Multi Objective Optimization of Surface Grinding Process by Combination of Response Surface Methodology and Enhanced Non-dominated Sorting Genetic Algorithm

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ABSTRACT

The present study is focused on the multi-objective optimization of performance parameters such as specific energy (u), metal removal rate (MRR) and surface roughness(Ra) obtained in grinding of Al-SiC$_{35P}$ composites. The enhanced elitist non-dominated sorting genetic algorithm (NSGA -II) is used to solve this multi-objective optimization problem. Al-SiC specimens containing 8 vol. %, 10 vol. % and 12 vol. % of silicon carbide particles of mean diameter 35µm, feed and depth of cut were chosen as process variables. A mathematical predictive model for each of the performance parameters was developed using response surface methodology (RSM). Further, an enhanced NSGA-II algorithm is used to optimize the model developed by RSM. Finally, the experiments were carried out to validate the results obtained from RSM and enhanced NSGA-II. The results obtained were in close agreement, which indicates that the developed model can be effectively used for the prediction.

General Terms

Computer Science, mathematical modeling, Genetic Algorithm.

Keywords

Discontinuously reinforced aluminium composites (DRACs), Surface grinding, Central composite design (CCD), Response surface methodology (RSM), enhanced non-dominated Sorting Genetic algorithm (NSGA-II), Multi objective optimization

1. INTRODUCTION

The aluminium alloy reinforced with discontinuous ceramic reinforcements is rapidly replacing conventional materials in various aerospace and automobile industries. But grinding of DRACs is one of the major problems, which resist its widespread engineering application. When Al-SiC specimen slides over a hard cutting tool edge during grinding, due to friction, high temperature and pressure the particles of Al-SiC adhere to the grinding wheel which affects the surface quality of the specimen [1]. Hence, cost effective grinding with generation of good surface finish on the Al/SiC-MMC specimen during the grinding operation is a challenge to the manufacturing engineers in practice.

Process modeling and optimization are two important issues in grinding. The grinding process is characterized by a multiplicity of dynamically interacting process variables. Surface finish, metal removal rate and specific energy are considered to be the important factors in predicting performance of grinding process. Several authors have developed the mathematical model for grinding process using RSM [2-5]. Wen et al. [6] applied quadratic programming [QP] to solve the problem by formulating the problem as a multi-objective function model. The optimization problem has also been solved applying various non-traditional optimization methods including genetic algorithms (GA) [7], particle swarm optimization (PSO) [8], scatter search (SS) [9], and differential evolution (DE) [10]. However, the classical multi-objective optimization technique, the method of weighted sum has been used in all these earlier works reported. Suresh et.al [11], applied genetic algorithm for optimization of surface roughness while machining mild steel using TiN-coated tungsten carbide tool. Saravanan et.al [12] applied multi-objective GA approach for optimization of grinding process and compared the results with quadratic programming and observed that improved results are obtained by GA approach. Hsu [13] demonstrated the superiority of GAs over other network capability in terms of its optimized search.

Optimization of machining parameters not only increases the utility for machining economics, but also the product quality to a great extent [14]. As a result, there have been a great many research development in modeling of performance parameters in machining and optimization of controlling parameters to obtain an output of desired level [15]. But such studies are far from complete since it is very difficult to consider all the parameters that control the performance parameters of a particular manufacturing process [16].

The proposed study discusses the application of RSM and enhanced NSGA-II for the multi-objective optimization of grinding process during grinding of Al-SiC$_{35P}$ composites. The task is to maximise the metal removal rate, minimise the surface the roughness and specific energy while considering vol % of SiC, feed and depth of cut as the process variables.

2. EXPERIMENTAL PROCEDURE

Al-SiC specimens having aluminum alloy 6061 as the matrix and containing 8 vol.%,10 vol.% and 12 vol.% of silicon

carbide particles of mean diameter 35µm by Stir casting process with pouring temperature 700-710°C, stirring rate 195rpm. The specimens were extruded at 457°C, with extrusion ratio 30:1, and direct extrusion speed 6.1m/min to produce length 120mm and Ø22mm cylindrical bars. The machined specimens were solution treated for 2 hours at a temperature of 540°C in a muffle furnace; Temperatures were accurate to within ±2°C and quench delays in all cases were within 20s. After solution treatment, the samples were water quenched to room temperature. Grinding method as machining process was selected.

Table 1. Levels of independent Factors

Factors	Levels		
	Low(-1)	Medium(0)	High(+1)
Percentage SiC (X_1)	8	10	12
Feed (mm/s) (X_2)	60	70	80
Depth of Cut (µm) (X_3)	8	12	16

Experiments were conducted on 1.5 HP, 2880rpm, conventional surface grinding machine (Bhuraji make) with automatic (hydraulic) table-feed and Norton make diamond grinding wheel ASD76R100B2. The honing stick having specification GN0390220K7V7 is used for dressing the wheel. The experiments were performed under dry conditions.

The experiments were conducted with three levels and three factors. Vol % of SiC, table feed and depth of cut were chosen as the input parameters for evaluating the performance parameters; specific energy, metal removal rate and surface roughness.

The levels and factors selected for the experimentation is given in Table 1. Selection of factors for optimization was based on preliminary experiments [17] and known instrumental limitations. The specific energy is calculated using the relation

$$u = \frac{F_t * v_s}{f * a * b} \qquad (1)$$

where F_t is the tangential cutting force, v_s is the peripheral speed of the grinding wheel, f is the table feed in mm/s, a is the depth of cut in mm and b is the width of cut in mm. The tangential cutting force necessary to calculate the specific energy is measured using Kistler dynamometer type 9272.

Metal removal rate is calculated by volume of material loss/unit time after grinding process. The surface roughness of the specimen is measured using Taylor/Hobson surtronoic 3+ surface roughness measuring instrument

3. RESULTS AND DISCUSSION

The necessary data for building the response models are generally collected by the experimental design. In this study, the collections of experimental data were adopted using 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 comprised of the six axial points and six central points (coded level 0) which is the midpoint between the high and low levels[18-20]. The axial points are on the face of the cubic portion of the design which corresponds to a value of rotatability index α =1 and this type of design is commonly called the face-centered CCD. Table 2 shows the data collected during the experimentation.

The mathematical relationship between the responses, specific energy (u), MRR and surface roughness (Ra) and the grinding variables SiC vol.% (X_1), feed (X_2), and depth of cut (X_3) were established using experimental test results from a planned set of experiments; face-centered CCD. The relationship between the performance parameters and grinding variables has been expressed as follows:

$$\hat{y}_1 = 543.669 + 18.469X_1 - 11.125X_2 - 37.725X_3 - 1.587X_1^2 + 0.089X_2^2 + 0.984X_3^2 + 0.03X_1X_2 + 0.628X_1X_3 + 0.098X_2X_3 \quad ----(2)$$

$$\hat{y}_2 = 42.4576 + 4.0029X_1 - 1.0834X_2 + 1.7761X_3 - 0.1221X_1^2 + 0.014X_2^2 - 0.0235X_3^2 - 0.0186X_1X_2 + 0.0034X_1X_3 - 0.0112X_2X_3 -----------(3)$$

$$\hat{y}_3 = 2.199 - 0.25466X_1 + 0.0078X_2 - 0.00852X_3 + 0.00955X_1^2 + 3.0E-05X_2^2 - 1.1E-04X_3^2 - 8.8E-04X_1X_2 + 0.00188X_1X_3 + 1.3-04X_2X_3 --(4)$$

where $\hat{y}_1, \hat{y}_2$ *and* $\hat{y}_3$ are the predicted responses for specific energy, metal removal rate and surface roughness respectively.

Table 2. Experimental results

Sr. No	Coded Values			Actual values			Response		
	A	B	C	SiC (Vol %) (X_1)	Feed (mm/s) (X_2)	DOC (µm) (X_3)	Y_1 (u, J/mm³)	Y_2 (MRR, mm³/s)	Y_3 (Ra, µm)
1	-1	-1	-1	8	60	8	99.044	7.324	1.05
2	1	-1	-1	12	60	8	76.436	9.293	0.62
3	-1	1	-1	8	80	8	148.768	6.054	1.15

4	1	1	-1	12	80	8	127.495	6.644	0.69
5	-1	-1	1	8	60	16	70.483	11.915	1.13
6	1	-1	1	12	60	16	66.933	14.102	0.80
7	-1	1	1	8	80	16	134.844	8.962	1.29
8	1	1	1	12	80	16	134.722	9.553	0.85
9	-1	0	0	8	70	12	90.904	7.894	1.14
10	1	0	0	12	70	12	65.471	8.558	0.75
11	0	-1	0	10	60	12	70.565	12.31	0.85
12	0	1	0	10	80	12	116.273	7.927	0.97
13	0	0	-1	10	70	8	113.858	6.799	0.86
14	0	0	1	10	70	16	85.552	9.877	0.95
15	0	0	0	10	70	12	91.942	8.379	0.92
16	0	0	0	10	70	12	95.097	8.994	0.95
17	0	0	0	10	70	12	84.498	8.379	0.89
18	0	0	0	10	70	12	88.498	8.364	0.92
19	0	0	0	10	70	12	94.436	8.994	0.91
20	0	0	0	10	70	12	95.543	8.979	0.93

3.1 Non-dominated Sorting Genetic Algorithm-II (NSGA-II)

In the following section the working of the NSGA-II algorithm is described as given in [21-22]. The original version has been enhanced by improving the non-dominated sorting method as given in [23]. This enhanced version is discussed further.

In NSGA-II, first the offspring population Q_t (of size N) is created using the parent population P_t (of size N), as shown in Figure 1. The usual genetic operators such as single-point crossover and bit-wise mutation operators are used in this process. Next, the two populations are combined to form an intermediate population R_t of size 2N. Thereafter, the fitness of each offspring in the 2N population is evaluated using the multiple objective functions. At this stage, the non-dominated sorting procedure is carried out over the 2N population to rank and divide the individuals into different non-dominated fronts. Thereafter, the new parent population P_{t+1} is created by choosing individuals of the non-dominated fronts, one at a time. The individuals of best ranked fronts are chosen first, followed by the next-best and so on, till N individuals are obtained

Since the intermediate population R_t has a size of 2N, those fronts which could not be accommodated are discarded. In case there is space only for a part of a front in the new population, the individuals as per existing order are selected, so as to complete the new parent population.

The complete NSGA-II procedure is explained below:

BEGIN

While generation count is not reached

Begin Loop

- Apply selection, crossover and mutation to new parent population P_{t+1} and obtain the new offspring population Q_{t+1}.
- Combine parent Pt and offspring population Q_t to obtain population R_t of size 2N.
- Perform Non-dominated Sorting on Rt and assign ranks to each pareto front with fitness F_i.
- Starting from the Pareto front with fitness F_1, add each Pareto-front F_i to the new parent population P_{t+1} until a complete front F_i cannot be included.
- From the current Pareto-front F_i, add individual members to new parent population P_{t+1} until it reaches the size N.
- Increment generation count.

**End Loop**

END.
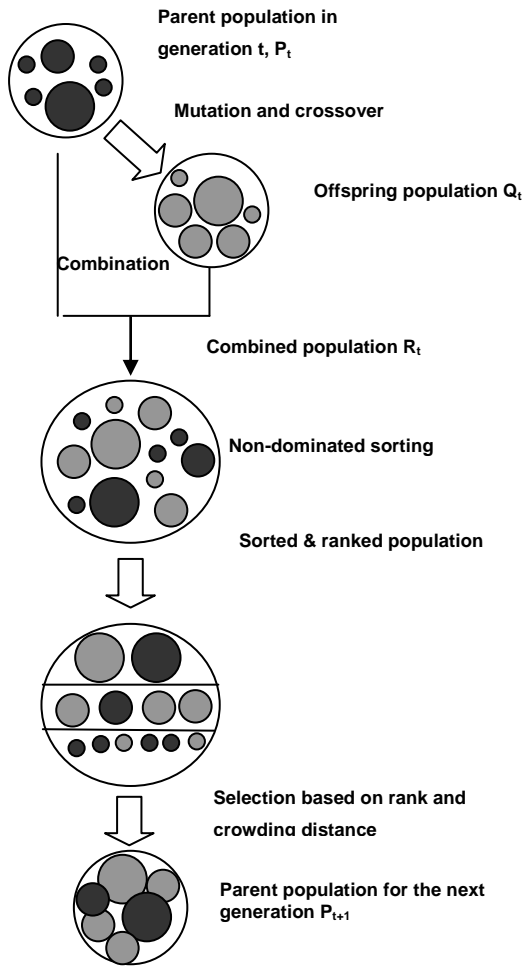
Fig 1: Working Principle of NSGA-II

3.2 Enhanced Non-dominated Sorting Genetic Algorithm

In the current enhanced version of non-dominated sorting genetic algorithm-II [23], sorting of individuals based on each of the objectives are performed, one after the other, till all objectives are considered. During this sort, the index of each individual is tracked so that the position value of any given individual in each sorted array is known. This information is critical since it helps in ranking the fronts in the next step.

Each individual is ranked by summing up the position value of that individual in all the objectives. Since similar position values were assigned to individuals having similar objective values, the sum of the position values becomes equivalent to the rank which the individual would have obtained through non-dominated comparison. Hence the non-dominated sort is completed in a single iteration of the sorted individuals, thereby reducing the time required for processing each generation.

The flow chart for optimization of the grinding of MMC using enhanced non-dominated sorting genetic algorithm is shown in Figure 2. In this figure, generate initial population means the

possible solutions of the optimization problem, and each possible solution is called an individual. The possible solution is formed by binary strings of Vol % of SiC, feed and depth of cut. Later these binary strings are converted into decimals to obtain the output. Thus generated population is selected based on roulette wheel selection and they are arranged depending on the dominance of one solution over the other
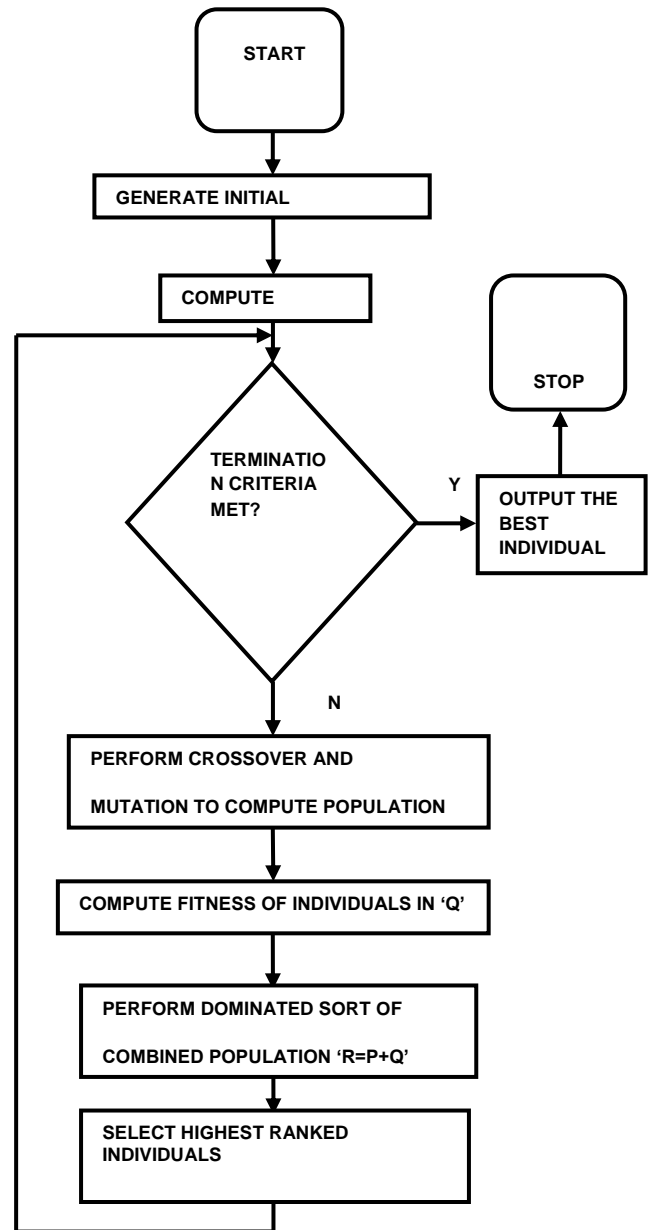
Fig 2: Flow chart of enhanced NSGA-II

The crossover and mutation genetic operators are applied on the selected population in a manner similar to that used during single objective GA. For real parameter implementations, binary crossover and mutation operators are used. Further an elitist recombination strategy is used by combining the current population and the offspring population. For an initial population size of N, the combined population contains 2N members. The new population is obtained by picking members

Table 4 Validation of experimental results

Test No.	Process variables			Method	Performance Parameters		
	SiC vol %	Feed (mm/s)	DOC (microns)		Specific energy (J/mm^3)	MRR (mm^3/s)	Surface roughness (microns)
1	10	60	12	Experimental	70.565	12.31	0.85
				RSM	69.427	11.53	0.90
				NSGA-II	69.42	11.58	0.85
2	8	60	12	Experimental	77.17	9.96	1.07
				RSM	70.95	10.07	1.08
				NSGA-II	72.0	9.73	1.08

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from each front successively until the size exceeds N. A suitable number of members from the first front that cannot be completely added are then picked so that a total of N members are obtained. All the steps starting from non–dominated sorting are repeated until the desired number of generations is completed.

3.3 Implementation of Enhanced NSGA-II for RSM Optimization

A multi objective algorithm was implemented using enhanced NSGA-II for performing the evolutionary optimization. Java (Version 2.0) programming language was used to code the algorithm. Each of the objective function was coded along with the parameters used for RSM Optimization. The constraints on each parameter were also specified in the program. As described in the NSGA-II algorithm in the previous section, a population of 100 individuals was generated with various initial values of parameters which were initialized randomly, keeping appropriate minimum and maximum ranges in view. Thereafter the program was allowed to iterate over 500 generations and the final optimized parameter values of the non-dominated solutions resulting from this run were noted. After several such runs, results were tabulated and analyzed

3.4 Validation of Results

The response surface models given by Eq. (2) –Eq. (4) were validated by the set of test runs. Table-4 gives the results obtained from experimental test, and the results obtained by the developed response surface model. Test No. 1 refers to the comparison of the results obtained from experiment, RSM and NSGA-II for the factor levels listed in Table-2. Test No.2 refers to the factors levels other than listed in Table-2.

It is observed from Table 4 that the variation among the results obtained from experiment, RSM and enhanced NSGA-II is within 9%. Hence the developed RSM model and enhanced NSGA-II model can effectively be used to predict the specific energy, MRR and surface roughness.

4. CONCLUSION

In this study, the Response surface methodology was applied for analyzing specific energy, MRR and surface roughness in the surface grinding of DRACs. Further, enhanced Non-dominated Sorting Genetic Algorithm-II (NSGA-II) an improved version of NSGA was used, to optimize the RSM models developed by experimentation. It can be observed from the analysis that RSM can be used to develop second order equations for specific energy MRR and surface roughness in terms of the process

variables. Genetic algorithm codes are developed in java for multi objective optimization of the responses. It is observed that results obtained by genetic algorithm are in very close agreement with those obtained by RSM.

Therefore, from this study, it may be concluded that the enhanced NSGA-II can effectively be used to optimize the model developed from RSM. This approach can be extended to optimize the parameters of other machining processes such as milling, drilling, cylindrical grinding and un-conventional machining processes

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