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Multi-objective optimization of drilling of Al5059-SiC-2%MoS_2 composites using NSGA-II

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ABSTRACT

The drilling process is a broadly renowned conventional machining process which has the capacity to produce a hole on the components. The aluminum alloy of A15059 matrix is reinforced with the two different reinforcement particles such as silicon carbide (SiC) and molybdenum disulphide (MoS_2). SiC particles are varied at three different sizes such as 10, 20 and 40 μm and three different weight percentages such as 5, 10 and 15%. MoS_2 is added in all composites at a constant level of 2 wt%. The input process parameters considered for this investigation are spindle speed, feed rate, the particle size of SiC and weight percentage of SiC and output parameters such as metal removal rate (MRR) and temperature are studied. The present work is to optimize the drilling parameters of aluminium metal matrix composites using Non-dominated sorting genetic algorithm II (NSGA-II) technique. The drilling experiments are conducted based on Taguchi L27 orthogonal design. At the end, the optimal setting of drilling process parameters is found using NSGA-II that simultaneously maximizes MRR and minimizes temperature. The set of Pareto-optimal front offers flexibility to the manufacturing industries to select better drilling conditions depending on applications.

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1. Introduction

Recently, aluminium metal matrix composites have a dominant role in manufacturing industries due to their superior physical, thermal and mechanical properties [1]. Therefore, using aluminum composites enhanced in order to replace the ferrous material in the entire commercial engineering applications such as automobile, marine and aerospace industries [2,3]. Usually, the dispersion of reinforced particles like ceramics into the aluminium matrix is to improve the wear-resistant and corrosion properties. However, the occurrence of brittle ceramic particles in the composites machining is quite problematic in the drilling process. As a result of this condition, it consequences in greater tool wear and bad quality of surface quality. Lastly to achieve the desired size and shape that already drilled materials should undergo some finishing operations. Hence, the necessity of research this drilling ability of this newly developed aluminum matrix materials have become due consideration.

Researchers like Davim [4] results show that while machining of AMMCs shows that the ANN model is the most effective method for prediction of response parameters than the developed regression model. Also, a lesser error for the response variable is achieved by the developed ANN model to predict the mechanical properties of AMMCs [5]. Bhattacharyya investigated an experimental study through ANOVA on machining of Al/SiC MMC and found that feed rate has a considerable effect on surface roughness and MRR [6]. Cutting force in Al356/3Mica with SiC reinforcement (2.5–15 wt %) the machining parameters were analyzed. By response surface methodology (RSM) the result says feed rate increases the thrust force and spindle speed has less effect on cutting forces [7]. Also, the Taguchi method was incorporated to examine the thrust forces in the drilling process of Al6061/15%SiC4%Gr MMCs.

They stated that the feed rate increases the cutting forces. Meanwhile, the surface roughness in drilling was studied in the drilling of Al-5%SiCp-5%B4Cp through high-speed steels (HSS). The reported that an increase in spindle speed forms build-up edge (BUE) were created around the reinforcement particles [8]. Meanwhile Sivasakthivel investigated that, increase in spindle speed results in temperature rise and forms BUE on the surface and this

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leads to poor surface finish. Increase in temperature also leads to deformation in work material that tends to poor machining accuracy [9].The abovementioned studies confirm that cutting force, temperature rise and surface roughness has a conflicting effect on MRR while minimizing or maximizing the control parameters. So, these criteria can be achieved through developing a multi-objective optimization technique to find the optimum control parameters and material parameters.

Through literature analysis, it was clear that many researchers have studied the drilling process by considering only the effect of weight percentage of reinforcement particle meanwhile there is only limited number of experiments were carried out to find the effect reinforcement particle size over the output parameters. In order to overcome these research gaps, along with machining parameters and reinforcement percentage, the effect of reinforcement size on responses variables were analyzed on surface roughness, temperature, material removal rate, and cutting force are considered in this study. The effect of each input parameters on every response variables has been analyzed and the optimal input conditions are identified. Additionally, the modeling of response parameters such as MRR and temperature is done by using regression analysis. Finally, the optimum parameter combination that gives a better multi-objective performance in the drilling process is identified through NSGA-II.

2. Material preparation

The matrix used in this work is A15059 aluminium alloy and its chemical composition is shown in Table 1. The reinforcements such as SiC and MoS_2 are selected for preparing the aluminum matrix composites. SiC particles of three different sizes (10, 20, 40 μm) were reinforced at three different weights% (5, 10 & 15) and weight fraction of MoS_2 is kept constant as 2%. The reinforcements were preheated in a crucible by heating it in a muffle furnace at 400 °C. The aluminium alloy is heated in a stir casting furnace up to a temperature of 700 °C to melt the base alloy completely and then cooled down (620 °C) to keep the slurry in the semi-solid state. At this stage, the preheated SiC particles and Molybdenum disulfide particles were added to the vortex in different combination. Automatic stirring was carried out with the help of mechanical stirrer for about 10 min at a stirring speed of 290 rpm. In the final stage of the mixing process, the furnace temperature was controlled within 700 ± 10 °C. After the stirring process, the mixture was poured into the mold to get the desired shape of the specimen. Table 2 shows input process parameters chosen for the experimental study which include cutting speed and feed rate, with material parameters such as size and percentage of SiC, each at three levels. Levels of each machining parameter are fixed based on literature, expert opinion and pilot experiments.

3. Experimentation

Aluminium matrix composites are machined with the dimensions of 100 mm × 65 mm × 15 mm. Uncoated fine-grained High-speed steel (HSS) tool with 6 mm diameter is used as a drilling tool for conducting the operations. The experimental tests were performed on a three-axis CNC machining center which has a spindle speed range of 60–6000 rpm with 802D BMV 40 320D control system (Fig. 1a). The specimens are drilled with this experimental setup is shown in Fig. 1 (b).

The aim of this study is to identify the effect of input parameters such as cutting speed and feed rate, particle size and weight percentages of SiC on the responses such as MRR and temperature. With the intention of analyses the process parameters, the experimental design was done using the Taguchi orthogonal array method. Based on the Taguchi design, L_{27} orthogonal array was selected based on the total degrees of freedom (Table 3).

4. Results and discussion

4.1. Regression models

Regression analysis was used to generate the relationship between input process parameters and responses through statistical software of Minitab 14. During regression analysis it was assumed that the process parameters and the responses are linearly related to each other. The second-order regression model was developed to predict the material removal rate over the results (equation (1)). For this analysis, the R2 value designates that the predictors explain 97% of the response deviation. Adjusted R2 for the number of predictors in the model 93.5% values demonstrations that the data are fitted well.

$$\begin{aligned} MRR = {} & 0.0707547 - -0.00189756 \times W + 0.000448993 \times P \\ & - 1.67070 \times 10^{-5} \times S + 0.000586972 \times F - 1.20658 \\ & \times 10^{-4} \times W^2 - 2.00741 \times 10^{-5} \times P^2 + 1.75872 \\ & \times 10^{-8} \times S^2 - 2.22231 \times 10^{-6} \times F^2 + 6.74146 \times 10^{-5} \\ & \times W \times P - 7.22127 \times 10^{-7} \times W \times S + 9.93801 \\ & \times 10^{-6} \times W \times F + 2.18722 \times 10^{-7} \times P \times S + 3.19278 \\ & \times 10^{-6} \times P \times F + 2.08045 \times 10^{-8} \times S \times F \end{aligned} \quad (1)$$

The second-order model was developed to predict the temperature over the results (Eq. (2)). For this analysis the R2 value describes that the predictors clarify 95.1% of the response nonconformity. Adjusted R2 for the number of predictors in the model 89.4% values demonstrations that the data are fitted well.

$$\begin{aligned} Temperature = {} & 12.5825 + 1.08106 \times W - 0.832203 \times P \\ & + 0.0364095 \times S + 0.441151 \times F - 0.0082 \\ & \times W^2 + 0.0152759 \times P^2 - 7.6157 \times 10^{-6} \\ & \times S^2 + 0.000250667 \times F^2 - 0.00104465 \times W \\ & \times P - 1.96738 \times 10^{-4} \times W \times S \\ & + 0.00740355 \times W \times F - 8.80734 \times 10^{-5} \\ & \times P \times S - 6.09908 \times 10^{-4} - 6.09908 \times 10^{-4} \\ & \times P \times F - 1.14907 \times 10^{-4} \times S \times F \end{aligned} \quad (2)$$

4.2. Multi-objective optimization

To solve the multi-objective optimization problem using NSGA-II, fitness function is essential. Here, a regression analysis was used to develop the mathematical models of MRR and temperature which establishes the relationship in between input and output.

Table1
Chemical composition of Al 5059 (wt. %).

Al	Mg	Mn	Zn	Fe	Si	Zr	Cr	Cu	Ti
91.5	5.32	0.8	0.68	0.45	0.42	0.19	0.21	0.23	0.2

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Table 2
Control parameters and corresponding levels.

S. No	Factors	Symbol	Unit	Values		
				I	II	III
1	Weight fraction of SiC	W	µm	5	10	15
2	Particle size of SiC	P	%	10	20	40
3	Spindle speed	S	rpm	600	1200	1800
4	Feed rate	F	mm/min	25	50	75

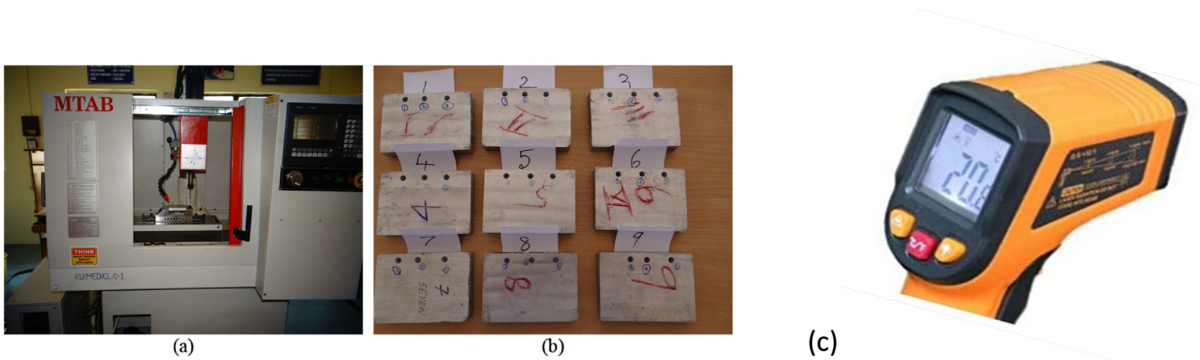

Fig. 1. (a) CNC drilling machine (b) Samples of drilled aluminium matrix composites (c) Infrared Thermometer.

Table 3
L27 orthogonal array and results.

Input parameters					Output parameters	
Sl. No	Weight % of SiC	Particle size of SiC	Spindle speed (rpm)	Feed Rate (mm/min)	MRR(g/min)	Temperature (°C)
1	5	10	600	25	0.071889	37.98
2	5	10	1200	50	0.095000	56.15
3	5	10	1800	75	0.129872	67.54
4	5	20	600	50	0.102076	48.21
5	5	20	1200	75	0.110168	64.90
6	5	20	1800	25	0.116615	54.98
7	5	40	600	75	0.102409	53.12
8	5	40	1200	25	0.081540	41.05
9	5	40	1800	50	0.127819	55.05
10	10	40	600	25	0.072141	42.32
11	10	40	1200	50	0.104248	58.61
12	10	40	1800	75	0.132969	67.91
13	10	10	600	50	0.071602	56.54
14	10	10	1200	75	0.095006	77.65
15	10	10	1800	25	0.085745	56.55
16	10	20	600	75	0.088770	62.35
17	10	20	1200	25	0.068900	47.00
18	10	20	1800	50	0.105324	58.10
19	15	20	600	25	0.047456	42.12
20	15	20	1200	50	0.069856	61.35
21	15	20	1800	75	0.105284	74.91
22	15	40	600	50	0.070804	57.45
23	15	40	1200	75	0.098208	72.90
24	15	40	1800	25	0.085655	54.30
25	15	10	600	75	0.066560	72.32
26	15	10	1200	25	0.045692	62.64
27	15	10	1800	50	0.068211	73.40

The developed mathematical models were transformed into a MATLAB (R2010a) function. This function was given as input into the GA Toolbox of MATLAB 2010a 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 4. The objective function values are obtained for maximization of material removal rate and minimization of temperature in the drilling of aluminium matrix composites. 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 of0.35. 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 4. Fig. 2 shows the formation of the Pareto-optimal front that consists of the final set of solutions. The shape of the Pareto optimal front is a consequence of the continuous nature of the optimization problem. The results reported in Table 3 clearly demonstration that in 21 Pareto-optimal solutions, the whole given range of input parameters is reflected and no bias towards the higher side or lower side of the parameters is seen. This may be attributed to the controlled NSGA-

Table 4
Pareto optimal solutions.

Sl.No	Weight % of SiC	Particle size of SiC	Spindle speed (rpm)	Feed (mm/min)	MRR(g/min)	Temperature (°C)
1	5.000358	29.4533	608.7708	25.00735	0.079259	33.13576
2	14.97346	10.72258	622.2788	25.04525	0.03798	47.96861
3	14.99464	12.71681	621.9072	25.05013	0.040282	46.86447
4	14.37094	19.84518	616.5766	25.04205	0.050249	43.24778
5	6.851433	22.5962	615.785	25.01899	0.075924	35.83152
6	14.31111	16.49337	620.6297	25.04035	0.047482	44.49006
7	14.99999	10.00184	622.3702	25.03608	0.036933	48.42129
8	5.839385	23.76741	610.5484	25.01983	0.078166	34.52241
9	14.54176	18.61329	611.49	25.0281	0.048445	43.6877
10	14.99999	10.00184	622.3702	25.03608	0.036933	48.42129
11	11.53793	24.39185	610.8214	25.04247	0.063751	39.64649
12	8.565194	25.12922	612.9812	25.01541	0.07246	36.91065
13	14.97882	11.9451	621.4829	25.04086	0.039443	47.25606
14	13.24539	20.60979	622.1475	25.01536	0.055405	42.1775
15	10.32436	25.90348	609.1616	25.01885	0.067999	38.31939
16	8.386784	29.4238	614.571	25.04007	0.073493	36.45912
17	9.036805	26.31327	615.928	25.01805	0.07157	37.25306
18	10.84337	25.67426	610.9405	25.02035	0.06642	38.84214
19	14.26255	22.29302	616.4059	25.04153	0.052613	42.48641
20	14.98644	15.30073	620.7909	25.02763	0.043184	45.55885
21	12.85214	21.52233	614.5295	25.02369	0.057546	41.45062

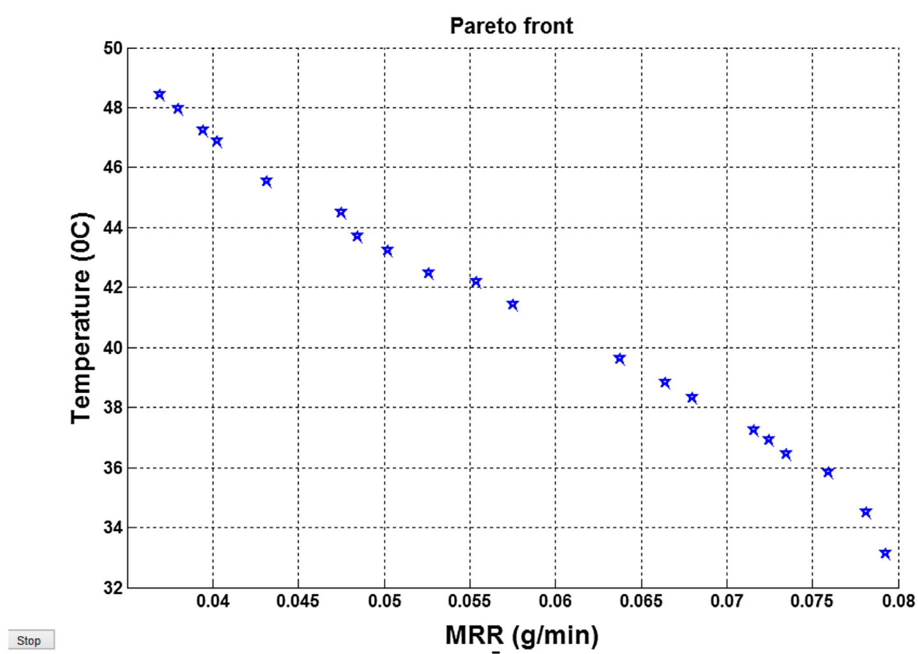

Fig. 2. Pareto optimal front.

II that compulsory permits the solutions from all non-dominated fronts to co-exist in the population. Since the performance measures are conflicting in nature, temperature decreases as MRR increases and the same behavior of performance measures are observed in the solutions obtained. Since none of the solutions in the Pareto optimal set is absolutely better than any other, anyone 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 the manufacturer's requirement.

5. Conclusion

The present work drilling experiments were performed using Taguchi L27 experimental design approach. The regression analysis has been accomplished to create a relationship between input process parameters and responses using statistical software. Then, the second-order models for MRR and temperature were developed to predict the responses. According to the multi-objective optimization using NSGA-II, the better MRR value attained was 0.078166 g/min and the better temperature value achieved was 34.5224 °C.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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