Application of grey-fuzzy approach in parametric optimization of EDM process in machining of MDN 300 steel

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Abstract. Maraging steel (MDN 300) find its application in many industries as it exhibits high hardness which are very difficult to machine material. Electro discharge machining (EDM) is an extensively popular machining process which can be used in machining of such materials. Optimization of response parameters are essential for effective machining of these materials. Past researchers have already used Taguchi for obtaining the optimal responses of EDM process for this material with responses such as material removal rate (MRR), tool wear rate (TWR), relative wear ratio (RWR), and surface roughness (SR) considering discharge current, pulse on time, pulse off time, arc gap, and duty cycle as process parameters. In this paper, grey relation analysis (GRA) with fuzzy logic is applied to this multi objective optimization problem to check the responses by an implementation of the derived parametric setting. It was found that the parametric setting derived by the proposed method results in better a response than those reported by the past researchers. Obtained results are also verified using the technique for order of preference by similarity to ideal solution (TOPSIS). The predicted result also shows that there is a significant improvement in comparison to the results of past researchers.

1. Introduction

Electro-discharge machining (EDM) emerges to be an important manufacturing process for machining hard materials [1] and its applications are widely accepted in many manufacturing industries [2]. For optimal machining performance measures in EDM, it is an important task to select proper combination of machining parameters as slight changes in a single parameter adversely affect the process. While controlling the process parameters it is capable of producing required dimensional accuracy and quality surface finish [3]. It is very necessary to select the appropriate machining parameters such as discharge current, pulse on time, pulse off time, arc gap, and duty cycle [4] which adversely affects the machining performance measures such as MRR, TWR, RWR and SR [2]. A considerable amount of work has been reported by the past researchers on the performance measurement of EDM process on the basis of MRR, TWR, RWR, and SR for various types of steels. Researchers have experimentally studied the response quality of EDM process and concluded that these qualities can be optimized by proper control of process parameters [5]. Thus, to exploit the full potential of the EDM process the control parameters are to be properly selected to obtain the optimum values of response parameters. Existing well known approaches such as grey relational analysis (GRA), analytic network process (ANP), preference ranking organization method for enrichment evaluation (PROMETHEE), VIKOR method etc. can be applied in this direction.

Deng [6] first introduced Grey systems. It is a powerful tool that deals with poor, unknown and vague data [7]. In recent years, a grey system has been effectively used for solving multiple conflicting
criteria in various fields of manufacturing [8, 9]. Fuzzy sets were first introduced by Zadeh [10] which can successfully deal with improper, uncertain and vague data. Fuzzy logic aided with GRA can further improve its performance in solving multi-objective optimization problems. Many researchers have effectively employed grey fuzzy logic in optimizing multi-objective problems [7, 9]. Soepangkat et al. [11] applied integrated fuzzy-logic based GRA in optimizing wire EDM process while machining AISI D2 steel for optimal responses of surface roughness and layer thickness. Krishnamoorthy et al. [12] improved the quality of the drilled holes in carbon fibre reinforced plastic (CFRP) composite materials by incorporating the optimal combination of drilling parameters using grey relational analysis aided with fuzzy logic.

An attempt has been made earlier by the past researchers in obtaining the parametric setting of EDM process on MDN 300 steel with copper as an electrode material. Nikalje et al. [13] studied the influence of EDM process considering discharge current, pulse on time, pulse off time, arc gap, and duty cycle as process parameters. They applied Taguchi method in obtaining the optimal parametric combination which optimizing performance measures MRR, TWR, RWR, and SR. Taguchi method is a single response optimization technique which deals with optimizing a single response while it does not take into account the effects of other performance measures. In this study emphasis has been made in optimizing the process parameters of this EDM process in machining of MDN 300 steel. GRA aided with fuzzy logic has been adopted and is applied to problems to further enhance the results obtained by past researchers.

2. Methodology

2.1. Design of experiments

The experiments are designed as per Taguchi’s L₉ orthogonal array of experiments with MRR, TWR, RWR and SR as responses. The three level variations for each of discharge current, pulse on time and pulse off time is chosen for this experimentation are shown in table 1. The experimental results for all the nine experiments are shown in table 2.

| Table 1. Process parameters of EDM process |
|--------------------------------------------|
| Sl. No. | EDM parameter  | Unit | Level 1 | Level 2 | Level 3 |
| 1     | Discharge current | A    | 10     | 15     | 20      |
| 2     | Pulse on time     | μs   | 25     | 45     | 65      |
| 3     | Pulse off time    | μs   | 24     | 36     | 48      |

| Table 2. Experimental Data |
|-----------------------------|
| Discharge current | Pulse on time | Pulse off time | MRR (mm³/min) | TWR (mm³/min) | RWR | SR (μm) |
| 1                  | 1              | 1              | 1              | 15.76        | 4.29 | 27.33   | 5.62    |
| 2                  | 1              | 2              | 2              | 25.92        | 5.22 | 20.15   | 6.6     |
| 3                  | 1              | 3              | 3              | 30.02        | 4.03 | 13.37   | 7.71    |
| 4                  | 2              | 1              | 2              | 28.65        | 7.97 | 27.76   | 6.48    |
| 5                  | 2              | 2              | 3              | 39.87        | 8.73 | 21.88   | 7       |
| 6                  | 2              | 3              | 1              | 29.99        | 7.14 | 23.83   | 7.32    |
| 7                  | 3              | 1              | 3              | 30.57        | 9.48 | 30.9    | 5.92    |
| 8                  | 3              | 2              | 1              | 41.31        | 10.46| 25.33   | 6.96    |
| 9                  | 3              | 3              | 2              | 51.38        | 13   | 25.38   | 8.15    |
2.2 Grey relational analysis
In grey system, the data in the decision matrix are needed to be normalized (data pre-processing) in a range between 0 and 1 to make the data dimensionless and comparable. The following expressions are utilized for data pre-processing depending on the type of the considered criterion, i.e. equation (1) for larger-the-better and equation (2) for smaller-the-better type [8, 9].

\[ x'_i(k) = \frac{x_i(k) - \min x_i(k)}{\max x_i(k) - \min x_i(k)} \quad i = 1,2,...,m \text{ and } k = 1,2,...,n \]  
\[ x'_i(k) = \frac{\max x_i(k) - x_i(k)}{\max x_i(k) - \min x_i(k)} \]  

where \( x_i(k) \) and \( x'_i(k) \) are the observed and normalized data respectively for \( i^{th} \) alternative and \( k^{th} \) criterion. After normalization, the grey relational coefficient (GRC) is calculated using equation (3).

\[ \xi_i(k) = \frac{\Delta_{0i}(k) + \zeta \Delta_{\text{max}}}{\Delta_{0i}(k) + \Delta_{\text{max}}} \]  

where \( \Delta_{0i}(k) \) is the difference between \( x'_i(k) \) and \( x'_i(k) \) (\( x'_i(k) \) is the ideal sequence). The distinguishing coefficient \( \zeta \) lies between 0 and 1, usually considered as 0.5. \( \Delta_{\text{min}} = \max_{i \in k} \| x_i(k) - x_j(k) \| \) is the smallest value of \( \Delta_{0i} \); and \( \Delta_{\text{max}} = \max_{i \in k} \| x_i(k) - x_j(k) \| \) is the largest value of \( \Delta_{0i} \). A higher value of GRC for an alternative indicates that it is closer to the optimal solution with respect to a particular criterion. Grey relational grade (GRG) for an alternative is computed by averaging the GRC values corresponding to each criterion using equation (4).

\[ \gamma_i = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k) \]  

where \( n \) is the number of criterion. A higher value of GRG indicates that the corresponding alternative is the best choice for the said application.

2.3 Fuzzy logic in grey relational analysis
Fuzzy set deals with imprecise and inadequate information in an efficient way to arrive at a logical conclusion for any decision making problem. Fuzzy set theory states that, in a universe of discourse \( X \), a fuzzy subset \( \tilde{A} \) of \( X \) is defined by a membership function \( f_{\tilde{A}}(x) \), which takes each element \( x \) in \( X \) to a real number \( R \) in the interval of \([0,1]\). The function value \( f_{\tilde{A}}(x) \) represents the grade of membership of \( x \) in \( \tilde{A} \). The larger the value of \( f_{\tilde{A}}(x) \) is, the stronger is the grade of membership for \( x \) in \( \tilde{A} \).

In GRA, the use of lower-the-better and higher-the-better characteristics results in some uncertainty in the derived results which can be effectively controlled using fuzzy logic. A fuzzy logic unit consists of a fuzzifier, fuzzy membership functions, a fuzzy rule base, an inference engine and a defuzzifier. In the fuzzy logic, the membership functions are the inputs to the fuzzifier in order to fuzzify the GRC values. The inference engine performs a fuzzy reasoning of the developed fuzzy rules to generate a fuzzy value. The defuzzifier finally converts the fuzzy value into an understandable value known as grey fuzzy reasoning grade (GFRG). A fuzzy rule base comprising a set of if-then control rules is developed to represent the inference relationship between the input and output. A set of such fuzzy rules is provided as below:

Rule 1: if \( x_1 \) is \( a_1 \) and \( x_2 \) is \( b_1 \) and \( x_3 \) is \( c_1 \) and \( x_4 \) is \( d_1 \), then output \( (G) \) is \( e_1 \), else
Rule 2: if \( x_1 \) is \( a_2 \) and \( x_2 \) is \( b_2 \) and \( x_3 \) is \( c_2 \) and \( x_4 \) is \( d_2 \), then output \( (G) \) is \( e_2 \), else
Rule \( n \): if \( x_1 \) is \( a_n \) and \( x_2 \) is \( b_n \) and \( x_3 \) is \( c_n \) and \( x_4 \) is \( d_n \), then output \( (G) \) is \( e_n \).
where $A_i, B_i, C_i$ and $D_i$ are the fuzzy subsets defined by the corresponding membership functions, i.e. $\mu_{A_i}, \mu_{B_i}, \mu_{C_i}$ and $\mu_{D_i}$ respectively. The inference engine performs fuzzy reasoning on fuzzy rules while taking max-min inference to generate a fuzzy value, $\mu_G(G)$.

\[
\mu_{G_i}(G) = (\mu_{A_i}(x_i) \land \mu_{B_i}(x_i) \land \mu_{C_i}(x_i) \land \mu_{D_i}(x_i) \land \mu_G(G)) \lor \ldots \ldots \ldots \\
(\mu_{A_1}(x_1) \land \mu_{B_1}(x_1) \land \mu_{C_1}(x_1) \land \mu_{D_1}(x_1) \land \mu_G(G)) \lor \ldots \ldots \ldots \\
(\mu_{A_n}(x_n) \land \mu_{B_n}(x_n) \land \mu_{C_n}(x_n) \land \mu_{D_n}(x_n) \land \mu_G(G))
\]

(6)

where $\land$ and $\lor$ are the minimum and maximum operation, respectively. Finally, a centric fuzzification method is utilized to transform the fuzzy multi-response output, $\mu_G(G)$ into a crisp value of GFRG ($G_0$).

\[
G_0 = \frac{\sum G\mu_{G_i}(G)}{\sum \mu_{G_i}(G)}
\]

(7)

The GFRG values are then arranged in descending order. The alternative with the maximum value of GFRG signifies it to the best choice with respect to a set of criteria/attributes.

3. Results and discussion

3.1. Grey-fuzzy analysis

The pre-processed data of experimental results is done using equation (1) and (2) where MRR is of ‘higher-the-better’ characteristics and TWR, RWR and SR is of ‘lower-the-better’ characteristics. GRC and GRG values are calculated using equation (3) and (4) and the results for each of the combination of parameters is given in table 3. In order to obtain an improved quality in the performances and to decrease the vagueness in the data, grey-fuzzy logic method is additionally used for computing the GFRG. In this paper, four inputs (GRC) and one output (GFRG) fuzzy-logic system are used. Mamdani inference engine is used which performs fuzzy reasoning with fuzzy rules for generating a fuzzy value. In total 9 fuzzy rules is developed based on ‘if–then’ control rule that shows inference relationship between the input GRC and output GFRG. In fuzzy logic, rules are usually developed based on the expert’s opinions. But it is not always feasible to derive those rules from the knowledge of the human expert as when the number of inputs to a fuzzy system is more. Several methods have already been proposed for generating fuzzy rules automatically from numerical/experimental data [14, 15]. Generation of fuzzy rules from the numerical data mainly consists of two steps, i.e. a) to divide the data pattern into corresponding fuzzy subsets and b) to define a rule for each fuzzy subset. Segmentation of the data pattern and fuzzy rule generation are always interdependent. One of such rule is given below.

If MRR= Lowest, TWR= Highest, RWR = Lowest and SR= Highest, then GFRG = Very High.
Table 3. Normalized data, GRC, GRG and GFRG

| Exp. No. | Normalized value | Grey relational coefficient | GRG | GFRG | TOPSIS Score |
|---------|------------------|----------------------------|-----|------|--------------|
|         | MRR   | TWR   | RWR   | SR    | MRR   | TWR   | RWR   | SR    | MRR | TWR | RWR | SR |                |
| 1       | 0     | 0.971 | 0.2037| 1     | 0.3333| 0.9452| 0.3857| 1     | 0.6661| 0.680| 0.4843 |
| 2       | 0.2852| 0.8673| 0.6132| 0.6126| 0.4116| 0.7903| 0.5638| 0.5635| 0.5823| 0.567| 0.5719 |
| 3       | 0.4003| 1     | 1     | 0.1739| 0.4547| 1     | 1     | 0.3770| 0.7079| 0.696| 0.6617 |
| 4       | 0.3619| 0.5608| 0.1791| 0.6601| 0.4393| 0.5323| 0.3785| 0.5953| 0.4864| 0.493| 0.4295 |
| 5       | 0.6769| 0.476 | 0.5145| 0.4545| 0.6074| 0.4883| 0.5074| 0.4783| 0.5203| 0.510| 0.5555 |
| 6       | 0.3995| 0.6533| 0.4033| 0.3281| 0.4543| 0.5905| 0.4559| 0.4266| 0.4819| 0.494| 0.4987 |
| 7       | 0.4158| 0.3924| 0     | 0.8814| 0.4612| 0.4514| 0.3333| 0.8083| 0.5136| 0.510| 0.3746 |
| 8       | 0.7173| 0.2832| 0.3177| 0.4704| 0.6388| 0.4109| 0.4229| 0.4856| 0.4896| 0.506| 0.4669 |
| 9       | 1     | 0     | 0.3149| 0     | 1     | 0.3333| 0.4219| 0.3333| 0.5221| 0.510| 0.4632 |

GRC values for MRR, TWR, RWR and SR are the inputs to the fuzzy logic system. The linguistic membership function for instance lowest (LT), low (L), medium (M), high (H) and highest (HT) are used to represent input variables of GRC. Likewise the output GFRG is being represented by the membership functions such as lowest (LT), very low (VL), low (L), medium low (ML), medium (M), medium high (MH), high (H), very high (VH), highest (HT). In this study triangular shaped membership function to define these membership functions are shown in figure 1 and 2. The rule-based fuzzy-logic reasoning is shown in figure 3. Maximum–minimum compositional operation by tracking the fuzzy reasoning yields a fuzzy output. At last, the defuzzifier converts the fuzzy predicted values into a crisp GFRG value by using MATLAB (R2013a) fuzzy toolbox. This GFRG values are tabulated in table 3. It can be seen from the table that experiment number 3 is having the highest GFRG value, signifying it to be the most preferred. A validation test with respect to technique for order preference by similarity to ideal solution (TOPSIS) reveals that the experiment number 3 actually gives the optimal parametric setting for the considered EDM process. It is a popular method that seeks to identify the best solution with the shortest distance to positive ideal solution and the longest distance from negative ideal solution. The computed TOPSIS scores are provided in table 3.

Table 4 and figure 4 shows the response table and corresponding graph for GFRG. It is obtained by calculating the average value of each input machining parameter at its corresponding level. The max–min column indicates that discharge current is the most significant factor among the three input parameters. In order to obtain the best responses, the optimal combination of the parameters as depicted from the table shows that discharge current must maintained at level 1 and while pulse on time and pulse off time at level 3 respectively.
Figure 1. Input membership function

Figure 2. Output membership function

Figure 3. Rule viewer

Table 4. Response table for GFRG

| EDM parameter       | Level 1 | Level 2 | Level 3 | Max-Min | Rank |
|---------------------|---------|---------|---------|---------|------|
| Discharge current   | 0.6477  | 0.499   | 0.5087  | 0.1487  | 1    |
| Pulse on time       | 0.5610  | 0.5277  | **0.5667** | 0.039   | 3    |
| Pulse off time      | 0.5600  | 0.5233  | **0.5720** | 0.0487  | 2    |
3.2. Predicted GFRG

Optimal levels of machining input parameters obtained from GFRG are A1 B3 C3 which are different from the obtained parameter settings by past researchers. The predicted GFRG for the parametric combination can be estimated using the formulae.

\[ G_p = G_m + \sum_{i=1}^{N} (\bar{G}_i - G_m) \]  

(8)

where, \( G_p \) is the predicted GFRG, \( G_m \) is the mean GFRG for all the 9 experiments, \( \bar{G}_i \) is the mean GFRG of the corresponding optimal \( i^{th} \) response and \( N \) is the total number of input parameters.

As shown in table 5 the predicted GFRG for both the previous and obtained input parametric combinations signifies that there is an improvement in the GFRG value from 0.6884 to 0.7064, which equals to 0.018, i.e., an improvement by 2.61%.

| Levels | Predicted GFRG | Optimum machining parameters by our method |
|--------|----------------|------------------------------------------|
|        |                | Discharge current= 15A,                  |
|        |                | Pulse on time= 45 \( \mu \)s and Pulse   |
|        |                | off time= 24 \( \mu \)s.                 |
|        | 0.6884         | Discharge current= 10A,                  |
|        |                 | Pulse on time= 65 \( \mu \)s and Pulse  |
|        |                 | off time= 48 \( \mu \)s.                |
|        |                 |                                          |
| GFRG   | 0.6884         | 0.7064                                   |
| Improvement in GFRG | -            | 0.018                                    |
| % improvement    | -             | 2.61%                                    |

So as to fully justify the superiority of derived parametric setting A1B3C3 over A3B3C2, the following regression equations (showing only the main effects) are developed. Based on these equations, a comparison within the various responses at two different parametric settings is provided in table 6. It is interesting to observe that for MRR there is a substantial improvement from 30.399 mm3/min to 32.323 mm3/min with the setting A1B3C3. Similarly, for the remaining three responses it was found that their values are also marginally better with respect to the setting A1B3C3. Hence, there is also an improvement in the GFRG value by 6.45% for the proposed parametric setting.
\[
\begin{align*}
MRR &= -13.5 + 1.72 \times \text{Discharge current} + 0.303 \times \text{Pulse on time} + 0.186 \times \text{Pulse off time} \quad (9) \\
TWR &= -2.97 + 0.647 \times \text{Discharge current} + 0.0202 \times \text{Pulse on time} + 0.0049 \times \text{Pulse off time} \quad (10) \\
EWR &= 27.6 + 0.692 \times \text{Discharge current} - 0.195 \times \text{Pulse on time} - 0.144 \times \text{Pulse off time} \quad (11) \\
SR &= 8.01 + 0.0367 \times \text{Discharge current} - 0.0330 \times \text{Pulse on time} + 0.0101 \times \text{Pulse off time} \quad (12)
\end{align*}
\]

\textbf{Table 6. Comparison of predicted responses at two different settings}

| Levels | Machining parameters previously obtained | Optimum parameters by our method |
|--------|----------------------------------------|----------------------------------|
|        | A3 B3 C2                               | A1 B3 C3                         |
| MRR (in mm\(^3\)/min) | 30.399 | 32.323 |
| TWR (in mm\(^3\)/min) | 7.7616 | 5.0482 |
| EWR    | 25.749 | 14.933 |
| SR (in \(\mu\)m)    | 6.8679 | 6.0668 |
| GFRG   | 0.594  | 0.695  |
| % improvement      | -      | 6.45%  |

\textbf{4. Conclusion}

From the above analysis it was found that a discharge current of 10 A, a pulse on time of 65 \(\mu\)s and a pulse off time of 48 \(\mu\)s are the optimal combination. It is also verified by the predicted results that the parametric combination found by the adopted approach significantly increases the output performance. Therefore, it is concluded that the optimization procedure proposed in this present paper significantly improved the machining of MDN 300 steel by EDM process.

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