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Optimization of cylindrical grinding process parameters using meta-heuristic algorithms

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Owing to the complexity of grinding process, it has been very difficult to predict the optimal machining conditions which have been resulted in smooth surface finish, accurate geometric measurements and higher production rate. In this work, empirical models for surface roughness, roundness error and metal removal rate have been developed based on regression analysis. These models have been associated the grinding process parameters (work speed, feed rate and depth of cut) with machining performances (metal removal rate, roundness error and surface roughness). Using these models, the optimization has been carried out based on simulated annealing (SA) and genetic algorithm (GA) which have been the two popular meta-heuristic optimization techniques. Finally, the results of the proposed techniques l have compared and experimentally validated.

Keywords: Cylindrical grinding, Modeling, Optimization, Regression analysis, Simulated annealing, Genetic algorithm

1 Introduction

Grinding is commonly used in industries to obtain smooth surface finish with accurate and precise measurements. In order to achieve this, factors such as machining parameters (wheel speed, work speed, feedrate, depth of cut), grinding wheel parameters (type of abrasive, grain size, structure, bond type) etc., need to be properly selected. In this work, selection of optimal machining parameters has been considered for study as they have greater influence on the machining performances. Optimization of parameters is a vital phase in grinding, that can trim down the production expenses and assure the desired quality of the finished product. Attempts have been made by researchers on optimization using various methods such as quadratic programming[1], enumeration method[2], computer simulation[3], monte-carlo simulation method[4], Taguchi method[4-6], Response Surface Methodology (RSM)[7-8], Genetic Algorithm[9-13], Particle Swarm Optimization[14], Ant Colony Optimization[15], and Simulated Annealing[16-18]. From the literature survey it has been found that the meta-heuristic algorithms provide better accurate results even for optimization of complex processes. In the present work, an attempt has been made to employ meta-heuristic algorithms for the optimization of cylindrical grinding process parameters. The algorithms considered in this study are Simulated Annealing (SA) and Genetic Algorithm (GA). To facilitate the process of optimization empirical models are developed using regression analysis as a tool.

2 Proposed Methodology

The experiments were designed based on Taguchi's Design of Experiments (DOE), which facilitates in minimizing the number of experiments required to extort significant inferences. Taguchi technique is an effective tool for examining the correlations among the parameters, which offers an easy, cost effective and methodical approach to find the optimal process parameters. From the experimental data, models are generated using SPSS (Statistical Package for Social Science) software for ascertaining the association of grinding parameters with the machining performances. The empirical models generated so are then used for predicting the optimal grinding process parameters. The optimization is carried out by employing Simulated Annealing and Genetic Algorithm (GA) approaches. Simulated Annealing (SA) is a popular meta–heuristic optimization technique which has been found successful in determining the optimal solution for various problems[18]. The main advantage of this method is its capability to avoid getting trapped at local minima. The execution of this meta-heuristic algorithm is easy

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and provides reliable solutions to a wide variety of problems[17]. Genetic Algorithm (GA) is another optimization tool which has been widely used due to its accessibility and global outlook. The genetic algorithm replicates the ideology of natural genetics and natural selection[19]. The search process in GA motivates the natural evolution and facilitates cogent exploitation of a random search[20].

3 Experimental Details

A series of experiments have been conducted on cylindrical grinding machine given in Fig. 1 to study the relationship between the machining parameters and their effect on responses and to develop an empirical model for the same. The machining parameters selected for research were work speed (V_w), feed rate (f) and depth of cut (d) as given in Table 1. The other aspects of grinding such as grain, bond, structure, workpiece, coolant (dry grinding) etc., were kept constant. Since three machining parameters of three levels are taken in this study, Taguchi L_9 Orthogonal array is considered for designing the experiments. The experiment was conducted on AISI 316 Stainless Steel (50 mm diameter), which has extensive applications demanding good corrosion resistance, resistance to erosion due to chloride ion solutions, and good strength at higher temperatures[21]. It is an austenitic chromium nickel stainless steel containing molybdenum. The chemical composition of the workpiece is given in Table 2.

In this experimental work aluminium oxide with vitrified bond (A60N5V10C) grinding wheel is used. The initial diameter of the wheel was 300 mm and width 25 mm. The grinding wheel was dressed before every experimental run using a single point diamond dresser. The metal removal rate was calculated using Equation 1 for every experimental run. The roundness error (R_e) was measured using a dial indicator and the surface roughness (R_a) was measured on the surface test instrument. The mean value of ten readings were taken to ascertain the roundness error and surface roughness for each experiment and recorded as shown in Table 3.

$$MRR = 50\, f\, d \qquad \ldots (1)$$

4 Results and Discussion

The purpose of this work is to develop an empirical model for metal removal rate (MRR), roundness error (Re) and surface roughness (R_a) and to carry out the optimization of grinding parameters (work speed, feed rate and depth of cut) for AISI316 stainless steel, so as to attain minimum surface roughness and roundness error with a maximum metal removal rate. This has been achieved using the above discussed methods.

4.1. Empirical modeling

In order to generalize the experimental results, the empirical models for the machining performances are developed using regression analysis. The coefficient values of regression models acquired from the analysis elucidates that decrease in work speed, decrease in

Fig. 1 — Experimental set up for cylindrical grinding.

Table 1 — Controllable factors and their levels.

Cutting parameters	Levels		
	1	2	3
Work speed, V_w (m/min)	9	18	36
Feed rate, f (mm/min)	5	15	25
Depth of cut, d (mm)	0.01	0.02	0.03

Table 2 — Chemical composition of the workpiece (AISI 316).

C	Mn	Si	P	S	Cr	Mo	Ni	N
0.08	2.0	0.75	0.045	0.03	18.0	3.0	14.0	0.10

Table 3 — L_9 orthogonal array and experimental results.

Sl. No	V_w	f	d	MRR (mm^3/min)	Re (mm)	R_a (µm)
1.	1	1	1	2.5	0.02	0.72
2.	1	2	2	15	0.01	0.48
3.	1	3	3	37.5	0.03	0.90
4.	2	1	2	5	0.10	0.56
5.	2	2	3	22	0.06	0.49
6.	2	3	1	12.5	0.01	0.57
7.	3	1	3	7.5	0.04	0.77
8.	3	2	1	7.5	0.01	0.59
9.	3	3	2	25	0.03	0.65

feedrate and decrease in depth of cut decreases the value of surface roughness whereas increase in work speed and depth of cut and decrease in feedrate decreases the value of roundness error. From the experimental results, for *MRR*, R_e and R_a the equation has been achieved in the following quadratic form:

$$MRR = -8.667 - 0.041V_w + f + 750d - 5 * 10^{-4}{V_w}^2 + 0.032f^2 + 400d^2 \quad \dots (2)$$

$$R_e = -0.04 + 0.001V_w - 0.004f + 9.5d - 0.1606 * 10^{-4}{V_w}^2 + 0.998 * 10^{-4}f^2 - 183.3d^2 \quad \dots (3)$$

$$R_a = 1.543 - 0.04V_w - 0.051f - 41.778d + 0.0008{V_w}^2 + 0.002f^2 + 1133.333d^2 \quad \dots (4)$$

The sum of the squares of the residuals given in Table 4, are calculated to ensure the best fit. The 'R^2' of the regression is the fraction of the variation in the dependent variable that is predicted by the independent variables. It gives an estimate of goodness of fit of the function. The 'R^2' value achieved in the investigation is 0.952 for *MRR* model, 0.955 for R_e model and 0.934 for R_a model which indicates that 95.2% of the alteration of the machining parameters can be described by the variation of the metal removal rate, 95.5% of the difference of the machining parameters can be elucidated by the deviation of the roundness error and 93.4% of the difference of the machining parameters can be described by the deviation of the surface roughness. The proposed model has shown better R^2 value, thus proving its fitness and applicability. To further validate, the proposed models are utilized to predict the experimental values. The predicted and experimental values were found to be very close as shown in Fig. 2. Thus for any values of operating parameters the models can be used to predict *MRR*, R_e and R_a.

Table 4 — ANOVA table for the quadratic model of MRR, Re and Ra.

Dependent variable: Metal Removal Rate
R squared = 0.952

Source	Sum of Squares	DF	Mean Squares
Regression	3012.5	7	430.357
Residual	50	2	25
Uncorrected Total	3062.5	9	
Corrected Total	1037.5	8	

Dependent variable: Roundness error
R squared = 0.955

Source	Sum of Squares	DF	Mean Squares
Regression	3.666	7	0.524
Residual	0.004	2	0.002
Uncorrected Total	3.670	9	
Corrected Total	0.085	8	

Dependent variable: Surface Roughness
R squared = 0.934

Source	Sum of Squares	df	Mean Squares
Regression	3.791	7	0.542
Residual	0.010	2	0.005
Uncorrected Total	3.801	9	
Corrected Total	0.153	8	

4.2. Computational results of SA

The optimal parameters for AISI 316 Stainless steel are predicted based on Simulated Annealing algorithm using MATLAB. The developed models, Eqs 2, 3 and 4 are considered as the fitness functions for evaluating the metal removal rate, roundness and surface roughness value of every new point. The optimization was carried out for several iterations and terminated when there was no change in fitness function. The simulation results are shown in Fig. 3. The optimal grinding parameters for maximum metal removal rate, minimum roundness, minimum surface roughness and minimum COF are predicted and presented in the Table 5. The optimal grinding parameters obtained for maximum metal removal rate result in very high roundness which is not preferable. Similarly the optimal grinding parameters for minimum roundness and surface roughness are predicted. But these parameters do not result in better values of other two machining performances. Hence, to obtain required machining performances for the

Table 5 — Comparison of results for MRR, R_e, R_a and COF.

Objective	Method	V_w (m/min)	*f* (mm/min)	*d* (mm)	MRR (mm^3/min)	Re (mm)	Ra (μm)	COF
Max MRR	SA	9.178	24.998	0.03	57.128	0.0331	0.829	0.11451
	GA	9	25	0.03	57.145	0.0328	0.83	0.11435
Min Re	SA	9.002	20.81	0.01	31.515	0.00039	0.62	-0.0238
	GA	9	20.10	0.01	29.86	0.00032	0.61	-0.0295
Min Ra	SA	22.99	15.52	0.0176	20.083	0.086	0.315	0.134
	GA	22.84	15.00	0.0178	19.35	0.087	0.314	0.139
Min COF	SA	13.15	16.30	0.01	20.34	0.028	0.476	0.01209
	GA	13.82	17.29	0.01	22.17	0.029	0.475	0.01217

same input parameters, the objective functions are combined together and the combined objective function (COF) is formed as given below:

$$Min\ COF = x_1\ MRR + x_2 R_e + x_3\ R_a \qquad \ldots (5)$$

Since grinding is a finishing operation, surface finish is the main objective to be achieved while maintaining minimum roundness and maximum *MRR*. The coefficients which accomplish this objective are x_1= -0.1, x_2=0.25 and x_3=0.65. As in Table 5 and in Fig. 3, the optimal machining parameters predicted using SA are work speed (V_w= 13.15 m/min), feed rate (f = 16.30 mm/min) and depth of cut (d = 0.01 mm) for a minimum surface roughness of 0.55µm. For these parameters the roundness is found to be 0.008mm with a metal removal rate of 23.04mm^3/min.

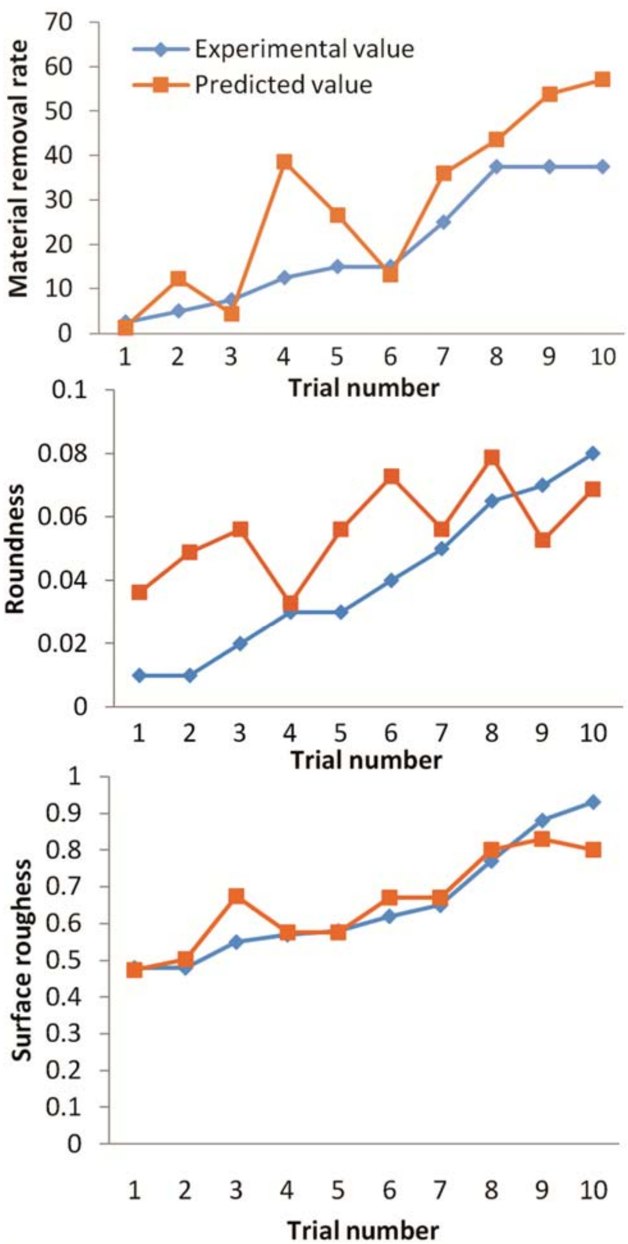

Fig. 2 — Validation of proposed model for MRR, R_e and R_a.

4.3. Computational results of GA

The optimal grinding parameters that yield minimum surface roughness, minimum roundness error and maximum metal removal rate are predicted based on GA using MAT lab. The regression models given as Equation 2, 3 and 4 are considered as the fitness functions for finding the metal removal rate, roundness and surface roughness value of every new individual. The GA operators used in this search process are:

Scaling Method: Rank
Selection Method: Roulette
Crossover Operator: Single point
Crossover Probability: 0.8
Mutation Probability: 0.1
Number of iterations: 1000
Population size: 100

The optimal grinding parameters for maximum removal rate, minimum roundness, minimum surface roughness and minimum COF are predicted using GA and presented in the Table 5 and Fig 4. As in SA optimization in GA also, the optimal grinding parameters for maximum MRR result in very high roundness which is not desirable. Similarly the optimal grinding parameters for minimum roundness and surface roughness do not result in better values of other two machining performances. So to obtain best machining performances for the same input parameters, the objective functions are combined together as in Equation 6 and the optimal machining parameters are predicted which is presented in Fig. 4. As given in Table 5 the optimal result obtained are work speed (V_w= 13.82 m/min), feed rate (f = 17.29 mm/min) and depth of cut (d = 0.01 mm) for a minimum surface roughness of 0.554µm. For these parameters the roundness is found to be 0.008mm with a metal removal rate of 25.04mm^3/min. The result obtained using GA approach is very similar to that of SA approach.

4.4. Comparison of results

The optimal grinding parameters for maximum MRR, minimum roundness error and minimum surface roughness are achieved using SA and GA and presented in Table 5.

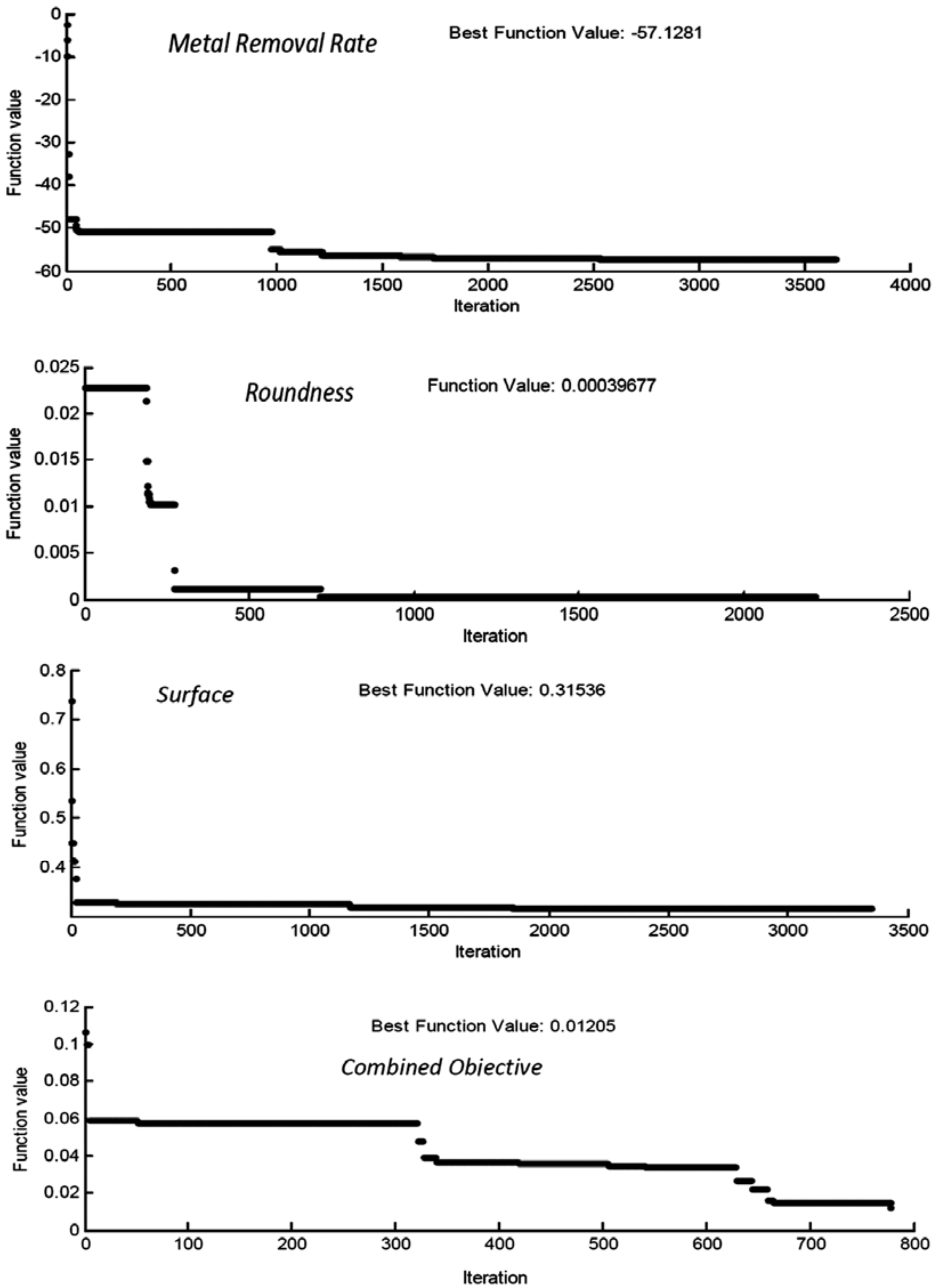

Fig. 3 — Prediction of maximum MRR, minimum R_e, minimum R_a and minimum COF using SA.

The result obtained from SA and GA are compared and found that the values achieved are very nearer. It is observed that GA exhibits a broad search and produced new population at random and advanced towards optimal results by the way of reproduction, crossover and mutation. By controlling the parameters of GA exploitation of information, good exploration, convergence in search and consistency in result is obtained. Because of various parameters with a large range, the tuning of algorithm is difficult.

In SA, the search is dependent on the start point and the initial temperature alone, so the tuning of the

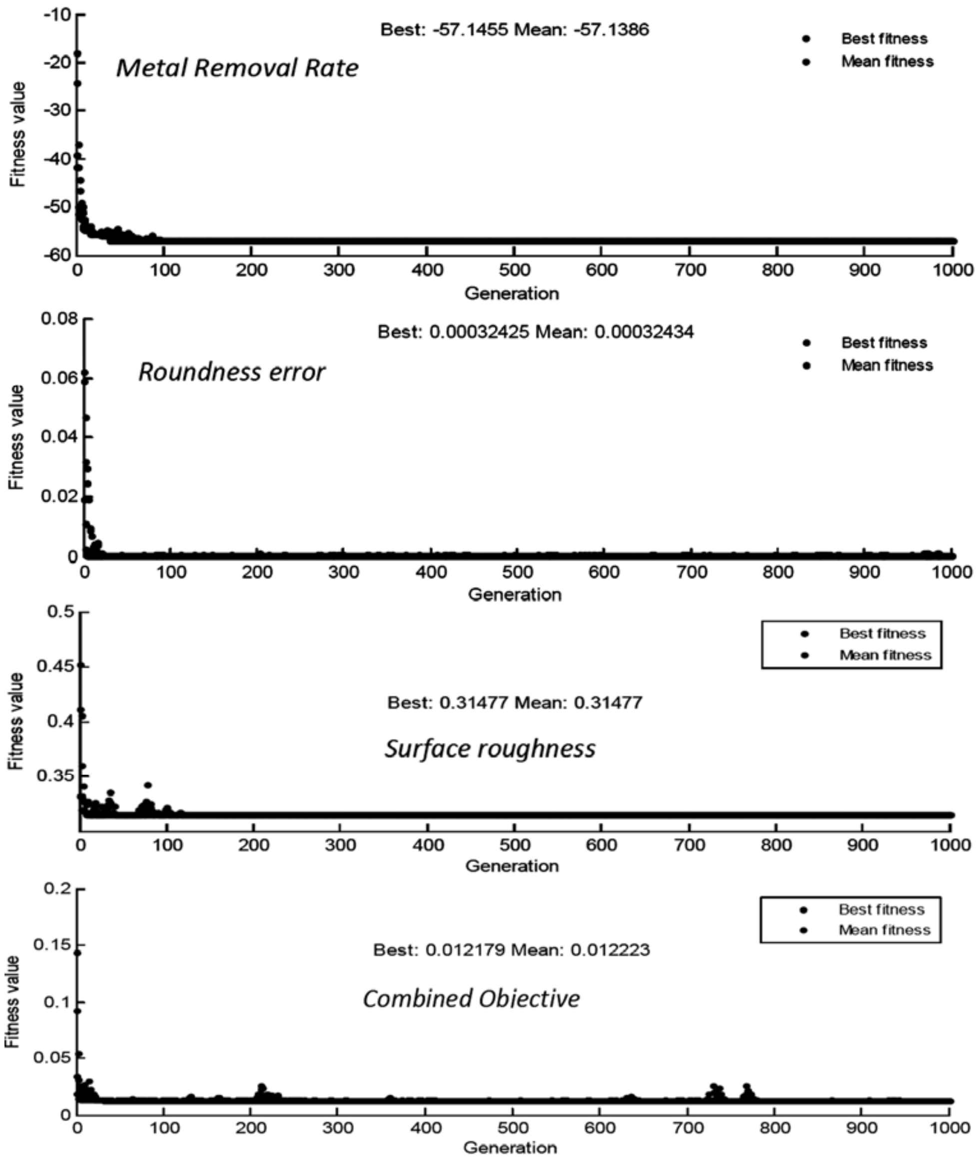

Fig. 4 — Prediction of maximum MRR, minimum R_e, minimum R_a and minimum COF using GA.

Table 6 — Experimental validation of SA and GA results.

Method	V_w (m/min)	*f* (mm/min)	*d* (mm)	MRR (mm^3/min)	Re (mm)	Ra (µm)	COF	% Error
SA	9	25	0.03	58.728	0.0094	0.929	0.1145	18.4
GA	9	25	0.03	58.745	0.0093	0.930	0.1143	18.2
Expt. value	9	25	0.03	37.5	0.01	0.98	0.0967	

program is very easy comparatively. But the exploration and consistency in result is very poor and hence the computation time and number of iterations performed to obtain the results are more when compared with GA. To validate the performance of SA and GA, for a set of machining parameters, the output parameters (MRR, R_e and R_a) were predicted and compared with that of experimental value as given in Table 6. The percentage of error for GA was observed to be comparatively less than SA.

5 Conclusions

An attempt has been made in this paper to optimize the cylindrical grinding parameters for maximum metal removal rate, minimum roundness error and minimum surface roughness of AISI 316. From the experimental investigations effective regression models are developed, which associates the process parameters (work speed, feed rate and depth of cut) with metal removal rate, surface roughness and roundness error. Regression analysis has proven to be an effective tool in generating the regression models which are of good accuracy and can be utilized in predicting these machining performances in cylindrical grinding of AISI 316. It also reveals the fact that decrease in work speed and increase in feedrate has a good effect on surface finish and metal removal rate, also decrease in depth of cut reduces the surface roughness and roundness error. Further in this paper, Simulated Annealing algorithm and Genetic Algorithm are applied to determine the optimal process parameters so as to achieve maximum metal removal rate, minimum surface roughness and minimum roundness error. The optimal cylindrical grinding process parameters obtained so are work speed (V_w = 13 m/min), feed rate (f = 17 mm/min) and depth of cut (d = 0.01 mm).

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