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2-3 พฤศจิกายน 2543 โรงแรม โนโวเทล เชียงใหม่

การหาค่าความหยาบของผิวงานขณะผลิตด้วยเครือข่ายระบบประสาท

Artificial Neural Network (ANNs) for In-Process Surface Roughness Estimating

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Abstract

This research aim to estimate surface roughness in process by using acoustic emission (AE) sensor signals to generate signals. AE sensor can produce signals in real time process that easy to mount both on-line and process without obstructing in turning process. The signals are generated from friction between stationary pin and rotation work piece, which are transformed into the power spectrum and mapped into the process parameters by Artificial Neural Networks. We use Artificial Neural Networks to analyze dynamic AE signals sensitive to the work-piece surface roughness finishing turning process and develop on-line AE sensor based method for in-process estimating. The proposed methodology is applying Artificial Neural Networks, emphasizing the feed-forward architecture and learning with back-propagation method to create analytical model which raw data came from AE signals. We use the trained Artificial Neural Networks to control surface roughness of work-piece in feed back control process. The proposed in-process roughness estimating is required from modern manufacturing to produce high quality, accuracy, reasonable cost, reduce standard time and it isn't unnecessary to interrupt process for roughness measurement and adjust process parameters.

1. Desirable properties of Artificial Neural Networks for roughness estimation:

1. The network should be able to learn at least partially in unsupervised mode so that the demands for supervised training data and training time are reduced. The collection of supervised training data involves measuring both the sensor readings as well as the corresponding surface roughness parameter. On the other hand, the collection of unsupervised training data involves the acquisition of sensor data only. It is important that an ANN in this application learns at least partially from unsupervised training data because this data can be generated on-line without interrupting a machining process. Generating supervised training data requires intermittent interruption of the cutting process for tool condition related measurements and as a result it will be expensive to collect supervised data.

2. The network should be fault-tolerant to the fluctuations in sensor signals caused by non-uniformity in work-piece material composition and hardness, and phenomena such as built-up edge and chip breaking.

By means of these specially adapted Artificial Neural Networks the surface roughness parameter R_a is computed continually from the features extracted through the wavelet based sensor data representation scheme.

2. Measuring System

Figure 1. shows the set up for acquiring AE signals sensitive to the work-piece surface roughness measurements.

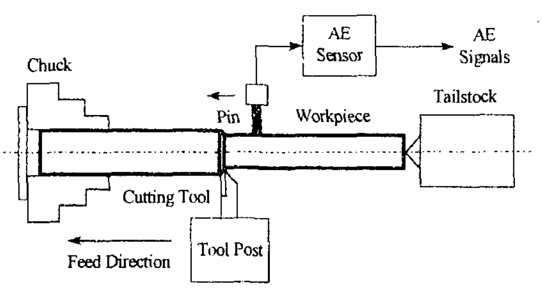

Figure 1: The setup acquiring AE signals.

3. Data collection

The finish cut is once started with a flesh insert edge. The AE sensor is placed in contact with the designed graphite square pin. And then set experiment of the cutting process is started, also collect AE signals. In each work-piece is measured roughness at those points by off-line with surface roughness gauge. We collected data 2 sets each, that is aluminum 2 sets and steel 2 sets. One set is used to trained network and other is used to input for test network.

4. The structure of feed forward networks with back-propagation learning

Artificial neural networks are biologically inspired devices used for mapping a set of inputs into outputs. The mapping is carried out by the processing elements, called artificial neurons or neurodes, which are interconnected to form a network divided into layers (this research use three layers): the input layer receives input from AE signals, the output layer sends outputs to the outside and one or more intermediate layers connect the input and output layers. The basic properties of neural networks, which are independent of the specific structure (number of layers, number of neurons) are the following:

1. Learning by back-propagation method: the capability of the network to adapt its behavior to the environment, or in other words to autonomously build a representation of the map from inputs to outputs on the basis of a set of examples.
2. Generalization: the ability to react in a coherent way to imperfect inputs or to input not explicitly seen during learning.
3. Soft degradation: the alteration or elimination of some elements of the network does not prevent it from working but only induces a smooth degradation in the performance.

5. The structure of the network

Within the network, neurons are organized in layers.

1. One input layer that receives signals from AE signals.
2. One or more intermediate (or hidden) layers whose neurons perform the processing (there is one hidden layer for this research).
3. One output layer which returns signals to the outside that are R_a, R_{max}, R_z.

6. Artificial Neural Networks mechanism for roughness estimating

We use AE signals to be input items of Artificial Neural Networks. After training Neural Networks, we received effective signals for each material below

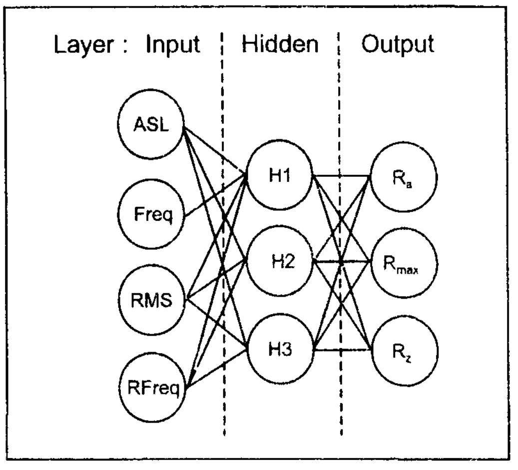

Figure 2: ANNs structure of aluminum roughness estimating (show effective parameters).

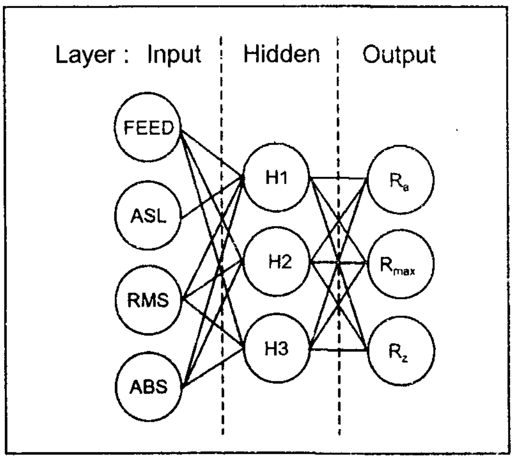

Figure 3: ANNs structure of steel roughness estimating (Show effective parameters).

In above figure, the neurons are grouped in three layers: Input layer, hidden layer and output layer. There are effective four inputs neurons (denote ASL, FREQ, RMS, RFREQ for aluminum and FEED, ASL, RMS, ABS for steel) , three hidden neurons (H1, H2, H3) and three output neurons(R_a, R_{max}, R_z). The structure is fully interconnected because each neuron in the input layer is connected with each neuron in the hidden layer, which in turn communicates directly with each neuron in the output layer. Each connection has an associated weight w_{ji}, the weight from neuron i to neuron j, which defines the strength of connection. The information received by the neuron flows only in the forward direction, from input to hidden to output, without feedback.

7. Learning in Artificial Neuron Networks

The aim of learning process is to choose values of the weights (w_{ji}) so as to realize the desired mapping from inputs to outputs. In supervised learning such as a mapping is learnt by reiterated presentation of a set of examples, each composed of input and an output vector. Such learning is supervised in the sense that the output of the network is compared to known target in order to define an error and to modify the existing weight to achieve a better performance.

The standard method used in the ANNs literature is the back-propagation algorithm. It allows the network to choose its weight in order to minimize a performance function defined over the output of the network and some targets. The performance function generally used is the sum of square error, where the sum is taken with respect to both the number of available patterns and the number of output neurons. Learning consists of repetitions following.

1. Present an AE signals pattern to the network.
2. From the input layers, propagate the signals through all layers of the network and finally to the output line.
3. Compare the output signals to the expected output signals (surface roughness from SR measurement). If they are equal, do nothing. Otherwise, adjust the weights of the Artificial Neural Networks according to some predefined function.

8. Mechanism of network training

1. Forward-propagation of the input signal
2. Backward propagation of error

9. Artificial Neural Networks Programming

Matlab program is use to perform both feed forward propagation of input signal and backward propagation of error for training network. After training, we use trained network to evaluate roughness estimating values by using effective parameter from collective data set2 in each work-piece (aluminum and steel).

10. Comparison Graph between actual value (SR measurement) and estimating value by ANNs.

10.1 Graph of Neural Network Testing (After training and substitute effective AE signals)

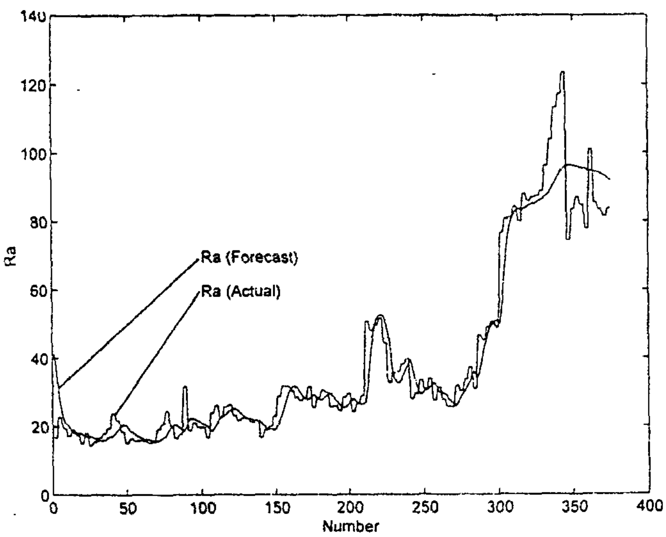

Figure 4: Graph of Testing between R_a and R_a (ANNs estimating): aluminum

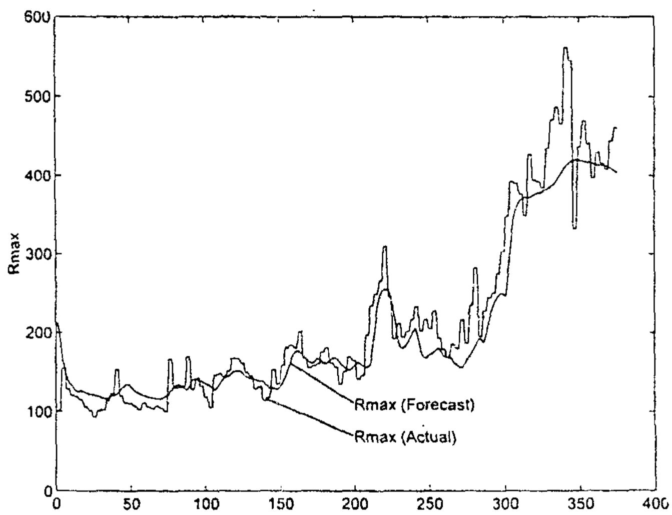

Figure 5: Graph of Testing between R_{max} and R_{max} (ANNs estimating)

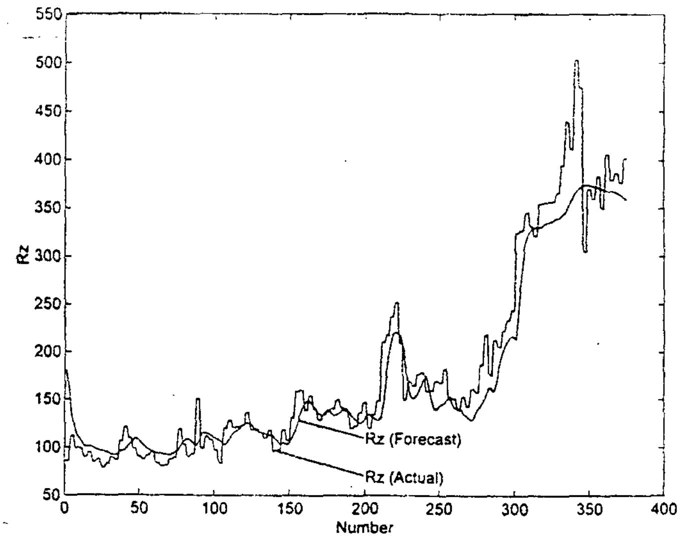

Figure 6: Graph of Testing between R_z and R_z (ANNs estimating): aluminum

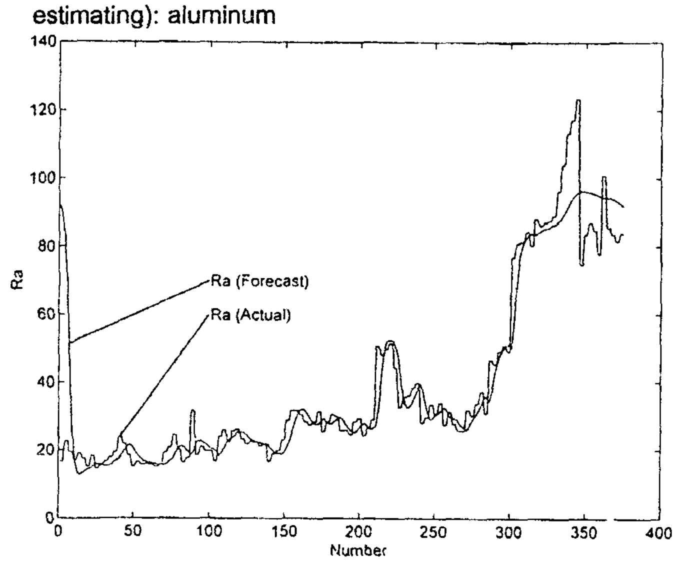

Figure 7: Graph of Testing between R_a and R_a (ANNs estimating): steel

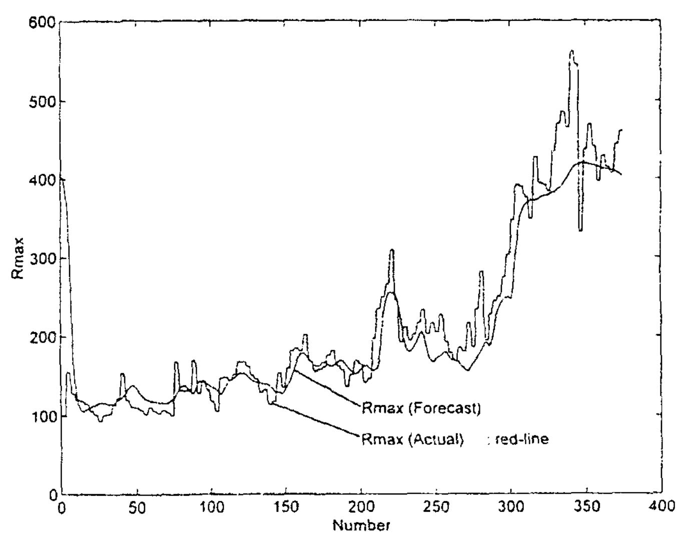

Figure 8: Graph of Testing between R_{max} and R_{max} (ANNs estimating): steel

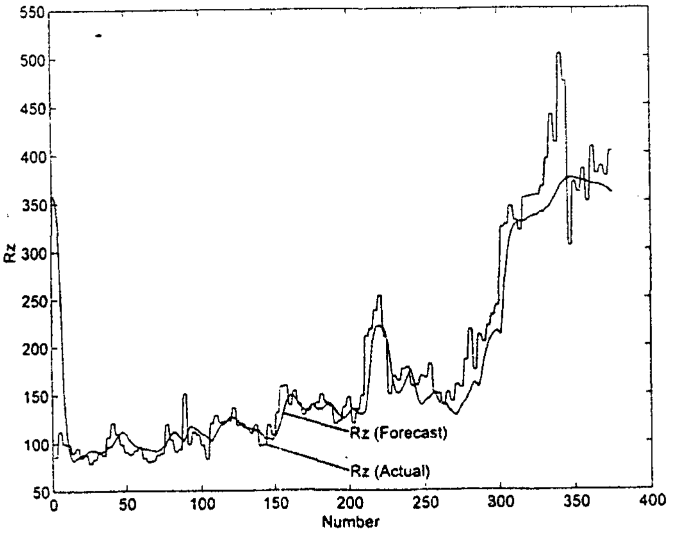

Figure 9: Graph of training between R_z and R_z (ANNs estimating): steel

15. Conclusions

In this research, an on-line and in-process estimation system applied in the area of roughness monitoring using AE signals. Artificial Neural Networks is used to perform in estimating by back-propagation method with percentage error are less than 10 %. Surface roughness from neural network is used to feed back process to control roughness. The estimating results show that this method can indicate the accuracy surface roughness. Furthermore, this method can reduce standard time for industrial measurement and can control process in real time.

16. Reference

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