Straightness Prediction in CNC Turning Process for Carbon Steel and Aluminum Workpieces Applying Artificial Neural Networks

S. Tangjitsitcharoen and W. Laiwatthanapaisan

Abstract—**An intelligent machine and manufacturing system has a significant role in the near future, especially when the circumstance of manufacturing industries are seriously competitive. New technologies are continuously being developed to serve future manufacturing. CNC turning machine is widely utilized in various advanced manufacturing industries. Straightness is a critical parameter in CNC turning process, which affects the workpiece assembly directly. However, control of straightness of the workpieces during in-process turning is difficult to be measured. Moreover, CNC turning machine cannot be adjusted real-time without stopping the operation. Hence, the aim of this research is to develop the straightness prediction model in the CNC turning process under various cutting conditions for carbon steel and aluminum workpieces in order to improve in-process monitoring and control of straightness. The cutting forces ratio has been adopted to estimate straightness. The Daubechies wavelet transform is utilized to decompose the dynamic cutting forces to remove the noise signals for better prediction. The straightness is calculated by employing the two-layer feed forward neural network, which is trained with the Levenberg-Marquardt back-propagation algorithm. As a result, the in-process straightness could be predicted well with greater accuracy and reliability using the proposed straightness model.**

Index Terms—**Artificial neural networks, cutting force ratio, straightness, wavelet transform.**

I. INTRODUCTION

Manufacturing industries presently have high competition. New technologies are continuously being developed to serve future manufacturing and response to customer requirements, which are rapidly changing. A desired manufacturing system in the future should produce products per customer requirements with fast response, high quality, and conform to design regulations. The system should have flexibility in production for certain customers, high product variety, and low volume. One key factor is the system should be able to monitor and inspect by itself. The system should simulate before start production for finding suitable production conditions and factors. Hence, an intelligent machine and manufacturing system will become more significant in the near future.

CNC turning machine was developed to perform a wider

variety of manufacturing tasks with a large volume and greater accuracy. CNC turning machine is important in manufacturing because it saves manufacturing cost, quick and high precision operation, and improves manufacturing productivity and efficiency.

In the turning process, product quality can be considered with different measures such as surface roughness, straightness, roundness, flatness, and cylindrical shape. However, straightness is considered as a critical parameter in this research since it directly affects the workpiece assembly, such as the shaft of the spindle motor parts, piston, and motion axis in the machine. If the workpieces cannot be assembled as designed, it will lead to abrasion, which generates heat and vibration when machine is operating. As a result, the machine cannot operate efficiently, consume a lot of fuel, and can cause damage in the long term.

After finished operating, straightness can be fully inspected. However, control of straightness of the workpieces during in-process turning is difficult to be measured directly. Moreover, CNC turning machine cannot be adjusted in real-time without stopping operation. Therefore, it is desirable to control the straightness during in-process cutting to avoid undesirable outputs at the end of the process.

Many researches developed the method to increase product quality. Researches concerning surface roughness are Qehaja, Doci, Bruqi, Abdullahu, Jakupi and Zhujani [1] proposed the mathematical modeling of surface roughness of the milling process by applying response surface methodology (RSM). The proposed model considered three parameters, which are the cutting speed, the feed rate, and the cutting time, to develop the surface roughness prediction for the milling process with steel (C62D) workpiece. Salgado, Alonso, Cambero, and Marcelo [2] developed an in-process procedure for surface roughness estimation of turning with AISI 8620 steel workpiece using Singular Spectrum Analysis (SSA) to decompose the cutting vibration signals and applied LS-SVM to predict surface roughness. Maohua, Xiaojie, You, Fei, Nong, Weihua, and Dan [3] constructed the roughness prediction model using the Taguchi design method, the central composite surface design in the RSM and optimized the cutting parameters of stainless steel turning. This model examined three influenced parameters, which are the cutting speed, the feed rate, and the depth of cut. Sung, Loh, and Ratnam [4] proposed the simulation approach to predict surface roughness in the interval for the turning process. This approach focuses on the factors of a tool, which are tool nose radius and tool chatter vibration. Chaijareenont and Somkiat Tangjitsitcharoen [5] studied the relation between the

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in-process surface roughness of aluminum (Al 6063) and the cutting forces ratio during the turning process under the various cutting conditions on the CNC turning machine and developed model by employing the exponential function. The multiple regression analysis is utilized to calculate the regression coefficients with the use of the least square method at a 95% confidence level. The proposed model considered five parameters, which are cutting speed, feed rate, depth of cut, nose radius, and cutting force ratio. Tangjitsitcharoen and Samanmit [6] indicated that the fifth level from the use of five levels of the Mayer wavelet transform was proper to predict the in-process surface roughness for the turning process with carbon steel (S45C) workpiece, as the Mayer wavelet transform could classify the broken chip and surface roughness signal from the dynamic cutting forces. The proposed model considered six parameters, which are cutting speed, feed rate, depth of cut, nose radius, rake angle, and cutting force ratio. Çaydas and Ekici [7] introduced three different type of support vector machines (SVMs) tools that were developed to estimate the surface roughness of AISI 304 austenitic stainless steel in CNC turning process. Turning parameters of cutting speed, feed rate, and depth of cut are considered as model variables. Samanta [8] presented the surface roughness model in end milling of aluminum (Al 6061) using adaptive neuro-fuzzy inference system (ANFIS) and genetic algorithms (GAs). The maching paramters are spindle speed, feed rate, depth of cut, and workpiece-tool vibration amplitude. Senthil Babu and Vinayagam [9] proposed the predictive model of surface roughness of drilling process using a feed forward neural network model and adaptive particle swarm optimization (APSO) algorithm for decreasing the variation between input and output. Three parameters are concerned in the model, which are cutting speed, feed rate, and depth of cut.

Other researches concerning straightness are Shansungnoen and Tangjitsitcharoen [10] proposed the cutting force ratio, which can be used to predict the straightness with the use of the Fast Fourier Transform (FFT) during the turning process with carbon, steel (S45C) workpiece by employing the exponential function. Six parameters are considered, which are cutting speed, feed rate, depth of cut, nose radius, rake angle, and cutting force ratio. Puangpad [11] developed a straightness prediction model by employing the exponential function. The relation between the in-process straightness of aluminum (Al 6063) and the cutting forces ratio during the CNC turning process are examined under the various cutting conditions. The developed model focused on five parameters, which are cutting speed, feed rate, depth of cut, nose radius, and cutting force ratio. Sassantiwong and Tangjitsitcharoen [12] applied the Daubechies wavelet transform to decompose the dynamic cutting forces and identify straightness signal from the other noise signals to gain more accuracy for the straightness prediction of turning process with carbon steel (S45C) workpiece. The dynamic cutting forces were decomposed into ten levels and the 8th level of wavelet transformation is recommended to monitor and predict the in-process workpiece straightness without the effects from the chip conditions. The proposed model considered six parameters, which are cutting speed, feed rate, depth of cut, nose radius, rake angle, and cutting force ratio.

Refer to previous researches, it is obvious that the influenced cutting conditions relate to the surface finish in CNC turning process are cutting speed, feed rate, depth of cut, nose radius, rake angle. Carbon steel and aluminum are considered as an important experimental workpiece due to the extensive use in different manufacturing industries like automotive and machine parts. Besides, the cutting forces ratio has been adopted to estimate surface roughness or straightness. Therefore, the considered parameters in this research are cutting speed, feed rate, depth of cut, nose radius, rake angle, and cutting force ratio with carbon steel and aluminum workpieces. However, to gain more accurate prediction the cutting force has to firstly be decomposed to classify the straightness signal from the noise signals.

The Daubechies wavelet transform is one of the useful methods to analyze the mechanical signal. As the obtained signals are mixed up with the other signals, the target signal cannot be used to calculate and analyze precisely. Consequently, the Daubechies wavelet transform is used to decompose the signals into many levels to separate the signals. Each level is different from other levels due to the different frequency intervals [13]. Therefore, the Daubechies wavelet transform will be applied in this research to classify the straightness signal from other noise signals.

Artificial neural networks (ANNs) [14] are new alternative data modelling tools in the mathematics model, which were introduced since the 1970s and are widely used and accepted. Artificial neural networks can solve a variety of problems in pattern recognition, prediction, optimization, associative memories, and control. The layered structure is similar to the networked structure of neurons in the human brain. It consists of three main layers, which are an input layer, one or more hidden layers, and an output layer. The layers are connected via nodes, or neurons, with each layer. Artificial neural networks are able to capture and present input-output relationships. They can be trained to recognize patterns and perform a particular function by adjusting the values of connections weights between elements, which is similar to regression coefficients in regression analysis. Consequently, a particular input leads to a specific output [15]. Therefore, the straightness prediction could be applied with artificial neural networks.

Hence, this research aims to develop the straightness prediction model in the CNC turning process under various cutting conditions for carbon steel and aluminum workpieces in order to improve in-process monitoring and control of straightness. The Daubechies wavelet transform is utilized to decompose the dynamic cutting forces to remove the noise signals for better prediction. Straightness is predicted by employing artificial neural networks.

II. WAVELET TRANSFORM AND THE RELATION OF DYNAMIC CUTTING FORCE AND STRAIGHTNESS

The dynamic cutting force corresponds to the straightness directly due to the effect of cutting conditions. It is understood that the frequency of the straightness is related to the frequency of the dynamic cutting forces in the frequency domain. The relation of the straightness and the cutting force

can be examined using the Fast Fourier Transform (FFT) in both time and frequency domains. However, the straightness signal is difficult to classify from the broken chip and other noise signals using the Fast Fourier Transform (FFT). Therefore, the wavelet transform is proposed to analyze the signals instead. Daubechies wavelet transform is one of the most powerful wavelets to analyze the mechanical signals. It can decompose the mixed signals into many levels as determined to separate the target signal from the noises or the other signals. In this research, the Daubechies wavelet transform will be used to decompose the dynamic cutting forces into 10 levels according to the previous research from Sassantiwong and Tangjitsitcharoen [12] and each level will consist of two signals, which are the approximation signal, and the detail signal as shown in Fig. 1.
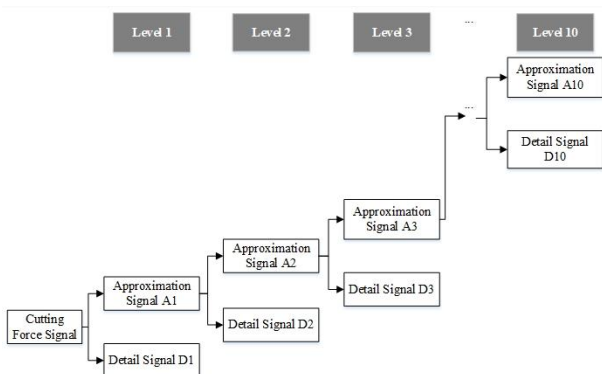

Fig. 1. Illustration of wavelet to decompose the dynamic cutting forces into 10 levels.
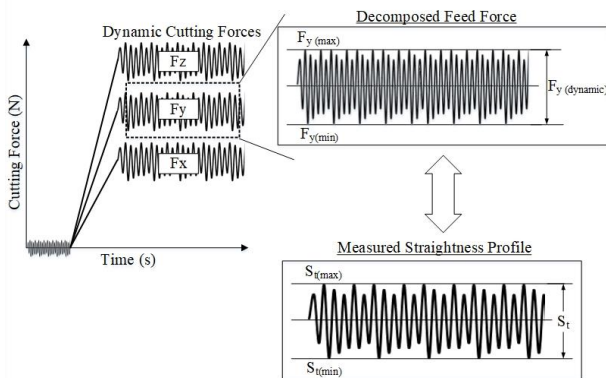

Fig. 2. Illustration of the dynamic cutting forces.

The cutting forces consist of three components, which are the radial force (Fx), the feed force (Fy), and the main force (Fz) as shown in Fig. 2. The feed force is applied for predicting straightness in many previous researches [10] – [12], [16] because it is sensitive to the straightness profile. Moreover, the measuring direction of the straightness profiles is parallel to the axis of the cylindrical workpiece, which is the same direction as the feed rate direction.

The measured feed force (Fy) can be divided into two portions, which are the static feed force (Fy(static)) and the dynamic feed force (Fy(dynamic)) as shown in Fig. 3. Normally, the static feed force varies according to the workpiece hardness whereas the dynamic feed force depends on the cutting conditions. To remove the effect of workpiece hardness and the cutting conditions, the cutting force ratio [10] is introduced in this case. It takes the ratio of the

dynamic feed force to its static feed force, which is calculated as the ratio of the difference between the maximum dynamic feed force (Fy(max)) and the minimum dynamic feed force (Fy(min)) to its static feed force (Fy(static)) as shown in (1). It is expected that the highest amplitude of the dynamic feed force will correspond with the straightness profile.

$$\text{Cutting force ratio} = \frac{F_{y(dynamic)}}{F_{y(static)}} = \frac{F_{y(max)} - F_{y(min)}}{F_{y(static)}} \quad (1)$$
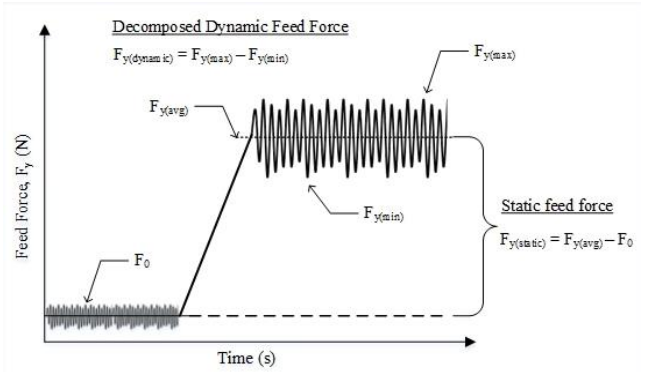

Fig. 3. Illustration of the portion of feed force.

III. AN ARTIFICIAL NEURAL NETWORK MODEL FOR STRAIGHTNESS PREDICTION

As there are multiple input factors to this straightness prediction model and the relationship between the factors is nonlinear, the two-layer neural network is employed. The network will be trained with the Levenberg-Marquardt with the back-propagation algorithm. The advantages of this algorithm are that it is easy to use, rapid, and useful in prediction or control for the nonlinear problem and the small to medium scale problem. As shown in Fig. 4, the developed neural network consists of three layers, which are the input layer, the hidden layer, and the output layer. The input layer has six nodes corresponding to the input factors, which are cutting speed, feed rate, depth of cut, tool nose radius, rake angle, and cutting force ratio. The hidden layer has ten nodes to adjust the weight and the bias with the smallest mean square error between calculated output and target value using the Sigmoid transfer function. The output layer has one node to return the predicted value, which is straightness (St) using the linear transfer function.
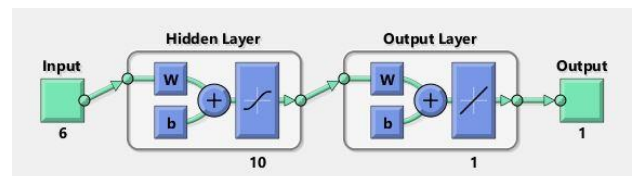

Fig. 4. Illustration of the two-layer feed forward neural networks with back-propagation algorithm.

IV. EXPERIMENTAL SETUP AND PROCEDURE

The Factorial design is applied in this research since the concerned parameters of the cutting conditions, which are related to the straightness, are more than two parameters. Thus, the effects between parameters can be examined at the same time. Each parameter level is considered and referred to

the cutting tool manufacturer's manual and previous relevant researches for the good finish cut. The cutting conditions are summarized in Table I.

TABLE I: CUTTING CONDITIONS

Parameter		Parameter level	
		Carbon steel (S45C)	Aluminum (Al 6063)
Cutting speed (m/min)		100, 150, 200	150, 200, 250
Feed rate	**(mm/rev)**	0.15, 0.20, 0.25	0.100, 0.125, 0.150
Depth of cut	**(mm)**	0.4, 0.6, 0.8	0.1, 0.2, 0.3
Nose radius	**(mm)**	0.4, 0.8	
Rake angle	**(degree)**	-6, +11	

The experiments are conducted on the 4-axis CNC turning machine (Mazuk NEXUS 200MY/MSY). The coated carbide tools with the different tool nose radiuses of 0.4 and 0.8 mm are used for the experiments with the carbon steel (S45C) and the aluminum alloy (Al 6063). The dynamometer (Kistler 9121) is installed on the turret to obtain the cutting force signals while the CNC turning machine is operating as shown in Fig. 5. The detected cutting forces are amplified through the charge amplifier (Kistler model: 5083) and displayed the result by the oscilloscope (Yokogawa DL750) before digitization and calculation within a personal computer. The sampling rate is set at 10 kHz and low-pass filtered with the cut-off frequency of 5 kHz. Straightness (St) is measured by the surface roughness tester (Mitutoyo SJ-400).
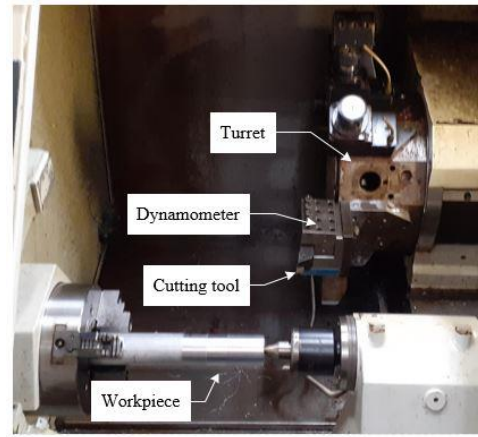

Fig. 5. Illustration of the experimental setup.

The experimental procedures are described as follow:
1) Set up a turning program on the CNC turning machine according to each cutting condition, cut and record the cutting force signal data.
2) Measure straightness using the surface roughness tester.
3) Check the relation between the dynamic cutting force signal and the straightness profile in the time and frequency domains and decompose noise signals applying Daubechies wavelet transform.
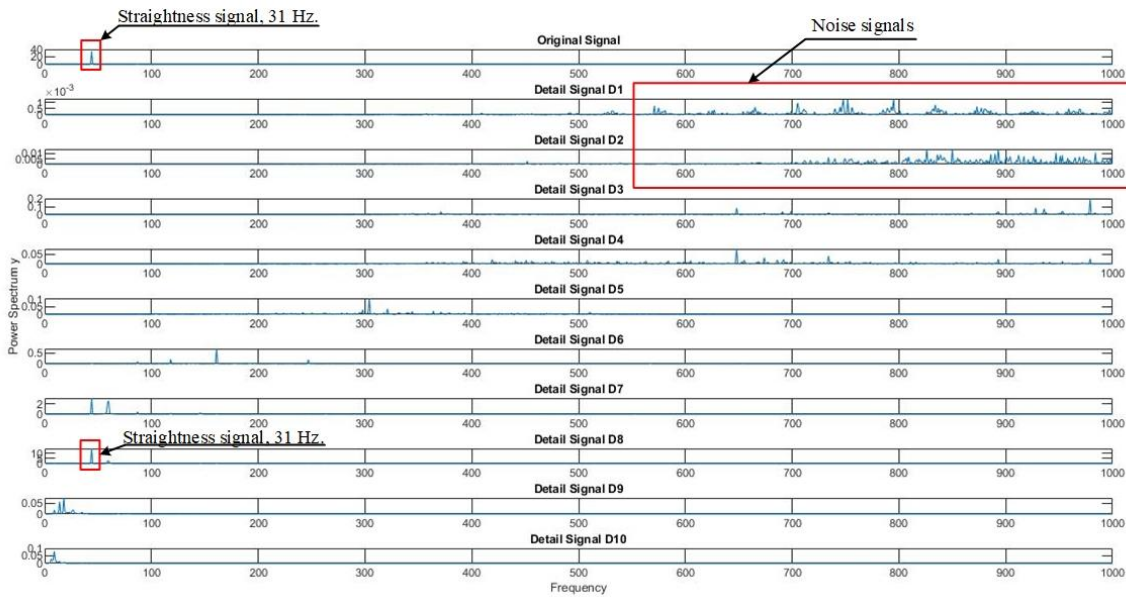4) Calculate the cutting force ratio, [Fy(max) - Fy(min)] / Fy(static).

Fig. 6. Illustration of the example of decomposing feed force into 10 levels in frequency domain.

5) Analyze the relationship between straightness and the cutting force ratio by plotting the relationship graph.
6) Train and test the artificial neural network with the input data sets, which are the cutting force ratios under the various cutting conditions, and the target output, which is the measured straightness.
7) Verify the accuracy of the developed straightness prediction model with the new cutting conditions.

V. EXPERIMENTAL RESULTS AND DISCUSSION

Result from the experiments indicated that Daubechies wavelet transform could classify the straightness signals from the noise signals. For example, the frequency of feed force of 31 Hz on the 8th level of wavelet transform in Fig. 6 corresponds to the straightness signal with the same frequency of 31 Hz. which is found in the PSD of the workpiece straightness as shown in Fig. 7. In conclusion, the decomposed feed force on the 8th level of wavelet transform can be used to predict the workpiece straightness without the effect from the chip condition.

The artificial neural networks for the straightness prediction model is developed by inputting data sets from the experimental results, creating and training a neural network,

and evaluating its performance using mean square error and regression analysis. However, validation and testing percentages of the neural networks can be varied for 7 levels, which are 5%, 10%, 15%, 20%, 25%, 30%, and 35%. Hence, 49 experiments of varying 7 levels of validation and testing percentages were carried out. Refer to the experiment results, the validation and testing percentages of the neural networks with the highest regression R value are 20% and 15% respectively. Therefore, 65% of training (70 samples), 20% of validation (22 samples) and 15% of testing (16 samples) are considered to use for developing the neural network.
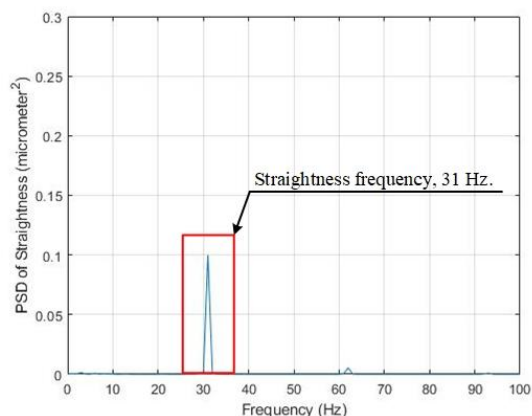

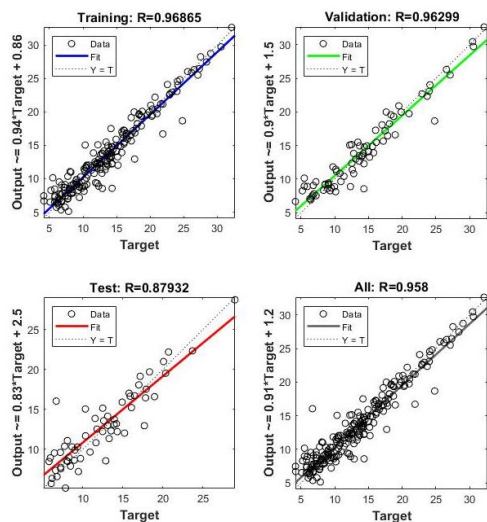Fig. 7. The example of the PSD of the workpiece straightness in frequency domain.

Fig. 8. The Illustration of the training, validation, and testing of the neural networks for the straightness prediction model.

The results of training, validation, and testing of the neural networks are shown in Fig. 8 with the high regression R value of 0.958, which means the correlation between outputs and targets of the neural networks have a close relationship.

VI. Verification of Straightness Model and Accuracy

New cutting conditions are conducted in order to verify the accuracy of the straightness prediction model as shown in Table II.

The prediction accuracy of the model is about 82.57%. In addition, the developed model can predict the straightness close to the measured straightness regardless of the cutting

condition as shown in Fig. 9.

TABLE II: New Cutting Conditions

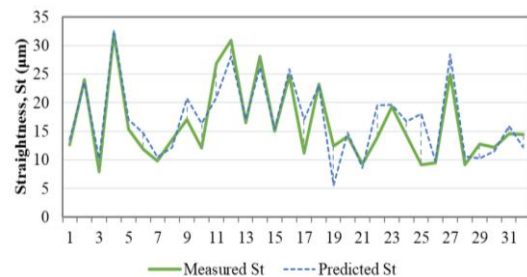| Parameter		Parameter level
		Carbon steel (S45C)
Cutting speed	(m/min)	100, 200
Feed rate	(mm/rev)	0.15, 0.25
Depth of cut	(mm)	0.4, 0.8
Nose radius	(mm)	0.4, 0.8
Rake angle	(degree)	-6, +11

Fig. 9. Comparison between the predicted straightness and the measured straightness.

VII. Conclusion

The relation between straightness and dynamic cutting force has been investigated under various cutting conditions. The results can be concluded as follows,

1. Daubechies wavelet transform can be utilized to decompose dynamic feed force into 10 levels in both time and frequency domains, and the decomposed feed force on the 8th level of wavelet transform can be used to predict the workpiece straightness without the effect of noise signals.

2. The cutting force ratio can eliminate the effects of cutting conditions, even when the material workpiece are different like aluminium (Al 6063) and carbon steel (S45C). Hence, the cutting force ratio is proposed to apply in this straightness prediction model.

3. The straightness can be predicted with high accuracy via the proposed straightness prediction model utilizing the two-layer feed forward neural network. In addition, the Levenberg-Marquardt with the back-propagation is a very advantageous algorithm that it is simple to use, rapid, and helpful in prediction or control for the nonlinear problem and the small to medium scale problem.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

W. L. conducted the research, analyzed the data, and wrote the paper; S. T. advised the research and reviewed the paper; all authors had approved the final version.

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References

[1] Q. Nexhat, D. Ilir, B. Mirlind, A. Fitore, J. Kaltrinë, and Z. Fatlume, "Mathematical modelling of surface roughness through machining

parameters and machining time during the dry milling process," *Annals of DAAAM & Proceedings*, vol. 27, pp. 187-194, 2016.

[2] D. R. Salgado, F. J. Alonso, I. Cambero, and A. Marcelo, "In-process surface roughness prediction system using cutting vibrations in turning," *The International Journal of Advanced Manufacturing Technology*, vol. 43, pp. 40-51, 2009.

[3] M. Xiao, X. Shen, Y. Ma, F. Yang, N. Gao, W. Wei, and D. Wu, "Prediction of surface roughness and optimization of cutting parameters of stainless steel turning based on RSM," *Mathematical Problems in Engineering*, pp. 1-15, 2018.

[4] A. N. Sung, W. P. Loh, and M. M. Ratnam, "Simulation approach for surface roughness interval prediction in finish turning," *International Journal of Simulation Modelling (IJSIMM)*, vol. 15, pp. 42-55, 2016.

[5] A. Chaijareenont and S. Tangjitsitcharoen, "Monitoring of surface Roughness in aluminium turning process," in *Proc. IOP Conference Series: Materials Science and Engineering*, 2017, vol. 21, no. 1, pp. 1391-1392.

[6] S. Tangjitsitcharoen, K. Samanmit, and S. Ratanakuakangwan, "Development of surface roughness prediction by utilizing dynamic cutting force ratio," *Proceedings of the Institution of Mechanical Engineers*, vol. 490, pp. 207-212, 2014.

[7] U. Çaydas and S. Ekici, "Support vector machines models for surface roughness prediction in CNC turning of AISI 304 austenitic stainless steel," *Journal of intelligent Manufacturing*, vol. 23, pp. 639-650, 2012.

[8] B. Samanta, "Surface roughness prediction in machining using soft computing," *International Journal of Computer Integrated Manufacturing*, vol. 22, pp. 257-266, 2009.

[9] S. S. Babu and B. K. Vinayagam, "Surface roughness prediction model using adaptive particle swarm optimization (APSO) algorithm," *Journal of Intelligent & Fuzzy Systems*, vol. 28, pp. 345-360, 2015.

[10] T. Shansungnoen and S. Tangjitsitcharoen, "Investigation of relation between straightness and cutting force in CNC turning process," *Applied Mechanics and Materials*, vol. 789, pp. 812-820, 2015.

[11] P. Puangpad and S. Tangjitsitcharoen, "A Study of relation between straightness and cutting force in aluminum turning," *Engng. J. CMU*, vol. 25, 2018.

[12] M. Sassantiwong and S. Tangjitsitcharoen, "In-process prediction of straightness in CNC turning by using wavelet transform," in *Proc. 2nd International Conference on Green Materials and Environmental Engineering*, 2015, pp. 199-203.

[13] S. Tangjitsitcharoen, T. Saksri, and S. Ratanakuakangwan, "Advance in chatter detection in ball end milling process by utilizing wavelet transform," *Journal of Intelligent Manufacturing*, vol. 26, pp 485-499, 2015.

[14] J. V. Tu, "Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes," *Journal of Clinical Epidemiology*, vol. 49, pp. 1225-1231, 1996.

[15] N. Senthilkumar and T. Tamizharasan, "Flank wear and surface roughness prediction in hard turning via artificial neural network and multiple regressions," *Australian Journal of Mechanical Engineering*, vol. 13, pp. 31-45, 2015.

[16] S. Tangjitsitcharoen and H. Lohasiriwat, "Hybrid monitoring of chip formation and straightness in CNC turning by utilizing daubechies wavelet transform," *Procedia Manufacturing*, vol. 25, pp. 279-286, 2018.

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