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Parametric Appraisal of Electrochemical Machining of AISI 4140 Chromoly steel using Hybrid Taguchi - WASPAS - Sunflower optimization algorithm

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Abstract. Electrochemical machining (ECM) is a significant technique for getting rid of metal that employs anodic dissolution to get complex contours and deep, precise holes, mostly in the components used in automotive or aerospace sectors. To achieve such high surface characteristics, the selection of factors is important. This work deals with the ECM of AISI 4140 Chromoly steel to investigate the surface roughness and material removal rate (MRR) on the machined specimen using a copper tool electrode. Factors like voltage, signal, and feed rate were optimized by hybrid optimization techniques. To acquire optimal factor configurations, the Taguchi-based WASPAS approach was utilised, accompanied by the Sunflower optimisation methodology. ANOVA was then used to determine the component that was the most impactful factor. A confirmation test is used to signify the outcomes of electrochemical machining. It was revealed that feed rate was among the most significantly relevant factors in affecting surface roughness and MRR. Also, all the optimization approaches provided similar predictions and agreed with the results fetched by the previous research.

1 Introduction

Electrochemical machining (ECM) is an intriguing processing technology that has lately gained popularity due to its many mechanical components. ECM is a practical electrochemical energy-based method through which material is removed by ion movement when it is exposed to an electrolyte [1]. It relies on Faraday's law of electrolysis. The substrates must decay to ensure they comply with Faraday's anodization rule [2]. Although there is the possibility of boosting the study's dependability, the reliance on regularity in several aspects needs thorough research to discover the source and influence of the numerous parameters [3]. The electrochemical (electrolysis) activity removes the metal, resulting in diminished surface roughness, residual stress, and higher precision [4-6]. Furthermore, little or minimal thermal or mechanical strains will be generated, but sparks will be generated due to the low working temperature, which must be eliminated so as to minimise tool wear [5].

Because it can manufacture all types of hard, complex-shaped, yet conducting substances with excellent surface quality, ECM is a widely popular and accepted non-conventional machining technology in current manufacturing sectors [6]. Many precision sectors, such as aerospace, tool and die production, and defence, use ECM. This machine can manufacture both exterior and interior geometry and may be used for large-scale manufacturing. Despite the fact that the efficient use of this machining technique necessitates the determination of the ideal consideration for answering some key machining issues like surface roughness, overcut, and so on, the significance of the same cannot be overstated [7]. The machining performance at each moment is determined not only by the completion of the discrepancy but also by additional factors. Furthermore, the increase in gap resistance causes a varying flow of current, leading to overcut issues and poor precision in the dimension of the workpiece [8]. However, controlling all of the factors at the same time is quite challenging. As a result, the input variables are chosen in a random order to optimise the replies. The best grade of precision in ECM may be obtained by correctly combining different machining process factors [9, 10].

To obtain the desired characteristics, the machining process variables should be prioritised in ECM. By performing tests using Taguchi methodology, the machining variables may be chosen sensibly rather than by random sampling, decreasing tooling and operational costs. Many academics have already worked on process optimisation in ECM. Khundrakpam et al. [1] explored the effect of ECM on stainless steel using copper electrodes employing the Taguchi technique and reported that voltage applied during the machining was the most prominent parameter for controlling roughness characteristics and MRR. Rajesh et al. [2] studied the MRR for an ECM-machined Aluminium metal matrix composite using the Taguchi process and reported that pulse on time highly dominated the increase in MRR. Saravanam et al. [3] inspected the ECM effect on TiC-reinforced AA6063 using the Taguchi process and reported that particle reinforcement is the dominant factor that controls the MRR. Rao and Padmanabhan [4] investigated the ECM effect on the LM6 Al/B4C composite using the Utility-Taguchi process and reported that feed rate can control the surface characteristics during machining. Charak and Jawalkar [5] reported that feed has the most influential effect on controlling material removal while machining stainless steel using ECDM with different electrolyte concentrations and abrasive particles using the Taguchi technique. Dubey [6] machined grey cast iron using ECH, optimised the factor using the Utility-Taguchi function, and reported that stick grit size can control the surface characteristics significantly. They also employed genetic algorithms for precise predictions. Liu et al. [7] investigated different aspects of ECM to analyse the parameter influence, which can improve performance measures. They also suggested that these problems can be overcome by the use of suitable electrolytes and optimization techniques. Soni and Thomas [8] investigated the ECM effect on the LM6 Al/B4C composite using the Taguchi process and a genetic algorithm. They conveyed that the voltage and conc. of the electrolyte could significantly control the surface characteristics during machining. Panda et al. [9] considered the effect of ECM on EN19 steel using Taguchi-based TOPSIS, MOORA, and DFA methods and feed rate as influential factors that can significantly control MRR and surface roughness. Gautam et al. [10] considered the ECM and EDM processes done on different materials with different tools. They suggested using a hybrid optimisation process to achieve greater machining characteristics. Kasdekar et al. [11] used ANN for the prediction of MRR during the ECM of AA6061-T6, which provided precise predictions. Tsai et al. [12] machined SS304 using masked ECM and optimised factors using the Taguchi process and reported that masked hole diameter and thickness were the most significant factors in controlling machining characteristics. Abdullah et al. [13] machined AA7024 using ECM, optimised the factors using the Taguchi process, and reported that current significantly controlled the surface characteristics. Das and Chakraborty [14] investigated the ECM effect on Inconel 825 using the Taguchi super ranking concept and reported that voltage can significantly control the machining characteristics. Tiwari et al. [15] inspected the effect of ECM on EN19 steel using the NSGA II process and reported conc. of electrolyte and feed rate significantly controlled the machining characteristics. Prayogo and Lusi [16] studied the effect of ECM on AISI D3 steel using the Taguchi process and reported that conc. of electrolyte and control MRR significantly increased during machining. Das et al. [17] explored the effect of ECM on EN31 tool steel using the Taguchi Grey method and reported that MRR and surface characteristics were significantly improved as the conc. of electrolyte increased. Jeykrishnan et al. [18] scrutinised the effect of ECM on SKD-12 tool steel using the Taguchi process and reported that MRR can be significantly controlled by the current supplied during machining. A similar result was reported by them while machining AISI D3 steel [19]. Tiwari et al. [20] reported that the voltage applied during the ECM of EN 19 steel significantly controlled the overcut. Selvan et al. [21] studied the micro-ECM effect on Inconel 718 using the Taguchi-Grey process and reported that the voltage supplied during machining can significantly control the surface characteristics, while MRR is controlled by the conc. of the electrolyte. Daniel et al. [22] reported that the inner gap between electrode and workpiece significantly controlled the surface characteristics, while the percentage of SiC controlled the MRR during the machining of hybrid Aluminium composites and was optimised using the Taguchi process.

Most of the researchers placed emphasis on the machining of Aluminium-based alloys. Less work has been done on harder materials like steel or super alloys. Most of the work is centred on the electrolyte concentration, neglecting other important machining factors. The most important gap identified was that most of the researchers used the Taguchi method, which did provide satisfactory results, giving an error output of more than 10%, which is not within the permissible limit. There is scope for using a more hybrid method using bio-inspired meta-heuristic optimisation, which can provide more precise results. Hence, to address these gaps, the surface roughness and material removal rate (MRR) of AISI 4140 Chromoly steel were investigated using ECM. Hybrid optimisation approaches were used to optimise factors such as voltage, signal, and feed rate. To acquire optimal factor settings, the Taguchi-based WASPAS approach was utilised, followed by the Sunflower optimisation technique. ANOVA was then used to determine which variables were the most influential factors, before carrying out a confirmation test confirming the electrochemical machining findings.

2 Experimental Methodology

2.1 Material and Setup

In this work, AISI 4140 Chromoly Steel (Table 1) has been selected as a work piece with dimensions of 15mm x 15mm x 10mm. It is a low-alloyed steel that is extensively used in a variety of industries and is an ideal material option because of its endurance, abrasion resistance, outstanding fatigue strength, and durability. This material is popularly used in manufacturing gears, suspension systems, hand tools, crankshafts, sporting goods, etc. Pure electrolytic copper has been selected as an electrode with a flat end and a circular cross section. The electrochemical machining apparatus (Make: METATECH, Model: ECMAC) is used for the trials. Because it does not cause a passivation reaction on the workpiece's surface, sodium chloride (NaCl) aqueous solution was chosen as the electrolyte. The workpiece is secured within the machining area, and the tool (cathode) is connected to the main knob and powered by a stepper motor. A current measuring circuit is connected across the stepper motor controller circuit and the tool to prevent short-circuits. When the current surpasses a safe level, a signal is transmitted to the stepper motor-control system, which promptly reverses the tool's movement. A reservoir is pneumatically pumped with electrolyte. Through electrochemical processes, metal removal isdone in the form of precipitates and sludge. In this manner, even the most difficult materials may be given a complex contour in one machining session [9].

Table. 1 Constituents and properties of AISI 4140 steel

Constituent	Content (%)	Properties	Value
Chromium, Cr	1.10	Density	7.85 g/cm3
Manganese, Mn	1.0	Melting point	1416°C
Carbon, C	0.43	Tensile strength	655 MPa
Silicon, Si	0.3	Yield strength	415 MPa
Molybdenum, Mo	0.25	Hardness	207 HV
Sulphur, S	0.04	Elastic modulus	210 GPa
Phosphorous, P	0.035	Poisson's ratio	0.30
Iron, Fe	balance		

2.2 Chemical reactions

It is important to study the chemical reactions happening in the whole ECM process to understand and monitor the machining of the workpiece. In this case, the whole setup contains AISI 4140 steel as the workpiece, which contains about 97% iron, a copper tool, and an aqueous electrolyte solution that is a combination of NaCl and H_2O. When a strong current is passed across this blend, it separates as follows:

$$H_2O = H^+ + OH^- \tag{1}$$
$$NaCl = Na^+ + Cl^- \tag{2}$$

As potential is applied across a tool and a workpiece, ions with negative and positive charges flow to the anode and cathode, respectively. Hydrogen ions at the cathode absorb electrons carried by the cathode and transform those into hydrogen gas.

$$2H^+ + 2e^- = H_2 \uparrow \tag{3}$$

On the end of the anode, Fe ions are produced by the workpiece, shed a pair of electrons, and mix with chloride ions to create iron chloride deposit.

$$Fe = Fe^{2+} + 2e^- \tag{4}$$
$$Fe^{2+} + Cl^- = FeCl_2 \tag{5}$$

In a similar vein, when hydroxyl ions combine with sodium ions, sodium hydroxide is formed.

$$Na^+ + OH^- = NaOH \tag{6}$$

The material is machined in this fashion, and the material that was eliminated appears as precipitation in the electrolyte. Besides, there is no deposit on the tool; mainly gaseous hydrogen is produced at the tool (cathode) [23].

2.3 Experimental design and response measurement

Table 2 shows the factors selected to design the L16 orthogonal array (Taguchi mixed design), using which experiments were piloted to find the MRR and surface roughness. The machining time of 10 minutes and DC supply of 200 A were kept fixed throughout the process. A surface roughness determining device (Make: Mitutoyo, Model: Surftest SJ-210) was used to measure surface roughness. The MRR is calculated as the weight loss of the workpiece during machining divided by the density of the material.

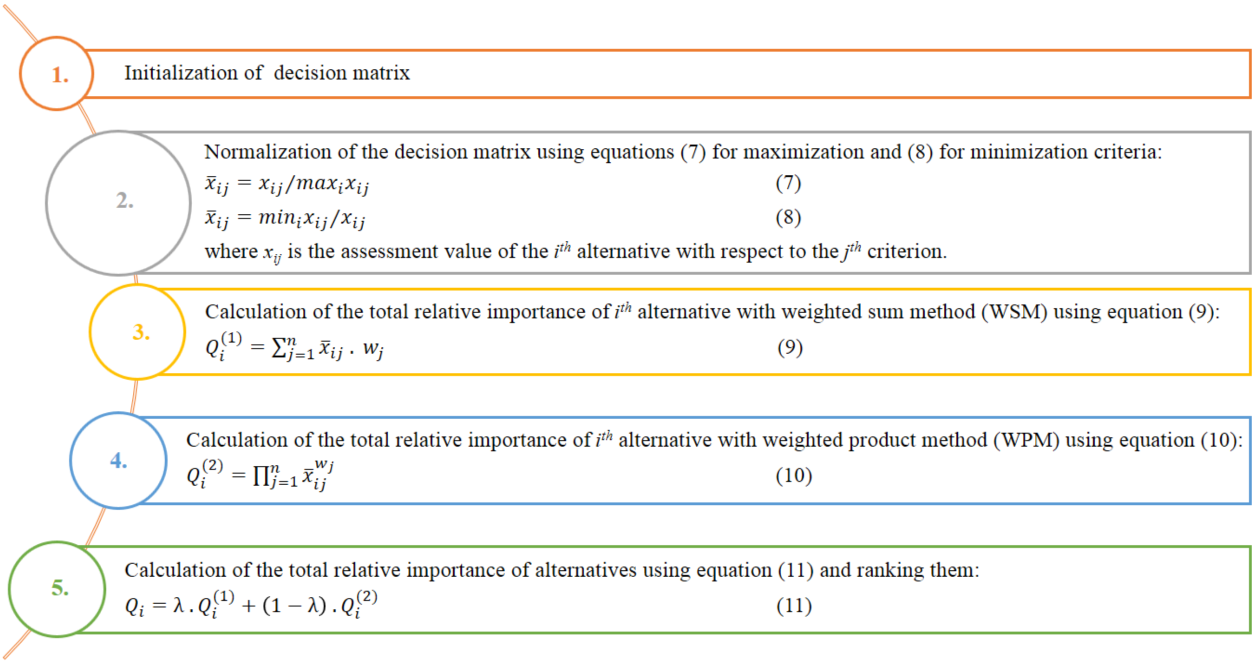
Table. 2 Input factors [9]

Factors	**Code**	**L1**	**L2**	**L3**
Signal	A	1	2	-
Feed Rate, mm/min	B	0.1	0.3	0.5
Voltage, V	C	8	10	12

3 Optimization methods

3.1 WASPAS Method

One of the best-known prominent and efficient procedures, the WASPAS method (Fig. 1), is based on three optimality conditions presented by Zavadskas et al. in 2012 [24]. The initial two are prominent multi-criteria selection strategies, viz. the weighted product model (WPM) and the weighted sum model (WSM), while the third is a combined extended standard of the initial one with an analytic hierarchy based on processes calculated weights [24-26].


1. Initialization of decision matrix

2. Normalization of the decision matrix using equations (7) for maximization and (8) for minimization criteria:
$\bar{x}_{ij} = x_{ij}/max_i x_{ij}$ (7)
$\bar{x}_{ij} = min_i x_{ij}/x_{ij}$ (8)
where x_{ij} is the assessment value of the i^{th} alternative with respect to the j^{th} criterion.

3. Calculation of the total relative importance of i^{th} alternative with weighted sum method (WSM) using equation (9):
$Q_i^{(1)} = \sum_{j=1}^{n} \bar{x}_{ij} \cdot w_j$ (9)

4. Calculation of the total relative importance of i^{th} alternative with weighted product method (WPM) using equation (10):
$Q_i^{(2)} = \prod_{j=1}^{n} \bar{x}_{ij}^{w_j}$ (10)

5. Calculation of the total relative importance of alternatives using equation (11) and ranking them:
$Q_i = \lambda . Q_i^{(1)} + (1 - \lambda) . Q_i^{(2)}$ (11)

Fig. 1 WASPAS method [27]

3.2 Sunflower Optimization

The approach is based on the life cycle of a sunflower: similar to the hand of a clock, they emerge and follow the sun every day. They travel the reverse way at night, anticipating their absence the next morning [28].

This nature-based optimisation starts with inverse square law radiation, where the amount of heat Q collected by each plant is specified by:

$$Q_i = \frac{P}{4\pi r_i^2} \tag{12}$$

where P signifies the power of the source and r_i defines the gap among the current best and the plant i.
Sunflowers take the following path heading towards sun:

$$\vec{S_i} = \frac{X^* - X_i}{\|X^* - X_i\|}, i = 1,2,\dots,n_p \tag{13}$$

The sunflowers' stride in the path s is considered by:

$$d_i = \lambda \times P_i(\|X_i - X_{i-1}\|) \times \|X_i - X_{i-1}\| \tag{14}$$

where λ is the perpetual value which defines a "inertial" dislocation of the plants, $P_i(\|X_i - X_{i-1}\|)$ is the possibility of crosspollination [29].
The max. phase is defined as:

$$d_{max} = \frac{\|X_{max} - X_{min}\|}{2 \times N_{pop}} \tag{15}$$

where X_{max} and X_{min} are the high and low limits, and N_{pop} is the total no. of plants.
The newest plant is:

$$\vec{X}_{i+1} = \vec{X}_i + d_i \times \vec{s}_i \tag{16}$$

The process begins by generating a population (even or random). The assessment of each individual helps us decide which individual will be transformed into the sun. Though it is planned for a future edition to incorporate the capacity to work with several suns, it is now confined to using just one in this study. The extra entities, like the sunflowers, will then orient themselves on the way to the sun, travel in an unplanned, controlled manner, and crosspollinate around the sun [30].

4 Result and Discussion

Table 3 displays the trails conducted using voltage, signal, feed rate, and recorded MRR, along with surface roughness. For value normalisation, surface roughness and MRR were normalised using equation 8 (minimization criteria) and equation 7 (maximisation criteria), respectively. Those values were combined using WSM and WPM. Finally, total relative importance was computed and rated from high to low. As per Table 4, sixteenth run has the greatest overall relative significance value. As a result, signal factor setting of 2 cycles, feed rate of 0.5 mm/min, and voltage of 8 V aided in achieving appropriate roughness characteristics and MRR utilising ECM.

Table. 3 Experimental run with outputs

Run No.	**A**	**B**	**C**	**Surface Roughness, µm**	**MRR, mm^3/min**
1.	1	0.1	8	4.164	0.0230
2.	1	0.1	10	5.966	0.0079
3.	1	0.1	12	3.832	0.0060
4.	1	0.3	8	4.232	0.0476
5.	1	0.3	10	6.033	0.0325
6.	1	0.3	12	3.900	0.0306
7.	1	0.5	8	4.232	0.0584
8.	1	0.5	10	6.033	0.0434
9.	1	0.5	12	3.900	0.0415
10.	2	0.1	8	3.854	0.0276
11.	2	0.1	10	5.655	0.0125
12.	2	0.1	12	3.522	0.0106
13.	2	0.3	8	3.922	0.0522
14.	2	0.3	10	5.723	0.0371

15.	2	0.3	12	3.590	0.0352
16.	2	0.5	8	3.922	0.0630
17.	2	0.5	10	5.723	0.0480
18.	2	0.5	12	3.590	0.0461

Table. 4 WASPAS computations

Run. No.	**Normalized Value $(\overline{x}_{ij})$**		Q_1	Q_2	Q_i	**Rank**
	Surface Roughness	**MRR**				
1.	0.8457	0.3648	0.6053	0.5555	0.5804	13
2.	0.5904	0.1255	0.3580	0.2723	0.3151	18
3.	0.9191	0.0957	0.5074	0.2966	0.4020	16
4.	0.8322	0.7554	0.7938	0.7929	0.7933	5
5.	0.5838	0.5161	0.5499	0.5489	0.5494	14
6.	0.9031	0.4863	0.6947	0.6627	0.6787	9
7.	0.8322	0.9278	0.8800	0.8787	0.8793	2
8.	0.5838	0.6885	0.6361	0.6340	0.6350	11
9.	0.9031	0.6586	0.7808	0.7712	0.7760	6
10.	0.9138	0.4376	0.6757	0.6324	0.6540	10
11.	0.6228	0.1983	0.4105	0.3514	0.3810	17
12.	1.0000	0.1684	0.5842	0.4104	0.4973	15
13.	0.8980	0.8282	0.8631	0.8624	0.8627	3
14.	0.6154	0.5889	0.6022	0.6020	0.6021	12
15.	0.9812	0.5590	0.7701	0.7406	0.7554	7
16.	0.8980	1.0005	0.9493	0.9479	0.9486	1
17.	0.6154	0.7612	0.6883	0.6845	0.6864	8
18.	0.9812	0.7314	0.8563	0.8471	0.8517	4

In the main effect plot illustrated in Fig. 2, Signal of 2 cycles, feed rate of 0.5 mm/min, and voltage of 8 V helped in attaining optimal roughness characteristics and MRR using ECM. From Table 5, factor B, feed rate, attained the highest SN ratio value, which shows its dominance in machining and controlling responses.

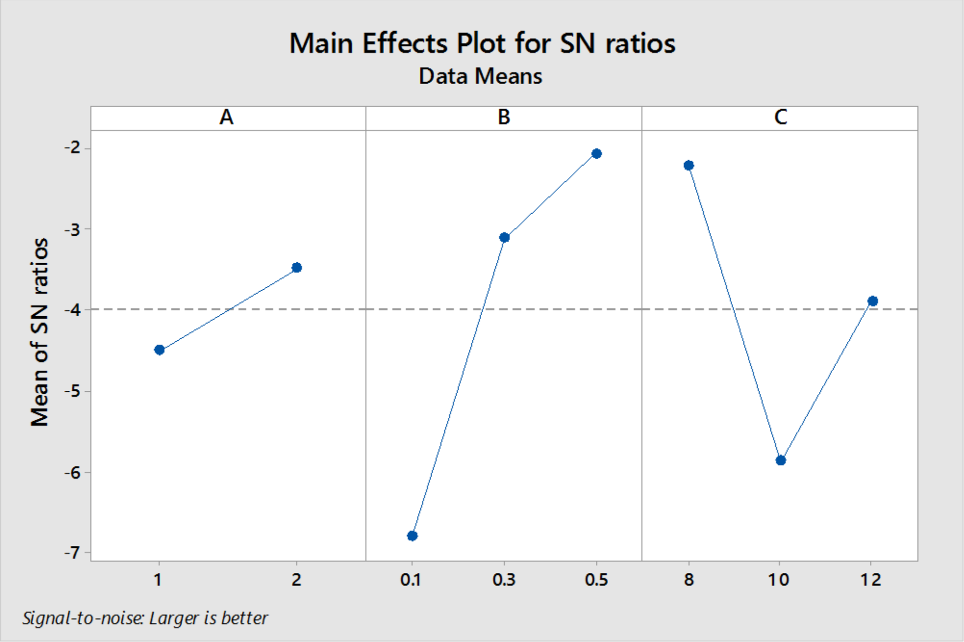


Fig. 2 Main effect plot.

Table. 5 SN ratios response table

Level	A	B	C
1	-4.502	-6.802	-2.214
2	-3.487	-3.118	-5.872
3		-2.064	-3.897
Delta	1.015	4.738	3.659
Rank	3	1	2

According to ANOVA outcome (Table 6), all the machining factors are noteworthy since the p value is less than 0.05. Among all, feed rate (60.36%) was found to be the most influential factor for both maximisation of MRR and minimisation of surface roughness during machining, followed by voltage (32.71%) and signal (3.77%). A similar result was also reported by Rao and Padmanabhan [4] while machining LM6 Al/B4C, Panda et al. [9], and Tiwari et al. [15] while machining EN 19 steel for achieving minimum surface characteristics and maximum MRR during ECM.

Whenever R-squared comes up to unity, the predicted output will be consistent with the real data. The result of R-squared is 96.84%, indicating that the data fits and the ECM procedure is right. The normal probability plot in Fig. 3 shows that all the points in the plot trace a straightforward path. The histogram additionally features the form of a bell, indicating the data's fit and accuracy.

Table. 6 ANOVA results

Factors	DoF	Adj SS	Contribution %	Adj MS	F-value	P-value
A (Signal)	1	4.632	3.77	4.6319	14.29	0.003
B (Feed Rate)	2	74.252	60.36	37.1259	114.54	0.000
C (Voltage)	2	40.240	32.71	20.1199	62.07	0.000
Residual Error	12	3.890	3.16	0.3241		
Total	17	123.013				

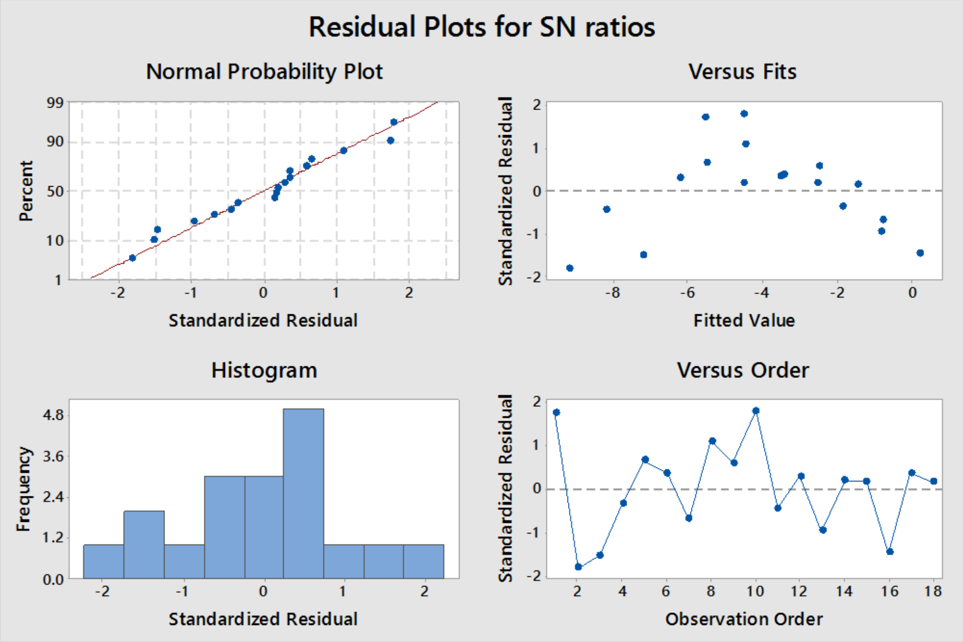


Fig. 3 Residual plots

The linear regression equations had been created using the various values that would be utilised as a function of fitness in the Sunflower optimisation process:

$$Fitness = 5.414 + 0.0502x_1 + 1.534x_2 - 1.0242x_3 - 1.826x_2x_2 + 0.04878x_3x_3 - 0.0322x_1x_2 + 0.00295x_1x_3 + 0.04216x_2x_3 \quad (17)$$

Subject to: $1 \leq x_1 \leq 2; 0.1 \leq x_2 \leq 0.5; 8 \leq x_3 \leq 12$

Fitness should be maximised to achieve maximum MRR and minimal surface roughness, according to the problem-solving statement. To attain an ideal ECM factor, some fixed parameters in the Sunflower optimisation method were created, with the total population set to 100 and the iteration threshold set to 100. Figures 4 and 5 illustrate the convergence plot and population plot generated by the Sunflower optimisation method, respectively. Table 7 summarises the best factor configuration as well as the anticipated fitness values.

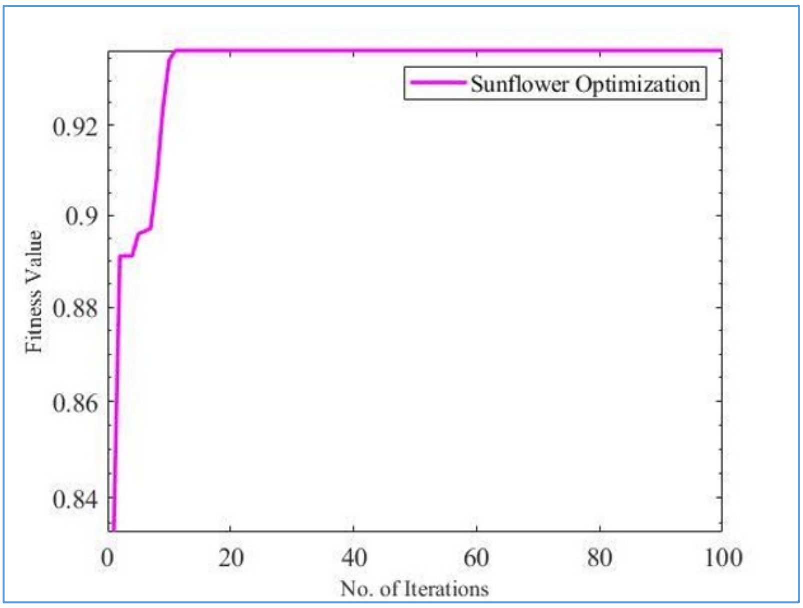


Fig. 4 Convergence plot

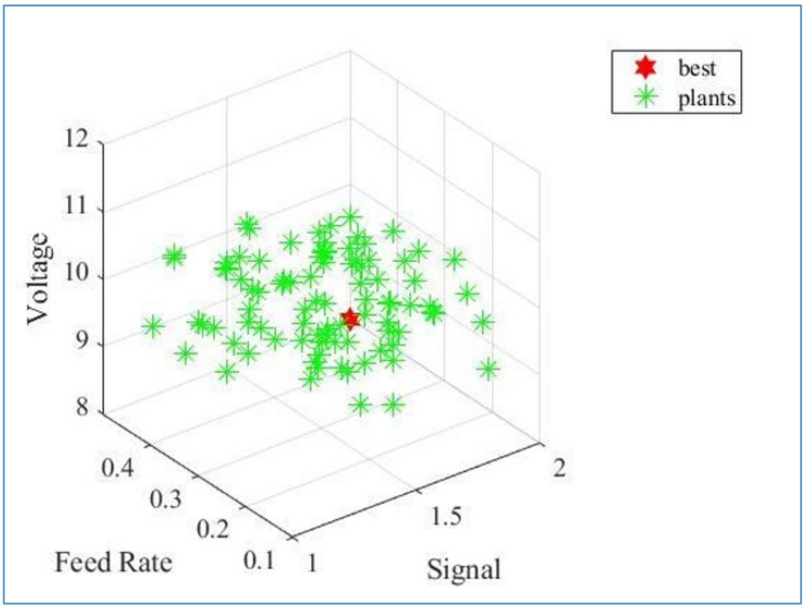


Fig. 5 Population plot

It is stimulating to notice that the factor setting predicted by WASPAS method, Sunflower optimization Algorithm and Taguchi WASPAS method are the same. Although the fitness values obtained by all three methods are equivalent, Using the predicted setting, surface roughness of 3.922 µm and MRR of 0.0630 mm/min were obtained, which can be termed our optimized results among the experimental runs. Such anticipated results are also obtained by distinguished researchers using different hybrid optimization approaches: Rao and Padmanabhan [4] and Dubey [6] used Utility-Taguchi process during ECM of LM6 Al/B4C composite and grey cast iron, respectively; Soni and Thomas [8] investigated the ECM effect on LM6 Al/B4C composite using Taguchi process and genetic algorithm; Panda et al. [9] explored the ECM effect on EN19 steel using Taguchi based TOPSIS, MOORA, and DFA methods; Kasdekar et al. [11] used ANN for prediction during ECM of AA6061-T6; Tiwari et al. [15] observed the effect of ECM on EN19 steel using NSGA II process; Das et al. [17] and Selvan et al. [21] used Taguchi Grey method to findout the effect of ECM on EN31 tool steel and Inconel 718, respectively.

Table. 7 Predicted results

Method	Signal (A)	Feed Rate (B), mm/min	Voltage (C), V	Predicted Fitness
WASPAS Method	2	0.5	8	0.9486
Taguchi WASPAS Method	2	0.5	8	0.9594
Sunflower Optimization Algorithm	2	0.5	8	0.9369

5 Conclusion

The research investigation was done to determine the effect of the ECM on AISI 4140 chromoly steel. Factors like voltage, signal, and feed rate were optimized by hybrid optimization techniques to obtain optimal roughness characteristics and MRR. Taguchi based WASPAS technique, followed by Sunflower optimization technique, was used to gain optimal control parameters. Important conclusions drawn are:

- The factor setting of Signal of 2 cycles, feed rate of 0.5 mm/min, and voltage of 8 V helped in attaining optimal roughness characteristics and MRR using ECM as per the WASPAS technique. A comparable finding was obtained using the Sunflower optimisation algorithm and the Taguchi-WASPAS approach.
- • Based upon the ANOVA, each of the machining constraints is within the confidence range of 95% and has significance for this study. The feed rate is a very important aspect of obtaining maximal MRR and minimising surface roughness. The R-squared number (determination coefficient), demonstrates the fit of the data and the accuracy of the cutting process.
- The predicted fitness values of WASPAS method, Taguchi-WASPAS method, and Sunflower optimization method are found to be equivalent to each other.
- It was also found that the findings are in good arrangement with the former research, as previous researchers also achieved precise results with copper tool electrode and hybrid optimization methods.

This investigation can be helpful in choosing a more accurate factor arrangement for ECM operation in the automobile and aerospace sectors, where complex contours or deep hole drilling are required. The current study opens up numerous possibilities for future research into many other elements of ECM, such as the use of other electrodes such as graphite and brass with different profiles, finite element analysis, machining of tougher material, and so on.

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