Optimization of Material Removal Rate of AlMg1SiCu in Turning Operation using Genetic Algorithm

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Abstract: - In the present study genetic algorithm was used to optimize the turning process parameters to obtain maximum material removal rate. The prediction of optimal machining condition for material removal rate plays an important role in process planning. Thus the objective of present study was to develop an empirical model to predict material removal rate in terms of spindle speed, feed rate and depth of cut using multiple regressions modeling method. Experiments were carried out on NC controlled machine tool by taking AlMg1SiCu as workpiece material and carbide inserted cutting tool. Finally, genetic algorithm has been employed to find out the optimal setting of process parameters that optimize material removal rate. The best response value for material removal rate obtained from single objective optimization by genetic algorithm was 6021.411 mm^3/min. Comparisons of experimental and predicted results at optimum conditions showed an error of 3.35 %.This provides flexibility to the manufacturing industries to choose the best setting depending on applications.

Key-Words: - Genetic algorithm, Aluminum alloy, Taguchi approach, Analysis of variance, Regression modeling, Material removal rate.

1 Introduction

Due to the widespread use of highly automated machine tools in the industry, manufacturing requires reliable models and methods for the prediction of output performance of machining processes. The need for selecting and implementing optimal machining conditions and most suitable cutting tool has been felt over the last few decades. Despite Taylor's early work on establishing optimum spindle speeds in machining, progress has been slow since all the process parameters need to be optimized. Furthermore, for realistic solutions, the many constraints met in practice, such as low machine tool power, torque, force limits and component surface roughness must be overcome.

Suresh et al. (2002) developed a mathematical model for predicting value of surface roughness while machining mild steel using response surface methodology and optimized the developed model using genetic algorithm, in order to attain the required surface quality [1]. Tzeng and Chen (2006) used grey relational analysis to optimize the process parameters in turning of tool steels. The optimum turning parameters were determined based on grey relational grade, which maximizes the accuracy and minimizes the surface roughness and dimensional precision [2]. Al-Refaie et al. (2010) used Taguchi method coupled grey analysis to determine the optimal combination of control parameters in milling, the measures of machining performance being the MRR and SR [3]. Kumar et al. (2010) optimized turning parameters based on the Taguchi's method with regression analysis. They developed model for prediction of surface roughness and material removal rate in machining of unidirectional glass fiber reinforced plastics composites with a polycrystalline diamond tool [4]. Mustafa and Tanju (2011) investigated the effect of feed rate, cutting speed and depth of cut on surface roughness, cutting temperature and cutting force in turning of aluminum 7075 alloy using diamond like carbon coated cutting tools [5]. Aruna and Dhanalaksmi (2012) developed a model for predicting the surface roughness based on cutting speed, feed and depth of cut using response surface methodology. Surface roughness contour for cutting speed-depth of cut is developed to describe the values resulting from the cutting parameters selected [6]. Saha and Mandal (2012) investigated multi-response optimization of turning process for an optimal parametric combination to yield the minimum power consumption, surface roughness and frequency of tool vibration using a combination of a grey relational analysis [7]. Kaladhar et al. (2011) formulated a multi-characteristics response optimization model based on Taguchi and utility concept to optimize process parameters, such as speed, feed, depth of cut, and nose radius on multiple performance characteristics namely, surface roughness and material removal rate during turning of AISI 202 austenitic stainless steel using a CVD coated cemented carbide tool [8]. Kaladhar et al. (2012) investigated the effects of process parameters on surface finish and material removal rate in turning of AISI 304 using PVD coated cermet inserts, to obtain the optimal setting of these parameters [9]. Prajapati et al. (2012) optimized surface roughness using grey relational analysis in straight turning operation of SS 316 [10]. Isik et al. (2010) investigated the effect of dry machining on the output parameters such as flank wear, cutting force and surface roughness. They found the conditions in dry cutting as satisfactory compared to the flooded type of cooling [11]. Dogra et al. (2011) investigated the effect of variation in tool geometry i.e. tool nose radius, rake angle, groove on the rake face, variable edge geometry, wiper geometry and curvilinear edge tools and on tool wear, surface roughness and surface integrity of the machined surface [12]. Sharma and Sharma (2012) [13] evaluated the best process environment which could simultaneously satisfy requirements of both quality as well as productivity with special emphasis on reduction of cutting tool flank wear. Selvaraj et al. (2010) investigated the cutting characteristics of AISI 304 austenitic stainless steel bars using TiC and TiCN coated tungsten carbide cutting tool [14]. Mahdavinejad and sharifi (2009) investigated the effect of precision of machine tools and the input setup parameters on output machining parameters such as stock removal, tool wear ratio and surface roughness [15]. Yadav et al. (2012) used Taguchi method to plan the experiments and EN 8 metal selected as a work piece and coated carbide tool as a tool material in this work and hardness after turning has been measured on Rockwell scale. The obtained experimental data has been analyzed using signal to noise and. The main effects have been calculated and percentage contribution of various process parameters affecting hardness also determined [16]. Motorcu et al. investigated tool life performance and wear mechanism of various cutting tools such as mixed alumina ceramic (KY 1615), coated ceramic (KY 4400) and cubic boron nitride (CBN/TiC) under different cutting conditions in turning of austenite and quenched AISI 52100 steels [17]. Based on the above literature survey it can be concluded that over two decades researchers are working on the modelling and optimization of turning process parameters. People have developed empirical models using multiple regression method with response surface methodology and Taguchi method as tool for designing and conducting experiments. These models were developed for a particular combination of workpiece-tool and cutting environment. Researchers have optimized the turning process parameters while machining alloy steels, tool steels and few aluminium alloys. Still there is no clear cut information available with the shop floor operator about optimal parameter setting of input parameters and the type of cutting tool to be used for machining different materials. Hence, the aim of the present study was to develop empirical model for predicting material removal rate in terms of spindle speed, feed rate and depth of cut using multiple regressions modelling method and optimize the process parameters to maximize material removal rate using genetic algorithm.

2 Material and Methods

Experiments were carried out on NC controlled machine tool of Hi-Cut 3503 make. Aluminium AlMg1SiCu alloy was used as work piece material of dimension ϕ35 mm x 300 mm long. Chemical composition and mechanical properties of workpiece material is shown in table 1 and table 2 respectively. Chemical composition of the workpiece is obtained by spectroscopy analysis. Carbide insert cutting tool (tool holder- SVJBL

2020K 11 and insert- DCMT 11T308- PM 4225) was used for machining work pieces.

Table 1 Chemical composition of workpiece

Element	Weight %
Al	97.9
Si	0.60
Cu	0.28
Mg	1.0
Cr	0.20

Table 2 Physical and mechanical properties of workpiece

Density	2.7 g/cc
Ultimate tensile strength	310 MPa
Tensile yield strength	276 MPa
Modulus of Elasticity	68.9 GPa
Brinell Hardness (500 gm load & 10 mm ball)	95 BHN

In this study, spindle speed, feed rate and depth of cut were considered as machining parameters and turning was carried out with application of cutting fluid. Experiments were designed using L_{27} (3^{13}) Taguchi orthogonal array. Table 3 shows the machining parameters and their levels.

Table 3 Machining parameters with their levels

Level	Spindle Speed (rpm)	Feed Rate (mm/rev)	Depth of Cut (mm)
1	280	0.0508	0.4
2	710	0.1016	0.8
3	1120	0.1524	1.2

Work pieces were cleaned prior to the experiments by removing 0.3 mm thickness of the top surface in order to eliminate any surface defects and wobbling. Fourteen equal parts of 20 mm length were marked on the work pieces. Material removal rate was calculated by using equation 1.

$$MRR = \pi/4 * (D_i^2 - D_f^2) * f * N \quad (1)$$

Where,

D_i = initial diameter, mm, D_f = final diameter, mm, f= feed rate, mm/rev, N= spindle speed, rpm

The philosophy of Taguchi's method is to minimize the variations in product or systems characteristics. Taguchi's philosophy defines three approaches to minimize variations namely, parameter, tolerance and system design. Orthogonal arrays are used in these approaches which reduces the experimental runs. Taguchi's method has few benefits such as with fewer number of trials run an acceptable solution is achieved. It minimizes the variability around the target value with lesser experimental cost. The optimal setting of parameters obtained from analysis can also be used in real production environment. To determine the effect of each variable on the output, the signal-to-noise ratios or the SN number, are calculated for each experiment [18]. For the case of minimizing the performance characteristic, the following definition of the SN ratio can be used:

$$SN_i = -10 \log \left(\sum_{u=1}^{N_i} \frac{y_u^2}{N_i} \right) \quad (2)$$

For the case of maximizing the performance characteristic, the following definition of the SN ratio can be used:

$$SN_i = -10 \log \left[\frac{1}{N_i} \sum_{u=1}^{N_i} \frac{1}{y_u^2} \right] \quad (3)$$

Where, i = experiment number, u = trial number, y = observed value, N_i = number of trials for experiment i [18].

3 Results and Discussions

In order to see the effect of process parameters on the MRR, experiments were conducted using L_{27} orthogonal array as shown in table 4. The average values of MRR for each parameter at levels 1, 2 and 3 for S/N data are plotted in figure 1.

Table 4 L_{27} orthogonal array and observed values

Trial No.	Spindle Speed (rpm)	Feed rate (mm/rev)	Depth of cut (mm)	MRR (mm^3/min)	S/N ratio (dB)
1	280	0.0508	0.4	306.67	8.87
2	280	0.0508	0.8	609.76	6.56
3	280	0.0508	1.2	909.28	5.68
4	280	0.1016	0.4	582.94	1.94
5	280	0.1016	0.8	1158.73	0.92
6	280	0.1016	1.2	1727.36	-0.83
7	280	0.1524	0.4	943.34	-4.24
8	280	0.1524	0.8	1875.96	-4.91
9	280	0.1524	1.2	2797.84	-6.73

10	710	0.0508	0.4	793.04	8.40
11	710	0.0508	0.8	1577.02	6.38
12	710	0.0508	1.2	2351.92	5.35
13	710	0.1016	0.4	1555.25	1.83
14	710	0.1016	0.8	3092.37	1.72
15	710	0.1016	1.2	4611.35	0.26
16	710	0.1524	0.4	2196.85	-5.67
17	710	0.1524	0.8	4366.50	-5.62
18	710	0.1524	1.2	6508.93	-6.15
19	1120	0.0508	0.4	875.13	10.8
20	1120	0.0508	0.8	1735.95	8.64
21	1120	0.0508	1.2	2582.46	8.40
22	1120	0.1016	0.4	1745.24	1.72
23	1120	0.1016	0.8	3461.88	2.05
24	1120	0.1016	1.2	5149.90	-0.91
25	1120	0.1524	0.4	2549.20	-4.86
26	1120	0.1524	0.8	5055.49	-5.53
27	1120	0.1524	1.2	7518.86	-5.20

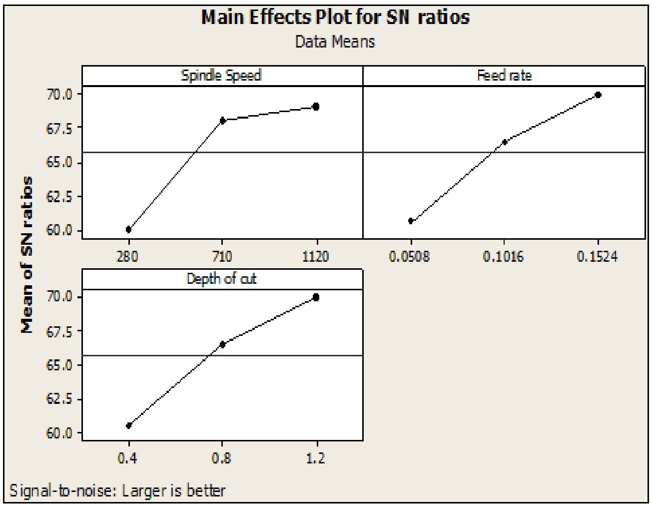

Fig. 1 Main effects plot for SN ratios of MRR

Figure 1 shows that the MRR increases with the increase in spindle speed, feed rate and depth of cut. From the cutting theory it is known that material removal rate is directly proportional to the spindle speed, feed rate and depth of cut. The same was observed from the experimental results. Spindle speed is the speed at which the work piece material is moving past the cutting tool. Feed always refers to the cutting tool, and it is the rate at which the tool advances along its cutting path. The feed rate is directly related to the spindle speed. Thus, as spindle speed increases the feed rate too increases, thereby resulting in increase in material removal rate. Depth of cut is the thickness of the layer being removed (in a single pass) from the work piece or the distance from the uncut surface of the work to the cut surface. Thus, the volume of material removed increases with increase in depth of cut. It is seen from the figure 2 that there is very weak interaction between the process parameters in affecting the MRR since the responses at different levels of process parameters for a given level of parameter value are almost parallel.

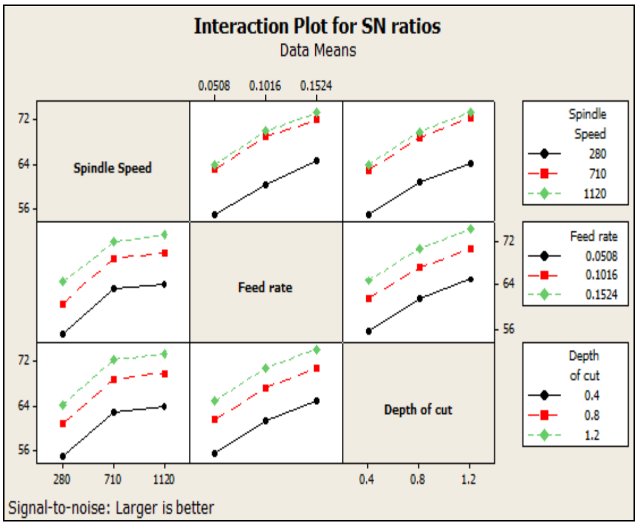

Fig. 2 Interaction plot for SN ratios of MRR

Regression analysis was carried out to ensure a least squared fitting to error surface in Minitab 16 environment. Regression analysis has been performed to find out the relationship between input factors and MRR. During regression analysis it was assumed that the factors and the response are linearly related to each other. The general first order model was developed to predict the MRR over the experimental region (equation 4). In general, the R^2adjustedstatistic will not always increase as variables are added to the model. In fact, if unnecessary terms are added, the value of R^2adjusted will often decrease. When R^2 and R^2 adjusted differ dramatically, there is a good chance that no significant terms have been included in the model. For this experiment the R^2 value indicates that the predictors explain 83.70% of the response variation. Adjusted R^2 for the number of predictors in the model 81.58% values shows that the data are fitted well.

$$MRR = -4269.91 + 2.6267*(\text{spindle speed}) + 24138*(\text{feed rate}) + 3140.31*(\text{depth of cut}) \quad (4)$$

The positive value of spindle speed, feed rate and depth of cut is indicative that increase in process parameters increases the material removal rate. Residual plots are used to evaluate the data for the problems like non normality, non-random variation, non-constant variance, higher-order relationships, and outliers. It can be seen from figure 3 that the residuals follow an approximately straight line in normal probability plot and approximate symmetric nature of histogram indicates that the residuals are normally distributed. Residuals possess constant variance except trail condition 1 and 27, as they are scattered randomly around zero in residuals versus the fitted values. Moreover, the experiments were carried out as per the run order generated by randomization principle. Since residuals exhibit no clear pattern, there is no error due to time or data collection order.

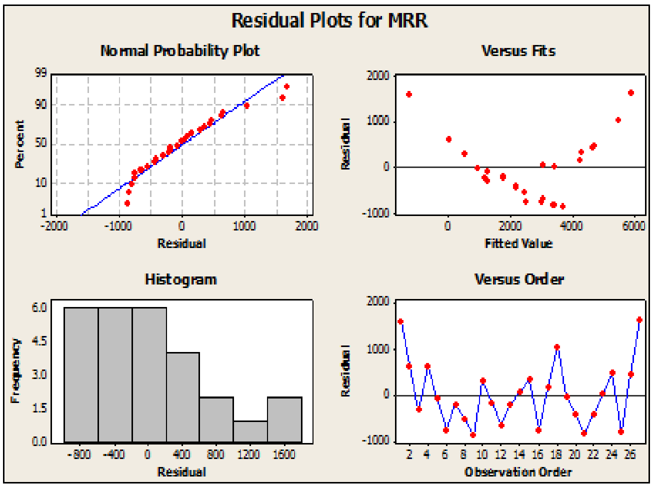

Fig. 3 Residual plot for MRR

In order to study the significance of the process variables towards MRR, analysis of variance was performed at a confidence interval of 95% i.e. a significance level of 0.05 (table 5). It was found that spindle speed, feed rate and depth of cut are significant process parameters for MRR. Significant process variables were predicted with an R^2 value of 86.62% and R^2 adjusted of 82.60%.

Table 5 Analysis of variance table for MRR

Source	DF	Adj SS	Adj MS	F	P
Regression	3	77377353	25792451	39.373	0.0
Spindle Speed	1	21911539	21911539	33.449	0.0
Feed rate	1	27064550	27064550	41.315	0.0
Depth of cut	1	28401265	28401265	43.356	0.0
Error	23	15066570	655068		
Total	26				

The response table (table 6) show the average of each response characteristic for each level of each factor. The tables include ranks based on delta statistics, which compare the relative magnitude of effects. The delta statistic is the highest minus the lowest average for each factor. Minitab assigns ranks based on delta values; rank 1 to the highest delta value, rank 2 to the second highest, and so on. The ranks indicate the relative importance of each factor to the response. The ranks and the delta values show that depth of cut have the greatest effect on material removal rate and is followed by feed rate and depth of cut.

Table 6 Response table for SN ratios of MRR

Level	Spindle Speed	Feed rate	Depth of cut
1	59.98	60.65	60.56
2	68.02	66.46	66.52
3	69.05	69.95	69.98
Delta	9.07	9.30	9.43
Rank	3	2	1

As MRR is the “higher the better” type quality characteristic and from the S/N data analysis, it can be seen from figure 1 that the third level of spindle speed, third level of feed rate, and third level depth of cut provide maximum value of MRR. In order to validate the results three runs of confirmation experiments were carried out at the optimal setting of input parameters. Table 7 shows the confirmation results with predicted values and S/N ratios.

Table 6 Confirmation experiments

Optimal set of parameters	Predicted value (mm^3/min)	S/N ratio (dB)	Actual value(avg. of 3 runs) (mm^3/min)	S/N ratio (dB)
$A_3B_3C_3$	5876.17	77.61	5996.37	75.55

4 Genetic algorithm for optimization of MRR

The developed mathematical model from Regression method was used for maximization of material removal rate in turning of Al alloy. Genetic algorithm is widely used for minimization problems, so the developed mathematical model was first converted into minimization problem and then converted into a MATLAB (R2009a) function. This function was input to the GA Toolbox of MATLAB

2009a as the objective function. Upper and lower bounds were specified as per the levels of the machining parameters and the number of variables was set at 3. The population type was set to double vector, population size of 20 and a generation of 100 was used for the analysis. Constraint dependent creation function and scattered type of cross over function were used for the analysis. Crossover fraction was set at 0.85 and mutation fraction was set at 0.15. Multiple runs of the algorithm were carried out at different settings of the available options of GA Toolbox to fine tune the maximum response value. The best response is shown in figure 4. The best response value for material removal rate obtained from GA was 6021.411 mm^3/min and the corresponding setting of process parameters are spindle speed of 1083.38 rpm, feed rate of 0.1524 mm/rev, and depth of cut of 1.2 mm.

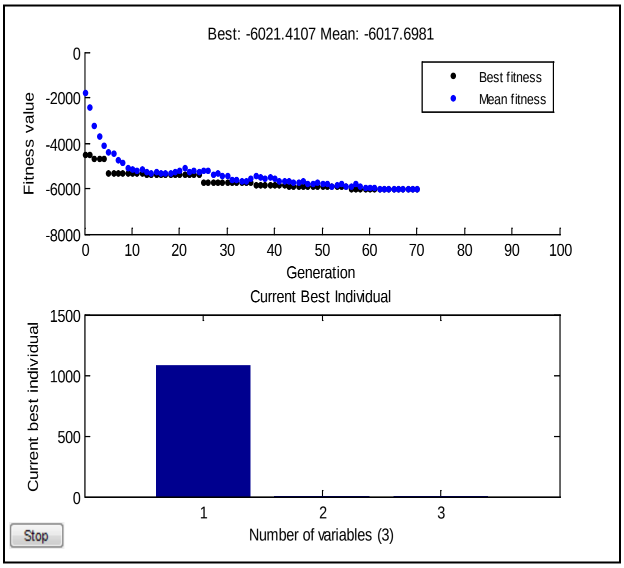

Figure 4 GA Toolbox to fine tune the maximum response value

Table 8 Confirmation experiments

Optimal Values	Predicted	Actual	%Error
S= 1083.38 rpm, F=0.1524 mm/rev, and D= 1.2 mm.	6021.411	6235.251	3.35

After optimization, further experiments were carried out to test the accuracy of the developed model. The model was experimentally validated and the results were tabulated in table 8. This time, the optimized values of cutting parameters corresponding to the best responses (obtained from GA) were selected for experiments. The resulting MRR (experimental) was compared with that predicted by the GA and percentage error was calculated. A good agreement was observed among the predicted and actual results.

5 Conclusions

In this study turning experiments were conducted by using the parametric approach of the Taguchi's method. Regression analysis has been performed to find out the relationship between input factors and responses using Minitab 16 statistical software. General first order model was developed to predict the material removal rate over the experimental region. Based on single objective optimization by genetic algorithm optimal analysis the best material removal rate value obtained was 6021.411 mm^3/min. For material removal rate, confirmation experiments resulted in an average percentage error of 3.35, underlining the satisfactory performance of the prediction model. This establishes the reliability of genetic algorithms as one of the most accurate optimization approaches.

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