Investigations on the effect of wire EDM process parameters on surface integrity of HSLA: a multi-performance characteristics optimization

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Surface roughness ($R_a$) and micro-hardness ($\mu h$) are two important constituents of the surface integrity (SI) of the machined component. In Wire Electric Discharge Machining (WEDM), the machining factors that affect SI are generally the pulse on-time, pulse off-time, current, etc. This paper presents a study that investigates the effect of the WEDM parameters on the surface roughness average and the micro-hardness of the High Strength Low Alloy steel (ASTM A572-grade 50). Nine experimental runs based on an orthogonal array of Taguchi method are performed and grey relational analysis (GRA) method is subsequently applied to determine an optimal WEDM parameter setting. The SI parameters i.e. surface roughness and micro-hardness are selected as the quality targets. An optimal parameter combination of the WEDM process is obtained using GRA. By analyzing the grey relational grade matrix, the degree of influence for each controllable process factor onto individual quality targets can be found. The pulse off-time is found to be the most influential factor for both the surface roughness and the micro-hardness. Further, the results of the analysis of variance reveals that the pulse off-time is the most significantly controlled factor for affecting the SI in the WEDM, according to the weighted sum grade of the surface roughness and the micro-hardness.

Keywords: WEDM; HSLA; surface integrity; grey relational analysis; optimization

1. Introduction

High Strength Low Alloy (HSLA) steel finds its wide application in the manufacturing of potentially high load bearing parts of automobiles because of its high strength to weight ratio, components such as steering, chassis parts, door intrusions, and suspension parts are made of this alloy steel. The use of HSLA steel is increasing, since it results in weight saving and a resulting saving in fuel and effluents. Its use is ever increasing and more parts of carbon steel are being replaced with HSLA steel. Several cutting and finishing operations are required to make these parts and various other products of HSLA steel. Owing to the inherent characteristics of HSLA steel such as high strength and hardness, its machinability is poor and it often requires high speed for machining. Further, the quality of the machined surface is also relatively not up to the mark. HSLA steels are usually 20 to 30\% lighter than carbon steel with the same strength

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HSLA steels provide better mechanical properties and greater resistance to atmospheric corrosion than conventional carbon steels. HSLA steels were developed for the automotive industry to reduce weight without losing strength. One of the largest uses of machining as a process of production is the automobile sector. Non-conventional machining processes such as Wire Electric Discharge Machining (WEDM) have the potential to machine this special category of alloy steel. Thus, the performance of WEDM process when applied to HSLA steel becomes contemporary important. However, it is important to select optimum combination of WEDM parameters for achieving optimal machining performance (Lin et al., 2000).

The electro discharge machining (EDM) process is one of the best alternatives for machining an ever increasing number of high-strength, non-corrosion, and wear-resistant materials (Abu Zeid, 1997). The technology of monitoring and control of the machining processes has been accelerated because of the need for improvement in machining efficiency and part quality. WEDM process has been a key process for the tooling and manufacturing industry. WEDM was introduced in the late 1960s’, and has revolutionized the tool and die, mold, and metal-working industries. It can machine anything that is electrically conductive regardless of the hardness, from relatively common materials such as tool steel, aluminum, copper, and graphite, to exotic space-age alloys including titanium, carbide, polycrystalline diamond (PCD) compacts, and conductive ceramics. The cutting of PCD and conductive PCBN tooling blanks is heavily dependent on WEDM although the application is specialized and from a global perspective, represents a small segment of the market (Aspinwall, Soo, Berrisford, & Walder, 2008). In WEDM, material is removed by means of rapid and repetitive spark discharges across the gap between the tool and the workpiece. The WEDM process plays a predominant role in some manufacturing sectors, because this process has the capability to cut complex and intricate shapes of components in all electrically conductive materials with better precision and accuracy (Mahapatra & Patnaik, 2006).

In past, a lot of work has been carried out to investigate the effect of WEDM parameters on various performance parameters. Scott, Boyina, and Rajurkar (1991) formulated a multi-objective optimization problem and presented a solution for the selection of the best parameter settings to achieve the desired metal removal rate (MRR) and surface quality during WEDM. Lajis, Radzi, and Amin (2009) optimized the process parameters in the cutting of tungsten carbide ceramic using EDM with a graphite electrode using Taguchi methodology. In their paper, EDM parameters such as peak current, voltage, pulse duration, and interval time were found to have a significant influence on machining characteristics such as MRR, electrode wear rate (EWR), and surface roughness. The results of their paper revealed that, in general, the peak current significantly affects the EWR and surface roughness, while the pulse duration mainly affects the MRR. Singh and Maheshwari (2007) presented an investigation on the optimization of process parameters for the EDM of 6061Al/Al2O3p/20p work specimens by employing the Taguchi Design of Experiment methodology. They selected one noise factor i.e. aspect ratio (with two levels), and five control factors, viz. pulse current, pulse on-time, duty cycle, gap voltage, and tool electrode lift time (three levels each), for the experiment to obtain the optimal settings of factors and the effect of these factors on multiple performance characteristics, namely, MRR, tool wear rate, and surface roughness. Tzeng and Chen (2007) performed an experimental study to optimize the precision and accuracy of the high-speed EDM process. Their paper describes the application of the fuzzy logic analysis coupled with Taguchi method to optimize the precision and accuracy of the high-speed EDM process. Kumar, Kumar, and Kumar (2012) made an attempt to
model the response variable i.e. surface roughness in WEDM process using response surface methodology. They varied six parameters i.e. pulse ON time, pulse OFF time, peak current, spark gap voltage, wire feed, and wire tension to investigate their effect on surface roughness and subsequently, they optimized the surface roughness using multi-response optimization through desirability. Rao and Sarcar (2009) evaluated the optimal parameters for machining brass with wire and studied the influence of these parameters on MRR and surface roughness.

Surface integrity (SI) is a composite property which describes the deviations of surface characteristics from the substrate. Its constituent parameters include change in surface metallurgy, residual stresses on surface, depth of surface affected by metallurgy and residual stresses, geometrical accuracy including accuracy of size and form, and surface roughness. Surface roughness and micro-hardness play major role in describing the deviations of surface characteristics from the substrate. In other words, these two surface characteristics may be aptly considered to define the SI of the machined component. The micro-hardness, indeed, represents the surface hardness due to several factors such as residual stresses, metallurgical changes, grain refinement, etc. Keeping this in view, in the present paper, these two important surface characteristics have been chosen to define SI.

The establishment of adequate machining guidelines requires the study of SI generated in the part by a machining operation. SI generated after machining is important, as it determines the functional behavior and reliability of the components such as fatigue life and wear resistance when they are put to use. Maintaining SI is one of the most critical requirements (Kundrak, Mamalis, Gyan, & Bana, 2011; Saini, Ahuja, & Sharma, 2012; Umbrello, Jayal, Caruso, Dillon, & Jawahir, 2010). In order to maintain a high production rate with an acceptable quality level and SI of the machined parts, it is important to select the optimum combination of WEDM parameters such as pulse on-time, pulse off-time, current, and feed rate as these parameters have impact on multi-performance characteristics like surface roughness, micro-hardness, and microstructure, which are indeed constituents of SI (Goel, Khan, Siddiquee, Kamaruddin, & Gupta, 2012). Among the several SI parameters, surface roughness and micro-hardness are very important as they correlate with the surface profiles in order to better characterize the different machining processes. Surface roughness plays an important role in many areas and is a factor of great importance in the evaluation of machining accuracy.

Taguchi method can be applied for optimization of process parameters to obtain optimum condition with lowest cost and minimum number of experiments which leads to production of high-quality products. Owing to the advantages offered by the Taguchi method, researchers have extensively used this method to plan experiments for the purpose of optimization of process and design parameters (Kamaruddin, Khan, & Wan, 2004; Verma, Agrawal, & Bajpai, 2012). Rao, Ramji, and Satyanarayana (2010) applied Taguchi method to find the optimal cutting parameters for surface roughness in WEDM machining of Aluminum BIS-24345. Saini, Khan, and Siddiquee (2013) used Taguchi method with analysis of variance (ANOVA) to optimize the WEDM parameters, while cutting composite material Al6061/SICP. Another Taguchi method-based study was conducted by Kaladhar, Subbaiah, and Rao (2012) to investigate the effect of cutting parameters on surface finish to obtain optimal setting of the cutting parameters.

The grey relational analysis (GRA) is a method for measuring the degree of approximation among the sequences using a grey relational grade (Siddiquee, Khan, & Mallick, 2010). It is a new technique for performing prediction, relational analysis, and decision-making in many areas. Theories of the GRA have attracted considerable interest among researchers (Khan, Siddiquee, & Kamaruddin, 2012). Some other researchers have also
performed the optimization of process parameters. For example, Ramanujam, Muthukrishnan, and Raju (2011) presented the detailed experimental investigation on turning aluminium silicon carbide particulate metal matrix composite (Al-SiC–MMC) using PCD 1600 grade insert. The objective was to establish a correlation between cutting speed, feed, and depth of cut to the specific power and surface finish on the work piece. The optimum machining parameters were obtained by GRA. Tzeng, Lin, Yang, and Jeng (2009) investigated the optimization of CNC turning operation parameters for SKD11 alloy tool steel using GRA method. Taguchi based grey relational analysis was applied by Sharma and Bhambri (2012) to investigate the optimization of two responses (surface roughness and material removal rate [MRR]) by varying three cutting parameters (cutting speed, feed rate, and depth of cut) during high speed turning of AISI H13 under dry conditions. Kuram and Ozcelik (2013) employed Taguchi-based GRA for multi-objective optimization of micro-milling parameters that simultaneously minimize tool wear, force, and surface roughness and they found that the combination of spindle speed of 10,000 rpm, feed per tooth of .5 µm/tooth, and depth of cut of 50 µm minimizes the tool wear, \( F_x \), \( F_y \), and surface roughness simultaneously. Ibrahim et al. (2011) studied the effect of process parameters (Injection pressure, injection temp, mold temp, injection time, holding time) in micro metal injection molding of 316L stainless steel micro component on multiple quality characteristics (Strength and density) using a Taguchi-based GRA. They reported that the optimum combination of micro injection molding parameter is A1 (Injection pressure at 11 bar), B2 (Injection temp at 160 °C), C1 (mold temp at 55 °C), D0 (Injection time at 5s), E0 (Holding time at 5s), and the significant parameters in descending order are injection time, injection pressure, holding time, mold temperature, and injection temperature. Lin and Lin (2002) studied the optimization of the EDM parameters, namely workpiece polarity, pulse on-time, duty factor, open discharge voltage, discharge current, and dielectric fluid with considerations of multiple performance characteristics including MRR, surface roughness, and electrode wear ratio using GRA. They observed that the performance characteristics of the EDM process such as MRR, surface roughness, and electrode wear ratio are improved together using the method and finally concluded that the machining performance in the EDM process can be improved effectively through this approach. Kumar, Babu, Venkatasamy, and Raajenthiren (2010) used Grey–Taguchi Method to demonstrate optimization of Wire Electrical Discharge Machining process parameters of Incoloy800 super alloy with multiple performance characteristics such as MRR, surface roughness, and Kerf. They considered gap voltage, pulse on-time, pulse off-time, and wire feed as input parameters and conducted experimental study using Taguchi’s L9 Orthogonal Array. They found that the optimal process parameters include a 50 V Gap Voltage, 10 µs pulse on-time, 6 µs pulse off-time, and 8 mm/minute Wire Feed rate. They also observed that while applying the Grey–Taguchi method, the MRR shows an increased value of .05351 g/min to .05765 g/min, the surface roughness shows a reduced value of 3.31 to 3.10 µm and the Kerf width shows a reduced value of .324 to .296 mm, respectively, which are positive indicators of efficiency in the machining process.

It appears from the literature presented above that a little amount of work has been done to investigate the effect of WEDM parameters on SI of the HSLA steel machined surface. The use of HSLA steel is growing rapidly and it subsumes several parts which were traditionally been manufactured by mild steel. Consequently, the machining activity on HSLA steel is also increasing. Keeping this in view, the present work is aimed to investigate the effect of three WEDM parameters (pulse on-time, pulse off-time, and current) on SI during WEDM of HSLA steel. Out of several SI parameters, surface
roughness and surface hardness are the most important and relevant to the present investigations. Hence, they were selected as measure for SI. The objectives of the study are to determine (i) optimum levels of the WEDM parameters that yield optimum multi-performance characteristics i.e. SI, (ii) the WEDM parameters that significantly affect SI, and (iii) the most influential WEDM parameters for individual constituents of SI i.e. surface roughness and micro-hardness. The Taguchi L9 (3^3) design is utilized for experimental planning for this purpose. The GRA is then applied to examine how the input factors influence the quality targets of surface roughness and micro-hardness. An optimal parameter combination was then obtained. Through analyzing the grey relational grade matrix, the most influential factors for individual quality targets of cutting operations can be identified. Additionally, the ANOVA is performed to investigate the more influencing parameters for the multi-performance characteristics i.e. surface roughness and micro-hardness, which are indeed constituents of SI.

2. Grey relational analysis

The following sections present the procedure for GRA that has been used in this study to obtain the optimum WEDM parameters and also to identify the most influential parameters that affect SI. The steps involved in the GRA are given below:

1. Normalization of the data sequence using data preprocessing.
2. Calculation of the corresponding grey relational coefficients.
3. Calculation of the grey relational grades.

2.1. Data preprocessing

Data preprocessing is used to transform the given data sequence into dimensionless data sequence and it involves the transfer of the original sequence to a comparable sequence. Let the original reference sequence and comparability sequence be represented as \( x_0^{(O)}(k) \) and \( x_i^{(O)}(k) \), \( i = 1, 2, \ldots, m \); \( k = 1, 2, \ldots, n \), respectively, where \( m \) is the total number of experiment to be considered, and \( n \) is the total number of observation data. Data preprocessing converts the original sequence to a comparable sequence. Several methodologies of preprocessing data can be used in GRA, depending on the characteristics of the original sequence (Deng, 1989; Tzeng et al., 2009; Yang, Shie, & Huang, 2007). For the original sequence ‘the-larger-the-better’, the original sequence is normalized as follows (Tzeng et al., 2009):

\[
x_i^{(C)}(k) = \frac{x_i^{(O)}(k) - \min (x_i^{(O)}(k))}{\max (x_i^{(O)}(k)) - \min (x_i^{(O)}(k))}
\]

For ‘the-smaller-the-better’ characteristic of the original sequence, the original sequence is normalized as follows (Tzeng et al., 2009):

\[
x_i^{(C)}(k) = \frac{\max (x_i^{(O)}(k)) - x_i^{(O)}(k)}{\max (x_i^{(O)}(k)) - \min (x_i^{(O)}(k))}
\]
There is an alternate simple method for normalizing the original sequence where the original sequence is divided by the first value of the sequence i.e. \( x_i^{(O)}(1) \) as follows:

\[
x_i^*(k) = \frac{x_i^{(O)}(k)}{x_i^{(O)}(1)}
\]  

(4)

where, \( x_i^{(O)}(k) \): the original sequence, \( x_i^*(k) \): the sequence after the data preprocessing, \( \max x_i^{(O)}(k) \): the largest value of \( x_i^{(O)}(k) \), and \( \min x_i^{(O)}(k) \): the smallest value of \( x_i^{(O)}(k) \).

### 2.2. Grey relational coefficients and grey relational grades

After the data preprocessing, a grey relational coefficient is calculated using the preprocessed sequences. The grey relational coefficient can be calculated as (Tzeng et al., 2009):

\[
\gamma(x_0^*(k), x_i^*(k)) = \frac{\Delta_{\min} + \zeta \Delta_{\max}}{\Delta_{0i}(k) + \zeta \Delta_{\max}} \quad \text{and} \quad 0 < \gamma(x_0^*(k), x_i^*(k)) \leq 1
\]  

(5)

where \( \Delta_{0i}(k) \) is the deviation sequence of the reference sequence \( x_0^*(k) \) and comparability sequence \( x_i^*(k) \); namely

\[
\Delta_{0i}(k) = |x_0^*(k) - x_i^*(k)|,
\]

\[
\Delta_{\min} = \min_{\forall j \in I} \min_{\forall k} |x_0^*(k) - x_i^*(k)|
\]

\[
\Delta_{\max} = \max_{\forall j \in I} \max_{\forall k} |x_0^*(k) - x_i^*(k)|
\]

with \( \zeta \): distinguishing coefficient, \( \zeta \in [0, 1] \).

After calculation of the grey relational coefficients, grey relational grade is calculated using the following relationship (Tzeng et al., 2009):

\[
\gamma(x_0^*, x_i^*) = \sum_{k=1}^{n} \beta_k \gamma(x_0^*(k), x_i^*(k)), \quad \text{where} \sum_{k=1}^{n} \beta_k = 1
\]  

(6)

The grey relational grade \( \gamma(x_0^*, x_i^*) \) represents the degree of correlation between the reference and comparability sequences. In case of two identical sequences, the grey relational grade is equal to 1. The grey relational grade also indicates the degree of influence exerted by the comparability sequence on the reference sequence. Consequently, if a particular comparability sequence is more important to the reference sequence than other comparability sequences, the grey relational grade for that comparability sequence and the reference sequence will exceed as compared to other grey relational grades. The GRA is actually a measurement of the absolute value of data difference between the sequences, and can be used to approximate the correlation between the sequences.
3. Experimental procedures and test results

3.1. Materials
A572-grade 50 HSLA steel (composition given in Table 1) with 200 mm × 40 mm × 10 mm size was used as workpiece material.

3.2. Schematic of machining
The experimental studies were performed on a Steer Corporation DK7712 NC WEDM machine. This machine can be used to cut workpiece in accordance with the predeter-
mined locus (The schematic is shown in Figure 1). Different settings of pulse on-time, pulse off-time, and current are used in the experiments. Frequency and voltage settings are kept constant throughout the experiments.

3.3. Experimental parameters and design
The experiments were conducted with three controllable 3-level factors and two response variables. Nine experimental runs based on the orthogonal array L9 (3³) were carried. Table 2 shows three controlled factors, i.e. pulse on-time (i.e. A (μs)), pulse off-
time (i.e. B (μs)), and the current (i.e. C (Ampere)) with three levels for each factor. Table 3 shows the nine cutting experimental runs according to the selected orthogonal table. After cutting, two quality objectives of the workpieces were chosen, including the

| Element       | Concentration | Element     | Concentration |
|---------------|---------------|-------------|---------------|
| Iron          | 98.31         | Aluminum    | .004          |
| Carbon        | .187          | Copper      | .011          |
| Silicon       | .039          | Tin         | .000          |
| Manganese     | 1.35          | Niobium     | .001          |
| Sulfur        | .025          | Cobalt      | .002          |
| Phosphorous   | .027          | Boron       | .000          |
| Nickel        | .012          | Lead        | .0001         |
| Chromium      | .010          | Vanadium    | .0001         |
| Molybdenium   | .014          | Zirconium   | .0001         |

Table 1. Chemical composition of ASTM A572-grade 50 HSLA steel.

Figure 1. Schematic of WEDM process.
surface roughness (i.e. $R_a$ (μm)) and micro-hardness (i.e. $\mu h$ (HV)). The surface roughness is detrimental for the in-service performance of the products especially under conditions of fatigue and tribological effects. Therefore, it is essential for effective in-service performance of the surface that the surface roughness should be minimum. Any change in surface hardness due to reasons such as heating and quenching, which is characteristics of WEDM, is considered to be undesirable for the satisfactory performance of the in-service parts. Hence, for optimal performance, the surface hardness of the machined part should not change and must remain as close as possible to that of hardness of the substrate. In light of these facts, typically, small values of surface roughness and target values of micro-hardness were considered as they are desirable for the SI in the machining operation.

3.4. Measuring apparatus

The surface roughness values were measured by the surface roughness tester (model: SURFTEST, SV-2100 (Resolution, $X$ axis – 0.05 μm, main unit – 0.01 μm (800 μm), stylus tip radius of 1 μm and angle 60°); make: Mitutoyo, Japan) which used cut-off length of 0.8 mm and evaluation length of 4 mm. Surface micro-hardness was measured using Mitutoyo Micro Vickers Hardness Testing Machine using a load of 2 N for 15s.

4. Results and discussion

The following sections describe the results of the present study and also present a discussion on the results in light of the available literature.

4.1. Best experimental run

The experimental results for the surface roughness and micro-hardness are listed in Table 4. A typical surface roughness profile for the three replicates of experiment
number 2 is shown in Figure 2(a)–(c). Typically, smaller values of the surface roughness and target values of micro-hardness are desirable for SI of the machined surface. Thus, the data sequences have a ‘the-smaller-the-better characteristic’ for surface roughness and therefore, Equation (2) was employed for data preprocessing. Similarly, Equation (3) was used for data preprocessing for micro-hardness. It may be noted that the average micro-hardness value of the workpiece material before machining was 206 HV, and therefore, the same is also the target value. The values of the surface roughness and the micro-hardness are set to be the reference sequence \( \mathbf{x}_{0}^{(O)}(k) \), \( k = 1, 2 \). Moreover, the results of nine experiments were the comparability sequences \( \mathbf{x}_{i}^{(O)}(k) \), \( i = 1, 2, \ldots, 9 \), \( k = 1, 2 \). Table 5 listed all of the sequences after implementing the data preprocessing using Equations (2) and (3). The reference and the comparability sequences were denoted as \( \mathbf{x}_{0}^{(O)}(k) \) and \( \mathbf{x}_{i}^{(O)}(k) \), respectively. Also, the deviation sequences \( \Delta_{0i} \), \( \Delta_{\max}(k) \) and \( \Delta_{\min}(k) \) for \( i = 1, 2, \ldots, 9 \), \( k = 1, 2 \) can be calculated.

The distinguishing coefficient \( \zeta \) can be substituted for the grey relational coefficient in Equation (5).

If all the process parameters have equal weighting, \( \zeta \) is set to be .5. Table 6 shows the grey relational coefficients and the grade for all nine comparability sequences. Figure 3 shows the grey relational grade for all experiments. It is clear from this figure that the experiment 2 has the maximum value of grey grade (.8172), and has the optimal parameters setting for best multi-response characteristics, such as surface roughness and micro-hardness. The grey relational graph for factor A (Pulse on-time), factor B (Pulse off-time), and factor C (Current) is shown in Figures 4, 5, and 6, respectively. These figures represent the level-wise effect of each factor on the grey relational grade.

This investigation employs the response table of the Taguchi method to calculate the average grey relational grades for each factor level, as illustrated in Table 7.

Since the grey relational grades represent the level of correlation between the reference and the comparability sequences, larger grey relational grade means the comparability sequence exhibiting a stronger correlation with the reference sequence. Based on this study, one can select a combination of the levels that provide the largest average response. Figure 7 shows the mean value of grey relational grade at different levels of each WEDM parameters. The dashed line in this figure is the value of the total mean of the grey relational grade. In Table 6 and Figure 7, the combination of \( A_1, B_2, \) and \( C_2 \) shows the largest value of the grey relational grade for the factors A, B, and C, respectively. Therefore, \( A_1B_2C_2 \) i.e. pulse on-time of 15 \( \mu s \), a pulse off-time of 4 \( \mu s \), and a current of 3 A is the optimal parameter combination of the cutting operations.

| Run no. | A   | B   | C   | Ra (\( \mu m \)) | \( \mu H \) (hV) |
|--------|-----|-----|-----|-----------------|-----------------|
| 1      | 1   | 1   | 1   | 4.507           | 173.46          |
| 2      | 1   | 2   | 2   | 4.388           | 219.4           |
| 3      | 1   | 3   | 3   | 5.690           | 206.8           |
| 4      | 2   | 1   | 3   | 4.317           | 140.1           |
| 5      | 2   | 2   | 1   | 4.528           | 179.5           |
| 6      | 2   | 3   | 2   | 4.703           | 181.9           |
| 7      | 3   | 1   | 2   | 4.492           | 167.9           |
| 8      | 3   | 2   | 3   | 4.367           | 152.3           |
| 9      | 3   | 3   | 1   | 5.417           | 155.1           |
4.2. Most influential factor

GRA is applied to examine how the process parameters influence the quality targets of workpieces. The values of the factor level in nine experimental runs are set to the comparability sequences for three controllable factors. Table 8 lists all of the sequences.

Data preprocessing was performed based on Equation (4), and Table 8 shows the normalized results. Subsequently, the deviation sequences were calculated using the method mentioned above. The deviation sequences and the distinguishing coefficient then were substituted into Equation (5) to obtain the grey relational coefficients. Additionally, the grey relational coefficients are averaged using an equal weighting to obtain

Figure 2. A typical surface roughness profile for experiment number 2.
Table 5. The sequence after data preprocessing.

| Reference/comparability sequence | $R_a$  | $\mu h$ |
|----------------------------------|--------|---------|
| Reference sequence               | 1.0000 | 1.0000  |
| Comparability sequences          |        |         |
| No. 1                            | .1384  | .4938   |
| No. 2                            | .0517  | .2033   |
| No. 3                            | 1.0000 | .0121   |
| No. 4                            | .0000  | 1.0000  |
| No. 5                            | .1537  | .4021   |
| No. 6                            | .2811  | .3657   |
| No. 7                            | .1275  | .5781   |
| No. 8                            | .0364  | .8149   |
| No. 9                            | .8012  | .7724   |

Table 6. The calculated grey relational coefficient and grey relational grade for nine comparability sequences.

| Experimental run (comparability sequences) | Orthogonal array $L_9 (3^3)$ | Grey relational coefficient | Grey relational grade |
|--------------------------------------------|-------------------------------|-----------------------------|-----------------------|
|                                            | A    | B    | C    | $R_a$ | $\mu h$ |                     |                       |
| 1                                          | 1    | 1    | 1    | .7832 | .5153   | .6493             |                       |
| 2                                          | 1    | 2    | 2    | .9063 | .7282   | .8172             |                       |
| 3                                          | 1    | 3    | 3    | .3333 | 1.0000  | .6667             |                       |
| 4                                          | 2    | 1    | 3    | 1.0000| .3414   | .6707             |                       |
| 5                                          | 2    | 2    | 1    | .7649 | .5677   | .6663             |                       |
| 6                                          | 2    | 3    | 2    | .6401 | .5916   | .6158             |                       |
| 7                                          | 3    | 1    | 2    | .7969 | .4750   | .6359             |                       |
| 8                                          | 3    | 2    | 3    | .9321 | .3895   | .6608             |                       |
| 9                                          | 3    | 3    | 1    | .3843 | .4025   | .3934             |                       |

Figure 3. Grey relational grade for multi-response.
Figure 4. Grey relational grade graph for factor A (Pulse on-time).

Figure 5. Grey relational grade graph for factor B (Pulse off-time).

Figure 6. Grey relational grade graph for factor C (Current).
the grey relational grade. Table 9 listed the grey relational coefficients and the grade of the surface roughness of the reference sequence and comparability sequences. Table 10 gives the grey relational coefficients and the grade of the micro-hardness for the reference sequence and the comparability sequences.
The grey relational grades in Tables 9 and 10 can be further arranged in a matrix form shown as follows:

\[
\gamma = \begin{bmatrix}
\gamma(R_a, A) & \gamma(R_a, B) & \gamma(R_a, C) \\
\gamma(\mu h, A) & \gamma(\mu h, B) & \gamma(\mu h, C)
\end{bmatrix}
\]

(7)

By comparing row 1 and row 2, some conclusions can be drawn from this matrix. In the first row \(\gamma(R_a, B) > \gamma(R_a, A) > \gamma(R_a, C)\), it means that the order of importance for the controllable factors to the surface roughness, in sequence, is the factor B, A, and C. Similarly, from the second row \(\gamma(\mu h, B) > \gamma(\mu h, C) > \gamma(\mu h, A)\), the order of importance for the controllable factors to the micro-hardness, in sequence, is the factor B, C, and A.

The most influential factors that affect the output variables are determined by identifying the maximum values in each row. Hence, based on the maximum values in the matrix of the grey relational \((\gamma(R_a, B), (\mu h, B)) = (.6957, .7026)\), it can be found that the factor B, the pulse OFF time, has the most influence on both the surface roughness and the micro-hardness with \(\gamma\) value of .6957 and .7026, respectively.

Additionally, Table 11 gives the results of the ANOVA for the surface roughness, and the micro-hardness using the calculated values from the grey relational grade of

| Grey relational coefficient | A     | B     | C     |
|-----------------------------|-------|-------|-------|
| Grey relational coefficient | 1.0000| 1.0000| 1.0000|
|                             | .6924 | .9015 | .7171 |
|                             | .7562 | .5551 | .4246 |
|                             | .5330 | .7561 | .3333 |
|                             | .6688 | .6688 | .9448 |
|                             | .6794 | .4897 | .5691 |
|                             | .4592 | .9490 | .5284 |
|                             | .4295 | .5688 | .3470 |
|                             | .4345 | .4345 | .8492 |
| Grey relational grade       | .6281 | .7026 | .6348 |

Table 10. The calculated grey relational coefficient and grey relational grade for experimental factors to experimental result of the \(\mu h\).
According to Table 11, the factor B, the pulse OFF time with 38.72% of contribution, is the most significant controlled parameters for the cutting operation; the factor A, the pulse on-time, is with 34.59% contribution and the factor C, the current with 25.35% of contribution if the minimization of the surface roughness and the target value of the micro-hardness is simultaneously considered.

It has been reported that an increase in the pulse on-time results in an increase in both the surface roughness and the discharge energy (Rao et al., 2010). The increased discharge energy as well as the increased duration for which this energy is discharged to the workpiece leads to the formation of bigger craters on the workpiece and thereby surface roughness increases. Further, increase in pulse on-time also provides more time for conduction of greater amount of heat to the workpiece. Consequently, the workpiece material is heated to a greater depth due to presence of high temperature and the same thickness of the workpiece gets hardened due to quenching during subsequent spark off. Pulse OFF time provides a pause in spark and the time for removal of debri produced during spark on. During this period, quenching of the workpiece also takes place. Hardness decreases on reducing pulse OFF time as its lower values result in lesser time being available for quenching of the workpiece. Further, when the pulse OFF time is short, next spark takes place before the work surface has fully cooled and quenched. This explains a reduction in hardness with a decrease in pulse OFF time and vice versa.

However, the current has a different effect on roughness and hardness. At a low current, a small quantity of heat is generated and a substantial portion of it is absorbed by the surroundings, consequently, the amount of utilized energy in melting and vaporizing the workpiece is not so intense. But by increasing the pulse current per unit pulse on-time, a stronger spark with higher thermal energy is produced, and a substantial quantity of heat is transferred to the work piece. Furthermore, as the current increases, discharge strikes the surface of the workpiece more intensely, and creates an impact force on the molten material in the crater and causes more molten material to be ejected out of the crater, so the surface roughness of the machined surface increases. On the other hand, an increase in current also increases the temperature of workpiece, which consequently increases the micro-hardness as it depends on the temperature of the work piece before quenching.

Thus, the combination of the parameters and their levels i.e. $A_1B_2C_2$ with minimum contribution of the current (25.35%) and maximum contribution of the pulse OFF time (38.72%) would set out just right parameter combination to cause minimum surface roughness along with the nominal micro-hardness leading to optimum SI.

### 4.3. Confirmation test

After identifying the most influential parameters, the final phase is to verify the surface roughness and the micro-hardness by conducting the confirmation experiments. The
A1B2C2 is an optimal parameter combination during WEDM process via the GRA. Therefore, the condition A1B2C2 of the optimal parameter combination was treated as a confirmation test. The result of the confirmation test gives the surface roughness average and the micro-hardness similar to those given in Table 4. The comparison of predicted and experimental values of surface roughness and micro-hardness using the optimal WEDM parameters is presented in Tables 12 and 13, respectively. Both Tables 12 and 13 reveal that the experimental value is very close to the predicted value and validate the correctness of the experimental investigation.

5. Conclusions

The effects of pulse on-time, pulse off-time, and current are experimentally investigated in machining of ASTM A572-grade 50 HSLA steel using NC Wire-cut EDM process. The GRA based on the Taguchi method’s response table was used to optimize the WEDM parameters for HSLA steel. Based on the results of the present study, the following conclusions are drawn:

(1) Increase in the pulse on-time leads to the increase in both the surface roughness and the micro-hardness.
(2) Increase in the pulse current leads to the increase in the surface roughness.
(3) From the response table of the average grey relational grade, it is found that the largest value of the grey relational grade is for the pulse on-time of 15 μs, the pulse OFF time of 4 μs, and the current of 3 A. It is the recommended levels of the controllable parameters of the WEDM machining process as the optimization of SI involving multi-performance characteristics with minimization of the surface roughness average and achieving the target value of the micro-hardness are simultaneously considered.
(4) The order of the importance for the controllable factors to the surface roughness average, in sequence, is the pulse OFF time, the pulse on-time, and the current. However, for micro-hardness the sequence is the pulse OFF time, the current and the pulse on-time.
(5) Through ANOVA, the percentage of contribution to the WEDM process, in sequence, is the pulse off-time, the pulse on-time, and the current. Hence, the
pulse off-time is the most significantly controlled factor for the WEDM operation when the minimization of the roughness average and achieving the target value of the micro-hardness are simultaneously considered.

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