ELSEVIER

Journal of Materials Processing Technology 108 (2001) 286–293

Journal of Materials Processing Technology

www.elsevier.com/locate/jmatprotec

Modeling the surface roughness and cutting force for turning

W.S. Lin*, B.Y. Lee, C.L. Wu

Department of Mechanical Manufacturing Engineering, National Hu-Wei Institute of Technology, Yunlin, Taiwan, ROC

Received 12 April 1999

Abstract

In this paper, an abductive network is adopted to construct a prediction model for surface roughness and cutting force. This network is composed of a number of functional nodes, which are self-configured to form an optimal network hierarchy by using a predicted square error (PSE) criterion. Once the process parameters (cutting speed, feed rate and depth of cut) are given, the surface roughness and cutting force can be predicted by this network. To verify the accuracy of the abductive network, regression analysis has been adopted in the paper to develop a second prediction model for surface roughness and cutting force. Comparison of the two models indicates that the prediction model developed by the abductive network is more accurate than that by regression analysis. Experimental results are provided to confirm the effectiveness of this approach. © 2001 Published by Elsevier Science B.V.

Keywords: Predicted square error criteria; Regression analysis; Nodes

1. Introduction

Machining operations confronted by a shortage of technical manpower and pricing competition, not only need to implement automated and operator-free technology, but also needed to meet requirements of precision through process planning, thus achieving maximum productivity, meaning a cutting condition with an optimal metal-removal rate.

This paper aims to develop a prediction model prior to the implementation of the actual machining, that serves to determine certain cutting conditions (cutting speed V, feed rate f and depth of cut d) in order to obtain a desired surface roughness value and cutting force value. Furthermore, using the cutting force thus obtained, the cutting power and optimal metal-removal rate can be further calculated.

Because the degree of surface roughness and the cutting force partially determine the cutting process, extensive attention has been given to the analysis and prediction of surface roughness and cutting force. For example, EI Baradie [1] and Vajpayee [2] analyzed the surface roughness generated in a turning operation. EI Baradie [3], Mital and Mehta [4], Bhattacharyya [5] and Taraman [6] used regression analysis to develop a prediction model for measuring the surface roughness value. Azouzi and Guillot [7] utilized a neural network to construct an on-line prediction model for surface roughness. Fang and Jawahir [8] used the fuzzy-set method to build a prediction model that concurrently defined surface roughness and cutting power (cutting force). In this paper, an abductive network [9] is developed from finite turning data to simulate the surface roughness and cutting force.

Abductive networks built upon the abductive modeling technique are able to represent complex and uncertain relationships between input and output variables [9]. Basically, abductive networks are composed of a number of polynomial functional nodes and are organized into several layers. The best network structure, number of layers and types of functional nodes can be automatically generated by using a predicted square error (PSE) criterion [10]. In other words, unlike most approaches to regression or neural networks, the abductive modeling technique can synthesize an optimal network architecture automatically, instead of requiring the user to specify the network hierarchy in advance. In addition, the iterative tuning process required in regression or neural networks is greatly reduced in the abductive approach. It has also been demonstrated that the accuracy of predictions made by abductive networks is much higher than that of neural networks [9]. In this paper, it is demonstrated that a reasonably accurate prediction can be derived from the proposed network in terms of surface roughness and cutting force under varied conditions of cutting speed, feed rate, and depth of cut. To verify the accuracy of the abductive network, a regression analysis has been adopted to develop a prediction model for surface

* Corresponding author. Fax: +886-5-6328863.
E-mail address: linwhs@sparc.nhit.edu.tw (W.S. Lin).

0924-0136/01/$ – see front matter
PII: S0924-0136(00)00835-9

roughness and cutting force. Comparison of the two models indicates that predictions based on the abductive network are more accurate than those based on regression analysis.

In this paper, the theory of abductive networks is described first. The experimental details of using abductive network and regression analysis to develop the prediction model for surface roughness and cutting force is described thereafter. The two methods are then compared for their differences. Finally, this paper concludes with a summary of results.

2. Description of abductive networks

It is generally known that reasoning from general principles and initial facts to obtain new facts under certain prescribed conditions is called deductive reasoning. However, reasoning in real problems is very often uncertain, therefore another class of reasoning, called abductive reasoning, is defined as reasoning from general principles and initial facts to obtain new facts under uncertain conditions [11]. An abductive network is a network where numerical information is modeled through abductive reasoning. As a result, abductive networks can be used effectively as predictors for estimating the output of a complex system, or as classifiers for processing difficult pattern-recognition problems, or as system identifiers to determine which input is more important to a modeling system.

In an abductive system, certain complex systems are broken down to smaller, simpler subsystems and regrouped into several layers by adapting polynomial functional nodes. At the same time, input signals are also subdivided into groups before being transformed into individual functional nodes. These nodes evaluate the limited number of inputs by a polynomial function, and generate an output to serve as an input for the subsequent node of the next layer. The general methodology of dealing with a limited number of input groups at a specific time generally requires summarizing the input information, and then passing the summarized information to a higher level. This process is essentially similar to human behavior, as discussed by Miller [12]. Therefore, an abductive network can be deemed as a special class of biologically inspired networks with mechanical intelligence [13].

To develop an abductive network, a training database with built-in input and output information is required first. Subsequently, PSE criteria are applied to generate an optimal network structure automatically [10]. The PSE criteria aims to pinpoint a network that is as accurate and simple as possible. To accomplish this, the PSE is defined by the following two terms, i.e.

$$\mathrm{PSE} = \mathrm{FSE} + \mathrm{KP} \tag{1}$$

in which FSE is the average square error within the network that serves to fitting the training data, and KP is the complex penalty within the network, as defined by the following equation:

$$\mathrm{KP} = \mathrm{CPM}\frac{2{\sigma_{\mathrm{p}}}^2 K}{N} \tag{2}$$

where CPM denotes the complex penalty multiplier, K the number of coefficients within the network, N the number of training data, and ${\sigma_{\mathrm{p}}}^2$ a pre-estimated error variance for the model.

As illustrated in Eq. (1), the fitting accuracy increases with decreasing FSE. Under normal circumstances, a more complex network has a greater fitting accuracy when there is a smaller value of FSE. On the other hand, the more complex the network, the larger the value of KP that will be Eq. (2). Hence, the PSE criteria generate a dilemma between model accuracy and model complexity. In the network synthesis and evaluation, the optimal abductive network is the network with the minimal value of PSE. In addition, the CPM (Eq. (2)) can be used to adjust the trade-off between model accuracy and complexity. A complex network will be penalized more in the PSE criteria as the CPM is increased. On the contrary, a complex network will be selected if the CPM is decreased. To provide greater accuracy for a network, the CPM should be designated at 0.1, as shown in the following network synthesis.

3. Piloting the prediction model

3.1. Experiment

As mentioned earlier, a training database with regard to process parameters and turning performance is essential to build an abductive network for modeling surface roughness and cutting force. To create this database, a number of turning experiments were carried out on a heavy duty lathe with a sintered carbide insert to machine S55C high carbon steel. In the experimental set-up for these tests, as depicted in Fig. 1, a cylindrical bar was chucked with a three-jaw chuck at one end, and supported by a live center at the tail stock. The workpiece chucking length was 60 mm, the specification of the tool holder was MTJNL2525M16, and the insert carbide tip was TNMG160404L2G. The workpiece diameter D was 64.5 mm, and the workpiece length (measured from chuck to tail stock) L was 250 mm. The parameters for the turning process were selected by varying the cutting speed V within the range between 86.1 and 202.6 m/min, varying the feed rate f within the range between 0.08 and 0.32 mm/rev, and varying the depth of cut d within the range between 0.35 and 1.25 mm. Each of these process parameters were set at three levels (Table 1); therefore, 27 (3^*3^*3) turning experiments were designated based on the combination of the process parameters.

The equipment used for measuring surface roughness was a surface roughness tester, Surfcorder SE-30H (Kosaka Laboratory). The surface roughness measure used in this paper is the arithmetic mean deviation of the surface rough-

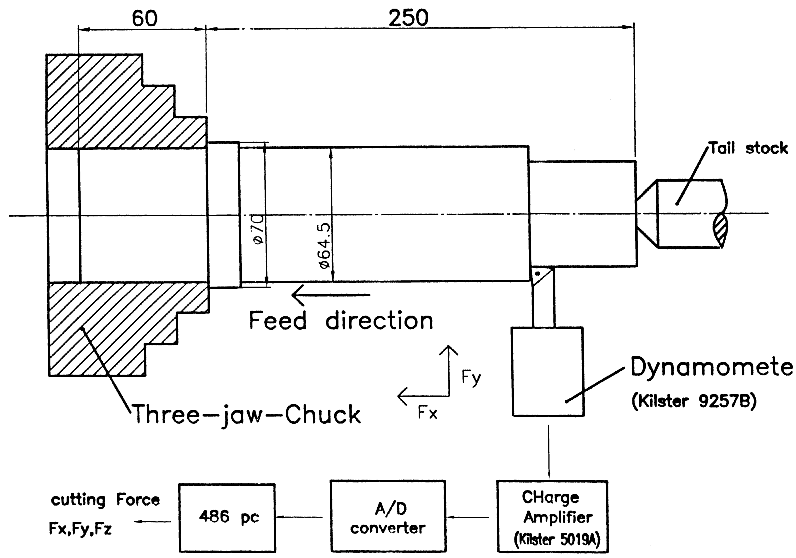

Fig. 1. Experimental set-up.

ness profile, R_a. The measurement of cutting force is shown in Fig. 1, for which the lathe was mounted atop a three component piezoelectric crystal type of dynamometer (Kistler type 9257B). Once the dynamometer detected cutting signals for the x, y and z axles, the charge amplifier (Kistler type 5017A) amplified the signals, which were then transmitted through an interface card into the computer to calculate the three axial cutting forces, F_x, F_y and F_z, before the combined force F was derived. The surface roughness and cutting force with corresponding process parameters (cutting speed, feed rate and depth of cut) are presented in Table 1.

Table 1
Experiment data

No.	V (m/min)	f (mm/rev)	d (mm)	F (N)	R_a (μm)
1	202.63	0.08	1.25	452.2	0.848
2	202.63	0.20	1.25	737.9	3.111
3	202.63	0.32	1.25	1019.8	8.279
4	202.63	0.08	0.80	316.8	1.065
5	202.63	0.20	0.80	529.7	3.154
6	202.63	0.32	0.80	762.2	7.568
7	202.63	0.08	0.35	192.4	1.087
8	202.63	0.20	0.35	283.8	2.813
9	202.63	0.32	0.35	396.2	7.004
10	121.58	0.08	1.25	490.0	0.715
11	121.58	0.20	1.25	825.6	3.794
12	121.58	0.32	1.25	1111.7	9.489
13	121.58	0.08	0.80	352.2	0.838
14	121.58	0.20	0.80	598.9	3.630
15	121.58	0.32	0.80	827.1	8.503
16	121.58	0.08	0.35	188.2	0.755
17	121.58	0.20	0.35	314.1	3.341
18	121.58	0.32	0.35	424.7	7.943
19	86.12	0.08	1.25	481.7	0.727
20	86.12	0.20	1.25	782.5	3.466
21	86.12	0.32	1.25	1076.1	9.031
22	86.12	0.08	0.80	339.5	0.858
23	86.12	0.20	0.80	588.4	3.247
24	86.12	0.32	0.80	801.0	8.115
25	86.12	0.08	0.35	185.9	0.900
26	86.12	0.20	0.35	298.8	3.055
27	86.12	0.32	0.35	432.7	7.555

3.2. Construct the prediction model with abductive network

Based on the developed training database, the abductive network for predicting surface roughness and cutting force is shown in Figs. 2 and 3. All polynomial equations used in the networks (Figs. 2 and 3) are listed in Appendix A.

3.3. Construct the prediction model with regression analysis

The experimental data shown in Table 1 is applied with a statistical analysis software system for multiple regression analysis. In this paper, the least square estimation is used to determine a model for surface roughness and cutting force in relation to the functions of cutting speed V, feed rate f, and depth of cut d.

The models for surface roughness R_a and cutting force F are derived from the data shown in Table 1 and as defined below:

$$R_a = -2.172026 + 0.035321V - 0.000103V^2 + 86.164152f^2 - 0.037214Vf + 3.856817fd \quad (3)$$

$$F = -161.988683 + 2.351115V + 429.783951f + 423.407407d - 0.009119V^2 - 147.407407d^2 + 1692.283951fd \quad (4)$$

According to the results shown in Tables 2 and 3, it is fairly easy to conclude that the correlation coefficient R is very close to unity, while the tables also indicates that the relationship between surface roughness and the cutting

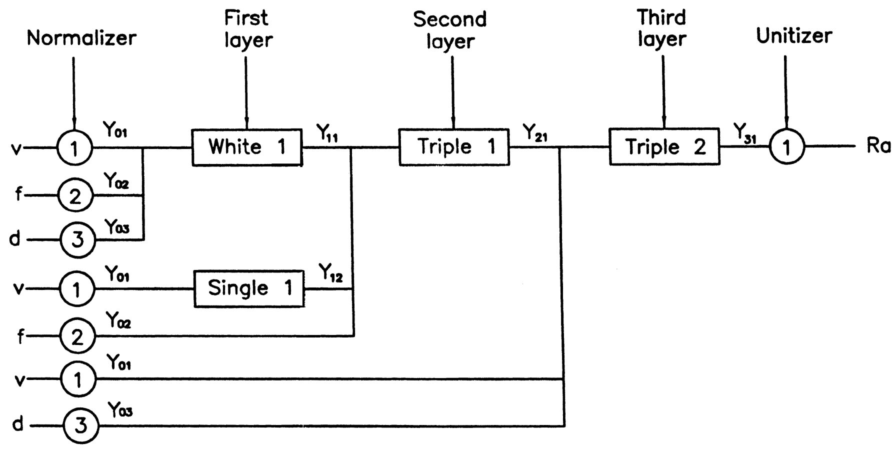

Fig. 2. Abductive network for surface roughness.

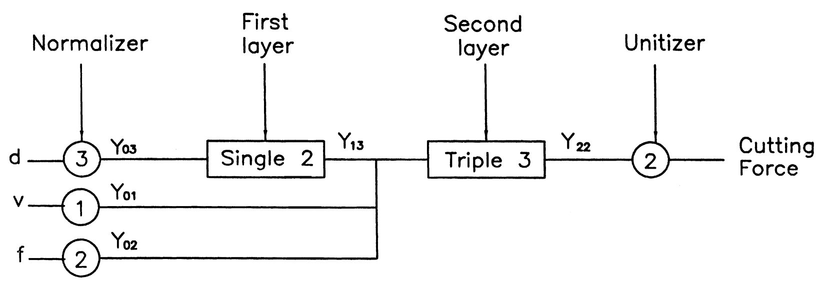

Fig. 3. Abductive network for cutting force.

parameters is well represented by the proposed model, as is the relationship between the prediction model on the cutting force.

4. Discussion

Figs. 4 and 5 compare the predicted values and experimented values for surface roughness. The solid lines in Fig. 4 represent the predicted curve derived through the abductive network, while the dashed line represents the predicted curve derived through regression analysis. The surface roughness value is found to increase substantially with increased feed rate, whereas when the feed rate decreases, the impact of changes in depth of cut on the surface roughness is not as significant. Conversely, when the feed rate is increased to 0.32 mm/rev, it can be seen clearly that the surface roughness increases with the

Table 2
Analysis of variance table for cutting force[a]

Source	Degree of freedom	Sum of square	Mean square	F-value	Probability $> F$
Model	6	1949917.294	324986.2157	908.621	0.0001
Error	Source	7153.392	357.6696		
Total	26	1957070.686			

[a] Root MSE: 18.91216; R-square: 0.9963.

Table 3
Analysis of variance table for surface roughness[a]

Source	Degree of freedom	Sum of square	Mean square	F-value	Probability $> F$
Model	5	253.16977	50.63395	854.993	0.0001
Error	21	1.24365	0.05922		
Total	26	254.41342			

[a] Root MSE: 0.24335; R-square: 0.9951.

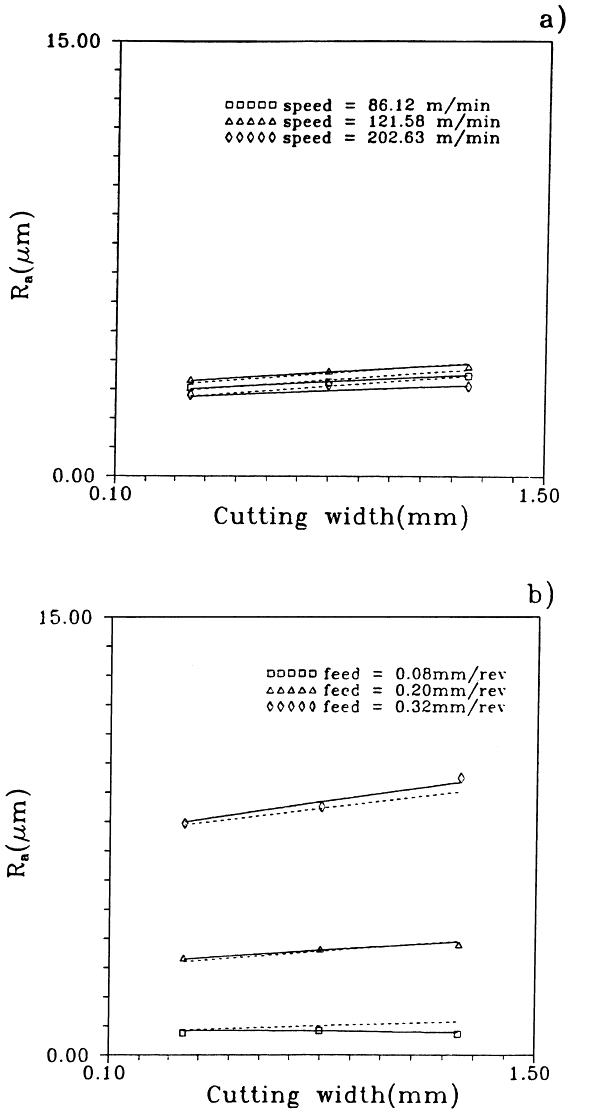

Fig. 4. Surface roughness comparison between abductive network and regression analysis: (a) feed rate $f = 0.2\,\mathrm{mm/rev}$; (b) cutting speed $V = 121.58\,\mathrm{m/min}$ (— predicted curve with abductive network; - - - - - predicted curve with regression analysis).

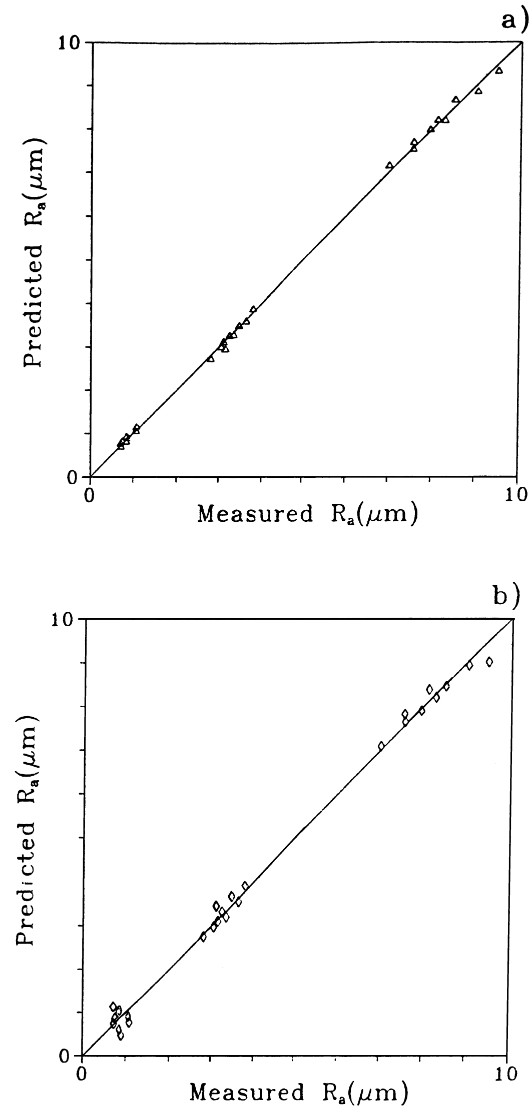

Fig. 5. Comparison of measured and predicted surface roughness: (a) using abductive network; (b) using regression analysis.

increased depth of cut, but the impact of changes in the cutting speed on the surface roughness is less significant. The figures indicate that despite using the abductive network, or the regression analysis, the predicted values and experimented values are fairly close, which indicates that the developed surface roughness prediction model can be effectively used to predict surface roughness from the cutting process.

Moreover, Table 4 also indicates that using the prediction model constructed with the abductive network yields an average absolute error of 2.79% at the time of prediction, which is smaller than that from the regression analysis. Furthermore, the percentage error on all predicted surface roughness values under various cutting conditions are generally within 10%, unlike the predictions using regression analysis, where the percentage error reached as high as 59.44%. Therefore, more accurate results are obtained from a model constructed with an abductive network to predict surface roughness values.

Figs. 6 and 7 depict a comparison of values of the cutting force obtained from prediction and from actual experiment; the solid line in Fig. 6 represents the predicted curve obtained from the abductive network, and the dashed line indicates the predicted curve derived from the regression analysis, where the cutting force tends to increase with increased feed rate and depth of cut. Both illustrations indicate that despite the choice of prediction method, the experimental values are very close to the predicted values, and as indicated in Table 5, the average absolute error obtained in the prediction of cutting force from both prediction models are also very close. These results

Table 4
Comparison of experimented and predicted surface roughness

V (m/min)	f (mm/rev)	d (mm)	Experimental value (μm)	Abductive network		Regression analysis	
				Predicted value (μm)	Absolute error percentage (%)	Predicted value (μm)	Absolute error percentage (%)
202.63	0.08	1.25	0.848	0.94	10.85	1.06	25.00
202.63	0.20	1.25	3.111	3.13	0.61	3.46	11.22
202.63	0.32	1.25	8.279	8.20	0.95	8.20	0.95
202.63	0.08	0.80	1.065	1.07	0.47	0.92	13.62
202.63	0.20	0.80	3.154	2.96	6.15	3.11	1.40
202.63	0.32	0.80	7.568	7.70	1.74	7.64	0.95
202.63	0.08	0.35	1.087	1.17	7.64	0.78	28.24
202.63	0.20	0.35	2.813	2.74	2.60	2.76	1.88
202.63	0.32	0.35	7.004	7.16	2.23	7.09	1.23
121.58	0.08	1.25	0.715	0.78	9.09	1.14	59.44
121.58	0.20	1.25	3.794	3.88	2.27	3.91	3.06
121.58	0.32	1.25	9.489	9.34	1.57	9.01	5.05
121.58	0.08	0.80	0.838	0.82	2.15	1.00	19.33
121.58	0.20	0.80	3.630	3.60	0.83	3.56	1.93
121.58	0.32	0.80	8.503	8.68	2.08	8.45	0.62
121.58	0.08	0.35	0.755	0.83	9.93	0.87	15.23
121.58	0.20	0.35	3.341	3.29	1.53	3.21	3.92
121.58	0.32	0.35	7.943	7.99	0.59	7.90	0.54
86.12	0.08	1.25	0.727	0.71	2.34	0.75	3.16
86.12	0.20	1.25	3.466	3.50	0.98	3.68	6.17
86.12	0.32	1.25	9.031	8.87	1.78	8.93	1.12
86.12	0.08	0.80	0.858	0.83	3.26	0.62	27.74
86.12	0.20	0.80	3.247	3.27	0.71	3.33	2.56
86.12	0.32	0.80	8.115	8.21	1.17	8.38	3.27
86.12	0.08	0.35	0.900	0.91	1.11	0.48	46.67
86.12	0.20	0.35	3.055	3.01	0.60	2.98	2.45
86.12	0.32	0.35	7.555	7.54	0.20	7.82	3.51
Average absolute error				0.0726	2.7937	0.1713	10.7504

indicate that the models constructed using either of the two methods are able to provide accurate prediction of cutting force during a prediction experiment. However, by further examination of the predicted errors of the cutting force for each cutting condition, it can be seen that when the abductive network is used, its margin of errors in prediction is not only smaller, but is also more eventually distributed.

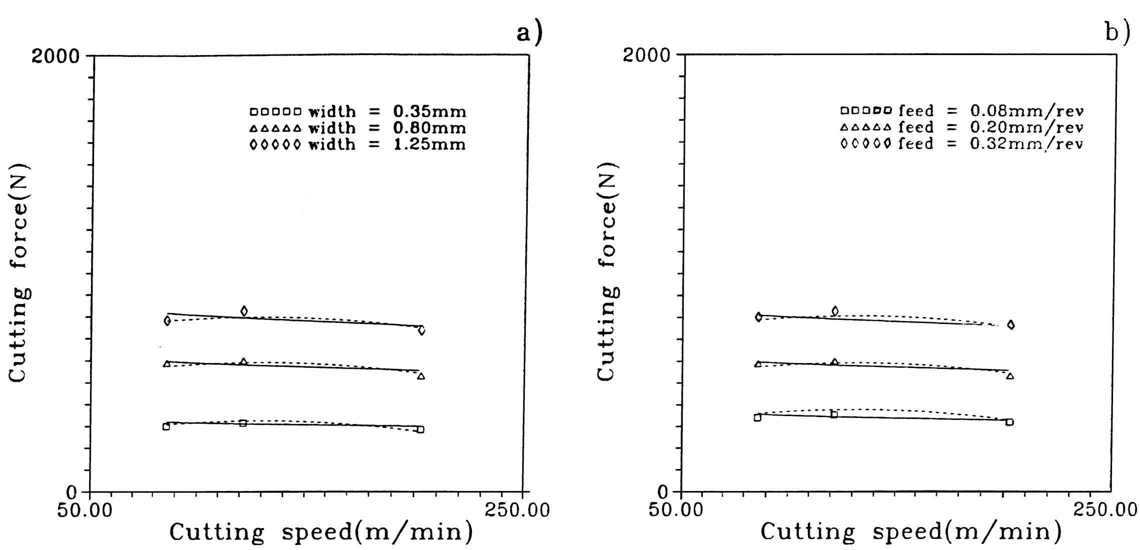

Fig. 6. Cutting force comparison between abductive network and regression analysis: (a) feed rate $f = 0.2\,\mathrm{mm/rev}$; (b) cutting speed $V = 121.58\,\mathrm{m/min}$ (— predicted curve with abductive network; - - - - - predicted curve with regression analysis).

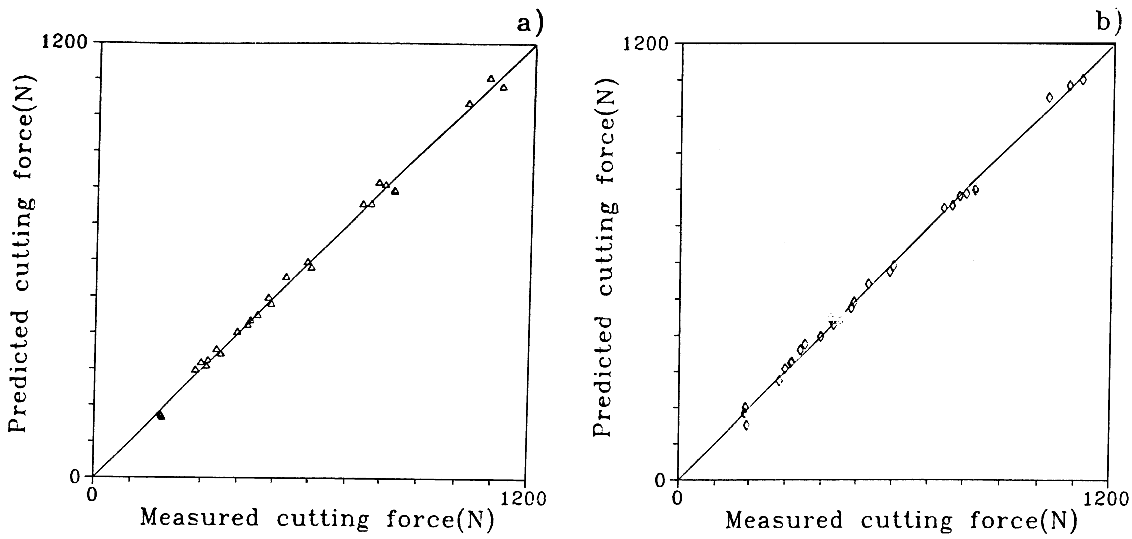

Fig. 7. Comparison of measured and predicted cutting force: (a) using abductive network; (b) using regression analysis.

Table 5
Comparison of experimented and predicted cutting force

V (m/min)	*f* (mm/rev)	*d* (mm)	Expected value (N)	Abductive network		Regression analysis	
				Predicted value (N)	Absolute error percentage (%)	Predicted value (N)	Absolute error percentage (%)
202.63	0.08	1.25	452.2	450.00	0.49	442.55	2.13
202.63	0.20	1.25	737.9	756.63	2.54	747.96	1.36
202.63	0.32	1.25	1019.8	1036.47	1.63	1053.38	3.29
202.63	0.08	0.80	316.8	325.10	2.62	327.08	3.24
202.63	0.20	0.80	529.7	554.29	4.64	541.11	2.15
202.63	0.32	0.80	762.2	756.68	0.72	755.14	0.93
202.63	0.08	0.35	192.4	167.64	12.87	151.90	21.05
202.63	0.20	0.35	283.8	299.20	5.43	274.55	3.26
202.63	0.32	0.35	396.2	403.96	1.96	397.20	0.25
121.58	0.08	1.25	490.0	480.61	1.92	491.61	0.33
121.58	0.20	1.25	825.6	795.02	3.70	797.03	3.46
121.58	0.32	1.25	1111.7	1082.64	2.61	1102.45	0.83
121.58	0.08	0.80	352.2	343.79	2.39	376.14	6.80
121.58	0.20	0.80	598.9	580.75	3.03	590.17	1.46
121.58	0.32	0.80	827.1	790.93	4.37	804.21	2.77
121.58	0.08	0.35	188.2	171.30	8.98	200.97	6.79
121.58	0.20	0.35	314.1	310.63	1.10	323.62	3.03
121.58	0.32	0.35	424.7	423.18	0.36	446.27	5.08
86.12	0.08	1.25	481.7	497.76	3.33	475.40	1.31
86.12	0.20	1.25	782.5	815.57	4.23	780.82	0.21
86.12	0.32	1.25	1076.1	1106.59	2.83	1086.24	0.94
86.12	0.08	0.80	339.5	355.71	4.77	359.93	6.02
86.12	0.20	0.80	588.4	596.08	1.31	573.96	2.45
86.12	0.32	0.80	801.0	809.66	1.08	788.00	1.62
86.12	0.08	0.35	185.9	176.65	4.98	184.76	0.61
86.12	0.20	0.35	298.8	319.39	6.89	307.41	2.88
86.12	0.32	0.35	432.7	435.33	0.61	430.06	0.61
Average absolute error				15.638	3.3848	13.1711	3.1430

5. Conclusions

From the foregoing analyses and discussions, the following conclusions can be drawn.

1. A prediction model, based on the abductive network, for assessing surface roughness and cutting force can accurately predict, and regression analysis has provided further verification of the accuracy of the abductive network.

2. Critical elements that affect surface roughness are the feed rate, where increasing feed rate will increase the surface roughness value, while a regression multiplier for the surface roughness demonstrates that the cutting speed does not have a significant impact on surface roughness.
3. Crucial factors that control the cutting force are the feed rate and the depth of cut, where the cutting force tends to increase with an increased feed rate and depth of cut.
4. Because the feed rate change may affect the surface roughness and the cutting force, when implementing process planning, measures shall be taken to maximize the cutting speed and the depth of cut, yet minimize the feed rate, in order to secure an optimal surface roughness value and an optimal metal-removal rate.

Appendix A.

1. Normalizer

$$Y_{01} = -1.74 + 0.0112V$$

$$Y_{02} = -2.02 + 10.1f$$

$$Y_{03} = -2.02 + 1.97d$$

2. Single node

$$Y_{12} = 0.0495 - 0.172Y_{01} - 0.139{Y_{01}}^2 + 0.143{Y_{01}}^3$$

$$Y_{13} = 0.0226 + 0.661Y_{03} - 0.023{Y_{03}}^2 + 0.0569{Y_{03}}^3$$

3. White node

$$Y_{11} = 0.0113Y_{01} + 0.964Y_{02} + 0.0919Y_{03}$$

4. Triple node

$$\begin{aligned} Y_{21} = {} & -0.302 + 0.939Y_{11} + 1.44Y_{12} - 0.706Y_{02} \\ & + 0.495{Y_{11}}^2 + 4.61{Y_{12}}^2 - 0.298{Y_{02}}^2 + 3Y_{11}Y_{12} \\ & + 0.124Y_{11}Y_{02} - 1.81Y_{12}Y_{02} - 0.422Y_{11}Y_{12}Y_{02} \\ & + 0.0204{Y_{11}}^3 + 0.5{Y_{02}}^3 \end{aligned}$$

$$\begin{aligned} Y_{31} = {} & Y_{21} - 0.0117Y_{03} - 0.0141Y_{21}Y_{01} \\ & - 0.0179Y_{21}Y_{01}Y_{03} + 0.00768{Y_{03}}^3 \end{aligned}$$

$$\begin{aligned} Y_{22} = {} & 0.0176 + Y_{13} - 0.1Y_{01} + 0.51Y_{02} + 0.0144{Y_{01}}^2 \\ & - 0.0259{Y_{02}}^2 - 0.0626Y_{13}Y_{01} + 0.305Y_{13}Y_{02} \\ & - 0.0201Y_{01}Y_{02} - 0.0101{Y_{01}}^3 + 0.0625{Y_{02}}^3 \end{aligned}$$

5. Unitizer

$$R_a = 4.21 + 3.19Y_{31}$$

$$F = 661 + 351Y_{22}$$

References

[1] M.A. EI Baradie, Computer-aided analysis of a surface roughness model for turning, Process. Technol. 26 (1991) 207–216.
[2] S. Vajpayee, Analytical study of surface roughness in turning, Wear 70 (1981) 165–175.
[3] M.A. EI Baradie, Surface roughness model for turning grey cast iron, J. Eng. Manuf. 207 (1993) 43–54.
[4] A. Mital, M. Mehta, Surface-finish production models for fine turning, Int. J. Product. Res. 26 (12) (1988) 1861–1876.
[5] A. Bhattacharyya, Regression analysis for predicting surface-finish and its application in the determination of optimum machining conditions, J. Eng. Ind. (August 1970) 711–714.
[6] K. Taraman, Multi-machining output — multi-independent variable turning research by response surface methodology, Int. J. Product. Res. 12 (2) (1974) 233–245.
[7] R. Azouzi, M. Guillot, On-line prediction of surface finish and dimensional deviation in turning using neural network based sensor fusion, Int. J. Mach. Tools Manuf. 37 (9) (1997) 1201–1217.
[8] X.D. Fang, I.S. Jawahir, Predicting total machining performance in finish turning using integrated fuzzy-set models of the machinability parameters, Int. J. Product. Res. 32 (4) (1994) 833–849.
[9] G.J. Montgomery, K.C. Drake, Abductive reasoning network, Neurocomputing 2 (1991) 97–104.
[10] A.R. Barron, Predicted square error: a criterion for automatic model selection, in: S.J. Farlow (Ed.), Self-Organizing Methods in Modeling: GMDH Type Algorithms, Marcel Dekker, New York, 1984.
[11] C. Peirce, Abduction and induction, in: Buckler (Ed.), Philosophical Writing of Peirce, Dover, New York, 1995.
[12] G.A. Miller, The magic number seven, plus or minus two: some limits on our capacity for processing information, Psychol. Rev. 63 (1956) 81–97.
[13] R.L. Barron, A.N. Mucciardi, F.J. Cook, J.N. Craig, A.R. Barron, Adaptive learning networks: development and application in the United States of algorithms related to GMDH, in: S.J. Farlow (Ed.), Self-Organizing Methods in Modeling: GMDH Type Algorithms, Marcel Dekker, New York, 1984.