International Journal of Hybrid Information Technology
Vol.9, No.2 (2016), pp. 75-82
http://dx.doi.org/10.14257/ijhit.2016.9.2.07

Development of Artificial Intelligence Model for the Prediction of MRR in Turning

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Abstract

In machining operations, the extents of important effect of the process parameters like speed, feed, and depth of cut are different for different responses. This paper investigates the effect of process parameters in turning of AA6061 T6 on conventional lathe. The problem appeared owing to selection of parameters increases the deficiency of turning process. Modeling can facilitate the acquisition of a better understanding of such complex process, save the machining time and make the process economic. Thus, the present work clearly defines the development of an artificial neural network (ANN) model for predicting the material removal rate. This study presents a new method to prediction the material removal rate (MRR) on a lathe turning Process. Firstly, Process parameters namely, Spindle speed, depth of cut and feed rate are designed using the Box behnken (DOE) was employed as the experimental strategy. The result shows that the ANN model can predict the material removal rate effectively. This approach helps in economic lathe machining.

***Keywords**: Turning, Box Behnken (DOE), Artificial Neural Network*

Nomenclatures

DOE	Design of Experiment
BBD	Box behnken
SS	Spindle Speed (rpm)
DOC	Depth of Cut (mm.)
FR	Feed Rate (mm/rev.)
MRR	Material removal rate (mm^3/sec)
MSE	Mean square error
ANN	Artificial Neural Network

1. Introduction

Turning is an important traditional method for machining with the distinct advantages. Turning operations are one of the most significant manufacturing processes in metal-cutting operations. In industry, manufacturing processes are planned and enriched in order to obtain either maximum quality or minimum cost. Requirements of higher machining quality and manufacturing efficiency have led to a great deal of researches aimed at controlling and monitoring the cutting processes. The scientists and technologies in the field of manufacturing are facing more and more challenges owing to use of high strength temperature materials especially in the aerospace and automobiles industries. These materials

have high strength to weight ratio, high strength, toughness and other improved properties. In recent years, the artificial neural network has been transformed into a very useful tool for modeling complex systems [1]. Li, *et al.*, [2] pointed that it is possible to

ISSN: 1738-9968 IJHIT

use a 'universal tool' (the abrasive jet) to achieve numerous axi-symmetric shapes that would otherwise require various tools, and long setup time on a conventional lathe. Ali and Wang [3] noticed that there is no other machining process where it is possible to turn cylindrical profiles without changing the tool, and possibly even without stopping the machine. The RSM was also adopted by Neseli, *et al.*, [4] they have studied the effects of tool geometry on the surface roughness in the turning operations of AISI 1040 steel with Al2O3/Tic tool. Also, they have used the RSM quadratic model and the composite desirability for finding the geometry parameters optimum values. In the recent years, manufacturing industry is exploring sustainable product development through sustainable manufacturing. This shift is a result of increased awareness among the manufacturer and the users [5]. Machining industry is the most energy consuming and waste generating industry. The major question is how to use a manufacturing process so that the emissions will be on lower side and will provide high productivity [6]. A three dimensional system approach by Yuan, *et al.*, [7] highlighted sustainability issues of manufacturing from pollution prevention point of view. Chinchanikar, *et al.*, [8] This paper presents a comprehensive literature review on machining of hardened steels using coated tools, studies related to hard turning, different cooling methods and attempts made so far to model machining performance(s) so as to give proper attention to the various researcher works. Liu, *et al.*, [9] an attempt has been made to investigate the effect of operating parameters on depth of penetration and surface roughness (Ra) in turning of alumina ceramics using abrasive water jet. Bouacha, *et al.*, [10] the present work concerns an experimental study of hard turning of AISI 52100 bearing steel, with CBN tool. The combined effects of process parameters on performance characteristics are investigated using ANOVA analysis. The relationship between process parameters and performance characteristics through the response surface methodology (RSM) are modeled. Dambhare, *et al.*, [11] this study was to investigate sustainability issues pertinent to turning process in an Indian machining industry. Parameters such as surface roughness, material removal rate and energy consumption were considered as sustainability factors. Analysis of Variance (ANOVA) was applied to test the data. The process was analysed using response surface methodology (RSM). M. Kaladhar, *et al.*, [12] have taken AISI 202 austenitic stainless steel for present investigation, full factorial experiment has been employed to determine the best combination of the machining parameters such as cutting speed, feed, depth of cut and nose radius to attain the minimum surface roughness and also predictive models obtained for surface roughness Hussain [13] developed a surface roughness prediction model for the machining of GFRP pipes using response surface methodology and carbide tool (K20). Four parameters such as cutting speed, feed rate, depth of cut and work piece (fiber orientation) were selected. Asilturk, *et al.*, [14] optimized cutting parameters based on Taguchi method to minimize surface roughness during turning of hardened AISI 4140 steel (51 HRC) with coated carbide tools. The results showed a significant effect of feed rate on the surface roughness. Several researchers have used this process for machining of wide variety of materials considering different process parameters. Suhail, *et al.*, [15] optimizes the cutting parameters such as cutting speed, feed rate and depth of cut based on surface roughness and assistance of work piece surface temperature in turning process. Singh [16] optimizes tool life of Carbide Inserts for turned parts. The experiments were carried to obtain an optimal setting of turning process parameters- cutting speed, feed rate and depth of cut, which may result in optimizing material removal rate.

2. Experimental Procedure

The experiments were performed on NH 22 HMT lathe machine that is equipped with a maximum spindle speed of 16 from 40-2040 forward and 8 from 60-2375 rpm and power of main motor for standard speed range is 11 kw, in optional speed range is 5.5 kw and for coolant pump motor is 0.1 kw. Height of centers is 220 mm. Type of bed in standard is straight and in optional is straight with removable bridge piece. Swing over bed size is 500 mm, swing over carriage wings is 480 mm, swing over cross slide is 270 mm and swing in gap is 720 mm. Spindle nose/bore in standard is A2-6/53 mm. Spindle socket taper is metric 60/53 mm bore in standard. Feed range in longitudinal direction is 60 from 0.04-2.24 and cross slide direction is 60 from 0.02-1.12. Lead screw pitch, metric threads, inch threads, module threads are 6 mm, 48 from 0.5-28, 60 from 56-1, 40 from 0.25-14 respectively. Process parameter optimization has been widely used in turning operations. The process parameters have effect on the characteristics of turned parts are: cutting tool parameters, tool geometry and its material; work-piece interrelated parameters metallography, hardness, *etc.;* cutting parameters-cutting speed, feed, dry/wet cutting, depth of cut. In this study, AA6061 (T6) was used as the work piece material. Singh and Kumar [17] form a fishbone cause and effect diagram from various conceptual elements which was recognized the process parameters that may affect the machining feature or quality of turned parts. In a turning operation, there are an abundance of factors that can be considered as parameters in a machining process. But, by the reviewing the literature, it indicates that the depth of cut (mm), spindle speed (rpm) and feed rate (mm/rev) are the most widespread machining parameters had taken by the researchers. In the present study spindle speed, depth of cut, feed rateare taken as design of factors while the other parameters have been supposed to be constant over the experimental domain. The levels of cutting parameters such as spindle speed, depth of cut and feed rate for the experiments. Experiments have been carried out according to the experimental plan based on central compound rotatable second order design. The performance tests were performed on AA6061 T6 .The Brinell hardness of the material is 781MPa. The work piece material used has a diameter of 32 mm size. This material is applicable for a wide variety of automotive-type applications, Aircraft and aerospace component, Bicycle frames, Drive shafts, Brake components, Valve, Couplings, etc. The chemical composition of Aluminum alloy is given in Table 1.

Table 1. Chemical Composition of A6061 T6 Aluminum Alloy

Element	Mg	Si	Fe	Cu	Ti	Cr	Zn	Mn	Al
%	0.81	0.98	0.14	0.041	0.041	0.069	0.022	0.54	Balance

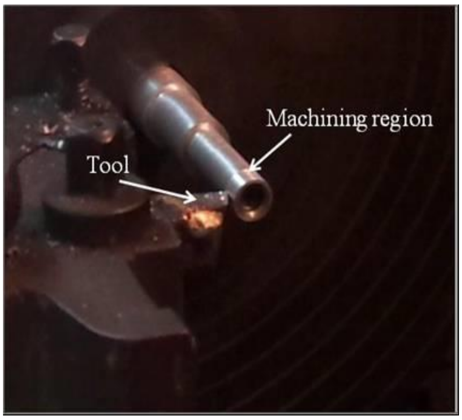


Figure 1. Experimental Set for Turning

3. Design of Experiment

Based on RSM, the parameters having maximum MRR can be acquired with minimum number of experiments without the need for studying all conceivable combinations experimentally. Further the input levels of the different variables for a specific level of response can also be determined. It is defined by Ferreira, *et al.,* [18]. That Box–Behnken Designs (BBD) is a class of rotatable or nearly rotatable 2nd-order designs based on three-level incomplete factorial designs. The turning process studied according to the BBD. Levels and values for three factors have been listed in Table 2. In this investigation, total 15 experiments were conducted. The design of experiment is generated using MINITAB 17.0 statistical package. Each time the experiment was performed, an optimized set of input parameters was chosen. In this study, the collection of experimental data adopts the BBD of experiments with three levels denoted in coded (-1, 0, 1) and actual values as shown in Table 2.

Table 2. Experimental Parameters and Their Levels

Design factor	Notation	Levels (Coded Value)		
		-1	0	1
Spindle speed (rpm)	X	500	550	600
Depth of cut(mm)	Y	0.10	0.20	0.3
Feed rate(mm/rev)	Z	0.20	0.24	0.28

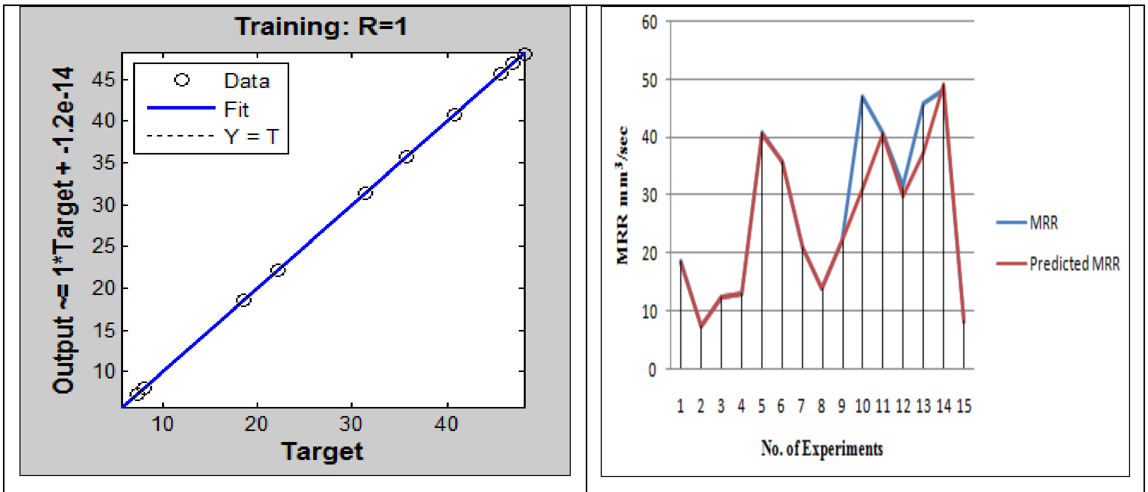
4. Result and Discussion

4.1 Development of ANN Model for Prediction of MRR

The prediction ability of different architecture is shown in Table 3. It is noticed that the observation 10 yields the lowest value of MSE as 4.57×10^{-28} and its linear correlation coefficients (r-value) is maximum (1.00). Accordingly, the neural network architecture for experimental trial 10, which is 3-7-1-1 (two hidden layer and seven neurons at first hidden layer one neuron at second hidden layer), is chosen as the best network in predicting MRR. Hence forth, the training is stopped and the weight values of the ANN are stored. In testing of the ANN model, the performance valuations such as MSE as well as the linear correlation coefficient of the model are found as 1.8303 and 1, respectively. Thus, it is readily perceived that the linear correlation coefficient obtained (1.0) is satisfactory. It is also observed that the MSE (1.8303) obtained are within the acceptable range. To investigate the line pattern of the data among the target values and artificial neural network outputs (from training and testing) two lines are generated on the same graph as shown in Figure 2 (b). It is found that the experimental and predicted values are very close to each other and the patterns of the two lines are alike except for a few data points. Thus, there is good agreement between neural network outputs and the experimental values. The regression analysis between the network response and the corresponding experimental values are presented in Figure 2 (a). All the points on the plot come close to forming a straight line, which indicates that the data are as per expected. According to this figure the value of R^2 (1.00) is over 90%, which indicates a very good correlation among the ANN model predicted value and the experimental value. Therefore, the developed neural network model is appropriate to illustrate the pattern of material removal rate in turning process. The results for confirmation tests (Table 4) indicates that the error between the observed value and the artificial neural network output is in the range of -1.1289-1.6472 with an average errors of 10.11%. Thus, it is obvious that the error is within the acceptable limit and the accuracy of the developed model representing MRR is satisfactory.

Table 3. Performance of Artificial Neural Network with Different Architectures

Experimental Trials	No. of Hidden Layer	Network Structure	No. of Training Repetitions	MSE	r-value
1	2	3-7-1-1	3	8.22×10^{-3}	0.9999
2	2	3-8-1-1	2	1.33×10^{-9}	1.0000
3	2	3-9-1-1	1	1.14×10^{-2}	0.9999
4	2	3-8-1-1	1	1.63×10^{0}	0.9963
5	2	3-7-1-1	1	1.26×10^{-3}	1.0000
6	2	3-9-1-1	1	5.77×10^{-2}	0.9999
7	2	3-7-1-1	1	2.84×10^{-3}	0.9999
8	2	3-8-1-1	2	2.96×10^{-1}	0.9996
9	2	3-9-1-1	2	10.00×10^{0}	0.9831
10	2	3-7-1-1	3	4.57×10^{-28}	1.0000
11	2	3-8-1-1	1	3.03×10^{0}	0.9948
12	2	3-9-1-1	1	3.28×10^{-20}	1.0000
13	2	3-7-1-1	1	10.98×10^{0}	0.9789
14	2	3-8-1-1	1	2.65×10^{-1}	0.9999
15	2	3-9-1-1	3	2.79×10^{-5}	1.0000
16	2	3-7-1-1	2	6.97×10^{-6}	1.0000
17	2	3-8-1-1	1	68.78×10^{0}	0.9313
18	2	3-9-1-1	2	1.79×10^{-2}	0.9999
19	2	3-7-1-1	3	1.57×10^{-10}	1.0000
20	2	3-8-9-1	1	12.99×10^{0}	0.9746
21	2	3-9-1-1	1	1.38×10^{-3}	1.0000
22	2	3-7-1-1	3	3.33×10^{0}	0.9921
23	2	3-8-1-1	1	50.83×10^{0}	0.9206
24	2	3-9-1-1	1	2.33×10^{-13}	1.0000



(a) (b)

Figure 2. Schematic Figure of: (a) Predicted Versus Experimental Material Removable Rate (b) Comparison between ANN Predicted and Experimental Values

Table 4. Error Analysis for the ANN Model of MRR

Trail No.	Experimental MRR (mm^3/sec.)	ANN Predicted	Error
1	18.51	18.50	0.0012
2	7.40	7.39	0.0036
3	12.34	12.33	0.0003
4	12.96	12.95	0.0019
5	40.74	40.73	0.0047
6	35.80	35.80	-0.0001
7	20.98	20.97	0.0006
8	13.88	13.88	-0.0035
9	22.22	22.22	-0.0011
10	46.91	31.11	0.1579
11	40.74	40.73	0.0006
12	31.48	29.83	1.6472
13	45.67	37.34	0.8324
14	48.14	49.26	-1.1289
15	8.15	8.14	0.0009

5. Conclusion

This study reveals that during machining of AA6061 (T6) on conventional lathe machine, MRR is affected by all the process parameters viz. spindle speed, depth of cut and feed rate. In this paper, the application of Box-behnken design based ANN on the AA6061 T6 was carried out for turning operation. The conclusions are as follows:

i. A neural network model of the process was developed to define the relationship between parameters and the performance characteristic. As the training data set is used to fit the model and analysis data set is used to evaluate the model, here the plot of testing data set was considered for estimation of best ANN model. From the plot of Mean Square Error (MSE) and R, Levenberg-Marquardt (LM) training algorithm and two hidden layer and seven neurons at first hidden layer one neuron at second hidden layer, are seen to be efficient for optimum value of response.
ii. 3-7-1-1 network architecture was selected for proficient ANN modeling.
iii. The error is within the agreeable limit and the developed neural network model is adequate for prediction the material removal rate (MRR).
iv. Experiments have been conducted to test the model and acceptable results are obtained.

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