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ORIGINAL ARTICLE

D.K. Sonar · U.S. Dixit · D.K. Ojha

The application of a radial basis function neural network for predicting the surface roughness in a turning process

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Abstract This study considers the performance of a radial basis function neural network for predicting the surface roughness in a turning process. A simple algorithm is proposed for finding the upper and lower estimates of the surface roughness. A code is developed that automatically fits the best network architecture for a given training and testing dataset. The validation of the methodology is carried out for dry and wet turning of mild steel using HSS and carbide tools, and is compared to the performance of the studied network with the reported performance of a multi-layer perception neural network. It is observed that the performance of the radial basis function network is slightly inferior compared to multi-layer perceptron neural network. However, the training procedure is simpler and requires less computational time.

Keywords Radial basis function neural networks · Surface roughness · Dry and wet turning

1 Introduction

Surface roughness is one of the important attributes of job quality in the turning process. The controlled surface roughness of a turned component is necessary to improve its tribological properties, fatigue strength, corrosion resistance and aesthetic appeal. However, it can be generally stated that the lower the desired surface roughness value, the more the manufacturing cost. For optimizing the turning process, one should be able to obtain a functional relationship between the process parameters and surface roughness. The process parameters include cutting parameters (feed rate, speed and depth of cut), as well as sensory feedback of the cutting process. A number of researchers have attempted to develop surface roughness prediction models. A review of important works may be found in the papers of Feng and Wang [1], Risbood, Dixit and Sahasrabudhe [2], and Bernardos and Vosniakos [3].

Since the last decade, researchers have been using neural networks for predicting the surface roughness in turning [1, 4–8]. Neural networks do not require an understanding of the physics of the process. Similar network architecture can be employed for predicting the surface roughness for different tool-work material combinations and other similar machining processes. Whereas physics-based models require the experimental determination of certain parameters of a machine tool, cutting tool and work material, the neural network models require only a dataset consisting of process parameters and corresponding surface roughness values. A certain amount of noise in the dataset is tolerable. In the literature, mostly multilayer perceptron (MLP) neural networks working on a back propagation algorithm have been used for predicting the surface roughness in turning. One promising neural network is the radial basis function (RBF) neural network, which has been reported to be faster and at times more accurate, as compared to a MLP neural network. There have been a few applications of radial basis function neural networks in the area of machining [9–13].

In this study, a radial basis function neural network is used for predicting the surface roughness value in the turning process. Given a combination of process parameters, the network predicts the most likely upper and lower estimates of the surface roughness value. Performance of the neural network is assessed by comparing the predictions with experimental data and with MLP neural network results of Kohli and Dixit [8].

2 Background of radial basis function neural networks

Neural networks are basically connectionist systems, in which various Nodes (called "neurons") are interconnected. A typical neuron receives one or more input signals. The output signal provided by the neuron depends on its processing function. This output is transferred to connecting neurons in varying intensities. The neurons in the input layer receive input signals from the user

D.K. Sonar · U.S. Dixit (✉) · D.K. Ojha
Department of Mechanical Engineering,
Indian Institute of Technology,
Guwahati – 781 039, India
E-mail: uday@iitg.ernet.in

and provide the output through the neurons in the output layers. Only the neurons in the input and output layers interact with the outside world/user; the rest are hidden. After choosing the network architecture, the network is trained. In the supervised training of the networks, the network is presented with training pairs, each consisting of a vector from an input space and a desired network output. Through a defined learning algorithm, the network performs the adjustment of its parameters so that the error between the actual and desired output is minimized. Once trained, the network can be used for predicting the output for any input vector from the input space. This is called the "generalization property" of the network.

A radial basis function (RBF) neural network [14] consists of three layers: an input layer, a single layer of non-linear processing neurons, and an output layer. The architecture of a typical network for surface roughness predictions is shown in Fig. 1. This network predicts the surface roughness (R_a) for a given feed rate (f), cutting speed (v), depth of cut (d) and acceleration of radial vibration (a). The output of the RBF neural network is calculated according to:

$$R_a = \sum_{k=1}^{N} w_k \phi_k \left(\|\boldsymbol{x} - \boldsymbol{c_k}\|_2\right) \tag{1}$$

where $\boldsymbol{x} = \{f, v, d, a\}^T$ is the input vector, $\phi_k(.)$ is the processing function of the kth node in the hidden layer, $\|.\|_2$ denotes the Euclidean norm, w_k are weights associated with the kth node in the hidden layer, the output node, N is the number of neurons in the hidden layer, and $\boldsymbol{c}_k$ are the RBF centers in the input vector space. For each neuron in the hidden layer, Euclidean distances between its associated center and the input to the network are calculated. The output of the neuron in a hidden layer is a nonlinear function of the distance. Finally, the output of the network is calculated as a weighted sum of the hidden layer outputs. The processing function used in this work is a Gaussian function of the following form:

$$\phi(x) = \exp(-x^2/\sigma^2) \tag{2}$$

where parameter σ controls the "width" of the radial basis function and is commonly referred to as the spread parameter.

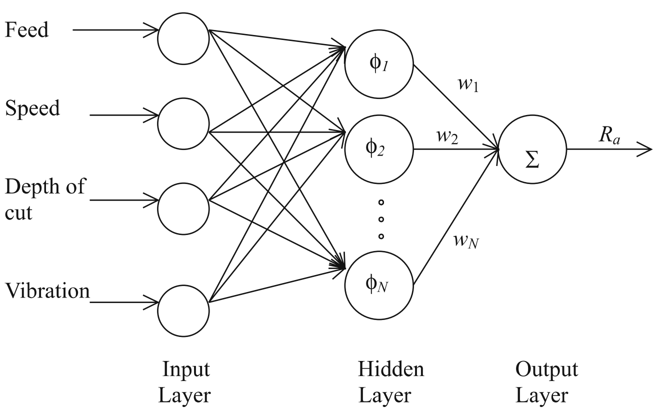

Fig. 1. A typical RBF neural network architecture

Referring to Eq. 1, it can be seen that there are two set of parameters governing the mapping properties of the radial basis function neural network: the weights w_k and the centers $\boldsymbol{c}_k$. The simplest form of RBF neural network is one with a fixed center, chosen in a random manner as a subset of the input dataset. Once the centers are chosen, the output of the network to the input vectors in the training data set can be calculated by:

$$R_a^{(p)} = \sum_{k=1}^{N} w_k \phi_k \left(\left\| \boldsymbol{x}^{(p)} - \boldsymbol{c_k} \right\|_2 \right), \quad p = 1, 2, \ldots, P \tag{3}$$

where P is the total number of the training pairs and the bracketed superscript on the input and output indicates the pair number. The weights w_k can be adjusted by a multiple linear regression procedure so that sum squared error between the predicted surface roughness values and the experimental values are minimized.

3 Prediction of lower and upper estimates using an RBF neural network

The procedure outlined in the previous section is used for finding out the most likely estimate of surface roughness. In this section, a methodology is proposed to predict the lower and upper estimates of surface roughness. Prediction of lower and upper estimates provides a range within which the surface roughness value can lie. The surface roughness value can thus be represented as a fuzzy number with a membership grade of 1 attached to the most likely estimate and 0.5 to the lower and upper estimates.

This methodology obtains the weights (w_k) using fuzzy linear regression model [15]. Thus, the weights to be used in Eq. 3 are obtained as interval numbers, thereby also providing the surface roughness value as an interval number. The simplest version of the fuzzy regression model is the interval regression model, in which the input vector $\boldsymbol{x} = \{x_1, x_2, \ldots, x_N\}^T$ is mapped to lower estimate Y_l and upper estimate Y_u according to:

$$Y_l(x) = A_0^l + A_1^l x_1 + \ldots + A_N^l x_N \tag{4}$$

and

$$Y_u(x) = A_0^u + A_1^u x_1 + \ldots + A_N^u x_N \tag{5}$$

where $A_0^l, A_1^l, \ldots, A_N^l$ are the coefficients for predicting the lower estimate and $A_0^u, A_1^u, \ldots, A_N^u$ are the coefficients for predicting the upper estimate of dependent variable Y. Assuming that P input-output pairs ($\boldsymbol{x}_p$; Y_p), $p = 1, 2, \ldots, m$, are given as training data, where $\boldsymbol{x}_p = (x_{p1}, x_{p2}, \ldots, x_{pN})$ is an N-dimensional real-number input vector and Y_p is a real-number output, the coefficients can be obtained by solving the following linear programming problem:

$$\text{Minimize} \sum_{p=1}^{P} (A_0^u - A_0^l) + (A_1^u - A_1^l)x_{p1} + \ldots + (A_N^u - A_N^l)x_{pN} \tag{6}$$

Subject to:

$$\left.\begin{array}{l} A_0^l + A_1^l x_{p1} + \ldots + A_n^l x_{pN} \leq Y_p, \\ A_0^u + A_1^u x_{p1} + \ldots + A_n^u x_{pN} \geq Y_p, \end{array}\right\} \quad p = 1, 2, \ldots, P \tag{7}$$

The objective of Eq. 6 is to minimize the sum of the widths of interval outputs. The constraint condition (Eq. 7) means that the interval output must include the given output. Given output can be viewed as the target surface roughness values, whereas x_{pk}, $k = 1, 2, \ldots, N$ corresponds to $\phi_k\left(\left\|\boldsymbol{x}^{(p)} - \boldsymbol{c_k}\right\|_2\right)$, $k = 1, 2, \ldots, N$.

4 Computer implementation

The procedure for choosing the initial training and testing data is similar to that given by Kohli and Dixit [8] and will not be repeated here. Three important network parameters are: the number of neurons in hidden layer, spread parameters, and centers. In this study, centers are chosen at random from the input training dataset. The spread parameter σ is commonly set according to the following simple heuristic relationship [16]:

$$\sigma = \frac{d_{\max}}{\sqrt{K}} \tag{8}$$

where $d_{\max}$ is the maximum Euclidean distance between the selected centers and K is the number of the centers. In our case, the four input parameters are normalized to lie between 0.1 and 0.9. Hence, the maximum possible $d_{\max}$ is 1.6. The range of number of hidden neurons is chosen between 2 and size of training dataset. For each K, the spread parameter was computed from equation Eq. 8. The performance of network was tested by taking three spread parameters: spread parameter calculated by Eq. 8, 0.5 times this value, and 1.5 times this value. Among all the networks, the network providing the least effective error (maximum of training and testing rms error) was taken as final. If the desired accuracy is not achieved, with the best network architecture, the size of the training and testing datasets is increased. Figure 2 depicts the flow chart of the methodology.

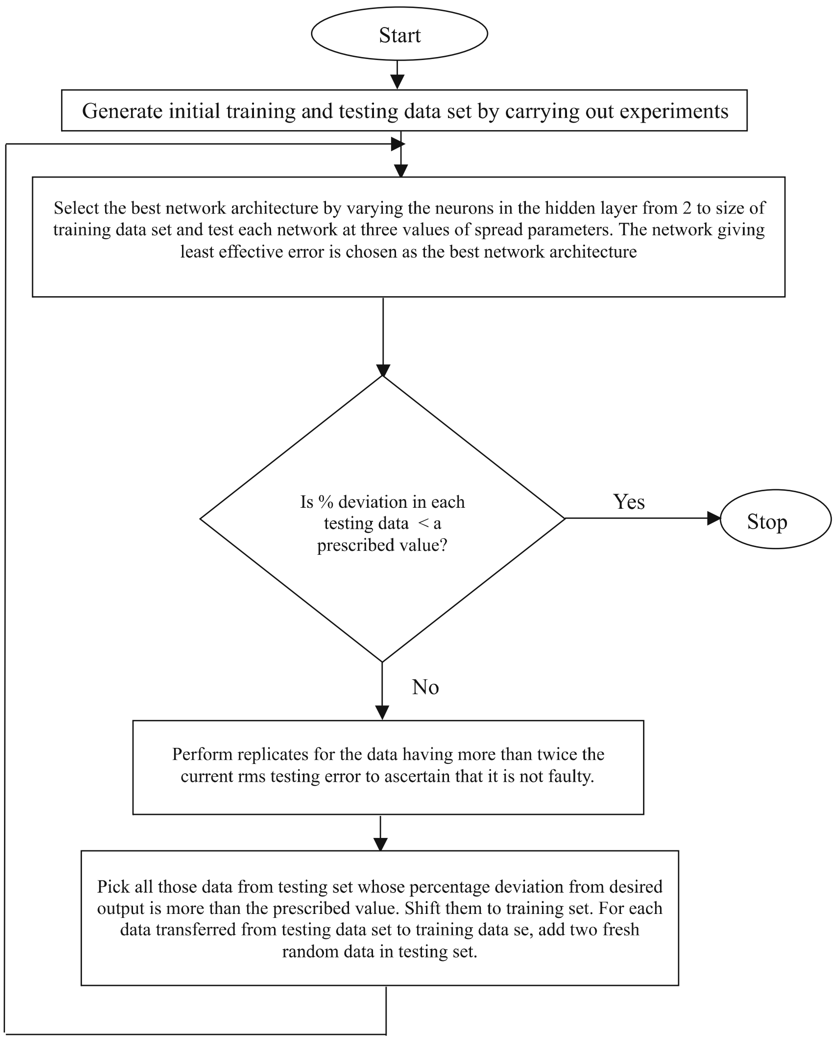

Fig. 2. Flow chart illustrating the methodology

5 Results and discussion

Experiments consisting of turning a mild steel with HSS and carbide tools were conducted at the Indian Institute of Technology, Guwahati [2, 8]. For carrying out the experiments, an HMT (NH-26 model) lathe machine was employed. In this lathe, a three phase 11 kW induction motor, providing 23 speeds between 40 and 2040 rpm, drives the spindle. The work-piece is held in a hydraulic chuck. The work-pieces used for surface roughness study were cut from rolled steel bars containing about 0.35% carbon. The hardness of steel was 130 BHN, yield strength 290 MPa and ultimate tensile strength 477 MPa. For studying the influence of cutting parameters on the surface roughness, a few experiments were conducted on work-pieces of diameters ranging between 30–46 mm, job length of 240 mm and cutting length of 110 mm. It was observed that length and diameter of the job have insignificant effect on surface roughness compared to cutting speed, feed rate, depth of cut, acceleration of radial vibration of the tool holder and the use of cutting fluid. For measuring the CLA surface roughness values (*Ra*), Pocket Surf (Mahr, GMBH) was used. Its measuring range is 0.03–6.35 μm. The surface roughness evaluation length in each case was taken as 2.4 mm. A piezoelectric type vibration meter (Syscon, model SI-327A01) measured acceleration of the radial vibration of the tool holder. It has a resolution of 0.01 m/s^2 and a linearity of ±2% of the full-scale output.

Table 1. Optimum numbers of centers, spread parameters and errors for different types of turning

Turning process type	Number of training data	Number of testing data	Number of centers	Spread parameter	% Training error	% Testing error
Wet turning by HSS tool	19	11	10	0.8	9.87	10.00
Dry turning by HSS tool	9	8	2	1.7	16.24	16.43
Wet turning by carbide tool	21	10	12	0.5	13.97	22.24
Dry turning by carbide tool	21	9	9	0.8	11.01	16.69

Four different types of experiments were conducted: (i) wet turning by HSS tool; (ii) dry turning by HSS tool; (iii) wet turning by carbide tool; and (iv) dry turning by carbide tool. To compare the performance of the radial basis function network to that of a multi-layer perceptron network using a back-propagation algorithm, the numbers of training and testing data in each case were kept same as that corresponding to results reported by Kohli and Dixit [8]. The program automatically calculated the best network architecture in terms of number of centers and spread parameters. The results are summarized in Table 1. It is observed that root mean square errors are nearly of the same magnitude as that obtained in [8]. However, in a few testing data, the errors were more than 20%.

To test the performance of these fitted networks, predictions were made for a number of validation data. These data were not seen by the network before. The most likely upper and lower estimates, along with the corresponding experimental values of surface roughness are depicted in Figs. 3–6 for four types of turning operations. It is observed that in most of the cases, the most likely estimate is close to experimental value, and experimental value falls in between the lower and upper estimate. To compare the performance of the radial basis function network with that of a multi-layer perceptron network using a back propagation algorithm, the results of this study are compared with [8] in Table 2. It can be seen that the performance of the radial basis function network is slightly inferior to the multi-layer perceptron network for the given sets of training and testing data. Also, the maximum error in prediction is much larger when compared to that of multi-layer perceptron network. However, the computational time in getting the best network architecture has been reduced. It is about one-fifth in comparison to the multi-layer

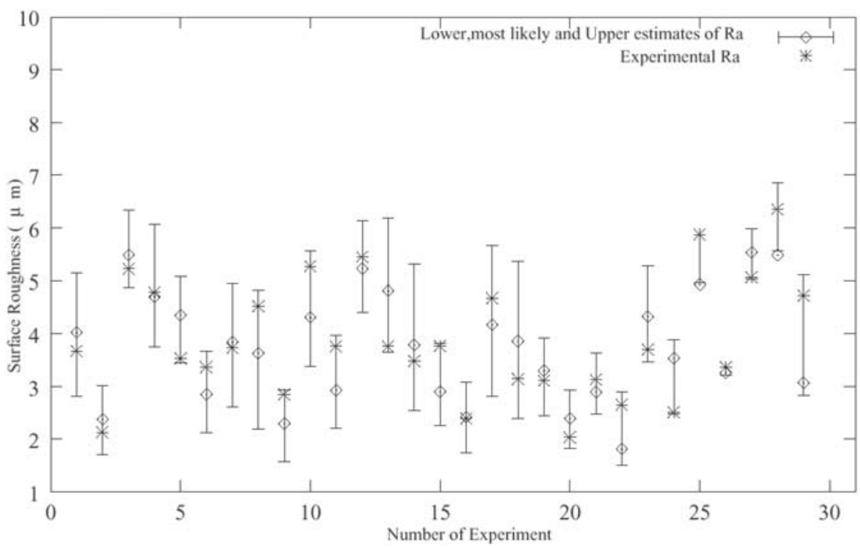

Fig. 3. Predicted values versus experimental values of surface roughness in turning by HSS tool in the presence of coolant

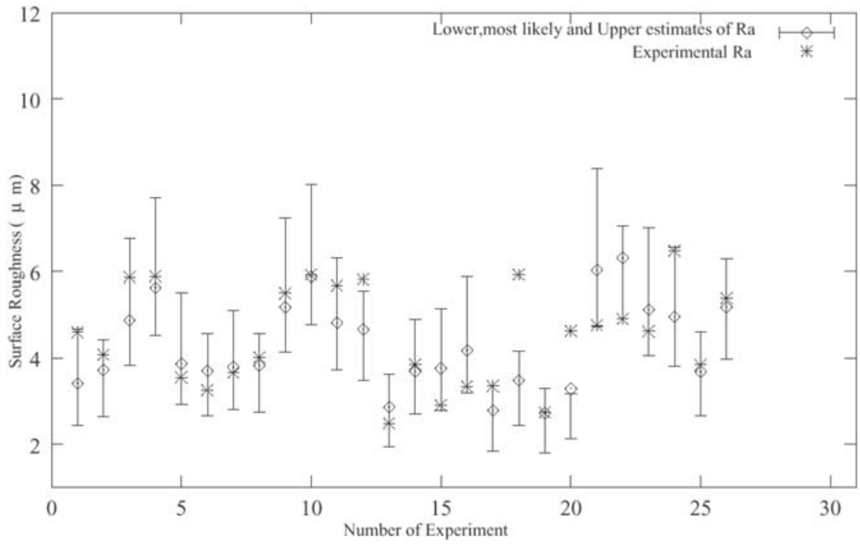

Fig. 4. Predicted values versus experimental values of surface roughness in turning by HSS tool in the absence of coolant

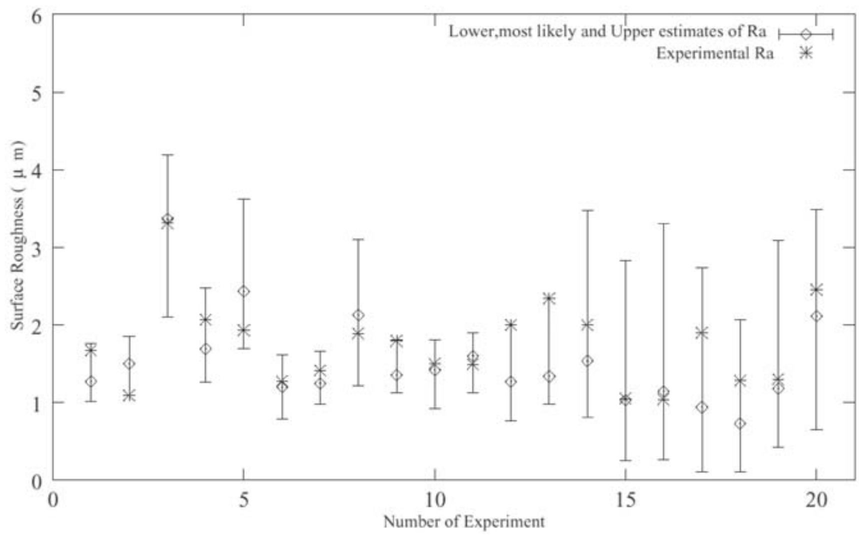

Fig. 5. Predicted values versus experimental values of surface roughness in turning by carbide tool in the presence of coolant

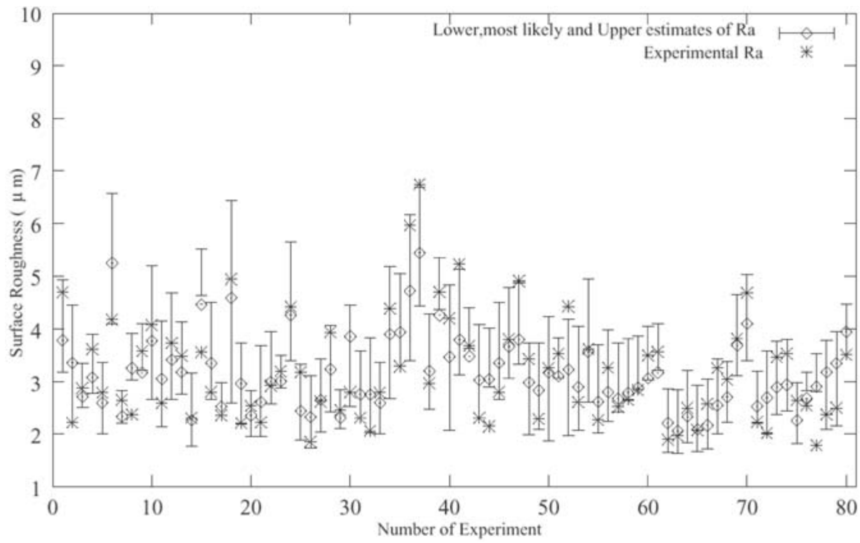

Fig. 6. Predicted values versus experimental values of surface roughness in turning by carbide tool in the absence of coolant

Table 2. Comparing the performance of a radial basis function network to a multi-layer perceptron network

Process type	RMS error of validation data		Number of data having error more than 25%		Maximum error	
	Present work	[8]	Present work	[8]	Present work	[8]
Wet turning by HSS tool	18.42%	15.01%	4	3	41.00%	27.47%
Dry turning by HSS tool	18.20%	16.05%	6	5	41.23%	29.94%
Wet turning by carbide tool	25.05%	17.66%	6	3	50.62%	34.48%
Dry turning by carbide tool	22.00%	16.64%	20	11	67.58%	33.43%

perceptron network. Increasing the number of training and testing data is expected to increase the accuracy. This is left for future work.

6 Conclusions

The main objective of this study is to consider the performance of a radial basis function network for predicting the surface roughness in a turning process. It is observed that the radial basis function network is able to predict the surface roughness with reasonable accuracy. However, its performance is slightly inferior compared to a multi-layer perceptron neural network using a back-propagation algorithm. With increases in training and testing data, this conclusion may be reversed, but this was not tried in this study. An algorithm has been proposed for finding the lower and upper estimate using a radial basis function network. The proposed algorithm gives satisfactory performance. The main advantage of present methodology in comparison to a multi-layer perceptron neural network is its simplicity and decreased computational time.

References

1. Feng CX, Wang X (2002) Development of empirical models for surface roughness prediction in finish turning. Int J Adv Manuf Technol 20(5):348–356
2. Risbood KA, Dixit US, Sahasrabudhe AD (2003) Prediction of surface roughness and dimensional deviation by measuring cutting forces and vibrations in turning process. J Mater Process Technol 132(1–3):203–214
3. Benardos PG, Vosniakos GC (2003) Predicting surface roughness in machining: a review. Int J Mach Tools Manuf 43(8):833–844
4. Azouzi R, Guillot M (1997) On-line prediction of surface finish and dimensional deviation in turning using neural network based sensor fusion. Int J Mach Tools Manuf 37(9):1201–1217
5. Azouzi R, Guillot M (1998) On-line optimization of turning process using an inverse process Neuro controller. ASME J Manuf Sci Eng 120(1):101–108
6. Lin WS, Lee BY, Wu CL (2001) Modeling the surface roughness and cutting force for turning. J Mater Process Technol 108(3):286–293
7. Feng CX, Wang XF (2003) Surface roughness prediction modeling: neural networks versus regression. IIE Transactions on Design and Manufacturing 35(1):11–27
8. Kohli A, Dixit US (2005) A neural network based methodology for prediction of surface roughness in turning process. Int J Adv Manuf Technol 25(1–2):118–129
9. Kuo RJ, Cohen PH (1999) Multi-sensor integration for on-line tool wear estimation through radial basis function network and fuzzy neural network. Neural Networks 12(2):355–370
10. Tsai KM, Wang PJ (2001) Comparison of neural network models on material removal rate in electrical discharge machining. J Mater Process Technol 117(1–2):111–124
11. Tsai KM, Wang PJ (2001) Predictions on surface finish in electrical discharge machining based upon neural network models. Int J Mach Tools Manuf 41(10):1385–1403
12. Briceno JF, El-Mounayri H, Mukhopadhyay S (2002) Selecting an artificial neural network for efficient modeling and accurate simulation of the milling process. Int J Mach Tools Manuf 42(6):663–674
13. Lin JT, Bhattacharyya D, Kecman V (2003) Multiple regression and neural network analyses in composite machining. Composites Sci Technol 63(3–4):539–548
14. Ham FM, Kostanic I (2001) Principles of neurocomputing for science and engineering. McGraw-Hill, New York
15. Tanaka H (1987) Fuzzy data analysis by possibilistic linear models. Fuzzy Sets Sys 24(3):363–375
16. Haykin S (1996) Adaptive Filter Theory, 3rd edn. Prentice-Hall, New York