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مقارنة بين مختلف اساليب استجابات المتعددة المثلى لعمليات تحويل أداة الصلب AISI O1

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الخلاصـة

في هذه المقالة، تأثير عوامل العمليات المتعددة لأدوات القطع مثل نصف قطر وسرعة وتلقيم وعمق على كفاءة الآلات الدوارة باستخدام AISI O1 أداة الصلب كمادة العمل. خصائص الآلات التي تم دراستها هي نسبة إزالة المواد (MRR) وخشونة السطح (SR) من سطح المشكل. واستخدمت طريقة تاجوشى لتحسين الاستجابة الفردية. ولتحسين الاستجابة المتعددة، نسبة الفردية الى الضوضاء (WSN) والتحليل القريب الرمادي (GRA) وفكرة وأسلوب لترتيب الأفضلية من خلال التشابه في طريقة مثالية الحل (TOPSIS) قد استخدمت وتم تقييم أدائها. وقد وجد أن طريق (WSN) تعطي أفضل النتائج لتحسين الاستجابات المتعددة لهذه الدراسة.

A comparison of the different multiple response optimization techniques for turning operation of AISI O1 tool steel

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ABSTRACT

In this article, the effect of several process parameters such as tool nose radius, speed, feed and depth of cut on the machining performance of turning operation has been studied using AISI O1 tool steel as a work material. The machining characteristics that are being studied are material removal rate (MRR) and surface roughness (SR) of machined surface. Taguchi method is utilized for single response optimization. For multi-response optimization, weighted signal-to-noise ratio (WSN), grey relational analysis (GRA), utility concept and technique for order preference by similarity to ideal solution (TOPSIS) method have been utilized and their performance is evaluated. WSN method has been found to produce best results for multi-response optimization for this study.

Keywords: Material removal rate; multi-response optimization; surface roughness; Taguchi method; weighted signal-to-noise ratio.

INTRODUCTION

The turning operation is the oldest and most common machining process, in which the removal of material takes place from the outer diameter of a rotating cylindrical work piece. Parts are held at the center and supported in a jaw chuck. In the turning operation, the machining performance is based on different characteristics such as material removal rate, tool life, cutting force and surface roughness. Basically these performance characteristics are correlated with process parameters such as cutting speed, feed rate, depth of cut and tool nose radius. The proper selection of these process parameters plays a vital role as it enhances the tool life, increases material removal rate, and improves the surface finish. A schematic diagram of turning operation is shown in Figure 1.

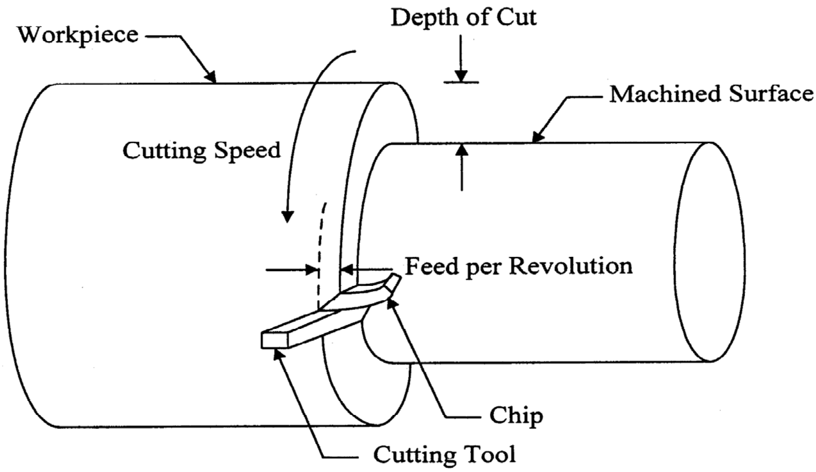


Fig. 1. Process of turning operation (Yoon & Hawang, 1995).

Many researchers have attempted to optimize process parameters for turning operation for different response variables using Taguchi method. By employing Taguchi method, the effects of a large number of process parameters can be assessed using lesser number of experimental trials. Taguchi method optimizes the process with respect to signal-to-noise (S/N) ratio of the response instead of the response itself and thus, it can make the performance of a process to be insensitive to noise factors. However, the limitation of Taguchi method is that it optimizes single performance characteristic at a time.

Singh & Kumar, (2006) reported the optimization of process parameters for turning EN24 steel bars using spindle speed, depth of cut and feed rate as controlled factors and feed force as response variable through the Taguchi approach. Ozel, *et al.* (2005) performed an experimental investigation and results revealed that the effect of spindle speed on the surface roughness was the most significant where the effect of cutting tool material was the least significant. Singh, (2008) investigated the tool life of Tic coated carbide inserts while turning EN 24 steel (0.4%C). The results indicated that cutting speed, depth of cut and feed rate have 34.89%, 25.80% and 8.78% contribution to the variation observed in the tool life, respectively. The predicted value of optimum tool life was 20.19 min. Bhattacharya, *et al.* (2009) estimated the effect of cutting parameters on surface finish and power consumption during high speed machining of AISI 1045 steel using Taguchi design and Analysis of variance (ANOVA). The cutting speed was most significant for the surface roughness and power consumption. Dhabale, *et al.* (2014) utilized genetic algorithm to find out the optimal setting of process parameters that optimize surface roughness. Feng & Wang, (2002) performed experimentation for the prediction of surface roughness in finish turning operation by developing an empirical model through considering working parameters as work piece hardness (material), feed, cutting tool point angle, depth of cut, spindle speed, and cutting time. Data mining techniques and, nonlinear regression analysis with logarithmic data transformation were employed for developing the empirical model to predict the surface roughness. Yang & Tarng, (1998) employed Taguchi method to find the optimal cutting parameters for turning operations. The signal-to-noise (SN) ratio was computed and the analysis of variance (ANOVA) was performed to investigate the cutting characteristics of S45C steel bars using tungsten carbide cutting tools. Kaladhar, *et al* (2010) performed the optimization of machining parameters in turning of AISI 202 Authentic stainless steel using CVD coated cemented carbide tool. The Full factorial design and ANOVA were used for study of the effect of process parameters (i.e., speed, feed, depth of cut, and nose radius) on surface roughness. It was observed from the result that the Feed rate was the most significant factor that influences the surface roughness. Neselia & Yaldiz, (2011) studied the effect of tool geometry parameters on the surface roughness of AISI 1040 steel in the turning operation. The result highlighted the tool noise radius as the dominant factor on surface roughness.

Almost all of the studies mentioned above have made the use of single response optimization concept. When we deal with practical problems, there is always a need to determine the process parameters in such a manner that multiple responses can be optimized simultaneously. In the literature, quite a few systematic procedures have been proposed for dealing with the multi-response optimization problems. While most of the methods use complex mathematics, some of them utilize simple procedures, which can easily be realized by the researchers. All the needed calculations for these methods can be executed using excel worksheet.

The objective of this research work is to optimize the process parameters for turning process using Taguchi method and also to carry out multi response optimization with various multi optimization techniques such as weighted signal-to-noise ratio (WSN), grey relational analysis (GRA), utility concept and technique for order preference by similarity to ideal solution (TOPSIS). Comparative analysis of the results produced by different multi-response optimization techniques has also been performed so as to identify the best technique for multi-response optimization of the turning operation of AISI O1 tool steel.

LITERATURE REVIEW ON MULTI-RESPONSE OPTIMIZATION METHODS

There are many different techniques proposed for the optimization of multiple-response problems in the available literature. The goal of multi response optimization is to find out a single, composite setting of the input variables that can achieve an optimal compromise of the response variables.

The desirability function approach was initially performed by Harrington (1965) and then modified by Derringer & Suich (1980). Castillo, *et al.* (1996) and Kim & Lin (2000) also developed desirability function based multi-response optimization methods. Pasandideh & Niaki (2006) proposed a methodology which would integrate desirability function and simulation approach using a genetic algorithm. Aggarwal & Singh (2008) also utilized the desirability function for multi-response optimization. Khuri & Conlon (1981) optimized various responses using polynomial regression models. These results have been achieved firstly by defining a distance function by considering the ideal solution, and then determined the optimal condition by minimizing this function.

Tong & Su (1997) developed a systematic procedure via the application of fuzzy set theory to optimize multi-response production processes. Hsieh & Tong (2001) resolved the multi-response problems with the application of artificial neural networks (ANN). Homami, *et al.* (2014) and Chiang & Su (2003) utilized techniques of ANN and GA together to perform optimization. Umar, *et al*. (2014), Mahapatra & Patnaik (2007), and Jeyapaul, *et al.* (2005) used multiple objective genetic algorithms. Chi, *et al.* (2002) utilized the neuro-fuzzy and genetic algorithm in multi response optimization. Deng, (1982) had proposed a new technique, Grey relation analysis which is used for the multi-response optimization. Pan *et al*. (2007) and Haq *et al*. (2007) used this technique. The basic concept of GRA is to find a Grey relational grade (GRG), which can be used for the optimization conversion from a multi-objective case to a single-objective case. Kumar & Singh (2014), Kaladhar, *et al.* (2011), Kumar *et al.* (2000), Walia *et al*. (2006) and Kumar & Khamba (2010) used Taguchi method and utility concept for multi response optimization. Tong *et al.* (2007) performed multi response optimization by using VIKOR method.

Pearson (1901) introduced the principal component analysis (PCA) and then developed by Hotelling, (1933). Su and Tong, (1997), Antony, (2000), and Liao, (2006) employed the principal component analysis (PCA) to solve multi-response problems. The PCA technique can transform several related original variables into a smaller number of uncorrelated principal components, which are linear combinations of the original variables. The optimal parametric settings are then determined based on one or more principal components. Tong & Wang, (2002) and Gauri, *et al.* (2008) proposed PCA- based GRA and Tong, *et al.* (2005) presented the PCA- based TOPSIS methods to optimize the multiple responses.

Tong & Su, (1997) solved a multi-response robust design problem using a multiple-attribute decision-making (MADM) method. They considered the quality loss of each response and then adopted a MADM method - a technique for order preference by similarity to ideal solution (TOPSIS) to optimize the multi-response robust design problem. Their approach precisely considered the sampling variability of each response by the Taguchi quality loss function. There are several common methodologies for MADM-simple additive weighting (SAW), technique for order preference by similarity to ideal solution (TOPSIS), analytical hierarchy process (AHP), data envelopment analysis (DEA) and so on.

METHODS USED FOR MULTI-RESPONSE OPTIMIZATION

Taguchi categorized the response variables into three different types, e.g. STB, LTB and NTB (Phadke, 1989). The formulae for the computation of MSD (mean square deviation) for y^{th} response corresponding to j^{th} trial are different for different types of response variables and these are given as below:

Larger the better

$$\left(S/N\right)_{HB} = -10\log\left(MSD_{HB}\right) \tag{1}$$

where

$$MSD_{HB} = \frac{1}{R}\sum_{j=1}^{R}\left(1/y^2_j\right)$$

Smaller the better

$$\left(S/N\right)_{SB} = -10\log\left(MSD_{SB}\right) \tag{2}$$

Where

$$MSD_{SB} = \frac{1}{R}\sum_{j=1}^{R}\left(y^2_j\right)$$

Nominal the best

$$\left(S/N\right)_{NB} = -10\log\left(MSD_{NB}\right) \tag{3}$$

Where

$$MSD_{NB} = \frac{1}{R}\sum_{j=1}^{R}\left(y_j - y_o\right)^2$$

R = Number of repetition;

It is a standard practice to first normalize or scale the input data for each response variable within a certain interval. The aim of this normalization procedure is to reduce the variability amongst different responses. The overall understanding and comparison of various methodologies can be better if these methods are applied using similarly transformed values. Different researchers have adopted different formulas for normalization of the input data. For example, Ramakrishna & Karunamoorthy,

(2006) and Singh, et al. (2004) have normalized the input data using the following equation:

$$Z_{jys} = Z_{jyi} / \overline{Z}_{yi} \tag{4}$$

Where Z_{jyi} is the input data and Z_{jys} is the normalized data for y^{th} response in j^{th} trial, and $\overline{Z}_{yi}$ is the average value of input data for y^{th} response, whereas Singh et al. (2004) have normalized the input data using the following equation:

$$Z_{jys} = \frac{Zjyi - \min Zyi}{\max Zyi - \min Zyi} \tag{5}$$

Where $\min Z_{yi} = \min \{Z_{1yi}, Z_{2yi}, \ldots\ldots, Z_{myi}\}$ and $\max Z_{yi} = \max \{ Z_{1yi}, Z_{2yi}, \ldots\ldots, Z_{myi}\}$

Thus, in this paper, all the four methods are described considering SN ratio values as the input data and the SN ratio of all the responses are scaled into (0,1) interval using the equation (5).

To solve a multi-response optimization problem, all the four methods considered in this paper involves the following three basic steps: (i) conversion of the multiple responses into a single PPI, (ii) estimation of the factor effects on the PPI and then determining the optimal factor-level combination that can optimize the PPI value, and (iii) validation of the optimal factor-level combination using confirmatory experiment. The four methods differ mainly with respect to the adopted approaches for conversion of the multiple responses into a single PPI and the second & third basic steps are the same for all the four methods.

WSN ratio method

In the WSN ratio method, the weighted signal-to-noise (WSN) ratio is considered as the PPI value. The procedure for calculation of WSN values for different trials and determination of the optimal process condition can be described as below:

Step 1: Compute the SN ratio values of each response for all the trials using Eqns. (1) – (3) as appropriate;

Step 2: Obtain the scaled SN ratio values of each response for all the trials using Eqn. (5)

Step 3: Compute the WSN ratio value for j^{th} trial using the following equation:

$$WSN_j = \sum_{y=1}^{p} (Wy \times Zjys) \tag{6}$$

where Z_{jys} is the scaled SN ratio for y^{th} response in j^{th} trial, and W_y is the assigned weight for y^{th} response and $\sum_{y=1}^{p} Wy = 1$.

GRA method

In this method, the grey relational grade (GRG) is considered as the PPI. The procedure for computation of GRG value for different trials and determination of the optimal process condition can be described as below:

Step 1: Compute the SN ratio values of each response for all the trials using Eqns. (1) – (3).

Step 2: Obtain the scaled SN ratio values for all the responses for all the trials using Eqn. (5).

Step 3: Compute the grey relational coefficients of each response for all the trials.

The grey relational coefficient (γ_{jy}) for y^{th} response in j^{th} trial can be computed as below:

$$\gamma_{jy} = \frac{\Delta_y^{min} + \xi\, \Delta_y^{max}}{\Delta_{jy} + \xi\, \Delta_y^{max}} \tag{7}$$

where $\Delta_{jy} = |1 - Z_{jys}|$, $\Delta_y^{min} = \min\{\Delta_{1y}, \Delta_{2y}, ..., \Delta_{my}\}$, $\Delta_y^{max} = \max\{\Delta_{1y}, \Delta_{2y}, ..., \Delta_{my}\}$ and ξ is the distinguishing coefficient ($\xi \in [0,1]$). The purpose of the distinguishing coefficient is to expand or compress the range of the grey relational coefficient and usually, it is set equal to 0.5

Step 4: Calculate the grey relational grade (GRG_j) corresponding to j^{th} trial using the following equation:

$$GRGj = \sum_{y=1}^{p} Wy\, \gamma jy \tag{8}$$

Step 5: Use arithmetic average to calculate the factor effects on GRG value and then decide the optimal factor level combination by higher-the-better factor effects.

The utility concept and method

Utility can be defined as the usefulness of a product or a process in reference to the expectations of the users. The overall usefulness of a process/product can be represented by a unified index termed as *utility* which is the sum of the individual utilities of various quality characteristics of the process/product. The methodological basis for utility approach is to transform the estimated value of each quality characteristic into a common index.

If X_y is the measure of effectiveness of an attribute or quality characteristic (response) y and there are p attributes evaluating the outcome space, and then the joint utility function can be expressed as:

$$U(X1, X2 ,..., Xp) = f (U1(X1),U2 (X2),...,Up (X p)) \tag{9}$$

where $U_y(X_y)$ is the utility of the y^{th} attribute or quality characteristic. The overall utility function is the sum of individual utilities if the attributes are independent, and is given as follows:

$$U(X_1, X_2, \ldots, X_p) = \sum_{y=1}^{p} U_y(X_y) \qquad (10)$$

The attributes may be assigned weights depending upon the relative importance or priorities of the characteristics. The overall utility function after assigning weights to the attributes can be expressed as:

$$U(X_1, X_2, \ldots, X_p) = \sum_{y=1}^{p} WyU_y(X_y), \qquad (11)$$

where W_y is the weight assigned to the attribute y . The sum of the weights for all the attributes must be equal to 1. A preference scale for each attribute or response variable is constructed for determining its utility value. Two arbitrary numerical values (preference number) 0 and 9 are assigned to the just acceptable and the best value of the response variable respectively. The preference number (P_y) for the y^{th} response variable can be expressed on a logarithmic scale as follows:

$$P_y = A_y \text{ x } \log(X_y / X'_y), \qquad (12)$$

where X_y = value of y^{th} response variable, X_y' = just acceptable value of y^{th} response variable and A_y = constant for the y^{th} response variable. The value of A_y can be found by the condition that if $X_y = X^*_y$ (where X^*_y is the optimal or best value for the y^{th} response), then $P_y = 9$. Therefore,

$$A_y = \frac{9}{\log(X^*_y / X'_y)} \qquad (13)$$

The overall utility (U) can be calculated as follows:

$$U = \sum_{y=1}^{p} W_y P_y, \qquad (14)$$

subject to the condition that $\sum_{y=1}^{p} W_y = 1$

The overall utility value is considered as the PPI in the utility method for multi-response optimization. This method can be implemented using the following six steps:

Step 1: Compute the SN ratio values for each response for all the trials using Eqns. (1) – (3) as appropriate.

Step 2: Determine the optimal process condition separately for each response variable using Taguchi method and then predict optimal value for each response variable.

For a response variable, the optimal process condition will be the one which maximizes the SN ratio value. The optimal SN ratio for the response variable can be estimated using additive model. Suppose the optimal SN ratio for a response variable is Z_{opt}. Then, the optimal value (V_{opt}) of the STB and LTB type response variable can be obtained using Eqns. (15) and (16) respectively.

$$V_{opt} = \sqrt{(10^{-(Zopt/10)})} \tag{15}$$

$$V_{opt} = \sqrt{(1/10^{-(Zopt/10)})} \tag{16}$$

Step 3: Determine the just acceptable values for all the response variables.

If the response variable is STB type, the maximum observed value of the response variable will be taken as the just acceptable value for the variable. On the other hand, if the variable is LTB type, the minimum observed value of the variable will be taken as the just acceptable value for the variable.

Step 4: Construct the preference scale for each response variable using Eqns. (12) and (13)

Step 5: Determine the overall utility value for each trial using Eqn. (14)

Step 6: Use arithmetic average to calculate the factor effects on the overall utility value and then decide the optimal factor-level combination by higher-the-better factor effects.

Technique for order preference by similarity to ideal solution (TOPSIS) method

The TOPSIS method was developed by Yoon & Hwang, (1995). This method is based on the concept that the chosen alternative should have the shortest Euclidean distance from the ideal solution, and the farthest from the negative ideal solution. The ideal solution is a hypothetical solution for which all attribute values correspond to the maximum attribute values in the database comprising the satisfying solutions; the negative ideal solution is the hypothetical solution for which all attribute values correspond to the minimum attribute values in the database. TOPSIS thus gives a solution that is not only closest to the hypothetically best, but also the farthest from the hypothetically worst. The main procedure of the TOPSIS method consists of the following steps:

Step 1: Compute the SN ratio values for each response for all the trials using Eqns. (1) – (3) as appropriate.

Step 2: Obtain the scaled SN ratio values for all the responses for all the trials using Eqn. (5).

Step 3: Decide on the relative importance of different attributes with respect to the objective. A set of weights w_y such that $\sum w_y = 1$ may be decided upon.

Step 4: Calculate the weighted normalized decision matrix. The weighted normalized value V_{jy} is calculated as;

$$V_{jy} = w_y R_{jy} \tag{17}$$

Step 6: Determine the ideal and negative-ideal solution in this step. The ideal and negative ideal solutions can be expressed as:

$$V^+ = \{(\max. V_{jy}/y \in Y), (\min. V_{jy}/y \in Y')\}; \tag{18}$$
$$= \{V_1^+, V_2^+, V_3^+, \ldots\ldots\ldots V_n^+\}$$

$$V^- = \{(\min. V_{jy}/y \in Y), (\max. V_{jy}/y \in Y')\}; \tag{19}$$
$$= \{V_1^-, V_2^-, V_3^-, \ldots\ldots\ldots V_n^-\}$$

where Y=(y=1,2,3….p)/y is associated with beneficial attributes, and

Y'=(y=1,2,3….p)/y is associated with non-beneficial attributes.

Step 7: Obtain the separation measures. The separation of each alternative from the ideal one is given by the Euclidean distance in the following equations.

$$S_j^+ = \{ \sum_{y=1}^{p} (V_{jy} - V_y^+)^2 \}^{1/2}, \qquad j = 1,2,\ldots\ldots\ldots\ldots,m \tag{20}$$

Similarly, the separation from the negative ideal solution is given as;

$$S_j^- = \{ \sum_{y=1}^{p} (V_{jy} - V_y^-)^2 \}^{1/2}, \qquad j = 1,2,\ldots\ldots\ldots\ldots,m \tag{21}$$

Step 8: The relative closeness of a particular alternative to the ideal solution, P_j, can be expressed in this step as follows;

$$P_j = S_j^- / (S_j^+ + S_j^-) \tag{22}$$

Step 9: P_j is also called the overall or composite performance score of corresponding alternative. Use arithmetic average to calculate the factor effects on the composite performance score and then decide the optimal factor-level combination by higher-the-better factor effects.

EXPERIMENTATION

AISI O1 tool steel was selected for investigation. AISI O1 (general purpose oil-hardening) tool steel is a versatile manganese-chromium-tungsten steel suitable for a wide variety of cold-work applications. Its main characteristics include good machinability, good dimensional stability in hardening and good combination of high surface hardness and toughness after hardening and tempering. These characteristics combine to give steel suitable for the manufacture of tooling with good tool life and production economy. Chemical composition and properties of AISI O1 tool steel are represented in table 1 and table 2 respectively.

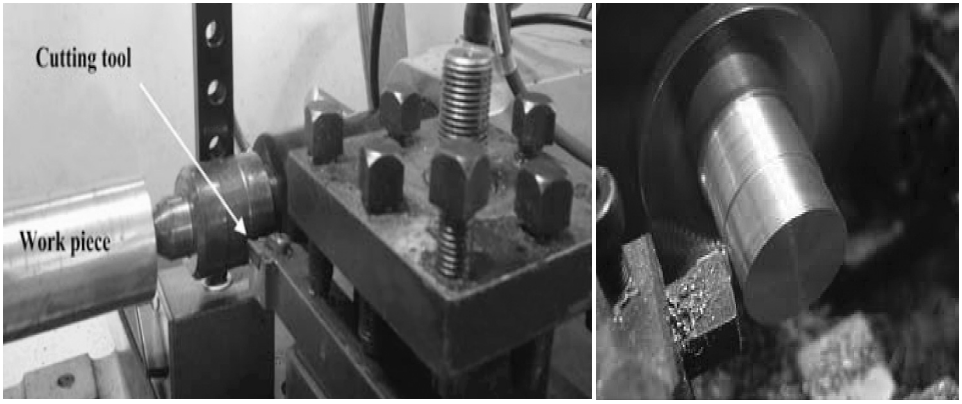
Table 1. Chemical composition of AISI O1 tool steel

Typical Analysis % C - 0.95 Mn - 1.1 Cr - 0.6 W - 0.6	
Standard specification	AISI O1, W-Nr 1.2510
Color code	Yellow

Table 2. Properties of AISI O1 tool steel

Temperature	20 ^{0}C	200 ^{0}C	400 ^{0}C
Density kg/M^3	7800	7750	7700
Modulus of elasticity N/mm^2	190000	185000	170000
Coefficient of thermal exp. Per ^{0}C from 20 ^{0}C	--	11.7 x 10^{-6}	11.4 x 10^{-6}
Thermal conductivity W/m ^{0}C	32	33	34
Specific heat J/kg C	460	--	--

Hindustan machine tool (NH22) lathe machine was used for this experimentation. The size and the shape of work piece were selected based on the availability from the supplier. Also the work piece design was finalized keeping in view the capabilities of the lathe machine to ensure better performance in machining the work piece. The Figure 2 (a) & (b) shows the experimental setup and machining zone respectively.



(a) (b)

Fig. 2. (a) Experimental setup; (b) Machining zone

To measure the MRR, the time taken for each operation was recorded using stop watch. The calculation for MRR was performed by taking the ratio of weight loss of workpiece during each operation to the machining time. Surface roughness was measured by using Perthometer. The experiments were planned using Taguchi's orthogonal array in the design of experiments (Ross, 1996). The experiments were conducted according to 3-level L-9 orthogonal array (Table: 4). Machining parameters and their levels are represented in Table 3.

Table 3. Process parameters and their levels

Symbol	Cutting Parameter	Level 1	Level 2	Level 3	Unit
A	Tool nose radius	0.2	0.4	0.8	mm
B	Speed	192	325	490	rpm
C	Feed	0.05	0.1	0.2	mm/rev
D	Depth of cut	0.2	0.4	0.6	mm

Table 4. Control log for experimentation based on L9 OA

Exp. No.	Run order	Nose radius (mm)	Spindle speed (rpm)	Feed (mm/rev)	DOC (mm)
1	5	0.2	192	0.05	0.2
2	3	0.2	325	0.1	0.4
3	6	0.2	490	0.2	0.6
4	1	0.4	192	0.1	0.6
5	7	0.4	325	0.2	0.2
6	2	0.4	490	0.05	0.4
7	9	0.8	192	0.2	0.4
8	7	0.8	325	0.05	0.6
9	8	0.8	490	0.1	0.2

Table 5. Experimental results for material removal and surface roughness

Exp. No.	Material removal rate (MRR)			Mean value	SN Ratio	Surface roughness			Mean value	SN Ratio
	1	2	3			1	2	3		
1	0.01615	0.01575	0.0163	0.0161	-35.8687	2.19	1.64	1.84	1.890	-5.5916
2	0.11255	0.12058	0.11692	0.1166	-18.6698	2.89	3.17	2.59	2.883	-9.2271
3	0.53336	0.44647	0.51815	0.4993	-6.11244	2.16	2.44	1.99	2.196	-6.86615
4	0.10444	0.08743	0.09508	0.0956	-20.4543	4.53	2.16	3.53	3.406	-10.9861
5	0.10951	0.10678	0.11489	0.1104	-19.1529	4.4	2.61	3.89	3.633	-11.3887
6	0.08517	0.0912	0.09367	0.0900	-20.9326	4.44	3.9	3.47	3.936	-11.9465
7	0.13322	0.14266	0.15124	0.1423	-16.9663	5.15	3.3	4.21	4.220	-12.6432
8	0.08821	0.07386	0.08010	0.0807	-21.9276	1.9	2.59	1.69	2.060	-6.42603
9	0.08244	0.08041	0.09172	0.0848	-21.4674	1.28	2.71	1.32	1.770	-5.53272

RESULTS AND DISCUSSION

A complete residual analysis has also been done for surface roughness and the graphs are shown in Figure 3. Normal probability plot (Figure 3a) of residuals shows that residuals are falling on a straight line, which means that the errors are normally distributed, confirming a good correlation between experimental and predicted values for the response. In graph of residuals versus fitted values (Figure 3(b)), only small variations can be seen. The histogram of residuals is also shown in Figure 3(c). Residuals against the order of experimentations are plotted as shown in Figure 3(d), both negative and positive residuals are apparent indicating no special trend which is worthy from statistical point of view. As a whole, all the yielded models do not show any inadequacy.

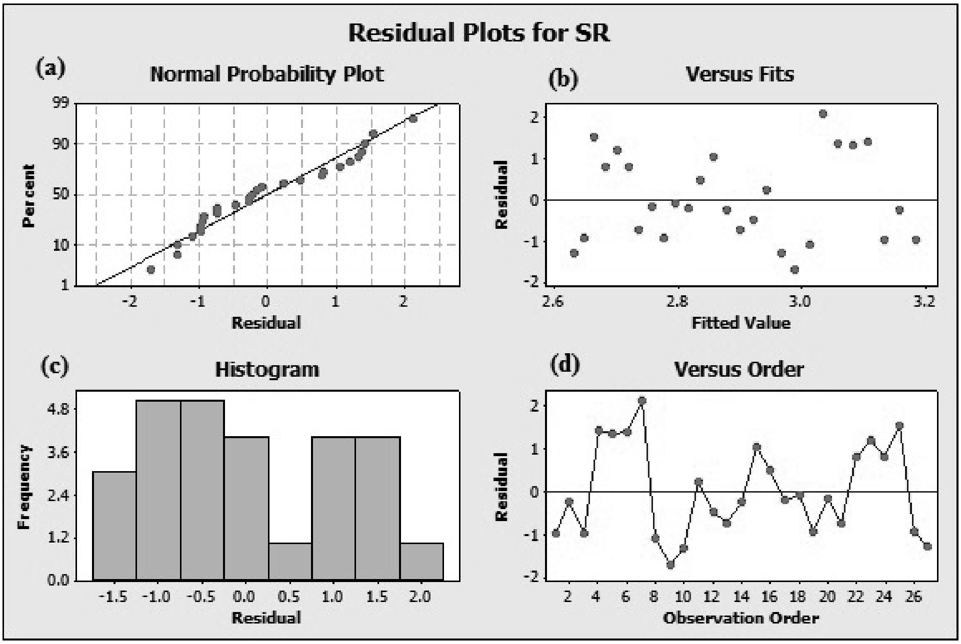
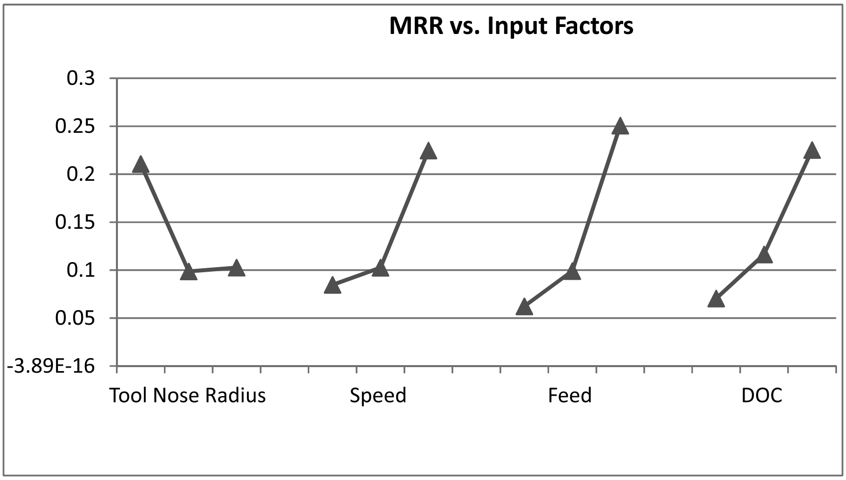


Fig. 3. Residual plot for surface roughness
((a) Normal probability plot of residuals, (b) residuals versus the fitted values, (c) histogram of the residuals, and (d) residuals against the order of data)

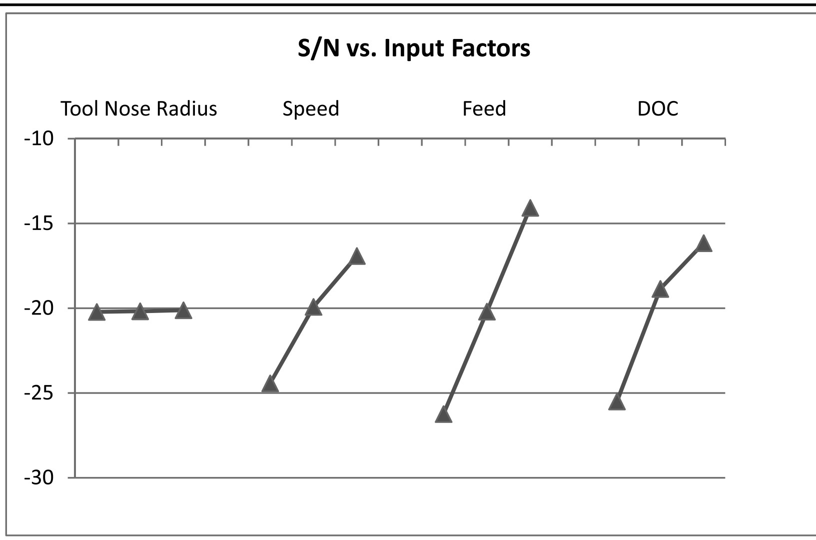
After conducting the experiments, the results are shown in Table 5. The S/N ratio is obtained using Taguchi's method. The S/N ratio represents the amount of variation present in performance characteristics. On the basis of objective of performance characteristics, there are three types of S/N ratios in Taguchi method. Here, the desirable objective is to maximize MRR while keeping the SR at minimum.



Optimized process setting for MRR response (raw data)

Tool nose radius - 0.2 mm
Cutting speed - 490 rpm
Feed rate - 0.2mm/rev
DOC - 0.6 mm

Fig. 4. Effect of process parameters on MRR (raw data)

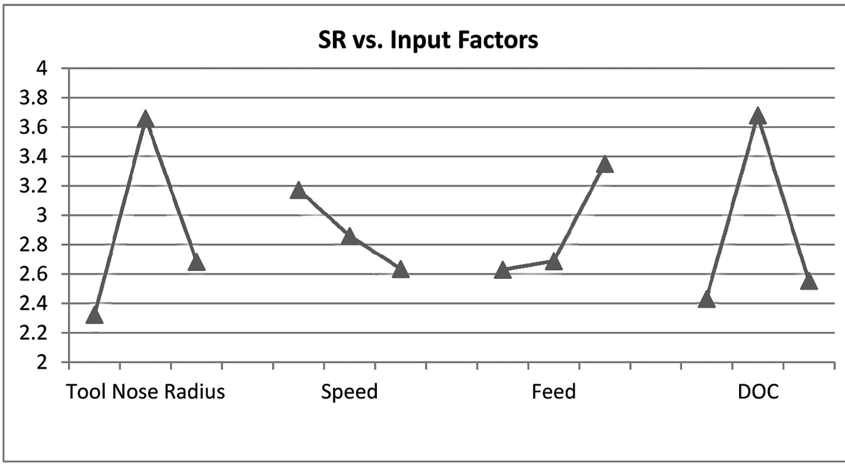


Optimized process setting for MRR response (S/N data)

Type of S/N- Larger-the-better

Tool nose radius - 0.2 mm
Cutting speed - 490 rpm
Feed rate - 0.2mm/rev
DOC - 0.6 mm

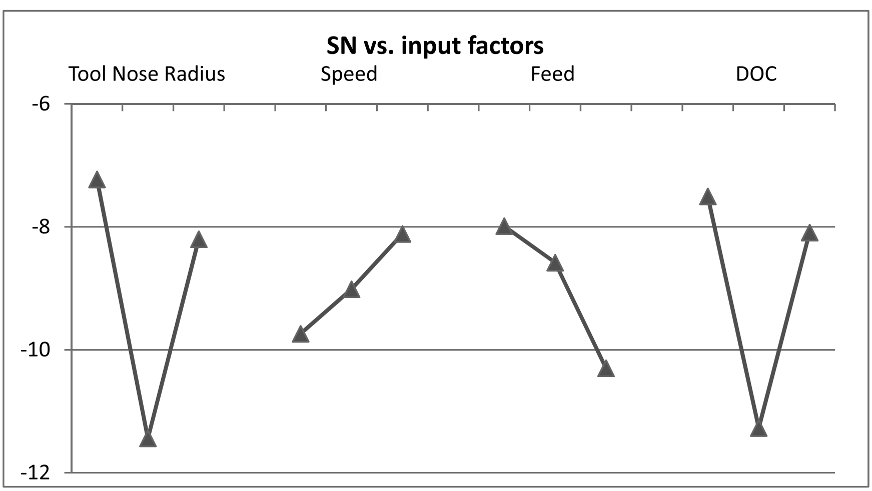
Fig. 5. Effect of process parameters on MRR (S/N data)



Optimized process setting for SR response (raw Data)

Tool nose radius	- 0.2 mm
Cutting speed	- 490 rpm
Feed rate	- 0.05mm/rev
DOC	- 0.2 mm

Fig. 6. Effect of process parameters on surface roughness (raw data)



Optimized process setting for SR response (S/N data)

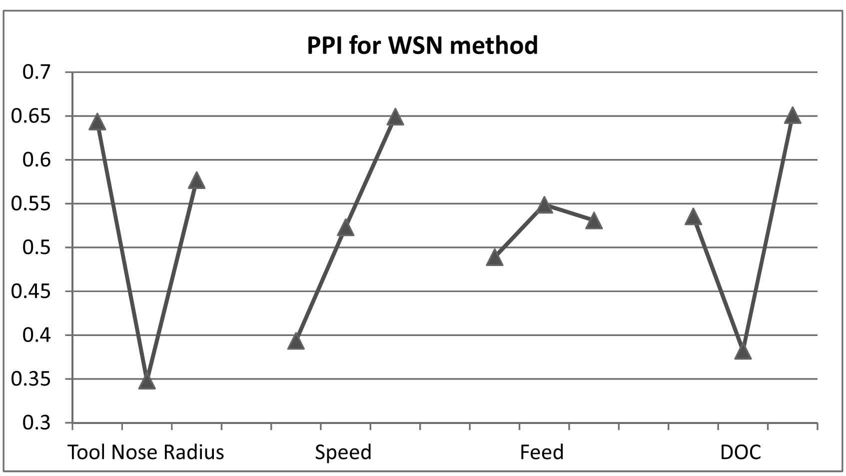
Type of S/N- Lower-the-better

Tool nose radius	- 0.2 mm
Cutting speed	- 490 rpm
Feed rate	- 0.05mm/rev
DOC	- 0.2 mm

Fig. 7. Effect of process parameters on surface roughness (S/N data)

The main effect can be studied by the level average response analysis of raw data or of S/N data. The analysis is performed by averaging the raw or S/N data at each level of each parameter (Montgomery, 2001) and plotting the value in graphical form. The level average response from the S/N data helps in optimizing the objective function. The main effect of raw data and those of the S/N ratio have been estimated and obtained in Figures 4-7.

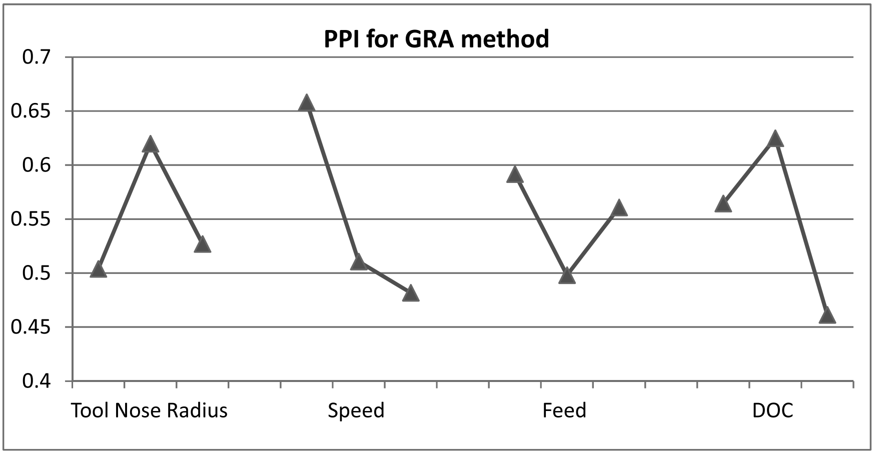
In order to compare different multi-response optimization methods i.e. WSN, GRA, Utility concept and TOPSIS, the calculation is performed by considering the weights for MRR and SR 0.5 and 0.5 respectively. All the computations involved in estimation of the PPI for the different methods have been done in accordance with the procedure specified in previous section (please refer section- Methods used for multi-response optimization). Figures 8-11 illustrates the main effect plots for WSN, GRG, UT and TOPSIS. The PPI values for WSN, GRA, Utility theory and TOPSIS techniques are calculated in sections 3. Table 5 shows the calculated values of PPI for the four multi-response optimization techniques.



Optimized process setting for turning operation (for WSN method)

Tool nose radius - 0.2 mm
Cutting Speed - 490 rpm
Feed rate - 0.1mm/rev
DOC - 0.6 mm

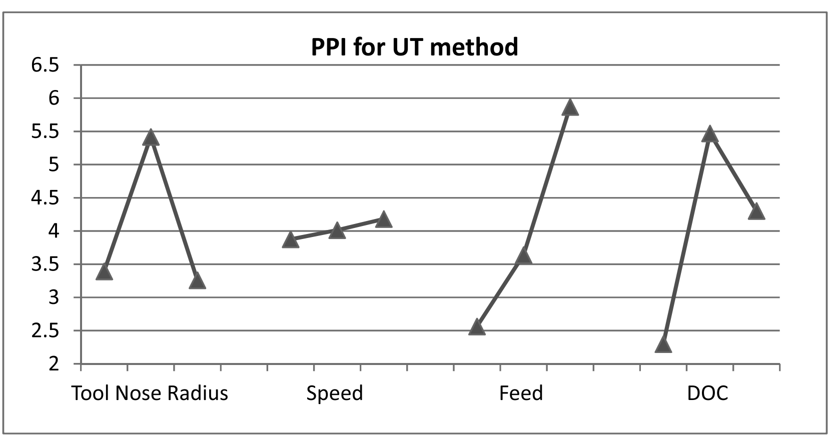
Fig. 8. Main effect plots for weighted S/N ratio



Optimized process setting for turning operation (for GRA method)

Tool nose radius - 0.4 mm
Cutting speed - 192 rpm
Feed rate - 0.05mm/rev
DOC - 0.4 mm

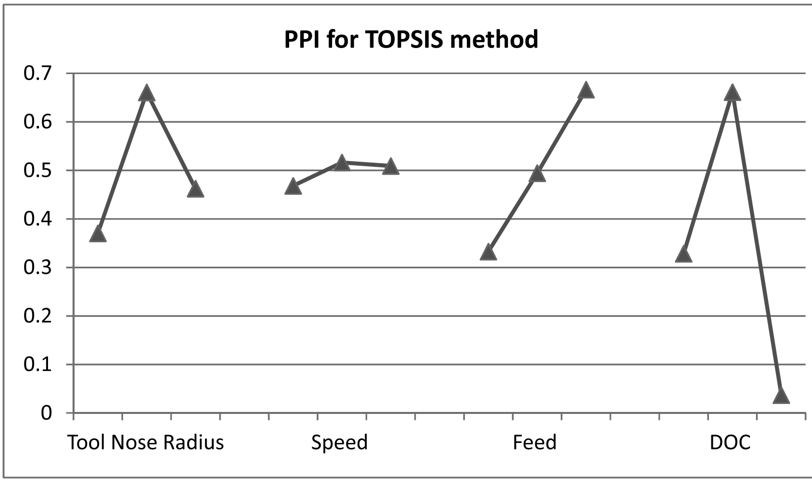
Fig. 9. Main effect plots for grey relational grade



Optimized process setting for turning operation (for UT method)

Tool nose radius - 0.4 mm
Cutting speed - 490 rpm
Feed rate - 0.2mm/rev
DOC - 0.4 mm

Fig. 10. Main effect plots for utility value



Optimized process setting for turning operation (for TOPSIS method)

Tool nose radius - 0.4 mm
Cutting speed - 4325 rpm
Feed rate - 0.2mm/rev
DOC - 0.4 mm

Fig. 11. Main effect plots for TOPSIS

Table 6. Computed PPI values

Exp. No.	Process Performance Index (PPI)			
	WSN	GRG	Utility Value	TOPSIS
1.	0.4959	0.6676	0.0576	0.0058
2.	0.5292	0.4869	4.4454	0.5486
3.	0.9062	0.3571	5.6757	0.5560
4.	0.3755	0.5866	5.1633	0.6335
5.	0.3691	0.6050	5.5265	0.6785
6.	0.3000	0.6676	5.5609	0.6704
7.	0.3176	0.7202	6.4037	0.7646
8.	0.6714	0.4400	2.0664	0.3216
9.	0.7420	0.4207	1.3054	0.3007

The level average of control factors on the PPI value of the four methods are given in Table 7. The optimal process setting for MRR and SR using Taguchi single response optimization is A1B3C3D3 and A1B3C1D1 respectively. While considering multi-response optimization techniques i.e. WSN, GRA, Utility concept and TOPSIS the optimized process setting is A1B3C2D3, A2B1C1D2, A2B3C3D2 and A2B2C3D2 respectively.

Table 7. Level averages on the WSN, GRG, Utility concept and TOPSIS

	WSN			GRG			Utility Concept			TOPSIS		
Factor	Level 1	Level 2	Level 3	Level 1	Level 2	Level 3	Level 1	Level 2	Level 3	Level 1	Level 2	Level 3
TNR	0.6438	0.3482	0.5770	0.5039	0.6198	0.5270	3.393	5.417	3.259	0.3702	0.6608	0.4623
Speed	0.3963	0.5232	0.6494	0.6581	0.5107	0.4818	3.875	4.013	4.181	0.4680	0.5162	0.5090
Feed	0.4891	0.5489	0.5310	0.5917	0.4981	0.5608	2.562	3.638	5.869	0.3326	0.4943	0.6664
DOC	0.5356	0.3823	0.6511	0.5645	0.6249	0.4613	2.297	5.470	4.302	0.3284	0.6612	0.5037

Table 8 shows the predicted SN ratio of responses for different methods. Based on the optimal condition, WSN method gives highest SN ratio which is preferable from the point of view of "robustness', as the larger value of S/N response is desirable for obtaining a better response with minimum noise. Hence, WSN method has yielded best results for multi-response optimization of the S/N responses considered in the study (MRR and SR) and using the optimized process setting obtained through the application of this method (A1B3C2D3) would enable the machinist to realize highly robust process performance.

Table 8. Predicted SN ratios of different optimization methods

Optimization Method	Performance characteristics	Optimized setting	Predicted SN ratio MRR(dB)	SR(dB)	Total(dB)
Taguchi method	MRR	A1B3C3D3	-6.113	-	-
Taguchi method	SR	A1B3C1D1	-	-3.965	-
WSN method	WSN ratio	A1B3C2D3	-12.233	-5.149	-17.482
GRA method	GRG	A2B1C1D2	-29.193	-13.751	-42.944
Utility concept	Utility value	A2B3C3D2	-8.773	-14.257	-23.030
TOPSIS	CPS	A2B2C3D2	-12.523	-15.156	-27.679

CONCLUSIONS

In present work, turning operation for AISI O1 tool steel has been optimized. Taguchi method, WSN, GRA, Utility Concept and TOPSIS methods were used to optimize the material removal rate (MRR) and surface roughness (SR) responses collectively. On the basis of results, the following conclusions can be drawn-

- The optimal parametric setting for material removal rate is A1B3C3D3, with predicted optimal S/N ratio -6.113. The optimal parameter setting for surface roughness is A1B3C1D1, with predicted optimal S/N ratio -3.965.

- For multi-response optimization, the optimal parametric settings for WSN, GRA, Utility Concept and TOPSIS are A1B3C2D3, A2B1C1D2, A2B3C3D2 and A2B2C3D3 respectively. Hence, there has been considerable difference among the optimal settings yielded by the methods investigated.
- On the basis of computations performed, WSN method yielded highest magnitude of S/N response (-17.482 dB) and therefore, may be recommended, provided that the range of parameters investigated is kept fixed.

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