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GLOBAL OPTIMIZATION OF CNC TURNING OF AL/SIC MMC USING RSM AND GENETIC ALGORITHM

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ABSTRACT

Composite materials, are now-a-days preferred as an alternative for conventional engineering materials and have got many applications in engineering fields such as automobiles, aerospace where less weight and high strength is required. Metal matrix composites are mostly preferred because of their excellent properties. In the present work, metal matrix composite specimens with 10% silicon carbide particles blended with aluminum metal matrix and casted using stir casting process. Experiments for turning operation were designed using response surface methodology. Cutting speed, feed and depth of cut were considered as control factors and surface roughness was considered as output response. A mathematical model was developed and the model was utilized in the process of optimization. A popular global optimization technique, genetic algorithm is used for optimization.

Keywords: *Al/SiC MMC, Stir casting, RSM, CNC Turning, Surface roughness, Genetic algorithm.*

1. Introduction

Composite materials are ideal for structural applications where high strength-to-weight and stiffness-to-weight ratios are required. Aircraft and spacecraft are typical weight-sensitive structures in which composite materials are cost-effective. When full advantage of composite materials is explored, these structures will be designed in a different manner from the present [1]. Metal matrix composites (MMCs) have a metal matrix. Examples of matrices in such composites include aluminum, magnesium, and titanium. Typical fibers include carbon and silicon carbide. The basic attributes of metals reinforced with hard ceramic particles or fibers are improved strength and stiffness, improved creep and fatigue resistance, and increased hardness, wear and abrasion resistance, combined with the possibility of higher operating temperatures than for the unreinforced metal [2]. Metals are mainly reinforced to increase or decrease their properties to suit the needs of design. Metal matrix composites are mainly used to provide advantages over monolithic metals such as steel and aluminum [3].

2. Literature Review

Composite materials are generating curiosity and interest among researchers throughout the world. Several research works have been carried out and still the investigations are taking place to explore the potentiality of composites.

Metal matrix composites (MMCs) due to the advantage of their properties, are mostly preferred. Especially, aluminium matrix with silicon carbide particles (Al/SiC) MMC and along with graphite as hybrid materials was considered by researchers. Investigations were carried to find the machinability of MMC [4], Al-SiC MMC in aerospace applications [5], metal matrix composites in automotive industry [6] and Al-SiC metal matrix composite subjected to different conventional and non-conventional machining processes such as cylindrical grinding [7], wire EDM [8], end milling [9], drilling [10]. Some works have been carried out to study properties and characterization of Al/SiC MMC [11, 12] and to estimate cutting forces and their effects on input parameters [13], analysis of chip formation while machining MMC [14]. A few works have been carried out in modeling and optimization of MMC. Pai Dayanand et al. [15] adopted Taguchi's optimization methodology to optimize cutting parameters of Al/SiC MMC. Muthukrishnan et al. [16] used artificial neural networks with backward propagation algorithm to determine input parameters of machining process. Sahoo et al. [17] presented the influence of process parameters like cutting speed, feed and depth of cut on flank wear and surface roughness in turning Al/SiC_p metal matrix composites using linear regression analysis.

In the present work, aluminium alloy 6061 is considered as matrix metal and 10% silicon carbide as reinforcement and test specimens are casted using stir casting process. The samples are then machined by using CNC turning considering cutting speed, feed and depth of cut as input parameters and surface roughness as output response. Mathematical model is developed by

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response surface methodology and then the model is used for optimization. Genetic algorithm, a popular global optimization technique is used to optimize the machining parameters of CNC turning.

3. Response Surface Methodology

The theory of Response Surface Methodology (RSM) was introduced by Box and Wilson [18] to develop the empirical models of complex processes. These models were used to represent the output characteristics (responses). Later, this methodology was used by Hill and Hunter [19] for empirical process modeling and optimization. RSM is a combination of mathematical and statistical techniques useful for modeling and analyzing the problem in which several independent variables influence a dependent variable or response. In the present study, mathematical relationships between input and output parameters have been developed through Response Surface methodology (RSM). The general second-order polynomial response surface mathematical model which analyses the parametric influences on various response criteria can be described as follows:

$$Y_u = b_0 + \sum_{i=1}^{n} b_i X_{iu} + \sum_{i=1}^{n} b_{ii} X_{iu} X_{ju} \qquad (1)$$

Where Y_u is the corresponding response, surface roughness, X_{iu} is the coded values of *i* th machining parameter for *u* th experiment, *n* is the number of machining parameters, b_i, b_{ii}, b_{ij} are the second order regression coefficients. The second term under summation sign of polynomial equation is attributable to linear effect, whereas the third term corresponds to higher order effect. The fourth term of equation includes interactive effects of process parameters.

4. Genetic algorithm

Genetic algorithms (GA) are search algorithms for optimization, based on the mechanics of natural selection and genetics [20, 21]. The mechanics of GA is simple, involving copying of binary strings and the swapping of the binary strings. The computations are carried out in three stages to obtain a result in one iteration. The three stages are reproduction, crossover and mutation.

Reproduction is a process in which copies of the strings are copied into a separate string called the mating pool, in proportion to their fitness values. This implies that strings with higher fitness values will have a higher probability of contributing more strings as the search progresses. In crossover operation, parent strings are swapped partially causing off-spring to be generated based on the random selection of crossover site. Mutation is the occasional random alteration of the value of a string position. In binary strings, this simply means changing 1 to 0, or vice versa.

5. Experimentation

The specimens of composite material were fabricated using liquid state method called, stir casting process. Aluminium alloy, Al 6061 was taken as metal matrix and 10% silicon carbide particles were added as reinforcement. Initially, graphite crucible of the furnace was heated to 500^0C then base metal was placed in the crucible and correspondingly the temperature of furnace was increased to maintain the molten state of matrix metal. Silicon carbide particles were mixed with matrix metal by means of mechanical stirring, at a temperature of 835^0C. The mixture was casted and subjected to natural cooling to obtain the specimens of ø30 x 80 mm size. The casting process is shown in fig. 1 and the specimens of Al/SiC MMC are shown in fig. 2 and the composition of specimen material is given in table 1.

Fig. 1 Casting process

Fig. 2 10% SiC-Al MMC Samples

Table 1. Composition of Al/SiC MMC material

Element (%)	Al	Si	Fe	Cu	Ti	Mg	Mn	Zn	Cr
Al/SiC MMC	87.64	0.62	0.54	0.018	0.046	0.81	0.038	0.062	0.0044

Machining operations were designed based on response surface methodology and feasible values of control factors are considered. The control factors and their levels are given in table 2. The turning operation was performed on SIEMENS-802D CNC lathe under dry conditions with CBN insert and the experimental set up is shown in fig. 3 and 4. The response, surface roughness was measured after machining. Surface roughness was measured in two directions, viz. along the axis and perpendicular to axis and average value of R_a was recorded as final value for each experiment. The experimental observations are presented in table 3.

Table 2. Control factors and their levels

S. No.	Control factor	Symbol	Level 1	Level 2	Level 3
1	Cutting speed (mm/min.)	X_1	228	450	740
2	Feed rate (mm/rev)	X_2	0.05	0.08	0.1
3	Depth of cut (mm)	X_3	0.4	0.6	1.0

Fig.3 SIEMENS - 802D CNC Lathe

Fig.4 Experimental setup of turning operation

6. Methodology

The analysis was performed based on the experimental observations presented in table 3 using Minitab 15 [22] to establish a relationship between control factors and response and to find the best fit. The experimental observations were not adequate to establish a full quadratic polynomial. Therefore, a linear model with interactions was developed. The fitness for linear model with interactions was found to be 0.9721 for the considered response at 95% confidence level. This shows that the linear model with interactions can explain the variation in R_a up to the extent of 97.2%.

Table 3. Experimental observations

Experimental Run	X_1	X_2	X_3	R_a (μm)
1	228	0.05	0.4	1.67
2	228	0.05	0.4	1.80
3	228	0.05	0.4	1.69
4	228	0.08	0.6	5.11
5	228	0.08	0.6	5.30
6	228	0.08	0.6	5.24
7	228	0.10	1.0	6.28
8	228	0.10	1.0	6.40
9	228	0.10	1.0	6.32
10	450	0.05	0.6	2.22
11	450	0.05	0.6	2.40
12	450	0.05	0.6	2.28
13	450	0.08	1.0	4.17
14	450	0.08	1.0	4.31
15	450	0.08	1.0	4.20
16	450	0.10	0.4	5.30
17	450	0.10	0.4	5.19
18	450	0.10	0.4	5.36
19	740	0.05	1.0	2.60
20	740	0.05	1.0	2.45
21	740	0.05	1.0	2.52
22	740	0.08	0.4	2.22
23	740	0.08	0.4	2.28
24	740	0.08	0.4	2.21
25	740	0.10	0.6	4.45
26	740	0.10	0.6	4.38
27	740	0.10	0.6	4.32

The higher correlation coefficient confirms the suitability of used model and the correctness of calculated constants. Therefore, it can be said that the developed model is adequate in representing the process. The normal probability plot for the response is shown in Fig.5. A check on this plot shows that residuals are located along the straight line and reveals that the errors are distributed normally which means that the regression model is fairly well fitted with the observed values.

The response surface model which analyses the parametric influences on response criterion is described as follows:

$$R_a = -5.972 - 0.003X_1 + 132.93X_2 + 10.75X_3 - 0.003X_1X_2 - 0.001X_1X_3 - 107.02X_2X_3 \quad (2)$$

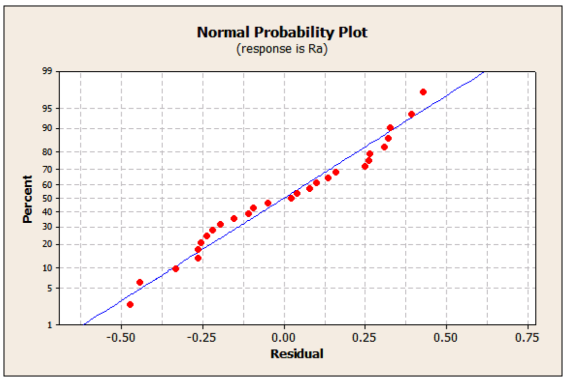

Fig. 5 Normal probability plot for surface roughness

The equation (2) was utilized in the process of optimization using genetic algorithm (GA). In manufacturing, quality requirement plays the vital role. Highest quality is always desirable with minimum effort and inputs. In turning process, fine surface finish of work piece is required after machining. Therefore, optimization problem was formulated with an objective of minimization of R_a which is subjected to variable bounds only. This is because, different settings of machine parameters are resulting the variation in output characteristic. The optimization problem is as follows:

Objective: Minimize R_a (3)
Subject to $228 < X_1 < 740$ (4)
$0.05 < X_2 < 0.1$ (5)
$0.40 < X_3 < 1.0$ (6)

The proposed algorithm was implemented with the following GA parameters: Population size = 300; Crossover probability = 0.85; Mutation probability = 0.01; Number of generations = 200; Total number of runs = 10. Roulette-wheel selection operator is used in this work to pick-up the good solutions from population. During the selection process, copies of the strings are copied into a separate string called the mating pool, in proportion to their fitness values. Higher fitness values will have a higher probability of contributing more strings as the search progresses. The fitness function has converged after 60 generations and the convergence graph of fitness function is shown in fig. 6. Moreover, genetic algorithm gives multiple solutions to the given problem rather than returning only one set of solution as it happens in some of the techniques such as Taguchi technique. The population size in the present optimization problem is considered as 300, the same number of solutions will be obtained after optimization process. Out of 300 solutions, a few sets of optimal solutions are presented in table 4. Further, the model is validated through verification of experiments and the deviation found to be around 26%. Engineers and operators can choose the feasible values based on the requirements.

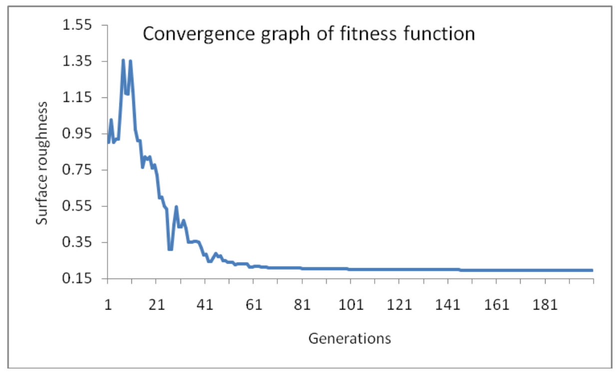

Fig. 6 Convergence graph for response, surface roughness

Table 4. A few sets of optimal solutions

S. No.	Speed (mm/min.)	Feed (mm/rev)	Depth of Cut (mm)	R_a (μm)
1	552	0.05	0.4	1.39
2	621	0.05	0.5	1.82
3	643	0.06	0.4	1.80
4	561	0.05	0.5	1.94
5	649	0.05	0.6	1.97
6	425	0.05	0.4	1.52
7	655	0.05	0.6	1.92
8	489	0.05	0.4	1.62
9	686	0.05	0.6	1.96
10	740	0.03	0.3	1.20

7. Conclusion

Metal matrix composites are the leading materials among composites, especially, particle reinforced aluminium MMCs have received considerable attention due to their excellent engineering properties. These materials are known as the difficult-to-machine materials because of the hardness and abrasive nature of reinforcement element-like silicon carbide particles. In this work, aluminium alloy as matrix metal and 10% silicon carbide particles are mixed and metal matrix composite material is casted.

Specimens are machined and optimized the machining parameters of CNC turning. Initially, response values are found to be very high including all the possible errors during experimentation and there is a need to optimize the machining parameters. Second order polynomial is not adequate to represent the process; hence a linear model with interactions with response surface methodology is developed and utilized in the process of optimization. Genetic algorithm, a global optimization technique is used to obtain optimal machining parameters. Genetic algorithm provides multiple solutions to a given problem. The solutions provided are the machine dependent solutions, therefore, operator can have a choice of machining parameters and correspondingly the value of response also can be predicted. Further, the process can be automated with optimized solutions which enhance the productivity.

References

1. *Robert M Jones (1999), "Mechanics of composite materials", Second edition, Taylor & Francis.*
2. *Bryan Harris (1999), "Engineering Composite Materials", the Institute of Materials, London, 22.*
3. *Autar K Kaw (2006), "Mechanics of Composite Materials", second edition, Taylor & Francis Group, LLC, 41.*
4. *Rabindra Behera Sutradhar G (2012) "Machinability of LM6/SiCp Metal Matrix Composites with Tungsten Carbide Cutting Tool Inserts", ARPN Journal of Engineering and Applied Sciences, Vol. 7, No. 2.*
5. *Cui Yan Wang Lifeng Ren Jianyue (2008), "Multi-functional SiC/Al Composites for Aerospace Applications", Chinese Journal of Aeronautics, Vol. 578-584.*
6. *John E Allison Gerald S Cole (1993), "Metal-Matrix Composites in the Automotive Industry: opportunities and Challenges", J. of Minerals, Metals and Materials Society, Vol. 45 (1), 19-24.*
7. *Chandrasekaran M Devarasiddappa D (2014) "Artificial neural network modeling for surface roughness prediction in cylindrical grinding of Al-SiCp metal matrix Composites and ANOVA analysis", Advances in Production Engineering & Management, Vol. 9, No. 2, 59–70.*
8. *Naga Raju B Raja Roy M Rajesh S Ramji K (2015), "Optimization of Machining Parameters for Cutting AMMC's on Wire Cut EDM using RSM", International Journal of Engineering Trends and Technology (IJETT) – Vol. 23, No. 2.*
9. *Arokiadass R Palaniradja K Alagumoorthi N (2011), "Surface roughness prediction model in end milling of Al/SiCp MMC by carbide tools", International Journal of Engineering, Science and Technology, Vol. 3, No. 6, 78-87.*
10. *Munia Raj A Manoharan N (2014), "Experimental Investigation and Analysis of Torque in Drilling Al–15%SiC–4% Graphite Metal Matrix Composites using Response Surface Methodology", Indian Journal of Science and Technology, Vol. 7(S6), 87–94.*
11. *Chennakesava Reddy A Essa Zitoun (2010), "Matrix Al-alloys for silicon carbide particle reinforced metal matrix composites", Indian Journal of Science and Technology, vol. 3, No. 12.*
12. *Vijaya Kumar G Venkataramaiah P (2012), "Development of aluminium metal matrix composite through selection of influential factors by using fuzzy logic", Elixir Mech. Engg., Vol. 53, 11905-11909.*
13. *Gurpreet Singh Bineet Pal Singh Kulwinder Singh (2014), "Optimization of Cutting Forces During Turning of Al/SiC/Gr Hybrid Metal Matrix Composite", International Journal of Research in Mechanical Engineering and Technology, Vol. 4, Issue 2, SPL – 2.*
14. *Radhika N Subramanian R Sajith A (2014), "Analysis of chip formation in machining aluminium hybrid composites", E3 Journal of Scientific Research, Vol. 2(1), 009-015.*
15. *Pai Dayanand Rao Shrikantha Shetty Raviraj (2012), "Application of Taguchi and Response Surface Methodologies for Metal Removal Rate and Surface Roughness in Grinding Of DRACS", International Journal of Engineering and Management sciences, Vol. 3(1), 1-8.*
16. *Muthukrishnan N Davim J P (2009) "Optimization of machining parameters of Al/SiC-MMC with ANOVA and ANN", Journal of Materials P Technology, Vol. 209(1), 225–232.*
17. *Sahoo A K Pradhan S (2013) "Modeling and optimization of Al/SiCp MMC machining using Taguchi approach", Elsevier science- Measurement, Vol. 46, 3064–3072.*
18. *Box GEP Wilson K B (1951), "Experimental attainment of optimum conditions", Journal of the Royal Statistical Society, Vol.13, 1-45.*
19. *Hill W J Hunter W G (1966), "A review of response surface methodology: a literature review", Techno metrics, Vol.8, 571-590.*
20. *Goldberg D E (1989), "Genetic algorithms in search, optimization and machine learning", Addison-Wesley.*
21. *Minitab 15 User's Guide 2: Data Analysis and Quality Tools. Minitab, State College, PA, 2007.*

