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Full Length Research Paper

On-line surface roughness recognition system by vibration monitoring in CNC turning using adaptive neuro-fuzzy inference system (ANFIS)

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This study presents a new method for modeling an adaptive neuro-fuzzy inference system (ANFIS) based on vibration for predicting surface roughness in the CNC turning process. The input parameters of the model are insert nose radius, cutting speed, feed rate, depth of cut and vibration amplitude, which determine the output parameter of the surface roughness. A Gauss type membership function was used to train on ANFIS. The predicted values derived from ANFIS were compared with experimental data. The obtained prediction accuracy of 97.52% demonstrates that the developed system's improved performance over other models available in the literature. The resulting ANFIS model based on vibration efficiently uses the fuzzy inference system for predicting surface roughness in turning of AISI 1040 steel.

Key words: Adaptive neuro-fuzzy inference system (ANFIS), CNC turning, surface roughness, prediction model.

INTRODUCTION

Surface roughness is important due to increased consumer demands for quality, less costly products, minimum friction, maximum lubrication, and minimum wear. It is a characteristic that could influence the performance of mechanical parts and the production costs.

Modeling of surface roughness is difficult because it is affected by different variables. On the other hand, fuzzy logic inference system (FLIS) is an effective technique for the identification and control of complex non-linear systems. fuzzy logic is particularly attractive due to its ability to solve problems in the absence of accurate mathematical models. Thus, these techniques appear to be suitable for modeling and simulating the complex and highly time-variable turning process. Recently, many surface roughness modeling, simulation and optimization systems were designed using different cutting parameters and methods.

Dejparvar and Akbari (2008) argued that surface roughness is not only an indication of metal quality but also an important factor impacting machining efficiency and cost. Cutting parameters, tool geometry, built-up edge, workpiece material, chatter, and cutting fluids etc. are among the parameters that affect surface roughness.

Abbreviations: FLIS, Fuzzy logic inference system; **ANFIS,** adaptive neuro-fuzzy inference system; **PEEK,** polyether ether ketone; **PCD,** Poly-Crystalline Diamond; **ANN,** artificial neural network; **MANFIS,** multi adaptive Network based fuzzy inference system; **RSM,** response surface methodology; **SVR,** support vector regression; **MF,** membership function.

A robust and reliable model depends on identifying the parameters as well as their weights on the surface roughness (Lela et al., 2009).

The effect of the length and diameter of working piece, cutting depth and feed were also investigated by Ay and Turhan (2011). They ignored cutting speed, which is an important machining parameter, which was kept constant in this study. Taguchi method was used to obtain more reliable and optimum results. The regression analysis was used to model relation between the dependent and independent variables modelled by. They explained that cutting force, surface roughness, cylindricity and vibration were minimised in machining process and production quality was improved.

Palanikumar (2010) carried out to model the delamination factor and surface roughness in machining of GFRP composites through response surface methodology. Three-factor five-level central composite design was employed in his study. The results of analysis of variance indicated that the developed models were adequate at 95% confidence level within the limits of factors being considered.

The cutting force model was proposed to predict the tool wear and surface roughness in end milling by Sarhan and El-Zahry (2011). By comparing the simulated and measured cutting force at different values of surface roughness, the maximum deviation was found to be less than 9.6%.

El-Hossainy (2010) aimed to enhance the surface finish quality by investigating a new method depending on the pattern left by the cutting tool. His technique improved surface roughness, straightness error, and roundness error by more than 50, 51, and 42%, respectively, at the proposed cutting condition for all used workpiece materials.

Mata et al. (2009) proposed regression model for the different roughness parameters characterizing machining of PEEK (Polyether Ether Ketone) composites when using PCD (Poly-Crystalline Diamond) and K10 tools. Experimental and regression model results have revealed that feed is the main cutting factor that influences surface roughness. Kohli and Dixit (2004) used speed, feed rate, depth of cut, and tool holder as inputs for an Artificial Neural Network (ANN) and predicted surface roughness with an accuracy of 74.3%. Gupta (2010) undertook a study to calculate surface roughness, tool wear and the required power depending on cutting speed, feed rate and cutting time. The obtained data was used to develop models using Response Surface Methodology (RSM), ANN and Support Vector Regression (SVR) methods. The results showed that ANN and SVR models yielded higher accuracy than the RSM model.

Reddy et al. (2009) developed the surface roughness prediction model for machining of aluminum alloys, using ANFIS. The experimental validation runs were conducted for validating the model. To judge the accuracy and ability of the model percentage deviation, an average percentage deviation had been used. The RSM was also applied to model the same data. Comparison of results showed that the ANFIS results were superior to the RSM results.

Suhail et al. (2011) proposed a method for cutting parameters identification using multi adaptive network based fuzzy inference system (MANFIS). They identified the initial values for the cutting parameters (cutting speed, feed rate, and depth of cut) using surface roughness as a single input. These parameters were modified and verified using another set of ANFIS models. Then, workpiece surface temperature was used as input for another set of ANFIS models to amend the final values of the cutting parameters. The test results showed that the proposed MANFIS model can be used successfully for machinability data selection.

A machine vision-based non-contact measurement of surface roughness of turned AISI 1045 steel workpiece was proposed by Shome et al. (2009). They developed ANFIS models, each of which utilizes a particular combination of image features for accomplishing non-contact prediction of surface roughness. Modeling and prediction of surface roughness of a workpiece by a computer vision in turning operations plays an important role in the manufacturing industry. Ho et al. (2002) proposed a method using an ANFIS to accurately establish the relationship between the features of surface image and the actual surface roughness. The proposed ANFIS-based method outperformed the existing polynomial network-based method in terms of modeling and prediction accuracy. The experimental results show that the optimal prediction error of the presented system is 4.06%.

Roy (2007) presented a method using an ANFIS to establish the relationship between cutting parameters and surface roughness in turning, and consequently to predict surface roughness of the work piece using input cutting parameters, namely cutting speed, feed rate and depth of cut. The comparison indicated that, the bell-shaped membership function (MF) in ANFIS achieves slightly higher prediction accuracy than other MF.

In the literature, researchers have measured sound emission, vibration signals, or electric current for monitoring. Unfortunately, these were not used for studies for modeling surface roughness. For this reason, our methodology was developed and is based on the monitoring of the vibration signals and their correlation between surface roughness.

The objectives of this work are as follows: Firstly, to

Table 1. Levels of the variables.

Parameter	Level 1	Level 2	Level 3
Cutting speed (m/min)	150	219	320
Feed rate (mm/rev)	0.12	0.2	0.35
Depth of cut (mm)	1	2	4
Nose radius of tool (mm)	0.4	0.8	1.2

develop a model for real time prediction of surface roughness using vibration in the turning process. Secondly, to conduct real time monitoring and process control via the accelerate sensor.

MODELING OF SURFACE ROUGHNESS

Based on the ISO 4287 norm, average surface roughness, *Ra*, can be defined as the arithmetical mean of the deviations of the roughness profile from the central line, *lm*, along the measurement (Stephenson and Agapiou, 2005; Nalbant et al., 2007; Sahin and Motorcu, 2002). This definition is given in Equation 1.

$$R_a = \frac{1}{L}\int_0^L |y(x)|dx \tag{1}$$

Where, *L* is the sampling length of the profile, and *y* is the coordinate of the profile curve. The relationship between surface roughness and cutting parameters can be defined in Equation 2:

$$R_a = C.V^n.f^m.d^p.D^l.a^s{}_z.\varepsilon \tag{2}$$

where, *Ra* is the arithmetic average surface roughness (µm). and *V*, *f*, a_p, *D and* a_z are the cutting speed (m/min), feed rate (mm/rev.), depth of cut (mm), tool nose radius (mm) and vibration amplitude (mV/g), respectively. *C*, *n*, *m*, *p, s and l* are constants, and ε is a random error. In order to distinguish constants and parameters in the equation, Equation 1 is expressed as in Equations 3 and 4. The surface roughness of turned surfaces defined by *Ra* and *Rt* can be computed as follows (Nalbant et al., 2007; Sahin and Motorcu, 2002; Asilturk and Unuvar, 2009):

$$R_a \approx \frac{f^2}{32.r} \tag{3}$$

$$R_t \approx \frac{f^2}{8.r}$$

Equations 3 and 4 show that while surface roughness proportionally increases with the feed rate, a large tool nose radius reduces the surface roughness of a turned workpiece. Imperfections caused by tool vibration and chip adhesion are not considered in this model.

EXPERIMENTAL SETUP AND PROCEDURE

An AISI 1040 working specimen was selected in this study because it is the most widely used work piece material in the industry. The specimen with a diameter and length of 100 and 500 mm, respectively, was hardened at 880°C and then normalized at 350°C to bring its hardness to 35 HRC.

Machining experiments were carried out on a Moriseiki NL2500MC/700 lathe. The cutting tool (MWLNR 25X25) which was used to carry out the cutting tests, this is a commercial product available from the Iscar Company. Carbide inserts with product number Tips WNMG 0804-04-08-12 TF MTCVD TiCN and a thick alpha Al_2O_3 CVD coating were used. Cutting parameters, that is, cutting speed, cutting depth, nose radius, and feed rate, were suggested by the cutting tool supplier and finally selected, as shown in Table 1. Three different levels were considered for each of the four parameters and a total of 81 experimental runs were carried out, one for each possible combination of parameter values.

The vibration signals were acquired using a Kistler 8692C50 sensor, which was mounted on the grinding wheel axis. (Acceleration range ±50 g, sensitivity 100 mV/g, frequency response ±5%). The sensor was connected to a Kistler (type 5134B) coupler, which provides a DC power and a signal processing with adjustable gains and cut-off frequencies. A data acquisition card from National Instruments (portable E Series NI DAQCard-6036E) was used. The card has a maximum acquisition rate of 200,000 samples per second and 16 channels. Software developed using Matlab 7, provided an interface to enter the constants and cutting parameters (Asilturk and Unuvar, 2009). The outputs were measured at a rate of 2500 samples/sec and their average values were recorded. A Mitotoyo (SJ-201) surface Roughness Tester was used to measure surface roughness (Ra) after each grinding operation. For each sample, three readings, 120° apart, were taken. The average is used as a measure of roughness of the surface resulting from turning. In order to eliminate the effect of tool wear, each experiment was performed with a new cutting tool. The experimental set up is shown in Figure 1.

PREDICTION OF SURFACE ROUGHNESS USING ANFIS

The field of fuzzy logic has been making great strides motivated by its practical success in modeling and control of industrial process (Chi and Teng, 2008; Parlak et al., 2006; Tinkir et al., 2010). Fuzzy systems can be used as modeling tools. Fuzzy modeling provides appropriate outputs based on real experimental data sets. Fuzzy logic models use a form of quantification of imprecise information (input fuzzy sets) to generate outputs by an inference scheme. The latter is based on a knowledge base. The advantage of this quanti-

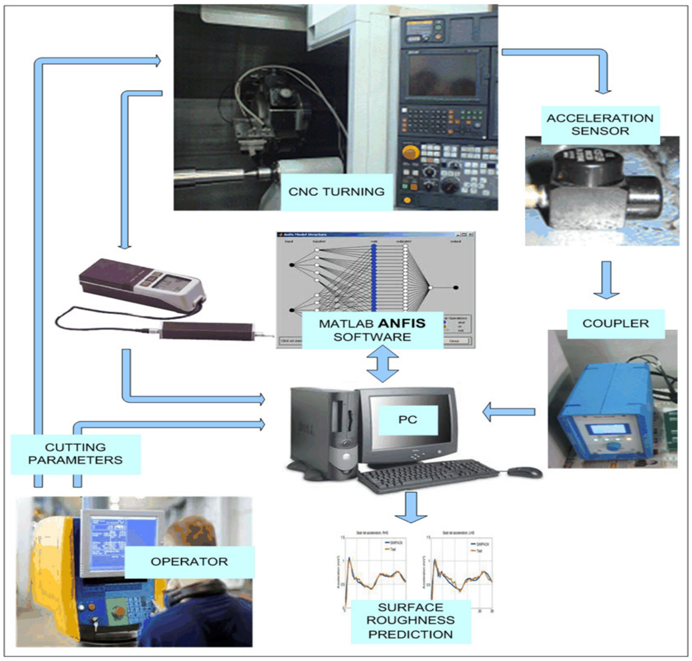

Figure 1. Experimental set-up.

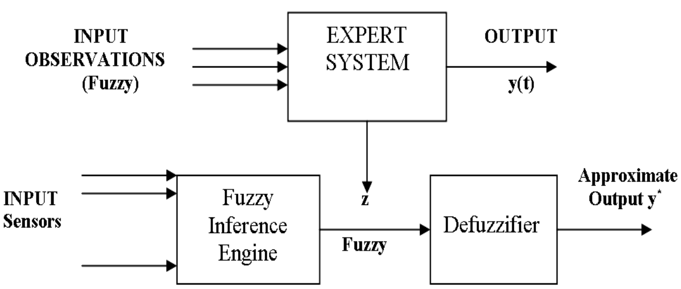

Figure 2. The basic configuration of the fuzzy system.

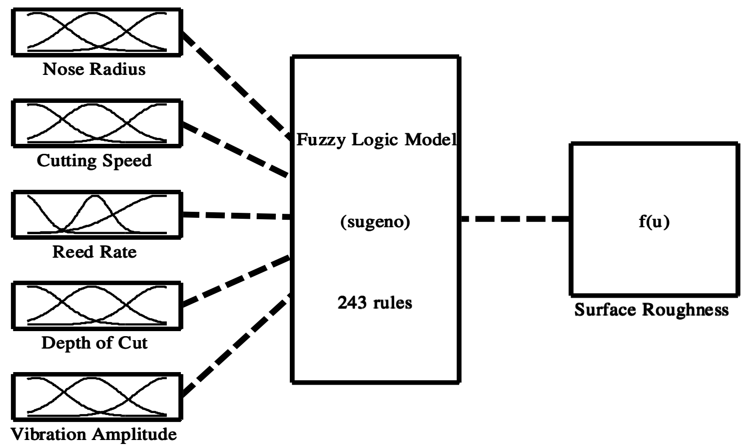

Figure 3. The structure of adaptive network based fuzzy logic model.

fication is that fuzzy sets can be represented by a unique linguistic expression, such as small, medium and large. The linguistic representation of a fuzzy set is known as a term, and a collection of such terms defines a term-set, or library of fuzzy sets. Fuzzy logic provides a means of converting a linguistic modeling strategy based on expert knowledge into an automatic control strategy.

Fuzzy logic is made of four main components: (1) Fuzzifier; (2) Knowledge base containing fuzzy IF-THEN rules and membership functions; (3) Fuzzy reasoning, and (4) Defuzzifier interface. The basic configuration of the fuzzy system which is used in this study is shown in Figure 2.

In this study, adaptive network based fuzzy inference system is used to predict the surface roughness using vibration in turning. Real data sets are obtained to create fuzzy logic model inputs and outputs. The number of inputs and outputs are determined from experiments of a turning workbench. Fuzzy logic model membership functions and rule bases are obtained based on actual Experimental data sets results. Figure 3, depicts the fuzzy logic prediction modelling workbench for turning.

In this configuration, the fuzzy logic model has five inputs (nose radius (mm), depth of cut (mm), feed rate (mm/rev), cutting speed (m/s), vibration (mV/g), and an output namely, surface roughness (µm). In this study, mean % error was used to compare experimental and prediction results.

The comparison was based on 81 test cases. The formulation of mean % error (e) is described as Equation 5 (Yu and Tang, 2010; Magaji et al., 2010):

$$e = \left[\sum_{i=1}^{m} \frac{\sum_{i=1}^{n} \left| X_{i_{Experimental}} - X_{i_{Modeling}} \right|}{\sum_{i=1}^{n} X_{i_{Modeling}}} \times 100 \right] \Big/ m \qquad (5)$$

where $X_{i_{Experimental}}$ represent the experimental outputs, $X_{i_{Modeling}}$ also represent the outputs of fuzzy logic model, n is the number of test data, and m is the number of outputs of ANFIS model. Two of the difficulties with the design of any fuzzy logic model are the shape of the membership functions and the choice of the fuzzy rules. In fact, the decision-making logic is the way in which the model output is generated. It uses the input fuzzy sets and the decision is made according to the values of the inputs. Moreover, the knowledge base consists of knowledge of application domain and the attendant modeling goals. It includes a database and a fuzzy logic model rule base. The fuzzification uses membership functions to determine the degree of inputs.

In this study, a sugeno-type inference is used to develop a fuzzy inference system. It provides efficient aggregation and defuzzification functions, which will be used to calculate the output

(Singh et al., 2001). It applies a combination of least-square methods. Three gauss type membership functions are used in fuzzification process for all inputs of the fuzzy logic model. Fuzzy logic rule base is made of 243 rules which are determined using the adaptive neural network based fuzzy inference system. ANFIS ensures an easy way to obtain optimum range of membership functions and rules which are based on experimental data. Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output.

The network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically, a large number of input/target pairs are needed to train a neural network. Neural networks have been trained to perform complex functions in various fields, including pattern recognition, identification, classification, modeling, speech, vision, and control systems.

ANFIS neural network architecture consists of five layers with output of nodes (Yu and Tang, 2010; Magaji et al., 2010), $O_{i,l}$, where *i* is the i^{th} node of layer *l*.

Layer 1: Generate the membership grades

$$O_{i,l} = \mu_{A_i}(x),\ i = 1,2 \tag{6}$$

Or

$$O_{i,l} = \mu_{B_i\,2}(y),\ i = 3,4 \tag{7}$$

where x (or y) is the input to the node and A_i (or B_{i-2}) is the fuzzy set associated with this node.

Layer 2: Generate the firing strengths by multiplying the incoming signals, and outputs the t-norm operator results, for example;

$$O_{2,i} = w_i = \mu_{Ai}(x) \times \mu_{Bi}(y),\ i = 1,2 \tag{8}$$

Layer 3: Normalize the firing strengths

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2},\ i = 1,2 \tag{9}$$

Layer 4: Calculate rule outputs based on the consequent parameters $\{p_i, q_i, r_i\}$

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \tag{10}$$

Layer 5: Compute the overall outputs as the summation of incoming signals

$$O_{5,l} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f}{\sum_i w_i} \tag{11}$$

Based on the aforementioned, the ANFIS modeling was developed. More specifically,

1. 300 training and 150 testing data was used for the ANFIS – based neural network.
2. The number and type of membership functions were determined.
3. Hybrid learning algorithm and 50 epochs was chosen to train network.

In this study, forward hybrid learning algorithm is used for the neural network part of ANFIS modeling. Nearly 50 epochs later mean errorrateis close to 10^{-2}. In the forward pass of the hybrid learning algorithm, node outputs go until layer 4 and the consequent parameters are identified by the least-squares method.

When the values of the promise parameters are fixed, the overall output can be expressed as a linear combination:

$$\begin{aligned} f &= \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \\ &= \overline{w}_1 f_1 + \overline{w}_2 f_2 \\ &= \overline{w}_1.x.p_1 + \overline{w}_1.y.q_1 + \overline{w}_1.r_1 + \overline{w}_2.x.p_2 + \overline{w}_1.y.q_2 + \overline{w}_1.r_2 \end{aligned} \tag{12}$$

The above relation is linear in terms of p_1, q_1, r_1, p_2, q_2 and r_2,

$$f = XW \tag{13}$$

If matrix X is invertible then,

$$W = X^{-1} f \tag{14}$$

Otherwise a pseudo-inverse is used to solve for W.

$$W = (X^T X)^{-1} X^T f \tag{15}$$

Due to the adaptive capability of ANFIS, its application to adaptive and learning control is natural/straightforward. The most common design techniques for ANFIS modeling are derived directly from counterpart neural network methodologies. However, certain design techniques apply exclusively to ANFIS. Once the fuzzy controller is activated, rule evaluation is performed and all the rules are true and fired. Utilizing the true output membership functions, defuzzification is then applied to determine a crisp control action. The defuzzification is to transform the fuzzy output into an exact model output. For Sugeno-style inference, we have to choose between the *wtaver* (weighted average) or *wtsum* (weighted sum) defuzzification methods. In the defuzzification process of fuzzy logic modeling, the method of weighted average (wtaver) was used, which is expressed as follows:

$$u = \frac{\sum_{i=1}^{N} w_i z_i}{\sum_{i=1}^{N} w_i} \tag{16}$$

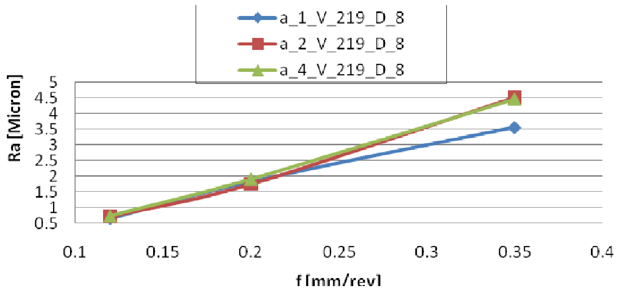

Figure 4. Effects of feed rate and depth of cut on surface roughness.

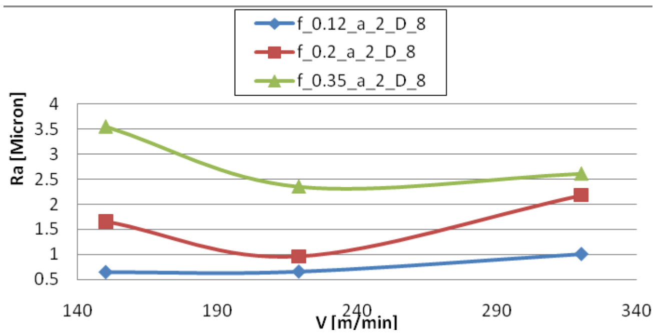

Figure 5. Effects of cutting speed and feed rate on surface roughness.

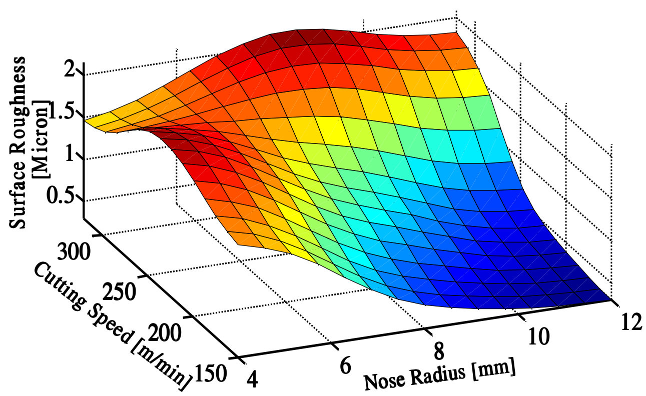

Figure 6. Effects of cutting speed and nose radius on surface roughness.

RESULTS AND DISCUSSION

Here, the results obtained from the experiments and ANFIS are shown and discussed. Figure 4 shows the effect of feed rate and depth of cut on the average roughness when the effects of cutting speed and no

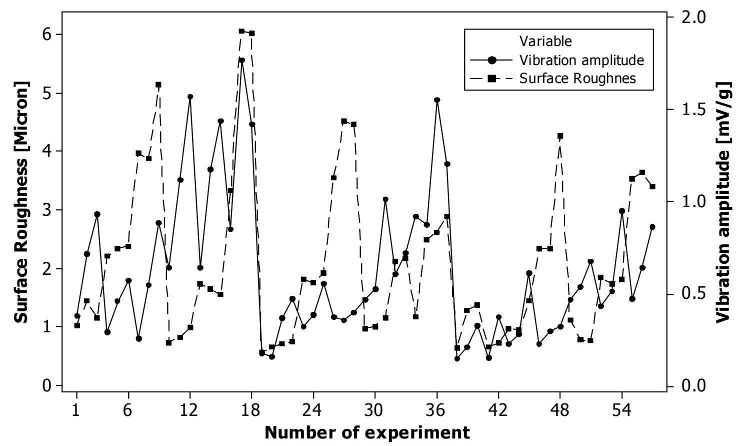

Figure 7. Time series plots of surface roughness and vibration.

radius are not considered. The results suggest that the larger the feed rate, the larger the average roughness value obtained after turning. Among the studies of the three feed rates, the feed rate of 0.12 mm/rev achieves the biggest drop in the average surface roughness value.

As shown in Figure 5, under the same feed rate and without considering the effects of the depth of cut and nose radius, the increase in cutting speed does not significantly reduce the average roughness.

As shown in Figure 6, the average roughness decreases as the nose radius increases. At the nose radius of 12 mm and the cutting speed of 219 m/min, the average roughness obtained is the lowest at around 0.95 micron (for f=0.2 mm/rev and a=2 mm).

The above analysis indicates that among the four turning process parameters discussed in this study, that is, nose radius, cutting speed, feed rate and depth of cut, changes in the feed rate have the most impact on surface roughness. These results agree with earlier literature (Nalbant et al., 2007; Sahin and Motorcu, 2002; Asilturk and Unuvar, 2009; Kuttolamadom et al., 2010; Abhang and Hameedullah, 2010; Fnides et al., 2008; Kopac and Bahor, 1999). In general, it is found that surface roughness increases with an increase in the feed rate and depth of cut and a decrease in nose radius and cutting speed. Roughness was drastically reduced up to a particular critical value of surface speed, which is attributed to the reduction in size of the built up edge (Kuttolamadom et al., 2010). With the increase in feed rate, section of chip increases and consequently friction increases as reported by Abhang and Hameedullah (2010), and Fnides et al. (2008). Surface roughness was also found to decrease with increasing cutting speed. It is known that the type of chip produced during the machining

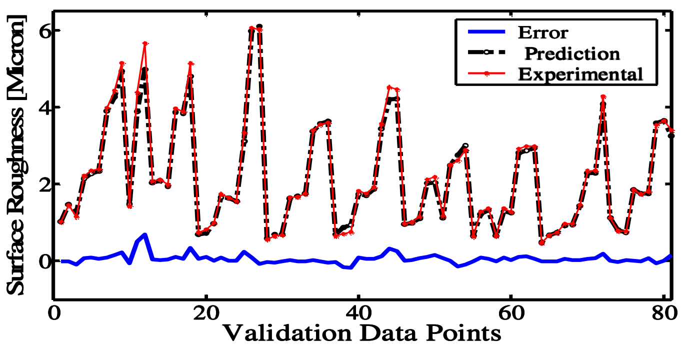

Figure 8. Comparison of the predicted and the experimental surface roughness.

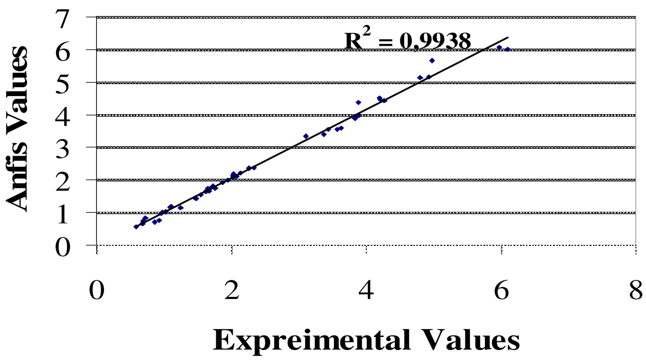

Figure 9. Scatter plot of the measured Ra and the predicted Ra of the ANFIS model for testing.

operation has a significant effect on the surface finish (Kopac and Bahor, 1999).

Figure 7 shows collected surface roughness and tool vibration data generated while turning the AISI 1040 mild carbon steel workpiece at different levels of cutting speed, feed rate, depth of cut, and nose radius. The correlation between surface roughness and vibration signals (az) revealed an efficient solution for on-line monitor of surface roughness in turning (Abouelatta and Ma, 2001).

A total of 69 sets of data were selected from the total of 81 sets obtained in the turning experiments for the purpose of training in ANFIS. The other 12 sets were then used for testing after the training was completed to verify the accuracy of the predicted values of surface roughness.

During the testing and training validation period, the mean of percentage of error for the ANFIS model for predicted parameters found 2.48 and 1.52%, respectively. The predicted values are a close match to the experimental values, as shown in Figures 8 and 9.

The error rates are considerably smaller than those of earlier studies for training and testing, as can be seen from the analysis of Figures 8 and 9. ANFIS model accurately proved capable of prediction of surface roughness. The performance results of *e* and determination coefficient (R^2) obtained using ANFIS are shown in Table 2.

Table 2. Performance indices for training and testing of ANFIS.

		e%	R^2
ANFIS	Training	1.52	0.9963
	Testing	2.48	0.9938

Conclusions

The present investigation has focused on surface roughness prediction and analysis during the turning of AISI 1040 steel using coated carbide inserts. An ANFIS predictive model based on vibration monitoring has been developed to predict surface roughness. The following conclusions can be drawn from this study:

The minimum surface roughness in this process was obtained for 35 HRC AISI 1040 workpiece by turning at D=12mm, V=219 m/min, f=0.12 mm/rev, a=1 mm, and az=0.22601 mV/g with Ra=0.47 µm.

The proposed ANFIS model produces results that parallel the experimental counterparts. The error of the surface roughness values predicted by ANFIS with the gauss type membership function is only 2.48%, reaching accuracy as high as 97.52%.

Among the four turning parameters of nose radius, cutting speed, feed rate and depth of cut, changes to the feed rate have the most significant impact on workpiece surface roughness, followed by nose radius, cutting speed and the depth of cut.

The most important difference between this experimental study and other research is the use of acceleration signals and four cutting parameters used in the model to present the effect of vibration values on surface roughness.

FUTURE REMARKS

According to our results, the fuzzy logic approach has a predictive ability, which makes fuzzy logic a powerful tool for solving complicated engineering problems. Monitoring turning is advantageous as it allows for optimizing process conditions, improving process control and producing high quality parts. In addition, these results may be further explored in other studies because they may give more information about the parallel of the vibration and surface roughness profile. Future research will focus on the feasibility of using ANFIS in a manufacturing facility to predict such characteristics as surface roughness, tool life, and wear, during the machining in terms of benefits, costs and real-time execution.

In the next study, an adaptive control system and cutting parameters optimization based on vibration signals will develop and enable the integration of the CNC turning process for desired surface roughness. Dynamic model of systems will be established using signal processing and different controllers will be tested on the experimental setup.

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