PREDICTION OF EDM PROCESS PARAMETERS FOR AISI 1020 STEEL USING RSM, GRA AND ANN

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ABSTRACT
AISI 1020 Steel is hard while machining because of its nature of harness and brittleness. Electrical Discharge Machining (EDM) is a significant technique for machining such materials. Current research examines the pulse current effect (A), discharge voltage (B), pulse on time (C), pulse off time (D), Oil pressure (E) and spark gap (F) on Surface Roughness and Metal Removal Rate (MRR) on EDM of AISI 1020 Steel. Experiments have been carried out in a methodical type taking up nearly 54 successive trails utilizing an EDM machine and a copper electrode of 10mm diameter. Three factors, three levels, Box Bekhen through response surface methodology design was utilized to analyze the outcomes. Gray relational analysis techniques are adopted for finding parameter influencing range for MRR and SR. A multi regression mathematical model was brought up in launching the association between parameters of machining and artificial neural network techniques are used for predicting the optimized parameters.

Keywords: Electro Discharge Machining, Response Surface Methodology, Gray Relational Analysis, Artificial Neural Network, Material Removal Rate, Surface Roughness.

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1. INTRODUCTION

Using the advancement of scientific technology, incorporation of products to aid multifunctional resolutions turn out to be the tradition. Product size reduction is consequently extremely necessary. Attaining this impartial could have need of fresh hard materials holding greater temperature-resistance and strength. Though, along the exclusion of drilling, traditional machining techniques are irrelevant to these novel materials. Hence, it is essential to cultivate innovative process of machining. EDM utilizes high frequency pulse discharge within the electrode and work piece for producing the vaporization phenomenon and melting at the point of electric discharge. At that point itself, heating of dielectric occurs straightaway to an enormously high temperature hence the work piece material’s small portion is raised up above its melting point and consequently that has been carried away. In EDM, the tool electrode never get in touch with the work piece, and is practically unloaded. The process functions very proficiently for AISI 1020 steel machining.

Dissimilar researchers have performed optimization of parameter of process of dissimilar types of EDM from time to time involving different models of optimization and solution techniques. Reviews of those past studies have variable bounds, objective functions, constraints, prominent decision variables, remarks and their limitation. The results were recapitulated as follows: Kuldeep Ojha et al.(2010), inform EDM research associating to enhancement in MRR together with few insight into material removal mechanism. Tolga Bozdana et al. (2010), report that experimental examination of EDM drilling of holes using electrode as brass with Ø2mm on Inconel718. Process parameters effect on process outputs was reported depending on minimum experiments count. Process of mathematical modeling has been performed involving Response Surface Methodology (RSM). Outcomes expresses that the model that is developed can attain reliable forecast of experimental outcomes inside satisfactory accuracy. MusraatAli et al.(2009), Differential Evolution (DE) is an influential however simple Evolutionary Algorithm (EA) to optimize real valued, multimodal functions. B.H. Yan, et al.(1999), reviews the characteristics of micro hole and minimal tool electrode wear rate in obtaining a high precision micro-hole in the carbide, the polarity changing effects, the shape and the rotational speed of tool electrode tool electrode are premeditated. S. S. Mahapatra, et al.(2006), proposed to research factors like pulse duration, discharge current, wire speed, pulse frequency, wire tension and dielectric flow rate and few preferred communications both for MRR maximizations and SR minimization in WEDM process involving Taguchi method. Qing GAO et al.(2008), depicts Artificial Neural Network (ANN) and Genetic Algorithm (GA) are exclusively utilized in creating the parameter optimization model. An ANN model that adapts L-M algorithm was set up to depict the association among MRR and input parameters, and GA is utilized in optimizing parameters to obtain results. The model exhibited is much efficient, and MRR is progressed using machining parameters that were optimized. M. R. Shabgard, et al.(2009), endeavor was involved in developing mathematical models to relate the MRR, TWR (Tool Wear Rate) and SR to machining parameters. Moreover, a study was performed in analyzing the machining parameters effects in respect of itemized technological characteristics. Sushant Dhar, et al.(2007), describes the hard aluminium matrix composites while machining because of the occurrence of brittle and hard ceramic reinforcements. EDM is a significant process to machine those materials. Work estimates the effect of current (c), pulse-on time (p) and air gap voltage (v) on MRR, TWR, and Radial Over Cut (ROC) on EDM of Al–4Cu–6Si alloy–10% weight SiCp composites. Circumstances favouring for extreme MRR with condensed TWR and ROC can also be achieved through linear programming. MRR, TWR and ROC goes up considerably in a nonlinear manner with enhanced current. Puertas et al.(2003), this work is concentrated on features associated to dimensional precision and surface quality, that seems to be the highly
predominant parameters form the point of view of choosing not only the processes conditions which are optimum but also the inexpensive aspects. Thillaivanan, et al.(2010), suggested practical method to optimize parameters of cutting for EDM under the least total machining time supported by Taguchi Method and ANN is accessible. Provided methodology is not only economical and less time consuming but effective and accurate in examining the parameters of machining. Current has been identified to be a noteworthy control on the total time of machining. As an outcomes, the performance attributes like total machining time could be made better through this technique. Sameh S. H(2009) shows the development of a extensive mathematical model to correlate the communicating and higher order manipulation of numerous EDM parameters through RSM, utilizes appropriate experimental data as acquired via conducting tests. The mathematical models was brought up on the basis of RSM, employing the data from practical noticeable settings of the EDM of work pieces. Exploration was performed to analyze the control circumstances demanded in controlling MRR, Electrode Wear Ratio (EWR), gap size and SR. Seung-Han Yanga et al.(2009), recommends a procedure to optimize for the choice of finest process parameters of EDM. Regular cutting experiments have been performed on die-sinking machine under dissimilar circumstances of process parameters. Current model is utilized to instantaneously maximize the MRR together with minimize the SR involving SA scheme. Ramezan Ali Mahdavi Nejad(2011), proposed the work which aims the optimization of SR and MRR of EDM of SiC parameters concurrently. As the output parameters are contradictory naturally, hence there exists no single association of parameters of machining, making available with the idle machining performance. ANN with back propagation algorithm has been utilized to reproduce the process. A method of optimization that is multi-objective, non dominating sorting genetic algorithm-II has been utilized in optimizing the process. Three significant process input parameters effect viz., discharge current, pulse on time (Ton), pulse off time (T_{off}) on EDM of SiC are believed. Experiments were performed over a collection of deliberated input parameters of model to train and verify. G. Krishna Mohana Rao et al.(2010), work is intended in surface hardness optimization formed in die dipping EDM by preferring the instantaneous effect of numerous parameters of input. The experiments are performed on Ti6Al4V, HE15, 15CDV6 and M-250 by modifying the peak current and voltage and the associated hardness values were measured. Majumder, et al.(2012), propose investigation of the process parameters of EDM has optimized for minimum EWR. The machining parameters used in this study are spark-current, pulse-on duration and pulse-off duration. The relation between electrode wear rate and parameters of machining was brought up by utilizing RSM. Chief reason of this work is to demonstrate the input process distinctiveness of EDM and has influenced by the process parameters. These works demonstrate a study of the intervening variable in EDM of material AISI 1020 Steel, the MRR and SR were studied. Six more influential parameters were used during the experiments. The result illustrate that current was the predominant parameter influencing the MRR. Different investigators were presents the cataloging of the numerous areas of research in EDM and probable upcoming directions of research as illustrated in Figure 1. The retro analysis of literature exposed and brought out into view that no works were performed in EDM of AISI 1020 steel and with more than three parameters.
2. EDM MACHINE

With Electronica 5030 Die Sinking EDM machine experiments were conducted as shown in Figure 2. The dielectric fluid and electrode flushing method was utilized.

3. EXPERIMENTAL PROCEDURE

The machining process is performed in ELECTRONICA EMS5030 machine; the work piece is mounted on the V-block which is located on the machine with magnetic table. The tool holder holds the tool and dial gauge has been used to test its alignment. The 54 runs were decided involving various parameter combinations based on Analysis of Variance. Portable roughness tester SJ201 has been utilized to measure roughness which is shown in Figure 3. The various input parameters level and the output are given in the Table 1 and 2.
### Table 1 Different Variables Used in the Experiment and Their Levels

| Variable                          | Coding | Level |
|-----------------------------------|--------|-------|
| Discharge Current (Ip) in A       | A      | 1     |
| Discharge Voltage in V            | B      | 2     |
| Pulse on Time (Ton) in μs         | C      | 3     |
| Pulse off Time (Toff) in s        | D      | 1     |
| Oil Pressure in kg/cm^2           | E      | 7     |
| Gap Width (mm)                    | F      | 9     |

### Table 2 Planning matrix of the Experiments with the Optimal Model Data

| Sl. No. | A Current (A) | B Voltage (V) | C Pulse on Time (μs) | D Pulse off Time(Sec) | E Oil Pressure (kg/cm^2) | F Gap Width (mm) | Experimental Output Through RSM | Predicted Output Through ANN |
|---------|---------------|---------------|----------------------|-----------------------|--------------------------|------------------|--------------------------------|-----------------------------|
|         |               |               |                      |                       |                          |                  | G MRR (mg/sec)                  | H SR (μm)                   |
|         |               |               |                      |                       |                          |                  |                                  |                             |
| 1.      | 15            | 50            | 20                   | 1.5                   | 25                       | 0.22             | 0.481                          | 3.110                       |
| 2.      | 15            | 50            | 20                   | 1.5                   | 25                       | 0.22             | 0.470                          | 3.163                       |
| 3.      | 15            | 50            | 20                   | 1.5                   | 25                       | 0.22             | 0.366                          | 2.673                       |
| 4.      | 15            | 75            | 20                   | 1.5                   | 25                       | 0.22             | 0.459                          | 2.950                       |
| 5.      | 15            | 50            | 20                   | 1.0                   | 25                       | 0.22             | 0.480                          | 3.300                       |
| 6.      | 15            | 25            | 20                   | 1.5                   | 25                       | 0.22             | 0.390                          | 2.371                       |
| 7.      | 15            | 50            | 20                   | 1.5                   | 25                       | 0.04             | 0.511                          | 3.535                       |
| 8.      | 25            | 50            | 20                   | 1.5                   | 25                       | 0.22             | 0.531                          | 3.490                       |
| 9.      | 15            | 50            | 20                   | 1.5                   | 20                       | 0.22             | 0.445                          | 2.970                       |
| 10.     | 15            | 50            | 25                   | 1.5                   | 25                       | 0.22             | 0.411                          | 2.750                       |
| 11.     | 15            | 50            | 20                   | 1.5                   | 25                       | 0.22             | 0.481                          | 3.110                       |
| 12.     | 15            | 50            | 20                   | 1.5                   | 25                       | 0.40             | 0.461                          | 3.468                       |
| 13.     | 15            | 50            | 20                   | 1.5                   | 30                       | 0.22             | 0.473                          | 3.011                       |
| 14.     | 5             | 50            | 20                   | 1.5                   | 25                       | 0.22             | 0.379                          | 2.391                       |
| 15.     | 25            | 25            | 25                   | 2.0                   | 20                       | 0.40             | 0.351                          | 2.930                       |
| 16.     | 5             | 25            | 15                   | 2.0                   | 30                       | 0.04             | 0.133                          | 0.870                       |
| 17.     | 5             | 25            | 15                   | 1.0                   | 20                       | 0.04             | 0.143                          | 1.187                       |
| 18.     | 15            | 50            | 20                   | 1.5                   | 25                       | 0.22             | 0.481                          | 3.110                       |
| 19.     | 25            | 25            | 15                   | 2.0                   | 30                       | 0.40             | 0.334                          | 2.824                       |
| 20.     | 25            | 75            | 15                   | 1.0                   | 20                       | 0.04             | 0.331                          | 2.986                       |
| 21.     | 25            | 25            | 25                   | 1.0                   | 30                       | 0.40             | 0.362                          | 3.421                       |
| 22.     | 5             | 75            | 75                   | 2.0                   | 30                       | 0.40             | 0.230                          | 2.640                       |
| 23.     | 25            | 25            | 25                   | 2.0                   | 20                       | 0.04             | 0.403                          | 2.947                       |
| 24.     | 5             | 75            | 15                   | 1.0                   | 20                       | 0.40             | 0.242                          | 2.379                       |
| 25.     | 15            | 50            | 20                   | 1.5                   | 25                       | 0.22             | 0.481                          | 3.110                       |
| 26.     | 5             | 75            | 25                   | 2.0                   | 20                       | 0.40             | 0.267                          | 2.410                       |
| 27.     | 25            | 75            | 15                   | 2.0                   | 30                       | 0.04             | 0.347                          | 2.660                       |
| 28.     | 5             | 75            | 25                   | 1.0                   | 30                       | 0.40             | 0.307                          | 2.682                       |
| 29.     | 25            | 25            | 15                   | 1.0                   | 20                       | 0.40             | 0.296                          | 3.100                       |
| 30.     | 5             | 25            | 25                   | 2.0                   | 20                       | 0.04             | 0.198                          | 1.040                       |
| 31.     | 5             | 25            | 25                   | 1.0                   | 30                       | 0.04             | 0.187                          | 1.281                       |
| 32.     | 25            | 75            | 25                   | 1.0                   | 30                       | 0.04             | 0.410                          | 2.648                       |
| 33.     | 15            | 50            | 20                   | 1.5                   | 25                       | 0.22             | 0.481                          | 3.110                       |
| 34.     | 15            | 50            | 20                   | 1.5                   | 25                       | 0.22             | 0.481                          | 3.110                       |
| 35.     | 25            | 75            | 15                   | 2.0                   | 20                       | 0.40             | 0.288                          | 2.630                       |
| 36.     | 25            | 25            | 25                   | 2.0                   | 30                       | 0.04             | 0.428                          | 2.960                       |
4. MODELING OF MRR AND SR

Based on the conditions of design matrix, the machining operations were performed at random to make error free measurement. In subsequent step, the plan in accomplishing the experiments implementing RSM utilizing a Box Behnken approach with six variables. Total count of experiments performed with the association of machining parameter are illustrated in Table 2. Models of MRR and SR are obtained by using Minitab software are equation 1 and 2. All the experimental values and the predicted input values are taken for the analysis for finding optimized inputs.

Ultimate response equation for MRR and SR is shared as follows:

\[
MRR = (-2.27473 + 0.01960A + 0.01238B + 0.15318C + 0.08097D + 0.04702E - 0.19114F - 0.00026A*A - 0.00009B*B - 0.00369C*C - 0.02323D*D - 0.00087E*E + 0.16025F*F - 0.00015A*B + 0.00104A*D + 0.00006 A*E - 0.00002 B*C - 0.00039 B*D + 0.00001B*E + 0.000085 B*F + 0.00142 C*D - 0.00011 C*E + 0.000431 C*F - 0.00128 D*E - 0.05278 D*F + 0.00472 E*F) \\
\]

\[
SR = (-10.3534 +0.2333A + 0.1146B +0.6798C -1.6742D + 0.2769E -7.7338F -0.0019 A*A -0.0008 B*B -0.0168 C*C +0.4028 D*D -0.0056 E*E +11.4411 F*F -0.0018 A*B -0.0025 A*D -0.0010 A*E -0.0004 B*C + 0.0061 B*D -0.0001 B*E +0.0046 C*D + 0.0003 C*E + 0.0193C*F -0.2288 D*F + 0.0994 E*F) \\
\]

Where

A - Working Current
B - Working Voltage
C - Pulse ON Time
D - Pulse OFF Time
E - Oil Pressure
F - Spark Gap

5. ARTIFICIAL NEURAL NETWORKS ARCHITECTURE

Generally ANN consists of a number of layers: the layer where the input patterns are applied is called the input layer, the layer where the output is obtained is the output layer, and the layers between the input and output layers are the layers that are hidden are shown in Figure 4. One or more hidden layers are present, which are so named because their outputs are not...
directly observable. When the size of the input layer is large, the addition of hidden layers makes possible the network to extract higher-order statistics which are predominantly valuable. Fully or partially interconnected neurons layers are preceding and subsequent layer of neurons with each interconnection having an associated connection strength (or weight). In a forward direction, the input signal propagates through the network, on a layer-by-layer basis which is commonly referred to as Multilayer Perceptrons (MLP). Many publications discuss the development and theory of ANN.

**Figure 4** General Configuration of Artificial Neural Network

6. BACK-PROPAGATION NETWORK ALGORITHM

The back-propagation network program algorithm is depicted beneath with the support of flow diagram as shown in Figure 5.

![Figure 5 Back-Propagation Network Program](http://www.iaeme.com/IJMET/index.asp)
Step 1: Confirm the hidden layers count.

Step 2: Confirm the neurons count for the input layer and the output layer. Neurons number equalizes the count of input variables for input layer and equalizes the count of outputs essential for the output layer. Set few neurons count for the hidden layer.

Step 3: Acquire the training input pattern.

Step 4: Allocate neurons with small weight values interconnected between the input, hidden and output layers.

Step 5: Compute all the neurons output layers that are in hidden and output layers utilizing the succeeding formula.

\[ \text{Out}_i = f \left( \sum_{w_{ij}} \text{Out}_j + q_1 \right) \]  

(3)

Where output\(_i\) is the output of the \(i\)th neuron in the layer under deliberation; output\(_j\) is the output of the \(j\)th neuron in the previous layer. \(f\) is the sigmoid function can be articulated as:

\[ f(\text{net}_1) = \frac{1}{1+e^{-\text{net}_1/q}} \]  

(4)

Where \(q\) is called as temperature.

Step 6: Regulate the output layer’s output and associate it with the anticipated output values. Regulate the output neurons error,

\[ \text{Error} = \text{desired output} - \text{actual output} \]  

(5)

Likewise, determine the root mean square error value of the output neurons.

Step 7: Regulate the error existing at the hidden layers neurons and back-propagate those errors to the weight values associated among the neurons of input layer and hidden layer. Likewise, back propagate the errors accessible at the output neurons to the weight values associated among the hidden layer neurons and output layer utilizing the ensuing formula.

\[ E_p = \frac{1}{2} \sum \left( t_{pj} - O_{pj} \right)^2 \]  

(6)

Where \(E_p\) is the error for the \(p\)th presentation vector, \(t_{pj}\) is the anticipated value for the \(j\)th output neuron and \(O_{pj}\) is the anticipated output of the \(j\)th output neuron.

\[ \text{error} \delta_{pi} = (t_{pi} - O_{pi})O_{pi}(1-O_{pi}) \]  

(7)

For output neurons,

\[ \text{error} \delta_p = (t_{pi} - O_{pi})O_{pi} \sum \delta_{pi}W_{ki} \]  

(8)

for hidden neurons Weight adjustment has been performed as follows:

\[ \Delta W_{ji}(t = 1) = \eta(\delta_{pi}O_{pi}) = \alpha \Delta W_{ji}(t) \]  

(9)

Where \(\eta\) is the learning rate parameter and \(\alpha\) is momentum factor.

Step 8: Go to Step 3 and perform the calculations up to Step 7 at the end of cycle regulate the root-mean-square error value, mean percentage of error and worst percentage of error above the complete patterns. For reaching Step 9 check for reasonable error, if so, go to Step 9 else go to Step 3 and reiterate the same from Step 3 to Step 7.
Step 9: Discontinue the iteration and the final weight values are noted that belongs to the neurons hidden layer and also to the output layer.

Step 10: Testing neural network model with the proficient weight values, regulate the output to test the pattern and check if the deviation from anticipated value is rationally less or not. If not, try the back propagation with reviewed network by modifying neurons count, varying learning rate parameters, momentum value and temperature values as well. Table 2 illustrates the typical observation of network performance while testing the pattern.

7. GREY RELATIONAL ANALYSIS

Grey Relational Analyses are implemented in determining appropriate choice of parameters of machining for Electrical Discharge Machining (EDM) process.

7.1. Steps IN GRA

Subsequent steps are adopted when implementing grey relational analysis for finding the Grey relational coefficients and the grey relational grade:

(a) Normalizing the experimental outcomes of MRR and surface roughness for avoiding the influence of adopting dissimilar units to decline the variability.

\[
Z_{ij} = \frac{y_{ij} - \min_{i=1,2,...,n} (y_{ij})}{\max_{i=1,2,...,n} (y_{ij}) - \min_{i=1,2,...,n} (y_{ij})}
\]  

\[
Z_{ij} = \frac{\max_{i=1,2,...,n} (y_{ij}) - y_{ij}}{\max_{i=1,2,...,n} (y_{ij}) - \min_{i=1,2,...,n} (y_{ij})}
\]

(b) Accomplishing the grey relational generating and estimating the grey coefficient for the normalized values yield:

\[
\gamma(y_0(k),y_j(k)) = \frac{\Delta_{\min} + \xi \Delta_{\max}}{\Delta_0(k) + \xi \Delta_{\max}}
\]

Where,

- \( j=1, 2...n; k=1, 2...m, n \) is the experimental data items count and \( m \) is the responses count.
- \( y_0(k) \) is the reference sequence (\( y_0(k)=1, k=1, 2...m \)); \( y_j(k) \) is the specific comparison sequence.
- \( \Delta_0 = \|y_0(k) - y_j(k)\| \) is The absolute value of the difference between \( y_0(k) \) and \( y_j(k) \).
- \( \Delta_{\min} = \min\min \|y_0(k) - y_j(k)\| \) is the smallest value of \( y_j(k) \).
- \( \Delta_{\max} = \max\max \|y_0(k) - y_j(k)\| \) is the largest value of \( y_j(k) \).
- \( \xi \) is the distinguishing coefficient which is defined in the range 0 ≤ \( \xi \) ≤ 1 (the value may adjusted based on the practical needs of the system).

(c) Calculating the grey relational grade by averaging the grey relational coefficient yields:

\[
\gamma_j = \frac{1}{k} \sum \gamma_j
\]

Where \( \gamma_j \) is the grey relational grade for the \( j^{th} \) experiment and the quantity of performance characteristics is \( k \). Equation (10) is utilized in normalizing the experimental value when the default value target is consuming the characteristic of ‘higher the better’. Here MRR is normalized utilizing the above Equation (11). When the ‘lower the better’ is a characteristic of the default sequence, then it is normalized implementing Equation (12), i.e., surface roughness is normalized via this equation. Using Equation (12), grey relational
A coefficient has been calculated for MRR and SR as illustrated in Table 2. Also, the grey relational grade is figured as per Equation (13).

| Sl. No. | MRR  | SR   | Normalized Values for MRR | Normalized Values for SR | GRC Values for MRR | GRC Values for SR | Grade |
|--------|------|------|---------------------------|-------------------------|-------------------|------------------|-------|
| 1      | 0.481| 3.11 | 0.108225                  | 0.14363                 | 0.822064          | 0.776844         | 0.799454 |
| 2      | 0.47  | 3.163| 0.132035                  | 0.125718                | 0.791096          | 0.79082          | 0.795089 |
| 3      | 0.366 | 2.673| 0.357143                  | 0.291315                | 0.583333          | 0.63186          | 0.607597 |
| 4      | 0.459 | 2.95 | 0.155844                  | 0.197702                | 0.762376          | 0.716638         | 0.739507 |
| 5      | 0.48  | 3.3  | 0.11039                   | 0.079419                | 0.819149          | 0.862934         | 0.841041 |
| 6      | 0.39  | 2.371| 0.305195                  | 0.393376                | 0.620968          | 0.559675         | 0.590321 |
| 7      | 0.511 | 3.535| 0.04329                   | 0                      | 0.920319          | 1                | 0.960159 |
| 8      | 0.531 | 3.49 | 0                  | 0.015208                | 1                  | 0.970482         | 0.985241 |
| 9      | 0.445 | 2.97 | 0.186147                 | 0.190943                | 0.728707          | 0.723649         | 0.726178 |
| 10     | 0.411 | 2.75 | 0.25974                  | 0.265292                | 0.65812           | 0.653345         | 0.655732 |
| 11     | 0.481 | 3.11 | 0.108225                  | 0.14363                 | 0.822064          | 0.776844         | 0.799454 |

For more information, please visit [http://www.iaeme.com/IJMET/index.asp](http://www.iaeme.com/IJMET/index.asp).
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As observed in Table 3 MRR enhances from 0.362 Mg/sec to 0.404 Mg/sec and SR value was reduced from 3.421µm to 2.06 µm. Depending upon the specified results, it has been noticed that quality characteristics proves to be significantly enhanced via this confirmation test.

Table 3 Optimal Input and Output Parameters for AISI1020 Steel

| Response | Process Parameters | Output Parameters |
|----------|--------------------|-------------------|
|          | A (V) Voltage      | C (s) Pulse ON Time | D (s) Pulse OFF Time | E (mm) Gap | F (Oil Pressure (Kg/cm²)) | MRR (Mg/sec) | SR (µm) |
| Initial  | 25                 | 25                | 25                 | 1.0       | 0.40                  | 30           | 0.362 | 3.421 |
| Optimal  | 25                 | 25                | 15                 | 1         | 0.4                   | 20           | 0.404 | 2.06  |

8. RESULT AND DISCUSSION

8.1. Result and Discussion for MRR
Machining parameters effect (I_p, V, T_on, T_off, P_oil and spark gap) on the response variables MRR too were assessed by performing experiments. Outcomes are shared with the Minitab software for auxiliary examination. Second-order model has been projected for finding association among the MRR and the process variables brought into account. Analysis of variance (ANOVA) has been utilized in checking the adequacy of the second order model.

Figure 7 illustrates the assessed response surface for MRR in association to the process parameters of pulse current and pulse on time which could be viewed from the figure, the MRR have a tendency to rise up, significantly with rise in peak current for whichever pulse on time value. Henceforward, maximum MRR is achieved at high peak current and high pulse on time which is because of their foremost switch towards the input energy i.e. with the rise in pulse current produces robust spark that produces greater temperature ending up in melting of more material and the work piece erosion.

The effect of I_p and T_off is on the projected response surface of MRR is illustrated in the Figure 8, the parameters T_on, V, spark gap and P_oil stays unchanged in its maximum level. MRR rises up when I_p goes up, the description is similar, like mentioned former, though along the rise in T_off, MRR declines, which is because when T_off increases, there exist an uninvited heat loss which does not subsidize to MRR leading to work piece temperature drop earlier the subsequent spark begins and hence MRR declines. Maximum MRR is attained with high I_p
and lower $T_{off}$ for the provided choice of input parameters. Figure 9 illustrates MRR as a purpose of $T_{on}$ and $T_{off}$, while the $I_p$, $V$, spark gap and $P_{oil}$ remains constant in its greater level that could be viewed that the greatest MRR values took place at the greater $T_{on}$ and at the lower $T_{off}$. Figure 10 depicts MRR as a function of $V$ and $I_p$, while the $T_{on}$, $T_{off}$, spark gap and $P_{oil}$ remains constant in its higher level which could be viewed that the highest MRR values took place at the higher $I_p$ and $V$.

Figure 11 represents MRR as a utility of $T_{on}$ and current, while the $I_p$, voltage, $T_{off}$, spark gap and $P_{oil}$ remains constant in its greater level with the maximum MRR values occurring at greater $T_{on}$ and current. Figure 12 signifies MRR as a function of Current and $T_{off}$, while the $I_p$, $T_{on}$, voltage, spark gap and $P_{oil}$ remains constant in its developed level with higher MRR values occurred at the higher current and lower $T_{off}$. Figure 13 represents MRR as a function of $P_{oil}$ and voltage, whereas the $T_{on}$, spark gap, $T_{off}$ and current remains constant in its higher level. It can be seen that the highest MRR values occurred at the higher voltage and medium $P_{oil}$.

Figure 14 illustrates MRR as a function of $T_{off}$ and $P_{oil}$, while the $I_p$, spark gap, $T_{on}$ and $V$ remains constant in its higher level with the highest MRR values occurring at the lower $T_{off}$ and of $P_{oil}$. Figure 15 represents MRR as a function of spark gap and voltage, while the $I_p$, $T_{off}$, $T_{on}$ and current remains constant in its higher level which can be seen that the highest MRR values occurred at the lower spark gap and higher voltage.

Figure 16 represents MRR as a spark gap and voltage functionality, while the $I_p$, $T_{off}$, $T_{on}$ and $V$ remains constant in its higher level which could be seen that the highest MRR values occurred at the lower spark gap and higher voltage. Figure 17 illustrates MRR as a purpose of spark gap and current, while voltage, $T_{off}$, $T_{on}$ and $P_{oil}$ remains constant in its higher level with high MRR values occurred at the lower spark gap and higher current. Figure 18 represents MRR as a function of spark gap and $p_{offs}$ while the $I_p$, $T_{on}$, $P_{oil}$ and $V$ remains constant in its higher level with highest MRR values occurred at the lower spark gap and lower pulse off time. Figure 19 for MRR is shown in along with the numerous parameters utilizing RSM and ANN. ANN is an appropriate tool, used in calculating the material removal rate in machining process. Outcomes illustrate that ANN model has been efficaciously functional to the machining parameters of AISI 1020 Steel. It is observed from Figure 19(Validation of RSM and ANN model for MRR) that predicted depending upon ANN model is very close to the experimental surveillance.

![Figure 7 MRR Vs Pulse On Time and Current](image7)

![Figure 8 MRR Vs Pulse Off Time and Current](image8)

![Figure 9 MRR Vs Pulse Off Time and Pulse on Time](image9)

![Figure 10 MRR Vs Current and Voltage](image10)
Prediction of EDM Process Parameters for AISI 1020 Steel Using RSM, GRA and ANN

Figure 11 MRR Vs Pulse on Time and Current

Figure 12 MRR Vs Pulse Off Time and Current

Figure 13 MRR Vs Oil Pressure and Voltage

Figure 14 MRR Vs Oil Pressure and Pulse On Time

Figure 15 MRR Vs Oil Pressure and Pulse OFF Time

Figure 16 MRR Vs Spark Gap and Voltage

Figure 17 MRR Vs Spark Gap and Current

Figure 18 MRR Vs Spark Gap and Pulse Off Time

Figure 19 Variation of MRR for RSM and ANN
8.2. Result and Discussion for SR

Machining parameters effect (Ip, V, T_on, T_off, spark gap and P_oil) on the response variables SR was assessed by accompanying experiments. Outcomes have been shared to the Minitab software for additional examination. The second-order model has been projected for finding association among the MRR and the process variables considered. Analysis of Variance (ANOVA) has been utilized in checking the adequacy of the second order model. Figure 20 illustrates SR as a function of T_off and current, while the V, T_on, spark gap and P_oil remains constant at its inferior levels with low range of SR values when T_off and V are greater. Figure 21 depicts SR as a function of current and T_on, while the V, T_off, spark gap and P_oil remains constant at its lower levels with SR values are high when current is low with higher T_off. Figure 22 illustratess SR as a function of T_on and T_off, while the I_p, spark gap, V and P_oil remains constant at its lower levels which is monitored that the SR values are low when T_on is low with elevated T_off. Even though two parameter influence is highly not as much of on comparison with the effect of I_p on SR.

Figure 23 illustrates the projected response surface for SR in association to the process parameters of I_p and T_on while T_off, V, spark gap and P_oil remain constant at their lowest values. Figure illustrates that the SR increases predominantly with rise in I_p for any value of T_on. Though, the SR be likely to to rise up with rise in T_on, particularly at elevated I_p. Hence forward, smallest SR is achieved at low peak current and low pulse on time which is because to their leading switch over the input energy, i.e. with the rise in I_p generating robust spark creating the greater temperature and crater, henceforth rough surface in the work piece and low I_p generates trivial crater and consequently surface that is smooth.

The effect of I_p and T_off is on the estimated response surface of SR is illustrated in Figure 24 T_on, V, spark gap and P_oil remains constant in its lower levels which could be renowned that the SR goes up when the I_p, T_off goes up.

Figure 25 represents SR as a function of V and I_p, while the T_on, spark gap, T_off and P_oil remains constant at its lower levels with the observation that low range of SR values when V and I_p are low. Figure 26 illustrates SR as a function of oil pressure and I_p, while the T_on, voltage, T_off and spark gap remains constant at its lower levels with the observation that low range of SR values on low oil pressure and I_p. Oil pressure effect and T_on is on the estimated response surface of SR is portrayed in Figure 27. T_off, current, voltage and spark gap remains constant in its lower levels with the observation that rise in SR takes place when the oil pressure increases and pulse on time decreases. Figure 28 illustrates SR as a function of oil pressure and voltage, while the T_on, current, T_off and spark gap remains constant at its lower levels with the observation that the SR values are low when oil pressure and voltage are low. Figure 29 illustrates SR as a function of V and spark gap, while the current, T_on, T_off and P_oil remains constant at its lower levels with the observation that the SR values are low when V and spark gap are high.

Figure 30 for SR is shown together with the numerous parameters utilizing ANN and RSM. ANN is an appropriate tool, used in calculating the surface roughness in machining process. ANN model has been tested and graph was plotted using determined and tested values. The results illustrate that ANN model was implemented fruitfully to the machining parameters of AISI 1020 Steel. It is observed from Figure 30 (Validation of RSM and ANN model for SR) that predicted based on ANN model is highly adjacent to the observation of the experiment.
Prediction of EDM Process Parameters for AISI 1020 Steel Using RSM, GRA and ANN

Figure 20 SR Vs Current and Pulse off Time

Figure 21 SR Vs Current and Pulse off Time

Figure 22 SR Vs Pulse off Time and Pulse on Time

Figure 23 SR Vs Pulse on Time and Current

Figure 24 SR Vs Spark Gap and Voltage

Figure 25 SR Vs Pulse off Time and Current

Figure 26 SR Vs Current and Voltage

Figure 27 SR Vs Pulse on Time and Oil Pressure

Figure 28 SR Vs Oil Pressure and Pulse off Time

Figure 29 SR Vs Oil Pressure and Voltage
9. CONCLUSION

In current research, the input parameters are Discharge Current, Discharge Voltage, Pulse ON time, Pulse Off Time, gap width, Oil Pressure and Metal Removal Rate, Surface Roughness are the parameters of machining which are known to be output. Various ranges of input conditions are consequential of RSM using Box Bekhen method. The experiments are performed on EDM machine, using the experimental results, two models viz., the RSM and ANN are created and calculated. GRA implemented to find the range of parameter influences in MRR and SR. The final conclusions depend on these two prediction models, an advanced technique output with a type of empirical model providing best outcome on comparison with RSM model in terms of acceptable error.

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