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OPTIMIZATION OF THE PROCESS CONSTRAINTS IN SPARK EROSION MACHINING OF ALUMINIUM ALLOY AA 6061 HYBRID COMPOSITES USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

The foremost objective of this research work is to implement Artificial Neural Network (ANN), to improve spark erosion machining performance of aluminum alloy AA 6061 hybrid composites by controlling the process constraints, which is suitable for bio medical applications. Aluminum composites are mostly used to replace the conventional materials attributable to their less weight, notable wear and corrosion resistances. These composites are used in automotive, aerospace, electronics and bio medical applications. Machining of aluminium composites using conventional machining technique is one of the major challenges because of the presence of hard particles in aluminium matrix. Unconventional machining techniques have been preferred for machining aluminium composites to enhance better surface quality. In the present study the composite specimen was processed through stir casting and machining was carried out using spark erosion machining, by varying four process constraints with the application of design of experiments. ANN trained with multi-layer feed forward through the error back-propagation training algorithm, was used to model the network and predict the material removal rate (MRR) of the composite. The outcomes exposed that the projected values found from the ANN model were in good agreement with the investigational values and to study the machining characteristics of composites, the model could be effectively applied.

Keywords: Aluminium Hybrid Composites, Spark erosion machining, Optimization, Artificial Neural Network (ANN), Composites, Bio-medical applications

INTRODUCTION:

The requirement of advanced materials in differrent industrial sectors led to the rapid development of aluminium composites. Garg et al., [2012] described that, the aluminium hybrid composite materials have been used in many applications such as aerospace, defense, bio medical and automotive industries due to its superior characteristics such as virtuous wear resistance, specific strength and strength-to-weight fraction. The physical and mechanical properties of these composites can be altering by choosing different reinforcements. So aluminium composites are recently is drawing interests of the researchers. Hassan et al., [2009] stated that, the aluminium alloys are used as the matrix material in aluminum composites because of their elated corrosion resistance, low density, high damping capacity and good electrical and thermal conductivities. There are various methods are available for fabricating aluminium composites. Among these methods, stir casting method, has evidenced to be comparatively inexpensive and comprehensible. In this method, usually the reinforcement particles are dispersed into the molten aluminum melt through mechanical stirring, which is the key part.

Aluminum composites by adding up to 30 % volume fractions of reinforcements could be fabricated using this method. Debaprasanna Puhan et al., [2013] found that, the major problem connected with this method is the separation of reinforcements due to settling of the particles during solidification process. This could be easily eluded, by selecting proper particle size and pouring temperature. The key benefit of using this method is its suitability for mass production. Balasubramanian and Senthilvelan [2013] reported that, spark erosion machining is mainly employed for machining stiff metals that would be challenging to machine with traditional techniques. This method is gained admiration, as various 3D intricate profiles can be machined using a simply formed electrode tool. It utilizes well-ordered sparks that discharges between the specimen and the tool in a di-electric liquid. Rao et al., [2010] found that spark erosion machining is used in wide area in the built-up of self-propelled, space and medical components. There is no direct interaction between work piece and electrode. So, it is very competent in machining high strength and very tough materials.

The choice of the apt machining settings to get optimal material removal rate through spark erosion machining process is built on the numerous process constraints linked to material removal rate (MRR). Conventionally, it is conceded, based on the worker's skill or technical records given by the spark erosion machining equipment makers. The background specified by the equipment manufacturers is merely appropriate for common steel grades. Ramezan Ali [2011] concluded that the preset conditions for newer materials such as aluminum composites, special steels, titanium alloys and advanced ceramics should be improved by conducting thorough experiments. Surappa [2003] reported that, the spark erosion machining process optimization is complicated, due to several controllable machining constraints. A minor change in one constraint will impact the process in an intricate way. Paramanantham Hema Prabha [2017] developed a model and optimized the parameters for packaging applications.

Markopoulos et al., [2008] stated that ANN is a model for computing, storing and recovering learnt information. It consists of solid unified computing elements that are similar to those in intricate neurons in biological systems. Through the learning method, information is learnt, and it is kept in synaptic bulks of the inter-nodal networks. Complex input/output relationships can be modeled using ANN. Raut and Shinde [2015] constructed an ANN model built on the experimental data and inputs and outputs were taught to exactly forecast the method. ANN acts in a chief part in solving linear and nonlinear problems. Paulo Davim [2008] concluded that, in ANN modeling, knowledge/teaching algorithms and numbers of unseen neurons are mixed to obtain the least inaccuracy. Shashikant et al., [2014] and Thillaivanan et al., [2010] developed mathematical model using ANN and optimized to improve the performance in spark erosion machining process. Sasikala et al., [2018] developed Artificial Neural Networks for vertical handoff prediction.

As the spark erosion machining process is associated with high cost, it is very important to develop a model and optimizing the same is very important. Grounded on the above respects, in this research work an aluminium hybrid composite containing 10 wt% SiC and 4 wt% graphite particulates were made-up using stir casting. This material was machined using spark erosion machine by changing the route constraints namely peak current, discharge time, voltage and flushing pressure. A model was established using ANN based on the experimental data with back-propagation learning algorithm to envisage the material removal rate. The results attained from the ANN model shows that the predicted material removal rate values are nearer to the recorded values.

MATERIALS AND METHODS

Materials: The matrix chosen for the present study was Aluminium alloy AA 6061 alloy. The selection of this alloy is due to high strength with the option of modifying its properties by directing appropriate heat treatment. The elemental composition of Aluminium alloy AA 6061 was obtained through spectrometer and is shown in table.1. Silicon carbide and graphite particles are added to improve wear resistance and reduce friction. The average size of the reinforcement particles used in the present study is 75 microns.

Table 1 Chemical composition of Aluminium alloy AA 6061

Element	Cr	Cu	Fe	Mg	Mn	Si	Ti	Zn	Al
wt.%	0.003	0.24	0.16	0.89	0.48	0.63	0.014	0.007	97.57

Specimen Preparation: Velmurugan et al., [2011] prepared hybrid composite specimens using stir casting method. The melting was made in a furnace. The matrix materials were placed inside the graphite crucible and kept inside the melting furnace. The reinforcement particulates were heated at a temperature of 673 K for 45 minutes to eradicate moisture. The heated aluminium melt was degassed at a temperature of 1063 K. The graphite stirrer was positioned in the crucible once the temperature of the melt touched 1073 K. Then the stirrer is used to stirrer the molten metal with the reinforcement particles at 600 rpm for 10 minutes. To improve the wettablity of matrix and reinforcement small amount of magnesium was added. When stirring is over, crucible was taken outside, and the molten slurry was transferred into a tubular steel mould of 15 mm diameter and 80 mm length. While pouring, the temperature was kept at 873 K. The mould was then cooled down and the cast composites were detached from it. Then the cast composite was machined to 10 mm diameter and 25 mm length (Figure.1) for conducting machining study.

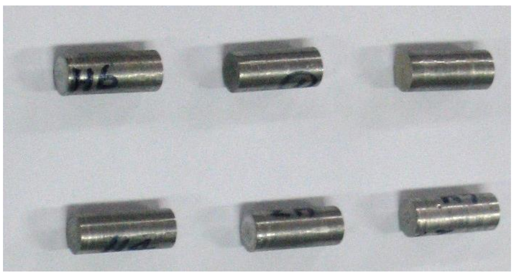

Fig. 1: Specimen used for spark erosion machining study

Spark erosion machining: Nilesh Ganpatrao Patil and Brahmankar [2010] stated that, in contemporary industrial applications spark erosion machining is used to perform high-precision machining of difficult-to-machine materials. Spark erosion machining uses thermo-electric energy for material removal. In this work, research was performed by ARD-make die-sinking spark erosion machining machine. A probe made of copper was used as the tool and the work part was Aluminium alloy AA 6061 composites strengthened with 10 wt% SiC and 4 wt%. graphite particulates. The dielectric fluid used is commercial grade spark erosion machining oil. A flushing jet method as revealed in Figure 2, was engaged to flush out the rubbles from the fissure zone. The required process constraints were fixed in the spark erosion machine. The research was performed according to the settings mentioned in the design matrix. The weights of specimen and tool were measured with an automatic balancing machine after each experiment.

Fig. 2: Jet flushing system in spark erosion machining

Process constraints and response variables: In this work, the process constraints selected are peak current, discharge time, voltage and flushing pressure. By conducting preliminary experiments using a distinct variable, the choice of the process constraints was fixed. The process constraints and their levels are specified in Table 2. The dependent response, carefully chosen for this work is the material removal rate (MRR).

Table 2 Machining constraints and their levels

Machining constraints	Symbols	Unit	Level				
			-2	-1	0	+1	+2
Peak current	I	A	3	6	9	12	15
Discharge time	T	µs	200	300	400	500	600
Voltage	V	V	30	40	50	60	70
Flushing Pressure	P	psi	1	2	3	4	5

The machining period taken was 10 minutes for each experiment. MRR is expressed (equation 1) as the ratio of the change in weight of the composite specimens before and after machining to the time taken for the machining, i.e,

$$MRR = \left[\frac{W_{ji} - W_{jf}}{t}\right] \quad (1)$$

where, weights of the composite specimens afore and afterward machining are W_{ji} and W_{jf}, and t is the machining period.

Design of Experiments: In this research, the trials were conducted based on the central composite second-order rotatable scheme (Table 3). Kannan and Murugan [2006] reported that, for 4 variables designated, 31 trials with 16 factorial points, 8 axial points are required to training the central composite design and to estimate the experimental error seven center points have been added. The experiments were carried out based on the run order mentioned in the design matrix. At the completion of each run, all the 4 constraints were wholly improved, in accordance with the design matrix and reset for the subsequent run to avoid errors in trial sets.

Table 3 Design Matrix for spark erosion machining study

Run order	Std. Order	Peak current (I) A	Discharge time (T) µs	Voltage (V) V	Flushing pressure (P) psi	Experimental Value	Predicted Value using ANN	Absolute percentage error (%)
						MRR (g/min)	MRR (g/min)	
1	6	1	-1	1	-1	0.481	0.475	1.26
2	**12**	**1**	**1**	**-1**	**1**	**0.53**	**0.535**	**-0.93**

3	27	0	0	0	0	0.464	0.476	-2.52
4	**18**	**2**	**0**	**0**	**0**	**0.583**	**0.562**	**3.74**
5	14	1	-1	1	1	0.515	0.517	-0.39
6	31	0	0	0	0	0.491	0.496	-1.01
7	10	1	-1	-1	1	0.524	0.529	-0.95
8	7	-1	1	1	-1	0.449	0.439	2.28
9	22	0	0	2	0	0.419	0.429	-2.33
10	**23**	**0**	**0**	**0**	**-2**	**0.431**	**0.442**	**-2.49**
11	1	-1	-1	-1	-1	0.45	0.461	-2.39
12	29	0	0	0	0	0.464	0.477	-2.73
13	24	0	0	0	2	0.521	0.512	1.76
14	30	0	0	0	0	0.497	0.491	1.22
15	4	1	1	-1	-1	0.51	0.519	-1.73
16	**19**	**0**	**-2**	**0**	**0**	**0.476**	**0.473**	**0.63**
17	25	0	0	0	0	0.483	0.489	-1.23
18	28	0	0	0	0	0.486	0.487	-0.21
19	15	-1	1	1	1	0.454	0.449	1.11
20	20	0	2	0	0	0.542	0.532	1.88
21	21	0	0	-2	0	0.495	0.484	2.27
22	11	-1	1	-1	1	0.461	0.473	-2.54
23	26	0	0	0	0	0.495	0.499	-0.80
24	**13**	**-1**	**-1**	**1**	**1**	**0.451**	**0.440**	**2.50**
25	16	1	1	1	1	0.519	0.529	-1.89
26	5	-1	-1	1	-1	0.441	0.428	3.04
27	8	1	1	1	-1	0.492	0.498	-1.20
28	2	1	-1	-1	-1	0.498	0.490	1.63
29	**9**	**-1**	**-1**	**-1**	**1**	**0.46**	**0.468**	**-1.71**
30	3	-1	1	-1	-1	0.453	0.459	-1.31
31	17	-2	0	0	0	0.41	0.425	-3.53

Artificial Neural Network modelling: Tsai and Wang [2001] stated that neural networks comprises of unpretentious processors, also termed as neurons and are connected by subjective networks. The neuron forms the root for organizing the neural networks. Every neuron has inputs and creates a response that can be seen as the likeness of native data kept in the connections. This response signal of a neuron is provided for the additional neurons as feedback signals through inter connections. Since the ability of an only neuron is incomplete, composite tasks could be comprehended by involving many processing elements. In this research work, a multi-layer feed forward neural network was established and taught using a back-propagation algorithm. A three-step procedure used in the improvement of the neural network model consists of collection of input and output dataset, pre-processing of feedback and response dataset and neural network training and testing. The measured experimental values of the material removal rate during spark erosion machining were used to develop the neural network model. In this research study, the inputs are the 4 main constraints, while the output data set is a single response (MRR). The neural network model was built using 31 experimental data. Among these, 25 data were selected for training; remaining 6 data (bold values in Table 3) were utilized for testing. The training and testing data are normalized using Equation 2 for balancing the importance of every constraint. It is recommended that the normalized values lie between 0.1 and 0.9 fairly than between 0 and 1 to avoid saturation of the sigmoid function (Equation 3) thereby leading to relaxed or no learning. Percentage absolute errors between experimental and predicted values are calculated using Equation 4.

$$\text{Normalized value} = \left[\frac{\text{Input value} - \text{Minimum value}}{\text{Maximum value} - \text{Minimum value}}\right] \quad (2); \qquad y = f(x) = \frac{1}{1+e^{-x}} \quad (3)$$

$$Percentage\ absolute\ error\ = \{Experimental\ value - Predicted\ value | Predicted\ value\} \quad (4)$$

In this research, overseen learning was employed and the teaching of the ANN was done using the neural network tool box utility accessible in the MATLAB R14 software. The multilayer feed forward neural network construction entails 4 neurons in the input layer, and only one neuron in the output layer (material removal rate). The neural network construction consists of the number of layers, neurons in every layer and how the layers inter connected. The neuron architecture was resolved using a trial-and-error approach. One concealed layer with 10 neurons shown in Figure 3 was engaged in the current work.

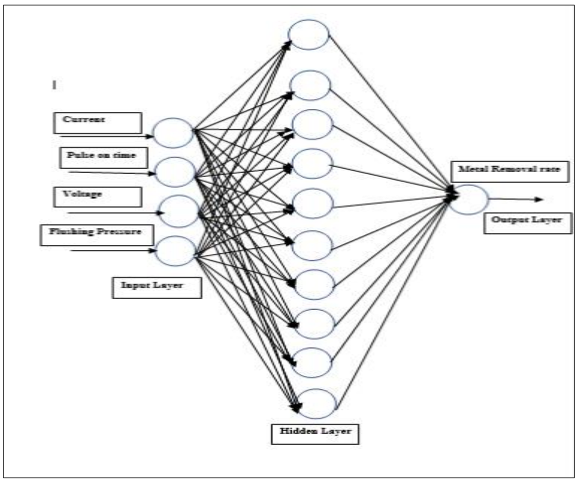

Fig. 3 Neural Network Architecture

The following learning factors were used as inputs for the neural network:
Number of input neurons: 4
Number of layers: 3
Number of output neurons: 1
Number of hidden neurons: 10
Weight initialization: Random weight initialization
Learning rate (η) = 0.04
Momentum constant (α) = 0.85
Minimum number of epochs = 1500
Error function: Mean square error function
Learning rule for training constraints: Back propagation

RESULTS AND DISCUSSION

Microstructure of spark erosion machined composite surfaces: Microstructures of the sparks erosion machined composite specimen's surface are shown in Figure 4a-b. The electric sparks strike the of the composite material's surface more hugely when the release current rises from 3A to 15A. In turn, the diameter and the depth of craters increase, and surface roughness also surge. Generally, at low liberation energies the craters are thin, and at high liberation energies the craters are cavernous. When there is an increase in flushing pressure, the debris scattered over the surface exhibits increased rate of solidification. The similar observation was reported by the earlier investigators Mandal et al., [2007] and Pramanik [2014], as they carried out studies on spark erosion machining of aluminium composites.

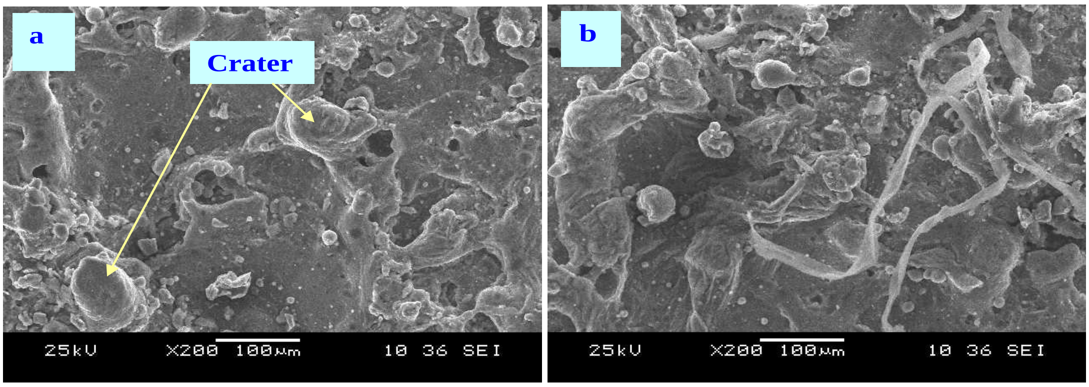

Fig. 4ab: SEM photograph of spark erosion machined surface of Al 6061 composites reinforced with SiC and graphite particles at a voltage 50V and a flushing pressure 3psi: a) 3A,400μs, b) 15A,400μs

Artificial Neural Network (ANN) modelling: A multilayer perceptron neural architecture has been developed with one concealed layer amongst the I/O layers. Single unseen layer is adequate for back-propagation neural web to outline the I/O charting. The number of neurons in the input layer and the output layer are based on the input and output constraints. The network model was taught using a feed forward back propagation algorithm. Patel et al., [2010] was used absolute error percentage was employed to appraise the presentation of the developed neural network model. It was detected that experimental and projected values of the material removal rate are very near to each other, in this study. The same observation was observed by the previous researcher Thillaivanan et al., [2010], who also developed ANN model to study the spark erosion machining characteristics. Figure 5 represents the error profile of material removal rate mutually for teaching and analysis data and the maximum proportion of error was estimated as 3.74 %. The errors due to experimental variation were found to be much higher than these levels of error. It was also perceived that the maximum and minimum total proportion errors of 3.04% and -3.53 % respectively, were attained for material removal rate prediction of the trained data. For the test data, it could be detected that a highest and least total proportion error of 3.74 % and -2.79 % respectively. Figure 6 and 7 shows the assessment of the experimental and predicted material removal rate for the teaching and recording data. From this graph, it could be plainly perceived that, the established neural network model was appropriately taught and also revealed consistent material removal rate values. The scatter diagram of trial and expected values of material removal rate for training and testing data is shown in Figure 8 and 9. It could also be clearly seen that the foreseen values of material removal rate are lying closer to the conforming trial values. These results obtained from the error profile graph and scatter diagram point out that, the well taught suggested network model has good precision in predicting the material removal rate through spark erosion machining of aluminium alloy AA 6061 hybrid composites.

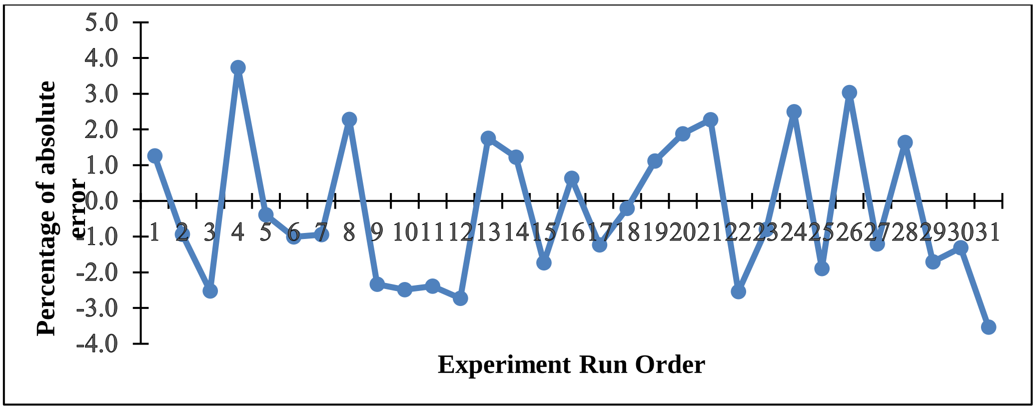

Fig.5 Error profile of material removal rate for training and testing data

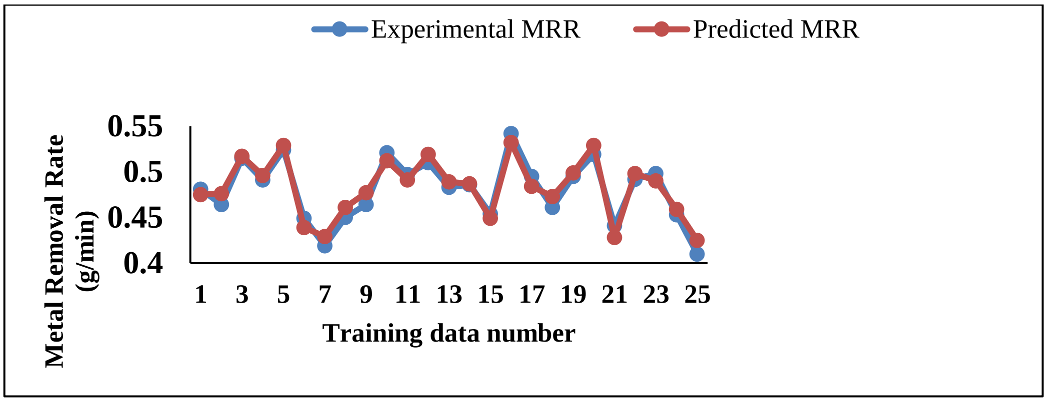

Fig.6 Comparison for the training data of metal removal rate

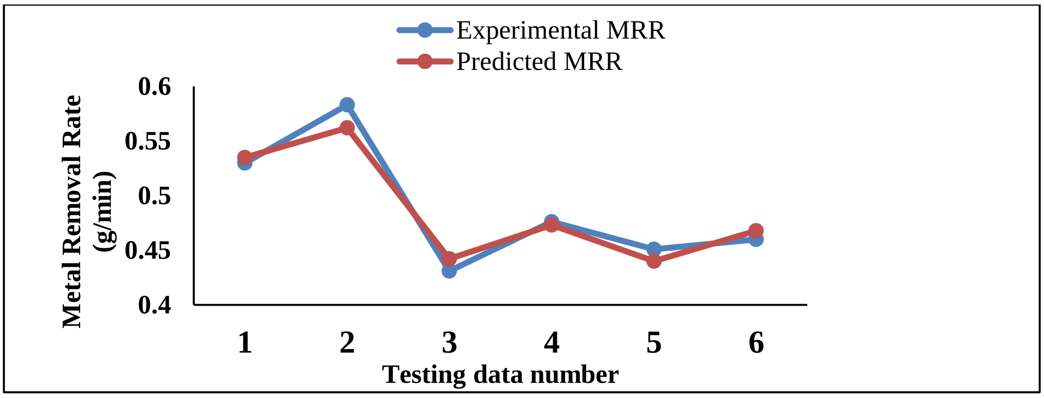

Fig. 7: Comparison for the testing data of metal removal rate

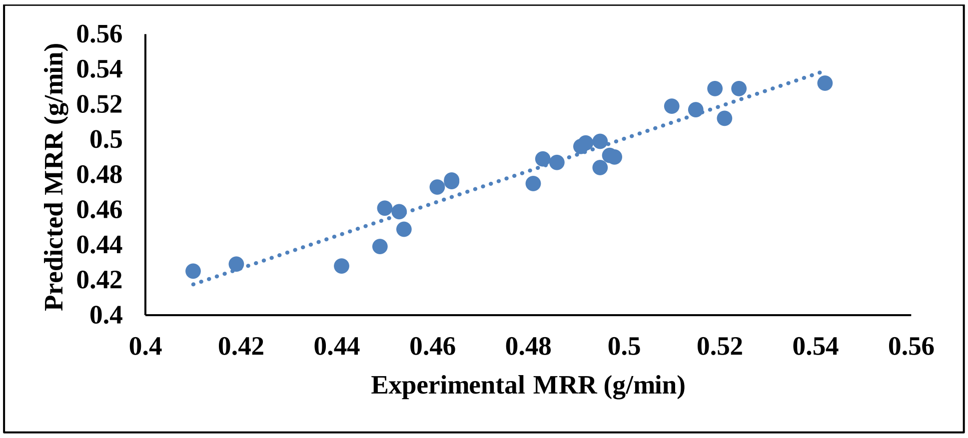

Fig. 8: Scatter plot for the training data of metal removal rate

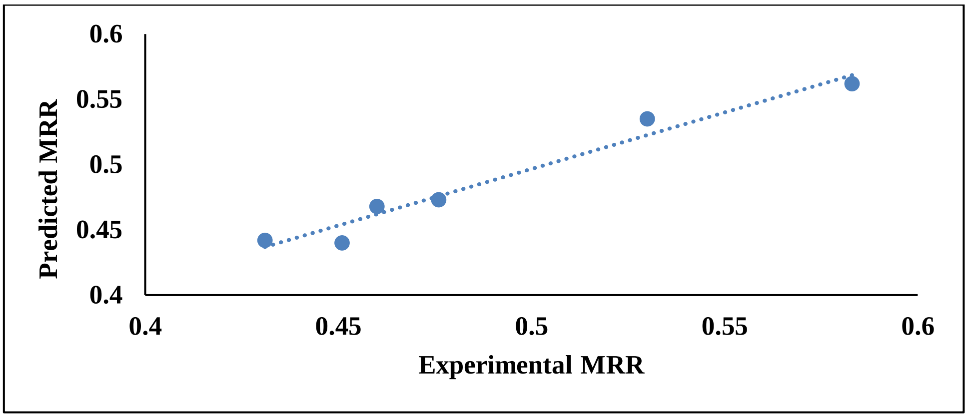

Fig. 9: Scatter plot for the testing data of metal removal rate

CONCLUSIONS

The following conclusions were drawn from the present investigations after conducting the machining studies on aluminium hybrid composites and the subsequent development of the neural network model:

- Aluminium hybrid composites were made-up using the stir casting method and machining studies were carried out using die sinking electric discharge machine.
- A multi-layer feed forward ANN taught by error back-propagation algorithm was used to develop the model to predict material removal rate.
- SEM micrographs of the spark erosion machined composite surface revealed that the plasma channel caused detachment of the reinforcements, by melting and drying up of the matrix material.
- The experimental values and predicted values were very closer to each other. Hence the experimental and ANN results obtained were in agreement. Henceforth, it could be stated that ANN could be effectively employed as a prediction method during machining of aluminium hybrid composites.

REFERENCES

Balasubramanian P. and T. Senthilvelan, Optimization of machining parameters in EDM process using cast and sintered copper electrode, Elsevier, Procedia Materials Science 6: 1292-1302 (2014).

Debaprasanna Puhan, Siba Sankar Mahapatra, Jambeswar Sahu, Layatitdev Das, A hybrid approach for multi-response optimization of non-conventional machining on AlSiCp MMC, Journal of International Measurement Confederation – Elsevier 46: 3581-3592 (2013).

Garg, M.P., Jain A. and G. Bhushan, Modeling and multi objective optimization of process parameters of WEDM using non-dominated sorting algorithm, Proceedings of Institution of Mechanical Engineers, Part B, Journal of Engineering Manufacture 226: 1986-2001 (2012).

Hassan A.M., Alrashdan, A., Hayajnesh, M.T. and A.T. Mayyas, Prediction of density, porosity and hardness in aluminium-copper based composite materials using artificial neural networks. Journal of Materials Processing Technology 209: 894-899 (2009).

Kannan T. and N. Murugan, Effect of flux cored arc welding process parameters on duplex stainless steel-clad quality, Journal of Materials Processing Technology 176: 230-239 (2006).

Markopoulos A.P., Manolakos, D.E.and N.M. Vaxevanidis, Artificial neural network models for the prediction of surface roughness in electrical discharge machining, Journal of Intelligent Manufacturing 19: 283-292 (2008).

Mandal D., Pal, S.K. and P. Saha, Modeling of electrical discharge machining process using back propagation neural network and multi-objective optimization using non-dominating sorting genetic algorithm-II. Journal of Materials Processing Technology 186: 154-162 (2007).

Nilesh Ganpatrao Patil and P.K. Brahmankar, Determination of material removal rate in wire electro-discharge machining of metal matrix composites using dimensional analysis. International Journal of Advanced Manufacturing Technology 599- 610 (2010).

Paramanantham Hema Prabha1 and Thottiam Vasudevan Ranganathan, Modelling and optimization of cassava starch-based film for food packaging applications, Pak. J. Biotechnol. 14: 571-586 (2017).

Patel K., M. Pulak M. Pandey and V.P. Venkateswara, Optimization of process parameters for multi-performance characteristics in EDM of Al_2O_3 ceramic composite. International Journal of Advanced Manufacturing Technology 137-1147 (2010).

Paulo Davim, J., Gaitonde, V.N. and S.R. Karnik, Investigations into the effect of cutting conditions on surface roughness in turning of free machining steel by ANN models. Journal of Materials Processing Technology 205: 16-23 (2008).

Pramanik A., Developments in the non – traditional machining of particle reinforced metal matrix composites. International Journal of Machine Tools and Manufacture – Elsevier 86: 44-61 (2014).

Rao G.K.M. and D.H. Rao, Hybrid modeling and optimization of hardness of surface produced by electric discharge machining using artificial neural networks and genetic algorithm, ARPN J of Engineering and Applied Sciences 5: 72-81 (2010).

Raut T. and M. Shinde, A review on optimization of machining parameters in EDM, International Journal of Innovative Research in Science, Engineering and Technology 4(3): 893-896 (2015).

Ramezan Ali Mahdavi Nejad, Modeling and optimization of Electrical Discharge Machining of SiC parameters, using Neural Networks and Non-dominating Sorting Genetic Algorithm, Material science and applications 2: 669-675 (2011).

Sasikala, E., Radha R., Sharanya S. and M. Gayathri, Artificial Neural Networks with vertical hand off prediction based on user behavior. Pak. J. Biotechnol. 15: 89-93 (2018).

Surappa M.K., Aluminum matrix composites: challenges and opportunities. Sadhana (28): parts 1& 2: 319-334 (2003).

Shashikant, Apurba Kumar Roy and Kaushik Kumar, Effect and optimization of various machine process parameters on the surface roughness in EDM for an EN 19 material using response surface methodology. Procedia Materials Science 5: 1702-1709 (2014).

Thillaivanan A, P. Asokan, K.N. Srinivasan and R. Saravanan, Optimization of operating parameters for EDM process based on the Taguchi Method and Artificial Neural Network. International Journal of Engineering Science and Technology 2: 6880-6888 (2010).

Tsai K.M. and P.J. Wang, Prediction on surface finish in electrical discharge machining based upon neural network models. International Journal of Machine Tools Manufacture 41: 1385-1403 (2001).

Velmurugan C., Subramanian R., Thirugnanm S., Kannan T. and B. Anandavel, Experimental study on the effect of SiC and graphite particles on weight loss of Al6061 hybrid composite materials. Journal of Tribology and Surface Engineering 2: 49-68 (2011).