Int. J. Mech. Eng. & Rob. Res. 2015

International Journal of Mechanical Engineering and Robotics Research

ISSN 2278 – 0149 www.ijmerr.com
Vol. 4, No. 1, January 2015

Research Paper

PREDICTION OF SURFACE ROUGHNESS IN TURNING PROCESS USING SOFT COMPUTING TECHNIQUES

G J Pavan Kumar[1]* and R Lalitha Narayana[1]

*Corresponding Author: G J Pavan Kumar, pavan935932@gmail.com

Surface quality and dimensional precision will greatly affect parts during their useful life especially in cases where the components will be in direct contact with other elements during their application. This paper deals with three soft computing techniques namely Adaptive Neuro Fuzzy Inference System (ANFIS), Neural Networks (NN) and regression in predicting the surface roughness in turning process. Some of machining variables that have a major impact on the surface roughness in turning process such as spindle speed, feed rate and depth of cut were considered as inputs and surface roughness as output. The procedure is illustrated using the experimental data of turning AA6063 Aluminium alloy. Here 27 data sets were considered for training and 9 data sets were considered for testing. The predicted surface roughness values computed from ANFIS, NN and Regression are compared with experimental data.

Keywords: Turning, Surface roughness, Soft computing techniques

INTRODUCTION

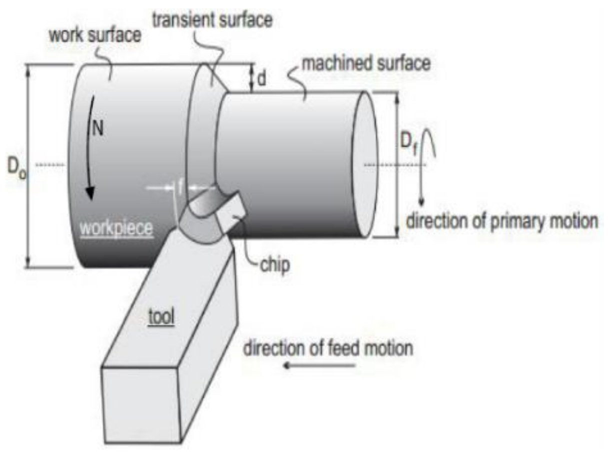
Today's competitive global manufacturing climate drives a strong demand for high-quality, low-cost products. Surface roughness is a common quality characteristic of parts produced in a machining operation, that plays a critical role in applications such as bearing surfaces, ultra clean surfaces, and sealing surfaces.

In various machining process turning processes are one of the most conventional and commonly used machining method for material removal over a cylindrical parts. Surface roughness is one of the important factors for evaluating work piece quality during the machining process as the quality of surface roughness affects the functional characteristics of the work piece such as compatibility, fatigue resistance and surface friction. The factors that affect the surface roughness during the turning process include tool geometry, feed rate, depth of cut and cutting speed.

1 Department of Mechanical Engineering, ASR College of Engineering, Tanuku, Andhra Pradesh, India.

Turning is a form of machining, a material removal process, which is used to create rotational parts by cutting away unwanted material as shown in Figure 1. The turning process requires a turning machine or lathe, work piece, fixture, and cutting tool. The work piece is a piece of pre-shaped material that is secured to the fixture, which itself is attached to the turning machine, and allowed to rotate at high speeds. The cutter is typically a single-point cutting tool that is also secured in the machine. The cutting tool feeds into the rotating work piece and cuts away material in the form of small chips to create the desire shape.

Figure 1: Schematic Illustration of Basic Turning Operation



LITERATURE REVIEW

In a highly automated cell, a prematurely worn cutting tool may produce an entire batch of defective parts. Defects may go undetected until someone either notices the increase in surface roughness or hears chatter in the process. Unfortunately, surface roughness can be difficult to notice visually, and chatter can be obscured by other noises. Monitoring surface roughness directly using measured and controlled parameters is therefore a more comprehensive way of detecting its variation.

Researchers and industry widely accept feed rate as a major factor in the surface roughness of a turned surface. The surface roughness can be predicted mathematically in an ideal turning operation, using the feed rate (Groover, 1996). While this equation does not consider spindle speed, this factor has been found to significantly affect surface roughness (Feng *et al.*, 2002). Depth of cut, on the other hand is not directly correlated to surface roughness.

Recent developments of surface roughness prediction systems have shown favorable results utilizing feed rate, speed and depth of cut (Knuefermann *et al.*, 2004; and Kohli *et al.*, 2005). Parameters such as cutting forces and vibrations were considered in predicting surface roughness in turning process (Risbood *et al.*, 2003).

Another important consideration in developing a prediction system is the modeling technique. Regression analysis is the prominent choice for this purpose and has shown considerable results (Chen *et al.*, 2003). Additionally intelligent systems such as fuzzy logics, neural networks, genetic algorithms, probabilistic reasoning and hybrids between these systems have been found to be superior to regression due to their ability to learn from experience in a complex system with number of variables such as in turning operation (Zilouchain *et al.*, 2001).

Intelligent systems have the ability to quickly incorporate new data and use it to learn itself whereas regression needs recalculation whenever new data was available (Jaio *et al.*, 2004). One type of intelligent system that has found popularity recently is a hybrid called Fuzzy-Nets (FN) also known as neuro-fuzzy systems or Fuzzy Neural Networks (FNN), FN is ideal because it combines the more efficient learning capability of neural networks and the advanced reasoning capability of fuzzy logic (Wang *et al.*, 2001). Training data in a real-world application tends to be sparse, thus limiting the ability of a neural network by itself (as well as regression, for that matter), so the inclusion of fuzzy logic to shorten the training and learning time of a neural network makes this combination an excellent solution (Badiru *et al.*, 2002). Various methods are available, with most variations found in training schemes, fuzzy logic membership schemes, and input/ output data types (Li *et al.*, 2001). At the present time, the application of FN systems to surface roughness prediction in a turning operation is limited. Jiao and Lei (2004) utilized a similar fuzzy adaptive network to create a prediction model using spindle speed, feed rate, and depth of cut. This study illustrates some advantages of such a system over regression modeling of complex systems such as turning. Abburi and Dixit [2006] did a similar study, comparing the use of a standard neural network system to that of a combined neural network and fuzzy-sets system. The prediction systems created in this study confirmed that the combination of fuzzy logic and neural networks is more capable and manageable than neural networks alone. The researchers involved in both of these studies conclude that their results indicate that these types of systems are well suited to turning operations.

Box and Draper (1987) classified mathematical models into mechanistic and empirical. In the study of some physical phenomenon, suppose that enough of its physical mechanism is known to deduce the form of functional relationship between the output and the input of a process or system, a mechanistic model can be developed for such a process or system. Otherwise, if the necessary physical knowledge of the system is absent or incomplete and consequently no mechanistic model is available. In these circumstances, an empirical model has to be developed to locally approximate the relationship between outputs and inputs based on observed data. Gershenfeld (1999) termed mechanistic models as analytical models and empirical models as observational models. In general, empirical models tend to be more specific than analytical models. They may be appropriate only under certain conditions or for certain products. Empirical models depend on data-its abundance, integrity, completeness and timeliness (Lam and Smith, 1997; and Coit, 1998).

Ship-Peng Lo (2003) developed an Adaptive-Network based Fuzzy Inference System (ANFIS) that was used to predict the work piece surface roughness using spindle speed, feed rate and depth of cut. He considered two different membership functions of ANFIS, triangular and trapezoidal, and were adopted during the training process in order to compare the prediction accuracy of surface roughness. Surjya Pal and Debabrata Chakraborty (2005) in this work, developed a back propagation neural network model for the prediction of surface roughness in turning operation using feed and the cutting forces as inputs to the neural network model.

PROBLEM DESCRIPTION

In this thesis, turning operations are performed on AA 6063 aluminum alloy with various process parameters such as spindle speed, feed and depth of cut to predict the surface roughness value. An attempt was made to predicted surface roughness values with soft computing techniques like ANFIS, NN and Regression analysis. Comparison between various prediction techniques such as ANFIS, NN and Regression analysis is performed to illustrate which technique holds well in predicting the surface roughness values. In addition to this variation of surface roughness value with respect to process parameters is also studied.

EXPERIMENTAL SETUP

This chapter deals with the selection of parameters which affect the surface roughness values, type of work piece material and experimental plan required to conduct the experimentation. In turning, the speed and motion of the cutting tool is specified through several parameters. These parameters are selected for each operation based upon the work piece material, tool material, tool size, and more. Turning parameter that can affect the process are: spindle speed, feed rate and depth of cut. A full-factorial design (Cobb, 1998) was created to include three turning process parameters and one response variable. The response variable is surface roughness, measured in micrometers. The process parameters include the three major turning parameters, i.e., spindle speed, feed rate, and depth of cut. The process parameters and their levels are shown in Table 1. The work piece material used in this study was AA 6063 aluminum alloy. The work pieces were 30 mm diameter aluminum alloy rod.

Table 1: Process Parameters and Levels

Machining Parameters	Level-I	Level-II	Level-III
Speed, S in rpm	88	150	250
Feed, F in mm/rev	0.05	0.07	0.1
Depth of cut, D in mm	0.2	0.3	0.4

An experimental setup was created for the purpose of generating turned surfaces, measuring their surface roughness data and analyzing this data. The hardware used in this experimental setup includes a HMT heavy duty convectional lathe, sample work pieces and a surface roughness measurement setup. The lathe was setup for performing straight cuts without the use of coolant, using carbide tool with a nose radius of 0.3 mm. Reduction of the effects of work piece dimensional inaccuracies and defects was done by rough-cutting each work piece with the same turning parameters, just prior to each finish cut, for the experimental design. Surface roughness measurements were conducted with a stylus profilometer to measure the work piece in the Z-axis (lay) direction. The device was a Pocket Surf stylus profilometer, set up to measure Ra in µm with a travel length of 8 mm. The above described experimental setup was used to turn the sample work pieces and collect data for the purposes of training the system. The experimental runs were performed under closely supervised conditions to ensure that no major problems occurred in the turning process. Immediately after all runs were completed, the surface roughness of the turned work pieces was measured and recorded. Each work piece was measured three times; in approximately above 900

Figure 2: Experimental Setup on Lathe Machine Used for Turning

Table 2: Experimental Values

S. No.	Speed S in rpm	Feed F in mm/rev	Depth of Cut D in mm	Surface Roughness Ra in µm
1.	88	0.05	0.2	1.12
2.	88	0.07	0.2	2.06
3.	88	0.1	0.2	2.85
4.	150	0.05	0.2	0.68
5.	150	0.07	0.2	0.95
6.	150	0.1	0.2	0.86
7.	250	0.05	0.2	0.76
8.	250	0.07	0.2	1.12
9.	250	0.1	0.2	1.05
10.	88	0.05	0.3	1.6
11.	88	0.07	0.3	2.55
12.	88	0.1	0.3	2.83
13.	150	0.05	0.3	1.27
14.	150	0.07	0.3	1.47
15.	150	0.1	0.3	1.54
16.	250	0.05	0.3	1.45
17.	250	0.07	0.3	1.05
18.	250	0.1	0.3	2.15
19.	88	0.05	0.4	2.44
20.	88	0.07	0.4	2.01
21.	88	0.1	0.4	3.33
22.	150	0.05	0.4	0.7
23.	150	0.07	0.4	0.88
24.	150	0.1	0.4	0.65
25.	250	0.05	0.4	0.95
26.	250	0.07	0.4	1.1
27.	250	0.1	0.4	1.01

increments around the circumference, and the average Ra value was used for data analysis. The parameters and the results of the experimental runs, including surface roughness measurements are shown in Table 1. Figure 2 shows the experimental setup on lathe machine used for machining the samples.

PREDICTION METHODOLOGY

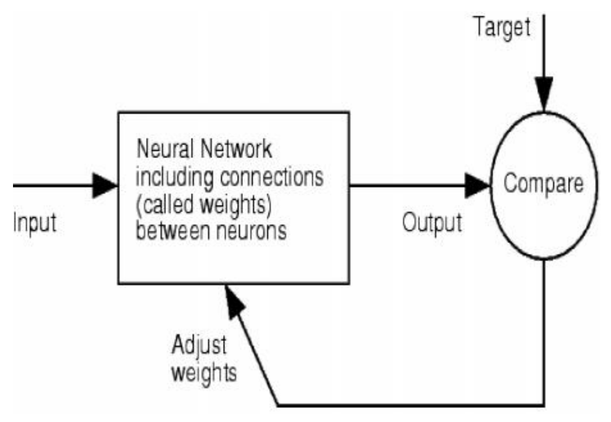
Adaptive Neuro Fuzzy Inference System (ANFIS)

ANFIS is the combination of fuzzy logic and neural networks. These tools apply fuzzy inference techniques to data modeling. In general fuzzy logic the shape of the membership functions depends on parameters, and changing these parameters will change the shape of the membership function. Instead of just looking at the data to choose the membership function parameters, we will see how membership function parameters can be chosen automatically using these Fuzzy Logic applications. The acronym ANFIS derives its name from adaptive neuro-fuzzy inference system. Using a given input/ output data set, the toolbox function ANFIS constructs a Fuzzy Inference System (FIS) whose membership function parameters are tuned (adjusted) using either a back propagation algorithm alone, or combination of back propagation with a least squares type of method. This allows your fuzzy systems to learn from the data they are modeling. In general, this type of modeling works well if the training data presented to anfis for training (estimating) membership function parameters is fully representative of the features of the data that the trained FIS is intended to model. This is not always the case, however. In some cases, data is collected using noisy measurements, and the training data cannot be representative of all the features of the data that will be presented to the model. This is where model validation comes into play. This training and testing will be clearly explain in results and conclusion module.

Neural Networks

Neural networks have a history of some six decades but have found solid application only in the past twenty years. The field is still developing rapidly. Thus, it is distinctly different from the fields of control systems or optimization, where the terminology, basic mathematics, and design procedures have been established and applied for many years. The Neural Network is not simply a summary of established procedures that are known to work well. Rather, it is designed to be a useful tool for industry, education, and research, a tool that will help users find what works and what doesn't, and a tool that will help develop and extend the field of neural networks. 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. Artificial Neural Networks (ANN) have a mathematical background and theory, with their development and refinement stemming from basic mathematical principles, modeled on biological neurons and nervous system. Neural networks can learn, and the neurons (building blocks), also known as the processing elements, perform their operations in parallel. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Such a situation is as shown in Figure 3. There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are needed to train a network.

Figure 3: Block Diagram of Neural Network Process



REGRESSION ANALYSIS

In statistics, regression analysis includes any techniques for modeling and analyzing several variables, when the focus is on the relationship between a dependent variable and one or more independent variables. More specifically, regression analysis helps us understand how the typical value of the dependent variable changes when any one of the independent variables is varied, while the other independent variables are held fixed. Regression analysis is widely used for prediction and forecasting. Regression analysis is also used to understand which among the independent variables are related to the dependent variable, and to explore the forms of these relationships. A large body of techniques for carrying out regression analysis has been developed. Familiar methods such as linear regression and ordinary least squares regression are parametric, in that the regression function is defined in terms of a finite number of unknown parameters that are estimated from the data. Nonparametric regression refers to techniques that allow the regression function to lie in a specified set of functions, which may be infinite-dimensional.

RESULTS AND COMPARISION

In order to verify the accuracy of the predicted values of surface roughness another nine sets of experimental data are performed, which are used for testing. The results obtained are analyzed and discussed in this section. Table 5.1 compares the experimental data and predicted data after training the ANFIS, NN and regression techniques. Figures 5.1 to 5.3 shows the scatter diagrams of the predicted values and measurement values of the surface roughness of 9 sets of testing data when ANFIS, NN and Regression techniques are used. Figure 5.1 shows the predicted values of surface roughness follow the regression line

Figure 4: Comparison of Experimental and Predicted Surface Roughness Values

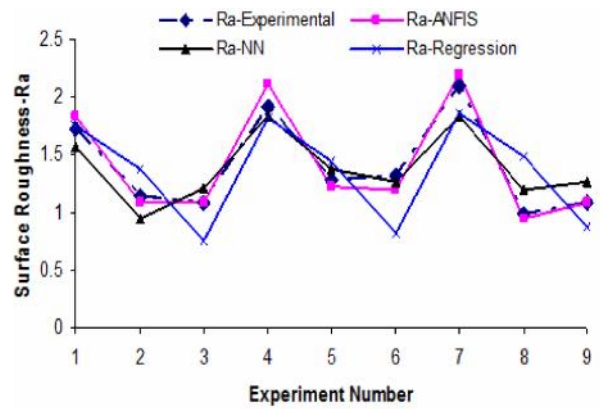


Figure 5: Interaction Plot of Process Parameters and Surface Roughness Values

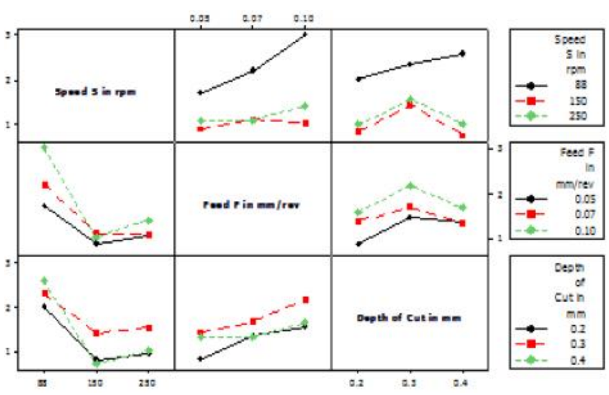


Table 3: Testing Data and Predicted Surface Roughness Values Using ANFIS, NN and Regression

S. No.	Speed S (rpm)	Feed F (mm/rev)	Depth of Cut D (mm)	Experimental Ra	ANFIS Ra	NN Ra	Regression Ra
1.	88	0.06	0.25	1.72	1.83	1.57	1.75
2.	150	0.06	0.25	1.14	1.09	0.94	1.37
3.	250	0.06	0.25	1.08	1.09	1.21	0.75
4.	88	0.06	0.325	1.91	2.11	1.83	1.82
5.	150	0.06	0.325	1.28	1.22	1.38	1.44
6.	250	0.06	0.325	1.32	1.19	1.27	0.82
7.	88	0.06	0.375	2.1	2.19	1.83	1.86
8.	150	0.06	0.375	0.99	0.94	1.19	1.48
9.	250	0.06	0.375	1.09	1.08	1.27	0.87

closely when compared to Figures 5.2 and 5.3. Figure 5.4 also depicts that the predicted values using ANFIS are in close agreement with the experimental values, which indicates the prediction accuracy of ANFIS is higher than that of NN and regression techniques.

Figure 5 depicts the effect of each turning process parameters like speed, feed and depth of cut on surface roughness. A small change in depth of cut results in greater change of roughness. A higher spindle speed achieves a smaller roughness value. For machining condition of a larger depth of cut at 0.4 mm, as the speed increases from 88 to 150 rpm, the average roughness value decreases and on further increase in speed the surface roughness value increases. The results indicate that the speed has a greater impact on quality at various depths of cuts. At larger feed rate of 0.1 mm/rev, as the speed increases from 88 to 150 rpm, the average roughness value decreases and increases slightly on further increase in speed The results indicate that the speed has a greater impact on quality at various feeds. The above analysis indicates that among the three turning process parameters discussed in this study, change in the feed rate has the most impact on surface roughness.

CONCLUSION

ANFIS, NN and regression techniques are used to predict the work piece surface roughness after the turning process and to analyze the effect of three turning parameters, including speed, feed rate and depth of cut, on the surface roughness. A total of 27 sets of experimental data are used for training. After the training is completed, another 9 sets of data are used as testing data. The following conclusions can be drawn from the above analysis:

1. The predicted values using ANFIS are in close agreement with the experimental results when compared to the remaining and hence ANFIS can be used as an efficient tool for predicting the surface roughness in turning process.
2. Based on the experimental results it is observed that, surface roughness value increases as the feed and depth of cut increases and as the spindle speed increases the surface roughness value decreases.
3. The minimum surface roughness value is observed at spindle speed of 150 rpm, feed of 0.05 mm/rev and a depth of cut of 0.2 mm respectively.

REFERENCES

1. Abburi N R and Dixit U S (2006), "A Knowledge-Based System for the Prediction of Surface Roughness in Turning Process", *Robotics and Computer-Integrated Manufacturing*, Vol. 22, No. 4, pp. 363-372.
2. Badiru A B and Cheung J Y (2002), "Fuzzy Engineering Expert Systems with Neural Network Applications", John Wiley & Sons, New York.
3. Barni M, Bartolini F and Piva A (2002), "Multichannel Watermarking of Color Images", *IEEE Transaction on Circuits and Systems of Video Technology*, Vol. 12, No. 3, pp. 142-156.
4. Box G E P and Draper N R (1987), "Empirical Model-Building and

Response Surfaces", John Wiley & Sons, New York.

5. Chen J C and Lee S S (2003), "An On-Line Surface Roughness Recognition System Using an Accelerometer in Turning Operations", *Journal of Engineering Technology*, Vol. 20, No. 2, pp. 12-18.

6. Cobb G W (19'98), "Introduction to Design and Analysis of Experiments", Springer, New York.

7. Coit D W, Jackson B T and Smith A E (1998), "Static Neural Network Process Models: Considerations and Case Studies", *International Journal of Production Research*, Vol. 36, No. 11, pp. 2953-2967.

8. Daren H, Jifuen L, Jiwu H and Hongmei L (2001), "A DWT-Based Image Watermarking Algorithm", in Proceedings of the IEEE International Conference on Multimedia and Expo, pp. 429-432.

9. Eggers J, Su J and Girod B (2000), "Robustness of a Blind Image Watermarking Scheme", Proc. IEEE Int. Conf. on Image Proc., Vancouver.

10. Feng C H and Wang X F (2002), "Development of Empirical Models for Surface Roughness Prediction in Finish Turning", *International Journal of Advanced Manufacturing Technology*, Vol. 20, pp. 348-356.

11. Gershenfeld N (1999), "The Nature of Mathematical Modeling", Cambridge University Press, Cambridge, UK.

12. Ghouti L, Bouridane A, Ibrahim M K and Boussakta S (2006), "Digital Image Watermarking Using Balanced Multiwavelets", *IEEE Trans. Signal Process.*, Vol. 54, No. 4, pp. 1519-1536.

13. Groover M P (1996), "Fundamentals of Modern Manufacturing Materials", *Processes and Systems*, Upper Saddle River, Prentice-Hall, New Jersey.

14. Hsu C and Wu J (1998), "Multi-Resolution Watermarking for Digital Images", *IEEE Transactions on Circuits and Systems-II*, Vol. 45, No. 8, pp. 1097-1101.

15. Jiao Y, Lei S, Pei Z J and Lee E S (2004), "Fuzzy Adaptive Networks in Machining Process Modeling Surface Roughness Prediction for Turning Operations", *International Journal of Machine Tools and Manufacture*, Vol. 44, No. 15, pp. 1643-1651.

16. Knuefermann M M W and McKeown P A (2004), "A Model for Surface Roughness in Ultra Precision Hard Turning", *CIRP Annals Manufacturing Technology*, Vol. 53, No. 1, pp. 99-102.

17. Kohli A and Dixit U S (2005), "A Neural-Network-Based Methodology for the Prediction of Surface Roughness in a Turning Process", *International Journal of Advanced Manufacturing Technology*, Vol. 25, Nos. 1-2, pp. 118-129.

18. Kumswat P, Ki Attakitmongcol and Striaew A (2005), "A New Approach for Optimization in Image Watermarking by Using Genetic Algorithms", *IEEE Transactions on Signal Processing*, Vol. 53, No. 12, pp. 4707-4719.

19. Kundur D and Hatzinakos D (2004), "Towards Robust Logo Watermarking

Using Multiresolution Image Fusion", *IEEE Transcations on Multimedia*, Vol. 6, pp. 185-197.

20. Lam S and Smith A E (1997), "Process Monitoring of Abrasive Flow Machining Using a Neural Network Predictive Model", Proceedings of the 6th Industrial Engineering Research Conference, May, pp. 477-482, Miami, FL.

21. Li H X, Chen C L P and Huang H P (2001), "Fuzzy Neural Intelligent Systems: Mathematical Foundation and the Applications in Engineering", CRC Press LLC, Boca Raton, FL.

22. Lu C S and Liao H Y M (2001), "Multipurpose Watermarking for Image Authentication and Protection", *IEEE Transaction on Image Processing*, Vol. 10, October, pp. 1579-1592.

23. Mehul R (2003), "Discrete Wavelet Transform Based Multiple Watermarking Scheme", in Proceedings of the 2003 IEEE TENCON, pp. 935-938.

24. Risbood K A, Dixit U S and Sahasrabudhe A D (2003), "Prediction of Surface Roughness and Dimensional Deviation by Measuring Cutting Forces and Vibrations in Turning", *Journal of Materials Processing Technology*, Vol. 132, Nos. 1-3, pp. 203-214.

25. Samhouri S M and Surgenor B W (2005), "Surface Roughness in Grinding: On-Line Prediction with Adaptive Neuro-Fuzzy Inference System", *Transactions of NAMRI/SME*, Vol. 33, pp. 57-64.

26. Ship-Peng Lo (2003), "An Adaptive-Network Based Fuzzy Inference System for Prediction of Work Piece Surface Roughness in End Milling", *Journal of Materials Processing Technology*, Vol. 142, No. 3, pp. 665-675.

27. Surjya K Pal and Debabrata Chakraborty (2005), "Surface Roughness Prediction in Turning Using Artificial Neural Network", *Neural Computing & Applications*, Vol. 14, No. 4.

28. Tay P and Havlicek J (2002), "Image Watermarking Using Wavelets", in Proceedings of the 2002 IEEE, pp. II.258-II.261.

29. Vernon A and Ozel T (1999), "Factors Affecting Surface Roughness in Finish Hard Turning", 17th International Conference on Production Research, VNE Corporation, Blacksburg, Virginia.

30. Wang J and Kusiak A (2001), "Computational Intelligence in Manufacturing Handbook", CRC Press LLC, Boca Raton, FL.

31. Zilouchian A and Jamshidi M (2001), "Intelligent Control Systems Using Soft Computing Methodologies", CRC Press LLC, Boca Raton, FL.