Optimization through NSGA-II during machining of A356Al/20%SiCp metal matrix composites using PCD Tool

M. Seeman\textsuperscript{a*}, D. Kanagarajan\textsuperscript{b}, P. Sivaraj\textsuperscript{c}, R. Seetharaman\textsuperscript{d} and A. Devaraju\textsuperscript{e}.

\textsuperscript{a, b, c} Department of Manufacturing Engineering, Annamalai University, Annamalainagar - 608 002, Tamilnadu, India.
\textsuperscript{d} Department of Mechanical Engineering, University College of Engineering, Anna University, Dindigul - 624 622, Tamilnadu, India.
\textsuperscript{e} Professor, Department of Mechanical Engineering, Adhi College of Engineering and Technology, Kanchipuram-631605, Tamilnadu, India.

\textsuperscript{*} Corresponding author Email: mfgseeman@gmailmail.com, seeman\_au575@rediffmail.com

Abstract

Metal matrix composite (MMC) has established growing usages in the engineering for lightweight high-strength application. However, because of abrasive nature of the reinforcement particles in MMC, machinability is reduced, tool wear is high, yet only diamond tools are appropriate for machining MMC. Being a complex process, it is very complicated to establish optimal parameters for improving cutting performance. Tool flank wear ($V_{B\text{max}}$) and Average surface roughness ($Ra$) are the most significant output responses, which decide the machinability of a material. The effect of cutting parameters on output responses of tool flank wear and average surface roughness are conflict with each one another so there is no single optimal mixture of cutting parameters. In this study multi regression model function, based on NSGA-II was used to optimize the machining of Al/20%SiCp MMC using tipped polycrystalline diamond (PCD) tool and also characterize the relationship among input parameters and output performance. The NSGA-II based non dominated solutions of 30 combinations chosen from 100 and presented; none of them superior to any other each and every one are best based on engineer requirement.

Keywords: metal matrix composite (MMC); tool flank wear ($V_{B\text{max}}$); average surface roughness ($Ra$); polycrystalline diamond (PCD); non-dominated sorting genetic algorithm (NSGA-II)

1 Introduction

Many of modern technologies require material with unusual combinations of properties that cannot be met by the conventional metals, alloys, ceramics and polymeric materials. This is particularly true for materials that are required for aeronautical, marine and automobile industries. The present day requirements are such that no material can satisfy all of them hence the new
materials have to be synthesized. This resulted the Metal Matrix Composite (MMC) are receiving more attention. Among the MMCs Particulate Metal-Matrix Composites (PMMCs) are of particular interest, because they exhibit superior ductility and lesser anisotropy than FRP and GFRP composites [1]. These materials might have a broad application, particularly for components, which are exposing to friction [2]. Several important applications of connecting rods, piston, piston rings, cylinder liners, bearings, turbine blades, impellers and space structures rings, etc. [3]. The commonly used matrix and reinforcements are magnesium, titanium, Aluminum and SiC, Al₂O₃. The various advanced manufacturing process available to produce near-net shaped MMC components, but component design and dimensional tolerance requirements, the need for machining cannot be completely eliminated [4].

The problem with MMCs is that they are difficult to machine material, due to the hardness and abrasive nature of the SiC or other reinforcing particles, e.g., 2400 Hv of SiC vs. 1800 Hv of tungsten carbide (WC) [5]. Diamond is exception, for case in point, which is approximately three to four times harder than hard metal and does not have a chemical tendency to react with the work material. That is the reason several researchers have suggested that polycrystalline diamond (PCD) tools are the only tool material that is capable of providing a useful tool life during the machining of Al/SiCp MMCs.

EL-GALLAB and SKLAD [6, 7] reported, in a study of wear mechanism of diamond tools in machining MMC, that abrasion/adhesion by reinforced particulates are the dominant wear mechanisms and severe machining conditions will result in chipping in PCD and peeling of CVD diamond coating. LIN et al. [8] observed the flank wear as the dominant mode of tool failure in machining Al-SiC MMC using PCD tool. ANDREWES et al. [9] investigated the tool wear in machining Al/SiC composites by diamond tools and found that tool wear involves two stages, one being initial flank wear caused by abrasion of hard particles, and the other combined adhesion-abrasion when the work materials start accumulatively adhering to the tool wear-land. PAULO DAVIM [10] reported that cutting velocity has the most influence on tool wear followed by cutting time and feed rate; with respect to surface finish feed rate observed to have greater influence.

The principles of bi-performance optimizations vary from single performance optimization. In bi-performance optimization, there are two objective functions, everyone have a diverse optimal solution. Mostly objectives differ with one another (optimizing one compromise another) [11]. The Genetic Algorithm is an evolutionary algorithm. It is based on the procedure of natural selection and it combines the individuality of direct search and probabilistic selection
methods. GA is simple and potent tool for getting final optimal solutions for multi-model and combinational problems. Its work based on the principle of feasible solutions on population, therefore used in optimization of multi-objective problems to get solutions at the same time [12].

In the multi-objective optimization set of solutions superior then other solutions considering the all objectives. The inferior solutions compare to other solution in a search space only depend on one or more objectives. It is called non-dominated or Pareto-optimal solutions and other solutions are called as dominated solutions [11]. The method of multi-objective optimizations like GA has sufficiently established their use in finding a sound diverged and well-spread solution set of near Pareto-optimal solutions [13]. The NSGA-II has nature of high speed and elitist multi-objective GA mainly used producing Pareto-boundary. Important benefits of solve multi objective problems is that it leads the search toward the global Pareto front while maintaining diversity of the solution set along that front.

In this paper study the machining of 20\%AlSiCp particulate metal matrix composites using tipped polycrystalline diamond (PCD) cutting tool. The turning experiments were conducted based on RSM design. Main cutting parameters like cutting speed (\(V\)), feed rate (\(f\)), depth of cut (\(d\)) and machining time (\(t\)) were optimized with respect to bi-performance character of flank wear (\(V_{Bmax}\)) and average surface roughness (\(R_a\)). Mathematical models were developed using RSM for tool flank wear and average surface roughness. The capability of the developed numerical models has been tested by the ANOVA test. With help of same models to optimize machining parameters using NSGA-II algorithm in the objective of minimizing tool flank wear and average surface roughness.

2 Experimental Study

Turning experiments were performed on a centre lathe which is having a spindle speed range of 30-1600 rpm with feed range 0.05-3.5 mm/rev with adequate spindle power. A356 (LM-25) aluminum alloy (7 Si, 0.33 Mg, 0.3 Mn, 0.5 Fe, 0.1 Cu, 0.1 Ni, 0.2 Ti) reinforced with green bonded silicon carbide average size of 25\(\mu\)m with a volume fraction of 0.20, which was manufactured through stir casting route was used as work material for carrying experimentation. The size of the work piece was 90 mm diameter and 250 mm length. The experimental setup for machining and A356 Al-20\%SiCp MMC work piece are shown Figure 1&2. Considering the abrasive nature of work material tipped polycrystalline diamond (PCD) was used for turning which shown in Figure 3. The cutting speed (\(V\)), feed rate (\(f\)), depth of cut (\(d\)) and machining time (\(t\)) are consider as machining parameter, and the responses are tool flank wear (\(V_{Bmax}\)) and average surface roughness (\(R_a\)).
The experiments were designed using face centered Central composite design (CCD). The factorial portion of CCD is a full factorial design with all combinations of the factors at two levels (high, +1 and low, −1) and composed of the eight star points and seven central points (coded level 0) which is the midpoint between the high and low levels. The star points are at the face of the cubic portion on the design which corresponds to a $\alpha$ value of 1 and this type of design is commonly called the face centered CCD. Table 1 shows the levels of four machining parameters and their ranges. The experimental plans were carried out using the stipulated conditions based on the face centered CCD involving 31 runs in the coded form as shown in Table 2. The design was generated and analyzed using MINITAB statistical package. The turning experiments were carried out as per the conditions given by the design matrix at random to avoid systematic errors.

**Table 1. Cutting parameter and their levels**

| Control Parameters | Unit  | Symbol | Levels  |
|--------------------|-------|--------|---------|
| Cutting speed      | m/min | $V$    | -1 50   |
| Feed rate          | mm/rev| $f$    | 0 0.05  |
| Depth of cut       | mm    | $d$    | 0.5 1.0 |
| Machining time     | min   | $t$    | 2 4 6   |

The tool flank wear was calculated using CLEMAX optical microscope. To measure the tool wear the maximum width of flank wear land was considered. The average surface roughness (Ra) is generally practiced in industries, was measured in this study. The surface roughness was measured by using MITUTOYO SURF III surface tester.
3 Empirical modeling for flank wear and surface roughness

The higher order polynomial equations of empirical models for tool flank wear and surface roughness are developed using experimental results given in Table 2. The models given blow as follows:

Tool Flank wear ($V_{B_{\text{max}}}$) = 0.06738 +0.00077V –0.31007f –0.00184d +0.00404t –0.00000V^2 +1.09747f^2 +0.00190d^2 –0.00013r^2 +0.00027Vf +0.00000Vd +0.00001Vt +0.00250fd +0.00063ft +0.00012dt  

(1)

Average surface roughness ($R_a$) = 1.14619 –0.00513V +4.06338f –0.00398d +0.03814t +0.00001V^2 –2.61867f^2 +0.0152 d^2 –0.00155r^2 –0.00225Vf +0.00005Vd +0.00003Vt –0.02500fd –0.01250ft +0.00250dt  

(2)
Table 2. Experimental results

| S. No | Coded factors | Actual cutting parameters | Response variable |
|-------|---------------|----------------------------|-------------------|
|       | X₁ X₂ X₃ X₄ | V  f d t Y₁ (VBₘₚₑₓ, mm) | Y₂ (Ra, µm) |
| 1     | -1 0 0 0     | 50 0.15 1.0 4              | 0.099 1.58       |
| 2     | 1 0 0 0     | 150 0.15 1.0 4             | 0.170 1.21       |
| 3     | 0 -1 0 0    | 100 0.05 1.0 4             | 0.142 1.08       |
| 4     | 0 1 0 0     | 100 0.25 1.0 4             | 0.153 1.62       |
| 5     | 0 0 -1 0    | 100 0.15 0.5 4             | 0.135 1.36       |
| 6     | 0 0 1 0     | 100 0.15 1.5 4             | 0.139 1.40       |
| 7     | 0 0 0 -1    | 100 0.15 1.0 2             | 0.130 1.31       |
| 8     | 0 0 0 1     | 100 0.15 1.0 6             | 0.142 1.43       |
| 9     | -1 1 1 1    | 50 0.25 1.5 6              | 0.126 1.94       |
| 10    | 1 -1 -1 -1  | 150 0.05 0.5 2             | 0.162 0.81       |
| 11    | -1 -1 1 1   | 50 0.05 1.5 6              | 0.116 1.33       |
| 12    | 1 1 -1 -1   | 150 0.25 0.5 2             | 0.176 1.39       |
| 13    | -1 -1 -1 1  | 50 0.05 0.5 6              | 0.113 1.28       |
| 14    | 1 1 1 1    | 150 0.25 1.5 2             | 0.180 1.43       |
| 15    | -1 -1 -1 -1 | 50 0.05 0.5 2              | 0.101 1.17       |
| 16    | 1 1 1 1    | 150 0.25 1.5 6             | 0.195 1.55       |
| 17    | -1 1 -1 1   | 50 0.25 0.5 6              | 0.122 1.91       |
| 18    | 1 -1 1 -1   | 150 0.05 1.5 2             | 0.165 0.85       |
| 19    | -1 1 -1 -1  | 50 0.25 0.5 2              | 0.106 1.81       |
| 20    | 1 -1 1 1    | 150 0.05 1.5 6             | 0.180 0.97       |
| 21    | -1 1 1 -1   | 50 0.25 1.5 2              | 0.109 1.83       |
| 22    | 1 -1 -1 1   | 150 0.05 0.5 6             | 0.184 0.93       |
| 23    | -1 -1 1 -1  | 50 0.05 1.5 2              | 0.103 1.21       |
| 24    | 1 1 -1 1    | 150 0.25 0.5 6             | 0.192 1.50       |
| 25    | 0 0 0 0     | 100 0.15 1.0 4             | 0.136 1.38       |
| 26    | 0 0 0 0     | 100 0.15 1.0 4             | 0.137 1.39       |
| 27    | 0 0 0 0     | 100 0.15 1.0 4             | 0.136 1.37       |
| 28    | 0 0 0 0     | 100 0.15 1.0 4             | 0.136 1.39       |
| 29    | 0 0 0 0     | 100 0.15 1.0 4             | 0.137 1.38       |
| 30    | 0 0 0 0     | 100 0.15 1.0 4             | 0.136 1.39       |
| 31    | 0 0 0 0     | 100 0.15 1.0 4             | 0.138 1.37       |

4 NSGA-II Optimization

The non-dominated genetic algorithm (NSGA-II) was used in this study to optimize the machining parameters in turning of 20%AlSiCp MMC using PCD tool. The main objectives of optimization are as given blow:

1) Minimization of tool flank wear (VBₘₚₑₓ)
2) Minimization of average surface roughness (Ra).

The two-objective genetic algorithm optimization method used is a fast, elitist non-dominated sorting genetic algorithm (NSGA-II) developed by DEB et al [14]. This algorithm uses
the elite-preserving operator, which favors the elites of a population by giving them an opportunity to be directly carried over to the next generation [15].

5 NSGA-II algorithm

The non-dominated sorting genetic algorithm has been criticized for its high computational complexity, lack of elitism and its choice of the optimal parameter value for sharing parameter $\sigma$. The NSGA-II is a modified version, which has a better sorting algorithm, incorporates elitism and does not require the choosing of a sharing parameter a priori. There are two key concepts in NSGA-II: a fast non-dominated sorting of the population and a crowding distance. The flow chart of the NSGA II program is shown in Figure 4.

5.1 Non-dominated sort

The initialized population is sorted based on non-domination. The non-domination is an individual and is said to dominate another if its objective function is no worse than the other and at least in one of its objective functions is better than the other. The fast-sort algorithm was described in Ref. [16].

5.2 Crowding distance

In NSGA-II, in addition to the fitness value, a new parameter called “crowding distance” is calculated for each individual. The crowding distance is a measure of how close an individual to its neighbors. Crowding distance is assigned front wise: comparing the crowding distance between two individuals in a different front is meaningless. The basic idea behind the crowding distance is finding the Euclidean distance between each individual in a front based on their $m$ objectives in $m$-dimensional hyperspace. Initially, a random parent population of $P_o$, of size $N$ is generated. The population is sorted based on non-domination level. Each solution is assigned a fitness level, and the best level is 1. Thus, minimization of fitness is assumed. Binary tournament selection, recombination and mutation operators are implemented to generate the child $Q_o$, of size $N$. The procedure for the remaining generation (for $i \geq 1$) can be found in Ref. [14].
6 Results and discussion

The 20%AlSiCp MMC manufactured through stir casting method machining performance were studied using PCD cutting tool. Empirical model for flank wear and surface roughness developed by means of MINITAB software are given in Eq. (1) and (2). The ANOVA table for the quadratic model for $V_{B_{\text{max}}}$ & $R_{a}$ is shown in Table 3. The standard percentage point of F distribution for 95% confidence limit is 4.06. From the Table 3 the F- values for $V_{B_{\text{max}}}$ and $R_{a}$ are 3.30 & 3.15 respectively for lack-of-fit be smaller than the standard value. The lack of fit is
insignificant as it is preferred. The other model terms are said to be significant. The value of $R^2$ calculated tool flank wear and surface roughness is 99.86% and 99.89% is higher than 99%, very close to unity, indicating a good correlation between the independent variables (factors) and the responses ($V_{B_{\text{max}}}$ & $R_a$). The P-value for the models is lower than 0.05 (i.e. $\alpha = 0.05$, or 95% confidence limit) which indicate that the model is measured to be statistically significant.

### Table 3 Test results of ANOVA

| Source        | Degree of freedom | Sum of square | Adjusted mean square | F-Value | P-Value |
|---------------|-------------------|---------------|----------------------|---------|---------|
|               |                   | $V_{B_{\text{max}}}$ | $R_a$ | $V_{B_{\text{max}}}$ | $R_a$ | $V_{B_{\text{max}}}$ | $R_a$ |
| Linear        | 4                 | 0.02219       | 2.316 | 0.00009 | 0.0122 | 47.32 | 78.1 | 0.00 | 0.00 |
| Square        | 4                 | 0.00068       | 0.002 | 0.00017 | 0.0007 | 87.45 | 4.34 | 0.00 | 0.01 |
| Interaction   | 6                 | 0.00003       | 0.002 | 0.00001 | 0.0004 | 3.17 | 2.53 | 0.03 | 0.06 |
| Lack of fit   | 10                | 0.00002       | 0.002 | 0.00000 | 0.0002 | 3.30 | 3.15 | 0.08 | 0.09 |
| Error         | 6                 | 0.00001       | 0.000 | 0.00000 | 0.0001 | 0.0001 | 0.0001 | 0.0001 |
| Total         | 30                | 0.02295       | 2.324 |                     |        |       |       |       |

$R^2$ for $V_{B_{\text{max}}}$ = 99.86% and $R^2$ for $R_a$ = 99.89%

Apart from the above, the interaction effects are also analyzed and given in Table 4. From the table it is observed that the linear effect of cutting speed, feed rate and machining time, square effect of cutting speed, interaction effect between cutting speed and feed rate are more significant for tool flank wear, whereas other linear, square and interactions effects are not so significant. For surface roughness the linear, square effect of cutting speed, feed rate, liner effect of machining time, cutting speed interaction with feed rate are most significant, whereas other effects are not so significant as shown in Table 4. Figure 5 & 6 displays the normal probability plot of the residuals for tool flank wear and surface roughness. It can be noticed both $V_{B_{\text{max}}}$ and $R_a$ residuals are located on a straight line, which means that the errors are normally distributed and the regression model is fairly adequate. Figure 5 (b) & 6 (b) indicates the maximum variation for tool flank wear and surface roughness are -0.0020 to 0.0015 and -0.03 to 0.03, which shows the high correlation that exists between fitted values and observed values.
Table 4 Estimated regression coefficients

| Symbol  | VB$_{\text{max}}$ Coefficient | P-value | Ra Coefficient | P-value |
|---------|-------------------------------|---------|----------------|---------|
| Constant | 0.06738                       | 0.000   | 1.64619        | 0.000   |
| V -m/min | 0.00077                       | 0.000<  | -0.00513       | 0.000<  |
| f -mm/rev | -0.31007                      | 0.000<  | 4.06338        | 0.000<  |
| d -mm    | -0.00184                      | 0.806   | -0.00398       | 0.952   |
| t -min   | 0.00404                       | 0.043<  | 0.03814        | 0.033<  |
| V$^2$    | -0.00000                      | 0.034<  | 0.00001        | 0.028<  |
| f$^2$    | 1.09747                       | 0.000<  | -2.61867       | 0.004<  |
| d$^2$    | 0.00190                       | 0.593   | 0.01525        | 0.630   |
| t$^2$    | -0.00013                      | 0.555   | -0.00155       | 0.437   |
| V f      | 0.00027                       | 0.001<  | -0.00225       | 0.002<  |
| V d      | 0.00000                       | 0.726   | 0.00005        | 0.694   |
| V t      | 0.00001                       | 0.094   | 0.00003        | 0.436   |
| f d      | 0.00250                       | 0.726   | -0.02500       | 0.694   |
| f t      | 0.00063                       | 0.726   | -0.01250       | 0.436   |
| d t      | 0.00012                       | 0.726   | 0.00250        | 0.436   |

(a) Normal probability plot for VB$_{\text{max}}$  
(b) Residual verses fitted value for VB$_{\text{max}}$

Figure 5. Residuals plot used for tool flank wear (VB$_{\text{max}}$)

A single objective optimization algorithm will generally be ended obtain an optimal solution. However, for the majority of the multi-objective problems, there could be a more number of optimal solutions. Appropriateness of one solution depends on a number of factors including user’s preference and problem atmosphere, and hence discovery the complete set of
optimal solutions may be preferred. Among the Pareto optimal result, none of the solutions is particularly superior to any other solution and hence this solution is extremely better than any other solution and therefore this solution is called as non-dominated solution.

![Graphs showing normal probability plot and residuals against fitted values for Ra](image)

**Figure 6. Residuals plot used for average surface roughness (Ra)**

Genetic algorithm is competent, adaptive, and healthy search and optimization technique, used to find solutions to linear and non-linear problems. Based on the principle of natural genetic system by simultaneously exploring multiple area of the solution space and exponentially exploit potential regions by means of selection, crossover and mutation. In genetic system information of each individual or possible solution is determined in structures called chromosomes. In common, the fittest individuals of population are more possible to reproduce and carry on to the next generation and improving succeeding generations. The Non-Dominating Sorting Genetic Algorithm (NSGA-II) developed by DEB in the year 2002 is finest method for generate the Pareto frontier and is used in this work.

The NSGA-II program positions the individuals as based on dominance. The fast non-dominated sorting process permits us to discover the non-domination frontiers where individuals of the frontier set are not dominated by any other solution. The crowding distance was calculated for every individual of the new population. Crowding factor gives the GA, the skill to differentiate individuals that have the same class. This forces the GA to homogeneously cover the frontier rather than bunch up at numerous high-quality points by trying to keep population variety. The comparison operator (<n) is used by GA to sort the population for selection purposes.

The procedure was repeated ten times to obtain a larger number of points in the Pareto solution set. Non-dominated solution set obtained over the entire optimization procedure is revealed in Figure 7. This indicates the arrangement of the Pareto front leading to the finishing set of solutions. The matching goal function values and decision variables of this non-dominated
solution set are given in Table 5. The 30 out of 100 sets be presented since no one of the solutions in the non-dominated set is absolutely better than any other; any one of them is an satisfactory solution. The selection of individual solution over another depends on the option of the process engineer. Either less tool wear or a good surface roughness is required; an appropriate mixture of parameters can be chosen from Table 5.

![Figure 7. Optimal chart obtain through NSGA-II](image)

From the experimental results presented in Table 2, the parameters listed in the experiment number 1 leads to minimum $V_B_{\text{max}}$ of 0.099 mm and corresponding $Ra$ of 1.58 µm, where the cutting speed, feed rate, depth of cut and machining time are 50 m/min, 0.15 mm/rev, 1 mm and 4 min respectively. By optimizing NSGA-II, the same experimental value has been selected from the Table 5, serial number 3. The $V_B_{\text{max}}$ value is 0.099 mm and corresponding $Ra$ is 1.23 µm and the pertinent parameters are cutting speed, feed rate, depth of cut and machining time are 50 m/min, 0.06 mm/rev, 0.5 mm and 2 min respectively. This indicates that values obtained from the optimization technique are in close agreement with the experimental values and more or less the same parameter settings. With reference to the minimum $V_B_{\text{max}}$ obtained through experimental results there are 7 set of readings with lesser $V_B_{\text{max}}$ obtained through NSGA-II are shown in Table 6.
Table 5 Optimal combination of parameter by NSGA-II

| S. No | Run | Actual cutting parameters | Response variable |
|-------|-----|--------------------------|-------------------|
|       |     | V  | f  | d  | t  | \(Y_1(V_{B_{\text{max}}}, \text{mm})\) | \(Y_2(Ra, \mu\text{m})\) |
| 1     | 1   | 50 | 0.13 | 0.5 | 2 | 0.094 | 1.47 |
| 2     | 2   | 150 | 0.05 | 0.6 | 2 | 0.182 | 0.86 |
| 3     | 3   | 50 | 0.06 | 0.5 | 2 | 0.099 | 1.23 |
| 4     | 4   | 50 | 0.10 | 0.5 | 2 | 0.095 | 1.37 |
| 5     | 6   | 84 | 0.05 | 0.6 | 2 | 0.130 | 1.05 |
| 6     | 10  | 150 | 0.05 | 0.7 | 2 | 0.159 | 0.94 |
| 7     | 11  | 121 | 0.05 | 0.6 | 2 | 0.166 | 0.91 |
| 8     | 16  | 50 | 0.11 | 0.5 | 2 | 0.094 | 1.41 |
| 9     | 24  | 75 | 0.05 | 0.6 | 2 | 0.122 | 1.08 |
| 10    | 29  | 50 | 0.05 | 0.6 | 2 | 0.101 | 1.20 |
| 11    | 33  | 141 | 0.05 | 0.5 | 2 | 0.175 | 0.88 |
| 12    | 35  | 81 | 0.05 | 0.6 | 2 | 0.127 | 1.06 |
| 13    | 43  | 115 | 0.05 | 0.6 | 2 | 0.154 | 0.95 |
| 14    | 45  | 146 | 0.05 | 0.5 | 2 | 0.179 | 0.87 |
| 15    | 49  | 50 | 0.12 | 0.5 | 2 | 0.094 | 1.44 |
| 16    | 50  | 65 | 0.05 | 0.5 | 2 | 0.144 | 1.12 |
| 17    | 52  | 136 | 0.05 | 0.5 | 2 | 0.171 | 0.89 |
| 18    | 59  | 56 | 0.05 | 0.6 | 2 | 0.107 | 1.15 |
| 19    | 60  | 50 | 0.05 | 0.5 | 2 | 0.100 | 1.21 |
| 20    | 61  | 105 | 0.05 | 0.7 | 2 | 0.147 | 0.98 |
| 21    | 69  | 61 | 0.05 | 0.6 | 2 | 0.111 | 1.14 |
| 22    | 72  | 125 | 0.05 | 0.6 | 2 | 0.163 | 0.92 |
| 23    | 73  | 100 | 0.05 | 0.7 | 2 | 0.142 | 1.00 |
| 24    | 75  | 50 | 0.07 | 0.6 | 2 | 0.098 | 1.26 |
| 25    | 76  | 91 | 0.05 | 0.6 | 2 | 0.135 | 1.03 |
| 26    | 79  | 110 | 0.05 | 0.7 | 2 | 0.150 | 0.97 |
| 27    | 83  | 50 | 0.09 | 0.5 | 2 | 0.096 | 1.33 |
| 28    | 84  | 71 | 0.05 | 0.6 | 2 | 0.119 | 1.09 |
| 29    | 90  | 50 | 0.08 | 0.6 | 2 | 0.097 | 1.29 |
| 30    | 93  | 95 | 0.05 | 0.6 | 2 | 0.138 | 1.01 |

The confirmation of the test outcome under the chosen optimum setting for the cases of \(V_{B_{\text{max}}}\) and \(Ra\) are given in the Table 7. The predicted cutting performance is compared with the real cutting performance and an excellent conformity is obtained among their performances. Analyzing validation test result of Table 7, noticed that the calculated error is small. The error between the experimental and the predicted values for \(V_{B_{\text{max}}}\) and \(Ra\) lie down within 1% and 2% respectively. Observably, this confirms outstanding reproducibility of the experimental conclusions.
Table 6 Optimal parameter for machining of Al/20%SiC using PCD tool

| S. No | Run | V (m/min) | f (mm/rev) | d (mm) | t (min) | Y₁ (VBmax, mm) | Y₂ (Ra, µm) |
|-------|-----|-----------|------------|--------|---------|----------------|--------------|
| 1     | 1   | 50        | 0.13       | 0.5    | 2       | 0.094          | 1.47         |
| 3     | 4   | 50        | 0.10       | 0.5    | 2       | 0.095          | 1.37         |
| 4     | 16  | 50        | 0.11       | 0.5    | 2       | 0.094          | 1.41         |
| 5     | 49  | 50        | 0.12       | 0.5    | 2       | 0.094          | 1.44         |
| 6     | 75  | 50        | 0.07       | 0.6    | 2       | 0.098          | 1.26         |
| 7     | 83  | 50        | 0.09       | 0.5    | 2       | 0.096          | 1.33         |
| 8     | 90  | 50        | 0.08       | 0.6    | 2       | 0.097          | 1.29         |

Table 7 Validation test outcome for Al/20%SiCp MMC using PCD tool

| Sl. No | Cutting speed (V) (m/min) | Feed rate (f) (mm/rev) | Depth of cut (d) (mm) | Machining time (t) (min) | VBmax (mm) | Ra (µm) |
|--------|--------------------------|------------------------|-----------------------|-------------------------|------------|---------|
|        | Predicted | Actual | % Error | Predicted | Actual | % Error | Predicted | Actual | % Error |
|        | 0.099       | 0.098   | 1%       | 1.23       | 1.20  | 2%       |

7 Conclusion

The machining parameter of particulate aluminum metal matrix composite using tipped PCD tool have been optimized via by means of Non-Dominated Sorting Genetic Algorithm (NSGA-II), and a non dominated solution set is obtained. The mathematical models developed for tool flank wear and surface roughness have been used for optimization. The choice of one solution over the other depends on the requirement of the process engineer. If the requirements of minimum tool flank wear or surface roughness, an appropriate mixture of cutting variables can be chosen. This technique will assist to enhance manufacture rate significantly by reducing machining time.
References

[1] Mannaa A and Bhattacharya B 2003 J Mater Process Technol. 140: 711–716
[2] M R Jadhav and U A Dabade 2016 IOP Conf. Ser.: Mater. Sci. Eng. 114 012122
[3] Diptikanta Das, Anil Kumar Chaubey, Bijaya Bijeta Nayak, Purna Chandra Mishra and Chandrika Samal 2018 IOP Conf. Ser.: Mater. Sci. Eng. 377 012110
[4] Seeman M, Ganesan G, Karthikeyan R and Velayudham 2010 Int J Adv Manuf Technol 48:613-624
[5] Vaccari J A and Lane C T 1993 American Machinist 11: 56-60
[6] El-Gallab M and Sklad M 1998 J Mater Process Technol. 83: 151–158, 277–285
[7] El-Gallab M and Sklad M 2000 J Mater Process Technol. 101: 10-20
[8] Lin J T, Bhattacharyya D and Lane C 1995 Wear 181–183: 883–888
[9] Andrewes C, Feng H and Lau W 2000 J Mater Process Technol. 102: 25–29
[10] Paulo Davim J 2002 J Mater Process Technol. 128: 100–105
[11] Kanagarajan D, Karthikeyan R, Palanikumar P and Paulo Davim J 2008 Int J Adv Manuf Technol. 2008, 36, 1124-1132
[12] Kuriakose S and Shunmugam M S 2005 J Mater Process Technol.170: 133–141
[13] Senthilkumar C, Ganesan G, and Karthikeyan R 2009 Proc. IMechE Vol. 224: 1399- 1407 Part B: J. Engineering Manufacture
[14] Deb K, Pratap A, Agarwal S and Meyarivan T. A 2002 IEEE Trans. Evol. Comput. 6(2): 182–197.
[15] Senthilkumar C, Ganesan G, and Karthikeyan R 2011 Trans. Nonferrous Met. Soc. China 21 2294–2300
[16] Seshadri A 2007 //http: //www.mathworks.com