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WEAR DETECTION IN TURNING OPERATIONS USING NEURAL NETWORKS

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ABSTRACT

On-line wear detection in turning operation is considered in this paper. A wear monitoring system based on hierarchical neural networks is suggested for this purpose. The changes in cutting force components are used for monitoring three wear components. The hierarchical neural network structure uses multilayered, feedforward, static and dynamic neural networks as specialized subsystem for each wear component to be monitored. Simulation studies are performed to investigate the overall suitability of the system.

1 INTRODUCTION

The problem of on-line tool wear monitoring in machining operations has been an active area of research for quite some time. Tool wear has a direct effect on the quality of surface finish, dimensional precision and ultimately the cost of the parts produced. Information about tool-wear, if obtained on-line, can be used to establish tool change policy, adaptive control, economic optimization of machining operations and full automation of machining operations. A reliable on-line tool wear measurement system does not exist yet and research in this area is continuing.

Various strategies developed for on-line tool wear monitoring can be categorized as employing either direct or indirect methods. The direct methods include measurement of wear using optical, radioactive or other sensors. On-line implementation of these methods is made difficult by the inaccessibility of the tool surface during cutting operation. In indirect methods, the tool wear is estimated by measuring a physical property of the cutting process which is affected by the tool wear. These include, temperature, surface finish, cutting forces and vibration. Of the indirect methods the most commonly employed is cutting force measurement [1].

The relationship between cutting force components and tool wear has been investigated by

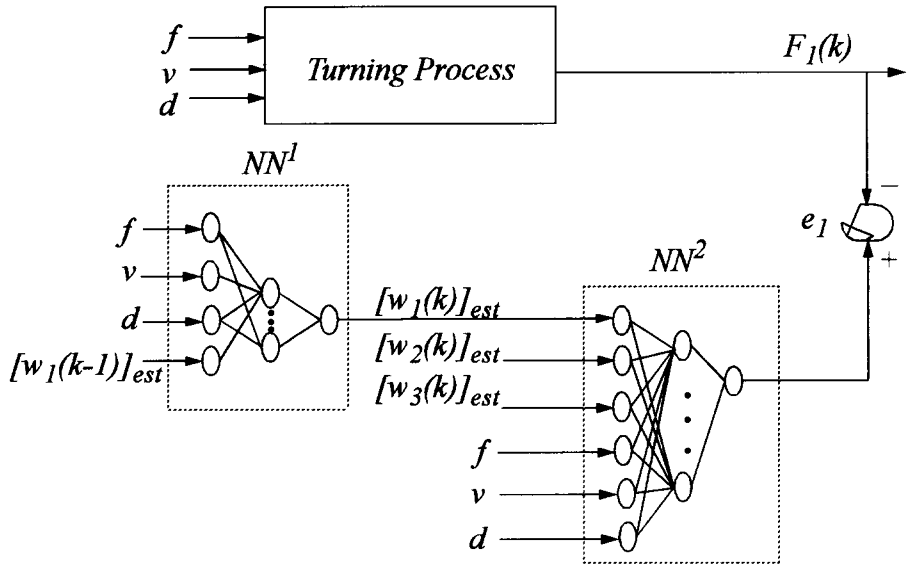

Fig. 1: System architecture for estimating one wear component.

many researchers [2]. It has been reported that cutting force signals are more sensitive to tool wear than vibration or power measurements [3]. The reliability of force measurements is another factor for their popularity in tool wear monitoring applications. However, cutting force components are quite sensitive to the cutting conditions (feed, speed, and depth of cut). Different methods have been suggested for separating the effects of cutting conditions from the effect of wear on the measured force. Danai and Ulsoy [4] used adaptive observer techniques to develop a linear observer based on a linearized flank wear model. Flank wear estimations were good under constant cutting conditions but the system could not be used under time varying cutting conditions. This is important since an on-line tool wear estimation system should be useful in cutting process control which is usually done by manipulating the cutting conditions. Koren et al. [5] have described several methods which can be used under stepwise constant variations in feed, speed, or depth of cut. However, these methods require a prior knowledge of the initial wear, and they cannot be applied when two or more of the cutting conditions are changed. Park and Ulsoy [6] extended the work by Danai and Ulsoy, by using a nonlinear observer for estimating the state of tool wear. Prior knowledge of the initial wear was not necessary but the system needed a continual recalibration which was done off-line using information obtained from a computer vision system.

This paper presents a method for simultaneous estimation of multiple wear components in turning operations by employing artificial neural networks which observe the cutting force signals. This method can deal with changes in the cutting conditions and eliminates the need for recalibration. Static and dynamic neural networks are used in hierarchial architectures which are based on a state space representation of the turning process. A continuous on-line training guarantees the adaptability of the system to variations in cutting conditions and thus fully utilizes the adaptability and generalization properties of feedforward neural networks. Simulation results are presented which demonstrate the feasibility of the approach.

2 APPROACH

It has been shown that the progress of tool wear in turning process can be cast into a nonlinear state space model [4]. Considering the wear components as states, the state equation relates the rate of change of states to input variables. For a turning process input variables are the feed,

f, the cutting speed, v, and the depth of cut, d. Therefore we have

$$\dot{\boldsymbol{W}} = \boldsymbol{G}\,(f, v, d) \tag{1}$$

where $\boldsymbol{W}$ is a vector comprised of different wear components (e.g. flank, nose, and notch wear). The cutting force components are selected as the outputs, i.e.,

$$[F_1, F_2, F_3]^T = \boldsymbol{HW} \tag{2}$$

where F_1, F_2, and F_3 are different components of the cutting force. For state equation (1) and output equation (2) to be fully determined, $\boldsymbol{G}$ and $\boldsymbol{H}$ must be identified. However, these relations are highly nonlinear and their identification in this form is not possible. Any attempt to simplify the problem by linearizing the relation will be accompanied by the loss of accuracy and requirement for off-line calibration [6].

The above discussion was the motivation for synthesis of a neural network based wear estimation system. Assume three wear components are to be estimated. Figure 1 shows a subsystem which can be used for estimating one of the wear components, w_1. The system is comprised of three such subsystems. Each subsystem has two hierarchial neural network. The neural network designated as NN^1 approximates the state relation,

$$\dot{w}_1 = g_1\,(f, v, d, t) \tag{3}$$

Since this is a dynamic system, a dynamic network is formed by feedback of the output of the network through a tapped-delay line [8].The inputs to NN^1, therefore, include cutting conditions (f, v, and d) and the last estimate of the wear component w_1. The output of the network will be an estimate for the first wear component, w_1. The second neural network in the subsystem, NN^2, approximates the output equation,

$$F_1 = h_1\,(f, v, d)\,\boldsymbol{W} \tag{4}$$

Since this is not a dynamic relation, a static network is selected for this purpose. The inputs to the network consist of cutting conditions, current estimate of the first wear component w_1 provided by NN^1, and current estimates of other wear components provided by two other subsystems. The output of the network will be an estimate of the current value of cutting force component, F_1. The combination of the two neural networks form a non-linear observer which attempts to estimate the non-measurable state w_1 by observing the measurable output F_1.

Since states (i.e., wear values) are not accessible in the system described above, error can be measured only at the output, i.e., error in estimating the cutting force components. This means that explicit error signals for training NN^1 cannot be generated. If the error in estimating the cutting force was to be used to train both networks, the system would approximate only the composition of the state and output equations and extraction of state estimates would become impossible [8]. To overcome this problem NN^2 is trained off-line. The data needed for training of NN^2 can be obtained relatively easily by experiment. If the inputs are chosen correctly the generalization ability of neural networks will ensure that NN^2 can work for all combinations of its inputs.

Once NN^2 networks are trained off-line, NN^1 networks can be trained on-line, therefore taking full advantage of the adaptability of neural networks. The error signal necessary for training NN^1 comes from the backpropagation of the measurable error e_1 through NN^2. The performance criterion for training NN^1 is the minimization of the mean square of this error, i.e.,

$$J_{min} = Minimize\,(e_1^2) \tag{5}$$

To minimize this error criterion by changing the parameters of NN^1 (i.e., its weights, θ_j), the gradient of J and therefore partial derivatives of e_1 with respect to θ_j are needed. Since,

$$e_1 = [F_1(k)_{estimate} - F_1(k)] \tag{6}$$

for partial derivatives we have [8],

$$\frac{\partial e_1}{\partial \theta_j} = \frac{\partial F_1(k)_{estimate}}{\partial \theta_j} = \frac{\partial F_1(k)_{estimate}}{\partial w_1(k)_{estimate}} \frac{\partial w_1(k)_{estimate}}{\partial \theta_j} \tag{7}$$

$\frac{\partial F_1(k)_{estimate}}{\partial w_1(k)_{estimate}}$ is computed by backpropagation through NN^2 and $\frac{\partial w_1(k)_{estimate}}{\partial \theta_j}$ is obtained by backpropagation through NN^1. Using the gradient information, the performance criterion can be minimized by changing the weights of NN^1 through a training process such as steepest descent.

When the NN^1 networks in all three subsystems are trained adequately, the estimate of the cutting force components will be very close to the actual values and since NN^2 networks are already trained, the estimate of the wear components will also be close to the actual values.

3 SIMULATION STUDIES

The capability of the proposed wear estimation system has been evaluated through simulation studies. The data for simulation was obtained from [9], where three wear components (flank w_f, nose w_{ns}, and notch w_{nt}) were measured in relation to the cutting force components (feed F_x, radial F_z, and tangential F_y) during the turning process. Using linear regression the experimental data regarding the evolution of wear components with time was cast into the following relations,

$$\begin{aligned} w_{ns} &= w_0 + 7.44 \times 10^{-4} v^{0.698} f^{0.403} d^{0.606} t^{0.602} \\ w_f &= w_0 + 3.83 \times 10^{-4} v^{0.786} f^{0.398} d^{0.513} t^{0.609} \\ w_{nt} &= w_0 + 5.83 \times 10^{-4} v^{0.613} f^{0.467} d^{1.004} t^{0.627} \end{aligned} \tag{8}$$

where

$$w_0 = 9.3 \times 10^{-3} v^{0.5133} f^{0.0059} d^{-0.0597} D^{0.0371} \tag{9}$$

here D is the workpiece diameter in millimeter. The relation between experimental measurement of the cutting forces and wear components were cast into the following relations using nonlinear regression techniques,

$$\begin{aligned} F_x &= 629 f^{0.3} d^{0.72} + 1199\,(w_{ns}^{3.58} - 0.023 v^{0.27})\,(w_f^{-0.66} - 0.023 v^{0.27})\,(w_{nt}^{0.03} - 0.023 v^{0.27}) \\ F_y &= 1862 f^{0.94} d^{1.11} + 2677\,(w_{ns}^{0.24} - 0.05 \ln v)\,(w_f^{0.23} - 0.05 \ln v)\,(w_{nt}^{-0.16} - 0.05 \ln v) \\ F_z &= 500 f^{0.46} d^{0.81} + 2377\,(w_{ns}^{1.93} - 0.007 \ln v)\,(w_f^{0.26} - 0.007 \ln v)\,(w_{nt}^{-0.33} - 0.007 \ln v) \end{aligned} \tag{10}$$

Figure 2 shows the architecture of the system for estimation of flank, nose, and notch wear from cutting force components. Equations (10) and (11) are used to simulate the cutting process through time. NN^1 in each subsystem should estimate its wear component by simply

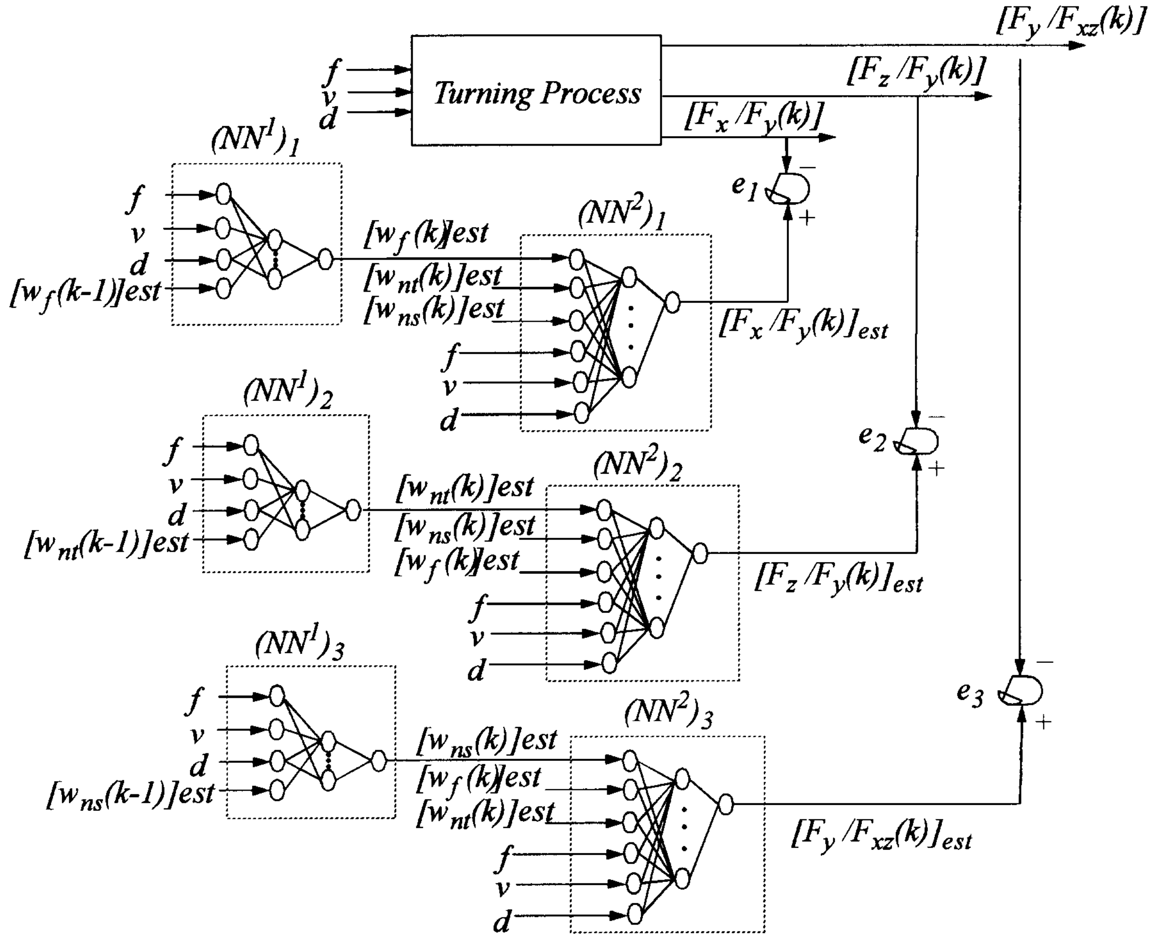

Fig. 2: Overall architecture of a system for estimating three wear components.

observing its relevant cutting force component. Therefore each subsystem is specialized in estimating one component of the wear and shares this estimate with other subsystems. The cutting force ratios selected for observation are F_x/F_y, F_z/F_y, and F_y/F_{xz}, where $F_{xz}=(F_x^2+F_z^2)^{1/2}$.

Neural networks NN^2 in all three subsystems were trained using data generated by Equation (11). The networks have 6 input nodes, 12 hidden nodes, and one output node. The neural network model used for NN^2 is a feedforward network with sigmoid activation functions. This implies that the output of NN^2, which is the estimated cutting force components, will be in the range $\{0,1\}$. Therefore scaling is needed and is accomplished using a linear mapping.

Measured cutting force signals will be influenced by process and measurement noise.To account for this phenomenon in the simulation studies, noise was added to the simulated force signal. The noise was modelled as a normally distributed, zero mean, white sequence with a standard deviation of 1% of nominal cutting force [7]. Noise was also assumed to be present in the signals for cutting speed and feed. The noise for these signals was again modelled as zero mean normally distributed white sequence with a standard deviation of 1 and 0.01 percent of nominal values, respectively, based upon the expected level of noise in these signals.

4 SIMULATION RESULTS

Figure 3 shows the simulation results for a particular set of cutting conditions (f=0.2 mm/rev., v=104.0 m/min., d=2.25 mm). NN^1 networks in the three subsystems start to learn the

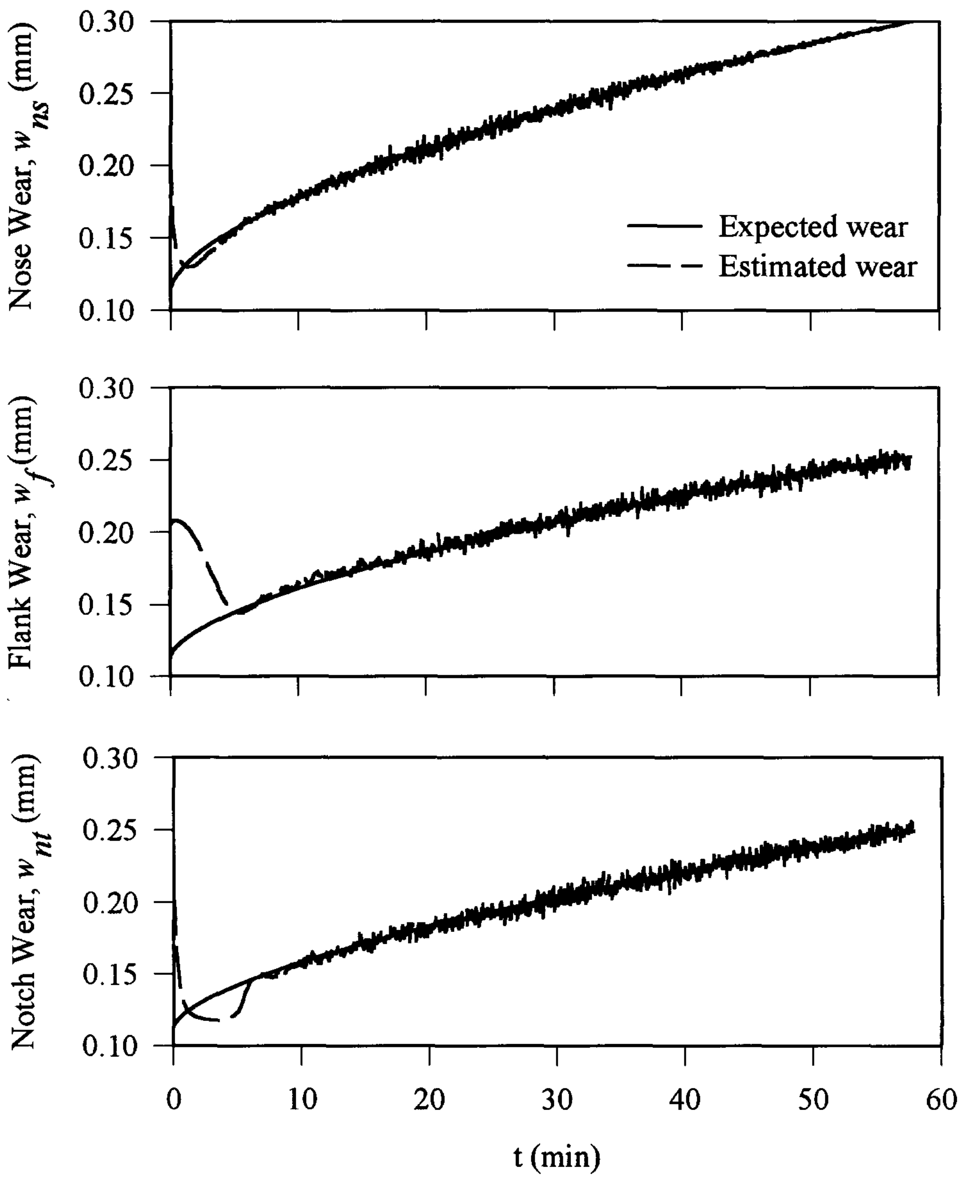

Fig. 3: Simulation of progress of nose, flank, and notch wear.

dynamics of the system from scratch (i.e, random weights). The initial estimate of wear components is unimportant since NN^1networks, by observing the cutting forces, estimate the correct wear value.The results show that although initial wear estimates are considerably off, the three subsystems learn the inherent dynamics of the system and estimate the three wear components correctly. The noise present in the tool wear estimates is a reflection of the noise in the cutting force and cutting condition signals.

The neural networks learn the dynamics of the system in approximately 6 min. This is 10% of the total cutting time. Since the initial phase of tool wear is not usually of interest (low level of wear) this should not pose a major problem. However, the use of faster learning algorithms such as conjugate gradient is under study to improve the initial learning time.

Figure 4 shows the situation where the cutting conditions are changed continuously. Again, after learning the basic dynamics of the process, the system is able to adjust to continuous changes in the feed rate and cutting speed.

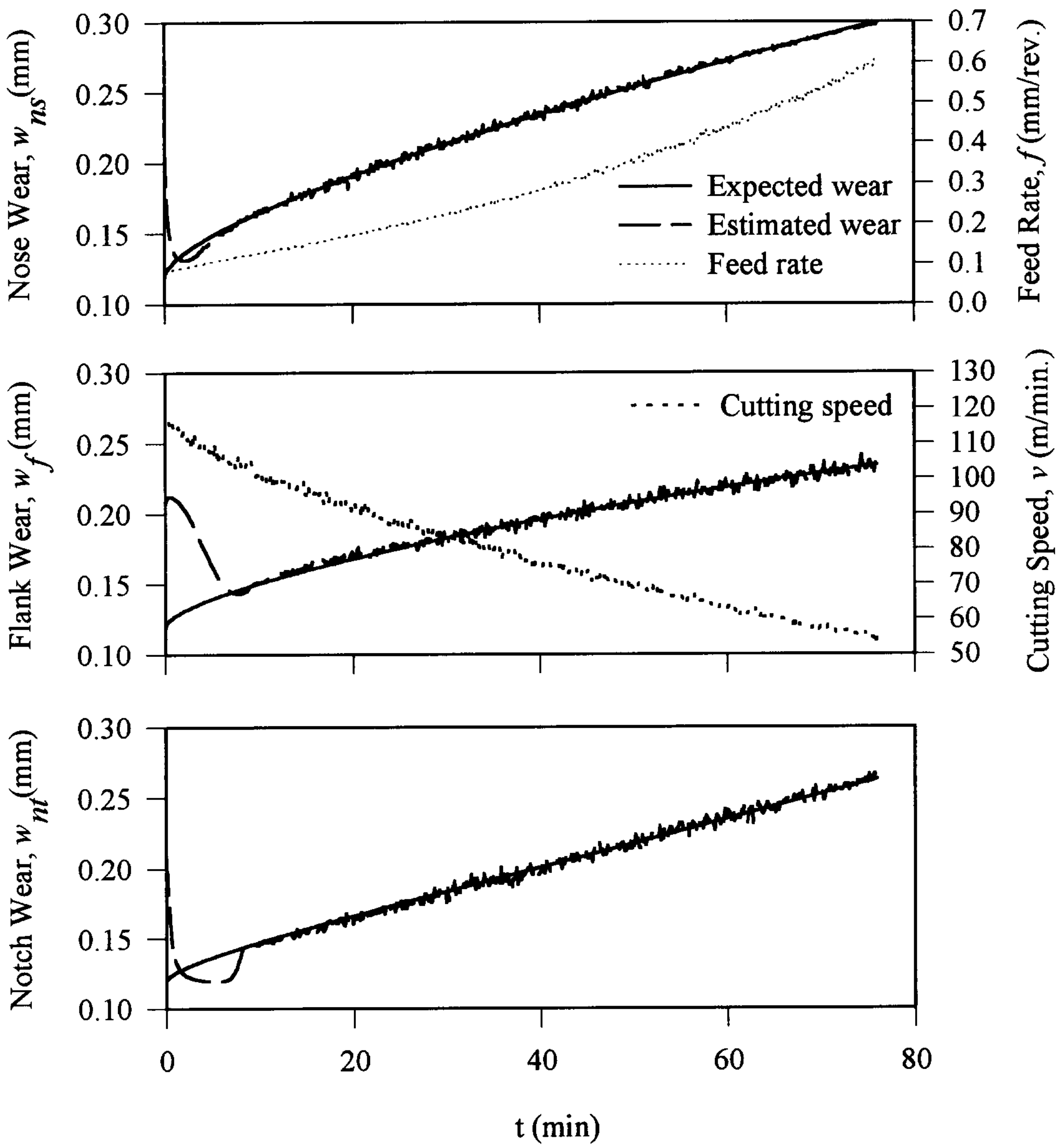

Fig. 4: Simulation results for continuous change of both cutting speed and feed rate.

5 CONCLUSIONS

In this paper a hierarchial neural network architecture is presented which acts as a nonlinear observer for estimating wear components in a turning process. The non-observable states (i.e., wear components) are estimated using the outputs (i.e., cutting forces) and inputs (i.e., the feed rate, the depth of cut, and the cutting speed). This method does not require a model for wear mechanisms or their relationship to cutting force signal and can be used under varying cutting conditions. The noise tolerance and generalization abilities of the neural networks ensures that noise and changes in the dynamics of the system will be handled adequately.

The simulation results presented have demonstrated the capability of the proposed architecture to estimate tool wear in turning. Estimations were found to be accurate even when the initial estimates were in considerable error and cutting conditions were changing. The system was also able to deal with the process noise incorporated in the simulation.

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