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 different 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 aluminium 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 Senthivelan [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 betw-
een 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, it is very important to eradicate moisture. The heated aluminium was degassed at a temperature of 1063 K. When pouring, the temperature was kept at 873 K. The mould was then cooled down and the cast composites were detached from it.

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>
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<th>Element</th>
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<th>Cu</th>
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**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 Brahmkar [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 dielectric fluid. 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](image)

**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

<table>
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<th>Machining constraints</th>
<th>Symbols</th>
<th>Unit</th>
<th>Level</th>
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<tr>
<td>Peak current</td>
<td>I</td>
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<td></td>
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<tr>
<td>Discharge time</td>
<td>T</td>
<td>μs</td>
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<td></td>
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</table>

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,

\[
MRR = \left[ \frac{W_{mf} - W_{mf'}}{t} \right]
\]

(1)

where, weights of the composite specimens afore and afterward machining are \(W_{mf}\) and \(W_{mf'}\), 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

<table>
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<tr>
<th>Run order</th>
<th>Std. Order</th>
<th>Peak current (I) A</th>
<th>Discharge time (T) μs</th>
<th>Voltage (V) V</th>
<th>Flushing pressure (P) psi</th>
<th>Experimental Value MRR (g/min)</th>
<th>Predicted Value using ANN MRR (g/min)</th>
<th>Absolute percentage error (%)</th>
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**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.

\[
\text{Normalized value} = \left[ \frac{\text{Input value} - \text{Minimum value}}{\text{Maximum value} - \text{Minimum value}} \right]
\]

\[ (2) \quad y = f(x) = \frac{1}{1 + e^{-x}} \]

\[ (3) \]

\[ (4) \]

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 num-

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ber 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](image1)

![Fig.6 Comparison for the training data of metal removal rate](image2)

![Fig. 7: Comparison for the testing data of metal removal rate](image3)
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


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