Optimization of Tool steel

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Abstract

Electro Discharge Machining (EDM) is a widely adopted non-traditional machining process used for shaping hard and electrically conductive materials, particularly tool steels. The present study focuses on optimizing the EDM process parameters for tool steel (D3) using a Grey-based Taguchi method to achieve improved machining performance. The primary objectives are to maximize the Material Removal Rate (MRR) while minimizing the surface roughness (Ra). Experiments were conducted on an ELECTRAPULS PS 35 EDM machine, utilizing copper electrodes with varying process parameters: voltage, current, and pulse-on time. A Taguchi L9 orthogonal array was employed to design the experiments. Grey Relational Analysis (GRA) was then applied to convert multi-response performance characteristics into a single Grey Relational Grade (GRG), facilitating multi-objective optimization. The results revealed that the optimal combination of process parameters for multi-performance characteristics was 70 V, 18 A, and 150 µs pulse-on time. The study confirms the effectiveness of integrating Taguchi design and GRA for simultaneous optimization of MRR and surface roughness in EDM, providing valuable insights for industrial applications and future research in advanced machining processes.

Keywords: Electro Discharge Machining (EDM), Tool Steel (D3), Material Removal Rate (MRR), Surface Roughness (Ra), Grey Relational Analysis (GRA)

1. Problem Statement

This work focuses on optimization of electro discharge machining considering the various process parameters. The aim is "To carryout experimental investigation and optimization of process parameter for machining of tool steel in order to achieve maximum MRR with lowest possible surface roughness."

2. Objectives

To investigate the effects of input process parameters (Machining) on the surface finish and material removal rate

3. LITERATURE SURVEY

It is an assessment of the present state of art of the wide and complex field of optimization of electro discharge machining by design of experiment and its application. In addition, this chapter separately reviews what did in the past in the area of application.Puri et. al. [1] employed mathematical modeling of white layer depth to correlate the dominant input parameters of the WEDM process, comprising of a rough cut followed by a trim cut In the process, typical die steel (M2 – hardened and annealed) was machined using brass wire as electrode. T. A. El-Taweel [2] investigated the relationship of process parameters in EDM of CK-45 steel with novel tool electrode material such as Al-Cu-Si-TiC composite product using powder metallurgy technique. In this study, peak current, dielectric flushing pressure and pulse on time are considered as input process parameters and the process performances such as MRR and TWR were evaluated. Sohani et. al. [3] presented the application of response surface methodology (RSM) for investigating the effect of tool shapes such as triangular, square, rectangular and circular with size factor consideration along with other process parameters like discharge current, pulse on time, pulse off time and tool area. S.H.Tomadi et. al. [4] Investigated the effect of process

parameters like Pulse on time, Pulse off time, Supply Voltage, peak current on material removed rate (MRR) and electrode wear (EW). The Tungsten Carbide was used as the workpiece material and Copper Tungsten as electrode. The full factorial design of experiment was used to analysis the optimum condition of machining parameters K.D. Chattopadhyay et.al.[5] derived an empirical mathematical model for predication of output parameters has been developed using linear regression analysis by applying logarithmic data transformations of non-linear equation. Asif Iqbal et. al.[6] established empirical relations regarding machining parameters and the responses in analyzing the machinability of the stainless steel AISI 304 using copper electrode. The machining factors used were voltage, rotational speed of electrode and feed rate over the responses MRR, EWR and SR. The response surface methodology was used to investigate the relationships and parametric interactions between the three control variables on the MRR, EWR and SR. the developed models show that the voltage and rotary motion of electrode are the most significant machining parameters influencing MRR, EWR and SR. Shailesh Dewangan et**.** al**.**[7] investigated the effect of process parameters like Pulse on time, Discharge current and Diameter of electrode on material removal rate (MRR), Tool wear rate (TWR) and over cut. The experiment used AISI P20 tool steel as workpiece and U-shaped copper tool as electrode with internal flushing system. The S/N ratios used for minimizing the TWR and A.Majumder [8] derived quadratic mathematical model to represent the process behaviour of Die-Sinking Electrical Discharge Machining. Experiments has been conducted with three process parameters viz. discharge current, pulse on time and pulse off time and to relate them with process responses viz. material removal rate (MRR) and electrode wear (EW). Experiment was performed with mild steel as workpiece and copper as electrode sand finding that the effect of supply current on material removal rate is higher than the other machining parameters while in case of electrode wear (EW) the most influential factor was the intensity of the pulse-on time

EXPERIMENTAL INVESTGATION

In order to satisfy the desired objectives, the method of DOE coupled with optimization techniques is identified, extensive literature review is carried out and following workflow to carry out the experimentation is formulated

3.1 Proposed workflow

In order to achieve the desired objective that is minimum surface roughness and maximum material removal rate for the optimization of Tool steel, the method of the design of experiment is identified and the proposed algorithm as follows

4.2. Experimental Setup

The experiment is going to be conducted on the electro discharge machine (EDM) at Shree Lila engineering services, Ambad, Nasik in following table 1 gives idea about the technical specification of the machines:

Table 1: Machine details

Description	Specification
ELECTRAPULS PS 35	
Table size	750*450mm
Maximum job weight	300 kg
Maximum job height	250mm
Maximum electrode weight	70kg
Maximum working current	60A

3.2 Selection of Material

The work piece material used in the experiment is ‘Tool steel(D3) which has a following property, the dimension of work piece are selected as 40x40x16mm.

Table 2 Work Material Specification

Parameter	Specification
Density	7700kg/m^3
melting point	1421^{0}C
Hardness	77HRC
Poisson’s ratio	0.28
Coefficient of thermal expansion	12×10^{-6}/C^0

4.4. Selection of Cutting Tool

It is decided to use the Copper tool having following details.
Table 3.Tool Material Specification

Parameter	Specification
Thermal conductivity	391 W/m^{0}K
Melting point	1083 ^{0}C
Resistivity	0.009-0.07 ohm-cm * 10^{-4}
Specific heat capacity	0.385 J/gm^{0}C

Fig 1. Copper tool of 10mm diameter

4. OPTIMIZATION OF TOOL STEEL

4.1 Selection of Input Parameters

For the present experimentation following input parameters are selected.

Table 4 Parameters and their levels

Parameter	Level		
Voltage(V)	60	70	80
Current(A)	12	15	18
Pulse on(micro sec)	50	100	150

5.2. Experimental data collection

As per the proposed workflow and DOE experiments conducted on the Tool steel, table 5.2. gives the details of the experimental data collected is as follows:
Table 5.: Experimental reading for D3

Voltage	Current	Pulse on	Ra(μm)	Rz (μm)
60	12	50	1.253	6.32
60	15	100	1.358	6.551

60	18	150	1.871	8.652
70	12	100	1.407	7.103
70	15	150	1.812	9.016
70	18	50	1.038	4.853
80	12	150	1.605	8.019
80	15	50	1.197	5.827
80	18	100	1.489	6.897

Fig 2. showing work piece after machining

5.3. Data Analysis

Table 6 L9 array and observation for Ra and S/N ratio and Mean

Voltage	Current	Pulse on	Ra	SN RA	MEAN
60	12	50	1.253	-1.959	1.25
60	15	100	1.358	-2.65	1.35
60	18	150	1.871	-5.441	1.87
70	12	100	1.407	-2.965	1.40
70	15	150	1.8	- 5.163	1.81
70	18	50	1.0	- 0.323	1.03

80	12	150	1.6	- 4.109	1.60
80	15	50	1.1	- 1.561	1.19
80	18	100	1.4	- 3.45	1.49

5. GREY BASED TAGUCHI ANALYSIS FOR COMBINE OBJECTIVE

Grey relational analysis is applied by several researchers to optimize control parameters having multi-responses through grey relational grade. The use of Taguchi method with grey relational analysis to optimize the face milling operations with multiple performance characteristics includes the following steps:

1. Identify the performance characteristics and cutting parameters to be evaluated.
2. Determine the number of levels for the process parameters.
3. Select the appropriate orthogonal array and assign the cutting parameters to the orthogonal array.
4. Conduct the experiments based on the arrangement of the orthogonal array.
5. Normalize the experiment results of MRR and surface roughness.
6. Perform the grey relational generating and calculate the grey relational coefficient.
7. Calculate the grey relational grade by averaging the grey relational coefficient.
8. Analyze the experimental results using the grey relational grade and statistical ANOVA.
9. Select the optimal levels of cutting parameters.
10. Verify the optimal cutting parameters through the confirmation experiment**.**

5.1 Data Pre-Processing

In grey relational analysis, the data pre-processing is the first step performed to normalize the random grey data with different measurement units to transform them to dimensionless parameters. Thus, data pre- processing converts the original sequences to a set of comparable sequences. Different methods are employed to pre-process grey data depending upon the quality characteristics of the original data. The original reference sequence and pre-processed data (comparability sequence) are represented by $x_0^{(0)}(k)$ and

$x_i^{(0)}(k)$, i =1,2,….,m; k =1,2,. ,n

respectively, where m is the number of experiments and n is the total number of observations of data. Depending upon the quality characteristics, the three main categories for normalizing the original sequence are identified as follows:
If the original sequence data has quality characteristic as 'larger-the-better' then the original data is pre-processed as 'larger-the- best:

$$x_i(k) = \frac{y_i(k) - \min y_i(k)}{\max y_i(k) - \min y_i(k)}$$

If the original data has the quality characteristic as 'smaller the better', then original data is pre-processed as 'smaller-the best':

$$x_i(k) = \frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)}$$

Xi=Compatibility sequence

5.1.1 Sample calculation of compatibility sequence for roughness value Tool steel

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$$xi(k) = \frac{\text{Max CT} - \text{First Value of CT}}{\text{Max CT} - \text{Min CT}}$$

$$xi(k) = \frac{5.44147 - 1.9524}{5.44147 - 0.32393} \qquad (\ )$$

$$\boldsymbol{xi(k) = 0.68178}$$

Table 7: Normalized S/N data (Grey relational generation) for Tool Steel

the relational degree between the twenty-seven sequences (x0(k) and *xi* (k), i=1, 2 . . . 27; k=1, 2). The grey relational coefficient ξi(k) can be calculated as:

5.1.2 Sample calculation of grey relation coefficient for Roughness value

$$\xi i(k) = \frac{\min\Delta + \theta * \max\Delta}{\Delta i(k) + \theta * \max\Delta} \qquad (\ )$$

ξi(k) =The grey relational coefficient θ is the distinguishing coefficient which is taken as 0.5

$$\xi i(k) = \frac{0 + (0.5 * 1)}{0.456091 + (0.5 * 1)} \qquad (\ )$$

Sr. No	S/N Ra	S/N MRR	Xi Ra	Xi MRR	Δ Ra	Δ MRR
1	1.9524	26.4692	0.68178	0	0.31822	1
2	2.65799	31.3898	0.543909	0.5031	0.456091	0.4969
3	5.44147	35.5543	0	0.9289	1	0.0711
4	2.96588	34.9109	0.483734	0.86315	0.51626	0.13685
5	5.16316	33.7506	0.05438	0.74454	0.94562	0.2554
6	0.32393	33.4844	1	0.71732	0	0.2826
7	4.1094	36.3689	0.26029	1	0.73971	0
8	1.5594	26.7092	0.758581	0.02445	0.24419	0.9755

9	3.45 76	32.72 48	0.38 766	0.6 399 5	0.612 34	0.3 600

ξi(k) = for second value = 0.52296

Similarly, all values of grey relation coefficient for roughness and material removal rate are calculated and tabulated in the table given below.

5.1.3 Sample calculation of grey relation grade for Roughness value and MRR

After averaging the grey relational coefficients, the grey relational grade γi can be computed as,

n

$\boldsymbol{Yi}$ = = i[k] $\frac{1}{n}\sum$

k=1

1

Similarly all values of compatibility sequence for surface roughness and material removal rate can be calculated. All values are show in Table

6.1 Where xi (k) is the value after the grey relational generation, min yi (k) is the smallest value of yi (k) for the k^{th} response, and max yi

(k) is the largest value of yi (k) for the k^{th} response.

An ideal sequence is x0(k) (k=1, 2) for two responses. The definition of the grey relational grade in the grey relational analysis is to show$\boldsymbol{Yi}$ = **2** (0.3333 + 0.61108)

Reading of grey relation grade is, **Yi**

= 0.47219

Similarly all values of grey relation grade of nine experiments are carried out and tabulated given below, Yi = grey relational grade

Where n = number of process responses.

The higher value of grey relational grade corresponds to intense relational degree between the reference sequence x0 (k) and the given sequence xi (k). The reference sequence x0 (k) represents the best process sequence. Therefore, higher grey relational grade means that the corresponding parameter combination is closer to the optimal**.**

Table 8: Grey Relation Grade, coefficient and Order

Sr. No	**GRC For Ra**	**GRC For MRR**	**GRG**	**Gray Order**
1	0.61108	0.3333	0.47219	9
2	0.52296	0.50155	0.512255	6
3	0.3333	0.875503	0.6044015	4
4	0.492	0.78511	0.638555	3

5	0.34587	0.66185	0.50386	8
6	1	0.63883	0.819415	1
7	0.40332	1	0.70166	2
8	0.67187	0.33885	0.50536	7
9	0.449502	0.58136	0.515431	5

6. EXPERIMENTAL RESULTS AND DISCUSSION

From the above experimentation following conclusions drawn

a. Considering the single objective function of Minimization of Ra for tool steel the optimum levels for the optimization are (2 3 1) and the optimum parameter are-
70 18 50.

b. Considering the single objective function of Minimization of Rz for tool steel the optimum levels for the optimization are (2 3 1) and the optimum parameter are-
70 18 50.

c. Considering the single objective function of Maximization of MRR .The optimum levels for the optimization are (2 3 3) and
the optimum parameter are- 70 18 150.

d. Considering the multi objective optimization with gray relational analysis; the optimum levels for the optimization are (2 3 3) and the optimum
parameter are- 70 18 15. .
To correlate the effect of process parameters on the material the effect plots are as follows

7. CONCLUSIONS

Existing experiment and its analysis provides following remarkable point

I. The present work has successfully demonstrated the application of Taguchi based Grey relational analysis for multi objective optimization of process parameters in EDM for tool steel subjected to various conditions.

II. In grey relational analysis higher the grey relational grade of experiment says that the corresponding experimental combination is optimum condition for multi objective optimization and gives better product quality. Also form the basis of the grey relational grade, the factor effect can be estimated and the optimal level for each controllable factor can also be determined.

8. FUTURE SCOPE

I. Tool conditioning monitoring (TCM) of the EDM for the different materials will be the scope for the future work till then only 6% work is till done on EDM.

II. Nontraditional algorithm like RCGA can be applied to optimize EDM parameters.

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