Multi-response Optimization using TGRA for End Milling of AISI H11 Steel Alloy Using Carbide End Mill

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Abstract. The AISI H11 steel is an important material used for making tools & dies. Machining is a very important activity in manufacture of tools & dies where the surface finish and metal removal rate play a very vital role. This paper presents the influence of the cutting speed, feed rate and depth of cut in end milling onto the surface roughness (SR) and metal removal rate (MRR). The machining experiments have been carried out on CNC vertical milling machine. Taguchi grey relational analysis (TGRA) with standard L₂⁷ orthogonal array has been selected to investigate the connection for studying surface roughness and metal removal rate (MRR). Both the responses viz. surface roughness and material removal rate are assumed to have equal weightage (W₁ = W₂ = 0.5) considering general machining conditions. The model significance tests have been conducted using ANOVA to find out which factors are statistically significant. The percentage contribution of cutting speed, feed rate and depth of cut are 29.13 %, 40.93 % and 17.4 % respectively. Optimization has been carried out to get optimum combination of SR and MRR.

Keywords: End milling, AISI H11, Surface Roughness, MRR, TGRA, and ANOVA.

1. Introduction

Machining parameters perform an essential contribution in metal machining. Parameters like cutting speed (CS), feed rate (FR) and depth of cut (DOC) have a primary impact on surface finish, production cost and productivity; therefore, their proper choice assumes significance. End milling is among the essential machining operations, especially employed for die making, due to its complex geometric shapes production capability with good precision and surface refinement. The present investigation studied the optimization of machining factors to obtain good surface and better production rate, to fill the gap between productivity & quality, economically.

Efforts have been done for simultaneously optimization of both quality and productivity. A relevant single quality indicator, known as GRG (grey relational grade), has been improved for both the objectives using TGRA (Moshat et al. 2010). Metal machining has been quite common...
manufacturing operation for more than a century. Although the significance of optimal machining parameters was identified in 1900s, but, the development in optimization strategies have been very slow (Sonmez et al., 1999). The brief review of recent research in relevant area (end milling of ferrous metals) is presented in this Section.

Yih-fong and Ming-der (2005) experimentally attempted dimensional quality improvement in high CS CNC end milling of steels SKD-11 and SKD-61. Circle, square and triangle were three typical geometries used as a test sample in the experimentation for representing the geometrical variations in the die and mould product. Milling type, tool material, rake angle, CS, film material, number of tooth, feed per tooth, and helix angle were the selected factors. Except milling type which has only two levels, all other parameters have three levels. From analysis milling type, number of teeth and CS were observed to be major influencing factors.

Tzeng (2007) combined Taguchi and PCA method for the improvement in the milling of steels SKD-11 and SKD-61. Milling type, rake angle, tool material, CS, film material, number of tooth, feed per tooth, and helix angle were the selected factors for response parameters like dimensional correctness and accuracy, surface roughness (SR) and tool life (TL). From the analysis of results milling type, number of teeth and CS were observed to be major important factors.

Gopalsamy et al. (2009) applied Taguchi and ANOVA in improving the machining factors for ball end milling of AISI H11 steel. Surface finish and tool life were the response parameters together with machining parameters like CS, FR, DOC and width of cut. A four-factor with three-level L18 OA was selected for performing the experimentation work. From the results analysis, CS was found to be the most important parameter.

Lu et al. (2009) proposed the GRA combined with PCA for optimizing the machining parameters in high CS end milling of SKD61 tool steels. Cutting tools formed of tungsten carbide with TiAlN coating were used for the machining operations. Tool life and MRR were the selected response characteristics. The weight-age values analogical to multiple performance features were evaluated with the use of principal component analysis (PCA). Milling type, CS, and feed per tooth were observed to be main significant factors affecting the multi-objective characteristics using ANOVA.

Pa et al. (2012) studied the influence of cutting factors for improving the surface quality in milling of medium carbon steel S50C. Ti coated carbide end mill was used as cutting tool. Machined surface inclination angle, axial DOC, CS and FR were the selected control factors. Standard L9 orthogonal array was selected for conducting the experimentation. The ANOVA test was applied to analyse the statistical significance of input factors. From the analysis, the axial DOC was observed to be best influencing parameter.

Shihab et al. (2014) studied the impact of CS, FR and DOC in turning of AISI 52100 alloy steel. The cutting temperature was selected as response parameter using TiN/TiCN/Al2O3/TiN coated carbide insert. Experiments were performed based on CCD for the collection of data. The best combination of machining variables was determined with the help of RSM. ANOVA was used for checking the significance of machining parameters. Also, the cutting temperature was found to be mainly influenced by CS and FR.

Asilturk et al. (2016) proposed a SR (Ra, Rz) model, during turning of Co28Cr6Mo medical alloy in dry conditions. The process parameters selected were spindle rotational speed, FR, DOC and tool tip radius. RSM and Taguchi L27 OA were applied to determine the best combination of parameter setting. The accuracy of the predicted results was found to be 92%.

Sales et al. (2017) studied the wear mechanisms in turning of Ti6Al4V alloy using PCD tools. Three different environments hybrid (liquid N2 + fluid at MQL), cryogenic (liquid N2), and flood (vegetable fluid) were used during the experimentation. The cryogenic coolant condition was observed to produce lower forces, compared to hybrid and flood conditions. From the results, crater and flank wear were found to be dominant wear.

Singh et al. (2018) optimized the cutting parameters during turning of Al5083-7%B4C composite in dry environment. Ant bee colony (ABC), Particle swarm optimization (PSO) and Bat
algorithm (BA) algorithm were applied to find the best parametric combinations for achieving better machining performance. $L_{25}$ OA was used for conducting the experiments. Based on results obtained, a linear regression model was developed. Among the three-optimization algorithm applied, PSO was found to give better results compared to other two.

Sivaiah and Chakradhar (2019) combined T-TOPSIS and TGRA for optimization of three responses (SR, flank wear and MRR) in turning of 17-4 PH SS. AlTiN coated KC5010 carbide inserts were used in cryogenic environment for the machining work. Liquid nitrogen was used as a cryogenic coolant and CS, FR and DOC as controllable process parameters. Results were found to improve by TGRA compared to T-TOPSIS.

The brief literature review on end milling reveals the state-of-the-art. The other relevant literature has been already presented by the authors (Saini, 2013; Singh et al., 2019). The work appears to have been carried out on various ferrous metals using different tool materials under several machining conditions. The common control parameters have been the CS, FR, DOC. The application of coolants, a few elements of tool geometry, surface inclination angle, etc. have also been considered the control parameter in a few studies. The most commonly used response parameters have been the SR, and MRR. The cutting forces (CF), and tool life (TL), and dimensional quality have also been considered as the response parameters in a few studies. The RSM & Taguchi approach have been quite common analysis methods. Application of PCA and GRA approaches have also been applied in a few studies.

The study on the material alloy steel AISI H11 will strengthen the insight into relationship among the control and the response parameters. The TGRA methodology with $L_{27}$ orthogonal array (OA) appears to be quite suitable for selection of machining parameters for the multi-response (minimization of SR and maximization of MRR) relationships in milling to make a useful contribution (Singaravel et al., 2014).

2. Design of Experiments and Analysis Methodology

The TGRA has been adopted in the present work for the problem being a multi-objective one. Here the experiments are designed in a way that the influence of all the parameters can be studied with least possible trials (Sahoo and Pal, 2008). The $L_{27}$ OA (Benardos & Vosniakos, 2002) has been selected for conducting the experiments for want of accuracy of the results and consideration of interaction effects. A detailed discussion on the methodology has been presented by Roy (2001) and Montgomery (2004) which includes the following steps:

a. Identification of the process parameters and response characteristics.
b. Determination of the process parameters levels.
c. Assignment of the cutting parameters to the appropriately selected OA.
d. Conducting the experiments based on selected OA.
e. Normalization of the experimental results of SR and MRR.
f. Generation and calculation of the grey relational coefficient (GRC).
g. Calculation of the grey relational grade (GRG) by assigning weightage to the GRC.
h. Analysis of the GRG using ANOVA.
i. Selection of the best combination of process factors with levels.

3. Experimental Details

Experiments were conducted on a BFW SURYA CNC, fitted with Alternating current alterable spindle speed motor till 6000 rpm and 3.7 kW, in dry conditions. The cutting inserts with 0.8 mm nose radius with the WIDAX end milling cutter of diameter 16 mm were used for experimentation. The machining tests were performed on AISI H11 steel alloy plates (117 mm x 80 mm x 20 mm). The chemical composition of AISI H11 obtained using Spectro-examination is abbreviated in Table 1.
process control factors with levels are shown in Table 2. Complete design layout for conducting experimentation and corresponding response results are represented in Table 3.

**Table 1. Chemical composition of AISI H11, % weight**

| Alloying elements | C   | Mn  | Si   | Cr  | Mo  | V   | P    | S    |
|-------------------|-----|-----|------|-----|-----|-----|------|------|
| % age             | 0.25| 0.36| 0.85 | 5.14| 1.20| 0.014| 0.010|

**Table 2. Process control parameters and their levels according to TGRA**

| Parameter (units) | Symbol | Level 1 | Level 2 | Level 3 |
|-------------------|--------|---------|---------|---------|
| Cutting speed (m/min) | A | 15 | 35 | 55 |
| Feed rate (mm/tooth) | B   | 0.12 | 0.20 | 0.30 |
| Depth of cut (mm) | C    | 0.20 | 0.40 | 0.60 |

**Table 3. Complete design layout and experimental results**

| Expt. No. | A: Cutting speed (m/min) | B: Feed rate (mm/tooth) | C: Depth of cut (mm) | Surface roughness (μm) | Metal removal rate (mm³/sec) |
|-----------|--------------------------|-------------------------|----------------------|-------------------------|-----------------------------|
| 1         | 15                       | 0.12                    | 0.2                  | 4.83                    | 0.32                        |
| 2         | 15                       | 0.12                    | 0.4                  | 4.11                    | 0.62                        |
| 3         | 15                       | 0.12                    | 0.6                  | 4.84                    | 0.93                        |
| 4         | 15                       | 0.20                    | 0.2                  | 5.70                    | 0.52                        |
| 5         | 15                       | 0.20                    | 0.4                  | 4.94                    | 1.04                        |
| 6         | 15                       | 0.20                    | 0.6                  | 6.58                    | 1.56                        |
| 7         | 15                       | 0.30                    | 0.2                  | 6.84                    | 0.78                        |
| 8         | 15                       | 0.30                    | 0.4                  | 6.89                    | 1.56                        |
| 9         | 15                       | 0.30                    | 0.6                  | 5.61                    | 2.34                        |
| 10        | 35                       | 0.12                    | 0.2                  | 2.29                    | 0.72                        |
| 11        | 35                       | 0.12                    | 0.4                  | 1.97                    | 1.45                        |
| 12        | 35                       | 0.12                    | 0.6                  | 1.88                    | 2.18                        |
| 13        | 35                       | 0.20                    | 0.2                  | 1.75                    | 1.23                        |
| 14        | 35                       | 0.20                    | 0.4                  | 2.22                    | 2.42                        |
| 15        | 35                       | 0.20                    | 0.6                  | 2.61                    | 3.64                        |
| 16        | 35                       | 0.30                    | 0.2                  | 2.58                    | 1.82                        |
| 17        | 35                       | 0.30                    | 0.4                  | 3.16                    | 3.64                        |
| 18        | 35                       | 0.30                    | 0.6                  | 3.17                    | 5.46                        |
| 19        | 55                       | 0.12                    | 0.2                  | 2.36                    | 1.14                        |
| 20        | 55                       | 0.12                    | 0.4                  | 2.36                    | 2.28                        |
| 21        | 55                       | 0.12                    | 0.6                  | 2.33                    | 3.43                        |
| 22        | 55                       | 0.20                    | 0.2                  | 2.48                    | 1.96                        |
| 23        | 55                       | 0.20                    | 0.4                  | 2.47                    | 3.81                        |
| 24        | 55                       | 0.20                    | 0.6                  | 2.20                    | 5.72                        |
| 25        | 55                       | 0.30                    | 0.2                  | 2.90                    | 2.86                        |
| 26        | 55                       | 0.30                    | 0.4                  | 2.22                    | 5.72                        |
| 27        | 55                       | 0.30                    | 0.6                  | 2.28                    | 8.58                        |
Although several parameters are concerned to surface roughness, but the most accepted parameter is centreline average (CLA) surface roughness value ($R_a$) (Bhardwaj et al., 2014). In this study, SR ($R_a$) of the specimens after milling was studied handling Mitutoyo SurfTest–4 (Tosum and Pihibli, 2010). The metal removal rate (MRR) has been assessed as material volume removed per unit time based on the geometry of the material removed and the parameters (RPM of cutter, table (machine) feed, feed/tooth of cutter, length of pass or cut, number of teeth on cutter, CS) of the machining process.

4. Results and Discussion

A series of 27 end milling tests have been conducted. Three parameters CS, FR and DOC are picked as control factors. The SR and MRR are selected as the response characteristics. The outcome of these control parameters on the results has been analysed using the TGRA approach in MS EXCEL for the analysis of mean (ANOM) and the ANOVA to recognise important parameters and their interactions.

4.1 Calculation of S/N Ratios and Subsequent Normalization

The term ‘signal’ signifies the average value while the ‘noise’ signify the unwanted value for the output feature. For surface roughness (smatter the better) and for MRR (larger the better) criterion has been used. Also, it is necessary to normalize the calculated S/N ratio values before proceeding for analysis. A suitable value is subtracted from the values in the common array to temper the value of present array $\approx 1$ (Haq et al., 2008). The computed and the normalized values of S/N ratio are obtained for SR and MRR.

| Expt. No. | Orthogonal array ($L_{27}$) | Grey relational coefficient | GRG for $W_1=W_2=0.5$ | Grade order |
|-----------|----------------------------|-----------------------------|------------------------|-------------|
|           | A  | B  | C  | $R_a$ | MRR |                     |            |             |
| 1         | 1  | 1  | 1  | 0.658586339 | 0.333333333 | 0.495959836 | 17          |
| 2         | 1  | 1  | 2  | 0.570131874 | 0.387340332 | 0.478736103 | 18          |
| 3         | 1  | 1  | 3  | 0.659898111 | 0.427894555 | 0.543896333 | 12          |
| 4         | 1  | 2  | 1  | 0.783267200 | 0.371507750 | 0.577387475 | 9           |
| 5         | 1  | 2  | 2  | 0.673156577 | 0.439861512 | 0.556508594 | 11          |
| 6         | 1  | 2  | 3  | 0.937045526 | 0.492912352 | 0.714978939 | 2           |
| 7         | 1  | 3  | 1  | 0.989482689 | 0.408854546 | 0.690969063 | 3           |
| 8         | 1  | 3  | 2  | 1.000000000 | 0.492912352 | 0.746456176 | 1           |
| 9         | 1  | 3  | 3  | 0.769272160 | 0.540514972 | 0.764893566 | 5           |
| 10        | 2  | 1  | 1  | 0.383505712 | 0.401818763 | 0.392662238 | 27          |
| 11        | 2  | 1  | 2  | 0.353708750 | 0.483000057 | 0.418354404 | 25          |
| 12        | 2  | 1  | 3  | 0.345372146 | 0.577325511 | 0.446552349 | 23          |
| 13        | 2  | 2  | 1  | 0.333333333 | 0.458592777 | 0.368643001 | 26          |
| 14        | 2  | 2  | 2  | 0.376956122 | 0.567425888 | 0.472199355 | 21          |
| 15        | 2  | 2  | 3  | 0.413797678 | 0.659003584 | 0.567884631 | 13          |
| 16        | 2  | 3  | 1  | 0.410928823 | 0.516600422 | 0.463714432 | 20          |
| 17        | 2  | 3  | 2  | 0.467819454 | 0.659003584 | 0.563411519 | 10          |
| 18        | 2  | 3  | 3  | 0.468830769 | 0.785695451 | 0.622760089 | 6           |
| 19        | 3  | 1  | 1  | 0.390079227 | 0.451278542 | 0.420678883 | 24          |
| 20        | 3  | 1  | 2  | 0.390079227 | 0.556286368 | 0.473182798 | 19          |
| 21        | 3  | 1  | 3  | 0.387258873 | 0.643935446 | 0.51559716 | 16          |
| 22        | 3  | 2  | 1  | 0.401412726 | 0.524144381 | 0.462785533 | 22          |
| 23        | 3  | 2  | 2  | 0.400468461 | 0.671401427 | 0.53933144 | 14          |
| 24        | 3  | 2  | 3  | 0.375088751 | 0.803416395 | 0.589252573 | 8           |
| 25        | 3  | 3  | 1  | 0.441914712 | 0.601331722 | 0.521623216 | 15          |
| 26        | 3  | 3  | 2  | 0.376956122 | 0.803416395 | 0.590186259 | 7           |
| 27        | 3  | 3  | 3  | 0.382568666 | 1.000000000 | 0.691284333 | 4           |
4.2 Grey relational coefficients (GRCs) and Grey relational grades (GRGs: General machining ($W_1 = W_2 = 0.5$))

The GRA is performed via calculating the GRC on the normalized S/N ratio values. Both the characteristics, viz. SR and MRR are assumed to have equal weightage ($W_1 = W_2 = 0.5$) considering general machining conditions. The results so obtained are presented in Table 4. Since calculating grey relational coefficients, next step is to calculate overall GRG which is average quantity of the GRC corresponding to chosen responses. Now, the execution of the multi-objective process totally depends on the calculated GRG.

Highest GRG gives indication for the optimal parametric combination in the multi-response process because the high GRG corresponds to a high relational limit between the reference sequence and the given sequence. Here reference sequence simply indicates the excellent process series. Thus, a highest GRG value represents that the corresponding combination is near to the best. The average response as well as the mean effect plot of the GRG are very crucial to select the best process combination.

4.3 Mean Effects on Overall Grey Relational Grades

Mean effect analysis of variables in orthogonal array of TGRA is very simple. It’s enough to calculate mean value of GRGs at the desired level to determine the effect of any parameter. For example, the average effect of $A_1$ is obtained by mean data for all 1-9 runs. In the same way the mean effect of other variable is also computed. The calculated mean effect of parameters is listed in Table 5. As large value of mean GRG is favourable, the best combination is $A_1 B_3 C_3$.

![Fig.1 Grey relational grades with varying input parameters](image)

**Table 5:** Mean effects on overall grey relational grades

| Level | Cutting speed (A) (m/min) | Feed rate (B) (mm/tooth) | Depth of cut (C) (mm) |
|-------|--------------------------|--------------------------|-----------------------|
| 1     | 0.6086540                | 0.465069                 | 0.492210              |
| 2     | 0.4796190                | 0.537934                 | 0.537219              |
| 3     | 0.5333908                | **0.618661**             | **0.592235**          |
| Average grade | 0.5405546                | 0.5405546                | 0.5405546             |
| Max. – Min. | 0.129035                | 0.153592                 | 0.100026              |
| Percent of deviation | 33.7211                 | 40.1387                  | 26.1401               |
| Rank | 2                         | 1                         | 3                      |
The second last row of the Table presents the percent of deviation for each parameter. Thus, the FR appears to be the most important process parameter, pursued by CS and DOC, that affect the optimization of multiple response characteristics. Figure 1 shows that the GRG value decreases from $A_1$ to $A_2$, and thereafter increases to $A_3$. Also, with enhancement in FR and DOC, the GRG values raise throughout.

4.4 Analysis of Variance (ANOVA)

Summary of the ANOVA results for general machining is shown in Table 6. It shows that all the 3 input parameters appear to be significant. The percentage contribution of CS, FR and DOC are 29.13 %, 40.93 % and 17.4 % respectively.

| FACTOR             | D.F | SUM OF SQUARES | MEAN SQUARES | F-RATIO  | PERCENT CONTRIBUTION | F > F table |
|--------------------|-----|----------------|--------------|----------|-----------------------|-------------|
| CUTTING SPEED (A)  | 2   | 0.075617968    | 0.037808984  | 13.444596| 0.291365667           | significant |
| FEED RATE (B)      | 2   | 0.106250547    | 0.053125273  | 18.890955| 0.409396896           | significant |
| DEPTH OF CUT (C)   | 2   | 0.045173456    | 0.022586728  | 8.0316736| 0.17405908            | significant |
| A × B              | 4   | 0.001814859    | 0.000453715  | 0.1613376| 0.006992882           |             |
| B × C              | 4   | 0.005770794    | 0.001442699  | 0.5130129| 0.022235605           |             |
| A × C              | 4   | 0.002404161    | 0.00060104   | 0.2137255| 0.009263538           |             |
| ERROR              | 8   | 0.022497655    | 0.002812207  | 0.08668632|                      |             |
| TOTAL              | 26  | 0.25952944     | 0.118830646  | 1        |                       |             |
| $F_{0.05(2,8)}$    |     |               |              | 4.459    |                       |             |
| $F_{0.05(4,8)}$    |     |               |              | 8.378    |                       |             |

4.5 Predicted Optimum Condition

The expected average at the best settings ($\mu$) is calculated using Equation (1) where $A_1$, $B_3$ and $C_3$ are the average values of the GRG with the corresponding parameters at best levels and $T_{gg}$ is the overall mean of grey grade (Table 6) (Ahilan et al., 2009). The confidence interval (CI) is obtained using Equation (2)

$$\mu = A_1 + B_3 + C_3 - 2T_{gg} \quad (1)$$

$$CI = \sqrt{F_{critical}(1, f_{e}) \times \frac{V_e}{N_e}} \quad (2)$$

Where, $F_{critical}(1, f_{e}) = F_{critical}$ (from F-table) at a required CI and at DOF = 1 (Trehan et al., 2015).

Error DOF $f_{e} = 8$ and $F_{critical}(1, f_{e}) = 5.3177$

$V_e$ (error mean square) = 0.002812207 (Table 6),

$N_e$ = Effective number of replications

$$N_e = \frac{\text{Total number of results}}{\text{DOF of mean} (= 1, \text{always}) + \text{DOF of all factors included in the estimate of the mean}} = \frac{27}{1+6} = 3.85$$
This yield, $\mu = 0.738$, and C.I = 0.0621. Therefore, at 95% confidence level, the predicted optimum condition becomes “$0.6759 \leq \mu \leq 0.8001$”, where the GRG value for the confirmation experiments at optimal combination (A1 B3 C3) lies.

4.6 Confirmation Experiment

After prediction of optimum settings, the confirmation is done with the best settings to verify the response characteristics. The best combinations for the predicted milling setting levels were applied, and two replicates were performed. To verify the closeness of the observed value with the predicted value, 95% confidence level was selected and the CI value for the optimum combination is determined as represented by Table 7. It is observed through the results that the multi-response problem has been successfully optimized using the TGRA method.

| Setting level | Predicted | Confirmed | Range          |
|---------------|-----------|-----------|----------------|
| Grade         | 0.738     | 0.752     | $(0.6759) \leq \mu \leq (0.8001)$ |

5. Conclusion and Future Scope

The outcome of machining factors such as CS, FR and DOC, has been studied on SR and MRR in end milling of AISI H11 steel alloy. Design of experiment-based TGRA with three factors at three levels ($L_{27}$ orthogonal array) has been utilized for predicting the optimal combination of input parameters for minimum SR & maximum MRR.

All three process parameters - CS, FR and DOC appear to be significant factor for the composite response (SR and MRR, with equal weightage). With increase in cutting speed the GRG first decreases from scale 1 to 2, and then improved from scale 2 to 3, whereas it is found to improve throughout with rise in DOC and FR.

In this work optimization has been attempted only for the two responses variables – SR and MRR. The performance can be further expanded to pursue more response characteristics, such as – tool life (TL), cutting force (CF) etc. Also, more machining parameters like coolant application, tool geometry and other types of milling operations (face milling etc.) may be considered to gain an improved insight inside the process.

References

1. Abdou, G. & Yien, J. (1995). Analysis of force patterns and tool life in milling operations. The International Journal of Advanced Manufacturing Technology, 10(1), 11-18.
2. Ahilan, C., Kumanan, S. & Sivakumaran, N. (2009). Multi-objective optimisation of CNC turning process using grey based fuzzy logic. International Journal of Machining and Machinability of materials, 5(4), 434-451.
3. Asiltürk, I., Neşeli, S., & Ince, M. A. (2016). Optimisation of parameters affecting surface roughness of Co28Cr6Mo medical material during CNC lathe machining by using the Taguchi and RSM methods. Measurement, 78, 120-128.
4. Benardos, P.G. & Vosniakos, G.C. (2002). Prediction of surface roughness in CNC face milling using neural networks and Taguchi’s design of experiments, Robotics and Computer Integrated Manufacturing, 18: 343–354.
5. Bhardwaj, B., Kumar, R. & Singh, P. K. (2014). An improved surface roughness prediction model using Box-Cox transformation with RSM in end milling of EN 353. Journal of Mechanical Science and Technology, 28(12), 5149-5157.
6. Bhardwaj, B., Kumar, R. & Singh, P. K. (2014). Surface roughness (Ra) prediction model for turning of AISI 1019 steel using response surface methodology and Box–Cox transformation. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 228(2), 223-232.

7. Bhardwaj, B., Kumar, R., & Singh, P. K. (2014). Effect of machining parameters on surface roughness in end milling of AISI 1019 steel. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 228(5), 704-714.

8. Gopalsamy, B. M., Mondal, B. & Ghosh, S. (2009). Taguchi method and ANOVA: An approach for process parameters optimization of hardened machining while machining hardened steel.

9. Haq, A. N., Marimuthu, P. & Jeyapaul, R. (2008). Multi response optimization of machining parameters of drilling Al/SiC metal matrix composite using grey relational analysis in the Taguchi method. *The International Journal of Advanced Manufacturing Technology*, 37(3-4), 250-255.

10. Kini, M. V. & Chincholkar, A. M. (2010). Effect of machining parameters on surface roughness and material removal rate in finish turning of ±30 glass fibre reinforced polymer pipes. *Materials & Design*, 31(7), 3590-3598.

11. Lu, H.S., Chang, C.K., Hwang, N.C. & Chung, C.T. (2009). Grey relational analysis coupled with principal component analysis for optimization design of the cutting parameters in high-speed end milling, *Journal of Materials Processing Technology*, 209: 3808–3817.

12. Maiyar, L. M., Ramanujam, R., Venkatesan, K. & Jerald, J. (2013). Optimization of machining parameters for end milling of Inconel 718 super alloy using Taguchi based grey relational analysis. *Procedia engineering*, 64, 1276-1282.

13. Montgomery, D.C. (2008) *Design and Analysis of Experiments*, Hoboken, NJ: John Wiley & Sons.

14. Moshat, S., Datta, S., Bandyopadhyay, A. & Pal, P. (2010). Parametric optimization of CNC end milling using entropy measurement technique combined with grey-Taguchi method. *International Journal of Engineering, Science and Technology*, 2(2), 1-12.

15. Pa, N. M. N., Sarhan, A. A. D. & Shukor, M. H. A. (2012). Optimizing the cutting parameters for better surface quality in 2.5 D cutting utilizing titanium coated carbide ball end mill. *International Journal of Precision Engineering and Manufacturing*, 13(12), 2097-2102.

16. 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 (TGRA). *The International Journal of Advanced Manufacturing Technology*, 56(1-4), 47-62.

17. Pradhan, S. K. & Saini, S. K. (2014). Multi-Objective Optimization of CNC Turning Machining Parameters. In *Advanced Materials Research* (Vol. 1016, pp. 172-176). Trans Tech Publications.

18. Ranganathan, S. & Senthivelan, T. (2011). Multi-response optimization of machining parameters in hot turning using grey analysis. *The International Journal of Advanced Manufacturing Technology*, 56(5-8), 455-462.

19. Ren, J., Zhou, J. & Wei, J. (2015). Optimization of cutter geometric parameters in end milling of titanium alloy using the grey-Taguchi method. *Advances in Mechanical Engineering*, 7(2), 721093.

20. Roy, R. K. (2001). *Design of experiments using the Taguchi approach: 16 steps to product and process improvement*. Hoboken, NJ: John Wiley & Sons.

21. Sahoo, P. & Pal, S. K. (2008). Tribological testing and optimisation of electroless Ni-P coatings based on Taguchi method and grey relational analysis. *Lubrication Science*, 14(2), 127-144.

22. Saini, P. (2013). Optimization of machining parameters in milling of AISI H11 steel alloy by Taguchi based grey relational analysis (M.Tech Thesis) Department of Mechanical Engineering, SLIET, Longowal.
23. Sales, W. F., Schoop, J., & Jawahir, I. S. (2017). Tribological behavior of PCD tools during superfinishing turning of the Ti6Al4V alloy using cryogenic, hybrid and flood as lubri-coolant environments. *Tribology International, 114*, 109-120.

24. Shihab, S. K., Khan, Z. A., Mohammad, A., & Siddiqueed, A. N. (2014). RSM based study of cutting temperature during hard turning with multilayer coated carbide insert. *Procedia materials science, 6*, 1233-1242.

25. Singaravel, B., Selvaraj, T. & Jeyapaul, R. (2014). Multi objective optimization in turning of EN25 steel using Taguchi based utility concept coupled with principal component analysis. *Procedia Engineering, 97*, 158-165.

26. Singh, R., Shadab, M., & Rai, R. N. (2018). Optimization of machining process parameters in conventional turning operation of Al5083/B4C composite under dry condition. *Materials Today: Proceedings, 5*(9), 19000-19010.

27. Singh et al. (2019). Multi Response Optimization of CNC End Milling of AISI H11 Alloy Steel for Rough and Finish Machining using TGRA. *Sādhanā (Revision submitted).*

28. Sivaiah, P., & Chakradhar, D. (2019). Performance improvement of cryogenic turning process during machining of 17-4 PH stainless steel using multi objective optimization techniques. *Measurement, 136*, 326-336.

29. Sonmez, A. I., Baykasoglu, A., Dereli, T. & Fılız, İ. H. (1999). Dynamic optimization of multipass milling operations via geometric programming. *International Journal of Machine Tools and Manufacture, 39*(2), 297-320.

30. Tosun, N. & Pihtili, H. (2010). Gray relational analysis of performance characteristics in MQL milling of 7075 Al alloy. *The International Journal of Advanced Manufacturing Technology, 46*(5-8), 509-515.

31. Trehan, R., Singh, S. & Garg, M. (2015). Optimization of mechanical properties of polyester hybrid composite laminate using Taguchi methodology–Part 1. *Proceedings of the Institution of Mechanical Engineers, Part L: Journal of Materials: Design and Applications*, 229(4), 263-273.

32. Tzeng, Y. F. & Chen, F. C. (2007). Multi-objective optimisation of high-speed electrical discharge machining process using a Taguchi fuzzy-based approach. *Materials & design, 28*(4), 1159-1168.

33. Yih-fong, T. and Ming-der, J. (2005) Dimensional quality optimisation of high-speed CNC milling process with dynamic quality characteristic, *Robotics and Computer-Integrated Manufacturing* 21: 506–517.