Parametric Optimization of Die Sinking EDM in AISI D2 Steel considering Canola oil as Dielectric using TOPSIS and GRA

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Abstract. A colossal research work is being consummated to propose the optimal machining parameters while necessitating current machining techniques to attain elegant products. This research work foregrounded the optimum process parameters of die sinking EDM with 8mm diameter copper electrode during machining AISI D2 steel. Taguchi’s L9 OA method was adopted to design 9 experiments in total and Pulse on time ($T_{on}$), Servo voltage (SV) and Peak current ($I_p$) are chosen as input parameters. Three levels of each parameter were selected for designing the experimentation. A natural vegetable oil named Canola oil which is an extract from Canola seeds is taken as dielectric and all the values of Material Removal Rate (MRR), Tool Wear Rate (TWR) and Surface Roughness (SR) for each experiment were noted as the output responses. Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Grey Relational Analysis (GRA) which are two Multi-Criteria Decision Making (MCDM) methods were accompanied for determination of ideal parameters for machining AISI D2 steel. Ultimately it is espied that the coalescence of level 3 of pulse on time, level 2 of Peak Current and level 2 of servo voltage propounds the optimum result by performing TOPSIS and GRA.

1. Introduction

Machining is remarkably regarded while manufacturing copious components that regale our everyday needs together with many engineering and industrial applications. As conventional machining process is scant to meet the presumption of latest manufacturing experts, advanced machining processes are chosen to adeptly effectuate the task with meliorated outcomes. Researchers are obliged to EDM i.e. Electric Discharge Machine that helped in manufacturing myriad newfangled materials that are arduous to achieve. Medical and surgical equipment, motorized industries, aerospace industries and die making and so on to name a few are among the copious applications that use EDM. It can also be utilitarian for producing byzantine shapes during machining [1]. Inter electrode gap does not bound the hardness of workpiece in the process of machining and electrically conductive materials such as Copper, Brass, Graphite, Tungsten etc., acting as electrodes remove the material [2]. The same can machine any material that is electric conductive regardless of strength or hardness. Being a thermo electrical machining process, EDM melts and vaporizes the work surface to remove material. The positive terminal in the case in question is the work piece that is supposed to be machined with the electrode being the negative terminal to the source of power. As the electrode moves closer to the
work piece, due to ionization in the inter-electrode gap, the electrons from electrode moves with very high velocity towards the work piece and strikes that triggers an electric spark of temperature about 10000° C. Hence such elevated temperature initiates material removal by the said mechanism [3]. The characteristics of EDM are scrutinized by effectuating parametric optimization of diverse input considerations like Pulse on time, Peak Current, Servo Voltage, Pulse off time, Duty cycle, etc.. In the trending scenario of research decision making models that fit into multi criteria framework like Grey Relational Analysis (GRA), Fuzzy logic Multi-attribute Utility Theory (MAUT), Technique for order of preference by similarity to ideal solution (TOPSIS) Analytical Hierarchy process (AHP) etc, have become popular and are used for optimizing various non-conventional manufacturing process parameters [4]. A material having relatively high wear together with abrasion resistance alike AISI D2 steel has been employed in making dies for stamping, punches and many other engineering and industrial applications which is high carbon high chromium tool steel in this study. Hence it is significant to machine such steel by die sinking EDM. Researchers found that Taguchi’s Orthogonal Array is a highly functional tool for designing the experiments which gives a matrix of combination of input parameters called Taguchi orthogonal arrays. These arrays are balanced and thus the unbiased evaluation can be done.

Routara et al. [5], in their investigation on the characteristics of machining of T6 – Al7075, carried out 9 experiments exercising Taguchi’s L9 orthogonal array, The input parameter used were spark gap, peak current and pulse off time at each level to record the output responses in terms of metal removal rate, surface roughness and tool wear rate. The study makes use of ANOVA to determine the significance of the above said parameters with relation to the output responses and further TOPSIS was chosen as an optimizing technique. Kannan et al. [6] used TOPSIS method for optimizing parameters for machining in Laser Beam Machining so as to design micro elliptical profiles on aluminum based composite. Their study made use of Taguchi’s L9 orthogonal array method. Rahul et al. [7] performed 25 experiments using Taguchi’s L25 orthogonal array in die sinking EDM. They used a rod of pure copper with a circular cross section of 20 mm diameter as electrode for machining Inconel 718 plates. The dielectric used was EDM oil with 0.763 gravity, the input parameters being Duty factor, Peak current, Open circuit voltage, Pulse on time and flushing pressure while White layer Thickness and Micro Hardness, Surface Roughness, Material Removal Rate, Surface Crack Density and Electrode Wear Rate, were chosen as Output responses. They also used optimization techniques like PCA along with TOPSIS for optimizing the process parameters. Dewangan et al. [8] in their studies came up with the optimization of the process parameters for micro EDM by using Fuzzy – TOPSIS approach. They have proposed that their research can be used the field of manufacturing and medical applications. Rajesh et.al [9] predicted the process parameters of EDM for AISI 1020 steel using RSM, GRA and ANN. They have taken Voltage, Ton, Toff, Oil pressure and Spark gap as input parameters and MRR and Surface roughness as response parameters. 54 experiments are conducted involving various parameter combinations. It is understood that, vegetable oil as dielectric can increase productivity and be environment friendly. Also, optimization of process parameters can reduce consumption of time in finding quality product.

2. Details of experimentation

2.1. Choice of workpiece, tool and machining process

An ASKAR Microns V3525 die sinking EDM incorporating a robust table to fix the work, CNC operated system and a motor operated pumping system for fluid circulation as shown in figure 1 is picked to perform the task. The input parameter employed can be enumerated as pulse on time, Servo voltage and Peak current with three levels each. The values of available pulse on time in this machine range from 100 µs to 800 µs among which 300 µs, 400 µs and 500 µs are selected for current experimentation. The available metrics for Peak current ranges from 1 A to 8 A among which 6 A, 7 A and 8 A are chosen and finally the available metrics range for servo voltage is from 40 V to 80 V among which 40 V, 50 V and 60 V are chosen as explained in table 1. For experimentation, a work piece of AISI D2 Steel with a dimension of 100mm x 60 mm x 5mm was chosen. Canola oil is picked
as dielectric fluid and an 8mm Copper rod is selected as electrode (tool). A weighing machine with 1mg least count is utilized to measure the weight of work and tool during process. A stop watch with 1 micro sec tolerance is used to note down the time for process and the SR measurement was facilitated by the use of Taly surf machine for running length of 4mm.

![Experimentation Setup](image)

**Figure 1.** Experimentation Setup

The calculation of MRR and TWR is done by the given equations (1) and (2).

\[
MRR = \frac{W_b - W_a}{t} \frac{mg}{min} \tag{1}
\]

\[
TWR = \frac{T_b - T_a}{t} \frac{mg}{min} \tag{2}
\]

Where,

- \(W_b\) is the work-material’s weight prior to machining.
- \(W_a\) is the work-material’s weight post machining.
- \(T_b\) is the copper electrode’s weight prior to machining.
- \(T_a\) is the copper electrode’s weight post machining.
- \(t\) is time taken for Manufacturing in minutes.

### 2.2. Control parameters and their levels

| Input parameter     | Level 1 | Level 2 | Level 3 |
|---------------------|---------|---------|---------|
| Pulse on time in µs | 300     | 400     | 500     |
| Peak current in A   | 6       | 7       | 8       |
| Servo Voltage in V  | 40      | 50      | 60      |

**2.3. Design of Experiments**
Experiments are conducted using Taguchi’s L9 orthogonal array[11,12] with the various combinations of input parameters for each experiment conducted as depicted in the table 2 given below.

| Experiment | T_on(µs) | SV (V) | IP(A) |
|------------|----------|--------|-------|
| 1          | 300      | 40     | 6     |
| 2          | 300      | 50     | 7     |
| 3          | 300      | 60     | 8     |
| 4          | 400      | 50     | 6     |
| 5          | 400      | 60     | 7     |
| 6          | 400      | 40     | 8     |
| 7          | 500      | 40     | 6     |
| 8          | 500      | 50     | 7     |
| 9          | 500      | 60     | 8     |

### 3. Results and discussions

At the end of each experiment, responses were calculated by using weighted machine and a stop watch for calculation of MRR and TWR and $R_a$ is calculated using Taly surf roughness tester. The results are listed below in the table 3.

| Experiment | MRR($10^3$ gm/min) | TWR ($10^3$ gm/min) | SR ($R_a$) in microns |
|------------|---------------------|----------------------|-----------------------|
| 1          | 5.97                | 0.3                  | 1.8                   |
| 2          | 4.83                | 0.62                 | 3.2                   |
| 3          | 3.2                 | 0.36                 | 3.1                   |
| 4          | 4.3                 | 0.31                 | 2.3                   |
| 5          | 5.1                 | 0.76                 | 3.1                   |
| 6          | 7.6                 | 0.76                 | 3.2                   |
| 7          | 8.18                | 0.47                 | 2.8                   |
| 8          | 17.1                | 0.37                 | 2.7                   |
| 9          | 8.28                | 0.68                 | 2.3                   |

### 3.1. S/N ratio of results

Signal to Noise ratio for each of the responses are listed as in table 4.

| Experiment | S/N ratio of MRR | S/N ratio of TWR | S/N ratio of SR |
|------------|------------------|------------------|-----------------|
| 1          | -6.02136         | -2.73402         | -0.65164        |
| 2          | -4.67784         | -0.43101         | -2.55177        |
| 3          | -2.55177         | -1.96867         | -2.41436        |
| 4          | -4.01282         | -2.58713         | -1.30847        |
3.2. TOPSIS method

With an aim to identify the alternatives that provide with positive ideal solution, Hwang and Yoon developed the TOPSIS technique, where it is believed that positive ideal solution augments benefit criteria and curtails the cost criteria. Antipode to it, negative ideal solution augments the cost criteria and curtails the benefit criteria. The following steps demonstrate the selection procedure of TOPSIS [13-15] for coming up with a best alternative among the available ones:

Step 1: Calculate Normalized Matrix

Normalized matrix for all the three output responses can be calculated by using equation 3 as given below and all the values are as projected in table 5.

\[ \bar{X}_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{n} X_{ij}^2}} \]  

(3)

Table 5. Normalized matrix

| Experiment | Weightage | 0.33 | 0.33 | 0.33 |
|------------|-----------|------|------|------|
|            | MRR       | TWR  | SR   |      |
| 1          | 0.2650263 | 0.338049 | 0.234005 |
| 2          | 0.22293   | 0.347388 | 0.353715 |
| 3          | 0.3833981 | 0.384119 | 0.341041 |
| 4          | 0.2933635 | 0.225989 | 0.240803 |
| 5          | 0.3538052 | 0.703699 | 0.373302 |
| 6          | 0.25225   | 0.169336 | 0.374454 |
| 7          | 0.2894323 | 0.16944  | 0.367541 |
| 8          | 0.2804234 | 0.053955 | 0.373302 |
| 9          | 0.5438663 | 0.10459  | 0.30302 |

Step 2: Calculate weighted normalized matrix

Weighted Normalized matrix for all the three output responses can be calculated by using equation 4 given below and all the values are as projected in table 6.

\[ V_{ij} = \bar{X}_{ij} \ast W_j \]  

(4)

Step 3: Calculating the ideal best and ideal worst value

It is always expected to have better MRR and less TWR as well as SR. So the highest among all the \( V_j \) values is treated as the ideal best for MRR and the lowest is treated as the ideal worst. Similarly the lowest among all the values of \( V_j \) is treated as the ideal best for TWR as well as SR and the highest is treated as the ideal worst for both TWR and SR.

The ideal best solution and ideal worst solutions of all the three output responses can be calculated by using equations 5 and 6 respectively and the same are as shown in table 6.

\[ V_j^+ = \{ \sum_{i=1}^{max} V_{ij} \ where \ j \in J, \sum_{i=1}^{min} V_{ij} \ where \ j \in J' \} \]  

(5)
\[ V_j^+ = \{ \sum_{i=1}^{\min} V_{ij} \text{ where } j \in J, \sum_{i=1}^{\max} V_{ij} \text{ where } j \in J' \} \quad (6) \]

**Step 4: Calculating the Euclidean distance from the ideal best.**

Euclidean distance from the ideal best can be determined by using the relation 7 as given below

\[ S_i^+ = \left( \sum_{j=1}^{m} (V_{ij} - V_j^+)^2 \right)^{0.5} \quad (7) \]

And all the Euclidean distances from the ideal best are as given in the table 6.

**Step 5: Calculating the Euclidean distance from the ideal worst.**

Euclidean distance from the ideal worst can be determined by using the relation 8 as given below

\[ S_i^- = \left( \sum_{j=1}^{m} (V_{ij} - V_j^-)^2 \right)^{0.5} \quad (8) \]

And all the Euclidean distances from the ideal worst are as given in the table 6.

**Step 6: Calculating the performance score**

The performance scores for all the three output responses can be calculated by using the relation ix as given below,

\[ P_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad (9) \]

And all the performance scores are as given in table 6.

**Table 6. Normalized decision matrix**

| Experiment | MRR     | TWR     | SR       | Si+     | Si-     | Si+ + Si- | Pi     | Rank |
|------------|---------|---------|----------|---------|---------|-----------|--------|------|
| 1          | 0.0874587 | 0.111556  | 0.077222 | 0.131634 | 0.130004 | 0.261368 | 0.497399 | 6    |
| 2          | 0.0735669 | 0.114638  | 0.116726 | 0.148842 | 0.117782 | 0.266623 | 0.441753 | 8    |
| 3          | 0.1265214 | 0.126759  | 0.112544 | 0.126186 | 0.118524 | 0.244709 | 0.484345 | 7    |
| 4          | 0.0968099 | 0.074576  | 0.079465 | 0.100308 | 0.16534  | 0.265647 | 0.622403 | 4    |
| 5          | 0.1167557 | 0.232221  | 0.12319  | 0.228081 | 0.04319  | 0.271271 | 0.159215 | 9    |
| 6          | 0.0832425 | 0.055881  | 0.12357  | 0.113397 | 0.176605 | 0.290001 | 0.608979 | 5    |
| 7          | 0.0955127 | 0.055915  | 0.121289 | 0.102196 | 0.177681 | 0.279877 | 0.634853 | 3    |
| 8          | 0.0925397 | 0.017805  | 0.12319  | 0.098341 | 0.215254 | 0.313594 | 0.686407 | 2    |
| 9          | 0.1794759 | 0.034515  | 0.099997 | 0.028247 | 0.225522 | 0.253769 | 0.888689 | 1    |

| Vj+        | 0.1794759 | 0.017805  | 0.077222 |
|------------|-----------|-----------|----------|
| Vj-        | 0.0735669 | 0.232221  | 0.12357  |

It is observed that the value of relative closeness is at its maximum at experiment 9, the value of which can be observed being 0.888689 corresponding to the input process parameters Pulse on time 500 micro seconds, Peak Current 8 A and Servo Voltage 60V.

### 3.3. GRA Method

Grey Relational Analysis (GRA), a Multi Criteria Decision Making tool, is carried out in four steps [9] to find the optimum parameters among the conducted experiments.

**Step 1: Normalizing the response parameters:**

Larger MRR, Smaller Surface Roughness and minimal TWR are always preferable while experimenting. Hence in GRA Larger the better equation as in (11) is chosen for normalizing the MRR and smaller the better equation as in (12) is chosen for normalizing the Surface Roughness and TWR.

Nominal – the best

\[ Y_i(k) = \frac{|X_i(k) - X_e(k)|}{\max X_i(k) - X_e(k)} \quad (10) \]

Larger the better
\[ Y_i(k) = \frac{X_i(k) - \min X_i(k)}{\max X_i(k) - \min X_i(k)} \quad (11) \]

Smaller the better

\[ Y_i(k) = \frac{\max X_i(k) - X_i(k)}{\max X_i(k) - \min X_i(k)} \quad (12) \]

The final normalized data for MRR, Surface Roughness (R_a) and TWR are as listed in table 7.

**Table 7. Normalized data of response parameters**

| Experiment | MRR  | SR      | TWR  |
|------------|------|---------|------|
| 1          | 0.199281 | 1       | 1    |
| 2          | 0.117266 | 0.304348 | 0    |
| 3          | 0     | 0.869565 | 0.071429 |
| 4          | 0.079137 | 0.978261 | 0.642857 |
| 5          | 0.136691 | 0       | 0.071429 |
| 6          | 0.316547 | 0       | 0    |
| 7          | 0.358273 | 0.630435 | 0.285714 |
| 8          | 1     | 0.847826 | 0.357143 |
| 9          | 0.365468 | 0.173913 | 0.642857 |

Step 2: Deviation Sequence: Normalized data is used to calculate the deviation sequence of Grey Relational Analysis by using equation (13) and the resulting data is listed in table 8.

\[ \Delta Y_i(k) = |Y_o(k) - Y_i(k)| \quad (13) \]

**Table 8. Deviation Sequence of response parameters**

| Experiment | MRR  | SR      | TWR  |
|------------|------|---------|------|
| 1          | 0.800719 | 0       | 0    |
| 2          | 0.882734 | 0.695652 | 1    |
| 3          | 1     | 0.130435 | 0.928571 |
| 4          | 0.920863 | 0.021739 | 0.357143 |
| 5          | 0.863309 | 1       | 0.928571 |
| 6          | 0.683453 | 1       | 1    |
| 7          | 0.641727 | 0.369565 | 0.714286 |
| 8          | 0     | 0.152174 | 0.642857 |
| 9          | 0.634532 | 0.826087 | 0.357143 |

Step 3: Grey Relational Coefficient: Grey Relational coefficients are obtained by substituting the Deviation sequence data in equation (14) and the same are listed in table 9.

\[ \xi_i(k) = \frac{\Delta_{min} + 0.5 \Delta_{max}}{\Delta Y_i(k) + 0.5 \Delta_{max}} \quad (14) \]

**Table 9. Grey Relational Coefficients of response parameters**

| Experiment | MRR  | SR      | TWR  |
|------------|------|---------|------|
| 1          | 0.384403 | 1       | 1    |
| 2          | 0.361602 | 0.418182 | 0.33333 |
| 3          | 0.333333 | 0.793103 | 0.35 |
| 4          | 0.351899 | 0.958333 | 0.583333 |
| 5          | 0.366755 | 0.333333 | 0.35 |
Step 4: GRA grade: Grey Relational Analysis grade value is calculated by using equation (15) which gives the average of Grey relational coefficients of response parameters of each experiment from table (6). The GRA grade along with their rank for each experiment conducted is listed in table 10 below.

$$n_i = \frac{1}{n} \sum_{k=1}^{n} E_i(k) \quad (15)$$

| Experiment | GRA grade | GRA Rank |
|------------|-----------|----------|
| 1          | 0.794801  | 1        |
| 2          | 0.371039  | 7        |
| 3          | 0.492146  | 4        |
| 4          | 0.631188  | 3        |
| 5          | 0.350029  | 9        |
| 6          | 0.363053  | 8        |
| 7          | 0.474899  | 5        |
| 8          | 0.734722  | 2        |
| 9          | 0.467031  | 6        |

The GRA grade ranking is given from the highest value to the lowest, the highest indicating optimum valued parameters for high MRR and low surface roughness and TWR. Observations on table 7 indicates that the experiment 1 has the highest rank, the input parameters of which are as follows

$T_{on} = 300 \text{ } \mu s,$
$SV = 40 \text{ } V,$
$I_p = 6 \text{ } A,$

4. Conclusion

The weighty intention of this study on die sinking EDM is to learn the parameters for optimum process for machining AISI D2 steel. Taguchi’s L9 OA is incorporated by the researchers in order to carry out the 9 experimentations for intuining the parameters like Material Removal Rate, Tool Wear Rate and $R_a$ that best suit our research requirement.

Equal weightage of all the response parameters were considered while performing TOPSIS and it was observed that the level 3 of all input parameters gave the optimum output whereas an another method GRA suggested that level 1 of all the input parameters yields the optimum output.

- In case of GRA, selection of normalized values was done by keeping the MRR the highest and other responses to be the least in mind and thus this method is proposed to be the ideal method to obtain optimized result as compared to TOPSIS.
- Both the MCDM methods have interestingly suggested that the eighth experiment stands to be the second ideal coalescence of input parameters. Thus the current work proposes this very experiment to be the best during machining AISI D2 Steel.

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