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An Integrated Approach To Optimize Parameters In Electrochemical Machining Process

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Abstract

Application of metal matrix composites (MMCs) in aerospace and automobile sectors by replacing conventional alloy materials is mainly slowed down by their difficult to machine nature. In this work an attempt is made to apply electrochemical drilling of silicon carbide reinforced, stir cast, aluminium matrix composite material. 54 trial runs are made on an electrochemical setup following statistical experimental design procedure Factors namely applied voltage, electrolyte concentration, electrode feed rate and amount of reinforcement are chosen as controllable factors and the material removal rate is calculated. To establish the relation between input variables and out response a multilayer artificial neural network with feed forward back propagation technique is employed. Data are divided into training data and testing data. The predicted output of the trained network showed a close matching with the experimental data and exhibits an average prediction error of 6.48%. The trained neural network is then integrated with a software optimizing tool to maximize the material removal rate.

Keywords: Composites; neural network; optimization; direct search

1. Introduction

Particulate reinforced metal matrix composites find most of their applications in automobile and aerospace industries where their high strength to weight ratio provides a weight saving alternative to conventional materials. Though metal matrix composites (MMCs) are manufactured with different methods, stir-cast composites are commercially more advanced because of low cost. But the tendency of the hard and abrasive particles, used as reinforcement, poses machining difficulty. In machining MMCs, different tooling with variety of materials and coating are tried with conventional methods and non conventional machining techniques like electro discharge machining (EDM), abrasive jet machining (ABM) and laser machining (LM) are found in literature [1, 2]. From these studies it is understood that EDM produces relatively low sub surface damage to the work material whereas ABM results with slotted edge damage and more likely suitable for only rough cuts while LM causes significant thermal induced micro structural changes in the machined surface. Thus, a need exists for a method and apparatus which provides a means for machining MMCs having hard and abrasive particulate together with a soft metal matrix. Electrochemical machining (ECM) is a non-conventional machining technique that can overcome these difficulties.

It is reported that the ECM process, in which the metal removal is due to ion displacement, can be applied to machine MMC[3]. But so far there is no appealing methodology presented to predict the metal removal rate in electro chemical machining for various reinforcement volumes. Since the process involves too many variables and that too the work material is a composite material, the theoretical relations will not hold good in predicting the output with reasonable accuracy. Moreover the complexity and non-linear nature of the process warrants the need for a non-traditional technique to model the data. Artificial neural network (ANN) which is applied to various kinds of industrial problems is now seems to be a reliable non traditional technique in modeling. In Ref. 4 the authors have applied ANN for modeling in machining discontinuously reinforced AMC. The usefulness of ANN in predicting the heat of pig iron in a steel plant is also dealt by Ref. 5. Similar research works carried out by various researchers[6, 7, 8] prove the ability of ANN in being a good modeling technique. Hence, in this paper, ANN with back-propagation algorithm is applied to develop a model with the data obtained and the trained model is integrated with an optimization technique.[1]

The methodology is illustrated by the following flowchart.

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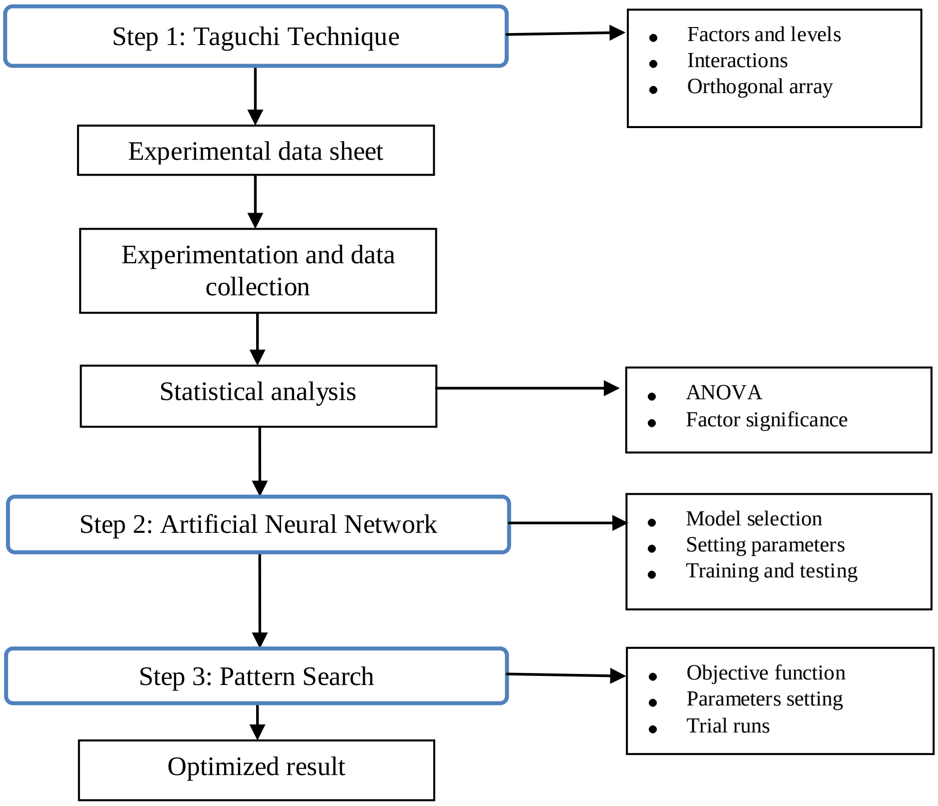

Fig. 1 Flowchart showing integration of various techniques

2. Experimentation

Metal matrix composites can be produced by different methods but liquid state route is an easy production route for manufacturing particle reinforced aluminium alloys that require metal mixing or stirring. Experiments as per Taguchi's orthogonal array design are conducted with an *EC MAC-II ECM* electrochemical machining set up.

2.1. *MMC preparation*

Aluminium matrix composite work materials are prepared with A356 aluminium alloy (Refer Table 1 for chemical composition) reinforced with 5%, 10%, and 15% SiC by wt using stir cast method. The modified method of preparing composite materials[9] has shown that preheating of reinforcing particle decreased the porosity occurrence in the solidified castings for a total of 68%. The aluminium alloy is heated at 800 ºC for 90 minutes and the preheated silicon carbide powder at 1000 ºC is mixed into the molten alloy. The mixing is carried out at 225 rpm for 15 minutes through mechanical stirrer. The mixture is poured into a pre heated (350 ºC – 400 ºC) steel die and castings of ϕ 25 mm x 150 mm are prepared.

Table 1. Composition of A356 aluminium alloy

Constituents	Cu	Si	Mg	Mn	Fe	Ni	Ti	Zn	Pb	Sn	Al
Percentage	0.08	7.08	0.52	0.12	0.36	0.005	0.054	0.014	<0.002	0.015	balance

2.2. *Machining*

ECM is an appreciable choice where high material removal is needed from high strength alloys of difficult to cut nature. In ECM process usually work piece behaves as anode as the material removal should take place and electrode as cathode. Copper, being the good conductor of electricity and heat, is the common electrode material. The electrolyte is any organic solutions that is electrically conductive and a means is provided to flow the pressurized electrolyte in the inter electrode gap. The gap between electrode and work material surface is maintained as 0.3 mm. This small distance, while the tool advances during machining may produce sparking in the presence of debris and can be avoided by allowing a flow rate more than 3 lpm[10].

Table 2. Factors and levels used in experiment based on Taguchi's method

Factors / Levels	**Applied voltage** (V)	**Electrode feed rate** (mm/min)	**Electrolyte concentration** (gpl)	**Amount of reinforcement** (% wt)
1	5	0.2	50	15
2	10	0.4	100	10
3	15	0.6	30	5

Among numerous ECM process parameters, applied voltage, electrode feed rate and electrolyte concentration are chosen based on the literature[11, 12]. The volume fraction of reinforcing particles as fourth factor is included upon authors' intuition. Experiments are planned according to the Taguchi's L_{27} orthogonal array as his parameter design is widely used in conducting and analyzing experiments for optimization. The method helps in reducing cost, material, and time in conducting experiments and makes the process robust i.e., least sensitive to uncontrolled factors involved in experimentation. The levels of the selected factors are detailed in the Table 2. The columns of L_{27} (3^{13}) orthogonal array are assigned with factors and interactions from corresponding linear graph. Two replications for each run are conducted with a machining duration of 10 minutes per run.

2.3. *Modeling*

In training the neural network, back propagation algorithm; which is built on high mathematical foundation, is a systematic approach that has very high application potential. The method was successfully applied for a wide range of industrial problems. Using only one input and output layers is capable of solving problems of very simple nature and in most of the cases a single hidden layer is capable of producing good results. A typical structure of the ANN system is illustrated in Figure 2**.** The number of neurons used in the hidden layer is finalized based on trial and error method and for our experimental data it is found that hidden layer with 7 neurons structure produced the least mean square error (MSE) of 1.378E-03. The error curve of MSE is obtained with learning rate of 0.9 and a momentum coefficient of 0.9

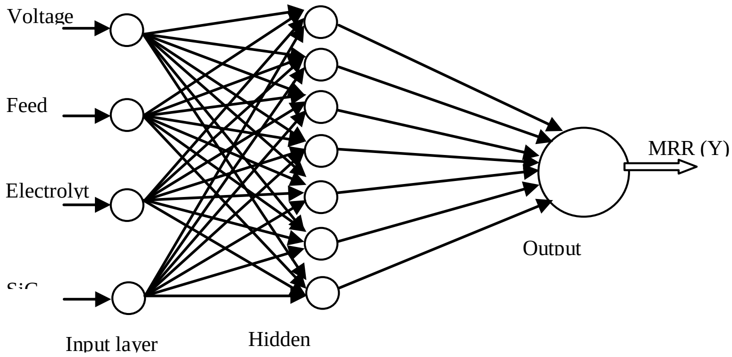

Fig. 2 Developed artificial neural network structure

2.4. *Pattern search method*

A comparison between simple genetic algorithm and pattern search is presented by Ref 14. Upon trying these methods with three different optimization problems, they have concluded that both the methods are good in optimizing their objective of cost reduction. Most of the traditional optimization methods need information about the gradient or higher derivatives to search for an optimal point. But in pattern search, no information about the gradient of the objective function is required. The algorithm looks for an objective function that is lower than the value at the current point, by searching around the current point. The working strategy of the pattern search technique is given as step by step procedure in the next section.

2.4.1. *Algorithm of pattern search*

- Input the start point vector of length equal to number of independent factors (n)
- Calculate new points by adding the start point to all possible combinations of the input vector (2n or n+1) which are multiplied by the mesh value for that iteration (which is 1 by default)
- Determine the objective functions with all these new points
- Poll the vector corresponding to minimum objective function value as start point fornext iteration
- In any iteration, if the objective function value obtained is smaller than the previous one, the poll is called successful and the current mesh value is doubled for next iteration or otherwise the value gets halved
- Steps 2 to 4 are repeated until the stopping criteria is met

By performing the above procedure the algorithm, finally, is able to minimize the given objective function, say f(x). For maximization problems the value of objective function can be taken as g(x) = - f(x)

3. Results and Discussions

The work material is weighed before and after machining to determine the weight of metal removed during each run. Every trial is repeated once and this is carried out at random manner in order to avoid any experimental bias. Observations are tabulated as in Table 3 in which the output response, the metal removal rate, is indicated by Y**.** To calculate signal-to-noise (S/N) ratio, Taguchi's higher the better characteristic[15] is used. ANOVA table for mean S/N ratio helps (Table 3**)** to identify the influencing variables (F values marked with *).

Table 3. Analysis of variance for mean S/N ratio

Symbol	**Parameters**	**SoS**	**dof**	**MSS**	**F**	**Cont**
A	Voltage	17.52	2	8.76	53.72*	**14.1**
B	Feed rate	49.28	2	24.64	151.15*	**40.1**
C	Concentration	31.96	2	15.98	98.02*	**25.9**
D	SiC %	12.57	2	6.28	38.54*	**10.0**
AxB	Interaction	2.95	4	0.74	4.52*	**1.9**
AxC	Interaction	0.83	4	0.21	1.28	**0.1**
BxC	Interaction	1.21	4	0.30	1.86	**0.5**
AxD	Interaction	0.91	4	0.23	1.39	**0.2**
e	Error	4.73	29	0.16		**7.1**
Total		121.96	53			**100.0**

* - $F_{0.05}(2, 29) = 3.33$ and $F_{0.05}(4, 29) = 2.70$

3.1. *Prediction of metal removal rate*

A multi layer ANN model is developed using MATLAB 7 software. Back propagation with a momentum factor is advantageous when some training data are different from the majority data. The total of 54 MRR values (27 trials with each two replica) is randomly divided into two groups. First group, used to train the net, is formed with 36 of the total data and second group, comprising of remaining 18 data is used to test the trained model. By doing so the network's ability in computing the output value (MRR) is tested with completely new inputs. From the graphical representation of computed and actual values (Figure 3) it is obvious that the MRR values derived from the trained ANN system are closely matching with the experimental values. From this comparison, the maximum, minimum and average percentage of prediction accuracies are calculated and known to be 13.13%, 0.89% and 6.48% respectively. This can still be improved by training the ANN system with more number of experimental results.

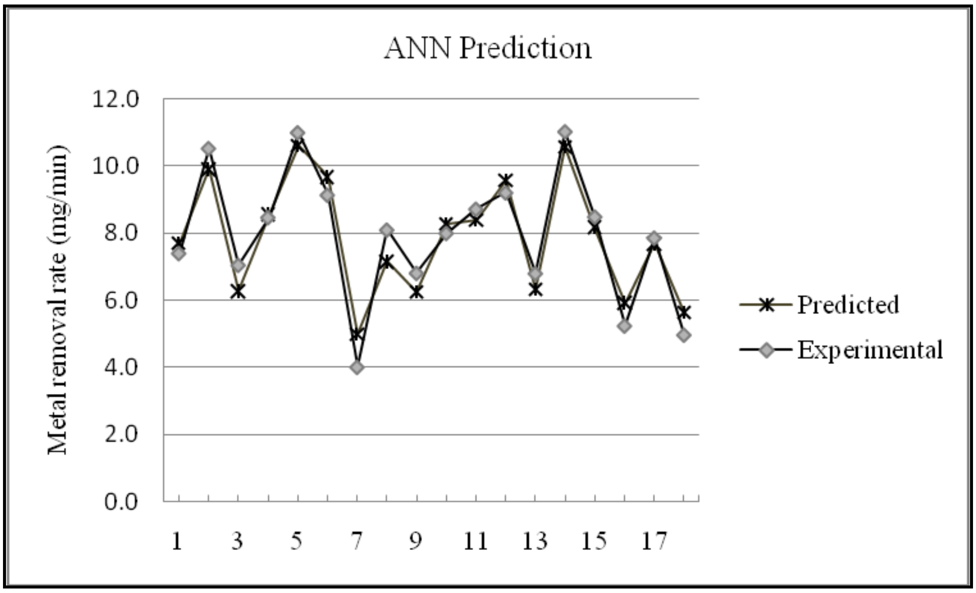

Fig. 3 Comparison of the predicted values with experimental values

3.2. *Optimization with pattern search*

When optimization is done using neural network, almost all the approaches are made to optimize the weights of the interconnected neurons. In our paper, maximization of metal removal is attempted by optimizing the parameters directly. This is done by interlinking neural network and pattern search algorithm tool boxes of MATLAB 7. The objective function used is a Matlab file that calls the output of trained neural net. The start point vector is selected randomly and after several trials the optimized function value is attained.

From the Figure 4, the best normalized function value achieved by the algorithm is 0.97675 (maximization) which on denormalization is 14.85 mg/min. The corresponding values of independent variables that results with this metal removal rate are as follows:

Applied voltage	: 20 V
Electrode feed rate	: 0.195 mm/min
Electrolyte concentration	: 121 gm/lit
Content of SiC	: 5.8%

Thus the integration of ANN and pattern search algorithms seems to be better methodology which could be used for optimization problems.

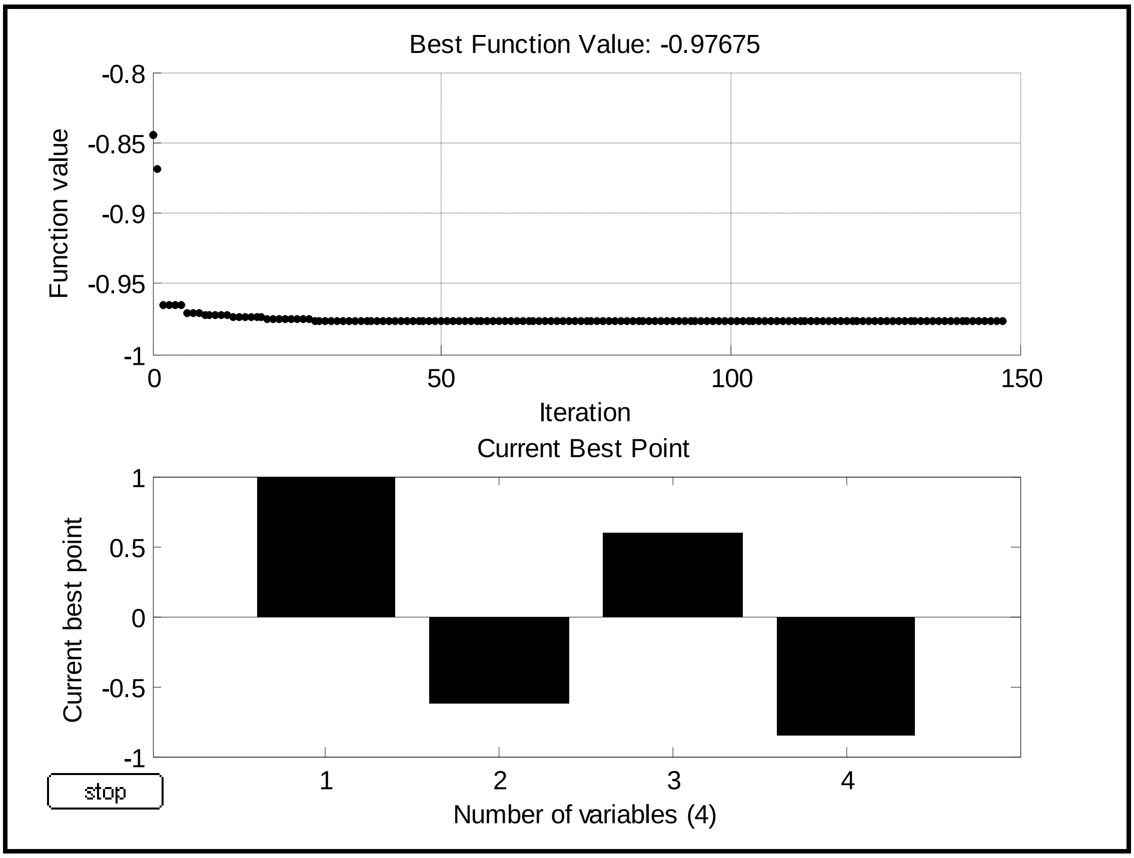

Fig. 4 Graph showing normalized values of objective function value and parameters

4. Conclusion

Electro chemical machining seems to be successful in machining SiC particulate reinforced A356 aluminium matrix composite material. Experiments are conducted based on Taguchi's parametric design to reduce the cost and time involved in gathering meaningful data set. Using MATLAB 7 software, an artificial neural network with back-propagation algorithm is trained to predict the output when presented with an input pattern. From the same software an optimization tool that used direct search technique is successfully applied. The outcomes of this research are summarized as follows:

- ✓ In addition to all the three process parameters used in this study, amount of reinforcement also influences the metal removal rate in machining particulate reinforced aluminium matrix composites
- ✓ ANN system is developed using feed forward-back propagation network and the predictions made by the trained model has very good agreement with experimental data
- ✓ The pattern search algorithm can be successfully integrated with neural network to maximize the metal removal rate

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