Machining Parameter Optimization Of Al/Sic$_p$ Composite Materials Using Genetic Algorithm

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Abstract: Composite materials have received potential applications in different fields. The major problem encountered during the machining of composite materials is the flank wear and surface roughness. For this study, metal matrix composite material namely Al/SiCp was considered. Mathematical modeling and experimentation results on the effect of wear and surface roughness were presented. In this work, genetic algorithm has been used for machining parameter optimization. On comparing the results produced from genetic algorithm model and mathematical modeling, the results of genetic algorithm model were found to be more accurate and nearer to the experimental values.

Keywords: Metal matrix composites, Machining Parameter, Optimization, Genetic Algorithm.

1. INTRODUCTION

Particulate reinforced Al- metal matrix composites is one which have SiC particles with aluminum matrix. These composites are rapidly replacing conventional materials in various automotive, aerospace and automobile industries [Allison et al. (1993)]. However, usage of composites in those applications is limited because of the difficulties in the machining [Cronjager et al. (1992)]. The presence of hard ceramic particles makes them difficult to machine as they lead to rapid tool wear [Davim et al. (2000)]. The machining parameters like speed, feed and depth of cut are influencing more in the tool wear and the surface roughness [Manna et al. (2003)]. Monaghan et al. (1994) studied the wear behaviour of carbide tools during the machining of 25% SiC at speed below 20 m min-1. Tomac et al. (1992) developed a tool life relationship for carbide tools during the machining of Al/SiC at speed lower than 100 m min-1. Ibrahim et al. (2004) concluded that the percentage volume of SiC and cutting speed are found to be the major factors affecting the tool wear. Gallab et al. (1998) stated the tool wear has direct relationship with cutting speed and indirect relationship with feed. In addition to the tool wear, machining produces poor surface finish due to build up edge formation [Manna et al. (2002)]. Further, Manna et al. (2005) recommended the machining parameters of high speed, low feed rate and low depth of cut for achieving better surface finish. Even though various researchers' focuses on the parameters studies on tool wear and surface roughness, effective optimization for the proper selection of parameters based on the required output need to be attended.

Hence in this investigation, in addition to the mathematical modeling, evolutionary optimization technique Genetic Algorithm (GA)is used for optimizing the machining parameters for tool wear and surface roughness. Many researchers have studied the effects of cutting tools and machining parameters on tool wear for example, Chou et al. (2002), Ozel et al. (2005) and many others.

Solving multi-objective problems with traditional optimization methods is very difficult and time consuming. Therefore evolutionary algorithms such as genetic algorithms and particle swarm optimization are more convenient and usually utilized in multi objective optimization problems. These methods are summarized by Zitzler et al. (2003). As for applications of evolutionary algorithms in solving multi-objective optimization problems in machining, studies by Cus and Balic (2003) on metal cutting optimization, Saravanan et al. (2002) on grinding optimization, and Karpat and Ozel (2005) on hard turning optimization, among others, have contributed more on this area.

Even though various researchers focused on the composite materials, a detailed study which combines both theoretical as well as experimental view on process parameters on tool wear and surface roughness need further attention. So the objective of this paper deals about the optimization of machining parameters using neural networks. The performance results are compared and the conclusions are presented.

2. EXPERIMENTAL ANALYSIS

The test specimens (Al/SiCp) were produced using stir casting technique which is the economical one. It consists of a resistance furnace in which metal is melted in the closed environment. The powder is introduced in to the melt through the powder feeder. The melt is stirred thoroughly. Then the molten metal is taken out at the bottom of the crucible and poured in to the mould. The formed billet is re-melted and again shaped casting is made. Green bonded Silicon Carbide particles were used as the reinforcements.

Carbide inserts K10 grade was used for turning operation. The experiment was repeated for the various cutting conditions like % volume of SiC, feed, speed, depth of cut and time of machining. The variables used in this study are given in the Table 1.

Table 1 Selected input variables and Outputs

Sl No	Input Variables	Variations	Output
1	% Volume of SiCp	10, 15, 20, 25 (%)	1. Tool wear 2. Surface roughness
2	Cutting Speed	50, 100, 140 (m/min)	
3	Feed	0.16, 0.32, 0.45 (mm/rev)	
4	Depth of Cut	0.5, 1, 1.5, 2 (mm)	
5	Time of Machining	5, 10, 15 (min)	

After each experiment, the tool insert was removed from the tool holder and the tool wear was measured using low magnification microscope. For required magnification, specified eye piece is selected (5x, 10x, 20x, 50x) and then the distance between the eye piece and tool is adjusted until to get the clear image of tool wear and the micrometer scale is fixed vertical to the width of the wear land. From the scale the width of wear land is measured and tabulated.

The surface roughness was measured using Taly-Surf tester. It is a contacting probe type surface tester, in which a stylus is moved along the work piece. The peaks and valleys of the specimen can be accurately found out from the upward and downward movements of the stylus. The average roughness value can be measured from this instrument.

2.1. Effect of parameters on Flank Wear

The figure 1(a) shows the effect of percentage volume of SiC on Flank wear. As expected, the percentage volume of the SiC particles showed their impact on tool wear. The flank wear, increases with increases in % volume of SiCp. When the SiC particles are fed while casting process, due to the dispersion hardening effect the possible dislocation movements in the Aluminium are restricted. So basically the hardness of the matrix improved. The tool which produces the compressive stress to the specimen on turning, need to exert more force to move the dislocations. This could be the reason why the tool wear increases with the percentage volume of particles.

The Effect of cutting speed on Flank wear is shown in figure 1(b). The flank wear increases on increasing the cutting speed. The rubbing area per unit time increase when cutting speed increases. This gives more cutting area experienced by the tool which will be one of the reasons for the increasing tool wear. And also the heat generated in the interface between the tool and work piece is directly proportional to the cutting speed. That interfacial temperature softens the tool material which produces more wear. Adhesive nature at elevated temperatures is also the reasons for the increase in the flank wear.

The effect of feed rate on flank wear is given in figure 1(c). As the cutting edge of the tool encounters the hard particles in the aluminum matrix, these particles chip away tiny flakes of the tool edge. Not like other metals, in metal matrix composite materials, the dispersed hard particles give an impact load when the tool contacted it. When feed rate is increased, residual stresses change from compressive to tensile. This also could be the reason for the increased flank wear. In addition to this the hard particles act as abraders and remove the materials from the flank surface. The increase in feed per tools increases force result in high chip tool interface temperature which also leads to increase in flank wear. The depth of cut plays a vital role in the tool wear. The flank wear is increasing on increasing the depth of cut. Since the tool used is a ceramic material, at elevated temperatures chemical wear becomes a leading wear mechanism and often accelerates weakening of cutting edge, resulting in premature tool failure (chipping), namely edge breakage of the cutting tool (figure 1(d)).

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Figure 1(e) shows the influence of time of machining on flank wear. The increase in time of machining increases the flank wear. The reason could be the increase in the time of contact between the tool and the work piece. As time increases the chip-tool interface temperature will also increase which tend to soften the flank surface of the tool. The rubbing time is also increased which lead to more flank wear due to the adhesion as well as abrasion.

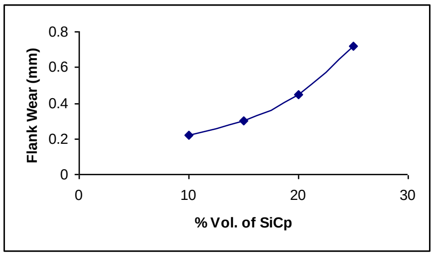


Fig.1(a) Effect of percentage volume of SiC on Flank Wear

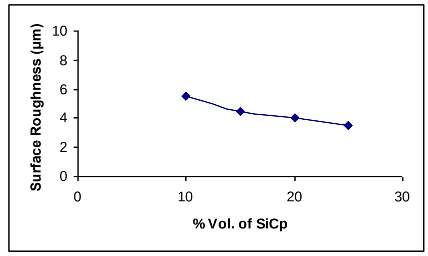


Fig.2(a) Effect of percentage volume of SiC on Surface roughness

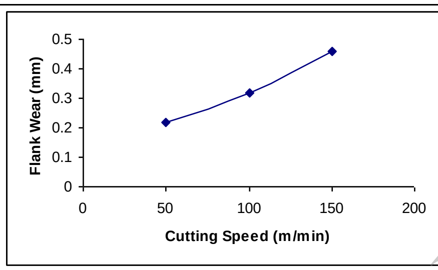


Fig.1(b) Effect of cutting speed on Flank wear

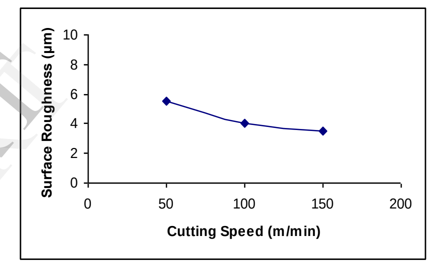


Fig.2(b) Effect of cutting speed on Surface roughness

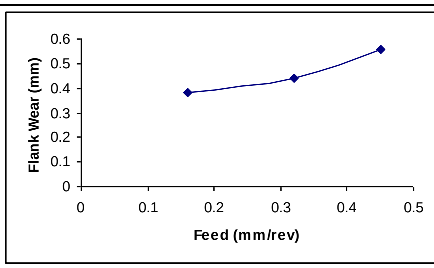


Fig. 1(c) Effect of feed rate on Flank wear

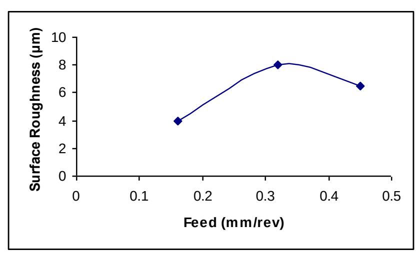


Fig. 2(c) Effect of feed rate on Surface roughness

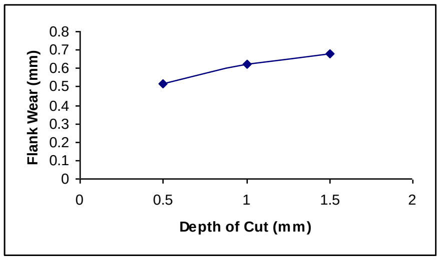
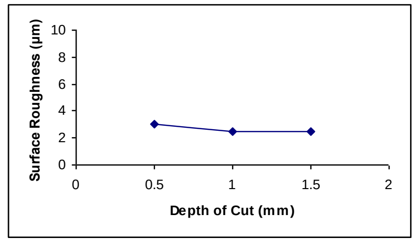
	

Fig. 1(d) Effect of Depth of cut on Flank wear	Fig. 2(d) Effect of Depth of cut on Surface roughness

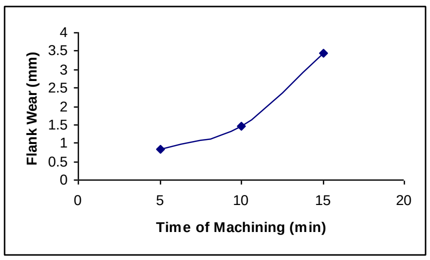
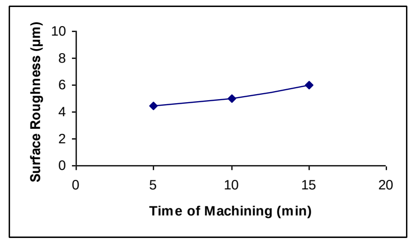

	

Fig. 1(e) Effect of Time of machining on Flank wear	Fig. 2(e) Effect of Time of machining on Surface roughness

2.2. Effect of parameters on Surface Roughness

Surface roughness in machining is depending upon the geometric factors of the operation, work material factors and vibration and machine tool factors. The figure 2(a) shows the effect of percentage volume of SiC on Surface roughness. This figure shows the increase in the percentage volume of SiC, increases the surface finish. The distributions of the SiC particles are uniform because of increase in the percentage volume which in turns gives improved surface finish.

Figure 2(b) shows the influence of cutting speed on the surface roughness. The surface roughness is gradually coming down with the increasing of cutting speed. At high speed, because of the increment in the interfacial temperature the softening of work piece is taking place which give smooth surface. The feed rate on surface finish does not show a proper trend (Figure 2(c)). The surface roughness remains more or less equal for varying depth of cut because of the less variations in the vibration of the lathe (Figure 2(d)). Figure 2(e) shows the effect of time of machining on surface roughness. Increase in time of machining increases the surface roughness, due to wear of tool inserts. As time of machining increases, the formation of build up edge is also producing surface roughness.

3. THEORETICAL ANALYSIS

For the mathematical modeling the basic model which is explaining the influence of various input parameters like percentage volume of SiC, speed, feed, depth of cut and the time of machining on the outputs is used. This basic model is given in equation (1)

$$Y = X * V^{a} * S^{b} * F^{c} * D^{d} * T^{e} \quad (1)$$

Where, 'Y' is the Output response like flank wear and surface roughness, 'V' is the Volume of SiCp, 'S'is the cutting speed, 'F' is the feed, 'D' is the depth of cut and 'T' is time of machining. Where, X, a, b, c, d, e are the constants. These constants are evaluated for each characteristic to develop the models by using SPSS software.

3.1. Mathematical Modeling

From the basic model, as in equation 1, the output 'Y' can be calculated from the parameters namely, percentage volume of SiCp(V), speed (S), feed (F), depth of cut (D) and time of machining (T). In that equation X, a, b, c, d and e are constants. These constants are playing a vital role in predicting the desired output factors like Flank wear and Surface roughness.

Through SPSS software, those constants were found. Mathematical modeling was constructed from the results obtained through the experiments. With the help of the Mathematical modeling the value of flank wear and surface roughness can be found for various inputs. Table 2 shows the result obtained through SPSS software.

The equation (2 and 3) shows the models which are used to find out the flank wear and surface roughness with respect to the input parameters. From the equation (2), for varying input parameters, the flank wear could be predicted. From the equation (3) for varying input parameters surface roughness could be predicted.

$$\text{Flank wear } (y_1) = 0.001 \times V^{0.8985} \times S^{0.1961} \times F^{0.0677} \times D^{0.146} \times T^{1.672} \quad (2)$$

$$\text{Surface Roughness } (y_2) = 373 \times V^{-0.682} \times S^{-0.4851} \times F^{0.5555} \times D^{0.121} \times T^{0.1909} \quad (3)$$

Table 2 Results obtained using SPSS

SOURCE	Flank Wear			Surface Roughness		
	Degree Of Freedom	Sum Of Square	Mean Square	Degree Of Freedom	Sum Of Square	Mean Square
Regression	6	17.381	2.891	6	289.63	48.21
Residuals	9	0.2010	0.022	9	3.37	0.37
Uncorrected total	15	17.581		15	293.0	
Corrected total	14	8.925		14		

Figure 3(a) and 3(b) show the comparison of experimental data with the predicted values of flank wear and surface roughness. From those figures it can be seen that the variation between the experimental and the mathematical values are minimum, so the mathematical modeling can be used for predicting flank wear and surface roughness for the given input values.

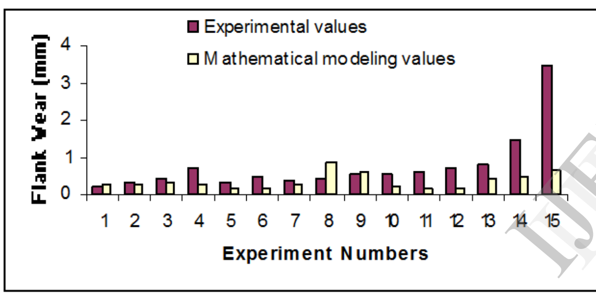


Fig.3(a) Comparison between Experimental and Mathematical modeling results for Flank wear

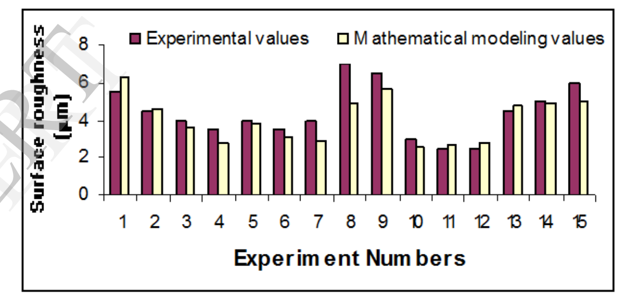


Fig 3(b) Comparison between experimental and Mathematical modeling results for Surface roughness.

3.2. Genetic Algorithm Based Model Development and Result Discussion

Genetic algorithms (Goldberg 1989; Deb 2002) attempt to mimic the properties of natural selection and natural genetics. They combine solution evaluation with randomized, structured exchanges of information between solutions to obtain optimality. They consider a population of potential solutions and then use a defined 'survival of the fittest' technique to produce a new generation of solutions which are hopefully better approximations to the ideal solution. The purpose of selecting GAs is i) uses probabilistic transition rules, not deterministic ones; ii) search from a population of points, not a single point; iii) work on an encoding of the parameter set, not the parameters themselves and iv) use objective function information, not derivatives.

3.2.1. Overview of Genetic algorithm

A chromosome is an encoded string of possible values for the parameters to be optimized. These chromosomes can be made up of real-valued or binary strings. Often one of the main challenges in designing a genetic algorithm to find a solution to a problem is finding a suitable way to encode the parameters. A set of potential solutions, called a population, is created. Each member of this set is referred to as an individual and they are evaluated by decoding the parameter values from the chromosomes and applying them to the problem to see how well they perform the task at hand (the objective that is to be optimized). The score that an individual achieves at performing the required task is called its fitness.

After the fitness of each individual has been calculated, a procedure known as selection is performed. Individuals are selected to contribute towards creating the next generation, the probability of selection being related to the individual's fitness. Once selection has occurred, crossover takes place between pairs of selected individuals. The strings of two individuals are mixed. In this way, new individuals are created that contain characteristics that come from different hereto relatively successfully individuals. A third operation that occurs is mutation, the random changing of bits in the chromosome. It is generally performed with a relatively low probability. Mutation ensures that the probability of searching a given part of the solution space is never zero.

3.2.2. Implementation of Genetic Algorithm

Genetic algorithm derives their power from genetic operators. A Simple Genetic Algorithm (SGA) that yields good results in many practical problems uses the following three genetic operators: i) Reproduction; ii) Crossover and iii) Mutation.

Selection is an essential component of genetic algorithm, since it determines the direction of search where other genetic operators propose new search points in an undirected way. The selection methods includes fitness proportionate selection, tournament selection, rank selection etc. all these methods use genetic operations in one form or another to create new search points. Crossover and Mutation are the two critical operators in which crossover facilitate exploration, while mutation facilitates exploitation of the space. Crossover is a recombination operator. In the crossover operator, new strings are created by exchanging information among strings of the mating pool. Mutation is a background operator which produces spontaneous random changes in various chromosomes.

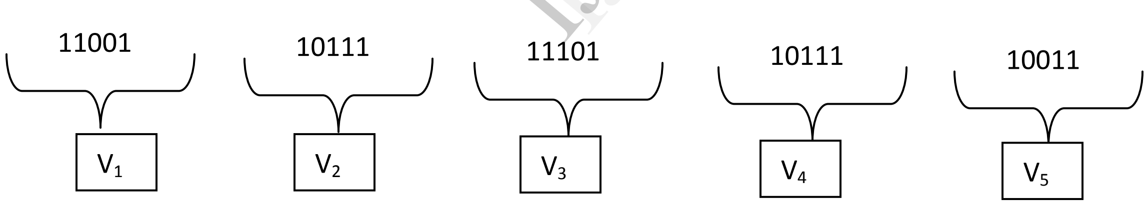
Starting with an initial population, the genetic algorithm exploits the information contained in the present population and explores new individuals by generating offspring using the three genetic operators which can then replace members of the old generation. Fitter chromosomes have higher probabilities of being selected for the next generation. After several generations, the algorithm converges to the best chromosome, which hopefully represents the optimum or near optimal solution.

When applying GA's to solve a particular optimization problem, two main issues must be addressed.

i) Representation of the decision variables

ii) Formation of the fitness function

While solving an optimization problem using GA, each individual in the population represents a candidate solution. In the binary-coded GA, the solution variables are represented by a string of binary alphabets. For problems with more than one decision variables, each variable is usually represented by a sub-string.



In GA, there are two ways to generate the initial population namely random initialization and heuristic initialization. All the control variables are represented as binary strings in the GA population. The length of the binary strings is based on their actual value to obtain accurate solution. Using random initialization method, the binary strings are randomly generated as follows.

In this problem, the objective is to minimize the error while satisfying the constraints. The objective function (FT) is given in equation (1). Generally, GA searches for a solution with

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maximum fitness function value. Hence, the minimization objective function is transformed into a fitness function (ft) to be maximized as $f = \frac{1}{1+F_T}$

3.2.3. Simulation Results

The proposed algorithm was run with an objective of minimization of error. In this study, two different cases namely i) Wear and ii) Surface roughness were considered and run the algorithm under all the cases. The proposed model was implemented in MATLAB with the following parameter setting, as given in Table 3.

Table 3 GA parameter setting

Parameter Setting criteria	CASE I	CASE II
Population Size	30	30
Crossover Probability	0.9	0.8
Mutation Probability	0.01	0.08
Tournament Size	2	2

The optimal values of the control variables obtained by using the proposed genetic algorithm are presented in the Table 4 and it was found that all the variables corresponding to these control variables satisfy their limits which are given in the Table 1. The value of the error obtained is also less than the value reported in the Table 2 for all the cases.

Table 4 Control variables obtained using GA

Control Variables	CASE I	CASE II
Percentage volume of material (%)	10	25
Speed (m/min)	100	135
Feed (mm/rev)	0.16	0.16
Depth of Cut (mm)	0.5	1
Time of machining (min)	5	6

4. CONCLUSION

Metal matrix composites are widely used in many applications due to their special characteristics. In this paper, Al/SiCp was selected and an attempt has been given to optimize the machining parameters using intelligent techniques. Mathematical modeling was developed through SPSS software. Experimentation results on the effect of wear and surface roughness were presented and discussed. GA based approach for optimizing the machining parameters of Al/SiCp composites. Verification experiments are conducted to prove the stability and reliability of the modeling and optimization.

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