Research Article

Application of Taguchi approach and Utility Concept in solving the Multi-objective Problem when turning AISI 202 Austenitic Stainless Steel

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Abstract

The traditional Taguchi method is widely used for optimizing the process parameters of a single response problem. Optimization of a single response results the non-optimum values for remaining. But, the performance of the manufactured products is often evaluated by several quality characteristics/responses. Under such circumstances, multi-characteristics response optimization may be the solution to optimize multi-responses simultaneously. In the present work, a multi-characteristics response optimization model based on Taguchi and Utility concept is used to optimize process parameters, such as speed, feed, depth of cut, and nose radius on multiple performance characteristics, namely, surface roughness (Ra) and material removal rate (MRR) during turning of AISI 202 austenitic stainless steel using a CVD coated cemented carbide tool. Taguchi's L8 orthogonal array (OA) is selected for experimental planning. The experimental result analysis showed that the combination of higher levels of cutting speed, depth of cut, and nose radius and lower level of feed is essential to achieve simultaneous maximization of material removal rate and minimization of surface roughness. The ANOVA and F-tests are used to analyze the results. Further, the confirmation tests are conducted and the results are found to be within the confidence interval.

Keywords: Multi response Optimization, Taguchi method, Utility concept, austenitic stainless steel, CVD coated carbide tool, Surface roughness & MRR.

1. Introduction

Surface roughness has become the most significant technical requirement and it is an index of product quality. In order to improve the tribological properties, fatigue strength, corrosion resistance and aesthetic appeal of the product, a reasonably good surface finish is desired. Nowadays, the manufacturing industries specially are focusing their attention on dimensional accuracy and surface finish. In order to obtain optimal cutting parameters to achieve the best possible surface finish, manufacturing industries have resorted to the use of handbook based information and operators' experience. This traditional practice leads to improper surface finish and decrease in the productivity due to sub-optimal use of machining capability. This causes high manufacturing cost and low product quality [1].

In addition to the surface finish quality, the material removal rate (MRR) is also an important characteristic in turning operation and high MRR is always desirable [22]. Hence, there is a need to optimize the process parameters in a systematic way to achieve the output characteristics/responses by using experimental methods and stastical models. Dr. Taguchi employed design

of experiments (DOE),which is one of the most important and efficient tools of total quality management (TQM) for designing high quality systems at reduced cost. Taguchi emphasizes on the fact that Quality provides robustness and immune to the uncontrollable factors in the manufacturing state. This approach helps to reduce the large number of experimental trials when the number of process parameters increases. Most of the works have been published so far focused on single response performance characteristic optimization by using Taguchi approach [3], [8], [9], [10], [16], [17], [23]. But the Taguchi approach is designed for optimizing the single response problems. It is not fit for optimizing the multi-response problems [20]. Optimization of a single response results the non-optimum values for remaining responses. In solving many problems in engineering, it is necessary to consider the application of multi-response optimization, because the performance of the manufactured products is often evaluated by several quality characteristics/responses. Though the Taguchi approach is used for a single response problem, most of the researchers proposed various methods for multi-response problem by modifying it [22]. Some of the researchers has been efficiently utilized the Taguchi method

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and utility concept for multi-response optimization for various processes such as face milling [12], gas tungsten arc welding [19], magnetic-field-assisted abrasive flow machining [18], V-process casting [5], electro-chemical honing [2], thermoforming process of polymeric foams [7], turning of Free-machining [22]. AISI 202 austenitic stainless steel finds its application in general industrial and process-industry machinery and equipment, electrical machinery/equipment, automotive industry, Structural, bus body etc., [11]. But, it is found that no work has been reported in the literature on multi-response optimization of surface roughness and material removal rate in turning of AISI 202 austenitic stainless steel. In the present investigation, a multi characteristics optimization model based on Taguchi method and utility concept has been employed to determine the best combination of the machining parameters such as cutting speed, feed, depth of cut and nose radius to attain the minimum surface roughness and maximum MRR simultaneously. The predictive models obtained for performance measures. Confirmation tests are also conducted to verify the results.

2. Materials and Methods

2.1 Work piece material

The work piece material used for present work was AISI 202 austenitic stainless steel. There are two types of austenitic stainless steel: 300-series and 200-series. Most stainless steel used around the world is of the 300-series type. The 200 series stainless steels have become popular in the Asian continent, particularly as an alternative to 300 series in view of increase in nickel prices. The 200 series are non-magnetic and austenitic. Hence, it is very difficult to distinguish from widely used 300 series of stainless steel, which are also non-magnetic. One such family of stainless steels is the 200-series. The 200-series are a technically valid family of stainless steels but, like all stainless steel they have their limitations [4]. The chemical composition of AISI 202 is given in Table 1.

Table 1. Chemical composition (wt %) of AISI 202.

Cr %	Ni %	Mn%	N%
17.0	4.0	7.5	0.25

2.2 Cutting inserts and cutting conditions

Coated carbide tools have shown better performance when compared to the uncoated carbide tools [14]. For this reason, commonly available Chemical Vapor Deposition (CVD) of Ti (C, N) +Al_2O_3 coated cemented carbide inserts of 0.8 and 0.4mm as nose radius are used in the present experimental investigation. The Process parameters and levels used in the experiment, experimental set up and conditions are given in the Tables 2 and 3.

Table 2. Experimental set up and conditions.

Machine tool:	ACE Designer LT-16XL CNC lathe, 7.5 kW (10 hp) and 4000 rpm, India
Work specimen Material:	AISI 202 austenitic stainless steel

Size:	Φ25 mm x 70mm
Cutting t inserts:	CNMG 120408, CNMG 120404 (SECO make)
Tool material:	CVD coated cemented carbide (TP-2500)
Tool holder:	PCLNL 252570012 (ISO specification)
Tool holder:	Dry machining

Table 3. Process parameters and levels used in the experiment.

Code	Process parameters	Level 1	Level 2
A	Cutting speed (m/min)	111	200
B	Depth of cut (mm)	0.25	0.75
C	Feed (mm/rev.)	0.15	0.25
D	Nose radius (mm)	0.4	0.8

2.3 Experimental procedure

Turning is a popularly used machining process. The CNC machines play a major role in modern machining industry to enhance product quality as well as productivity [21]. In the present work, two levels, four factors and eight experiments are identified. Appropriate selection of orthogonal array is the first step of Taguchi approach. The minimum number of experimental trails required in orthogonal array is given by N_{min}= (L-1) F + 1; Where F= no. of factors= 4, L= no. of levels=2, N_{min}= 5; According to Taguchi approach L8 has been selected. Cutting tests were carried out on 10 hp CNC lathe machine under dry conditions. The machining process on CNC lathe is programmed by speed, feed, and depth of cut. In total 8 work pieces are prepared. These work pieces are cleaned prior to the experiments by removing 0.5mm thickness of the top surface from each work piece in order to eliminate any surface defects and wobbling. Two different nose radii of CVD coated inserts have been taken to study the effect of tool geometry. The rough nesses of machined surfaces are measured by a Mitutoyo SJ-201 surface roughness tester and measurements are repeated 3 times. The experimental design and results are given in Table 4.

Table 4. L8 orthogonal array with the responses.

Levels				Responses	
A	B	C	D	Ra	MRR (cm³/min)
1	1	1	1	1.32	4.162
1	1	2	2	1.56	6.937
1	2	1	2	0.813	12.487
1	2	2	1	2.736	20.812
2	1	1	2	0.7	7.5
2	1	2	1	1.713	12.5
2	2	1	1	1.3	22.5
2	2	2	2	1.683	37.5

Methodology:

Taguchi Approach
The reason why Design of experiment (DOE) is selected rather

than the other approaches to conduct experiment is that it has a systematic planning of experiments. Taguchi technique for DOE has been the most widely used technique for the last two decades. One of the important steps involved in Taguchi's technique is selection of orthogonal array (OA).Which will further help to conduct experiments to determine the optimum level for each process parameters and establish the relative importance of individual process parameters. An OA is a small set from all possibilities which helps to determine least no.of experiments. To obtain optimum process parameters setting, Taguchi proposed a statistical measure of performance called signal to noise ratio [15]. This ratio considers both the mean and the variability. In addition to S/N ratio, ANOVA is used to indicate the influence of process parameters on performance measures.

Utility Concept

Quality is a key attribute that customers use to evaluate product or services. So the modern quality control and improvement programs have to make their products more acceptable by the customers. On the other hand, customer evaluates a product performance based on a number of diverse qualitative characteristics. To improve the rational decision making, the evaluations of various attributes should be combined to give a composite index. Such a composite index is known as utility of a product. The sum of utilities of each quality attribute represents the overall utility of a product. It is difficult to obtain the best combination of process parameters, when there are multi-responses to be optimized. The adoption of weights in the utility concept help in this difficult situations by differentiating the relative importance of various responses [5]. If x_i represents the measure of effectiveness of i th process response characteristic and n represents no. of responses, then the overall utility function can be written as [6]:

$$U(x_1, x_2 \dots x_n) = f\left[U_1(x_1), U_2(x_2),\dots\dots U_n(x_n)\right];$$

where $U(x_1, x_2 \dots x_n)$ is the overall utility of n process response characteristics and $U_i(x_i)$ is utility of i th response characteristic. Assignment of weights is based on the requirements and priorities among the various responses. Therefore the general form or weighted from of Eq.(1) can be expressed as

$$U(x_1, x_2 \dots x_n) = \sum_{i=1}^{n} W_i U_i(x_i)$$

Where $\sum_{i=1}^{n} W_i = 1$, Where W_i is the weight assigned to the i th response characteristic.

3. Results and Analysis

The objective of the present work is to minimize surface roughness and maximize the MRR in turning process optimization. The following equation is used to calculate MRR,

$$MRR = f\,v\,d \ (cm^3/min)$$

Where f is feed rate in mm/rev, v is cutting speed in m/min, d is depth of cut in mm. Taguchi technique uses S/N ratio as a performance measure to choose control levels. The S/N ratio considers both the mean and the variability. In the present work, a multi-response methodology based on Taguchi technique and Utility concept is used for optimizing the multi-responses (Ra and MRR). Taguchi proposed many different possible S/N ratios to obtain the optimum parameters setting [15]. Two of them are selected for the present work. Those are, Smaller the better type S/N ratio for Ra,

$$\left[\eta_1\right] = -10\log_{10}\left[R_a^2\right];$$

Larger the better S/N ratio for MRR

$$\left[\eta_2\right] = -10\log_{10}\left[\frac{1}{MRR^2}\right]$$

From the utility concept, the multi-response S/N ratio of the overall utility value is given by

$$\eta_{obs} = W_1\eta_1 + W_2\eta_2 \tag{1}$$

Where W_1 & W_2 are the weights assigned to the Ra and MRR. Assignment of weights to the performance characteristics are based on experience of engineers, customer's requirements and their priorities. In the present work equal importance is given for both Ra and MRR. Therefore W_1 & $W_2 = 0.5$.

Determination of optimal range for Surface roughness and MRR at single response stage:

Performance of Ra at the optimum conditions (based on estimated average)

$$\bar{\mu}_{C_1 D_2} = \bar{C}_1 + \bar{D}_2 - \bar{T}$$
$$= 1.033 + 1.189 - 1.478$$
$$= 0.7$$

(From Table 4, $\bar{T} = 1.478$)

$$CI = \sqrt{\frac{F_{95\%,1,dof_{error}} * V_{error}}{n_{efficiency}}}$$

Where $\eta_{efficiency}$ = N/1+dof of all parameters associated to that level,

$$n_{efficiency} = \frac{8}{1+1+1} = 2.666$$

$V_{error} = 0.072$ (from Table 7), $F_{95\%,1,3} = 10.1$

$$CI = \sqrt{10.1 * 0.0720/2.66} = \sqrt{0.27338}$$
$$= \mathbf{0.523}$$

The predicted optimal range at 95% confidence level is obtained as,

$$0.744 - 0.523 \leq \bar{\mu}_{C_1 D_2} \leq 0.744 + 0.523$$
$$0.221 \leq \bar{\mu}_{C_1 D_2} \leq 1.267$$

Performance of MRR at the optimum conditions (based on estimated average)

$$\bar{\mu}_{B_2 A_2} = \bar{B}_2 + \bar{A}_2 - \bar{T}$$

$$= 23.325 + 20.00 - 15.55$$
$$= 27.775$$

(From Table 4, $\bar{T}$=15.55)

$$n_{efficiency} = \frac{8}{1+1+1} = 2.666$$

V_{error}=26.577 (from Table 8), $F_{95\%,1,3}$=10.1

$$CI = \sqrt{10.1 * 26.577 \ / 2.66} = \sqrt{100.9126}$$

$$= \mathbf{10.045}$$

The predicted optimal range at 95% confidence level is obtained as,

$$27.775 - 10.045 \leq \bar{\mu}_{B_2 A_2} \leq 27.775 + 10.045$$

$$17.73 \leq \bar{\mu}_{B_2 A_2} \leq 37.82$$

Analysis of Single response stage

The optimal settings and the predicted optimal values for surface roughness and MRR are determined individually by Taguchi's approach. Table 6 shows these individual optimal values and its corresponding settings of the process parameters for the specified performance characteristics. Further, the ANOVA is used to determine the optimum combination of process parameters more accurately by investigating the relative importance of process parameters [12].Tables 7 & 8 reveal the results of ANOVA for Ra and MRR respectively. It is observed that the feed (61.428%) is most significantly influences the Ra followed by nose radius (25.96%). In case of MRR, depth of cut (63.183%) is the most significant parameter followed by cutting speed (20.697%). In both the cases, error contribution (0.0838%) and (0.104%) reveals that the interaction effect of the process parameters is negligible.

Table 5. Means of Surface roughness and MRR at different levels.

	Mean values of Ra (µm)				Mean values of MRR (cm³/min)			
Level/process parameters	A	B	C	D	A	B	C	D
1	1.607	1.323	1.033	1.767	11.100	7.775	11.663	14.994
2	1.349	1.633	1.923	1.189	20.00	23.325	19.438	16.106

Table 6. Individual optimal values and its corresponding settings of the process parameters.

Performance Characteristics	Optimum parameter level	Predicted optimal level
Surface roughness	A2-B1-C1-D2	0.46 µm
Material removal rate	A2-B2-C2-D2	31.05 cm³/min

Table 7. ANOVA results for Surface roughness (Ra).

Source	SS	DOF	MS	F	C (%)
A	0.133	1	0.133	1.847	5.161
B	0.192	1	0.192	2.666	7.450
C	1.583	1	1.583	21.986	61.428
D	0.669	1	0.669	9.291	25.960
Error	0.216	3	0.072		0.0838
Total	2.577	7			

Table 8. ANOVA results for material removal rate (MRR).

Source	SS	DOF	MS	F	C (%)
A	158.420	1	158.420	5.960	20.697
B	483.605	1	483.605	18.196	63.183
C	120.901	1	120.901	4.549	15.795
D	2.475	1	2.475	0.093	0.323
Error	79.732	3	26.577		0.104
Total	765.401	7			

Analysis of Multi- response stage

The optimal combination of process parameters (A2-B2-C1-D2) for simultaneous optimization of Surface roughness (Ra) and material removal rate (MRR) is obtained by the mean values of the multi-response S/N ratio of the overall utility value are shown in Table 10. According to the Table 11 for the results of ANOVA multiple performance characteristics, depth of cut (54.439%) is the most significant parameter affecting the performance followed by the cutting speed (33.442%).The percent contribution of the nose radius (11.169%) is lower and the feed is much lower, being 0.948%. The error contribution (1.973%) reveals that the interaction effect of the process parameters is negligible.

Table 9. L8 OA with multi-response S/N ratios.

Levels				S/N ratio(dB)		
A	B	C	D	η_1 for Ra	η_2 for MRR	η_{obs}
1	1	1	1	-2.41148	12.38708	4.987803
1	1	2	2	-3.86249	16.82406	6.480784
1	2	1	2	1.798189	21.92951	11.86385
1	2	2	1	-8.74232	26.36649	8.812082
2	1	1	2	3.098039	17.50123	10.29963
2	1	2	1	-4.67515	21.9382	8.631527
2	2	1	1	-2.27887	27.04365	12.38239
2	2	2	2	-4.52168	31.48063	13.47947

Table 10. Means of η_{obs} at different levels.

	Mean values of η_{obs}			
Level / Process parameters	A	B	C	D
1	8.036	7.6	9.883	8.703
2	11.198	11.634	9.351	10.531

Table 11. ANOVA results for multi-response case.

Source	SS	DOF	MS	F	C (%)
A	19.998	1	19.998	50.842	33.442
B	32.554	1	32.554	82.752	54.439
C	0.5670	1	0.5670	1.441	0.948
D	6.679	1	6.679	16.978	11.169
Error	1.18	3	0.3933		1.973
Total	59.798	7			

Interpretation of plots

The data is given in Tables 4-7 and plots are developed with the help of a software package MINITAB 14. These results are analyzed using ANOVA for the purpose of identifying the significant factors, which affect the surface roughness and material removal rate. The above plots show the variation of individual response with the four parameters i.e. cutting speed, feed, depth of cut and nose radius separately. In the plots, the x-axis indicates the value of each process parameter at two level and y-axis the response value. Horizontal line indicates the mean value of the response. Figure 1 shows the main effect plot for surface roughness. The results show that with the increase in cutting speed and the nose radius there is an increment in Ra value. The feed and the depth of cut are directly proportional to the corresponding Ra values. Figure 2 shows the main effect plot for MRR. It is observed that the maximum MRR is obtained at the 200m/min of cutting speed, 0.25mm/rev of feed and 0.75mm depth of cut. The flat line almost shows that there is a little effect due to nose radius. Figure 3 shows the optimum levels of process parameters for the multi-response optimization are thus determined to be A2-B2-C1-D2. Figure 4 illustrates the interaction effects of process parameters for the multi-response optimization. It is observed that the lines are parallel to each other in the plots. If the lines are parallel and not overlapping then there is little or no evidence of an interaction in the parameters. There is less interaction effect between the feed and nose radius.

Table 12. Comparison of Results.

	Performance characteristics	Optimal setting level	Predicted optimal values	95% Confidence interval (CICE)	Actual confirmation experiment values
Single-response optimization	Ra	A2-B1-C1-D2	0.46 µm	$0.221 \leq \bar{\mu}_{C_1D_2} \leq 1.267$	0.693µm
	MRR	A2-B2-C2-D2	31.05 cm³/min	$17.73 \leq \bar{\mu}_{B_2A_2} \leq 37.82$	37.5 cm³/min
Multi-response optimization	Ra, MRR	A2-B2-C1-D2	14.395dB	$11.167 \leq \bar{\mu}_{B_2A_2} \leq 15.262$	12.88dB

Optimality Confirmation:

Once the optimal level is selected, the next step is to predict and verify the improvement of the value of multiple responses of AISI202.The predicted optimal value (η_{opt}) can be calculated by means of additive law.

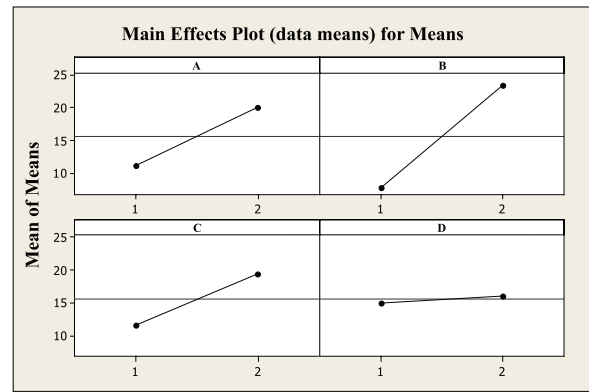$$\eta_{opt} = m + \sum_{j=1}^{n} [(m_{i,j})_{max} - m]$$
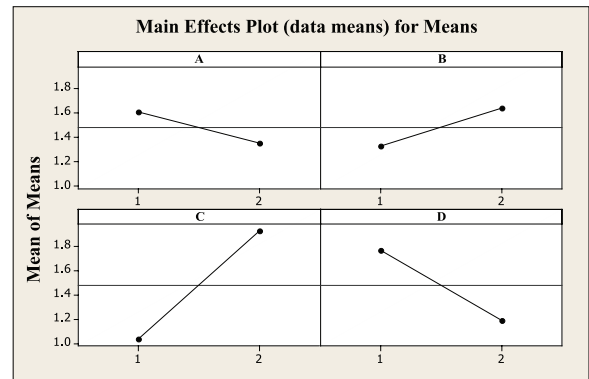

Figure 1. Main effect plot for Ra

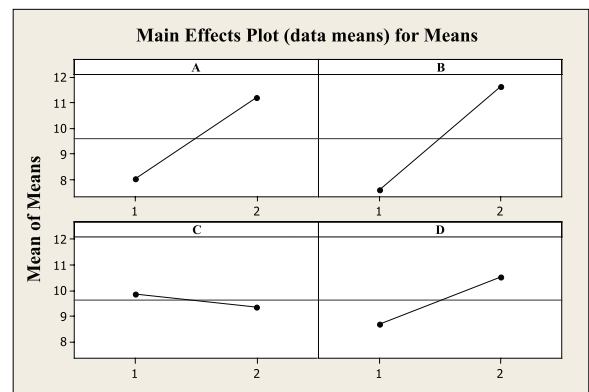**Figure 2.** Main effect plot for MRR

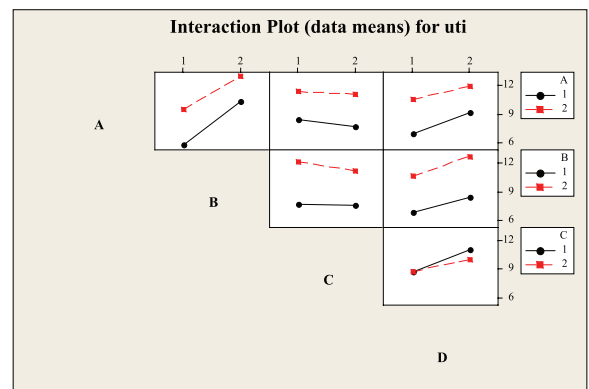**Figure 3.** Main effects plot for Multi-response S/N ratio

Figure 4. Interaction plot for Multi-response

Where m= overall mean of η with eight trials; $(m_{ij})_{max}$= S/N ratio at optimal level and parameter; n is the number of main designing parameters that affect the machining process. The predicted optimal S/N ratio of multiple responses ($η_{opt}$) for the optimum parameter levels (A2-B2-C1-D2) is 14.395 dB. In order to validate, the experiment (two trials) is conducted according to the optimal parameters levels (A2-B2-C1-D2) and the corresponding values of performance measures are taken. The average value of surface roughness is 1.159μm and the calculated value of MRR is 22.5cm³/min. The multi-response S/N ratio of overall utility value ($η_{obs}$) obtained by using Eq.[1] is 12.880dB. The confidence interval (at 95%) value of $η_{opt}$ for the predicted mean on a confirmation experiment run can be computed using the following equation.

$$CI = \sqrt{F_{95\%,1,dof_{error}} * V_{error}\left(\frac{1}{n_{efficiency}}+\frac{1}{R}\right)}$$
$$= \pm 2.0476$$

$F_{95\%,1,dof_{error}}$ =F value at 95% confidence level = 10.1;

V_{error} =0.3933 (from Table 11)

$n_{efficiency} = \frac{N}{1+d} = \frac{9}{1+4} = 1.8;$

d=Total degree of freedom in associated with process parameters. R= Trial number for confirmation test =2.

$$\bar{\mu}_{B_2A_2} = \bar{B}_2 + \bar{A}_2 - \bar{T}$$
$$=11.634+11.198 - 9.6171$$
$$=13.215$$
(From Table 9, $\bar{T}$ =9.6171)

The predicted optimal range for optimal multi-respsponse S/N ratio at 95% confidence level is obtained as,

$13.215 - 2.0476 < \mu_{B_2A_2} < 13.215 + 2.0476$

$$11.167 < \mu_{B_2A_2} < 15.262$$
The prediction error = $η_{opt} - η_{obs.}$
$$=14.395 - 12.88$$
$$=1.515dB$$

From the above relation, the prediction error is within the respective CI (at 95%) value of ±2.0476dB. Hence, it is observed that from the results of confirmation test, the adequacy of the additivity law model is justified and the results are validated.

4. Conclusions

The present work is concerned with exploring to determine the optimum setting of process parameters for multi-response optimization during turning of AISI 202 austenitic stainless steel using CVD coated carbide insert. On the basis of Taguchi approach and Utility concept, a model was developed to achieve this. The L8 OA was used for experimental planning. In first stage (single-response), optimal settings and optimal values of Ra and MRR were obtained individually. And from their corresponding ANOVA results, the feed (61.428%) is the most significant parameter followed by cutting speed (20.697%) for Ra, the depth of cut (63.183%) is the most significant parameter followed by cutting speed (20.697%) for MRR response. In second stage (multi-response), the analysis of means establishes that a combination of higher levels of cutting speed, depth of cut, nose radius and lower level of feed is necessary for obtaining the optimal value of multiple performances. Based on the ANOVA and F-test analysis, the most statistical significant and percent contribution of the process parameters for multiple performances are depth of cut, cutting speed, whereas feed and nose radius are less effective. In both the stages the interaction effect of process parameters is negligible. Table12 shows the results comparison. The validation experiment confirmed that the adequacy of law of additivity is justified. It is found that the proposed model based on Taguchi approach and Utility concept is simple, useful and provides an appropriate solution for multi-response optimization problems.

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