Multi response optimization in WEDM of H13 steel using hybrid optimization approach

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Abstract. Surface roughness and material removal rate (MRR) are important technological parameters which describe quality of machined surfaces and productivity of machining process. Surface roughness and MRR are significantly influenced by many interactive process parameters dynamically but those are difficult to quantify adequately in any machining process. Wire electrical discharge machining (WEDM) is one of the advanced machining processes which used thin wire as cutting tool for creating intricate features on machined parts. In WEDM, optimizing surface roughness (Ra) and material removal rate (MRR) combinedly by controlling process variables namely pulse on time, pulse off time, wire feed, voltage gap, etc, is difficult task and much needed area of research. In the present work, investigation is made to study and optimize the surface roughness of H13 steel in WEDM. L16 orthogonal array of Taguchi methodology has been used to conduct the experiments. Analysis of variance (ANOVA) has been applied on experimental data to determine the significance of input parameters on surface roughness and MRR. Mathematical relationships are developed to correlate the machining parameters and output responses: surface roughness and MRR. Contour plots have been drawn to illustrate the combined effects of process parameters on output responses. Multi-objective jaya optimization algorithm (MJOA) applied on developed mathematical equations to predict the multi-responses simultaneously. From the study, it is stated that hybrid Taguchi method, RSM and MJOA is useful for studying, modeling and optimizing the multiple responses: surface roughness and MRR, simultaneously in WEDM of H13 steel.

1. Introduction

Electric discharge machining (EDM) is a non-conventional metal removal technology which uses an electrical spark to cut excess material from the work material immersed in a dielectric fluid [1]. In this process, electrical spark is created between the electrode and workpiece. EDM is used to cut, hard to cut materials and conductive with intricate shapes on it. Wire cut EDM is one of the types of EDM process which emerged as an economical substitute to create three dimensional or sharp angles on
machined surfaces like blanking dies, extrusion dies, punches, etc. Since, WEDM is advanced machining process and useful to create complex features on machined parts, surface finish of WEDM’ed parts has greater influence on the qualities of job [2]. Surface finish in WEDM has been found to be affected by varying several factors: input parameters: discharge current, pulse duration, pulse frequency, wire speed, wire tension, dielectric flowrate[3], etc., work material characteristics, use of cutting fluids, etc., WEDM is complicated machining process which required to control many interaction parameters to obtain the process efficiency. The systematic analysis is required to conduct the WEDM process economically and predictably.

Taguchi method is a robust design tool useful to understand the manufacturing processes / systems effectively to produce better output responses. Response surface methodology (RSM) is important techniques which are useful to postulate mathematical relations between parameters and responses [4]. Jaya optimization algorithm (JOA) is an advanced probabilistic technique used to solve engineering problems [5]. In the present work, Taguchi methodology, response surface methodology (RSM) and multi-jaya optimization algorithm (MJOA) is applied to analyze, model and optimize the control parameters in WEDM to optimize multi-responses: surface finish and material removal rate (MRR) of WEDM’ed H13 tool steel material.

2. Literature Survey

Literature review is made in the present work to study the reported articles based on the various aspects of analysis and optimization of WEDM of H13 tool steel and other steel materials using Taguchi method and statistical analysis of variance. The details of literature review are given as follows:

Singh et al.[6] had been carried out experimental research work based on WEDM of H13 die tool steel material to analyze and optimize the surface roughness and MRR. Experimental plans were made by orthogonal array of Taguchi method by considering pulse on time, pulse off time, wire type, and peak current, as input variables. The effects of input parameters on output responses were determined by analysis of variance technique. Lodhi and Agarwal [7] had optimized the surface roughness of AISI D3 steel by controlling the pulse-on-time, pulse-off-time, peak current, and wire feed in WEDM using Taguchi method. L9 orthogonal array design was used to conduct experimental runs. They stated from the research that discharge current was most significant parameter for surface roughness. They were confirmed the predicted parametric condition by Taguchi validator test. Sharma et al. [8] had conducted a experimental work to study the factor effects on output performances of WEDM of high strength low alloy steel material. Authors used RSM to create mathematical relationships between the process variables and output responses and predict the multiple responses. They used ANOVA to determine the significant parameters on responses.

Neeraj et al.[9] were planned to investigate the significances of parameters on surface roughness and MRR in WEDM of high strength steel material using RSM approach. They observed from their study that both the responses were increasing with increase of pulse on time and decreasing with increase of pulse off time. Both responses were modeled and optimized by using RSM. Sunkara et al. [10]performed analysis on WEDM of aluminum alloy to model and optimize the multi responses using genetic algorithm. Agarwal et al. [11] had optimized the input parameters of EDM of D2 steel to predict multi-responses: surface roughness and MRR using RSM and jaya optimization algorithm. Again, Agarwal et al. [12] had used RSM along with JOA to predict radial over cut in EDM of titanium alloy. Rao et al. [13] had optimized the multi responses in EDM, plasma arc machining and micro-EDM using RSM along with multi-objective JOA and found improved responses.
3. Methodology

3.1 Taguchi method, RSM and jaya algorithm

Taguchi’s methodology is an optimization technique which used to predict response through experimental analysis and to enhance the system performance without increasing production cost and time. The idea of orthogonal array of experiments in Taguchi technique is useful to determine the factors which most affect part quality with a reduced number of experiments. It uses statistical method of signal-to-noise (S/N) ratio to quantity performance of input parameters where signal is favourable and noise is unwanted value. S/N ratio in Taguchi method uses three different objective functions: larger-the-better, smaller-the-better and nominal-the better to analyze the response variable. The equation for smaller is the better and larger-the-better criterions are shown in Equations 1 and 2 respectively.

\[
\text{Smaller the better: } S/N = -10 \log_{10} \left( \frac{1}{n} \sum_{i=1}^{n} y_i \right) \\
\text{Larger-the-Better: } S/N = -10 \log_{10} \left( \frac{1}{n} \sum_{i=1}^{n} y_i^2 \right)
\]

3.2 Response Surface Methodology

RSM is a statistical based mathematical modeling tool which is used to generate the relationships between the process parameters and performance variables. Second-order polynomial regression model is proposed and generated to correlate the independent process variables and dependent responses variable and given in Equation 3.

\[
Y = \beta_0 + A \times \beta_1 + B \times \beta_2 + C \times \beta_3 + D \times \beta_4 + A_2 \times \beta_{11} + B \times \beta_{22} + C_2 \times \beta_{33} + D_2 \\
\times \beta_{44} + A \times B \times \beta_{12} + A \times C \times \beta_{13} + A \times D \times \beta_{14} + B \times C \times \beta_{23} + B \times D \times \beta_{34}
\]

Where, \( Y \) is output response, \( A, B, C \) and \( D \) are input parameters and \( \beta \)'s are constants which are determined from experimental data by using least square method

3.3 Jaya algorithm

Let \( f(x) \) is the objective function to be optimized. In each runi, ‘m’ number of design parameters(j=1,2,…, m), and ‘n’ number of candidate solutions (population size, k=1,2,…,n) are selected. Let the best candidate best attains the best value of \( f(x) \) in the total candidate solutions and the worst candidate worst attains the worst value of \( f(x) \) in the entire solutions alternatives. If \( X_{jk,i} \) is the value of \( j^{th} \) variable for the \( k^{th} \) candidate during the \( i^{th} \) repetition, then this value is altered based on Equation 4.

\[
X'_{jk,i} = X_{jk,i} + r_{1,j,i} (X_{j,\text{best},i-} - X_{j,k,i}) - r_{2,j,i} (X_{j,\text{worst},i-} - X_{j,k,i})
\]

Where, \( X_{j,\text{best},i-} \) is the value of the variable \( j \) for the best candidate and \( X_{j,\text{worst},i-} \) is the value of the variable \( j \) for the worst candidate. \( X'_{jk,i} \) is the updated value of \( X_{jk,i} \) and \( r_{1,j,i} \) and \( r_{2,j,i} \) are the two random numbers for the \( j^{th} \) variable during the \( i^{th} \) iteration in the range [0, 1]. The term “\( r_{1,j,i} (X_{j,\text{best},i-} - X_{j,k,i}) \)” indicates the tendency of the solution to move closer to the best solution and the term “\( r_{2,j,i} (X_{j,\text{worst},i-} - X_{j,k,i}) \)” indicates the tendency of the solution to avoid the worst solution.
is accepted if it gives better function value. All the accepted function values at the end of iteration are maintained and these values become the input to the next iteration.

4. Experimentation
The material used for this study is tool steel of H13 steel material. The experimental runs have been conducted on WEDM using L16 orthogonal array of Taguchi methods with four factors four levels each. The selected input variables and L16 orthogonal array designs for performing experiments are shown in Table 1. Experimental runs have been carried out on WEDM of H13 tool steel material.

5. Results and discussion
As mentioned earlier that experimental runs are performed on WEDM machine when machining of H13 steel material as per L16 orthogonal array of Taguchi method and response, surface roughness is measured and shown in Table 1. The data given in the Table 1 used to analyze, interpret and optimize using analysis of signal-to-noise ratio and Taguchi methodology.

Table 1. Full factorial design matrix and output response

| S. No | Input parameters | Output responses |
|-------|------------------|-----------------|
|       | A    | B    | C    | D    | Surface roughness | MRR   |
| 1     | 17   | 3    | 116  | 50   | 2.652             | 11.625|
| 2     | 17   | 4    | 118  | 57   | 2.640             | 15.500|
| 3     | 17   | 5    | 120  | 54   | 2.690             | 19.375|
| 4     | 17   | 6    | 122  | 51   | 3.220             | 23.250|
| 5     | 18   | 3    | 116  | 54   | 2.576             | 11.625|
| 6     | 18   | 4    | 116  | 51   | 2.399             | 15.500|
| 7     | 18   | 5    | 122  | 60   | 2.771             | 19.375|
| 8     | 18   | 6    | 120  | 57   | 2.474             | 22.250|
| 9     | 19   | 3    | 120  | 51   | 2.639             | 13.625|
| 10    | 19   | 4    | 122  | 54   | 2.772             | 15.500|
| 11    | 19   | 5    | 116  | 57   | 2.343             | 19.375|
| 12    | 19   | 6    | 118  | 60   | 2.611             | 23.250|
| 13    | 20   | 3    | 122  | 57   | 2.838             | 11.625|
| 14    | 20   | 4    | 120  | 60   | 2.579             | 15.500|
| 15    | 20   | 5    | 118  | 51   | 2.929             | 19.375|
| 16    | 20   | 6    | 116  | 54   | 2.629             | 23.250|

5.1 Analysis of variance for output responses
The statistical tool analysis of signal-to-noise (AS/N) ratio from MINITAB 16.2 applied on experimental data of surface finish and MRR in WEDM’ed H13 steel. AS/N ratio tables for surface roughness and MRR are given in Tables 2 and 3 respectively. AS/N is very useful to determine the influences of processing variables on output performances [14]. AS/N results are assessed based on Probability (significant parameter, P) statistics [15]. From the Table 2, it is noted that process parameters like voltage gap (A) and pulse on time (C) have significant effects on surface finish (Ra), as its P values are less than 0.05. Pulse off time (D) have considerable influence on surface finish,
because its P value is very close to 0.05 as found from Table 2. From the A S/N ratio of MRR as shown in Table 3, it is observed that wire feed (B) is most influential for MRR, as its P value is less than 0.05 and very close to zero. Process parameters: voltage gap (A) and pulse off time (D) also have considerable influences on MRR, because its values of P are closer to 0.05, as seen from Table 3.

Table 2. AS/N for surface roughness (Ra)

| Source | DF  | Seq SS  | Adj SS  | Adj MS  | F       | P     |
|--------|-----|--------|---------|---------|---------|-------|
| A      | 3   | 1.7138 | 1.7138  | 0.57125 | 15.39   | 0.025 |
| B      | 3   | 0.351  | 0.351   | 0.11699 | 3.15    | 0.186 |
| C      | 3   | 3.4934 | 3.4934  | 1.16446 | 31.37   | 0.009 |
| D      | 3   | 0.9652 | 0.9652  | 0.32175 | 8.67    | 0.055 |
| Residual Error | 3 | 0.1114 | 0.1114  | 0.03712 |
| Total  | 15  | 6.6347 |         |         |         |       |

S = 0.1927; R-Sq = 98.3%; R-Sq(adj) = 91.6%

Table 3. Analysis of variance for MRR

| Source | DF  | Seq SS  | Adj SS  | Adj MS  | F   | P  |
|--------|-----|--------|---------|---------|-----|----|
| A      | 3   | 0.4496 | 0.4496  | 0.1499  | 1   | 0.5|
| B      | 3   | 70.2388| 70.2388 | 23.4129 | 156.21 | 0.001|
| C      | 3   | 0.1864 | 0.1864  | 0.0621  | 0.41 | 0.756|
| D      | 3   | 0.4496 | 0.4496  | 0.1499  | 1   | 0.5|
| Residual Error | 3 | 0.4496 | 0.4496  | 0.1499 |
| Total  | 15  | 71.7741|         |         | S = 0.3871; R-Sq = 99.4%; R-Sq(adj) = 96.9% |

5.2 Mathematical modelling and contour plots

The mathematical relationships between the WEDM control parameters and output responses: surface roughness and MRR are made by RSM approach by following the procedure given in Section 3.1. The obtained mathematical equations are given in Equations. 5 and 6.

\[ Y_{Ra} = -421.564 + 6.23765 \times A + 15.7102 \times B + 6.21234 \times C + 1.48215 \times D - 0.147583 \times A \times A + 0.0322500 \times B \times B - 0.0232500 \times C \times C + 0.0172593 \times D \times D + 0.0454633 \times A \times B - 0.00744812 \times A \times C - 0.00441134 \times A \times D - 0.1030000 \times B \times C - 0.0823333 \times B \times D \]  

\[ M_{RR} = (-4074.71 + 81.0380 \times A + 144.217 \times B + 56.0376 \times C + 11.1203 \times D - 1.56250 \times A \times A + 0.0625000 \times B \times B - 0.203125 \times C \times C + 0.125000 \times D \times D - 0.115708 \times A \times B - 0.189097 \times A \times C - 0.0272938 \times A \times D - 0.9375000 \times B \times C - 0.5000000 \times B \times D) \]

Contour plots are drawn from the mathematical equations of Ra (Equation 5) and MRR (Equation 6) using RSM applications in MINITAB 16.1 software. Contour plots for Ra are shown in Figure 1 for MRR are given in Figure 2. Contour plots are very useful for visualize the direct and combined effects of input parameters graphically on output responses [16, 17]. From the Figures 1 and 2, it is observed that process parameters are most significant for both the responses, because curved lines / bent lines / elliptical nature found in said plots.
5.3 Optimization by multi-jaya optimization algorithm (MJOA)

The weightage multi-objective JOA is applied on mathematical models of Ra and MRR of WEDM’ed H13 steel as given in Equations 5 and 6 respectively to predict both the responses simultaneously with weightage of 22% for surface roughness and 78% weightage for MRR. And obtained parametric condition which corresponding to optimize both responses according to given weightage and corresponding response values are given in Table 4.

![Figure 1 Contour plots showing effects of process parameters on Ra](image1.png)

![Figure 2 Contour plots showing effects of process parameters on MRR](image2.png)

| Figure 1 | Contour plots showing effects of process parameters on Ra |
| Figure 2 | Contour plots showing effects of process parameters on MRR |

**Table 4. Multi-objective optimization by MJOA**

| Parametric condition | Output response |
|----------------------|-----------------|
| Voltage (A) 17.98 volts | Y_{Ra,min} = 2.56 μ |
| Wire feed (B) 6 mm/min | |
| Pulse on time (C) 116 μs | Y_{MRR,max} = 25.82 mm³/min |
| Pulse off time (D) 60 μs | |

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5.4 Confirmatory test

Confirmatory experiments are conducted for each response to validate the optimized WEDM parametric conditions obtained by MJAO for H13 material. From the confirmatory result, it is noticed that optimum parametric conditions provided are satisfactory results and those are good agreement with the experimental values given in Table 1.

6. Conclusion

Experimental investigation made to optimize the $R_a$ and MRR in WEDM of AISI H13 tool Steel using Taguchi method, RSM and MJOA. The followings are the conclusions drawn from the study:

- From the Analysis of signal-to-noise ratio, it is found that voltage gap and pulse on time are significant for $R_a$ and wire feed is significant for MRR
- Mathematical models are developed for input parameters and output responses by using RSM Contour plots reveals that direct and interactions effects of process parameters are most significant for both the responses
- Multi-responses: surface roughness and MRR optimized simultaneously using multi-JOA
- Confirmatory test confirms the predicted WEDM condition for optimizing both the responses simultaneously
- From the recent investigation, it is stated that hybrid Taguchi method, RSM and MJOA is advantages for analyzing, modeling and optimizing multi responses in WEDM process.

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