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Optimum Machining Parameters for Al 7075 Hybrid Metal Matrix Composites Using Multi-objective Optimization Technique and the Modified Taguchi Approach

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Abstract

Lightweight composite materials with improved mechanical properties are widely used in industries. There is a need to obtain optimum machining parameters of such hybrid composites. This paper uses reliable multi-objective optimization technique and modified Taguchi approach to determine optimal machining parameters such as speed (N_S) varying from 1000 rpm to 1500 rpm, feed rate (F_R) from 0.10 mm/rev to 0.20 mm/rev, depth-of-cut (D_C) varied from 0.5 mm to 1.5 mm and percentage reinforcement ($R_{\%}$) varied from 2 to 6 to achieve maximum material removal rate (MRR) and minimum surface roughness (SR) of the hybrid composites. The hybrid metal matrix composite (i.e., Al 7075 reinforced with B_4C and rice husk ash, RHA) is manufactured using a stir casting technique. A set of optimum machining parameters is found to be N_S = 1500 rpm, F_R = 0.1 mm/rev, D_C = 1.5 mm and $R_{\%}$ = 2. Empirical relationship for MRR and SR are developed in terms of the machining parameters. A confirmatory experiment is performed and the optimal solution is validated.

Keywords: Depth-of-cut, Feed rate, Material removal rate, % reinforcement, Rice husk ash, Speed, Surface roughness, Turning operation.

INTRODUCTION

The automobile, marine and aerospace industries use lightweight composite materials to improve the performance of structural components [1]. The composites have desirable mechanical, thermal and tribological characteristics and can be produced at minimal cost [2]. Metal matrix composites (MMCs) offer elevated ductile properties over ceramic matrix composites (CMCs) and better environmental stability than polymer matrix composites (PMCs). Hand layup techniques and liquid state processing techniques (including stir casting, squeeze casting) are commonly used to fabricate composites [3]. Friction stir processing (FSP), a solid-state material modification technique, has proven its potential in surface composite fabrication [4]. Powder metallurgy, diffusion bonding, stir-casting, and in-situ processes are used to fabricate MMCs [5]. Stir casting and powder metallurgy processes are used to determine the grade of Al MMC. Cost-effective liquid state technology contributes to material selection and process environment [6].

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Kumar et al. [7] used the FSP technique to produce A364 alloy reinforced with industrial waste, and showed improvement in strength, ductility and wear rate resistance. Industrial and agricultural waste rice husk ash (RHA) is processed to remove impurities prior to use in various applications. MMC produced by reinforcing RHA with aluminum. Silica in RHA has improved composite properties [8–11]. Taskesen and Kutukde [12] specified optimal machining parameters by performing grey relational analysis (GRA) in drilling B_4C reinforced MMCs. Abhang and Hameedullah [13] used GRA to determine the optimum parameters (such as cutting speed, feed, nose radius of tool, %solid–liquid oil coolant) in a turning operation to investigate surface behavior and thickness of chips.

The Taguchi method is well suited to single objective optimization problems. In case of multi-objective optimization problems, Taguchi-generalized quality loss functions including GRA were used in turning, drilling, and WEDM operations [14, 15]. Depth-of-cut (D_C) has little influence on surface roughness (SR). However, increasing D_C leads to higher SR in machining with cutting force and tool-to-workpiece contact area. Nataraj and Balasubramanian [16] observed this phenomenon while machining aluminum composites with SiC and fly ash reinforcement. The Taguchi method including GRA translates the multi-objective into a single objective and provides the optimum solution [17]. Stir casting technique can be used in processing Al MMC for improved properties at minimum cost. Optimum machining parameters are required to obtain lightweight high strength Al hybrid MMC.

The Taguchi method [18] recommends an orthogonal array (OA) for performing a few tests for levels assigned to a specified number of process variables. Analysis of variance (ANOVA) results from test data provide the influence of output responses on their grand mean and indicate a set of optimal process parameters for which confirmatory tests are mandatory. To accumulate scatter from repeated tests, S/N ratio transformation was introduced [18]. Most researchers applied the S/N ratio transformation to a single test data, with no additional benefit other than additional computational burden. Such a transformation may not be required to obtain accurate results as evidenced by the following studies: reliability and safety evaluation on satellite separation process [19], optimum heat pipe operating conditions [20], engine testing of biodiesels with additives [21], optimal process welding [22–25], parameters of machining [26–30], spray painting [31], and gear design [32]. In the present study, the optimum turning process parameters for Al hybrid MMC under dry condition are determined to obtain maximum material removal rate (MRR) and minimum surface roughness (SR) by following modified Taguchi technique and reliable multi-objective optimization procedure. Empirical relationships are developed to determine MRR and SR for specified process variables.

MATERIALS AND METHODS

Industrial and agricultural waste rice husk ash (RHA) is processed to remove impurities. Al 7075 reinforced with B_4C and RHA (a hybrid metal matrix composite) is manufactured using a stir casting technique. The chemical composition of Al 7075, B_4C and RHA are given in Tables 1 to 3. Figure 1 shows the SEM and EDAX image of RHA. The details of the samples produced by stir casting process are in Figure 2 and Table 4. For machining of hybrid metal matrix composites in CNC turning process, speed (N_S), feed rate (F_R), and depth-of-cut (D_C) are the 3 machining parameters (see Figure 3). Table 5 gives the 3 levels assigned to each machining parameter. Speed varies from 1000 rpm to 1500 rpm, feed rate varies from 0.1 mm/rev to 0.20 mm/rev, and depth of cut from 0.5 mm to 1.5 mm. Taguchi's L_9 orthogonal array (OA) is chosen for the 3 input parameters and specified 3 levels to each parameter. It can accommodate one more parameter without increasing the number of experiments. Hence, RHA (wt %) varying from 2 to 6 is introduced as an additional parameter.

Table 1. Chemical composition of Al 7075 (wt %)

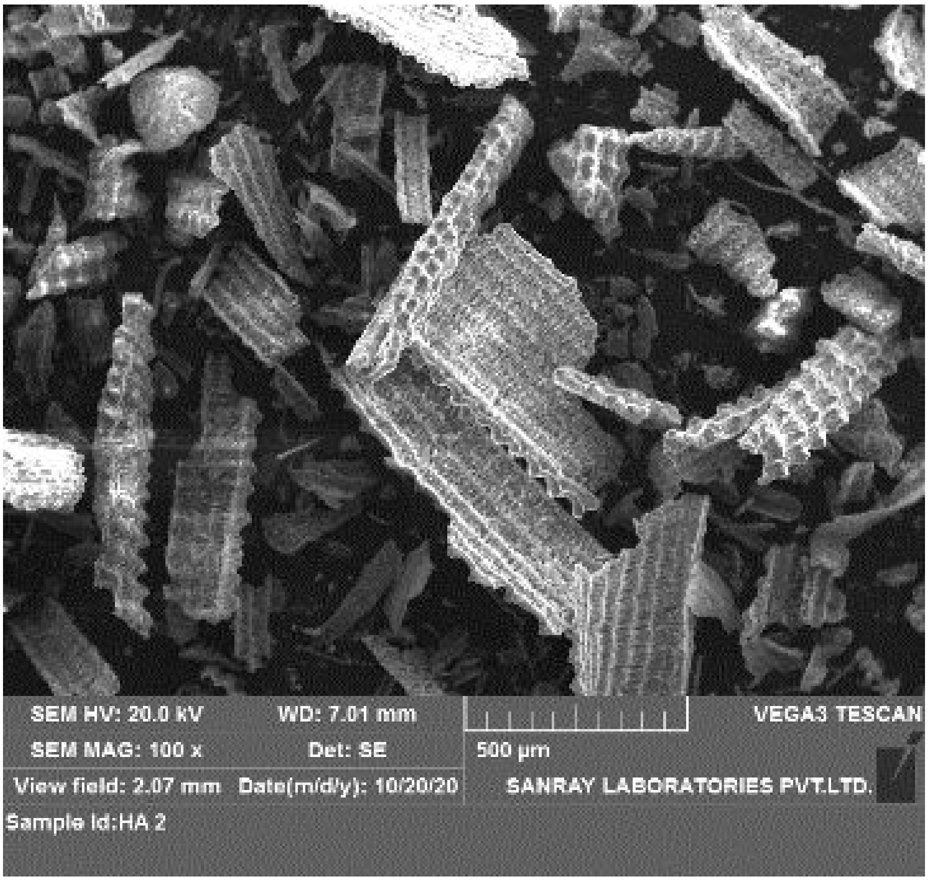
Zn	Mg	Cu	Fe	Si	Mn	Ti	Cr	Al
5.1-6.1	2.1-2.9	1.2-2	0.5	0.4	0.3	0.2	0.18-0.28	Balance

Table 2. Chemical composition of B_4C particles (wt %)

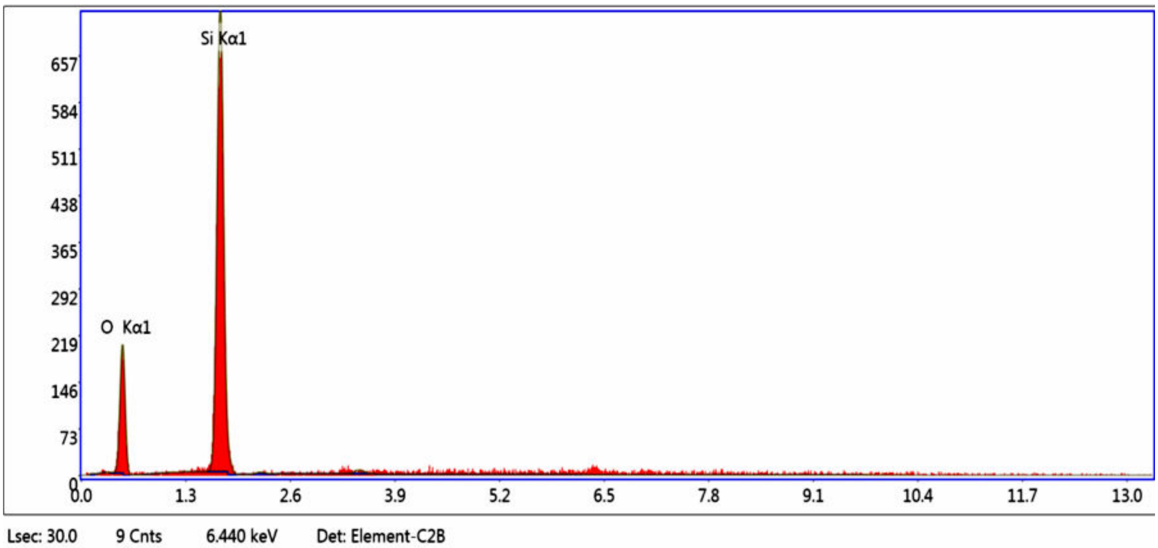
C	Ca	Fe	Si	F	Cl	B
18.1	0.3	1.0	0.5	0.025	0.075	80.0

Table 3. Chemical composition of RHA particles (wt %)

SiO_2	Al_2O	Fe_2O_3	CaO	$Na_2O + K_2O$	LoI
88.9	2.5	2.19	0.22	0.69	Balance



(a)



(b)

Figure 1. (a, b)SEM and EDAX image of RHA.

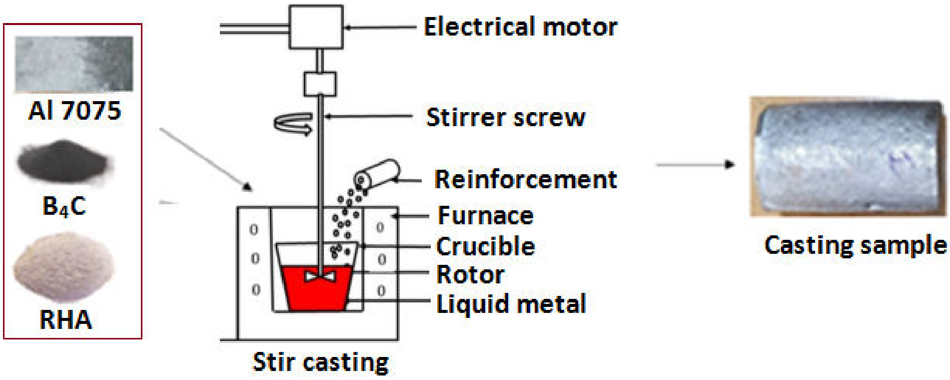


Figure 2. Stir casting process.

Table 4. Sample composition

Sample	Element (wt %)		
	B_4C	*RHA*	*Al 7075*
1	2	2	96
2	2	4	94
3	2	6	92

Figure 3. Process variables and output responses in the machining process.

Table 5. Levels assigned to machining parameters

Machining Parameter	Designation	Level		
		1	*2*	*3*
Speed (rpm)	N_S	1000	1250	1500
Feed (mm/rev)	F_R	0.10	0.15	0.20
Depth of Cut (mm)	D_C	0.5	1.0	1.5
RHA (wt %)	$R_{\%}$	2	4	6

RESULTS AND DISCUSSION

Taguchi's L_9 OA (orthogonal array) is selected for the assigned 3 levels to each CNC machining parameter. For the total number of parameters, $n_p = 4$ and number of levels, $n_l = 3$ assigned to each parameter, eq. (1) gives number of experiments as per the Taguchi method is [18]

$$N_{Taguchi} = 1 + n_p \times (n_l - 1) = 1 + 4 \times (3 - 1) = 9 \quad (1)$$

In fact, the number of experiments for all possible combinations of levels and parameters is: $n_l^{\,n_p} = 3^4 = 81$, whereas Taguchi method recommends only 9 tests as per the L_9 OA.

Experiments were conducted for the set of parameters (see Table 6) in each test run and reported the output responses (viz., material removal rate, MRR; and the surface roughness, SR). MRR is determined as in [33] and measured SR using talysurf surface roughness tester.

Using the measured output responses from Table 6, analysis of variance (ANOVA) is performed and presented the results in Table 7. The depth-of-cut (D_C) has maximum influence on MRR with 65.94 %Contribution. The feed rate (F_R) has major influence on SR with 94.15 %Contribution. The

Table 6. Measured output responses (MRR and SR) for the specified process parameters as per the Taguchi's L9 OA.

Test Run	Process parameters and their levels				Output responses	
	Speed, N_S (rpm)	*Feed rate, F_R (mm/rev)*	*Depth-of-cut, D_C (mm)*	*RHA, $R_{\%}$ (wt %)*	*MRR (g/min)*	*SR (μm)*
1	1000	0.1	0.5	2	9.13	0.47
2	1000	0.15	1	4	15.00	1.21
3	1000	0.2	1.5	6	24.00	1.55
4	1250	0.1	1	6	9.47	0.69
5	1250	0.15	1.5	2	22.22	0.98
6	1250	0.2	0.5	4	15.79	1.45
7	1500	0.1	1.5	4	23.23	0.58
8	1500	0.15	0.5	6	8.18	0.94
9	1500	0.2	1	2	22.11	1.43

Table 7. ANOVA results on performance characteristics (MRR and SR)

Parameters	1st Mean	2nd Mean	3rd Mean	SoS	%Contribution
Metal Removal Rate, MRR: Grand mean=16.57 g/min					
N_S	16.043	15.827	17.840	7.33	2.15
F_R	13.943	15.133	20.633	76.42	22.38
D_C	11.033	15.527	23.150	225.12	65.94
$R_{\%}$	17.820	18.007	13.883	32.53	9.53
Surface roughness, SR: Grand mean= 1.033 μm					
N_S	1.0767	1.0400	0.9833	0.01	1.04
F_R	0.5800	1.0433	1.4767	1.21	94.15
D_C	0.9533	1.1100	1.0367	0.04	2.88
$R_{\%}$	0.9600	1.0800	1.0600	0.02	1.94

influence of other parameters (N_S, F_R and $R_{\%}$) on MRR are: 2.15 %, 22.38 % and 9.53 % respectively. The influence of parameters (N_S, D_C, $R_{\%}$) on SR are: 1.04 %, 2.88 % and 1.94 % respectively. The speed (N_S) has little influence on both MRR and SR. The grand mean value of MRR= 16.57 g/min and the grand mean value of SR=1.033 μm.

From the mean values of the output responses in ANOVA Table-7, it is possible to estimate the output responses for the specified levels of the process parameters using the additive law [18]:

$$\hat{\alpha} = \sum_{i=1}^{n_p} \overline{\alpha}_{ik} - \left(n_p - 1\right)\alpha_g \quad (2)$$

Here, $\hat{\alpha}$ is the estimate of the output response. α_g is the grand mean of the output response. $\overline{\alpha}_{ik}$ is the mean value of the output response corresponding to i[th] process parameter (i.e., *i*=1 for N_S; *i*=2 for F_R; *i*=3 for D_C; and *i*=4 for $R_{\%}$) and k[th] level (i.e., k=1,2,3). Estimates of MRR and SR using equation (2) are exactly matching with the measured data in Table-6.

Considering the mean values of MRR and SR from ANOVA Table 7 and the additive law in equation (2), empirical relationships are developed in terms of N_S, F_R, D_C and $R_{\%}$ in the form:

$$MRR = 14.78 + 0.8983\xi_1 + 1.1150\xi_1^2 + 3.3450\xi_2 + 2.1550\xi_2^2 + 6.0583\xi_3 + 1.5650\xi_3^2$$

$$-1.9683\xi_4 - 2.1550\xi_4^2 \tag{3}$$

$$SR = 1.17 - 0.0467\xi_1 - 0.01\xi_1^2 + 0.4483\xi_2 - 0.015\xi_2^2 + 0.0417\xi_3 - 0.1150\xi_3^2 + 0.05\xi_4$$
$$-0.07\xi_4^2 \tag{4}$$

Here, $\xi_1 = 0.004N_S - 5$, $\xi_2 = 10F_R - 1.5$, $\xi_3 = 2D_C - 2$, and $\xi_4 = 0.5R_{\%} - 2$. Estimates of MRR and SR using equations (3) and (4) for the set of process parameters in each test run of Table 6 are presented in Table 8. Test data in Table 8 matches well with estimates of MRR and SR.

From the mean values of the output responses in ANOVA Table 7, maximum MRR mean values correspond to the 3rd level of N_S, 3rd level of F_R, 3rd level of D_C and 2nd level of $R_{\%}$. Hence, MRR_{max} (maximum MRR) can be achieved for a set of parameters ($N_{S3}F_{R3}D_{C3}R_{\%2}$). Number subscripts indicate the level of the process parameters. Similarly, a set of parameters ($N_{S3}F_{R1}D_{C1}R_{\%1}$) found for minimum SR ($SR_{min}$). Two different sets of process parameters found for MRR_{max} and SR_{min}. Multi-objective optimization scheme [34–39] is appropriate to have a set of parameters for achieving MRR_{max} and SR_{min}. To handle such problems, all the output responses should be normalized and converted to minimization of a single objective function [36]:

$$\zeta = \omega_1\zeta_1 + \omega_2\zeta_2 \tag{5}$$

Here, $\zeta_1 = (1 - MRR/MRR_{max})$; $\zeta_2 = (SR/SR_{max})$; $\omega_1$and $\omega_2$are the positive weighing factors such that $\omega_1 + \omega_2 = 1$; $MRR_{max} = 24$ g/min; and $SR_{max} = 1.55$ µm. Minimizingζ, results in higher MRR and lower SR. Assuming $\omega_1 = \omega_2 = 0.5$, and using mean values of MRR and SR from ANOVA Table 7 in equation (5), ANOVA results for ζ are obtained (see Table 9). A set of parameters ($N_{S3}F_{R1}D_{C3}R_{\%1}$) found from the minimum mean values of ζ. Hence, optimal process parameters to attain minimum $\zeta$are: N_S = 1500 rpm; F_R = 0.1 mm/rev; D_C = 1.5 mm; and $R_{\%}$ = 2. The output responses corresponding to these optimal process parameters obtained from equations (3) and (4) are: MRR=23.04 g/min and SR=0.457 µm. Confirmatory tests performed for the above optimal solutions and presented results in Table 10. Estimates of MRR and SR are in good agreement with measured ones.

Table 8. Comparison of measured MRR and SR with estimates from equations (3) and (4)

Test Run	Levels of the parameters				MRR (g/min)		SR (µm)	
	***N_S* (rpm)**	***F_R* (mm/rev)**	***D_C* (mm)**	***$R_{\%}$***	***Test***	***Eq.(3)***	***Test***	***Eq.(4)***
1	1000	0.1	0.5	2	9.13	9.127	0.47	0.467
2	1000	0.15	1	4	15.00	14.997	1.21	1.207
3	1000	0.2	1.5	6	24.00	23.997	1.55	1.547
4	1250	0.1	1	6	9.47	9.467	0.69	0.687
5	1250	0.15	1.5	2	22.22	22.217	0.98	0.977
6	1250	0.2	0.5	4	15.79	15.787	1.45	1.447
7	1500	0.1	1.5	4	23.23	23.227	0.58	0.577
8	1500	0.15	0.5	6	8.18	8.177	0.94	0.937
9	1500	0.2	1	2	22.11	22.107	1.43	1.427

Table 9. ANOVA for ζ

Parameters	1st Mean	2nd Mean	3rd Mean
N_S	0.5595	0.5520	0.5011
F_R	0.4435	0.5646	0.6045
D_C	0.6057	0.5783	0.4286
$R_{\%}$	0.4943	0.5277	0.5905

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Table 10. Comparison of MRR and SR estimates with measured data for the optimal solution of case studies.

Speed, N_S (rpm)	Feed rate, F_R (mm/rev)	Depth-of-cut, D_C (mm)	RHA, $R_{\%}$ (wt %)	MRR (g/min)	SR (μm)
Case study-I: Single-objective optimization Set of optimal parameters ($N_{S3}F_{R3}D_{C3}R_{\%2}$) for maximum MRR					
1500	0.2	1.5	4	29.92 (30.42)$^+$	1.473 (1.49)
Case study-II: Single-objective optimization Set of optimal parameters ($N_{S3}F_{R1}D_{C1}R_{\%1}$) for minimum SR					
1500	0.1	0.5	2	10.92 (11.34)	0.373 (0.33)
Case study-III: Multi-objective optimization Set of optimal parameters ($N_{S3}F_{R1}D_{C3}R_{\%1}$) for maximum MRR and minimum SR					
1500	0.1	1.5	2	23.04 (22.17)	0.457 (0.49)
$^+$ Measured data					

For the full factorial design of experiments, 81 sets of process parameters specified are:

$(((((N_{S_i}, F_{R_j}, D_{C_k}, R_{\%_l}), l = 1 to 3), k = 1 to 3), j = 1 to 3), i = 1 to 3)$. MRR and SR values generated using equations (3) and (4) to these 81 sets of parameters and shown in Figures 4 and 5. Measured data in Table 6 are in line with estimates.

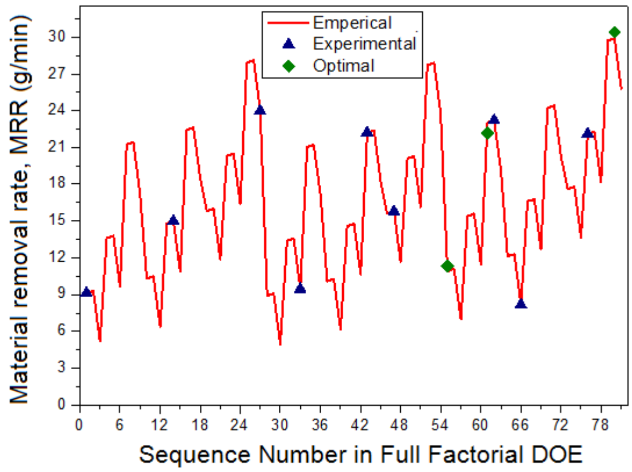

Figure 4. Estimates of metal removal rate, MRR for the full factorial design of experiments.

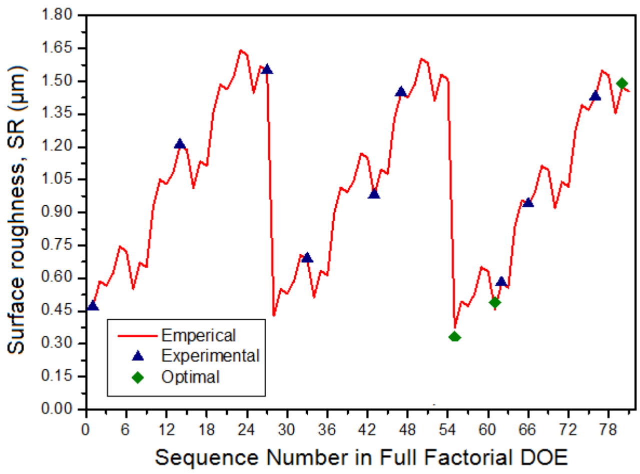

Figure 5. Estimates of surface roughness, SR for the full factorial design of experiments.

CONCLUSIONS

This paper deals with the optimum turning process parameters for Al hybrid MMC (Al 7075 reinforced with B_4C and rice husk ash, RHA) in dry condition. Experiments conducted according to Taguchi's L_9 OA (orthogonal array). Spindle speed, feed rate, depth-of-cut are the turning process parameters. RHA is introduced as an additional parameter. The measured output responses from the tests are material removal rate (MRR) and surface roughness (SR). A reliable multi-objective optimization procedure is followed and the optimal turning process parameters for the maximum MRR and minimum SR determined are: spindle speed= 1500 rpm; feed rate= 0.1 mm/rev; depth-of-cut= 1.5 mm; and RHA (wt %) = 2. Confirmatory experiments conducted to confirm the optimal solution. Empirical relationships are developed for MRR and SR in terms of process variables and validated with measured data.

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