The study attempts to investigate tool wear (flank wear) and surface roughness during finish hard turning of AISI D3 steel (58HRC) with coated carbide (TiSiN-TiAlN coated) cutting tool. Taguchi L9 $(3^3)$ orthogonal array has been applied for experimental design. S/N ratio and ANOVA analyses were performed to identify significant parameters influencing tool wear and surface roughness. The cutting speed and feed were the most significant factors influencing tool wear (flank wear), and feed is the most significant factor influencing surface roughness (Ra). Mathematical models for both response parameters i.e. tool wear and surface roughness were obtained through regression analysis. The confirmation experiments carried out at optimal combination of parameters given by Taguchi’s analysis, predicted the response factors with less than 5% error. In addition, Desirability function module in RSM was applied to arrive at the optimal setting of input parameters to minimize tool wear and surface roughness. The optimal solution provided by desirability function optimization was compared with the optimal setting of parameters given by Taguchi analysis. The optimization results provided by both techniques are in close proximity.

Keywords: hard turning; Taguchi orthogonal array; S/N ratio; flank wear; surface roughness

1. Introduction

The modern machining industries are mainly focused on the achievement of high quality, in terms of work piece dimensional accuracy, surface finish, high-production rate, minimum tool wear, economical machining and improving the performance of the product with reduced environmental impact. Conventional tool materials for hard turning applications are PCBN, Ceramics and PCD because of their high hardness and toughness. But these tool materials are quite costly as compared to carbides. Coated carbides on the other hand been tried for a number of the applications in the metal-working industry and provide a suitable alternative for most turning applications (Patil, 2010). Carbides are tough and can be used for machining at higher cutting speed, feed rate, also tried for some intermittent machining operations successfully. Coated carbides tools consist of a hard carbide substrate with a surface coating (carbides, nitrides, oxides and their combinations), which increases the thermochemical stability. These high-quality materials provide high rate of material removal even during intermittent machining. Tungsten carbide (TiC) thin films provided on carbide inserts act as heat barrier, protect...
the tools from being exposed to high cutting temperature in the cutting zone thereby enabling these to retain high hardness even at elevated temperatures of the order of 400 °C (Quinto, Wild, & Balzers Limited, 1998; Sundgren & Hentzell, 1986). Researchers are showing keen interest in developing WC-C composite coating, which have high heat resistance (Hoffman, Evans, Choen, & Paterson, 1992; Quinto et al., 1998). The use of coating materials to enhance the performance of cutting tools is not a new concept. Coated carbides are the most popular and most common high-production tool materials available today (ASM Metals Handbook-Machining, 1980). The boost in wear resistance gave room for a significant increase in cutting speed and thereby improved productivity on shop floor. Coated carbide tools account for nearly 70% of the tools used in the industry (Abdullah, 1996). The majority of carbide cutting tools in use today are coated with chemical vapor deposition or physical vapor deposition (PVD) techniques. The high hardness, wear resistance and chemical stability of these coatings have been proved beneficial in terms of longer tool life and improved machining performance (Abdullah, 1996; ASM Metals Handbook-Machining, 1980; Layyous, Freinkel, & Israel, 1992; Lux, Colombier, Altena, & Stjernberg, 1986; Prengel, Pfouts, & Santhanam, 1998). CBN and Ceramics tools are used for hard turning applications owing to their higher hardness Viz. Clutch discs, Gears, hubs, rock drills, bearings, shafts and axles, nozzles having hardness in the range of 40–70HRC.

In present investigation, a newly developed coated carbide grade TH1000 (PVD coated SECO grade) has been employed as cutting tool for hard turning of AISI D3 steel. The superior edge toughness of this grade provides excellent performance in continuous and interrupted cutting of hardened steels. This coated carbide grade (TH1000) was selected for current investigation owing to its low cost compared to costlier CBN and ceramic grades to provide an economical alternative for the applications in industry predominantly machined by CBN and ceramic grades as mentioned above. This paper is organized as follows: Section 2 describes the Taguchi DOE and surveys the literature on Taguchi orthogonal array used for optimization of hard turning parameters; numerical optimization using desirability function is explained in Section 3; the experimental procedure is given in Section 4; the Taguchi analysis of results is given in Section 5; modeling of flank wear and surface roughness is given in Section 6; optimization of cutting conditions (RSM) is given in Section 7; and finally, conclusions and future research directions are given in Section 8.

2. Taguchi design of experiments

The DOE is a technique used to define what data, in what quantity and conditions should be collected during an experiment, to satisfy two major goals: the statistical accuracy of the response parameters along with lower cost (Gunasegaram, Farnsworth, & Nguyena, 2009; Montgomery, 1997). The traditional experimental design methods are too complex and difficult to use. Additionally, large numbers of experiments have to be carried out with an increase in number of machining parameters. Therefore, a preliminary investigation must be carried out under laboratory conditions to evaluate important factors causing variations. These, studies are considered under the scope of off-line quality improvement (Hasçalı & Çağdaş, 2008). The Taguchi method is an experimental design technique, which is useful in reducing the number of experiments dramatically using orthogonal arrays and also tries to minimize effects of the factors out of control. An orthogonal array means the design is balanced so that factor levels are weighted equally. Because of this, each factor can be evaluated independently of all the
other factors, so that effect of one factor does not influence the estimation of another factor. In robust parameter design, we first choose control factors and their levels and choose an orthogonal array appropriate for these orthogonal arrays. The basic philosophy of the Taguchi method is to ensure quality in the design phase. The greatest advantages of the Taguchi method are to decrease the experimental time, to reduce the cost and to find out significant factors in a shorter time period (Chattopadhyay & Chattopadhyay, 1982). The most significant feature of Taguchi’s techniques is the use of parameter design, which is an engineering method for product or process design that focuses on determining the parameter (factor) settings producing the best levels of a quality characteristic (performance measure) with minimum variation. Taguchi analysis comprise determining signal-to-noise (S/N) ratio as the quality characteristic of choice i.e. the ratio of useful information to false or irrelevant data in a conversation or exchange (Anyılmaz, 2006). Taguchi empirically found that the two-stage optimization procedure involving S/N ratios indeed gives the parameter level combination, where the standard deviation is minimum while keeping the mean on target.

Numerous studies have been carried out using Taguchi designs to arrive at optimal setting of machining conditions in finish machining. Singh and Kumar (2003, 2004a, 2004b, 2005) have applied Taguchi’s technique for optimizing surface finish, tool wear, cutting force and power consumed in turning operations for machining En24 steel with titanium carbide-coated tungsten carbide inserts. Aslan, Camuçu, and Birgören (2007) employed Taguchi method and ANOVA techniques to optimize flank wear and surface roughness during hard turning of AISI 4140 steel with mixed ceramics (Al2O3 + TiC) tool. Sahoo, Barman, and Routara (2008) optimized surface profile in CNC turning using L27 orthogonal design. Thamizhmanii, Sarapudin, and Hasan (2007) analyzed surface roughness by turning process using Taguchi method. Thamizhmanii, Kamarudin, Rahim, Sarapudin, and Hasan (2007) used Taguchi method parameter design to optimize the surface roughness, tool wear and cutting force by hard turning process. They stressed that Taguchi parameter design is an efficient method in which response variable can be optimized, given various controls and using fewer experimental runs. Gopalsamy, Mondal, and Gosh (2009) applied Taguchi method and ANOVA to find optimum process parameters for end milling of hardened steel using L18 orthogonal array. The results of Taguchi modeling matched that of ANOVA. Kazancoglu, Esme, Bayramo, Guven, and Ozgun (2011) investigated the multi-response optimization of the turning process for an optimal parametric combination to yield the minimum cutting forces and surface roughness with the maximum material removal rate (MRR) using a combination of a Grey relational analysis (GRA) and the Taguchi method. Kolahan, Manoochehri, and Hosseini (2011) applied Taguchi method to arrive at the best sets of cutting parameters and tool geometry specifications to minimize surface roughness during machining of AISI1045 steel parts. Bagawade, Ramdasi, Pawade, and Bramhankar (2013) in their review paper explained the steps and procedures used to optimize turning parameters using Taguchi’s design of experiment and stressed that the Taguchi approach is a form of DOE technique with special application principles. Ananthakumar, Ramesh, and Parameshwari (2013) revealed that quality attributes considered in turning operation are surface finish, material removal rate and tool flank wear. Optimizing one quality attribute may lead to loss of other quality attribute. Hence, in order to simultaneously satisfy all the three quality requirements a multi-objective optimization is required. To achieve this, PCA with grey or utility-based Taguchi method was applied to find the optimum combination of process parameters for the optimizing correlated multiple responses. By comparing the existing Taguchi-based multi-response optimization method, the proposed
approach meets the objectives of multiple responses simultaneously and produces best optimum combination of process parameter where simultaneous optimization of huge responses is required. Radovanovic (2012) Optimized cutting parameters by Taguchi method based on cutting force in tube turning of S235 G2T steel by coated carbide tool using smaller-the-better quality characteristic. In addition, ANOVA was applied to evaluate statistically significant parameters influencing cutting forces. They reported that Taguchi method provides an efficient design of experiment technique to obtain simple, systematic and efficient methodology for the optimization of the cutting parameters. Puh, Šegota, and Jurković (2012) used Taguchi orthogonal design and ANOVA to find optimum process parameters for hard turning of AISI 4142 steel using PCBN tool. Multiple Linear regressions were applied to predict model for surface roughness in terms of process parameters. It was confirmed from confirmation experiments that Taguchi design was successful in optimizing turning parameters for surface roughness. Yuce et al. (2014) in their study presented a method to improve the quality control for the identification of wood veneers defects through the integration of the PCA and ANN. The proposed method allows the ANN classifier to identify defects in real time and increase the response speed during the quality control stage so that veneers with defects do not pass through the whole production cycle but are rejected at the beginning.

Thus, from above and as reported in introduction section, Taguchi modeling is an excellent technique to predict responses in machining applications with fewer experimental runs, and is less sensitive to variation due to uncontrolled or noise variables. This is particularly suitable for predicting tool wear, surface roughness and cutting forces during hard turning requiring fewer tests.

To fit mathematical models of tool flank wear and surface roughness, multiple linear regression has been applied in terms of input parameters viz. cutting speed (A), feed rate (B), depth of cut (C). Thereafter, ANOVA has been applied on observed responses (F-test and lack of fit tests) to establish the reliability of developed models for making future predictions.

3. Numerical optimization using desirability function

Myers and Montgomery (1995) described a multiple response optimization method called desirability function optimization. It is an attractive method for industry seeking simultaneous optimization of multiple quality characteristic problems. The method uses an objective function, \( D(X) \), called the desirability function and transforms an estimated response into a scale-free value \( (d_i) \) called desirability. The desirable ranges are from zero to one i.e. from least to most desirable, respectively. The factor settings with maximum total desirability are considered to be the optimal parameter conditions. The simultaneous objective function is a geometric mean of all the transformed responses as given by:

\[
D = (d_1 \times d_2 \times d_3 \times \ldots \times d_n)^{1/n} = \left( \prod_{i=1}^{n} d_i \right)^{1/n}
\]

where \( n \) is the number of responses in the measure. If any of the responses falls outside the desirability range, the overall function becomes zero.

To reflect the possible difference in the importance of various responses, it can be extended to
\[ D = (d_1^{w_1} \times d_2^{w_2} \times d_3^{w_3} \times \ldots \times d_n^{w_n}) \]  

where the weight \( w_i \) is such that \( 0 < w_i < 1 \) and \( w_1 + w_2 + \ldots + w_n = 1 \).

Desirability is an objective function that ranges from zero outside of the limits to one at the goal. The numerical optimization finds a point that maximizes the desirability function. Adjusting the weight or importance may alter the characteristics of a goal. For several responses, all the goals get combined into one desirability function. For simultaneous optimization, each response must have a low and high values assigned to each goal. The Goal field for responses must be one of the following five choices: none, maximum, minimum, target or in range. Factors will always be included in the optimization at their design range by default, or as a maximum, minimum of target goal. The meanings of the goal parameters are described below:

**Maximum**
- \( d_i = 0 \) if response < low value
- \( 0 \leq d_i \leq 1 \) as response varies from low to high
- \( d_i = 1 \) if response > high value

**Minimum**
- \( d_i = 1 \) if response < low value
- \( 1 \leq d_i \leq 1 \) as response varies from low to high
- \( d_i = 0 \) if response > high value

**Target**
- \( d_i = 0 \) if response < low value
- \( 0 \leq d_i \leq 1 \) as response varies from low to target
- \( 1 \geq d_i \geq 0 \) as response varies from target to high
- \( d_i = 0 \) if response > high value

**Range**
- \( d_i = 0 \) if response < low value
- \( d_i = 1 \) as response varies from low to high
- \( d_i = 0 \) if response > high value

The \( d_i \) for in range are included in the product of the desirability function \( D \), but are not counted in determining \( n \):

\[ D = \left( \prod d_i \right)^{1/n} \]

If the goal is none, the response will not be used for the optimization.

Dureja, Gupta, Sharma, and Dogra (2009, 2010) and Dureja (2012) in their studies applied RSM-Desirability Function Optimization for minimizing tool wear and surface roughness of hard-turned specimens (AISI H11) in terms of input parameters (Cutting speed, feed, depth of cut and work piece hardness). Jou, Lin, Lee, and Yeh (2014) integrated Taguchi method and RSM desirability optimization methodology for process parameter optimization of the Injection Molding process. The study revealed that the integration of the Taguchi Method and RSM could effectively improve the quality.

4. Experimental details

4.1. Equipment and materials

The AISI D3 was selected as the work piece material in the form of round bars with 25 mm diameter and 190 mm axial cutting length. The specimens were through hardened to achieve hardness of 58HRC. The chemical composition of work material is...
given in Table 1. Specific application D3 steel are: high-quality press tools, drawing and cutter dies, Shear blades, thread rollers, punches, measuring tools, pressure casting moulds, blanking, reamer, etc. The turning tests were conducted under dry conditions on a CNC lathe (Make: Batliboi, Sprint 16 TC, India) having a maximum spindle speed of 5000 rpm.

The cutting tool used was coated carbide TH1000 (SECO grade) TiSiN-TiAlN nano PVD coated which enhances edge toughness and results in improved surface finish. The inserts with ISO designation (DNMG150604-MF1) were clamped on 25/25 M left hand tool holder with ISO designation DDJNL2525M15-M. Three levels were specified for each of the parameter as indicated in Table 2. These levels were selected based on the recommendations of manufacturer and are supported by previous work of various authors (Anyilmaz, 2006; Aslan et al., 2007; Chattopadhyay & Chattopadhyay, 1982; Hasçalik & Çaydaş, 2008).

Each test was performed by using a fresh cutting edge and over a constant helical cutting length of 900 m. The average values of tool flank wear (VB) and surface roughness (Ra) were measured at the end of each test. The average flank wear was monitored with the help of a tool maker’s microscope (Mitutoyo TM-505R) and surface roughness with a surface roughness analyzer (Mitutoyo Surftest SJ-301).

The experiment was terminated when either of the following two conditions reached:

Condition 1: VB ≥ 200 μm;
Condition 2: Ra ≥ 1.6 μm.

The limiting value of average flank wear (i.e. 200 mm) was selected as the tool life criterion according to JIS B4011–1971 standard, whereas for hard turning to replace grinding, the surface roughness (Ra) should be less than 1.6 mm.

4.2. Design of experiments

The cutting parameters are cutting speed (A), feed rate (B) and depth of cut (C). The objectives are to minimize surface roughness (Ra) of machined specimen and tool wear (flank wear, VB).

Three levels were specified for each of the factors as indicated in Table 2. The L9 orthogonal array comprising of 9 experiments (3 trials for each experiment: 9 × 3 = 27 experiments) was used for designing experimental plan, Table 3.

5. Analysis of results (Taguchi method)

Tables 4 and 6 illustrates the experimental results for VB and Ra. The main effects can be evaluated by analyzing raw data or S/N ratios for flank wear and surface roughness as indicated in Tables 5 and 7. The analysis is done by averaging the raw data or S/N data at each level of all input parameters and plotting these values in graphical form (Figures 1–3). The level average responses from the raw data help in analyzing the trend of the performance characteristics with respect to the variation of the factor under consideration.

Table 1. Composition of AISI D3 steel.

| C    | Si | Mn | Cr  | Mo | V |
|------|----|----|-----|----|---|
| 1.7  | .3 | .5 | 13.0 | .8 | .8 |
Table 2. Machining parameters for experimentation.

| Level | Cutting speed (A) (m/min) | Feed (B) (mm/rev.) | Depth of cut (C) (mm) |
|-------|---------------------------|-------------------|----------------------|
| 1     | 130                       | 155               | 180                  |
| 2     | .05                       | .10               | .15                  |
| 3     | .1                        | .25               | .4                   |

Table 3. Taguchi experimental plan.

| Experiment | A Speed | B Feed | C DOC |
|------------|---------|--------|-------|
| 1          | 1       | 1      | 1     |
| 2          | 1       | 2      | 2     |
| 3          | 1       | 3      | 3     |
| 4          | 2       | 1      | 2     |
| 5          | 2       | 2      | 3     |
| 6          | 2       | 3      | 1     |
| 7          | 3       | 1      | 3     |
| 8          | 3       | 2      | 1     |
| 9          | 3       | 3      | 2     |

Table 4. Experimental results for (VB).

| Experiment | A | B | C | R1 | R2 | R3 | Avg. VB (μm) | S/N Ratio |
|------------|---|---|---|----|----|----|--------------|-----------|
| 1          | 130| .05| .10| 130| 110| 125| 121.67      | -41.72    |
| 2          | 130| .1 | .25| 100| 105| 90 | 98.33       | -39.87    |
| 3          | 130| .15| .40| 90 | 110| 120| 106.67      | -40.62    |
| 4          | 155| .05| .25| 160| 170| 160| 163.33      | -44.27    |
| 5          | 155| .1 | .40| 130| 125| 115| 123.33      | -41.83    |
| 6          | 155| .15| .10| 140| 125| 130| 131.67      | -42.40    |
| 7          | 180| .05| .40| 145| 160| 150| 151.67      | -43.63    |
| 8          | 180| .1 | .10| 160| 180| 150| 163.33      | -44.29    |
| 9          | 180| .15| .25| 175| 210| 220| 201.67      | -46.13    |

Note: S/N ratio (lower is better) = \(-10\log_{10} \left\{1/n \sum y^2\right\}\).

Table 5. Flank wear (VB): response for S/N ratios (smaller the better).

| Level | Speed (A) | Feed (B) | DOC (C) |
|-------|-----------|----------|---------|
| 1     | -40.74    | -43.20   | -42.80  |
| 2     | -42.83    | -42.00   | -43.42  |
| 3     | -44.68    | -43.05   | -42.03  |
| Range (Max–Min) | 3.94 | 1.2 | 1.39 |
| Rank  | 1         | 3        | 2       |
5.1. S/N ratio and ANOVA analysis for flank wear (VB)

It is clearly indicated from Figure 1 that flank wear (VB) increases with increase cutting speed, whereas S/N ratio decreases with increase in cutting speed. Corresponding to minimum cutting speed (130 m/min), minimum flank wear and highest S/N ratio have been observed. Thus, cutting speed 130 m/min is the optimal level to attain minimum flank wear (VB).

Figure 2 shows the plot of S/N ratio and (VB) vs. feed rate. The flank wear initially decreases with increase in feed rate up to .1 mm/rev followed by an increase in VB.
with feed rate to .15 mm/rev. Corresponding to feed rate of .1 mm/rev, the S/N ratio is observed to be highest, thereby indicating that feed rate of .1 mm/rev to be the optimal level.

Figure 3 depicts a plot of S/N ratio and (VB) vs. depth of cut (DOC). The flank wear initially increases with increase in DOC followed by a sharp decreasing trend up to .4 mm depth of cut. The S/N ratio observed a decreasing trend initially followed by an increasing trend reporting maximum value at DOC = .4 mm, thereby indicating this to be the optimal level. The ANOVA analysis for S/N suggested percentage contribution of input parameters influencing flank wear (VB) as: speed = 73.65%, feed rate = 8.18% and DOC = 9.28%, signifying the cutting speed to be the most contributing factor influencing flank wear.

5.2. S/N ratio and ANOVA analysis for surface roughness (Ra)

Figure 4 shows a plot of S/N ratio and (Ra) vs. speed. The best surface finish and highest S/N ratio have been reported at cutting speed of 155 m/min, indicating this to be the optimal level. Figure 5 depicts a plot of S/N ratio and (Ra) vs. feed rate. S/N ratio initially increases with increase in feed rate and is highest at .1 mm/rev, with best surface finish achieved at this level. S/N ratio and surface finish report decreasing trend with further increase in feed rate. Thus, feed rate of .1 mm/rev is the optimal level to
achieve best surface finish. Figure 6 gives a plot of S/N ratio and (Ra) vs. DOC. Surface finish and S/N ratio improve with increase in DOC and report highest value at .25 mm DOC. Surface finish and S/N ratio decrease with further increase in DOC to .4 mm, indicating DOC = .25 mm as the optimal level. The ANOVA analysis for S/N suggested percentage contribution of input parameters influencing surface roughness (Ra) as: speed = 19.47%, feed rate = 52.98% and DOC = 12.98%, signifying the feed rate to be the most contributing factor influencing surface roughness.

The S/N ratios for (VB) vs. input parameters (speed, feed and DOC) at all levels are reported in Table 5 and for Ra vs. input parameters (speed, feed and DOC) at all levels are reported in Table 7. The speed and the depth of cut are two factors that have the highest range (max–min) i.e. 3.94 and 1.39 for flank wear (VB) and feed whereas, feed and speed are the parameters having highest range (max–min) i.e. 4.4340 and 2.6704 for surface roughness (Ra), respectively. Based on the Taguchi prediction, larger difference will have a more significant effect on tool wear and surface roughness (Ra). Thus, speed and DOC influence the flank wear (VB) significantly, on the other hand, feed and DOC significantly influences the surface roughness (Ra). The optimal setting of
parameters obtained from Taguchi main effects plot for flank wear (VB) and surface roughness (Ra) is in Table 8. The optimal parameters-level combination obtained through Taguchi analysis to minimize flank wear (VB) is 1-2-3 i.e. first level for cutting speed, second level for feed rate and the third level for DOC (Table 8). In order to validate this optimal solution provided by Taguchi analysis, confirmation experiment was performed at this parameter-level combination i.e. speed = 130 m/min, feed rate = .1 mm/rev, DOC = .4 mm. The flank wear (VB) observed at this combination is = 96 μm. The optimal setting of parameters given by Taguchi’s analysis 1-2-3 is closest to the 1-2-2 combination of parameters in Taguchi’s orthogonal array. Thus, the error between initial (I) and final (F) observed values of (VB) is calculated as:

$$\text{Error} = \text{Mode} \left( \frac{I - F}{I} \right) \times 100$$

Thus, the error between initial (I) and final (F) for VB = 2.33% is within 95% confidence interval. Similarly, the optimal parameters-level combination to obtain minimum surface roughness (Ra) is 2-2-2. A confirmation experiments were also performed at this parameters-level combination i.e. speed = 155 m/min, feed rate = .1 mm/rev and DOC = .25 mm. The surface roughness observed at this combination is Ra = .57 μm. This optimal parameter-level combination is closest to the parameters-level combination in Taguchi’s orthogonal array of 2-2-3. Thus, the error between initial (I) and final (F) observed values of (Ra) was evaluated and it came out to be 3.4% again within 95% confidence interval.

6. Modeling of flank wear and surface roughness

The Taguchi method enables designing experimental plan and arriving at optimal setting of parameters, but there is no module to develop models of responses in terms of input
parameters. Therefore, Response Surface Methodology (RSM) and Multiple Linear regression were applied to generate models of VB and Ra. The Taguchi’s orthogonal array L(OA)₉ (3)³ design gave a total of 27 experiments as reported earlier. The observed responses corresponding to these 27 experiments were analyzed through Historical Data Module of RSM using Design-Expert software, Table 9.

2F1 models were fitted for flank wear and surface roughness. The regression models of both responses i.e. VB and Ra in terms of input parameters speed (A), feed (B) and depth of cut (C) are given:

\[
VB = + 69.56 + .75233 \times A - 1814.83 \times B - 205.91 \times C + 8.90 \times A \\
 \times B - .080 \times A \times C + 2013.65 \times B \times C
\]  
(4)

\[
Ra = + .73 + .12 \times A + .55 \times B - .38 \times C - .18 \times A \times B + .27 \times A \times C + .34 \\
 \times B \times C
\]  
(5)

The analysis of variance (ANOVA) test was performed to evaluate statistical significance of the fitted 2F1 models and factors involved therein. In addition to this, the goodness of fit of the fitted 2F1 models was also evaluated through Lack of Fit test. For ANOVA analysis VB, some of the non-significant terms were eliminated by backward elimination, and ANOVA was again applied. The results obtained are summarized in

| Run no. | Speed (A) | Feed (B) | DOC (C) | Flank wear (VB) | Surface roughness (Ra) |
|---------|-----------|----------|---------|-----------------|------------------------|
| 1       | 155       | .10      | .40     | 125             | .69                    |
| 2       | 180       | .05      | .40     | 160             | 1.15                   |
| 3       | 130       | .15      | .40     | 130             | 1.05                   |
| 4       | 180       | .15      | .25     | 220             | 1.07                   |
| 5       | 130       | .05      | .10     | 130             | .82                    |
| 6       | 130       | .05      | .10     | 110             | .86                    |
| 7       | 130       | .05      | .10     | 125             | .90                    |
| 8       | 180       | .05      | .40     | 150             | 1.18                   |
| 9       | 180       | .10      | .10     | 160             | .59                    |
| 10      | 130       | .10      | .25     | 105             | .62                    |
| 11      | 155       | .10      | .40     | 130             | .66                    |
| 12      | 155       | .15      | .10     | 130             | 1.01                   |
| 13      | 155       | .05      | .25     | 170             | .51                    |
| 14      | 130       | .15      | .40     | 110             | 1.03                   |
| 15      | 155       | .05      | .25     | 150             | .47                    |
| 16      | 180       | .10      | .10     | 180             | .62                    |
| 17      | 155       | .10      | .40     | 115             | .52                    |
| 18      | 155       | .05      | .25     | 160             | .55                    |
| 19      | 130       | .15      | .40     | 90              | 1.01                   |
| 20      | 180       | .15      | .25     | 175             | 1.13                   |
| 21      | 130       | .10      | .25     | 90              | .68                    |
| 22      | 155       | .15      | .10     | 125             | .98                    |
| 23      | 130       | .10      | .25     | 100             | .56                    |
| 24      | 180       | .15      | .25     | 210             | 1.10                   |
| 25      | 155       | .15      | .10     | 140             | .96                    |
| 26      | 180       | .10      | .10     | 170             | .66                    |
| 27      | 180       | .05      | .40     | 145             | 1.11                   |
Tables 10–13. Both the 2F1 models are found to be significant. The $p$ value (Prob $> F$) for both the responses was observed to less than .0001 clearly shows that the flank wear model and surface roughness model are statistically significant.

The lack of fit for the fitted 2FI models for VB and Ra was found to be insignificant, Tables 10 and 12. The ‘Lack of Fit F-value’ of 2.28 for (VB) implies the Lack of Fit is not significant relative to the pure error. There is a 12.12% chance that a ‘Lack of Fit F-value’ this large could occur due to noise. On the other hand, ‘Lack of Fit F-value’ of 3.52 observed for Ra (Table 12) implies there is a 5.56% chance that a ‘Lack of Fit F-value’ larger than this could occur due to noise. The $R^2$ values for both VB and Ra .8587 and .9630 are approaching 1.0. The predicted and adjusted $R^2$ values for VB (Table 11) are in reasonable agreement whereas, for Ra these values are in excellent agreement (Table 13), which again signifies fitness of the developed models. The coefficient of variation, $CV = (SD/Mean) \times 100$, is a measure of error associated

Table 10. RSM-ANOVA Results for flank wear (VB).

| Source     | Sum of squares | DF | Mean square | $F$ value | Prob. $> F$ | Remarks   |
|------------|----------------|----|-------------|-----------|-------------|-----------|
| Model      | 22970.70       | 5  | 4594.14     | 21.88     | <.0001      | Significant |
| A          | 14956.08       | 1  | 14956.08    | 71.23     | <.0001      |           |
| B          | 43.10          | 1  | 43.10       | 21        | .6559       |           |
| C          | 3.71           | 1  | 3.71        | .018      | .8957       |           |
| AB         | 669.95         | 1  | 669.95      | 3.19      | .0909       |           |
| BC         | 1284.62        | 1  | 1284.62     | 6.12      | .0236       |           |
| Residual   | 3779.30        | 18 | 209.96      |           |             |           |
| Lack of Fit| 1183.47        | 3  | 394.49      | 2.28      | .1212       | Not significant |
| Pure Error | 2595.83        | 15 | 173.06      |           |             |           |
| Cor Total  | 26750.00       | 23 |             |           |             |           |

Table 11. Statistical summary of model for flank wear (VB).

| Std. dev. | 14.49 | $(R^2)$ | .8587 |
| Mean      | 140.00 | Adjusted $(R^2)$ | .8195 |
| CV (%)    | 10.35  | Predicted $(R^2)$ | .7391 |
| PRESS     | 6978.72 | Adequate Precision (AP) | 13.348 |

Table 12. RSM-ANOVA table for surface roughness (Ra).

| Source     | Sum of squares | DF | Mean square | $F$ value | Prob. $> F$ | Remarks   |
|------------|----------------|----|-------------|-----------|-------------|-----------|
| Model      | 1.12           | 6  | .19         | 102.15    | <.0001      | Significant |
| A          | .38            | 1  | .38         | 207.83    | <.0001      |           |
| B          | .84            | 1  | .84         | 459.79    | <.0001      |           |
| C          | .41            | 1  | .41         | 224.94    | <.0001      |           |
| AB         | .39            | 1  | .39         | 213.86    | <.0001      |           |
| AC         | .83            | 1  | .83         | 453.58    | <.0001      |           |
| BC         | .36            | 1  | .36         | 197.92    | <.0001      |           |
| Residual   | .031           | 17 | 1.832E-003  |           |             |           |
| Lack of Fit| 9.953E-003     | 2  | 4.977E-003  | 3.52      | .0556       | Not significant |
| Pure Error | .021           | 15 | 1.412E-003  |           |             |           |
| Cor Total  | 1.15           | 23 |             |           |             |           |
with the model. The low value of CV obtained for both the models indicates improved precision and reliability of the experiments carried out. The value of adequate precision (AP), defined as the signal to noise ratio, for both the models are significantly higher than 4 (Tables 11 and 13), which indicates suitability of model, Equations (4) and (5) for making future predictions.

### 7. Optimization of cutting conditions (RSM)

In the present study, desirability function optimization has been employed for multi-response (VB and Ra) optimization. The optimization module searches for a combination of factor levels that simultaneously satisfy the requirements imposed on each of the response factor, in an attempt to establish the appropriate model. The objective of optimization is to find the optimal values of input parameters to minimize the value of flank wear (VB) and surface roughness (Ra) during machining of AISI-D3 tool steel with coated carbide tool. The constraints used for optimization are given in Table 14. The lower and upper limits of input parameters correspond to the range of input parameters selected in this study. The optimal solutions obtained are reported in Table 15 in order to their decreasing desirability level.

It is clear from Table 15 that for simultaneously optimizing both the responses i.e. VB and Ra, the most optimal solution is: speed = 130 m/min, feed rate = .13 mm/rev. and DOC = .21 mm with VB and Ra approaching 93.35 μm and 1.18 μm, respectively.
This solution provided by Desirability function optimization is quite close to the optimal solutions provided by Taguchi analysis although for one response parameter (VB or Ra) at time.

8. Conclusions

- This study has proved the viability of coated carbide cutting tools for hard turning application in the range of parameters selected in this study, which provides an economical alternative to costlier PCBN and ceramic tools.
- The optimum setting of input parameter-level combination suggested by both the techniques Viz. Taguchi method as well as RSM is in close agreement, validating the use of both techniques in response factors optimization.
- The Taguchi analysis has suggested percentage contribution of input parameters influencing flank wear (VB) as: speed = 73.65%, feed rate = 8.18% and DOC = 9.28%, signifying the cutting speed to be the most contributing factor influencing flank wear.
- The percentage contribution of input parameters influencing surface roughness (Ra) is: speed = 19.47%, feed rate = 52.98% and DOC = 12.98% signifying the feed rate to be the most contributing factor influencing surface roughness.
- The optimal machining conditions for minimizing tool wear (VB) as per Taguchi analysis are approaching: cutting speed = 130 m/min, feed = .10 mm/rev, depth of cut = .40 mm with an estimated flank wear of 96 μm.
- The optimized machining conditions for minimizing surface roughness as per Taguchi analysis are approaching: cutting speed = 155 m/min, feed = .10 mm/rev., depth of cut = .25 mm with an estimated surface roughness of .57 μm.
- The results of ANOVA test and validation experiments confirm that the mathematical models developed for tool flank wear and surface roughness excellently fit and predict the values of response factors close to experimentally achieved values with 95% confidence interval.
- The desirability function optimization for simultaneously optimizing both the responses i.e. VB and Ra gives the most optimal solution as: speed = 130 m/min, feed rate = .13 mm/rev. and DOC = .21 mm and the VB is approaching 93.35 μm and Ra approaching 1.18 μm. This solution provided by Desirability function optimization is quite close to the optimal solutions provided by Taguchi analysis although for one response parameter (VB or Ra) at time.
- This study has proved the viability of cheaper coated carbide cutting tools for hard turning of AISI D3 steel in the range of parameters selected in this study, which provides an economical alternative to costlier PCBN and ceramic tools. In future, researchers may explore the suitability of coated carbide tools for more tool and die steel grades viz. AISI – H11, H12, H13, D2 and other high strength materials like various Inconel and stainless steel grades, which are otherwise machined dry or under minimum quantity lubrication conditions with costlier PCBN and ceramic tools.

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