Modelling and multi objective optimization of WEDM of commercially Monel super alloy using evolutionary algorithms

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Abstract: In this research work, development of a multi response optimization technique has been undertaken, using traditional desirability analysis and non-traditional particle swarm optimization techniques (for different customer's priorities) in wire electrical discharge machining (WEDM). Monel 400 has been selected as work material for experimentation. The effect of key process parameters such as pulse on time (TON), pulse off time (TOFF), peak current (IP), wire feed (WF) were on material removal rate (MRR) and surface roughness(SR) in WEDM operation were investigated. Further, the responses such as MRR and SR were modelled empirically through regression analysis. The developed models can be used by the machinists to predict the MRR and SR over a wide range of input parameters. The optimization of multiple responses has been done for satisfying the priorities of multiple users by using Taguchi-desirability function method and particle swarm optimization technique. The analysis of variance (ANOVA) is also applied to investigate the effect of influential parameters. Finally, the confirmation experiments were conducted for the optimal set of machining parameters, and the betterment has been proved.

2. Introduction
WEDM is recognized as an effective machining technique used in a wide range of applications namely automotive, aerospace, defence, electronics, telecommunications, healthcare, environmental, industrial and consumer products of micro-feature with good surface finish. Advanced machining has become crucial in manufacturing industry with the development of MEMS systems and devices. There is a growing need for fast, direct and mass manufacturing of miniaturized products from super alloys in many applications. To machine these materials and to meet the demands of manufacturing industry, many unconventional machining methods have been developed in the recent years. Wire electrical discharge machining (WEDM) is one of them which uses the thermal energy generated due to the controlled discrete sparks occurring between the tool electrode and work piece[1]. It transforms electrical energy into thermal energy for eroding the material. The electrodes are immersed in dielectric liquid or flowing pressurized dielectric medium. A very small amount of work materials melt and vaporize by a series of discharge energies between tool and work piece. Debris materials are flushed out from the sparking area by the dielectric fluid. Due to the lack of contact between tool and work piece, any conductive material can be machined by WEDM regardless of its hardness and toughness.
WEDM can machine any electrically conductive material such as tool steel, aluminum, copper, graphite, exotic space-age alloys including Hastaloy, Inconel, titanium, tungsten carbide, polycrystalline diamond compacts, Ni based alloys and ceramics. WEDM process enables higher accuracy and surface finish along with reasonable cutting efficiency. WEDM process is generally used in aerospace, automobile, tool and dies industries where accuracy and surface finish have great importance [2]. Fig. 1 represents the WEDM set up used for this research work.

4. Literature Review

Wire electrical discharge machining (WEDM) is one of the nonconventional machining which uses the thermal energy generated due to the controlled discrete sparks occurring between the tool electrode and work piece. A suitable dielectric is continuously supplied to the inter-electrode gap. Wire electrical discharge machining (WEDM) is a variant of WEDM technique, in which, a continuously traveling wire made of thin copper, brass, or tungsten is used as electrode. The wire movement is controlled numerically to obtain the desired complex three-dimensional shapes on difficult to machine materials such as super alloys [3]. With the advantages of micro-WEDM over the other micromachining methods, it has been widely accepted in aerospace and nuclear space industry to machine difficult to machine materials.

Nickel-based super alloys find wider applications in modern industries such as space vehicles, rocket engines, experimental aircrafts, nuclear reactors, submarines, steam power plants, gas turbines, nuclear reactors, petrochemical equipment and other high temperature applications. However due to their properties such as high tensile strength, abrasiveness, work hardening, high hardness, low thermal conductivity, strong tendency to weld and formation of built-up edge, it is difficult to machine super alloys [4].

WEDM is an advanced micromachining technique which can be used for machining of titanium alloys. Due to its complex and stochastic nature and the increased number of variables involved, achieving the optimal performance measures of micromachining of super alloys is still a challenging task in manufacturing industry. Hence, the machinability of WEDM process on super alloys needs to be explored. Only a few researchers have been reported, on the machining of Monel using WEDM [5]. But there is a need for the modelling and multi objective optimization of WEDM process.

Balasubramanian and Ganapathy investigated WEDM process using grey relational analysis. An optimal process parameter setting was found out in this paper. Lin and Lin presented the use of gray relational grade to the machining parameter optimization of the EDM process. Jangra et al. presented optimization of performance characteristics such as cutting speed, surface roughness and dimensional lag using Taguchi method and gray relational analysis in WEDM process [6].

Aniza Alias et al. performed experiments on titanium alloy for finding the influence of machining feed rate in the WEDM process. The results show that surface roughness and MRR were increased by increasing feed rate whereas Kerf width was decreased [7]. Anil Kumar et al. investigated the
influence of aluminium powder mixed with electrical discharge machining process using Hastelloy steel. The experimental results show that the size of the particle and its concentration has significant effects in additive mixed EDM process[8]. There are significant improvements in material removal rate, reduction of tool wear and surface finish using medium mesh size 325 aluminium additive powders.

From literature, it has been found that many researchers have focused on the developments of EDM, WEDM, and micro-WEDM. Hence, in this study, an attempt has been made to determine the effect of process parameters on the responses like MRR and surface roughness. Taguchi’s orthogonal array has been used for conducting the experiments. Desirability analysis was used to predict the optimum process parameters for WEDM of Monel. Finally, PSO was used to predict the optimal process parameter for multi performance characteristics optimization of WEDM process. Experimental results confirm the feasibility of the strategy and are in good agreement with predicted results over a wide range of machining conditions.

5.Methodology
5.1.Experimental Design using Taguchi method
Taguchi proposed the robust design based on design of experimentation[9]. This method provides a best tool for parameter design of response characteristics. Design of experiments consists of selection of appropriate orthogonal array and assignment of factors and interaction in appropriate column.

Taguchi method reduces the number of experiments by using orthogonal array thus reducing the efforts of large experimentation. The statistical analysis of variance (ANOVA) method is applied to the outcome of experiments which helps to determine percentage contribution of individual process parameter on responses against predefined level of confidence. Ishikawa’s cause and effect diagram was selected to identify the potential process parameters affecting the response characteristics of WEDM process. (Fig. 2)

![Figure 2. Cause and effect diagram for WEDM process](image-url)
In this work, the effects of four process parameters, i.e., as pulse on time (Ton), pulse off time (Toff), peak current (IP), wire feed (WF) and wire tension (WT) have been investigated on two response characteristics – material removal rate (MRR) and surface roughness (SR) using L9 orthogonal array. ANOVA and mean effect plot were determined using Minitab16 Software.

6. Experimentation
The experiments were performed on Ezecut NXG CNC WEDM Machine setup with RC circuit positional accuracy of 1µ. The experimental setup of WEDM process is shown in Fig. 1. Different settings of pulse on time (Ton), pulse off-time (Toff), peak current (IP) and wire feed (WF) were used in the experiments (Table 1). Sensitivity and gap width were kept constant throughout the experiments.

Table 1. Process parameters with their values at three levels

| Factors                  | Symbol | Range  | Levels |
|--------------------------|--------|--------|--------|
| Pulse on time (µs)       | (Ton)  | 0-99   | 70 80 90 |
| Pulse off time (µs)      | (Toff) | 0-10   | 4 6 8   |
| Peak current (A)         | (Ip)   | 0-8    | 3 4 5   |
| Wire feed (mm/min)       | WF     | 0-99   | 70 80 90 |

Cu-Zn37 master brass wire with 0.25 mm diameter (900 N/mm² tensile strength) was used in this work. As work piece material, commercial Monel 400 in the form of rectangular slab (size 200 x 200 x 10.5 mm) was used (Fig. 3). During the experiments, a punch of 20mm x 8mm x 10.5 mm was cut during each trial (Fig 4), for this purpose the WEDM machine was programmed accordingly. Chemical composition of Monel 400 is given in Table 2.

Table 2. Chemical composition of Monel 400

| Element  | Percentage Composition |
|----------|------------------------|
| Carbon   | 0.3 max                |
| Silicon  | 0.5 max                |
| Manganese| 2.0 max                |
| Sulphur  | 0.024 max              |
| Iron     | 2.5 max                |
| Copper   | 28.0-34.0              |

Cutting speed was obtained directly from the display panel of CNC WEDM set up during the experiment. Material removal rate was calculated by using the following formula:

\[
MRR \text{ (mm}^3/\text{min}) = \text{Average machining rate} \times \text{thickness of plate} \times \text{width of cut} \\
\text{Width of cut} = (2 \times \text{Spark gap}) + \text{Wire Diameter}
\]

Figure 3. Work pieces after WEDM machining
Experiments were repeated two times to minimize the experimental error induced by the action of noise factors.

MAHR Surface Testing tester was used for measurement of surface roughness (Ra) of the machined surface. Two independent readings were taken on each of the machined surfaces and average was considered to reduce the variability caused by the measurement error. Table.3 represents Taguchi’s L-9 orthogonal array with assigned factors for the various experimental results for the material removal rate and surface roughness responses.

Table 3. L9 orthogonal Array and Experimental Results

| Exp Run | T ON | T OF | IP | WF | SR-I (µm) | SR-II (µm) | Average SR (µm) | MRR-I (mm³/min) | MRR-II (mm³/min) | Average MRR (mm³/min) |
|---------|------|------|----|----|-----------|-------------|-----------------|-----------------|-----------------|---------------------|
| 1       | 1    | 1    | 1  | 1  | 11.3641   | 11.0412     | 11.20265        | 4.0026          | 4.1258          | 4.0642              |
| 2       | 1    | 2    | 2  | 2  | 10.0482   | 10.9169     | 10.4825         | 2.9048          | 3.2196          | 3.0622              |
| 3       | 1    | 3    | 3  | 3  | 8.7453    | 7.5854      | 8.16535         | 0.6327          | 0.6488          | 0.64075             |
| 4       | 2    | 1    | 2  | 2  | 11.1998   | 10.9003     | 11.05005        | 4.5174          | 4.7117          | 4.61455             |
| 5       | 2    | 2    | 3  | 1  | 10.6030   | 8.9557      | 9.77935         | 1.1956          | 1.1252          | 1.1604              |
| 6       | 2    | 3    | 1  | 2  | 12.5158   | 11.1335     | 11.82465        | 3.6166          | 3.6112          | 3.6139              |
| 7       | 3    | 1    | 3  | 2  | 11.9223   | 11.2912     | 11.60675        | 2.9628          | 2.9349          | 2.94885             |
| 8       | 3    | 2    | 1  | 3  | 11.7762   | 11.8151     | 11.79565        | 3.0499          | 3.3154          | 3.1827              |
| 9       | 3    | 3    | 2  | 1  | 9.9571    | 10.0241     | 9.9906          | 0.8186          | 1.2402          | 1.0294              |

7. Results and Discussion
This section discusses an experimental finding of the parametric influences on the response characteristics and optimization of WEDM characteristics using Desirability analysis and Particle Swarm Optimization techniques.

7.1. Influence of process parameters on material removal rate and surface roughness
Single response optimization was carried out to investigate the effects of machining parameters on MRR and SR. According to the Taguchi method, S/N ratios were calculated for each experiment. The objective of optimization was to maximize the MRR and minimize the SR. The response table for S/N ratios of MRR was calculated considering the fact that MRR was a larger-the-better performance characteristic; the maximization of the quality characteristic of interest is sought and is expressed as:

\[ S/N \text{ Ratio} = -\log_{10}(1/n) \sum_{i=1}^{n} \frac{1}{y_{ij}^2} \]  \hspace{1cm} (1)

\( y_{ij} \) = observed response value
\( i = 1, 2, \ldots, n; j = 1, 2 \ldots k \)
\( n \) = number of replications

The surface roughness was the lesser-the-better performance characteristic and the S/N ratio for SR was calculated by:

\[ S/N \text{ Ratio} = -\log_{10}(1/n) \sum_{i=1}^{n} y_{ij}^2 \]  \hspace{1cm} (2)
The S/N ratio values are presented in table 4.

Single response optimization values for MRR and SR can be identified through main effect plots for MRR and SR. The response table for MRR and SR was presented in table 5. The ANOVA for MRR and SR was performed with help of Minitab software.

Table 6 summarizes the effect of individual process parameters on MRR and SR through ANOVA. Figure 6 shows the impact of each input parameter on MRR. The influence of process parameters on SR is given in Figure 7.

The results of experiments by considering single response optimal parameters are shown in Table 7.

### Table 4. S/N Ratios of Experimental Results

| Exp. Run | Average SR(µm) | S/N Ratios of SR(db) | Average MRR (mm³/min) | S/N Ratios of MRR(db) |
|----------|----------------|----------------------|-----------------------|-----------------------|
| 1        | 11.20265       | -20.9864             | 4.0642                | 12.1795               |
| 2        | 10.4825        | -20.4093             | 3.0622                | 9.720                 |
| 3        | 8.16535        | -18.2395             | 0.64075               | -3.8662               |
| 4        | 11.05005       | -20.8673             | 4.61455               | 13.2826               |
| 5        | 9.77935        | -19.8062             | 1.1604                | 1.2922                |
| 6        | 11.82465       | -21.4558             | 3.6139                | 11.1595               |
| 7        | 11.60675       | -21.2942             | 2.94885               | 9.3931                |
| 8        | 11.79565       | -21.4344             | 3.1827                | 10.0559               |
| 9        | 9.9906         | -19.9918             | 1.0294                | 0.2517                |

### Table 5. Response Table of MRR and SR

#### Response Table of MRR

| Level | T ON | T OFF | IP | WF |
|-------|------|-------|----|----|
| 1     | 2.589| 3.876 | 3.620| 2.085|
| 2     | 3.130| 2.468 | 2.902| 3.208|
| 3     | 2.387| 1.761 | 1.583| 2.813|
| Delta | 0.743| 2.115 | 2.037| 1.124|
| Rank  | 4    | 1     | 2   | 3   |

#### Response table of SR

| Level | T ON | T OFF | IP | WF |
|-------|------|-------|----|----|
| 1     | 9.950| 11.286| 11.608| 10.324|
| 2     | 10.885| 10.686| 10.508| 11.305|
| 3     | 11.131| 9.994| 9.850| 10.337|
| Delta | 1.181| 1.293| 1.757| 0.980|
| Rank  | 3    | 2     | 1   | 4   |
The experimental results were used to obtain the mathematical relationship between process parameters and machining outputs. The coefficients of mathematical models were computed using method of multiple regressions. In this study, MINITAB 16 (Software Package for Statistical Solutions) was used for the regression analysis. Quadratic models were developed by using regression analysis to determine the relation of process parameters with MRR and SR. These models were developed at 95% confidence level.

Regression equation of MRR

\[
MRR = 6.33 - 0.101(T_{on}) - 1.06(T_{off}) - 1.02(I_p) + 0.364(WF) \quad (3)
\]

The correlation coefficient, $R^2$ has a value of 85.2% which tells us that the equation models MRR quite accurately.

Regression equation of SR

\[
SR = 12.5 + 0.590(T_{on}) - 0.646(T_{off}) - 0.879(I_p) + 0.006(WF) \quad (4)
\]

Correlation coefficient is 80.5%.

**Table 6.** Analysis of variance (ANOVA) for response characteristics

| Source          | D | F | Sum of Squares | Mean sum of Squares | %Contribution |
|-----------------|---|---|----------------|---------------------|---------------|
| Pulse On Time   | 2 |   | 0.8845         | 0.44227             | 5.46          |
| Pulse Off Time  | 2 |   | 6.9520         | 3.47601             | 42.94         |
| Peak Current    | 2 |   | 6.4039         | 3.20197             | 39.55         |
| Wire Feed       | 2 |   | 1.9491         | 0.97456             | 12.04         |
| Error           | 0 |   | 0              | 0                   |               |
| Total           | 8 |   | 16.1896        |                      |               |
7.2. Multi-objective optimization of response parameters by desirability approach

The main aim of the present study is to find the optimal machining conditions of WEDM process. The Taguchi optimization based on desirability analysis is an ideal technique for finding the optimal machining condition of WEDM process. Here the goal was to maximize the material removal rate and minimize the surface roughness. Desirability approach helps us to map between the predicted response ‘y’ and desirability function ‘d’. The desirability value varies from 0 to 1. If the desirability value is zero, it indicates that predicted value was completely undesirable and the desirability value of one was idle. The desirability of corresponding response increases as the value of d increases. The one-sided transformation desirability function of maximization for MRR as shown in Eq. (5) and minimization of surface roughness as shown in Eq. (6).

\[
d_i = \begin{cases} 
\left( \frac{y - y_{\min}}{y_{\max} - y_{\min}} \right)^{wt} & \text{if } 0 \rightarrow y \leq y_{\max} \\
0 & \text{if } y_{\min} \leq y \leq y_{\max} \\
1 & \text{if } y \geq y_{\max}
\end{cases} \quad (5)
\]

\[
d_i = \begin{cases} 
\left( \frac{y - y_{\max}}{y_{\max} - y_{\min}} \right)^{wt} & \text{if } 1 \rightarrow y \leq y_{\min} \\
0 & \text{if } y_{\min} \leq y \leq y_{\max} \\
1 & \text{if } y \geq y_{\max}
\end{cases} \quad (6)
\]

Where, \(d\) was a desirability function of \(y\), \(y_{\min}\) and \(y_{\max}\) are lower and upper limits of response value of ‘y’, respectively, \(wt\) was weight, which can be varied from 0.1 to 10 to adjust the shape of desirability function. An overall desirability function \(D\) (0 ≤ D ≤ 1) was defined as the geometric mean of individual desirability functions. The multi objective function was a geometric mean of all transformed responses of single objective problem shown in Eq. (7). The higher the \(D\) value, better was the desirability of the combined response levels.

\[
D = (d_1 \times d_2 \times \ldots \times d_n)^{1/n} \quad (7)
\]

Multi-response optimization was carried out using desirability function in conjunction with Taguchi method. The ranges of input parameters viz pulse on time, pulse off time, current and wire feed rate. The goal was to maximize the material removal and minimize the surface roughness. The weight values are assigned for MRR and SR as one and equal importance given to each response.
A set of 9 optimal solutions were derived for the specified design space constraints (Table 7) for material removal rate and surface roughness using Minitab statistical software. The set of conditions possessing highest desirability value was selected as optimum condition for the desired responses. Table 7 shows the optimal set of condition with higher desirability function required for obtaining desired response characteristics under specified constraints.

Figure 8 shows the main effects plotted for the composite desirability at different levels of the processing parameters. Basically, the larger the composite desirability, the better is the multiple performance characteristics. However, the relative importance among the parameters for the multiple performance characteristics will still need to be known so that the optimal combinations of the process parameter levels can be determined more accurately.

From the figure 8, it is clear that the optimal set of process parameters from desirability analysis was TON 1-T OFF 1-IP 2-WF 1.

Table 7. Set of Optimal Solutions for WEDM process.

| Run | Average SR (µm) | Average MRR (mm³/min) | Desirability MRR | Desirability SR | Composite Desirability | Rank |
|-----|----------------|-----------------------|-----------------|----------------|------------------------|------|
| 1   | 11.20265       | 4.0642                | 0.92817         | 0.41228        | 0.38267                | 2    |
| 2   | 10.4825        | 3.0622                | 0.60935         | 0.60562        | 0.36903                | 3    |
| 3   | 8.16535        | 0.64075               | 0               | 1              | 0                      | 8    |
| 4   | 11.05005       | 4.61455               | 1               | 0.46008        | 0.46008                | 1    |
| 5   | 9.77935        | 1.1604                | 0.36162         | 0.74762        | 0.27035                | 4    |
| 6   | 11.82465       | 3.6139                | 0.86498         | 0              | 0                      | 8    |
| 7   | 11.60675       | 2.94885               | 0.76212         | 0.24402        | 0.18597                | 6    |
| 8   | 11.79565       | 3.1827                | 0.7998          | 0.08902        | 0.071198               | 7    |
| 9   | 9.9906         | 1.0294                | 0.31273         | 0.70796        | 0.2214                 | 5    |

Table 8. Response Table of Composite Desirability

| Process Parameters | Average Composite Desirability | Rank |
|--------------------|--------------------------------|------|
|                    | Level 1 | Level 2 | Level 3 | Max - Min | |
| Pulse on-time      | 0.2506  | 0.2435  | 0.1595  | 0.0911    | 4    |
| Pulse off-time     | 0.3429  | 0.2369  | 0.0738  | 0.2691    | 1    |
| Peak Current       | 0.1513  | 0.3502  | 0.1521  | 0.1989    | 2    |
| Wire feed          | 0.2915  | 0.185   | 0.1771  | 0.1144    | 3    |

Mean value of composite desirability , $y_m = 0.2179$
7.3. Analysis of Variance for Composite Desirability:
The results obtained from the experiments were analyzed using Analysis of Variance to find the significance of each input factor on the measures of process performances, Material Removal Rate and surface roughness. Using the composite desirability value, ANOVA was formulated for identifying the significant factors. The results of ANOVA are presented in the Table 9.

**Table 9. ANOVA of Composite Desirability**

| Source          | Degree of Freedom | Sum of Squares | Mean of Squares | Percentage Contribution |
|-----------------|-------------------|----------------|-----------------|-------------------------|
| Pulse on-time   | 2                 | 0.01539        | 0.007694        | 6.723                   |
| Pulse off-time  | 2                 | 0.1103         | 0.01978         | 48.182                  |
| Peak current    | 2                 | 0.07878        | 0.03939         | 34.411                  |
| Wire feed       | 2                 | 0.02448        | 0.01224         | 10.694                  |
| Error           | 0                 | 0              |                 |                         |
| Total           | 8                 | 0.22891        |                 |                         |

The results of the ANOVA were represented in the above table and from the table it is clear that pulse off time was the major influencing factor contributing 48.182% to performance measures, followed by peak current contributing 34.411%, and wire feed contributing 10.7% and pulse on time contributing 6.723%.

After the optimal settings have been obtained, verification of the results with the predicted results has done. The formula for estimated composite desirability was given by

\[ y_m = \left( \frac{1}{q} \sum_{i=1}^{q} y_i \right) \]

Where \( y_m \) is the total mean of the composite desirability, ‘j’ is the mean of the composite desirability at the optimum levels and ‘q’ is the number of machining parameters that affect the machining process. After substituting the values in the formula, we get the predicted desirability as 0.5815.
Table 10. Comparison of Initial Settings with Optimized Experimental Results

| Setting level | Initial machining parameters | Optimal machining parameters | Percentage change in responses |
|---------------|-----------------------------|-----------------------------|-------------------------------|
| A1B1C1D1      | A1B1C2D1                    |                             |                               |
| Surface roughness (SR) | 11.20265 µm | 11.1028 µm | 0.891% Decrease |
| Material removal rate (MRR) | 4.0642 mm³/min | 4.8595 mm³/min | 19.568% Increase |
| Composite Desirability | 0.38267 | 0.5815 (Predicted) | 51.96% Increase |

**Improvement in desirability index = 0.19883**

From desirability analysis, TON 1-T OFF 1-IP 2-WF 1 was found as the set of optimal process parameters. These settings were used for confirmation experiments. There was a reduction in surface roughness of the job when compared to the base experiment. A 0.891 % reduction in surface roughness was achieved. Also, an increase of 19.568 % was also obtained in MRR after the confirmation experiment. There is also an increase in the composite desirability of the setting. The results are definitely satisfactory and show an improved response value.

7.4. Multi-objective optimization of response parameters by Particle Swarm Optimization

Particle Swarm Optimization is a complex non-linear optimization problem which is established by imitating the behavior of bird flocks. It was first developed by Kennedy and Eberhart in 1995 [10]. The basic algorithm of PSO consists of three parts: generating particle’s position and velocities, velocity update and position update. A particle in swarm intelligence technology refers to a point in the design space that changes its position after each iteration. It is basically a response which is to be optimized using the technique. First, the position and velocity of i\(^\text{th}\) particle is randomly generated within the limits of its design variables.

\[
X_{i0} = X_{\text{min}} + \text{rand}(X_{\text{max}} - X_{\text{min}})
\]

The second step of PSO involves updating of velocities of all the particles using the fitness values of the particles in the design space. The function value of a response characteristic determines the best position of that particle in the entire design space, called \(g_{\text{best}}\), and also determines the best position of each particle over time, called \(p_{\text{best}}\). These two data points are used in the velocity update formula to provide the search direction, \(v_{i}(t+1)\), for the next iteration.

\[
v_{i}(t+1) = w v_{i}(t) + c_{1} r_{1}(p_{\text{best}}(t) - X_{i}(t)) + c_{2} r_{2}(g_{\text{best}}(t) - X_{i}(t))
\]

In the equation, \(c_{1}\) is the cognitive constant, \(c_{2}\) is the social constant and \(r_{1}\) and \(r_{2}\) are random numbers generated between the limits. The condition to be followed is \(c_{1} + c_{2} \leq 4\).

The last step is updating of position in each iteration. The updated position is given by:

\[
X_{i}(t+1) = X_{i}(t) + v_{i}(t+1)
\]
In the algorithm, a specified number of iterations are performed and the minimum fitness value of the function is taken as the global optimum of the design space, since the objective function is to be minimized.

7.5. Algorithm of PSO:

Steps for optimizing the micro-WEDM process parameters are as follows [11]:

1. Generation and initialization of an array of ten particles with random positions and velocities. Velocity vector has four dimensions: gap voltage, capacitance, feed rate, and wire tension.
2. Evaluation of objectives (MRR and SR) functions for each particle.
3. The MRR and SR values are calculated for new positions of each particle. If a better position was achieved by a particle, the Pbest value was replaced by the current value.
4. Determination of the particle which has achieved the best objective. If the new Gbest value was better than previous Gbest value, the Gbest value was replaced by current Gbest value and stored. The result of optimization was vector Gbest (gap voltage, capacitance, feed rate, and wire tension).
5. Computation of particles new velocity.
6. Update particle’s position by moving toward the objective function.
7. Steps 1 and 2 are repeated until Computation of particles new velocity.
8. Update particle’s position by moving toward the objective function.
9. Steps 1 and 2 are repeated until the iteration number reaches a predetermined iteration.

Regression models are used for obtaining the optimization results with PSO algorithm. A single objective optimization normally gives one optimal solution. In practical situations, most of the problems are multi objective; there could be a number of optimal solutions maximizing the MPCI value that is necessary to determine the optimal process parameters.

We have used an open source MATLAB PSO toolbox (Figure 9) available online. The code was verified and then used for our project. In the code, \( c_1 = 1.2, c_2 = 0.012 \) and \( w = 0.0004 \). Maximum number of iterations is taken as 2000 and the population size is 50.

7.6. Regression Equations:

Using Minitab 16 software, we got the linear regression equation which models the variation of MRR and SR quite accurately, in the experiments.

**Regression equation of MRR**

\[
MRR = 6.33 - 0.101(Ton) - 1.06(Toff) - 1.02(Ip) + 0.364(WF)
\]

The correlation coefficient, \( R^2 \) has a value of 85.2% which tells us that the equation models MRR quite accurately.

**Regression equation of SR**

\[
SR = 12.5 + 0.590(Ton) - 0.646(Toff) - 0.879(Ip) + 0.006(WF)
\]

Correlation coefficient is 80.5%.

As maximization of any function is equivalent to minimization of function which is equivalent to minimization of \( 1/(1+\text{MPCI}) \). The maximization of MPCI was achieved by minimizing the fitness function \( f(x) = 1/ (1+\text{MPCI}) \) using PSO. In the present study, the objective is to get the maximum MRR and minimum SR. The new objective function for multi optimization is defined as follows:

The fitness function used for multi-objective optimisation is given by :

\[
\text{Min}(Z) = w_1SR - w_2MRR
\]

Where \( w_1 \) and \( w_2 \) were weights assigned to each equation. In our case, \( w_1 = w_2 = 0.5 \)

\[
\text{Min}(Z) = 3.085 + 0.3455(Ton) + 0.207(Toff) + 0.705(Ip) - 0.179(WF)
\]
Figure 14. shows the convergence of PSO to obtain an optimized trend and the best objective value achieved during each iteration. It describes the efficiency of the algorithms to initially explore through the solution space and converge to a near optimal or best optimal solution towards the termination of the algorithm. The algorithm was executed for several times to make sure the repeatability of the results. Table 10 shows the optimized and experimental results. The error between the experimental and predicted results was reasonably small, i.e. less than 10%. Results showed that this approach can be effectively used to find the near optimum performance of WEDM of Monel alloy.

Figure 7. PSO Toolbox in MATLAB

The multi-objective function was minimized and the minimum value obtained after PSO is 4.93. From the image above, the optimal conditions can be easily noted down.

6.1.5 Results:

From optimization based on PSO, T ON 1- TOFF 1- IP 1- WF 3 was found as optimal process parameter.

Table 11. Comparison of Initial Settings with Optimized Experimental Results

| Setting level | Initial machining parameters A1B1C1D1 | Experimental machining parameters A1B1C1D3 | Percentage Change in Responses |
|---------------|--------------------------------------|-----------------------------------------|--------------------------------|
| Surface roughness (SR) | 11.20265 µm | 10.5603 µm | 5.7339% Decrease |
| Material removal rate (MRR) | 4.0642 mm³/min | 4.8063 mm³/min | 18.259% Increase |

From the table, we can easily note the change in surface roughness and material removal rate. After applying the optimal combination of settings, we achieve a 5.7339% decrease in surface roughness and 18.259% increase in material removal rate.
Conclusions

In this paper the multi objective optimization of process parameters of WEDM on Monel 400 super alloy was done. Based on the results and discussions, the following conclusions were drawn.

- Monel 400 can be easily machined using WEDM process with a reasonable cutting speed and surface finish. Because of work hardening, it is difficult to machine Monel using traditional methods. In order to improve MRR response characteristics using Taguchi analysis, pulse off-time and peak current must be adjusted as they have the highest impact on it. Pulse on-time and wire feed have the least impact on the process.

- Particle Swarm Optimization was used for multi-objective optimisation of the process. The recommended optimal setting for the process after optimization was T ON 1- T OFF 1- IP 1- WF 3. In the confirmation experiment, there was 5.7339 % decrease in surface roughness and 18.259 % increase in MRR.

- Another optimization technique, known as Desirability approach was used to optimize the process. The parameter combination obtained after the technique was T ON 1- T OFF 1- IP 2- WF 1. After the confirmation experiment, a decrease of 0.891 % in surface roughness and an increase of 19.568% in material removal rate were observed. Overall, there was 51.96 % increase in desirability of the settings after optimization.

- Desirability doesn’t depend on any equation and instead measures the desirability index of each parametric setting. It was very suitable for work and is therefore satisfactory and reliable.

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