COMMUNICATIONS IN SCIENCE AND TECHNOLOGY
Homepage: cst.kipmi.or.id

Predictive mapping of surface roughness in turning of hardened AISI 4340 using carbide tools

Armansyah Ginting[a,*], Zuhrina Masyithah[b]

[a]*Department of Mechanical Engineering, Universitas Sumatera Utara, Medan 20155, Indonesia,*
[b]*Department of Chemical Engineering, Universitas Sumatera Utara, Medan 20155, Indonesia*

Article history:
Received: 22 March 2024 / Received in revised form: 19 June 2024 / Accepted: 25 June 2024

Abstract

This study presents a novel approach to predict surface roughness in the hard turning of AISI 4340 steel using carbide tools, aimed to develop a comprehensive predictive map. The hypothesis that surface roughness can be accurately predicted using a linear regression model was tested and confirmed. Experimental results showed surface roughness in the range of 1.946 to 5.636 microns. Statistical analysis revealed a normal distribution of surface roughness data with linear regression as the best-fit model, significantly determined by feed rate and explaining 98.41% of the variance. Machine learning validated this model, achieving high prediction accuracy (R^2 = 96.91%, MSE = 0.058, RMSE = 0.242). The innovative predictive map, created using a full factorial design, demonstrated a strong agreement between predicted and validated values. This work highlights the potential of integrating statistical and machine learning techniques for precise surface roughness prediction, recommending industrial validation to enhance machining productivity.

Keywords: Hard turning; linear regression; machine learning; productivity

1. Introduction

The study deals with an effort to predict the surface roughness of machined surface in the hard turning of AISI 4340 steels using carbide cutting tools. The prediction of surface roughness is beneficial to support our industrial partners whose business is to produce machine components made of hardened steels for agricultural machinery. Providing and supporting the related industry by this kind of information and/or technology would bring an impact on higher production capacity, thus becoming potential to obtain high revenue [1].

Experimental study is the most rational way to fulfill the objective of study. In engineering study, experiment can be arranged in design of experiment (DoE) such as factorial, response surface [2], and Taguchi [3]. It is well-known that experiment can be costly and time consuming when much data is required. As the objective in this study is a map of surface roughness, then the wide range and large number of data are needed. Therefore, the objective could not be fulfilled only via experimental study. In this case, prediction technique sounds promising as a way out.

Today, the main issue related to prediction is solved through the utilization of machine learning technique. Prediction is a key aspect of machine learning where algorithms use historical data to identify patterns and make informed forecast about future outcomes. Machine learning models, through training on data, can predict trends, behaviors, or values contributing to decision-making processes [4–6]. In this study, the training data were collected through the experiment on turning of hardened AISI 4340 with the hardness number of 50 HRc. The experiment was carried out by DoE response surface method in which surface roughness was studied as the response parameter.

As the subset of artificial intelligence technique, machine learning has been applied not only in engineering process research [7,8] but also in life aspects [9,10]. Machine learning excels in condition monitoring and predictive maintenance studies. Of many characteristics and/or aspects studied, surface roughness turns out to be the most concerned parameter [11]. Concerned in machine learning but focused on the combination of traditional approach and artificial intelligent [12], this study explored the impact of cutting parameters on surface roughness in the turning of Al 7075 hard ceramic and hybrid composites using a PCD tool. The application of response surface methodology (RSM) and artificial neural network (ANN) validated and predicted system behavior. Moreover in [13], experimental investigation in the hard turning of Duplex 2205 considered cutting speed, feed rate, cutting depth, and nose radius. A second-order mathematical model was created with

* Corresponding author.
Email: armansyah.ginting@usu.ac.id
https://doi.org/10.21924/cst.9.1.2024.1417

RSM. ANN models, trained and tested, suggested the least predicted surface roughness.

Similar to [13] but enriched with optimization technique, Genetic Algorithm (GA) was reported in [14,15]. In [14], the study investigated minimizing surface roughness in AISI 4340 alloy steel components on a CNC machine using parameters such as feed rate, rotational speed, and depth of cut. The study incorporated the ANN approach to enhance regression coefficients (R^2) for the GA. Confirmation tests revealed that GA and RSM were good in predicting surface roughness values. In [15], the study optimized turning process parameters through support vector regression (SVR), ANN, and GA integration. The study demonstrated artificial intelligence's superiority in training data for better predictions besides emphasized multi-objective optimization for tool wear and surface roughness. The combination technique among machine learning SVR algorithm, ANN, and GA offered significant industrial applications.

Furthermore, machine learning with Bayesian linear regression was implemented in studying the surface roughness in milling process of 6061 aluminum alloy. It was reported that linear regression showed a good predictive performance [16,17]; the authors stated that, as a novel approach in predicting the surface roughness, machine learning in addition to be helpful, useful, and time efficient, was a suitable tool for making prediction, reducing the wastage of material and minimizing energy usage.

Bearing the above in mind, this study introduces a novel methodology combining statistical analysis and machine learning to develop a predictive map of surface roughness in the hard turning of AISI 4340 steel using carbide tools. The novelty of this research lies in the integration of linear regression models and machine learning techniques to accurately predict surface roughness outcomes under varied cutting conditions.

2. Materials and Methods

Hardened AISI 4340 steels with the hardness number of 50 HRc, cylindrical in geometry with the diameter of 80 mm and length of 250 mm was the work piece material in this study. During the hard turning experiment, the work piece was rigidly mounted in the spindle and supported by the tailstock of a CNC lathe machine model CKA6136. The carbide cutting tool coded DCMT11T304-F2 TP40 was used as the cutting tool for hard turning of the work piece.

Surface roughness in Ra parameter was the response variable in this study. The measurement of surface roughness value was carried out by using stylus profilometer equipment Mitutoyo Surftest SJ-210.

The cutting condition for hard turning experiment was received from our industrial partner as shown in Table 1. The cutting condition was then applied in the DoE Box-Behnken design with surface roughness (Ra) as the response variable. The measurement of Ra was taken 5 times/pass and observed until the cutting tool reached the flank wear at VB of about 200 microns. Finally, the measurement from the last pass was then averaged.

The data collected from the experiment were then statistically analyzed and the experimentation data were taken as the training set data for the development of machine learning model. As the behavior of experimentation data could be categorized under supervised learning, the linear regression algorithm was utilized for the model development.

Table 1. Cutting conditions for hard turning experiment

	Factor	Unit	Low	High
v	Cutting speed	m/min	90	120
f	Feed	mm/rev	0.10	0.20
a	Depth of cut	mm	0.25	0.50

The application of machine learning linear regression technique in this study has been done by Python code line program. The algorithm of linear regression technique and the overview of the program are presented in Table 2 and Fig. 1, respectively. Furthermore, the Python code line program was developed by the support of scikit-learn library [4,5,18]. As shown in Fig. 1, there were 2 (two) data sets used as the input, namely training data sets and testing data sets. Training data was the Box-Behnken design with the result of data collected from hard turning experiment. Testing data was designed by full factorial with 7 (seven) levels to provide much more combinations of cutting condition than the training data. The testing data sets was aimed for the prediction map of surface roughness as the objective of study.

Table 2. Linear Regression algorithm

Initializing the parameters	It started with random values for the initial values of the predictors' coefficients
Defining the linear equation	
Computing the predictions	It used the current values of coefficients to make predictions on the training data sets
Calculating the loss	It defined a loss function to quantify the difference between the predicted values and the actual (experiment) values and calculated mean squared error (MSE) and/or root mean squared error (RMSE)
Gradient descent	It updated the coefficients to minimize the loss and used gradient descents optimization algorithm
Repeating	Steps 3 to 5 were repeated until the algorithm converged to a set of coefficients that minimized the loss

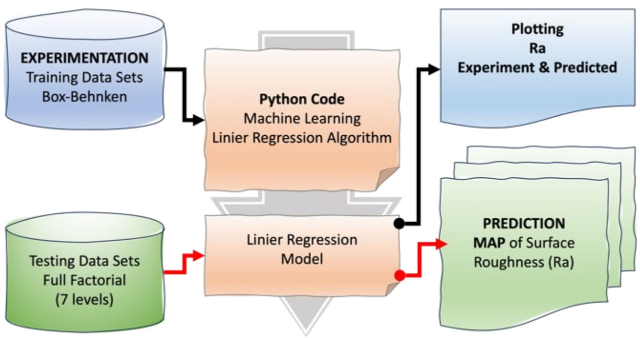

Fig. 1. The overview of the Python program

3. Results and Discussion

3.1. Hard turning experiment

The results of hard turning experiment with DoE Box-Behnken design are presented in Table 3. It can be seen that the values of surface roughness were varied from 1.946 microns (Run 9) to 5.636 microns (Run 4). The values, from the lowest to the highest, indicated that the range of surface roughness resulted from hard turning experiment was in the range of roughness grade number N7 to N9 [19].

From the aspect of tool wear, those 15 cutting tools used for the testing experienced flank wear. The worn area was observed mainly at the vicinity or the tool nose region of the cutting tool. Fig. 2 and Fig. 3 show the evidence of the worn cutting tools used for Runs 4 and 9. The worn area at the tool nose radius was due to the cutting condition where feed (*f*) and depth of cut (*a*) were less and/or about equal to the tool nose radius (0.4 mm) of the cutting tool.

Table 3. The results of turning experiment

Run	*v* m/min	*f* mm/rev	*a* mm	Ra microns
1	90	0.10	0.375	2.193
2	120	0.10	0.375	2.674
3	90	0.20	0.375	4.986
4	120	0.20	0.375	5.636
5	90	0.15	0.250	3.212
6	120	0.15	0.250	3.532
7	90	0.15	0.500	3.917
8	120	0.15	0.500	4.437
9	105	0.10	0.250	1.946
10	105	0.20	0.250	4.848
11	105	0.10	0.500	2.401
12	105	0.20	0.500	5.323
13	105	0.15	0.375	3.930
14	105	0.15	0.375	3.920
15	105	0.15	0.375	3.580

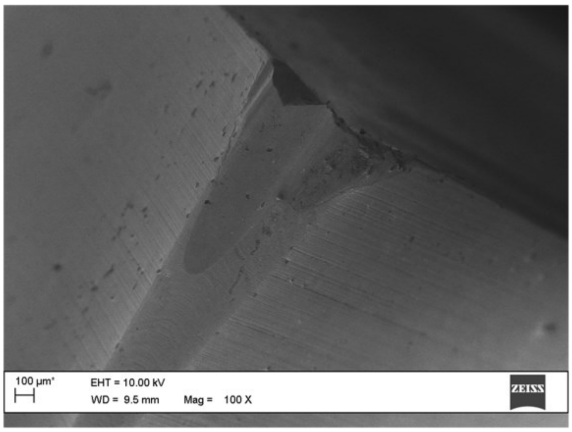

Fig. 2. Flank wear at the tool nose region after turning at *v* 120 m/min, *f* 0.20 mm/rev, and *a* 0.375 mm (Run 4)

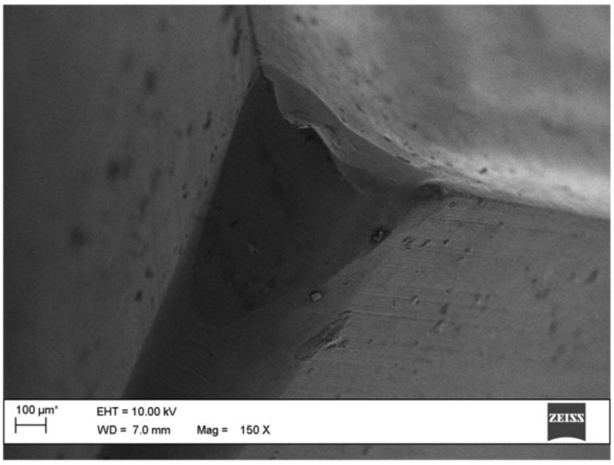

Fig. 3. Flank wear at the tool nose region after turning at *v* 105 m/min, *f* 0.10 mm/rev, and *a* 0.250 mm (Run 9)

The success of carbide in turning of hardened AISI 4340 steels in this study is similar with the ones as reported in many previous researchers. Carbide cutting tool had been reported suitable for cutting of hardened steels up to 58 HRc [20]. In line with the result, other researchers also reported the performance of carbide, both uncoated and coated, in cutting of hardened steel [21–28].

3.2. Statistical analysis

The distribution of data resulted from the experiment was firstly checked by assessing the goodness-of-fit. Minitab application was utilized for this purpose. As shown in Fig. 4 the probability plot of Ra data from Table 3 was plotted with 95% of confidential interval.

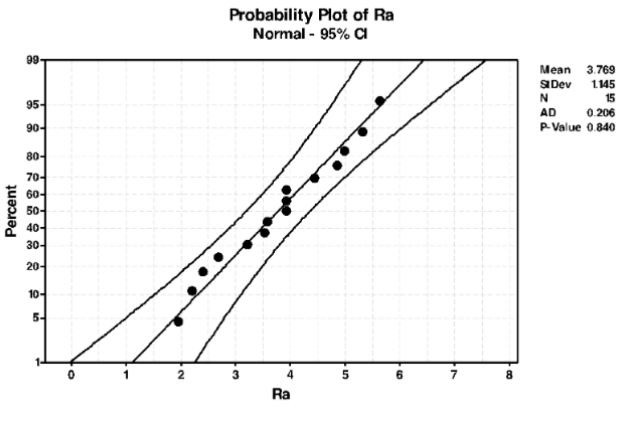

Fig. 4. Probability plot of surface roughness (Ra)

The plot showed that the Ra data were scattered along the diagonal line and inside the corridor. It indicated that the distribution of data was good and followed the normal distribution. The information in the plot's legend also explained the goodness-of-fit of the data where the Anderson-Darling (AD) test 0.206 (the lower the better) suggested a better fit. Moreover, the high P-value of 0.840 (closer to 1), meaning that there was not enough evidence to reject the hypothesis that the data came from a normal distribution. According to the fact of probability plot, it can be concluded that the Ra data resulted by the experimentation is feasible for model development.

Bearing the result from the latter paragraph, the analysis of model was continued by response surface regression. Minitab application was also utilized for this analysis. Fig. 5 shows the surface plot of Ra data. The topography of surface plot was wavy but relatively flat and downhill from higher to lower values of feed (*f*). There was no tendency to form parabolic surface (quadratic model). Based on the facts, it seems that linear model is the best fit model to represent the data.

In fact, the response surface regression analysis showed that linear regression model was the best fit model to represent the data. The result of ANOVA under surface regression showed that linear model was suggested with the coefficient of determination of 98.41%. In case of input parameters, feed (*f*) was affected at most with a significant contribution of 91.37% to the response parameter Ra. Feed rate as a significant parameter to surface roughness, meanwhile, was in line with the results as reported in [12].

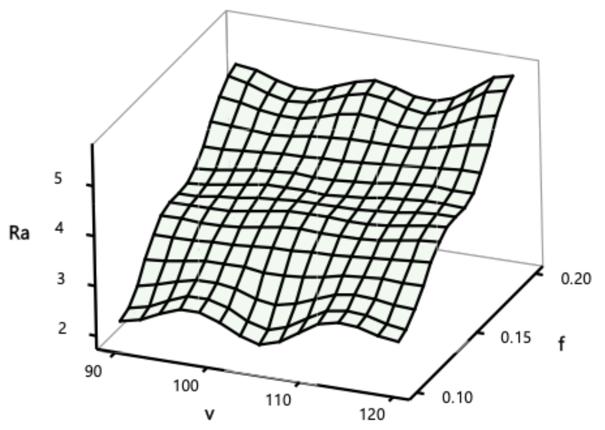

Fig. 5. The topography of surface plot (Ra vs. *v* and *f*) as linear model

3.3. Machine learning and prediction

The data resulted from the experiment activity in Table 3 was used as the training data sets for the Python program and as the output, linear regression model resulted with coefficient of determination (R^2) 96.91%, mean squared error (MSE) 0.058, and root mean squared error (RMSE) 0.242. The value of R^2 (closer to 1) indicated that the model was best fit, and it was also supported by the smaller values of MSE and RMSE. They indicated the reliability of the linear regression model in accurately predicting Ra values.

The visualization of Ra data (Table 3) between experiment and predicted Ra is plotted in Fig. 6. Those 15 runs of Box-Behnken design were used as testing data sets to obtain their predicted Ra values. From the plot, the Ra values resulted by experiment and linear regression model showed a good agreement one to another. This agreement indicated that linear regression model was successfully used for predicting Ra values for hard turning process of AISI 4340 in this study. The similar result to this study was also reported by the previous researchers [17] for turning of AISI 304.

For achieving the objective of study, the cutting conditions as given in Table 1 were extended up to 7 levels (Table 4). The DoE full factorial was then applied for the cutting conditions as shown in Table 4, and 343 combinations of cutting condition were available. Those combinations would be the testing data sets for creating the Map of Surface Roughness (Ra) Prediction.

The testing data sets were input into the linear regression model. As a results, the prediction values of Ra for all 343 combinations of cutting conditions were calculated by the Python program. All 343 data of predicted Ra were then plotted, and the Map of Surface Roughness (Ra) Prediction was done as seen in Fig. 7 and the values are detailed in Table 5. However, due to the limitation space of manuscript, not all of data can be shown in Table 5.

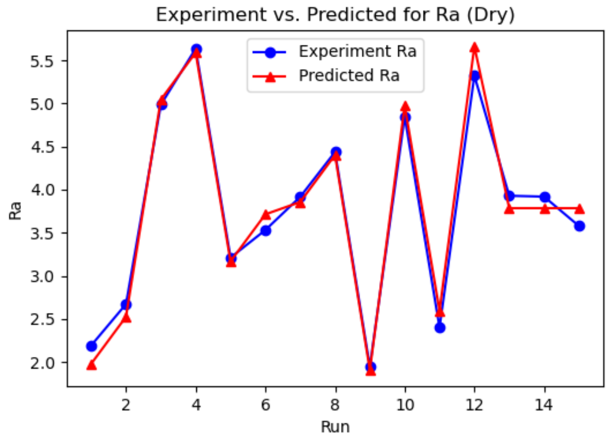

Fig. 6. Ra values: experiment vs. prediction

Table 4. Cutting conditions for the Map of Ra prediction

Factor	Levels						
	1	2	3	4	5	6	7
v	90	95	100	105	110	115	120
f	0.10	0.12	0.14	0.15	0.16	0.18	0.20
a	0.25	0.30	0.35	0.375	0.40	0.45	0.50

Fig. 7 presents the plot of surface roughness (Ra) based on the result of prediction carried out randomly among all 343 cutting conditions resulted by 7 levels DoE full factorial design as per Table 4. From the plot, as earlier mentioned, the varieties of surface roughness (Ra) values were in the range of N7 to N9 roughness grade numbers or associated with Ra values between 1.6 to 6.3 microns [19]. In fact, it was the range of surface roughness that averagely achieved in turning operation [29].

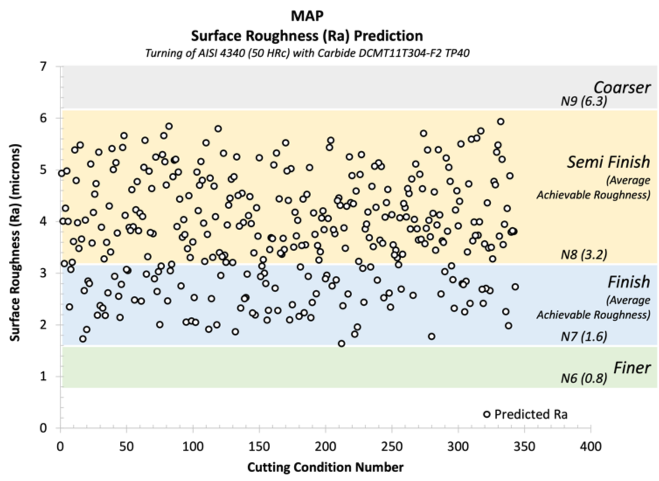

Fig. 7. The Map of surface roughness (Ra) prediction

Unlike the predicted Ra randomly plotted in Fig. 7, the predicted Ra in Table 5 had been sorted and presented continuously from the smallest to largest values of Ra. Rather than listing all 343 cutting conditions and associated Ra values, there were 8 (eight) cutting conditions associated with the predicted Ra values presented in the table (due to limitation of the manuscript). All 8 (eight) predicted Ra values in Table 5 had also been validated by re-hard turning experiment and the results were found quite accurate as shown under column validated (last column). In general, the validation showed agreement to the predicted Ra and vice versa. Although it is early to generalize that all validations would show the similar agreement, but based on the loss calculation that the linear regression model (R^2 = 96.91%, MSE = 0.058, and RMSE = 0.242); it may be safe to conclude that the validation would never run far away from the predicted Ra. Yet, recommendation to our industrial partner is still to do validation whenever taking the cutting condition of invalidated predicted Ra for production line. Continuous validation would give benefit to productivity.

Table 5. Detail values of the Map of surface roughness prediction

No	Grade	Cutting Condition			Ra (microns)	
		v	*f*	*a*	Predicted	Validated
1	*N7 Finish*	90	0.1	0.25	1.637	1.697
2		95	0.1	0.25	2.250	2.340
3		90	0.1	0.3	2.862	2.782
…		…	…	…	…	…
100		100	0.14	0.375	3.182	3.292
101	*N8 Semi finish*	90	0.14	0.375	3.206	3.336
…		…	…	…	…	…
341		120	0.2	0.45	5.797	4.899
342		115	0.2	0.5	5.843	5.182
343		120	0.2	0.5	5.934	5.764

4. Conclusion

The study on hard turning of AISI 4340 steel with the hardness number of 50 HRc using carbide tools revealed surface roughness (Ra) ranging from 1.946 to 5.636 microns, corresponding to N7 to N9 roughness grades. The surface roughness data followed a normal distribution, and linear regression emerged as the best-fit model, significantly determined by feed rate. Machine learning further validated the linear regression model, achieving high prediction accuracy with predictions matching typical turning operations' surface roughness values. A predictive map of surface roughness was successfully created and showing a strong agreement between predicted and validated values. The study highlights the potential and effectiveness of machine learning linear regression technique in predicting surface roughness values in hard turning processes. The predictive map of surface roughness is beneficial to support industry whose business is in producing machine components made of hardened steels.

Acknowledgements

Part of this study received a financial support under the international research collaboration scheme from Universitas Sumatera Utara with grant No. 4167/UN5.1.R/PPM. Thanks all students and laboratory members for a good cooperation and for creating a nice teaching learning environment.

References

1. B. Wibowo, N.A. Masrurah, Y.U. Kasanah, F. Trapsilawati, Subagyo, and M.A. Ilhami, *towards a taxonomy of micro and small manufacturing enterprises*, Commun. Sci. Technol. 4 (2019) 74–80.
2. D.C. Montgomery, *Design and Analysis of Experiments*, *10th Ed.,* Wiley, 2019.
3. T. Mori, and S.-C. Tsai, *Taguchi Methods*, ASME, 2011.
4. A.C. Müller, and S. Guido, *Introduction to Machine Learning with Python and Scikit-Learn*, O'Reilly, 2016.
5. A.C. Müller and S. Guido, *Introduction to Machine Learning with Python A Guide for Data Scientists*, O'Reilly, 2016.
6. T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning, 2nd. Ed.,* Springer, 2009.
7. M. Soori, B. Arezoo, and R. Dastres, *Machine learning and artificial intelligence in CNC machine tools, A review*, Sustain. Manuf. Serv. Econ. 2 (2023) 100009.
8. P. Srikanth, P.S. Teja, B.L. Prasad, and V.P. Kalyan, *A comprehensive review of machine learning techniques in computer numerical controlled machines*, Int. J. Sci. Res. Arch. 9 (2023) 627-637.
9. T.G. Pratama, R. Hartanto, and N.A. Setiawan, *Machine learning algorithm for improving performance on 3 AQ-screening classification*, Commun. Sci. Technol. 4 (2019) 44–49.
10. M.A. Putra, N.A. Setiawan, and S. Wibirama, *Wart treatment method selection using AdaBoost with random forests as a weak learner*, Commun. Sci. Technol. 3 (2018) 52–56.
11. K. Ullrich, et al., *AI-based optimisation of total machining performance: A review*, CIRP J. Manuf. Sci. Technol. 50 (2024) 40–54.
12. R. Kumar, and S. Chauhan, *Study on surface roughness measurement for turning of Al 7075/10/SiCp and Al 7075 hybrid composites by using response surface methodology (RSM) and artificial neural networking (ANN)*, Meas. 65 (2015) 166–180.
13. M. Gopal, *Prediction of surface roughness in turning of duplex stainless steel (DSS) using response surface methodology (RSM) and artificial neural network (ANN)*, Mater. Today. Proc. 47 (2021) 6704–6711.
14. A.J. Santhosh, et al., *Optimization of CNC turning parameters using face centred CCD approach in RSM and ANN-genetic algorithm for AISI 4340 alloy steel*, Res. Eng. 11 (2021) 100251.
15. A.K. Gupta, S.C. Guntuku, R.K. Desu, and A. Balu, *Optimisation of turning parameters by integrating genetic algorithm with support vector regression and artificial neural networks*, Int. J. Adv. Manuf. Technol. 77 (2015) 331-339.
16. D. Kong, J. Zhu, C. Duan, L. Lu, and D. Chen, *Bayesian linear regression for surface roughness prediction*, Mech. Syst. Signal Process. 142 (2020) 106770.
17. V. Dubey, A.K. Sharma, and D.Y. Pimenov, *Prediction of Surface Roughness Using Machine Learning Approach in MQL Turning of AISI 304 Steel by Varying Nanoparticle Size in the Cutting Fluid*, Lubricants 10 (2022) 81.
18. A. Zollanvari, *Machine Learning with Python: Theory and Implementation*, Springer, 2023.
19. ISO Standard, *Geometrical Product Specifications (GPS) - Indication of surface texture in technical product documentation*, ISO 1302 (2002).
20. W. Koenig, R. Komanduri, H.K. Toenshoff, and G. Ackershott,

Machining of hard materials, CIRP Annals, 33 (1984) 417-427.

21. R. Suresh, S. Basavarajappa, V.N. Gaitonde, G.L. Samuel, and J.P. Davim, *State-of-the-art research in machinability of hardened steels*, Proc. Inst. Mech. Eng. B J. Eng. Manuf. 227 (2013) 191-209.
22. W.F. Sales, J. Schoop, L.R.R. da Silva, Á.R. Machado, and I.S. Jawahir, *A review of surface integrity in machining of hardened steels*, J. Manuf. Process. 58 (2020) 136-162.
23. S. Chinchanikar, and S.K. Choudhury, *Machining of hardened steel - Experimental investigations, performance modeling and cooling techniques: A review*, Int. J. Mach. Tools Manuf. 89 (2015) 95-109.
24. A. Sharma, M. Kalsia, A.S. Uppal, A. Babbar, and V. Dhawan, *Machining of hard and brittle materials: A comprehensive review*, Mater. Today. Proc. 50 (2021) 1048-1052.
25. R. Bag, A. Panda, A.K. Sahoo, and R. Kumar, *Sustainable high-speed hard machining of AISI 4340 steel under dry environment*, Arab J. Sci. Eng. 48 (2023) 3073-3096.
26. R. Suresh, S. Basavarajappa, and G.L. Samuel, *Some studies on hard turning of AISI 4340 steel using multilayer coated carbide tool*, Meas. 45 (2012) 1872-1884.
27. A. Ginting, C.H.C. Haron, I. Bencheikh, and M. Nouari, *Study on characteristics of AlTiN and TiCN coating layers deposited on carbide cutting tools in hard turning of steel: Experimental, simulation and optimisation*, Int. J. Mach. Machina. Mater. 23 (2021) 88-112.
28. A. Ginting, M. Nouari, and I. Bencheikh, *Increasing productivity in hard turning of steels using CVD-coated carbide*, Int. J. Mach. Machina. Mater. 22 (2020) 309-330.
29. S. Kalpakjian, S.R. Schmid, and K.S. Vijay Sekar, *Manufacturing Engineering & Technology, 7th Ed.*, Pearson, 2021.