Harmony search optimization in dimensional accuracy of die sinking EDM process using SS316L stainless steel

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Abstract. Electric discharge machine (EDM) is one of the widely used nonconventional machining processes for hard and difficult to machine materials. Due to the large number of machining parameters in EDM and its complicated structural, the selection of the optimal solution of machining parameters for obtaining minimum machining performance is remain as a challenging task to the researchers. This paper proposed experimental investigation and optimization of machining parameters for EDM process on stainless steel 316L work piece using Harmony Search (HS) algorithm. The mathematical model was developed based on regression approach with four input parameters which are pulse on time, peak current, servo voltage and servo speed to the output response which is dimensional accuracy (DA). The optimal result of HS approach was compared with regression analysis and it was found HS gave better result y giving the most minimum DA value compared with regression approach.

1. Introduction
Manufacturing can be defines as the integration of the complex process of mechanical, physical and chemical to make finish part of products [1]. In manufacturing process, machining is the most important and widely used in manufacturing process instead of molding, casting and joining as the machining process can gives the closer dimensional and also can performed the external and internal geometric features as well as sharp corners and flatness. Machining generally can be defined as a process of material removing from the work piece in a form of chips. Machining consists of three major which are machine tools, cutting tool and work piece. There are two types of machining; conventional and modern machining. Conventional machining consists of traditional process work piece removal in the form of chips such as turning, milling, grinding and boring while modern machining comes in terms of chemical items or advanced technologies such as Electric Discharge Machining (EDM), wire electric discharge machining (WEDM), electrochemical machining (ECM), abrasive water jet (AWJ) and laser beam machining (LBM) [2]-[4]. EDM is one of the mostly used modern machining processes for hard material and complex shapes which are difficult-to-machine by conventional machining. 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 [5]. For die sinking EDM, the machining process occurs by the 3D movement of an electrode with the numerical control monitors the gap conditions and synchronously controls the different axes and the pulse generator. In WEDM, the material is eroded from the work piece by a series of discrete sparks occurring between the work piece and the wire separated by the existence of dielectric fluid. Micro-EDM is a process that is capable not only for micro-holes and micro-shafts with 5 µm in diameter but also capable for complex 3D micro-cavities. Lastly, powder-mixed EDM is basically differs from conventional EDM when a suitable material in powder form is mixed into dielectric fluid. The spark gap filled up additive particles when a suitable voltage is applied and the gap distance setup between tool and work piece increase from 25-50 to 50-150 µm.

There are several machining performances that are evaluated by major measure, such as cutting force, tool wear, material removal rate, tool life, chip form and surface finish [6]. Dimensional accuracy is also one of the important parameters that are considered by many researchers [7] – [8]. Dimensional Accuracy (DA) which also can be defines as diameter overcut is significantly influences the precision and accuracy of the product. Dimensional accuracy is crucial when close tolerance components are required to be produced for space applications and tools, plastic molding and die casting. Tiwari et al. [7] optimized four machining parameters which are electrolytic concentration, voltage, feed rate and inter electrode gap using Taguchi method in order to find the optimal solution of overcut in ECM process. The experiment was conducted based on design of experiment L27 orthogonal array using EN19 tool steel material. The mathematical model was developed using regression analysis and it was found that voltage and concentration were the most influence machining parameters for overcut value. Pradhan and Das [8] investigate radial overcut in EDM process based on general regression neural network using AISI D2 tool steel. A full factorial design was used to conduct the experiments. The result shows that the proposed models can be successfully employed to predict the EDM process. Thanigaivelan and Arunachalam [9] investigated the effect and parametric optimization of machining rate and overcut of electrochemical micromachining based on grey relational analysis. the experiments is conducted using stainless steel 304 material with four machining parameters, which are tool tip shape, voltage, pulse on time and electrolyte concentration. The result found that the optimization of the multiple performances can be simplified and improved through Taguchi and grey relational analysis approach.

A new trend of optimization process using artificial intelligent approach has been evolves significantly over the years [2]. Meta-heuristic approaches such as artificial bee colony (ABC), 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 [10]-[14]. These optimization approaches are proven to give better results compared with conventional optimization approaches. Yusup et al [15] investigate the optimal machining parameters of AWJ machining using artificial bee colony and it was found that ABC approach gave better results compared with other method such as regression and artificial neural network (ANN). Rao and Venkaiah [16] optimized WEDM parameters of nimonic-263 alloy using particle swarm optimization. The mathematical model for material removal rate (MRR) and surface roughness (Ra) were developed based on response surface methodology (RSM). The result shows that PSO gave better performance compared with RSM. Raja et al. [17] optimized the EDM parameters on hardened die steel using firefly algorithm 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. 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 dimensional accuracy parameters in EDM process. The mathematical model was developed based on multi linear regression approach [18, 19]. The development of mathematical model for DA is important in order to have better understanding to the machining process [20].
2. Experimental Procedure
The experiment is conducted using AG40L die sinking EDM as shown in Figure 1. The material used in this experiment is stainless steel 316L as shown in Figure 2, and the electrode is copper impregnated graphite is shown in Figure 3. The details chemical composition and mechanical properties of SS 316L are shown in Table 1 and Table 2 respectively.

![Figure 1. AG40L model of die sinking EDM](image1)

![Figure 2. Stainless steel 316L](image2)

![Figure 3. Copper impregnated carbide electrode](image3)
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    | -        |

The design setting is important process 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 of four input variables. Design of Experiment (DOE) is implemented to observe the process characteristic since it provides the best parameters of EDM to fulfill the machining objectives. DOE is a systematic and powerful tool that applies principles and techniques at the data collection stage, to ensure the generations of valid, defensible and supportable engineering conclusions. DOE can observe and identify the change that has been made from input variables. The experiment implies 2 levels of 4 input factors which consist of 16 runs ($2^4$). Before conducting the experiment, the range for low and high level for each factor is determined. In this study the selection of the range for EDM parameters is based on manual EDM handbook and recommendation from previous researchers. Table 3 shows the range value of EDM parameters.

Table 3. The range value of EDM parameters

| Variables         | Unit | Levels |
|-------------------|------|--------|
| Pulse on time (ON)| µs   | 100    |
| Peak Current (IP) | A    | 5.7    |
| Servo Voltage (S) | V    | 30     |
| Servo Speed (S)   | -    | 74     |
Dimensional Accuracy (DA) which also can be defined as diameter overcut is one of the important responses in machining process. Dimensional accuracy is crucial when close tolerance components are required to be produced for space applications and tools, plastic molding and die casting. Dimensional accuracy can be calculated as follows:

$$DA = \frac{(D_b - D_a)}{D_b} \times 100\%$$ (1)

Where $D_b$ is the diameter electrode before the machining and $D_a$ is the diameter electrode after the machining.

3. Experimental Result and Analysis

The machining experimental has been conducted in full factorial design which given 16 number of runs. Figure 4 shows the materials cutting after the machining process while Table 4 shows the experimental result of DA value.

Table 4: Experimental data

| No. | ON  | IP  | SV  | S   | DA  |
|-----|-----|-----|-----|-----|-----|
| 1   | 100.00 | 5.70 | 30.00 | 74.00 | 0.023 |
| 2   | 100.00 | 10.50 | 30.00 | 74.00 | 0.0223 |
| 3   | 100.00 | 5.70 | 90.00 | 74.00 | 0.0158 |
| 4   | 100.00 | 10.50 | 90.00 | 74.00 | 0.0280 |
| 5   | 100.00 | 5.70 | 30.00 | 92.00 | 0.0133 |
| 6   | 100.00 | 10.50 | 30.00 | 92.00 | 0.0275 |
| 7   | 100.00 | 5.70 | 90.00 | 92.00 | 0.0150 |
| 8   | 100.00 | 10.50 | 90.00 | 92.00 | 0.0228 |
| 9   | 200.00 | 5.70 | 30.00 | 74.00 | 0.0223 |
| 10  | 200.00 | 10.50 | 30.00 | 74.00 | 0.0240 |
| 11  | 200.00 | 5.70 | 90.00 | 74.00 | 0.0125 |
| 12  | 200.00 | 10.50 | 90.00 | 74.00 | 0.0238 |
| 13  | 200.00 | 5.70 | 30.00 | 92.00 | 0.0238 |
| 14  | 200.00 | 10.50 | 30.00 | 92.00 | 0.0303 |
| 15  | 200.00 | 5.70 | 90.00 | 92.00 | 0.0183 |

Figure 4. Holes of materials after machining
Based on the table, it can be found that the most minimum Da value is 0.0125. The regression model was developed based on experimental data and analyzed using analysis of variance (ANOVA). Sum square (SS), mean square (MS), F-ratio and P-values associated with each other levels and interaction were presented in Table 5. From the table, it shown that the model is statistically significant with the P-value Prob >F is 0.0157, which is less than 0.05, while peak current is the only parameter that is significant to the dimensional accuracy value with the p-value of 0.0021. The rest of the parameters show insignificant with the p-value are greater than 0.05. Figure 5 shows the graphical plots if normal plot of residuals for dimensional accuracy in EDM process.

| Source | SS       | DF | MS     | F       | P-value |
|--------|----------|----|--------|---------|---------|
| Model  | 2.690E-004 | 4  | 6.726E-005 | 4.96     | 0.0157 |
| ON     | 8.410E-006  | 1  | 8.410E-006  | 0.62     | 0.4477 |
| IP     | 2.176E-004  | 1  | 2.176E-004  | 16.04    | 0.0021 |
| SV     | 4.225E-005  | 1  | 4.225E-005  | 3.11     | 0.1053 |
| S      | 8.100E-007  | 1  | 8.100E-007  | 0.060    | 0.8114 |
| Residual | 1.492E-004 | 11 | 1.356E-005 |         |         |
| Cor Total | 4.182E-004 | 15 |         |         |         |

Figure 5. Normal plot of residual for DA

Based on the plots, it can be seen that all the points are scattered normally and distributed along the line as well as no abnormality found. There are no obvious patterns even though some data points are far from the centre line and all the results are within the acceptable range. These are the desirable plots when analyzing the data. Therefore, it can be concluded that the model was valid and adequate. The multiple linear regression for DA can be stated as in Equation 2:

$$DA = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_1 x_2 + \beta_6 x_1 x_3 + \beta_7 x_1 x_4 + \beta_8 x_2 x_3 + \beta_9 x_2 x_4 + \beta_{10} x_3 x_4$$

(2)
Where $\beta_n$ are the regression coefficients and $x_n$ are the variable of machining parameters. Based on the experimental data, the final mathematical model for DA can be stated as in Equation 3:

$$DA = +8.24219E-003 +1.45000E-005 \times ON +1.53646E-003 \times IP -5.41667E-005 \times SV +2.50000E-005 \times S$$

(3)

4. Harmony Search Optimization

Harmony Search (HS) [21] is a new meta-heuristic algorithm mimicking the improvisation of music players in searching for a perfect state of harmony. The optimization process is applied when musician plays different notes of different musical instrument to find the best combination of frequency for a best tune [22]. The aesthetic quality of music produced by its musical instruments can be determined by its pitch, timbre and amplitude. HS has simple mathematical model and only few lines of algorithm involve. The objectives function for optimization problems are normally stated as follows:

Minimize $f(x)$,
Subject to $x_i = X_i, i = 1, 2, 3, ... n$

where $f(x)$ is the objective function; $x$ is the set of each decision variable $x_i$; $n$ is the number of decision variables, $X_i$ is the set of the possible range of values for each decision variable, that is $x_i^L \leq x_i \leq x_i^U$ and $x_i^L$ and $x_i^U$ are the lower and upper bound for each decision variable. Steps for HS algorithm describes as follow:

Step 1: Initialize the parameters.
   i. The HS algorithm parameters are specified in this step. These parameters are:
      ii. Harmony Memory Size (HMS), or the number of solution vectors in the harmony memory
      iii. Harmony Memory Considering Rate (HMCR), HMCR $\in [0, 1]$ to determine the rate of selecting the value from the memory;
      iv. Pitch Adjusting Rate (PAR) $\in [0, 1]$ which determines the probability of local improvement
      v. The fret width (FW) which determines the distance of adjustment
      vi. Number of improvisations (NI) or number of iterations.

Step 2: Initialize the Harmony Memory (HM)
   HM is a repository of the population individuals, $HM = [x^1, x^2 ... x^{HMS}]^T$ of the size HMS. In this step, these individuals are randomly generated as $x_i^t = L_i + (U(B_i - L_i) \times U(0,1), \forall = 1, 2, ..., N$ and $\forall j = 1, 2, ..., HMS$, and $U (0, 1)$ generates a uniform random number between 0 and 1.

Step 3: Improvise a new harmony.
   A New Harmony vector is generated, $x' = (x'_1, x'_2, ..., x'_N)$, based on three operators: (i) memory consideration (MC), (ii) pitch adjustment (PA), and (iii) random consideration (RC). The three operators assign a value for each decision variable $x'_i$ in the New Harmony as formulated in Equation 5 as follows:

$$x'_i \left\{ \begin{array}{l}
           x'_i \in \{x^1_i, x^2_i, ...x^{HMS}_i\} \quad \text{w.p HMCR} \times (1 - PAR) \{MC\} \\
           x'_i = x^t_i + U(-1,1) \times FW \quad \text{w.p HMCR} \times PAR \{PA\} \\
           x'_i \in X_i \quad \text{w.p} \ (1 - HMCR) \{RC\}
           \end{array} \right.$$

(5)

Step 4: Update the HM
The new harmony vector, \( x' = (x'_1, x'_2, ..., x'_N) \), replaces the worst harmony stored in HM.

Step 5: Check the stop criterion

Step 3 and step 4 of HS algorithm are repeated until the stop criterion (which is normally depends on NI) is met.

The optimization process of harmony search is conducted using Matlab software in order to find the optimal solution of dimensional accuracy. HS is expected to give the minimum value of DA for EDM process. Figure 6 shows the flowchart of HS optimization while the result of HS optimization is stated in Table 6.

![Flowchart of HS Optimization](image)

**Figure 6.** Flowchart of HS Optimization

**Table 6.** Optimization results for dimensional accuracy

| Optimal cutting points (ON,OFF,IP,SV,S) | Minimum DA (%) | Percentage Error (%) |
|----------------------------------------|----------------|----------------------|
| Experimental 100,50,5,7,30,74          | 0.0125         | -                    |
Table 6 shows the results of multi linear regression and HS optimization compared with experimental data. The percentage error of multi linear regression and HS were calculated in order to find the best approach for DA optimization of EDM process. Based on the result, it can be seen that Harmony Search optimization outperformed multi linear regression by 0.25% of percentage error compared with 0.34% of percentage error. The optimal solution can be achieved when pulse on time 110.0211µs, peak current 5.7A, servo voltage 89.1258V and servo speed is 74.0169, which giving the most minimum DA value is 0.0156%.

5. Conclusion
Machining experiment was conducted using stainless steel 316L and copper impregnated carbide electrode for optimization of dimensional accuracy parameters in electric discharge machining process. The experiment was conducted based on full factorial design with four machining parameters which are pulse of time, peak current, servo voltage and servo speed. The mathematical model was developed based on multi liner regression approach and the model was analyzed using ANOVA analysis. ANOVA and regression approach provide a systematic and effective methodology for the optimization process. It is found that peak current is the most influence parameters to the dimensional accuracy value compared with pulse on time, servo voltage and servo speed.

The optimization process is conducted using harmony search approach in order to find the optimal solution of dimensional accuracy for EDM process. The minimum DA value of harmony search then compared with multi linear regression and it was found that HS gave the better results by giving the less percentage error. Hence, optimization process using HS approach is the most effective method compared with conventional optimization techniques such as ANOVA and regression approaches.

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