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The development of an in-process surface roughness adaptive control system in turning operations

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Abstract This research shows the development of an in-process surface roughness adaptive control (ISRAC) system in turning operations. An artificial neural network (ANN) was employed to establish two subsystems: the neural network-based, in-process surface roughness prediction (INNS-RP) subsystem and the neural network-based, in-process adaptive parameter control (INNAPC) subsystem. The two subsystems predicted surface roughness and adapted feed rate using data from not only cutting parameters (such as feed rate, spindle speed, and depth of cut), but also vibration signals detected by an accelerometer sensor. The INNSRP subsystem predicted surface roughness during the finish cutting process with an accuracy of 92.42%. The integration of the two subsystems led to the neural-networks-based surface roughness adaptive control (INNSRAC) system. The 100% success rate for adaptive control of the test runs proved that this proposed system could be implemented to adaptively control surface roughness during turning operations.

Keywords Surface roughness · Turning operations · Adaptive control · Neural-networks

Introduction

An automatic manufacturing process that includes aspects of artificial intelligence, such as the capacity to learn and reason, is classified as possessing an advanced level of automation (Degarmo, Black, & Kohser, 1997). Developing a CNC turning machine at this level of automation has been an industry goal for many years. During the past decade, several researchers have attempted to manufacture artificially intelligent machine tools (Risbood, Dixit, & Sahasrabudhe, 2003).

Surface roughness of a part produced in turning operations is an important quality indicator since it may affect the aesthetic appeal of machined parts and the fatigue stress, economic cost, etc., of assembled parts. An excessively fine surface finish usually involves advanced equipment, manufacturing procedures, and skilled labor, all which increase the cost of manufacturing. However, the dynamic and non-linear nature of turning operations means that surface roughness can be influenced by a number of factors, such as feed rate, spindle speed, depth of cut, workpiece material characteristics, tool geometry (tool nose, tool angle), tool conditions (such as the amount of wear), cutting forces, and cutting vibrations (Fang & Yao, 1997; Ho, Lee, Chen, & Ho, 2002; Kopac, Bahor, & Sokovic, 2002; Risbood et al., 2003; Beauchamp, Thomas, Youssef, & Masounave, 1996; Yang & Tarng, 1998). Small variations in any of these factors may cause scrap in the finishing turning process, which could, in turn, result in unnecessary waste, especially when quite a few manufacturing processes have already been completed on the part. Thus, there is a need for a system that enhances the intelligence of CNC turning machines, giving the machines the ability to detect machining process conditions and even adjust them in real time to avoid defects.

Traditionally, surface roughness monitoring depends heavily on stylus instruments (Ho et al., 2002). However, measuring surface roughness through stylus devices is a post-process, off-line quality monitoring approach as turning operations must be paused; therefore, it does not allow users to take full advantage of the CNC machines.

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Since the 1980s, the industry has started with the development of non-contact, on-line surface roughness prediction during the finishing process through pneumatic, electrical, or optical approaches, instead of measuring surface pattern directly (Yan, Cheng, Popplewell, & Balakrishnan, 1995). In order to overcome the limitations of these methods caused by measuring range, poor resolution, instability, or heavy reliance on empirical modeling, Yan et al. designed a laser measuring system that employs a linear charge-coupled device sensor to capture the light pattern scattered from the workpiece surface. Such measurements are more accurate than conventional stylus measurements.

The estimation of roughness using computer vision has also received a great deal of attention (Al-kindi, Baul, & Gill, 1992; Hoy & Yu, 1991; Kiran, Ramamoorthy, & Radhakrishnan, 1998; Lee & Tarng, 2001; Mainsah & Ndumu, 1998), but a major drawback of the computer vision-based technique is that the modeling of the relationship between the actual surface roughness of the workpiece and the surface images is not accurate enough due to the involvement of empirical approaches (Ho et al., 2002). To improve the accuracy of on-line surface roughness prediction, Ho et al. enhanced their computer vision system by incorporating a fuzzy neural network, which is a more powerful learning tool, to solve the problem. However, the computer vision-based surface roughness prediction system and the laser measuring system reviewed above require an extra light source to operate.

Another alternative approach to controlling surface roughness in real time involves the modeling of surface roughness by incorporating a variety of machining parameters and machining process signals. Applying an artificial neural networks (ANN), Lee and Chen (2003) developed an on-line surface roughness recognition system including vibration signals. Also applying ANN, the surface roughness prediction system created by Risbood et al. (2003) included cutting forces and vibrations signals in the turning process. Although these systems can recognize surface roughness without stopping the machining operation and with reasonable accuracy, they do not possess adaptive control strategies to correct surface finish defects. Therefore, there is a need to move the research regarding on-line surface roughness recognition to a new stage of implementing adaptive control. This paper proposes an in-process surface roughness adaptive control (ISRAC) system able to automatically avoid defects by recognizing the surface finish of a part and adjusting process parameters based on real-time information from the cutting process.

In order to develop such an in-process surface roughness adaptive control ISRAC system, two important components must be in place: a real-time sensor for collecting cutting process signals related to surface profile, and a decision-making mechanism.

A number of studies proved that vibration plays an important role in influencing surface finish in turning operations. Jang et al. (1996) found that the workpiece surface profile and a specific vibration frequency have strong a correlation in hard turning. Lin and Chang (1998) found that the vibration frequency ratio is an important factor influencing the characterization of the surface finish profile. L. Huang and J. C. Chen (2001) reported that the multiple regression model including vibration signals for predicting in-process surface roughness showed significantly improved accuracy in comparison to the one without. Abouelatta and Madl (2001) also confirmed the impact of vibration signals. Therefore, the current study employed an accelerometer sensor to detect turning vibration signals.

With respect to the decision-making mechanism, B. Huang and J. C. Chen (2001) and other researchers have proved ANN to be an effective tool not only for dealing with the non-linear and multivariable turning processes to predict surface roughness, but also for monitoring other industrial applications (Elanayar & Shin, 1995; Fang & Yao, 1997; Zuperl & Cus, 2003). Thus, this study employed ANN as the decision-making mechanism in the proposed (ISRAC) system. A great deal of research has shown that feed rate is the most significant factor affecting surface finish (Abouelatta & Madl, 2001; Ho et al., 2002; Lee & Chen, 2003; Risbood et al., 2003). Thus, the adaptive control system was designed to alter the feed rate as the adaptive control variable to control the production of surface finish.

In summary, this study shows the development of an in-process neural network-based surface roughness adaptive control (INNSRAC) system by incorporating real-time 3D vibration signals collected through an accelerometer. This system is designed to evaluate the surface quality of turned parts and adaptively control changes in feed rate in order to consistently produce parts that meet specifications.

Artificial neural networks system

An ANN is a parallel, distributed information processing structure that mimics the human brain to learn from examples or mistakes (Freeman & Skapura, 1991). Neural networks, based on their biological counterparts, attempt to model the parallel, distributed nature of processing in the human brain. Since this concept was introduced in 1950s, ANN technology has been adapted in many applications that are complex and non-linear in nature, with an unknown and hard-to-identify algorithm (Lippmann, 1999).

The mathematical model of an artificial neuron's behavior is the simplification of the biological brain neuron shown in Fig. 1. Various inputs $x(n)$ to the network multiplied by weights $w(n)$ are sent to a neuron. Performing accumulation

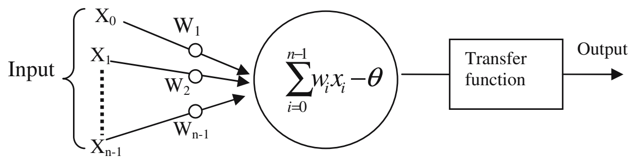

Fig. 1 The behavior of an artificial neuron

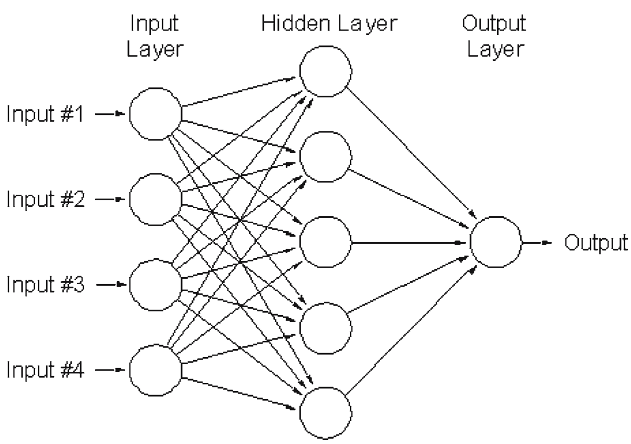

Fig. 2 Artificial neural network

and threshold, the neuron sums the weighted inputs, passes the result through a non-linear transfer function and provides an output Y_i

$$Y_i = f\left(\sum_{i=0}^{n-1} w_i x_i - \theta\right), \tag{1}$$

where the inputs of x_i in this study corresponds to feed rate, spindle speed, depth of cut and vibration signals; θ is the internal threshold or offset of a neuron; and f is the non-linear transfer function. The most commonly used f is defined by the sigmoid logistic function as:

$$f(x) = \frac{1}{1 + e^{-x}}. \tag{2}$$

A neural networks provides a networking structure in which artificial neurons are interconnected, as shown in Fig. 2. Each neuron in a layer receives weighted inputs from the neurons in the previous layer. The output of the neuron in the previous layer is in turn connected as the input to several other neurons in the following layer, which forms a complete network. Beyond the input and output layers, several other layers of neurons in the middle, called hidden layers, might be needed to build an effective neural network that is capable of solving problems.

The principle underlying neural networks is pattern recognition. Among the variety of neural network algorithms, back-propagation (BP) is the most commonly used due to BPs superior strength in pattern recognition and reasonable speed (McClelland & Rumelhart, 1988). The training procedure for a back-propagation network (BPN) is usually iterative and involves a trial-and-error approach that consists of the following steps (Lippmann, 1999):

Step 1: Initialize weights and offsets, starting from a small random value.
Step 2: Present inputs and desired outputs to the neural network model.
Step 3: Calculate actual outputs, y_m.
Step 4: Calculate the error between the output from the neural network and the desired output by E

$$E = \frac{1}{nm} \sum_m \sum_n (y_{m,n} - d_{m,n})^2, \tag{3}$$

where m is the number of neurons in the output layer (in this study $m = 1$), and n is the number of training data set. If E is smaller than the required accuracy, then no other learning procedures are needed.
Step 5: If E is larger than the required accuracy, adjust the weights of the networks. The weights are adjusted by

$$w_{ij}(t+1) = w_{ij}(t) + \eta \delta_j x_i', \tag{4}$$

where x_j' is either the output of neuron i or an input, η is a gain term, and δ_j is an error term for neuron j.
Step 6: Repeat steps 3–6 until the error of the entire set is less than the required accuracy.

Structure of the INNSAC system

The INNSAC system in Fig. 3 includes two subsystems: an in-process neural-networks-based surface roughness prediction (INNSRP) subsystem and an in-process neural networks-based adaptive parameter control (INNAPC) subsystem. As the turning process proceeds, the accelerometer sensor simultaneously records the vibration in the X, Y, and Z directions. The INNSRP subsystem is able to predict the surface roughness of the workpiece (R_a^{P}) while the turning operation is in process, based on cutting parameters and the changing trends in cutting vibration. If the predicted value is better than the desired surface roughness (R_a^{D})($R_a^{\mathrm{P}} < R_a^{\mathrm{D}}$), the turning process will continue. If it is worse ($R_a^{P} > R_a^{\mathrm{D}}$), the detected surface roughness difference ΔR_a will trigger the INNAPC subsystem to function.

$$\Delta R_a = R_a^{\mathrm{P}} - R_a^{\mathrm{D}}. \tag{5}$$

As feed rate is the most significant cutting parameter influencing surface roughness, which is also confirmed in the first stage of this research, the adaptive degree of feed rate change (ΔFr) is selected to be the output of the INNAPC subsystem.

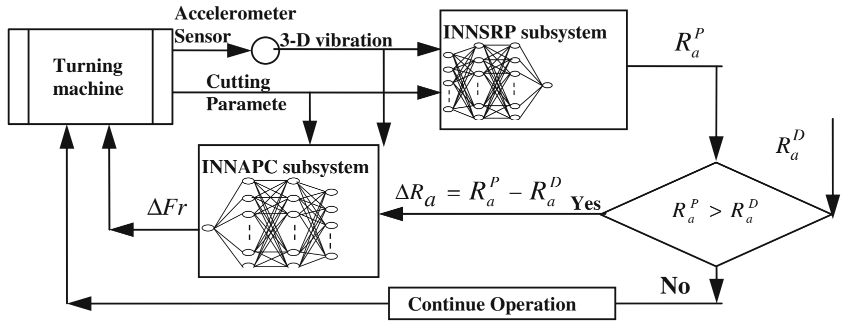

Fig. 3 The structure of the INNSAC system

Methodology

This section describes the experimental setup and design for the proposed INNSAC system. The procedure employed to build the system is also included.

Experimental setup and design

The experimental hardware setup shown in Fig. 4 includes a Storm CNC lathe (Fanuc Series 21i-T), a VNE Versa Turning insert (VNE Corp.), a workpiece (6061 aluminum $\Phi 1.5'' \times 2.25''$), a 3-axis accelerometer sensor (PCB Piezotronics, Inc.), a battery power supply, PCB amplifiers, a DBK11A Screw Terminal Expansion Card (IOtech, Inc), a DaqBook 100 data acquisition system (IOtech, Inc), an A/D board for converting data from analog to digital and a PC for saving data. A stylus profiler (Federal PocketSurf) is used for measuring roughness offline. The surface roughness is measured four times at different spots around the turned surface, and the average value is taken as the surface roughness.

The software in this system consists of the following components:

1. An NC program that directs the CNC turning machine to cut the workpiece.
2. DaqView 11.8 (IOtech, Inc.), which records vibration signals detected by the 3D accelerometer sensor. This software is a Windows-based data acquisition program that can be automatically trigged. It produces a data output file compatible with Microsoft Excel. The simultaneously acquired data can be displayed in real time.
3. JMP (SAS Institute) statistical program for correlation analysis between surface roughness and the explanatory variables.
4. Microsoft Excel, which prepares the data for training the neural network model.
5. PCN Neural network training software package.

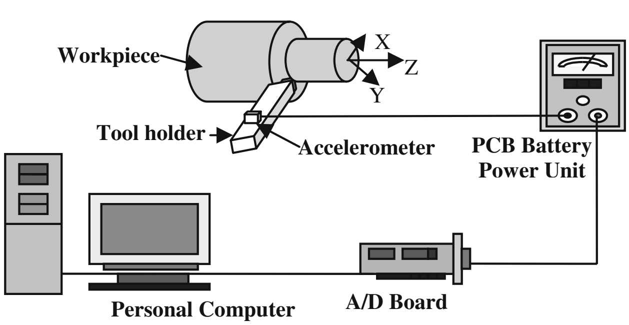

Fig. 4 Experimental setup for the MRISAC system

Design of experiment

A full factorial design is used in the experimental design listed in Table 1. Spindle speed, feed rate and depth of cut (full cutting parameters) are the experimental factors. Spindle speed is set at three levels (2,500, 3,000, and 3,500 revolutions per minute (RPM)), feed rate at eight levels (0.002, 0.0034, 0.0048, 0.0062, 0.0076, 0.009, 0.0104, and 0.0118 in per revolution (IPR)), and depth of cut at three levels (0.006, 0.012, and 0.018 in). The turning parameters are determined by recommendations of machinist's literature (Oberg, Jones, Horton, & Ryffel, 1996), the cutting tool manufacturer (VNE Corp., 1999), and previous experience with this machine. The feed rate and depth of cut are selected from the range of parameters for finish turning (Harig, 1978). The spindle speeds, while slightly lower than those normally used for turning aluminum workpieces (Harig, 1978), are chosen for safety reasons, due to the limitations of the machine being used. Each experimental combination is conducted twice. A total of 144 raw data sets were collected in the experiment. One turning insert is used throughout the experiment to restrict variation created by different tools. The cutting sequence of samples was randomized in order to eliminate the systematic bias incurred by tool wear conditions on surface roughness.

Development of the INNSRP subsystem

This section describes how the vibration is selected as an input to the INNSRP subsystem, how the data set is prepared, how the INNSRP subsystem is trained, and how this subsystem is tested.

Table 1 Design of experiment

	SP(rpm)	2,500			3,000			3,500		
Fr(IPR)	DC(in)	.006	.012	.018	.006	.012	.018	.006	.012	.018
.002										
.0034										
.0048										
.0062										
.0076										
.009										
.0104										
.0118										

Table 2 Pearson correlation analysis of cutting parameters with the response

Variable	Pearson correlation coefficient*	
SP	−0.0213	
Fr	0.9516	**
DC	−0.0010	
Vx	0.7637	**
Vy	0.7369	**
Vz	0.8488	**

*Response = R_a
**Significantly different from 0, with $\alpha = 0.01$

Table 3 Comparison of the neural network structure

Structure	RMS error for training
4-10-10-1	0.03440
4-9-9-1	0.03663
4-8-8-1	0.03525
4-7-7-1	0.03642
4-6-6-1	0.03530
4-9-8-1	0.03646
4-8-9-1	0.03562
4-8-7-1	0.1858
4-7-8-1	0.03616

Determine the input variables in the vibration signals

The output of this subsystem is the predicted surface roughness. Besides the cutting parameters such as spindle speed, depth of cut, and feed rate, the inputs of this subsystem also include significant vibration signals. As shown in Table 2, all the vibration signals have significant correlation coefficients. An informal analysis of the trends in the data also indicated that depth of cut and spindle speed affect vibration in all three directions. To avoid multi-linearity, only the vibration with the highest correlation coefficient, Vz, is selected as an input. In summary, the training data including feed rate, spindle speed, depth of cut, and vibration in the Z direction, expressed as:

$$[Fr_i, SP_i, DC_i, Vz_i; Ra_i], \qquad \text{for } i = 1 \text{ to } 144.$$

Scale the training data set

Some pre-processing procedures are needed to obtain good training and prediction results. In this process, all the input and output values are scaled within the interval of [0, 1]. In this study, the simple linear mapping method is applied and expressed as:

$$U' = \frac{U - U_{\min}}{U_{\max} - U_{\min}}, \tag{6}$$

where U' is the scaled value, $U_{\max}$ and $U_{\min}$ are the maximum and minimum value of each factor. For example, the data set of [3.4, 2500, 0.06, 0.2826, 33.50] can be scaled as [0.143, 0, 0, 0.0788, 0.1637].

Train the INNSRP subsystem model

The neural networks model for the surface roughness prediction subsystem was trained following the training procedure as described in Section "Artificial neural network system". In the training process, the "trial-and-error" method is employed to determine the number of hidden layers, the neurons in each hidden layer, the learning rate, and the momentum factor in the neural networks model. A few neural networks structures with varied numbers of hidden neurons are compared (listed in Table 3) and the structure of 4-8-8-1 that creates the least RMS errors is selected as the INNSRP subsystem model. By following the same procedure, the learning rate is set as 1 and the momentum factor is set as 0.5. As a result, the architecture of the INNSRP subsystem is specified as 4-8-8-1, as shown in Fig. 5.

After the training procedure, the weights between each neuron and the bias of each neuron were obtained and listed in Appendix 1. This neural networks model can be used for predicting surface roughness in real time.

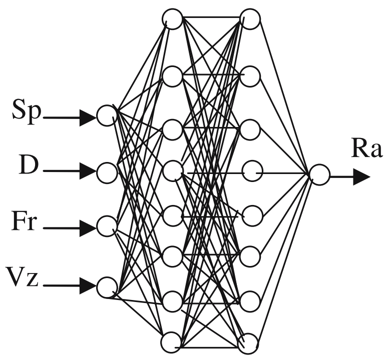

Fig. 5 Architecture of INNSRP subsystem

Test the INNSRP subsystem

After establishing the surface roughness prediction model, an additional 24 samples are produced to test the performance of the INNSRP subsystem. The model's accuracy is defined by the average accuracy of the tested samples (A_{Ra}) as:

$$A_{Ra} = \left[1 - \frac{1}{n} \sum_{i=1}^{n} \frac{\left| R_{a,i}^{\mathrm{P}} - R_{a,i} \right|}{R_{a,i}} \right] \times 100\% \quad (7)$$

where A_{Ra} is the average accuracy of surface roughness prediction; R_a^{P} is the predicted surface roughness by the INNRSP subsystem;R_a is the actual surface roughness (as measured by the profilometer), and n is the number of testing samples.

All the cutting conditions were set within the experimental range, but they differed from those in the experimental runs. The testing results are displayed in Table 4. The average prediction accuracy is 92.42%, with a 0.22% standard deviation.

Development of the INNAPC subsystem

Although the INNSRP subsystem is able to predict surface roughness (R_a^{P}) when finishing turning is in-process, this subsystem alone cannot provide a corrective function when R_a^{P} is worse than R_a^{D}. In order for the CNC machine to be able to detect defects and further adjust the cutting conditions to prevent defects, an adaptive control strategy must be in place. The INNAPC subsystem is designed to generate an adaptive feed rate change while the finishing turning is in-process if the surface roughness is larger than the desired surface precision. In other words, if $R_a^{\mathrm{P}} > R_a^{\mathrm{D}}$, then the INNAPC subsystem will perform its function by:

$$\Delta Fr = f(\Delta Ra, SP, FR, DC, Vz). \quad (8)$$

This equation shows that the output of the INNAPC subsystem is the adaptive degree of feed rate change and inputs include spindle speed, depth of cut, feed rate, vibration signals in the Z direction, and the recognized surface roughness difference. When training the model, similar training procedures to those applied in the INNSRP subsystem are employed. Since ΔFr and ΔRa cannot be obtained directly from the experiment, the desired training data must be prepared as follows:

Step 1: Organize the raw data to form subgroups.

In the experiment, 72 cutting combinations are conducted twice. One of the combinations is used for training the INNAPC subsystem. As the goal of the INNAPC subsystem is to generate the adaptive degree of feed rate change, the selected 72 combinations are reorganized in such a way that within each subgroup, data sets have the same spindle speed and depth of cut, but different feed rates. In this way, a total of nine subgroups are formed as 2,500 rpm × 0.06 in..., 3500 rpm × 0.018 in, with each subgroup containing eight data sets. The elements of each data set are feed rate, spindle speed, depth of cut, vibration in the Z direction and actually measured surface roughness. Using the scaled data, one of the subgroups is listed in Table 5.

Step 2: Obtain ΔR_a and ΔFr.

Within each subgroup, every two samples are compared to generate the surface roughness difference (ΔR_a), and the corresponding response variable of the adaptive feed rate change (ΔFr). Between the two-sample combination, the larger, actual Ra is assumed as the predicted surface roughness from the INNSRP subsystem and the smaller value is assumed as the desired surface specification (R_a^{D}). For example, compare sample 1 and sample 2. Sample 2 has the greater actual surface roughness (0.1525), which is used as R_a^{P}, while sample 1 has the smaller value (0.0605), which is used as R_a^{D}. Thus, ΔR_a is obtained as 0.092 by plugging the identified R_a^D and R_a^P values into Eq. (5). At the same time, ΔFr is obtained by:

$$\Delta Fr = Fr^{\mathrm{P}} - Fr^{\mathrm{D}}, \quad (9)$$

where Fr^{P} and Fr^{D} are the feed rate settings corresponding to the R_a^{P} and R_a^{D} selected above, respectively. In the example above, Fr^{P} is 0.143 and R_a^{D} is 0.000. Therefore, ΔFr is generated as 0.143. The full data set is listed as Table 6.

According to this strategy, each subgroup generates $C_2^8 = 28$ data sets and a total of 252 ($9 \times C_2^8$) data sets for training the INNAPC subsystem. Due to natural variability, four out of the 252 data sets show a predicted surface roughness that is less than the actual surface roughness. Therefore, 248 data sets are employed to construct the INNAPC subsystem.

After the training data are prepared, a similar method to the one stated in Section "Train the INNSRP subsystem model" is employed to train the INNAPC subsystem. By going through this trial-and-error procedure, the 5-5-5-1 neural networks is identified as the INNAPC subsystem model, shown in Fig. 6. The learning rate is set as 0.95 and the momentum factor is set as 0.5, respectively. The weight and

Table 4 Testing results for the INNSRP subsystem

Testing #	Feed (in/min)	Speed (rpm)	Depth of cut (in)	Vz (mV)	R_a	R_a^{P}	A_{Ra}
1	4	2750	0.009	0.3784	29.00	25.68	88.56%
2	4	2750	0.015	0.3934	29.25	25.65	87.7%
3	4	3250	0.009	0.4219	22.00	24.61	88.13%
4	4	3250	0.015	0.4292	22.50	24.63	90.54%
5	7	2750	0.009	0.6136	43.25	46.29	92.97%
6	7	2750	0.015	0.6541	52.25	46.21	88.45%
7	7	3250	0.009	0.6467	49.25	44.29	89.93%
8	7	3250	0.015	0.7423	48.00	44.41	92.54%
9	9	2750	0.009	0.6850	78.75	76.44	97.06%
10	9	2750	0.015	0.8331	75.75	76.23	99.36%
11	9	3250	0.009	0.8299	77.00	78.36	98.24%
12	9	3250	0.015	0.9040	78.25	74.99	95.84%
13	4	2750	0.009	0.4056	31.25	26.04	83.32%
14	4	2750	0.015	0.4276	24.75	26.09	94.61%
15	4	3250	0.009	0.4437	28.25	24.86	87.99%
16	4	3250	0.015	0.4384	21.25	24.74	83.58%
17	7	2750	0.009	0.6656	43.25	48.01	89.00%
18	7	2750	0.015	0.6578	42.75	46.32	91.65%
19	7	3250	0.009	0.6731	47.00	45.15	96.06%
20	7	3250	0.015	0.7620	46.00	45.02	97.89%
21	9	2750	0.009	0.7430	77.50	79.14	97.89%
22	9	2750	0.015	0.8699	83.75	77.85	92.96%
23	9	3250	0.009	0.8159	74.00	77.68	95.02%
24	9	3250	0.015	0.9250	75.00	75.95	98.73%

Table 5 Data sets of the subgroup #1

Fr	SP	DC	Vz	Ra
0.000	0.000	0.000	0.0000	0.0605
0.143	0.000	0.000	0.1044	0.1525
0.286	0.000	0.000	0.1959	0.0852
0.429	0.000	0.000	0.2702	0.1480
0.571	0.000	0.000	0.3048	0.3341
0.714	0.000	0.000	0.4173	0.4910
0.857	0.000	0.000	0.5487	0.7422
1.000	0.000	0.000	0.6031	0.9552

Table 6 Sample of the INNAPC subsystem data set

Fr	SP	DC	Vz	ΔRa	ΔFr
0.143	0.000	0.000	0.1044	0.0919	0.143

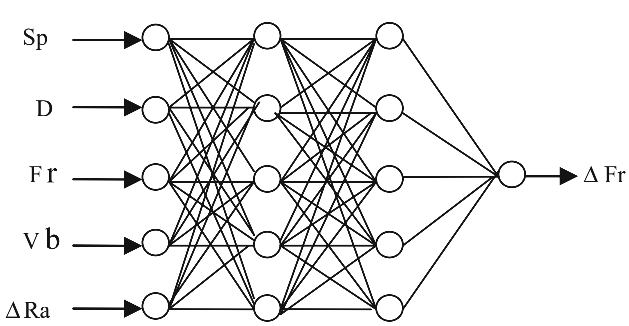

Fig. 6 Structure of INNAPC subsystem

bias of each neuron are listed in Appendix 2. So, the INNAPC subsystem model can be used for predicting feed rate change.

Integration and testing of the INNSAC system

After the INNSRP and INNAPC subsystems are established, the INNSAC system can be established through the integration of the two subsystems, as shown in Fig. 7. These two subsystems are connected by the triggering variable of the INNAPC subsystem, surface roughness difference (ΔRa).

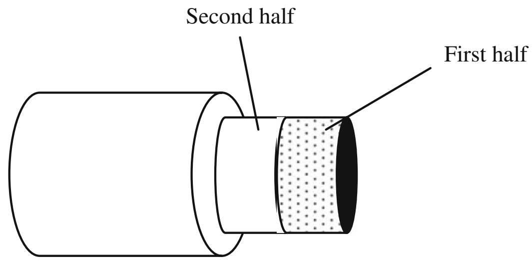

Fig. 7 Testing workpiece

This system enables the CNC turning machine to adjust the feed rate when detecting surface roughness error while turning is in-process.

When testing the INNSAC system, the same hardware setup is used, except for a brand new tool insert. The software setup consists of a NC program and the INNSAC system, which can predict the surface roughness and the adaptive degree of feed rate change when the predicted surface roughness is worse than the required quality. First, half of the total length of the cut on workpiece is turned. Within this half-length cutting, the INNSAC system is activated. Based on the cutting parameters and the Z vibration, the INNSAC predicts the surface roughness (R_a^{P}). Then, according to the surface roughness requirement (R_a^{D}), the INNSAC system generates the adaptive feed rate change, ΔFr. The feed rate in the NC program is updated by typing in this feed rate change. The second half of the workpiece is cut under the new feed rate conditions. After the entire workpiece is turned, the surface roughness in the second half of the piece is measured in order to determine if the surface quality is equal to or better than the surface requirement. In all, 15 testing samples were carried out. The testing results are listed in Table 7.

Once the system is developed, testing runs are conducted to examine whether the proposed system is able to adaptively control surface roughness while the finish turning is in process. First, the testing workpiece is turned for the first half of the cut and its roughness is measured (R_a). The INNSRP subsystem then provides a predicted surface roughness based on the cutting conditions and sensed vibration signals. According to the surface roughness requirement, the INNAPC subsystem will generate the adaptive feed rate change ΔFr. By using ΔFr, cutting parameters are reset and the remaining half of the workpiece is cut. Its surface roughness is then measured to see if it meets the requirement. The overall success rate is then evaluated by the percentage of successful tests out of the total number of test runs. Testing only has been done in the specified turning center in this study. Surface roughness potentially can be impacted by multiple variables that are not considered in the ANN models developed in this study, and different types of equipment may have different characteristics affecting surface roughness; however, the ANN training approach used in study can be applied for other CNC turning machines to adaptively control surface roughness quality.

Conclusions and recommendations for future study

This research integrated an accelerometer sensor and the BP neural networks in order to develop an ISRAC system. A few conclusions can be drawn from this study:

1. The vibration signal detected by the accelerometer employed in the proposed system was a good indicator of surface roughness. This result is consistent with the

Table 7 Testing runs of the INNSRAC system

#	Machine setting			Vz (mV)	$R_a^{\mathrm{P}}(\mu\mathrm{in})$	$R_a^{\mathrm{D}}(\mu\mathrm{in})$	Trigger ΔFr	ΔRa	ΔFr	New Fr	New R_a^{M}	Success ($R_a^{\mathrm{M}} \le R_a^{\mathrm{D}}$)
	Fr (IPR)	SP (rpm)	DC (in)									
1	7.5	3200	0.007	1.0851	49.1	32	Yes	17.1	3.1	4.4	19	Yes
2	10.9	3300	0.007	1.1930	116.2	63	Yes	53.2	3.8	7.1	46	Yes
3	8.5	3200	0.008	1.0589	80.3	32	Yes	48.3	4.7	3.8	21	Yes
4	8.3	3200	0.011	1.1326	71.6	32	Yes	39.6	4.4	3.9	20	Yes
5	8.8	2700	0.014	0.9304	796.8	25	Yes	51.8	5.3	3.5	17	Yes
6	9.8	2900	0.007	0.9901	100.1	63	Yes	37.1	3.7	6.0	32	Yes
7	8.8	2500	0.007	0.7462	78.6	25	Yes	53.6	5.4	3.4	18	Yes
8	11.3	3300	0.008	1.2611	119.5	63	Yes	56.5	3.7	7.6	53	Yes
9	9.7	3000	0.011	1.0876	96.8	32	Yes	64.8	5.3	4.4	20	Yes
10	10.3	2500	0.014	0.8971	103.0	30	Yes	73.0	6.3	4.0	30	Yes
11	11.5	2600	0.006	0.8221	119.3	80	Yes	39.3	3.5	8.0	57	Yes
12	12	3200	0.006	1.1717	122.9	80	Yes	42.9	3.3	8.6	77	Yes
13	10.8	2800	0.01	0.9550	112.3	50	Yes	62.3	4.5	6.3	37	Yes
14	8.3	2900	0.01	1.0088	71.2	32	Yes	39.2	4.4	3.8	20	Yes
15	8.6	3200	0.009	1.1455	78.5	40	Yes	38.5	4.1	4.5	25	Yes

conclusions proposed by Jang et al. 1996 and Risbood et al. (2003).

2. The data analysis in this study confirmed again that feed rate is the most significant factor impacting the surface quality of turned products.
3. The proposed neural networks-based ISRAC system predicted surface roughness at an average accuracy of 92.42% and adapted feed rate with a 100% success rate in order to control surface roughness to meet customer requirements in real cutting processes. Testing results suggested that the BP-ANN was effective in modeling the decision-making mechanism of adaptive control.
4. The cutting parameters in the testing stage were randomly set but different from the original experimental design and the desired surface roughness was set following industrial norms. The success of being able to perform in-process adaptive surface roughness control indicated that the proposed system was flexible enough to meet cutting conditions in industry settings.

Indeed, the proposed INNSAC system was successful in controlling surface roughness in real time by suggesting an adapted feed rate, when the predicted value was recognized as worse than the desired value. This research found 15 testing samples in which adapting the feed rate resulted in actual surface roughness values that were generally far less than the desired values. This variation might lead to further research in identifying the cause of surface roughness and even optimizing the current algorithm to ensure surface roughness quality while maintaining productivity.

In this study, tool wear conditions were controlled using a brand new tool and randomizing the cutting sequence. However, tool wear situation is a very important factor related to surface quality. Future study is therefore also necessary to develop a model that includes cutting tool conditions. After the decision-making algorithm is fully enhanced in future studies, it will be possible to develop a controller that integrates the INNSRAC system with the CNC machine controller in order to fulfill the proposed in-process surface roughness adaptive control ISRAC system on the actual manufacturing floor.

Appendix

Appendix 1 The weights and biases between each neuron for INNSRP subsystem

		Inputs								
		Fr	SP	DC	Vz	θ				
Hidden layer 1	1	1.2920	−0.3775	0.2046	0.4539	0.6382				
	2	3.4620	0.0381	−0.3931	0.5650	3.6520				
	3	1.4500	−0.3090	−0.0791	0.7578	0.8803				
	4	0.1497	−0.3999	0.0061	0.7299	−0.3441				
	5	2.6880	−0.3150	−0.1711	0.3993	2.7180				
	6	1.9600	0.1378	−0.0169	0.2103	1.6030				
	7	2.5160	−0.1563	0.0782	0.1366	2.3600				
	8	1.3650	−0.3786	0.1032	0.4553	0.8158				
		Hidden layer 1								
		1	2	3	4	5	6	7	8	θ
Hidden layer 2	1	−0.8112	−1.0790	−0.8288	0.0356	−1.2180	−0.3911	−0.6464	−0.6896	0.1692
	2	0.0616	−3.2680	−0.1426	1.3900	−2.1640	−1.0380	−1.9470	−0.2820	−3.4710
	3	−0.3524	−0.8167	−0.7157	−0.2989	−0.9251	−0.4064	−0.7213	−0.5057	0.8289
	4	−0.3471	−1.0590	−0.8589	−0.2946	−0.7406	−0.4555	−0.7276	−0.7765	0.5105
	5	−0.4411	−1.6870	−0.3058	−0.1779	−1.2800	−0.7065	−0.8606	−0.1822	−0.2844
	6	0.4709	1.0200	0.2777	0.1963	0.4842	0.8366	0.8906	0.3247	−0.0023
	7	−0.3102	−1.4540	−0.6583	−0.4624	−1.1410	−0.6398	−0.8317	−0.3083	−0.1030
	8	−0.5043	−1.2530	−0.8789	−0.0342	−0.6925	−0.6436	−1.0360	−0.2812	0.4287
		Hidden layer 2								
		1	2	3	4	5	6	7	8	θ
Output		−1.1720	−4.4400	−0.5170	−0.7734	−1.7340	4.9440	−1.4160	−1.0960	0.0007

Appendix 2 Weights and biases between each neuron for INNPAC subsystem

		Inputs					
		FR	SP	DC	Vz	ΔRa	θ
Hidden layer 1	1	2.7990	0.0413	−0.3940	2.9080	3.4730	1.1980
	2	0.9100	−0.2643	0.4126	0.3180	−0.2643	0.1951
	3	−3.5080	0.8376	0.4242	−0.5218	4.2210	1.4670
	4	−2.4610	0.1229	−0.1218	−0.2537	3.1400	0.9758
	5	2.1880	1.0360	−0.1854	0.2653	−2.1980	0.0850
		Hidden layer 1					
		1	2	3	4	5	θ
Hidden layer 2	1	−1.1510	−0.0156	−1.5110	−1.6290	1.1560	0.0852
	2	−2.2800	1.5600	−3.6200	−2.3950	3.0290	−1.0410
	3	−1.3120	0.4256	−1.7500	−1.4250	1.4150	0.0209
	4	−1.3730	0.3305	−1.9530	−1.6730	1.6730	−0.4546
	5	2.1930	0.0401	1.1240	0.7169	−0.4006	−0.1629
		Hidden layer 2					
		1	2	3	4	5	θ
		−1.5990	−4.1410	−1.8200	−2.1260	5.7470	−0.0006

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