A New Computational Intelligence Approach to Predicting the Machined Surface Roughness in Metal Machining

Ning Fang and P. Srinivasa Pai

***Abstract*—Machined surface roughness is an important parameter used in the evaluation of the surface integrity of machined parts and components. This paper proposes a new computational intelligence approach to predicting the machined surface roughness in metal machining. In this approach, wavelet packet transform (WPT) is incorporated into artificial neural networks (ANN) to develop two ANN models for predicting average roughness *Ra* and root-mean-square roughness *Rq*, respectively. Each model has eight inputs, including the cutting speed, the feed rate, energy of wavelet packets for three cutting force components, and energy of wavelet packets for three cutting vibration components. Forty-five machining experiments were performed to collect relevant data to train and test the ANN models. Based on the test data, the average mean square errors (MSE) were 1.23% for predicting average roughness *Ra* and 2.85% for predicting root-mean-square roughness *Rq*. These results show that the ANN models developed from the present study have high prediction accuracy.**

***Index Terms*—Artificial neural networks (ANN), machined surface roughness, predictive modeling, wavelet packet transform (WPT).**

I. Introduction

Metal machining is a material removal technology widely employed in a variety of modern manufacturing industries, such as automotive, aerospace, as well as mould and die making industries. In machining processes, a significant amount of signals, such as the cutting forces, the cutting vibrations, and the cutting temperatures, is often generated [1], [2]. These big data signals are often employed to develop a variety of theoretical, empirical, or hybrid models to predict or evaluate a variety of machining performance measures, such as tool wear, tool life, and surface integrity of the machined parts and components [3]-[5].

Machined surface roughness is an important parameter used in the evaluation of the surface integrity of machined parts and components [6]-[8]. Experimental research has been conducted to study how the machined surface roughness is affected by cutting parameters and tool geometry [9], [10]. The artificial neural network (ANN) model is often established to predict the machined surface roughness so as to optimize the selection of cutting parameters and tool geometry.

For example, Risbood *et al*. [11] developed an ANN model to predict the machined surface roughness in turning operations. Their model has three inputs: the cutting speed, the feed rate, and the acceleration of radial vibration of tool holder. The prediction errors for average roughness *Ra* varied between 0.51% and 18.21% in their ANN model [11]. They also reported that neural network models can be fitted for different tool materials and machining conditions in dry or wet machining.

This paper proposes a new computational intelligence approach to predicting the machined surface roughness in aluminum alloy machining. In this approach, wavelet packet transform (WPT) is incorporated into artificial neural networks (ANN) to predict average roughness *Ra* and root-mean-square roughness *Rq*, two parameters most commonly used for evaluating surface roughness. This paper describes this approach and relevant experimental measurements. The results and analysis are presented. A conclusion is made at the end of the paper.

II. New Computational Intelligence Approach

A. Wavelet Packet Transform (WPT)

The wavelet package transform (WPT) is a method of signal processing that decomposes both approximate and detail parts of signals [12], particularly unsteady and non-stationary signals, such as those generated in metal machining. As compared to the conventional wavelet transform technique, which has poor resolution in the high frequency region and is unable to recognize high frequency signals, WPT extracts more information from non-stationary signals including both low and high frequency signals [13].

A wavelet packet function is a function with three indices (*i*, *j*, *k*) satisfying [14].

$$W_{j,k}^{n}(t) = 2^{j/2} W^{n}(2^{j} t - k) \tag{1}$$

where *j* and *k* are index of scale and translation operations, respectively; the index n is called the modulation parameter or the oscillation parameter, and $n = 0,1,2,\ldots.2^{j\text{-}1}$.

Wavelet packet functions are determined as:

$$W_{2n}(x) = \sqrt{2}\Sigma_k h(k) W_n(2x-k) \tag{2}$$

$$W_{2n+1}(x) = \sqrt{2}\Sigma_k g(k) W_n(2x-k) \tag{3}$$

where *h*(*k*) and *g*(*k*) are the low-pass and high-pass filters; $W_0(x) = \phi(x)$ is the scaling function; $W_1(x) = \psi(x)$ is the wavelet function, and the discrete filters *h*(*k*) and *g*(*k*) are quadrature mirror filters associated with scaling function and wavelet function [14].

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B. Feature Selection Using WPT

In the present study, WPT was employed to select dominant features of signals generated in metal machining processes. The signals subjected to WPT include surface roughness data (used for calculating two surface roughness parameters *Ra* and *Rq*), three-dimensional cutting force signals (i.e., the cutting force *Fc*, the feed force *Ff*, and the passive force *Fp*), and three-dimensional cutting vibration signals (i.e., the cutting vibrations *Vx*, *Vy*, and *Vz* in the direction of the cutting speed, the feed rate, and the depth of cut, respectively).

Daubechies 8 wavelet (i.e., db8 function in MATLAB wavelet transform toolbox) was employed with three levels selected for multi-level signal decomposition. The dominant wavelet packet coefficient was identified by calculating the energy for each wavelet packet coefficient and then selecting the one with the highest value.

Based on the WPT analysis on the experimentally-measured signals, the dominant wavelet packet was $W_{(3,0)}$ for machined surface roughness data; $W_{(3,0)}$ for cutting force signals; and W$(_{3,2})$, $W_{(3,3)}$ and $W_{(3,2)}$ for the cutting vibration signals in the direction of the cutting speed, the feed rate, and the depth of cut, respectively. The methods of experimental measurements will be described in Section III.

C. Artificial Neural Networks (ANN)

Artificial neural networks (ANN) are computing mechanisms modeled after biological brains. ANN have one or more layers of processing elements called neurons. Neurons are uni-directional computing elements that receive and sum multiple inputs to generate outputs through a non-linear transfer function.

In the present study, the ANN based on multi-layer perceptron (MLP) [15]-[21] were employed to develop two predictive models for machined surface roughness parameters *Ra* and *Rq*, respectively. Each ANN model contains three layers: an input layer that receives relevant input information, a hidden layer that processes the information, and an output layer the presents the output. Weighted connections exist between neurons (i.e., layers of processing elements in ANN) to move the output of a neuron to other neurons.

In the present study, each ANN model has eight inputs and one output. The eight inputs include:

- The cutting speed *Vc*
- The feed rate *f*
- Energy of wavelet packet $W_{(3,0)}$ for *Fc*
- Energy of wavelet packet $W_{(3,0)}$ for *Ff*
- Energy of wavelet packet $W_{(3,0)}$ for *Fp*
- Energy of wavelet packet $W_{(3,2)}$ for *Vx*
- Energy of wavelet packet $W_{(3,3)}$ for *Vy*
- Energy of wavelet packet $W_{(3,2)}$ for *Vz*

The output is the energy of wavelet packet $W_{(3,0)}$ for machined surface roughness data.

The ANN models were first trained using a set of training data generated from metal machining experiments, and were then tested using another set of test data generated from other metal machining experiments.

III. Experimental Set Up

A. Machining Conditions

A total of 45 bar turning experiments were performed on a computer-numerically-controlled machining center HAAS SL-10. The workpiece material was aluminum alloy 2024-T351 (ASTM B211 grade). The cutting tool were three coated carbide inserts TPG 432 KC 8050 made by Kennametal Inc. These tool inserts had average tool-edge radii of 45.5 µm, 54.7 µm, and 72.4 µm, respectively.

The machining conditions employed in the experiments were as follows. The cutting speed varied at three levels: 150, 250, and 350 m/min. The feed rates were chosen based on the ratio of feed rate to tool edge radius that varied at five levels: 1.0, 1.5, 2.0, 2.5, and 3.0. The depth of cut was kept constant at 0.8 mm, the same as tool nose radius. No coolants were employed in order to facilitate the experimental measurements of the cutting forces, the cutting vibrations, and machined surface roughness.

B. Measurement of the Cutting Forces and the Cutting Vibrations

Fig. 1 shows the experimental measurements of the cutting forces and the cutting vibrations. The equipment used to measure the cutting forces include a quartz three-component dynamometer Kistler 9257B, a multi-channel dual-mode charge amplifier Kistler 5010 B, and a computer data acquisition system Labview. The sampling rate was 10 kHz. MATLAB was employed to filter the high-frequency noise from the collected three-dimensional signals: the cutting force *Fc*, the feed force *Ff*, and the passive force *Fp*. Figs. 2-4 shows representative examples of raw signals collected for measuring *Fc*, *Ff*, and *Fp*, respectively.

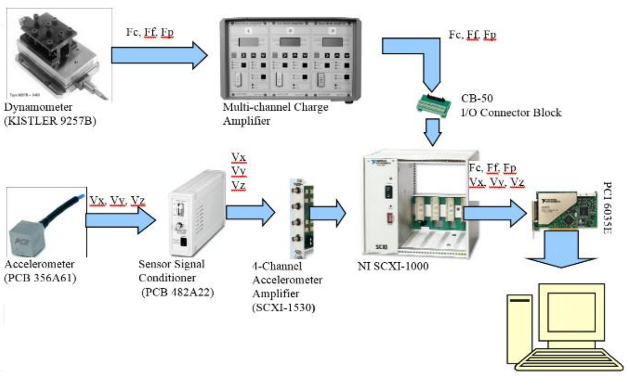


Fig. 1. Experimental measurements of the cutting forces and the cutting vibrations.

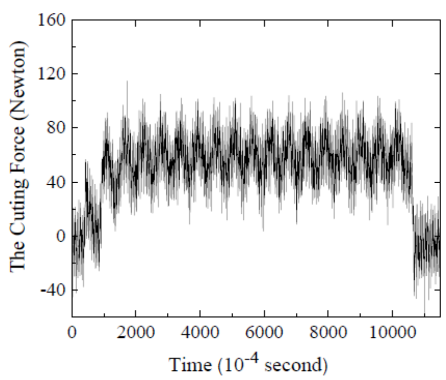


Fig. 2. A representative example of raw signals collected for measuring the cutting force *Fc*.

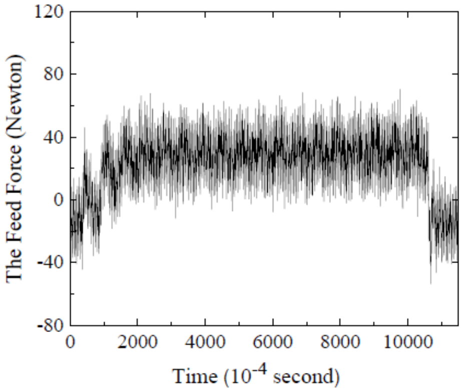


Fig. 3. A representative example of raw signals collected for measuring the feed force *Ff*.

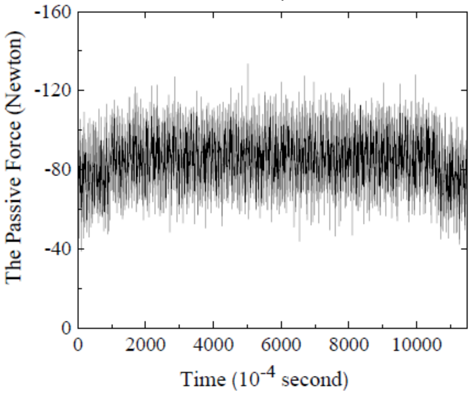


Fig. 4. A representative example of raw signals collected for measuring the passive force *Fp*.

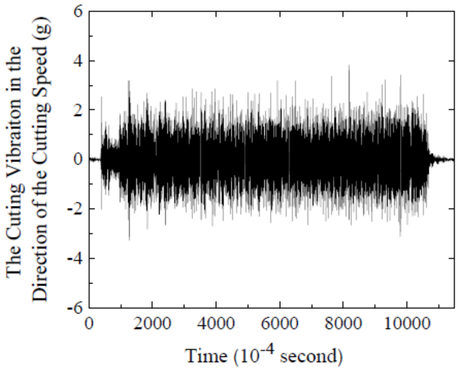


Fig. 5. A representative example of raw signals collected for measuring the cutting vibration *Vx* in the direction of the cutting speed.

The cutting vibration signals were simultaneously measured online using an accelerometer (356A63Triaxial ICP) that was fixed to the tool holder. The sensitivity of the accelerometer was 10 mV/g (±15 %), and its measurement range was ± 5 g (peak). The accelerometer sensed the vibration signals in the x-, y- and z-directions, that is, the cutting speed, feed rate, and depth of cut directions, respectively.

MATLAB was also employed to filter the high-frequency noise from the collected three-dimensional vibration signals. Figs. 5-7 shows representative examples of raw signals collected for measuring the cutting vibrations *Vx*, *Vy*, and *Vz*, respectively.

C. Measurement of the Machined Surface Roughness

The surface roughness parameters and profiles were measured offline using a fine contour measuring instrument Mitutoyo type-SV602. This instrument has a diamond stylus with a tip radius of five μm. After each cutting experiment was conducted, the workpiece was removed from the chuck of the turning center and was taken to the fine contour measuring instrument to measure the machined surface roughness parameters and the profiles at three equally spaced locations around the circumference of the workpiece in order to obtain statistically significant data. The average of the values was used for evaluation.

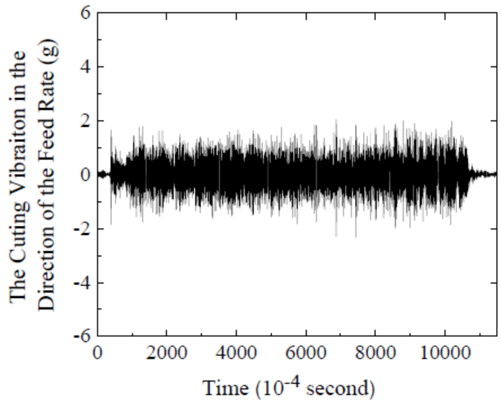


Fig. 6. A representative example of raw signals collected for measuring the cutting vibration *Vy* in the direction of the feed rate.

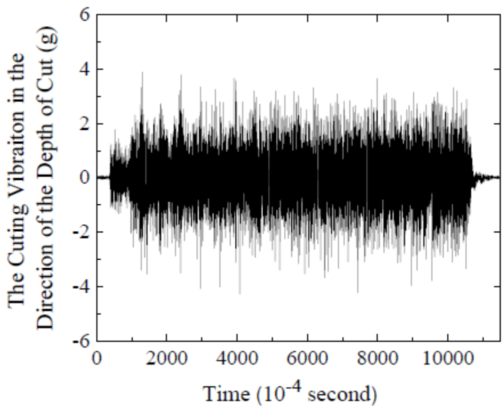


Fig. 7. A representative example of raw signals collected for measuring the cutting vibration *Vz* in the direction of the depth of cut.

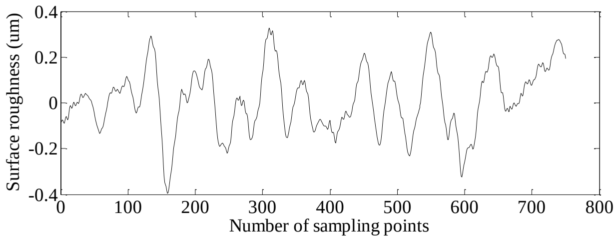


Fig. 8. An example surface profile generated at the cutting speed of 150 m/min and the feed rate of 0.0455 mm/rev.

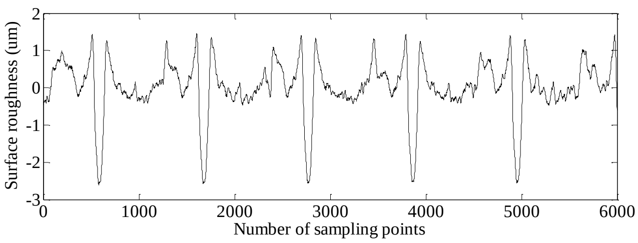


Fig. 9. An example surface profile generated at the cutting speed of 350 m/min and the feed rate of 0.0724 mm/rev.

Two parameters most commonly used for evaluating surface roughness were measured, including:

1) Average roughness *Ra*: arithmetic average of the absolute values of the roughness profile ordinates.

2) Root-mean-square (RMS) roughness *Rq*: the root mean square average of the roughness profile ordinates

Figs. 8 and 9 show two example surface profiles obtained from two cutting experiments. Figs. 10 and 11 show the surface profiles reconstructed from wavelet packet $W_{(3,0)}$.

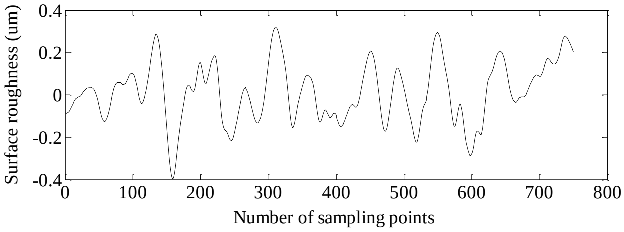


Fig. 10. An example surface profile reconstructed from wavelet packet $W_{(3,0)}$ for the cutting speed of 150 m/min and the feed rate of 0.0455 mm/rev.

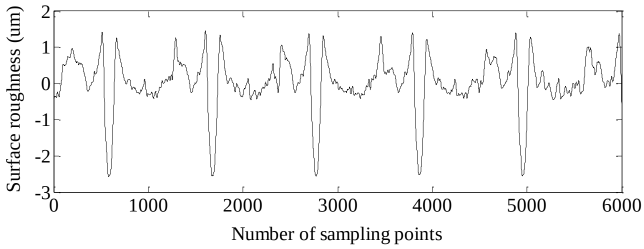


Fig. 11. An example surface profile reconstructed from wavelet packet $W_{(3,0)}$ for the cutting speed of 350 m/min and the feed rate of 0.0724 mm/rev.

IV. Results and Discussions

The output of the ANN models developed from the present study is the energy of wavelet packet $W_{(3,0)}$ of machined surface roughness data. To relate the energy of wavelet packet $W_{(3,0)}$, with the magnitudes of machined surface roughness parameters, the following empirical equations were developed based on the experimental data:

$$Ra = 0.144 + 0.084 \cdot W_{(3,0)} \tag{4}$$

$$Rq = 0.180 + 0.122 \cdot W_{(3,0)} \tag{5}$$

Among the total of 45 machining experiments carried out in the present study, 38 machining experiments (84%) were randomly selected to provide data to train the ANN models. The remaining seven machining experiments (16%) were employed to provide data to test the ANN models.

To assess how well the ANN models fit with training or test data, mean square error (MSE) was further calculated using the following formula:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(\text{measured value}\, i - \text{predicted value}\, i\right)^2 \tag{6}$$

The lower the MSE value, the higher prediction accuracy the model has. Tables I and II show the training of the ANN models for average roughness *Ra* and root-mean-square roughness *Rq*, respectively.

To more vividly show how the predicted values are close to the measured values, the data included in Tables I and II were employed to draw Figs. 8 and 9. As can be seen from Figs. 8 and 9, the ANN models fit well with the training data. The average mean square error (MSE) was 0.0011 (0.11%) for average roughness *Ra* and 0.0015 (0.15%) for root-mean-square roughness *Rq*.

TABLE I: Prediction of Average Roughness (Training Data)

Training No.	Measured value	Predicted value	Mean squared error
1	0.103	0.1582	0.00152352
2	0.190	0.1698	0.00020402
3	0.128	0.1768	0.00119072
4	0.153	0.1710	0.00016200
5	0.122	0.1683	0.00107185
6	0.143	0.1616	0.00017298
7	0.195	0.2067	6.8445E-05
8	0.216	0.1821	0.00057461
9	0.242	0.1846	0.00164738
10	0.271	0.2117	0.00175825
11	0.265	0.1843	0.00325625
12	0.244	0.2061	0.00071821
13	0.286	0.2830	4.5E-06
14	0.291	0.2492	0.00087362
15	0.257	0.2255	0.00049613
16	0.222	0.1919	0.00045301
17	0.493	0.3627	0.00848905
18	0.527	0.5463	0.00018625
19	0.615	0.6750	0.00180000
20	0.209	0.1914	0.00015488
21	0.184	0.1947	5.7245E-05
22	0.216	0.2099	0.00001861
23	0.221	0.1967	0.00029525
24	0.269	0.2561	8.3205E-05
25	0.249	0.2168	0.00051842
26	0.242	0.2144	0.00038088
27	0.572	0.5159	0.00157361
28	0.566	0.5428	0.00026912
29	0.643	0.7031	0.00180601
30	0.567	0.6079	0.00083641
31	0.509	0.5056	5.78E-06
32	0.103	0.1582	0.00152352
33	0.190	0.1698	0.00020402
34	0.128	0.1768	0.00119072
35	0.153	0.1710	0.00016200
36	0.122	0.1683	0.00107185
37	0.143	0.1616	0.00017298
38	0.195	0.2067	6.8445E-05

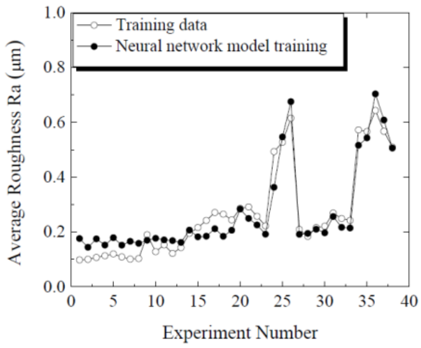


Fig. 8. The training of the artificial neural network (ANN) model for average roughness *Ra*.

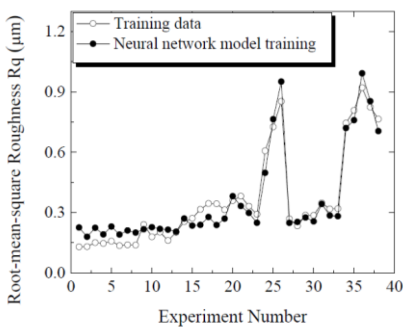


Fig. 9. The training of the artificial neural network (ANN) model for root-mean-square roughness *Rq*.

TABLE II: PREDICTION OF ROOT-MEAN-SQUARE ROUGHNESS (TRAINING DATA)

Training No.	Measured value	Predicted value	Mean squared error
1	0.130	0.2263	0.00463685
2	0.131	0.1799	0.00119561
3	0.151	0.2247	0.00271585
4	0.147	0.1918	0.00100352
5	0.158	0.2311	0.00267181
6	0.136	0.1912	0.00152352
7	0.14	0.2113	0.00254185
8	0.139	0.2007	0.00190345
9	0.241	0.2174	0.00027848
10	0.180	0.2276	0.00113288
11	0.203	0.2192	0.00013122
12	0.162	0.2153	0.00142045
13	0.202	0.2056	6.48E-06
14	0.255	0.2710	0.00012800
15	0.272	0.2354	0.00066978
16	0.316	0.239	0.00296450
17	0.345	0.2783	0.00222445
18	0.344	0.2385	0.00556513
19	0.314	0.2702	0.00095922
20	0.360	0.3819	0.00023981
21	0.382	0.3328	0.00121032
22	0.332	0.2984	0.00056448
23	0.292	0.2496	0.00089888
24	0.607	0.4977	0.00597325
25	0.726	0.7643	0.00073345
26	0.853	0.9512	0.00482162
27	0.269	0.2489	0.00020201
28	0.234	0.2537	0.00019405
29	0.287	0.2756	6.498E-05
30	0.286	0.2565	0.00043513
31	0.348	0.3428	1.352E-05
32	0.318	0.2857	0.00052165
33	0.320	0.2823	0.00071065
34	0.745	0.7202	0.00030752
35	0.808	0.7592	0.00119072
36	0.921	0.9921	0.00252761
37	0.824	0.8537	0.00044105
38	0.765	0.7051	0.00179401

TABLE III: PREDICTION OF AVERAGE ROUGHNESS (TEST DATA)

Test No.	Measured value	Predicted value	Mean squared error
1	0.100	0.0885	0.00006125
2	0.099	0.1687	0.00242905
3	0.563	0.8012	0.02836962
4	0.506	0.3244	0.01648928
5	0.193	0.1601	0.00054121
6	0.229	0.4671	0.02834581
7	0.274	0.4147	0.00989825

TABLE IV: PREDICTION OF ROOT-MEAN-SQUARE ROUGHNESS (TEST DATA)

Test No.	Measured value	Predicted value	Mean squared error
1	0.129	0.0994	0.000438
2	0.127	0.2159	0.003952
3	0.793	1.1345	0.058311
4	0.736	0.442	0.043218
5	0.253	0.2034	0.001230
6	0.284	0.6493	0.066722
7	0.346	0.5732	0.025810

Tables III and IV show the testing of the ANN models for average roughness *Ra* and root-mean-square roughness *Rq*, respectively. For the prediction of average roughness *Ra*, the average mean square error (MSE) varies between 0.00006125 (0.006125%) and 0.02836962 (2.836962%) for different tests, with the average MSE of 0.0123 (1.23%). For the prediction of root-mean-square roughness *Rq*, the average mean square error (MSE) varies between 0.000438 (0.0438%) and 0.058311 (5.8311%) for different tests, with the average MSE of 0.0285 (2.85%). These low values of MSE mean that the ANN models developed in the present study have high prediction accuracy.

V. CONCLUSION

A new computational intelligence approach has been proposed to predict the machined surface roughness in metal machining. Wavelet packet transform (WPT) has been used to extract features from 3D cutting force signals and cutting vibration signals. The energy of these features, along with the cutting speed and the feed rate, have been used as inputs of artificial neural networks (ANN) models. Forty-five machining experiments have been performed to collect data to train and test the ANN models.

Based on the test data, the average mean square errors (MSE) were 1.23% for predicting average roughness *Ra* and 2.85% for predicting root-mean-square roughness *Rq*. These results show that the ANN models developed from the present study have high prediction accuracy.

REFERENCES

[1] M. C. Shaw, *Metal Cutting Principles*, Oxford, U.K.: Oxford University Press, 2008.

[2] P. K. Wright and E. M. Trent, *Metal Cutting*, 4th ed., Oxford, U.K.: Butterworth-Heinemann, 2000.

[3] S. Khamel, N. Ouelaa, and K. Bouacha, "Analysis and prediction of tool wear, surface roughness and cutting forces in hard turning with CBN tool," *J. Mech. Sci. Tech.*, vol. 26, pp. 3605-3616, Nov. 2012.

[4] P. G. Benardos and G. C. Vosniakos, "Predicting surface roughness in machining: a review," *Int. J. Mach. Tools Manuf.*, vol. 43, pp. 833-844, June 2003.

[5] E. Tóth-Laufer and R. Horváth, "Fuzzy model based surface roughness prediction of fine turning," *FME Trans.*, vol. 45, pp. 181-188, Jan. 2017.

[6] S. Wojciechowski and K. Mrozek, "Mechanical and technological aspects of micro ball end milling with various tool inclinations," *Int. J. Mech. Sci.*, vol. 134, pp. 424-435, Dec. 2017.

[7] P. R. Provencher and M. Balaziski, "Automatic identification of feed marks in machined surface roughness profiles by correlating random variations," *Int. J. Adv. Manuf. Tech.*, vol. 82, pp. 1305-1315, Feb. 2016.

[8] A. R. Natasha, J. A. Ghani, C. H. Che Haron, and J. Syarif, "The influence of machining condition and cutting tool wear on surface roughness of AISI 4340 steel," *IOP Conf. Ser.: Mater. Sci. Eng.*, vol. 290, 012017, Jan. 2018.

[9] V. Gutakovskis, E. Gerins, J. Rudzitis, and A. Kromanis, "The effect of the cutting parameters on the machined surface roughness," *Solid State Phen.*, vol. 260, pp. 219-226, Jan. 2017.

[10] C. E. H. Ventura, H. S. Chaves, J. C. Campos Rubio, A. M. Abrao, B. Denkena, and B. Breidenstein, "The influence of the cutting tool microgeometry on the machinability of hardened AISI 4140 steel," *Int. J. Adv. Manuf. Tech.*, vol. 90, pp. 2557-2565, June 2017.

[11] K. A. Risbood, U. S. Dixit, and A. D. Sahasrabudhe, "Prediction of surface roughness and dimensional deviation by measuring cutting forces and vibrations in turning process," *J. Mate. Proc. Techn.*, vol. 132, pp. 203-214, Jan. 2013.

[12] R. Paul and A. Sengupta, "Design and application of discrete wavelet packet transform based multiresolution controller for liquid level system," *ISA Trans.*, vol. 71, pp. 585-598, Nov. 2017.

[13] R. R. Coifman and M. V. Wickerhauser, "Entropy-based algorithms for best basis selection," *IEEE Trans. Inform. The.*, vol. 38, pp. 713-7182, Mar. 1992.

[14] S. Mallat, "A theory of multiresolution signal decomposition: the wavelet representation," *IEEE Trans. Patt. Analy. Mach. Intellig.*, vol. 11, pp. 674-693, Jan. 1989.

[15] S. K. Pal and D. Chakraborty, "Surface roughness prediction in turning using artificial neural network," *Neu. Com. & Appl.*, vol. 14, pp. 319-3244, Dec. 2005.

[16] Z. W. Zhong, L. P. Khoo, and S. T. Han, "Prediction of surface roughness of turned surfaces using neural networks," *Int. J. Adv. Manuf. Tech.*, vol. 28, pp. 688-693, Apr. 2006.

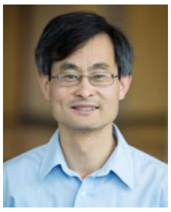
[17] S. O. Haykin, *Neural Networks and Learning Machines*, 3rd ed., Upper Saddle River, NJ: Prentice Hall, 2008.

[18] C. Lu, "Study on prediction of surface quality in machining process," *J. Mate. Proc. Tech.*, vol. 205, pp. 439-450, Aug. 2008.

[19] M. Mia, M. A. Khan, and N. R. Dhar, "Study of surface roughness and cutting forces using ANN, RSM, and ANOVA in turning of Ti-6Al-4V under cryogenic jets applied at flank and rake faces of coated WC tool," *Int. J. Adv. Manuf. Tech.*, vol. 93, pp. 975-9911-4, Oct. 2017.

[20] U. M. R. Paturia, H. Devarasettia, and S. K. R. Naralab, "Application of regression and artificial neural network analysis in modelling of surface roughness in hard turning of AISI 52100 steel," *Mate. Tod.: Proc.*, vol. 5, pp. 4766-4777, Mar. 2018.

[21] D. Kumar and P. Chandna, and M. Pal, "Efficient optimization of process parameters in 2.5 D end milling using neural network and genetic algorithm," *Int. J. Sys. Ass. Eng. Man.*, vol. 9, pp. 1198-1205, Oct. 2018.



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