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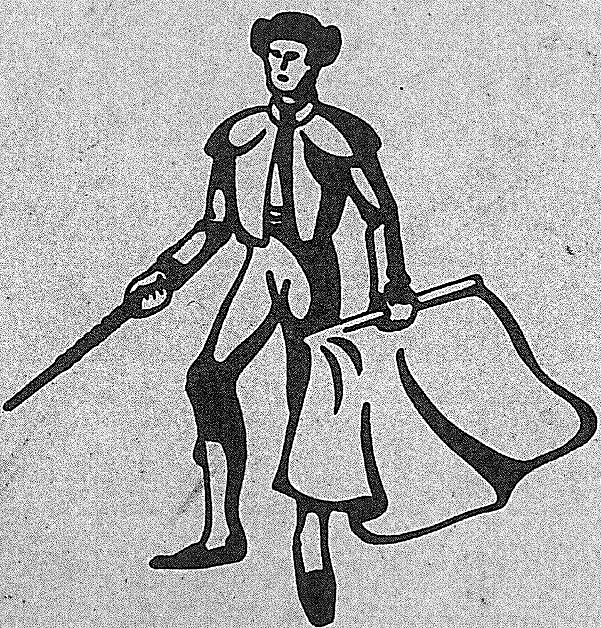

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CONDITION MONITORING OF CUTTING TOOLS USING ARTIFICIAL NEURAL NETWORKS

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SUMMARY

The paper presents a methodology for using neural network techniques and simple data processing algorithms for monitoring the condition of milling cutters during peripheral milling . The learning algorithms considered in this research utilise artificial neural networks to map some machining parameters to sensory signals. Cutting force and acceleration signals recorded during machining are first simplified and then fed into the input layer of the neural network. Using the back-propagation method, the output of the neural network is used to recognise "normal" as well as "faulty" milling cutters and the depth of cut used. The experimental results show that the proposed approach of using simple data processing algorithms with neural networks is capable of successfully identifying common fault conditions in milling cutters in peripheral operations.

Keywords: condition monitoring, artificial neural networks, milling, tool breakage, pattern recognition

INTRODUCTION

The drive for improved product quality and reducing inspection costs is attracting many companies towards exploring the potential of condition monitoring of machine tools, cutting tools and manufacturing processes as means of early detection of faults during component manufacture and improving performance through operating under optimal conditions. The underlying hypothesis is that "if the machine and process are "normal" then the component produced should be within tolerance and therefore there is less need for inspection to prove that this is the case".

In spite of several decades of research, the complex nature of manufacturing processes such as machining makes the use of analytical techniques and establishing accurate predictive mathematical models a very difficult task. Taking advantage of the learning ability of artificial neural networks is therefore becoming an attractive option in dealing with such complex problems.
In this article, real-time sensory data is recorded, processed and analysed automatically during machining, and is then used as training data set for a 16-input artificial neural network shown in Figure 1. After a process of system validation the neural network is used for on-line fault identification and breakage monitoring of cutting tools.

The experimental system is based upon force signals obtained during peripheral milling of test pieces mounted on a three-component Kistler force measuring dynamometer. The force signals are filtered, smoothed and simplified using signal processing techniques and algorithms and fed into the input layer of an artificial neural network with Sigmoid transfer function. Using back-propagation, the output of the artificial neural network is then used for pattern recognition and classification of cutter condition.

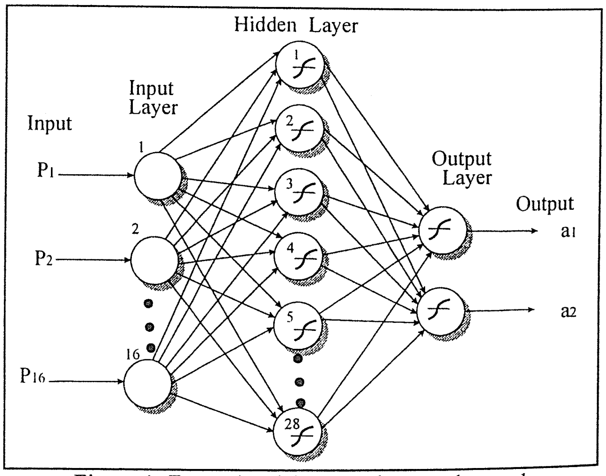

Figure 1: Example of the neural networks used

The basic structure of machine condition monitoring system is shown in Figure 2 [3]. Process signals are transferred from sensors to the system model where process characteristics are identified. Based on previous knowledge and past experience, the impact of the current situation on the part being machined can be evaluated. At that stage, the recognised characteristics are compared with design values. If process status proves to be incapable of meeting the design values, the control parameters are adjusted such that the design parameters are satisfied. Hence, new machining parameters are calculated and sent to the controller to drive the actuators.

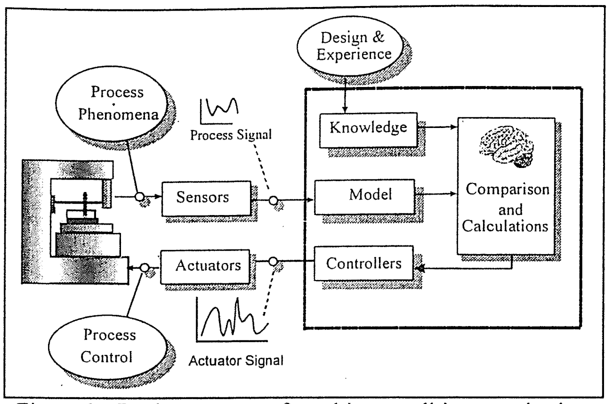

Figure 2 : Basic structure of machine condition monitoring

In order to provide the system with "learning" capabilities, all activities are considered, evaluated and memorised by a computer system which stores all the information in a data base and modifies the algorithms for self-development of the total system. To maintain high precision the required sensing, calculations , and actuation have be accomplished in real time.

EXPERIMENTAL INVESTIGATION

The experimental investigation was designed to test the applicability of neural networks for identifying the fault conditions of a milling cutters and the depth of cut used. The experiments involved a peripheral milling of aluminium parts by using a knee-and-column type milling machine and two values of depth of cut (2.5mm and 5 mm) as shown in Figure 3.

A side straight-tooth milling cutter of 16 teeth and a diameter of 100 mm is used to machine straight slots in the aluminium parts, under constant rotational speed (420 RPM) and feed rate (89 mm/minute). Two types of sensors were used, an accelerometer to measure the vibration and a three component force dynamometer for measuring cutting forces.

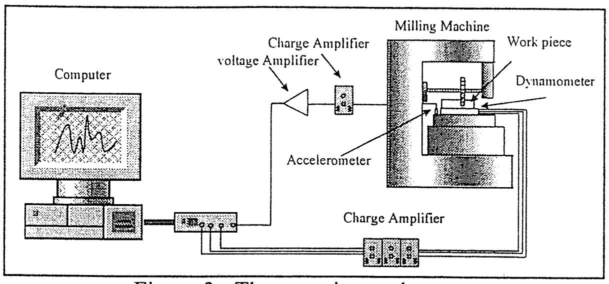

Figure 3 : The experimental set-up

The signals generated are amplified using charge amplifiers and fed to a computer for data analysis. Figure 4 shows the milling process implemented and the direction of the measured cutting forces.

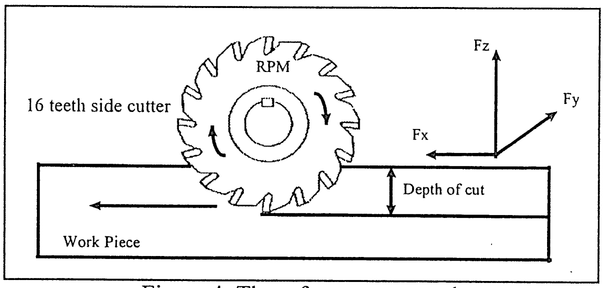

Figure 4: Three forces measured.

Example cutting forces and vibration signals for three cutter revolutions at a 5 mm depth of cut are shown in Figure 5. A cyclic behaviour of the cutting forces caused by deflection of the rotating shaft can be observed.

After processing, the recorded signals are to identify the following conditions: a "normal" i.e. acceptable milling cutter; a milling cutter but with one broken tooth and a cutter with two teeth broken. This type of information can be used later to relate part quality parameters (e.g. tolerance, surface finish etc.) to the condition of the cutter through the signals produced.

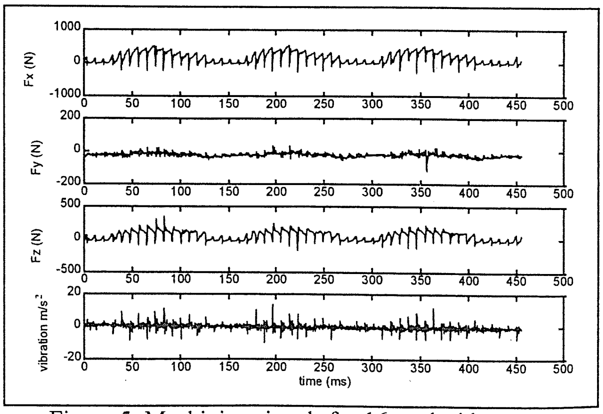

Figure 5: Machining signals for 16 teeth side cutter.

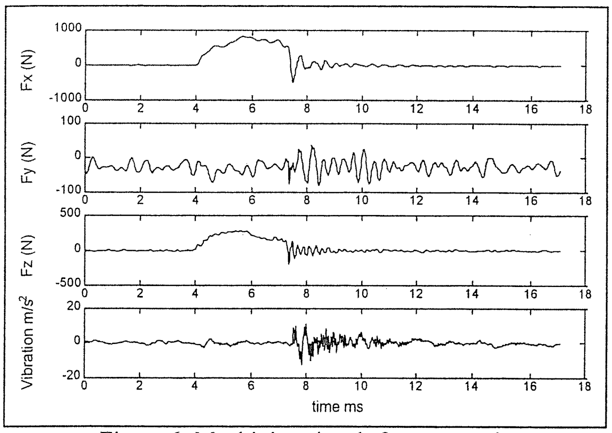

Figure 6: Machining signals for one tooth

The cutting force and vibration signals isolated for one cutter tooth is also shown in Figure 6. It can be seen from the signals that the cutting Fy is very small compared with the other two forces and that Fx and Fz are similar in nature but the magnitude of Fx is approximately twice that of Fz. From the vibration trace the point at which the cutter tooth disengages from the part material can be easily recognised. To simplify data analysis procedures, and based on the results obtained, the value of Fx alone was considered representative of process characteristics, and therefore sufficient to identify the desired cutter conditions without the need to use other recorded signals. The force signals in the x direction (Fx) for both a normal cutter and a cutter with one tooth and two teeth broken are shown in Figure 7.

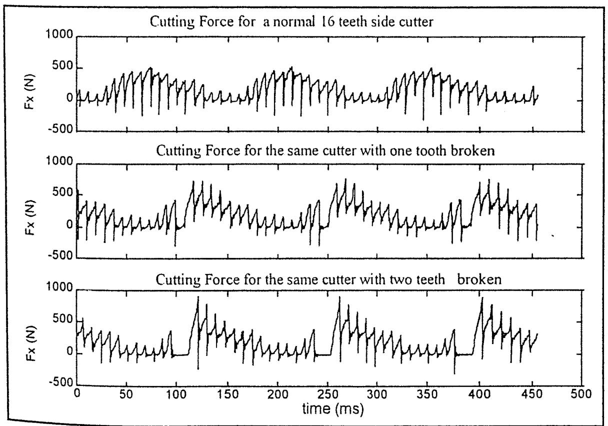

Figure 7 : The Cutting force Fx for the normal cutter, one tooth broken cutter, and two teeth broken cutter.

SIGNAL PROCESSING

Figure 8 shows the main stages the cutting force signal pass through to be identified by the neural networks. Different signal processing techniques are used to prepare the signals for neural networks.

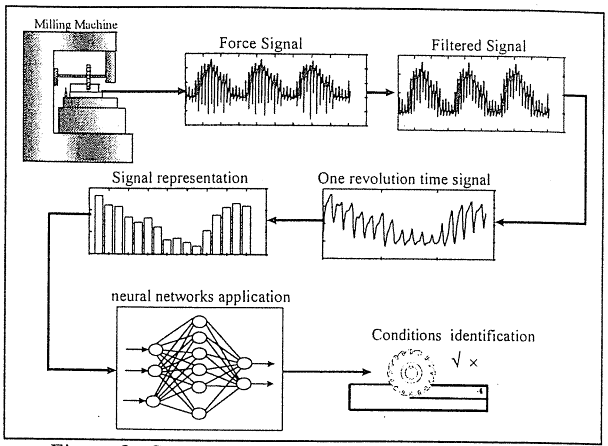

Figure 8 : Summary of the signal processing stages.

The signal is first filtered and smoothed ready for further processing using a low pass filter to eliminate sudden changes in the force signal. The filtered signal, shown in Figure 8, is based on three full revolutions of cutter rotation. A 16-input neural network is used for signal analysis.

Figure 9 shows the cutting force signals for one revolution of a normal cutter, one tooth broken, and two teeth broken cutters. The presentation of the same data as the input for the neural network is shown in Figure 10.

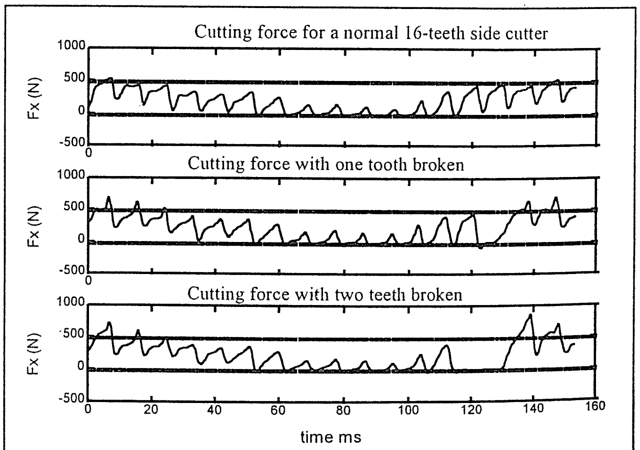

Figure 9 : Cutting force for single revolution (5mm depth of cut).

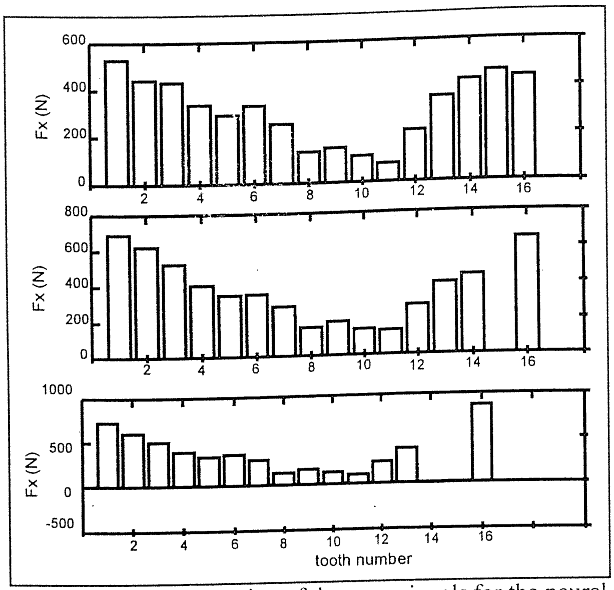

Figure 10: The presentation of the same signals for the neural network

Comparing the three signals in Figure 9, the differences which occurs between the time 100 ms and 140 ms time markers can be easily recognised. For the one-tooth broken cutter, there is a critical point missing. Moreover, the values of the cutting forces for the next teeth have increased. Similarly, the differences are much more pronounced for the two-teeth-broken cutter. The gap between the specified interval of time has increased and the subsequent forces have also increased more than previously.

A look-ahead algorithm which identifies the "maximum critical point" within a specific period of time (based on the time period of each tooth) is used for simplifying the signal before presenting it to the neural networks. If there is no critical maximum value, a zero value is assigned to that tooth.

THE NEURAL NETWORKS APPLICATION

Two main experiments were performed during this investigation :

1. The identification of cutter condition (normal cutter, one tooth broken, and two teeth broken cutters) at two values of depth of cut (2.5 and 5mm) at identifiable sampling conditions with respect to cutter teeth.
2. The identification of cutter conditions for randomly sampled signals. (i.e. signals are identified regardless of the starting point of sampling).

The identification of the three conditions of the cutter for 5mm depth of cut only

Based on the results of a comprehensive set of designed experiments, a (16:28:2) neural network with Sigmoid function was considered the most appropriate structure found for representing the problem. The suggested neural network (shown in Figure 1) has a learning momentum of 0.4 and a acceptable error of 0.01. A data set based on 30 samples (bar charts), ten samples for each cutter condition, was used to train the network. Figure 11 shows the identification results for 15 samples tested, five of each type.

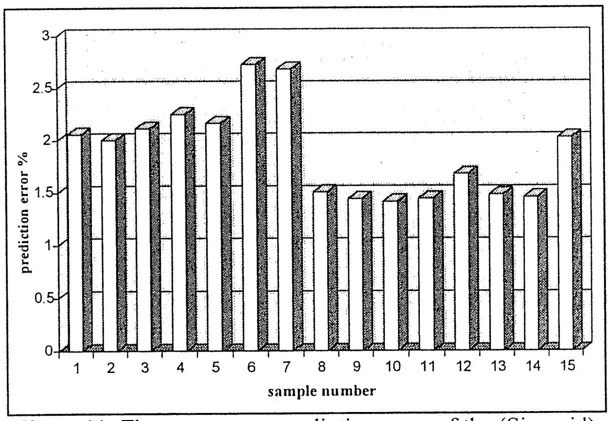

Figure 11: The percentage prediction error of the (Sigmoid) network for the new fifteen sample with α=0.4 .

In this case, the average prediction error is found to be 2.02% and the maximum error is found to be less than 2.8% for the 144 training cycles needed to train the neural network.

The identification of the cutter conditions and depth of cut

Here, six types of cutting signals are discussed and identified by the neural network. As before, there are three conditions concerning the cutter: normal cutter, one tooth broken, and two teeth broken cutter. Furthermore, two types of cutting conditions are identified in this section: 5 mm and 2.5 mm depth of cut. Hence, we have six combinations of the cutter conditions and the depth of cut values. Figure 12 shows the filtered cutting force (Fx) for the three conditions of the cutter at 2.5 mm depth of cut.

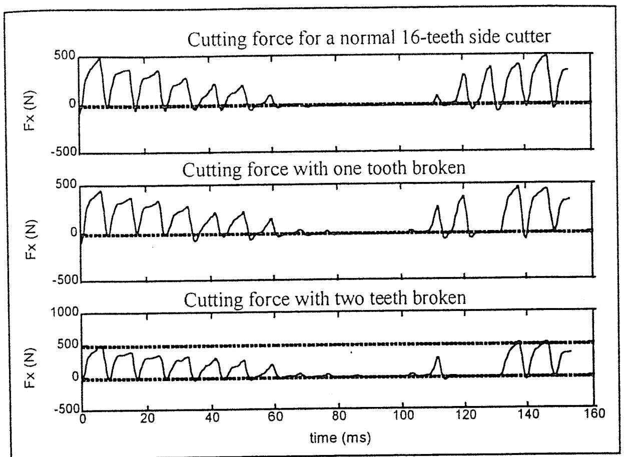

Figure 12: Cutting signals for 2.5 mm depth of cut.

The "critical point method" is used to simplify the signals fed to the neural network. Figure 13 shows examples of a normal cutter signal, one-tooth broken cutter, and two teeth broken cutter signal, with 2.5 mm depth of cut. Again a (16:28:3, Sigmoid) neural network is used to identify the six different conditions.

A total number of 36 signals, 6 of each type, are fed to the neural network. 334 training cycles are needed to reach an error of 0.01. Figure 14 shows the bar chart of percentage prediction error of the 18 samples tested after training the neural network. The average prediction error for all signals is 2.05 %, and the maximum error is 5.18% .

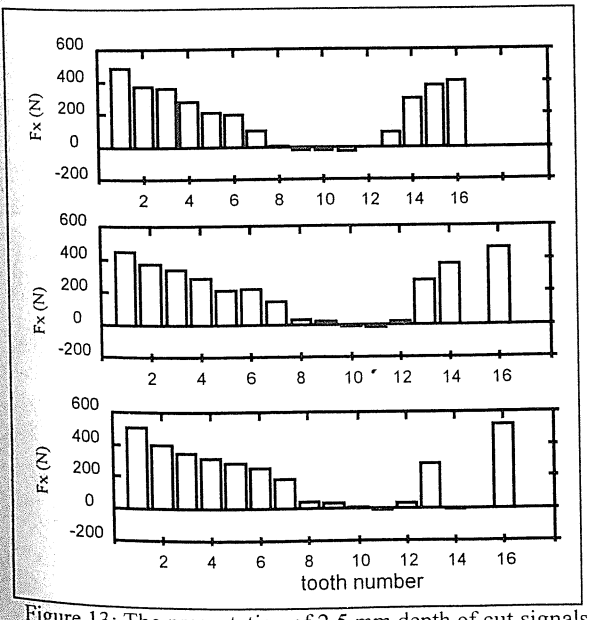

Figure 13: The presentation of 2.5 mm depth of cut signals for the neural network.

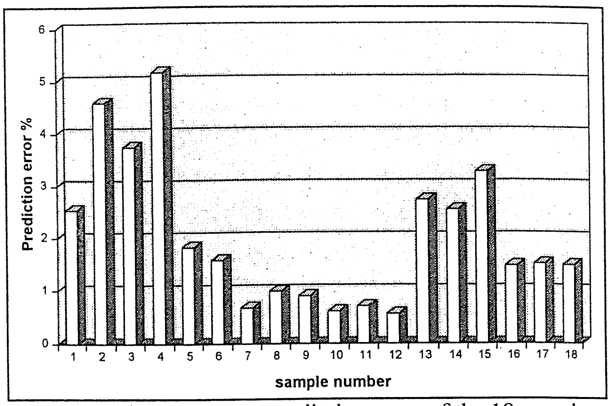

Figure 14: The percentage prediction error of the 18 samples.

Random Starting Point

As in the previous analysis, all data is defined to be in one cutter revolution starting from a fixed reference point. Thus, the broken teeth are always number 15 in the case of the one-tooth-broken cutter or numbers 14 and 15 the in case of two-teeth-broken cutter. However, such an assumption is not practical, since it is difficult to identify the beginning of a revolution for different cutters under different machining conditions. To overcome this difficulty, each of the training signals was presented to the neural network in several different ways, so that the signal can be identified regardless of the starting point of sampling. Figure 15 shows four possible representations for the data shown in Figure 10 for the two teeth broken cutter.

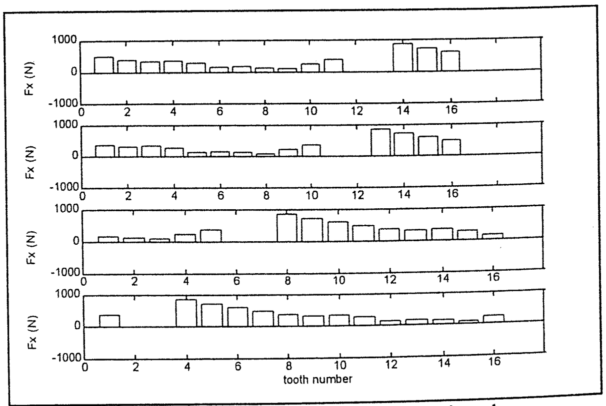

Figure 15: Different methods of representing the same cutting force signal according to the reference point of sampling.

The signals are obtained from rotating the original signal. One of the restrictions of this method is that the sampling process must start from a local minimum of the signal.

For each 30 training signals of 5mm depth of cut, 16 different signals (as described before) are generated. Hence, the total number of training signals is 480. In the same manner, the 15 test samples have become 240 samples. A (16:28:2, Sigmoid) neural network is implemented with the same training parameters described previously. The number of training cycles is found to be 133,332. The average prediction error for the 240 samples is found to be 1.51%. Figure 16 shows this prediction error.

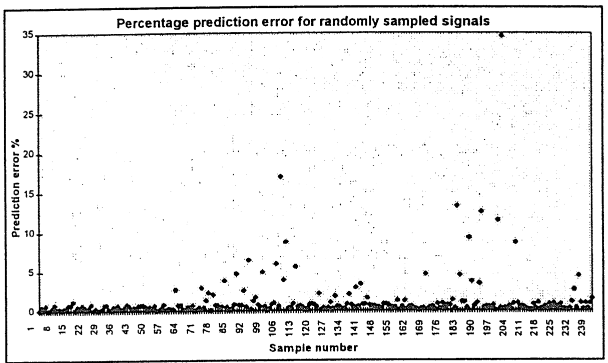

Figure 16: The percentage prediction error for randomly sampled signals.

As shown , the maximum error is found to be as high as 35%. However, the majority of the samples errors are below 2%.

CONCLUSION

The experimental methodology and signal processing algorithms reported in this paper proved capable of detecting tool breakage and differentiating between acceptable and unacceptable milling cutters, based upon the number of broken teeth in addition to the depth of cut used during machining.
In order to implement on-line fault identification and monitoring systems, the detection algorithms should be kept as simple as possible to reduce processing and calculation times. The reported results show that a combination of simple signal processing algorithms and artificial neural networks is a suitable approach useful for identifying certain faults on the cutting tools used in peripheral milling operations.

The methodology used permits the application of artificial intelligence techniques which have the potential to allow machine tools to exhibit intelligence in terms of being aware of its environment and conditions.
Such methodologies can help to reduce the frequency of component inspection and increase the productivity of milling operations.

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