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Research Article

TURNING PROCESS PARAMETERS OPTIMIZATION OF AL7075 HYBRID MMC'S COMPOSITE USING TOPSIS METHOD

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ABSTRACT

This research article elaborates the processes involved in optimization studies in turning process with multi-response features on the basis of Multi-Criteria Decision Making (MCDM) Methodology by utilizing the integrated approach of Criteria importance through inter criteria (CRITIC) and Technique for Order Preference by Similarity Ideal Solution (TOPSIS) approaches. In the study, the researchers optimized the cutting speed, feed and depth of cut with multi-response characteristics which are inclusive of Material Removal Rate (MRR) as well as a surface roughness (Ra). When using a combination of the turning process parameters such as cutting speed of 115 m/min, the feed of 0.2 rev/m, and depth of cut of 0.8 mm, the approach was able to achieve high MRR and low Ra. The study results inferred that the TOPSIS method can be used to enhance the multi-response characteristics of theAl7075/FA/SiC MMC used during the turning process. ANOVA was conducted in order to find out the noteworthy factors for the turning process.
Keywords: Turning, Surface Roughness, MRR, MCDM, CRITIC, TOPSIS.

1. INTRODUCTION

Turning operation is one of the most common machining operation in which rotational parts are being produced by removing material there by obtaining reduced size of required diameter. The turning operation can be performed generally in lathe machine with the use of single point cutting tool. For turning the work piece in lathe, it is required to fix the cutting tool in the fixture and the work piece made to be rotated continuously. In various kinds of industries, the turning is the most widely used machining operation to produce required shape of different components.[1–2]. According to the wide research conducted in the area of MMC cutting process by the researchers around the globe, it has been found that the main aspects, affecting MMC turning operation predominantly depends on the type of material being used [3–4].

Usually, according to the guidelines set by standard handbooks, the experience of operators, and the knowledge, the machining parameters are selected. However, if the chosen machining parameters are not optimum, then it may eventually increase the cost of the product [5]. By choosing the best machining parameters, one can achieve high machining performance [6]. In the process of choosing the best combination of best machining parameters, the researcher makes use

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of the optimization techniques [7]. Novel materials are manufactured to meet certain industry-based requirements in the manufacturing arena. However,it may not be feasible to make use of it directly. So, an experimental study is required here [8]. AA7075/FA/SiC 10% wt. hybrid MMC gives better mechanical properties compared to base alloy and 5% wt. hybrid MMC [9]. Metal matrix composites (MMCs) find applications in areas like aircraft components, automobile, marine, structural equipment's, etc., as they possess a combination of properties like superior hardness, enhanced strength and better wear resistance. N. Sathiya Narayanan et. al [10] has conducted experiment on polytetrafluoroethylene (PTFE) polymers to evaluate and optimize the surface roughness and material removal rate using TOPSIS optimization technique. S. Karthik et. al [11] has identified the combination of Taguchi's and TOPSIS optimization techniques yields better result on machining parameters on WEDM of Al, MMC.

Among various MCDA/MCDM strategies created to understand genuine choice problems, TOPSIS keeps on working attractively in altereduse areas.As an outstanding old style MCDA/MCDM technique, TOPSIS has gotten much enthusiasm from specialists and experts. The worldwide enthusiasm for the TOPSIS technique has exponentially developed, which we wish to record in this paper.

TOPSIS algorithm was utilized by Vijay et al. to choose the best CNC machine. The TOPSIS algorithm is known as an efficient MCDM tool and is made use of, to find the best solutions for such difficult decision-making challenges in the areas of manufacturing. The studies conducted earlier [12] proved that when using TOPSIS algorithm, it is easy to compute, evaluate, and capable of choosing the best suitable machine tool from the alternatives available. Abhang et al.[13]using a combination of MADMmethods and finalized the best lubricant for turning process from the available substitute lubricants when they machined EN31 steel workpiece. In their research work, the researchers leveraged TOPSIS and AHP methods. According to their conclusion, the lubricant index assesses and positions the best lubricant when executing steel turning operation. A combination of TOPSIS and AHP methods was found to be the best approach to resolve complex MADM challenges in the domain of manufacturing. Nikunj et al. proposed a logical technique based on three well established MADM methods, for instance, AHP, TOPSIS and revised AHP in the process of tool insert assortment for conducting a turning operation on CNC turning centre. According to the conclusion, it can be inferred that there is a similarity of ranking the 'tool insert'with that of the performance score achieved in tool insert selection index in all MADM methods [14].

TOPSIS, one of the MADM techniques, was applied by P. Senthil et al. to find a solution for multi-criteria optimization of EDMprocess parametersin Al-CuTiB2 MMCs. When compared with the alternative choices, the TOPSIS algorithm showed better assessment, and the study concluded that this is an easy, simple, computationally effective and understandable approach [15]. A novel method, TOPSIS, was recommended by arun kumar et al [16] to optimize the turning operation parameters on GFRP composites. This method has a primary advantage i.e., no requirement of computing challenging modeming formulations or process simulations.

A blend of TOPSIS and AHP method was used by Balasubramaniyan et al. [17] in order to find the best blend of machining parameters in order to conduct turning operation of EN25 steel. According to the study conclusion, this combination method can be deployed in all the machining operations that work towards a high number of objectives simultaneously. TOPSIS algorithm was used in the study conducted by Dinesh et al. [18] to optimize the die-sinking EDM parameters with the working material, EN-353 grade stainless steel. In this TOPSISalgorithm based study, the researcher conducted the computational experiments using Simple Additive Weighing (SAW)-based MCDM method. The study inferred the efficiency of TOPSIS algorithm and proved the efficacy of MADM problems in EDM. N. Yuvaraj et al. executed the optimization of AWJ cutting process parameters of aluminum alloy AA5083-H32 unit that possess multi-response features, on the basis of MCDM methodology using TOPSIS approach. It was observed from the investigation that the multi-response features of AWJ cutting process could be enhanced when using TOPSIS algorithm [19]. The TOPSIS algorithm was utilized by R. Manvinnan et al.to assess the machining parameters of micro-EDM of AISI 304 steel and the study results inferred that the TOPSIS algorithm enhanced the micro-EDM's process parameters [20].

Subjective and objective are the two well-known methods of weight assignment. The system of subjective weight assignment is based on expert judgment, and pair-wise comparison (i.e., analytical hierarchy process (AHP) and simple multi-attribute rating technique (SMART) are the most common techniques used [21]. While the objective weight assignment methodology collects data from requirements data and calculates weights accordingly without the decision-maker's involvement [22]. Entropy, CRITIC, and the standard deviation approach are the most common techniques used [23]. The choice of the expert is not applicable, as in the present study, so an objective form of weighting is applied. Compared to entropy and standard deviation methods, CRITIC is a superior approach because it includes both conflict and comparison strength to the weights in decision-making issues and thus represents specific weight assignment conditions. So The CRITIC method, integrated with the TOPSIS method, is used in the present study to assess the response weights.

With the expanding number of new materials accessible in the market each year, the producers are confronting incredible troubles in choosing the most fitting material for their items. In this manner, there is continuously a passionate need to receive a basic deliberate strategy for productive and compelling assessment of machinability of different work materials. In this paper, MCDM method i.e TOPSIS is connected to contemplate the machinability qualities of AA7075/FA/SiC 10 wt.% hybrid MMC. The TOPSIS strategy, being an effectively intelligible MCDM system and having a solid numerical foundation, is additionally very reasonable to this sort of assessment and determination issue. The TOPSIS strategy hence causes the researchers to assess the machinability charactertics of the considered metal combinations for a given machining application.

2. EXPERIMENTAL SETUP

In the figure, the study's experimental setup is shown. A lathe machine manufactured in Germany (S 3015, Germany; traverse length: 60 mm) was used to conduct the experiments. Ra and MRR were the output responses considered for the study. These response parameters were made use of, in the performance evaluation of turning process by altering different levels of input process parameters. Table 1 shows the process parameters along with their level values.

Figure 1. Turning of Al composites

Table 1. Selected factors and their levels

S.No	Factor	Notation	Unit	Levels of Factors			
				L 1	L 2	L 3	L 4
1	Cutting Speed	v	m/min	20	50	75	115
2	Feed	f	mm/rev	0.05	0.10	0.16	0.20
3	Depth of cut	d	Mm	0.2	0.4	0.6	0.8

By utilizing the Mitutoyo's Surftest SJ-210, the average surface roughness (Ra) of 16 specimens was calculated. The surface roughness was measured thrice at various locations from which the average value was taken. In the present research, MRR was determined by utilizing the weight loss technique i.e material removal weight over period of time in seconds.

3. METHODOLOGY

3.1. CRITIC METHOD

D. Diakoulaki, suggested the CRITIC methodology [24], which attempts to determine objective weights of relative importance in the decision making problems of multiple criteria. The derived weights provide both contrast strength and conflict that are found in the decision problem framework. The approach developed for extracting all the information found in the evaluation criteria is based on an empirical investigation of the evaluation matrix. The steps given below are followed to calculate objective weights for output responses.

First, by using the Equation (1) and (2), first multi-criteria problem is mapped into the interval [0,1]. In Equation (1) is chosen when better output is suggested by the high value of output. Equation (2) is used when better output is suggested by lower value of output. By using Eq.(1&2) the normalized values of material removal rate and surface roughness are calculated and shown in Table 2.

Secondly, the initial assessment matrix is converted into a relative score matrix with the generic factor qij. Each vector xi, which quantifies the contrast strength of the corresponding criterion, is characterised by the standard deviation σi. In Table 2, the score matrix and standard deviation of the MRR and surface roughness are given.

Third, a symmetric matrix is constructed with an m-m dimension and a rij generic element, which is the coefficient of linear correlation between the xi and xj vectors. It can be shown that the more inconsistent the ratings of the alternatives in criteria I and j, the lower the rij value. Table 3 shows the correlation matrix containing the values of the linear coefficients for each pair of parameters.

Finally, by composing the measures that calculate the contrast strength and conflict of decision criteria by multiplicative aggregation Eq.(3), the amount of information Ci, emitted by the ith criterion, can be calculated. According to the above analysis, the higher the Ci value, the greater the amount of information that the corresponding criterion transmits, and the greater the relative importance of the Ci value for the decision-making process. By normalizing these values to unity according to Eq.(4), objective weights wi are determined.

$$x_i = \frac{y_i - y_{min}}{y_{max} - y_{min}} \tag{1}$$

$$x_i = \frac{y_{max} - y_i}{y_{max} - y_{min}} \tag{2}$$

$$P_i = \sigma_i \sum_{i=1}^{m} (1 - q_{ij}), j=1,2....m \tag{3}$$

$$w_i = \frac{P_i}{\sum_{j=1}^{m} P_i} \tag{4}$$

Table 2. Normalized values for output responses

Exp.No.	Ra	MRR
1	0.141	1.000
2	0.315	0.922
3	0.785	0.800
4	1.000	0.348
5	0.275	0.904
6	0.128	0.922
7	0.651	0.130
8	0.678	0.330
9	0.034	0.783
10	0.114	0.174
11	0.557	0.600
12	0.624	0.383
13	0.000	0.478
14	0.054	0.130
15	0.268	0.000
16	0.463	0.557

Table 3. Correlation matrix and objective weights of each response

Output Response	Ra	MRR	Objective Weight
Ra	1	-0.1667	0.48
MRR	-0.1667	1	0.52

3.2. TOPSIS METHOD

MCDM methods are extensively deployed in the domain of manufacturing to select the optimal solution from the available few alternatives. These methods are powerful, efficient and widely preferred for the past ten years. Among MCDM methods, TOPSIS is one such method to solve multiple criteria. This method works on the basis of selecting the best choice that is placed nearby the positive solution and far away from negative solution. Such critical and complex solutions communicate to the minimum and maximum attributes in the database which is composed of satisfy solutions. The best solution is obtained by utilizing the nearby hypothetical favorable and farthest hypothetical unfavorable. TOPSIS assess the number of substitutes as well as the tangible attributes in an efficient manner. However, every objective's weight criteria must be identified. In TOPSIS method, the steps given below are followed to choose the best substitutes.

Step 1. Being the best-ranking method, the TOPSIS method chooses the substitutes which get rid of the units of all criteria and considers a normalized value. In the table 4 too, the normalized performance matrix (N_{ij}) is shown and is obtained with the help of the equation given below.

$$N_{ij} = \frac{y_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}} \tag{5}$$

where i denotes the number of alternatives and j denotes the number of output responses, y_{ij} is nothing but the normalized value of i^{th} alternative which is in association with j^{th} output response.

Step 2. The weighted normalized matrix (K_{ij}) is attained by multiplying the weighted values and normalized value i.e.,

$$K_{ij} = w_j \, x N_{ij}\text{ , i = 1,2…..16, j = 1,2.} \tag{6}$$

Where w_j is the weight of output response, the objective weights of output responses are derived from CRITIC method.

Step 3. Every response which seems to be the best alternative to the best (K^+) and worstalternative performance(K^-)was determined. When the i^{th} criteria exhibits the required optimal performance:

$$K^+ = \{(\max K_{ij}/j \in J), \min (K_{ij}/j \in J')/\ i = 1,2\ldots.16\}.$$
$$=\{K^+_1, K^+_2, \ldots\ldots K^+_{16}\}. \tag{7}$$

$$K^- = \{(\max K_{ij}/j \in J), \min (K_{ij}/j \in J')/\ i = 1,2\ldots.16\}.$$
$$=\{K^-_1, K^-_2, \ldots\ldots K^-_{16}\}. \tag{8}$$

Where K^+ denotes the positive ideal solution whereas K^- denotes the negative ideal solution.

Step 4. In this stage, the criteria's performances were measured with the optimum substitute distance (R^-_{ij}) from K^- values and the poorest alternative distance (R^+_{ij}) from the K^- values. With the help of the equations (9) and (10), the values of R^+_{ij}, R^-_{ij} were calculated. The table 5 shows the outcomes of every substitute in terms of best and worst conditions.

$$R_{ij}^{+} = sqrt.\left(\sum_{i=1}^{16}(K_{ij} - S_j^{+})^2\right) \tag{9}$$

$$R_{ij}^{-} = sqrt.\left(\sum_{i=1}^{16}(K_{ij} - S_j^{-})^2\right) \tag{10}$$

Step 5. The closeness coefficient (CC_i) valueswere calculated for every alternative with the help of the equation given below.

$$CC_i = \frac{R_{ij}^{-}}{R_{ij}^{+} + R_{ij}^{-}};\ 0 \leq CC_i \leq 1; \tag{11}$$

According to the preference grading devised by CC_i value, being close to the ideal solution, the best substitute was selected.

4. RESULTS AND DISCUSSIONS

This study has chosen two performance characteristics such as minimization and maximization. In order to attain the optimal machining performance, the researcher took the maximization features for MRR and minimization features for surface roughness. With the help of equation (5), the two responses were normalized at the initial stage. Since the priority given to both output responses is based on CRITIC method, the responses weight criterion was taken as 0.48 for surface roughness and 0.52 for MRR. Based on the equation (6), the weight criterion was multiplied in order to attain the normalized weighted matrix from which the best and the worst solutions were calculated. Using the equations (9) and (10), the researcher calculated the separation measures of each criterion from the best as well as the worst solutions.

The relative Closeness Coefficient (CC) value was calculated at last for every combination of turning process factors with the help of equation (11) as shown in the table 4.

Table 4. Normalized, weighted normalized data, Separation measures and Closeness coefficient values

Exp. No.	Normalized data		Weighted Normalized data		Separation measures		Closeness coefficient
	MRR	Ra	MRR	Ra	R_{ij+}	R_{ij-}	CC_i
1	0.0338	0.1971	0.0169	0.0986	0.1948	0.0830	0.2987
2	0.0642	0.2308	0.0321	0.1154	0.1817	0.0679	0.2719
3	0.1115	0.3216	0.0558	0.1608	0.1730	0.0441	0.2030
4	0.2873	0.3631	0.1436	0.1815	0.1179	0.1267	0.5181
5	0.0710	0.2230	0.0355	0.1115	0.1778	0.0725	0.2896
6	0.0642	0.1945	0.0321	0.0973	0.1796	0.0857	0.3230
7	0.3718	0.2957	0.1859	0.1478	0.0678	0.1723	0.7176
8	0.2940	0.3008	0.1470	0.1504	0.0917	0.1338	0.5933
9	0.1183	0.1764	0.0591	0.0882	0.1521	0.1025	0.4025
10	0.3549	0.1919	0.1774	0.0960	0.0356	0.1819	0.8365
11	0.1893	0.2775	0.0946	0.1388	0.1284	0.0887	0.4086
12	0.2738	0.2905	0.1369	0.1452	0.0957	0.1254	0.5670
13	0.2366	0.1699	0.1183	0.0849	0.0929	0.1401	0.6011
14	0.3718	0.1802	0.1859	0.0901	0.0259	0.1921	0.8813
15	0.4225	0.2217	0.2112	0.1109	0.0259	0.2068	0.8886
16	0.2062	0.2594	0.1031	0.1297	0.1170	0.1006	0.4622

Table 5. Response means of CCi

Level	v	f	d
1	-10.342	-8.396	-8.697
2	-6.999	-5.944	-7.008
3	-5.539	-6.383	-6.847
4	-3.312	-5.469	-3.641
Delta	7.030	2.927	5.056
Rank	1	3	2

The factor response results were taken into account by utilizing ‘higher-the-better’ expectation through MINITAB software. As per table 5, the role played by ‘f’ remains insignificant, whereas the contribution made by the parameters, ‘v’ and ‘d’, seemed to have significantly enhanced the closeness coefficient value. Fig.2 depicts the main effects plots for S/N ratio and optimal settings are shows as $v_4f_4d_4$ i.e 115 m/min, 0.20 mm/rev and 0.8 mm. ANOVA can be used to calculate the amount of effect of process variables upon the performance features. Table 4 lists the ANOVA results for the preference solution by taking 95% CI as statistically significant.

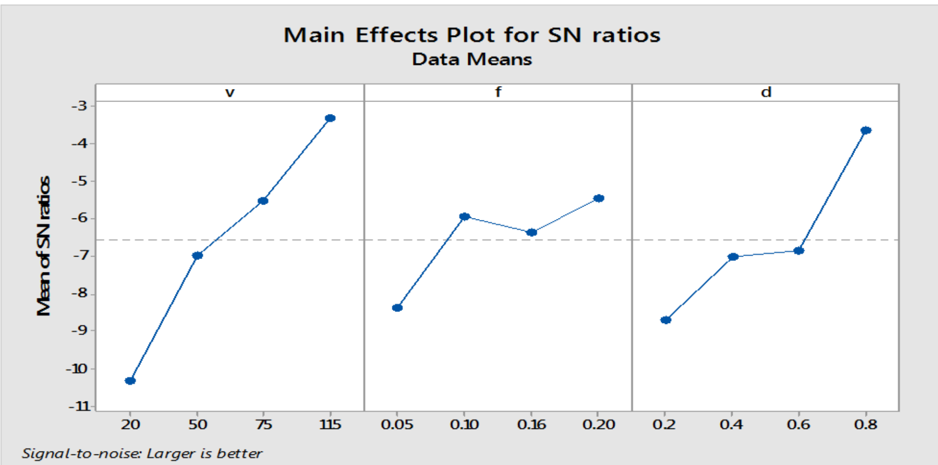


Figure 2. Main Effects plot for S/N ratios.

Table 6. ANOVA for CC.

Source	DF	Seq SS	Adj SS	F-Value	P-Value	Contribution
v	1	0.304246	0.000014	0.00	0.958	40.45%
f	1	0.031048	0.001952	0.42	0.541	4.13%
d	1	0.162485	0.025701	5.52	0.057	21.61%
v*v	1	0.001573	0.006839	1.47	0.271	0.21%
f*f	1	0.039978	0.034987	7.52	0.034	5.32%
d*d	1	0.000295	0.000333	0.07	0.798	0.04%
v*f	1	0.043237	0.039622	8.52	0.027	5.75%
v*d	1	0.031488	0.029057	6.25	0.047	4.19%
f*d	1	0.109804	0.109804	23.60	0.003	14.60%
Error	6	0.027913	0.004652			3.71%
Total	15	0.752066				100.00%

S= 0.0682072 R-sq = 96.29% R-sq(adj) = 90.72%

In the table 6, the impact created by input process parameters upon turning can be observed. Among the parameters, the order of influence is as follows v (40.45%), d (21.61%), f*d (14.60%) and finally v*f (5.75%). Table 7 shows a comparison of the assessment outcomes for beginning and best choice of turning process parameters for the expected as well as the test conditions. Once the best level parameters for machining were decided, the tests for confirmation were conducted in order to ensure the improvement in the multi response feature of turning. Using optimal level of turning parameters and using the equation [12], the forecasted response value ($\gamma_{predicted}$) can be calculated.

$$\gamma_{predicted} = \gamma_m + \sum_{j=1}^{n}(\gamma_0 - \gamma_m) \tag{12}$$

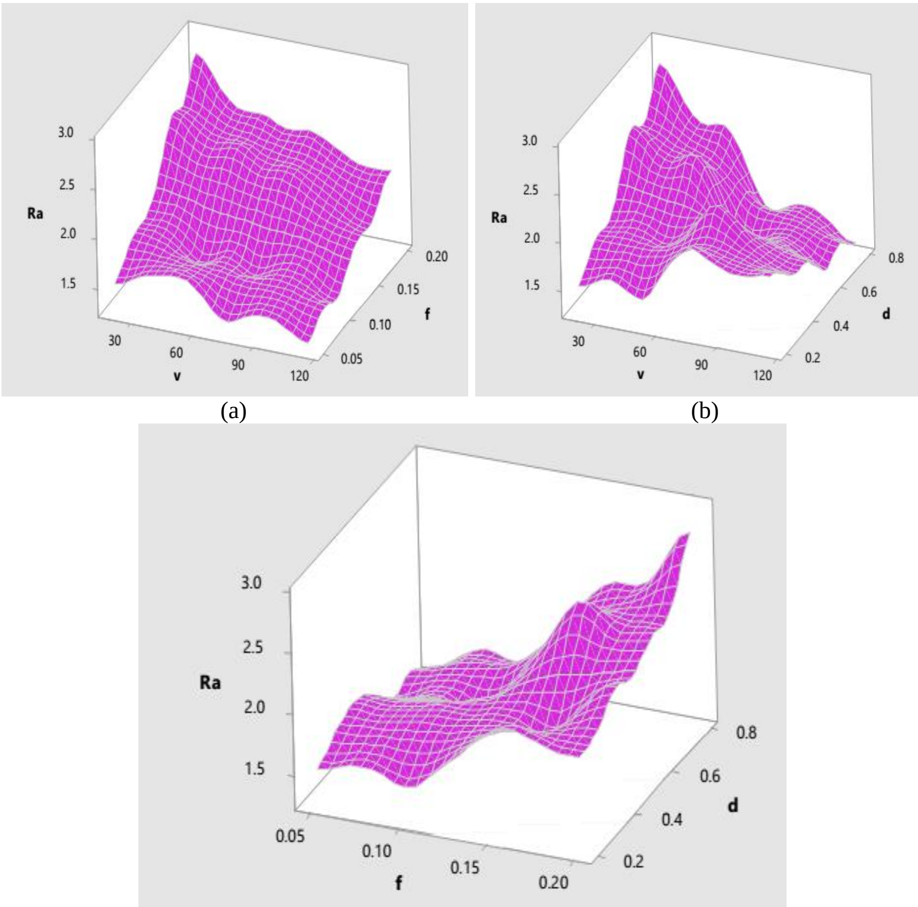
In which, the γ_m denotes the overall mean multiresponse value and γ_0 denotes the mean multiresponse value at the optimum level of factors. In the equation, n denotes the number of input process parameters. From the outcomes, it can be inferred that the total CC_i value of the optimal parameter condition (v4f4d4) seems to be high when compared with the initial setting parameter condition (v1f1d1). In addition to that, the forecasted response value also seems to be closer to the experimental value.

Table 7. Predicted and Experimental values

Levels	Initial machining parameters level	Optimum machining parameters level	
	v=20 f=0.05 d=0.2	v=115 f=0.2 d=0.8	
		Predicted	Experimental
Ra	1.52		1.69
MRR	0.020		0.23
CC_i	0.2987	0.8788	0.8650
Improvement in the CC_i		0.5801	0.5663

5. EVALUATION OF PARAMETERS BY USING 3D PLOTS

Fig. 3 portrays the impact of different process parameters on Ra and Fig.4 portrays the impact of various process parameters on MRR. Surface roughness shows fading pattern with adevelopment of cutting speed from 20 m/min to 115 m/min. In the present investigation, when the process parameters increments from low level to high level, expanded pattern was observed for MRR.



(a) (b)

(c)

Figure 3. 3D plot for Ra (a) v Vs f (b) v Vs d (c) f Vs d.

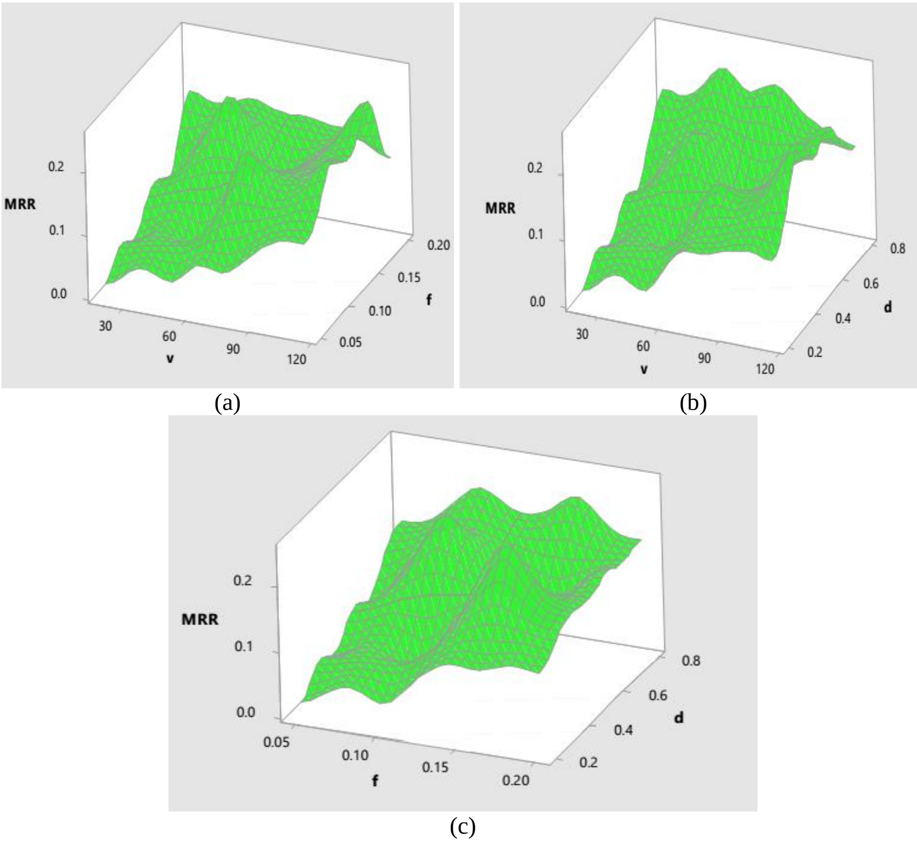


Figure 4. 3D plot for MRR (a) v Vs f (b) v Vs d (c) f Vs d.

6. CONCLUSIONS

The current study utilized the hybrid approach of CRITIC - TOPSIS method in addition to orthogonal array so as to best enhance the process parameters in the turning process of Al7075/FA/SiC hybrid MMC for multiresponse features. The researcher identified a best combination of turning parameters along with their levels when it comes to achieving the least surface roughness (Ra) value and a better Material Removal Rate (MRR). Based on the response noted from CC_i values, the researcher found out the optimum combination levels of input process parameters: Cutting speed 115 m/min, feed 0.2 mm/rev. and depth of cut 0.8 mm. Further, the study concluded with the proposed method (a blend of Analysis of Variance and TOPSIS) showing efficiency in finding a solution for turning multi-response problems when compared to the methods used earlier.

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