Surface Roughness and MRR Analysis and Prediction for VMC-Five-Axis Machining of EN47 Steel using RSM and MTLBO

Dr. Arun Patil*[1], Dr. Ramesh Rudrapati*[2]
[1]Asst. Prof. JSPM, BSIOTR,Wagholi, [2]Asst. Prof. Industrial Engineering Department, Bule Hora University, Ethiopia
[1]patil.mailme@gmail.com,
[2]rameshrudrapati@gmail.com

***Abstract*— For milling processes based on rotary cutters, the contemporary machining approach known as VMC five-axis is employed to remove extra work material. In order to achieve cutting economics in VMC-5-axis manufacturing, the choice of the best processing parameters is crucial. Key response factors include the roughness of the surface and the rate of material removal, and the combined examination and optimization of these responses is a significant area of milling research. The purpose of the present study is to identify, model, and simulate the ideal milling parametric condition for VMC-5-axis cutting of EN47 tool steel in order to predict surface roughness and MRR simultaneously by introducing response surface methodology and multi-objective teaching learning-based optimisation (MTLBO). The tests were designed using the Box-Behnken design of the response surface technique. Statistical Variance Analysis (ANOVA) has been employed to assess the relevance of milling parameters for milling output characteristics. The results of the ANOVA show that for MRR, milling processing parameters are of greater significance than surface roughness. RSM provides response modelling services. Established mathematical models are used to create contour plots, which are used to illustrate the direct and combined implications of milling parameters on both responses. The MTLBO technique is used to resolve multiple responses. The anticipated milling conditions are validated by confirmatory tests. Based on the results of the present research, milling responses have been enhanced at the anticipated condition achieved by the combined use of RSM and MTLBO.**

***Keywords*— EN47 steel, VMC-5 axis machining, surface roughness, MRR, MTLBO**

I. Introduction

Milling operations are frequently used to make intricate forms such as holes, bags, precise moulds and dies, etc. for aerospace manufacturing, the automotive sector, and various other areas where high-quality surfaces are of significant importance [1]. Vertical machining centre (VMC) five-axis machining is becoming increasingly prevalent in contemporary manufacturing sectors since it can be used to construct intricate/complex features on components with exceptional quality at reduced production costs and reduced production times [2]. The needs of the VMC process are correctly recognized in order to utilize all of its special qualities to produce components of outstanding quality with economical machining. Certain errors, such as surface roughness, dimensional inaccuracy, burr, etc., are frequently seen in work items after the five-axis milling process of VMC [3]. The reasons for the inaccuracies include incorrect control variable selection, vibration during machining, progressive wear-out of the insert, loss of stiffness in machine tool systems, faults in the material of the work piece [4], etc. In addition to the other errors, choosing the best milling process settings can be achieved through an experimental investigation based on experiment design. DOE is a comprehensive technology used to evaluate various errors and optimise milled surface parameters in production processes like VMC five-axis machining [5]. The right choice of process parametric setup can also be helpful in achieving enhanced milling economics in VMC five axis machining. Surface roughness is defined [3] in order to assess the quality of machined components. It is ideal for various industrial usage for structures and products to have a fine surface finish. The material removal rate is a quantitative factor commonly used to evaluate productivity in milling operations. The higher output rate alludes to a higher MRR. Getting the best surface quality and MRR possible for industrial practices is a crucial area of research. Maximizing all the responses, such as surface roughness and MRR, is challenging for researchers. The multi-performance features of machining processes have been successfully evaluated, modelled, and optimized using integrated response surface methodology (RSM) and multi-objective optimization of teaching-learning based optimization (MTLBO) [6].

One of the significant statistical techniques for planning, analyzing, and modelling experiments while keeping track of the conditions of any industrial process is the response surface methodology [5]. A probabilistic approach known as teaching learning-based optimization appears to be helpful in resolving engineering issues [7]. It replicates the approach of teaching learning [7]. The literature review covers the research work and is based on the analysis, modelling, and optimization of production / processes using experiment design, analysis of variance, statistical modelling, and optimization of process responses using RSM, Taguchi procedure, TLBO, and other analytical methods or techniques.

Malvade and Nipanikar 2014 [8] conducted experimental investigations on end milling on VMC in order to improve the multiple responses, such as SR and MRR, utilizing variance analysis and the Taguchi procedure and from the analyses concluded that process variable impacts were crucial for both responses. Raja et al. [9] addressed the mathematical model of surface roughness in the face milling process employing the particle swarm optimization (PSO) method. Lu et al. [10] applied GRA paired with PCA to optimize the cutting parameters to attain the target surface roughness and MRR simultaneously in high-speed end milling operation. The hybrid RSM and TLBO approach was utilized by Rudrapati et al. in 2016 [12] to forecast the performance reaction of aluminum alloy in CNC turning and discovered enhanced outcomes using TLBO and advanced RSM optimisation techniques. Once more, Rudrapati et al. 2016 [13] optimized the process variables of the turning operation with the aid of RSM and elitist TLBO. Mild steel milling study was carried out on VMC by Tejas et al. in 2014[11] in order to forecast different surface roughness responses and MRR and found that responses were improved in comparison to the first test runs, according to researchers from the report. Moi et al. 2019 [7] used parametric analysis to keep track of the processing variables in order to maximize output response when TIG welding stainless steel utilizing RSM and TLBO.

The current study aims to evaluate the influence of milling parameters on the surface roughness and MRR of the VMC five-axis machined EN47 steel component. The outcomes of machining factors have been determined through the use of RSM in milling investigations. ANOVA is used to investigate and evaluate the significance of milling production parameters for improved surface finish and MRR. To improve milling economics, RSM and multi-objective TLBO technique also use simulation and optimization.

II. Approaches to Analysis and Optimization

A. *Response surface methodology*

The Response Surface Methodology (RSM) is a compilation of computational and mathematical techniques for generating empirical models [14]. By meticulously organizing the experiment, the goal to maximize the responses (output variables) that are influenced by a number of independent variables (input variables) can be achieved where, the input variables are altered to examine the degree to which the output responses change. The best way for analyzing the results of factorial research is the response surface method and is an essential component for modelling and analyzing the output problems. It provides more information while using fewer investigative numbers. It is a research approach for measuring the constraints of the input information and the emerging experiential statistical model for the analyzed response by approximating the association among the response and the parameters of the input process. The surface response methodology involves a process parameter limit to be established, and a preliminary test carried out to determine the milling factors that affect surface roughness and MRR, as well as to demonstrate the spectrum of cutting factors chosen. [15] Eq.1 represents the complete quadratic relationship between the output response and the input parameters in RSM.

$$Y = \beta_0 + \beta_1 (A) + \beta_2 (B) + \beta_3 (C) + \beta_{11} (A * A) + \beta_{22} (B * B) + \beta_{33} (C * C) + \beta_{12} (A * B) + \beta_{13} (A * C) + \beta_{23} (B * C) \quad (1)$$

Where Y is the output response, A, B, and C represent the process variables, and β's are input parameter coefficients.

B. *Teaching-learning-based Optimization (TLBO)*

Teaching-learning-based optimisation (TLBO) is a stochastic optimisation methodology that imitate the teaching-learning method proposed by Rao et al.[16]. The operation of TLBO is given below.

Teacher stage: The teacher teaches from the learners in the first step of the algorithm. At this step, a teacher's purpose is to elevate the average classroom outcome from any M1 value to its level (i.e. TA). Eqs.2 explains how to keep students' knowledge up to date.

$$Difference\ \_\ Mean_i = r_i\,(M_{new} - M_j) \quad (2)$$

Based on this Difference_Mean, the existing solution is updated by using Eq. 3.

$$X_{new,i} = X_{old,i} + Difference\ \_\ Mean_i \quad (3)$$

Where, $X_{new,\,i}$= new solution; $X_{Old,\,i}$ = existing solution / solution in the i^{th} iteration.

Learner stage: The learner stage is the second component of the TLBO algorithm. Eqs. 4 and 5 empirically define the learner's process learning phenomena. Taking into account two distinct X_i and X_j learners at any iteration I, where $i \neq j$.

$$X_{new,i} = X_{old,\,i} + r_i\,(X_i - X_j) \qquad \text{if } f(X_i) < f(X_j) \quad (4)$$

$$X_{new,i} = X_{old,i} + r_i\,(X_j - X_i) \qquad \text{if } f(X_j) < f(X_i) \quad (5)$$

Consider X_{new} if it provides a superior function value. where X_i and X_j are two independent learners in the class who have distinct knowledge levels and are engaging with one another in order to enhance their knowledge levels.

III. Experimental Procedure

The Box-Behnken design based on RSM was employed to design the experiments using DOC(A), cutting speed (B), and feed (C) as input control parameters for VMC-five-axis machining of EN47 steel component. Table 1 displays the specified milling settings and their varying levels. Table 2 shows the Box-Behnken experimental design. Figure 1 depicts the experimental setup. MRR is calculated and displayed in Table 2. The experimental data for surface roughness and MRR for EN47 steel materials is utilised to analyse, simulate, and optimise the control parameters of the VMC-5-axis machine using ANOVA, RSM, and MTLBO.

Table I
Input control parameters and their levels

Properties / Bed Material	Units	Level-1	Level-2	Level-3
Depth of cut (A)	mm	0.1	0.15	0.2
Speed (B)	rpm	3000	3500	4000
Feed (C)	rev/min	1500	2000	2500

Table II
Box-Behnken experimental design and results

Sr.	Input Parameters			Output Responses	
	A	B	C	SR	MRR
1	0.10	3000	2000	2.028	4.692
2	0.15	3500	2000	2.933	5.517
3	0.15	4000	2500	2.635	5.926
4	0.15	4000	1500	3.251	5.372
5	0.10	4000	2000	3.843	3.842
6	0.20	3000	2000	3.323	6.500
7	0.20	3500	1500	3.611	7.328
8	0.15	3500	2000	2.933	5.517
9	0.20	4000	2000	1.890	7.500
10	0.10	3500	1500	1.686	5.361
11	0.20	3500	2500	1.989	8.434
12	0.10	3500	2500	5.211	3.965
13	0.15	3500	2000	2.933	5.517
14	0.15	3000	2500	3.038	5.878
15	0.15	3000	1500	2.087	5.330

IV. Results and analysis

Surface roughness (Ra) and MRR of EN47 steel material are the focus of the current research, which aims to investigate the significance of VMC processing factors. Using the statistical techniques of ANOVA and RSM, the data presented in Table 2 were utilized to model, assess, and interpret the Ra and MRR. Creating contour plots allows us to visualize the combined effects of milling parameters on both performance indicators. After that, both responses' mathematical models were solved using multi-objective TLBO.

A. Variance Analysis for surface roughness and MRR

The experimental results shown in Table 2 are subjected to analysis of variance (ANOVA) utilising the MINITAB 16.2 programme to determine the important control variables that have an adverse effect on surface roughness and MRR. Tables 3 and 4 for surface roughness and MRR, respectively, show the ANOVA results. At a 95% confidence level, or 5% significant level, the ANOVA test is conducted. Probability (P) values under 0.05 are indicative of major impacts of process variables on corresponding responses [2].

According to Table 3's ANOVA results for surface roughness (Ra), the direct influence of feed (C) has a significant impact on surface roughness because its P value is below 0.05. As can be seen from Table 3's process parameters, speed (B) has little bearing on Ra whereas depth of cut (A) has a large impact on surface roughness due to its P value being so near to 0.05.

Table III

Variance analysis for SR of VMC-five axis machined EN47 steel's

Source	DF	Adj SS	Adj MS	F Value	P Value	Adj SS	Adj MS	F Value	P Value
Model	09	6.17726	0.68636	025.78	0.001	2.68712	0.29857	0.001	035.47
Linear	03	1.31761	0.43920	016.50	0.005	2.01334	0.67111	0.000	079.73
A	01	1.09150	1.09150	040.99	0.001	0.06808	0.06808	0.036	008.09
B	01	0.02195	0.02195	000.82	0.406	0.20801	0.20801	0.004	024.71
C	01	0.20416	0.20416	007.67	0.039	1.73725	1.73725	0.000	206.39
Square	03	4.10702	1.36901	051.42	0.000	0.44698	0.14899	0.004	017.70
A * A	01	0.01491	0.01491	000.56	0.488	0.32927	0.32927	0.002	039.12
B * B	01	3.27323	3.27323	122.94	0.000	0.02691	0.02691	0.134	003.20
C * C	01	1.09386	1.09386	041.08	0.001	0.09000	0.09000	0.022	010.69
2-Way Interaction	03	0.75264	0.25088	009.42	0.017	0.22680	0.07560	0.019	008.98
A * B	01	0.62489	0.62489	023.47	0.005	0.00366	0.00366	0.539	000.43
A * C	01	0.08066	0.08066	003.03	0.142	0.11391	0.11391	0.014	013.53
B * C	01	0.04709	0.04709	001.77	0.241	0.10923	0.10923	0.016	012.98
Error	05	0.13313	0.02663			0.04209	0.00842		
Lack of Fit	03	0.12646	0.04215	012.65	0.074	0.04209	0.01403	*	*
Pure error	02	0.00667	0.00333			0.00000	0.00000		
Total	14	6.31039				2.72920			

B. Surface roughness (Ra) and MRR mathematical modelling

To construct the second-order mathematical correlations among the VMC-5-axis process variables: depth of cut (A), speed of cutting (B) and feed (C), and output response surface roughness (Ra) and MRR, RSM from MINITAB 19 software has been used to experimental data as presented in Table 2. For this objective, the fundamental mathematical model shown in Eq. 1 will be used. Using least squares calculations, the constant beta values were determined from the experimental data, and the resulting mathematical models for surface roughness and MRR are presented in Eqs. 6 and 7.

C. Processing variables' influence on SR and MRR

RSM applied contour plots are generated to investigate the effects of various milling input variables, including DOC (A), speed (B), and feed (C), on Ra and MRR. By using the RSM application from the MINITAB 19 software, contour plots have been generated from the proposed mathematical models of Ra and MRR. The contour plots in Fig. 2 (a)–(c) indicate how input factors have an impact on Ra, and Fig. 3 (a)–(c) illustrates the effect of input factors on MRR. It is clear from the surface roughness (Ra) contour plots shown in Figs. 2(a)–(c) that the milling variables DOC(A), speed(B), and feed(C) have a significant impact on Ra as seen by the curvature/bent lines found in said contour plots. Minimum surface roughness (Ra) can be obtained using parametric parameters from the dark red colour region in a contour plot (Fig. 2(a)-(c)). According to Fig. 2 (a), optimum SR is attained at lower levels of all input variables when milling variables are kept at lower levels.

According to the contour plots of MRR displayed in Fig. 3(a)–(c), it can be seen that milling input variables are the most important for MRR since the plots' elliptical form and curvature lines are evident. In a contour plot [Fig. 3(a)-(c)], parametric combinations falling from dark purple colour zones can yield maximised MRR values. According to the MRR contour plots for EN47 steel, milling conditions at level 3 while using higher levels (i.e. level 3) of all input parameters can produce the highest MRR values. The input parameter ranges where the response is at its best may be revealed using contour plots. However, these graphs are not helpful in determining the precise value of the ideal conditions for the input parameters and output responses. Ra and MRR responses are optimised using MTLBO in a research study.

D. Employing multi-TLBOs for multi-objective optimisation

Surface roughness and MRR mathematical models are solved using multi-TLBO. The following is how TLBO operates and is put into action [Rudrapati et al 2016]:

1. Setting up the design parameters and size of population for the optimisation problem using random generation.
2. Determining the mean result for learners in each subject and selecting the topic's best learner to serve as that subject's teacher.
3. Comparing the present mean result to the best possible mean result.
4. Using teachers to assist learners update their knowledge.
5. Making use of the knowledge of another learner to enrich the learners' knowledge.
6. Repetition of steps B through E until the termination criterion is reached.

Optimal parametric conditions and the corresponding output response value are generated in each of the MTLBO runs. Table 5 displays the ideal parametric condition that MTLBO determined for simultaneously optimising surface roughness and MRR.

TABLE IV

OPTIMUM PARAMETRIC COMBINATION BY MTLBO.

S. No	Optimum Input Parameters		Optimized Responses
1	Depth of cut (A)	0000.10 mm	Ra = 3.27 micron MRR = 8.32 mm^3/min
2	Speed (B)	3636.36 rpm	
3	feed (C)	2500.00 rev/min	

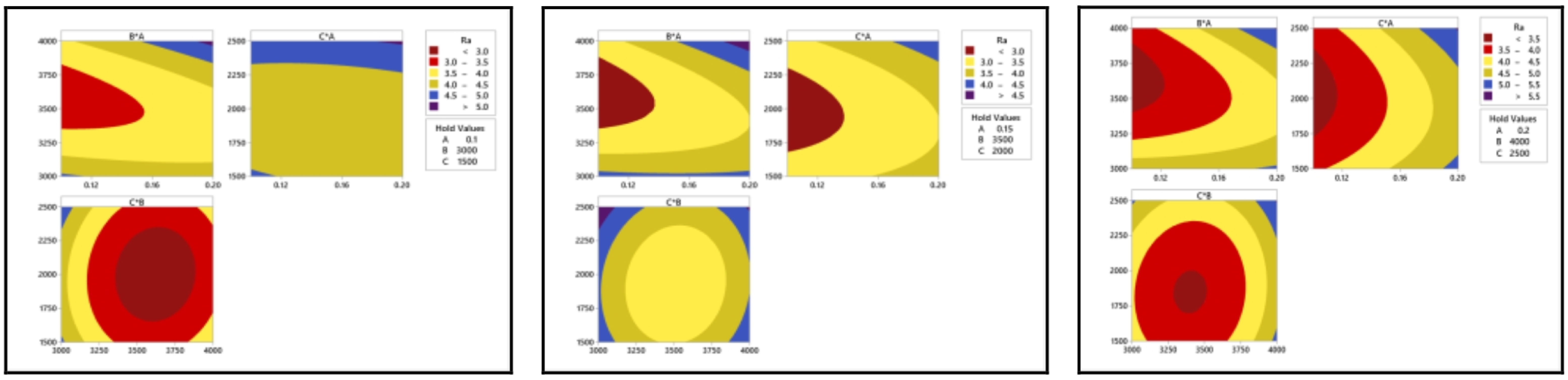

Fig. 1 Contour plots showing the process parameters effects on SR of EN47 steel by keeping the input parameters at a) level 1, b) level 2 and c) level 3.

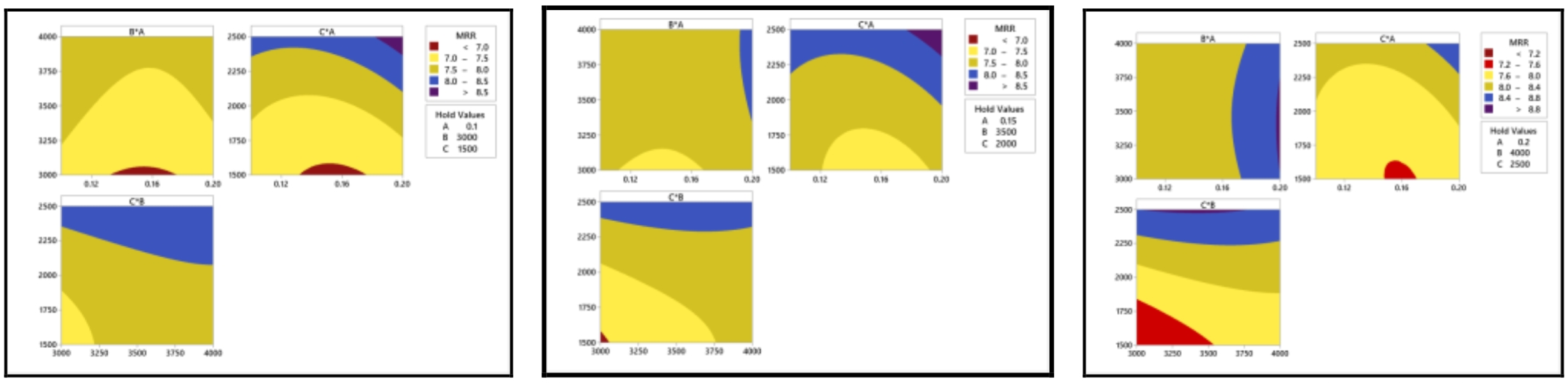

Fig. 3 Contour plots showing the process parameters effects on MRR of EN47 steel by keeping the input parameters at a) level 1, b) level 2 and c) level 3.

E. Confirmatory findings

The anticipated milling combination to optimise both the response measures of VMC five axis machined EN47 steel was confirmed by laboratory experiments. Confirmatory outcomes, as given in Table 2, imply that the predicted setup is in good agreement with the initial tests conducted.

V. CONCLUSION:

The conclusions from the current investigation of surface roughness and MRR in VMC-5-axis machined EN47 steel material using integrated RSM and MTLBO for the prediction of multiple responses:

The ANOVA findings for

- Surface roughness show that all input milling parameters, including feed, interact significantly to affect R_a
- The depth of cut, square combinations of depth of cut*depth of cut, feed*feed, and interactions of depth of cut*speed, speed*feed are significant factors in MRR
- Contour plots, milling conditions are the most important factor for both responses (R_a and MRR)
- The anticipated condition and the initial test run have a good association in confirmatory tests.
- According to the study, RSM and MTLBO are helpful for modelling, predicting, and analyzing multi-performance characteristics in VMC five axis machining when EN47 tool steel is used.

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