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Research Article

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Intelligent Modeling and Optimization of Performance Characteristics in Electro-chemical Machining of HMMC

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Abstract

The advanced machining processes have attracted the attention of researchers due to their better machining performances, especially for hard-to-cut materials. Among all advanced machining processes Electro-Chemical Machining (ECM) has the capability to generate complex profile on electrically conductive difficult to machine materials. In this paper, authors have tried to investigate the process behavior of ECM on Aluminum-Silicon Carbide-Graphite (Al-SiC-Gr) composite material. Further, the hybrid approach of Artificial Neural Network (ANN) and Genetic Algorithm (GA) has been utilized for modeling and optimization of machining performance during ECM of Al-SiC-Gr. The experimental results are used for generating the ANN based model. It was observed that the predicted results of responses through model appropriately fit with experimental results. The optimization results reveal that the material removal rate and surface roughness have improved by 137% and 58%, respectively as compared to average experimental values.

Keywords

Composite, Electro-chemical machine, Material removal rate, Surface roughness, Artificial neural network, Genetic algorithm

Introduction

Nowadays, there are various industries such as aerospace, automobile, biomedical, and sports which utilize one of the key characteristics of Metal Matrix Composites (MMCs) i.e., low weight to height strength ratio whereas other attributes viz., high formability and resistance to corrosive damage can also be applicable in many other sectors [1, 2]. MMCs coupled the advantageous properties of metal alloys and ceramics. Also, another composite material called Hybrid MMCs (HMMCs). HMMCs have various reinforcing materials having particular characteristics obtained in a single matrix material [3, 4]. Generally, the mechanical properties and strength of HMMCs are improved at high temperature conditions due to better chemical and wear stability. Due to these characteristics of HMMCs it is the superior choice in automotive and aviation applications for manufacturing of pistons, cylinder liners, and brake drums [5]. The manufacturing of components using HMMCs materials by conventional machining is a difficult job due to high hardness of reinforcing materials which are inserted into matrix materials. Advanced machining processes also face some issues like melting of reinforcements and formation of recast layer when machining of HMMCs. Some research articles also noticed these issues [6, 7].

ECM process is broadly used in most of the advanced major manufacturing sectors for shaping of such materials which are electrically conductive and hard-to-cut. Various researchers have tried to use the potential of ECM process on

electrically conductive materials. Xuezhen et al. [8] explored the machining characteristics of ECM process on Ti60, titanium based superalloy. The machining characteristics have also been optimized. It was found that the applied voltage is the most influencing parameters for Surface Roughness (SR). Optimization results also show that the optimum value of SR obtained at applied voltage of 20 V and electrolyte concentration of 13%. Ayyappan et al. [9] used magnetic flux assisted vibrating tool for enhancing the machining performance during ECM of alloy steel. It was observed that both Material Removal Rate (MRR) and SR effectively improve by applying the magnetic flux during shaping. Senthilkumar et al. [10] used response surface methodology to develop the model for machining characteristics of ECM process. It was found that the concentration of electrolyte supply voltage and are most significant input variables for MRR and SR. Low SR was noticed at approximately mid value of process parameters. Rao et al. [11] also check the effect of input variables on machining performances such as machining efficiency and overcut during ECM of aluminum based composite material. It was concluded that machining efficiency is significantly affected by the supply voltage and feed rate. Rahi and Dubey [12] studied about surface characteristics of machined surface and check the effect of control factors on this. They found that the formation of oxide layer efficiently affects surface characteristics of machined components as well as MRR. Ren et al. [13] proposed a flow pattern with auxiliary fluid for improving the uniformity of flow during machining. It was observed that flow velocity in machining zone increases up to 10 m/s. Zong et al. [14] used two step blade for improving the machining accuracy during ECM process. They conclude that the machining accuracy improves by using two-step blade ECM method due to reduction in overcut. Wang et al. [15] studied about process performance of ECM using MFS-ball as an electrolyte absorption materials. It was noticed that the flow of machining current through electrolyte film on the surface and inside the MFS-ball simultaneously. Rahi and Dubey [16] performed the experiments on in house fabricated set-up of electro-chemical surface grinding to studied the effect of applied voltage on MRR.

Above discussed literatures reveal that most of the research in ECM is focused on metal and alloys. Limited research articles are available which explore the machining characteristics of MMCs. Further, hardly research works are available on machining of HMMCs specifically Al-SiC-Gr which is widely used for making of piston and piston ring. Moreover, authors could not find any research articles on modeling and optimization using soft computational methods for predicting the ECM process behavior. In this research article, authors have tried to develop an ANN-based model for MRR and SR. Further these developed models have been used as an objective function during optimization of responses. Concentrations of electrolyte, table speed, and applied voltage have been considered as an input variable in this study.

Experimentation

In this research work, Al-SiC-Gr HMMC has been considered as a workpiece during performing the experiments. The specification of the workpiece is 45 x 10 x 5.5 mm^3. Cupper bonded with diamond abrasive tool and sodium nitrate ($NaNO_3$) has been taken as cathode and electrolyte, respectively. The experiments have been carried out on electrochemical machine using one parameter at a time approach. Figure 1 shows the experimental set-up of ECM. The control factors during experimentation have been decided based on the earlier published research articles and restriction of ECM machine. The levels and range of process variables have been selected based on pilot experiments. Table 1 represents the levels and range of process variables. MRR has been considered as a response variable. MRR is defined as the rate at which mass of materials removed from the workpiece at a time. It can be calculated after measuring the workpiece before and after machining. The observation of responses has been given in figure 2.

ANN-based modeling

The ANN is a non-linear soft computational method, which may effectively predict the process behavior of the system. It consists of artificial neurons that are set in the form of layers and connected with some coefficient (weights) and activation functions [17]. ANN is based on the functioning of the

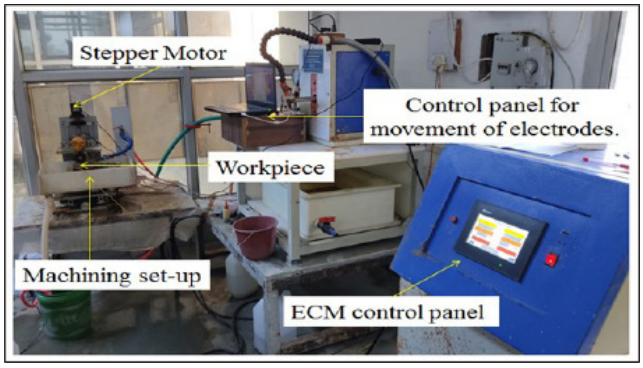


Figure 1: Experimental set-up of ECM.

Table 1: Levels and range of process variables.

Control Factors	Symbol	Range	Level				
			-2	-1	0	-1	2
Applied Voltage (V)	X_1	6 - 22	6	10	14	18	22
Electrolyte Concentration (g/L)	X_2	10 - 50	10	20	30	40	50
Table Speed (mm/s)	X_3	0.1 - 0.5	0.1	0.2	0.3	0.4	0.5

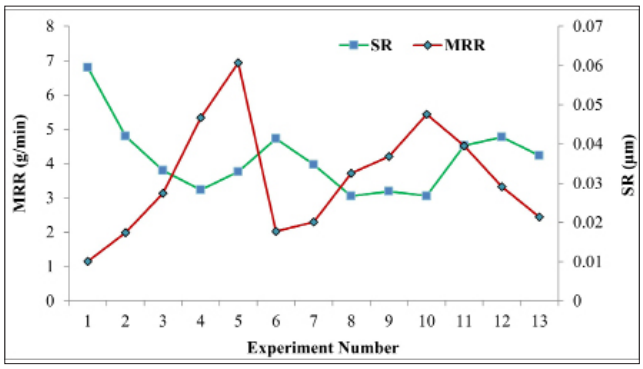


Figure 2: Observation of responses.

human brain during development of models for various performance characteristics. ANN model involves input, hidden and output layer that contains various numbers of neurons. Every layer is inter-connected by another layer with synapses [18]. The network building is generated for a given responses through proper assignment of weights and bias to the layers. Network building, training, and testing data size and weight and bias assigned to layer are influencing parameters in the performance of ANN. The number of neurons is selected on the basis of minimum mean square error. Figure 3 shows the structure building of ANN model. In this research article the output of hidden layer has been determined on the basis of logistic sigmoid transfer function. Whereas pure linear function was used for evaluating the output of responses. Equation 2 and 3 [18] are used for output of hidden layer output layer, respectively.

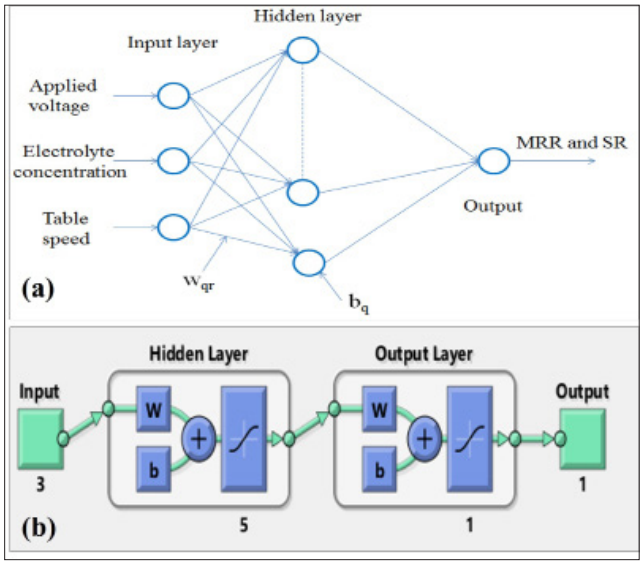


Figure 3: Structure of ANN for output **(a)** flow diagram and **(b)** actual generated structure.

$$y_k = \frac{1}{1+e^{[-(NET)k]}} \quad (2)$$

$$y_k = (NET)_k \quad (3)$$

Where,

$$(NET)_k = \sum_{k=1}^{n} x_i w_{ik} + b_k$$

Where, w_{ik} = Weight for connecting the jth hidden neuron from ith input neuron, $x_{i=}$ Control factors merge on ith neuron, b_k = Bias for kth neuron, and n = Control factors for kth neuron.

In this study, the ANN toolbox of MATLAB R2014a software was used for generating the model for responses. A total of 13 experimental results were used for generating the ANN based model, where 70% of experimental results i.e., 9 observations were used for training, whereas 15 - 15% of experimental results were used for validation and testing, respectively. The number of neurons and hidden layer has been decided on the basis of minimum mean square error which is obtained by hit and trial runs of training. Thus 3-5-1 network of structure as shown in figure 4. Weights and biases of hidden and output layer have been given in table 2. Afterward ANN based models were developed for MRR and SR by using the values of these weights and biases. The developed model for MRR and SR has been represented as equations 4 and 5, respectively. Suggested values of responses through developed model have been tabulated in table 3.

$$MRR = 0.22126 + 0.13964\ Z_1 - 0.8733\ Z_2 - 0.91839\ Z_3 + 0.06311 Z_4 + 0.57479 Z_5 \quad (4)$$

$$SR = 1.3738 - 0.54794 Z_1 - 1.4615 Z_2 - 0.792903 Z_3 - 2.6635 Z_4 + 0.31942 Z_5 \quad (5)$$

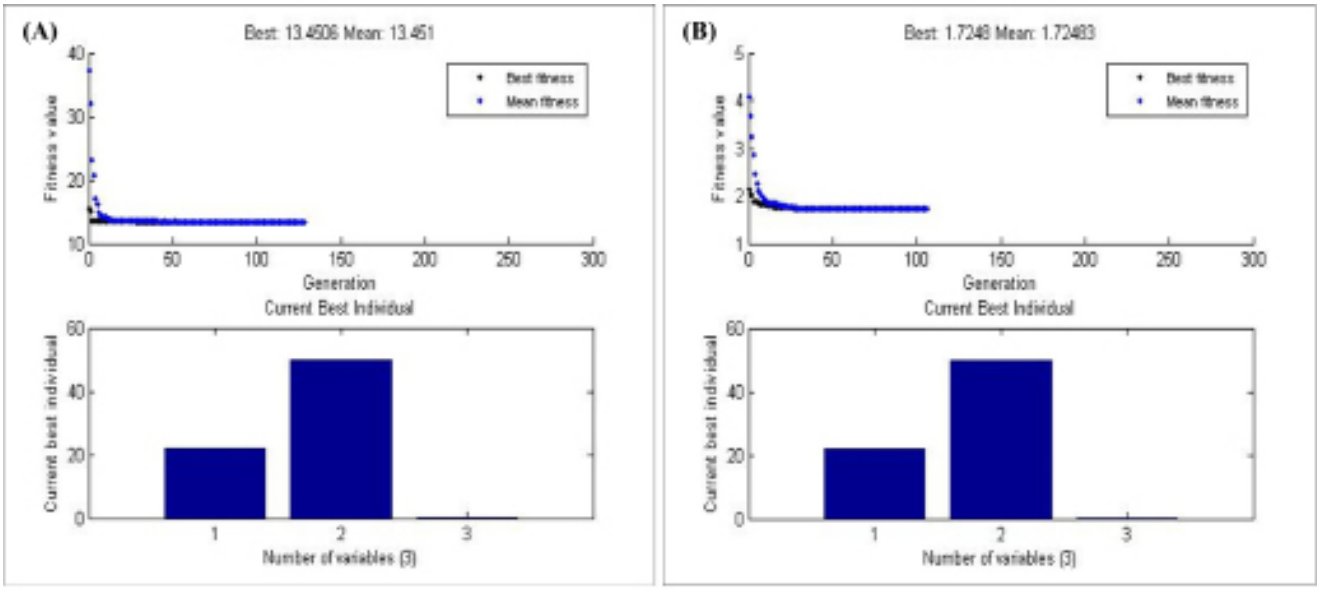


Figure 4: Optimized results of responses **(a)** MRR and **(b)** SR.

Table 2: Weights and bias of responses.

Output	Weights	Bias
MRR	[1.715 -0.10672 1.6668	[-2.394
	-1.1946 -1.1813 -1.7054	1.197
	-1.404 1.5309 1.1902	0
	-1.6303 0.55843 1.6618	-1.197
	1.5978 0.68462 -1.6461]	2.394]
	[0.13964 -0.8733 -0.91839 0.063411 0.57479]	[0.22126]
SR	[1.5045 -1.8117 -0.53219	[-1.2852
	0.66879 1.388 -1.4866	-0.85069
	-5.9768 -0.77692 0.6864	3.8769
	2.311 1.5593 3.6082	2.2551
	2.6485 -0.95154 0.2234]	-6.0847]
	[-0.54794 -1.4615 -0.72903 -2.6635 0.31942]	[1.3738]

Table 3: Suggested values of developed model for responses.

S. No.	X_1	X_2	X_3	MRR	SR
1	6	30	0.3	0.0109	6.7709
2	10	30	0.3	0.0189	4.8056
3	14	30	0.3	0.0320	3.6819
4	18	30	0.3	0.0448	3.3859
5	22	30	0.3	**0.0519**	3.7287
6	14	10	0.3	0.0150	4.7164
7	14	20	0.3	0.0210	4.0013
8	14	40	0.3	0.0362	3.2079
9	14	50	0.3	0.0362	**3.0749**
10	14	30	0.1	0.0449	3.7581
11	14	30	0.2	0.0387	4.5189
12	14	30	0.4	0.0264	4.0752
13	14	30	0.5	0.0221	4.2406

Where, Z_1, Z_2, Z_3, Z_4 and Z_5 represent the output of hidden layer.

In which $Zj = \frac{1}{1+e^{-m}}$ and $m = \sum_{i=1}^{5} w_i x_i + b_i$

Where, w_i represents the weight for connecting input to hidden layer while b_i shows the bias of the hidden layer. Moreover, suggested values of responses through developed models have been compared and verified with experimental results at different sets of input parameters. For scientific validation of forecasted values of performance characteristics, statistical factors like average percentage prediction error have been calculated and found to be very close to experimental values with negligible error.

Genetic algorithm

GA propounded by John Holland is an evolutionary computation method based on Darwin's survival of fittest theory. GA is a robust optimization method that is quite suitable for solving non-linear optimization models. It is based on natural evolution and the concepts of natural genetics, specifically survival of the fittest [19]. GA has capability to search complex, multimodal landscapes and large solution spaces, and provide fittest optimum solution for objective or fitness function of optimization problem [20].

Optimization Results of Responses

The generated ANN based mathematical model for MRR and SR (equation 4 and 5) was utilized as an objective function for finding the optimum value of responses. In this study, authors want to minimum SR and maximum MRR. Therefore, the reciprocal of MRR has to be minimized. The generated mathematical equation of SR and reciprocal of equation of MRR were put in the in the M-file of MATLAB software for minimizing the responses. Afterward, the range of input variable was taken as constraint during optimization process which is given in table 1. In this optimization, the optimum value of GA operating parameters like population size, crossover rate and mutation rate have been considered as a 50, 0.9, and 0.01, respectively. Double point crossover has been used for crossover. GA based optimization solver has been started after putting all these values and terminated after 125 and 105 generations for MRR and SR, respectively. The optimized results of MRR and SR have been presented in figure 4. It may be seen from figure 4a and 4b that the improvements in MRR and SR have been observed up to 45 and 25 generation for MRR and SR, respectively. After that no further improvement was noticed. The best optimum value for MRR and SR i.e., 0.0743 g and 1.7248 µm were obtained at 22 V of applied voltage, 50 g/L of electrolyte concentration and 0.1 mm/s of table speed. The optimum results reveal that MRR and SR were improved by 137% and 58% from average experimental results. Table 4 shows that comparison between optimum results and average experimental results.

Table 4: Comparison results of average experimental and optimized values.

	Performance Characteristics	
	MRR (g/min)	SR (µm)
Average experimental values	0.0313	4.1482
Optimum predicted values	0.0743	1.7248
Improvement (%)	137	58

Conclusions

In this article, a hybrid approach of ANN-GA was used for optimizing the performance characteristics during ECM of Al based hybrid composite. The outcomes of the presented article are:

- The developed models for performance characteristics have been found to be well fitted with observed values and efficiently predict the MRR and SR with negligible absolute percentage error.
- Optimization results reveal that the MRR and surface finish are improved by 137% and 58%, respectively as compared to average experimental results.
- The optimum value for performances characteristics *viz.*, MRR and SR have been found as 0.074 g/min and 1.72

μm, respectively at 22 V of applied voltage, 50 g/L of electrolyte concentration and 0.1 mm/s of table speed.

Acknowledgements

None.

Conflict of Interest

Authors declare that there is no conflict of interest.

Credit Author Statement

Dhruv Kant Rahi: Study conceptualization, Design, Material preparation, Data collection, Analysis, Writing - original draft preparation; Avanish Kumar Dubey and Ashutosh Maurya: Study conceptualization, Design, Material preparation, Data collection, Analysis, Writing - review and editing. All the authors read and approved the manuscript.

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