 Experiment and measurement of the WEDM operation

In contrast, an increased CU and/or DV lead to an increment in the discharge energy. Higher intensity of the electrical spark is produced, which significantly processes material. An increased material volume is melted and vaporized, which results in the formation of bigger holes, cracks, and craters. Therefore, higher roughness is generated.Fig. 7b indicated that an increased *RMSR* is associated with an increment in the *Ton* and/or *WS*. After a maximal point, a further value of the *Ton* and/or *WS* leads to a smoother surface. At a low value of the *Ton* and/or *WS*, a low electrical spark is obtained and evenly distributed on the machined surface. Less material is then processed and removed, which leads to a reduction in the roughness.

In contrast, an increased pulse duration results in increased intensity of discharge energy, and higher material volume is removed. Therefore, higher *RMSR* is obtained. Similarly, higher *WS* causes increased discharge energy and intensive spark is produced. A higher amount of material is processed and removed, which causes a higher value of the *RMSR*. Fortunately, at the highest levels of the *Ton* and/or *WS*, the electrical spark is evenly distributed, leading to a reduction in the *RMSR*. A smoother surface is obtained at employing highest *Ton* and/or *WS*.





Figure 4 The values of the depth of the recast layer at different inputs









Figure 5 The root mean square roughness at the different inputs

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	Table 2 Experimental results of the WEDM operation														
No	CU	Ton	DV	WS /	RMSR	DL	CS	No	CU	Ton	DV	WS	RMSR	DL	CS
INO.	/ A	/ μs	/ V	m/min	/ µm	/ µm	/ mm/min	INO.	/ A	/ μs	/ V	/ m/min	/ μm	/ µm	/ mm/min
1	4	1	60	5	3.67	8.68	3.07	14	4	4	90	5	6.91	14.92	4.30
2	10	1	60	5	5.25	12.16	3.50	15	10	4	30	5	5.73	11.86	3.57
3	4	7	60	5	4.32	16.83	5.09	16	10	4	90	5	8.51	18.64	4.62
4	10	7	60	5	5.90	20.44	5.39	17	7	1	30	5	2.98	6.37	3.02
5	7	4	30	3	2.13	6.17	3.30	18	7	1	90	5	5.73	12.99	3.96
6	7	4	30	7	4.49	9.15	3.80	19	7	7	30	5	3.61	14.59	4.82
7	7	4	90	3	4.89	13.69	4.37	20	7	7	90	5	6.39	21.19	6.06
8	7	4	90	7	7.25	14.86	4.91	21	4	4	60	3	2.89	8.96	3.48
9	7	1	60	3	1.79	6.08	3.16	22	4	4	60	7	5.12	10.91	3.93
10	7	1	60	7	3.86	9.75	3.77	23	10	4	60	3	4.34	12.38	3.79
11	7	7	60	3	2.14	15.88	5.21	24	10	4	60	7	6.84	14.58	4.36
12	7	7	60	7	4.80	16.36	5.63	25	7	4	60	5	5.10	11.64	3.82
13	4	4	30	5	4.16	8.48	3.17		4	4	90	5	6.91	14.92	4.30



Figure 7 Interaction effects of processing conditions on the RMSR



Figure 8 Interaction effects of processing conditions on the DL



Figure 9 Captured surface at the various experiments

The effects of processing inputs on the DL are shown in Fig. 8. In the WEDM process, a low depth is a desirable indicator.

Fig. 8a has revealed that an increased DL is associated with an increment in the CU and/or DV. At a low value of the CU and/or DV, low electrical spark obtained causes less

molten material. A small amount of material is released and solidified on the workpiece surface, which causes a low DL. When the CU and/or DV increase, increased discharge energy causes an increment in the volume of the molten material and machined zones. More material is processed and melted which causes thicker DL.

Fig. 8b indicated that an increased *DL* is associated with an increment in the *Ton* and/or *WS*. When the *Ton* and/or *WS* increases, the higher intensity of the electrical spark is generated. Higher material volume is processed and evaporated, which increases the thickness of the solidified layer.

The captured surfaces with various processing inputs are presented in Fig. 9. A coarsen surface is observed at an increased WS, while the smooth one is obtained with the low condition.

Fig. 10 presents the influences of the processing inputs on the CL. In the WEDM process, a higher CS is an important indicator to enhance productivity.

Fig. 10a revealed that an increased CS is associated with an increment in the CU and/or DV. At a lower value

of CU and/or DV, low intensity of discharge energy and electrical spark is generated. Less material is molten and evaporated; hence, the value of the CS is reduced. In contrast, a higher intensity of discharge energy is produced when the CU and/or DV increases. More material volume is processed and higher CS is obtained.

Fig. 10b indicated that an increased CS is associated with an increment in the *Ton* and/or *WS*. When the *Ton* and/or *WS* increases, an increment in the electrical spark is obtained. As a result, more material volume is vaporized, which causes higher CS value. Moreover, the debris is effectively flushed out at high value of the wire speed, contributing to faster cutting speed.



The ANOVA analysis is used to analyze the contributions of the inputs [20, 21]. Fig. 11a presents parametric contributions for the *RMSR* model. For single factor, the contributions of the *DV*, *WS*, *CU*, and *Ton* are 19.48%, 16.67%, 11.16% and 4.56%. For the quadratic factors, the contributions of the *Ton*<sup>2</sup>, *WS*<sup>2</sup>, *CU*<sup>2</sup>, and *DV*<sup>2</sup> are 13.86%, 13.69%, 9.41%, and 7.91%, respectively.

Fig. 11b illustrates parametric contributions for the *DL* model. For a single factor, the contributions of the *Ton*, *DV*, *CU*, and *WS* are 25.17%, 20.26%, 10.87%, and 6.36%, respectively. For the quadratic factors, the contributions of the *Ton*<sup>2</sup>, *CU*<sup>2</sup>, *WS*<sup>2</sup>, and *DV*<sup>2</sup> are 9.79%,10.89%, 7.48%, and 3.49%, respectively.

Parametric contributions for the *CS* model are depicted in Fig. 11c. The contributions of the *Ton*, *DV*, *WS*, and *CU* are 32.51%, 18.14%, 8.53%, and 6.08%, respectively. The contributions of the *Ton*<sup>2</sup>,  $DV^2$ ,  $WS^2$ , and  $CU^2$  are 16.50%, 4.95%, 4.13%, and 1.80%, respectively.

#### 4.3 Optimal Results

The optimization factors are determined using the developed RBF models and PSO algorithm. The values of the operating parameters, including the maximum iterations, number of particles, inertia, global increment, particle increment, maximum velocity are 50, 20, 0.9, 0.9, 0.9, and 0.2, respectively.

Fig. 12 depicts the graphical relations between the WEDM responses for showing optimization solutions. It was found that the WEDM responses have a contradictory trend. An increased CS leads to a reduction in the surface quality or an increase in the *RMSR* and *DL*. The point labeled No. 522 is selected as a proper solution, which satisfies optimization issues.



(a) The parametric contributions for the RMSR



The optimal WEDM inputs and outputs are presented in Tab. 3. The CU of 5.0 A, DV of 33 V, Ton of 6.0  $\mu$ s, and WS of 4.0 m/min are optima. As a result, the reductions of the RMSR and DL are 60.98% and 15.55%, respectively, while the CS is improved by 8.90% in comparison with initial values



Figure 12 Pareto fronts produced by NSPSO

Table 3	Optimization	results	pro	oduced	b	y NSPS	30

Annroach	Optimum parameters				Optimum responses				
Арргоаси	CU/A	DV/V	Ton / μs	WS / m/min	<i>RMSR</i> / µm	$DL/\mu m$	<i>CS</i> / mm/min		
Values used	7.0	60.0	4.0	5.0	5.10	11.64	3.82		
NSPSO	5.0	33.0	6.0	4.0	1.99	9.83	4.16		
Improvement / %					-60.98	-15.55	8.90		

## 5 CONCLUSIONS

The current research addressed the WEDM input based-optimization of SS304 that decreases the root mean square roughness as well as the depth of the recast layer and improves the cutting speed. The nonlinear correlations of the machining targets were developed using *RBF* models. The PSO was employed to obtain optimal outcomes of processing inputs and technical performances. The findings can be summarized as follows:

1. The *RBF* correlations of the WEDM characteristics have shown a higher precision for prediction purposes. The modeling technique is employed to depict complex data instead of traditional ones. These correlations may be satisfactorily applied for the prediction of the objective's values.

2. The optimal factor settings obtained by NSPSO of the *CU*, *Ton*, *DV*, and *WS* are 5.0 A, 6.0  $\mu$ s, 33.0 V, and 4 m/min, respectively. As compared to random values, the *RMSR* and *DL* are decreased by 60.89% and 15.55%, respectively. The *CS* value is improved by 8.90%.

3. The developed approach could be employed to solve the relations between the contradictory responses. The proposed optimization approach effectively supports the WEDM operator to select the optimum process parameters. 4. An integrative approach comprising the *RBF* model and PSO effectively supports the optimizing WEDM operation and generates reliable results, as compared to the human trials or experience.

5. This work addressed the three machining responses including the *RMSR*, *DL*, and *CS* that were considered as objective outputs. Other responses such as the tool wear rate and energy used should be studied in order to holistically optimize the WEDM process. Moreover, additional parameters including the residual stress and machining costs will be analyzed in future works.

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