

EFFECTIVE TOOL WEAR ESTIMATION THROUGH MULTISENSORY INFORMATION FUSION USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

On-line tool wear monitoring plays a significant role in industrial automation for higher productivity and product quality. In addition, an intelligent system is required to make a timely decision for tool change in machining systems in order to avoid the subsequent consequences on the dimensional accuracy and surface finish of the product. The present study deals with developing an intelligent system using Artificial Neural Network (ANN) to monitor and estimate the tool wear in face milling operation using Acoustic Emission (AE) and cutting force sensor signals. This Paper also highlights the significance of multi sensory information fusion for effective tool wear estimation by using ANN. Further, it provides a sequential approach to minimize the error in tool wear estimation by illustrating the influence of ANN parameters, stopping criterion, modes of training the network, adaptation of learning rate parameter using fuzzy logic and population size on wear estimation.

Keywords: Monitoring, Tool Wear, Face Milling, Cutting Force, Acoustic Emission, Sensor Fusion, Artificial Neural Networks.

INTRODUCTION

Over the past two decades, the manufacturing industry has felt the need for more comprehensive automatic control of the machining processes, owing to the increased global competition and the potential economic benefits of automation like reducing the labor cost, avoiding the personal oversight, enhancing the flexibility, reliability, productivity and quality of the products produced.

Monitoring the automated system has become mandatory, especially in the field of wearing of the cutting tool, negligence of which would cause breakdown resulting in extensive damages to machinery and work pieces [21]. In addition to that, the downtime associated with the unpredicted tool wear is expensive, in terms of time and financial cost.

Therefore, it is important to evaluate the status of the cutting tool throughout the machining process. This can be achieved by using on-line sensors such as AE, cutting force, temperature etc [1] and by estimating the tool wear using an intelligent system.

A single sensor may not be efficient in stating the wear progression under varying cutting conditions and may not be sensitive to phenomena occurring over the entire life of the tool. But, the reliability can be improved by fusing the information from multiple sensors.

The function of the intelligent system is to analyze the information provided by the sensors and to estimate the tool wear. It is difficult to obtain analytical models to estimate the tool wear since complex phenomena occurs during the machining process. ANN, the most prominent tool of artificial intelligence, has become widely acknowledged as the best possible tool for assessing the stochastic machining processes since it posses a number of properties for modelling processes: such as universal function approximation capability, learning from experimental data, tolerance to noisy or missing data, and good generalization capability.

In this work, an intelligent system has been developed by using Multiple Layer Perceptron (MLP), the most popular model of ANN, to estimate the tool wear in face milling operation by fusing cutting force and AE parameters.

LITERATURE SURVEY

Many researchers have used single sensory data fused along with cutting parameters for the purpose of identification of tool status. In [7], cutting force was used as input to MLP along with the cutting condition parameters to classify the tool status. The same approach was followed by [14] for tool wear monitoring in end milling operation. Similarly, [21] used AE to monitor the tool in face milling operation. However, single sensory information often remains unreliable and tool condition monitoring may fail to

recognize the very complex nature of the cutting process.

Many literatures emphasize on multisensory information fusion. In [17], MLP was used to fuse static force data with speed, feed and depth of cut parameters for the estimation of flank wear and surface finish of the product during lathe operation. Also, [3] reported in their review that force and AE signal were most widely used sensory signals for the purpose of fusion and tool status evaluation. In [8], the authors used AE and Force data to estimate the wear in face milling operation. In [9], vibration and cutting force signals of milling process were fused by using MLP which obtained 97% success in identifying the tool wear state. In [18], AE and cutting force signals were fused through MLP and was observed a high success rate of 95% for tool wear recognition under a range of process conditions during turning operation.

Though a number of researchers have used MLP for fusing the information and estimating the tool status, enough literatures are not available to state the influence of neural network parameters which may affect the accurate estimation of the tool status. This point also has been emphasized in [4], where the authors stated that the parameters of the network had to be carefully selected for the precise output of the network.

So, the main objective of this work is to arrive at a network with best possible error minimization capability in estimating the tool wear using the multisensory data. Further, this paper provides a specific methodology, by which one could arrive at an optimal neural network model and thereby could achieve good performance. These provide a good scope for the present study.

ARTIFICIAL NEURAL NETWORK

New approaches and techniques are continuously and rapidly being introduced and adopted in the current manufacturing environment. Currently, there has been an explosion of interest in applying ANN to the manufacturing field. ANN has several advantages that are desired in manufacturing practice, including learning and adapting ability, parallel distributed computation, robustness, etc. There is an expectation that ANN techniques can lead to the realization of truly intelligent manufacturing system. This is due to the fact that their properties of learning and nonlinear

behavior make them useful to model complex nonlinear processes, better than the analytical methods.

In this paper, MLP trained using Back Propagation Algorithm (BPA) has been chosen on account of its capability to solve nonlinear complex problems.

Fig.1 shows the general architecture of 3-layered MLP. MLP became popular among researchers and users of neural networks after the development of BPA for training the network in a supervised manner. Supervised learning requires a 'teacher' that knows the correct output for any input.

BPA is a steepest-descent method, where weight values are adjusted in an iterative fashion while moving along the error surface to arrive at minimal range of error, when input patterns are presented to the network for learning the environment. The learning process consists of two passes through different layers of the network: a forward pass and a backward pass. In the forward pass, the input pattern is applied to the nodes of the input layer and its effect propagates through the network, layer by layer. During the forward pass, synaptic weights are all fixed. The error which is the difference between the actual output of the network and the desired output is propagated back during the backward pass to adapt the synaptic weights according to the following equations 1 and 2.

$$w(n+1) = w(n) + \Delta w(n) \quad (1)$$

$$\Delta w(n) = -\eta * \frac{\partial E(n)}{\partial w} + \mu * \Delta w(n-1) \quad (2)$$

Where

η - learning rate parameter ($0 < \eta \leq 1$)

μ - momentum factor ($0 \leq \mu < 1$)

$\Delta w(n-1)$ - Correction applied to weight vector $w(n-1)$ at $(n-1)^{th}$ epoch.

$\Delta w(n)$ - Correction applied to weight vector $w(n)$ at n^{th} epoch.

$w(n)$ - Weight vector between the nodes at n^{th} epoch.

$w(n+1)$ - New weight vector between the nodes at $(n+1)^{th}$ epoch.

$E(n)$ - Sum of squared error of the network at n^{th} epoch.

The weights are continuously updated every time the input patterns are presented to the network and this process continues till the actual output of the network comes closer to the desired output (presenting all the patterns of the training set to the network once constitutes an epoch) [5]. Detailed algorithm is available in [5].

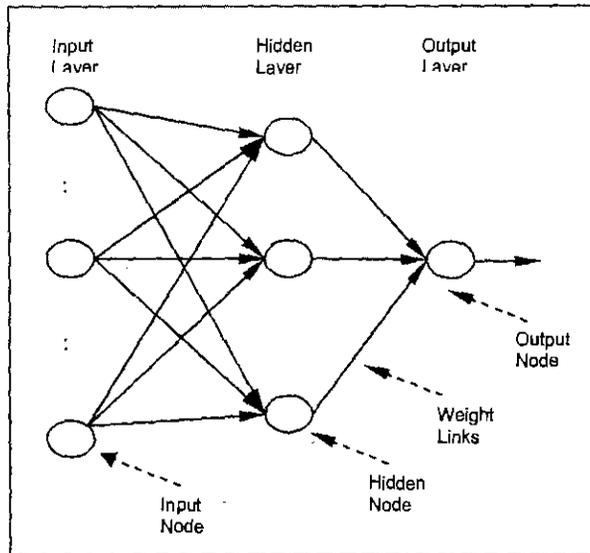


Figure 1 Architecture of multiple layer perception

EXPERIMENTAL DETAILS

Face milling trials on C60 steel workpiece have been carried out in Fritz Werner vertical milling machine using TiN coated K20 cemented carbide tool inserts to monitor the tool wear.

In the early research, tool wear was measured off-line using microscope and later on using tool-maker's microscope. Since this leads to frequent interruption of the machining process, on-line monitoring of tool wear came into practice. On-line tool wear sensing techniques are broadly classified into direct and indirect methods. Direct methods such as Radioactive technique, Optical measurement, etc are to measure the actual wear of the tool while the indirect methods like cutting force, AE, etc are to measure parameters which are indirectly related with tool wear by tapping information from the workpiece by fixing sensors through suitable fixtures.

In this work, AE and Force sensors have been used to get on-line indirect measurements about the tool wear. However, to relate the sensor values to the

actual wear, axial flank wear has also been measured off-line at regular intervals by interrupting the machining process. However, it is difficult to obtain analytical model by relating the sensor values and the axial flank wear to estimate the tool wear since complex phenomena occurs during the machining process. The actual relationship between the measured sensor values and flank wear can be obtained from ANN model at the end of the training process.

Cutting Force Components: A 3-component piezoelectric crystal type dynamometer (Kistler type 9265A) has been used along with charge amplifiers to measure cutting force components i.e., main cutting (F_x), feed (F_y) and axial (F_z) force components (Calibrated range: F_x, F_y : 0-15 KN, F_z : 0-30 KN)

The charge amplifier type 5007 converts the charge yielded by the piezoelectric transducers (Transducer Sensitivity: 0.1-11000 pC/M.U) into proportional electric signals which are displayed on the indicators.

Acoustic Emission Signal: AE signal is widely used in many applications as an automatic diagnostic process indicator. It is an active sensory data and is responsive for changes in material behavior such as deformation, crack initiation, crack propagation and chipping. Such changes in material behavior will affect the cutting process and hence the wear. So, one can use such signal for continuous monitoring of the tool wear status indirectly. Some characteristic features such as Ringdown Count (number of times the signal amplitude crosses a pre-set reference threshold), Rise Time (time taken to reach peak amplitude from the first threshold crossing of the signal), Event (microstructural displacement that produces elastic waves in a material under load or stress), Event Duration (time taken from the first to the last threshold crossing), Energy (energy of AE) have been collected to represent AE in this work.

In this work, piezoelectric sensor (100 KHz - 2 MHz range) has been used to acquire AE. Electrical signal from the sensor is of low amplitude and high frequency content. So, it must be first amplified with a low noise pre-amplifier and unnecessary frequencies must be filtered out prior to processing. The AE has been preamplified to a gain of 60 dB. The amplified signal then processed through AET 5500 system. The AET 5500 is a computer-based

general-purpose AE monitoring system comprising of a signal processing unit, an intelligent graphics display terminal and a 30 KHz - 2 MHz bandpass filter.

Flank Wear Characteristics: During machining, TiN coated carbide inserts undergo certain dynamic changes such as deformation of coating material, formation of ledge over the rake face and continuously changing wedge geometry, which influence the nature of machining. Typical flank wear characteristics of coated carbide when machining the steel workpiece is illustrated in Fig 2. It is seen that the coated carbide experienced rapid tool wear (up to a flank wear land of 0.115mm), followed by a slow propagating wear region (0.115 mm – 0.18 mm), beyond which there is a further rise in the propagation rate.

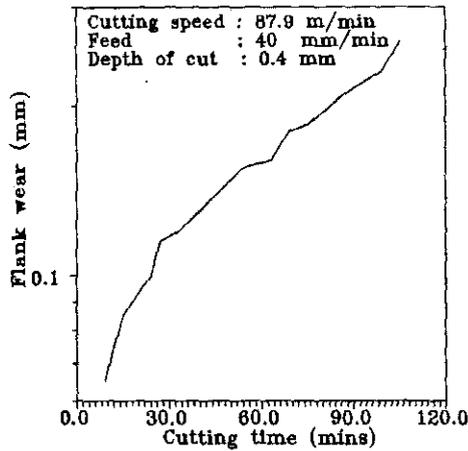


Figure 2 Flank wear characteristics

Observations of Cutting Force Components: The effect of flank wear on cutting force components is illustrated in Fig.3. The dynamic behavior of the coating results in a steadily increasing F_z component of the cutting force superimposed with number of spikes. The spikes are attributed to deformation of the coating influencing the cutting wedge geometry and consequently the cutting force.

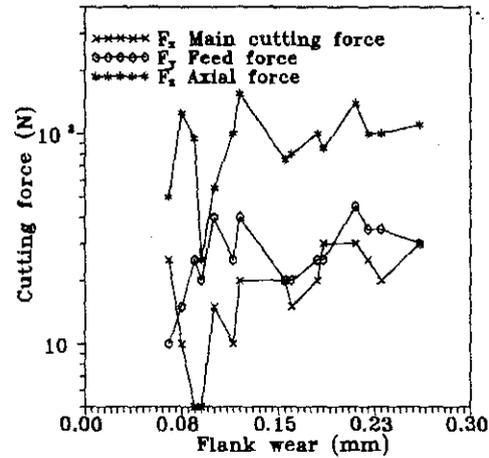


Figure 3 Effect of flank wear on cutting force components

Observations of AE Parameters: The effect of flank wear on one of the typical AE parameter such as Ringdown Count is shown in Fig.4. An interesting observation is that they show three distinct zones indicating possible correlation between the flank wear and AE parameter. With fresh tool, during the early phase of machining, the coating deforms due to indenting action of the chip-curl over the rake face; this results in displacement of coating material over the flank portion as well and thereby resulting in more negative wedge geometry of the cutting nose. This is associated with production of shorter segmental chips. Accordingly, burst type of AE occurs. The recorded observation of low order

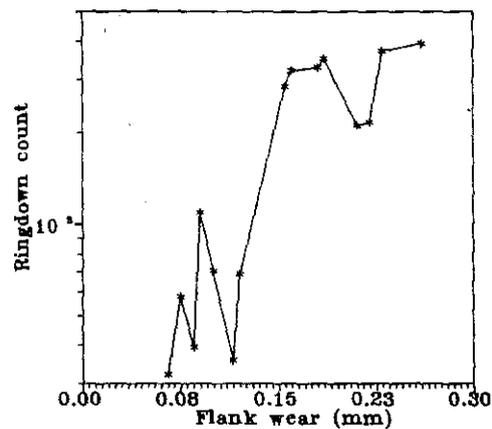


Figure 4 Effect of flank wear on AE parameter

AE signal parameter during this phase of machining illustrates the occurrence of burst type emission. As machining progresses, continuous sliding of the chip over the rake face induces formation of a ledge over the rake face [10]; this facilitates improved machining and also steadier/slow propagating flank wear. This is associated with continuous AE signal as indicated by higher order magnitude.

Also, with the final phase of the tool wear, the tool-work interface experiences more/intense sliding due to wider flank land. This sliding action results in continuous mode of AE as illustrated by the higher order AE signal parameter.

Accordingly, during the early phase of tool life, burst type emission has been observed; while in the middle phase of tool wear, continuous emission associated with increasing order magnitude of AE signal parameter has been observed. Further, increase in the magnitude of AE signal characteristics during the final phase of tool wear can be attributed to intense rubbing of flank wear over the just machined work surface.

ANN MODEL DEVELOPMENT

A sequential approach is adopted in this work for evaluating the effects of some of the influencing factors of MLP on tool wear estimation and the best approach is suggested for the precise estimation of tool flank wear using fused data through MLP trained using BPA. The following are the steps followed to build the ANN model.

Step 1: Selecting Representative Patterns

Data acquired through sensors during machining (5 AE parameters and 3 force components) are normally highly variant due to the stochastic nature of the tool-wear process.

Figure5 illustrates the variance of fused data for different flank wear values. It is seen that as tool wear progresses, there is a reduction in variance; this indicates that as tool wear progresses, the cutting performance becomes relatively more stable and good; however, with higher wear values, there is again a rise in variance due to the dominant rubbing action.

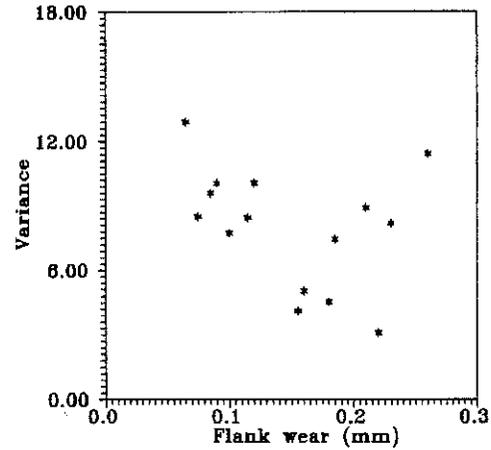


Figure 5 Variance of fused data

For proper training of MLP and to achieve the desired performance, it is necessary to input data with higher order variance among the acquired during training [6], [15]. Usually, this may work out to 50-70% of the acquired data [22]. In the present study, 60% of the data of relatively higher order variance is used during training and the trained network is tested with all 100% of data acquired. Though 60% of the testing data is redundant, it is useful to know the deviation of estimated characteristics from experimental tool wear characteristics. In other words, testing with 100% of the patterns will be helpful to know the training accuracy (due to 60% of the patterns drawn from the original training set) and generalization accuracy (due to 40% of the patterns drawn from outside the training set but from the same distribution function) [11]. The variance of data has been calculated as follows:

$$A_p^2 = \sum_{j=1}^{n1} ((x_{pj} - \bar{x}_j)^2 / \sigma_j^2) \quad 1 \leq p \leq P \quad (3)$$

$$\sigma_j^2 = \frac{1}{P} * \sum_{j=1}^P (x_{pj} - \bar{x}_j)^2 \quad (4)$$

Where

$n1$ = number of input features

P = number of input patterns

\bar{x}_j = mean of j^{th} feature

A_p^2 = maximum variance of j^{th} pattern

σ_j^2 = variance of j^{th} feature

x_{pj} = j^{th} feature of p^{th} pattern

Step 2: Normalization

Scale down the feature values between 0 and 1.

Step 3: Basic Approach

It involves selection of the number of hidden layers, number of input, hidden and output nodes, η and μ factor for the minimization of testing error of the network.

It has been proved that only one hidden layer is enough to approximate any continuous function [2]. So, a single hidden layer is used in this work.

The nodes in the input and output layers are ascertained by the number of independent and dependent features of the collected data respectively. In the present work, the number of input nodes equals 8 (5 AE and 3 force components) with single output node (to estimate the flank wear).

For good performance of the network, it is necessary to achieve not only higher order training accuracy but also to achieve satisfactory generalization accuracy. While training accuracy calls for as large a number of hidden nodes as possible, generalization accuracy may suffer due to overtraining. Hence, it is necessary to either prune or grow the network and arrive at an adequate number of hidden nodes [11]. In MLP, number of hidden nodes, η and μ can only be fixed through a laborious training effort.

To understand the influence of the number of hidden nodes on testing error, the network has been trained and tested for 1 to 20 number of hidden nodes and the sample results pertaining to the combinations of $\eta = \{0.9\}$ and $\mu = \{0.6\}$ are shown in the following figures 6a and 6b and in Table.1. Training process is stopped when the mean squared error of the network reached a value of 6.6×10^{-5} . Minimum testing error is considered as the criterion for the selection of network configuration and parameters.

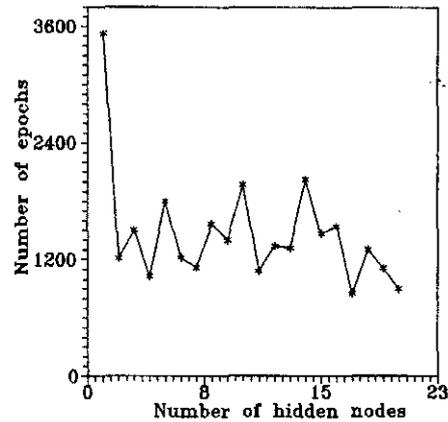


Figure 6a Effect of hidden nodes on number of epochs

It is seen that with increase in number of hidden nodes, i.e., as the network grows, it exhibits oscillatory performance characteristics (Fig 6b). Based on the above results, it is better to select a single hidden node as it yields minimum testing error compared to other hidden node configurations.

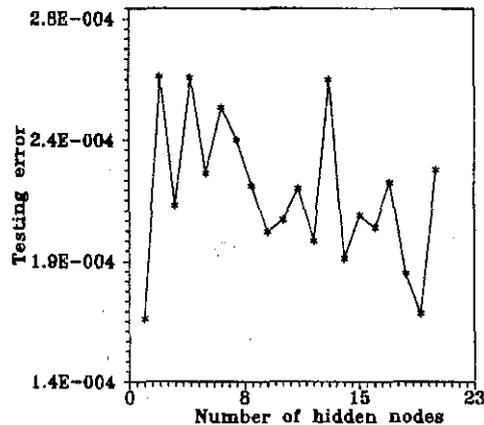


Figure 6b Effect of hidden nodes on testing error

Table 1: Effect of number of hidden nodes on testing error

Number hidden nodes	$\eta = 0.9, \mu = 0.6$		$\eta = 0.5, \mu = 0.6$	
	Number of epochs	Testing error (x 10 ⁻⁴)	Number of epochs	Testing error (x 10 ⁻⁴)
1	3527	1.64912	6250	1.64718
2	1216	2.61074	2198	2.60509
3	1502	2.10025	2792	2.08824
4	1030	2.60612	1855	2.60194
5	1799	2.22814	3270	2.21722

Generally, as the network learns the environment, i.e., as the process of modeling progresses, weights are continuously updated. This updating is mostly dependent on η and μ parameters. Table.2 shows the significance of different network parameters on testing error. According to the minimum testing error criterion, 0.1 and 0.7 values are selected for η and μ respectively.

Table 2: Effect of network parameters on testing error

Learning rate parameter, η	Momentu m, μ	Number of epochs	Testing error ($\times 10^{-4}$)
0.9	0.7	2632	1.64920
0.8	0.7	2950	1.64877
0.7	0.7	3360	1.64829
0.6	0.7	3907	1.64781
0.5	0.7	4675	1.64723
0.4	0.7	5829	1.64659
0.3	0.7	7754	1.64591
0.2	0.7	11606	1.64521
0.1	0.7	23167	1.64447

Step 4: Modified Approach

A network after good training might have acquired the best possible memorization capability; however, it may not be able to generalize, especially when the training process is stopped during the overfitting period. Hence, it is necessary to find a proper Stopping Criterion (SC) which would ensure a network having good generalization and adequate memorization capability [20] followed a method to ascertain the overfitting point during training by evaluating the performance of the network with validation patterns. In the present study, 40% of the patterns are used for validation. When the error during validation goes up, overfitting is said to begin and the weights corresponding to the lowest validation error can be the optimum set of weights for the given data set. So, in this work, a small error threshold of value 6.6×10^{-5} along with minimum validation error forms the hybrid criterion for stopping the training process. So, the network is trained until its output converged to the point defined by the SC. The training and validation error characteristics while implementing the SC is illustrated in Fig.7. Epoch 141 and 1162 correspond to the point at which validation error reached minimum and peak value respectively. The corresponding testing errors are shown in Table.3. Testing errors pinpoint the consequence of inadequate training which may lead to training inaccuracy and the danger of stopping the training

process at an irrelevant point. Also, it is clear from Table.3 that stopping at 23167th epoch with respect to SC is better with respect to validation and testing error when compared to the other two epochs.

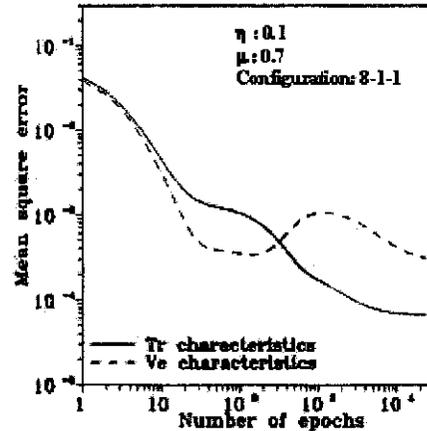


Figure 7 Training and validation error characteristics

Table 3: Network Performance While Incorporating SC

Epoch	Training error ($\times 10^{-4}$)	Validation error ($\times 10^{-4}$)	Testing error ($\times 10^{-4}$)
141	9.0253	3.3864	6.7698
1162	1.6018	1.0613	5.20638
23167	0.6667	3.1112	1.6445

Step 5: Training Mode

Influence of training modes on tool wear estimation is presented in this section. There are two approaches for training the network; one is based on continuous weight updation, while the other is based on Periodic Weight Updation (PWU). In continuous weight updation, the weights are updated after each training pattern presented to the network, while in PWU, the weights are updated only once an epoch, after all the training patterns are presented to the network. The results pertaining to the PWU along with SC, is shown in the Table. 4. There is an improvement compared to the modified approach which is explained in step 4.

Step 6: Adaptation of Learning Rate Parameter Using Fuzzy Logic

The value of η determines the step length when it moves along the error surface. Since, different regions of the error surface may have different characteristic gradients, it is preferable to dynamically change the parameter based on

the nature of the surface. Fuzzy logic can also be used to determine η dynamically since fuzzy reasoning provides a way to interpolate between the error difference and η . In [12], fuzzy logic was employed to determine μ , η and steepness of activation function to improve the speed of learning. In the present study, fuzzy logic has been employed for η adaptation to improve the performance of the network.

Generally, fuzzy algorithm consists of (a) fuzzification, which converts the measured values into linguistic values, (b) a knowledge base, which is a set of linguistic control rules, (c) an inference mechanism which performs fuzzy reasoning of the linguistic rules and (d) defuzzification [19].

The fuzzy logic inference mechanism results in a fuzzy value. In order to generate a crisp output, defuzzification method is used to calculate a value that best represents the output membership value $M(\eta)$. In this work, the difference between mean square error of the $(n-1)^{\text{th}}$ and n^{th} epochs has been taken as the input to the fuzzy logic algorithm. At the end of every epoch, this error difference has been passed through the inference mechanism and defuzzification method and η is determined. Fig. 8 shows the dynamic change of η over epochs. The results pertaining to η adaptation using fuzzy logic in addition to PWU and SC approaches is shown in Table 4.

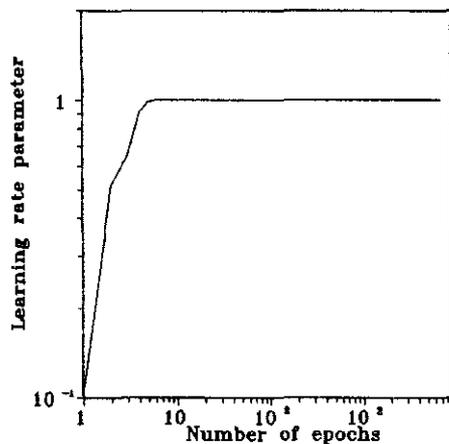


Figure 8 Training and validation error characteristics

Table 4: Network performance while implementing different approaches

Approaches	Epoch	Validation error ($\times 10^{-4}$)	Testing error ($\times 10^{-4}$)
SC + PWU	26831	2.25379	1.30290
SC + PWU + Fuzzy Logic	2681	2.25322	1.30256

Step 7: Data Size

Performance can further be improved by studying the effect of other influencing factors on estimation. So, the next factor that has been considered is data size as the performance is very much dependent on the number of patterns available for training and testing the network. So, to study this effect, a new dataset has been created that includes all the data obtained by experiments (15) and by interpolation (15). The new dataset has been subjected to basic and modified approaches to select the appropriate network parameters and configuration. The resultant network has been subjected to η adaptation using fuzzy logic since among all the approaches; η adaptation using fuzzy logic seems to be favorable. Table 5 shows the corresponding result. Table 6 shows the percentage improvement of new (large) dataset in validation and testing error with respect to the previous approaches. The approach followed shows a continuous improvement in tool estimation.

Table 5: Network performance – new dataset

Approaches	Epoch	Validation error ($\times 10^{-4}$)	Testing error ($\times 10^{-4}$)
SC + PWU + Fuzzy Logic	353	2.01663	1.20622

Table 6 Percentage improvement of new dataset over the experimental dataset while applying SC + PWU + η adaptation using Fuzzy logic

Percentage improvement over data set		
Epoch	Testing error	Validation error
86.83%	10.50%	7.39%

CONCLUSIONS

The following conclusions have been drawn:

1. A methodology for tool status monitoring through sensor fusion presented here gives a closer estimation of tool wear which will facilitate process control and thereby improved product quality.
2. MLP is found to be an effective tool status identifier. For the efficient use of the network, one has to choose the optimum number of hidden nodes and optimum values for the network parameters.
3. Further, the methodology accentuates the importance of an apt SC for the desired network performance. This gives a caution that training should not be stopped based only on rate of convergence or small error threshold or small gradient threshold but by adopting a hybrid criterion along with minimum validation error criterion.
4. PWU approach was better when compared to the continuous weight updation approach.
5. Adaptation of η parameter using fuzzy logic showed better improvement in estimation of tool status.
6. Data size is also an important influencing factor and showed a good improvement over the previous approaches.
7. These approaches when followed sequentially can give good network performance irrespective of the area of application.

LIMITATIONS

1. Any method of condition monitoring calls for acquisition of as large data as possible; however, it was limited due to time and economical constraints.
2. The methodology/approach adopted for tool status monitoring is based on data collected for a particular tool-work material pair only.

SCOPE FOR FUTURE WORK

1. Experiments can be done for acquiring additional process indicators such as cutting temperature and vibration to correlate with the tool flank

wear. The effect of cutting fluids can also be studied.

2. Surface finish, chip form, chip morphology, chip strain can also be used apart from flank wear since the present day industries emphasize on workpiece specifications rather than tool wear.
3. Effect of multisensory information fusion can be studied through ANN with multi-input and multi-output.
4. Generalization capability of the network can be improved through the study of the following influencing factors:
 - Gain of the activation function
 - Adapt η for each weight link of the network.
 - Adapt μ after every epoch with respect to mean squared error using fuzzy logic.
 - Adapt weight links using fuzzy logic.

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