Development of Predictive Model for Surface Roughness Using Artificial Neural Networks

Nikhil Rai(✉), M. S. Niranjan, Prateek Verma, and Prince Tyagi

Department of Mechanical Engineering, Delhi Technological University, Delhi, India
nikhilrai637@gmail.com

1 Introduction

Engineering application utility of metallic components depends heavily on their surface roughness values. In the present scenario of heavy industrialisation and emerging automation techniques, the importance of surface properties has increased manifold making it a determining factor of product quality. Good surface finish is appreciable for improved tribological properties and enhanced resistance to corrosion. Machining and finishing operations on the automated CNC lathes render components variable surface roughness values depending on the process parameters like speed of cutting, feed rate and depth of cut. Researchers have created various prediction models for proper planning and control of cutting conditions and figuring out the optimal parameters for machining.

The consideration of machining parameters becomes crucial so as to perform economical machining with the desired characteristics in the product. The surface integrity produced after machining is recognised to have a great impact on the lifecycle of the product. It represents the nature of the surface condition of the workpiece after machining. In today's dynamically changing world, manufacturing industries are relying more and more on application of optimisation methods in the metal cutting process so that production units can perform optimally under the rigorous competition pressure in the market and produce products of superior quality.

This research paper is focussed on figuring out the optimal combination of speed of cutting, feed rate and depth of cut to minimise the surface roughness in a CNC lathe turning operation using the ANN technique.

In this work, we have tried to compute the influence of speed of cutting, feed rate and depth of cut on surface roughness, and an optimisation model has been created using the artificial neural network technique. Data have been collected from various published papers to train the model and validate the results.

2 Literature Review

A lot of work has been done to optimise the input variable parameters of machining. Residual stress developed during machining impacts the life time and quality of machined components. Neural network-based prediction models are used to predict the accuracy of residual stress development. ANN-FPA models prediction had the accuracy of 99.8%

R. M. Singari et al. (eds.), *Advances in Manufacturing Technology and Management*,
Lecture Notes in Mechanical Engineering,
https://doi.org/10.1007/978-981-16-9523-0_16

and 99.7%, respectively [1]. Surface roughness prediction is done using convolution neural networks directly from the digital image of surface texture of the machined component instead of doing feature extraction and image segmentation by the virtue of image segmentation [2]. Good material removal rate enhances productivity of machining. Tool chatter degrades MRR [3]. Optimal cutting parameters are predicted using ANN for the stable machining operation in turn increasing the productivity. Accurate prediction of tool life prevents the catastrophic stoppage of machining processes due to tool wear. ANN models are used for the prediction of tool life and cutting-edge wear to make it industry ready [4]. Experiments were performed that are designed on the basis of Taguchi's methodology for optimal result. The study demonstrates that the surface roughness increases when the feed rate is increased, the influence of cutting speed was found to be less than that of feed followed by the effect of change in depth of cut [5]. Another researcher has studied the influence of tool overhang along with other parameters on residual stress and surface roughness developed during the turning of aluminium alloy by designing the experiments based on Taguchi's technique. The results obtained reveal that the most optimal result for surface roughness could be obtained by using tool overhang in the medium or lower range [6]. Regression models were developed for predicting the surface roughness and an artificial neural network to account the combined influences of the tool vibration amplitudes and cutting force which provides a model with higher accuracies of prediction [7]. A comparative study has been established with aluminium alloys and brass machining on computer numerical control machine and analysed by the help of prediction techniques. It was found that surface properties are dependent on cutting force which is ultimately decided by speed of cutting, feed rate and depth of cut [8]. Some other researchers have also used the Taguchi technique. Experiments were conducted by taking feed rate, speed of cutting and depth of the cut as cutting process parameters. Experiments are designed on the basis of Taguchi's technique for optimisation using orthogonal arrays. In hindsight, it was inferred that speed of cutting highly influences the surface roughness than feed and in case of MRR, depth of cut is the primary parameter and then the speed of cutting [9]. Artificial neural networks are being developed for the prediction of tool life, failure-mode on the basis data obtained by recording different experiments based on multiple values of speed of cutting and feed rate and constant depth of cut. The neural network best predicted the failure-mode prediction. The network training could be improved using the real-time datasets [10].

An artificial neural network is developed for predicting so as to control the surface roughness in a computer numerically controlled lathe. Experiments were conducted, and the cutting parameters were the speed of cutting, feed rate and depth of cut. It is found that we can predetermine optimised parameters of cutting for surface roughness of machining operation using the control algorithm and artificial neural network [11]. An on-line fuzzy neural network (FNN) model [12] to estimate the flank and crater wear on the basis of modified least square backpropagation [13]. It has been found that an on-line FNN model has great accuracy for the estimation of progressive flank and crater wear with very less time for computation [14]. A linear model was generated for three responses, i.e. material removal rate, surface roughness and chip thickness ratio (CTR), and experiments were conducted based upon the Taguchi's technique of optimised response using orthogonal array. ANOVA was used to find out the main influences of S/N ratio, and graphs are plotted. The resulting optimised value for depth of cut, time and the speed of cutting are best fit for the optimised metal cutting to extract the competitive results from commercial mild steel [15]. Mathematical models were also developed for predicting surface roughness [16] on the basis of parameters for cutting and tool vibrations. Tool vibrations were measured using an FFT analyser. It is inferred that tool vibrations and cutting parameters based prediction models are more accurate [17, 18]. Multiple attribute decision making methods [19] had been used for investigating multiple parameters and their impacts on surface roughness. The investigation is done to devise an optimised procedure for selection of tool insert for improved surface finish in turning operation whilst working on different materials. After analysing the previous research works, it was observed that enormous work had been done on optimising cutting parameters using statistical tools and techniques for better surface finish but this is felt that a lot better predictions can be done by the virtue of neural networks. Here, an attempt is made to train an artificial neural network for the prediction of surface roughness of the mild steel whilst being machined on CNC lathe. In order to train the model well, experimental readings from other prediction and optimisation-based research work are used. In the end, the neural network was validated with two unseen datasets to gauge the efficiency of the model.

3 Methodology

Artificial neural network (ANN) algorithms are modern information processing models used to make approximations from real objective functions. The algorithm has taken the inspiration from working of neural cells in the human brain. Artificial neural networks have the scope of modelling linear and non-linear systems. A trained neural network depicts a quick mapping of the given input with the expected output quantities. We have incorporated this modern technique to quantify the effect of process parameters on surface properties of the material during turning operations on CNC lathe machine tools.

An artificial neural network is represented as an acyclic graph. Different sets of nodes comprise different layers.

Mainly, there are three categories of layers.

Input layer

Different formats of inputs provided by the programmer.

Hidden layer

It is responsible for the calculations to figure out the hidden features and patterns in the data.

Output layer

Sequential transformation is done on the input received in accordance with the functions of hidden layers, and the finally obtained result is conveyed by the virtue of the output layer (Fig. 1).

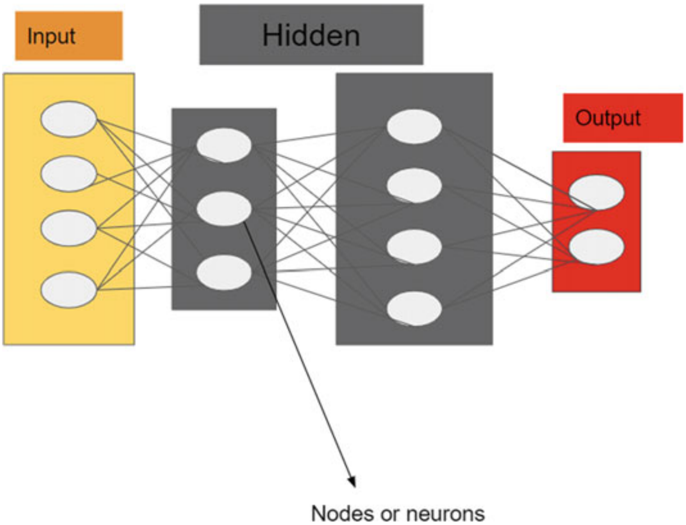

Fig. 1 Perceptron in the form of acyclic graph

ANN calculates the weighted sum of the inputs and adds the bias effect. The following is the representation of the transfer function.

$$\sum Wi * Xi + b \tag{1}$$

The determined weighted sum is passed to an activation function. Activation functions decide whether a node should fire or not. Only those who are fired reach the output layer. Ample activation functions are available that can be applied to the tasks that we perform.

ANN is significantly powerful computer modelling techniques which is being used these days in multiple engineering fields for modelling of complicated relationships which are difficult to optimise using traditional techniques. Neural networks gain information by detection of patterns in the data and are trained for futuristic predictions. The proposed system is based on the ANN training technology to optimise the machining parameters.

4 Dataset

See Tables 1, 2 and 3.

5 Results and Discussion

Table 1 is used for training the neural network whilst Tables 2 and 3 are the unseen datasets for validating the neural networks. The neural network architecture is made of three dense layers each containing 250,100,100 neurons and the finally an output layer.

ReLU activation [20] was applied in each layer. The network was trained using SGD and was validated on 10% of this data during training time. The feed rate, speed of cutting and depth of cut were provided as input to the neural network, whilst surface roughness was predicted on the basis of these inputs (Fig. 2). The network was evaluated on the basis of MSE, MAE, MAPE error and was trained on 2000 epochs during which the model finally converged. Final training errors are listed in Table 4 as shown.

Table 1 Experimental data from for depth of cut (DOC), feed rate (FR), cutting speed (CS) and resulting surface roughness on machining of mild steel on CNC lathe [5]

S. No.	CS (mm/min)	FR (mm/rev)	DOC (mm)	SR (μm)	S/N ratio (dB)
1	60	0.25	0.2	5.6	−14.96
2	60	0.25	0.3	7.1	−17.02
3	60	0.25	0.4	7.4	−17.38
4	60	0.35	0.2	7.1	−17.02
5	60	0.35	0.3	6.03	−15.6
6	60	0.35	0.4	6.98	−16.87
7	60	0.45	0.2	4.85	−13.71
8	60	0.45	0.3	5.55	−14.88
9	60	0.45	0.4	6.31	−16
10	80	0.25	0.2	4.23	−12.52
11	80	0.25	0.3	4.44	−12.94
12	80	0.25	0.4	5.14	−14.21
13	80	0.35	0.2	3.84	−11.68
14	80	0.35	0.3	5.57	−14.91
15	80	0.35	0.4	5.73	−15.16
16	80	0.45	0.2	4.06	−12.17
17	80	0.45	0.3	4.85	−13.71
18	80	0.45	0.4	6.28	−15.95
19	100	0.25	0.2	4.12	−12.29
20	100	0.25	0.3	3.57	−11.05
21	100	0.25	0.4	3.3	−10.37
22	100	0.35	0.2	3.41	−10.65
23	100	0.35	0.3	3.12	−9.88
24	100	0.35	0.4	3.42	−10.68
25	100	0.45	0.2	2.63	−8.39
26	100	0.45	0.3	4.33	−12.72
27	100	0.45	0.4	4.1	−12.25

Table 2 Experimental data from for depth of cut (DOC), feed rate (FR), cutting speed (CS) and resulting surface roughness on machining of mild steel on CNC lathe [9]

Exp	FR (mm/rev)	DOC (mm)	CS (mm/min)	SR (μm)
1	0.1	0.5	75	1.464
2	0.1	0.75	125	2.062
3	0.1	1	175	2.972
4	0.2	0.5	125	3.284
5	0.2	0.75	175	4.264
6	0.2	1	75	2.22
7	0.3	0.5	175	3.662
8	0.3	0.75	75	2.549
9	0.3	1	125	3.586

Table 3 Experimental data from for depth of cut (DOC), speed and resulting surface roughness on machining of mild steel on CNC lathe [15]

Speed (revolutions/min)	Time	DOC (mm)	SR (μm)	Chip thickness ratio	MRR
2000	8	1	0.86	1.08	30
2000	8.2	1.3	0.02	1.12	38.05
2000	8.3	1.5	1.5	1.15	43.37
1500	8	1	1.6	1.09	30
1500	8.2	1.3	0.42	1.1	34.67
1500	8.3	1.5	0.47	1.14	45
900	8	1	0.38	1.09	21.81
900	8.2	1.3	6.18	1.13	28.36
900	8.3	1.5	2.72	1.15	30

The network was tested on two unseen datasets each containing 10 data points. The errors during testing training and validation are quite close to each other, hence the model is able to learn patterns in the data really well during training period.

The loss for network is defined as squared difference summation of predicted and truth values of surface roughness over all data points divided by total number of data points.

During training period, we have received MSE, MAE, MAPE loss as 0.3415, 0.5293, 20.2629, respectively, whilst during testing, it is 0.5654, 0.6178, 38.5695 and 1.0916, 1.1089, 97.7567, respectively, for unseen dataset 1 and 2. From these results, we can clearly see that neural network is capable of predicting surface roughness on the basis of feed rate, speed of cutting, depth of cut.

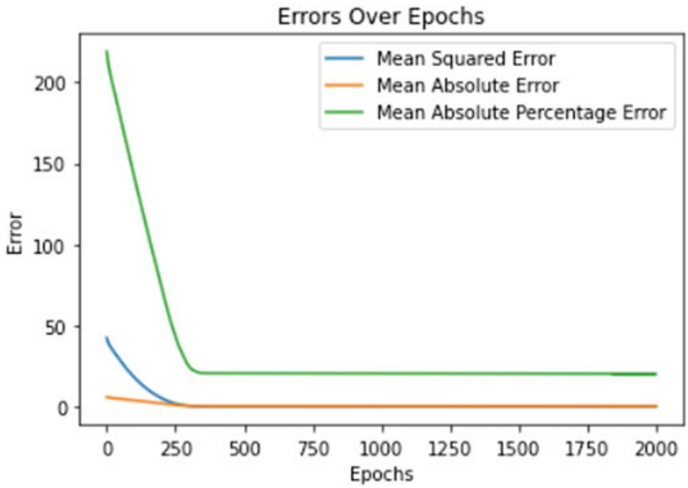

Fig. 2 Error versus epochs curve during training time

6 Conclusion

In this study, we have used the ANN model for CNC turning. The artificial neural network was trained upon 27 data points with parameters feed rate, speed of cutting, depth of cut for the corresponding surface roughness. Further, the dataset is validated upon 18 unseen data points. It is been found that unseen data values of surface roughness and predicted values of surface roughness are significantly close. The predicted values give us a mean absolute error of 0.86. In conclusion, there is very close agreement between predicted and actual surface roughness value. The prediction of surface roughness as done using the ANN algorithm has shown comparatively better results than the existing models and hence can be relied upon for further prediction for industrial standards application.

We can know about the surface roughness on a mild steel upon selecting feed rate, speed of cutting, depth of cut which in turn will help tremendously in the decision-making for getting a high standard surface finish. Further, the study can be integrated with optimisation algorithms like genetic modelling for optimisation of the multiple

Table 4 Errors during training, validation and testing period

	MSE	MAE	MAPE
Training	0.3415	0.5293	20.2629
Validation	0.7040	0.8391	23.3986
Test			
On dataset-1	0.5654	0.6178	38.5695
On dataset-2	1.0916	1.1089	97.7567

turning parameters to enable better parameter selection on the CNC lathe to produce quality products in the competitive market landscape.

References

1. Khoshaim AB et al (2021) Prediction of residual stresses in turning of pure iron using artificial intelligence-based methods. J Mater Res Technol (2021)
2. Rifai AP, Aoyama H, Tho NH, Dawal SZM, Masruroh NA (2020) Evaluation of turned and milled surfaces roughness using convolutional neural network. Measurement 161:107860
3. Gupta P, Singh B (2020) Local mean decomposition and artificial neural network approach to mitigate tool chatter and improve material removal rate in turning operation. Appl Soft Comput 96(2020):106714
4. Mikołajczyk T, Nowicki K, Bustillo A, Pimenov DY (2018) Predicting tool life in turning operations using neural networks and image processing. Mech Syst Signal Process 104:503–513
5. Sharma SK, Kumar ES (2014) Optimization of surface roughness in CNC turning of mild steel (1018) using Taguchi method. Carbon 100(2014):0–26
6. El-Axir MH, Elkhabeery MM, Okasha MM (2017) Modeling and parameter optimization for surface roughness and residual stress in the dry turning process. Eng Technol Appl Sci Res 7(5):2047–2055
7. Vasanth XA, Paul PS, Varadarajan AS (2020) A neural network model to predict surface roughness during turning of hardened SS410 steel. Int J Syst Assur Eng Manage 11(3):704–715
8. Bharilya RK, Malgaya R, Patidar L, Gurjar RK, Jha AK (2015) Study of optimised process parameters in turning operation through force dynamometer on CNC machine. Mater Today: Proc 2(4–5):2300–2305
9. Ezugwu EO, Arthur SJ, Hines EL (1995) Tool-wear prediction using artificial neural networks. J Mater Process Technol 49(3–4):255–326
10. Goyal S, Kandra VS, Yadav P (2016) Experimental study of turning operation and optimization of MRR and surface roughness using Taguchi method. Int J Innov Res Adv Eng
11. Karayel D (2009) Prediction and control of surface roughness in CNC lathe using artificial neural network. J Mater Process Technol 209(7):3125–3137
12. Wang N, Er MJ, Meng X (2009) A fast and accurate online self-organizing scheme for parsimonious fuzzy neural networks. Neurocomputing 72(16–18):3818–3829
13. LeCun Y, Touresky D, Hinton G, Sejnowski T (1988) A theoretical framework for back-propagation. In: Proceedings of the 1988 connectionist models summer school, vol 1, pp 21–28
14. Chungchoo C, Saini D (2002) On-line tool wear estimation in CNC turning operations using fuzzy neural network model. Int J Mach Tools Manuf 42(1):29–40
15. Jaiganesh V, Yokesh Kumar B, Sevvel P, Balaji AJ (2018) Optimization of process parameters on commercial mild steel using Taguchi technique. Int J Eng Technol 7(11):138–142
16. Tse R, Cruden DM (1979) Estimating joint roughness coefficients. Int J Rock Mech Min Sci Geomech Abs 16(5)
17. Abouelatta OB, Madl J (2001) Surface roughness prediction based on cutting parameters and tool vibrations in turning operations. J Mater Process Technol 118(1–3):269–277
18. Rahman MZ, Das AK, Chattopadhyaya S, Reyaz M, Raza MT, Farzeen S (2020) Regression modeling and comparative analysis on CNC wet-turning of AISI-1055 & AISI-4340 steels. Mater Today: Proc 24:841–850

19. Tzeng G-H, Huang J-J (2011) Multiple attribute decision making: methods and applications. CRC Press
20. Li Y, Yuan Y (2017) Convergence analysis of two-layer neural networks with relu activation. arXiv preprint arXiv:1705.09886
21. Taka M, Raygor SP, Purohit R, Parashar V (2017) Selection of tool and work piece combination using multiple attribute decision making methods for computer numerical control turning operation. Mater Today: Proc 4(2):1199–1208
22. Kumar MV, Kumar BJK, Rudresha N (2018) Optimization of machining parameters in CNC turning of stainless steel (EN19) by Taguchi's orthogonal array experiments. Mater Today: Proc 5(5):11395–11407