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Neural Network Application in On-line Monitoring of Turning Processes

by G.M. Zhang and R.G. Khanchustambham

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Neural Network Applications in On-line Monitoring of a Turning Process

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Abstract

The need to improve quality and decrease scrap rate while increasing the production rate is motivating industry to consider untended machining as a viable alternative. On-line monitoring of a machining process is the key component to success for an untended machining operation. In this chapter, a framework for sensor-based intelligent decision-making systems to perform on-line monitoring is proposed. Such a monitoring system interprets the detected signals from the sensors, extracts the relevant information, and decides on the appropriate control action. Emphasis is laid on applying neural networks to perform information processing, and to recognize the process abnormalities in a machining operation. A prototype monitoring system is implemented to demonstrate the working mechanism. For successful implementation of the developed intelligent monitor, an instrumented force transducer is designed for signal detection and is used in a real time turning operation. A neural network monitor based on feedforward back-propagation algorithm is developed and tested under the machining of advanced ceramic materials and steel. The monitor is trained by the detected cutting force signal, the measured surface finish, and the observed tool wear. The superior learning and noise suppression abilities of the developed monitor enable high success rates for monitoring the machining process.

1 Introduction

In recent years, manufacturing engineers have been faced with the difficult task of improving productivity without compromising on quality. The complexity of modern day components makes this task difficult. Computer Integrated Manufacturing (CIM) systems have emerged in response to the demands for greater flexibility, productivity, precision and quality. The manufacturing industry is now considering untended machining as a viable alternative to meet these demands. In an untended machining process various tasks, such as sensing the effect of process variables and adjusting the conditions accordingly, have to be done by appropriate sensors and associated monitors. Consequently, the development of an effective on-line monitoring system is the key to the successful implementation of an untended machining process.

Substantial research has been done in the area of on-line monitoring of machining processes [1-6]. Recognizing the need of an intelligent human operator out of the manufacturing loop, powerful sensors, either built-in or attached to machine tools, have been designed and fabricated with great success. Examples of typical sensors are force dynamometers and vibration detectors. When they are used in a machining system, information related to the machining process can be abstracted from the measured signals and interpreted through signal processing. Based on the interpretation, an inference is usually made whether the machining process should continue on, or a control action should be taken to make correction. It has been well accepted that a general on-line monitoring system consists of, at least, sensing elements, signal processing devices, signal processing algorithms, information interpretors, and a decision-making mechanism. A literature survey of the developed on-line monitoring system indicates that the major concern of an automated machining system is the identification of the tool wear status as the machining process is going on [1-6]. This concern would be more evident in precision machining since the tool wear has a direct influence on part dimensions and the finish of the machined surfaces. Furthermore, prompt identification of a severe tool wear assures a safe cutting operation. Consequently, on-line tool wear information is indispensable in order to achieve a fully automated machining operation.

The main objective of this research is to develop an intelligent on-line monitoring system through a neural network approach. The monitoring system detects the cutting force produced during machining, estimates the tool wear status, and finish quality from dynamic variation of the detected cutting force signals, and makes the decision for taking corrective action when it is needed. This research work consists of the design of a force transducer and its application to signal detection in a real-time machining process, and the development of a neural network monitor. The monitor is built on feedforward back-propagation algorithm. Under an application circumstance, the monitor is first trained for information processing, and later applied for the cutting force and surface finish monitoring during the machining of advanced ceramic materials.

2 On-line Monitoring Methodology

The productivity of the factory of the future and the quality of the products it produces will, in part, depend on the intelligent utilization of computers to monitor and control the machines involved in production. This demands that the supervising personnel and the computer systems provide accurate and reliable information about the status of the machines and the quality of the operations they perform. This requires, therefore, a much better understanding of the machining processes and the functions they perform, so that sensors and the associated decision-making systems can be designed. According to Balakrishnan, one can achieve a fully untended machining if one can monitor the following tasks successfully [9].

- Workpiece monitoring (eg., surface finish, automatic setup, gauging)
  measurement)
- Process monitoring (eg., adaptive control, chip congestion detection)
- Machine monitoring (eg., vibrations of gearbox, spindle and machine tool table)

Figure 1 presents a general picture of an on-line monitoring system. The three major parts of the implemented monitoring system are: a force transducer, a neural network monitor, and a decision-making advisor. The basic working principle of this monitoring system is in-process verification through indirect measurement. It means that the detected cutting force signal may not directly reflect the tool wear status or surface finish quality. However, a mathematical model is built to establish the inherent relationships between the detected force signal and the monitoring targets, such as tool wear and surface finish quality. Interpretation of the detected signals retraces the actual machining operation. Neural networks are of particular help in such an application.

2.1 *Force Transducer*

The designed force transducer shown in Figure 1 consists of a tool holder, four strain gages, two bridge amplifiers, and a data acquisition device. The strain gages are attached to the tool holder. During machining, the generated cutting force produces strains on the tool holder. The strain gages convert the strains to measurable voltage signals through the bridge amplifiers. The data acquisition device digitizes and stores the voltage signals. A quantitative relation between the cutting force and the measured voltages, established from a calibration process, helps in determining the magnitude of the cutting force from the measured voltage signals.

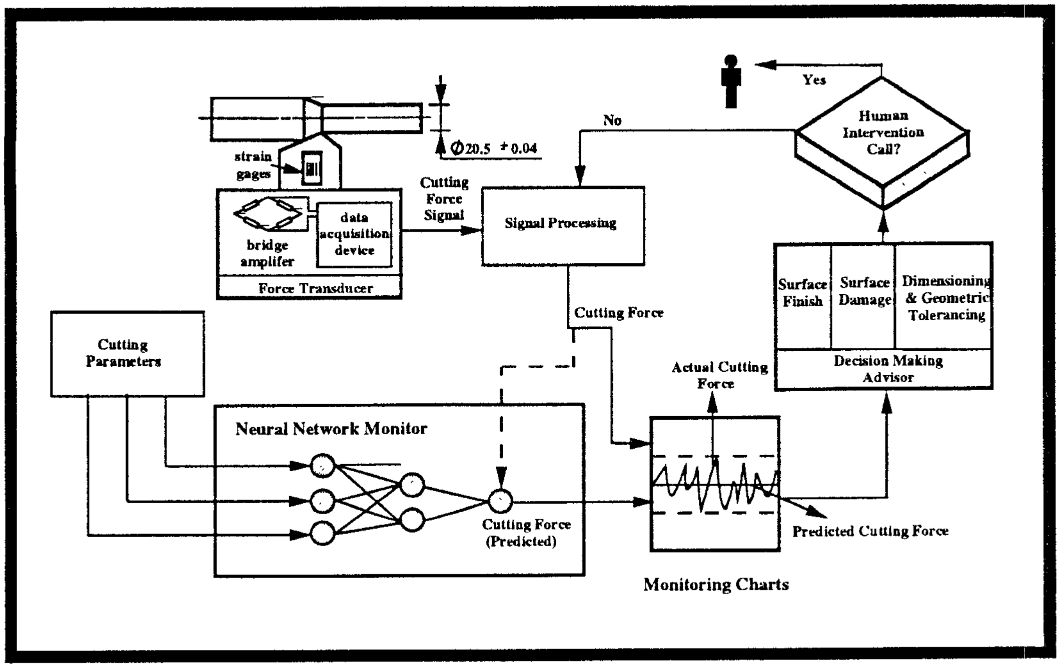

Figure 1: Basic Structure of the Implemented On-Line Monitoring System

The strain gage-base sensor system was calibrated prior to the tests to establish the transformation matrix relating the voltage signals and the cutting force generated during the machining process. The relationship between the applied forces and the voltage outputs of the strain gage are shown in Figures 2 and 3. The transformation matrix, T_r, is defined as the relation between the forces and voltages:

$$[T_r] = \frac{Input}{Output} = \frac{V_{out}}{F}$$

The above relation can be written in matrix form as:

$$[T_r] = \begin{bmatrix} \frac{\Delta V_z}{\Delta F_z} & \frac{\Delta V_z}{\Delta F_x} \\ \frac{\Delta V_x}{\Delta F_z} & \frac{\Delta V_x}{\Delta F_x} \end{bmatrix}$$

From the values of tables in figures 2 and 3, we have:

$$[T_r] = \begin{bmatrix} T_{11} & T_{12} \\ T_{13} & T_{14} \end{bmatrix} = \begin{bmatrix} 0.0283 & 0.0000 \\ -0.0003 & 0.0253 \end{bmatrix}$$

Each element of $[T_r]$ is the transformation relation of the i^{th} voltage output and the j^{th} cutting force component. The values of elements of $[T_r]$ were obtained by finding the slopes of the graphs of figures 2 and 3. The force matrix is calculated as:

$$[F] = (inv([T_r]))\,[V]$$

The above reaction can be written as:

$$\begin{bmatrix} F_z \\ F_x \end{bmatrix} = \begin{bmatrix} 35.3357 & 0.0000 \\ 0.4190 & 39.5257 \end{bmatrix} \begin{bmatrix} V_z \\ V_x \end{bmatrix}$$

where, F_z and F_x are components of cutting force in tangential and feed directions, respectively.

Load (lbs)	Voltage Tangential (volts)	Voltage Feed (volts)
10.0	0.1186	0.4204
20.0	0.1227	0.7054
30.0	0.1192	0.9452
40.0	0.1119	1.2148
50.0	0.1097	1.4136
60.0	0.1036	1.7138
70.0	0.1038	1.9307
80.0	0.0976	2.2067
90.0	0.1039	2.4667

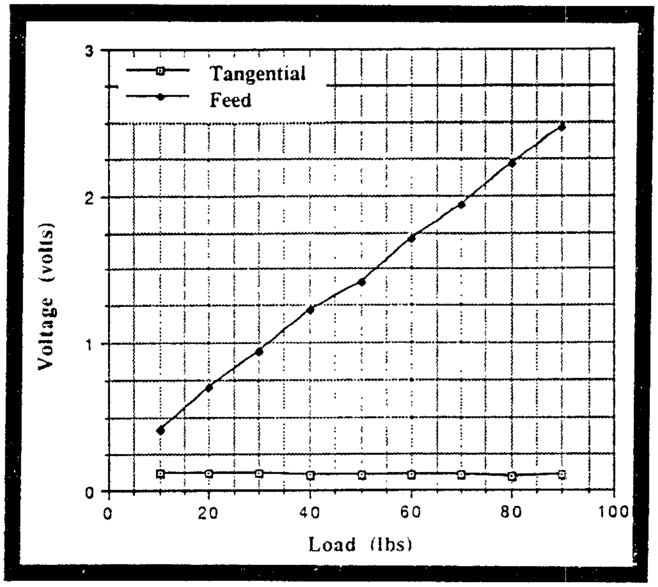

Figure 2: Calibration in Feed Direction

Load (lbs)	Voltage Tangential (volts)	Voltage Feed (volts)
10.0	0.4137	0.2173
20.0	0.7137	0.2199
30.0	0.9815	0.2209
40.0	1.2855	0.2193
50.0	1.5800	0.2206
60.0	1.8426	0.2199
70.0	2.1349	0.2189
80.0	2.4064	0.2198
90.0	2.4064	0.2198

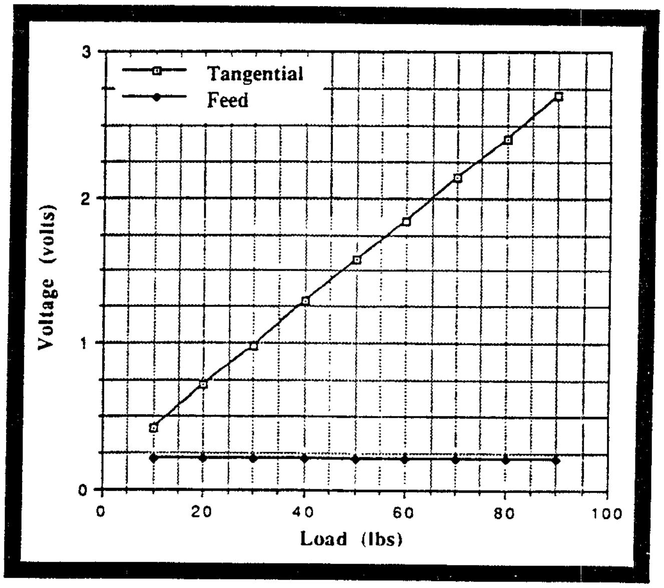

Figure 3: Calibration in Tangential Direction

It is evident that the higher the measured voltage, the larger the cutting force produced during machining. Since the cutting force increases with tool wear, detection of the dynamic variation of the cutting force produced during machining may provide useful information on tool wear status and the finish quality of the surface being machined.

2.2 *Neural Network Monitor*

In order to perform information processing from the detected signals, a neural network monitor based on feedforward back-propagation algorithm has been developed and implemented in an on-line monitoring system [7-8]. The main characteristics of the on-line monitor are: 1) layered architectures; 2) strictly feedforward connections between the neurons; and 3) no lateral, self, or back-connections. Based on the principle of back-propagation network (BPN), all the information flow is feedforward. The important characteristic of the back-propagation network is that it forms a mapping from a set of input stimuli to a set of output nodes using features (hidden layer) extracted from the input patterns. By features, we mean the correlation of the activity among different input nodes. The ability to make the complex distinctions, even when the presented pattern is different from those on which the network was previously trained, is due to the feature detection and generalization abilities which the network was trained into the middle or hidden layer nodes. These networks undergo supervised learning, i.e., they are taught to classify input into one of the several *a priori* categories.

The neural network monitor developed to monitor a machining process is divided into two stages. The first stage is the process of obtaining a set of weight connections between individual nodes and a set of threshold values of nodes in hidden layer and output layer. The second stage is to implement the trained network in a real time machining operation, as shown in Figures 1 and 12.

In this work, variable thresholds on the hidden nodes and the output nodes, and variable weight connections between individual nodes are used. As the activity of neuron is closely modeled by a sigmoid function, for each node a sigmoid shape (S-shape) transfer function is used. Therefore, each node represents a non-linear function of the form,

$$Y_j = \frac{1}{[1 + exp(-(X_j + \theta_j))]}$$

where, $X_j = \sum Y_i W_{ij}$, Y_j = output of node in layer j, Y_i = output of node in preceding layer i, and W_{ij} =weights of interconnections.

The three main stages in training the monitor (i.e., finding useful set of values for the interconnection weights and threshold values of nodes) are listed as follows.

1. The forward pass: where the output of each node is calculated.

2. The backward pass: where weight and threshold changes of each node takes place.
   Weights are adjusted by:

$$w_{ij}(t+1) = w_{ij}(t) + \eta\delta_j Y_i + \alpha(W_{ij}(t) - W_{ij}(t-1))$$

$$\theta_j(t+1) = \theta_j(t) + ch\_thre$$

   In this equation $w_{ij}(t)$ is the weight from the hidden node i or from an input node j at time t; Y_i is either the output of node i, or is an input; η is a gain term; α is a momentum term; δ_j is an error from node j; and *ch_thre* is change in the threshold value of each node. If node j is an output node, then

$$\delta_j = Y_j(1 - Y_j)(d_j - Y_j)$$

$$ch\_thre(t+1) = \eta\delta_j + \alpha(\theta_j(t) - \theta_j(t-1))$$

where d_j is the desired output of node j, and Y_j is the actual output.
If node j is an internal hidden node then

$$\delta_j = Y_j(1 - Y_j)\sum_{0}^{k} \delta_k W_{jk}$$

$$ch\_thre(t+1) = \eta\delta_j + \alpha(\theta_j(t) - \theta_j(t-1))$$

where k is over all nodes in the layers above node j.

3. Termination: where the network stops training when the network's output is close to the desired output.

   The error for the network is calculated as follows:

$$E = \frac{1}{2}\sum_{i=1}^{k}(d_j - Y_j)^2$$

2.2.1 *Ceramics Monitor*

It has been known that the cutting force is related to the cutting parameters such as feed, depth of cut, and the spindle speed. For the purpose of monitoring a machining process through the cutting force and surface finish detection, a mapping function between the two detected signals and the three cutting parameters should be established. Figure 4 illustrates the basic structure of the implemented on-line monitor in this work. The monitor has two independent models, namely the cutting force model and the surface roughness model. Each of the two models consists of an input layer, a hidden layer, and an output layer. In the cutting force model, the three nodes in the input layer represent feed, depth of cut, and the cutting speed. In the hidden layer, two nodes are chosen for maximizing the effect to generalize the input information into the correlation of the activity among the three input nodes, rather than to simply memorize the input patterns [5].

2.2.2 *Steel Monitor*

It is well known that a tool will produce relatively higher loads as it begins to wear during the cutting operation. For effective process monitoring it is important that the signal used should vary progressively as the tool wears, and not just at the point when it breaks. Force measurement is currently the most reliable and accurate sensing method in metal cutting operations, as the cutting force increases with flank wear due to an increase in the contact area of the wear land with the workpiece. It is generally assumed that the components of cutting force are related to flank and crater wear [10-12]. According to Wright, however, cutting force information by itself is inadequate for tool wear detection because its magnitude also depends on the cutting velocity [13]. Another problem is that although flank wear tends to increase the cutting force, the accompanying crater wear tends to reduce it, so that the magnitude of the cutting force may not show any sensitivity to tool wear [13]. But Ramalingam proposed a model, in which the ratio of the feed force to the cutting force (tangential force) is used as the measure of flank wear of a cutting tool during turning [6]. According to him, for the same cutting conditions, both cutting force and feed force increases with the flank wear. But feed force is more sensitive to the flank wear compared to the tangential cutting force. So, the resulting cutting force direction in the feed-tangential plane will change with increasing flank wear, as the feed force increases more rapidly than tangential cutting force. By using cutting force ratio as an indicator of wear regime, one can take the account of change in the magnitude as well the direction of cutting force with the flank wear. Also this eliminates the problem of using the force magnitude to the sensitivity of tool wear. At high temperatures, the magnitude of the cutting force may decrease due to the decrease of work hardening at the tool-workpiece interface. Due to this

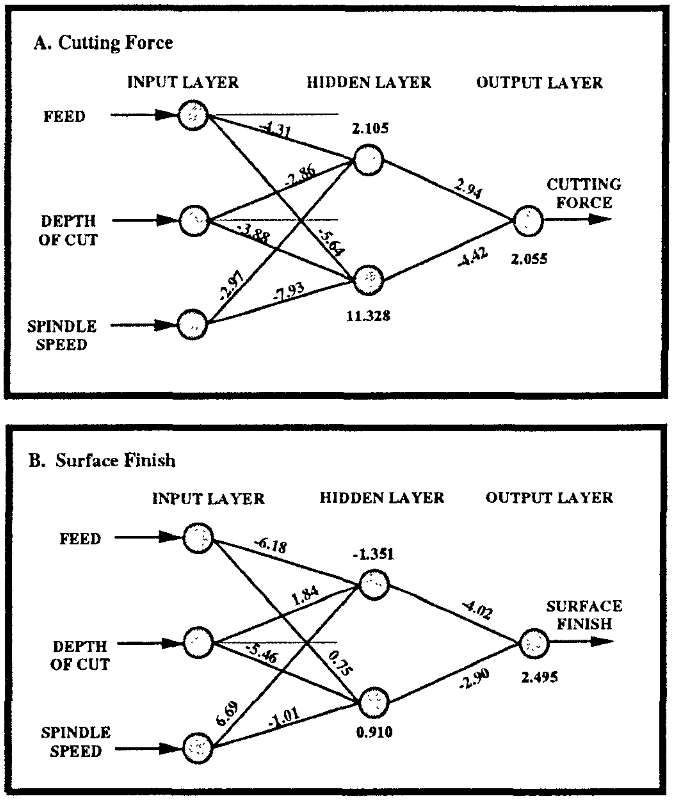

Figure 4: Basic Structure of the Network used for Ceramics

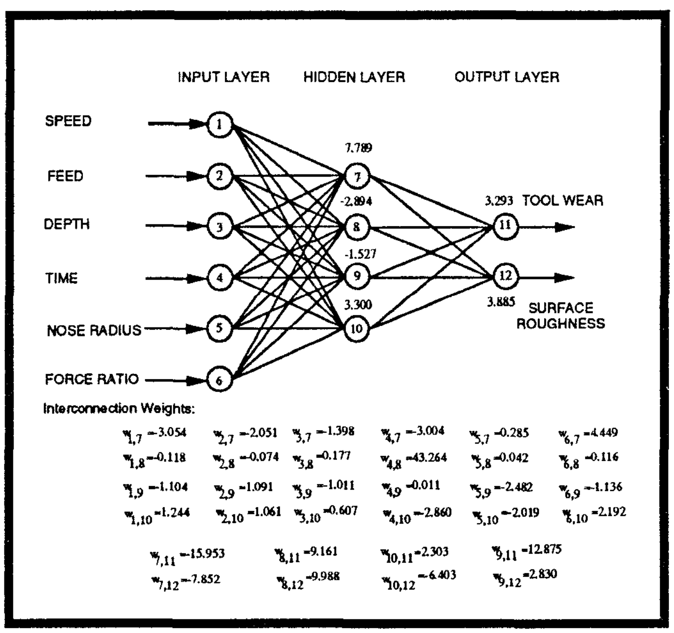

Figure 5: Basic Structure of the Network used for Steel

fact, the magnitude of the cutting force may decrease, but the ratio of the feed force to the cutting force will not be effected (i.e., it will increase with flank wear) as both components are affected by work hardening. Apart from force ratio, other machining parameters, like feed, speed, nose radius of the cutting insert or tool etc., also affect the machining process. When a high cutting speed is chosen, the insert may deform plastically as a result of the high tangential force. This is usually caused by several interrelated factors. For example, high cutting speed causes the temperature of the tool to increase locally, a factor which is further exacerbated when a small nose radius is used. This local increase in temperature, coupled with the high speed causes the tool geometry to change. So the chip flow pattern is modified accordingly, leading to tool wear. By using a larger nose radius on the insert, the heat can be more easily dissipated. It is possible to increase the cutting tool life substantially by a proper variation of the cutting feed rate throughout the cutting process [14].

Figure 5 illustrates the basic structure of the network used to monitor the machining of the steel work piece. The model has six input nodes, four hidden nodes, and two output nodes. The six nodes in the input layer represent cutting speed, feed, depth of cut, time, nose radius, and force ratio. Each of the output nodes represent tool wear and surface roughness. The four hidden nodes are chosen to minimize the memorization of input data rather than to generalize by the trained network.

2.3 *Experimentation and Training Process*

2.3.1 *Experimentation*

Experimental tests on machining of a specific ceramic material were conducted to provide training examples for adjusting the weights connecting the nodes distributed in the input, hidden and output layers. The experiments were conducted in the Advanced Design and Manufacturing Lab of the Mechanical Engineering Department at the University of Maryland, College Park campus. The experimental setup used to perform the tests is illustrated in Figure 6. A CNC milling machine was used to conduct the machining tests. A tool holder with Polycrystalline Diamond Compact (PDC) tool insert and a designed force transducer were fixed on the machine tool table with the help of a fixture. The workpiece, aluminium oxide ceramic, were mounted to the spindle of the machine, which could be rotated at any desired speed. The setup for measuring the cutting forces is shown in Figure 6.

Ceramic bars of length 10 cm and diameter 2 cm were used for machining tests. To ensure that the train examples are information rich, a method called *factorial design at two levels* was used to set the values of the three cutting parameters. Specifically, 0.2 mm/rev and 0.40 mm/rev for feed, 0.1 mm and 0.2 mm for depth of cut, and 400 rpm and 600 rpm for spindle speed were used. For a combination of these cutting parameter settings, several machining tests were carried out for obtaining the measurements of the cutting force and surface finish. Different cutting fluids were used during machining to determine their effect on cutting force and surface finish. Figures 7a and 7b present the recorded cutting force and surface finish measurements. Note that the mean value of the cutting force data and the mean value of the surface profile heights served as their representatives in the training process. Figures 8a and 8b graphically represent of the mean values of the measured cutting force and surface finish for one of the cutting fluid used. The quality of the training examples, with regard to the information carried with, can be evidenced by examining four pair measurements, for example, under two-level feed settings. The average of these four pair measurements is a good estimate of the main effect of feed on the cutting force, or the surface finish.

2.3.2 *Training Process*

Once the architecture of the network is determined, the network has to be trained on the examples. All the values of training examples are normalized between 0 and 1. This is because each node represents a nonlinear sigmoid function and gives an output which lies between the same limits; i.e.,

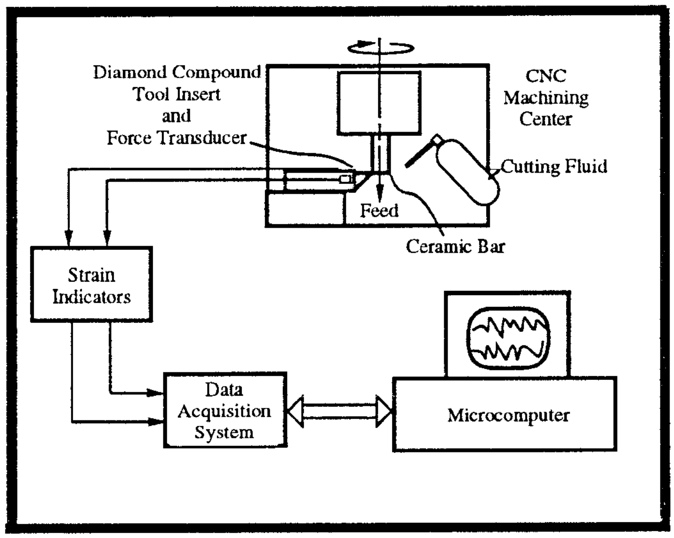

Figure 6: Experimental Setup For Machining of Ceramic Bars

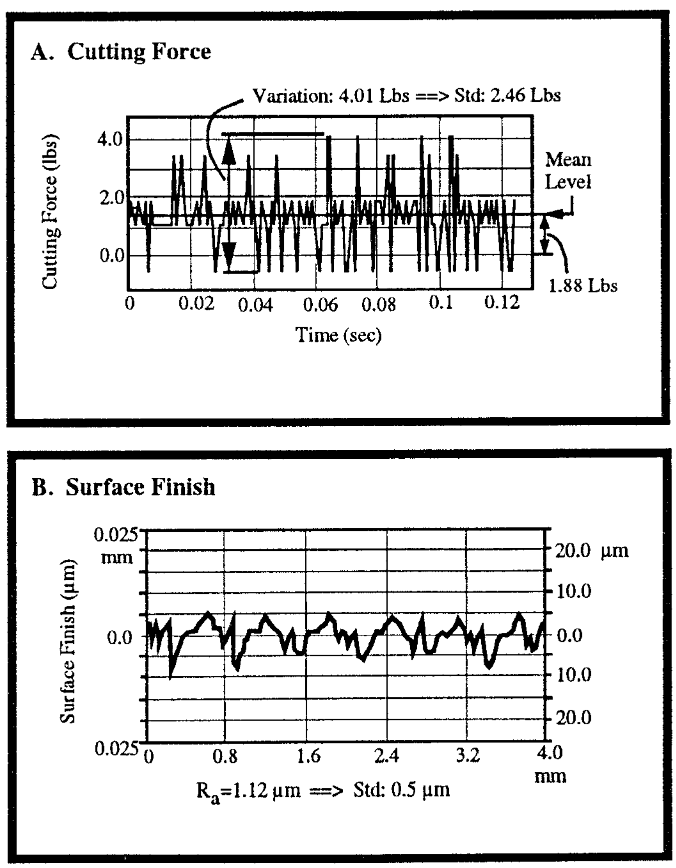

Figure 7: Recorded Cutting Force and Surface Finish Measurements

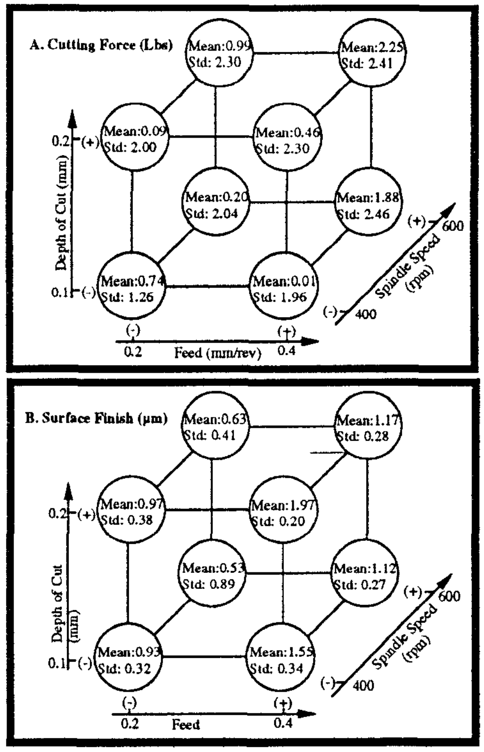

Figure 8: Measured Mean Values of Cutting Force and Surface Finish

0 and 1. This also eliminates the saturation of the sigmoid function. The values of training examples are normalized using the relation:

$$V_{nor} = [(0.9 - 0.1)/(V_{max} - V_{min})(V_{cur} - V_{min})] + 0.1$$

where,
V_{max} = maximum value of the parameter
V_{min} = minimum value of the parameter
V_{cur} = current value of the parameter
V_{nor} = normalized value of the parameter.

The weights and threshold values derived from the training of the networks used for monitoring the machining of ceramics, using the training examples, are illustrated in Figures 4a and 4b. By feeding the values of cutting parameters to the input nodes of the trained network, cutting force and surface roughness can be predicted. Comparisons between the predicted and measured cutting forces and surface roughness, as shown in Figures 9a and 9b, can be made to show the closeness between them, indicating the superior learning and noise suppression abilities of the developed neural network monitor in information processing. The success rate of monitoring the cutting force and the surface roughness was above 90% ((desired output - actual output)/ desired output), from the trained network.

To further verify the applicability of the feedforward back-propagation network is also trained with the experimental data, taken from [4]. The derived weights and threshold values are illustrated in Figure 5. Tool wear and surface finish were predicted using testing examples and Figures 10a and 10b illustrates the correlation between the predicted and the actual values. Three types of network architectures were used to train the monitor—tool wear alone was predicted in the first type, surface finish alone was predicted in the second type and both were predicted in the third type. Prediction

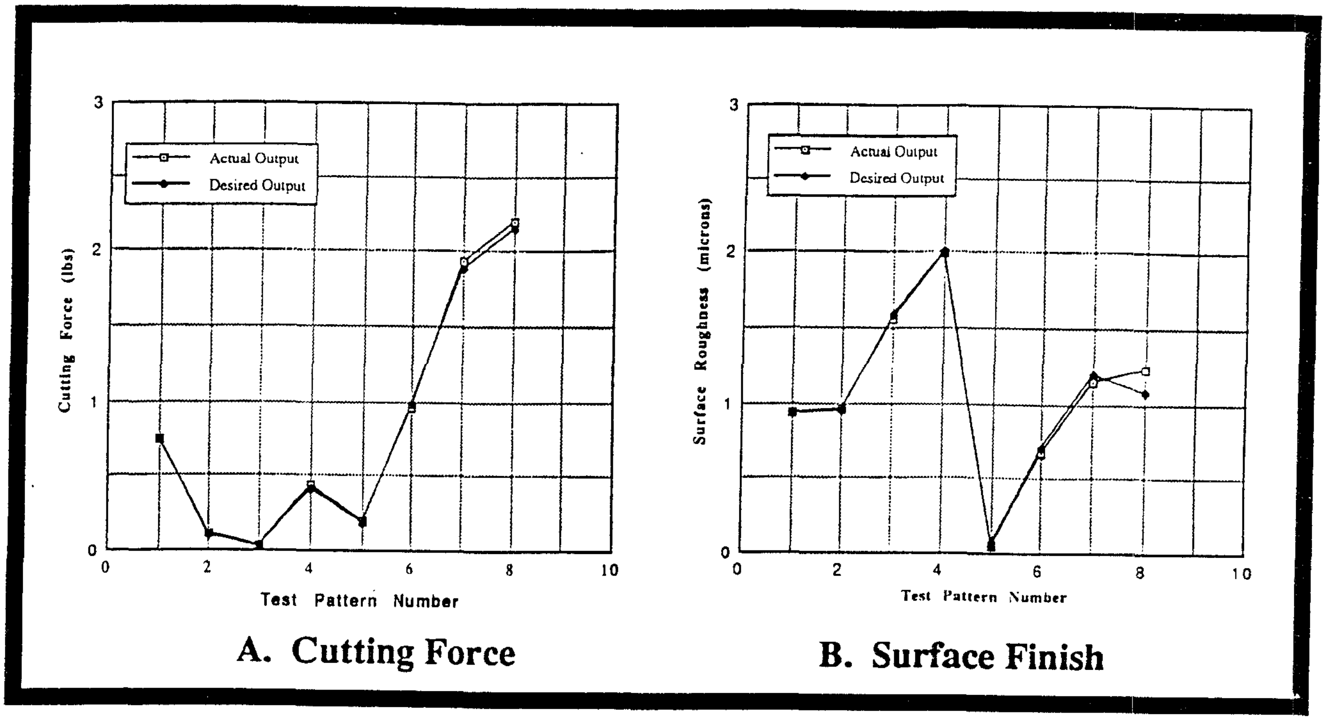

Figure 9: Plots of Correlation Between the Predicted and Actual Values for Ceramic Bars

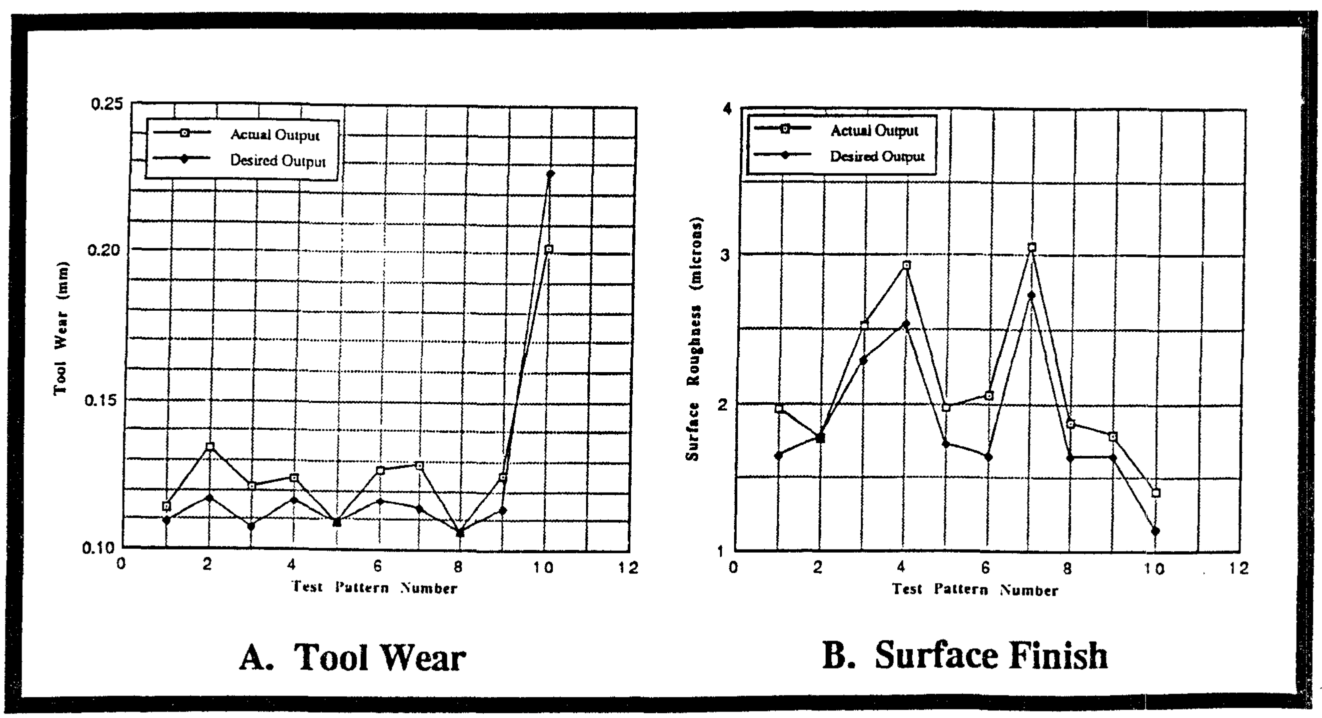

Figure 10: Plots of Correlation Between the Predicted and Actual Values for Steel Bars

Table 1: Effect of Cutting Parameters on Cutting Force

PARAMETER VALUE	CHANGED PARAMETER	ACTUAL OUTPUT	CHANGED OUTPUT	PERCENTAGE CHANGE
0.40 mm/rev	0.36 mm/rev	1.88 lbs	1.523 lbs	-18.99%
0.10 mm	0.09 mm	1.88 lbs	1.836 lbs	-2.3%
600 rpm	540 rpm	1.88 lbs	1.0156 lbs	-45.98%

Table 2: Effect of Cutting Parameters on Surface Roughness

PARAMETER VALUE	CHANGED PARAMETER	ACTUAL OUTPUT	CHANGED OUTPUT	PERCENTAGE CHANGE
0.40 mm/rev	0.36 mm/rev	1.12 μm	0.8015 μm	-28.44%
0.10 mm	0.09 mm	1.12 μm	1.086 μm	-3.1%
600 rpm	540 rpm	1.12 μm	1.503 μm	+34.19%

of surface finish was found closer to actual value in the third type of network compared to the second type, where only surface finish was predicted. This is because the tool wear effect on surface roughness was taken into consideration for terminating the training process; i.e., for obtaining the weights and threshold values. The third type of network was thus chosen to minimize the false alarms for both tool wear and surface roughness.

3 Applications

3.1 *Effect of Cutting Parameters on Cutting Force and Surface Roughness*

For a ceramic material, the developed monitor is used to find the relationship between the cutting parameters, and the cutting force and surface roughness. Machining of ceramics is more difficult than machining of metals. Unlike metal machining, the feed force is more than the tangential force. This is mainly because of the hardness of ceramics and due to the change in the cutting mechanism; i.e., the material is removed by fracture mechanism. The machining of steel is primarily by plastic deformation. One way of knowing the effect of cutting parameters on cutting force and surface roughness is by decreasing the original value of the cutting parameter under consideration by 10% and finding its effect on the output from the trained neural network by keeping other cutting parameters unchanged.

Table 1 shows the results for one particular set of cutting parameters on cutting force. It can be seen from table 1 that, the depth of cut has the least effect on the cutting force and speed has the greatest positive influence on cutting force. Feed has a medium effect. Other factors, such as tool wear etc., affect the process minimally. After considering all other set of cutting parameters, it was found that the most efficient way of machining i.e., low cutting force, can be obtained by having a low feed (0.2 mm/rev) and a low cutting speed (78.5 ft/min), which was confirmed with the experimental results.

Table 2 shows the results on surface roughness. It can be seen from the table 2 that, as speed is decreased, surface roughness increases. Again the depth of cut has least effect on surface roughness. Feed has a medium effect. After considering all other parameter settings, it was found the best surface quality can be obtained by having a low feed (0.2 mm/rev) and a high cutting speed (118 ft/min), which was confirmed with the experimental results.

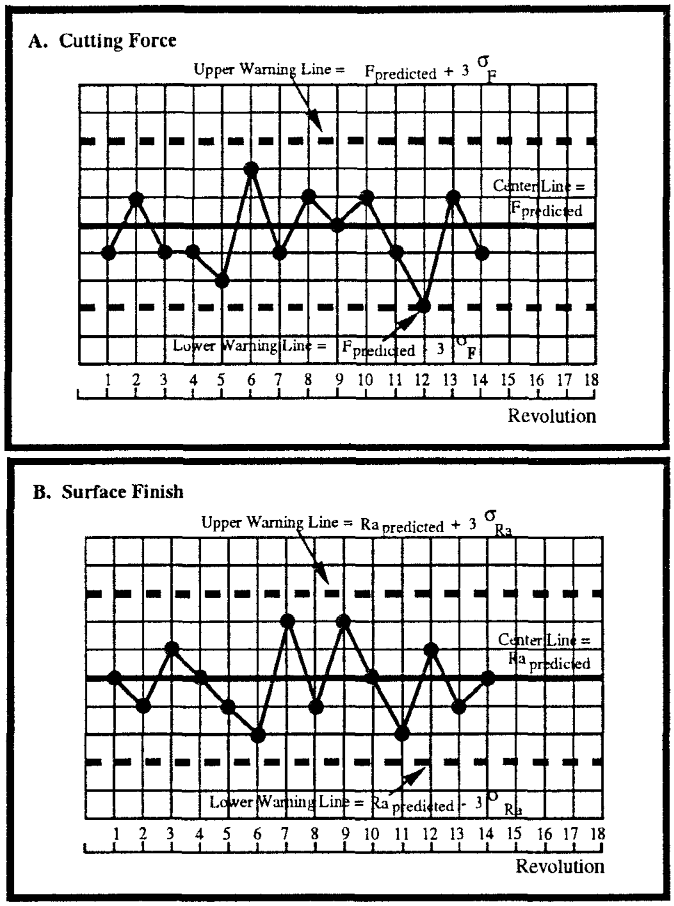

Figure 11: On-Line Monitoring Charts Recorded During Machining

3.2 *On-Line Monitoring of a Turning Process*

It should be pointed out that the implementation of the developed monitor in a real time machining operation requires an additional piece of information, i.e., the estimate of the dynamic variation of the monitoring target(s), such as the cutting force and/or surface finish. This additional information enables the monitor to distinguish the external noise related to the machining process abnormalities from the natural, or inherent process variations, evidences of which are shown in Figures 7a and 7b. In this work, estimates of the dynamic variations of the two monitoring targets were obtained by two steps. The first step was to obtain the two estimates at each of the turning tests. These estimates are presented in Figures 8a and 8b. In the second step, two pooled estimates, representing the natural variation of the cutting force and surface finish during machining were calculated from the measured estimates. These two pooled estimates were the standard deviations of the cutting force (2.12 Lbs.) and the surface finish (0.52 μ m), respectively.

To demonstrate applicability of the proposed on-line monitoring system, a prototype monitoring system using the developed neural network monitor has been implemented on a CNC milling machine to monitor the machining of advanced ceramic materials, as shown in Figure 1. The objective of such a monitoring system is to control the appearance of micro-cracks on the machined surface, the dimensional accuracy, and the finish quality of the machined surface. It is assumed that a large cutting force leads to severe surface damage. Therefore, the two monitoring targets are the cutting force and the surface finish. Figures 11a and 11b are the two monitoring charts obtained during the

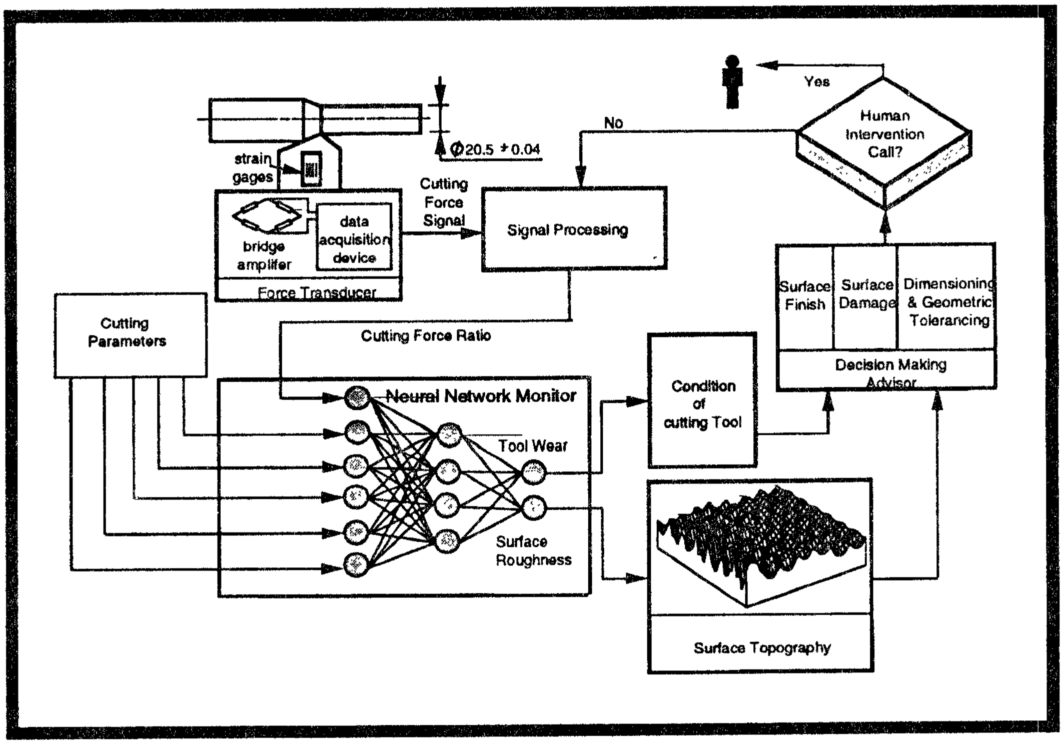

Figure 12: Basic Structure of the Implemented On-Line Monitoring System for Machining of Steel

turning process. The center lines of these two charts respectively represent the predicted cutting force and surface finish through training. The upper and lower limits on the two charts are the warning lines of the monitoring system. The limits are constructed based on the 3-σ principle, which indicates that the turning process is in its normal status as long as the detected cutting force signal, or the measured surface finish, is within the upper and lower limits. Whenever a detected signal is out of the two limits, the machining process goes on to an abnormal status. It is evident from the two monitoring charts shown in Figures 11a and 11b, the turning process under monitoring is in a normal status because all the detected and measured signals are within the limits. At the initial stages of the turning process, the neural network function i.e., the trained weights and thresholds, is static in nature. As neural networks allows incremental improvement as new data is made available, the neural network function can be made dynamic. To make the neural network function dynamic, the current monitoring data (either cutting force or surface roughness) is fed back to the monitor. The monitor compares this new data with the previously stored data in the knowledge base and retrains its weights and thresholds if the data is different. Therefore, the network constantly keeps the new information stored in and the database will be updated, which is not possible with any other statistical methods, like, linear regression. As the reliable information is accumulated, more aspects of the true nature of the turning process will be revealed. By this process a trained neural network learns from experience and updates its knowledge and stores it in the interconnection weights.

The prototype system has been tested with satisfaction on the turning operation. Under many circumstances, the detected cutting force signal hit the upper warning line. The machining operation was stopped immediately and severe surface damage was observed. The worn tool was replaced by a new tool and the turning process was resumed to its normal status. When the detected cutting force signal hit the lower warning line, a severe tool breakage was observed. The breakage caused the depth of cut during machining to drop to a level where there was almost no contact between advisor built in the monitoring system will call on human intervention only under circumstances when the two monitoring targets are hitting their warning lines. There is, however, an associated side-effect, i.e., the decrease of the sensitivity of the monitoring system for an effective detection of the process abnormalities. Further improvements are being made to balance the need between the false alarm elimination and the detection sensitivity.

The proposed on-line monitoring system has been tested with satisfaction to predict the monitoring targets, such as tool wear and surface finish, directly. Figure 12 illustrates the implementation of an on-line monitoring system for machining of steel, where tool wear and surface roughness are monitored directly. The force signals from sensors are low pass filtered and force ratio (feed to tangential force) is determined. This ratio, along with the other machining parameters, is fed into the trained neural network and tool wear and surface finish are predicted. By monitoring the predicted values, the human operator (or control system) can act accordingly to optimize the turning process.

4 Conclusions

A prototype system to perform an untended machining operation has been developed. Through an on-line detection of the cutting force and the control of surface finish measurements, the monitoring system has been successfully used to assure satisfactory performance during the machining of advanced ceramic materials. The success rate of monitoring was above 90%. A neural network monitor can serve as one of the most efficient tools in finding an optimum set of machining parameters to a quality engineer as well as to a machining operator by predicting the effect of machining parameters on the machining process beforehand. Serving as the brain of the untended machining system, the neural network monitor processes the machining-related information from the detected signals, compares the extracted information with the pre-determined warning limits, and passes the results to the built-in decision-making advisor. The advantages of artificial neural networks are explored in this work. It has been shown that through appropriate selection of architecture of the network, noise can be minimized and the process variables can be predicted accurately, indicating that neural networks can become a promising modeling tool for use in on-line monitoring of machining processes.

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References

1. S. M. Arsovski, "Wear sensors in the adaptive control systems of machine tools", *Int. J. of Production Research*, 21 (3), 1983.

2. S. Jetly, "Measuring tool wear on-line: some practical considerations", *Manufacturing Engineering*, July 1984.

3. H. Suzuki, and K. J. Weinmann, "An on-line tool wear sensor for straight turning operations", *J. of Engineering for Ind., Trans. of ASME*, 107, Nov. 1985.

4. K. F. Arnold, "Measurement of cutting forces as they relate to flank wear", *M. S. Thesis*, Dept. of Mechanical Engineering., University of Missouri-Columbia, MO, 1989.

5. Raju G. Khanchustambham, "A neural network approach to on-line monitoring of machining processes", *M. S. Thesis*, Dept. of Mech. Engineering, University of Maryland, May 1992 .

6. T. Shi and S. Ramalingam, "Real-time flank wear sensing", *Fundamental issues in machining*, PED-Vol, 43, 1990.

7. R. Lippmann, "An introduction to computing with Neural Nets", *IEEE ASSP Magazine*, April 1987.

8. J. L. McClelland, D. Rumelhart, et al., *"Parallel Distributed Processing"*, The MIT Press, 1986.

9. P. Balakrishnan, and J. C. Macbain, "Monitoring Systems For Unmanned Machining", *SME technical paper* MR 85-479, 1985.

10. K. Danai, and A. G. Ulsoy, 1987,"An Adaptive Observer for On-Line Tool Wear Estimation in Turning", Part 1-theory, Part 2-Results.

11. A. De Filippi, and R. Ippolito, 1969, "Adaptive Control in Turning: Cutting Forces and Tool Wear Relationships for P10, P20, p30 Carbides", CIRP Annals, Vol. !7 pp. 377-379.

12. G. F. Micheletti, De Filippi., and R. Ippolito, *"Proceedings of the CIRP International Conference on Manufacturing Technology"*, Ann Harbor, Michigan, Sep. 1967, pp. 513-524.

13. D. W. Yen, and P. K. Wright, "Adaptive Control in Machining - A new approach based on the physical constraints of Tool Wear Mechanisms", *ASME J. of Engineering for Industry*, Vol. 105, No. 1, Feb. 1983, pp. 31-38.

14. Clement Fortin and Marek Balazinski et. al, "Study of the influence of Feed Variation on Tool Wear", *Fundamental Issues In Machining*, PED-Vol. 43, 1990.

15. Raju. G. Khanchustambham & G.M. Zhang, "A Neural Network Approach to On-line Monitoring of a Turning Process", *Proceedings of 1992 International Joint Conference on Neural Networks*, Baltimore, Maryland,Vol. 2, pp. 889-894, 1992.