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Procedia Materials Science 6 (2014) 961 – 966

Procedia Materials Science

www.elsevier.com/locate/procedia

3rd International Conference on Materials Processing and Characterisation (ICMPC 2014)

Multi-Objective Optimization of Turning Process during Machining of AlMg1SiCu Using Non-Dominated Sorted Genetic Algorithm

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Abstract

Parametric optimization of turning process is a multi-objective optimization task. In general no single combination of input parameters can provide the best material removal rate and the best surface finish simultaneously. Genetic algorithm has been proven as one of the most popular multi-objective optimization techniques for the parametric optimization of conventional machining processes. In this study non-dominated sorted genetic algorithm has used to optimize the process parameters. Aim of the present study was to develop empirical models for predicting material removal rate and surface roughness 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, a non-dominated sorted genetic algorithm has been employed to find out the optimal setting of process parameters that simultaneously maximize material removal rate and minimize surface roughness. The set of Pareto-optimal front provides flexibility to the manufacturing industries to choose the best setting depending on applications.

Selection and peer review under responsibility of the Gokaraju Rangaraju Institute of Engineering and Technology (GRIET)

Keywords: Multi-objective optimization; Non-dominated sorted genetic algorithm;Material removal rate;Surface roughness;AlMg Alloy

1. Introduction

Manufacturing industry aims at producing a large number of products within relatively lesser time. But it is felt that reduction in manufacturing time may cause severe quality loss. In order to embrace these two conflicting

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Selection and peer review under responsibility of the Gokaraju Rangaraju Institute of Engineering and Technology (GRIET)
doi:10.1016/j.mspro.2014.07.166

criteria it is necessary to check quality level of the item either on-line or off-line. The purpose is to check whether quality lies within desired tolerance level which can be accepted by the customers. Quality of a product can be described by various quality attributes. The attributes may be quantitative or qualitative. This invites optimization problem which seeks identification of the best process condition or parametric combination for the said manufacturing process. Optimization of process parameters of turning is a multi-objective optimization task as in practice the performance measures (material removal rate and surface roughness) are conflicting in nature. Though much work has been reported in literature to improve the process performance, proper selection of process parameters still remains a challenge. There are several multi-objective optimization techniques for the same like goal programming, simulated annealing (SA), grey relation, and genetic algorithms (GA). GA is very different from most of the traditional optimization methods. GA finds applicability in the field of conventional machining processes. It works with a random population of solution points and a set of Pareto-optimal solutions is obtained for the best performance measures. 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. 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.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. Kumar et al. (2011) 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. 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. 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. Saha and Mandal (2013) 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.

2. Experimental Details

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 ϕ35mm x 300 mm long. Carbide insert cutting tool (tool holder-SVJBL 2020K 11 and insert- DCMT 11T308- PM 4225) was used for machining work pieces. 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 1 shows the machining parameters and their levels. The experimental design and observed values of responses are shown in table 2.

Table 1. 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 0.3mm thickness of the top surface in order to eliminate any surface defects and wobbling. Fourteen equal parts of 20mm length were marked on the work pieces. Surface roughness of the machined surfaces were measured by Talysurf (Taylor Hobson make) and material removal rate was calculated using following formula;

$$\text{MRR} = \frac{\pi}{4} \times (D_i^2 - D_f^2) \times f \times N \quad (1)$$

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

Table 2. Taguchi orthogonal array with observed values

Sr. No.	Spindle speed (rpm)	Feed rate (mm/rev)	Depth of cut (mm)	MRR (mm^3/min)	Ra (μm)
1	280	0.0508	0.4	306.67	0.36
2	280	0.0508	0.8	609.76	0.47
3	280	0.0508	1.2	909.28	0.52
4	280	0.1016	0.4	582.94	0.8
5	280	0.1016	0.8	1158.73	0.9
6	280	0.1016	1.2	1727.36	1.1
7	280	0.1524	0.4	943.34	1.63
8	280	0.1524	0.8	1875.96	1.76
9	280	0.1524	1.2	2797.84	2.17
10	710	0.0508	0.4	793.04	0.38
11	710	0.0508	0.8	1577.02	0.48
12	710	0.0508	1.2	2351.92	0.54
13	710	0.1016	0.4	1555.25	0.81
14	710	0.1016	0.8	3092.37	0.82
15	710	0.1016	1.2	4611.35	0.97
16	710	0.1524	0.4	2196.85	1.92
17	710	0.1524	0.8	4366.50	1.91
18	710	0.1524	1.2	6508.93	2.03
19	1120	0.0508	0.4	875.13	0.29
20	1120	0.0508	0.8	1735.95	0.37
21	1120	0.0508	1.2	2582.46	0.38
22	1120	0.1016	0.4	1745.24	0.82
23	1120	0.1016	0.8	3461.88	0.79
24	1120	0.1016	1.2	5149.90	1.11
25	1120	0.1524	0.4	2549.20	1.75
26	1120	0.1524	0.8	5055.49	1.89
27	1120	0.1524	1.2	7518.86	1.82

3. Results and Discussions

3.1. Multiple regression models

The 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. During regression analysis it was assumed that the factors and the responses are linearly related to each other. General first order model was developed to predict the material removal rate over the experimental region (equation 2). For this experiment the R^2 value indicates that the predictors explain 83.70% of the response variation. Adjusted R2 for the number of predictors in the model 81.58% values shows that the data are fitted well.

MRR = -4269.91 + 2.6267*(spindle speed) + 24138*(feed rate) + 3140.31*(depth of cut) (2)

The positive value of spindle speed, feed rate and depth of cut is indicative that increase in process parameters increases the material removal rate. General first order model was developed to predict the surface roughness over the experimental region (equation 3).Adjusted R2 for the number of predictors in the model 93.96% values shows that the data are fitted well.

Ra = -0.552042 - 6.39734e-005*(spindle speed) + 14.3154 *(feed rate) + 0.261111* (depth of cut) (3)

3.2. Multi-object optimization

To solve optimization problem using GA, fitness value is required. Fitness values, in fact, are the objective function values. In this work, multiple regressions modeling method has been employed to developed the mathematical model which establishes the relation between input and output. The developed mathematical model was 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 objective function values are obtained for maximization of material removal rate and minimization of surface roughness in turning of AlMg1SiCu alloy. Here, an initial population size of 60 is taken and optimization is carried out by setting simple crossover and bitwise mutation with a crossover probability Pc = 0.8, migration interval of 20, migration fraction of 0.2 and Pareto fraction of 0.35. According to the algorithm, ranking and sorting of solutions are done. The Pareto-optimal solutions (along with corresponding performance measure values) are reported in table 3.

Table 3. Pareto optimal solutions

Sr. No.	Response parameters		Machining parameters		
	MRR (mm^3/min)	Ra(μm)	Spindle Speed (rpm)	Feed Rate (mm/min)	Depth of Cut (mm)
1	-6054.12	1.87	1095.34	0.15	1.20
2	-1106.51	0.21	1099.93	0.05	0.40
3	-3639.15	0.45	1095.70	0.05	1.20
4	-5329.21	1.54	1096.98	0.13	1.14
5	-1106.51	0.21	1099.93	0.05	0.40
6	-2375.96	0.35	1098.22	0.05	0.79
7	-4968.93	1.40	1097.21	0.12	1.09
8	-3849.75	0.58	1096.66	0.06	1.19
9	-2935.17	0.39	1099.67	0.05	0.97
10	-2020.44	0.29	1099.83	0.05	0.69
11	-4350.28	0.87	1095.49	0.08	1.20
12	-4035.45	0.69	1095.58	0.07	1.19
13	-4908.50	1.20	1096.68	0.11	1.20
14	-3360.22	0.42	1098.88	0.05	1.10
15	-4148.91	0.85	1096.95	0.08	1.13
16	-5197.29	1.45	1094.18	0.12	1.15

Fig. 1 shows the formation of Pareto-optimal front that consist of the final set of solutions. The shape of the Pareto optimal front is a consequence of the continuous nature of the optimization problem posed. The results reported in table 3 clearly show that in 16pareto-optimal solutions, the whole given range of input parameters is reflected and no bias towards higher side or lower side of the parameters is seen. This may be attributed to the controlled NSGA that forcible allows the solutions from all non-dominated fronts to co-exist in the population. Since the performance measures are conflicting in nature, surface quality decreases as MRR increases and the same behavior of performance measures is observed in the solutions obtained. Since none of the solutions in the Pareto optimal set is absolutely better than any other, any one of them is an acceptable solution. The choice of one solution over the other depends on the requirement of the process engineer. It should be noted that all the solutions are equally good and any set of input parameters can be taken to achieve the corresponding response values depending upon manufacturer's requirement.

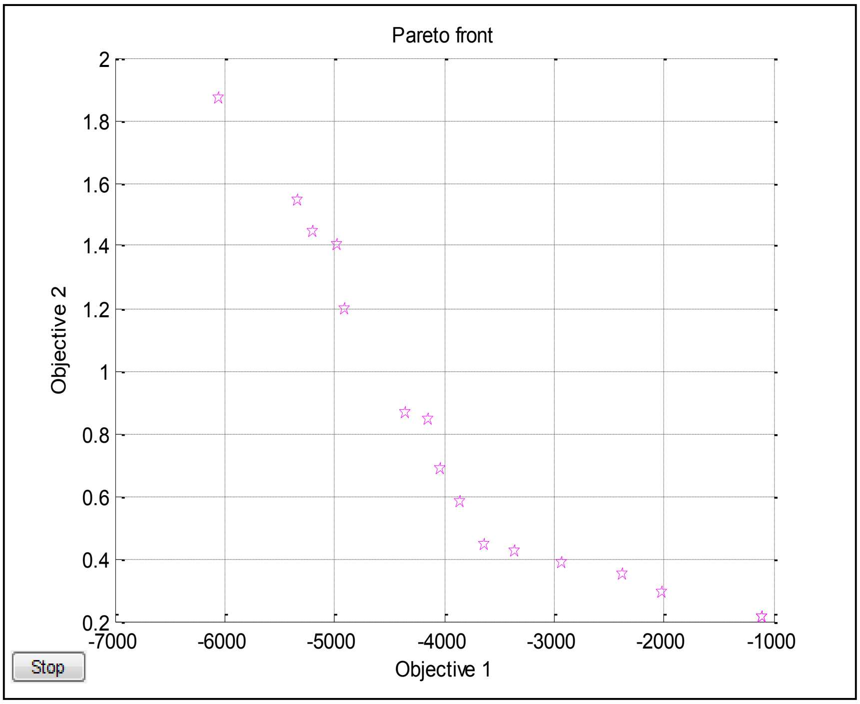

Fig.1. Pareto optimal front

3.3. Confirmation experiments

From the Pareto-optimal solution, randomly five runs were chosen to verify the prediction of responses (MRR and Ra). Validation experiments showed a good agreement with the predicted values of responses with an error less than 10% (table 4).

Table 4 Validation experiment results based on multi-objective optimization

Optimal values	Predicted		Actual		%Error	
	MRR (mm^3/min)	Ra (μm)	MRR (mm^3/min)	Ra (μm)	MRR	Ra
1100rpm, 0.05mm/min, 0.4 mm	1106.51	0.21	1155.51	0.22	4.43	4.76
1100 rpm, 0.05mm/min, 0.69mm	2020.44	0.29	2130.54	0.31	5.45	6.89
1095 rpm, 0.15mm/min,1.2mm	6054.12	1.87	6324.21	1.98	4.46	5.88
1097rpm, 0.13mm/min, 1.14mm	5329.21	1.54	5247.47	1.49	1.56	3.24
1094rpm, 0.12mm/min, 1.15mm	5197.29	1.45	4908.30	1.4	5.56	3.45

4. 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 and surface roughness over the experimental region. Based on multi-objective optimization by non-dominated sorted genetic algorithm Pareto-optimal analysis the best material removal rate obtained was 6054.12 mm^3/min and the best surface roughness value obtained was 0.21μm. For material removal rate, confirmation experiments resulted in a maximum percentage error of 5.56% and an average percentage error of 4.29% and for surface roughness, confirmation experiments resulted in a maximum percentage error of 6.89% and an average percentage error of 4.84%, 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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