INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

RESEARCH ARTICLE

Effects of Coated Carbide Insert on Surface Finish of Multiple Hardened EN31 Alloy Steel Using Regression, ANN, and RSM

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OPEN ACCESS

Received: 21-09-2024
Accepted: 28-10-2024
Published: 08-11-2024

Citation: Bhivsane S, Chel A, Sayyed S (2024) Effects of Coated Carbide Insert on Surface Finish of Multiple Hardened EN31 Alloy Steel Using Regression, ANN, and RSM . Indian Journal of Science and Technology 17(41): 4287-4295. https://doi.org/10.17485/IJST/v17i41.2388

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Funding: None

Competing Interests: None

Published By Indian Society for Education and Environment (iSee)

ISSN
Print: 0974-6846
Electronic: 0974-5645

Abstract

Objectives: Surface finish plays an essential role in every machining process. The current study mainly focuses on multiple hardened EN31 alloy steel, using various machining parameters and optimizing using regression, ANN, and RSM. **Methods:** The experimentation was performed using a commercial CNC machine and a surface roughness tester, using machining parameters such as tool nose radius (re), cutting speed (v), feed (f), depth of cut (d), and hardness (H) of the material ranging from 0.4 to 1.2 mm, 160 to 260 m/min, 0.1 to 0.20 mm/rev, 0.05 to 0.15 mm, and 45 to 49 HRC, respectively. **Findings:** The study revealed that cutting speed and feed rate significantly affect the surface finish, followed by tool nose radius. With the help of optimization techniques, the surface roughness predicted through RSM was 99.91%, followed by Regression and ANN. The contour plot predicts Ra using the best possible combinations of machining parameters. **Novelty:** The current research compares the surface finish results of multiple hardened EN31 alloy steels predicted through regression, RSM, and ANN with experimental values. The generated correlations will undoubtedly assist researchers in determining surface finish for the defined ranges of machining parameters.

Keywords: Hard Turning; Coated Carbide; EN31 Steel; Surface Roughness; Optimization; RSM

1 Introduction

Materials exhibiting superior hardness and wear resistance have a wide range of applications, and fine geometric tolerances are critical in machining operations[1]. Turning uses a single-point cutting tool to shape a workpiece rotating about its axis by shearing away unwanted material from its surface[2]. In recent years, achieving the maximum manufacturing rate while maintaining the lowest production cost has been crucial. Numerous researchers strive to attain these objectives by determining appropriate machining settings influencing surface finish, tool life, and wear [3]. Authors Revel et al. [4] used a CBN insert to conduct experiments on AISI52100 steel with a hardness of 61 HRC. The study found that the feed rate has a substantial impact on the surface finish. The experimentation was conducted for the study by utilizing v, f, and d within the range of 210-260 m/min, 50-100 mm/rev, and 5-10 μm, resp. Similar to this, Panda et al. [5] experimented with uncoated carbide inserts on 55 HRC AISI52100 steel utilizing machining parameters (v, f, and d) ranging from 70-190 m/min, 0.04-0.16 mm/rev, and 0.1-0.4 mm, respectively. The study came to the conclusion that surface finish is greatly reduced at greater cutting speeds and lower feed rates. Using a precise center lathe and several TiC-coated carbide inserts, Mondal and Das [6] turned AISI52100 steel in wet condition. Using v, f, and constant d varying from 41-253 m/min, 0.063-0.1 mm/rev, and 0.5 mm, the study was conducted in batches. According to the study, built-up edge development was noticed at lower v's, while optimal performance was noted at v range from 161-253 m/min. Sankar and Rao [7] used a PCBN insert to execute a Taguchi L_{27} orthogonal array on 58 HRC AISI52100 steel in order to optimize the operational parameters of turning through ANOVA. Parameters from v (400-900 rpm), f (0.04-0.08 mm/rev), d (0.4-0.8 mm), and r_e (0.4-1.2 mm) were used to perform the operation. The study found that, in hard turning operations, r_e plays a considerable role, regardless of the machining parameters taken into consideration. Siraj et al. [8] used CBN with a TiN-coated insert to study the 60 HRC AISI52100 steel. Wet turning was done with multiple r_e of 0.4-1.2 mm and machining parameters v, f, and d ranging from 280-360 m/min, 0.05-0.15 mm/rev, and 0.1-0.2 mm, respectively. The investigation came to the conclusion that decreased feed rates have a significant impact on surface finish.

Additionally, Umamaheswarrao et al. [9] optimized the surface finish of 57 HRC AISI 52100 steel using a variety of optimal procedures. Five machining parameters, starting with v (200-1000 rpm), f (0.02-0.1 mm/rev), d (0.4-0.8 mm), r_e (0.4-1.2 mm), and negative rake angle (α = -5° to -45°), were used in the experiment. According to the study's findings, the best surface finish was seen at v = 1000 rpm, f = 0.02 mm/rev, d = 0.4 mm, r_e = 1 mm, and α = 5°. Allu et al. [10] performed experimentation on 50 HRC AISI 52100 steel with coated carbide insert using v (70-150 m/min), f (0.05-0.15 mm/rev), d (0.1-0.3 mm), and r_e (0.8-1.2 mm) through response surface method (RSM). The study concluded that the quadratic correlation model predicts R^2 = 99.03% and optimum surface finish observed at 1.69 μm at v = 70 m/min, f = 0.05 mm, d = 0.2 mm, and r_e = 1.2 mm. Karthik et al. [11] used the machining parameters v (100-300 m/min), f (0.04-0.12 mm/rev), and d (0.1-0.3 mm) to study 60 HRC EN31 bearing steel with CBN insert. The analysis came to the conclusion that the optimum machining parameters may result in a surface finish of 0.149 μm. Further, the performance of Al_2O_3+TiC coated ceramic insert on 55 HRC 52100 steel was studied by Kumar et al. [12] on varying v (100-250 m/min), and constant f (0.16 mm/rev), d (0.5 mm). The literature analysis revealed that machining parameters significantly impact turning operations. Lower feed rates with faster cutting speeds improve the surface finish. In contrast, the tool nose radius has an equal impact on the operation since a larger tool nose radius reduces the surface finish. Many researchers have also explored the research area where machine learning plays an important role in predicting machining parameters. Umamaheshwarrao et al. [13] utilized the multi-criteria decision-making model TOPSIS to predict the cutting parameters of AISI 52100 steel. Similarly, George et al. [14] applied multivariate statistical control, Shivakoti et al. [15] applied ANFIS-model, Sahu et al. [16] applied ANOVA with TiAlN coated inserts, further Sivarajan et al. [17] applied Fuzzy logic, Varma and Shrivasatava [18] applied DOE ANOVA to study the MRR, Jai Prakash et al. [19] applied DOE ANOVA with TiN + Al_2O_3 + TiCN coated carbide insert to optimize MRR and SR, Yildiz et al. [20] applied the Box-Behnken approach to AISI 52100 steel, and in recent years, Tran et al. [21] used the MQL of Al_2O_3/MoS_2 nano-fluid in optimization of surface finish of AISI 52100 steel. The present research mainly focused on multiple hardened EN31 alloy steel having hardness in the range of 45-49 HRC with coated carbide insert using multiple machining parameters named tool nose radius, cutting speed, feed rate, depth of cut, and hardness. The experiments' runs were identified using the Box-Behnken method of RSM, and three optimization techniques, regression, RSM, and ANN, were applied to predict the surface finish. The graphs are plotted to compare the experimental values with predicting the surface finish using these techniques.

2 Methodology

The experimental program begins with experimentation on multiple hardened EN31 alloy steel using a commercial CNC machine and measurement of surface finish using a surface roughness tester, followed by optimization using regression, ANN, and RSM. The chemical composition of EN31 alloy steel shows the significant contribution of alloying elements such as carbon, manganese, and chromium. In contrast, nickel, silicon, molybdenum, and sulfur contribute marginally to enhancing the steel's hardness performance. Table 1 shows the contribution of alloying elements with their ranges in the chemical composition.

Table 1. Alloying elements with their ranges in the chemical composition of EN31 alloy steel

Alloying Elements/ Properties	Range/ Unit
Carbon (C)	0.98 to 1.10 %

Continued on next page

Table 1 continued

Manganese (Mn)	0.25 to 0.45 %
Chromium (Cr)	1.30 to 1.60 %
Nickel (Ni)	0.25 %
Silicon (Si)	0.15 to 0.30 %
Sulfur (S)	0.025 % max.
Phosphorous (P)	0.025 % max.
Molybdenum (Mo)	0.1 %
Density	7.81 g/cm^3
Bulk modulus	140 GPa
Modulus of Elasticity	190 to 210 GPa
Rockwell Hardness (Oil quenching with tempering at 150°C)	62-64 HRC
Rockwell Hardness (Water quenching with tempering at 150°C)	64-66 HRC

Initially, the raw material's hardness was evaluated with a Rockwell hardness tester and found to be between 25 and 27 HRC. Furthermore, the EN31 alloy steel specimen was sliced in accordance with the surface response method's prescribed runs. A total of 40 samples were prepared for experimentation, with plane turning and facing operations done first, followed by the standard hardening process. After hardening, the hardness of all specimens was measured again, and the experiment was carried out on 25 mm diameter EN31 alloy steel utilizing a commercial CNC machine on several hardened alloy steels ranging from 45 HRC to 49 HRC. The turning operation used a triangular-coated carbide insert with a tool nose radius (r_e) of 0.4 to 1.2 mm. In addition, various machining parameters such as cutting speed (v), feed (f), and depth of cut (d) were taken into account to optimize the surface finish. The surface finish (R_a) was measured with a Mitutoyo surface roughness tester, and the experimental runs were created using the Box-Behnken approach of the surface response method, which used five input parameters with three levels. Table 2 shows the machining parameters and their levels.

Table 2. Machining parameters and their levels

Parameters	**Units**	**Levels**		
		-1	**0**	**+1**
Tool Nose Radius (r_e)	mm	0.4	0.8	1.2
Cutting Speed (ν)	m/min	160	210	260
Feed (f)	mm/rev	0.1	0.15	0.2
Depth of cut (d)	mm	0.05	0.1	0.15
Hardness (H)	HRC	45	47	49

The regression analysis plays a vital role in statistical prediction. The current study shows that surface finish is predicted by using five input parameters, re, v, f, d, and H, as a function. Using the same terminology, an artificial neural network is applied to predict the surface finish. The neural network model was trained on 70% of the data, tested on 15%, and validated the remainder.

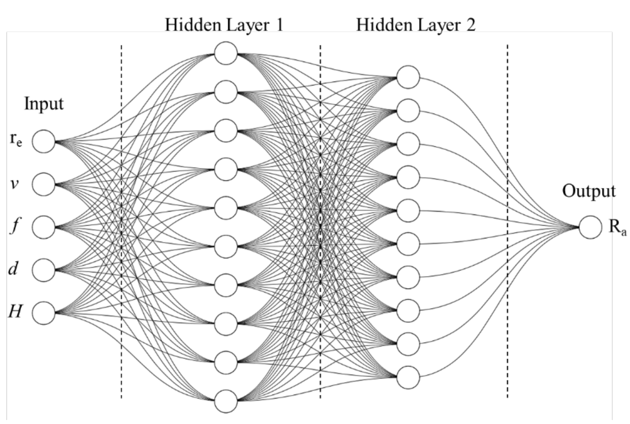

Fig 1. Neural network architecture

Figure 1 depicts the neural network design for the current investigation. The regression equation for the present research work is presented as,

$$R_a = 2.4125 + 0.02969r_e - 0.008613v + 1.8250f + 4.7d + 0.02312H \quad (1)$$

The Box-Behnken approach of the surface response method has already been applied to the calculation of experimental runs. In total, forty runs were calculated by using five input parameters with three levels. The quadratic equation predicted through RSM is presented as,

$$\begin{aligned} R_a = {} & 2.47 + 0.0119r_e - 0.4306v + 0.0913f + 0.235d + 0.0462H + 0.0025r_e * v + 0.00r_e * f + 0.0125r_e * d \\ & + 0.0075r_e * H + 0.0025v * f + 0.0025v * d - 0.01v * H + 0.0025f * d - 0.02f * H + 0.0025d * H - 0.0075r_e^2 \\ & - 0.0108v^2 - 0.0067f^2 - 0.0117d^2 + 0.00H^2 \end{aligned} \quad (2)$$

3 Results and Discussion

A wet turning operation on commercial CNC machines was successfully performed on multiple hardened EN31 alloy steel, and the surface finish was measured using the roughness tester. The results are plotted for the experimental surface finish, and the surface finish is optimized using regression, RSM, and ANN. From the experimentation, significant variations in surface finish were observed at 0.8 mm tool nose radius, 0.15 mm/rev feed, and 47 HRC hardness. Similarly, the surface finish decreases with increased cutting speed, and outliers are observed at 0.05 and 0.15 mm depth of cut. An increasing trend is observed in all machining parameters that accept cutting speed.

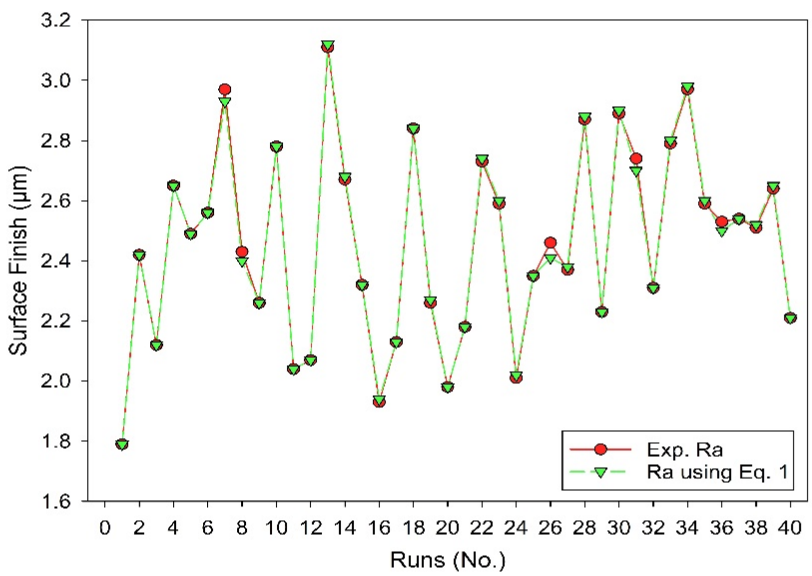

Fig 2. Comparison of Exp. Ra and Ra using Equation (1)

Figure 2 compares the experimental Ra and Ra using Equation (1) (Regression). Marginal variations are observed in experimental and predicted Ra. The highest variation, 1.915%, is observed in Ra at run 26, whereas four runs showed large residuals in Ra of around 1% in all the runs under consideration. The linear equation prediction accuracy is observed as 99.81% using regression. Similar kinds of results based on regression analysis are observed in open literature[8]. Compared to regression analysis, the surface response method also showed the highest accuracy in predicting surface finish. The quadratic equation, given in Equation (2), predicts the surface finish with an accuracy of 99.91%. The individual machining parameters show a more significant effect on surface finish, whereas the effect decreases with increased machining parameters in combination. Combinations such as tool nose radius versus feed and hardness and feed versus hardness showed marginal effects on surface finish. Large residuals, 1.905%, are observed at run 26. The quadratic equations are also given in open literature[16,19,20] and similar kinds of trends are observed for the present study.

Figure 4 illustrates the comparison of experimental Ra and Ra using ANN. The neural network was successfully applied to the experimental data using feed-forward backpropagation. 70% of data was utilized in training, 15% in testing, and the remaining 15% in validation. The bias weights are manually adjusted to get optimum surface finish output. Figure 5 illustrates the comparison of neural network results for the present study. The training shows 99.684% accuracy in prediction, whereas testing is 99.506%, validation is 99.882%, and overall accuracy is 99.629%. Similar kinds of methods and results are observed in the open literature[22].

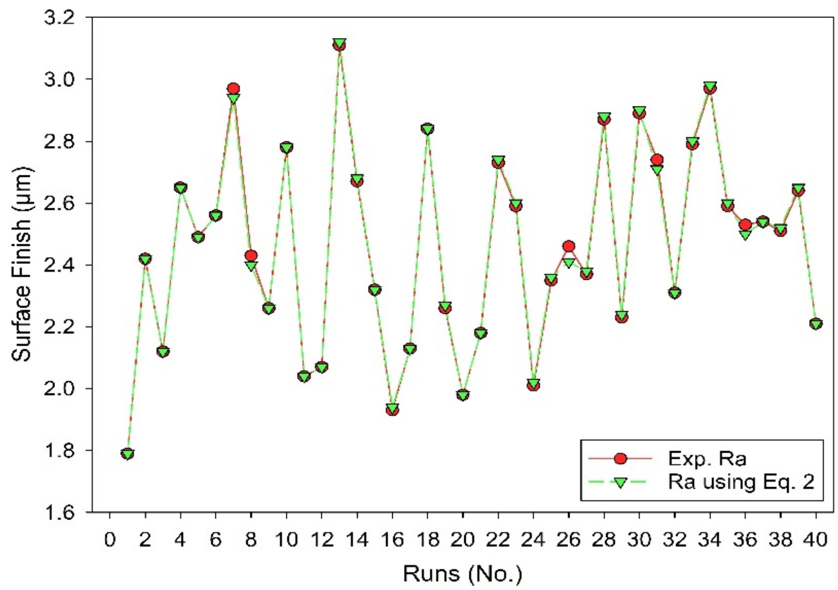

Fig 3. Comparison of Exp. Ra and Ra using Equation (2)

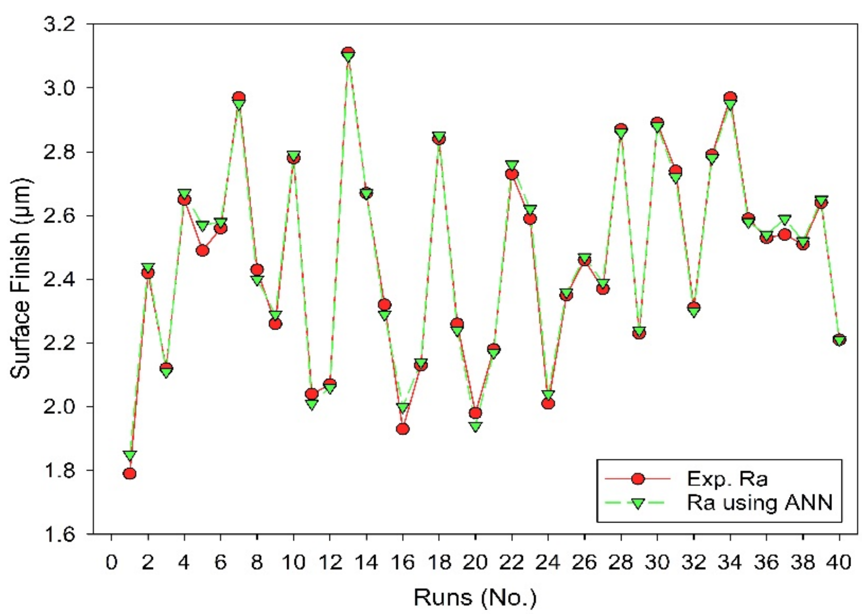

Fig 4. Comparison of Exp. Ra and Ra using ANN

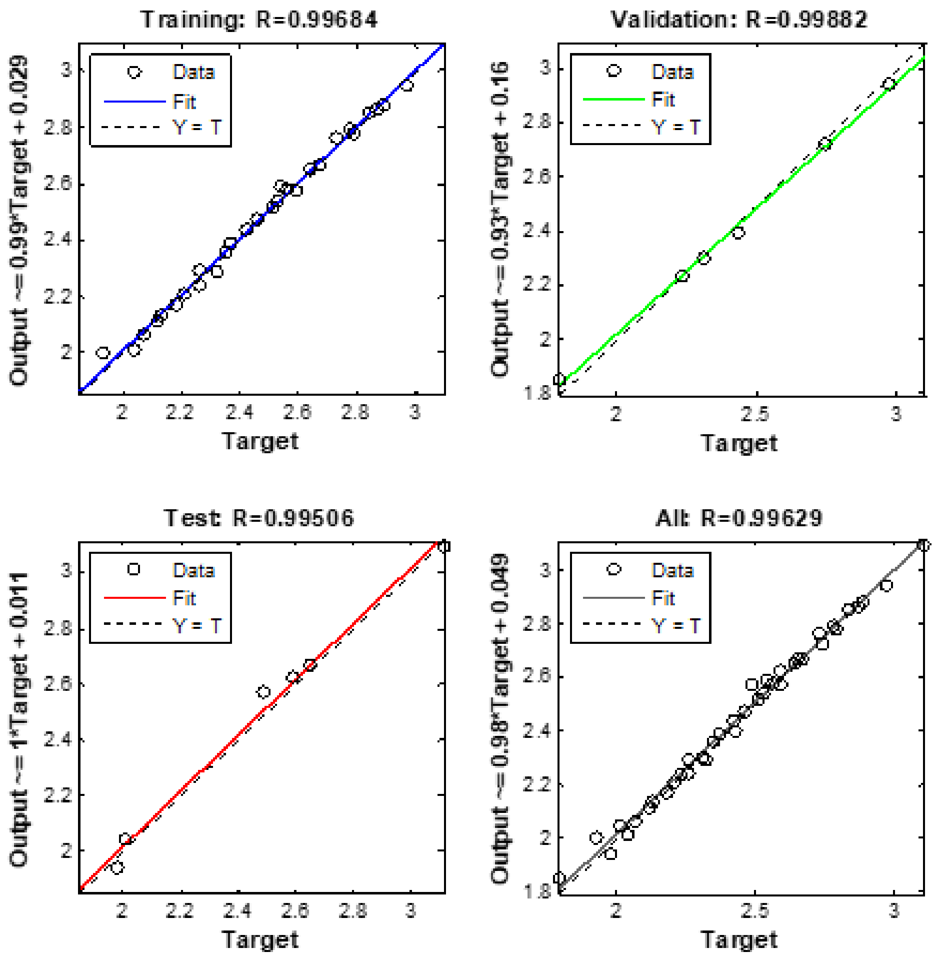

Fig 5. Comparison of neural network results

Figure 6 illustrates the contour plots for predicting surface finish using possible combinations of machining parameters. Figure 6(**a**) shows the contour plot for tool nose radius and cutting speed versus Ra. The cutting speed is inversely proportional to Ra, whereas the tool nose radius is directly proportional. The lowest and highest surface finish, 2.2 μm and 2.8 μm, are observed at 240 and 170 m/min cutting speeds. Figure 6(**b**) shows the contour plot for tool nose radius and feed versus Ra. The feed and tool nose radius have a decreasing trend for all the surface finishes. The highest 2.55 μm Ra at 0.8 mm tool nose radius and lowest 2.4 μm Ra observed below 0.12 mm/rev feed for all tool nose radiuses. Figure 6(**c**) shows a similar trend to Figure 6(**b**). Figure 6 (**c**) illustrates the tool nose radius and depth of cut versus Ra contour plot. The specific surface finish range is observed as 2.3 μm to 2.6 μm for all depth of cuts under consideration.

A non-linear trend is observed in Figure 6(**d**). Hardness plays a vital role in surface finish as it increases with Ra. The optimum values of surface finishes are observed at 0.8 mm tool nose radius. The inclined lines of the surface finish in Figure 6(**e**) show that cutting speed and feed significantly affect Ra, and both are inversely proportional. The range of Ra is observed as 2 μm to 2.8 μm at entire cutting speeds and feeds under consideration. More stripper lines are observed in Figure 6(**f**) compared to Figure 6(**e**). Higher depth of cut significantly affects the surface finish at lower cutting speeds. More significant than 2.8 μm Ra is observed above 0.10 mm depth of cut, and less than 2 μm Ra is observed above 240 m/min cutting speed. Similar trends are observed in Figure 6(**g**) compared to Figure 6 (**e**). The surface finish range is between 2.2 μm to 2.8 μm for entire cutting speeds.

Figure 6(**h**) shows a decreasing trend in Ra when feed increases with decreased depth of cut. The marginal variations 2.2 μm to 2.7 μm are observed in Ra. Again, hardness plays a non-linear trend in Figure 6(**i**), similar to Figure 6(**d**). Feed and hardness have marginal variations in surface finish ranging from 2.35 μm to 2.55 μm. Figure 6 (**j**) illustrates the variations in surface finish when predicted through depth of cut and hardness. The increasing trend in surface finish is observed when both the depth of cut and hardness increase. Both have marginal variations in surface finish ranging from 2.3 μm to 2.7 μm.

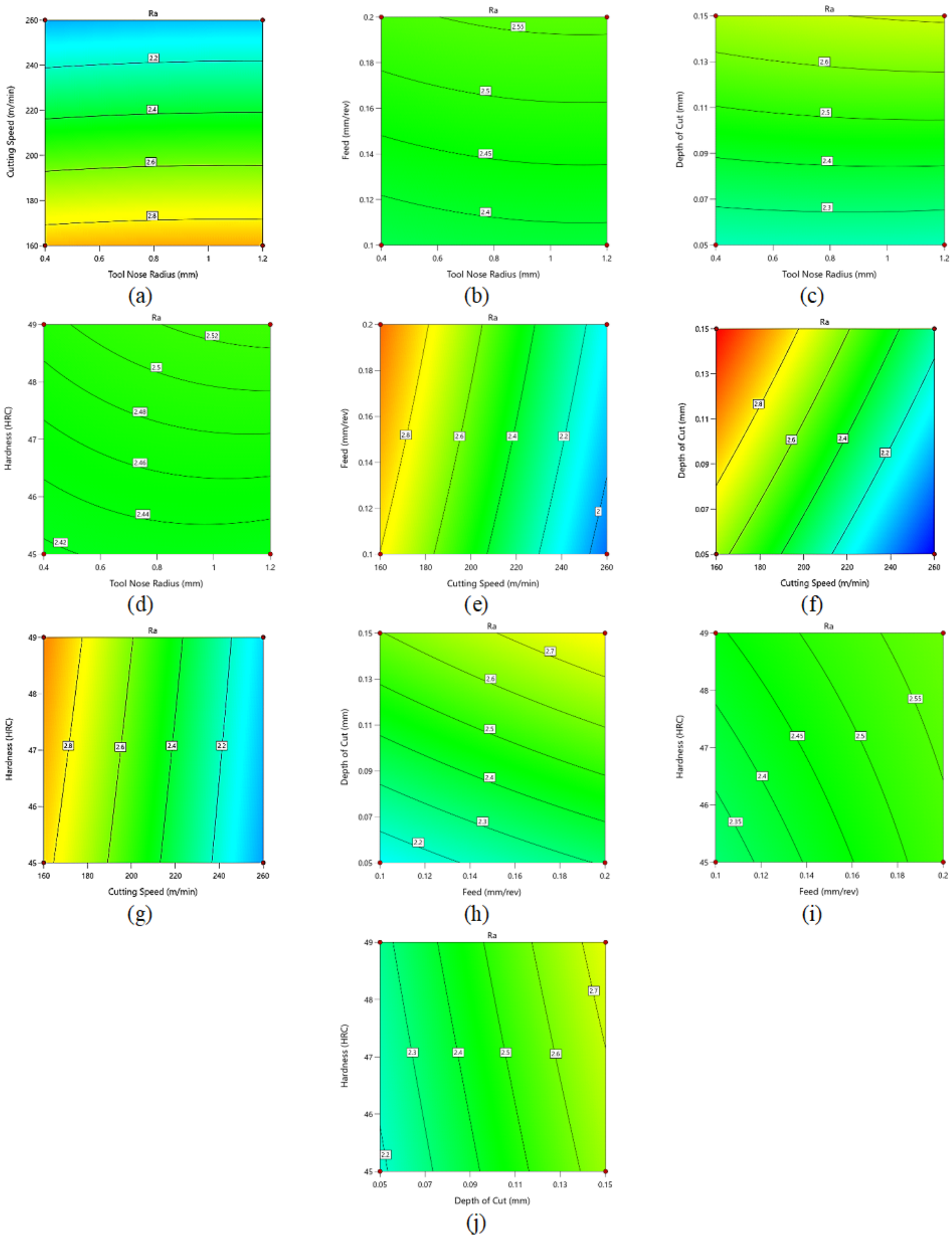

Fig 6. Contour plots to predict the Surface finish

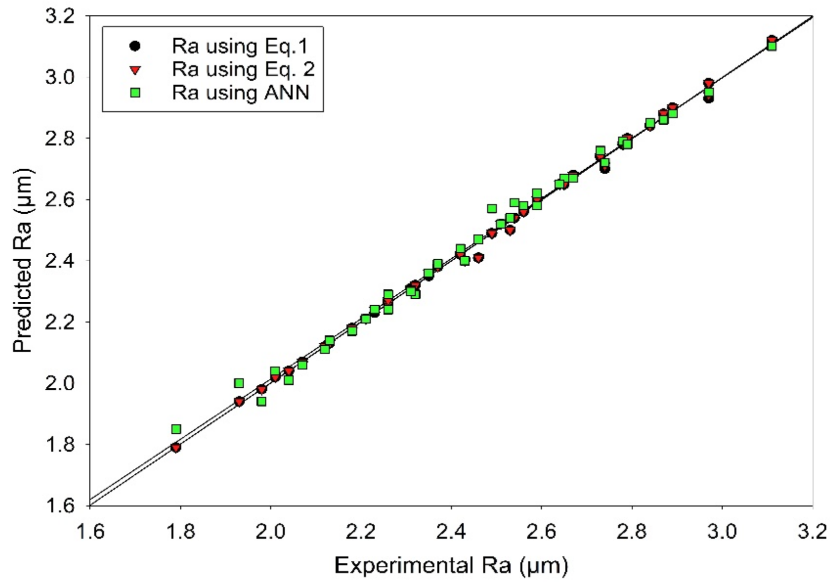

Fig 7. Comparison of experimental and predicted Ra

Figure 7 illustrates the comparison of experimental and predicted surface finish. The figure shows that Ra predicted through regression and RSM values are much closer to the experimental values than Ra predicted through ANN. Marginal variations of 0.1% are observed in Ra predicted through regression and RSM. RSM shows higher accuracy in the prediction of Ra, followed by regression and ANN.

4 Conclusion

A wet turning operation has been performed on multiple hardened EN31 alloy steel using a commercial CNC machine with a coated carbide insert. A total of 40 runs were calculated through the surface response methodology for the experimentation using tool nose radius, cutting speed, feed, depth of cut, and hardness as input functions. In contrast, surface finish is predicted through regression, RSM, and ANN techniques. The conclusions are drawn based on experimentation and optimization of surface finish using the above-specified techniques.

- Ra is observed between 1.79 to 3.11 μm for all the machining parameters under consideration.
- An increasing trend is observed for Ra in all machining parameters except v.
- Significant variations in Ra are observed at 0.8 mm r_e, 0.15 mm/rev f, and hardness 47 HRC.
- The contour plots offer a precise Ra prediction tool by utilizing the most optimal combinations of machining settings.
- The Ra is predicted to be 99.91% through RSM, followed by Regression and ANN.
- Ra is significantly affected by v and d, whereas f has a marginal effect.
- The highest 3.11 μm and lowest 1.79 μm Ra is achieved for constant r_e (0.8 mm), f (0.15 mm/rev), and hardness (47 HRC).
- According to the current study, coated carbide inserts provide an additional affordable option for hardened steel machining.

Acknowledgment

The authors are thankful to the management of MIT College, Aurangabad for providing a research facility. Also declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Authors Contribution

The Conceptualization, Investigation, Methodology, and Writing-original draft were completed by the research scholar Shivaji Bhivsane whereas Supervision, Validation, Writing-review, and editing were performed by Dr. Arvind Chel and Dr. Siraj Sayyed.

References

1) Das DK, Sahoo AK, Das R, Routara BC. Investigations on hard turning using coated carbide insert: Grey based Taguchi and regression methodology. *Procedia Materials Science*. 2014;6:1351–1359. Available from: https://doi.org/10.1016/j.mspro.2014.07.114.
2) Senthilkumar N, Tamizharasan T, Anandakrishnan V. Experimental investigation and performance analysis of cemented carbide inserts of different geometries using Taguchi based grey relational analysis. . *Measurement*. 2014;58:520–556. Available from: https://doi.org/10.1016/j.measurement.2014.09.025.
3) Sinzato MK, Alves UC, Antonialli AI, Ventura CE, Fontes JVDC, Rech J. Surface integrity after hard turning using specially ground cemented carbides. *Procedia CIRP*. 2024;123:101–107. Available from: https://doi.org/10.1016/j.procir.2024.05.020.
4) Revel P, Jouini N, Thoquenne G, Lefebvre F. High precision hard turning of AISI 52100 bearing steel. . *Precision Engineering*. 2016;43:24–33. Available from: https://doi.org/10.1016/j.precisioneng.2015.06.006.
5) Panda A, Sahoo A, Rout A. Statistical regression modeling and machinability study of hardened AISI 52100 steel using cemented carbide insert. *International Journal of Industrial Engineering Computations*. 2017;8(1):33–44. Available from: https://doi.org/10.5267/j.ijiec.2016.7.004.
6) Mondal K, Das S. Wet turning of AISI 52100 steel-an experimental investigation. *J Assoc Eng, India*. 2017;87(3-4):46–59. Available from: https://doi.org/10.22485/jaei/2017/v87/i3-4/166113.
7) Sankar BR. Analysis of forces during hard turning of AISI 52100 steel using Taguchi method. *Materials Today: Proceedings*. 2017;4:2114–2122. Available from: https://doi.org/10.1016/j.matpr.2017.02.057.
8) Siraj S, Dharmadhikari HM, Gore N. Modeling of roughness value from tribological parameters in hard turning of AISI 52100 steel. . *Procedia Manufacturing*. 2018;20:344–353. Available from: https://doi.org/10.1016/j.promfg.2018.02.050.
9) Umamaheswarrao P, Raju DR, Suman KN, Sankar BR. Hybrid optimal scheme for minimizing machining force and surface roughness in hard turning of AISI 52100 steel. *International Journal of Engineering, Science and Technology*. 2019;11(3):19–29. Available from: https://doi.org/10.4314/ijest.v11i3.3.
10) Allu VP, Raju DL, Ramakrishna S. Performance investigation of surface roughness in hard turning of AISI 52100 steel-RSM approach. *Materials Today: Proceedings*. 2019;18:261–270. Available from: https://doi.org/10.1016/j.matpr.2019.06.299.
11) Karthik MS, Raju VR, Reddy KN, Balashanmugam N, Sankar MR. Cutting parameters optimization for surface roughness during dry hard turning of EN 31 bearing steel using CBN insert. *Materials Today: Proceedings*. 2020;26:1119–1144. Available from: https://doi.org/10.1016/j.matpr.2020.02.224.
12) Kumar CS, Patel SK, Fernandes F. Performance of Al2O3/TiC mixed ceramic inserts coated with TiAlSiN, WC/C and DLC thin solid films during hard turning of AISI 52100 steel. *Journal of Materials Research and Technology*. 2022;19:3380–93. Available from: https://doi.org/10.1016/j.jmrt.2022.06.092.
13) Umamaheswarrao P, Raju R, Suman D, N K, Sankar R, B. Optimizing cutting parameters in hard turning of AISI 52100 steel using topsis approach. *Journal of Mechanical and Energy Engineering*. 2019;3. Available from: https://doi.org/10.30464/jmee.2019.3.3.227.
14) Evangelista G, Peruchi RS, Brito TG, Junior PR, Rocha LC. A multivariate statistical quality control of AISI 52100 hardened steel turning. *IEEE Access*. 2020;8:109092–104. Available from: https://doi.org/10.1109/ACCESS.2020.3000585.
15) Shivakoti I, Rodrigues LRL, Cep R, Pradhan PM, Sharma A, Bhoi AK. Experimental Investigation and ANFIS-Based Modelling During Machining of EN31 Alloy Steel. *Materials 13*. 2020;14:3137–3137. Available from: https://doi.org/10.3390/ma13143137.
16) Sahu AK, Sivarajan S, Padmanabhan R. Optimization of machining parameters in turning of EN31 steel with TiAlN coated cutting tool. *Materials Today: Proceedings*. 2021;46:7497–7501. Available from: https://doi.org/10.1016/j.matpr.2021.01.180.
17) Sivarajan S, Elango M, Sasikumar M. Prediction of surface roughness in hard machining of EN31 steel with TiAlN coated cutting tool using fuzzy logic. *Materials Today: Proceedings*. 2022;65(1):35–41. Available from: https://doi.org/10.1016/j.matpr.2022.04.161.
18) Verma AMK, Srivastava. Investigation about machining issues in turning process of EN-31 steel. *Materials today: Proceedings*. 2022;50(5):2361–2364. Available from: https://doi.org/10.1016/j.matpr.2021.10.238.
19) Prakash J, Equbal A, Ravindrannair P. Optimizing the machining parameters during turning of EN 31 steel using TiN + Al2O3 + TiCN coated tungsten carbide tool. *Materials Today: Proceedings*. 2023. Available from: https://doi.org/10.1016/j.matpr.2023.04.473.
20) Yıldız A, Uğur L, Parlak İE. Optimization of the cutting parameters affecting the turning of AISI 52100 bearing steel using the Box-Behnken experimental design method. . *Applied Sciences*. 2022;13. Available from: https://doi.org/10.3390/app13010003.
21) Ngoc TB, Duc TM, Tuan NM, Long TT. Influence of Al2O3/MoS2 hybrid nanofluid MQL on surface roughness, cutting force, tool wear and tool life in hard turning. *Forces in Mechanics*. 2024;16:100285–100285. Available from: https://dx.doi.org/10.1016/j.finmec.2024.100285.
22) Paturi UM, Devarasetti H, Narala SK. Application Of Regression And Artificial Neural Network Analysis In Modelling Of Surface Roughness In Hard Turning Of AISI 52100 Steel. *Materials Today: Proceedings*. 2018;5(2):4766–4777. Available from: https://dx.doi.org/10.1016/j.matpr.2017.12.050.