Parametric Optimization of Cylindrical Grinding Process through Hybrid Taguchi Method and RSM Approach using Genetic Algorithm

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The present investigation proposes a hybrid technique: Taguchi method, response surface methodology (RSM) and genetic algorithm (GA), to analyze, model and predict vibration and surface roughness in traverse cut cylindrical grinding of aluminum alloy. Experiments have been conducted as per L_9 orthogonal array of Taguchi methodology using several levels of the grinding parameters. Analysis of variance has been done to identify the influential process parameters on output variables. RSM has been applied to develop relationship between output responses with input parameters. Multi-objective overlaid contour plots have been made to study the interaction effects on both responses simultaneously. Developed models are then solved individually, first and then combinedly by GA, for process optimization. Predicted output responses are then confirmed by confirmatory experiments.

Keywords: Cylindrical grinding, Surface roughness, Grinding vibration, Response surface methodology, Genetic algorithm

1 Introduction

Aluminum and aluminum alloys have gained their importance in automobile [1], naval [2], aeronautics and aerospace industries [3], aircraft [4-6], high performance engine bearings [7] and various automotive components such as brake rotor and pistons, machinery components, structural and electronic applications [8] etc., due to excellent properties: high strength to weight ratio, high ratio of stiffness to weight and strength to weight, resistance to corrosive effects, co-activation with steel shafts, high thermal conductivity, fatigue strength, lightness, workability and low cost [9] etc. The effective utilization of the aluminum alloys in such functional applications demands good surface finish and close tolerances. These materials are manufactured by near net process; finishing still needs for obtaining desired dimensions. Most metal parts are manufactured / processed by machining processes to obtain most important characteristic of all metal parts which is the surface finish of the machined parts [10].

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Determining the optimal cutting conditions has always been a important task to attain high performance in machining processes [11]. Machining of aluminum alloys needs special attention due to its low melting point and low mechanical resistance [12]. Improving the surface qualities of aluminum alloys has an important area of research [5, 7, 10, and 13-20]. Grinding is a precision machining process which is mainly used for improving the work-piece surface roughness [21, 22]. Analysis of grinding process is usually carried out to control the process more precisely and improve the grinding performance. This is often achieved by developing the empirical relationships between the process parameters and output responses. Cylindrical grinding is one of the important and widely used grinding processes in aerospace, space and other engineering industries, mostly used for making the cylindrical parts requiring good surface finish and high dimensional accuracy [23, 24]. Surface finish is one of the most important quality characteristics of the machined part [10], as already mentioned earlier and hence it is used to determine and evaluate the quality of the ground part [25] as well as competitiveness of the overall grinding system [26]. Surface roughness ensures proper functioning, reliability and longevity of ground / machined parts [7, 27].

In grinding operation, surface finish, dimensions and form of machined part depend strongly on process parameters [27] wheel speed, work speed, depth of cut, feed, and work-piece properties, grinding wheel properties, cutting fluid and other cutting conditions, the irregularities in grinding operation such as tool wear, vibrations and tool deflections [28-31].

Vibration in grinding process is critical because it limits the ability of the grinding process to achieve higher form accuracy and better surface finish [32-34]. It also affects the productivity and machine life [35]. Vibrations generated in grinding are classified into two types [36, 37]: forced vibration and self-exited vibration. Forced vibration is that which is generated when there exists a vibration source that forcibly drives the mechanical structure to vibrate. This is due to imbalance of grinding wheel, low dynamic stiffness of the wheel spindle system [36] etc. And second source of vibration is the self-exited vibration; this is often related to the natural vibration modes of the machine-tool-structure [37]. During grinding process a relative displacement is generated between the grinding wheel surface and work-piece surface. This effect will leave marks / traces on the grinding wheel surface / work surface in the form of cyclic waviness. This effect grows quite rapidly in subsequent revolutions due to variations in the cutting force thus causing dynamic excitation of the machine-tool-fixture-workpiece–system, which results in dynamic change in depth of cut (infeed). This unstable condition generated by vibration taken place one revolution earlier is called self-exited vibration resulted from the regenerative effect [38]. The regenerative effect is considered to be a major cause of chatter vibration in grinding [32] The present work, however, does not take into consideration on the theoretical model of chatter but vibration data have been collected from a plan of experiments, and then analyzed.

Especially in traverse cut cylindrical grinding process, understanding the source(s) of vibrations and controlling them (sources), are not so easy task due to simultaneous rotation of work speed, traverse movement of work table, high speed grinding wheel etc. So, it is necessary to select the stable grinding condition that would suppress the progress of vibration and thereby improve accuracy and surface finish of the ground part [39, 40]. But, this demands a deep knowledge of the grinding phenomenon, mainly concerning the relations between the input parameters and output characteristics [41]. Grinding process is characterized by a multiplicity of dynamically interacting process parameters [42]. Besides, unlike other processes, in grinding, the cutting tool presents an unknown geometry, which makes the process control even more difficult [43].

In cylindrical grinding, desired surface finish and improvement in process efficiency may be obtained by process or parametric optimization [44, 45] that identifies and determines the region of critical process control variables leading to desired output responses with acceptable variations. Parametric optimization in grinding also ensures lower cost of machining [46].
Mukherjee and Ray, (2008) mentioned that grinding process analysis, modeling and optimization for better process performance was still a challenging task for researchers and practitioners, due to numerous inherent complexities in it (grinding process) [47].
On the other hand, statistical design of experiments methods like Taguchi method and RSM, combined with soft computing technique like genetic algorithm [48] are found to be efficient in process analysis, modeling and optimization of complex machining or manufacturing processes like grinding [49], turning [50], milling [51], drilling [52], electric discharge machining [53**],** welding [54] etc.Taguchi methodology’s tools such as orthogonal array and signal-to-noise ratio are useful for experimentation and factor analysis [55]. Response surface methodology is an intelligent technique that is used for developing mathematical relationships between input and output parameters [56, 57]. Genetic algorithm is a probabilistic direct search tool that uses natural genetic to produce global optimum conditions by solving the given problem [58, 59].

1.1 Literature survey

In the following paragraphs a literature survey is made covering some past investigations on machining / grinding of aluminum alloy and / or some other alloy materials, done by the researchers, where process analysis, process modeling, process improvement, optimization, applications of optimization techniques etc., had been addressed.
Tsai et al., (1999) had improved the surface qualities of milled 6061-T6 aluminum alloy [5]. Ertekin et al., (2003) made an analysis to identify the influential common sensory features for dimensional accuracy and surface roughness of 6061-T6 aluminum alloy, 7075-T6 aluminum alloy and ANSI-4140 materials in computer numerical control milling operation [7]. Brezocnik et al., (2004) had predicted surface roughness of milled 6061 aluminum material based on cutting parameters and vibration [60]. Kamguem et al. (2013) made an investigation to control machining parameters to improve surface finish, and reduce dust generation during milling of 6061-T6, 7075-T6 and 2014-T351 aluminum alloys [13]. Surasit et al., (2014) determined influential cutting parameters on surface roughness and tool wear in face milling of semi solid AA 7075 material [16]. Horvath and Agota, (2015) analyzed the turning operation to minimize the surface roughness of turned aluminum alloy [10]. Hatem et al., (2017) Experimented, analyzed and modeled the ball burnishing process to minimize surface roughness of 2017A-T451 aluminum alloy [57].

Shaji and Radhakrishnan, (2003) analyzed and optimized the process parameters such as speed, feed, infeed and mode of dressing in surface grinding with the use of Taguchi method [61]. Jae et al., (2006) modeled and predicted the grinding power and surface roughness for external cylindrical grinding process by using response surface methodology (RSM) [62]. Kwak and Kim, (2008) conducted experiments for grinding of aluminum based metal matrix composites based on Taguchi’s orthogonal array design. Factor effects on surface roughness and grinding force were evaluated by signal-to-noise ratio technique. Mathematical relationship between the grinding factors and measured output responses (i.e. surface roughness and grinding force) had been developed by using applications of RSM technique [63]. Jae, (2005) utilized the integrated Taguchi-RSM to analyze the effects of grinding parameters on geometric errors, and he developed a mathematical model to find the optimum grinding parameters for minimum geometric errors in surface grinding operation [64].

Dhavlikar et al., (2003) identified the optimum levels of process parameters for minimization of out of roundness error of work-pieces in center-less grinding operation; the investigators used combined Taguchi and dual response method [65]. Lee and Lee, (2007) attempted to analyze and model centreless grinding process for optimizing surface roughness with the application of hybrid Taguchi method and response surface methodology, and found improved surface roughness [66].

Krajnik and Kopac, (2005) carried out a research work, for minimization of surface roughness in centreless grinding process. RSM technique was used to develop a mathematical model. Researchers utilized non-linear programming and genetic algorithm to optimize grinding conditions [49]. Experimental analysis in Si-C (silicon carbide) grinding operation was carried out by Gopal and Rao, (2003) to maximize material removal rate (MRR), and to study the effect of wheel parameters: grain size and grain density and grinding parameters: depth of cut and feed, on surface roughness and surface damage. Significant input parameters were identified by analysis of variance (ANOVA) technique. Mathematical models were postulated to develop relationships between grinding process parameters and output responses. And then, genetic algorithm (GA) had been used to solve the mathematical models for maximizing MRR, by imposing surface roughness and surface damage as constraints [67]. Pai et al., (2011) used RSM to analyze and model the surface grinding process by considering multi-response characteristics. Obtained mathematical models were solved simultaneously by non-sorted genetic algorithm. They found from the analysis that predicted results were in good agreement with the experimental results [68]. In other study, Li et al., (2002) used computer-based simulation process to optimize cylindrical plunge cut grinding process, for minimization of production time while ensuring part quality requirements [69].

Reddy and Rao, (2006) applied integrated Taguchi method – response surface methodology (RSM) combined with genetic algorithm (GA) in end milling process to predict surface roughness. Experiments had been done by orthogonal array of Taguchi method. The experimental results had been analyzed, modeled and optimized by using hybrid RSM combined with GA to minimize surface roughness [51].

Tung et al., (2007) conducted experiments in nano-particle milling process using orthogonal array experiments. Analysis of variance and main effect plots were drawn, and used to identify the significant parameters on grain size and variance in grain size of milled nano-particles. RSM was then used to build the relationship between the input parameters and output responses; finally, genetic algorithm (GA) was applied to find the optimal parametric setting. They found improved results in milling operation with the use of hybrid optimization approach: integrating Taguchi method - RSM – GA [70].

1.2 Objective and scope of the present work

Literature indicates that various aspects of traverse cut cylindrical grinding had been investigated by the researchers. These aspects include surface finish and vibration as well. However, research still being continued [8, 22, 29, 33, 40, 42 and 71]. This indicates the need of further research. The effects of the process parameters on surface roughness and vibration, though studied by some investigators, conclusive relationship between process parameters, and surface finish and vibration – explain the effects will only emerge through more extensive research. The present study is planned to identify the significant grinding process parameters which influence vibration and surface roughness of aluminum alloy grinding, by the application of Taguchi method along with analysis of variance. Investigation has been extended to develop the mathematical models to correlate the input parameters and output responses using RSM technique, and then, by applying genetic algorithm (GA) for setting the optimum parametric levels. Prediction of the responses is also made.

Multi-objective overlaid contour plots have also been made using developed mathematical models (vibration and surface roughness), to study the interaction effects of grinding process parameters on both the responses in a single contour plot. The experiments and analyses made are in the context of traverse cut cylindrical grinding of 6061T4 aluminum alloy; the literature is not found to be rich in this context. The present work is done taking into consideration that more and extensive research work in the area of cylindrical grinding on its several aspects, will lead to a sound knowledge – base. This may finally help the persons in the actual field i.e. in industry to control the process more effectively, reliably and predicatively [72] The study made presently is only one step towards this end. And the optimization approach used here is newer in respect of research in grinding made by earlier researchers.

2 Taguchi method, response surface methodology and genetic algorithm

In the present study, Taguchi method, response surface methodology (RSM) and genetic algorithm (GA) are used for planning the experiments, analyzing the data and optimizing the traverse cut cylindrical grinding process for minimization of both vibration and surface roughness individually as well as combinedly. Taguchi technique was first proposed by Genichi Taguchi [73]. Taguchi method is a systematic application of design and analysis of experiments for the purpose of designing and improving product quality at minimum cost by reducing the variance [73, 74]. Standard tables, known as orthogonal arrays (OA) are used for constructing the design of experiments in Taguchi method.

In orthogonal arrays, number of experimental runs is minimized [63, 55] and every parameter is analyzed by keeping the other parameters constant, effects of one parameter being studied separable from the effects of other factors, and significant parameters are decided on the basis of statistical analysis of experimental results. It makes the process in-sensitive to the effect of variations of process parameters. Further, the contribution and optimum level of each factor can be determined in the balanced experiment [75]. Taguchi method recommends analyzing the mean response for each run in the inner array and it also suggests analyzing variation using an appropriately chosen signal–to–noise (S/N) ratio which serves as objective functions for optimization [76]. These S/N ratios are derived from the quadratic loss function and three of them (Eqs. 1 - 3) are considered to be standard and widely applicable. “Smaller is the better (Eq. 2)” is selected for the present study for both vibration and surface roughness responses, because it is desired that both vibration and surface roughness are minimum.

Nominal is the better: $S/N = 10\log \bar{y}/S_y^2$ (1)

(1)

Smaller is the better: $S/N = -10\log 1/n\left(\sum y^2\right)$

(2)

Higher is the better: $S/N = -10\log 1/n\left(\sum 1/y^2\right)$

(3)

Where, $\bar{y}$ is the average of observed data, s_y^2 is the variation of ‘y’, n is the number of observations, and ‘y’ is the observed data.

In the Taguchi method, the statistical analysis of signal-to-noise ratio has been used to identify the significance of each parameter towards the response(s). Then analysis has been continued to develop the mathematical model for correlating the input and output parameters, for which response surface methodology (RSM) is used.

RSM is an empirical modeling approach for determining the relationship between the process parameters and output responses, by means of which one can further search the significance of these process parameters on the coupled responses [77].

As per RSM, all the input parameters are assumed to be measurable [78]. The corresponding responses can be expressed as follows:

$$Y = f(x_1, x_2 \ldots x_p) \quad (4)$$

where, x_1, x_2, ….. x_p are input parameters and ‘Y’ is the response which is required to be optimized. The behavior of the system is explained by the following empirical first-order mathematical model which is as follows.

$$Y= b_0 +b_1x_1 + b_2x_2 + b_3x_3 +\ldots.. b_nx_p \quad (5)$$

Where, all b’s are regression coefficients determined by least squares method; x_1, x_2, x_3 and x_p are input variables; ‘n’ is an integer number which is equal to the number of input parameters (n=p); In RSM, significance of the process parameters can be studied by generating the contour, surface and overlaid contour plots. In the present work, overlaid plots are used to analyze the combined effect of grinding parameters on both vibration and surface roughness. Overlaid contour plot is a multi-objective plot which provides factor effects on two or more responses in a single plot [79]. Finally, genetic algorithm (GA) has been applied to solve the mathematical models of response(s).

Genetic algorithm (GA) is a computerized search and probabilistic optimization technique which works based on the biological evolution process in nature [80]. GA is a population based technique used to solve both the linear and non-linear problems, and it produces ever improved solutions by exploring all regions of the stated space and range, based on the ‘survival to fittest’ philosophy [81]. For that purpose, it uses fitness function to select the best solution to the problem. Genetic algorithm can be an efficient tool for optimization; solution more likely converges to a global optimum [12]. In the solution procedure, best data setting leading to optimal solution is determined from randomly selected set of data combinations. GA uses three genetic operators like reproduction, crossover (i.e. recombination) and mutation for providing global optimal solutions to a given problem. After initialization, a new set of individual data points are generated according to some probability distribution, called as generations**.** In each iteration, several data points are randomly chosen from the current population, based on the crossover probability, and modified through mutation to form a new population [82]. Genetic algorithm is a well-known optimization technique used by the many researchers for solving various engineering problems; more details of genetic algorithms are reported in literature [12, 59, and 80-84].

In the present work, L_9 orthogonal array (OA) has been used to design the experiments. The statistical techniques like analysis of variance (ANOVA) and signal-to-noise (S/N) ratio have been utilized to analyze the experimental data. RSM and GA has been employed for modeling the output responses, and then optimize them (output responses) individually as well as simultaneously.

3 Experimental plans

In the present study, three process parameters: infeed, longitudinal feed and work speed, at three levels each Table (1) are selected. L_9 orthogonal array (OA) is one standard OA which has been used here to design the experiments. L_9 orthogonal array design matrix is shown in Table (2). Each row of the matrix represents one trial.

Aluminum alloy (6061-T4) work material has been selected for experimentation. For each sample, diameter has been 38mm, length = 50mm. In a long aluminum alloy bar, four such samples have been made by turning; suitable grinding allowance has been kept.

In between two samples, a recess of small depth and suitable width has been provided; three such bars have been used. Traverse cut cylindrical grinding has been made as per L_9 orthogonal array, on an HMT cylindrical grinding machine. Aluminum oxide grinding wheel with specifications A 70 K 5 V with outside diameter 70 mm, face width 40 mm and bore 50 mm has been used. RPM of the wheel has been kept constant throughout the experimentation (N = 2000 rpm). Surface roughness (treated as quality factor) and acceleration of vibration (treated as disturbing factor) are selected as output responses. For each and every experiment, vibration is sensed by accelerometer mounted at tailstock of the cylindrical grinding machine. The accelerometer converts the vibration signal into electrical signal, which is then fed to the vibration meter. Vibration signal has been measured in the direction perpendicular to the axis of the work piece, in the horizontal plane. From the vibration meter, the vibration signals corresponding to the above experiments have been noted in terms of acceleration (m/s^2).

The observations are taken in acceleration mode because of low frequency response and low sensitivity of displacement and velocity modes. The experimental setup is shown in Figure (1). After completing the experiments, surface roughness has been measured by Talysurf. Surface roughness of each sample has been measured at three different places, and these values are then averaged. Surface roughness parameter R_a, which is center line average (CLA) value has been selected for present investigation, because, it is universally accepted quality parameter in respect of surface finish [63]. The observed data are discussed and analyzed in the next section. The major specifications of cylindrical grinding machine, vibration meter, accelerometer and Talysurf instrument are given below.

Cylindrical grinding machine:

Make: Hindustan Machine Tools (HMT)

Model: K130 U

Machine No: 57169

Grinding Wheel:

Wheel signature: A 70 K 5 V 10

Diameter: 270 mm

Face width: 40 mm

Bore: 50 mm

Vibration meter:

Make: Syscon Instruments Private Limited, Bangalore

Model No: 12DM-2C

Serial No: 7177

Accelerometer:

Make: Syscon Instruments Private Limited, Bangalore

Model: 353B31

Serial No: 33899

Talysurf:

Make: Taylor Hobson Ltd.
Model: SUBTRONIC 3+

Product code: 112/1590

Machine No.: M123413

Table 1 Input parameters

Parameters	Symbol	Unit	Low level	Medium level	High level
Infeed	A	mm in each cycle	0.04	0.05	0.06
Longitudinal feed	B	mm/s	70	80	90
Work speed	C	rpm	80	112	160

Table 2 L_9 orthogonal array design matrix

S. No.	Infeed, A (mm in each cycle)	Longitudinal feed, B (mm/s)	Work speed, C (rpm)
1	0.04	70	80
2	0.04	80	112
3	0.04	90	160
4	0.05	70	112
5	0.05	80	160
6	0.05	90	80
7	0.06	70	160
8	0.06	80	80
9	0.06	90	112

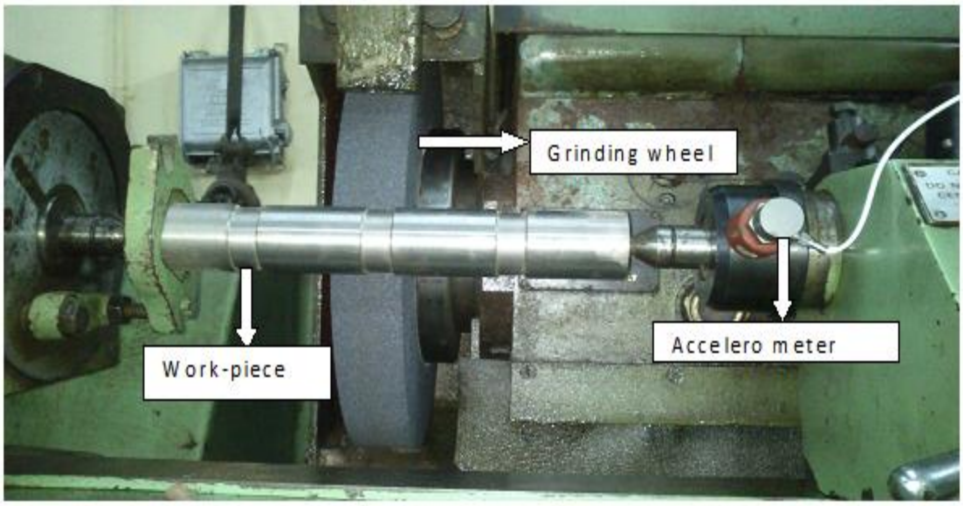

Figure 1 Experimental setup

4 Results and analysis

As mentioned earlier, L_9 orthogonal array experiments have been carried out and the corresponding responses are observed by measuring acceleration of vibration and surface roughness (R_a). The results are listed in Table (3). The data shown in the list have been used to carry out analysis of variance (ANOVA) and signal-to-noise ratio for vibration and surface roughness as well. Analysis made in the present work is based on integration of Taguchi method, response surface methodology (RSM) and genetic algorithm (GA).

Table 3 L_9 orthogonal array and output responses

S. No.	Infeed, A (mm in each cycle)	Longitudinal feed, B (mm/s)	Work speed, C (rpm)	Surface roughness, R_a (μm)	Acceleration of vibration (m/s^2)
1	0.04	70	80	0.963	6.40
2	0.04	80	112	0.910	8.61
3	0.04	90	160	0.987	10.35
4	0.05	70	112	0.914	7.90
5	0.05	80	160	0.901	10.90
6	0.05	90	80	0.762	7.76
7	0.06	70	160	0.802	10.87
8	0.06	80	80	0.680	6.78
9	0.06	90	112	0.672	9.81

4.1 Analysis of variance (ANOVA)

ANOVA test is carried out to determine the dependency of vibration and surface roughness on selected process parameters. The ANOVA test is conducted at ‘smaller is the better’ criterion, and the results of ANOVA test are shown in Table (4) for vibration and Table (5) for surface roughness (where DF is degree of freedom, F variance ratio and P significant factor). The ANOVA test is performed at a significance level of 5% i.e., confidence level of 95%. Since P values given in Table (4) and Table (5) are less than 0.05, the developed model is significant. According to the other hypothesis, if at least one of these coefficients is not equal to zero, the model will be accepted [85]; it is seen from Table (4) and Table (5) that this hypothesis is confirmed. It can be concluded from Table (4) and Table (5) that work speed (C) is significant factor for vibration and infeed (A) is significant variable for surface roughness as corresponding ‘P’ values are less than 0.05. Infeed (A) and longitudinal feed (B) have insignificant for acceleration of vibration as its ‘P’ values are more than 0.05, and longitudinal feed (B) and work speed (C) may have considerable effect on surface roughness as their ‘P’ values are close 0.05, as found from Tables (4) and (5) respectively.

Values of signal to noise ratio under the smaller –the-better criterion for both vibration and surface roughness are obtained from the Taguchi method and shown in Table (6). Delta statistics in Table (6) measures the size of the effects by taking the difference between the highest average and lowest average value for each response characteristic. Based on the delta values, process variables are ranked from the highest to the least effect. It is evident from the Table (6) that work speed (C) is the most significant parameter for vibration, next is longitudinal feed (B) followed by infeed (A). Infeed (A) is the most significant factor (Table 6) for surface roughness, next is work speed (C). Longitudinal feed (B) is the least significant factor among the three input parameters, in so far as surface roughness is concerned (Table 6).

Table 4 Analysis of variance for acceleration of vibration

Source	DF	Seq SS	Adj SS	Adj MS	F	P
A	2	0.7339	0.7339	0.3670	0.72	0.580
B	2	1.6504	1.6504	0.8252	1.63	0.380
C	2	21.0295	21.0295	10.5148	20.76	0.046#
Residual error	2	1.0130	1.0130	0.5065		
Total	8	24.4269				

Significant factors

Table 5 Analysis of variance for surface roughness (R_a)

Source	DF	Seq SS	Adj SS	Adj MS	F	P
A	2	9.4692	9.4692	4.7345	78.23	0.013#
B	2	1.4833	1.4833	0.7416	12.25	0.075
C	2	1.6754	1.6754	0.8377	13.84	0.067
Residual error	2	0.1210	0.1210	0.0605		
Total	8	12.7489				

Significant factors

Table 6 Response table for signal to noise (S/N) ratios (smaller is the better)

Level	Infeed (A)		Longitudinal feed (B)		Work speed (C)	
	Acceleration of vibration	Surface roughness (R_a)	Acceleration of vibration	Surface roughness (R_a)	Acceleration of vibration	Surface roughness (R_a)
1	-18.37	0.4201	-18.27	1.0084	-16.85	2.0127
2	-18.83	1.3492	-18.69	1.6915	-18.83	1.6843
3	-19.06	2.9063	-19.31	1.9757	-20.59	0.9786
Delta	0.69	2.4862	1.04	0.9674	3.74	1.0342
Rank	3	1	2	3	1	2

4.2 Factor effects

In the process of applying the Taguchi methodology, main effect plots are drawn at mean level of signal-to-noise (S/N) ratio corresponding to each level of process parameters. The main effect plots for vibration and surface roughness are shown in Figures (2) and (3) respectively. Significance of the parameters can be found from the main effect plots. Higher the difference between the minimum and maximum values of output responses in each factor, higher is the effect on the output response. From Figure (2), it is found that work speed (C) is the dominant parameter for vibration and next is the longitudinal feed (B) followed by infeed (A). In case of surface roughness (Figure 3), infeed (A) is the most significant factor and next is work speed (C) followed by longitudinal feed (B).

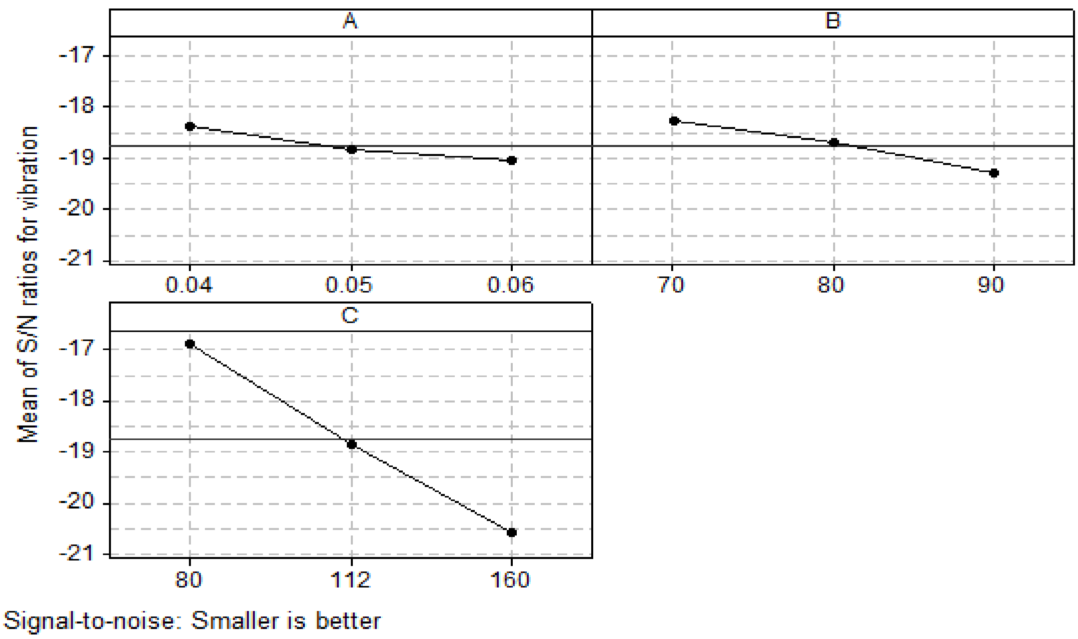

Figure 2 Main effect plots for vibration

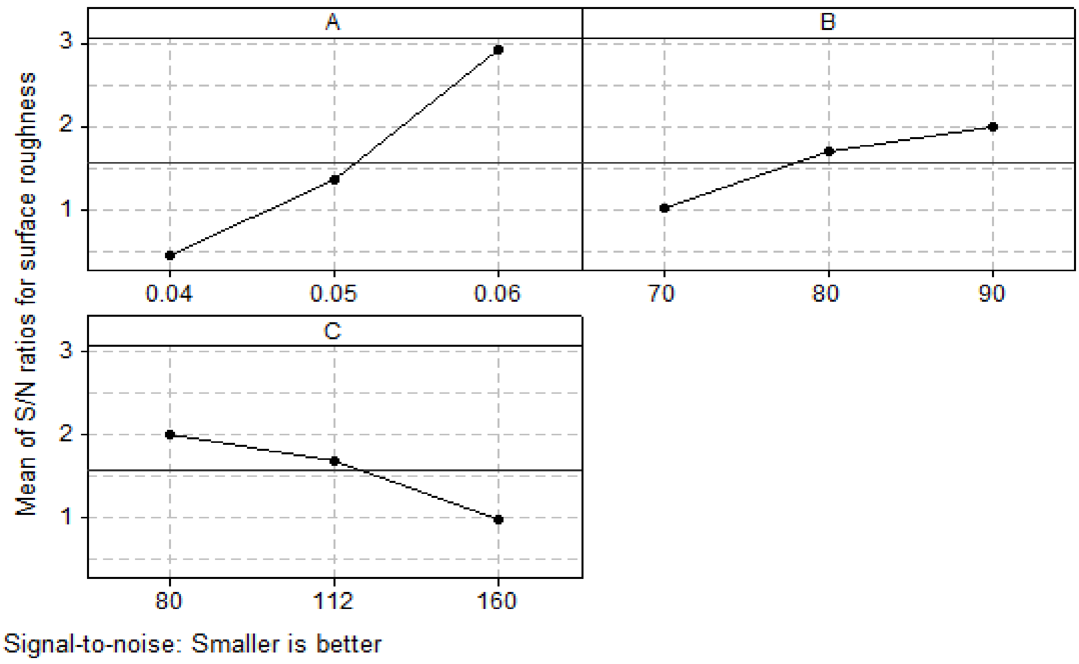

Figure 3 Main effect plots for surface roughness (R_a)

4.3 Mathematical modeling and multi-objective overlaid counter plots

Response surface methodology from MINITAB 16.1 software is applied on experimental data for developing the response surface model for output responses: vibration and surface roughness. Mathematical model for vibration in m/s^2 ($Y_{Vibration}$) is obtained in terms of infeed (A) in mm in each cycle, longitudinal feed (B) in mm/s, and work speed (C) in rpm, and the relationship is shown in Eq. 6. Similarly, surface roughness (Y_{Ra}) in micron is expressed in terms of the same input parameters and it is shown in Eq. 7. Both the mathematical models are developed by considering the un-coded items [un-coded items correspond to the values that are selected to perform the analysis using the values that are assigned in the factors sub-dialog box (examples: infeed = 0.04, 0.05 and 0.06 mm/cycle, longitudinal feed (B) = 70, 80 and 90 mm/s and work speed (C) = 80, 112 and 160 rpm)].

$$Y_{vibration} = -2.00404 +35.0000*A +0.0458333*B +0.0460855*C \quad (6)$$

$$Y_{Ra} = 1.63496 -11.7667*A -0.00430000*B + 0.00120011*C \quad (7)$$

With use of the RSM, multi-objective overlaid counter plots are drawn and shown in Figures (4–8). and some other typical overlaid counter plots are shown in Appendix. Overlaid counter plots are very useful to show the combined effect of two input parameters on both the responses (in the present case acceleration of vibration and surface roughness) while the third or remaining input parameter(s) remains (remain) constant at some fixed level.

From these plots, one can establish the operating conditions that produce desirable multi-response values. In the present study, two output responses: vibration and surface roughness have been shown in a single overlaid contour plot corresponding to two input parameters: infeed and longitudinal feed / infeed and work speed / longitudinal feed and work speed, while third input variable i.e. infeed / longitudinal feed / work speed has been kept constant at some selected level.

In the overlaid contour plots:

- ☐ Solid thick dark lines and thick dark dashed lines denote lower and upper bounds of surface roughness (R_a), respectively. Solid thick light lines and thick light dashed lines show lower and upper bounds of vibration signal, respectively.
- ☐ Any parametric combination along thick dark solid line and shaded region above / below this line indicates lower values of R_a (i.e. R_a < 0.672 μm), and parametric conditions in this region provide feasible vibration signal (6.4<vibration>10.9).
- ☐ Any input parametric combination along thick dark dashed line represents higher values of R_a. Any combination of the parameters within the shaded region above / below this thick dark dashed line also indicates higher values of R_a (i.e. R_a > 0.987 μm), but, parametric combinations in this region provide feasible vibration signal (6.4<vibration>10.9).
- ☐ Any factor combination in the plot along thick solid light line and shaded region below / above thick solid light line indicates lower values of vibration (i.e. vibration < 6.4 m/s^2), and parametric settings from this region provide feasible R_a values ($0.672<R_a>0.987$).
- ☐ Any parametric combination in the plot along thick dashed light line and shaded region above / below thick dashed light line indicates higher values of vibration (i.e. vibration > 10.9 m/s^2), but, parametric settings from this region provide feasible R_a values ($0.672<R_a>0.987$).
- ☐ Any factor combination within entire white region in the plot provides feasible result for both the responses i.e. R_a value and vibration signal lie between lower and higher limits ($0.672<R_a>0.987$ and 6.4<vibration>10.9) which have been obtained through initial experimentation (Table 3).

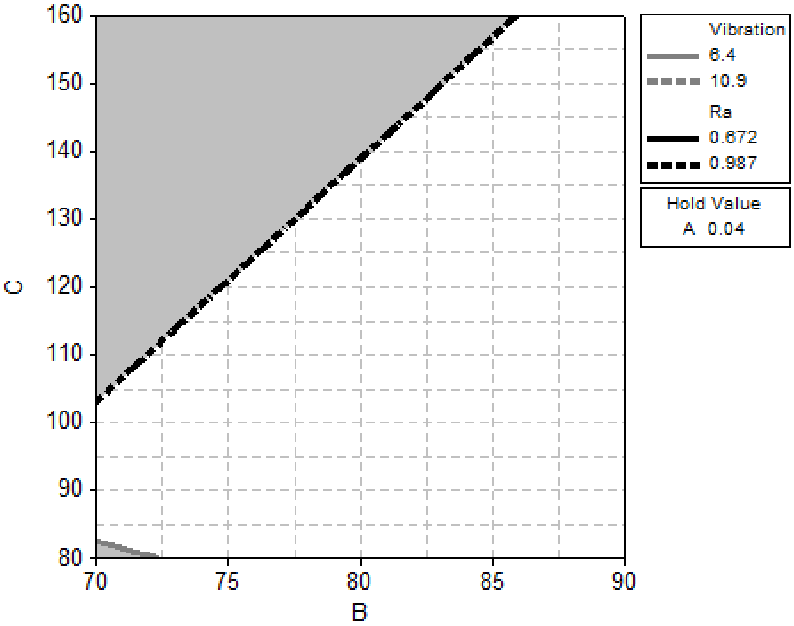

Figure 4 Overlaid contour plot showing combined effect of longitudinal feed (B) and work speed (C) on vibration and surface roughness (R_a) at infeed (A)= 0.04 mm in each cycle

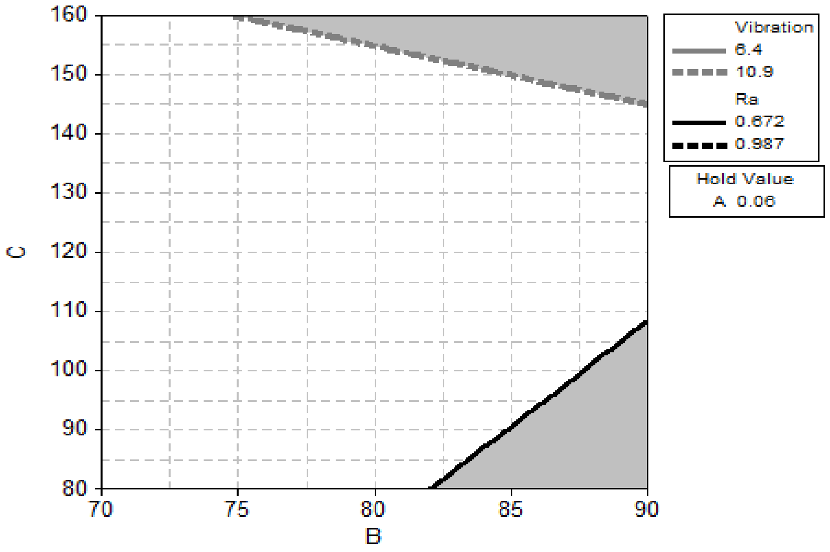

Figure 5 Overlaid contour plot showing combined effect of longitudinal feed (B) and work speed (C) on vibration and surface roughness (R_a) at infeed (A)= 0.06 mm in each cycle

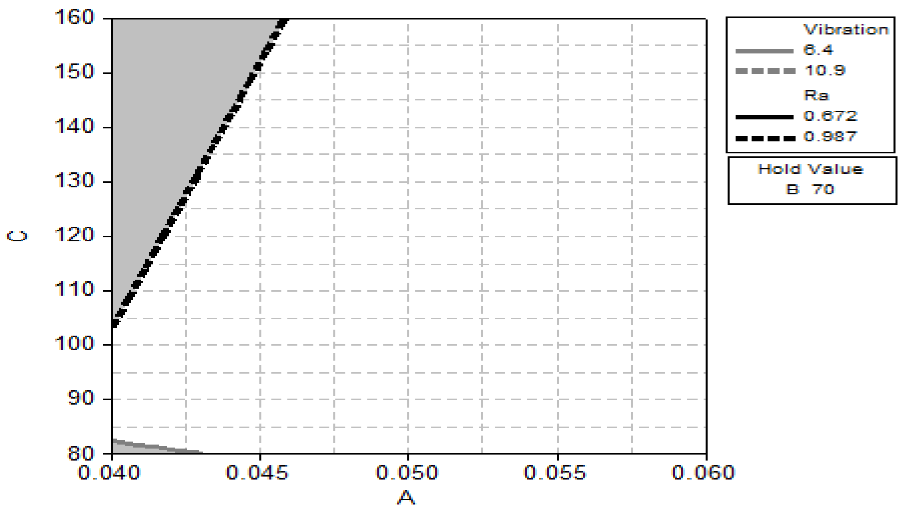

Figure 6 Overlaid contour plot showing combined effect of infeed (A) and work speed (C) on vibration and surface roughness (Ra) at longitudinal feed (B) = 70 mm/s

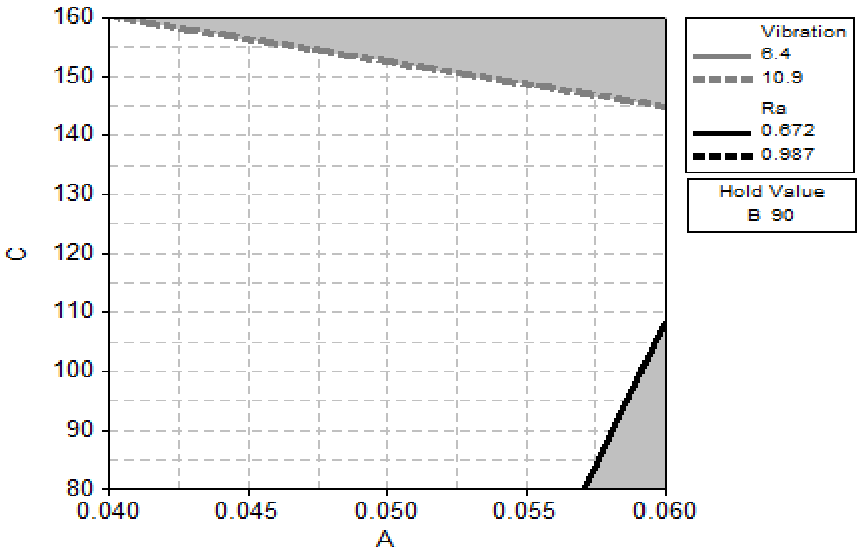

Figure 7 Overlaid contour plot showing combined effect of infeed (A) and work speed (C) on vibration and surface roughness (Ra) at longitudinal feed (B) = 90 mm/s

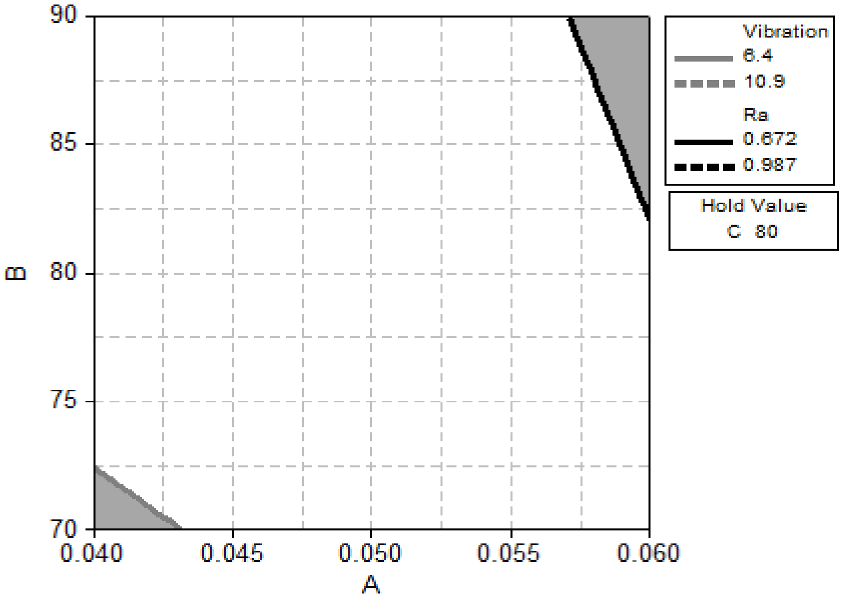

Figure 8 Overlaid contour plot showing combined effect of infeed (A) and longitudinal feed (B) on vibration and surface roughness (Ra) at work speed = 80 rpm

Figures. (4), (6) and (8) show that the parametric combinations from lower levels (Level 1) of input parameters [infeed (A), longitudinal feed (B) and work speed (C)] may provide minimum vibration signal whereas minimum R_a values (Figures. 5, 7 and 8) obtained at parametric conditions from higher levels of infeed (A) and longitudinal feed (B) and lower level of work speed (C). But, from these plots (Figures 4-8), it is difficult to identify the levels of input parameters at which both the responses will be optimized.

The analysis is continued for solving the mathematical models of acceleration of vibration (Eq. 6) and surface roughness (Eq. 7) of 6061-T4 aluminum alloy grinding for minimizing both the responses individually, by using genetic algorithm (GA). Then mathematical models of both the responses [i.e. surface roughness (R_a) and acceleration of vibration] are converted into single coefficient mathematical equation with the use of optimal response values, obtained earlier by GA. and then coefficient equation is further solved by using the same technique (GA) mentioned above for optimizing both the responses simultaneously.

4.4 Optimization for 6061-T4 aluminum alloy grinding by GA

Genetic algorithm from optimization toolboxes in MATLAB 7.1 is selected for the present study and several parametric conditions are considered, in order to optimize surface roughness and acceleration of vibration. Mathematical models developed and given in Eq.6 for acceleration of vibration and in Eq. 7 for surface roughness are used for that purpose**.** The optimization process for GA using the optimization toolboxes in MATLB 7.1 software is carried away in the following manner.

- Selecting the solver (genetic algorithm is selected in the present case)
- Selecting the fitness function [i.e. (objective function) that is to be optimized (i.e. minimized)]

- ☐ Selecting number of input variables (in the present case – three i.e., infeed, longitudinal feed and work speed)
- ☐ Fixing lower and upper bounds of input parameters [infeed (A), longitudinal feed (B) and work speed (C)]: lower bound = (0.04, 70 and 80); upper bound = (0.06, 90 and 160) and
- ☐ Running the solver

The model equations [i.e. Eq. 6 for acceleration of vibration and Eq. 7 for surface roughness (R_a)] are successfully optimized, individually, with the use of genetic algorithm via MATLAB toolboxes. In each generation, of the GA run, different combinations of grinding parameters along with corresponding output response values are produced. This program is then run until the feasible input parametric combination is obtained. The optimal parametric combination is selected within the range of grinding machine used in the present work.

Optimum grinding conditions obtained by GA are given in Table (7). and then, multi-objective optimization has been planned for minimization of surface roughness and vibration simultaneously by converting multi-mathematical models of vibration (Eq. 6) and surface roughness (Eq. 7) of aluminum alloy grinding, into single mathematical model (coefficient mathematical model which represents both the responses) with the use of normalized multi-objective function model proposed by Rao and Kalyankar, (2013), [86] and Rao and Patel, (2013), [87]. The normalized multi-objective function (Y) with different weight factors to two objectives is given in Eq. 8.

$$Y_{Coefficient} = w_1 (Y_{Ra} / Y_{Ra,\ Min}) + w_2 (Y_{Vibration} / Y_{Vibration,\ Min}) \tag{8}$$

where, w_1 and w_2 are the weight values assigned to surface roughness and acceleration of vibration, respectively. $Y_{Coefficient}$ = Coefficient equation representing both the responses; $Y_{Vibration,\ Min}$ and $Y_{Ra,\ Min}$ are the minimum values of the objectives functions $Y_{Vibration}$ (Eq.6) and Y_{Ra} (Eq. 7), respectively which can be obtained by attempting an individual objective function.

Table 7 Single-objective optimization results for aluminum alloy grinding by GA

	Optimum condition for surface roughness (R_a)		Optimum condition for acceleration of vibration	
	Parametric condition	$Y_{Ra,\ min}$	Parametric condition	$Y_{Vibration,\ min}$
Infeed (A)	0.06 mm in each cycle	0.637 µm	0.04 mm in each cycle	6.291 m/s^2
Longitudinal feed (B)	90 mm/s		70 mm/s	
Work speed (C)	80 rpm		80 rpm	

$Y_{Ra,\ min}$ = Minimized surface roughness (R_a); $Y_{Vibration,\ min}$ = Minimized vibration signal.

Previously, obtained optimum (i.e. minimized) values of surface roughness and acceleration of vibration for single objective optimization as shown in Table (7), are put in to the Eq. 8 for converting multi objective problem into single objective problem and corresponding equation is given in Eq. 9. In so far grinding concerned, obtaining good surface finish on ground part is desirable as mentioned earlier. In the present work, relatively higher importance is given to surface roughness (i.e. 80% weightage) and lesser emphasis has been given to acceleration of vibration (20% weightage) while developing the coefficient mathematical model (Eq. 9). The final coefficient equation after simplification is given as Eq. 10.

$$Y_{Coefficient} = 1.256\,[1.635 - 11.767*A - 0.004*B + 0.001*C] + 0.032[-2.00404 + 35.000*A + 0.046*B + 0.046*C] \tag{9}$$

$$Y_{COF} = 1.989 + -13.659*A - 0.001B + 0.003*C \tag{10}$$

where, Y_{COF} is coefficient value for combined mathematical model; $w_1 = 0.8$; $Y_{Ra,Min} = 0.637$; $w_1 / Y_{Ra,Min} = 1.256$; $w_2 = (1-w_1) = 0.2$; $Y_{Vibration,\ Min} = 6.291$;
w_2 / $Y_{Vibration,\ Min} = 0.032$; w_1 is weightage for surface roughness; w_2 is weightage for acceleration of vibration; $Y_{Vibration,\ Min}$ and $Y_{Ra,Min}$ are minimized values of acceleration vibration and surface roughness respectively, obtained by GA (Table 7).

Again, GA is applied to solve the Eq. 10 for optimizing (i.e. minimizing) coefficient value. The parametric setting at minimum value of coefficient corresponds to minimized surface roughness as well as acceleration of vibration as per given weightage. As already mentioned, that GA provides different combinations of input parameters with coefficient value.

The feasible parametric combination is selected as per specifications of grinding machine used in the present study. Optimized parametric condition for simultaneously optimizing both the responses and corresponding coefficient value are given in Table (8). Minimized values of surface roughness (R_a) and vibration signal are obtained by substituting the predicted parametric condition [i.e. infeed (A) = 0.06 mm in each cycle, longitudinal feed (B) = 90 mm/s and work speed (C) = 80 rpm] in Eqs. 6 and 7, respectively. These values along with the optimal parametric condition are also shown in Table (8).

Table 8 Multi-objective optimization results for aluminum alloy grinding by GA

Parametric condition		Output responses		coefficient value
		Surface roughness (R_a)	Acceleration of vibration	
Infeed (A)	0.06 mm in each cycle			
Longitudinal feed (B)	90 mm/s	0.6490 μm	7.91 m/s^2	1.050
Work speed (C)	80 rpm			

5 Confirmatory experiments

Confirmatory experiments have been conducted at optimized input parameters infeed (A) = 0.06 mm in each cycle, longitudinal feed (B) = 90 mm/s and work speed (C) = 80 rpm. Confirmatory test results are shown in Table (9). The observed vibration and surface roughness (R_a) values at optimized condition are found to be in good agreement with the predicted values.

Table 9 Confirmatory test results

Input parameters and their values		Obtained results by experimental	
		Acceleration of vibration	Surface roughness (R_a)
Infeed (A)	0.06 mm in each cycle	7.85 m/s^2	0.646 µm
Longitudinal feed (B)	90 mm/s		
Work speed (C)	80 rpm		

6 Conclusions

In the present study, L_9 orthogonal array of Taguchi methodology and response surface methodology (RSM) coupled with genetic algorithm (GA) are employed for analyzing and optimizing the process parameters in traverse cut cylindrical grinding of 6061-T4 aluminum alloy. The following conclusions are drawn in the above respect.

- From the results of analysis of variance, it is found that work speed has significant influence on vibration signal, and infeed has significant effect on surface roughness.
- Decreasing order of significant input parameters in respect of vibration is**:** work speed, longitudinal feed and infeed. In the context of surface roughness this order is: infeed, work speed followed by longitudinal feed. This is as per response table for signal-to-noise ratio.
- Based on the main effect plots, It is found that work speed is the most significant factor for acceleration of vibration and infeed is most influential factor for surface roughness (R_a).
- The mathematical models are developed for identifying the relationships of output responses: vibration and surface roughness with the input parameters, by using RSM.
- The overlaid contour plots are drawn from developed mathematical models to show how both the responses are varying with variation of input parameters, in the single plot(s). This type of plot has not yet been reported to a reasonable extent in the literature.
- Optimal parameters for the minimum vibration signal obtained by GA is: infeed at low level (0.04 mm in each cycle), longitudinal feed at low level (70 mm/s) and work speed at low level (80 rpm); for minimum surface roughness it is: infeed at high level

(0.06 mm in each cycle), longitudinal feed at high level (90 mm/s) and work speed at low level (80 rpm).

- For simultaneous minimization of vibration and surface roughness, the optimal levels of input variables have been identified by using GA. These levels are: infeed at 0.06 mm in each cycle, longitudinal feed at 90 mm/s and work speed at 80 rpm. The predicted optimum condition of the parametric setting has been validated by confirmatory test.
- The optimization approach (i.e. integrated Taguchi method and RSM combined with GA) used in the present work may be very useful for multi – objective optimization in the context of any machining or manufacturing process, involving not only two but also for more than two responses.

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Appendix

Some of the typical multi-objective overlaid contour for acceleration of vibration and surface roughness parameters R_a are shown in Figs. (9) through (12).

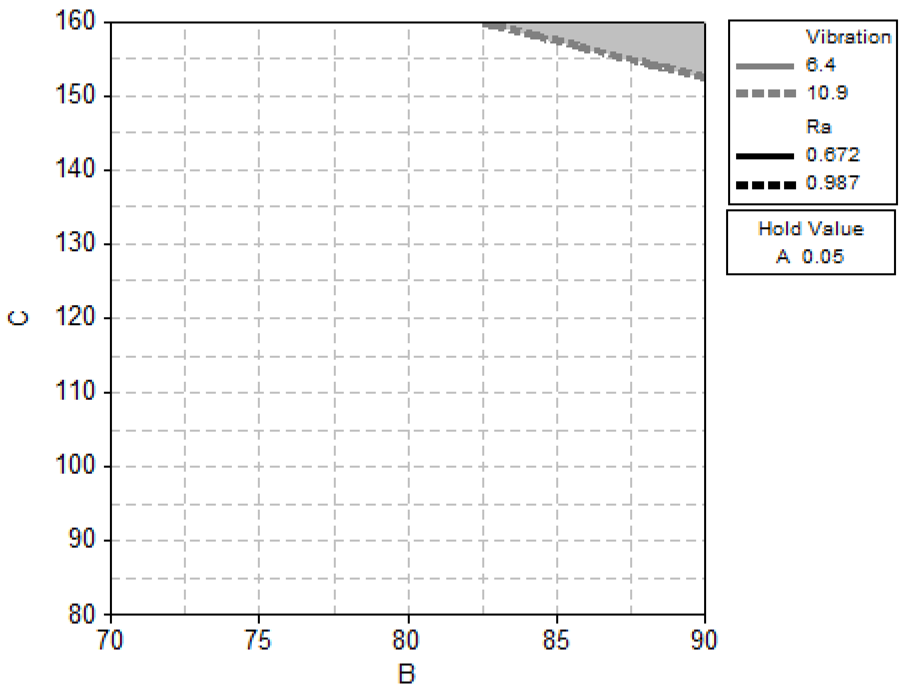

Figure 9 Overlaid contour plot showing combined effect of longitudinal feed (B) and work speed (C) on vibration and surface roughness (R_a) at infeed (A)= 0.05 mm in each cycle

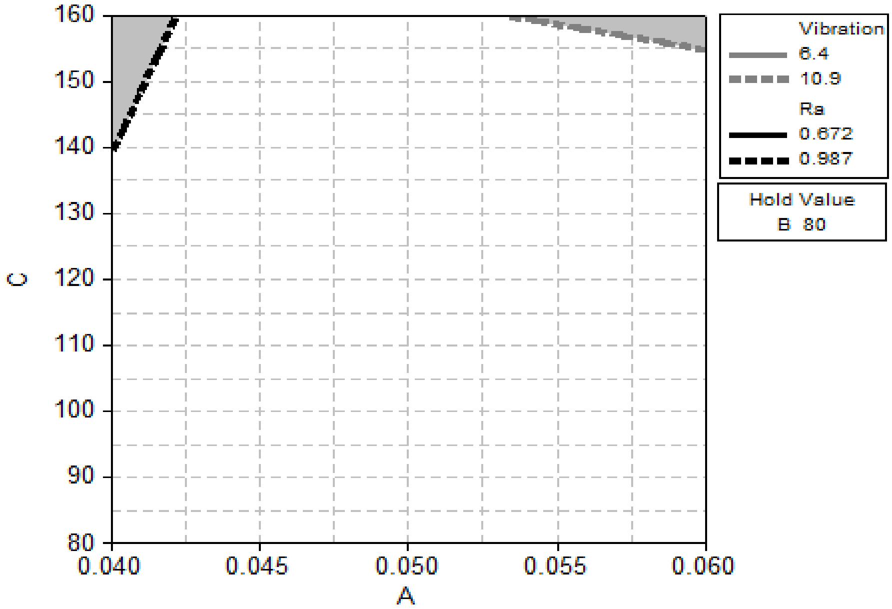

Figure 10 Overlaid contour plot showing combined effect of infeed (A) and work speed (C) on vibration and surface roughness (R_a) at longitudinal feed (B) = 80 mm/s

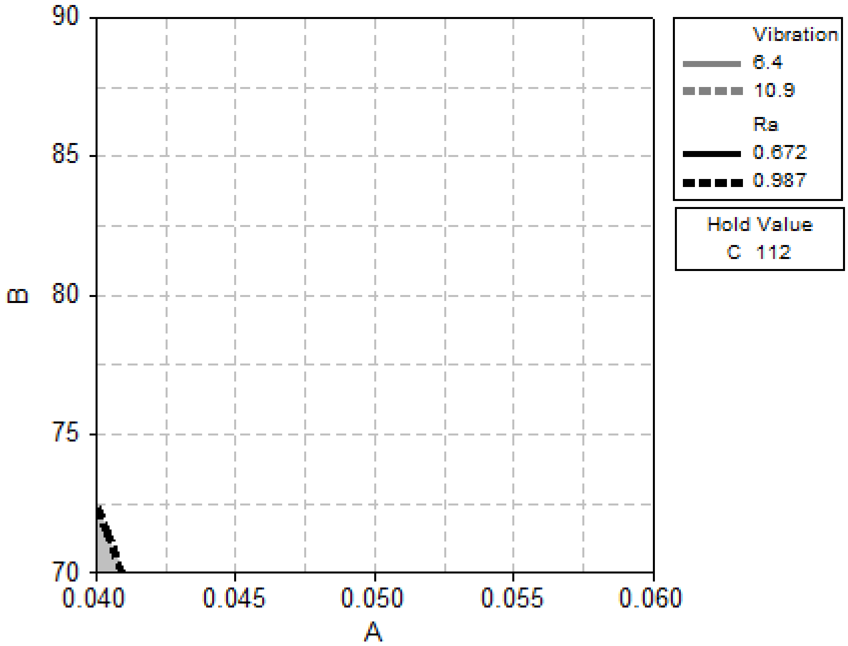

Figure 11 Overlaid contour plot showing combined effect of infeed (A) and longitudinal feed (B) on vibration and surface roughness (R_a) at work speed = 112 rpm

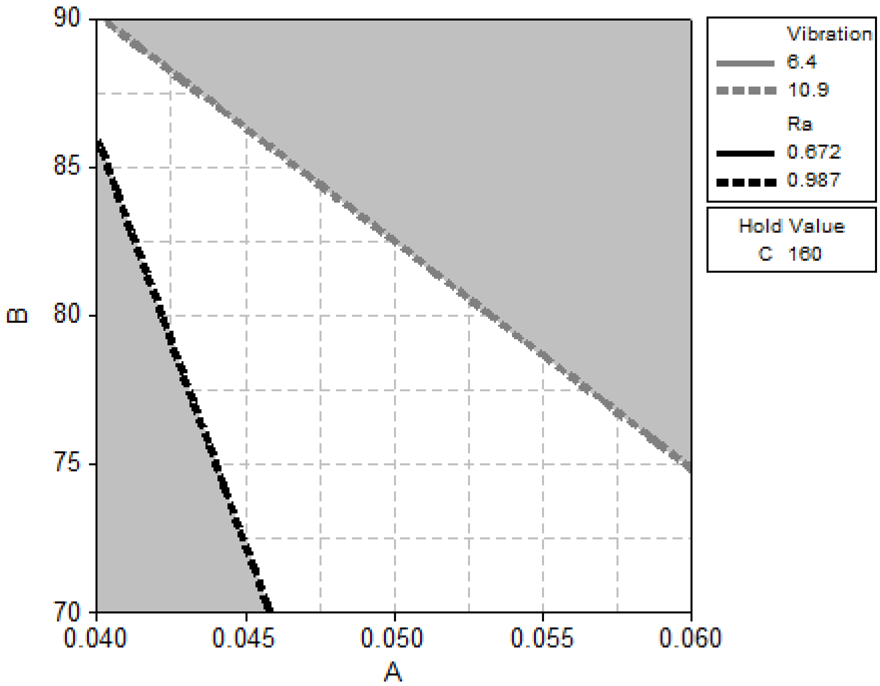

Figure 12 Overlaid contour plot showing combined effect of infeed (A) and longitudinal feed (B) on vibration and surface roughness (R_a) at work speed = 160 rpm

چکیده

مطالعه حاضر، روشی ترکیبی بر مبنای روش تاگوچی، شیوه پاسخ سطح و اگوریتم ژنتیک را برای تحلیل، مدل کردن و پیش بینی رفتار ارتعاشی و صافی سطح در برش عرضی آلومینیوم به روش سنگ زنی استوانه‌ای ارائه می‌کند. آزمایشات برای تمامی L9 آرایه‌ی روش تاگوچی و با به کارگیری سطوح متفاوت از پارامترهای سنگ‌زنی انجام پذیرفته‌اند. تحلیل واریانسی برای تعیین اثر پارامترهای مختلف بر روی پارامترهای خروجی انجام پذیرفته است. شیوه پاسخ سطح برای بدست آوردن رابطه بین پارامترهای خروجی و پارامترهای ورودی به کار گرفته شده است. منحنی های چندهدفه پوششی برای مطالعه تاثیرات متقابل هر دو پاسخ به صورت هم زمان ترسیم شده‌اند. آنگاه مدلهای پیشنهادی ابتدا به صورت مجزا و سپس در ترکیب با الگوریتم ژنتیک به منظور مراحل بهینه‌سازی تحلیل شده‌اند. به منظور صحت‌سنجی، پاسخ خروجی های پیش‌بینی شده با نتایج آزمایش مقایسه شده‌اند.