SCIENTIFIC PAPER

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

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Abstract

Electrochemical micromachining (ECMM) finds application in various industries especially in surface finishing process 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 analysis the ECMM performance simple additive weighting (SAW) CRiteria Importance Through Intercriteria Correlation (CRITIC) and Artificial Neural Network (ANN) was 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 was 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 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.

Highlights of the research:

- An aluminum scrap metal matrix material is fabricated, and machinability studies are performed.
- ECMM performance is analysed 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 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.

Introduction

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 bio medical, aerospace and automobile. In ECMM, the cathode is the tool electrode and 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. In manufacturing industry perspective, productivity, quality and cost will go in holding hands and hence optimizations of machining process were performed by many researchers[1].Ganesan et al. [2]have optimized the 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 network (ANN). They reported that for obtaining 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 differential search algorithm, genetic algorithm and desirability function approach and proved that the differential search algorithm is suitable method as a global optimization tool. Geethapriyan et al. [5] have optimized the ECMM variables using grey relational analysis with Taguchi method. Based on the experimental study, it is evident that micro-tool feed speed is most significant factor for sodium chloride electrolyte and voltage is 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 TOPSIS method. The study reveals that the sodium nitrate electrolyte of 35 g/L concentration, the machining voltage of 11 V, and 70% duty cycle is the optimal combination for higher MRR and lesser OC. Senthilkumar et al. [8] used 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 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, delamination and to maximize the MRR. Nagarajan et al. [10] compared different multi criteria decision making algorithm such as grey wolf, moth-flame and particle swarm methods. The study resulted 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 VIKOR method. Out of three weight evaluation methods, analytic hierarchy process is found to produce 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 optimised the ECMM factors on machining rate,radial overcut and delamination factor. They used entropy method to determine the weights of the output performance. The grey relational grade is used to optimise the multi performance and reported that 80V,20 gm/lit,50% duty cycle and 40℃ 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 optimise the ECMM factors on aluminium boron carbide composites. The found that the electrolyte concentration of level 35 g/L, the voltage at 11 , 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 application 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 ANN model. Hence in this research Nitric acid mixed sodium nitrate electrolyte is used and mixed L_{18} orthogonal array (OA) experimental plan is used for the conduct of the experiments. The factors considered are 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 constant track radius. The different load levels of 10N, 20N, 30N were applied on the specimen at constant speed and time of 380 rpm,5 minutes 30 seconds respectively. The test results show that for 10N load the height loss wear is 52 µ and frictional force generated is 3.9 N. On further increase in load to 20N and 30N for 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 frictional force is more. 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 Rz, Rt, and Ra are 24.5 µm, 55.4 µm, and 3.04 µm, respectively.

Figure 1

Experimental Setup

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 house the workpiece holder made up Perspex material. The capacity of the machining chamber holds 2 litres of electrolyte. The electrolyte supply system consists of chemical pump, filter to remove the debris and electrolyte supply pipe and nozzle. The pulse power supply unit with specification of 0-30V, current of 0-5amps and frequency of 100Hz is used for the experiments. The tool advance mechanism comprises the stepper motor, lead screw and tool holder. The stepper motor is controlled by microcontroller program. The tool holder is made up of hollow copper tube and provides with screw to fix the electrode. The tool electrode is isolated from the tool feeding arrangement. The workpiece is given with positive power supply and tool electrode is given with negative power supply. The workpiece used for the experiment is the alloy wheel matrix composites of thickness 300µm. The Figure 2 presents the optical microscope image of the workpiece sample which witnesses the presences of the silica. Figure 3 shows the EDAX image of the workpiece sample used for the machining. The figure shows the presence of aluminum, nickel, magnesium, carbon, oxide, chromium, iron, and silica. The tool electrode of diameter 600µm is coated with bonding liquid for insulation purpose to avoid stray current. The type, concentration, voltage, and duty cycle of the electrolyte are the parameters that were used in the studies. The performances are measured using MMR in µm/sec and OC in µm. The L_{18} mixed OA is considered and levels are identified based on the past the experiments and presented in the table 1. In this study the total number of factors are four at 3 levels, hence the degrees of freedom calculated is eight. Therefore the OA selection should be more than eight hence L_{18} is selected since there is two type of electrolyte, mixed OA is considered for this study. The electrolyte sodium nitrate ($NaNO_3$) salt is mixed with the distilled water of 1 liter and stirred properly. Another type of mixed electrolyte ie acidified $NaNO_3$ is prepared and used. To prepare 0.05M of nitric acid 3.20ml of nitric acid is added to the 1 liter of distilled water, while $NaNO_3$ of varying grams were added to the mixed electrolyte [16].

Figure 2

Figure 3

Table 1

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 to take decision based on the importance of criteria, moreover it eliminates the non 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. In order to use SAW, the decision matrix must be normalised 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 result 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 in order 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 ith alternative with regard to the jth criterion in an initial decision matrix.

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

$$d_{ij} = \frac{\phi_{ij} - \phi_j^{min}}{\phi_j^{max_j^{min}}} \quad (1)$$

Whereϕ_j^{max}= max (φ_{ij},i=1…., a), and ϕ_j^{min}= min (φ_{ij},i=1…., a).

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 jth criterion wj in the following way [11]:

$$\eta_j = \frac{w_j}{\sum_{i=1}^{m} w_i} \quad (2)$$

where w_j is the amount of information present in the j^{th} criterion and can be obtained as follows:

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

where is the correlation coefficient between the jth and ith criteria, and σ_j is the standard deviation of the jth 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 ith Criterion for the jth Alternative by using equations (4 &5):

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

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

where ρ_{ij} is the normalized decision matrix

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

$$S_i = [\rho_{ij}][\eta_j] \qquad (6)$$

Arrange the final results according to value, with the highest number being the best experimental combination for the highest performance metrics (MRR& 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 show the correlation between the performance measures.

Table 2

Table 3

For MRR and OC, respectively, the weight values of the performance metrics obtained using Equations (4) and (5) are 0.549 and 0.45. The SAW method use equation 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 28g/lit $NaNO_3$+0.05M HNO_3, 10 V, and 80% duty cycle. This is the second-best set of parameters: 28g/lit $NaNO_3$+0.05M HNO_3, 8 V, and 90% duty cycle. It is evident from the optimised parameter combinations that acidified $NaNO_3$ is one of the factor influence the output performance. Acidic electrolytes are utilised to improve the dissolution efficiency, nitric acid, hydrochloric acid, sulfuric acid, perchloric acid 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 28g/lit $NaNO_3$+0.05M HNO_3, 10 V, and 80% duty cycle, depicts that good circular micro-hole with over-etched and corroded surface [23].

Figure 4

ANN Prediction

In recent research, implementation of advanced non-traditional method in optimization is highly required for accurate outcomes. Here ANN is implemented in order to predict the suitable inputs and its 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, random data revision type MATLAB inbuilt algorithm is used. ANN prediction consists of three important stages. Initially network development and followed by training. Final stage in ANN is output prediction [25]. Here all the experimental inputs are considered as training variables. For training, experimental outputs are considered as target values. Totally 5000 iteration training is given to ANN and its parameters. Based on training and target variables, training is given with total time limit of 1 minutes and 23 seconds.

Figure 5

Figure 6

It is observed that the total ANN training is achieved 5000 iterations without any errors. The blue training line gradually reaches the target while training. For better understanding, a narrow straight line in 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. From figure 6, it represents 99.9% in training with overall performance of 97.85% [26-27]. With respect to training ANN predicted time is 614 sec of machining time with 0.520 MRR and 23.8 OC. ANN predictions is presenting similar trend of CRITIC and SAW. The predicted parameters and their levels are given in table4

Table 4

Conclusions

1. Wear test was conducted on the fabricated metal matrix composites and on applying 30N load and 380rpm speed the height loss wear is 34µ and frictional force developed was 13.2N.
2. The wear investigated sample surface roughness depth profile shows the values of Rz, Rt, and Ra are 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 electrolyte.
4. 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. This is the second best set of parameters: 28g/lit $NaNO_3$+0.05M HNO_3, 8 V, and 90% duty cycle.
5. The performance measures that were acquired by the SAW approach have weight values of 0.549 and 0.45.
6. The optimal output performances predicted by ANN are MRR of 0.520 µm/sec and OC of 23.8 µm. The expected values and the experimental values are reasonably close. Hence ANN is best suits for ECMM performance prediction.
7. Based on ANN prediction the best level of parameters is 28g/lit of $NaNO_3$+0.05M HNO_3 with 10V and 80% duty cycle.

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Figure captions

Figure 1.Surface roughness depth profile

Figure 2. Optical image of the workpiece surface

Figure 3. EDAX image of the sample workpiece.

Figure 4.SEM picture of micro-hole

Figure 5. Neural Network with algorithm

Figure 6. ANN Gradient curve

Table 1.L_{18} OA

S.No	Electroyte (E)	Electrolyte Concen-tration (EC) in g/lit	Voltage (V) in volts	Duty Cycle (DC) in %	MRR in µm/sec	Overcut in 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

Table 2. Normalization original values through CRITIC and SAW

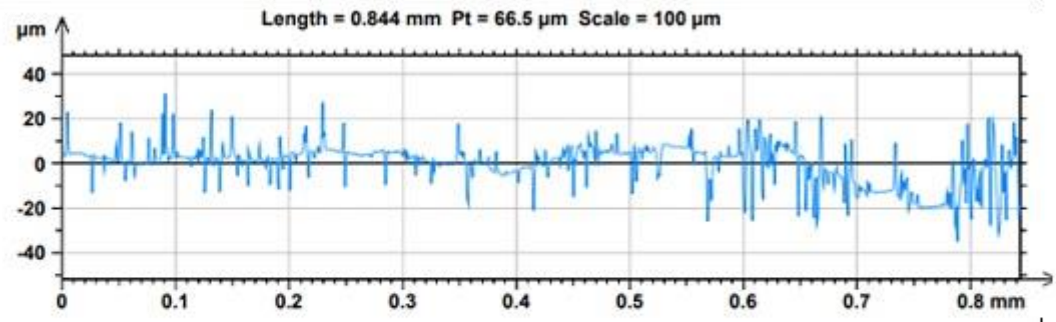
	Normalization - CRITIC		Normalization - SAW		S_i	Rank
Sl.No	MRR	OC	MRR	OC		
1	0.1304	0.6039	0.1476	0.2198	0.2781	16
2	0.2348	0.7829	0.1771	0.1364	0.3635	8
3	0.1531	0.8721	0.154	0.0948	0.3823	7
4	0	0.7705	0.1107	0.1422	0.2661	17
5	0.1531	0.3814	0.154	0.3234	0.2639	18
6	0.205	0.3282	0.1687	0.3481	0.2809	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

Table 4.Results of 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



ISO 4287			
Amplitude parameters - Roughness profile			
Rz	24.5	µm	Gaussian filter, 0.025 mm
Rt	55.4	µm	Gaussian filter, 0.025 mm
Ra	3.04	µm	Gaussian filter, 0.025 mm
Rv	*****	µm	Gaussian filter, 0.8 mm

Figure 1

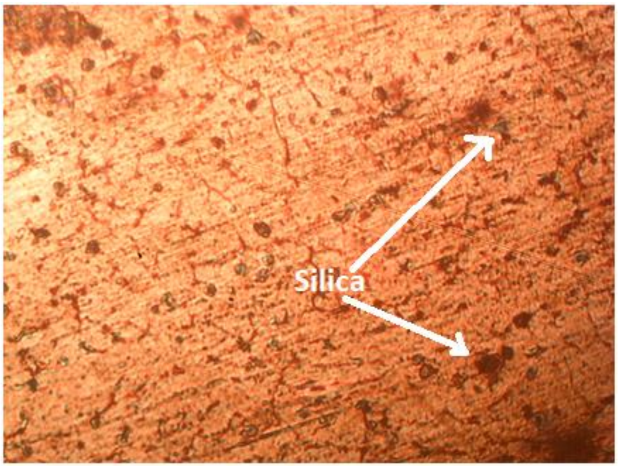
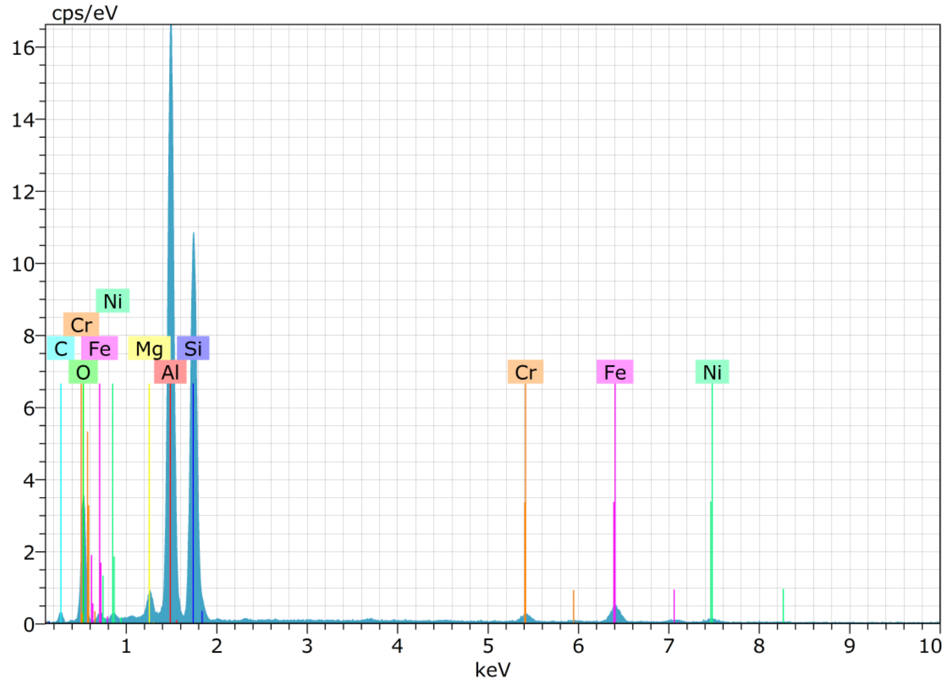


Figure 2


cps/eV
16
14
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10
8
6
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5
6
7
8
9
10
keV

Figure 3

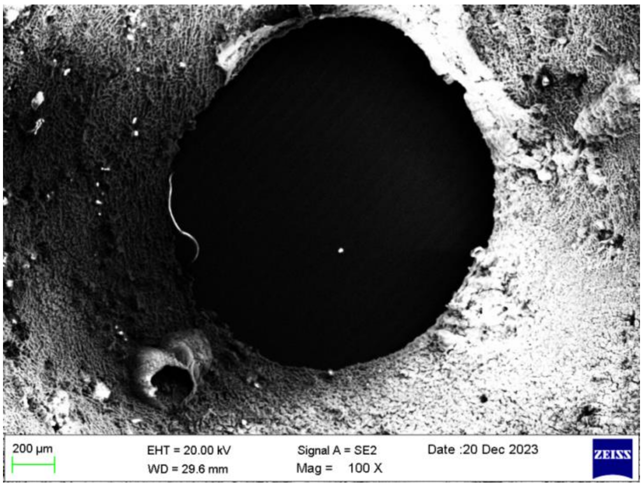
200 µm
EHT = 20.00 kV
WD = 29.6 mm
Signal A = SE2
Mag = 100 X
Date :20 Dec 2023
ZEISS

Figure 4


Neural Network
Hidden Layer
Output Layer
Input
Output
W
b
W
b
4
10
4
4
Algorithms
Data Division: Random (dividerand)
Training: Levenberg-Marquardt (trainlm)
Performance: Mean Squared Error (mse)
Calculations: MATLAB
Progress
Epoch: 0 5000 iterations 5000
Time: 0:01:23
Performance: 4.41e+04 2.10e-09 0.00
Gradient: 4.05e+04 0.000367 1.00e-07
Mu: 0.00100 1.00e-06 1.00e+10
Validation Checks: 0 4994 5000
Plots
Performance (plotperform)
Training State (plottrainstate)
Regression (plotregression)
Plot Interval: 1 epochs
Opening Regression Plot

Figure 5

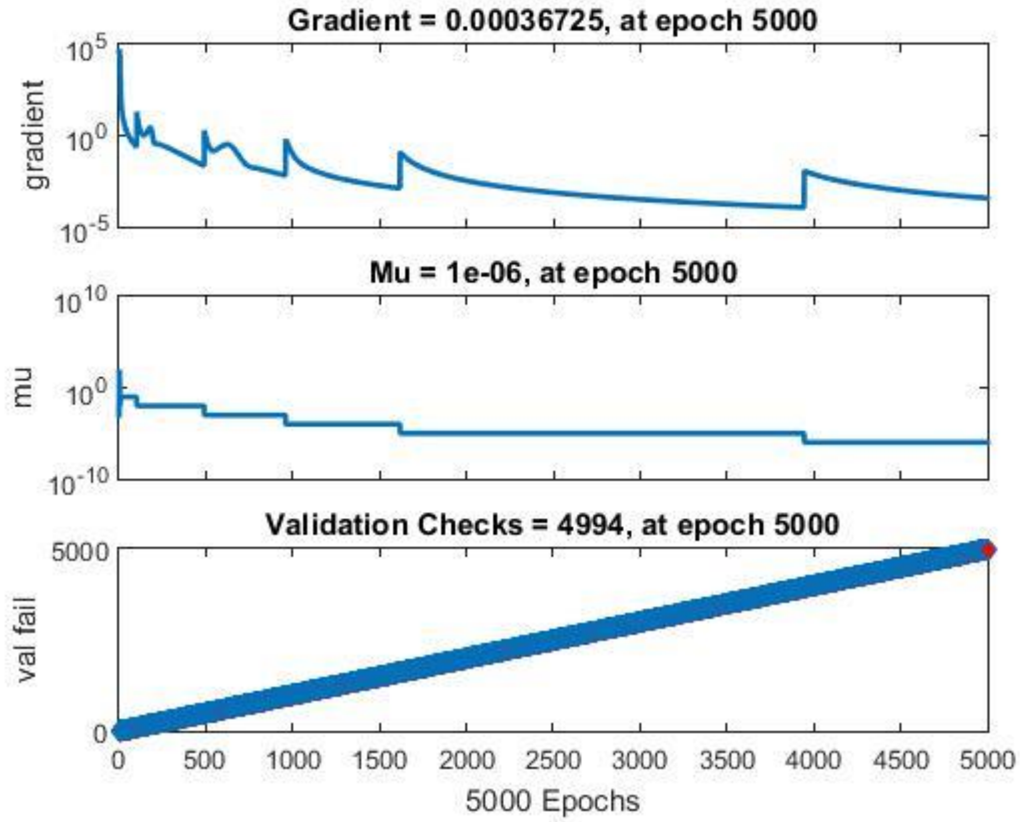
Gradient = 0.00036725, at epoch 5000
gradient
10^5
10^0
10^{-5}
Mu = 1e-06, at epoch 5000
mu
10^{10}
10^0
10^{-10}
Validation Checks = 4994, at epoch 5000
val fail
5000
0
0
500
1000
1500
2000
2500
3000
3500
4000
4500
5000
5000 Epochs

Figure 6