RSM–VIKOR Based Optimization of Machining Parameters for Improved Surface Integrity of HEAs

Anusha *Peyyala*[1], Movva Naga *swapna sri*[2], Bhiksha *Gugulothu*[3], Dhasarathan *Nagarajan* [4], Amaleswari *Rajulapati*[5], Vijayakumar *Sivasundar*[6,*],

[1]Department of Mechanical Engineering, P V P Siddhartha Institute of Technology, Vijayawada. India.
[2]Department of Mechanical Engineering, P V P Siddhartha Institute of Technology, Vijayawada. India.
[3]Professional trainer, Saudi Electrical Services Polytechnic, Ras Tanura, Saudi Arabia.
[4]Department of Electronics and Communication Engineering, Sri Venkateshwara College of Engineering, Bengaluru-562157.
[5]Department of Electrical and Electronics Engineering, Academy of Maritime Education and Training (AMET) Deemed University, East Coast Road, Kanathur, Chennai
[6]Department of Mechanical Engineering, Saveetha School of Engineering, SIMATS, Saveetha University, Chennai 602105, Tamil Nadu, India.

Abstract. This work employed Response Surface Methodology (RSM) with the VIKOR multi-criteria decision-making model to investigate the machining performance of the high-entropy alloy (HEA) in ECM method. Three electrolyte systems were employed such as sodium nitrate ($NaNO_3$), sodium chloride (NaCl) and $NaNO_3$/ NaCl mixed electrolyte. The tests were conducted by varying the feed rate (0.4–0.6 mm/min) and electrolyte concentration (100–200 g/L). The MRR model was found to be significant ($p = 0.03814$) by most significant parameters, electrolyte type and concentration. Feed rate ($p = 0.03166$) and electrolyte type ($p = 0.01301$) also influenced surface roughness respectively. Perturbation analysis has shown that the type of electrolyte is the most influential factor for increasing MRR and reducing SR. Multi-objective optimization using the RSM–VIKOR method identified the optimal factors at EC = 100 g/L, mixed electrolyte ($NaNO_3$ + NaCl), and feed rate of 0.5 mm/min, yielding a high MRR of 67.3 mm³/min and a minimum SR of 1.26 µm. The results demonstrate the effectiveness of the hybrid RSM–VIKOR approach in resolving performance and enhancing ECM efficiency for HEAs.

1 Introduction

Electrochemical Machining (ECM) is a non-traditional manufacturing process widely employed for machining electrically conductive and hard-to-machine materials such as superalloys, titanium alloys, stainless steels, and advanced metal matrix composites. Unlike conventional machining processes, ECM has eliminated the direct physical contact between the cutting tool and workpiece by shifting material removal from mechanical-cum-electrochemical process using Faraday's laws of electrolysis [1-3]. In the ECM process, a small inter-electrode gap is filled with electrolyte and the workpiece. The removal of material occurs through the electrochemical reactions, which are dominated by electrical, chemical molecular, hydrodynamic and thermal phenomenon [4][5].ECM performance is highly influenced by process parameters, hence selecting the proper parameters is very important for achieving the desired machined part. Applied voltage, current density, pulse on-time, pulse off-time and duty cycle are crucial electrical parameters influencing the surface finish, machining accuracy and MRR. Ion transfer, dissolution efficiency, as well as stability of the process are significantly affected by electrolyte parameters such as type, concentration, temperature and pressure and flow rates [6].Statistical, mathematical and artificial optimization have been used increasingly for enhancing the performance of the ECM process. Design of Experiments (DOE) refers to a variety of techniques which are employed for the purpose of analysis and modelling. Multi-criteria decision-making (MCDM) methods such as GRA, TOPSIS, VIKOR, and MOORA have been increasingly adopted for concurrent optimization of conflicting performance features.

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[*]Corresponding Author: vijayakumarbe@gmail.com

For instance, the hybrid optimization methods such as Taguchi–GRA, GRA–TOPSIS, and RSM–TOPSIS have become increasingly robust and effective in decision making. Moreover, machine learning and soft computing techniques such as ANN, ANFIS, GA, PSO, DE and fuzzy logic have been effectively employed for the prediction of ECM responses in searching for global optimal solutions [7-10]. Some of the works related to ecm process are mentioned in the paper. The work shows the machinability of Al 6061 reinforced with GGBS employing electrochemical micromachining for MRR and radial overcut (ROC). The L18 mixed-level orthogonal array is applied to study experiments and the Taguchi technique is used to optimize process parameters. A multi-criteria decision-making tool has also been used for selecting best machining parameters for minimum ROC and maximum MRR. 10 V, 50%, 35 g/l and GGBS composition of 12% is the optimum combination to get maximum MRR and minimum ROC [11]. Zahid A. Khan et al. [12] studied the effect of WEDM process parameters on surface roughness and kerf width during machining of SS 304. An orthogonal test of nine experiments is performed to obtain the optimum parameter setting for WEDM. The optimized quality characteristic response has been taken as kerf and surface roughness. It is found that the pulse ON time has the most significant influence on both kerf width and surface roughness. In another research [13], Ti-6Al-2Sn-4Zr-2Mo alloy was machined by WEDM. The results show that the material removal rate is 0.293 mm 3 /min for pulse duration of 10 µs, a wire feed rate of 7 m/min, and wire tension of 12 g and the surface roughness is found to be 2.129 µm at pulse duration of 6 µs, wire feed rate of 3 m/min, and wire tension of 8 g. According to Shyam Lal et al.'s study [14], Optimal setting of process parameter for maximum quality level machined characteristics was obtained using multi-response optimization technique. ANOVA results revealed that the wire drum speed (2.75%), pulse on time (50.02%), pulse current (39.50%) and pulse off time (4.58%) contributed to enhanced accuracy of machining process. The robustness of grey relational analysis was also confirmed by performing a confirmation test Empirical models that clarified the effect of variables on machining of 55NiCrMoV7 tool steel in Ra, WL and MRR were produced by RSM. Surface and subsurface integrity were characterised using optical microscopy and a scanning profilometer. ANOVA was applied to evaluate the statistical significance of the process parameters. The contribution analysis revealed that discharge current was the dominant factor affecting the MRR, followed by pulse-on time [15]. The effectiveness of statistical and multi-response optimization techniques in improving machining performance has been demonstrated in previous works. The minimum surface roughness of 0.066 µm has been obtained while using spindle speed (200 rpm), magnetic abrasive quantity (5 mg), mesh number (270) and machining time (60 min) based on L16 orthogonal array design [16].In another study, feed rate has been recognised as the significant parameter in electrochemical drilling of Inconel 625 by the Taguchi–Grey Relational Analysis method. The validation studies have validated substantial overall improvements in machining performance [17]. Another research work applied grey relational analysis and ANOVA with RSM to optimize a multi-objective process in milling operation to minimize surface roughness and maximize material removal rate. The optimal cutting conditions were assessed by using ANOVA to check the significance of the projected model. Optimal cutting parameters were found to be the spindle speed 2600 rpm, the feed rate 720 mm/min and the depth of cut 1.8 mm [18].

This work aims to explore and optimize MRR and surface roughness in electrochemical machining (ECM) of HEAs using RSM combined with VIKOR multi-criteria decision-making technique based on the literature review. To find out the optimal machining conditions, the quantitative relationships between selected input parameters and output responses are also examined and identify the most significant process control factors affecting MRR and surface roughness.

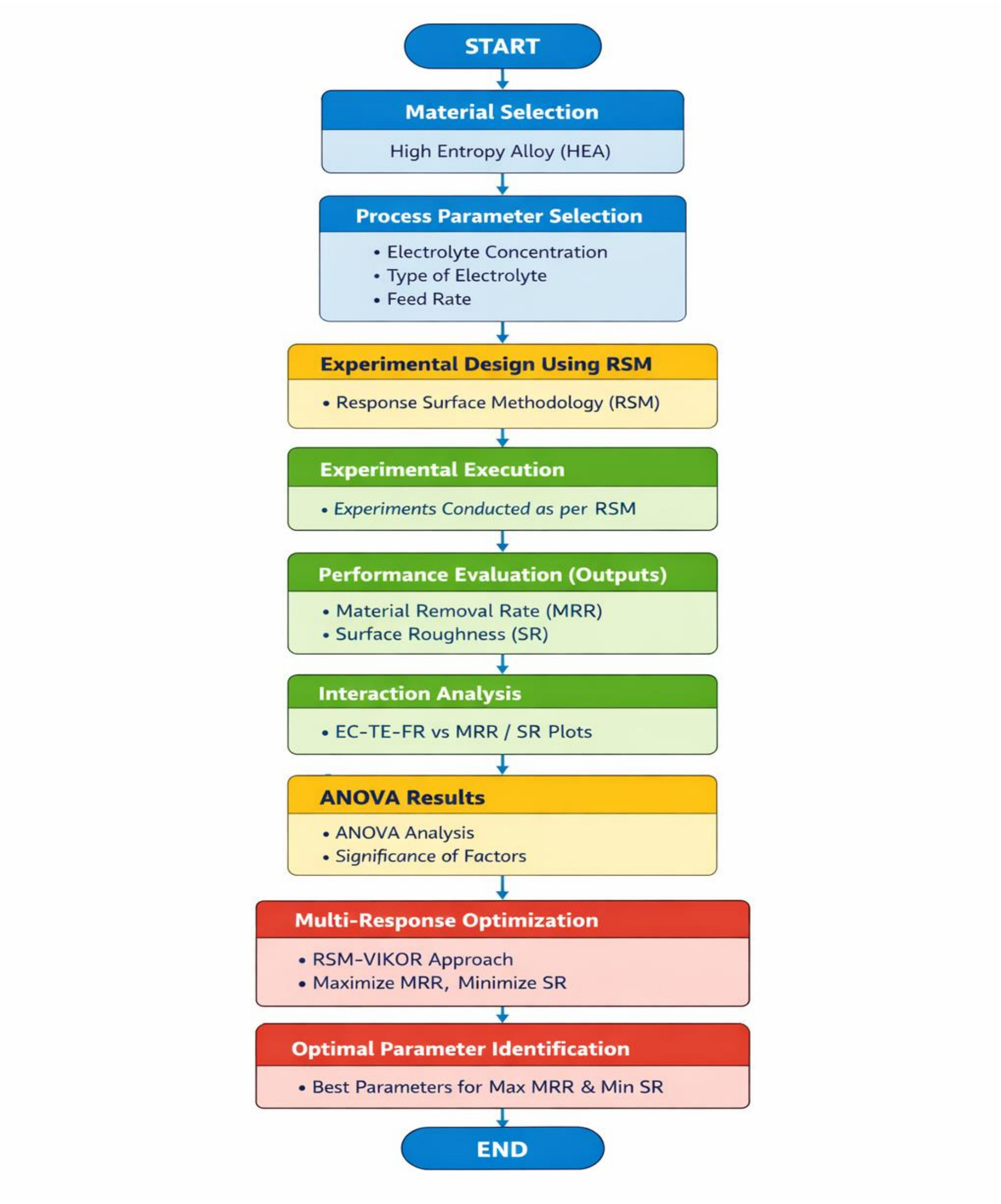

Fig 1 Flow process of this work

Table 1. ECM parameters with three levels

Parameters	Unit	Level-1	Level-2	Level-3
Electrolyte Concentration (EC)	g/L	100	150	150
Types Of Electrolyte (TE)	-	1 ($NaNO_3$)	2 (NaCl)	3 ($NaNO_3$+Nacl)
Feed Rate (FR)	mm	0.4	0.5	0.6

Table 2 Experiment results for MRR and SR

S.No	EC	TE	FR	MRR	SR
1	150	1	0.5	55.2	2.89
2	150	3	0.5	68.3	1.43
3	100	1	0.5	50.3	2.94
4	100	2	0.4	52.9	2.72
5	100	3	0.5	67.3	1.26
6	150	2	0.4	57.6	2.15
7	125	1	0.4	55.7	3.1
8	125	3	0.4	64.1	2.63
9	150	2	0.6	61.4	2.54
10	125	1	0.6	60.7	1.96
11	125	3	0.6	65.9	1.89
12	100	2	0.6	31.7	2.08

2 ECM process

The flow process of this work was mentioned in Fig.1. The ECM process was carried out on a HEA workpiece with a copper tool as a cathode and the workpiece as an anode. To minimise lateral machining, the side faces of the tool were also electrically insulated. The HEA samples were cleaned with acetone, and the initial weights were recorded before they were machined. Three types of electrolyte, namely sodium nitrate (NaNO3), sodium chloride (NaCl)and mixed electrolyte with NaNO3 and NaCl were examined at concentrations ranging from 100 to 200 g/L by using distilled water. The tool was gently brought up against the workpiece, and it was ensured that the machining current seemed to settle down. Once flushed of reaction products and after a proper machining depth had been obtained, both the tool feed and power supply were switched off. After thorough washing and drying, the machined samples were evaluated for their machining performance such as MRR and SR. There are three levels for each parameter is shown in the table. 1. Twelve experimental runs were made on HEAs with three factors at three levels using the Box–Behnken design (BBD) method. The maximum MRR is obtained at EC of 150 g/L, TE of 3 and FR of 0.6 mm/min as depicted in Fig. 2, which suggests that the three parameters have a strong synergistic effect. The MRR increases when $NaNO_3$ + NaCl (TE-3) are used together, attributed to better charge transport, enhanced ionic conductivity, and more stable anodic dissolution with the combined electrolyte than the use of individual salts. $NaNO_3$ is a supporting electrolyte that maintains current continuity and prevents over passivation, the NaCl provides Cl^- ions in mixed electrolyte, which locally destroy passive film layers and enhance active dissolution [19-21]Conversely, the minimum MRR occurs at EC of 100 g/L, TE of 1, and FR of 0.6 mm/min**,** indicating that lower electrolyte concentration and less effective electrolyte type significantly reduce the material removal efficiency even at higher feed rates. When $NaNO_3$ (TE-1) is used individually, the electrochemical process becomes less efficient in material removal rate.

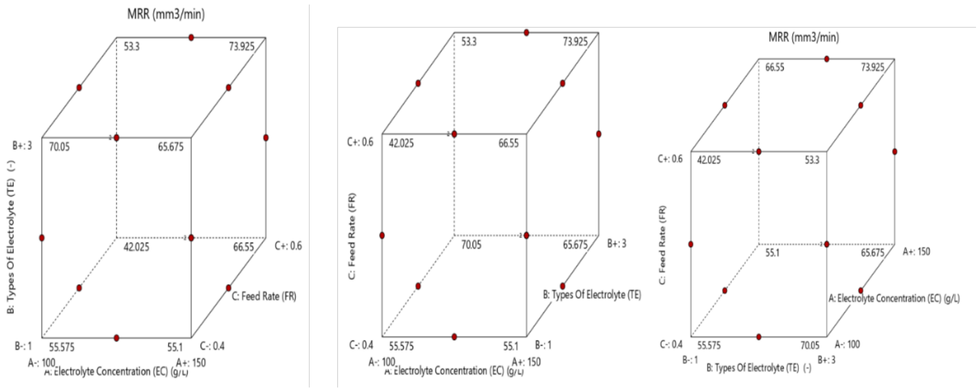

Fig.2. 3D Cube plot between inputs (EC, TE, FR) and MRR

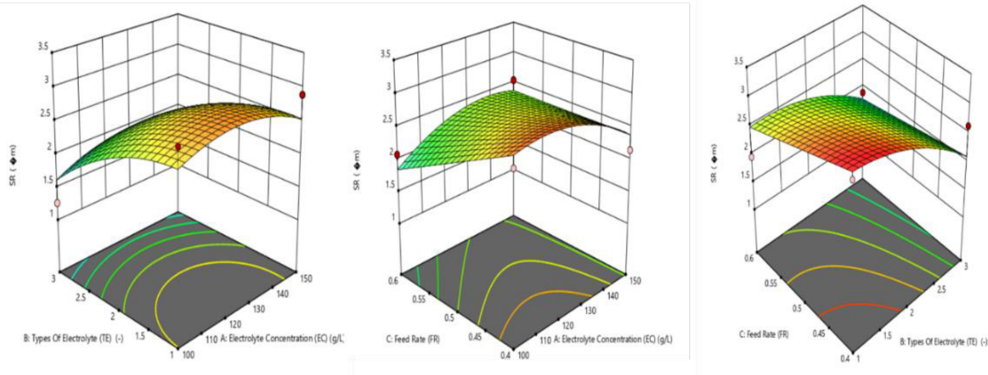

Fig.3. 3D surface plot between inputs (EC, TE, FR) and SR

The SR decreases with increasing electrolyte concentration, superior electrolyte types, and the highest feed rate. The minimum SR is obtained at a high electrolyte concentration of 150 g/L (EC3), combined electrolyte type $NaNO_3$ + NaCl (TE3), and a feed rate of 0.6 mm/min (FR3), due to stable and uniform electrochemical dissolution. Conversely, the maximum SR occurs at a low concentration of 100 g/L electrolyte (EC1), a single type of electrolyte (TE 1) and a feed rate of 0.4 mm/min (FR1), where unstable anodic reactions and insufficient ionic conduction are responsible for the poor surface quality. Statistical significance of the developed model (p= 0.03814) signifies good agreement between the experimental data and observed responses, as confirmed by ANOVA results for the quadratic model of MRR. Electrolyte concentration (EC) and type of electrolyte (TE) are two selective linear factors with p-values of 0.01862 and 0.01611 respectively. The combined effect of electrolyte strength and feed rate on electrochemical dissolution is then illuminated by the interaction term EC*FR, which is also significant (p = 0.02310). Besides, it is also found that there is a quadratic effect of the TE^2 (p = 0.02102), which represents the nonlinear effect of electrolyte type on MRR.

Table.3 ANOVA for Quadratic model for MRR

Source	SS	DF	F	p
Model	890.56	8	1.60	0.03814
A-Electrolyte Concentration (EC)	203.01	1	2.92	0.01862
B-Types Of Electrolyte (TE)	238.71	1	3.43	0.01611
C-Feed Rate (FR)	14.04	1	0.2018	0.06837
AB	3.80	1	0.0546	0.08302
AC	156.25	1	2.25	0.02310
BC	2.56	1	0.0368	0.08601
A^2	3.51	1	0.0505	0.08367
B^2	175.78	1	2.53	0.02102
C^2	0.523	1	0.00412	0.14234
Residual	208.77	3		
Cor Total	1099.33	11		

Table.4 ANOVA for Quadratic model for SR

Source	Sum of Squares	df	F	p
Model	2.75	8	0.8712	0.06128
A-Electrolyte Concentration (EC)	0.00124	1	0.0000	0.09959

B-Types Of Electrolyte (TE)	1.69	1	4.29	0.01301
C-Feed Rate (FR)	0.5671	1	1.44	0.03166
AB	0.0121	1	0.0307	0.08721
AC	0.2652	1	0.6722	0.04724
BC	0.0400	1	0.1014	0.07711
A^2	0.1404	1	0.3560	0.05928
B^2	0.1176	1	0.2981	0.06231
C^2	0.0011	1	0.0253	0.10362
Residual	1.18	3		
Cor Total	3.93	11		

The type of electrolyte (TE) and feed rate (FR) are the most influential factors, and the ANOVA for the quadratic model indicates that it is a suitable function to describe the change of surface roughness (SR). From the linear terms, TE is significant (p = 0.01301), indicating that electrolyte composition exerts a significant effect on surface quality and FR affects significantly at 5% (p =0.03166), implying that SR value is affected by increasing feed rate. The interaction term TE*FR, which is moderately significant (p = 0.04724), indicates a co-action of concentration and feed rate on surface finish.

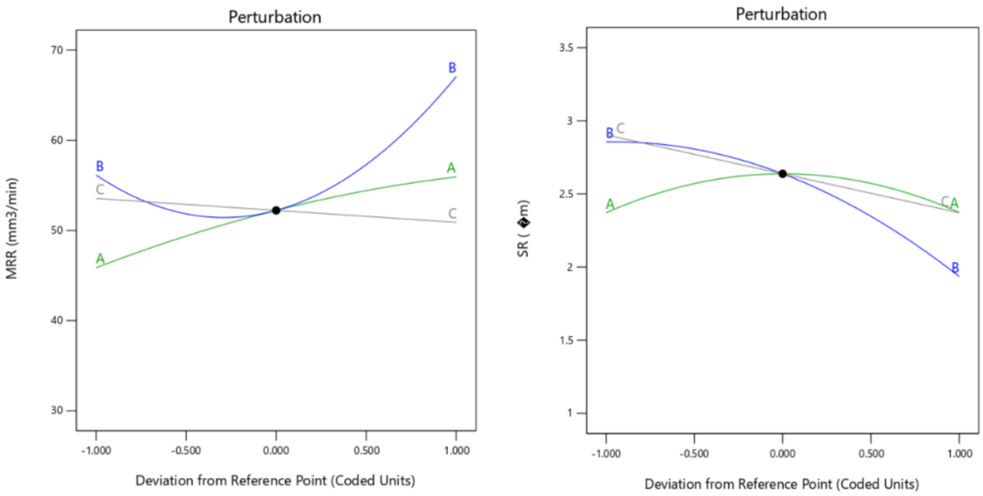

Fig.4 perturbation plots for MRR and SR

The perturbation charts clearly demonstrate the proportional influence of the process parameters on both MRR and SR. It can be seen that the electrolyte type has the largest effect on MRR, followed by electrolyte types and it indicates an increasing trend at higher concentration. Feed Rate responds nearly flatly with a small slope, pointing to an insubstantial effect on MRR. For SR, Types of Electrolyte demonstrates the most pronounced effect, showing a strong decreasing trend, which indicates improved surface finish with the advanced electrolyte type. Electrolyte Concentration shows a moderate influence on SR, while Feed Rate has the least effect. In general, on the basis of the perturbation analysis performed, it is observed that at the selected operating conditions feed rate has a marginal effect, whereas the type of electrolyte is the most significant parameter for enhancing MRR and minimising SR followed by the concentration of electrolyte.

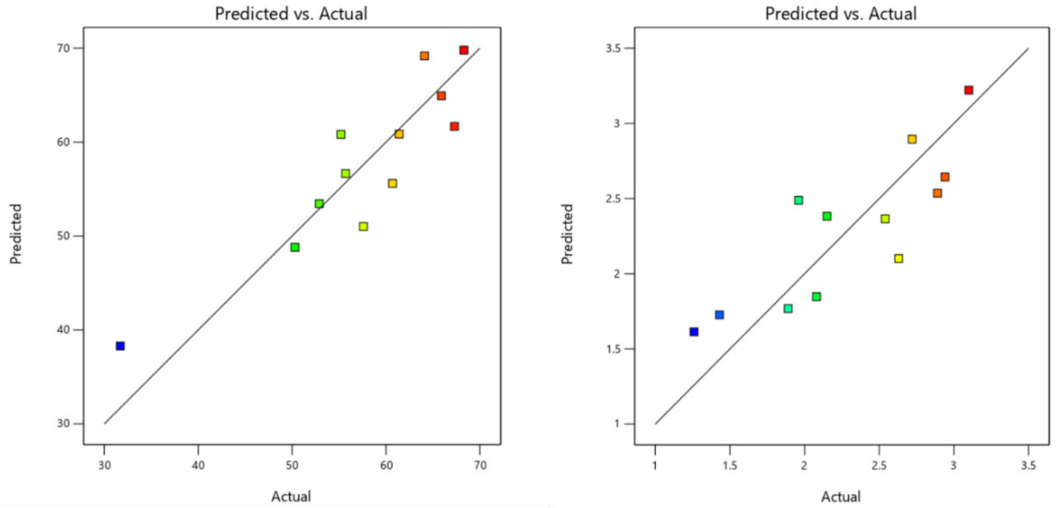

Fig.5. predicted value versus actual value plots for MRR and SR

The agreement between the experimental results and model predictions for both MRR and SR is decent in predicted versus actual plots. The trend in MRR and SR is accurately predicted by the quadratic model, which is proven by most of the data points being concentrated around an axis-aligned 45° line. The RSM is a good model for ECM process parameters on the high entropy alloy confirmed by both plots indicating minimum scatter and lowest prediction error.RSM is employed to develop the mathematical models of MRR and SR on the basis of the experimental data, which predicts the response at any combination of process parameters. The RSM–VIKOR is a hybrid multi-objective optimization technique which generates an optimal solution for the maximisation of MRR and minimization of SR. These predicted values are used as inputs for the VIKOR method, which ranks the experimental runs [22][23]. Since MRR is a beneficial criterion, its normalized regret is calculated from Equation (1) and the non-beneficial criterion and the normalized regret is calculated using Equation (2) for SR. the group utility measure (S_i and R_i) and VIKOR index Q_i are determined by Equation(3) and Equation (4) respectively.

$$d_{i,\mathrm{MRR}} = \frac{f^{*}_{\mathrm{MRR}} - f_{i,\mathrm{MRR}}}{f^{*}_{\mathrm{MRR}} - f^{-}_{\mathrm{MRR}}} \quad (1)$$

$$d_{i,\mathrm{SR}} = \frac{f_{i,\mathrm{SR}} - f^{*}_{\mathrm{SR}}}{f^{-}_{\mathrm{SR}} - f^{*}_{\mathrm{SR}}} \quad (2)$$

$$S_i = \sum_j w_j d_{ij}, \quad R_i = \max_j \left(w_j d_{ij}\right) \quad (3)$$

$$Q_i = v\frac{S_i - S^{*}}{S^{-} - S^{*}} + (1 - v)\frac{R_i - R^{*}}{R^{-} - R^{*}} \quad (4)$$

where $S^{*}$and $R^{*}$are the best (minimum) values, $S^{-}$and $R^{-}$are the worst (maximum) values, and $v$is the weight reflecting the decision-maker’s preference for group utility versus individual regret.

Table.5. RSM VIKOR results

Run	(Si)	(Ri)	(Qi)
1	0.6134	0.4430	0.9058
2	0.0462	0.0462	0.0564
3	0.6767	0.4921	1.0000
4	0.6004	0.3967	0.8278
5	0.0137	0.0137	0.0000
6	0.4366	0.2418	0.5681
7	0.5574	0.5000	0.8677
8	0.4065	0.3723	0.5653
9	0.4204	0.3478	0.5726
10	0.2940	0.1902	0.3792
11	0.2040	0.1712	0.2961
12	0.4457	0.2500	0.5908

Using the experimental data from 12 runs, the best and worst values for each response were identified and used to calculate the normalized regret values. Subsequently, the utility measure (S_i), regret measure (R_i), and VIKOR index (Q_i) were computed for each experimental run. The alternatives were then ranked in ascending order of (Q_i), where a lower (Q_i) value indicates better overall performance. The results indicated that the solution with the least preference distance to be the best compromise one is EC = 100, TE = 3 and FR = 0.5, which also corresponded to the minimum VIKOR index (Qi = 0.0000). This result produced a high MRR of 67.3 mm^3/min along with the minimum SR of 1.26 µm, demonstrating superior machining efficiency with excellent surface quality. The second-best alternative was achieved at EC = 150 g/L, TE = 3, FR = 0.5mm, which exhibited the highest MRR of 68.3 mm3/min among all runs but with a slightly higher SR 1.43µm. Both runs satisfy the VIKOR compromise solution conditions because of a small difference between the first and second VIKOR indexes. Overall, the VIKOR analysis effectively compromised the conflict between MRR and SR and provided a practical way to decide on the optimal process parameters. The results verify that electrolyte type -3 (NaNO 3 + NaCl) and feed rate of 0.5mm were key factors to obtain a better machining performance, while electrolyte concentration should be carefully selected to balance productivity and surface integrity.

3 Conclusions

The ECM of the high-entropy alloy has been successfully investigated using different electrolyte types (NaNO3, NaCl and NaNO3+NaCl), concentration of electrolyte (100–200 g/L) and feed rate (0.4–0.6 mm/min) for examining surface roughness and MRR. The combined electrolyte system ($NaNO_3$ + NaCl) provided better material removal rates as compared to single electrolytes due to the fact of improved ionic conductivity and stable anodic dissolution. Surface roughness decreased with improved electrolyte composition, higher electrolyte concentration, and increased feed rate within the investigated range.

The ANOVA showed that the fitted quadratic RSM model for MRR and surface roughness was found to be statistically highly significant, and it compared well with experimental values. The type of electrolyte was found to be the most influential factor on both MRR and surface roughness, followed by the concentration of electrolyte for MRR, and feed rate for surface roughness. The accuracy and reliability of the developed RSM models were validated by perturbation and predicted-versus-actual evaluations. Multi-objective optimization using the RSM–VIKOR method effectively resolved the trade-off between maximizing MRR and minimizing surface roughness. The optimal compromise condition was achieved at EC = 100 g/L, mixed electrolyte ($NaNO_3$ + NaCl), and feed rate of 0.5 mm/min, yielding high MRR and excellent surface quality.

Overall, High-entropy alloys utilized in advanced manufacturing, energy, aerospace, and marine applications can be precisely machined using the adjusted ECM parameters. For enhancing the machining performance of innovative materials in electrochemical manufacturing, the suggested RSM–VIKOR framework offers a reliable and adaptable optimization technique.

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