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SCIENTIFIC PAPER

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PERFORMANCE ANALYSIS OF ELECTROCHEMICAL MICROMACHINING USING SIMPLE ADDITIVE WEIGHTING, CRITERIA IMPORTANCE THROUGH INTERCRITERIA CORRELATION, AND ARTIFICIAL NEURAL NETWORK METHODS

Article Highlights

- An aluminum scrap metal matrix material is fabricated, and machinability studies are performed
- ECMM performance is analyzed using (SAW), (CRITIC) and (ANN) techniques
- The best results show high MRR and low OC at 28 g/lit $NaNO_3$+0.05M HNO_3, 10 V, and 80% duty cycle
- The weight values of the performance metrics obtained using the SAW method are 0.549 and 0.45
- The optimal output performance predicted by ANN is MRR of 0.520 μm/sec and OC of 23.8 μm

Abstract

Electrochemical micromachining (ECMM) finds application in various industries, especially in surface finishing processes in aerospace industries. In this research, the workpiece made from aluminum scrap metal matrix reinforced with alumina is subjected to wear, surface profile, and machinability studies. To analyze the ECMM performance, simple additive weighting (SAW) CRiteria Importance Through Intercriteria Correlation (CRITIC) and Artificial Neural Network (ANN) were used. The wear studies show that at high loads the height wear loss is less and frictional force is more. The L_{18} mixed orthogonal array experiments were conducted and analysis of experiments shows that the most crucial parameter values for high MRR and low OC are 28g/lit $NaNO_3$+0.05M HNO_3, 10 V, and 80% duty cycle. The weight values of the performance metrics obtained using the SAW method are 0.549 and 0.45. The optimal output performance predicted by ANN is MRR of 0.520 μm/sec and OC of 23.8 μm.

Keywords: mixed electrolyte; sodium nitrate; nitric acid; duty cycle; optimization; overcut.

Electrochemical micromachining (ECMM) is the key machining process for machining burr-free micro features on the components. The ECMM is applied in diverse fields, such as biomedical, aerospace, and automobile. In ECMM, the cathode is the tool electrode and the anode is the workpiece which is the one to be machined. The electrodes are bridged by the electrolyte and while applying the voltage the material removal takes place. The removal of material in the range of 0-999μm from the anode is denoted as micromachining. From a manufacturing industry perspective, productivity, quality, and cost will go in holding hands and hence optimizations of the machining process were performed by many researchers [1]. Ganesan *et al.* [2] have optimized the

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laser parameter on dimple accuracy using principal-component-analysis-coupled grey relational grade. The optimal factor setting is 15 kHz (frequency), 12 W (average power), and 1500 ns (pulse duration). Sivashankar *et al.* [3] have optimized the ECMM parameters for machining magnesium alloy using TOPSIS and artificial neural networks (ANN). They reported that for obtaining a high material removal rate (MRR) the optimal combination is 13 V machining voltage, 75% duty cycle, and 30 g/L electrolyte concentration. Debkalpa Goswami *et al.* [4] have comparatively studied the ECMM performance using a differential search algorithm, genetic algorithm, and desirability function approach and proved that the differential search algorithm is a suitable method as a global optimization tool. Geethapriyan *et al.* [5] have optimized the ECMM variables using grey relational analysis with the Taguchi method. Based on the experimental study, it is evident that micro-tool feed speed is the most significant factor for sodium chloride electrolyte, and voltage is a significant factor for sodium nitrate electrolyte. Prakash *et al.* [6] have optimized the ECMM parameters using response surface methodology and Teaching-Learning-Based Optimization algorithm. When the results are examined, they agree with the RSM result when a target surface roughness value of 0.4 μm is taken into consideration. This confirms that the TLBO algorithm is better than the RSM approach. Rajan *et al.* [7] have optimized the ECMM characteristics for machining metal matrix composites using the TOPSIS method. The study reveals that the sodium nitrate electrolyte of 35 g/L concentration, the machining voltage of 11 V, and the 70% duty cycle are the optimal combination for higher MRR and lesser OC. Senthilkumar *et al.* [8] used the non-dominated sorting genetic algorithm II to optimize the electrochemical machining settings. The optimal value of surface roughness is found to be 2.172 μm and the related MRR is 0.413 g/min. Chandrasekhar *et al.* [9] have optimized the ECMM factors using the Entropy-VIKOR method for micro-drilling of AA6061-TiB_2. The electrolyte concentration of 2 mol, applied voltage of 16 V, and current of 4 A of current is the optimal parameter combination to minimize the overcut, and delamination, and to maximize the MRR. Nagarajan *et al.* [10] compared different multi-criteria decision-making algorithms such as grey wolf, moth-flame, and particle swarm methods. The study showed that the grey wolf and moth-flame algorithm shows the same result for machining Monel 400 alloys with ECM. Using the CRiteria Importance Through Intercriteria Correlation (CRITIC) -AHP technique, Venugopal *et al.* [11] optimized the ECMM parameters and found that the electrolyte concentration is the key component influencing conicity. Maniraj *et al.* [12] have applied three different weight evaluation methods for optimizing the ECMM parameters with the VIKOR method. Out of three weight evaluation methods, the analytic hierarchy process is found to produce the best result in ECMM. Manivannan *et al.* [13] have established the relationship between the ECMM process variables and output performance namely machining rate and OC They reported that the established is more efficient and accurate. Kaliappan *et al.* [14] have optimized the ECMM factors on machining rate, radial overcut, and delamination factor. They used the entropy method to determine the weights of the output performance. The grey relational grade is used to optimize the multi-performance and reported that 80 V,20 gm/lit, 50% duty cycle, and 40 °C electrolyte temperature is the optimal combination for achieving the higher machining rate, lower radial overcut, and lower delamination factor in metal matrix composites. Rajan *et al.* [15] have used TOPSIS and principal component analysis to optimize the ECMM factors on aluminum boron carbide composites. They found that the electrolyte concentration of level 35 g/L, the voltage at 11 V, and the duty cycle at 70% were the optimal combination for the machining rate, the diametric overcut, and the delamination factor, moreover ANOVA analysis shows that the duty cycle is the most significant factor. It is apparent that research on ECMM and process optimization were performed worldwide and the application of the multi-criteria decision-making (MCDM) method, namely Simple additive weighting (SAW) combined CRITIC in ECMM is sparse. Moreover, the results are predicted with the help of the ANN model. Hence in this research Nitric acid mixed sodium nitrate electrolyte is used and a mixed L_{18} orthogonal array (OA) experimental plan is used for the conduct of the experiments. The factors considered are the type of electrolyte, concentration of electrolyte, voltage, and duty cycle on MRR and OC.

Wear and surface estimation

The wear studies were performed on the sample with a constant track radius. The different load levels of 10 N, 20 N, and 30 N were applied on the specimen at constant speed and time of 380 rpm, 5 minutes 30 seconds respectively. The test results show that for a 10 N load, the height loss wear is 52 µ and the frictional force generated is 3.9 N. On further increase in load to 20 N and 30 N for the same speed and time condition the height loss wear and frictional force were 44 µ and 7.9 N & 34 µ and 13.2 N respectively. It is evident from the wear results that at low loads, the height loss wear is greater and the frictional force is less. It is due to the fact the poor distribution of reinforcement increases the height wear loss. At high loads, the height wear loss is less, and the frictional force is higher. The amalgamation of reinforcement attributes for more frictional force. The wear-investigated sample surface roughness depth profile is shown in Figure 1, where the values of *R*z, *R*t, and *R*a are 24.5 µm, 55.4 µm, and 3.04 µm, respectively.

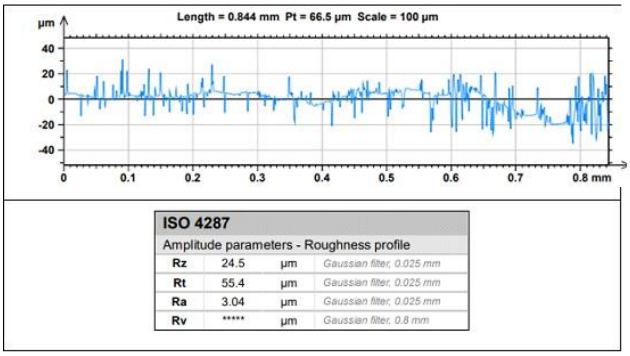

Figure 1. Surface roughness depth profile.

Experimental setup

The ECMM setup, which included a machining chamber, an electrolyte supply system, a pulsed power supply, and a tool advance mechanism, was used to conduct the experiments. The machining chamber housed the workpiece holder made up of Perspex material. The capacity of the machining chamber held 2 L of electrolyte. The electrolyte supply system consisted of a chemical pump, a filter to remove the debris, and an electrolyte supply pipe and nozzle. The pulse power supply unit with the specification of 0–30 V, current of 0–5 A, and frequency of 100 Hz was used for the experiments. The tool advance mechanism comprised the stepper motor, lead screw, and tool holder. The stepper motor was controlled by a microcontroller program. The tool holder was made up of a hollow copper tube and provided with a screw to fix the electrode. The tool electrode was isolated from the tool feeding arrangement. The workpiece was given with a positive power supply and the tool electrode was given with a negative power supply. The workpiece used for the experiment was the alloy wheel matrix composites of thickness of 300 µm. Figure 2 presents the optical microscope image of the workpiece sample which witnesses the presence of the silica. Figure 3 shows the EDAX image of the workpiece sample used for the machining. It shows the presence of aluminum, nickel, magnesium, carbon, oxide, chromium, iron, and silica. The tool electrode with a 600 µm diameter was coated with bonding liquid for insulation purposes to avoid stray current. The type, concentration, voltage, and duty cycle of the electrolyte were the parameters used in the studies. The performances were measured using MMR in µm/sec and OC in µm. The L_{18} mixed OA was considered and levels were identified based on past experiments and presented in Table 1. In this study, the total number of factors was four at three levels, hence the degrees of freedom was eight. Therefore, the OA selection should be more than eight, and hence, L_{18} was selected. Since there were two types of electrolytes, a mixed OA was considered for this study. The electrolyte sodium nitrate ($NaNO_3$) salt was mixed with 1 L of distilled water and stirred properly. Another type of mixed electrolyte, i.e., acidified $NaNO_3$ was prepared and used. To prepare 0.05 M of nitric acid, 3.20 mL of nitric acid was added to 1 L of distilled water, while $NaNO_3$ of varying grams was added to the mixed electrolyte [16].

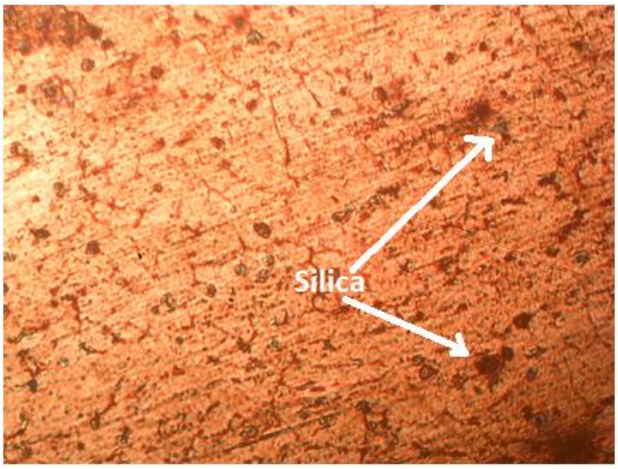

Figure 2. Optical image of the workpiece surface.

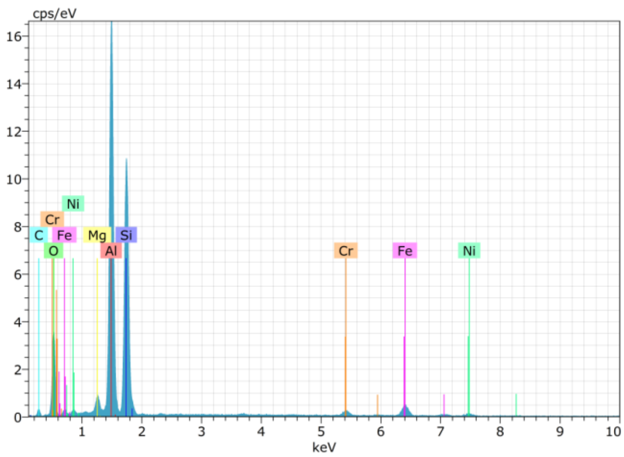

Figure 3. EDAX image of the sample workpiece.

RESULTS AND DISCUSSION

The MCDM approach uses the conflicting criteria to characterize the conflicting correlation between the decision criteria, or the alternatives that are taken into consideration in an MCDM problem. CRITIC method handles the multi-criteria problems more efficiently and at the same time it describes the weight and assists the decision maker in making a decision based on the importance of criteria, moreover it eliminates the non-

Table 1. L_{18} OA.

S.No	Electrolyte (*E*)	Electrolyte Concen-tration (*EC*), g/L	Voltage (*V*), V	Duty Cycle (*DC*), %	MRR, µm/sec	Overcut, µm
1	$NaNO_3$	20	8	70	0.208	140.17
2		20	9	80	0.250	86.98
3		20	10	90	0.217	60.49
4		24	8	70	0.156	90.67
5		24	9	80	0.217	206.23
6		24	10	90	0.238	222.02
7		28	8	80	0.278	119.49
8		28	9	90	0.263	176.77
9		28	10	70	0.208	131.25
10	$NaNO_3$+0.05M HNO_3	20	8	90	0.250	319.51
11		20	9	70	0.278	218.23
12		20	10	80	0.227	116.24
13		24	8	80	0.500	151.76
14		24	9	90	0.313	60.99
15		24	10	70	0.500	131.73
16		28	8	90	0.417	37.49
17		28	9	70	0.500	62.07
18		28	10	80	0.556	22.51

salient attributes. The multi-attribute process known as SAW is founded on the idea of a weighted summation. The method will attempt to find a weighted total of how well each alternative performed across all alternative criteria. The option with the highest score will be the best and will be suggested. The SAW method's fundamental idea, which is to determine the number of weighted performance ratings for each choice on all qualities, is useful. To use SAW, the decision matrix must be normalized to a scale that can be compared to all of the ratings of the available choices.

In this study, it was challenging to achieve lower OC and higher MRR at the same time. Greater MRR typically results in the acquisition of more reaction products and greater OC. When analyzing a contradictory correlation, the CRITIC approach uses the Pearson correlation coefficient, which ranges from -1 to 1 [17]. CRITIC was first envisioned by Diakoulaki *et al.* [18], this technique is based on the analysis of the assessment matrix to mine all the data included in the evaluation criteria. This method evaluates criterion weights by considering a criterion's standard deviation as well as its correlation with other criteria.

"*a*" is the number of alternatives, "*b*" denotes the number of criteria, and $A = [\phi_{ij}]_{a\times b}$, φ_{ij} is the performance measure of the i[th] alternative with regard to the j[th] criterion in an initial decision matrix.

Using the CRITIC approach, the initial decision matrix is normalized by using equation (1).

$$d_{ij} = \frac{\phi_{ij} - \phi_j^{\min}}{\phi_j^{\max_j^{\min}}} \tag{1}$$

where, $\phi_j^{\max} = \max\left(\varphi_{ij}, i = 1....,a\right)$

and $\phi_j^{\min} = \min\left(\varphi_{ij}, i = 1....,a\right)$.

The standard deviation of each criterion and its correlation with other criteria are taken into consideration when determining the weights assigned to them. Thus, it is possible to determine the weight of the j[th] criterion w_j in the following way [11]:

$$\eta_j = \frac{w_j}{\sum_{i=1}^{m} w_i} \tag{2}$$

where w_j is the amount of information present in the *j*[th] criterion and can be obtained as follows:

$$w_j = \sigma_j \sum_{i=1}^{m}\left(1-\rho_{ij}\right) \tag{3}$$

where is the correlation coefficient between the *j*[th] and *i*[th] criteria, and σ_j is the standard deviation of the *j*[th] criterion.

Based on the weighted average, the SAW methodology is a simple multi-attribute decision-making method that was initially adopted by Churchman *et al.* [19]. The SAW method's steps are as follows:

- Create a decision matrix $[X_{ij}]$ for different performance scenarios.
- Normalizing the value of *i*[th] criterion for the *j*[th] Alternative by using Eqs., (49) and (5):

$$\rho_{ij} = \frac{X_{ij}}{\max X_{ij}} \quad \text{if } j \text{ is a gain/MRR attribute} \tag{4}$$

$$\rho_{ij} = \frac{\min X_{ij}}{X_{ij}} \quad \text{if } j \text{ is a loss/OC attribute} \tag{5}$$

where ρ_{ij} is the normalized decision matrix.

Determine the SAW (S_i) value by using Eq. (6).

$$S_i = [\rho_{ij}][\eta_j] \tag{6}$$

Arrange the final results according to value, with the highest number being the best experimental combination for the highest performance metrics (MRR and OC). The normalized values for MRR and OC obtained using the CRITIC and SAW techniques are shown in Table 2. Using the normalized values obtained using CRITIC, the standard deviations for MRR and OC were computed, and they are, respectively, 0.3126 and 0.2566. Table 3 shows the correlation between the performance measures.

Table 2. Normalization of original values through CRITIC and SAW.

	Normalization - CRITIC		Normalization - SAW		S_i	Rank
Sl.No	MRR	OC	MRR	OC		
1	0.1304	0.6039	0.1476	0.2198	0.2781	16
2	0.2348	0.7829	0.1771	0.1364	0.3635	8
3	0.1531	0.8721	0.154	0.0948	0.3823	7
4	0	0.7705	0.1107	0.1422	0.2661	17
5	0.1531	0.3814	0.154	0.3234	0.2639	18
6	0.205	0.3282	0.1687	0.3481	0.2809	14
7	0.3043	0.6735	0.1968	0.1874	0.3593	9
8	0.2677	0.4806	0.1864	0.2772	0.3174	11
9	0.1304	0.6339	0.1476	0.2058	0.2831	13
10	0.2348	0	0.1771	0.501	0.2788	15
11	0.3043	0.341	0.1968	0.3422	0.3209	10
12	0.1779	0.6844	0.161	0.1823	0.3117	12
13	0.8609	0.5648	0.3542	0.2379	0.5609	5
14	0.3913	0.8705	0.2214	0.0956	0.4749	6
15	0.8609	0.6323	0.3542	0.2065	0.5710	4
16	0.6522	0.9496	0.2952	0.0588	0.6820	2
17	0.8609	0.8668	0.3542	0.0973	0.6573	3
18	1	1	0.3936	0.0353	0.9990	1

Table 3. Correlation between the performance measures.

Performance measures	MRR	OC	C_j	w_j
MRR	1	0.3683	-	-
OC	0.3683	1	-	-
MRR	0	0.63169	0.1975	0.5492
OC	0.63169	0	0.1621	0.4508

For MRR and OC, respectively, the weight values of the performance metrics obtained using Eqs. (4) and (5) are 0.549 and 0.45. The SAW method uses Eq. (6) to estimate the final S_i value by taking the computed weight values into account. The greatest value is ranked 1 and given the highest importance, with the remaining values being ranked in order of descent [20–21]. According to Table 2, the most crucial parameter values for high MRR and low OC are 28 g/L $NaNO_3$+0.05 M HNO_3, 10 V, and 80% duty cycle. The second-best set of parameters is 28 g/L $NaNO_3$+0.05M HNO_3, 8 V, and 90% duty cycle. It is evident from the optimized parameter combinations that acidified $NaNO_3$ is one of the factors that influence the output performance. Acidic electrolytes are utilized to improve the dissolution efficiency; nitric, hydrochloric, sulfuric, and perchloric acids are a few examples of acidic electrolytes. Since the ions and other reaction products are firmly dissolved in the electrolytic solution, there is a significant reduction in the inter-electrode gap. Additionally, this solves the clogging issue and enhances the machining efficacy in ECMM [22].

The SEM picture shown in Figure 4 was machined at 28 g/L $NaNO_3$+0.05 M HNO_3, 10 V, and 80% duty cycle, depicting a good circular micro-hole with an over-etched and corroded surface [23].

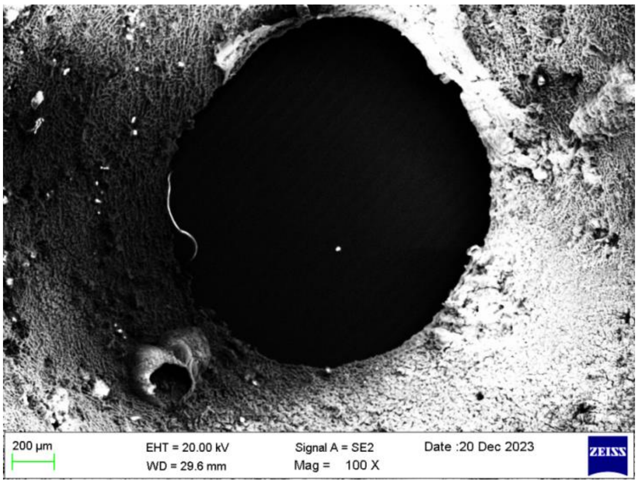

Figure 4. SEM picture of micro-hole.

ANN prediction

In recent research, the implementation of the advanced non-traditional method in optimization is highly required for accurate outcomes. Here ANN is implemented to predict the suitable inputs and outputs. Here developed ANN model will predict the accurate inputs and output parameters with the help of training and targets. MATLAB 15 software was utilized for architecture development. This architecture is developed with different layers as given in Figure 5. Here 4 inputs are used to carry out the experiments [24]. Hence ANN is developed to process 4 inputs with ten hidden layers. A hidden layer in ANN is used to process the input values while training. Output layers are generally predicting the processed output. For input and output processing, a random data revision type MATLAB inbuilt algorithm is used. ANN prediction consists of three important stages. Initially network development and followed by training. The final stage in ANN is output prediction [25]. Here all the experimental inputs are considered as training variables. For training, experimental outputs are considered target values. Totally 5000 iteration training is given to ANN and its parameters. Based on training and target variables, training is given with a total time limit of 1 minute and 23 seconds.

It is observed that the total ANN training has achieved 5000 iterations without any errors. The blue training line gradually reaches the target while training.

Figure 5. Neural network with algorithm.

For better understanding, a narrow straight line in the gradient curve (Figure 6) reveals error-free training of ANN architecture. Totally 4994 iterations are verified by ANN which is 99.8% accuracy of developed architecture. As can be seen in Figure 6, it represents 99.9% of training with an overall performance of 97.9% [26-27]. With respect to training, ANN predicted time is 614 s of machining time with 0.520 MRR and 23.8 OC. ANN predictions present a similar trend to CRITIC and SAW. The predicted parameters and their levels are given in Table 4.

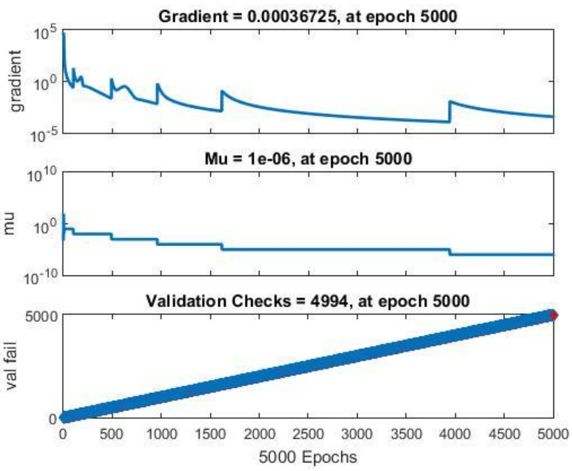

Figure 6. ANN gradient curve.

Table 4. Results of the ANN model.

Parameters	Optimal process parameters	
	CIRTIC and SAW	ANN Prediction
Levels	$E_2EC_3V_3D_2$	$E_2EC_3V_3D_2$
Time (min)	540	614
MRR (µm/s)	0.556	0.520
OC (µm)	22.51	23.8

CONCLUSION

1. A wear test was conducted on the fabricated metal matrix composites and on applying a 30 N load and a 380 rpm speed, the height loss wear was 34 µ, and the frictional force developed was 13.2 N.
2. The wear-investigated sample surface roughness depth profile showed the values of *Rz*, *Rt*, and *Ra* of 24.5 µm, 55.4 µm, and 3.04 µm, respectively.
3. The OA experiment was successfully conducted using $NaNO_3$ and $NaNO_3$ +HNO_3 electrolytes.
4. The most crucial parameter values for high MRR and low OC were 28 g/L $NaNO_3$+0.05M HNO_3, 10 V, and 80% duty cycle. The second-best set of parameters were 28 g/L $NaNO_3$+0.05M HNO_3, 8 V, and 90% duty cycle.
5. The performance measures acquired by the SAW approach had weight values of 0.549 and 0.45.
6. The optimal output performances predicted by ANN are MRR of 0.520 µm/s and OC of 23.8 µm. The expected values and the experimental values were reasonably close. Hence ANN was best suited for the ECMM performance prediction.

Based on ANN prediction, the best levels of parameters were 28 g/L of $NaNO_3$+0.05 M HNO_3 with 10 V and 80% duty cycle.

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NAUČNI RAD

ANALIZA PERFORMANSE ELEKTROHEMIJSKE MIKROMŠINSKE OBRADE KORIŠĆENJEM JEDNOSTAVNIH ADITIVNIH TEŽINA, VAŽNOSTI KRITERIJUMA METODAMA KORELACIJE MEĐUKRITERIJUMA I VEŠTAČKE NEURONSKE MREŽE

Elektrohemijska mikromašinska obrada (ECMM) nalazi primenu u različitim industrijama, posebno u procesima završne obrade površina u vazduhoplovnoj industriji. U ovom radu, radni komad napravljen od matrice starog aluminijumskog metala ojačanog glinicom je podvrgnut istraživanjima habanja, površinskog profila i obradivosti. Za analizu performansi ECMM-a, korišćene su jednostavne aditivne težine (SAV) važnosti kriterijuma kroz međukriterijumsku korelaciju (CRITIC) i veštačka neuronska mreža (ANN). Studije habanja pokazuju da je pri velikim opterećenjima gubitak habanja po visini manji, a sila trenja veća. Sprovedeni su eksperimenti sa mešovitim ortogonalnim nizom L_{18}, koja je pokazala najvažnije vrednosti parametara za visok MRR i nizak OC: 28g/l $NaNO_3$+0,05 M HNO_3, 10 V i 80% radnog ciklusa. Vrednosti težine metrike performansi dobijene metodom SAV su 0,55 i 0,45. Optimalne izlazne performanse koje predviđa ANN je MRR od 0,52 µm/s i OC od 23,8 µm.

Ključne reči: mešani elektrolit; natrijum-nitrat; azotna kiselina; radni ciklus; optimizacija; prekomerno sečenje.