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Multi-response optimization in dry turning process using Taguchi's approach and utility concept

Yogendra Kumar[a]*, Hari Singh[b]

[a]M.Tech. Scholar,Mechanical Engineering, National Institute of Technology, Kurukshetra 136119, India
[b]Mechanical Engineering Department, National Institute of Technology, Kurukshetra 136119, India

Abstract

Taguchi's technique is used for optimizing the process parameters of a single response problem. A single setting of process parameters may be optimal for single quality characteristic but the same settings may yield detrimental results for other quality features. Under such circumstances, multi-characteristics response optimization may be the solution to optimize multi-responses simultaneously. In this case study, a multi-characteristics response optimization based on Taguchi's design of approach and utility concept is used to optimize multiple performance characteristics, namely, axial force, radial force, main cutting force and material removal rate (MRR) during dry turning of EN-47 steel. Taguchi's L-18 orthogonal array is selected for the experiment. The optimal values obtained using the multi-characteristics optimization model have been validated by confirmation experiments.

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Keywords: EN-47 Spring steel; carbide cutting tool; Taguchi approach; Utility concept; cutting force; MRR.

1. Introduction

The Taguchi's approach for determining the optimal settings of controllable parameters through offline experiments focuses on products with a single quality characteristic. But most of the products have several quality features of interests. A single setting of process parameters may be optimal for one response but the same settings may yield detrimental results for other responses. In solving many problems in engineering, it is necessary to consider the application of multi-response optimization, because the performance/quality of products is often evaluated by several quality characteristics/responses. In such cases, a need arises to obtain an optimal setting of the

*Corresponding author. Tel.: +91 999 6402670,
E-mail address: yogendrakumardwivedi860@gmail.com

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Process parameters so that the product can be produced with optimum or near optimum responses. This problem has been investigated by researchers who developed approaches for products with multiple characteristics.

Different researchers have used a number of techniques for optimizing multiple quality characteristics of the products. Surinder et al. (2013) presents a case study for optimizing multi-response in turning process using Taguchi's design approach in conjunction with utility concept for GFRP composite material with the help of carbide (K10) cutting tool. The process parameters selected for this study were tool nose radius, tool rake angle, feed rate, cutting speed, depth of cut and cutting environment for optimization with considerations of the performance characteristics, including surface roughness and material removal rate with the help of ANOVA. Antony (2001) proposed the methodology to develop a simple and practical step-by-step approach for tackling multi-response or quality characteristics problems by Taguchi's quality loss function for identifying the significant factor/interaction effects and also for determining the optimal condition of the process. Liao (2003) illustrates an effective method for multi-response problem by using PCR-TOPSIS that is based on process capability ratio theory and on the theory of order preference by similarity to ideal solution (TOPSIS). PCR-TOPSIS, multiple responses in each experiment are transformed into a performance index and the optimal factors/levels combination for the multi-responses can thus be determined. The results of two case-studies clearly indicate the usefulness of this approach which yields a satisfactory solution for multi-response problem.

Nomenclature

R	Nose radius (mm)
V	Cutting speed in (m/min)
F	Feed rate (mm/rev.)
D	Depth of cut (mm)
F_x	Axial force (N)
F_y	Radial force (N)
F_z	Main cutting force (N)
MRR	Material removal rate (g/sec)

Singh et al. (2006) presents a simplified methodology on Taguchi's approach and utility concept during case study of EN24 steel turned parts for determining optimal settings of the process parameters for multi-characteristics product. The trade-off between conflicting quality characteristics is made objective in the developed model through utility concept. Gupta et al. (2011) reports the use of Desirability function in conjunction with response surface methodology for turning of AISI P-20 tool steel for modeling of the response. A face centered central composite design was used for experimentation. Aggarwal et al. (2008) present the use of fuzzy logic in the Taguchi method to optimize the turning process with multiple performance characteristics. Taguchi's concept of orthogonal arrays, signal to noise (S/N) ratio, ANOVA have been fuzzified to optimize the high speed CNC turning process parameters through a single comprehensive output measure (COM). Kaladhar et al. (2011) used a multi-characteristics response optimization model based on Taguchi and utility concept to optimize process parameters on multiple performance characteristics, namely, surface roughness and material removal rate during turning of AISI 202 austenitic steel using a CVD coated cemented carbide tool. The experimental results 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.

Datta et al. (2010) used the application of principle component analysis is to convert correlated responses into uncorrelated quality indices called principle components is used for turning of mild steel. Finally based on utility concept, Taguchi method has been applied for multi-response optimization problem. The study demonstrates detailed methodology and concludes robustness and flexibility of the proposed optimization techniques. Tzeng et al. (2009) reports the use of Grey relational analysis for optimization of CNC turning of SKD11 (J19) tool steel considering multiple performance parameters. A predictive model is proposed by Sahoo et al. (2012) for surface roughness and material removal rate in machining of AISI 1040 steel. Grey relational approach with regression analysis is used for optimization of multiple quality/performance characteristics. Pawade et al. (2011) proposed the methodology for the practical machining of Inconel 718 for which response table and the grey relational grade for each level of the machining parameters have been established. In this case, Depth of cut shows statistical significance on overall turning process with 95% confidence interval.

In this study, a multi-response model based upon Taguchi's design approach and the utility concept was employed to determine the best combination of the turning parameters that included tool nose radius, cutting speed, feed rate and depth of cut to attain maximum MRR and minimum cutting forces (axial force, radial force and main cutting force). The predictive model was employed for the performance measures. Confirmation tests were also conducted to verify the results.

2. Experimental procedure

2.1 Material

In this study, a chromium-vanadium spring steel (EN47), with a diameter of 27 mm and a length of 500 mm was used. The chemical composition of EN47 alloy steel is given in table 1.

Table 1. Chemical composition of EN47 steel

Element	C	Si	Mn	Cr	V	S	P
Weight %	0.45-0.55	0.50	0.50-0.80	0.8-1.20	0.15	0.06	0.06

This steel is high carbon alloy steel with good harden ability developed for the applications in making crank shaft, steering knuckles, gear spindle and pumps. It can be used in high duty volute and leaf springs, heavy engine valve springs, helical and torsional bar springs. It has a high ratio of yield point to tensile strength and torsional fatigue strength. EN-47 steel is a tough oil quenching spring steel which when heat treated, offers good wear resistance.

2.2 Method

The Taguchi method is a commonly applied approach in optimizing the design parameters. This method was originally used to improve the quality of products with the use of statistical and engineering concepts. The method which is based on the orthogonal array (OA) provides a significantly reduced variance for the experiment, resulting in the optimum setting of the process parameters. OA provides a set of well-balanced experiments, with less number of experiment runs. This technique is used for the data analysis and in the prediction of the optimal results. The S/N ratio is the ratio of the mean (signal) to the standard deviation (noise). The ratio depends on the quality characteristics of the product to be optimized. Standard S/N ratios are generally identified as lower-the-better (LB), nominal-the-best (NB) and higher-the-better (HB). The optimal setting is the parameter combination with the highest S/N ratio. In this study, smaller-the-better and larger-the-better principle are considered to minimize cutting forces and to maximize MRR. The corresponding loss function is expressed as follows (Ross, 1988):

$$\text{Smaller-the-better, S/N ratio} = -10 \log 1/n \, \Sigma \, y^2 \tag{1}$$

$$\text{Larger–the-better, S/N ratio} = -10 \log 1/n \, \Sigma \, 1/y^2 \tag{2}$$

Where n is the number of observations and y is the observed data.

2.3 Present problem

The Taguchi's mixed level design was selected because the two level of nose radius were used in the study. The three parameters were selected at three levels. The two-level parameters had 1 DOF, and the remaining three parameters with 2 DOF had total 6 DOF. Thus the total degrees of freedom required was 7 [= 1×1 + 3×2]. The most appropriate OA in this case was L_{18} ($2^1 \times 3^7$). L_{18} OA was selected for the experiments implementing the Taguchi's design approach.

The parameters selected, the designated symbols, and their ranges are listed in Table 2. The machining tests were conducted using a conventional lathe machine with the following specification; spindle speed range from 42 rpm to the 2040 rpm; feed range from 0.04 mm/rev. to 2.24 mm/rev; depth of cut range from 0.2 mm to 4.8 mm. the control voltage for the machine is 220 V and rated current is 23 A. The carbide cutting inserts having geometry of the cutting tool CCMT 060204 EN/ 060208 EN with nose radius of 0.4 and 0.8 mm were used for machining of EN47 steel. The experiment had been replicated three times with 54 data points. The cutting environment throughout the study is dry. For measuring the cutting forces the dynamometer is used which is manufactured by the DEE Ltd. A simplified multi- criterion methodology based on the Taguchi's design approach and utility concept is employed to achieve the objective of this study. The observed values of the response parameters are given in Table 3.

Table 2. Control parameters with levels

Process parameters	Designation	Level 1	Level 2	Level 3
Nose radius (mm)	A	0.4	0.8	Nil
Cutting speed (m/min.)	B	46.65	78.88	102.63
Feed rate (mm/rev.)	C	0.05	0.1	0.2
Depth of cut (mm)	D	0.4	0.6	0.8

Table 3. Test data summary of the cutting forces and MRR

Trial	F_x (N)			F_y (N)			F_z (N)			MRR (g/sec.)		
No.	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3
1	58.84	63.74	58.84	39.23	39.23	44.13	156.91	161.81	166.71	0.096	0.094	0.091
2	127.49	132.40	132.40	88.26	78.45	98.06	235.36	230.45	235.36	0.423	0.429	0.437
3	171.62	166.71	176.52	117.68	117.68	122.58	362.85	367.75	362.85	1.015	1.018	1.012
4	49.03	49.03	49.03	34.33	29.42	29.42	147.10	152.01	147.10	0.345	0.351	0.368
5	117.68	107.87	122.59	78.45	93.16	78.45	225.55	215.75	220.65	0.773	0.776	0.767
6	156.91	147.10	147.10	107.87	102.39	117.68	333.42	338.32	323.62	1.298	1.289	1.292
7	78.45	78.45	88.26	49.03	49.03	53.94	137.29	137.29	137.29	0.427	0.441	0.435
8	147.10	137.29	137.29	98.06	93.16	93.16	274.59	279.49	279.49	0.758	0.749	0.755
9	122.58	127.49	127.49	63.75	58.84	63.75	215.75	220.65	225.55	0.712	0.714	0.719
10	107.87	117.68	112.77	98.06	98.06	88.26	264.78	269.68	264.78	0.582	0.587	0.578
11	98.06	98.06	107.87	73.55	68.65	73.55	225.55	215.75	215.75	0.389	0.379	0.384
12	137.29	147.10	142.20	127.49	132.39	122.59	323.62	328.52	328.52	0.762	0.765	0.758
13	68.65	68.65	68.65	58.84	63.74	68.65	196.13	201.03	196.13	0.692	0.695	0.687
14	127.49	117.68	137.29	112.77	112.77	117.68	304.01	313.81	313.81	1.112	1.104	1.114
15	117.68	112.77	127.49	93.16	88.26	93.16	294.20	284.40	289.30	0.856	0.861	0.847
16	137.29	142.20	156.91	88.26	98.06	107.87	245.16	245.16	245.16	0.738	0.734	0.744
17	107.87	117.68	122.58	73.55	78.45	73.55	240.25	235.36	235.36	0.684	0.692	0.687
18	156.91	147.10	156.91	98.06	83.35	93.16	289.30	289.30	284.40	0.981	0.987	0.976

3. Utility concept

Quality is a key attribute that customers require into the product or services. So the modern quality control and improvement program focus that their product should be made as par the customer requirements. On the other hand, customer evaluates a product performance based on number of diverse quality characteristics of the product. To able to make rational choice, these performance evaluation on different characteristics should be combined to give a composite index. Such a composite index shows the utility of the product. The utility of a product on a particular characteristic measures the usefulness of that particular characteristic of product/service. In this paper it is assumed that the overall utility of product is the total sum of utilities of each particular quality characteristic of a product. Thus if x_i is the measure of effectiveness of an attribute (characteristics) i and there are n attributes evaluating the outcome space, then the combined utility function can be expressed as (Derek, 1982):

$$U(x_1, x_2, x_{3\ldots}\, x_n) = f\,[U_1(x_1),\, U_2(x_2) \ldots\, U_n(x_n)] \tag{3}$$

Where $U_i(x_i)$ is the utility of the i^{th} attribute.
The overall utility function is the sum of individual utilities. If the attributes are independent, then

$$U(x_1, x_{2\ldots}\, x_n) = \sum_{i=1}^{n} U_i(x_i). \tag{4}$$

Depending upon the customer's requirements, the characteristics might be given priorities. The priorities could be adj-usted by providing a weight to the individual utility index. The overall utility function by assigning weights to attributes could be written as:

$$U(x_1, x_2 \ldots\, x_n) = \sum_{i=1}^{n} W_i\, U_i(x_i) \tag{5}$$

Where, W_i is the weight assigned to the attribute i and the total sum of the weight for all the attributes is equal to one.
The utility function is of 'higher-the-better' type characteristic. If the composite measure, the overall utility, is to be maximized, the quality characteristics considered for the evaluation of utility index will be optimized (minimized or maximized).

3.1 Determination of utility value

To determine the overall utility value for a number of quality attributes, a preference scale for each quality attributes is constructed. Later these scales are given weight to calculate the overall utility. The weighting is done to satisfy the test of indifference on the various quality attributes. The preference scale may be linear, logarithmic or exponential depending upon the requirement. The minimum acceptable quality level for each quality attributes is set at a preference scale of 0 and the best available quality is assigned a preference number of 9. In this experiment, logarithmic scale was used. The preference number is given by (Gupta et al., 1980):

$$Pi = A \times \log\,(x_i / x_i') \tag{6}$$

Where x_i is the value of quality characteristics or attribute i, x_i' is the minimum acceptable value of the quality characteristics or attributes i and A is a constant. Arbitrarily, A has been chosen such that $P_i=9$ at $x_i = x^*$, where x^* is the optimum value of x_i with the assumption that such a number exists. The next step is to assign weights or relative importance to the quality attributes. A number of methods exist for the assessment of weights (AHP and conjoint analysis) (Bosser, 1991) this assignment is basically done also by the experience and it is purely subjective. Moreover, it depends on the end use of the product. The weight should be assigned such that it can hold following conditions:

$$\sum_{i=1}^{n} W_i = 1. \tag{7}$$

The overall utility value can be calculated by using following equation.

$$U = \sum_{i=1}^{n} W_i P_i \tag{8}$$

4. Results and discussions

The optimal settings of the process parameters and the predicted optimal values of the cutting forces and MRR (when individually optimized) are given in the Table 4 based on Taguchi's design approach. The stepwise procedure for the transformation of experimental data into utility data is tabulated in Table 5 which can shows the values used for the cutting forces and MRR to obtain the overall utility value. The utilities are calculated based on equation (8) and are given in Table 6. The S/N ratio is also given in Table 6. The mean responses in terms of their utility value are calculated and given in Table 7. The mean values of S/N ratio are reported in Table 8.

Table 4. Optimal settings and values of the process parameters (individual quality characteristics optimization)

Quality Characteristics	Optimal settings of process parameters	Significant process parameters (95% confidence Level)	Predicted optimal value of quality characteristics
Axial force	A_1 B_2 C_1 D_1	A, B, C, D	48.66 N
Radial force	A_1 B_3 C_1 D_1	A, B, C, D	28.17 N
Main cutting force	A_1 B_3 C_1 D_1	A, B, C, D	126.87 N
MRR	A_2 B_2 C_3 D_3	A, B, C, D	1.344 g/sec.

Table 5. Parameters used to find utility value.

Terms	Axial force	Radial force	Main cutting force	MRR
Optimum value x^*	48.66	28.17	126.87	1.344
Acceptable value x_i'	180	135	370	0.090
Weight W	0.25	0.25	0.25	0.25

Table 6. Calculated Raw data (utility value) based on quality characteristics.

Trial No.	Raw data (utility values) R1	R2	R3	S/N ratio (dB)
1	5.55	5.33	5.21	14.58
2	3.44	3.60	3.25	10.68
3	2.33	2.36	2.22	7.24
4	7.26	7.42	7.53	17.38
5	4.34	4.33	4.31	12.72
6	2.99	3.14	3.04	9.70
7	6.26	6.29	5.94	15.79
8	3.21	3.34	3.36	10.38
9	4.59	4.58	4.44	13.13
10	3.59	3.41	3.66	11.00
11	4.17	4.34	4.09	12.46
12	2.61	2.40	2.56	8.02
13	5.88	5.71	5.65	15.18
14	3.35	3.42	3.10	10.32
15	3.62	3.84	3.51	11.24
16	3.69	3.47	3.18	10.70
17	4.34	4.16	4.18	12.51
18	3.20	3.55	3.30	10.48

The figure 1 reveals that the first level of nose radius, second level of cutting speed, first level of feed rate and first level of depth of cut would yield best performance in terms of utility value within the selected range of parameters. It is clear from the Table 9 that feed rate (C) and depth of cut (D) affect significantly the variation of utility value since these are significant in ANOVA. All the four process parameters are significant. The percent contribution of process parameters is; feed rate (44.51%), depth of cut (30.90%), cutting speed (10.49%) and nose radius (6.44%) is clearly shown by the ANOVA table of the utility value (raw data).

Table 7. Main effects value of the utility value (raw data: cutting forces and MRR)

Level	Nose radius (A)	Cutting speed (B)	Feed rate (C)	Depth of cut (D)
1	4.432	3.562	5.279	4.898
2	3.777	4.580	3.797	4.257
3	----	4.172	3.238	3.159

The optimal setting of the turning process parameters for the multi-response optimization (axial force, radial force, main cutting force and material removal rate) of EN47 spring steel turned parts using carbide inserts is A_1 B_2 C_1 D_1.

Table 8. Average S/N ratio values of the responses

Level	Nose radius (A)	Cutting speed (B)	Feed rate (C)	Depth of cut (D)
1	12.40	10.66	14.11	13.55
2	11.32	12.76	11.51	12.15
3	----	12.16	9.97	9.89

Table 9. ANOVA (raw data: cutting forces and MRR)

Source	DOF	SS	V	F- ratio	p	% contribution
Nose radius (A)	1	5.795	5.795	38.67*	0.000	6.44%
Cutting speed (B)	2	9.444	4.722	31.51*	0.000	10.49%
Feed rate (C)	2	40.076	20.038	133.72*	0.000	44.51%
Depth of cut (D)	2	27.820	13.910	92.82*	0.000	30.90%
Error	46	6.893	0.150			7.66%
Total	53	90.029				

SS= sum of square, DOF = degree of freedom, V= variance, * Significant at a 95% confidence level

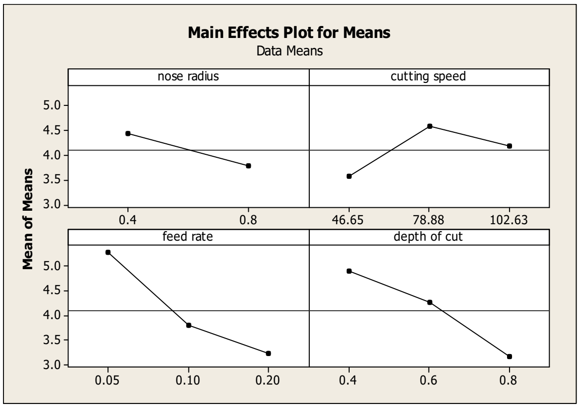

Fig 1. Main effects plot for multi-response utility value

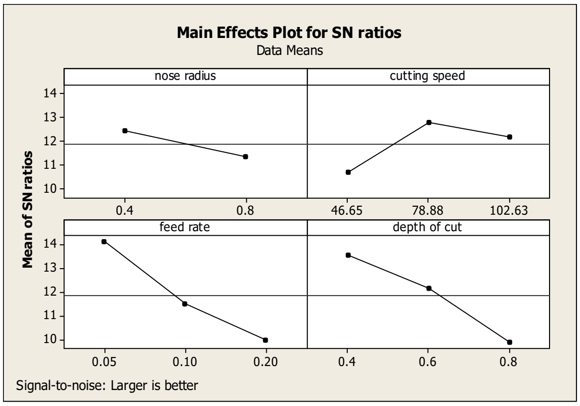

Fig 2. Main effects plot for Multi-response S/N ratio

5. Optimal values of the quality characteristics (predicted means cutting forces and MRR)

5.1 Axial force

The average values of axial force at the first level of nose radius (A_1), second level of cutting force (B_2), first level of feed rate (C_1) and first level of depth of cut (D_1) are given in Table 10. The overall mean of axial force is 117.41N. The predicted mean (optimal value) of axial force is:

$$\mu_{AF} = \bar{A}_1 + \bar{B}_2 + \bar{C}_1 + \bar{D}_1 - 3\bar{T}_{AF} = 48.66 \text{ N}$$

The 95% confidence interval of confirmation experiments (CI_{CE}) was calculated by using the following equation [16].

$$CI_{CE} = \sqrt{F\alpha(1, fe)Ve[\frac{1}{Neff} + \frac{1}{R}]} \quad (9)$$

Where F_α (1, fe) = F ratio required for α, α = risk, f_e =error DOF, V_e =error variance,

N_{eff} =effective no. of replication = $\frac{N}{1+[Total\ DOF\ associated\ in\ the\ estimate\ of\ mean]}$

R = number of repetitions for confirmation experiment, N = total number of experiments

The specific values are required in equation (9) are; f_e=46, V_e =109.9, N = 54, R =3, $F_{0.05}$ (1, 46) = 4.0157

So, CI_{CE} = ± 14.587

The predicted optimal range (for a confirmation run of three experiments) of axial force is:

$34.07 < \mu_{AF}$ (N) < 63.24

Table 10. Average values of quality characteristics at optimum levels

Levels	Axial force (F_x)	Radial force (F_y)	Main cutting force (F_z)	MRR
A_1	114.05	75.33	233.0	0.6513
B_2	105.15	82.30	249.8	0.8459
C_1	86.35	63.20	192.9	0.4825
D_1	95.34	62.18	212.8	0.5149

5.2 Radial force

The average values of radial force at the first level of nose radius (A_1), the second level of cutting speed (B_2), the first level of feed rate (C_1) and the first level of depth of cut (D_1) are given in Table 10.

The overall mean of radial force is 83.82 N. So, the predicted mean of radial force is:

$\mu_{RF} = \bar{A}_1 + \bar{B}_2 + \bar{C}_1 + \bar{D}_1 - 3\bar{T}_{RF} = 31.55$ N.

The 95% confidence interval of confirmation experiment was calculated by using the following values in equation (9):

f_e = error DOF = 46; V_e = 67.6; N = 54; R = 3; $F_{0.05}$ (1, 46) = 4.0157

So, CI_{CE} = ± 11.44

The predicted optimal range (for a confirmation run of three experiments) of radial force is:

$20.11 < \mu_{RF}$ (N) < 42.99

5.3 Main cutting force

The average values of main cutting force at the first level of nose radius (A_1), the second level of cutting speed (B_2), the first level of feed rate (C_1) and the first level of depth of cut (D_1) are given in Table 10.

The overall mean of main cutting force is 248.71 N. So, the predicted mean of main cutting force is:

$\mu_{MCF} = \bar{A}_1 + \bar{B}_2 + \bar{C}_1 + \bar{D}_1 - 3\bar{T}_{MCF} = 142.37$ N

The 95 percent confidence interval (for three confirmation experiments) of the predicted mean has been calculated using equation (9). The specific values as required in equation (9) are:

f_e = error DOF = 46; V_e = 144; N = 54; R = 3; $F_{0.05}$ (1, 46) = 4.0157

So, CI_{CE} = ± 16.69

The predicted optimal range (for a confirmation run of three experiments) of main cutting force is:

$125.68 < \mu_{MCF}$ (N) < 159.06

5.4 Material removal rate

The average values of material removal rate at the first level of nose radius (A_1), the second level of cutting speed (B_2), the first level of feed rate (C_1) and the first level of depth of cut (D_1) are given in Table 10.

The overall mean of material removal rate is 0.7029 g/sec. So, the predicted mean of material removal rate is:

$$\mu_{MRR} = \bar{A}_1 + \bar{B}_2 + \bar{C}_1 + \bar{D}_1 - 3\bar{T}_{MRR} = 0.386 \text{ g/sec.}$$

The 95 percent confidence interval (for three confirmation experiments) of the predicted mean has been calculated using equation (9).

f_e = error DOF = 46; $V_e = 0.00325$; $N = 54$; $R = 3$; $F_{0.05}(1, 46) = 4.0157$

So, $CI_{CE} = \pm\, 0.0793$

The predicted optimal range (for a confirmation run of three experiments) of material removal rate is:

$$0.307 < \mu_{MRR} \text{ (g/sec.)} < 0.465$$

6. Confirmation experiment

The three confirmation experiments are performed at the optimal settings of turning process parameters of utility data. The following average values have been found for the quality characteristics considered:

- Average axial force = 49.03 N
- Average radial force = 31.06 N
- Average main cutting force = 148.74 N
- Average material removal rate = 0.355 g/sec.

7. Summary results and comparison with single characteristics optimization

The summary results and comparison with single characteristics optimization are reported in Table 11.

Table 11. Summary and comparison results

Method	Characteristics	Optimal condition	Optimal value
Single characteristics optimization	Axial force (F_x)	$A_1^*, B_2^*, C_1^*, D_1^*$	48.66 N
	Radial force (F_y)	$A_1^*, B_3^*, C_1^*, D_1^*$	28.17 N
	Main cutting force (F_z)	$A_1^*, B_3^*, C_1^*, D_1^*$	126.87 N
	MRR	$A_2^*, B_2^*, C_3^*, D_3^*$	1.344 g/sec
Multi-characteristics optimization	Axial force, Radial force Main cutting force, MRR	$A_1^*, B_2^*, C_1^*, D_1^*$	F_x = 48.66 N F_y = 31.55 N F_z = 142.37 N MRR = 0.386 g/sec

Notes: * Significant at 95 % confidence level

8. Conclusion

1. A simplified model based on Taguchi's design approach and utility concept is used to determine the optimal settings of process parameters for a multi-characteristics product. The model is used to predict optimal settings of turning process parameters to yield the optimum quality characteristics of EN47 spring steel turned parts using carbide inserts.
2. All the four process parameters, namely, nose radius, cutting speed, feed rate and depth of cut had a significant effect on the utility function based on the ANOVA for multiple performances.
3. The percentage contribution of the feed rate (44.51%), depth of cut (30.90%), cutting speed (10.49%) and nose radius (6.44%) for the multiple responses.
4. The weights assigned to the selected quality characteristics/responses have been assumed equal. However, with a different set of weights, a different set of optimal parameters for the quality characteristics will result. The optimal

set predicted will be closer to the optimal set predicted for the single quality characteristics which is having the maximum weight.
5. The model can used for the any number of quality characteristics provided proper utility scales for the characteristics are available from the realistic data.

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References

Surinder Kumar, Meenu, Satsangi, P., S., 2013. Multi-response optimization of turning machining by the Taguchi method and the utility concept using uni-directional glass fiber-reinforced plastic composite and carbide (k10) cutting tool. Journal of mechanical science and technology, 27, 2829-2837.
Antony, J., 2001. Simultaneous optimization of multiple quality characteristics in manufacturing processes using Taguchi's quality loss function. International Journal Advanced Manufacturing Technology 17, 134-138.
Liao, H., C., 2003. Using PCR-TOPSIS to optimize Taguchi's multi-response problem. International Journal Advanced Manufacturing Technology,22, 649-655.
Singh, H., Kumar, P., 2006. Optimizing multi-machining characteristics through Taguchi's approach and utility concept. Journal of Manufacturing Technology Management 17, 255-274.
Gupta, A., Singh, H., Aggarwal, A., 2011. Taguchi-fuzzy multi-output optimization (MOO) in high speed CNC turning of AISI P-20 tool steel. Experts Systems with Application 38, 6822-6828.
Aggarwal, A., Singh, H., Kumar, P., Singh, M., 2008. Optimization of multiple quality characteristics for CNC turning under cryogenic cutting environment using desirability function. Journal of Materials Processing Technology 205, 42-50.
Kaladhar, M., Subbaiah, K., V., Rao, Ch., S., Rao, K., N., 2011. Application of Taguchi approach and utility concept in solving the multi-objective problem when turning AISI 202 austenitic stainless steel. Journal of engineering science and technology review 4(1), 55-61.
Datta, S., Mahapatra, S., S., 2010. Simultaneous optimization of correlated multiple surface quality characteristics of mild steel turned product. Intelligent Information Management 2, 26-39.
Tzeng, C., J., Lin, Y., Yang, Y., Jeng, M., 2009. Optimization of turning operation with multiple performance characteristics using the Taguchi method and grey relational analysis. Journal of Materials Processing Technology 209, 2753-2759.
Sahoo, A., Baral, A., N., Rout, A., K., Routra, B., C., 2012. Multi-objective optimization and predictive modeling of surface roughness and material removal rate in turning using grey-relational and regression analysis. International Conference on Modelling, Optimization and Compu -ting Procedia Engineering 38, 1606-1627.
Pawade, R., S., Joshi, S., S., 2011. Multi-objective optimization of surface roughness and cutting forces in high-speed turning of Inconel 718 using Taguchi-Grey relational analysis. International Journal of Advance Manufacturing Technology 56, 4-62.
Ross, P., J., 1988. Taguchi techniques for quality engineering. McGraw-Hill Book Company New York.
Derek, W., B., 1982. Analysis for optimal decisions. John Wiley and Sons. New York.
Gupta, V., Murthy, P., N., 1980. An introduction to engineering design method. Tata McGraw-Hill, New Delhi.
Bosser, J., L., 1991. Quality function development – A practitioner approach. Marcel Dekker New York.