UDK 620.1:620.168:669.71
Original scientific article/Izvirni znanstveni članek

ISSN 1580-2949
MTAEC9, 53(2)263(2019)

OPTIMIZATION OF MACHINING PARAMETERS IN TURNING OF HYBRID ALUMINIUM-MATRIX (LM24–SiC_p–COCONUT SHELL ASH) COMPOSITE

OPTIMIZACIJA PARAMETROV STRUŽENJA HIBRIDNEGA KOMPOZITA (LM24–SiC_p–PEPEL KOKOSOVIH LUPIN) Z MATRICO NA OSNOVI ALUMINIJA

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Prejem rokopisa – received: 2018-08-21; sprejem za objavo – accepted for publication: 2018-11-22

doi:10.17222/mit.2018.184

In any machining process, the vital part is determination of the optimum values for the process parameters to attain the highest desired quality at a low machining cost. This paper mainly focuses on the surface-roughness optimization in the turning of a hybrid aluminium-matrix (LM24-SiC_p-coconut shell ash) composite through the Taguchi method and a genetic algorithm. All composite samples for the study were prepared under the optimal squeeze-casting conditions and experimental trials were selected based on the L_9 $(3)^4$ orthogonal array. The main response considered in this study related to the surface roughness, and machining parameters such as the cutting speed, feed rate, depth of cut and tool-nose radius were taken into consideration. The surface roughness was tested on the composites turned with a high-speed CNC lathe machine. From the experimental data, a regression model of the surface roughness was developed. The optimum machining conditions were obtained through the Taguchi method and a genetic algorithm and checked through confirmation experiments. In this study, it was concluded that the genetic algorithm used for determining the optimum machining conditions showed better results than the experimental outcome based on the orthogonal array and the optimum conditions obtained with the Taguchi method.

Keywords: LM24 aluminium alloy, silicon carbide particles, coconut shell ash, surface roughness, Taguchi method, genetic algorithm

V katerem koli postopku mehanske obdelave je ključnega pomena določitev optimalnih procesnih parametrov, ki omogočajo najvišjo zahtevano kakovost obdelave pri najmanjših stroških. Avtorji so se v glavnem osredotočili na optimizacijo parametrov struženja, ki določajo površinsko hrapavost hibridnega kompozita (LM24-SiC_p-pepel kokosovih lupin) z Al matrico. Za to so uporabili Taguchijevo metodo in genetski algoritem. Vsi vzorci za pričujočo študijo so bili izdelani s postopkom visoko tlačnega litja v testastem stanju (angl.: squeeze casting) pri optimalnih parametričnih pogojih. Eksperimentalni preizkusi so temeljili na izbrani L_9 $(3)^4$ ortogonalni matrici. Glavni vplivni parametri površinske hrapavosti, obravnavani v tej študiji, so bili: hitrost rezanja, hitrost podajanja, globina reza in polmer konice ploščice rezilnega orodja. Površinsko hrapavost kompozitnih vzorcev so preverjali z merilnikom Mitutoyo SJ-210 po zelo hitrem struženju na računalniško vodeni (CNC) stružnici. Na osnovi eksperimentalnih podatkov so razvili regresijski model za površinsko hrapavost. Optimalne pogoje mehanske obdelave so dosegli s pomočjo Taguchijeve metode in genetskega algoritma in jih preverili s pomočjo eksperimentalnih postopkov. Avtorji zaključujejo, da optimalni pogoji mehanske obdelave, določeni z genetskim algoritmom, dajejo boljše rezultate kot eksperimentalni rezultati, ki temeljijo na optimalnih pogojih, določenih s Taguchijevo metodo za izbrano ortogonalno matrico.

Ključne besede: Al zlitina LM24, silicij karbidni delci, pepel kokosovih lupin, površinska hrapavost, Taguchijeva metoda, genetski algoritem

1 INTRODUCTION

Engineering applications require new types of materials due to the inability of the conventional materials to fulfill the requirements of the rapidly changing global market. In the past three decades, extensive research has been reported by numerous researchers with respect to mechanical property enhancement. Composite materials are mostly preferred over the conventional materials for the advanced engineering applications in the aerospace, automotive and marine industries due to their flexibility in tailoring the mechanical properties. Aluminium-matrix composites always have a firm position in the light-weight-material category due to their wide range of desirable characteristics such as low density, good wear and corrosion resistance and excellent mechanical properties over the other metal-matrix composites at reasonable costs.[1–6]

In the past, ceramic reinforcements were used to enhance the mechanical properties but this led to an increase in the weight and cost for the production of the composites. This shortcoming induces the quest for high-performance materials with a low density. The widely adopted method for producing low-cost composites enhance the use of inexpensive materials such as industrial and agro-wastes as secondary reinforcements.[7]

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The hybrid metal-matrix composites are the current research interest due to their favorable properties: high specific strength, toughness, impact strength, low sensitivity to temperature changes, etc. Usually, MMCs are fabricated through any of the following techniques: solid-state processing (powder metallurgy), liquid-state processing (stir casting, squeeze casting, compo casting) and infiltration technique. Among these methods, the stir-casting method is widely used because it is an easy and economical process compared with the other methods. Any fabrication method should ensure a few essential requirements regarding the casting such as a uniform distribution of the reinforcement particles within the matrix and better bonding between them. However, the major problems associated with the production of hybrid composites through the stir-casting method are a non-uniform dispersion, poor wettability and porosity, and these issues are minimized through the squeeze-casting method.[8–12]

The machining characteristics and qualities of composite parts are another major focus of research because they directly influence the functional and operational behavior. One of the major machining qualities of machined parts is their surface roughness, which plays a vital role in dynamic working conditions. Due to poor surface characteristics, fatigue-loaded components are highly prone to failure.[13] The hard reinforcements (SiC_p, B_4C_p, TiC_p and WC_p) of the MMCs lead to a very complicated machining process due to a hard abrasive nature of the particles, which results in a high tool wear and poor surface finish.[14–16] This problem is usually addressed by adding soft particles such as organic reinforcements like coconut shell ash or rice husk ash to hard ceramics particles.[17–20]

The process of determining the optimum machining parameter is usually achieved through selected methods known as the optimization techniques. A number of techniques have been adopted for optimizing the process parameters and they may be categorized as conventional tools (Taguchi method, response-surface method, grey-relationship analysis) and soft-computing tools (genetic algorithm, artificial neural network, particle-swarm optimization, fuzzy logics).[21–23] Generally, regression models are developed by relating the process parameters to the desired output and are obtained with the conventional tools, whereas the soft-computing tools are adopted for obtaining the correct solution. Many researchers attempted to optimize the machining parameters to achieve certain response criteria such as the surface roughness, metal-removal rate and tool wear. The turning process is the basic machining process performed on most of the fundamental machine elements. The major influencing parameters, reported in the literature for the turning process, are the cutting speed, feed rate, depth of cut, workpiece variables, cutting-tool variables and cutting fluids.[24]

Turning parameters for Al-SiC-Gr hybrid metal-matrix composites were optimized using a grey-fuzzy algorithm. Researchers investigated the effects of the spindle speed, depth of cut, feed rate and mass fraction of SiC_p on the tool-flank wear, and they further optimized the parameters using the response-surface methodology. The optimization of the machining parameters of the hybrid composite materials directly affects the production cost and life of the components.[25–27]

Agro-wastes such as rice husk, red mud, fly ash, coconut shell ash, corncob ash etc. can serve as promising reinforcements for aluminium-matrix composites. Coconut shell ash as one of the potential reinforcements for aluminium-matrix composites has not been studied adequately due to its machinability characteristics. The LM24 aluminium alloy, widely used to fabricate automotive parts like cylinder blocks, pistons, piston rings, camshafts etc., was used as the matrix material in this study. The purpose of the present study was to investigate the effects of high-speed turning parameters like the cutting speed, feed rate, depth of cut and tool-nose radius on the surface roughness of hybrid aluminium-metal-matrix composites. The Taguchi method and genetic algorithm were employed to predict the optimum cutting conditions for obtaining the optimum surface roughness on the turned hybrid composite components.

2 MATERIAL AND THEIR CHARACTERISTICS

2.1 Materials used

The LM24 aluminium alloy was used as the matrix material and its chemical composition is shown in **Table 1**. SiC_p with the average particles size of 150 µm and coconut-shell-ash particles (150 µm) were used as reinforcement materials. The fabricated hybrid metal-matrix composite had fixed shares of the reinforcements: 2.5 % of the coconut-shell-ash particles and 7.5 % of SiC_p. However, the resulting percentage of the reinforcement particles decreased the mechanical properties.[28]

An LM24 aluminium alloy ingot was melted in an electric furnace capable of heating up to 1200 °C. The reinforcement particles including 2.5 % of coconut shell ash and 7.5 % of SiC_p were preheated at 500 °C in a separate crucible furnace. The molten metal was fully degassed using hexachloroethane (C_2Cl_6) tablets to remove the entrapped gases and other impurities present.

Table 1: Chemical composition of LM24

Element	Si	Fe	Cu	Mn	Mg	Cr	Ni	Zn	Al
JIS (*w*/%)	7.5–9.5	≤ 3	3.0–4.0	≤ 0.5	≤ 0.3	≤ 0.5	≤ 0.5	≤ 3	Balance
Ingot (*w*/%)	7.848	0.785	3.433	0.14	0.15	0.025	0.049	1.334	86

The use of hexachloroethane (C_2Cl_6) tablets is probably the most common method of degassing in foundries. Even though it may be the oldest technique, C_2Cl_6 tablets normally provide for effective degassing in the case of a small amount of aluminium melt. The preheated reinforcement particles were gradually added into the pure molten metal while maintaining the constant stirring speed at 500 min^{-1} for 10 min.[28] The optimum squeeze-casting parametric conditions are given in **Table 2**.

Table 2: Squeeze casting process parameters

Parameter	Value
Squeeze pressure	200 MPa
Pouring temperature	690 °C
Die preheating temperature	500 °C
Mold temperature	211 °C
Pressure duration	15 s

2.2 Microstructure analysis

The specimens were prepared for a microstructure analysis; they were polished and the surfaces were cleaned with Keller's reagent. The casting samples obtained under the optimal squeeze-casting parametric conditions showed a homogeneous dispersion of the reinforcement particles in the matrix phase and good wettability. The quality of the castings was determined in terms of porosity, agglomeration of reinforcement, shrinkage defects etc., which were not visible in the micro-examination of the specimens, exposing the quality of the castings. A sample microstructure is shown in **Figure 1**.

2.3 High-speed turning

A high-speed turning operation was performed on the casting samples using a computer-numerical-control

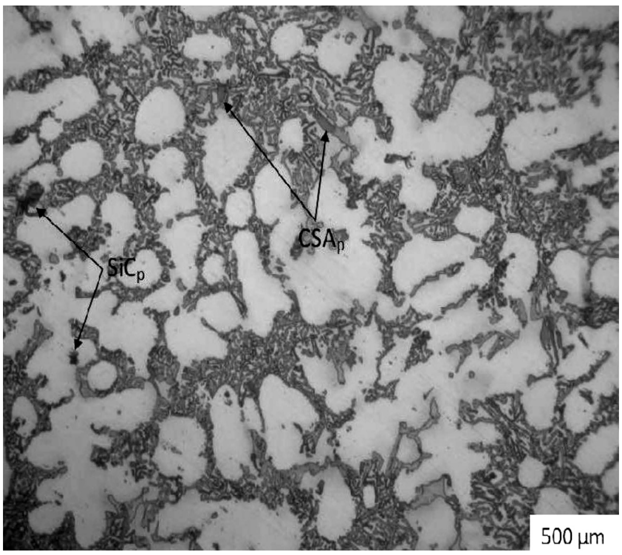

Figure 1: Optical microstructure of LM24/SiC$_p$/coconut shell ash composite

Figure 2: High-speed CNC turning center

(CNC) turning center (ECOTURN-25) manufactured by Geedee weiler pvt ltd., Coimbatore, India, shown in **Figure 2**. The dimensions of the casting samples used for the turning operation were 25 mm in diameter and 100 mm in length. Tool holder PDJNL 1616H11 and uncoated carbide-insert 332-SF H13A cutting tool were used in the turning operation as shown in **Figure 3**. The surface roughness (R_{avg}) of the turned casting samples was measured with a surface-roughness tester (Mitutoyo SJ-210).

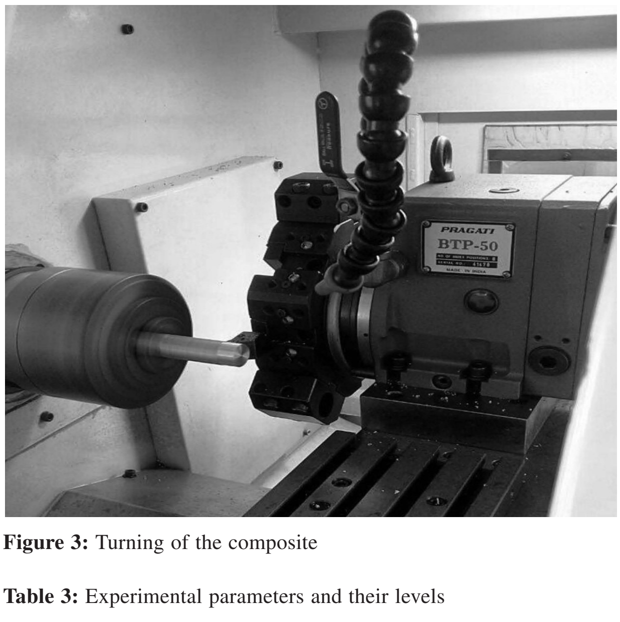

Figure 3: Turning of the composite

Table 3: Experimental parameters and their levels

Parameter	Notation	Level		
		1	2	3
Cutting speed (min^{-1})	A	3250	3500	3750
Feed rate (mm rev^{-1})	B	0.1	0.15	0.2
Depth of cut (mm)	C	0.1	0.2	0.3
Tool-nose radius (mm)	D	0.4	0.8	1.2

2.4 Design of experiments

The most influential parameters affecting the surface roughness, namely, the cutting speed (A), feed rate (B), depth of cut (C) and tool-nose radius (D) were considered and their levels are given in **Table 3**.

3 RESULTS AND DISCUSSION

3.1 Taguchi method

The Taguchi method is a powerful statistical tool, widely applied to improve the performance of machining processes with an extensive reduction of the time for conducting experiments; it also considerable reduces the machining cost and improves the product quality.[27,28] The orthogonal array developed for the set of experiments and the importance of the signal-to-noise (S/N) ratio, which together determine how the average value (signal) of the input variables was attained, and the amount of variability (noise) were examined.

3.1.1 S/N ratio response

The surface roughness was treated as the output response and the category of quality characteristics was the smaller-the-better. The *S/N* ratio for this response was estimated using Equation (1) for each experimental condition and their values are given in **Table 4**.

$$S/N(\mathrm{dB}) = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{R_i^2}\right) \tag{1}$$

where $i = 1, 2, \ldots, n$ (here $n = 4$) and R_i is the response value for an experimental condition. The mean value ($\overline{Y}$) of the *S/N* ratios was also calculated using Equation (2) and the results are given in **Table 5**.

$$\text{Mean, } \overline{Y} = \frac{1}{N}\left(\sum_{i=1}^{N} Y_j\right) \tag{2}$$

where $j = 1, 2, \ldots, N$ (here $N = 9$) and Y_j is the *S/N* ratio for the j^{th} parametric setting.

In order to find the optimum level of the process parameters, the average *S/N* ratio response was estimated for every level of the parameters and the corresponding details are given in **Table 6**. Based on the highest value of the *S/N* ratio, the optimum level for each parameter (A: 2nd level; B: 3rd level; C: 1st level; D: 2nd level) was noted.[29–32] Thus, the optimum parametric setting $A_2B_3C_1D_2$ (cutting speed: 3500 $\min^{-1}$, feed rate: 0.2 mm/rev, depth of cut: 0.1 mm and nose radius: 0.8 mm) was obtained for the output response.

Table 4: Experimental observations and S/N ratio

Ex. No.	Parameters and their levels				Surface roughness (μm)					S/N Ratio (dB)
	A	B	C	D	R_1	R_2	R_3	R_4	R_{avg}	
1	3250	0.1	0.1	0.4	2.15	2.17	2.13	2.15	2.15	–6.6488
2	3250	0.15	0.2	0.8	1.64	1.66	1.68	1.62	1.65	–4.3497
3	3250	0.2	0.3	1.2	1.87	1.82	1.83	1.88	1.85	–5.3434
4	3500	0.1	0.2	1.2	1.12	1.13	1.13	1.17	1.13	–1.2140
5	3500	0.15	0.3	0.4	1.26	1.22	1.24	1.25	1.24	–1.9382
6	3500	0.2	0.1	0.8	0.42	0.46	0.47	0.45	0.45	2.4988
7	3750	0.1	0.3	0.8	2.52	2.56	2.55	2.54	2.54	–8.1308
8	3750	0.15	0.1	1.2	1.96	1.94	1.94	1.93	1.94	–5.8007
9	3750	0.2	0.2	0.4	1.76	1.75	1.74	1.76	1.75	–4.8608
$\overline{Y}$	–3.9764									

Table 5: Average S/N ratio response

	A	B	C	D
Level 1	–5.4473	–5.3312	–3.3169	–4.4826
Level 2	–0.2178	–4.0295	–3.4748	–3.3272
Level 3	–6.2641	–2.5685	–5.1375	–4.1194
Max-Min	6.0463	2.7627	1.8206	1.1553
Rank	1	2	3	4
Optimum	A2	B3	C1	D2
% Contribution	51.3	23.4	15.4	9.8

The response graph shown in **Figure 4** describes the variation of each process control parameter with the output response. From the response graph, the peak points were taken as the optimum levels of the machining parameters, i.e., the cutting speed at the second level, the feed rate at the third level, the depth of cut at the first level and the tool-nose radius at the second level.

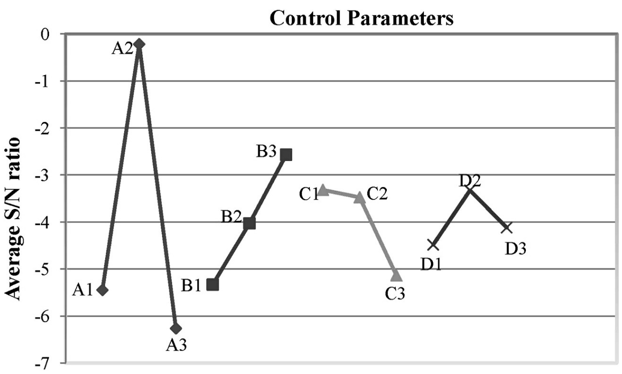

Figure 4: Response graph

3.2 Genetic algorithm

Genetic algorithm (GA) is a soft-computing tool for solving both constrained and unconstrained optimization problems based on boundary conditions. The optimum machining conditions were created using the GA tool in the MATLAB software. GA is a faster and more efficient tool than the other soft-computing tools.[30] The GA optimization tool is based on machining-performance-prediction models based on experimental results and numerical methods. The GA tool provided the optimum machining conditions in a short time.

3.2.1 Mathematical model

The empirical relationship between the surface roughness (R_{avg}) and turning of the LM24 aluminium alloy reinforced with SiC_p and coconut-shell-ash particles was a function of the machining parameters such as the cutting speed (*A*), feed rate (*B*), depth of cut (*C*) and tool-nose radius (*D*) that can be indicated as:

$$R_{avg} = f(A, B, C, D) \tag{3}$$

The relationship between the control parameters and their effects on the average surface roughness (R_{avg}) was modeled using a second-order polynomial regression analysis with the help of statistical software MINITAB 14.

$$R_{avg} = 6.3500 - 4.03333\,A - 0.43333\,B - 0.55000\,C - 0.56667\,D + 1.03333\,A^2 + 0.03333\,B^2 + 0.183333\,C^2 + 0.13333\,D^2 \tag{4}$$

For this regression model, it was found that $r^2 = 0.99$ where *r* is the coefficient of correlation. The value of r^2 indicates the accuracy of the model representing the process. As r^2 is nearing unity, this model can be taken as an objective function for the application of the genetic algorithm.

3.2.2 Inputs into the GA

The genetic-algorithm solver available in the MATLAB software was used to find the optimum parametric settings for the minimization of the average surface roughness of the squeeze castings (R_{avg}) from this study. The regression model given in Equation (3) was used as the fitness function (objective function). The following values of the genetic parameters were taken as the inputs into the MATLAB solver.

Population type: double vector
Number of variables: 04
Bounds (lower): [3250 0.1 0.1 0.4]
Bounds (upper): [3750 0.2 0.3 1.2]
Selection function: stochastic
Crossover fraction: 0.8
Mutation rate: 0.03
Migration: forward
Total number of iterations: 53
Level of display: iterative

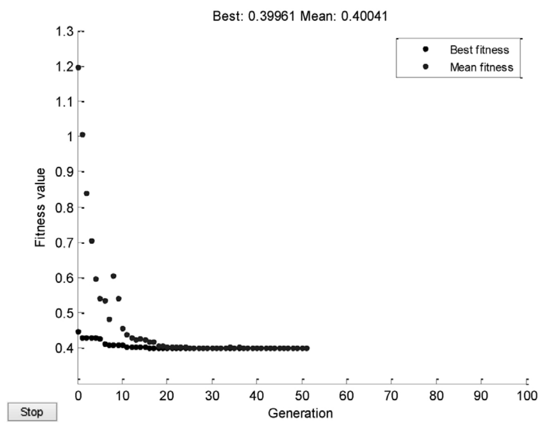

Figure 5: GA result

It was observed that the fitness value decreased through generations as shown in **Figure 5** and the optimized average surface roughness (0.399 µm) was obtained in the 53rd generation. The optimum parametric settings of the last generation are given in **Table 5**.

Table 5: Optimum parametric settings

Control parameter	Coded condition	Uncoded condition
Cutting speed	2	3500 min^{-1}
Feed rate	3	0.2 mm rev^{-1}
Depth of cut	1.5	0.15 mm
Tool-nose radius	2.126	0.8 mm

3.3 Confirmation experiments

Confirmation experiments were conducted for the optimum parametric conditions suggested by the Taguchi method and genetic algorithm. The average surface-roughness values (predicted and tested) are given in **Table 6**. It is evident that there is good agreement between the predicted average surface roughness and actual surface roughness since the error is less than 4 %. The optimum settings for the cutting speed (3500 min^{-1}) and feed rate (0.2 mm rev^{-1}) were found to be same in the Taguchi method and genetic algorithm. According to the percentage-contribution analysis, the effects of depth of cut and nose radius on the surface roughness are minimum compared to the other machining parameters. The confirmation experiments proved that the genetic algorithm gives better results than the Taguchi method with respect to the surface quality and also, indirectly, with respect to energy savings and production time.

Table 6: Confirmation-test results

S. no.	Optimization technique	Average surface roughness, R_a (µm)		% error
		Predicted	Tested	
1	Taguchi method	0.467	0.450	3.78
2	Genetic algorithm	0.399	0.386	3.37

4 CONCLUSIONS

The conclusions drawn were based on the surface-roughness tests conducted on a hybrid aluminium-metal-matrix composite during a turning operation. From the percentage-contribution analysis, it was noted that the cutting speed (51.3 %) and feed rate (23.4 %) were the most important parameters influencing the surface roughness, while the depth of cut (15.4 %) and tool-nose radius (9.8 %) were the least important parameters for the surface roughness. It is evident that there is good agreement between the predicted average surface roughness and actual average surface roughness since the error is less than 4 %. The recommended levels for the turning parameters of the CNC lathe, minimizing the surface roughness, were the cutting speed at level 2 (3500 min^{-1}), feed rate at level 3 (0.2 mm rev^{-1}), depth of cut at level 1 (0.1 mm) and tool-nose radius at level 2 (0.8 mm). The optimum settings of the high-speed turning process parameters regarding the optimum surface roughness can be used wherever aluminium-metal-matrix composites require a high degree of surface finish. Confirmation experiments proved that the genetic algorithm gives better results than the Taguchi method with respect to the surface quality and also, indirectly, with respect to energy savings and production time.

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