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Modeling and Optimization of Electric Discharge Machining Performances using Harmony Search Algorithm

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Abstract: Electric Discharge Machining (EDM) is one of the widely used non-conventional machining processes for complex and difficult-to-machine materials. EDM technology has been improve significantly and has been developed in many ideas especially in the manufacturing industries that yielded enormous benefits in economic as well as generating keen interest in research area. A major issue in EDM process is how to obtain accurate results of the machining performance measurement value at optimal point of cutting conditions. Thus, this study proposed harmony search algorithm approach for optimization of surface roughness (Ra) in die sinking electric discharge machining (EDM). The mathematical model was developed using regression analysis based on four machining parameters which are pulse on time, peak current, servo voltage and servo speed. The result shows that the optimal solutions for Ra can be found with the minimum values of 1.3031 µm.

Keywords: Harmony Search, Regression, Electric Discharge Machining, Surface Roughness, Electrode Wear Rate

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1. INTRODUCTION

Machining can be defined as a material removing process from the work piece in a form of chips. There are three major components in machining process which are work piece, cutting tool and machine tool. Machining process can be divided into two types namely conventional and non-conventional machining. Conventional machining consists of traditional way of work piece removal process such as turning, milling, grinding and boring while non-conventional machining consist of chemical items or advanced technologies used for the cutting process such as electric discharge machining (EDM), electrochemical machining (ECM), abrasive water jet (AWJ) and laser beam machining (LBM) [1]. This study only focuses on EDM process which is well known as a successfully applied machining process for the geometrically complex parts, hard and difficult-to-machine materials [2]. EDM technology is a reliable, affordable and accurate process which is commonly used in automobile, surgical industries, molds, and aerospace fields.

EDM has unique feature that differs from other machining process. The direct contact does not occurred in EDM during the cutting process between the work piece and electrode when eliminating mechanical stresses, chatter and vibration problems. EDM technology has been improve significantly and has been developed in many ideas especially in the manufacturing industries that yielded enormous benefits in economic as well as generating keen interest in research area. There are different types of EDM that have been interest by researchers including die-sinking EDM, wire EDM (WEDM), powder-mixed EDM, Dry EDM and Micro-EDM [3].

EDM process was widely studied by previous researcher including modeling and optimization of machining performances using different approaches. Dewangan et al. [4] investigate the optimal solution of Ra in EDM process based on hybrid grey-fuzzy optimization approach on AISI P20 tool steel. The experiment was conducted using response surface methodology with pulse on time, tool lift time and tool work time as process parameters. The optimal solution was found and the result indicates that pulse on time is the most significant parameters affecting Ra value. Garg et al. [5] applied grey relational analysis (GRA) to find the optimal solution of Ra in EDM process using aluminum metal matrix composite. The experiment was conducted with pulse on time, pulse off time, peak current and gap voltage as input parameters. The optimal solution of Ra was found with pulse on time contributed more significantly to Ra. A new trend of optimization process using artificial intelligent approach has been evolves significantly over the years [6]. Meta-heuristic approaches such as simulated annealing (SA), ant colony optimization (ACO), bat algorithm (BA), firefly algorithm (FA), cuckoo search algorithm (CS) and harmony search (HS) optimization among the interest of many researchers [7-9]. These optimization approaches are proven to give better results compared with conventional optimization approaches.

Raja et al. [10] optimized the EDM parameters on hardened die steel using FA and it was found that FA is suitable for solving machining parameters optimization problem as the proposed model reduces time and cost of machining trials for surface roughness prediction. Teimouri and Baseri[11] optimized EDM parameters to determine the optimal solution of MRR and Ra based on ACO approach. The experiment was conducted with SPK (X210Cr12) cold work steel work piece with 99.9% copper electrode. The result found that continuous ACO has successfully determined the optimal solution of EDM performances. Rao and Venkaiah [12] optimized WEDM parameters of niminic-263 alloy using PSO algorithm. The mathematical model for material removal rate (MRR) and surface roughness (Ra) were developed based on RSM. The result shows that PSO gave better performance compared with RSM. Based on the review, the optimization of EDM parameters based on Harmony Search approach is still lacking, hence this paper proposed HS approach in order to find the optimal solution of Ra performance in EDM process.

2. METHODOLOGY

The experiment is conducted using AG40L die sinking EDM with stainless steel 316L as a work piece and copper impregnated graphite electrode. The work piece and electrode are shown in Figure 1 and Figure 2 respectively. The details chemical composition and mechanical properties of SS 316L are shown in Table 1 and Table 2 respectively.

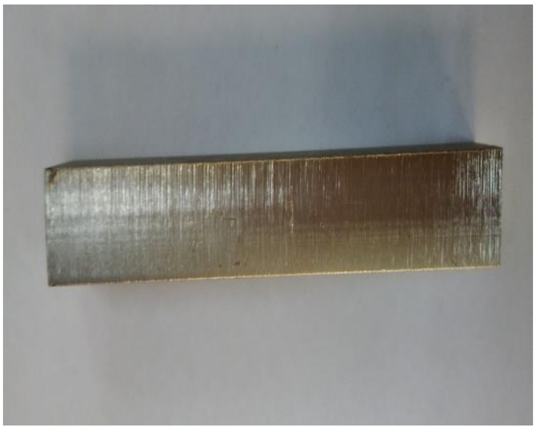

Figure 1. Stainless steel SS316L work piece

Figure 2. Copper impregnated graphite electrode

Table 1. Chemical composition of SS 316L

Elements	316L (wt %)
C	0.026
Si	0.37
Mn	0.16
Cr	16.55
Cu	0.16
Ni	10.0
P	0.029
S	0.027
Mo	2.02
N	0.036
Fe	Balance

Table 2. Mechanical properties of SS 316L

Mechanical Properties	Typical	Minimum
Tensile Strength	600Mpa	485Mpa
Proof Strength, (offset 0.2%)	310Mpa	170Mpa
Elongation (Percent in 50mm)	60	40
Hardness (Brinell)	217	-
Hardness (Rockwell)	95	-
Endurance (Fatigue Limit)	240Mpa	-

DOE is the design setting that needs to be completed prior to the experimental process can be run. In this study, the experiment is conducted based on two levels full factorial design which involves four parameters as input variables. Before conducting the experiment, the ranges for low (-) and high (+) levels for each parameter are determined based on EDM manual handbook or previous studies. Table 3 shows the range value for EDM parameters.

Table 3. The range value of EDM parameters

Machining Parameters	Unit	Levels	
		1	2
Pulse on time (T_{ON})	μs	100	200
Peak Current (Ip)	A	5.7	10.5
Servo Voltage (Vs)	V	30	90
Servo Speed (S)	s	74	92

Based on the Table 3, it can be seen that there are four machining parameters considered in this study which are pulse on time (T_{ON}), Peak Current (Ip), Servo Voltage (Vs) and Servo Speed (S). The range value for T_{ON} is [100, 200], range value for Ip is [5.7, 10.5], range value for Vs is [30, 90] and the range value for S is [74, 92]. After conducting the machining experiment, the machining data for Ra was collected and analyzed. The value of surface roughness value was measured using surface roughness tester. Table 4 shows the experimental result of Ra.

2.1 Modeling

The data collected was used to develop a mathematical model based on regression approach. It acts as an objective function for optimization process. To validate the model developed, analysis of variance (ANOVA) is used.

Table 4. Ra experimental result

No	Parameters				Ra (µm)
	T_{ON} (µs)	Ip (A)	Vs (V)	S (s)	
1	100.00	5.70	30.00	74.00	1.8791
2	100.00	10.50	30.00	74.00	2.3766
3	100.00	5.70	90.00	74.00	1.5366
4	100.00	10.50	90.00	74.00	4.0896
5	100.00	5.70	30.00	92.00	1.6486
6	100.00	10.50	30.00	92.00	5.5439
7	100.00	5.70	90.00	92.00	1.7243
8	100.00	10.50	90.00	92.00	2.9212
9	200.00	5.70	30.00	74.00	1.6429
10	200.00	10.50	30.00	74.00	2.7060
11	200.00	5.70	90.00	74.00	1.7071
12	200.00	10.50	90.00	74.00	2.5712
13	200.00	5.70	30.00	92.00	3.4499
14	200.00	10.50	30.00	92.00	4.1105
15	200.00	5.70	90.00	92.00	1.4481
16	200.00	10.50	90.00	92.00	2.4101

ANOVA is a statistical approach of portioning variability into identifiable sources of variation and the associated degree of freedom in an experiment. In modeling of Ra, it is generally expressed mathematically in terms of arithmetic average deviation from the mean. The mathematical model equation for Ra modeling is specified in Equation 1 [6].

$$R_a = \frac{1}{L}\int_0^L |\, Y\,(x)|dx \qquad (1)$$

where$L$ is the sampling length and Y is the ordinate of the profile curve. The minimization of the Ra must be formulated in the standard mathematical model which can be expressed as in in Equation 2.

$$R_a = k\ \prod_{i=1}^{n} c_i^{e_i} \qquad (2)$$

The final Ra mathematical model is written as in Equation 3 [13].

$$R_a = k\ {c_1}^{e_1}{c_2}^{e_2}{c_3}^{e_3}\ \ldots .\, {c_n}^{e_n} \qquad (3)$$

Where R_a is the predicted surface roughness (respond variable), $c_1 \ldots c_n$ is the EDM parameters, and k, e_1, $e_2 \ldots e_n$ are the model parameters to be predicted using the experimental data. To develop the regression model for Ra, the model given in Equation 3 is linearized by performing a logarithmic transformation. Multi linear regression model of Ra can be expressed as in Equation 4:

$$\text{MLR (Ra)} = -1.65988-2.09263E003*T_{ON} +0.30449*Ip-0.010311*Vs +0.032769*S \qquad (4)$$

Where Ra is surface roughness in µs, T_{ON} is pulse on time in µs, Ip is peak current in A, Vs is servo voltage in V and S is servo speed. The Ra model then analyzed using ANOVA analysis. Table 5 shows the ANOVA result of MLR for Ra.

Table 5. ANOVA of MLR for Ra

EDM parameters	Sum Square	DF	Mean Square	F Value	P-value
Model	11.66	4	2.91	3.65	0.0398
T_{ON}	0.18	1	0.18	0.22	0.6488
Ip	8.54	1	8.54	10.69	0.0075
Vs	1.53	1	1.53	1.92	0.1938
S	1.41	1	1.41	1.76	0.2112
Residual	8.79	11	0.80		

From Table 5, the result of the ANOVA indicates that the MLR model for Ra is statistically significant with the P-value of 0.0398. P-value that is equal or less than 0.05 is considered as significant, while P-value that is higher than 0.05 is considered as insignificant. For each machining parameter in MLR model, the result shows that only peak current is the significant to the model with the P-value =0.0075, while other machining parameters are insignificant to the model with the P-values are greater than 0.05. The value of R-Squared for the model is 0.5701, which is the model considered as a reasonable to be accepted.

2.2 HS Optimization

Harmony Search is a new meta-heuristic algorithm that mimicking the improvisation of music players to search for a perfect state of melody or harmony [14]. The optimization process is applied when musician plays different music notes on different instrument to find the best combination of frequency for a best tune. The steps for HS optimization as follows:

Step 1: Initialization of HS parameters.

i. Harmony memory size (HMS) defines the number of solution vectors in HM.
ii. Harmony memory considering rate (HMCR), HMCR$\in[0,1]$ which determine the selection rate from the memory.
iii. Pitch Adjusting Rate (PAR) $\in[0,1]$which determines the probability of local improvement.
iv. The fret width (FW) which determines the adjustment of the distance.
v. Number of iterations (NI) or number of improvisations.

Step 2: Initialization of harmony memory (HM).

HM is a storage area for the population individuals, which is called as solution vector where HM = $[x^1,\ldots x^{HMS}]^T$ of the size HMS. In this step, these solution vector are generated randomly as $x_i^j = LB_i + (UB_i - LB_i)\text{x}\, U(0,1), \forall = 1,2,\ldots,N$ and $\forall j = 1,2,..HMS,$ and U (0, 1) generates a uniform random number between 0 and 1.

Step 3: Improvisation of a new harmony.

Harmony vector is improvised to generate a new harmony vector$x' = (x_i', x_2', \ldots, x_N')$, based on three rules: (i) memory consideration (MC), (ii) pitch adjustment (PA), and (iii) random selection (RS). The three rules assign a value for each decision variable x_i' in the new harmony as formulated in Equation 5 as follows:

$$x_i^l \leftarrow \begin{cases} x_i' \in \{x_i^1, x_i^2, \dots x_i^{HMS} \text{ w.p HMCR x}(1 - PAR)\{MC\} \\ x_i' = x_i' + U(-1,1)x\, FW \quad \text{w.p. HMCR x } PAR \quad \{PA\} \\ x_i' \in X_i \text{ w.p } (1 - HMCR) \quad \{RC\} \end{cases} \tag{5}$$

Step 4: Update the HM

The worst harmony is replaced by a new harmony vector, $x' = (x_i', x_2', \dots, x_N')$, that is stored in HM.

Step 5: Check the stop criterion

Repeat step 3 and step 4 until the stopping requirement (which is normally depends on NI) is met.

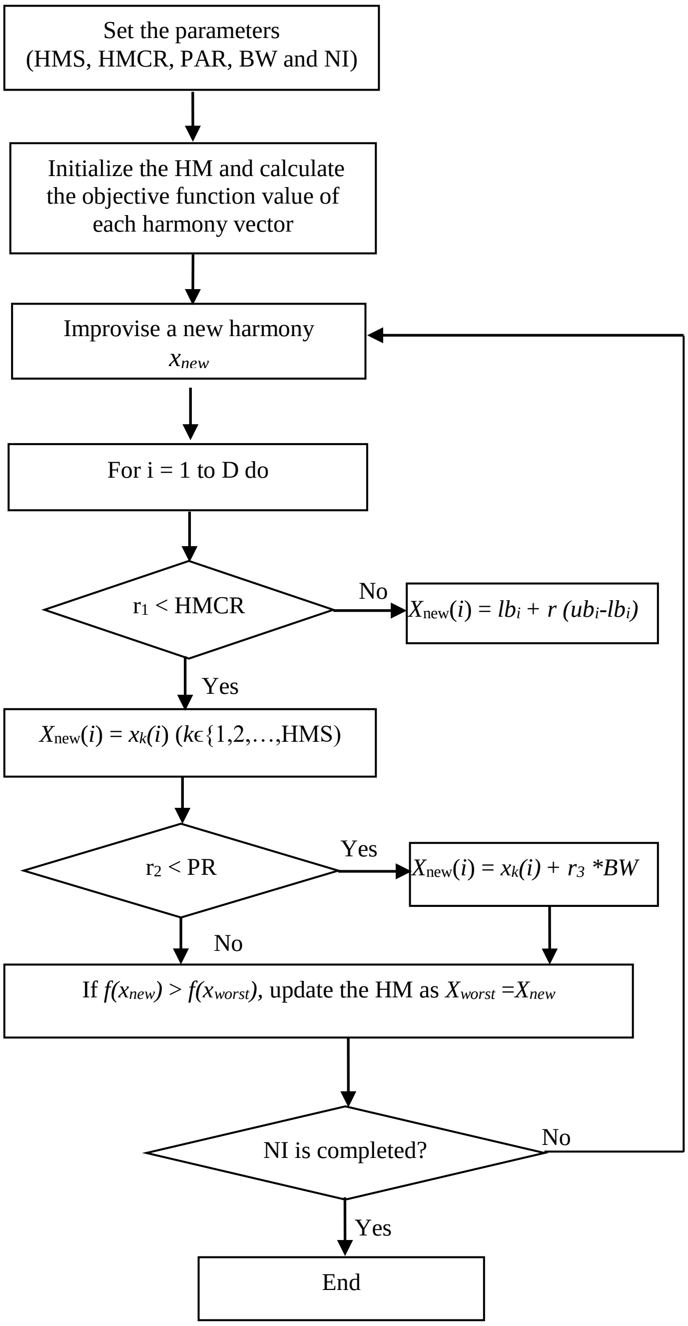

Figure 3. HS flowchart

3. RESULT ANALYSIS

The aim of optimization process for Ra is to find the optimal value for each machining parameters that lead to the minimum value of Ra. Table 6 shows the optimization result of Ra.

Table 6. HS optimal solution for Ra

Models	Optimal parameters T_{ON}, Ip, Vs, S (μs, A, V, S)	Minimum Ra (μm)	Error (%)
EXP	200, 5.7, 90, 92	1.4481	-
MLR	197.6991, 5.8559, 83.1139, 74.7832	1.3031	10.01

From Table 6, it can be seen that minimum Ra =1.3031μm for MLR was given by the combination of optimal cutting solution of machining parameters T_{ON} = 197.6991 μs, I_p = 5.8559 A, Vs = 83.1139 V and S= 74.7832 with the computing time 0.473s. For 2FI, minimum Ra = 1.3346 μm was given by T_{ON} = 100.0429 μs, I_p = 5.7 A, Vs = 36.0441 V and S= 75.0415 with the computing time 0.456s. For SR, the minimum Ra = 1.8796 μm was given by T_{ON} = 129.0690μs, I_p = 5.7 A, Vs = 77.9637V and S= 89.7334 with the computing time 0.420, while for PR model, minimum Ra = 1.2444 μm was given by T_{ON} = 193.0109μs, I_p = 5.7 A, Vs = 87.3162 V and S= 74.5226 with the computing time 0.364s, The percentage error of 2FI model is the lowest compared to other models, which is 7.84%. The results of HS optimization for Ra was validate with the substitution of the optimal combination of machining parameters to the mathematical equation in order to compare the values of machining performances, as in Equation 5. The result can be taken as the indicators that the same results will obtained when this optimal solution are tested through the actual experiment process.

$$Ra = -1.65988-2.09263E003\,(197.6991) + 0.30449(5.8559) - 0.010311(83.1139) + 0.032769(74.7832) = 1.3031\ \mu m \qquad (5)$$

4. CONCLUSION

Experiment data shows lowest Ra which is 1.4481 μm, was obtained at the combination of high pulse on time, low peak current, high servo voltage and high servo speed. Low energy discharges to the work piece material causing the better surface finish which resulted in lower Ra value. Increasing value of peak current generates the higher energy that leads to the strong spark during the machining process. Thus, the rougher surface finished is obtained.

Choosing the right approach to develop mathematical model is crucial task as it will affect the optimization result. The developed models were used as objective function in optimization process. The regression model developed for Ra was found significant by giving the p-value less than 0.05.

HS has been proven to give better result in solving optimum solution of optimization problem. With the few parameters involved, HS has been widely considered by previous researchers in various fields including machining and manufacturing. In this study, HS optimization give better result compared with experimental by giving the minimum value of Ra, 1.3031 μm with the 10.01% improvement.

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