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EFFECT OF MACHINING PARAMETERS ON SURFACE ROUGHNESS FOR ALUMINIUM MATRIX COMPOSITE BY USING TAGUCHI METHOD WITH DECISION TREE ALGORITHM

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The intend of this research work is to explore the effect of various parameters in a CNC turning process like cutting speed (V), feed (F), and depth of cut (D) on surface roughness (Ra) of turning AA7075 filled with 10 wt.% of TiO_2 composite fabricated through stir casting method. Taguchi method and decision tree (DT) algorithm were utilized to foresee the surface roughness (Ra) of the proposed composite. The microstructure of composite was ensured with the presence of TiO_2 particles dispersed in a homogeneous manner within the matrix material. The machining of composite was carried out by using the CNC turning center and tungsten carbide insert as tool material. This experimental work was designed on L27 (3^3) orthogonal array using Taguchi's design of experiments. From its signal-to-noise (S/N) ratio study, the minimum surface roughness (Ra) was obtained at the optimum level of parameters with the cutting speed at 1500 rpm, feed at 0.15 mm/rev and depth of cut at 0.3 mm. Analysis of variance (ANOVA) and decision tree (DT) algorithm were used to identify the significant effect of parameters. The experimental result shows that depth of cut was the major significant parameter on surface roughness (Ra) when compared to cutting speed and feed.

Keywords: AA7075; TiO_2; CNC turning; surface roughness; taguchi method; ANOVA; decision tree algorithm.

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1. Introduction

In recent decades, metal matrix composites (MMC) have been extensively utilized in most of the automotive, aerospace, defence, marine, and mineral processing industries owing to their advantageous combination of properties like high specific strength, light weight, more stiffness, high resistance to wear and corrosion, and having low thermal expansion coefficient.[1,2] In the production of MMCs, aluminium, magnesium, and titanium alloys are normally applied as matrix material and aluminium oxide (Al_2O_3), silicon carbide (SiC), zirconium diboride (ZrB_2), titanium dioxide (TiO_2), and boron carbide (B_4C) are commonly used as reinforcement materials.[3,4] Among them, aluminium matrix composites (AMC) emerged as the precursor used for a diversity of broad and particular applications owing to its excellent mechanical and thermal related properties.[5,6] In many series of aluminium alloys, heat treatable alloys of aluminium 7xxx series have more significance. Recently, aluminium alloy AA7075 has been playing an important role in aerospace and automobile industries in the production of aircraft equipment, gear wheels and shafts, rock climbing equipment, bicycle frames, and defence applications owing to its natural aging characteristics and high strength-to-weight ratio.[7] Hence, AA7075 is taken as a matrix material for this investigation. Usually, AMCs are fabricated by various methods like mechanical alloying, powder metallurgy, stir casting, compo-casting, and spray deposition. Among them, stir casting technique is one of the most opt route for production of AMCs owing to their simplicity, flexibility, cost effectiveness, mass production, and uniform distribution of reinforcement particles can be promoted by stirring action.[8]

Machining process of AMC is focused with considerable attention for the reason of high tool wear associated during machining as it leads to poor surface finish in the components due to the presence of hard reinforcement material enhanced its strength and hardness property. From the literatures, studies about machinability of particulate reinforced AMC observed that only polycrystalline diamond (PCD) tools serve a longer tool life for machining these composites, which is harder than SiC, TiO_2, B_4C, Al_2O_3, etc. However, considering the high cost of PCD tools, carbides and ceramics tools are less expensive being used for machining these composite materials.[9,10] In several kinds of machining process, precision turning is an universal and fundamental type in metal cutting. The surface quality of the turned parts depends upon several factors like work piece, cutting tool material, tool geometry, conditions of coolant and cutting parameters, etc. Particularly, the cutting parameters like cutting speed, feed, and depth of cut play a significant role on surface quality of manufactured parts.[11] Hence, it is essential to choose the right parameter settings in order to determine the surface quality of turned parts. Therefore, suitable optimization technique should be applied to identify the optimum parameter settings. Taguchi method is one of the powerful statistical tools to resolve the single objective problems in manufacturing progression. Palanikumar *et al.*[12] analyzed the effects of machining parameters on surface finish in turning LM25 Al/SiC particulate composite using Taguchi's experimental technique. They reported that the improved surface finish is usually obtained at high cutting speed and at lower feed rate. Sener karabulut *et al.*[13] used S/N ratio method to get the optimum cutting parameters for better surface quality in milling process on AA7039/B_4C composite. Kumar *et al.*[14] investigated the results of cutting parameters on surface quality in turning Al7075/SiC and Al7075 hybrid composite with a PCD tool. They understood that the surface quality of the Al7075 with reinforced 10 wt.% SiC composite was higher than the Al7075 hybrid composite. Tamizharasan *et al.*[15] employed Taguchi method to conclude the optimal turning parameters on the chip thickness ratio of Al-4% Cu-7.5% SiC composite. Devinder Priyadarshi *et al.*[16] optimized the parameters such as cutting speed, feed, depth of cut in turning, and weight percentage of reinforcements for surface finish in hybrid Al6061-SiC-Gr hybrid nanocomposites. They reported that depth is a significant affecting parameter on surface finish followed by feed. Ramanujam *et al.*[17] presented a thorough study with an orthogonal array to obtain the optimum machining parameters on surface finish during turning of Al-SiC_p composites. They noticed that depth of cut was the primary influencing parameter then followed by cutting speed. Joel *et al.*[18] used the Taguchi method to optimize machining parameters on responses of surface roughness and cutting force while turning aluminium alloy (Al6061, AA2024, and AA7075) reinforced with 2 wt.% graphene hybrid composite using carbide insert. They found that the better surface finish was obtained by AA7075-based composite. Nataraj *et al.*[19] revealed the influence of turning parameters on surface roughness during machining of hybrid MMC using CNC lathe. ANOVA results showed that depth of cut was the most significant parameter and then followed by cutting speed and feed rate. Harding *et al.*[20] presented the usage of data mining in the field of manufacturing engineering in the production process, decision support, fault detection, product quality improvement, and maintenance.

In view of exhaustive literatures, the major objective of this work is to examine the effect of various cutting parameters, namely cutting speed, feed, and depth of cut on surface roughness. The Taguchi method is utilized for designing the orthogonal array of experimental work during turning process of AA7075-10 wt.% TiO_2 composite. The S/N ratio analysis is performed to decide the optimal parameter setting on minimum surface roughness. Furthermore, ANOVA and the decision tree algorithm have been utilized to investigate about more significance parameters on the surface roughness of machined composites.

2. Materials and the Method

2.1. *AMC fabrication*

In this investigation, the matrix AA7075 was procured from Coimbatore Metal Mart, Coimbatore and reinforcement material TiO_2 was obtained from LOBA Chemie, Mumbai. The chemical composition of AA7075 is furnished in Table 1. The grounds for selecting reinforcement material are that the particles of TiO_2 are one among the most extensively used oxides due to its very excellent mechanical properties, good wear, and corrosion resistance.[21]

AA7075 matrix composite reinforced with 10 wt.% of TiO_2 particulates was synthesized via stir casting route. First, a 900 g of AA7075 ingot in a graphite crucible was melted at a temperature of 850°C in an electrical furnace. By using a muffle furnace, 100 g of

Table 1. Aluminium alloy 7075 — Chemical composition.

Elements	Zn	Mg	Cu	Fe	Cr	Si	Mn	Ti	Al
Weight %	5.4	2.42	1.42	0.42	0.21	0.13	0.12	0.11	rest.

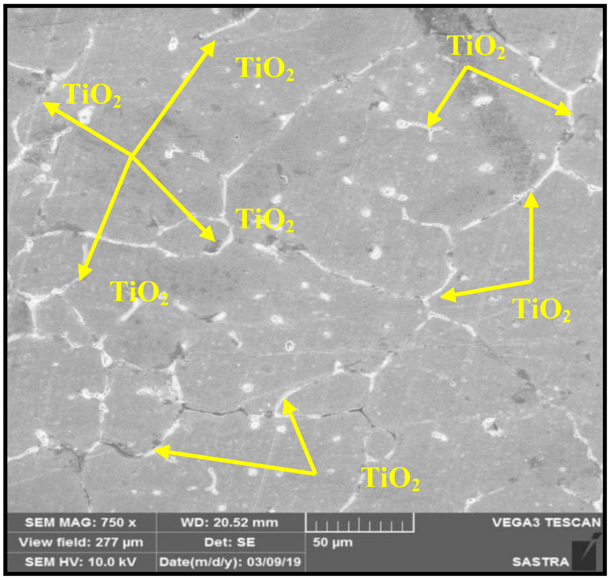

Fig. 1. (Color online) SEM micrograph of AA7075-10 wt. % TiO_2 composite.

TiO_2 particulates were preheated to a temperature of 200°C. The preheated TiO_2 particulates were physically added to the vortex of the molten slurry. The stirring process was carried out for 10 min at 280 rpm. At last, the composite slurry was transferred into a mould cavity and then solidified at a room temperature. The VEGA3, TESCAN scanning electron microscopy (SEM) was used to examine the microstructure of the fabricated composite, as shown in Fig. 1. It was ensured that the presence of TiO_2 particles uniformly dispersed in the grain boundary of the matrix. The mechanical and tribological properties of developed composite were previously reported.[22]

2.2. *Plan of experiments*

From the literature reviews,[23,24] the process parameters which commonly influence the surface roughness (Ra) are cutting speed (rpm), feed (mm/rev), and depth of cut (mm) and selected levels are presented in Table 2. The selection of orthogonal array depends upon the number of parameters and the number of levels involved. In this study, three parameters with three levels were considered. Hence, a standard Taguchi L27 (3^3) orthogonal array was formed to carry out the experiments. The experimental layout of L27 orthogonal array design of input parameters is given in Table 3.

Table 2. Process parameters and levels.

Notation	Process parameter	Units	Level 1	Level 2	Level 3
V	Cutting speed	rpm	500	1000	1500
F	Feed	mm/rev	0.10	0.15	0.20
D	Depth of cut	mm	0.3	0.6	0.9

Table 3. Experimental layout of L27 (3^3) orthogonal array design.

Ex. No	V	F	D	Cutting speed, V (rpm)	Feed, F (mm/rev)	Depth of cut, D (mm)
1	1	1	1	500	0.10	0.3
2	1	1	2	500	0.10	0.6
3	1	1	3	500	0.10	0.9
4	1	2	1	500	0.15	0.3
5	1	2	2	500	0.15	0.6
6	1	2	3	500	0.15	0.9
7	1	3	1	500	0.20	0.3
8	1	3	2	500	0.20	0.6
9	1	3	3	500	0.20	0.9
10	2	1	1	1000	0.10	0.3
11	2	1	2	1000	0.10	0.6
12	2	1	3	1000	0.10	0.9
13	2	2	1	1000	0.15	0.3
14	2	2	2	1000	0.15	0.6
15	2	2	3	1000	0.15	0.9
16	2	3	1	1000	0.20	0.3
17	2	3	2	1000	0.20	0.6
18	2	3	3	1000	0.20	0.9
19	3	1	1	1500	0.10	0.3
20	3	1	2	1500	0.10	0.6
21	3	1	3	1500	0.10	0.9
22	3	2	1	1500	0.15	0.3
23	3	2	2	1500	0.15	0.6
24	3	2	3	1500	0.15	0.9
25	3	3	1	1500	0.20	0.3
26	3	3	2	1500	0.20	0.6
27	3	3	3	1500	0.20	0.9

2.3. *Machining of AMC*

Turning process was performed on the cylindrical composite material of AA7075-10 wt.% TiO_2 with the help of CNC lathe ($JOBERX_L$) machine, as is shown in Fig. 2. The operation conditions of turning are provided in Table 4. For turning operation, tungsten carbide insert with an ISO designation of TNMG 115100 was used as the cutting tool. It possesses high hardness, toughness, and greater wear resistance, which can result in enhancing the machining performance and increase the tool life. The cost of tungsten carbide tool is very less compared to PCD tool, which promotes higher productivity at low cost.[25] Figure 3 shows the photographic view of tungsten carbide inserts. The turning operations were made as per L27 orthogonal array design, as is shown in Table 3. Surface roughness (Ra) is commonly used to evaluate the quality of the turned parts. The surface roughness of the turned surface was measured at two different locations and an average of them is

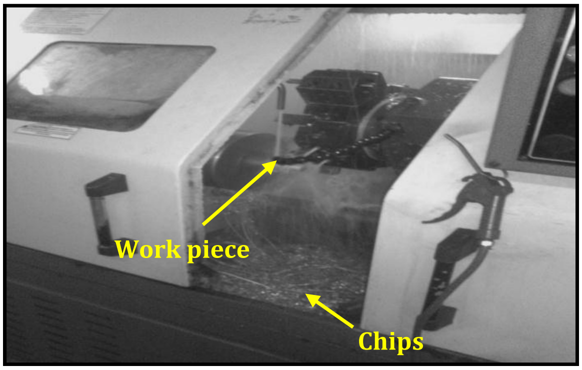

Fig. 2. (Color online) JOBBERXL-CNC turning center.

Table 4. Operation conditions.

Conditions	Details
Work piece material	AA7075-10 wt.% TiO_2 composite
Geometry of work piece	Diameter – 25 mm; Length – 100 mm
Lathe used	$JOBBERX_L$
Insert used	Tungsten carbide – TNMG 115100
Measuring instrument	Mitutoya Talysurf SJ-210
Process parameters	Cutting speed (V), Feed (F), and Depth of cut (D)

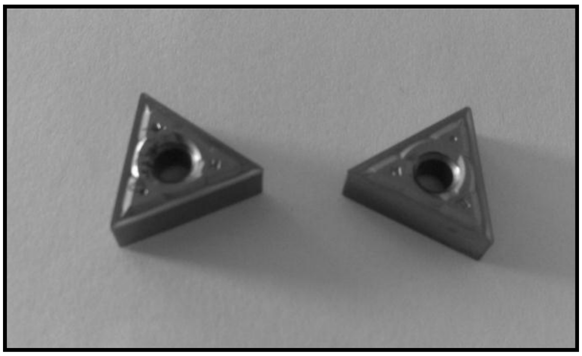

Fig. 3. Cutting tool — tungsten carbide inserts (TNMG 115100).

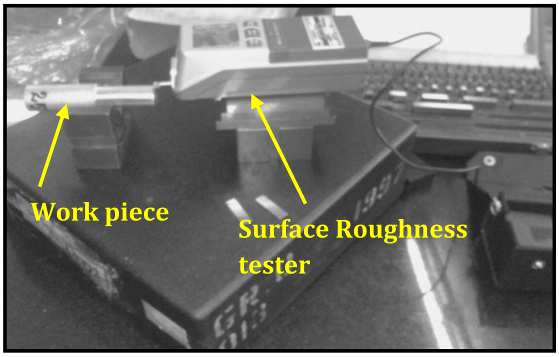

Fig. 4. (Color online) Surface roughness testing setup (Mitutoya Talysurf SJ-210).

taken as the final value of output response. Figure 4 displays the photographic view of Mitutoya Talysurf SJ-210 surface roughness tester measuring setup. Table 5 illustrates the measured values of surface roughness (Ra).

Table 5. Experimental results and their corresponding S/N ratio.

	Surface roughness, Ra (μm)			
Ex. No	Ra_1	Ra_2	Ra_{Avg}	S/N ratio (dB)
1	1.95	1.91	1.93	−5.711
2	2.70	2.84	2.77	−8.849
3	4.04	3.92	3.98	−11.99
4	1.90	1.71	1.81	−5.153
5	2.70	2.71	2.71	−8.659
6	4.42	4.41	4.42	−12.90
7	1.99	2.00	2.00	−6.020
8	2.70	2.86	2.78	−8.880
9	4.23	4.49	4.36	−12.78
10	2.03	2.07	2.05	−6.235
11	2.93	2.92	2.93	−9.337
12	4.10	4.28	4.19	−12.44
13	1.87	1.98	1.93	−5.711
14	3.36	3.07	3.22	−10.15
15	4.35	4.31	4.33	−12.72
16	1.99	1.98	1.99	−5.977
17	3.11	3.06	3.09	−9.799
18	4.12	4.45	4.29	−12.64
19	2.19	2.71	2.45	−7.783
20	2.84	2.93	2.89	−9.218
21	4.43	4.41	4.42	−12.90
22	1.83	1.90	1.87	−5.436
23	2.85	2.96	2.91	−9.277
24	3.15	3.25	3.20	−10.10
25	1.84	1.80	1.82	−5.201
26	2.92	2.90	2.91	−9.277
27	3.16	3.09	3.13	−9.910

2.4. *Taguchi method*

Taguchi method is a statistical technique and it is one of the conventional approaches for producing high quality products at low cost.[26] Taguchi method of designing experiments is an efficient and effective way of identifying the input parameters which influence the output responses. Taguchi has suggested many methods to analyze the experimental data, namely signal-to-noise ratio (S/N), analysis of variance (ANOVA), interaction graphs, plot of average response curves, etc. In general, the S/N ratio is applied to represent the quality characteristics of observed data with the Taguchi design of experiments.[27] A high value of S/N ratio specifies the signal is too higher than the effect of the noise factor. Depending upon the experimental objectives, three quality characteristics are possible to evaluate the S/N ratio, namely "smaller-the-better" (SB), "nominal-the-better" (NB), and "larger-the-better" (LB). In this study, we need minimum surface roughness (Ra); and hence SB characteristic was considered and the following equation can be used:

$$\text{S/N ratio}(\eta) = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} y_{ij}^2\right), \qquad (1)$$

where n is the number of observations, Y_{ij} is the observed response value where $i = 1, 2, 3, \ldots, n$; $j = 1, 2, 3, \ldots, k$. The calculated S/N ratio value for surface roughness is provided in Table 5.

2.5. *Decision tree (DT) algorithm*

Decision tree (DT) algorithm is an efficient and powerful technique in data mining, which has been extensively applied by researchers. When comparing to other techniques, the DT is faster and presents closure accuracy.[28] The DT algorithm can be employed to produce the graphical representation and then interpretability is high. It converts dataset into a tree-based structure based on entropy function or information gain. It is a measure of the present disorder in the data set. Quinlan[29] developed an algorithm for DT known, Iterative Dichotomiser 3 (ID3) and enhanced version is C4.5. The algorithm searches through the attributes of instances in the set of data and selects the most excellent splitting attributes based on information gained. The output of DT algorithm is like tree structure or If-Then else rules.

The low-level knowledge existing in the data set can be represented in the form of high-level knowledge. To apply C4.5 algorithm for the proposed work, dataset through an orthogonal array of L27 is prepared for a produced aluminium matrix composite during the CNC turning process. To study the surface roughness (Ra), attributes, such as (i) cutting speed, (ii) feed, and (iii) depth of cut, are taken into consideration.

3. Results and Discussion

3.1. *Analysis of S/N ratio on surface roughness (Ra)*

Figures 5 and 6 show the main effect plot for mean S/N ratio and surface roughness (Ra) mean with respect to input process parameters such as cutting speed, feed, and depth of cut. Generally, the highest value of the mean S/N ratio is considered as the optimal level of process parameters. In graph 5, it can be observed that the minimum surface roughness (Ra) was obtained from the optimal level of parameters that are $V_3F_2D_1$, which shows cutting speed at level 3 (1500 rpm), feed at level 2 (0.15 mm/rev) and depth of cut at level 1 (0.3 mm). Figure 6 shows the high level setting of depth of cut (0.9) getting maximum surface roughness (4.42 μm), which means surface roughness increases with more depth of cut.

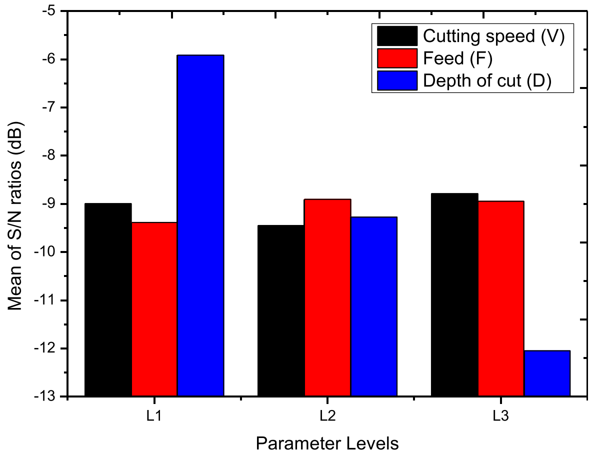

Fig. 5. (Color online) Main effect plot for S/N ratio of surface roughness (Ra).

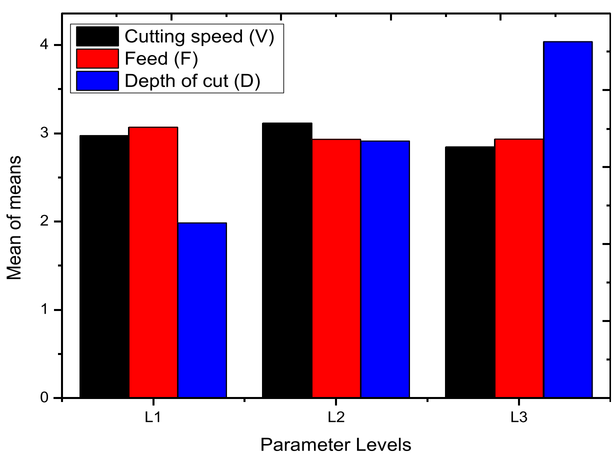

Fig. 6. (Color online) Main effect plot for mean of surface roughness (Ra).

The response tables for means and S/N ratio of surface roughness (Ra) are provided in Tables 6 and 7. From the tables, the order of impact process parameters was found out by the variation between the maximum value and minimum value of surface roughness and it is denoted as delta (Δ). The highest value of delta (Δ) is defined as the most impact parameter which is assigned as rank 1. According to Tables 6 and 7, it can be understood that the depth of cut was the most influencing parameter on surface roughness (Ra) of the produced composite then followed by cutting speed and feed, respectively. The surface roughness increases on increasing depth of cut due to formation of chip fracture, which leads to flaw

Table 6. Response table for means of surface roughness (Ra).

Level	Cutting speed (V)	Feed (F)	Depth of cut (D)
1	2.973	3.068	1.983
2	3.113	2.930	2.912
3	2.844	2.933	4.036
Delta	0.269	0.138	2.052
Rank	2	3	1
	Average means of Ra = 2.977		

Table 7. Response table for S/N Ratio of surface roughness (Ra).

Level	Cutting speed (V)	Feed (F)	Depth of cut (D)
1	−8.997	−9.387	−5.914
2	−9.449	−8.904	−9.273
3	−8.791	−8.945	−12.049
Delta	0.658	0.483	6.135
Rank	2	3	1
	Average mean S/N ratio of Ra = −9.076		

on the surface of the work piece and results in higher surface roughness. High level of cutting speed and medium level of feed make the minimum surface roughness. The reason is that the higher cutting speed may occur and thermal softening of tool materials removes the built up edge (BUE) formation on the tool and it consequently minimizes the surface roughness.

3.2. *ANOVA for surface roughness (Ra)*

ANOVA is a standard statistical technique to determine the effect of machining parameter on the output responses.[30,31] In this study, ANOVA has been applied to identify the significant contribution of turning parameters, namely cutting speed, feed, and depth of cut on surface roughness (Ra) during machining of AA7075-10 wt.% TiO_2 composite. The obtained results of ANOVA for surface roughness (Ra) are tabulated in Table 8. In general, the P-value of parameter is less than 0.05, and it indicates that the parameter has a significant effect on the output response statistically. According to Table 8, it is noted that the depth of cut (P-value $= 0.000$) was the most significant factor on output response, the surface roughness (Ra). The frequency (F-ratio) test was executed at 95% confidence interval (CI). The calculated F-ratio for depth of cut was found greater than the F distribution table value ($F_{0.5,2,20} = 3.49$). Therefore, depth of cut was confirmed as the statistical physical influencing parameter on surface roughness. The percentage contribution of parameter is calculated from the ratio of individual sum of square to the total sum of square. From Table 8, it can be observed that depth of cut was the most significant parameter among the others that contribution of 87.96%. Palanikumar *et al.*[12] reported similar observations during the turning process of hybrid MMC, where a depth of cut was the more dominant

Table 8. ANOVA for surface roughness (Ra).

Source	DF	Seq.SS	Adj.SS	Adj.MS	F	P
Cutting speed (V)	2	0.3255	0.3255	0.1628	1.50	0.246
Feed (F)	2	0.1112	0.1112	0.0556	0.51	0.606
Depth of cut (D)	2	19.0090	19.0090	9.5045	87.83	0.000
Residual error	20	2.1642	2.1642	0.1082	—	—
Total	26	21.6100	—	—	—	—

$S = 0.328955$; R-Sq $= 89.99\%$; R-Sq (adj) $= 86.98\%$

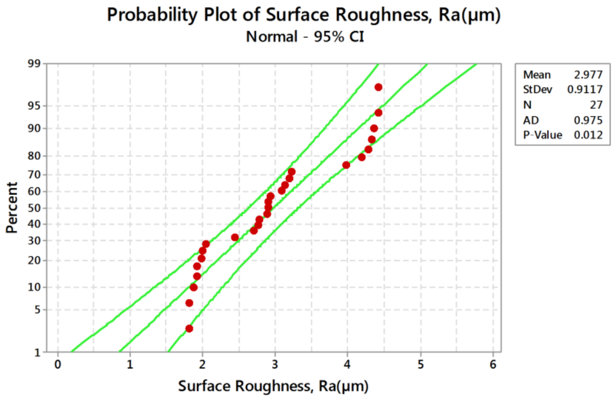

Fig. 7. (Color online) Normal probability plot of surface roughness (Ra).

factor which affects the surface roughness (Ra). The R-Sq (89.99%) and R-Sq (adj) (86.98%) values are very close to each other which confirms that the formulated design was able to predict with high accuracy. Figure 7 shows the normal probability plot of surface roughness and it was evident that all the residuals were found to be normally distributed along the straight line at 95% confidence level.

3.3. *Prediction value of surface roughness (Ra)*

The predicted value of surface roughness (μ_{Ra}) is determined at the selected optimal level of machining parameters. Referring to the graph (Fig. 5), it could be observed that the minimum surface roughness (Ra) is obtained in the combination of optimum parameters is $V_3F_2D_1$. The expected mean at the optimum settings can be estimated from the following equation:

$$\mu_{\mathrm{Ra}} = V_3 + F_2 + D_1 - 2^*T_{\mathrm{Ra}}. \tag{2}$$

The corresponding S/N ratio can be predicted as follows:

$$\eta_{\mathrm{Ra}} = \eta V_3 + \eta F_2 + \eta D_1 - 2^*\eta T_{\mathrm{Ra}}, \tag{3}$$

where T_{Ra} is the overall mean of surface roughness, ηT_{Ra} is the S/N ratio's overall mean of surface roughness, V_3, F_2 and D_1 are the means of mean values of the surface roughness with parameters at optimum levels (referring to Table 6).

ηV_3, ηF_2, and ηD_1 are the S/N ratio mean values of the surface roughness with parameters at optimum levels (referring to Table 7).

By substituting in Eq. (2)

$$\mu_{\mathrm{Ra}} = V_3 + F_2 + D_1 - 2^{*}T_{\mathrm{Ra}}$$
$$= (2.811 + 2.930 + 1.983 - 2^{*}2.977),$$
$$\mu_{Ra} = 1.77\,\mu m.$$

By substituting in Eq. (3)

$$\eta_{\mathrm{Ra}} = \eta V_3 + \eta F_2 + \eta D_1 - 2^{*}\eta T_{\mathrm{Ra}}$$
$$= (-8.791 - 8.904 - 5.914) - (2^{*} - 9.076),$$
$$\eta_{\mathrm{Ra}} = -5.457\,\mathrm{dB}.$$

Hence, the predicted value of surface roughness (Ra) is 1.77 μm and its corresponding S/N ratio value is -5.457 dB.

3.4. *Implementation of DT algorithm for surface roughness (Ra)*

The DT algorithm can develop a training model that can be used to predict the class or target variables from learning decision rules inferred from training data. To implement the DT for the prediction of surface roughness (Ra), the input process variables, such as cutting speed, feed, and depth of cut, are called as predictor variables and output variable i.e. surface roughness (Ra) is called decision variable or target variable or class attribute. The target variable is usually categorical variable so that it is easy to classify the given input process variables. In this work, two types of categorical attributes i.e. low and high, are used for finding surface roughness (Ra). From the experimentation of L27 orthogonal array, the values from 1.81 to 2.93 are classified as "Low" and values above 2.93 to 4.42 are termed as "High". Table 9 shows the L27 experimental values along with output variables.

To construct the DT for every attribute, the entropy (information gain) has to be calculated. The value of information gain or entropy is defined by C. E. Shannon (father of information theory) as follows:

Information gain or Entropy

$$(P_1, P_2, \ldots, P_n) = -P_1 \log_2 P_1 - P_2 \log_2 P2 - \cdots - P_n \log_2 P_n. \quad (4)$$

Step 1: Construction of Root node

Step 1.1: Calculating of information gain of class attribute

Table 9. Experimental values of L27 orthogonal array design for construction of DT.

	Input variables (Predictor attributes)			Output variable (Class attribute)	
Instance no.	Cutting speed, V(rpm)	Feed, F(mm/rev)	Depth of cut, D(mm)	Surface roughness, $\mathrm{Ra}_{\mathrm{Avg}}(\mu m)$	Categorical attribute
1	500	0.10	0.3	1.93	Low
2	500	0.10	0.6	2.77	Low
3	500	0.10	0.9	3.98	High
4	500	0.15	0.3	1.81	Low
5	500	0.15	0.6	2.71	Low
6	500	0.15	0.9	4.42	High
7	500	0.20	0.3	2.00	Low
8	500	0.20	0.6	2.78	Low
9	500	0.20	0.9	4.36	High
10	1000	0.10	0.3	2.05	Low
11	1000	0.10	0.6	2.93	Low
12	1000	0.10	0.9	4.19	High
13	1000	0.15	0.3	1.93	Low
14	1000	0.15	0.6	3.22	High
15	1000	0.15	0.9	4.33	High
16	1000	0.20	0.3	1.99	Low
17	1000	0.20	0.6	3.09	High
18	1000	0.20	0.9	4.29	High
19	1500	0.10	0.3	2.45	Low
20	1500	0.10	0.6	2.89	Low
21	1500	0.10	0.9	4.42	High
22	1500	0.15	0.3	1.87	Low
23	1500	0.15	0.6	2.91	Low
24	1500	0.15	0.9	3.20	High
25	1500	0.20	0.3	1.82	Low
26	1500	0.20	0.6	2.91	Low
27	1500	0.20	0.9	3.13	High

The information gain of class attribute is calculated as follows:

Total no. of Low – 16,
Total no. of High – 11.

Therefore

$$\mathrm{Info}(16, 11) = -16/27 \times \log_2 16/27 - 11/27 \times \log_2 11/27$$
$$= 0.4473 + 0.5277$$
$$= 0.975.$$

The info (16, 11) shows the overall gain or entropy function of the L27 orthogonal array.

Step 1.2: Calculation of information gain and tree structure of predictor attributes

(Input variables)

(i) Information gain of cutting speed (V)

To calculate the information gain of cutting speed, the number of low and high class attributes for

Table 10. Number of class attributes for various cutting speed.

Cutting speed (V)	No. of low (L)	No. of high (H)
500	6	3
1000	4	5
1500	6	3

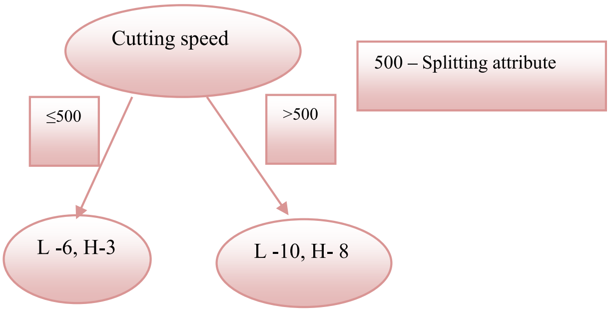

Fig. 8. (Color online) Tree structure for cutting speed.

corresponding cutting speed is noted, as shown in Table 10.

The above table is converted in the form of tree structure using appropriate split value. For finding the best split value, the information gain has been calculated on both upward and downward directions by appending one by one. The value that gives maximum information gain is considered as attribute split value. The above attribute '500' gives maximum gain when compared to the remaining cutting speed and the corresponding tree structure is shown in Fig. 8.

$$\begin{aligned}
&\text{Info}(6,3)\\
&\quad = -6/9 \log_2 6/9 - 3/9 \log_2 3/9\\
&\quad = 0.9182,\\
&\text{Info}(10,8)\\
&\quad = -10/18 \log_2 10/18 - 8/18 \log_2 8/18\\
&\quad = 0.9910.\\
&\text{The combined info}((6,3),(10,8))\\
&\quad = 9/27 \times 0.9182 + 18/27 \times 0.9910\\
&\quad = 0.9667.\\
&\text{The gain of attribute(cutting speed)}\\
&\quad = \begin{array}{l}\text{overall gain}\\ \text{class attribute}\end{array} - \begin{array}{l}\text{combined info}\\ \text{of cutting speed}\end{array}\\
&\quad = 0.975 - 0.9667\\
&\quad = 0.00826.
\end{aligned}$$

(ii) Information gain of feed (F)

To calculate the information gain of feed, the number of low and high class attributes for corresponding feed is noted and shown in Table 11. From the table, attribute '0.10' shows maximum gain as when compared to the remaining feed rate and the corresponding tree structure is shown in Fig. 9.

$$\begin{aligned}
&\text{Info}(6,3)\\
&\quad = -6/9 \log_2 6/9 - 3/9 \log_2 3/9\\
&\quad = 0.9182,\\
&\text{Info}(10,8)\\
&\quad = -10/18 \log_2 10/18 - 8/18 \log_2 8/18\\
&\quad = 0.9910.\\
&\text{The combined info}((6,3),(10,8))\\
&\quad = 9/27 \times 0.9182 + 18/27 \times 0.9910\\
&\quad = 0.9667.\\
&\text{The gain of attribute(feed)}\\
&\quad = \begin{array}{l}\text{overall gain}\\ \text{class attribute}\end{array} - \begin{array}{l}\text{combined info}\\ \text{of feed}\end{array}\\
&\quad = 0.975 - 0.9667\\
&\quad = 0.00826.
\end{aligned}$$

(iii) Information gain of depth of cut (D)

To calculate the information gain of depth of cut, the number of low and high class attributes for

Table 11. Number of class attributes for various feed.

Feed (F)	No. of low (L)	No. of high (H)
0.10	6	3
0.15	5	4
0.20	5	4

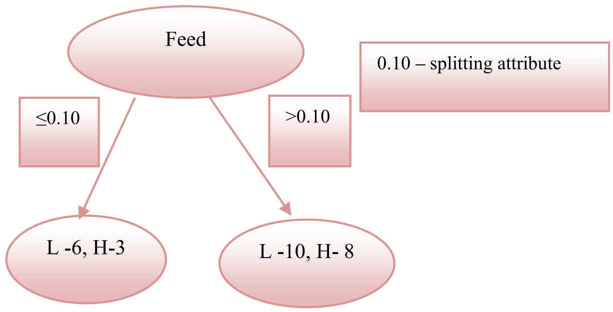

Fig. 9. (Color online) Tree structure for feed.

Table 12. Number of class attributes for various depth of cut.

Depth of cut (D)	No. of low (L)	No. of high (H)
0.3	9	0
0.6	7	2
0.9	0	9

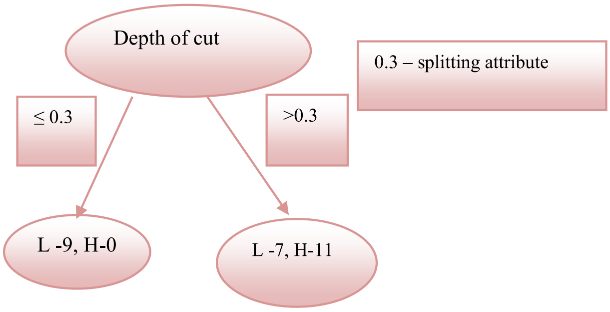

Fig. 10. (Color online) Tree structure for depth of cut.

corresponding depth of cut are noted and shown in Table 12. From the table, attribute '0.3' intends maximum gain as compared to all the remaining depth of cut and the corresponding tree structure is shown in Fig. 10.

$$\begin{aligned}
&\text{Info}(9,0)\\
&\quad = -9/9 \log_2 9/9 - 0/9 \log_2 0/9\\
&\quad = 0,\\
&\text{Info}(7,11)\\
&\quad = -7/18 \log_2 7/18 - 11/18 \log_2 11/18\\
&\quad = 0.9640.\\
&\text{The combined info } ((9,0),(7,11))\\
&\quad = 9/27 \times 0 - 18/27 \times 0.9640\\
&\quad = -0.6426.\\
&\text{The gain of attribute(depth of cut)}\\
&\quad = \substack{\text{overall gain}\\ \text{class attribute}} - \substack{\text{combined info}\\ \text{of depth of cut}}\\
&\quad = 0.975 - (-0.6426)\\
&\quad = 1.6176.
\end{aligned}$$

The values of information gain of all predictor attributes are provided in Table 13. From the table, it is inferred that the attribute depth of cut was the most significant parameter to decide on surface roughness (Ra). Whereas, the cutting speed and feed are insignificant factor or even it cannot be considered on surface roughness (Ra).

Table 13. Information of gain of various predictors attributes.

Sl. no.	Predictor attributes	Information gain
1	Cutting speed (V)	0.00826
2	Feed rate (F)	0.00826
3	Depth of cut (D)	1.6176

4. Conclusions

In this work, the effect of CNC turning parameters on surface roughness (Ra) for AA7075-TiO_2 composite was examined and the subsequent conclusions were drawn.

- AA7075 filled with 10 wt.% of TiO_2 particulate composites was fabricated by stir casting route. The SEM analysis clearly shows the uniform spreading of TiO_2 particles in the grain boundary of matrix.
- Taguchi method and DT algorithm was employed to analyze the effect of parameters such as cutting speed (V), feed (F), and depth of cut (D) on surface roughness (Ra) of produced composite.
- From the S/N ratio analysis, the minimum surface roughness (Ra) was attained by the optimum parameters are cutting speed of 1500 rpm, feed of 0.15 mm/rev, and depth of cut at 0.3 mm.
- From the ANOVA analysis, it was found that the P-value of depth of cut has less than 0.05, which is the most significant parameter on surface roughness (Ra) of produced composite. The percentage contribution of that parameter is 87.96%.
- The DT algorithm reveals that depth of cut plays a predominant role for influencing the surface roughness (Ra) as compared to cutting speed and feed.
- From this experimental study and investigation of optimization of parameters, it is very useful in the fields of automotive and aerospace industries in CNC turning of AA7075 matrix composites reinforced with TiO_2 particles.

References

1. G. B. Veeresh Kumar, R. Pramod, Ch. Guna Sekhar, G. Pradeep Kumar and T. Bhanumurthy, *Heliyon* **5** (2019) e02858.

2. B. Praveen Kumar and A. K. Birru, *Trans. Nonferrous Met. Soc. China* **27** (2017) 2555.
3. A. Mazahery and M. O. Shabani, *Ceram. Int.* **38** (2012) 4263.
4. K. Shirvanimoghaddam, H. Khayyam, H. Abdizadeh, M. Karbalaei Akbari, A. H. Pakseresht, F. Abdi, A. Abbasi and M. Naebe, *Ceram. Int.* **42** (2016) 6206.
5. S. Ozden, R. Ekici and F. Nair, *Compos.: Part A* **38** (2007) 484.
6. M. Meignanamoorthy and M. Ravichandran, *Mater. Res. Express* **5** (2018) 1.
7. J.-F. Li, Z.-W. Peng and C.-X. Li, *Trans. Nonferrous Met. Soc. China* **18** (2008) 755.
8. H. B. Michael Rajan, S. Ramabalan and I. Dinaharan, *Arch. Civ. Mech. Eng.* **14** (2014) 72.
9. R. Singh, M. Shadab and R. N. Rai, *Mater. Today: Proc.* **5** (2018) 19000.
10. E. Baburaj, K. M. Mohana Sundaram and P. Senthil, *J. Mech. Sci. Technol.* **30** (2016) 89.
11. S. Rajesh, D. Devaraj, R. Sudhakara Pandian and S. Rajakarunakaran, *Int. J. Adv. Manuf. Technol.* **67** (2013) 811.
12. K. Palanikumar and R. Karthikeyan, *Mach. Sci. Technol.* **10** (2006) 417.
13. S. Karabulut, U. Gokmen and H. Cinici, *Arab. J. Sci. Eng.* **43** (2017) 1071.
14. R. Kumar and S. Chauhan, *Measurement* **65** (2015) 166.
15. T. Tamizharasan, N. Senthilkumar, V. Selvakumar and S. Dinesh, *SN Appl. Sci.* **1** (2019) 160.
16. D. Priyadarshi and R. K. Sharma, *Mater. Manuf. Process.* **31** (2016) 1342.
17. R. Ramanujam, N. Muthukrishnan and R. Raju, *Int. J. Precis. Eng. Manuf.* **12** (2011) 651.
18. J. Joel and M. Anthony Xavior, *Mater. Res. Express* **6** (2019) 1.
19. M. Nataraj and K. Balasubramanian, *Int. J. Adv. Manuf. Technol.* **93** (2016) 215.
20. J. A. Harding, M. Shahbaz, M. Srinivas and A. Kusiak, *J. Manuf. Sci. Eng.* **128** (2006) 969.
21. M. Ravichandran, A. Naveen Sait and V. Anandakrishnan, *Int. J. Mater. Res.* **105** (2014) 358.
22. S. V. Alagarsamy and M. Ravichandran, *Mater. Res. Express* **6** (2019) 1.
23. S. Thakur and S. R. Chauhan, *Int. J. Mach. Mach. Mater.* **12** (2012) 398.
24. D. Selvam, P. Senthil and N. M. Sivaram, *Int. J. Mach. Mach. Mater.* **19** (2017) 554.
25. R. K. Bhushan, S. Kumar and S. Das, *Int. J. Adv. Manuf. Technol.* **50** (2010) 459.
26. J. Antony and M. Kaye (Springer, Boston, MA, 2000) 103, doi:10.1007/978-1-4615-5293-2.
27. M. Mia and N. Ranjan Dhar, *Int. J. Adv. Manuf. Technol.* **88** (2017) 739.
28. A. M. Ahmed, A. Rizaner and A. H. Ulusoy, *PLoS One* **13** (2018) e0194168.
29. J. R. Quinlan, *Mach. Learn.* **1** (1986) 81.
30. A. Hascalik and U. Caydas, *Int. J. Adv. Manuf. Technol.* **38** (2008) 896.
31. A. Palanisamy and T. Selvaraj, *Surf. Rev. Lett.* **1** (2018) 1850139.