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Multi-response optimization of AISI H11 using Taguchi and Grey relational analysis

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Abstract

Tool & Die is one of the important department in the manufacturing industries that takes care of proper designing and fabrication of tools and dies required for the production. In this sector, tool steels are used as the primary source of materials. These tool steels belongs to the family of carbon and alloy steels. Mostly used alloying elements are chromium, tungsten, molybdenum and vanadium and are heat-treated. The objective of the work involves machinability study of AISI H11 chromium hot-worked steel extensively used for tool & die making. It deals with the analysis of machining parameters and its influences on the responses considered. Here the controlling parameters considered are cutting speed (Cs), feed rate (Fr) and depth of cut (Dc) and responses as surface roughness (Ra) and material removal rate (Mrr). Each controlling parameters are assigned with 3 levels and experimental runs were executed as per taguchi robust design. To determine multi-objective optimal solution, grey relational analysis (GRA) is employed. GRA is used as it provides a feasible platform for converting a multi-objective function into single-objective function. The experimental runs were performed as per L27 orthogonal array sequence in CNC end-milling. The responses recorded are then analyzed using analysis of variance (ANOVA) and optimal solutions are validated through confirmatory runs. The entire machinability study of AISI H11 is performed in two conditions involving rough machining and finish machining. This has been addressed based on the machining scenario followed in industries taking up job orders. The confirmatory results for rough machining recorded was found to be 0.7871 microns against predicted value of 0.7654 microns resulting with a deviation error of 2.88%. Similarly, for finish machining, confirmatory runs recorded 0.8579 microns against predicted value of 0.8357 microns resulting with a deviation error of 2.66%. The deviation level indicated above between predicted and observed values are minimum, which shows the reliability of the optimal solutions arrived in.

1. Introduction

The current competition in manufacturing sectors revolves around providing good quality finished products at an affordable cost. The term ‘good quality finished products’ is often related to surface texture or surface integrity of machined components. Obviously, the above can be achieved with sophisticated CNC Machines and providing means of utilizing it for delivering the defined requirements. High skill and thinking required to provide effective usage of these machines as huge investment is made in procurement of these machines. Therefore, consistent efforts are made in finding ways of effective usage of these machines through research in the field of machinability. In the world of machinability, Ra and material removal rate (Mrr) are inevitable factor that are contradictory in nature and cannot be controlled directly. Therefore, Machinability is a very complex field that requires proper understanding and reasoning to arrive at a best feasible solution [1].

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In machining world, machined surface is measured in terms of surface roughness. In general roughness can be measured in terms of average roughness ($R_a$), root mean square average ($R_q$) value or maximum peak value ($R_z$). Mostly, average surface roughness ($R_a$) is considered for the studies. It is the outcome of the machining that finally governs the cost incurred in machining. Past studies revealed that few failures occurred due to deviation in $R_a$ leading to critical failure and higher cost. Whereas, $M_{tr}$ plays a crucial role in the determination of production time & overall cost of production. As the above stated factors $R_a$ and $M_{tr}$ are uncontrollable, means and measures are required for controlling it. This is usually achieved by precise controlling of the parameters considered in a machining operation. In machining, few controllable factors that plays significant role over $R_a$ and $M_{tr}$ are spindle-speed ($S_s$), feed rate ($F_r$), depth of cut ($D_c$) and coolant flow rate ($C_f$). Achieving the best combination of these controlling parameters are very vital to attain the objective function of either minimizing $R_a$ or maximizing $M_{tr}$. Earlier, ‘trial and error’ approach was followed in arriving at the best feasible solutions which was time consuming and mostly dependent on the experience and critical thinking of the person.

Nowadays, different tools and techniques of optimizations are available for optimization with in-built accuracy and precision. Few optimization techniques that are prominently used are taguchi design, box-behnken design, central composite design, genetic algorithm, neural networks, etc. In the world of machining, CNC End milling has its strong foundation as it offers best-in-class output while dealing with complicated intricate shapes with good accuracy and precision. The best-in-class delivery of these machines depends on the effective parameters selection. The presented work deals with the experimental investigation of CNC end milling operation on AISI H11 alloy in predicting optimized solution using RSM and GRA [2]. AISI H11 is taken for investigation as it is most sought material finding its applications in landing gears of an aircraft, helicopter rotor blades, shafts, cutting tools, dies etc. It’s one of the most commonly used chromium based alloys offering extraordinary toughness to impact, crack resistance including thermal fatigue. It also has other appreciable properties like resistance towards thermal shock, and has least distortion. Moreover, these alloys are easily formed using machining and forging. The above salient features of AISI H11 paves way for way for carrying out experimental investigations in various domains and the presented work is one among them.

2. Literature review

The world has witnessed the progress of metal machining since its inception, but the significance of optimizing the parameters of machining was noticed only in 19th century. The pace of improvement was very slow for initial period. In the past two decades tremendous changes and noteworthy improvements has been witnessed in formation of new tools and techniques for the improvement of quality in terms of tool life, $R_a$ and $M_{tr}$. Singh T, et al [3] performed an experimental research in EN 31 steel on machinability using taguchi design and GRA. The machining operation involved controlling parameters as $S_s$, $F_r$, and $D_c$ for governing the responses namely $R_a$ and tool vibration. The study also involved application of cooling effect through MQL technique. Samtas G, et al [4] investigated the performance of cutting inserts in terms of surface roughness and wear while milling cryogenically processes Al 6061-T651 alloy. In this study untreated and cryogenically treated TiN-TiCN-Al2O3-coated cutting inserts were used. The experimental runs were performed as per taguchi L18 orthogonal array with three levels assigned for cutting speed and feed rates. The roughness and wear were recorded and optimized using taguchi design. The result showed that minimum roughness was achieved by cryogenically treated insert when cutting speed was maintained at 250 m min$^{-1}$ and feed rate at 0.45 mm rev$^{-1}$. Whereas, for wear it was found to be 350 m min$^{-1}$ cutting speed and 0.30 mm rev$^{-1}$ feed rate. Further, the authors performed combined optimization using GRA. The optimum results were achieved when cutting speed was maintained at 250 m min$^{-1}$ and feed rate at 0.15 mm rev$^{-1}$. The study concluded with a note that GRA provided better outcomes in multi response cases. Singh T, et al [5] investigated the performance of MQL while machining EN31 steel. The investigation involved analysis of responses cutting temperature and $R_a$. The study involved taguchi based GRA for identification of optimal solution involving parameters $D_c$, $F_r$, $C_f$ and coolant rate of flow. The results showed that the optimal solutions were attained when the parameters are assigned at speed of 700 rpm, feed at 140 mm min$^{-1}$, depth of cut as 0.3 mm and flow rate as 150 ml h$^{-1}$. Moreover, the study showed the importance of lubricant as the significant factor compared to other parameters.

Singh P K, et al [6] evaluated machining parameter behaviour while performing milling operation on AISI H11 steel. The study involved responses as $R_a$ and $M_{tr}$. The experimental runs were performed on a CNC vertical milling machine with controlling factors as $S_s$, $F_r$, and $D_c$. The optimization was carried out using taguchi design and GRA. The study was performed as rough machining and finish machining. In rough machining, $R_a$ was assigned with 20% weightage and $M_{tr}$ with 80% weightage. The result showed that $F_r$ dominated as the influencing factor with 37.49% followed by $D_c$ and $S_s$ with contribution of 35.61% and 18.48% respectively. In finish machining, $S_s$ dominated with 71.55% followed by $F_r$ and $D_c$ with 13.88% and 1.09% respectively. An interpreting model was created for evaluating tool life in end milling of 190 BHN steel by HSS slot drills.
Experimental runs were performed in dry conditions with parameters namely Ss, Fr, Dc. Central composite design (CCD) was followed for trial runs [7]. The result showed that Ss and Fr had significant influence on tool life. Bhardwaj B, et al [8] studied the machinability characteristics on EN 353 using box-cox transformation. In this study an attempt was made to improve the Ra using the prediction model developed by box-cox transformation. The result revealed that Ss and Fr were the significant factor in both 1st and 2nd order models. Whereas, Dc found to be significant in 2nd order model alone. Choudhury S K, et al [9] performed a study on orthogonal turn milling while machining rotationally symmetrical work pieces. The study was conducted for brass and mild steel on CNC turning and evaluated for roughness. The experiments were conducted by using 10 mm with 4 flute end mill cutter. CCD design is opted for runs with Ss and Fr as the controlling parameters for governing Ra. The results showed that Ss played significant role in governing Ra followed by Fr. As Ss was increased, it resulted in better Ra. Whereas, in the case of Fr, it was vice-versa [10].

Benardos P G, et al [11] made an experimental study for prediction of Ra in aluminium alloy while performing CNC face milling as per taguchi robust design. The controlling factors considered were Dc, Fr, Ss tool wear (Tw), cutting fluid (Cf) and cutting force components. The result showed that Fp, x-axis cutting force, Dc and Cf were the most influencing parameters affecting Ra. Suresh Kumar R, et al [12–14] performed detailed study using taguchi, RSM, GRA for the optimization of machining parameters. The study involved materials that are extensively used in the commercial market and in industrial sectors. The result showed the significance of the machining parameters on responses. It also highlighted the interactive effect of parameters. In most cases, Ss was found to be the most influencing parameter followed by Fr and Dc. Ghani J A, et al [15] made an attempt to arrive at the optimal solution while performing end milling process on AISI H13 using TiN coated carbide inserts. Trail runs were performed as per L27 sequence followed with ANOVA for interpretations. The controlling parameters considered were Sn, Fr, and Dc and Ra was taken as the response. The result revealed that when Ss is maintained at high level with Fr and Dc between lower to middle level, minimum roughness is achieved.

Yih-fong T, et al [16] made an attempted in high-speed end milling towards optimization of dimensional quality. The study was made on two types tool steels (SKD-11 and SKD-61). The investigations were made on three different geometries viz., circle, square and triangle. The parameters considered for the investigation were milling type, Sn tool type, number of tool, helix angle. Experiments were based on L18 design. The results clearly showed that, milling type, number of teeth and Ss were the governing factors affecting Ra. A model was developed using neural network (NN) and genetic algorithm (GA) for the prediction of Ra. The entire study was carried out in CNC end milling with aluminium alloy Al 7075-T6. Design of experiments (DOE) was applied with controlling factors as Sn, Fr, Dc (axial and radial) and Ra as the response. The study further developed a feed forward neural network model (FFNNM) for analysis and interpretation [17].

Tseng Y F, et al [18] analyzed the combined effect of Taguchi and principal component analysis (PCA) while performing optimization in end milling on SKD-11 and SKD-61. The controlling factors considered were tool material, Sn, Fr, milling method, number of tooth, rake angle and helix angle. The responses were dimensional accuracy, Ra and tool life (Tl). Balamurugan G, et al [19] presented an approach towards process parameter optimization while machining hardened steel. The study involved application of taguchi for experimental analysis followed by ANOVA. The controlling factors taken were Sn, Fr, Dc and width of cut (Wc) were the controlling factors. Ra and Tl were the responses taken for study. Sn was the most influential parameter. Lu H S, et al [20] performed cutting parameters optimization in high-speed end milling using GRA and principal component analysis (PCA). The machining were performed on SKD61 using TiAlN tool. The machining parameters considered were Sn, Fr, Dc (axial and radial), with responses as Tl and Mtr. L18 arrangements with three levels was taken up for machining. PCA was employed for evaluation of performance characteristics. The results revealed that Sn and Fr were the significant factors influencing the multi-objective function defined.

Multi objective optimization was performed by Yazdi M S, et al [21] on Al 6061 in face milling using RSM and artificial neural network (ANN). The machining process employed face mill cutter having 4 flutes. The study involved Sn, Fr, Dc as controlling factor and responses as Ra and Mtr. The results of the study showed that Sn and Fr were the prominent factor affecting the Ra. Whereas, Dc, Fr were the prominent factors affecting Mtr. A study towards the improvement of surface quality was carried out by Pa N M N, et al [22] in end milling while performing end milling operation on S50C steel with cutting tool as titanium coated carbide. The trials were executed as per L9 orthogonal array (OA) arrangements. The results showed that Dc (axial) was the influencing parameter affecting the Ra. Shahrom M S, et al [23] studied the behaviour of Ra in different machining conditions viz. wet machining, MQL, and dry machining (DM). The study was performed on AISI 1360 aluminium alloy with controlling factors as Fr, Dc, and Sn. The trail runs were performed based on L16 arrangements with 3 factors 4 levels. The analysis showed that Fr was the significant factor followed by Ss and Dc in the case of dry run. Whereas, MQL showed better surface finish with cost reduction and less environmental impact. Kant G, et al [24] proposed a multi-response predictive model for Ra and power consumption while machining AISI 1045 steel. The entire employed GRA, PCA, and RSM. Fr was found to governing factor
minimizing power consumption and Ra followed by Dc and Sr. A 6.72% reduction in power consumption and 2.63% improvement in Ra could be evidenced.

Sahu S, et al [25] investigated the performance study of multilayer TiN coated and uncoated in AISI 4340. Taguchi robust design was employed for the prediction of Ra considering Sr, Fr, and Dc as the input parameters. SEM images for surface texture and tool wear rate (TWR) were taken. The end result revealed that coated tool improves the machinability of hard materials at higher Sr. Investigation under no coolant condition was carried out by Manivel D, et al [26] to analyze the optimized machining parameters for turning ductile iron. The experimental runs were performed using CVD coated carbide inserts with coating of Al2O3/ MT TICN. L18 arrangements was opted for experimental runs with Sr, Dc and Fr as controlling factors each having 3 levels and 2 levels for nose radius. The validation results recorded a close deviation of 9.27% and 1.05% between predicted and experimental values respectively. In another study Suresh Kumar R, et al [14] optimized the controlling parameters while performing end milling in EN19 by taguchi. The experimental sequence were performed as per L9 pattern involving Sr, Dc and Fr as controlling factors with 8 mm diameter Sn coated carbide tool having 4 flutes. Parashar V, et al [27] investigated the effects of machining parameters on EN19 steel while performing end milling operation. The influence of controlling parameters on Mrr was studied through S/N ratio and ANOVA. L27 orthogonal array was opted with Sr, Fr and Dc as the controlling factors. The result showed significant influence of Fr and Dc on Mrr.

An investigation was carried out by Mia M, et al [28] involving multi-objective optimization of Ra, Tm, and Mrr while turning AISI 1060 steel under MQL environment. The machining were performed using coated cemented carbide. The entire work was performed based on taguchi design involving Sr, Dc and Fr as controlling factors. The end result showed that minimum Ra and higher Mrr are obtained when the parameters are assigned with 90 m min−1 Sr, 1.5 mm rev−1 Fr and 1.5 mm Dc. Also, it was noteworthy to state that assigning minimum levels of controlling factors resulted in smaller Fw. The presented literature review on end milling [29–32] involved work carried out on different materials and machining environment. Moreover, in most of the cases Sr, Fr, and Dc are the commonly used machining parameters. In some cases, experiments have been carried out in MQL and dry conditions. Few of them considered tool geometries. Mostly the responses taken up for the study between Ra, Mrr, Tm, Tw, etc. Various tools were used for determining the optimized parameters for machining ranging from DoE to ANN. Singaravel B, et al [33] performed multi-objective optimization of surface integrity in milling Ti6Al4V alloy. Experimental analysis was made in the above material using taguchi and GRA by considering L27 design pattern for identifying the multi-objective optimized parameters for Ra and Mrr. The most critical stage in optimization of any machining process is the appropriate selection of machining parameters [34–37] and its range. Many statistical tools and techniques are available for performing optimization. Taguchi robust design is found to be one of the easy and affordable approach towards optimization [38, 39]. Moreover, this technique involves lesser cost, improved quality with robust design solutions. Also, taguchi offers simultaneous optimization of numerous factors and offers extraction of quantitative information with minimum experimental trials. This feature adds value to taguchi design when compared with other techniques [40, 41].

The extensive literature survey conducted provides a lucid view on the opportunities available in machinability studies for most-sought after materials. From the point of applications and requirements AISI H11 is extensively used in different industrial sectors from aerospace industries to shop floor involving machining and die preparation. The presence of various appreciable salient features as discussed in introduction, this alloy has large scope of applications in varied field. From the literature study one could find that the work mostly revolved around either optimizing Ra or Mrr. In few cases, multi-objective optimization has been performed. However, no evidences could be traced towards machinability studies under rough machining and fine finishing operations. Thus, an attempt has been made to investigate the machinability characteristics of AISI H11 when it is subjected to finish machining and rough machining.

3. Optimization techniques

The main objectives of the study is to identify the optimum relationship between the machining parameters for attaining minimum Ra and maximum Mrr, surface roughness, cutting forces and tool tip temperature. The optimization of the machining parameters were performed using taguchi robust design and GRA.

3.1. Taguchi design

Taguchi design is an optimization technique for any process/product that includes planning, conducting of experiments, evaluation of results for determining the best levels of controlling factors. In this design, the objective is to maintain the output variance in lower order in midst of noises present in the experimentation. This salient feature makes this design robust. In Taguchi design, optimization refers to determination of
‘best levels’ for the assigned controlling factors. The term ‘best levels’ refers to those controlling factors that maximizes the signal-to-noise (S/N) ratios which is the log functions of output desired in an experimentation. In taguchi design, the experimental runs are performed as per the defined orthogonal arrays (OA). The significance of OA is that they offer balanced set of minimum sequence of experimental runs required for determining the best levels. The minimum requirement of experimental runs leads to reduced requirement of material and time. Generally, taguchi design involves two categories of analysis namely static and dynamic. Static analysis does not require signal factor and the optimization is determined by three defined modes viz. smaller-the-better, larger-the-better and nominal-the-best. Whereas, dynamic problem involves signal factor where the optimization is performed using slope and linearity.

3.2. Grey relational analysis (GRA)
GRA is a technique adopted for the calculation of grey relational degree and for the determination of contributing measure of the influencing parameters in a process that governs overall behaviour the system. Following are the detailed steps involved in this process:

3.2.1. Normalization of responses
This stage involves pre-processing or normalization of data with respect to objective function defined. Equation (1) is used if ‘larger-the-better’ is chosen for normalization and equation (2) is used for ‘smaller-the-better’ function. This stage is performed for reduction of variation in the experimental data to make the analysis easier one.

\[
X_i(k) = \frac{x_i(k) - \min x_i(k)}{\max x_i(k) - \min x_i(k)} \quad (1)
\]

\[
X_i(k) = \frac{\max x_i(k) - x_i(k)}{\max x_i(k) - \min x_i(k)} \quad (2)
\]

In the above equations, \(i = 1, \ldots, m; k = 1, \ldots, n\), \(m\) represents number of experimental runs \(n\) is the responses.

\(X_i(k)\) - value post data pre-processing
\(x_i(k)\) - the original sequence data
\(\max x_i(k)\) - largest value of \(x_i(k)\)
\(\min x_i(k)\) - minimal value.

3.2.2. Computation of deviation sequence
The deviation is computed based on the nature of responses and its objective function. In the case of \(R_a\) smaller-the-better criteria is opted as the outcome needs to be minimized. Whereas, for \(M_t\) larger-the-better option is considered for maximizing the response outcome. This stage involves calculation of deviation from the normalized values. The deviation is computed based on higher normalized value attained from the experimental data.

3.2.3. Computation of grey relational coefficients (GRC)
Equation (3) as shown below is applied for the computation of GRC.

\[
\xi_i(k) = \frac{\Delta \min + \psi \Delta \max}{\Delta \delta_i(k) + \psi \Delta \max} \quad (3)
\]

where, \(\xi_i(k)\) - represents grey relational coefficient (GRC)
\(\Delta \min\) and \(\Delta \max\) - Absolute differences (minimum and maximum)
\(\psi\) - represents distinguishing or identification coefficient (usually varies between 0–1) Here taken as 0.5

3.2.4. Computation of grey relational grade (GRD)
The correlation level between the reference and comparability sequences is represented by GRD (\(\gamma\)). This stage involves conversion of a multi-objective function into single objective function. The governing equation followed for determining GRD is given in equation (4).

\[
\gamma_i = 1/n \sum_{k=1}^{n} \xi_i(k) \quad (4)
\]

3.2.5. Optimal parameters
This stage involves identification of ranks for each values. The ranks thus identified provides the sequence of run resulting in optimum solution.
4. Methodology

Figure 1 shows the methodology followed in this study. The methodology includes three stages namely preliminary stage, machining stage and analysis stage. In preliminary stage, extensive literature survey is carried out with identification of gap resulting in problem statement. Based on the survey and problem identified best suited optimization technique is selected for further processing. In machining stage, CNC end-milling operation is opted and the machining process is performed in Co-India, Coimbatore with AISIH11 as the work material. The work material is selected based on the usage in industrial sector involved in die making. The controlling factors or input factors are fixed based on the type of machine employed, manufacturer handbook and previous research articles. Based on which, for the present study cutting speed ($C_s$), $D_c$ and feed rate $F_r$ are considered as machining parameters for controlling the responses namely $R_a$ and $M_{rr}$. Table 2 highlights the controlling factors and assigned levels.

4.1. Experimental details
The experimental runs were conducted as per taguchi robust design following L27 orthogonal array as shown in table 1. In the analysis stage, the experimental data recorded were taken up for ANOVA analysis at 95% confidence interval followed by application of GRA techniques. Finally, the results arrived were validated through confirmatory runs.

4.2. CNC end milling
3-axis CNC vertical milling machine in COINDIA, Coimbatore was used for machining. Carbide end mill cutter with 4 flutes was taken up. 16 mm diameter end mill cutter is employed for machining. AISI H11 steel alloy plates of 120 mm x 80 mm x 20 mm is used as work material. Table 3 shows the chemical composition of the work material.
4.3. Response parameters

Mostly, centre-line average roughness ($R_a$) [10, 29, 33] value is taken for measurement and in this study the same is considered. The $R_a$ was measured using Mitutoyo surface tester by taking average of three measured values. $M_{rr}$ was assessed according to the work piece geometry and machining parameters considered. The responses of the machining are highlighted in table 4.

5. Result and discussion

Table 4 summarizes the entire experimentation details. $C_s$, $F_r$, $D_c$ are the controlling parameters identified for optimizing the responses $R_a$ and $M_{rr}$. The parameter interaction effect on responses were studied using GRA and ANOVA. In TGRA analysis, smaller-the-better criteria is opted for optimizing $R_a$ and larger-the-better criteria is taken up for $M_{rr}$. While analyzing TGRA considers $S/N$ ratio to arrive at the best interpretation. Further, the calculated $S/N$ ratio is normalized prior to analysis for better outcome. Tables 5 and 6 records the normalized and computed $S/N$ ratios for the responses.

5.1. Condition 1:

In this condition, an unequal weightage of $W_1 = 20\%$ (for $R_a$) and $W_2 = 80\%$ (for $M_{rr}$) was assigned [30]. The assumption were applied on rough machining alone. Table 7 shows the outcome based on overall grey relational grade (GRG).

Maximum GRG attained represents the best value among the set of data considered for analysis. This maximum GRG represents the combination of machining parameters that offers the best possible optimal solution. It is also noteworthy to state that the selection of optimal combination involving the mean effect of GRG and average responses of the experimental runs played a crucial role. Table 8 shows the calculated grey relation grade.
### Table 4. Experimental results.

| Runs | Cx | Fx | Dx | Ra  | Mi |
|------|----|----|----|-----|----|
| 1    | 15 | 0.12 | 0.2 | 4.83 | 0.13 |
| 2    | 15 | 0.12 | 0.4 | 4.11 | 0.24 |
| 3    | 15 | 0.12 | 0.6 | 4.84 | 0.36 |
| 4    | 15 | 0.20 | 0.2 | 5.70 | 0.20 |
| 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 | 0.80 |
| 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 | 0.28 |
| 11   | 35 | 0.12 | 0.4 | 1.97 | 1.46 |
| 12   | 35 | 0.12 | 0.6 | 2.28 | 2.18 |
| 13   | 35 | 0.20 | 0.2 | 1.77 | 1.13 |
| 14   | 35 | 0.20 | 0.4 | 2.22 | 2.46 |
| 15   | 35 | 0.20 | 0.6 | 2.61 | 3.60 |
| 16   | 35 | 0.30 | 0.2 | 2.58 | 1.82 |
| 17   | 35 | 0.30 | 0.4 | 3.16 | 3.60 |
| 18   | 35 | 0.30 | 0.6 | 3.17 | 3.60 |
| 19   | 35 | 0.12 | 0.2 | 2.36 | 1.14 |
| 20   | 35 | 0.12 | 0.4 | 2.36 | 2.28 |
| 21   | 35 | 0.12 | 0.6 | 2.33 | 3.32 |
| 22   | 35 | 0.20 | 0.2 | 2.48 | 1.90 |
| 23   | 35 | 0.20 | 0.4 | 2.47 | 3.81 |
| 24   | 35 | 0.20 | 0.6 | 2.20 | 5.72 |
| 25   | 35 | 0.30 | 0.2 | 2.90 | 2.86 |
| 26   | 35 | 0.30 | 0.4 | 3.16 | 5.40 |
| 27   | 35 | 0.30 | 0.6 | 3.17 | 5.40 |

### Table 5. Normalized and Computed S/N ratio for Ra.

| Runs | Ra  | S/N ratio | Normalized |
|------|-----|-----------|------------|
| 1    | 4.83 | −13.6789  | 0.7407     |
| 2    | 4.11 | −12.2768  | 0.6230     |
| 3    | 4.84 | −13.6969  | 0.7423     |
| 4    | 5.7  | −15.1174  | 0.8616     |
| 5    | 4.94 | −13.8745  | 0.7572     |
| 6    | 6.58 | −16.3645  | 0.9664     |
| 7    | 6.84 | −16.7011  | 0.9946     |
| 8    | 6.89 | −16.7643  | 1.0000     |
| 9    | 5.61 | −14.9791  | 0.8500     |
| 10   | 2.29 | −7.1967   | 0.1962     |
| 11   | 1.97 | −5.8893   | 0.0864     |
| 12   | 1.88 | −5.4831   | 0.0522     |
| 13   | 1.75 | −4.8607   | 0.0000     |
| 14   | 2.22 | −6.9270   | 0.1735     |
| 15   | 2.61 | −8.3328   | 0.2916     |
| 16   | 2.58 | −8.2323   | 0.2832     |
| 17   | 3.16 | −9.9937   | 0.4312     |
| 18   | 3.17 | −10.0213  | 0.4335     |
| 19   | 2.36 | −7.4582   | 0.2182     |
| 20   | 2.36 | −7.4582   | 0.2182     |
| 21   | 2.33 | −7.3471   | 0.2088     |
| 22   | 2.48 | −7.8890   | 0.2543     |
| 23   | 2.47 | −7.8539   | 0.2514     |
| 24   | 2.2  | −6.8484   | 0.1669     |
| 25   | 2.9  | −9.2479   | 0.3685     |
| 26   | 2.22 | −6.9270   | 0.1735     |
| 27   | 2.28 | −7.1586   | 0.1930     |
Since the objective of the analysis is higher GRG mean value, the same is achieved when the parameter combination were assigned to be Cs-3, Fr-3 & Dc-3, where 3 represents the level assigned as depicted in table 7. Based on the deviation percentage, Fr found to be the significant parameter followed by Dc. The least affecting parameter in this study is found to be Cs. GRG values with respect to controlling parameters are depicted in figure 2. From the graph, it is predictable that the values of GRG is directly proportional to Cs, Fr and Dc. On careful analysis, it worthy to note that Fr and Dc are more sensitive while compared to Cs playing the role of significance in machinability.

The interaction effect among the parameters on the responses is must to identify the optimal solution. Table 9 clearly depicts the significance of the parameters considered. The shown analysis is performed at 0.05 significance level. The percentage contribution were found to be 18.50%, 37.52% and 35.71% for Cs, Fr and Dc respectively.

5.1.1. Prediction of optimal solution (condition 1)

The objective of the study is to arrive at the best possible solution that provides least Ra and high Mrr. Equation (1) is used to calculate the optimal settings. Equation (2) is followed to arrive at the confidence interval.

\[ \alpha = Cs3 + Fr3 + Dc3 - 2\xi \]  
(5)

where,

- \( \alpha \) is the optimal solution
- \( Cs3 \) is the cutting speed at level 3
- \( Fr3 \) is the feed rate at level 3
- \( Dc3 \) is the depth of cut at level 3
- \( \xi \) is the gross GRG average

\[ CI = \sqrt{F_r \times \left( \frac{Me}{Ne} \right)} \]  
(6)

where,

- CI is the confidence interval
- \( F_r \) is the F-critical value at the required CI = 5.3177
Me is the Mean square error \(= 0.00198 \) (table 8).

Ne is the number of effective replications.

The optimum condition at 95% CI is achieved when \( \mu = 0.7654 \) and CI \(= 0.0512 \). The above solution is attained at the setting point (Cs3, Fr3 and Dc3).

5.2. Condition 2:

In this case, Ra is assigned with 80% weightage and Mrr with 20% weightage for machining involving finishing conditions. Overall GRG and its results are shown in table 10.

Table 11 highlights the calculated mean effect of parameter. For higher Mrr, higher mean GRG is required, and the combination that fulfills that was found to be Cs1 Fr3 Dc3. The percentage deviation is recorded in the table 10. From the table, Cs found to be the most influencing factor followed by Fr and Dc governing multi-objective optimization. The GRG values based on the controlling parameters are depicted in figure 3. It is noteworthy from the graph, that GRG values for Cs gradually decreases from level 1 to 2 and once again increase as it reaches level 3. Whereas, for other parameters, the GRG values increases as the level increases. The above pattern clearly justifies that Cs tends to govern the outcome when compared with the other parameters.

M_s is the Mean square error \(= 0.00198 \) (table 8).

Ne is the number of effective replications.

The optimum condition at 95% CI is achieved when \( \mu = 0.7654 \) and CI \(= 0.0512 \). The above solution is attained at the setting point (Cs3, Fr3 and Dc3).

### Table 7. Calculated GRG for condition 1.

| Exp | C_s | F_r | D_c | Cs Fr Dc Ra MRR | Grade for Condition 1 | Grade Order |
|-----|-----|-----|-----|-----------------|-----------------------|--------------|
| 1   | 1   | 1   | 1   | 0.65858         | 0.33333               | 0.39838      | 26           |
| 2   | 1   | 1   | 2   | 0.57013         | 0.38734               | 0.42389      | 25           |
| 3   | 1   | 1   | 3   | 0.65989         | 0.42789               | 0.47429      | 20           |
| 4   | 1   | 2   | 1   | 0.78326         | 0.37150               | 0.45385      | 22           |
| 5   | 1   | 2   | 2   | 0.67315         | 0.43986               | 0.48652      | 19           |
| 6   | 1   | 2   | 3   | 0.93704         | 0.49291               | 0.58173      | 11           |
| 7   | 1   | 3   | 1   | 0.98948         | 0.40865               | 0.52482      | 14           |
| 8   | 1   | 3   | 2   | 1               | 0.49291               | 0.59432      | 9            |
| 9   | 1   | 3   | 3   | 0.76927         | 0.56051               | 0.60226      | 8            |
| 10  | 2   | 1   | 1   | 0.58350         | 0.40181               | 0.39815      | 27           |
| 11  | 2   | 1   | 2   | 0.55370         | 0.48300               | 0.45714      | 21           |
| 12  | 2   | 1   | 3   | 0.34537         | 0.54773               | 0.50726      | 16           |
| 13  | 2   | 2   | 1   | 0.33333         | 0.45859               | 0.43354      | 24           |
| 14  | 2   | 2   | 2   | 0.37695         | 0.56744               | 0.52934      | 13           |
| 15  | 2   | 2   | 3   | 0.41379         | 0.65900               | 0.60996      | 7            |
| 16  | 2   | 3   | 1   | 0.41092         | 0.51660               | 0.49546      | 18           |
| 17  | 2   | 3   | 2   | 0.46781         | 0.65900               | 0.62076      | 5            |
| 18  | 2   | 3   | 3   | 0.46883         | 0.78569               | 0.72232      | 2            |
| 19  | 3   | 1   | 1   | 0.39007         | 0.45127               | 0.43903      | 23           |
| 20  | 3   | 1   | 2   | 0.39007         | 0.55628               | 0.52304      | 15           |
| 21  | 3   | 1   | 3   | 0.38725         | 0.64393               | 0.59260      | 10           |
| 22  | 3   | 2   | 1   | 0.40141         | 0.52414               | 0.49959      | 17           |
| 23  | 3   | 2   | 2   | 0.40046         | 0.67140               | 0.61721      | 6            |
| 24  | 3   | 2   | 3   | 0.37508         | 0.80341               | 0.71775      | 4            |
| 25  | 3   | 3   | 1   | 0.44191         | 0.601331              | 0.56944      | 12           |
| 26  | 3   | 3   | 2   | 0.37695         | 0.80341               | 0.71812      | 3            |
| 27  | 3   | 3   | 3   | 0.38256         | 1                      | 0.87651      | 1            |

### Table 8. Mean effects- Overall Grey Relational Grades (condition 1).

| Level | C_s  | F_r  | D_c  |
|-------|------|------|------|
| 1     | 0.50475 | 0.46821 | 0.46803 |
| 2     | 0.53044 | 0.54773 | 0.55227 |
| 3     | 0.61705 | 0.63601 | 0.63164 |

(Average) \(= 0.55067 \) \(= 0.55064 \) \(= 0.55066 \).

(Max-Min) \(= 0.11260 \) \(= 0.16780 \) \(= 0.16370 \).

(% Deviation) \(= 25.3397 \) \(= 37.7835 \) \(= 36.8780 \).

(Rank) \(= 3 \) \(= 1 \) \(= 2 \).

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In case of multiple-response, one has to identify the interactive influence of controlling parameters to put forth optimum solution. Table 12 highlights ANOVA for finish machining. From the analysis, it is evident that both Cs and Fr are significant factors in this investigation at 95% confidence level. The analysis records the percentage contribution of 71.55%, 13.88% and 1.09% for Cs, Fr and Dc respectively.

5.2.1. Prediction of optimal solution

The objective of the experimental analysis is to attain minimum Ra and higher Mrr. The optimal solution is arrived by using equation (3).

\[ \alpha = Cs1 + Fr3 + Dc3 - 2\xi \]  

(7)

where,

\( \alpha \) is the optimal solution

\( Cs1 \) is the cutting speed at level 1

\( Fr3 \) is the feed rate at level 3

\( Dc3 \) is the depth of cut at level 3

\( \xi \) is the gross GRG average

The calculation of confidence interval is performed using equation (4).

\[ CI = \sqrt{F_\alpha \times \left( \frac{Me}{Ne} \right)} \]  

(8)

where,

\( CI \) is the confidence interval

\( F_\alpha \) is the F-critical value at the required CI = 5.3177

\( Me \) is the Mean square error = 0.00741 (table 11)

\( Ne \) is the number of effective replications

The optimum condition at 95% CI is attained when \( \mu = 0.8357 \) and CI = 0.1010. The above solution was attained at best setting point (Cs1, Fr3 and Dc3).

![Figure 2. Grey Relational Grades for W1 = 0.2 and W2 = 0.8.](image)

**Table 9. ANOVA for rough machining W1 = 0.2, W2 = 0.8.**

| Parameters | DF | Sum of squares | Mean squares | F ratio | % Contribution | F > F_\alpha |
|------------|----|----------------|--------------|---------|----------------|-------------|
| Cs         | 2  | 0.06254        | 0.03127      | 15.7618 | 0.1850         | significant |
| Fr         | 2  | 0.12682        | 0.06341      | 31.9614 | 0.3752         | significant |
| Dc         | 2  | 0.12047        | 0.06023      | 30.3612 | 0.3571         | significant |
| Cs x Fr    | 4  | 0.00225        | 0.00056      | 0.28354 | 0.0066         |             |
| Fr x Dc    | 4  | 0.00461        | 0.00115      | 0.58165 | 0.0136         |             |
| Cs x Dc    | 4  | 0.00570        | 0.00142      | 0.71899 | 0.0168         |             |
| (Error)    | 8  | 0.01587        |              | 0.00198 | 0.0469         |             |
| (Total)    | 26 | 0.33829        | 0.16005      | 1       | 1              |             |

F_{0.05,2,8} = 4.459

F_{0.05,4,8} = 3.8378

In case of multiple-response, one has to identify the interactive influence of controlling parameters to put forth optimum solution. Table 12 highlights ANOVA for finish machining. From the analysis, it is evident that both Cs and Fr are significant factors in this investigation at 95% confidence level. The analysis records the percentage contribution of 71.55%, 13.88% and 1.09% for Cs, Fr and Dc respectively.
5.3. Summary

The analysis of the experimental data resulted in the following outcomes:

a) Table 9 shows the outcome of the rough machining (condition 1: $w_1 = 0.2; w_2 = 0.8$). It is clearly depicted that controlling factors considered has its appreciable significance on the responses. The analysis was performed at 95% confidence interval and their contribution were found to be 18.50%, 37.52% and 35.71% for $C_s$, $F_r$ and $D_c$ respectively.

b) The optimum condition at 95% CI was found to be achieved when $\mu = 0.7654$ and CI = 0.0512. The above solution was attained at best setting point ($C_s3, F_r3$ and $D_c3$).

c) Table 12 shows the outcome of the finish machining at (condition 2: $w_1 = 0.8; w_2 = 0.2$). From the analysis, it is evident that both $C_s$ and $F_r$ are significant factors in this investigation at 95% confidence level. The analysis records the percentage contribution of 71.55%, 13.88% and 1.09% for $C_s$, $F_r$ and $D_c$ respectively.

d) The optimum condition at 95% CI was achieved at the following condition when $\mu = 0.8357$ and CI = 0.1010. The above solution was attained at best setting point ($C_s1, F_r3$ and $D_c3$).
6. Validation

The confirmatory runs were performed with the optimal solution to authenticate the reliability of attained results. The experimental runs were performed for calculating the deviation between observed and predicted values at 95% confidence level. Table 13 shows the comparative analysis of the confirmatory runs performed. For rough machining 2.84% deviation could be seen with the predicted and observed values. Similarly, for finish machining a deviation of 2.66% could be observed. The minimum deviation shows the reliability of the optimization technique applied for arriving at the optimal solutions.

Study conducted by Bhardwaj B, et al [29] on AISI 1019 showed a deviation of 4.2% between the predicted value of 0.769 microns and experimental value of 0.738 microns while performing finish machining. Based on the above two results, it is noteworthy to state that the optimization performed by GRA resulted in much better outcome with minimum deviation.

7. Conclusion

In this study the following important points are observed:

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Table 12. ANOVA - Finish Machining ($W_1 = 0.8, W_2 = 0.2$).

| Parameters | DoF | Sum of squares | Mean squares | F-ratio | % contribution | F > Fcr |
|------------|-----|----------------|--------------|---------|----------------|---------|
| $C_s$      | 2   | 0.45105        | 0.22552      | 30.46383| 0.71355        | significant |
| $F_r$      | 2   | 0.08750        | 0.04375      | 5.90933 | 0.13880        | significant |
| $D_c$      | 2   | 0.00691        | 0.00345      | 0.46654 | 0.01096        | insignificant |
| $C_s \times F_r$ | 4 | 0.01113      | 0.00278      | 0.37602 | 0.01766        |               |
| $F_r \times D_c$ | 4 | 0.01109      | 0.00277      | 0.37459 | 0.01760        |               |
| $C_s \times D_c$ | 4 | 0.00345      | 0.00086      | 0.11643 | 0.00347        |               |
| Error      | 8   | 0.05922        | 0.00741      | 0.09395 |                 |         |

Total 26 0.63035 0.28654 1

\( F_{0.05(2,8)} = 4.459 \)

\( F_{0.05(4,8)} = 3.8378 \)

Table 13. Confirmatory Run.

| Condition             | Predicted Value | Confirmation Value | Deviation |
|-----------------------|-----------------|--------------------|-----------|
| Rough Machining       | 0.7654          | 0.7871             | 2.84%     |
| Finish machining      | 0.8357          | 0.8579             | 2.66%     |
1. The response $R_a$ found be significantly governed by $C_s$. The response $R_a$ improved as an increase in $C_s$ is witnessed. Moreover, from the experimental study, it is found that $R_a$ decreased when the level raised from 1 to 2 and then increases as the $C_s$ level is increased to 3.

2. Throughout the study it is noteworthy to state that all parameters ($C_s,F_r,D_c$) influenced $M_{tr}$. $M_{tr}$ increased as the prescribed levels increased.

3. In rough machining, $F_r$ was the least significant parameter followed by $D_c$ and $C_s$.

4. In finish machining, $C_s$ and $F_r$ played a vital role with least affecting parameter as $D_c$.

5. In rough machining (condition 1), the significant influence of machining parameters on responses were found to be 18.50%, 37.52% and 35.71% for $C_s,F_r$ and $D_c$ respectively.

6. In rough machining (condition 1), the optimum condition at 95% CI was found to be achieved when $\mu = 0.7654$ and $CI = 0.0512$. The above solution was attained at best setting point ($C_s3,F_r3$ and $D_c3$).

7. In finish machining (condition 2), the significant influence of machining parameters on responses were found to be 71.55%, 13.88% and 1.09% for $C_s,F_r$ and $D_c$ respectively.

8. In finish machining (condition 2), the optimum condition at 95% CI was achieved at the following condition when $\mu = 0.8357$ and $CI = 0.1010$. The above solution was attained at best setting point ($C_s1,F_r3$ and $D_c3$).

7.1. Limitations
The main limitation of the Taguchi method is that it provides only relative outcomes and therefore, identification of exact parameter that influences the most in terms of performance becomes tedious. Whereas, GRA provides good platform for arriving at optimal solutions much easier compared to other available techniques.

Data availability statement
No new data were created or analysed in this study.

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