Decision making on the machining parameters of Electrical Discharge Machined AISI D2 tool steel by AHP and PROMETHEE method

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Abstract. This paper determines the optimum process parameters of the non-conventional electrical discharge machining (EDM). The performance of the EDM machine depends upon the process parameter used. In this analysis weight percentage, pulse current (Ip), discharge voltage (V) and pulse duration (Ton) used as process parameters. The optimized output parameters are MRR, TWR, surface roughness and flatness. By using face centered composite design nine trials were conducted on the work piece which is made up of AISI D2 tool steel. The trial results obtained were used in AHP and PROMETHEE multi attribute decision making method. The weights of the responses were determined by the AHP method and select the best alternative by AHP and PROMETHEE method. Machining parameters and accuracy of the component produce by EDM can be control by using the obtained results.

1. Introduction
Electrical discharge machine (EDM) is the well know advanced machining process for making component which has complex geometry and difficult to machine. Now a day’s interest on the advanced materials is more because they are used in aerospace industry, complex mould and die making, and medical appliances. The component use in these industries requires properties such as light weight, high strength, better surface properties, high damping corrosion resistance and low thermal expansion. The biggest challenge for these industries is to produce high dimensional accuracy and better surface property which leads to high cost of machining of these components [1]. AISI D2 tool steel have such properties and it should be explored to survive in steel industries [2]. From the last few years EDM extensively used to make desired shape, size and high dimensional accuracy of the advanced material which is difficult to machine. EDM remarkably used in aerospace, automobile, medical and consumer electronics industries [3-4]. EDM process accuracy, productivity and versatility increases due to the technological advancement. In this research the key interest is to set the optimum input parameter which gives increased MRR and accuracy as well as reduction in the radial over cut, TWR, surface roughness and flatness.

To create several holes in AISI D2 tool steel, Prathipati et al. [5] used EDM. Peak current, pulse off time and pulse on time considered as input parameters. Cu used as a tool electrode. Taghuchi method L18 orthogonal array used to design the experiment and the experimental results are analyzed by statistical approach. Edm performance MRR and TWR calculated.

Dhar et al. [6] used aluminum alloy Al–4Cu–6Si and mixed with 10% by weight silicon carbide (SiCp) particulate to make composites which is difficult to machine. And for machining of such hard material EDM is used. To analyse the process output such as Material removal rate (MRR), Tool wear rate (TWR) and Radial overcut (ROC) it uses three level full factorial design with Ip, V, and Ton as process input parameters. They found that MRR, TWR and ROC increases by increasing Ip, V and Ton. Pradhan et
al. [7] used AISI D2 tool steel as workpiece material and copper as electrode. Two neuro-fuzzy and one neural network models are used for study of the MRR, TWR and radial overcut performance parameters. For planning the experiment uses full factorial design and Ip, V, duty cycle and Ton of various level as input process parameters. The most influential parameters for MRR and ROC were found to be Ip. And V is for TWR. Chiang and Chang [8] used wire EDM and Ton, Toff, cutting radius, wire feed, and V as input process parameter and as output parameters MRR and surface roughness (Ra). They were used Grey relational analysis (GRA) for multi objective analysis to optimize the wire EDM process. Salonitis et al. [9] use Ip, V, and Ton as input parameters and MRR, surface roughness (Ra) as output parameters. They found that by increasing the Ip, V, and Ton results in increase of MRR and surface roughness (Ra) and by reducing the idling time MRR increased.

Moreover, the process recognized as good when the proposed model gives similar behaviour at vital parameters. For constructing the model, it is important to correlate the different aspects of the process. It will be better to predict the process by the model instead of doing trial directly with the process because it is expensive and time consuming. By the literature and working characteristics input parameter of the machine chosen. Pulse current (Ip), discharge voltage (V), pulse of time (Ton), and pulse of time are the input process parameters in this analysis (Toff). These were used as input parameters by some of the EDM researchers. Multi criteria decision-making (MCDM) approach used to pick the best process parameters Analytic Hierarchy Process (AHP) and Preference Rating Organization Method for Enrichment of Assessment (PROMETHEE) of AISI D2 tool steel.

The experimenters have made several attempts to enhance the performance of EDM, but the hybridization of the AHP and PROMETHEE process on AISI D2 tool steel EDM was never used for optimization. Thus, the aforementioned combination attempted in this study.

2. Description of the Experiment
Workpiece material as AISI D2 tool steel
The chemical elemental composition of the tool steel material follows

| Elements | C | Si | Mn | Mo | Cr | Ni | V | Co | Fe |
|----------|---|----|----|----|----|----|---|----|----|
| Wt. %    | 1.5 | 0.3 | 0.3 | 1.0 | 12.0 | 0.3 | 0.8 | 1.0 | Balance |

Cu as tool electrode and EDM oil used as dielectric. The machining time for each experiment set at 15 minutes.

Material removal rate (MRR)
The MRR is obtained as the loss of weight of workpiece per unit time and then modified to volumetric erosion per unit time

\[
MRR = \frac{\Delta V_w}{T} = \frac{\Delta W_w}{(\rho_w g T)}
\]

Where, \( \Delta V_w \) is the loss of volume from the work piece, \( \Delta W_w \) is the loss of weight from the workpiece (it is calculated by taking the difference of mass of workpiece before and after machining), T is processing time and \( \rho_w = 7,700 \text{ kg/m}^3 \) is the mass density of the workpiece.

Tool wear rate (TWR)
The TWR is presented as the tool volumetric loss per unit time, presented as

\[
TWR = \frac{\Delta V_t}{T} = \frac{\Delta W_t}{(\rho_t g T)}
\]

Where \( \Delta V_t \) the loss of volume from the electrode, \( \Delta W_t \) is the loss of weight from the electrode (it is calculated by taking the difference of mass of tool before and after machining), T is the time of machining and \( \rho_t = 8,960 \text{ kg/m}^3 \) is the mass density of the copper electrode.
To see the effect of all the selected input parameter in the smaller number of experiment proper planning of experiment requires. Here uses Taguchi L9 Orthogonal array design of experiment [10] to plan the experiment.

**Table 2. Input parameters and its level**

| Input process parameters | Low Level | Medium | High |
|--------------------------|-----------|--------|------|
| Ip (A)                   | 4         | 8      | 12   |
| Ton (µs)                 | 0.5       | 1      | 1.5  |
| Toff (µs)                | 5         | 10     | 15   |
| Voltage (V)              | 45        | 50     | 55   |

**Table 3. Experimental results**

| Alternative. No. | Ip(A) | Ton (µs) | Toff (µs) | Voltage (V) | MRR (mm³/min) | TWR (mm³/min) | Ra (µm) | Flatness (µm) |
|------------------|-------|----------|-----------|-------------|----------------|----------------|---------|---------------|
| 1                | 4     | 0.5      | 5         | 45          | 1.1102         | 0.0273         | 4.7400  | 0.0370        |
| 2                | 4     | 1        | 10        | 50          | 2.4297         | 0.0663         | 5.2800  | 0.0220        |
| 3                | 4     | 1.5      | 15        | 55          | 2.8174         | 0.1047         | 4.4600  | 0.0400        |
| 4                | 8     | 0.5      | 10        | 55          | 1.4466         | 0.0220         | 4.1800  | 0.0440        |
| 5                | 8     | 1        | 15        | 45          | 2.0232         | 0.0756         | 3.6000  | 0.0230        |
| 6                | 8     | 1.5      | 5         | 50          | 3.0052         | 0.1563         | 2.6600  | 0.0470        |
| 7                | 12    | 0.5      | 15        | 50          | 1.4015         | 0.0368         | 2.4600  | 0.0110        |
| 8                | 12    | 1        | 5         | 55          | 2.3034         | 0.0571         | 2.2600  | 0.0480        |
| 9                | 12    | 1.5      | 10        | 45          | 2.8895         | 0.1763         | 3.0200  | 0.0260        |
3. **Analysis Method**

3.1 *Analytic Hierarchy Process (AHP) Method:* [11]

Step 1: First, take the decision table as we produce the experimental results in Table 3.

Step 2: Form a standardized table to create a useful and non-beneficial attribute on a common scale without disturbing the differences in the range of values. Making the values between 0 to 1.

Step 3: Make a comparison matrix using a scale of relative importance to find the contribution (i.e. weight) of each attribute. The attribute compared with itself the value will be assigned as 1. The numbers 2, 3, 4, 5, 6, 7, 8 and 9 correspond to the 'moderate importance', 'strong importance', 'very strong importance' and 'absolute importance' of verbal judgments.

| Attributes | B_1 | B_2 | B_3 | - | - | B_M |
|------------|-----|-----|-----|---|---|-----|
| B_1        | 1   | b_{12}| b_{13}| - | - | b_{1M} |
| B_2        | b_{21} | 1   | b_{23} | - | - | b_{2M} |
| B_3        | b_{31} | b_{32} | 1   | - | - | b_{3M} |
| -          | -   | -   | -   | - | - | -   |
| B_M        | b_{M1} | b_{M2} | b_{M3} | - | - | 1   |

This square matrix denoted as \( A_1 \)

The geometric mean of each row is determined and all geometric means are calculated by:

\[
GM_j = \sqrt[M]{\prod_{j=1}^{M} b_{ij}}
\]

And \( w_j = GM_j \div \sum_{j=1}^{M} GM_j \)

To test the reliability of the judgement, perform these steps.

Make \( A_2 \) with the help of \( w_j \) values.

\( A_2 = \frac{w_1}{w_2} \) and find \( A_3 \),

\( A_3 = A_1 \times A_2 \) and \( A_4 = A_3 \div A_2 \)

Determine the maximum Eigen value \( \lambda_{\text{max}} \) that is the average of matrix \( A_4 \).

Calculate the Index of consistency \( CI = (\lambda_{\text{max}} - M) / (M-1) \)

\( M \) is the order of matrix \( A_1 \).

Calculate the consistency ratio (CR) by using the table of Random index (RI) values given below

| Attributes | 3 | 4 | 5 | 6 | 7 | 8 |
|------------|---|---|---|---|---|---|
| RI         | 0.52 | 0.89 | 1.11 | 1.25 | 1.35 | 1.4 |

\( CR = CI \div RI \)
If the CR value is less than one, the measured weights are accurate and significant, with a maximum of 10% error.

Step 4: The scores of each alternative are determined by using the measured weights.

The score of an alternative can be calculated by

\[ P_i = \sum_{j=1}^{M} w_j m_{ij} \]

Where,

- \( w_j \) = weight of each attributes
- \( m_{ij} \) = normalized value of alternative regarding to each attribute

\( P_i \) = overall or composite score of the alternative

The higher value of \( P_i \) is considered as the best alternative.

Step 5: give the ranking to the alternative in the decreasing order of score calculated.

3.2 PROMETHEE Method:

In this method alternatives are compared with alternatives during making the matrix for a particular attribute [11].

Step 1: The dominant alternative with other respect to other assign the value 1 and 0 for non-dominating alternatives with respect to other. The no. of matrix is equal to the no. of attributes

Step 2: make an overall matrix by using the weights assigned to each attribute.

Step 3: Calculate the sum of each row and each column in the overall matrix.

Step 4: The difference between the corresponding row and column gives the score for the alternatives.

Step 5: Arrange the score in the descending order and accordingly gives the ranking to the alternatives.

By using these two-method selecting best alternatives

4. Result and Discussion

Taguchi based designed experiments perform on the electrical discharge machine. During the workpiece and instrument measurement weight trial, before and after machining using the weight measuring system, and also time of machining of each experiment measured by using stop watch. Responses such as MRR, TWR, Ra and flatness are determine using above mentioned formula. From the 9 experiment it is difficult to find which value of input parameter giving optimum value of responses because responses are different natures i. e. MRR required maximum value and other three TWR, SR, and flatness required minimum value. So, to find the optimum value of responses at selected range of parameter used decision making method MCDM, AHP and PROMETHEE. By following the above-mentioned steps of AHP and PROMETHEE find the score of each alternative.

Score Calculated by AHP method ranking of the alternatives can be
6-9-3-2-8-5-4-1-7

Score Calculated by PROMETHEE method ranking of the alternatives can be
6-9-8-3-2-5-7-4-1
The process provides the same results for both AHP and PROMETHEE analysis i.e. In the selected set of input parameters, alternative 6 has the best EDM input parameter for AISI D2 tool steel. Alternative 6 has input parameter current (Ip) 8 A, Ton 1.5 μs, Toff 5μs and discharge voltage (V) 50 V and gives maximum MRR 3.0052 mm$^3$/min in the selected range of parameter. In this input parameter output TWR, Ra and flatness got optimum value 0.1563 mm$^3$/min, 2.66 μm and 0.0470 μm respectively.

5. Conclusion
This study determines the values of input process parameters on the EDM of AISI D2 tool steel to get the optimum value of MRR, TWR Ra and Flatness. The method used AHP and PROMETHEE give the same result i.e. alternative number 6 as the best alternative. The optimal value of input parameter determines by the AHP and PROMETHEE methods are given as: current (Ip) 8 A, Ton 1.5 μs, Toff 5μs and discharge voltage (V) 50 V. These outcomes would help to reduce the cost of machining, error, and time needed for the process of machining and also increase the machine's surface characteristics and productivity. In other manufacturing industry to enhance the performance these methods can be used to find the optimum responses in multi response system.

References

[1] Kozak J. and Rajurkar, K.P. 2000 September Hybrid machining process evaluation and development. In Proceedings of 2nd international conference on machining and measurements of sculptured surfaces Keynote Paper Krakow 501-536

[2] Bin Abdul Rahim, M.A.S., bin Minhat, M., Hussein, N.I.S.B. and bin Salleh, M.S. 2018 A comprehensive review on cold work of AISI D2 tool steel. Metallurgical Research & Technology 115(1) 104

[3] Ho, K.H. and Newman, S.T., 2003 State of the art electrical discharge machining (EDM). International Journal of Machine Tools and Manufacture, 43(13) 1287-1300
[4] Kung, K.Y., Horng, J.T. and Chiang, K.T. 2009 Material removal rate and electrode wear ratio study on the powder mixed electrical discharge machining of cobalt-bonded tungsten carbide. The International Journal of Advanced Manufacturing Technology 40(1-2) 95-104

[5] Prathipati, R.P., Devuri, V., Cheepu, M., Gudimetla, K. and Kiran, R.U. 2018 Machining of AISI D2 tool steel with multiple hole electrodes by EDM process. In IOP Conf. Ser. Mater. Sci. Eng. 330 012067

[6] Dhar, S., Purohit, R., Saini, N., Sharma, A. and Kumar, G.H., 2007 Mathematical modeling of electric discharge machining of cast Al–4Cu–6Si alloy–10 wt.% SiCP composites. Journal of materials processing technology 194(1-3) 24-29

[7] Pradhan, M.K. and Biswas, C.K., 2010 Neuro-fuzzy and neural network-based prediction of various responses in electrical discharge machining of AISI D2 steel. The International Journal of Advanced Manufacturing Technology 50(5-8) 591-610

[8] Chiang, K.T. and Chang, F.P., 2006. Optimization of the WEDM process of particle-reinforced material with multiple performance characteristics using grey relational analysis. Journal of Materials Processing Technology, 180(1-3) 96-101

[9] Salonitis, K., Stournaras, A., Stavropoulos, P. and Chryssolouris, G., 2009 Thermal modeling of the material removal rate and surface roughness for die-sinking EDM. The International Journal of Advanced Manufacturing Technology 40(3-4) 316-323.

[10] C Montgomery, D., 1997 Montgomery Design and Analysis of Experiments.

[11] Patel, R.K. and Dwivedi, R.K., 2020 Determination of Critical Component Failure in Thermal Power Station by Using Multi-criteria Decision-Making Methods Journal of Failure Analysis and Prevention 1-5