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Application of Regression Analysis and Evolutionary Algorithms for Modeling and Optimization of Cylindrical Grinding Process Parameters for the Prediction of Surface Roughness of AISI 316

R. Rekha[#1], N. Baskar[#2], K.Padmanaban[#3], V.Venkatraman[*4]
[#1,#2&#3]*Department of Mechanical Engineering, Saranathan College of Engineering, Tiruchirapalli, Tamilnadu, India.*
[*4]*Department of Mathematics,School of Humanities and Science, Sastra University, Thanjavur, Tamil Nadu, India.*
[#1]*rekhame76@gmail.com*, [#2]*baskarnaresh@yahoo.co.in*,
[#3]*krispad49@gmail.com*, [*4]*mathvvr@yahoo.co.in*

Abstract

This paper discusses a simple and economical procedure developed for the prediction of optimal cylindrical grinding process parameters for surface roughness of AISI 316 stainless steel. With a minimum number of experimental data an effective regression model is developed which correlates the grinding process parameters (work speed, feed rate and depth of cut) with surface roughness. The evolutionary optimization techniques such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are employed to find the optimal values of process parameters with the objective of achieving minimum value of surface roughness. Finally, the experiments are carried out to identify the effectiveness of the proposed method.

Keywords: Cylindrical grinding. Surface roughness. Regression analysis. Genetic Algorithm. Particle Swarm Optimization.

Introduction

The quality of a machined surface is very important for satisfying the specific demands of sophisticated component performance like longevity and reliability which are in turn dependent on the geometric, dimensional and surface characteristics. Surface roughness is of great importance for product quality and its function in manufacturing industries. It is generally regarded as an important factor in terms of fatigue life performance. Grinding is a widely used machining process in industry for close dimensional and geometric accuracies and smooth surface finish. It involves material removal by the contact between a grinding wheel with a randomly structured topography and the workpiece. It is a complex manufacturing process, influenced by factors such as wheel, work piece, machine and process setting.

A lot of research work has been carried out to characterize and understand the grinding process [1-4], to examine the effect of coolant on surface integrity [5,6] and to evaluate the influence of grinding variables on surface roughness [7-9]. Attempts have also been made by researchers to develop a surface roughness model using Response Surface Methodology (RSM) [10 -11, 15-18] and Back Propagation Neural Network [19-21]. Since grinding is a complex manufacturing process with a lot of factors which influence each other, modeling can be a useful tool for understanding and simulating the process itself. Regression analysis is an efficient mathematical and statistical tool to develop an empirical model [10]. It is more practical, economical and relatively easy to use when compared with neural network modeling, because development of an adequate network structure is rather complex and needs powerful data processing computer and artificial intelligence technology. In this research work, regression analysis is employed to develop an empirical model for predicting the surface roughness of AISI 316 stainless steel during cylindrical grinding operation.

The success of any grinding operation depends upon the proper selection of various operating conditions like wheel speed, work speed, traverse feed, in feed, area of contact, grinding fluids, balancing of grinding wheels, dressing etc. Usually the process parameters are selected based on the operator’s experience or from the manufacturer’s manual, and this does not provide optimal results. Hence, optimization of operating parameters is an important step in machining, which will reduce the machining cost and ensure the quality of the final product. Researchers have worked on optimization of grinding process parameters using computer simulation and enumeration method [12-14]. Many researchers have attempted on optimization of process parameters for different machining processes using various evolutionary algorithms such as Genetic Algorithm and Particle Swarm Optimization [18-28], Ant Colony Optimization[25,29], Tabu Search and Simulated Annealing [25], Differential Evolution and Non-dominated Sorting Genetic Algorithm-II [30]. Among all these evolutionary techniques Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) have been widely used as an optimization tool in various problem domains owing to its broad applicability, ease of use and global perspective. In this work, it is proposed to implement GA and PSO to optimize the machining parameters for the required surface roughness of AISI 316 stainless steel during cylindrical grinding operation.

Proposed Methodology

Although work has been done in modeling and optimization of cylindrical grinding using GA and PSO [24, 26], a different procedure is adopted in this work as presented in Fig.1. In the present work, effort has been taken to reduce the number of experiments to make the procedure more cost-effective. Experiments were carried out for AISI 316 stainless steel under different grinding conditions based on Taguchi’s design of experiments and the corresponding surface roughness values were measured. Based on this experiment the effect of grinding parameters on surface roughness of AISI 316 stainless steel were analyzed using S/N ratio and ANOVA. From the data collected a multiple non-linear regression model was generated using SPSS (Statistical Package for Social Science) software for establishing the relationship of various process parameters towards surface roughness. The empirical model developed is subsequently used for optimization of process parameters for minimum surface roughness. The optimization problem was solved by using Genetic Algorithm (GA) and Particle Swarm Optimization (PSO).

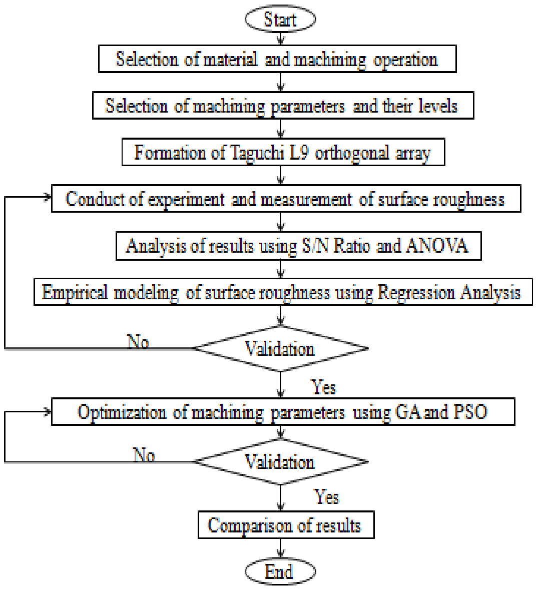

Figure 1: Flowchart for proposed methodology

Design of Experiments

To evaluate the influence of process parameters, numerous experimental runs are required to explore the parameter space. The experiments are planned using Taguchi's Design of Experiments (DOE), which helps in reducing the number of experiments needed to extract meaningful conclusions [34]. Since three controllable factors (operating parameters) of three levels are considered in this study, Taguchi L_9 orthogonal array is preferred to design the experiments.

Taguchi method is useful for studying the interactions between the parameters, and also it is a powerful design of experiments tool, which provides a simple, efficient and systematic approach to determine optimal cutting parameters. In Taguchi, Signal to Noise (S/N) ratio represents quality characteristics for the observed data. The term signal refers to desirable value and noise represents the undesirable value. The high value of S/N ratio corresponds to a better performance of the parameter in the presence of noise factors. Since minimum value of surface roughness is always preferred, the smaller-the-better characteristic of S/N ratio is chosen, which is given in Equation 1. The influence of cutting parameters on surface roughness is studied using

S/N ratio, and ANOVA is used to determine the significant process parameter and the contribution of each process parameter towards the output characteristic.

$$\eta = -10 \log_{10}\left(\frac{1}{r}\sum_{i=1}^{r} R_i^2\right) i = 1,2, \ldots r \quad (1)$$

Where η is the Signal-to-Noise ratio, R_i is the value of surface roughness for the i^{th} trial and r is the number of trials.

Regression analysis

Regression analysis is a statistical technique for modeling and analyzing several variables, when the focus is on the relationship between a dependent variable and one or more independent variables. It is used when a continuous dependent variable from a number of independent variables is to be predicted. For nonlinear regression the second and higher derivatives are not zero, and thus an iterative process is required to calculate the optimal parameter values. Based on the model of name “Ratio of Quadratics” a regression model for surface roughness is developed in the form given below:

$$R_{a=}\ a + bx + cy + dz + ex^2 + fy^2 + gz^2 \quad (2)$$

The size of the coefficient for each independent variable (x, y, z) of the model gives the size of the effect that variable has on dependent variable, and the sign on the coefficient (positive or negative) gives the direction of the effect. In this work, the nonlinear regression is used to develop a surface roughness model for cylindrical grinding operation.

Genetic Algorithm (GA)

The genetic algorithm is an adaptive search and optimization algorithm that mimics the principles of natural genetics and natural selection [25]. The searching process in GA stimulates the natural evolution and enables intelligent exploitation of a random search [18]. GA produces ever-improving solutions based on the rule ‘the best one survives’. The most important feature that distinguishes GA from other algorithms is selection [23]. Generally, the GA mechanism consists of three fundamental operations: reproduction, crossover, and mutation. Reproduction is the random selection of copies of solutions from the population, according to their fitness value, to create one or more offspring. Crossover defines how the selected chromosomes are recombined to create new structures for possible inclusion in the population. Mutation is a random modification of a randomly selected chromosome. Its function is to guarantee the possibility to explore the space of solutions for any initial population. Both crossover and mutation occur at every cycle, according to an assigned probability. The aim of the three operations is to produce a sequence of populations that, on the average, tends to improve the search towards optimal solution [22]. Every good optimization method needs to balance the extent of exploration and exploitation of information. If solutions obtained are exploited too much, premature convergence is expected. On the other hand, if too much importance is given for exploration, information obtained thus has not been properly used. These issues can be controlled in GA by varying the parameters involved in the genetic operators. Therefore, GA provides an ideal platform for performing flexible search [31].

Particle Swarm Optimization (PSO)

Particle Swarm Optimization is a population based stochastic optimization technique developed by Dr.Eberhart and Dr.Kennedy in 1995, inspired by social behavior of birds flocking [32]. This PSO algorithm [25] initializes a number of particles randomly and searches for optimal solution. At the end of every iteration each particle is updated by following two 'best' values. One best value is population best called pbest, which is the best solution achieved by the particle in the generation. Another 'best' value is global best called gbest, which is the best solution obtained so far by any particle. After finding the two 'best' values, the particle updates its velocity and positions with following equations (3) and (4) [32].

$$v[\ ] = \omega * v[\ ] + c1 * rand(\ ) * (pbest[\ ] - present[\ ]) + c2 * rand() * (gbest[] - prsent[]) \tag{3}$$

$$present[] = present[] + v[] \tag{4}$$

Where v[] is the velocity for the i^{th} particle which represents the distance to be traveled by the particle from the current position, ω is the inertia weight which is usually 0.8 to 0.9, Rand() is a random number between (0 to 1), c1& c2 are learning factors usually 0 to 2, present [] is the location of the i^{th} particle i.e., particle position,

pbest [] is the best previous position of the i^{th} particle and gbest[] is the index of the best particle among all the particles in the population.

In comparison with other heuristic algorithms, PSO has less number of parameters to be tuned by the user. PSO has been found to be an attractive algorithm for the reasons that the concepts are very simple, coding is very easy, computational burden is less and there is fast convergence and high accuracy [27, 33].

Experimental Details

The literature survey reveals that the grinding variables greatly influence the surface roughness of the workpiece. To comprehend the relationship between the grinding conditions and their influence on surface roughness, and develop an empirical model, a series of experiments have been conducted. The work material and the experimental work done are explained below.

Work Material

The experiment is conducted on AISI 316 Stainless Steel, which is widely used in applications requiring good corrosion resistance, resistance to pitting from chloride ion solutions, and high strength at elevated temperatures [7].

It is an austenitic chromium nickel stainless steel containing molybdenum. The chemical composition of the workpiece is listed in Table1. Literature survey shows that limited work has been carried out on AISI 316. To be specific, one work deals with EDM process parameter optimization [28] and the other with surface grinding performance under cryogenic cooling [7]. This forms the basis for attempting more research work on this material.

Experimental set up and procedure

Experiments were conducted on the cylindrical grinding machine as shown in Fig.2, on austenitic steel AISI 316 of 40mm diameter to determine the effect of machining parameters on surface finish. Grinding wheel (A60N5V10C) used for this experimental work had aluminum oxide abrasives with vitrified bond.

Table 1: Chemical composition of the work piece (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 2: Controllable factors and their levels

Cutting parameters	Levels		
	1	2	3
V_w (m/min)	70	98	126
f (mm/rev)	0.073	0.093	0.113
d (mm)	0.003	0.004	0.005

The initial dimensions of the wheel were 580mm in diameter and 50mm in width. A single point diamond dresser was used for dressing the grinding wheel before the conduct of each experiment.

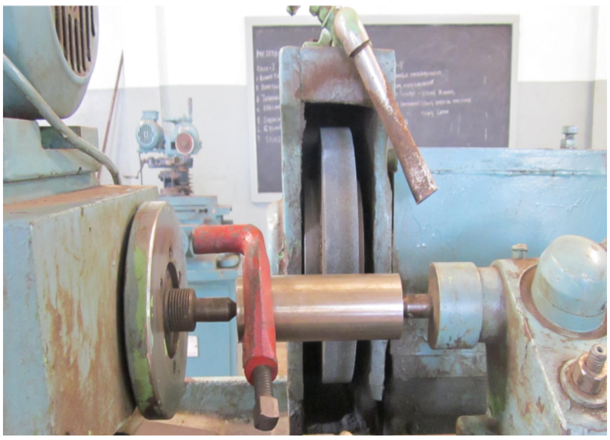

Figure 2: Experimental set up for cylindrical grinding

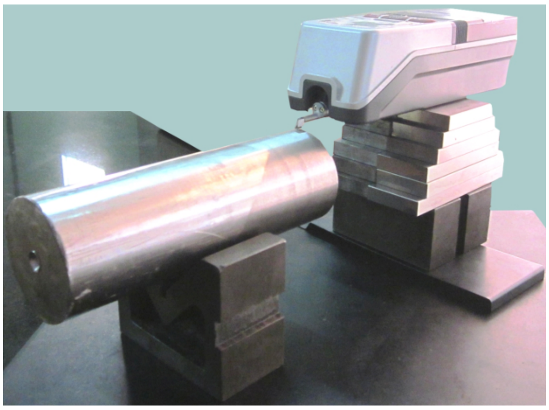

Figure 3: Measurement of surface roughness

Table 3 L_9 orthogonal array and experimental results for surface roughness

Sl.No	V_w m/min	f mm/rev	d mm	R_a µm	S/N Ratio
1.	1	1	1	0.79	2.04746
2.	1	2	2	0.76	2.38373
3.	1	3	3	0.84	1.51441
4.	2	1	2	0.60	4.43697
5.	2	2	3	0.58	4.73144
6.	2	3	1	0.67	3.47850
7.	3	1	3	0.71	2.97483
8.	3	2	1	0.75	2.49877
9.	3	3	2	0.73	2.73354

The grinding parameters selected for investigation were work speed (V_w), feed rate (f) and depth of cut (d). The ranges of parameters are given in Table 2. The other factors such as of abrasive, workpiece and spark out were kept constant. The surface roughness (R_a) of the job was evaluated on the Taly surface test instrument as shown in Fig.3. The average of ten readings was taken to determine the surface roughness value for every experimental run and recorded as shown in Table 3.

Results and Discussions

The objective of this work was to investigate the effect of cylindrical grinding parameters on surface roughness of AISI stainless steel and to develop an empirical model for surface roughness and to optimize the grinding parameters (work speed, feed rate and depth of cut) in order to achieve minimum value of the surface roughness. This has been accomplished by using the above mentioned methodologies.

Effect of Grinding Parameters on Surface Roughness of AISI 316 Stainless Steel
The effect of controllable factors (V_w, f, d) on surface roughness is investigated using S/N ratio approach. The S/N ratio for the measured surface roughness value is calculated using the Eq. 1 and presented in Table 3. The mean S/N ratio of surface roughness obtained for different levels of the machining parameters and the rank obtained by the parameters are given in Table 4. It is evident from Table 4 that the work speed is the dominant parameter followed by the feedrate and depth of cut since the maximum mean S/N ratio is obtained for level 2 of work speed (4.216) and then for level 2 of feedrate (3.205) and level 2 of depth of cut (3.185). This also establishes the fact that level 2 of work speed, feedrate and depth of cut will result in minimum surface roughness of AISI stainless steel during cylindrical grinding. Experiments were conducted to validate the result and it was found that a work speed of 98m/min, a feedrate of 0.093mm/rev and a depth of cut of 0.004mm produced a surface roughness of 0.51µm which is comparatively less than other experimental values given in Table 3. The results match with that presented in literature [17, 18, and 35].

The response graphs given in Fig. 4 elucidate the influence of each machining parameter on the surface roughness. These figures show the ideal machining conditions (the level with the highest point on the graphs), and also the relative effect of each parameter on the surface roughness (the general slope of the line) [17]. In the S/N ratio effects graphs, the slope of the line which connects between the levels illustrates the power of influence of each control factor. The work speed is discovered to have a strong effect on surface roughness and its S/N ratios. The feed rate and depth of cut have a smaller effect, as confirmed by the shallow slope of the lines.

Table 4 S/N ratio response table for surface roughness

Level	Cutting Parameters		
	V_w	f	d
1	1.982	3.153	2.675
2	4.216	3.205	3.185
3	2.736	2.575	3.074
Delta	2.234	0.629	0.510
Rank	1	2	3

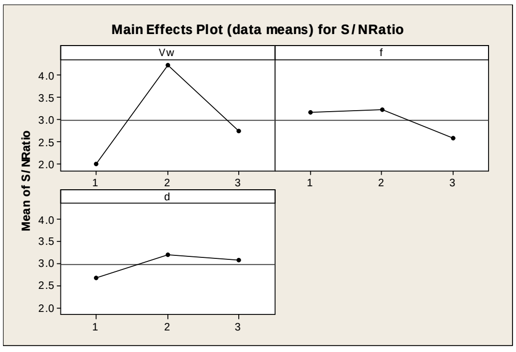

Figure 4: S/N ratio response graph for surface roughness

Table 5: ANOVA table for surface roughness

Source	DOF	Sum of square	Mean square	F- ratio	P- value
V_w	2	0.0497	0.0248	36.66	0.027
f	2	0.0047	0.0023	3.46	0.224
d	2	0.0025	0.0012	1.84	0.353
Error	2	0.0013	0.0007		
Total	8	0.058			

The results of S/N ratio are confirmed with analysis of variance (ANOVA) conducted for surface roughness. The results of ANOVA as shown in Table 5 exhibits a P – value of 0.027 for work speed, which expresses the significance of work speed on surface roughness. ANOVA also proves that work speed is a greater influencing parameter than feedrate and depth of cut.

Empirical Modeling of Surface Roughness

The empirical model for surface roughness is developed based on experimental data given in Table 3, in order to generalize the result. In the regression analysis using SPSS software, the iteration run stopped after 3 model evaluations and 2 derivative evaluations because the relative reduction between successive parameter estimation was at most PCON = 1.00E-008. The coefficient values obtained from the analysis depicts that increase in work speed and decrease in feedrate and depth of cut reduces the surface roughness. From the observed data for surface roughness, the response function has been achieved in the following quadratic form:

$$R_a = 3.219 - 0.0398V_w - 4.588f - 226.667d + 1.9119 * 10^{-4}{V_w}^2 + 26.632f^2 + 26670d^2 \tag{5}$$

The sum of the squares of the residuals given in Table 6, 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.

$$R^2 = 1 - \left(\frac{Residual\ Sum\ of\ Squares}{Corrected\ Sum\ of\ Squares}\right) \tag{6}$$

The 'R^2' value obtained in the analysis is 0.977 which means that 97.7% of the variation of the operating parameters can be explained by the variation of the surface roughness.

Table 6: ANOVA table for the quadratic model

Source	Sum of squares	Degree of freedom	Mean squares
Regression	4.651	7	0.664
Residual	0.001	2	0.001
Uncorrected total	4.652	9	
Corrected total	0.058	8	

Similarly linear and cubic models were developed, which are summarized in Table 7. Among all the models, quadratic model has shown better R^2 value and the surface roughness predicted using this model is found to be very nearer to the experimental value. Hence quadratic model is proposed for further analysis.

To further validate, surface roughness values are predicted using the proposed model and compared with the experimental values. The predicted values were found to be very close to the experimental values with a maximum deviation of 20.38% as shown in Fig.5. Thus, the model can be used to predict the surface roughness for any values of process parameters.

Table 7: Summary of surface roughness models

Source	Model	R^2	Surafce roughness, R_a (µm)		% Deviation
			Experimental value	Predicted value	
Linear	$R_a = 0.776 - 0.001V_w - 1.167\, f - 13.333\, d$	0.189	0.51	0.733	43.14
Quadratic	$R_a = 3.219 - 0.0398V_w - 4.588f - 226.667d + 1.9119 * 10^{-4}{V_w}^2 + 26.632f^2 + 26670d^2$	0.977	0.51	0.477	6.47
Cubic	$R_a = 1.682\, {V_w}^{-0.206} f^{0.149} d^{-0.0.078}$	0.252	0.51	0.706	38.43

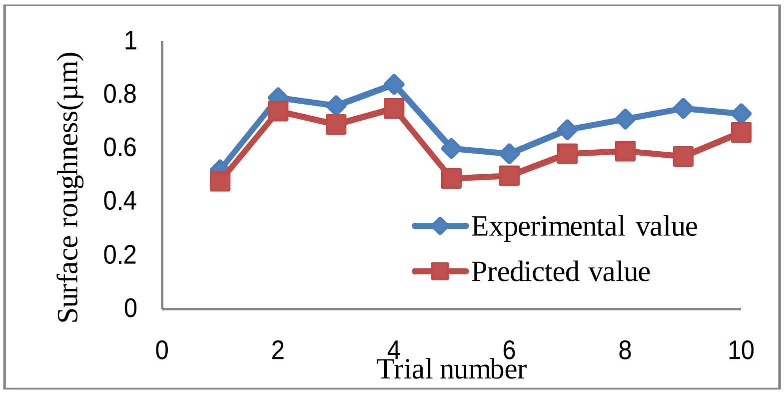

Figure 5: Validation of experimental results for surface roughness

Computational results of GA

The optimal grinding parameters are found to be 103.730 m/min work speed, 0.086 mm/rev feedrate, 0.004 mm depth of cut for a minimum surface roughness of 0.47703 µm. These values are predicted based on genetic algorithm. The developed empirical model, Equation 5 is used as the fitness function for determining the surface roughness value of each new individual.

The optimization was run for a 1000 number of iterations with a population size of 100. Trials were conducted for different settings of the GA operators to investigate the search process.

Table 8: GA operators and search result

Trial No.	Genetic algorithm operators			Result				
	Scaling-Selection Function	Crossover Function-Fraction	Mutation Function	Exploitation	Exploration	Convergence	Consistency	Reference
1.	Rank-Roulette	Single Point-0.6	Uniform-0.01	Good	Good	Poor	Poor	Fig.6a
2.	Rank-Roulette	Single Point-0.8	Uniform-0.01	Good	Good	Good	Poor	Fig.6b
3.	Rank-Roulette	Single Point-0.8	Uniform-0.1	Good	Very Good	Poor	Good	Fig.6c
4.	Rank-Roulette	Two Point-0.8	Uniform-0.1	Good	Very Good	Poor	Good	Fig.7d
5.	Rank-Roulette	Single Point-0.8	Gaussian	Very Good	Beyond Boundary Conditions	Very Good	Very Good	Fig.6e
6.	Proportional-Tournament	Single Point-0.8	Gaussian	Very Good	Beyond Boundary Conditions	Very Good	Very Good	Fig.6f
7.	Proportional-Tournament	Single Point-0.8	Uniform-0.01	Very Good	Good	Good	Poor	Fig.6g
8.	Rank-Tournament	Single Point-0.8	Uniform-0.01	Good	Good	Good	Very Poor	Fig.6h
9.	Proportional-Roulette	Single Point-0.6	Uniform-0.1	Good	Very Good	Poor	Good	Fig.6i

The GA operators namely scaling function, selection function, crossover function, crossover fraction, mutation function and mutation fraction were varied during each trial and the simulation was observed. The simulation results obtained from selected trials are given in Fig. 6 and presented in Table 8. On comparison of trials 2, 7 and 8, it is found that Rank-Tournament selection method performs better in eliminating bad solutions and replacing good solutions thereby improving the convergence in search. But the search sometimes gets struck in sub-optimal conditions and hence the consistency of the result is poor. Conversely Rank-Roulette method always produces optimal solution with good consistency in the result but convergence in the search is poor.

Crossover operator enhances the exploration and mutation operator diversifies the search. On the analysis of various trials it was found that the higher fraction of crossover (0.1 -1.0) and mutation (0.01 – 0.1) produced best solution with consistency in the result, but of course the convergence in the search was poor.

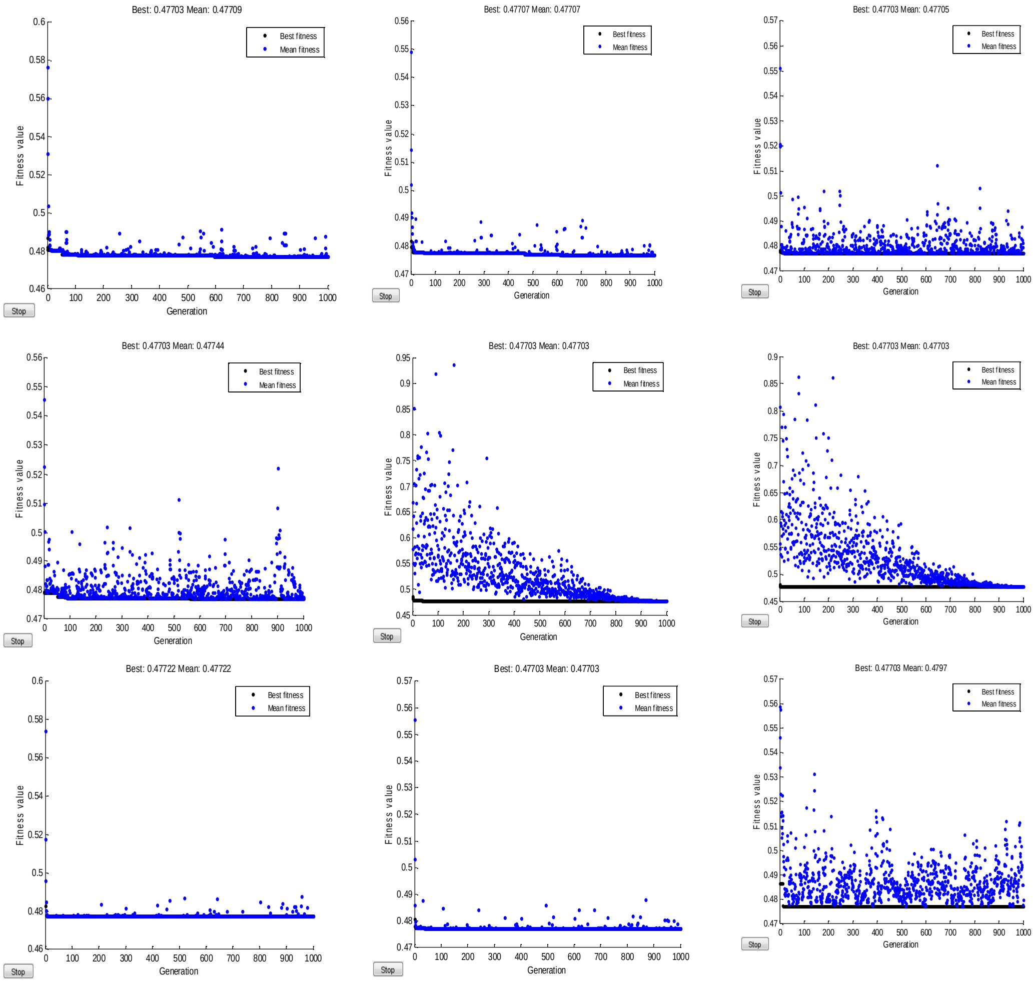

Figure 6: Results obtained from GA for various parameter settings

Though Trial 3 with single point crossover and Trial 4 with two point crossover produced similar results, the computational effort and time for single point crossover was found to be comparatively less. The Gaussian mutation function instigated a diversified search with good convergence ending at an optimal solution but the only downside was that the initial search occurred beyond the boundary conditions. This can be overcome by providing the necessary constraints. Among all the trials the suitable genetic algorithm parameters can be suggested as:

Scaling Function	: Rank
Selection Function	: Roulette
Crossover Function	: Single point operator
Crossover Fraction	: 0.8
Mutation Fraction	: 0.1

These parameters exhibited a very good exploration, good exploitation of information and consistency in the result as presented in Table 8. Z.H.Deng et al. [20] had also applied roulette wheel selection based on ranking algorithm with 0.7 as uniform crossover probability and 0.03 as uniform mutation probability.

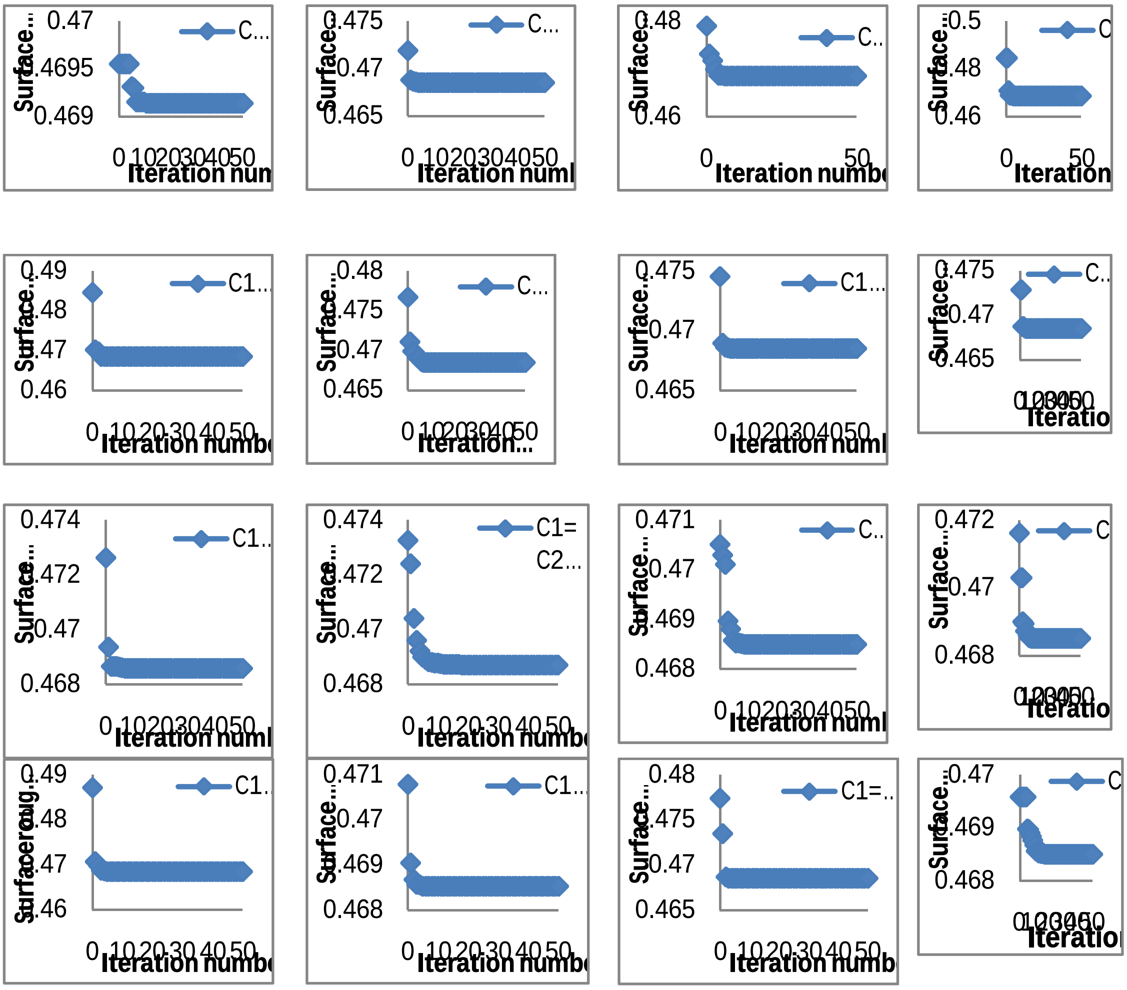

Figure 7: Results obtained from PSO for various values of learning factors (C1 and C2) and inertia weight (ω)

It was reported that for these GA parameters the predicted values were with a percentage error ranging between ± 10%. This is similar to the result obtained in present work and an example is shown in Table 10. T.S Lee et al. [26] reported that tournament based selection with 0.85 as crossover probability and 0.3 as mutation probability yielded better results, which is contrary to the result obtained in the present work. This difference may be due to the higher fraction of mutation probability.

Computational results of PSO

The optimal grinding parameters predicted using PSO are 104.091 m/min work speed, 0.086 mm/rev feedrate, 0.004 mm depth of cut for a minimum surface roughness of 0.46850 µm. The developed regression model, Equation 5 is used as the objective function for determining the surface roughness value of each new particle generated.

The particles are randomly generated in the search space to facilitate effective exploration. As Genetic algorithm, PSO algorithm was also run for 1000 iterations for a population size of 100. The optimization was run for various settings of inertia weight and learning factors. The details of various trials are given in Table 9 and Fig.7.

Table 9: PSO operators and search result

Trial No.	PSO algorithm operators		Result				
	Inertia weight , w	Learning factor C1=C2	Exploitation	Exploration	Convergence	Consistency	Reference
1.	0.8	0.5	Good	Poor	Poor	Poor	Fig.7a
2.	0.8	1.0	Very Good	Good	Good	Good	Fig.7b
3.	0.8	1.5	Very Good	Good	Poor	Good	Fig.7c
4.	0.8	2.0	Good	Good	Poor	Poor	Fig.7d
5.	0.85	0.5	Very Good	Good	Very Good	Very Good	Fig.7e
6.	0.85	1.0	Very Good	Good	Good	Poor	Fig.7f
7.	0.85	1.5	Very Good	Very Good	Very Good	Very Good	Fig.7g
8.	0.85	2.0	Good	Good	Good	Good	Fig.7h
9.	0.9	0.5	Good	Poor	Good	Poor	Fig.7i
10.	0.9	1.0	Very Good	Poor	Good	Poor	Fig.7j
11.	0.9	1.5	Very Good	Good	Good	Good	Fig.7k
12.	0.9	2.0	Very Good	Very Good	Good	Good	Fig.7l
13.	0.95	0.5	Very Good	Good	Good	Poor	Fig.7m
14.	0.95	1.0	Very Good	Good	Good	Poor	Fig.7n
15.	0.95	1.5	Very Good	Good	Good	Poor	Fig.7p
16.	0.95	2.0	Poor	Good	Good	Good	Fig.7q

Table 10: Prediction of optimal parameters for a given surface roughness value using GA and PSO

Algorithm	Work speed, V_w (m/min)	Feedrate, *f* (mm/rev)	Depth of cut, *d* (mm)	Surface roughness, R_a (μm)	% Error	% of Accuracy
GA	98.39	0.101	0.004	0.49172	3.58	96.42
PSO	97.001	0.093	0.004	0.49368	3.20	96.8
Experiment	98	0.093	0.004	0.51		

Inertia weight ‘ω’ regulates the trade-off between exploration and exploitation competency. The optimization was performed for various values of ω and it was found that an inertia weight of 0.85 produced optimal solution for all values of C_1 and C_2. C_1 and C_2 are the learning factors which accelerate the search direction towards the optimal solution. From the optimization analysis it was found that the learning factors $C_1 = C_2 = 1.5$ produced optimal solution consistently for most of the values of inertia weight. Among all the trials the suitable PSO parameters can be suggested as:

Inertia weight : $\omega = 0.85$

Learning factors : $C_1 = C_2 = 1.5$

The particle swarm optimization process converged between the iteration numbers 5 to 19 for any value of learning factor and inertia weight. The Fig.7 presents the iteration number at which the convergence of search commenced for a value of C1, C2 and ω. The inferences of this analysis are in agreement with that published in literature [26].

Comparison of Results

The optimal machining parameters for minimum surface roughness obtained using GA and PSO are compared and found that the surface roughness value achieved using PSO is better than that of GA. As stated in literatures [25-26] it is realized that PSO algorithm is more comfortable and yields optimal results when compared to GA. This is because the underlying concepts of PSO are very simple and it is easy to relate with the problem, and so coding for PSO is very easy. In PSO, comparatively less number of parameters are used hence tuning of the program is very simple. PSO involves less computation and provides optimal results. The exploration is very good in both GA and PSO, but PSO proves better because of very good exploitation of the solution and very good convergence with consistency in the result obtained. To validate the performance of GA and PSO, surface roughness was predicted for a set of input parameters and compared with experimental value as presented in Table 10. The % of error for PSO was found to be less than GA.

Conclusions

From this experimental and analytical work the following conclusions are drawn:

- The results of S/N ratio and ANOVA reveal that work speed has a greater effect on surface roughness than feedrate and depth of cut.
- Regression analysis is a useful tool in developing an empirical model for surface roughness. The developed model has an accuracy of 97.7% and can be used for prediction of surface roughness in cylindrical grinding of AISI 316 stainless steel.
- The regression analysis also reveals the fact that increase in workspeed and decrease in feedrate and depth of cut reduces the surface roughness.
- The optimal grinding parameters predicted using GA are 103.730 m/min work speed, 0.086 mm/rev feedrate, 0.004 mm depth of cut for a minimum surface roughness of 0.47703 µm.
- The optimal grinding parameters predicted using PSO are 104.091 m/min work speed, 0.086 mm/rev feedrate, 0.004 mm depth of cut for a minimum surface roughness of 0.46850 µm.
- GA exhibited a diversified search and generated new population at random and progressed towards optimal solution by its mechanism of reproduction, crossover and mutation. But the tuning of algorithm was difficult due to a greater number of parameters and their wide range. Convergence of the search was also poor. The results of GA were less accurate when compared with PSO.

- PSO algorithm was observed to be an effective evolutionary technique due to its wide search and fast converging characteristics which generates optimal results consistently with an accuracy of 96.8%. The tuning of the algorithm was found easy due to less number of parameters.
- PSO is suggested as comfortable and effective tool in solving optimization problems.
- Above all, this procedure can be adopted as an effective tool for predicting the optimal parameters for other machining processes also.

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