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CUTTING TOOL CONDITION MONITORING USING SURFACE TEXTURE VIA NEURAL NETWORK

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Abstract-For defining surface finish and monitoring tool wear is essential for optimisation of machining parameters and performing automated manufacturing systems. There is very close relationship between tool wear and surface finish parameters as surface roughness (R_a) and maximum depth of profile (R_t). The machined surface reflects the rate of tool wear and the plot of surface provides reliable information about tool condition. In this paper an approach for estimating R_a and R_t in milling process using the artificial neural networks is proposed. Feed-forward multi-layered neural networks, trained by the back-propagation algorithm are used. In training phase seven input parameters (v, f, d, F_x, F_y, F_z and Vb) and two output parameters are used and the network architecture is as 7x6x6x6x2. It was found that the ANN results are very close to the experimental results. The developed model can be used to define the quality of surface finish in tool condition monitoring systems.

Keywords- Tool condition monitoring, neural networks, surface texture analysis, tool wear.

1. INTRODUCTION

In recent years automated manufacturing systems have been more widely used in the production industry. Modern machining systems need the developing reliable on-line cutting tool condition monitoring (TCM) systems. Such an on-line TCM system is essential to change the tool in right time. The quality of products depends on performance of their related machining operations to a great extent. For this reason, intelligent sensing techniques have been developed for detecting factors such as chip formation, tool condition, surface texture, machine-tool vibrations and diagnosing failures occurring on machine tools. Among these the most active researches have been intensified on tool wear and surface texture. In this study, cutting forces accepted as reference to identify tool wear [1, 2] and surface roughness to identify surface texture measurements [3, 4] have been performed. Tool wear affects the surface texture seriously and therefore tool geometry changes. The surface texture, even under stable machining conditions changes considerable rate because of variations on tool geometry. Since the cutting tool being directly contacts on the machining surface, it provides source of reliable and detectable information about the process, including tool wear and machine vibrations to identify tool condition [5]. Many researchers have investigated the correlation between surface roughness and tool condition. Whitehouse [6], has been used random process analysis techniques, including spectral analysis of the surface waviness, to characterise the surface machined by sharp and dull tools and Peklenik [7], applied auto-correlation to characterise the machined surfaces.

A machined surface is negative replica of the shape of the cutting tool and it reflects the volumetric changes in the shape of the cutting edge. Since metal cutting process that is influenced by a large number of interrelated parameters, has a complex character, it needs intelligent decision-making device to establish a reliable and accurate TCM. In the last few years' neural networks (NN) were widely used for solving non-linear problems, particularly on TCM systems based on single and multi-sensor signals. In this subject, some neural network architectures and training and learning methodologies are reported by many researchers [8, 9].

In this study, a monitoring approach for estimating surface finish parameters (R_a, R_t) by means of artificial neural network (ANN) is proposed based on cutting force and tool flank wear (*Vb*) in milling. In addition to cutting force, machining parameters, i.e. cutting speed (v), feed rate (f) and depth of cut (d), are also used as input parameters to provide input data to the network.

2. EXPERIMENTAL INVESTIGATIONS

2.1. Experimental Set-up and Conditions

The experiments were performed on a knee-type high precision milling machine (FU315 V2). The used experimental samples were medium-carbon steel Ç1040 (with the size of 60x120) and the inserts were uncoated cemented carbide having zero rake angle (SPMW 120408 P15-P30). The cutting parameters with four levelled used in these experiments are shown in Table 1.

Table 1. The cutting parameters used

Cutting speed v (m/min)	Feed f (mm/min)	Depth of cut d (mm)
113	200	1.0
140	250	1.5
178	315	2.5
226	400	3.5

The cutting force signals received from three-components dynamometer were amplified and recorded in a PC using a microprocessor controlled data acquisition card. Since the cutting in milling is intermittent and oscillating is generated in force signals, the average values of signals were recorded. The milling operation lasted until the inserts reached to catastrophic failure. After the number of determined pass the flank wears (*Vb*) were measured with a toolmaker's microscope (Fowler-Sylvac 25) in accuracy of 0.001/0.0001 mm and surface roughness (R_a) and maximum depth of profile (R_t) are measured using a stylus-based instrument (Taylor Hobson-Mitutoyo) in accuracy of 0.1 μm.

2.2. The Experimental Results

In the experiments, number of 129 data patterns was extracted from 16 tests. It was found that the depth of cut had less effect on the flank wear and surface finish parameters and while flank wear increases with machining at low feed rates, it reduces at high feed rate in response to same metal removal rate [10]. Figure 1 shows the variation of R_a and R_t with machining time for different *Vb* rates.

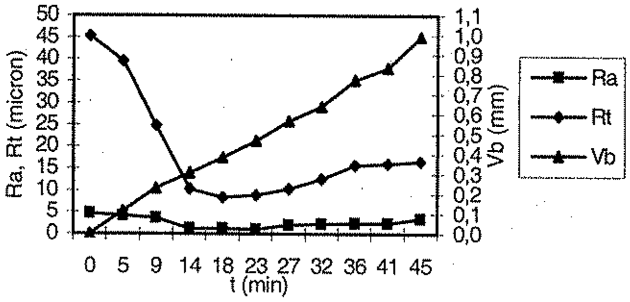
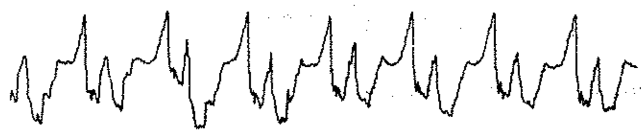
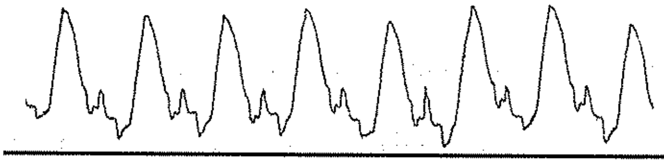


Figure 1. Variation of R_a and R_t with machining time for various Vb

It can be seen in the figure that the *Vb* increase gradually as proportional to machining time in steady-state portion. The R_a and R_t decrease until to a certain *Vb* and then start to increase. Therefore the variation of R_a and R_t is strongly related to *Vb*. Table 2 shows the variation of R_a, R_t plots depends on the number of pass and *Vb* obtained in one test. This situation can even be observed by sight. As can be seen in Table 2, the tip of 3rd insert has micro-fractured at 30th pass; therefore the shape of curve has changed as different as the others. When the catastrophic failure occurs on the inserts, the surface texture deteriorates rapidly and surface finish parameters increase considerably. The surface machined with a sharp tool differs from the surface machined with a dull tool. The marks generated by a cutter are predominant in the actual machined surfaces. As the cutting edge becomes more irregular with scars at the cutting tip, the appearance of machined surface tends to be more smeared and the grooves corresponding to feed marks become less predominant [5]. The plots clearly show that the area increases as the quality of surface deteriorates. As the image deteriorates, the non-uniformity of the vertical images increases. So in order to estimate the surface finish, a relationship can be set up between tool wear and surface finish parameters.

Table 2. The plots of R_a and R_t corresponding to various number of pass

The plots of R_a and R_t	Cutting parameters (v=113 m/min; f=200 mm/min; d=1 mm)			
	Number of pass	*Vb* (mm)	*Ra* (μm)	*Rt* (μm)
	24	0.383	1.2	8.3
	30	0.469	1.1	8.8
	36	0.568	2.1	10.3

	42	0.639	2.2	12.6
	48	0.774	2.4	15.7
	54	0.837	2.5	16.0
	60	0.994	3.5	16.6

3. DESIGN OF A NN FOR ESTIMATING SURFACE ROUGHNESS

3.1. The Structure of NN Used

The artificial neural networks are based on the neural architecture of human brain, which process information by means of interaction between simple processing elements, called neurons. Each neuron is connected to the neurons of in adjacent layer with weigh vector, which represent the strength of information. A threshold value (θj) is associated with each neuron. The output of each neuron is determined by the level of the input signal in relation to θj. They are trained through examples patterns rather than programmed by software [11]. The network consists of three processing unit: the input layer (L_i), the hidden layer/layers (L_h) and the output layer (L_o). For modelling surface roughness, multi-layered neural networks were used in the present work. The activation function in the NN is sigmoid function, which is a non-linear function. The NN have to be trained as off-line with BB type training algorithm [12] and then can be tested on-line with feed-forward method. NNs work through a connectionist model where, the input nodes supply weighted values (ω) of each node after adding a threshold value to the nodes in the hidden layer. A similar process is used between the hidden and output layer. The weights and threshold values are adjusted until the error comes to preset limit, or the desired number of iterations is reached [11].

The activation function $f(x)$ (used here is the sigmoid function) is given by:

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

where;

$$x = \sum \omega u + \theta \text{ and } x = \sum \omega v + \theta \tag{2}$$

u= input node values, v= hidden node values

At the training phase, the initial values of ω and θ are randomised and usually lie between –1 and +1. When the error (E) between the target value (T) and output value

(O) of the process is large, ω and θ are modified and the outputs recalculated. The error between target and calculated output is given by:

$$E = \frac{1}{2}\sum_{i=1}^{p}\sum_{k=1}^{m}(T-O)^2 \tag{3}$$

where i is the index for the input, k is index for the output, p is the number of patterns and m is the number of output nodes.

The weights are up-dated as follow by considering the error for the output layer (δ_2) and for the hidden layer (δ_1) can be expressed as:

$$\delta_2 = O(1-O)(T-O) \tag{4}$$

$$\delta_1 = v(1-v)\ \sum \delta_2 \varpi \tag{5}$$

The error is then back propagated through the network in such a way that the weights are modified by an amount $\Delta\omega(N)$. Incremental changes in the weights during Nth iteration, between the nodes of two layers are modified as follows:

$$\Delta\omega(n) = \eta\delta + \alpha\Delta\omega(N-1) \tag{6}$$

where η is learning rate, which determines the influence of error over weight change, and α is the momentum factor which affects the performance of the network.

3.2. Training of The Neural Network

The NN is trained using a large number of input data with corresponding output data [13]. An increase in input features generally improves classification performance. While the input data consists of information about test conditions, the output identifies the failure level of specimen. All the patterns were normalized in the intervals 0-1 dividing the feature value by its maximum in the training set to fit to sigmoid function.

As first step in the training phase, various NN architectures have been tested to obtained effective input features, the number of hidden layer (NH) and the number of nodes in each hidden layers (NH_j), number of iteration (NI), learning rate (η) and momentum factor (α). Finally, it was selected 7 features (3 sensor features and 4 process features) for input layer, and 2 features for output layer. After several pre-training experiments, NN architecture and training parameters were kept constant as η=0.5, α=0.5, NI=20.000 and NH_j=7x6x6x6x2 respectively. In order to find optimum training parameters, their effects on the NN performance must be analysed.

3.2.1. Training error

The training error is a criterion for obtaining optimum training parameters and network performance. The back-propagation of error is continued for a number of iterations until an acceptable error level is achieved. Training with BB, large number of iterations are required to back-propagate the error from output to input layer. Such process is carried out to adjust the values of weight to achieve certain estimation accuracy. The average error can converge to a global or a local minimum. The average training error as a function of the number of iteration has been given in Fig. 2.

It is seen that while the error too high in low iteration it is decreased rapidly with the increased NI. The average training error obtained was 7.16% for R_a and 4.85% for

R_t at 20.000 iterations. To obtain an acceptable error, further training experiments should be carried out using different values of training parameters.

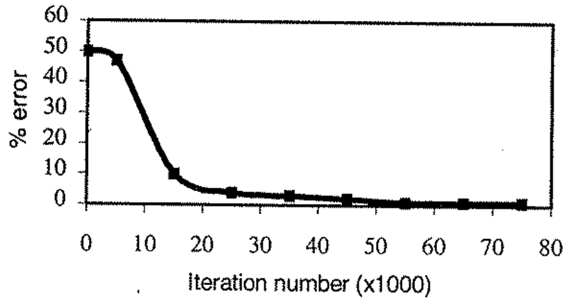


Figure 2. The variation of training error with the iteration number

3.2.2. Defining the number of hidden layers and the neurons in the hidden layers

Depending upon the NN architecture, the testing error can be nearly constant with the increase of iteration, or more than training error. NH_j is important factor to establish NN architecture. Variation in hidden layer size affects the system performance. The NN with two or more hidden layers provides better performance than with a single hidden layer at solving complex problems. After a certain point, more layer and more nodes in a hidden layer does not improve network performance, because of increasing complexity and reduce learning speed. It sometimes cannot be achieved. With the increase of neurons in L_h, the error converges faster to a smaller value. The optimum NH and NH_j were found as three and 6x6x6 respectively. The more layer and the more nodes in the hidden layers were tested but this caused increasing average training error.

3.2.3. Defining the learning rate

During the training a new weight value is formed by stepping from the present position in the direction of steepest descent, wherein the size of the step is governed by η, which affects the training speed. The large η provides rapid learning but might also result in oscillation; the network may converge to a local minimum instead of the global minimum in the error space. It is better to initialise the training with a low value of η, and to increase it gradually. This would prevent large number of iterations. The NN was trained with various learning rates (η=0.05-1.5). Optimum learning rate was found as η=0.8 including training error 11%.

3.2.4. Defining the momentum factor

To avoid oscillation in the results, Rumelhart and McClelland [12] suggested momentum term. The momentum term allows fast learning at low η by taking into consideration the changes made in the weights during the last iteration [13]. The NN was trained in range α=0.1-1. Optimum momentum factor was found as α=0.3.

As a result, the NN model was trained further with the training parameters of η=0.8 and α=0.3 at 50.000 iteration and average training error was reduced to 4%. The NN architecture established as 7x6x6x6x2 is shown in Fig. 3. By training the NN with 6 input features, 0.5 learning rate, 0.4 momentum factor, 1000 iteration number, 2 hidden layer and 9 nodes in each hidden layer, the average training error were found 15%. Also when the number of hidden layer and the nodes in each layer was taken too more the learning speed of NN has decreased considerable but the expected result could not have obtained. After training the NN model, the optimum training parameters are recorded, and then the NN is ready for application in real machining conditions to evaluate the surface texture with the set of data of input features.

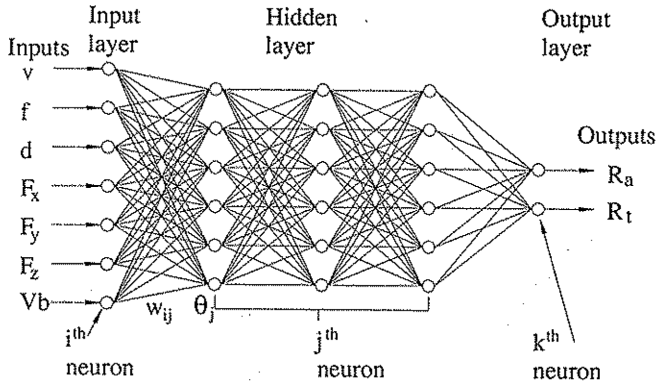


Figure 3. Neural network model used

4. COMPARISON THE RESULTS OF NN BASED MODEL TO THE EXPERIMENTAL RESULTS

The results of the NN model trained with extracted patterns for estimating R_a and R_t were compared to the experimental data. The data recorded are noisy and effected by many cutting parameters and cutting conditions either defined or undefined. Therefore, during training, error convergence became slower and to a high value. At high learning rate oscillation of average error occurred, and it converged to a very high value. To keep the training error in an acceptable limit, we have to use a large iteration and three hidden layer. In test phase, in order to observe the performance of NN architecture, six test patterns were selected. The comparatively test results has been given in Table 3.

Table 3. The results of ANN and experiments for surface finish (R_a and R_t)

d mm	v (m/min)	f (mm/min)	F_x (N)	F_y (N)	F_z (N)	Vb (mm)	Exp. results R_a (μm)	ANN R_a (μm)	Exp. results R_t (μm)	ANN R_t (μm)
1	113	200	62	89	169	0.228	3.7	3.4	25	26
1	113	200	87	115	225	0.383	1.2	1.1	8.3	9
3.5	226	400	203	240	477	0.367	3.0	3.0	16.7	16
3.5	226	400	208	300	505	0.424	3.0	3.0	16.2	16
1.5	178	250	78	108	200	0.203	2.6	2.5	14.6	14.7
1.5	178	250	88	120	250	0.305	2.1	2.0	10	11

The graph of experimental results and ANN results have been shown in Fig 4 and 5 obtained with the cutting parameters of v=113 m/min, f= 200 mm/min and d=1 mm.

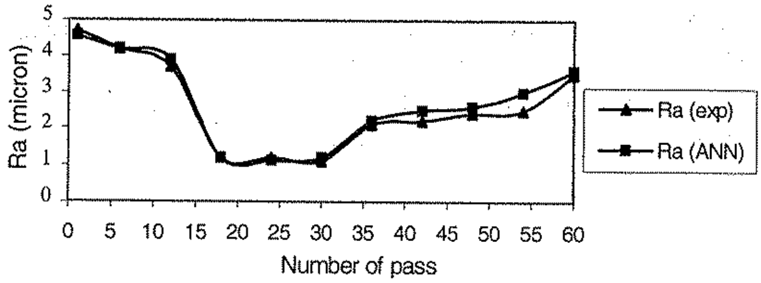


Figure 4. The comparison of experimental and ANN test results for R_a

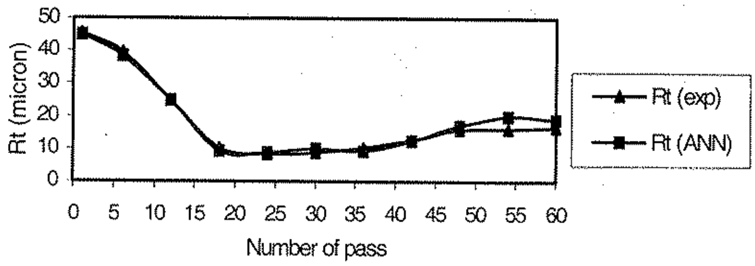


Figure 5. The comparison of experimental and ANN test results for R_t

As a result, optimum surface finish parameters have been obtained including testing error 5.9% for R_a and 3.9% for R_t. It was found that the ANNs results were very close to values of R_a and R_t on experimental results. Very good network performance has been achieved with the designed NN.

5. CONCLUSIONS

1. To establish an analytical modelling for estimating surface finish is difficult because of large number of definable and indefinable interrelated parameters. Instead of it, NN based model was proposed.
2. It is clear that the plots of surface finish parameters point to increased deterioration and tool breakage even before it happens. So by measuring machined surfaces, tool condition can be monitored indirectly. By analysing machine surface the condition of cutting tool (sharp, dull or catastrophic failure) can be detected effectively.
3. The calculated test error is a few higher than the training error. This result can be attributed to presence of some contradicting patterns in the training set, build-up edge formation, chipping, vibration and intermittent cutting.
4. The proposed NN was established with the network architecture including seven input parameters (v, f, d, F_x, F_y, F_z, Vb), two output parameters (R_a, R_t) and three hidden layers that contain six neurons in each layer. The NN was trained with learning rate 0.8, momentum factor 0.3 and number of iteration 50.000. As a result, R_a and R_t were estimated with the average error of 5.9% and 3.9% respectively. The more hidden layer and nodes were not found useful to get less error.

5. During machining, it is not practical measuring R_a and R_t with a stylus-based instrument. For on-line measurement a CCD camera, connected to computer equipped with an image acquisition capability, must be used, so surface structure can be monitored continuously and the machined surface images can be analysed rapidly.
6. The developed surface finish-estimating model can be used for analysing machined surfaces and defining tool wear in real-time tool condition monitoring systems.

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