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# Multi-Objective Optimization of Machining Parameters During Dry Turning of AISI 304 Austenitic Stainless Steel Using Grey Relational Analysis

Shreemoy Kumar Nayak, Jatin Kumar Patro, Shailesh Dewangan, Soumya Gangopadhyay *

*Department of Mechanical Engineering, National Institute of Technology, Rourkela-769008, Odisha, India*

**Abstract**

The current study aims at investigating the influence of different machining parameters such as cutting speed ($V_c$), feed (f) and depth of cut (t) on different performance measures during dry turning of AISI 304 austenitic stainless steel. ISO P30 grade uncoated cemented carbide inserts was used a cutting tool for the current purpose. L27 orthogonal array design of experiments was adopted with the following machining parameters: $V_c$= 25, 35, 45 m/min., f= 0.1, 0.15, 0.2 mm/rev. and t= 1, 1.25, 1.5 mm. Three important characteristics of machinability such as material removal rate (MRR), cutting force ($F_c$) and surface roughness ($R_a$) were measured. Attempt was further made to simultaneously optimize the machining parameters using grey relational analysis. The recommended parametric combination based on the studied performance criteria (i.e. MRR, $F_c$ and $R_a$) was found to be $V_c$ =45m/min, f=0.1mm/rev, t=1.25mm. A confirmatory test was also carried out to support the analysis and an improvement of 88.78% in grey relational grade (GRG) was observed.



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*Keywords:* *AISI 304 stainless steel;,dry machining; machining parameters; MRR; cutting force; surface roughness; multi-objective optimisation; grey relational analysis.*

## 1. Introduction

AISI 304 austenitic stainless steel is one of the strategic grades of steel having wide engineering applications particularly in chemical equipments, food processing, pressure vessels, cryogenic vessels and paper industry.

* Corresponding author. Tel.: +91-661-2462528
*E-mail address:*soumyag@nitrkl.ac.in



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However, the machinability of the current grade of steel is rather poor compared to most of the other grades of steel due to high strength, low thermal conductivity and tendency of work hardening. Some research work has been reported on the machinability characteristics of AISI 304 stainless steel. Korkut et al. (2004) investigated the influence of cutting speed on surface roughness, chip characteristics and tool wear during turning of AISI 304 steel. Tekiner and Yeşilyurt (2004) utilized unique process sound technique to determine optimal condition of cutting speed and feed in order to achieve favorable chip form and minimum flank wear, built-up edge and surface roughness. Xavior and Adithan (2009) studied the influence of different cutting fluids on the tool wear and surface roughness during turning of AISI 304 steel. It was observed that coconut oil performed best. The optimization of cutting speed and feed in order to obtain favorable performance characteristics has also been reported recently (Kalidass et al. (2013), Kaladhar et al. (2013), Kulkarni et al. (2013)). However, it is also essential to consider productivity (MRR), quality of the machined part (surface roughness) and requirement of cutting power (from the knowledge of cutting force, $F_c$) simultaneously and optimize the machining parameters accordingly.

Taguchi method is a powerful tool for design of experiments (DOE) which serves as a basis for optimization of various engineering processes. It is an important tool to identify the critical parameters and also predict optimal settings for each process parameter. This methodology has been widely adopted in the experimental design related to a large variety of machining processes (Nalbant et al. (2007), Thakur et al.(2009), Tzenga et al. (2009), Dewangan and Biswas (2013)). Optimisation of the process parameters has assumed significant research interest in machining operations (including turning) (Nian et al. (1999), (Sardinas et al. (2006), Abburi and Dixit (2007), Asiltürk and Akkus (2011)), since it has the capability to recommend optimal parametric combination under a given set of constraint(s), thus providing useful information to the machining industries.

Grey relational analysis (GRA) utilises a specific concept of information. It defines situations with no information as black, and those with perfect information as white (Chan and Tong (2007)). In other words, GRA converts a multi-objective optimization problem in to a single objective optimization process. Chakradhar and Gopal (2011) performed multi-objective optimization of electrochemical machining of EN31 steel using GRA. Gupta and Kumar (2013) have used grey relation based optimization technique to optimize the performance characteristics such as surface roughness and material removal rate in unidirectional glass fiber reinforced plastic composites during rough cutting operation. Similarly, grey relational analysis has been used in a great deal of studies pertaining to machining operations (Fung (2003), Singh et al. (2004), Tosun (2006), Gopalsamy et al. (2009), Dewangan and Biswas (2013)) for optimizing the related processes.

During the current study, the influence of all the machining parameters such as cutting speed ($V_c$), feed (f) and depth of cut (t) has been investigated on MRR, cutting force and surface roughness during dry machining of AISI 304 stainless steel. Grey-relational analysis has been utilized for simultaneous optimization of cutting parameters in order to obtain favorable performance characteristics in machining.

## 2. Experimental detail and methodology

During the experiment, a round bar of AISI 304 stainless steel having diameter of 60 mm and length of 200 mm was machined under dry environment. A heavy duty lathe (Make: HMT Ltd., Bangalore, India; Model: NH26) in combination with a cutting tool made up of ISO P30 grade uncoated cemented carbide insert was used for the current purpose. Fig. 1 shows the magnified view of tool and workpiece combination during the experiment. L27 orthogonal array-based DOE was adopted with the following machining parameters: $V_c$= 25, 35, 45 m/min., f= 0.1, 0.15, 0.2 mm/rev. and t= 1, 1.25, 1.5 mm. Determination of MRR and cutting force was carried out during the experiment while surface roughness was measured after the machining operation. MRR in $mm^3$/min. was calculated using the following standard expression

$$MRR = 1000Vcft \tag{1}$$

Cutting force was measured using a piezoelectric type dynamometer (Make: Kistler, Model: 9272A), whereas

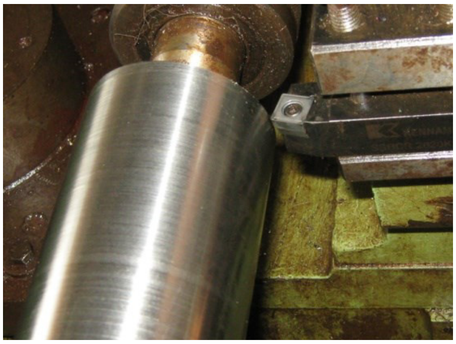

Fig.1. Magnified view of the tool and workpiece as part of the experimental set up

measurement of surface roughness was performed using a 2D surface profilometer (Make: Taylor Hobson, Model: Talysurf, Surtronic 3+)

### *2.1. Design of experiment*

The three process parameters in turning each taken in three levels as shown in Table-1 are represented in an orthogonal array. The experiment was designed using Taguchi method. To get more accurate results and the dependency of the process outputs not only on the individual parameters but also on their all possible combinations, we followed $L_{27}$ design. In this paper the considered process parameters are speed, feed rate and depth of cut. And we are optimizing the values of MRR, surface roughness and cutting force. As we need the MRR to be high and the other two values to be low, so this problem falls under multiple-objective optimization. As mentioned above we have used grey relational analysis to convert this multi objective optimization problem to a single objective optimization.

## 3. Gray relational analysis and data preprocessing-

In grey relational analysis, the first step is data pre-processing. This avoids the problem of different scales, units and targets. The following steps are followed in GRA:

- Experimental data are normalised in the range between zero and one.
- Next, the grey relational coefficient is calculated from the normalised experimental data to express the relationship between the ideal (best) and the actual experimental data.
- Grey relational grade is then computed by averaging the weighted grey relational coefficients corresponding to each performance characteristic.
- Statistical analysis of variance (ANOVA) is performed for the input parameters with the GRG and the parameters significantly affecting the process are found out.
- Optimal levels of process parameters are then chosen.

### *3.1 Normalization-*

The indication of the better performance in turning process for MRR is “higher the better “whereas it is “lower the better for Surface Roughness and Cutting Force. In the analysis of grey relation for ‘higher is better’ response normalizing was done by equation (2) and when the response is ‘lower is better’, normalizing was done by equation (3).

Table 1 Experimental results and GRG

| Run | $V_c$ | F | t | $R_a$ | $F_c$ | MRR | Normalized | | | GRC$\zeta_i$(k) | | | GRG($\gamma$) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (m/min.) | (mm/rev) | (mm) | (μm) | (N) | ($mm^3$/min.) | $R_a$ | $F_c$ | MRR | $R_a$ | $F_c$ | MRR | |
| 1 | 35 | 0.2 | 1.5 | 0.68 | 1453 | 10500 | 0.1700 | 0.1015 | 0.7273 | 0.3759 | 0.3575 | 0.6471 | 0.4602 |
| 2 | 25 | 0.2 | 1 | 0.72 | 1090 | 5000 | 0.0326 | 0.4868 | 0.2273 | 0.3407 | 0.4935 | 0.3929 | 0.4090 |
| 3 | 25 | 0.15 | 1 | 0.61 | 894 | 3750 | 0.3932 | 0.6939 | 0.1136 | 0.4518 | 0.6203 | 0.3607 | 0.4776 |
| 4 | 35 | 0.1 | 1 | 0.56 | 635 | 3500 | 0.5814 | 0.9687 | 0.0909 | 0.5443 | 0.9411 | 0.3548 | 0.6134 |
| 5 | 25 | 0.1 | 1 | 0.49 | 676 | 2500 | 0.8148 | 0.9244 | 0.0000 | 0.7297 | 0.8686 | 0.3333 | 0.6439 |
| 6 | 35 | 0.15 | 1 | 0.57 | 839 | 5250 | 0.5367 | 0.7525 | 0.2500 | 0.5191 | 0.6689 | 0.4000 | 0.5293 |
| 7 | 35 | 0.2 | 1.25 | 0.67 | 1141 | 8750 | 0.1837 | 0.4327 | 0.5682 | 0.3798 | 0.4685 | 0.5366 | 0.4616 |
| 8 | 45 | 0.15 | 1 | 0.54 | 780 | 6750 | 0.6376 | 0.7939 | 0.3864 | 0.5798 | 0.7081 | 0.4490 | 0.5790 |
| 9 | 45 | 0.1 | 1 | 0.64 | 605 | 4500 | 0.3137 | 1.0000 | 0.1818 | 0.4215 | 1.0000 | 0.3793 | 0.6003 |
| 10 | 25 | 0.15 | 1.25 | 0.62 | 1085 | 4687.5 | 0.3779 | 0.4916 | 0.1989 | 0.4456 | 0.4958 | 0.3843 | 0.4419 |
| 11 | 25 | 0.2 | 1.5 | 0.73 | 1549 | 7500 | 0.0000 | 0.0000 | 0.4545 | 0.3333 | 0.3333 | 0.4783 | 0.3816 |
| 12 | 35 | 0.1 | 1.25 | 0.46 | 770 | 4375 | 0.9185 | 0.8251 | 0.1705 | 0.8598 | 0.7408 | 0.3761 | 0.6589 |
| 13 | 25 | 0.1 | 1.25 | 0.50 | 820 | 3125 | 0.8025 | 0.7713 | 0.0568 | 0.7169 | 0.6861 | 0.3465 | 0.5832 |
| 14 | 25 | 0.2 | 1.25 | 0.72 | 1322 | 6250 | 0.0147 | 0.2401 | 0.3409 | 0.3366 | 0.3969 | 0.4314 | 0.3883 |
| 15 | 45 | 0.2 | 1.25 | 0.64 | 1183 | 11250 | 0.3024 | 0.3880 | 0.7955 | 0.4175 | 0.4497 | 0.7097 | 0.5256 |
| 16 | 45 | 0.1 | 1.25 | 0.44 | 734 | 5625 | 1.0000 | 0.8631 | 0.2841 | 1.0000 | 0.7850 | 0.4112 | 0.7321 |
| 17 | 45 | 0.2 | 1 | 0.63 | 975 | 9000 | 0.3183 | 0.6086 | 0.5909 | 0.4231 | 0.5609 | 0.5500 | 0.5113 |
| 18 | 25 | 0.15 | 1.5 | 0.62 | 1271 | 5625 | 0.3654 | 0.2946 | 0.2841 | 0.4407 | 0.4148 | 0.4112 | 0.4222 |
| 19 | 25 | 0.1 | 1.5 | 0.50 | 962 | 3750 | 0.7924 | 0.6222 | 0.1136 | 0.7066 | 0.5696 | 0.3607 | 0.5456 |
| 20 | 35 | 0.2 | 1 | 0.67 | 1022 | 7000 | 0.2003 | 0.5582 | 0.4091 | 0.3847 | 0.5309 | 0.4583 | 0.4580 |
| 21 | 45 | 0.2 | 1.5 | 0.64 | 1386 | 13500 | 0.2894 | 0.1733 | 1.0000 | 0.4130 | 0.3769 | 1.0000 | 0.5966 |
| 22 | 45 | 0.1 | 1.5 | 0.44 | 860 | 6750 | 0.9911 | 0.7298 | 0.3864 | 0.9824 | 0.6492 | 0.4490 | 0.6935 |
| 23 | 35 | 0.15 | 1.5 | 0.58 | 1192 | 7875 | 0.5108 | 0.3779 | 0.4886 | 0.5054 | 0.4456 | 0.4944 | 0.4818 |
| 24 | 45 | 0.15 | 1.5 | 0.55 | 1137 | 10125 | 0.6129 | 0.4367 | 0.6932 | 0.5637 | 0.4703 | 0.6197 | 0.5512 |
| 25 | 35 | 0.15 | 1.25 | 0.57 | 1018 | 6562.5 | 0.5225 | 0.5627 | 0.3693 | 0.5115 | 0.5335 | 0.4422 | 0.4957 |
| 26 | 45 | 0.15 | 1.25 | 0.55 | 970 | 8437.5 | 0.6241 | 0.6130 | 0.5398 | 0.5708 | 0.5637 | 0.5207 | 0.5517 |
| 27 | 35 | 0.1 | 1.5 | 0.46 | 902 | 5250 | 0.9091 | 0.6853 | 0.2500 | 0.8461 | 0.6137 | 0.4000 | 0.6199 |

$$x_i^*(k) = \frac{x_i(k) - x_{imin}(k)}{x_{imax}(k) - x_{imin}(k)} \tag{2}$$

$$x_i^*(k) = \frac{x_{imax}(k) - x_i(k)}{x_{imax}(k) - x_{imin}(k)} \tag{3}$$

Where $x_i^*$(k) and $x_i$(k) are the normalised data and observed data, respectively, for $i^{th}$ experiment using $k^{th}$ response. The smallest and largest values of $x_i$(k) in the $k^{th}$ response are $x_{imin}$(k) and $x_{imax}$(k), respectively.

### *3.1. Determination of grey relation coefficient -*

After pre-processing the data, the grey relation coefficient (GRC) $\zeta_i$(k) for the $k^{th}$ response characteristics in the $i^{th}$ experiment can be expressed as following:

$$\zeta_i(\mathrm{k}) = \frac{\Delta_{min} + \varsigma\Delta_{max}}{\Delta_i(k) + \varsigma\Delta_{max}} \tag{4}$$

$x_0^*(k)$ = denotes reference sequence.
$x_j^*(k)$ = denotes the comparability sequence
$\varsigma \in [0, 1]$ , is the distinguishing factor; 0.5 is widely accepted.
$\Delta_i = \left|x_0^*(k) - x_j^*(k)\right|$ = difference in absolute value between $x_0^*(k)$ and $x_j^*(k)$
$\Delta_{min} = \min_{(\forall j \epsilon i)} \min_{(\forall k)} \left|x_0^*(k) - x_j^*(k)\right|$ = smallest value of$\Delta_i$.
$\Delta_{max} = \max_{(\forall j \epsilon i)} \max_{(\forall k)} \left|x_0^*(k) - x_j^*(k)\right|$ = largest value of$\Delta_i$.

*3.2. Calculation of grey relation grade-*

After calculating GRC, the grey relational grade (GRG) is obtained as:

$$\gamma_i = \frac{1}{m}\sum_{k=1}^{n} w \times \zeta_i(k) \tag{5}$$

Here $\gamma_i$ is the Grey Relational Grade, n is the number of responses, m is the number of run and w is the weight factor. We can control the amount of influence of a response in deciding the optimum machining parameters varying the value of w keeping in mind $\sum_{k=1}^{n} w$ should be equal to 1. The GRC and corresponding GRG for each experiment for turning operation are calculated. The higher value of GRG is near to the product quality for optimum process parameters.

## 4. Results and discussion

Here using grey relational analysis, multiple performances are unified to a single response, i.e., GRG, for ease in optimisation. Three turning process parameters are considered for optimising MRR, Cutting Force and Surface Roughness, simultaneously. The steps for calculation of GRG are mentioned in Section 3. The experimental findings in Table 1 are used to calculate the normalised MRR, Cutting Force and Surface Roughness, which are presented in same table. These normalised values are used to calculate GRC's for both the responses using equations (3). Subsequently, GRG is evaluated from GRC's for each experimental run using equation (4). According to GRG rules, all the experimental run are related to 'higher is better policy' (Tosun and Pihtili(2010)). The experimental run verse GRG plot is shown in Fig. 2.

Maximum value of GRG has been found to be 0.7321. In addition, the mean of the GRG for each level of the machining parameters, and the total mean of GRG is summarised in Table 2 for each factor levels. The higher value of GRG means comparability sequence has a stronger correlation to the reference sequence. Fig. 2 represents graphically in main effect plot for GRG and this graph exposes that the optimal machining parameters ($V_c$=45m/min, f=0.1mm/rev, t=1.25mm). Fig. 2 and Table 2 indicate the effect of machining parameters on the multi-performance characteristics for maximum MRR, minimum cutting force and minimum surface roughness. The significance of the factors on overall quality characteristics of the turning process has also been evaluated quantitatively with ANOVA for GRG (Table 3). Result of ANOVA indicates that only Speed and Feed Rate are the significant factors and other factors are not significant.

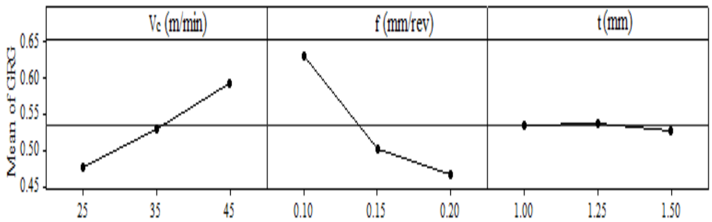


Fig.2 Main effect plot on GRG on process parameters of turning

Table 2 Response table for GRG

| Level | Average GRG ($\gamma_i$) by factor level | | | Delta |
|---|---|---|---|---|
| | Level1 | Level2 | Level3 | |
| $V_c$(m/min) | 0.4770 | 0.5310 | 0.5935 | 0.1165 |
| f(mm/rev) | 0.6323 | 0.5034 | 0.4658 | 0.1665 |
| t(mm) | 0.5357 | 0.5377 | 0.5281 | 0.0096 |
| Mean of GRGs ($\gamma_m$)=0.5338 | | | | |

Table 3 ANOVA for GRG

| source | DF | Seq SS | Adj. SS | Adj. MS | $F_t$ | P |
|---|---|---|---|---|---|---|
| $V_c$ | 2 | 0.06113 | 0.06113 | 0.03057 | 38.18 | 0.000 |
| f | 2 | 0.13726 | 0.13726 | 0.06863 | 85.72 | 0.000 |
| t | 2 | 0.00046 | 0.00046 | 0.00023 | 0.29 | 0.757 |
| $V_c$*f | 4 | 0.00347 | 0.00347 | 0.00087 | 1.08 | 0.426 |
| $V_c$*t | 4 | 0.00989 | 0.00989 | 0.00247 | 3.09 | 0.082 |
| f*t | 4 | 0.00642 | 0.00642 | 0.00161 | 2 | 0.187 |
| Residual Error | 8 | 0.00641 | 0.00641 | 0.0008 | | |
| Total Error | 26 | 0.22503 | | | | |
| NOTE: sources having P >0.05 are insignificant. | | | | | | |

*4.1. Confirmatory experiment-*

The estimated or predicted GRG ($\hat{\gamma}$) at the optimum level of the machining parameter can be calculated by equation (6).

$$\hat{\gamma} = \gamma_m + \sum_{i=1}^{q}(\bar{\gamma}_i - \gamma_m) \tag{6}$$

Where $\gamma_m$ is the mean of GRGs all experimental runs, $\bar{\gamma}_i$ is the mean of GRG at the optimum level of $i^{th}$ parameter, and q is the number of machining parameters that significantly affect GRG. To demonstrate the method of quantifying the quality improvement, the initial machining parameters are assumed to be $V_c$=25m/min, f=0.2mm/rev, t=0.1mm. With this setting, the experimental values of Surface roughness, Cutting force and MRR were 0.715438$\mu$m, 1089.677N and 5000 mm$^3$/min, respectively. Table 4 shows the optimum parameters and the predicted $R_a$, $F_c$, MRR and GRG.

Table 4 Confirmatory experiment result

| Response | Initial data | Optimal Machining parameter | |
|---|---|---|---|
| | | Predicted | Experiment |
| | $Vc_1f_3t_1$ | $Vc_3f_1t_2$ | $Vc_3f_1t_2$ |
| $R_a$ ($\mu m$) | 0.715438 | | 0.437897 |
| $F_c$ (N) | 1089.677 | | 734.2438 |
| MRR($mm^3$/min) | 5000 | | 5625 |
| GRG | 0.4090 | 0.6922 | 0.7321 |
| Percentage increase in GRG=88.78% | | | |

From the above table we can see that surface roughness decreased by 38.79%, cutting force decreased by 32.62% and MRR increased by 12.5%. Thus, it can be concluded that the quality characteristics can be greatly improved through this study.

## Conclusions

During the current study, $L_{27}$ orthogonal array Taguchi design was used to study the influence of machining parameters on material removal rate, cutting force and surface roughness during dry machining of AISI 304 austenitic stainless steel. The grey relation analysis was adopted to optimise the machining parameters in turning operation. The optimal setting of machining parameters was found to be $V_c$ = 45m/min, f = 0.1mm/rev, t = 1.25mm. A confirmatory test was done to support the findings and an improvement of 88.78% in GRG was observed.

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