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GA Approach for Optimization of Surface Roughness Parameters in Machining of Al Alloy SiC Particle Composite

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Experiments were carried out using carbide turning inserts on AA7075/10 wt.% SiC (particle size 10-20 μm) composites to get actual input values to the optimization problem, so that the optimized results are realistic. By using experimental data, the regression model was developed. This model was used to formulate the fitness function of the genetic algorithm (GA). This investigation attempts to perform the application of GA for finding the optimal solution of the cutting conditions minimum value of surface roughness. The analysis of this investigation shows that the GA technique is capable of estimating the optimal cutting conditions that yield the minimum surface roughness value. With the highest speed, the lowest feed rate, the lowest depth of cut, and the highest nose radius of the cutting conditions' scale, the GA technique recommends 1.039 μm as the best minimum predicted surface roughness value. This means that the GA technique has decreased the minimum surface roughness value of the experimental sample data, regression modeling and desirability analysis by about 3%, 1%, and 2.8%, respectively.

Keywords desirability analysis, genetic algorithm, regression modeling, response surface methodology, surface roughness, 7075Al alloy/SiC composites

1. Introduction

In many real machining applications, three conflicting objectives are often considered: the maximum production rate, the minimum operational cost, and the quality of machining. In terms of quality of machining, the criterion for the assessment usually refers to the surface quality of the machined part. Improvement in the quality could be indicated by referring to a performance measure known as surface roughness (R_a). The conventional optimization approach can optimize the machining problem by using some techniques, such as the Taguchi, the factorial, and the response surface methodology (RSM) techniques (Ref 1). The new trend of optimization of the machining process is for soft computing approaches such as GA to be the alternative technique in estimating the optimal result of the cutting parameters, particularly for the R_a value in the turning process. Some established soft computing techniques have been applied by previous studies to suggest the optimal cutting conditions for machining/cutting problems, such as the genetic algorithm (GA), simulated annealing (SA), Tabu search (TS), ant colony optimization (ACO) (Ref 2), and particle swarm optimization (PSO) (Ref 1, 3). Considering the ability factors of GA for the machining optimization problem, an effort is made to estimate the best combination of cutting conditions for the R_a performance measure in the turning process. A few advantages of GA in optimizing cutting conditions for machining problems are listed below (Ref 1, 4, 5):

(i) GA is preferred for near-optimal conditions instead of the exact optimal solution. It is readily acceptable for implementation by the manufacturers.
(ii) It uses a derivative-free approach for near-optimal point(s) search direction.
(iii) It can handle objective functions of any complexity with both discrete and continuous variables.
(iv) It involves simple construction of the model by new input parameters without modifying the existing model structure.
(v) It enables an automatic search for the nonlinear connection between the inputs and outputs.
(vi) It is a fast and simple optimizing technique.

This study is taken up to find optimum values of cutting speed, feed, depth of cut and nose radius at which R_a is minimum. Comparison of results of minimum surface roughness obtained by experiments, regression analysis, desirability analysis, and GA is made to find out which result is better. The percentage variation in the value of R_a, obtained by these four approaches, is also described.

2. Literature Review

Surface roughness is an important machining performance measure, especially, in finish turning operations. The well known ideal surface roughness equation, which represents the best possible finish that may be obtained for a given tool shape and feed, is given by the following geometric expression (Ref 6)

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$$\mathrm{Re} = \frac{0.0321 f^2}{r_e} \quad \text{(Eq 1)}$$

where f represents the feed, and r_e represents the tool-nose radius.

This equation works quite well for moderate machining involving medium cutting conditions, but finish-turning operations always seem to give much higher measured R_a values than the predicted theoretical values by this equation (Ref 7). This is because the real surface roughness can be attributed to the influence of physical and dynamic phenomena such as friction of the cut surface against tool point and vibrations (Ref 8). Hence, the database for surface roughness is experimentally created and a cubic spline interpolation method is applied to obtain the surface roughness function.

The Al-2124/SiCp composites with 20 and 30 vol.% of SiCp reinforcements and of 220 and 600 mesh sizes were fabricated by the powder metallurgy route. The surface roughness was considered as a dependent variable. The magnitudes of feed-rate (10, 60, and 110 mm/rev) and depths of cut (50, 100, and 150 mm) were chosen such that they are closer to the sizes of reinforcement (15 and 65 µm). The tool-nose radii of (0.2, 0.4, and 0.8 mm) were selected based on the available geometry of PCD tools. A response surface-based D-optimal design, consisting of 29 experimental runs, which considers five factors of which two are at two-levels and the remaining three at three-levels, was found to provide the suitable framework for this experimentation. A total of 58 experimental runs (including one replication), as per the design, were performed. ANN-based model was developed to predict roughness of machined surfaces, which uses a feed-forward network and an algorithm involving Bayesian regularization combined with the Levenberg-Marquardt modification to train the neural network. Analysis of machined surface quality and development of an ANN-based model to predict surface roughness in machining of composites shows that; the size of reinforcements in the composite material influences roughness of the machined surfaces significantly; when its magnitude is comparable to that of the feed-rate and the tool-nose radius employed during machining of the composite material. The best surface quality was obtained at the lowest value of feed-rate, the smaller particle size, and the largest tool-nose radius. The predicted response of the ANN model is in very good agreement (correlation coefficient of 0.977 and the mean absolute error of 10.4%) with experimental data (Ref 9).

With GA, R_a increases with an increase in the depth of cut and nose radius (Ref 10). With GA, for the cutting conditions of feed rate, cutting speed and axial depth of cut, a R_a value that is lower than the values of experimental results was obtained (Ref 11). With GA, R_a decreases with high cutting speed and very low feed rate (Ref 12). GA reduces the R_a value on mild steel from 2.60 to 0.71 µm for cutting speed, feed rate, and depth of cut cutting conditions (Ref 13). With feed rate, cutting speed, axial depth of cut, radial depth of cut, and machining tolerance cutting conditions, GA reduces the R_a value in the mould cavity from 0.412 to 0.375 µm, corresponding to about a 10% improvement (Ref 14).

Saravanan et al. (Ref 15) used GA and simulated annealing (SA) to optimize the machining parameters for carbide tools on turning a cylindrical stock into a continuous finished profile. The constraints considered were cutting force, power constraint, and tool-tip temperature. Because of high complexity of this machining optimization problem, a SA) and GA were applied to resolve the problem. The results obtained from GA and SA were compared.

Chien and Tsai (Ref 16) investigated to find the optimum cutting conditions to achieve the maximum material removal rate for coated carbide tools during machining of 17-4PH stainless steel. The back-propagation neural network (BPN) was used to construct the predictive model. The GA was used in the optimization model. The Taguchi method (TM) was used to find the optimum parameters for both the above models. It has been shown that the predictive model is capable of predicting the tool flank wear in an agreement behavior. The optimization model had shown that it is a convenient and an efficient method to find the optimum cutting conditions associated with the maximum metal removal rate (MMRR) under different constraints.

Wang and Jawahir (Ref 17) used AIS1 1045 steel as study material and (TNMG331-CG1) as cutting tool for multi-pass turning process. No cutting fluids were applied. They optimized the multi-pass turning process using GA, and the effect of progressive tool wear was also studied on the optimization of the process. The results show that this methodology can balance the cutting conditions very well between passes, and it is effective for determining optimum cutting conditions as well as for the selection of cutting tool inserts for multi-pass turning operations. By considering the effect of tool-wear, the optimization results are shown to be more reasonable and practical.

Amiolemhen and Ibhadode (Ref 18) used GA for optimizing machining parameters for multi-pass machining on mild steel using carbide inserts. They proposed an optimization technique based on GAs for the determination of the cutting parameters in multi-pass machining operations by simultaneously studying multi-pass roughing and single-pass finishing operations. The optimum machining parameters are determined by minimizing the unit production cost of converting a cylindrical bar stock into a continuous finished profile involving seven machining operations; with each operation subject to many practical constraints. The cutting model developed for each machining operation is a nonlinear, constrained problem. Experimental results show that the proposed technique is both effective and efficient. Sbaizero and Raj (Ref 19) attempted to optimize wear rate in the ceramic cutting tool against material removal rate and surface finish using system-level approach on machining AISI 4340 steel.

With reference to the published literature, it is clear that, currently the usage of the GA technique, which is labeled as a soft computing approach for the turning process, is given less consideration by researchers. Much of the optimization study has been done on steel using carbide cutting tools or HSS tools, and no study has been done on AA7075/10% SiC composites. The increasing acceptance of AA7075/10% SiC composites by aircraft and space industries has necessitated a machining process producing the minimum value of surface roughness. Therefore, it is necessary to know the optimum machining parameters for machining of AA7075/10% SiC composites, which can produce very good surface finish.

3. Methodology

Surface roughness is influenced by many factors such as machining parameters, cutting phenomena, workpiece properties, and cutting tool properties as shown in Fig. 1. Optimization of

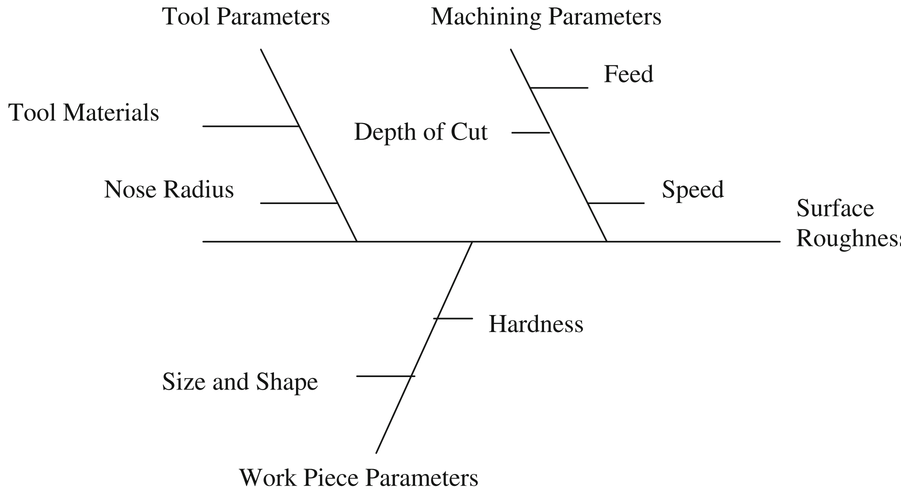

Fig. 1 Parameters affecting surface roughness

cutting speed, feed rate, depth of cut, and nose radius for the R_a performance measure in the turning/machining process by means of the GA technique can be taken as the new contribution to the machining area. This study is implemented in four phases to obtain the optimal operating conditions that minimize machining surface roughness (R_a) values in the turning process, which are as follows:

(i) Studying the real machining experimental data, set to examine the cutting conditions used (cutting speed, feed rate, depth of cut, and nose radius), which contribute to the surface roughness results. For this purpose, AA7075/SiC composites were turned by using carbide insert. The machining experiments were designed using RSM (face-centered-central composite design).

(ii) Developing the machining model to describe the relationship between parameters, viz., cutting speed, feed rate, depth of cut, and nose radius, and responses (surface roughness) using the regression technique. This regression model is selected as the choice for the fitness function (objective function) in the GA optimization module.

(iii) Finding the optimal values of parameters to present the minimum objective function using the GA technique. The objective function or fitness function of GA leads to the minimum (lower) value of surface roughness. Matlab optimization toolbox is used to find the optimal solutions that lead to the minimum value of surface roughness.

(iv) Evaluating the GA optimization solution. The optimal cutting conditions that give minimum surface roughness values generated from GA are compared to the values obtained by experiments, the regression model, and desirability analysis.

4. Experimental study

4.1 Material

Chemical composition of 7075 Al alloy used as matrix for AA7075/SiC composite is shown in Table 1.

Table 1 Chemical composition of 7075 Al alloy

Metal matrix	Zn	Mg	Cu	Cr	Si	Fe	Al
Al 7075	5.62	2.52	1.63	0.22	0.06	0.18	89.77

4.2 Cutting Tools

Details of inserts and tool holders used for turning the AA7075/10 wt.% SiC are given in Table 2.

4.3 Machining Parameters and Their Levels

The ranges of process parameters for the experiment were decided on the basis of the literature survey and the results of pilot experiments conducted using one variable at a time approach. Their values are given in Table 3.

4.4 Computer Numerical Control (CNC) Machine

The basic objective behind the use of CNC machine is the reduction of cost of production and improvement in product quality. Machining by CNC is done for better precision than conventional lathe. Better selection of range of cutting speed, feed, and depth of cut is possible on CNC machine. Any combination of cutting speed, feed, and depth of cut is possible on CNC, but on lathe, a particular combination of cutting speed, feed, and depth of cut is only possible. CNC Turning Machine (Model TC 20) was used for these experiments. This machine is shown in Fig. 2.
The Machine parameters are given below:

Parameter	Specifications
Distance between centers	575 mm
Swing over telescopic cover	500 mm
Spindle speed range	40-4000 rpm
Positioning Accuracy	
X-axis	±0.005 mm
Z-axis	±0.0075 mm
Main motor	7.5 kW

Table 2 Details of inserts and tool holders

Turning tool holder	Type of insert	Clearance angle, °	Back rake angle, °	Nose radius (r), mm	Feed (f), mm/rev	Depth of cut, mm
PCLNL 2525	Carbide insert	0	7	0.8	f_{min} = 0.15 f_{max} = 0.60	a_{pmin} = 1.0 a_{pmax} = 6.0
M12 KT 809	CNMG					
	120404EM			0.4		
	120408EM			0.8		
	120412EM			1.2		
	Grade 6615					

Table 3 Machining parameters and their level

Parameters	Level 1	Level 2	Level 3
Cutting speed, m/min	90	150	210
Feed, mm/rev	0.15	0.2	0.25
Depth of cut, mm	0.2	0.4	0.6
Nose radius	0.4	0.8	1.2

Fig. 2 CNC turning machine

5. Response Surface Methodology

Response surface methodology is a collection of mathematical and statistical techniques that are useful for modeling and analysis of problems in which a response of interest is influenced by several variables, and the objective is to optimize this response. By using the design of experiments and applying regression analysis, the modeling of the desired response to several independent input variables can be gained. In the RSM, the quantitative form of relationship between the preferred response and independent input variables could be represented as (Ref 20)

$$y = f(x_1, x_2, x_3, \ldots, x_n) \pm e_r \qquad \text{(Eq 2)}$$

where y is the preferred response, f is the response function (or response surface), x_1, x_2, x_3, …, x_n are the independent input variables, and e_r is fitting error.

The appearance of response function is a surface as plotting the expected response of f. The identification of suitable approximation of f will determine whether the application of RSM is successful or not. In this study, the approximation of f will be proposed using the fitted second-order polynomial regression model, called the quadratic model. The quadratic model of f can be written as following (Ref 21).

$$Y = b_0 + \sum_{i=1}^{k} b_i X_i + \sum_{i=1}^{k} b_{ii} X_i^2 + \sum b_{ij} X_i X_j \pm e_r \qquad \text{(Eq 3)}$$

where Y is the corresponding response, and X_i's are the values of the ith machining process paramete rs. The terms b… are the regression coefficients, and the residual e measures the experimental error of the observations.

This assumed surface Y contains linear, squared, and cross product terms of variables X_i's. In order to estimate the regression coefficients, a number of experimental design techniques are available. Box and Hunter (Ref 22) have proposed that scheme based on central composite rotatable design fits the second-order response surface very accurately.

The second-order response surface representing the surface roughness (R_a, μm) can be expressed as a function of cutting parameters, such as cutting speed (A), feed (B), depth of cut (C), and nose radius (D). The relationship between the surface roughness and machining parameters is expressed as

$$\begin{aligned} R_a = {} & b_0 + b_1(A) + b_2(B) + b_3(C) + b_4(D) + b_5(A^2) \\ & + b_6(B^2) + b_7(C^2) + b_8(D^2) + b_9(AB) + b_{10}(BC) \\ & + b_{11}(CD) + b_{12}(AD) \end{aligned} \qquad \text{(Eq 4)}$$

In this phase of experimentation RSM has been used for studying the influence of four machining parameters (cutting speed, feed, depth of cut, and nose radius) on surface roughness. Thirty experiments were performed. Each experiment was repeated twice in each of the trial conditions. Trials were randomized. Machining was done under dry conditions.

5.1 Planning for Experiments

Designs of experiments are considered as a very useful strategy for arriving at clear and accurate conclusions from the experimental observations. Experimentation technique, viz., RSM was used for studying the influences of the four parameters (cutting speed, feed rate, depth of cut, and nose radius) on surface roughness in machining of AA7075/10 wt.% SiC composites. Face-centered-central (fcc) composite design was preferred in this case. Experiments were performed at three different levels. Thirty experiments were performed. Table 4 shows the experimental results and predicted values of R_a calculated from regression equation. Table 5 represents RSM experimental model (30 Std array).

5.2 Regression Model for Surface Roughness

The regression coefficients of the second-order equations are obtained from the experimental data (Table 4). Consequently,

Table 4 **Experimental results and predicted value of R_a**

Expt. no.	Cutting speed (A), m/min	Feed (B), mm/rev	Depth of cut (C), mm	Nose radius (D), mm	Experimental surface roughness (R_a), µm	Predicted surface roughness (R_a), µm
1	90	0.15	0.20	0.40	1.499	1.527
2	210	0.15	0.20	0.40	1.284	1.288
3	90	0.25	0.20	0.40	1.562	1.574
4	210	0.25	0.20	0.40	1.338	1.337
5	90	0.15	0.60	0.40	2.269	2.221
6	210	0.15	0.60	0.40	1.923	1.984
7	90	0.25	0.60	0.40	2.412	2.402
8	210	0.25	0.60	0.40	2.189	2.164
9	90	0.15	0.20	1.20	1.251	1.285
10	210	0.15	0.20	1.20	1.071	1.050
11	90	0.25	0.20	1.20	1.302	1.339
12	210	0.25	0.20	1.20	1.115	1.097
13	90	0.15	0.60	1.20	1.826	1.802
14	210	0.15	0.60	1.20	1.569	1.564
15	90	0.25	0.60	1.20	1.999	1.982
16	210	0.25	0.60	1.20	1.732	1.744
17	90	0.20	0.40	0.80	1.913	1.903
18	210	0.20	0.40	0.80	1.688	1.666
19	150	0.15	0.40	0.80	1.797	1.791
20	150	0.25	0.40	0.80	1.862	1.904
21	150	0.20	0.20	0.80	1.461	1.375
22	150	0.20	0.60	0.80	1.991	2.046
23	150	0.20	0.40	0.40	2.064	2.012
24	150	0.20	0.40	1.20	1.698	1.688
25	150	0.20	0.40	0.80	1.879	1.845
26	150	0.20	0.40	0.80	1.851	1.845
27	150	0.20	0.40	0.80	1.848	1.845
28	150	0.20	0.40	0.80	1.824	1.845
29	150	0.20	0.40	0.80	1.821	1.845
30	150	0.20	0.40	0.80	1.802	1.845

the regression equation for the response characteristics as a function of the four input process parameters, viz., cutting speed, feed rate, depth of cut and nose radius considered in this experiment is given below.

$$\begin{aligned}\text{Surface roughness } (R_a) = {} & +0.72412 + 0.00324 * A \\ & - 0.19694 * B + 4.19915 * C \\ & - 0.18753 * D - 0.0000174 * A^2 \\ & - 3.42419 * C^2 + 3.33125 * B * C \\ & - 0.56484 * C * D \end{aligned} \qquad \text{(Eq 5)}$$

By putting the values of cutting speed, feed rate, depth of cut, and nose radius in Eq 4, as shown in Table 4, 30 predicted values of surface roughness are obtained. Comparison of experimental results and regression results of surface roughness is made, which is shown in Fig. 3. Surface roughness scores have shown a similar pattern between the experimental results and regression model results.

Therefore, it could be stated that the surface roughness results predicted by regression model are very close to experimental values of surface roughness.

6. Optimization by Desirability Analysis

In desirability function approach, the measured properties of each predicted response is transformed to a dimensionless desirability value d. The scale of desirability function ranges between $d = 0$ (which suggests that the response is completely unacceptable) and $d = 1$ (which suggests that the response is exactly the target value). The value of d increases as the desirability of the corresponding response increases (Ref 23, 24). In desirability-based approach one-sided transformation is used to transform the response into a desirability value. In this study, the transformation of surface roughness assumes a smaller-the-better characteristic. The response is transformed into di following the equation below:

$$d = \left|\frac{\bar{y} - L}{U - L}\right|^{\alpha}, \quad L \le y^{-} \le U \text{ with } d = 0 \text{ for } y^{-} > U \qquad \text{(Eq 6)}$$

and $d = 1$ for $y^{-} > L$, α represents the weight, L and U are selected according to the mathematical models in RSM.

The optimization analysis was carried out using DESIGN-EXPERT software. In recent years, desirability function approach is used by some of the researchers for finding the optimal solutions using multiperformance objective (Ref 23-26). In the present study, single objective optimization is carried out using desirability-based method. The optimization is carried out in two steps:

(i) obtaining the desirability for the response (R_a);
(ii) maximizing the desirability and identifying the optimal value.

The input variables used and their limits and goal settings are shown m in Table 6. In desirability-based approach,

Table 5 RSM experimental model (30 Std array)

Expt. no.	Cutting speed (*A*), m/min	Feed (*B*), mm/rev	Depth of cut (*C*), mm	Nose radius (*D*), mm	Experimental surface roughness (R_a), µm	Predicted surface roughness (R_a), µm
1	−1	−1	−1	−1	1.499	1.527
2	+1	−1	−1	−1	1.284	1.288
3	−1	+1	−1	−1	1.562	1.574
4	+1	+1	−1	−1	1.338	1.337
5	−1	−1	+1	−1	2.269	2.221
6	+1	−1	+1	−1	1.923	1.984
7	−1	+1	+1	−1	2.412	2.402
8	+1	+1	+1	−1	2.189	2.164
9	−1	−1	−1	+1	1.251	1.285
10	+1	−1	−1	+1	1.071	1.050
11	−1	+1	−1	+1	1.302	1.339
12	+1	+1	−1	+1	1.115	1.097
13	−1	−1	+1	+1	1.826	1.802
14	+1	−1	+1	+1	1.569	1.564
15	−1	+1	+1	+1	1.999	1.982
16	+1	+1	+1	+1	1.732	1.744
17	−1	0	0	0	1.913	1.903
18	+1	0	0	0	1.688	1.666
19	0	−1	0	0	1.797	1.791
20	0	+1	0	0	1.862	1.904
21	0	0	−1	0	1.461	1.375
22	0	0	+1	0	1.991	2.046
23	0	0	0	−1	2.064	2.012
24	0	0	0	+1	1.698	1.688
25	0	0	0	0	1.879	1.845
26	0	0	0	0	1.851	1.845
27	0	0	0	0	1.848	1.845
28	0	0	0	0	1.824	1.845
29	0	0	0	0	1.821	1.845
30	0	0	0	0	1.802	1.845

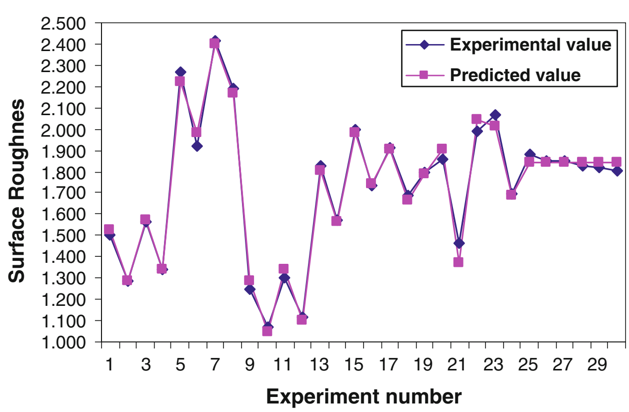

Fig. 3 Comparison of experimental and regression results

different solutions were obtained. The solution with high desirability is preferred. There are 10 solutions generated for getting the true optimal solution, and the best solution is achieved based on the desirability.

Results of desirability analysis are presented in Table 7. The maximum desirability obtained in these cases is 1. Based on the criterion of maximum desirability, the global solution is obtained for minimizing the surface roughness in machining of AA7075/10 wt.% SiC (particle size 10-20 µm) composites. This is given below:

Cutting speed = 209.48 min/m
Feed = 0.18 mm/rev
Depth of cut = 0.2 mm
Nose radius = 1.19 mm

7. Genetic Algorithm Optimization

Genetic Algorithms are search algorithms for optimization, based on the mechanics of natural selection and genetics (Ref 27, 28). The power of these algorithms is derived from a very simple heuristic assumption that the best solution will be found in the regions of solution space containing high proposition of good solution, and that these regions can be identified by judicious and robust sampling of the solution space. The mechanics of GAs is simple, involving copying of binary strings and the swapping of the binary strings. The simplicity of operation and computational efficiency are the two main attractions of the GA approach. The computations are carried out in three stages to get a result in one generation or iteration. The three stages are (a) reproduction, (b) crossover, and (c) mutation (Ref 27, 28).

(a) *Reproduction*. This is the first of the genetic operators. It is a process in which copies of the strings are copied into a separate string called the "mating pool," in proportion

Table 6 Constraints used for optimization

Name	Goal	Lower limit	Upper limit	Lower weight	Upper weight	Importance
Cutting speed	Is in range	90	210	1	1	3
Feed	Is in range	0.15	0.25	1	1	3
Depth of cut	Is in range	0.2	0.6	1	1	3
Nose radius	Is in range	0.4	1.2	1	1	3
Surface roughness	Minimize	1.071	2.412	1	1	5

Table 7 Optimum solution for minimum surface roughness

Number	Cutting speed	Feed	Depth of cut	Nose radius	Surface roughness	Desirability	Selection
1	209.48	0.18	0.20	1.19	1.0689	1.000	Selected
2	208.45	0.15	0.20	1.19	1.06296	1.000	
3	210.00	0.22	0.20	1.20	1.0854	0.989	
4	210.00	0.15	0.20	1.07	1.09272	0.984	
5	210.00	0.16	0.22	1.19	1.10642	0.974	
6	184.61	0.25	0.20	1.20	1.18894	0.912	
7	210.00	0.25	0.20	0.73	1.23865	0.875	
8	125.77	0.16	0.20	1.20	1.27617	0.847	
9	99.23	0.15	0.20	1.20	1.28754	0.839	
10	95.81	0.15	0.20	1.20	1.28782	0.838	

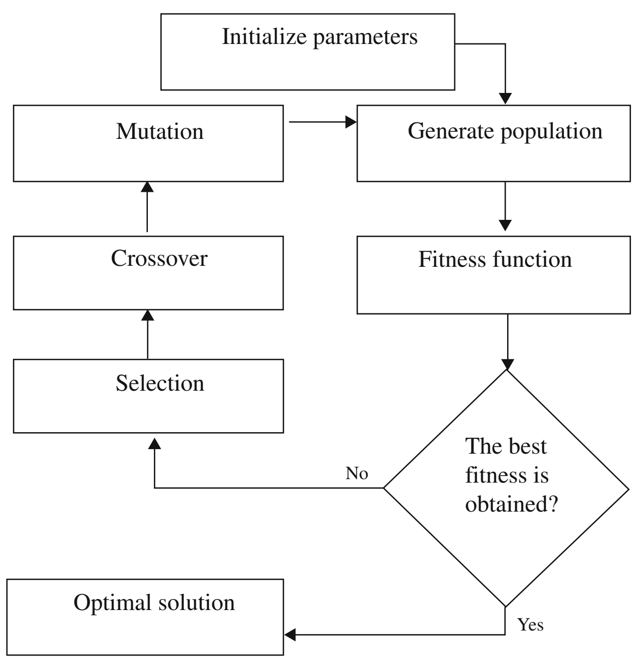

Fig. 4 The flow of GA for optimization (Ref 2)

to their fitness values. This implies that strings with higher fitness values will have a higher probability of contributing more strings as the search progresses.

(b) *Crossover*. This operator, second among the genetic operators, is mostly responsible for the progress of the search. It swaps the parent strings partially, causing offspring to be generated. In this, a crossover site along the length of the string is selected randomly, and the portions of the strings beyond the crossover site are swapped.

(c) *Mutation*. It is one of last GA operators; this is the occasional random alteration (with a small probability) of the value of a string position. In binary strings, this simply means changing 1 to 0, or vice versa.

Figure 4 illustrates the flow of the way by which the GA technique operates when optimizing a problem. Some conditions for obtaining the best fitness function are

(i) The algorithm stops when the number of generations reaches the value of generations.
(ii) The algorithm stops after running for a duration of time in seconds equal to the time limit.
(iii) The algorithm stops when the value of the fitness function for the best point in the current population is less than or equal to the fitness limit.
(iv) The algorithm stops when the weighted average changes in the fitness function value.
(v) The algorithm stops if there is no improvement in the objective function during an interval of time in seconds equal to stall time limit.
(vi) The algorithm runs until the weighted average changes in the fitness function value over stall generations and is less than function tolerance.
(vii) The nonlinear constraint tolerance is not used as a stopping criterion. It is used to determine the feasibility with respect to nonlinear constraints.

Primarily, the evaluation process is repeated until one chromosome with the best fitness criterion is obtained. Then, this best fitness is taken as the optimum solution for the problem (Ref 2).

7.1 Genetic Algorithm Optimization Solution

In this study, the target of the optimization process is to determine the optimal values of process parameters that contribute to make the minimum value of surface roughness as low as possible. To formulate the optimization problem, the surface roughness prediction model which is proposed in Eq 5 is selected.

7.2 Problem Formulation

The problem of machining consists of determining the process parameters, usually the cutting speed, feed, depth of cut, and the nose radius, to optimize the objective function (surface roughness). For effective results in the optimization machining parameters, it is better to provide the actual values of the process parameters, and for this purpose experimental machining study was carried out. The following options are selected for formulating the problem:

Number of variables = 4;
Population type = Double vector;
Population = 20;
Lower bound [90 0.15 0.20 0.40];
Upper bound [210 0.25 0.60 1.20].

7.3 Objective Function

Surface roughness is the main objective function for this problem. The fitness function used in this study for optimization of machining parameters is given as under.

Function y = simple_fitness(x)

$$\begin{aligned} y = {} & 072412 + 000325 * x(1) - 019694 * x(2) + 419915 * x(3) \\ & - 018753 * x(4) - 0000018 * x(1)^2 - 342419 * x(3)^2 \\ & + 333125 * x(2) * x(3) - 056484 * x(3) * x(4) \end{aligned} \qquad \text{(Eq 7)}$$

The minimization of the fitness function value of Eq 7 is subjected to the boundaries (limitations) of cutting condition values. The range of values of experimental cutting conditions given in Table 4 is selected to present the limitations of the optimization solution and is given as follows:

$$90 \leq A \leq 210 \qquad \text{(Eq 8a)}$$

$$0.15 \leq B \leq 0.25 \qquad \text{(Eq 8b)}$$

$$0.2 \leq C \leq 0.6 \qquad \text{(Eq 8c)}$$

$$0.4 \leq D \leq 1.2 \qquad \text{(Eq 8d)}$$

Basically, obtaining the best optimal results depends on some criteria. By following the flow of the optimization procedure given in Fig. 4, the major criteria most influencing the optimal result are the number of the initial population size, the type of selection function, the crossover rate, and the mutation rate. The value or parameter setting for these criteria is obtained by the process of trial and error for giving the most optimal result that is expected from this study. As far as reviews on the previous studies go, there is no guideline yet given by the researchers which could be followed in recommending the best combination for setting the value of the parameters for the best optimal result.

By using the Matlab optimization toolbox, this study has tried several combinations of the set values for cutting conditions to present the best optimal results. The best combination of these values for cutting conditions will lead to the minimum surface roughness. Several numbers of trials were conducted with different value settings for the cutting conditions for searching the minimization values of surface roughness using the Matlab optimization toolbox. The best combination of the parameters applied, which leads to the minimum values of the fitness function is shown in Table 8.

Table 8 Combination of GA parameter rates leading to the optimal solution

Parameters	Setting value
Population size	20
Mutation rate	0.8
Crossover rate	0.2

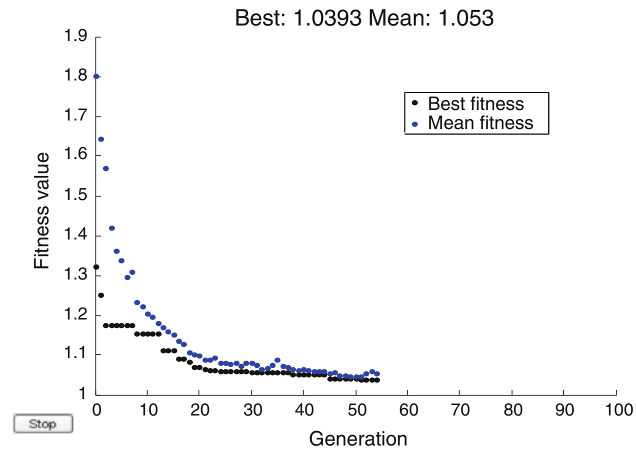

Fig. 5 Plot functions of the best fitness

Table 9 Results of the Matlab optimization toolbox

	Results
Minimum fitness function	
Surface roughness	1.039 μm
Optimal cutting conditions	
Cutting speed	207.055 m/min
Feed	0.151 mm/rev
Depth of cut	0.201 mm
Nose of radius	1.199 mm

By using the fitness function formulated in Eq 8, the limitations of cutting conditions formulated in Eq 8a-8d and the GA parameters given in Table 6, the results of the Matlab optimization toolbox are given in Fig. 5 and Table 8. From Table 9, it can be observed that the minimum surface roughness value is 1.039 μm. The set values of cutting conditions, which lead to the minimum surface roughness value are 207.055 m/min for cutting speed, 0.151 mm/rev for feed rate, 0.201 mm for depth of cut, and 1.199 mm for nose radius. It is also indicated that the optimal solution is obtained at the 54th generation (iteration) of the GA algorithm. As discussed in section 7.1, in order to get an optimal solution, the generated population is evaluated by employing a certain fitness criteria.

Based on the result of Table 9, it is observed that the criterion used by the GA algorithm to stop extending from the further process of finding the optimal solution is the weighted average change in the fitness function value over stall a generation which is less than function tolerance. From Fig. 5, the plot functions indicate that the mean fitness value is 1.053 μm with the best fitness value being 1.039 μm.

7.4 Evaluation of the GA Result

To evaluate the GA result, the issues concerned in this study are

(i) Surface roughness value (best fitness function) predicted by GA is expected to be lower than the minimum (smallest) R_a value of the experimental, regression model, and desirability analysis.
(ii) GA average-predicted surface roughness value (the mean fitness) is expected to be lower than the average (mean) surface roughness value of the experimental and regression model.
(iii) Optimal cutting conditions obtained at the last iteration of GA, which lead to the best fitness function are expected to be in the same range of values as those with the cutting conditions of the experimental design.

For the first issue, by referring to Table 4, the minimum surface roughness value for the real machining experiment is 1.071. By referring to Table 4, the minimum surface roughness value for the regression model is 1.050. Table 8 shows that the best-predicted surface roughness value of GA is 1.039 µm. Therefore, it can be concluded that the GA technique has given the minimum result of surface roughness value compared to the result of the experimental and regression model.

Since the optimal values that are estimated by GA for each cutting condition are in the range of the actual setting cutting conditions, it can be stated that the minimum (best) fitness function of the surface roughness value (R_a = 1.039 µm) could be obtained if used in the real machining experiment.

Theoretically, to validate the result of optimal cutting conditions that are produced by GA techniques, these values will be transferred into the regression model Eq 5, and the best regression model equation, which is taken as the objective function of the optimization GA solution, is used to validate the optimal cutting conditions. With x_1 = optimal solution of the cutting speed, x_2 = optimal solution of the feed rate, x_3 = optimal solution of the depth of cut, and x_4 = optimal solution of the nose radius, the solution is obtained as follows:

$$\begin{aligned} R_a = & + 0.72412 + 0.00324 * 207.055 - 0.19694 * 0.151 \\ & + 4.19915 * 0.201 - 0.18753 * 1.199 \\ & - 0.0000174 * (207.055)^2 - 3.42419 * (0.201)^2 \\ & + 3.33125 * 0.151 * 0.201 - 0.56484 * 0.201 * 1.199 \\ R_a = & 1.0633 \end{aligned} \tag{Eq 9}$$

By transferring the optimal cutting values of GA into Eq 5, as shown in Eq 9, the predicted surface roughness value obtained is 1.0633 µm. This value is compared to the minimum fitness function value of the GA technique. As shown in Table 9, the minimum fitness function value of the GA technique is 1.039 µm. This is very close to the result of the transformation process. This can be taken as the indicator that the same result (R_a = 1.039 µm) might be obtained when the set optimal cutting conditions that are estimated by means of the GA technique are used in the real experiment process.

8. Discussion

This study has applied the GA technique to estimate the optimal solutions of cutting conditions that lead to the minimum surface roughness value. By reviewing the application of GA for the machining optimization problem involving machining parameter in the turning process of AA 7075/10 wt.% SiC, which focuses on the surface roughness performance measure as discussed in the literature review, it has been found that this issue has not yet been taken up by other researchers. Hence, it can be said that this study has given a new contribution to the machining area of study.

In the evaluation of the GA result, the output of GA is evaluated and discussed in term of three issues. The first and second issues are related, respectively, to the best point and average values estimated by the GA technique. The results of the GA outputs discussed in point 7.4 have been summarized in Table 10. The classification of cutting conditions scale for comparing the optimal results is shown in Table 11.

Table 10 Summary of the GA result

Variables	Consideration factors	Issue 1: the best point of R_a	Issue 2: average of R_a	Issue 3: optimal *A*, *B*, *C* and *D* of GA	Remarks
R_a	Experimental result	1.071	1.728		
	Regression result	1.050	1.727		
	GA result	1.039	1.063		Compared to the experimental and Regression, the GA technique gave the more minimal value of the best andaverage R_a values
Cutting speed (*A*)	Required range: 90-210			207.055	
Feed (*B*)	Required range: 0.15-0.25			0.151	All optimal points of *A*, *B*, *C* and *D* cutting conditions of the GA techniquewere in the range of required values.
Depth of cut (*C*)	Required range: 0.2-0.6			0.201	
Nose radius (*D*)	Required range: 0.4-1.2			1.199	

Table 11 Classification of cutting conditions scale for comparing the optimal result

Machining parameters	Units	Lowest	Lower	Medium	Higher	Highest
Cutting speed (*A*)	m/min	90	120	150	180	210
Feed (*B*)	mm/rev	0.15	0.17	0.2	0.22	0.25
Depth of cut (*C*)	Mm	0.2	0.3	0.4	0.5	0.6
Nose radius (*D*)	Mm	0.4	0.6	0.8	1.0	1.2

Table 12 Comparison the optimal cutting condition results of GA and desirability analysis

Technique	Speed optimal	Speed level	Feed optimal	Feed level	Depth of cut optimal	Depth of cut level	Nose radius optimal	Nose radius level	The best predicted point of R_a
GA	207.55	Highest	0.151	Lowest	0.201	Lowest	1.199	Highest	1.039
Desirability analysis	209.48	Highest	0.18	Lowest	0.20	Lowest	1.19	Highest	1.0689

9. Conclusions

From Table 12, as indicated at the last column, it is clear that this study has found that the GA technique has been the effective technique for estimating the better results in terms of the best point and average minimum values of surface roughness compared to the experimental and desirability analysis results. It has also been discovered that the optimal value for each of the cutting conditions recommended by the GA which leads to the minimum surface roughness values are satisfied by the cutting conditions range applied in the real experiment.

From Table 12, it is observed that the GA technique outperforms the RSM technique by looking to the best (minimum) surface roughness predicted value. With the highest speed, the minimum feed rate, the minimum depth of cut, and the maximum nose radius of the cutting conditions scale, the best surface roughness value estimated by desirability analysis is 1.069 µm. However, with the highest speed, the lowest feed rate, the minimum depth of cut, and the maximum nose radius of the cutting conditions scale, the GA technique estimates the lower value 1.039 µm of the best surface roughness value compared to the desirability analysis technique.

As highlighted before, the aim of the optimization process in this study is to determine the optimal values of decision variables, which could lead to make the minimum value of surface roughness as low as possible. Therefore, with the best surface roughness value (1.039 µm) as shown in Table 12, the percentage ratio of GA to decrease the minimum surface roughness is calculated. When comparing the best surface roughness values of the experiment sample data (1.071 µm), the regression model (1.050 µm), and the desirability analysis (1.069 µm), it has been found that the GA techniques decrease the surface roughness values which are about 3%, 1%, and 2.8%, respectively, in respect of the three models.

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