Development of a System for Monitoring Tool Wear using Artificial Intelligence Techniques

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Abstract

The main objective of the work reported here was to develop an intelligent condition monitoring system able to detect when a cutting tool was worn out. To accomplish this objective the use of a hybrid intelligent system, based on an expert system and two neural networks was investigated. The neural networks were employed to process data from sensors and the classifications made by the neural networks were combined with information from the knowledge base to make an estimate of the wear state of the tool.

The novelty of this work is mainly associated with the configuration of the developed system that estimates tool wear in a new way. The combination of sensor-based information and inference rules, results in an on-line system that can be updated when the cutting conditions fall outside of the trained zone of the neural networks. The neural networks resolved the problem of interpreting the complex sensor inputs while the expert system, by keeping track of previous success, estimated which of the two neural networks was more reliable. Mis-classifications were filtered out through the use of a rough but approximate estimator, Taylor's tool life model. The use of Taylor's tool life model, although weak as a tool life estimator, proved to be crucial in achieving higher performance levels. The application of the Self Organizing Map to tool wear monitoring proved to have a slightly larger zone of influence and make slightly more accurate estimates of tool wear than the Adaptive Resonance Theory neural network and overall the system made reliable, accurate estimates of the tool wear.

Keywords

Turning, Neural Network, Expert System, Monitoring, Tool Wear

Nomenclature

b	Slope of linear regression equation
C	Constant in Taylor's tool life equation
w	Width of cut (mm)
f	Feed rate (mm/rev)
F	Cutting force (N)
n	Exponent in Taylor's tool life equation
N_p	Number of previous classifications
P_{ART2}	ART2 outlier counter
P_{NN}	Total number of mis-classifications to date (general)
P_{SOM}	SOM outlier counter
r	Linear regression coefficient
r_h	Linear regression correlation coefficient of previous P_{NN} samples
S_i	Sample reference number
t	Time (s)
T	Tool life (min)
V	Cutting speed (m/min)
VB_B	Average flank wear (mm)
VB_i	VB_B for sample S_i (mm)
VB_{REF}	Reference values of tool wear to define membership of a wear class
μ	Membership function

1. Introduction

One important challenge posed by the requirement to ensure high machine utilisation is the ability to correctly classify the wear state of the cutting tool. Probably this task is so difficult because the tool wear is a small change in a process with large variations. However the mechanisms by which the cutting tool wears and the types of wear geometry created depend on the cutting tool material, work piece material, tool geometry and cutting conditions have been well documented [1]. Analytical models have been used to study the effects of tool geometry on, for example, cutting forces [2, 3] and although these models are of value they may be too complex to implement in a real-time tool wear monitoring system. Empirically derived relationships tend to be reliable for a limited set of conditions and can normally only be used for approximate calculations [4]. On the other hand, a rule based empirical inference method requires an expert familiar with the relevant relational mechanisms and an ability to translate those into inference rules. As such 'experts' do not exist (except in a narrow sense), another empirical, non-expert-based method is needed.

The development of tool condition monitoring systems for machining has attracted a large research effort with systems that focus on chatter, tool breakage and different manifestations of tool wear. One approach is the development of monitoring indices such as the ratio of the force and vibration at the natural frequency of the tool holder, or using spectral components of the sound [5 to 10] that are sensitive to tool condition but insensitive to cutting conditions. Table 1 summarises some of the results when monitoring tool wear. These indices attain only limited success over a relatively small range of machining conditions as the relationships that they rely on breakdown. Some work has been undertaken to investigate when this happens [10]. What is needed is a monitoring system that is able to reform the relationships between the parameters monitored and the machine condition as the machine conditions change.

Table 1: Turning Tool Monitoring Indices

Monitoring Indices	**Reference**
Ratio of the force amplitude at first natural frequency of tool-holder and the vibration amplitude at the same frequency	Rao [5]
Frequency analysis of dynamic forces	Choi *et al.* [6]
Frequency band energy of the tool holder vibration	Sokolowski *et al.* [7]
Spectral components of the sound radiated during cutting	Lee [8]
Motor Current mean value	Agogino *et al.* [9]
Ratio of forces	Bayramoglu and Dungel [10]

In order to achieve reliable tool wear monitoring it is necessary to incorporate some degree of intelligence into the software and perhaps also utilise multiple sensors [11]. Numerous approaches have been described in the open literature and Table 2 summarises several examples [5 and 12 to 18] from recent studies applied to the turning. According to these authors, these monitoring methods may achieve a classification success of 90% or higher under controller laboratory conditions. Although these techniques achieve very good results under limited conditions, it is probable that the parameters that lead to the successful prediction of tool wear under one set of conditions will change in importance (at the very least) under different conditions. One approach would be to allow the system to re-learn or generate new relationships when asked to make classifications for conditions where it is not confident of making a good prediction. This approach might be implemented in the system as a methodology for automatically gathering data for situations where the system has little knowledge, which implies that the system must have knowledge of where it can operate effectively. Therefore, there is a need to address the robustness and generality of any developed system, something that has not been widely undertaken in the reported literature [19].

Table 2: Application of Condition Monitoring Using AI and Sensor Fusion

Sensor Signal	**Monitoring Indices**	**Classification Method**	**Reference**
Vibration and forces	Ratio between force and vibration amplitude	Wear index	Rao [5]
Force and AE	Power Spectrum	Neural networks	Burke and Rangwala [12]
Sound Emission	Power spectrum	Least-squares minimum-distance	Trabelsi and Kannatey-Asibu [13]
Forces	Force ratio	Neural network	Lee *et al.* [14]
AE, forces and spindle current	AR models and power spectrum	Neural network	Dornfeld [15]
Vibration	Power spectrum	Data Dependent System (DDS) modelling	Pandit and Kashou [16]
Force and vibration	Time and frequency analysis	Neural network	Dimla *et al.* [17 and 18]

The overall objective of this work was to develop a tool wear monitoring system in which signal processing, neural networks and decision-making techniques were used. This paper focuses on the development of the tool condition monitoring system for the turning process with an emphasis on the system robustness. In order to achieve this robustness the system consisted of two neural networks to interpret the sensor information and an Expert System to act as a mediator, synthesising information from different sources, namely; the neural networks, awareness of cutting conditions, work piece material and cutting tool, cutting time, and empirical knowledge based on Taylor’s model with fuzzy logic resulting in a new way of estimating tool wear.

2. Experimental Apparatus, Procedure and Primary Results

In order to develop the system a set of data was collected from; the vertical vibration of the turning centre, the sound emission whilst cutting, two components of cutting force and the spindle current for different amounts of tool wear whilst machining a 75mm diameter bar of mild steel (EN1A), with a coated cemented carbide insert. The instruments used to make these measurements are described in Table 1. The experiments were carried out on a MT 50 CNC Slant Bed Turning Centre (Figure 1). The analogue signals were sampled with an Amplicon PC-30PGL data acquisition board at a sample rate of 20 kHz per channel for a time period of 26 ms. Data were acquired at intervals of 2 minutes of cutting time at which point tool wear was also measured, taking into account an expected life of about 15 minutes for the inserts, six different inserts were used at each condition (to construct test and validation sets) and three different wear levels were defined; new (VB_B=0 mm), half-worn (VB_B≈0.15 mm) and worn (VB_B≈0.3 mm). The cutting conditions investigated during the 'training phase' were selected so that the tool would wear under realistic production conditions; cutting speed 350 m/min, feed rate of 0.25 rev/min, width of cut of 1 mm [20].

Table 3: Instrumentation

Sensor	Description	Mounting
Accelerometer	Kistler 8752A50 & Piezotron Coupler - Kistler 5108	Base of the turning centre, to measure whole body vibrations.
Microphone	ECM-1028, matching amplifier	Tool Post, directed at the insert
Strain gauges	Two half Wheatstone bridges, constructed from one strain gauge per side of the tool holder	Feed and tangential direction
Current Meter	CNC built in sensor	

Figure 1: MHP Moog-Turn 50 Slant Bed Turning Centre

2.1 Feature Extraction

Each 512 point data record, from the middle of the cut, was processed to generate features of; the absolute deviation, mean, kurtosis, skewness of all sensors and the energy in the frequency bands 2.2-2.4 kHz and 4.4-4.6 kHz obtained from the power spectrum of the sound, vibration and cutting forces. Previous work by the current authors [21 and 22] had already demonstrated that tool wear classification was improved when all features were included over that achieved using only features, such as the cutting forces that were found to correlate most with the tool wear level. These features were then passed directly to the two neural networks for classification; with the training data coming from four wear tests and the validation data from two tests not used during the 'training phase'. Figure 2 shows the evolution of flank wear with cutting time for the six tools that allowed the derivation of a relationship between cutting time and flank wear, whilst Figures 3 and 4 show examples of the results of signal processing. Observation of the evolving peak in Figure 3 at 2.4 kHz was a typical variation, although the peak that occurs in this figure at high flank wear would often be of a different magnitude for different samples, leading to a non-monotonic variable relationship with flank wear. For Figure 4 typically the variation of the statistical parameters with flank wear resulted in increased scatter at higher values of flank wear, although again the variation was far from consistent.

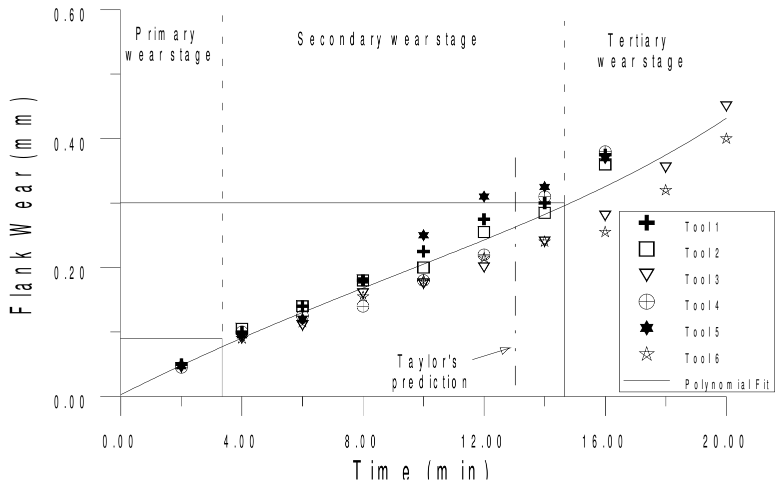

Figure 2: Flank Wear Evolution with Time: 350 m/min, 0.25 mm/rev and 1 mm

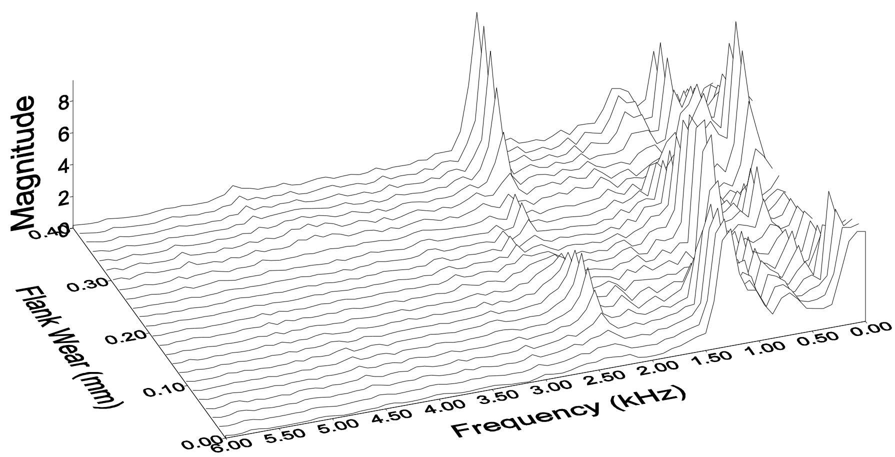

Figure 3: Vibration Spectrum vs. Flank Wear

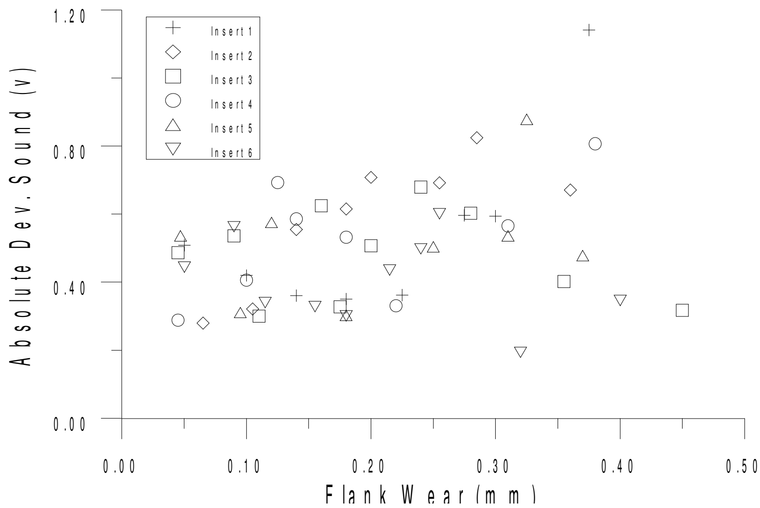

Figure 4: Sound Deviation vs. Flank Wear

In order to assess the 'zone of influence' of the tool wear monitoring system systematic experiments were conducted to investigate as large a range of cutting conditions as possible for this tool and work piece combination [20]. This was achieved by varying the cutting conditions in both a fine and coarse manner (Table 4) about the cutting conditions used during the training experiment. Data from three tool states (VB_B=0, VB_B≈0.15 mm, and VB_B≈0.3 mm) were collected at each set of cutting conditions, as the time required to wear out a tool at each point would have been prohibitive. According to the range of cutting conditions allowed by the tool manufacturer's handbook the following limits were established for the cutting conditions; feed rate 0.2 to 0.5 mm/rev, cutting speed 200 to 350 m/min and a depth of cut up to 5 mm. To keep the number of experiments within reasonable limits, tests were conducted with the neural networks on-line to establish the range of adaptability of a network trained for a given set of cutting conditions. Following the determination of the range of depth of cut, feed rate and cutting speed under which the neural networks could still perform tool wear monitoring accurately; finer variations were introduced within the area of tolerance for each of the cutting conditions.

3.Tool Wear Monitoring System Design

The monitoring system consisted of two neural networks; a self organising map and an adaptive resonance theory network, linked with an Expert System by fuzzy logic. Section 3.1 heavily summarises the training and testing of the neural networks as this has already been published in detail elsewhere [21 and 22], and so only a summary will be presented here.

3.1 Neural Network Implementation

When using neural networks it is important to be aware of the effect of computational limitations. Relevant features have to be determined externally and the task of the neural network is to determine the relationship between the incoming data and the tool wear classes. In this application, it is desirable to know the tool wear rate so that it is possible to take corrective actions. The two networks used in this work (a Self Organising Map (SOM) [23] and Adaptive Resonance Theory (ART2) [24]) make classifications of approximate values of wear for each set of input features. The objective was to be able to classify the present wear stage so that it is possible to take appropriate action in the future regarding tool change.

Table 4: List of Cutting Conditions Tested

Feed (mm/rev)	Speed (m/min)	Depth (mm)
0.250	350	1.000
0.275	350	1.000
0.250	350	1.500
0.200	350	1.000
0.225	350	1.000
0.250	350	1.250
0.250	337	1.000
0.250	350	1.125
0.300	350	1.125
0.200	350	1.125
0.250	344	1.000
0.300	344	1.000
0.250	344	1.125
0.300	344	1.125
0.275	344	1.000
0.225	344	1.000
0.225	350	1.125
0.275	350	1.125
0.225	344	1.125
0.275	344	1.125
0.300	350	1.000
0.250	325	1.000
0.250	344	1.000
0.200	344	1.125
0.175	350	1.000
0.325	350	1.000

Self-Organising Feature Map. The SOM typically has two layers; the input layer is fully connected to a two-dimensional SOM or 'Kohonen' layer. In the SOM layer, none of the neurones are connected to each other, regardless of relative position. The SOM layer neurones each measure the Euclidean distance of their weights to the incoming input vector. During recall, the SOM layer neurone with the minimum Euclidean distance is called the winner adjusts its weights to be closer to the input vector [23]. In addition, the neighbours of the winning neurone also adjust their weights to be closer to the same input data vector. In order to evaluate the performance of the SOM network it was necessary to interpret the SOM topological output. This was achieved by using the Kriging method for surface meshing [25] with this meshed surface being stored in a file ready for classification.

Adaptive Resonance Theory 2. An ART2 algorithm can classify and recognise input patterns without a teacher and consists of two interconnected layers of neurones. For tool wear identification, the magnitude of features, such as the mean cutting force, has been found to be an indicator of tool wear. However the ART2 algorithm relies on an explicitly normalised input vector and automatically normalises the vectors during processing. It was therefore decided to use the normalised inputs taking into account their limit values, thus adopting a fixed scale for each feature. The duration of the training period was set according to the network's performance, during which weights were adapted and after which weights were frozen based on a stability test.

Figures 5 and 6 show the wear estimates made by the two neural networks. Figure 5 shows the results for the networks predicting wear for the data with which they were trained and as can be clearly seen both networks have learnt the underlying relationships between the features and the flank wear evolution. Figure 6 shows the predictions for a tool wear evolution not presented during training. As can be seen from Figure 6 initially both neural networks overestimate the tool wear, although the SOM makes slightly better estimates than the ART2. By the time the tool is approximately half worn ($VB_B \approx 0.15$ mm) both neural networks make reliable estimates of the flank wear resulting in an accurate estimate of when to change the insert.

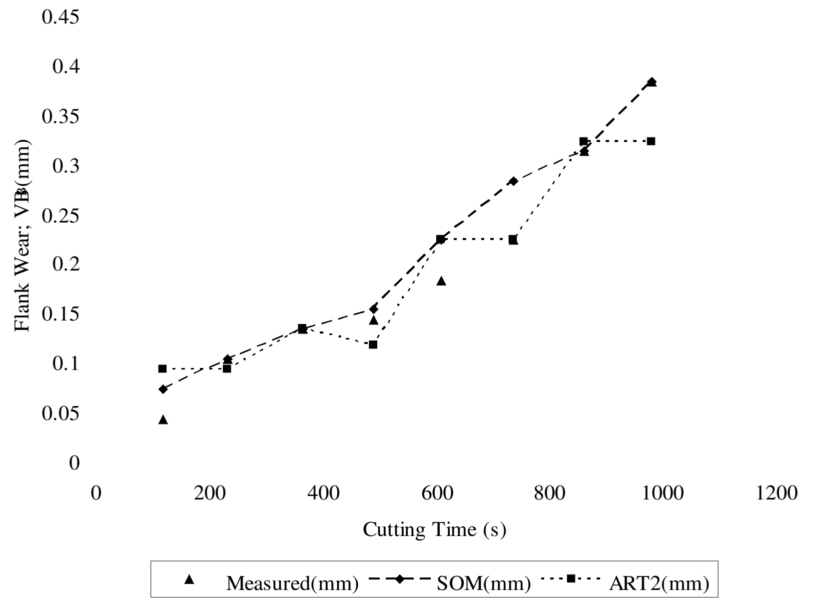

Figure 5: Comparison of the Predictions Made by the SOM and ART2 Networks with the Actual Flank Wear Measurements (Data Presented During Training)

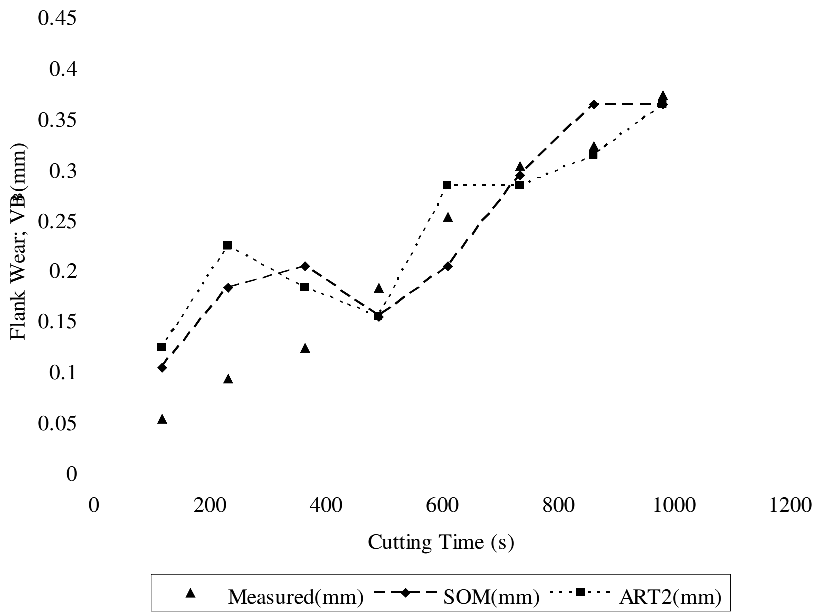

Figure 6: Comparison of the Predictions Made by the SOM and ART2 Networks with the Actual Flank Wear Measurements (Data *Not* Presented During Training)

3.2 Expert System Development

The Expert System interpreted the ANN output by the use of a knowledge base that mapped the outputs of the ANNs into specific wear detector states. This was achieved by determining their membership value (i.e. how worn the tools are) in terms of a threshold value selected according to tool wear criteria. The final result was then selected based on a reliability measure for the neural networks which took into account their performance. Knowledge was encoded in the form of rules which enabled the Expert System to perform any reasoning required for tool wear prediction. The rule priority allowed the determination of the order of precedence in the reasoning path when more than one rule applied.

*Removal of Neural Network Mis-classifications***.** In order to reduce the effects of the small number of mis-classifications by the two ANNs, rules were encoded which encapsulated Taylor's empirical tool life model (Table 5). The prediction made by Taylor's tool life model ($VT^n=C$) was used to establish preliminary wear intervals with mis-classifications being removed if they fell outside these intervals (Figure 7).

Table 5: Rules Based on Cutting Time

Rule No	**IF**	**THEN**	**Priority**
1	VB_B (NN) > VB_B (Taylor) + 0.15	Exclude	2
2	VB_B (NN) < VB_B (Taylor) - 0.15	Exclude	2

The parametric values of Taylor's tool life equation for the work piece and tool material, that is n and C, have to be known in order to determine the above rules, and for a given set of working materials and cutting tools a data base was constructed to cover the material investigated, these values were C = 823, n = 0.33 [26]. Taylor's tool life equation yields a life in minutes and it was necessary to convert this to a flank wear values using an empirical equation derived from Figure 2.

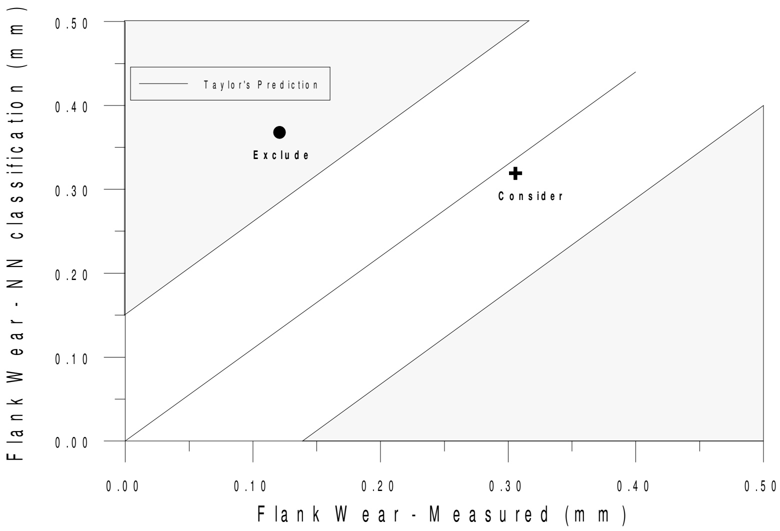

Figure 7: Outlier detection example

Interpreting Uncertainty Using Fuzzy Rules. At this stage the tool wear level was classified by combining the ANN predictions with the outlier detector using a fuzzy function which returned a continuous grading of set membership between 0 and 1. The membership function [Equation 1] determined the level of tool wear (Figure 8). Membership of a class was defined by the sigmoid function which used VB_{REF} as an exponent constant. This value might also be selected to account for surface finish, machine stability, or different wear criteria and it is also important to account for small deviations from the predicted results. For this work a value of VB_{REF} = 0.28 mm was found to be suitable, giving $\mu(0.3)=0.8$. A fuzzy membership function eliminated the 'hard barrier' created by crisp sets (worn or not), thus for each classification a grade was given which specified the level of tool wear. Table 6 shows rules 3 and 4 which account for outliers or calculate the membership value.

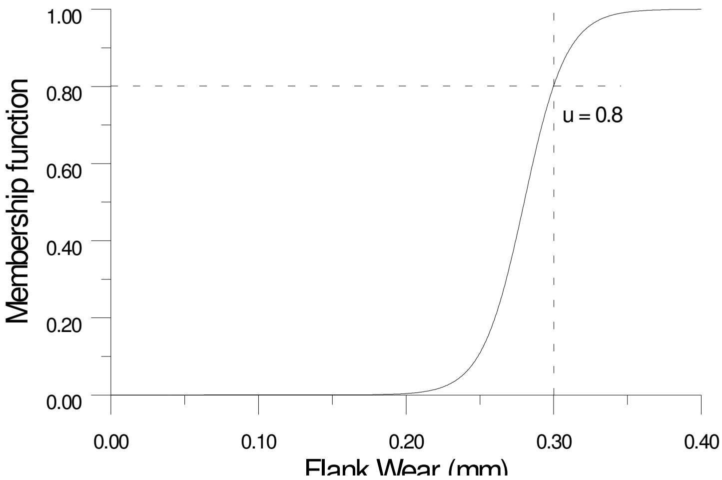

Figure 8: Worn Out - Membership Function

$$\left(VB_B\right) = \frac{1}{1 + e^{-70\left(VB_B - VB_{REF}\right)}}$$

[1]

Table 6: Membership Rules for Non-Outliers

Rule No	IF	THEN	ELSE	Priority
3	VB_B (ART2) ≠ Unknown	μ (VB_B (ART2))	P_{ART2} + 1	1
4	VB_B (SOM) ≠ Unknown	μ (VB_B (SOM))	P_{SOM} + 1	1

Neural network performance was also taken into account by tracking previous failures recorded by the outlier detectors (P_{ART2} *or* P_{SOM} value). Membership values were only calculated for predictions that were found to pass the outlier detector; otherwise they reinforced the determination of a neural network's ineffectiveness at tool wear classification (P_{NN} value).

*The Use of Historical Data***.** In order to increase the confidence of classification, each prediction was compared with *Np* previous classifications to establish the final assessment of the classifications made by the neural networks (Rules 5 and 6) by obtaining the linear correlation coefficient for the last *Np* samples.

Table 7: List of Rules to Account for Historical Weighting

Rule No	**IF**	**THEN**	**Priority**
5	VB_B (ART2) ≠ Unknown	r_h (ART2)	1
6	VB_B (SOM) ≠ Unknown	r_h (SOM)	1

If the last *Np* predictions were well correlated a value near 1 was achieved for r_h. Although the evolution of wear with time may not be linear it is probably valid to assume a linear relationship for small time intervals. The number of previous samples (N_p) was set to a value of 3 in this work.

Tool Wear Diagnosis. Finally, to obtain the overall assessment of the tool wear state it was necessary to examine the results of the combined Rules 3 to 6. Since the aim was to determine whether the tool had failed due to excessive wear, a *Goal* had to be established within the Expert System to ask, ''In What State is the Tool?'', which triggered the rule interpretation process. If the ANNs agreed as to the state of the tool, or one reported an *unknown* state, a solution was possible; otherwise the determination of the tool state was resolved from a reliability perspective. Reliability was determined using the NN wear prediction correlation (determined from previous data) and the present prediction. The diagnosis consisted of the integration of both neural network predictions using the weights provided from the analysis of their performance, based on the evolution of historical data, r_h, and previous successful classifications obtained, P_{NN}. The most reliable neural network prediction carried the most weight in the classification of wear. Table 8 shows the rules, which resolve conflict between the neural networks by comparing their reliability and historical success based on up to date information processed each time a verdict was triggered by a new data sample. The prototype tool wear monitoring system then was a hybrid integration of the neural networks and the expert system and its knowledge. Within this hybrid architecture, the neural networks were employed to detect the state of the tool based on the classification of sensor output as it changed with time. The knowledge-based expert system was used to determine confidence limits of tool wear stages via Taylor's tool life model, interpret the ANN results, and provide an overall monitoring assessment.

Table 8: Rule to Resolve Conflicts between Predictions

Rule No	IF	THEN	Priority
7	P_{NN}(ART2)/ r_h(ART2) < P_{NN}(SOM)/r_h (SOM)	ART2	0
8	P_{NN}(ART2)/ r_h(ART2) >= P_{NN}(SOM)/r_h (SOM)	SOM	0
9	Both Unknown	Unknown	0

A proprietary environment (KAPPA-PC) was used to combine the neural network and expert system technologies and to develop the tool wear monitoring system, although external programs performed some numerically intensive processing. Figure 9 shows a schematic diagram of the structure of the monitoring system.

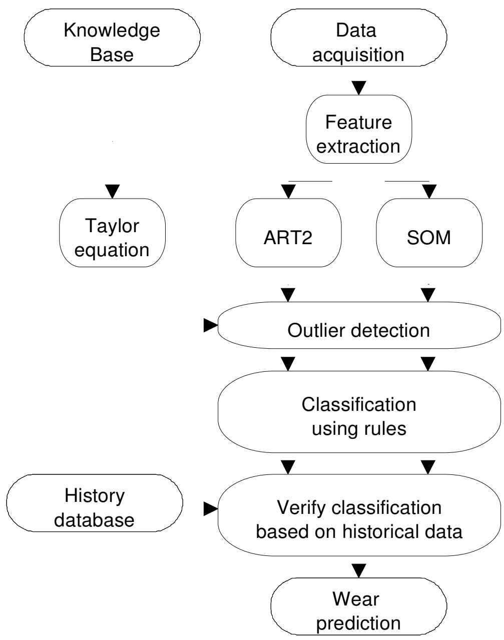

Figure 9: Stages in Tool Wear Estimation

4. Hybrid System Results

This section presents a summary of the results obtained with the neural networks as this has been published elsewhere [21 and 22] with the results obtained from the complete monitoring system being presented in detail.

4.1 Summary of Neural Network Results for Fixed Cutting Conditions

A summary of the results for both neural networks is given in Table 9. This table presents both correlation coefficient (*r*) and linear slope (*b*). Two results are presented for each neural network configuration, for the training feature vectors and the test set. As can be see the SOM outperforms the ART2 network slightly both in terms of the correlation coefficient and the slope variation from the ideal.

Table 9: Performance Results for the ART2 and SOM Networks

Tests	***b***	***R***
ART2, training set	0.930	0.960
ART2, unseen test set	*0.858*	*0.914*
SOM, training set	0.946	0.964
SOM, unseen test set	*0.871*	*0.946*

4.2 Summary of Neural Network Results for Variable Cutting Conditions

Examination of the results obtained from each sensor showed that there were some subtle and some coarse variations in the sensor output as cutting conditions changed. This resulted in a zone around the training conditions where the neural networks classified satisfactorily. The features obtained from processing the force transducer output were the factors that influenced neural network performance the most. Performance measurements were obtained by averaging two consecutive samples from each test condition (Table 4) with individual sample performance being calculated as the percentage error of the prediction compared to the actual wear value. The maximum percentage error at each wear level was chosen as the final performance measure. The system was capable of generalising over a small range of cutting conditions and this capacity differed slightly between the two neural networks as will be shown in the following sections.

Self-Organising Map Results: The self organising map was trained with the data from 4 inserts obtained from fixed cutting conditions for 30,000 epochs and, after this period, organised areas, representative of different wear levels, were created on a 6 by 6 neurone output layer. To determine the optimum number of epochs several tests were undertaken in order to achieve good classification results. The measurement of performance for the self-organising map consisted simply of plotting the classification results against the measured ones, the straight line representing the ideal fit and the dashed the data fit through the origin. A value of performance was obtained by determining the correlation coefficient of the linear fit through the origin, only accounting for the test data. Classification was successful (>80%) for variations in feed (Figure 10) between 0.2 and 0.275 mm/rev with the other cutting conditions kept constant. For increases in the width of cut (Figure 11) up to 1.175 mm, classification was successful but decreased sharply afterwards. Cutting speed changes (Figure 12) also resulted in reduced performance of the SOM, with only one set of cutting conditions achieving 60% classification a speed of 344 m/min. The deterioration rates for individual cutting conditions are; cutting speed 7 %/(m/min), feed rate 10%/(0.01 mm/rev), and width of cut 20%/(0.1 mm).

Adaptive Resonance Theory: The adaptive resonance theory neural network gave its best performance when trained for 1,000 epochs with a vigilance parameter equal to 0.996. These were determined after successive tests from which the best configuration was chosen. The parameters were set to give a reliable training time as well as a minimum of 10 data clusters. The number of data presentations was determined by the magnitude with which the weights changed, as for small weight changes clusters cease to be created. The same criteria for performance evaluation, as the one used for the SOM, was applied to the ART2 network. Here, variations in feed rate (Figure 10) between 0.23 and 0.285 mm/rev result in a classification success greater than 80%. The ART2 was successful in classifying patterns with widths of cut up to 1.225 mm (Figure 11), but the performance deteriorated rapidly beyond this. Cutting speed (Figure 12) significantly influences the ART2 performance, it being unable to generalise when presented with data acquired at cutting speeds lower than 344 m/min. At some isolated cutting conditions the ART2 succeeded in classifying the test samples, but general performance was constrained to a limited zone of influence. The deterioration rates were approximately; cutting speed 100% after 344 m/min, feed rate asymmetrical for feed > 0.275 mm/rev, 100% and for feed < 0.25 mm/rev, 10%/(0.01 mm/rev), width of cut 20%/(0.1 mm) average.

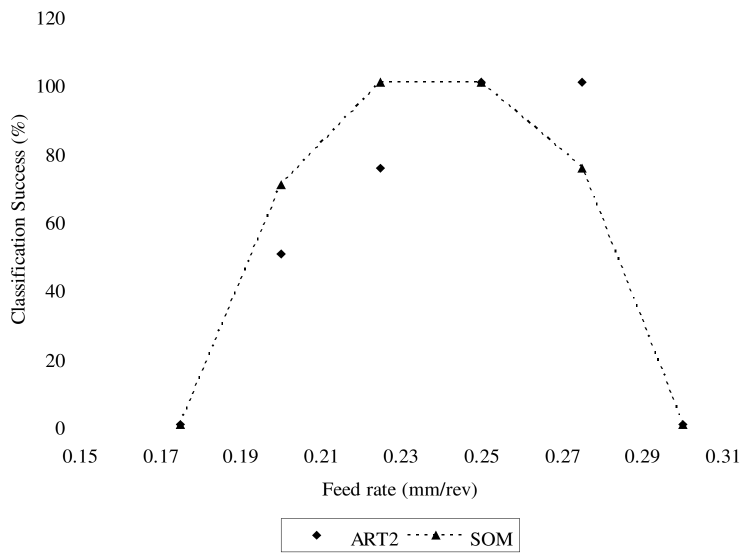

Figure 10: Reduction in Classification Success for the ART2 and SOM Networks with Feed Rate

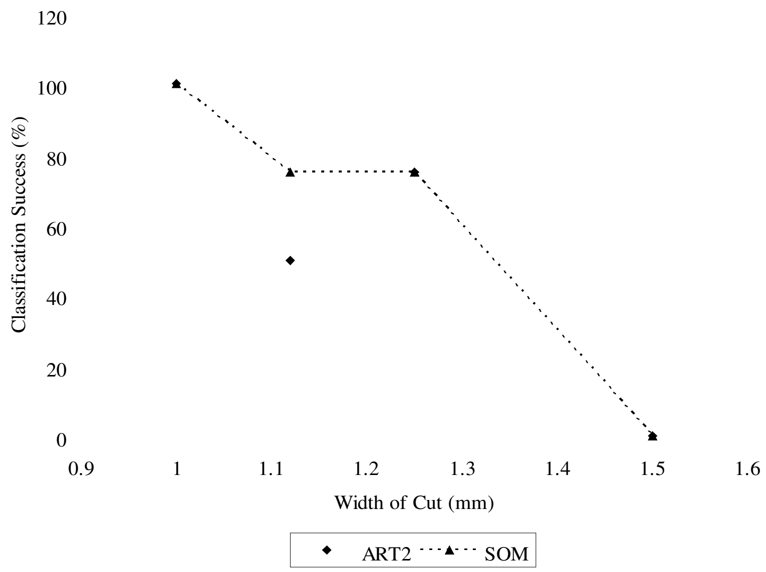

Figure 11: Reduction in Classification Success for the ART2 and SOM Networks with Width of Cut

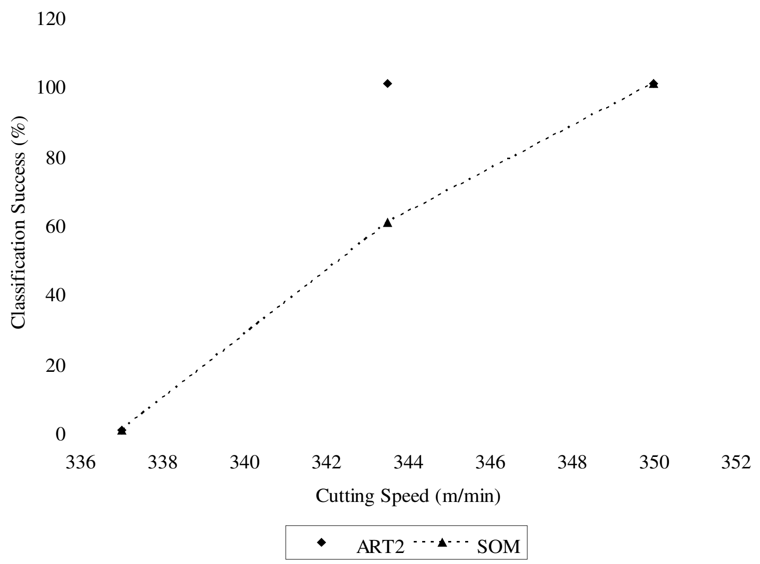

Figure 12: Reduction in Classification Success for the ART2 and SOM Networks with Feed Rate

4.3 Hybrid System Assessment and Discussion

The linking of an expert system with the neural networks allowed for the removal of obvious mis-classifications, thereby increasing overall system performance. Generally, the overall system modularity contributed largely to the success of this application, mainly due to the flexibility that it provided when implementing or modifying the embedded knowledge. Modularity becomes essential in a system like this because adaptability is not always possible with a fixed architecture. Furthermore, knowledge in the form of rules can be updated or added as required with little effort, which would not alter the overall structure of the system. The present system was custom built for a specific tool/work piece combination. However the modular approach resulted in a system that enables new materials and tool configurations to be incorporated by updating the knowledge base with new parameters for Taylor's tool life model and/or by training the neural networks under new cutting conditions. The database can be easily updated through a user-friendly interface that allows the neural networks to be trained with test data acquired in a few tests, which can then be stored for future use.

In order to improve the performance of the system past experience was taken into account for each tool life. This consisted of keeping track of classifications and then using a number of classifications to assess the consistency of classification. Through the use of historical data the system becomes aware of previous performance and can judge its reliability. Therefore system 'awareness' provides a certain degree of 'intelligence' that enables the system to know, according to the 'past', what the 'present' may or may not be. This methodology resembles, to a certain extent, the cognitive process of the operator when confronted with doubtful information and enables the 'machine' to make more reliable decisions. As the Taylor model makes a conservative estimate of tool wear, its use allows the elimination of some outliers generated from poor neural network classification or sporadic noisy signals picked up by the sensors. In order to allow the neural networks and expert system to interact, a ±0.15 mm margin was applied around the optimum prediction so as to prevent the expert system from removing good classifications, which resulted in an improved performance. Overall the system results achieved a successful classification rate of 100% for all *worn* states although for a new tool the system overestimated the flank wear by approximately 0.1mm. Thus, the linking of an Expert System based on empirical data and two neural networks enabled the monitoring system to achieve consistently better results than either classification technique alone. Figures 13 and 14 show the results obtained for two tool wear evolutions at the cutting conditions of cutting speed 350 m/min, feed rate of 0.25 rev/min and width of cut of 1 mm. Figure 13 shows the results for a tool life that was used to train the neural networks and Figure 14 the results for data not presented during training. These figures correspond to the neural network results presented in Figures 5 and 6. Figure 13 demonstrates that the system has been properly configured for this condition whilst Figure 14 demonstrates the result of the expert system monitoring the performance of the neural networks, removing misclassifications. If Figures 6 and 14 are compared it is possible to observe that for a new tool the expert system picks the SOM network for the first three wear estimates. The predictions made by both the SOM and ART2 then both agree, after which the expert system picks the ART2 network estimate before then again relying on the SOM until the end of the life of the tool.

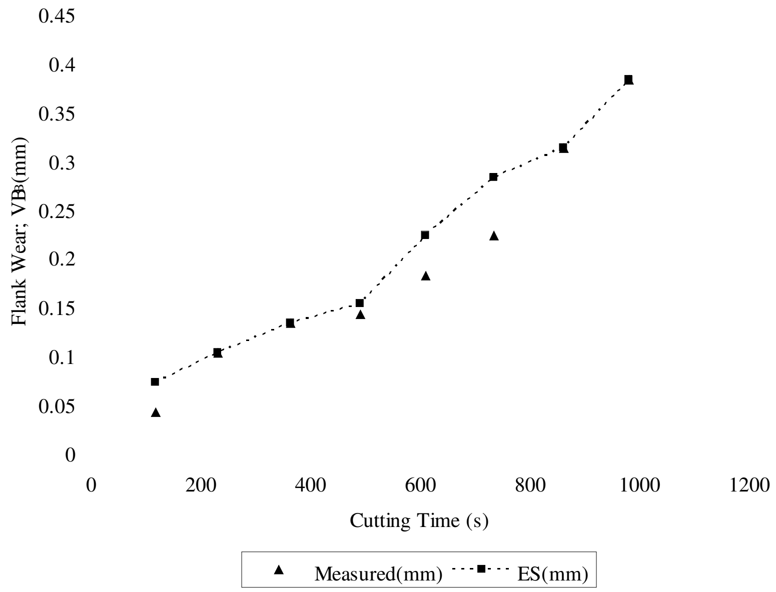

Figure 13: Comparison of the Classification by the Hybrid System and the measured Flank Wear (Data Presented During Training)

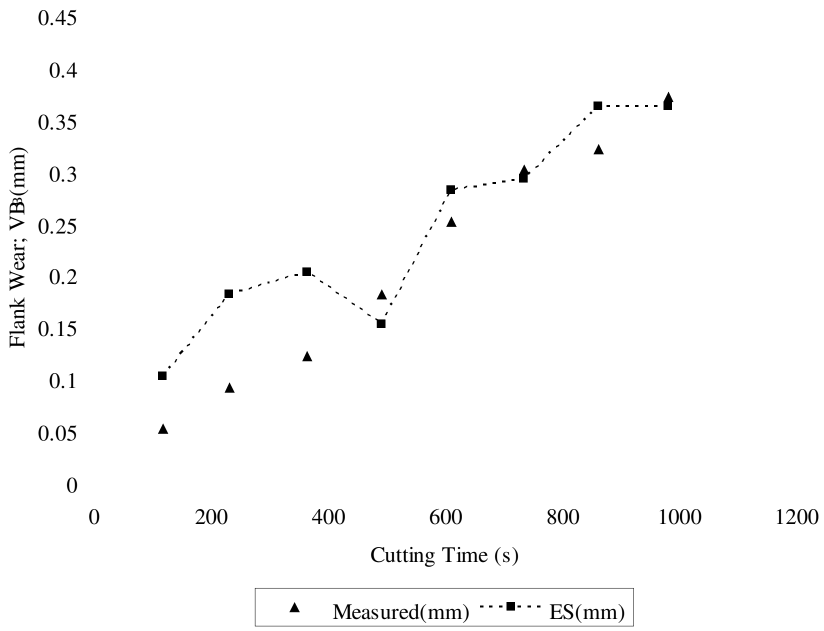

Figure 14: Comparison of the Classification by the Hybrid System and the measured Flank Wear (Data *Not* Presented During Training)

Both the self-organising map and ART2, each acting alone, have a large capacity to categorise the different wear stages. The training period had a large effect on the performance of the

SOM and more training time was required for the SOM than the ART2, although at the interpretation stage both had similar processing speeds since the basic calculations are relatively simple.

Of the two networks the SOM, compared to the ART2, was better able to extract the complex relationship between tool wear and the selected features, it was less prone to the influence of noise and was able to generalise more completely (Table 9 and Figures 10 to 12). This was perhaps due to the fact that with the SOM more graduations on the wear scale were available (6x6) given that each neurone can tune to a different wear level, whereas the ART2 was subject to the number of classes created during training. To increase the accuracy of the ART2 it would be necessary to reduce the vigilance parameter, which controlled how fine the classes generated were. It might be possible to increase the robustness of the system if a selection of points at various cutting conditions were added to the training set, allowing the neural networks to learn the combined effect of tool wear and cutting conditions. A useful training set would however have to be large enough to reflect reliably a range of cutting conditions, and would imply a large number of experiments. The cost of knowing this might be too large and perhaps a better approach would be, as in this system, to work reliably for a small set of conditions that are commonly used on the machine and then expand its range as and when needed, thereby spreading the cost of attaining the knowledge.

It has been demonstrated that the majority of outliers can be successfully eliminated by the application of rules based on Taylor's model of tool life, resulting in an improved monitoring system performance. As can be seen from Table 9, the NN predictions tend to slightly overestimate the wear, whereas the Taylor equation used here is slightly conservative. The use of the Taylor equation to eliminate outliers improves the NN predictions in that the correlation coefficients increase towards the ideal value of unity, as does the gradient. From a study of alternative Taylor equations it appears that the slope of the Taylor line will always exceed unity. Overall, this means that the combined approach succeeds in its aim of giving an on-line estimate of tool condition without the conservatism associated with the use of empirical rules.

Ideally, the tool monitoring system should be relatively independent of the cutting conditions, but as has already been observed this is not the case. The experiments have shown that the sensor-based component of a hybrid system shows a modest, but useful, range of cutting conditions over which its performance will not degrade to an unacceptable level. At worst, this type of information could be used to assess the minimum necessary number of test and training points required to cover all foreseeable cutting conditions. Also, if the effect of cutting conditions on the sensor signals can be modelled a level of adaptability could be built into the system by modifying the feature values to account for variation in cutting conditions, which might be possible by encapsulating models by such authors as [3].

5. Conclusions

It has been demonstrated that the combination of an Expert System and two neural networks is an appropriate way to monitor tool wear. Although, it has only been possible to classify tool wear successfully over a limited range of cutting conditions without retraining, the methodology adopted during this work would allow re-training of the monitoring system in a short period of time perhaps with the machine tool in service. The use of multiple sensors has proved to be of great value towards tool wear evaluation since the noisy character of each sensor alone would lead to certain failure of the monitoring system. The tangential and feed forces proved to be the strongest features of all but also varied the most with changes in cutting conditions. The other sensors; spindle current, vibration and sound, were related to the evolution of wear, although more weakly.

Feature extraction proved to be adequate for the present monitoring system, generating an enormous amount of information, which although very complex, was successfully interpreted by the neural networks. In this hybrid approach, the neural networks classified the abnormal and normal operating states, while the knowledge base interpreted the ANN results and classified the state of the tool with the expert knowledge encoded in it. In particular, this investigation has shown that:-

- The Self Organizing Map (SOM) and Adaptive Resonance Theory (ART2) neural networks can classify different tool wear levels based on sensory information even in the presence of large amounts of noise.
- That the Expert System complements the neural networks by removing neural network misclassifications and increases the overall prediction capacity by the use of process history.
- The use of multiple neural networks enhances classification by monitoring their reliability and thereafter selecting the one performing better.

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