Mechanical Systems and Signal Processing 23 (2009) 1719–1729

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

journal homepage: www.elsevier.com/locate/jnlabr/ymssp

On modeling of tool wear using sensor fusion and polynomial classifiers

Ibrahim Deiab [a,*], Khaled Assaleh [b], Firas Hammad [a]

[a] Mechanical Engineering Department, American University of Sharjah, P.O. Box 26666 Sharjah, United Arab Emirates
[b] Electrical Engineering Department, American University of Sharjah, P.O. Box 26666 Sharjah, United Arab Emirates

ARTICLE INFO

Article history:
Received 27 March 2008
Received in revised form
29 January 2009
Accepted 3 February 2009
Available online 13 February 2009

Keywords:
Tool wear
Feature extraction
Neural networks
Polynomial classifiers

ABSTRACT

With increased global competition, the manufacturing sector is vigorously working on enhancing the efficiency of manufacturing processes in terms of cost, quality, and environmental impact. This work presents a novel approach to model and predict cutting tool wear using statistical signal analysis, pattern recognition, and sensor fusion. The data are acquired from two sources: an acoustic emission sensor (AE) and a tool post dynamometer. The pattern recognition used here is based on two methods: Artificial Neural Networks (ANN) and Polynomial Classifiers (PC). Cutting tool wear values predicted by neural network (ANN) and polynomial classifiers (PC) are compared. For the case study presented, PC proved to significantly reduce the required training time compared to that required by an ANN without compromising the prediction accuracy. The predicted results compared well with the measured tool wear values.

1. Introduction

In tool condition monitoring (TCM), the system gathers information about the overall process. It is done through cues captured by different types of signals. These signals represent various operation parameters such as cutting speed, energy consumption, sound, and others. Considerable research used acoustic emission, vibration, force, and temperature sensors [1].

After having these signals as inputs to TCM system, an intelligent system is needed to interpret them. This system will then make a decision about the status of the process, as an output. Artificial Neural Networks (ANNs) are a typical tool for intelligent system that is able to learn and adapt to any change in the operation parameters. Previously published work indicates that feed-forward neural networks trained by back-propagation are among the most commonly used ANNs for this application [2–7]. Also, adaptive resonance theory has been used to study the wear propagation [8]. Besides ANNs, several other methods have been used to predict tool wear such as support vector machine (SVM) [9,10].

Dimla and Lister [7] used ANN to predict tool condition in an online mode. This method added intermediate classifications for the tool between the end states of "worn" or "sharp". This gives more reliability for the system and reduces the cost. Attempts to study the effects of changing the cutting conditions, such as tool materials and cutting area, revealed that the ANN was not able to adapt the new settings. This prompted the use of hybrid methods that combine two types of classification techniques. Silva et al. [8] used a hybrid AI system that consist of two ANNs, namely self-organizing map (SOM) and adaptive resonance theory (ART), linked with a fuzzy logic to monitor tool wear. The fuzzy functions are

* Corresponding author. Tel.: +971 6 515 2578; fax: +971 6 515 2979.
E-mail address: ideiab@aus.edu (I. Deiab).

0888-3270/$ - see front matter © 2009 Elsevier Ltd. All rights reserved.
doi:10.1016/j.ymssp.2009.02.001

used to compare the prediction of the two ANNs, in order to decide which one is more reliable. SOM showed better feature extraction than ART, however, it needs longer training time.

Sun et al. [10] presented the importance of the careful selection for the training data sets in ANN. The study was carried out using an AE sensor and a cutting force sensor.

Astakhov [12] indicated that stress, normal and shear are not the only reasons to cause the tool wear in the flank contact face; a plastic deformation of the cutting wedge, called plastic lowering, is a major cause in the tool failure.

Li [13] reviewed the various acoustic emissions sensing (AE) research on tool wear in turning. Various signal processing techniques are used to extract the physical features of tool wear. Time series analysis is used with ANNs to get the autoregressive (AR) parameters and AR residual signal to analyze tool wear. It is found that the power of residual signal of AE increases with increase in flank wear. Fourier Transform (FT) proves that the magnitude of AE in the frequency domain is sensitive to the change in the tool wear.

Lu and Kannatey-Asibu [14] presented the tool wear based on the sound generated during turning process. The asperities on the tool and the workpiece were considered as source of exciting the system to generate sound signals.

In this paper, a novel approach to model and predict cutting tool wear using statistical signal analysis, pattern recognition and sensor fusion is presented. The data are acquired from two sources: an acoustic emission sensor and a tool post dynamometer. The pattern recognition used here is based on two methods: Artificial Neural Networks (ANN) and Polynomial Classifiers (PC).

2. Methodology

The tool wear prediction system consists of four main elements: signal acquisition, signal pre-processing, feature extraction, and classification. Artificial neural networks was used as a benchmark because of its well-known capabilities and because it has been used previously with in this field [15]. While for the latter classifier, up to our knowledge, no work in the field of tool wear prediction has used polynomial classifiers.

2.1. Design of experiments and experimental procedure

In this work, mild steel is chosen as a workpiece material. The cutting experiments were carried out on a CNC lathe machine using coated carbide inserts. A tool post kistler dynamometer was used to measure the cutting forces in the three directions, namely tangential, axial (feed), and radial forces. Fig. 1 shows the experimental setup, the piezoelectric AE sensor, kistler model 815B, is placed on the upper surface of the dynamometer using powerful magnetic clamp.

Pilot runs were carried out at different combinations of machining parameters. The three main machining parameters (cutting speed, feed, and depth of cut) are set according to their effect on the tool wear. Five levels of cutting speed ($v = 110$–190 m/min with an increment of 10), three levels of feed ($f = 0.15$, 0.2, and 0.3 mm/rev), and one level of depth of cut ($d = 1$ mm) were used. These runs were to examine the effect of machining parameters on the signals acquired. Next, cutting tests were conducted to record progressive tool wear conditions. Prior to machining runs, Nielsen-Hsu method [16], or pencil lead break test, was performed. This test checks the transmission of AE signal in workpiece and tool material. The piezoelectric AE sensor detects signals above 50 kHz and up to 400 kHz. To minimize the influence of noise signals and aliasing errors, signals coming out of the AE sensors are passed through an AE band-pass filter (Piezotron Coupler 5125B) between 200 kHz and 1 MHz. The band-pass filter reduces the influence of disturbances such as noise or other non-measurable contributions [15]. A total of 113 experiments were carried out with a coated carbide sharp tool edge. The flank wear progression was measured intermittently according to the prescribed intervals using a tool maker microscope.

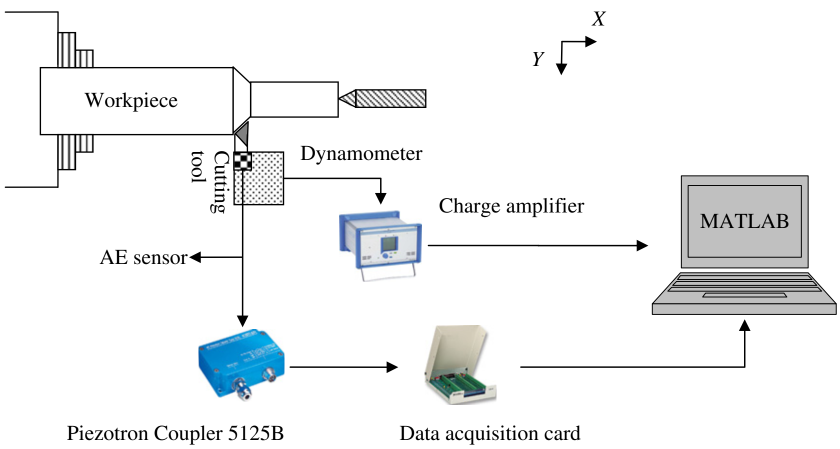

Fig. 1. Experimental setup to measure tool wear.

2.2. Signal pre-processing

In turning, useful information about tool status is only present when the tool is in direct contact with the workpiece which requires end-pointing the acquired signal to get rid of the irrelevant data and to indicate the beginning and the end of the cutting. Fig. 2 depicts this procedure for one force signal before and after treatment. The arrows indicate where the actual cutting starts and ends.

Whereas the cutting force signal needs only removal of non-machining part form both signal ends, AE signal needs further treatment. Some burst signals with high peak amplitude, not related to tool wear, are due to the friction between the tool and workpiece. Hence, it is mandatory to eliminate these bursts from AE signal to have true information about tool wear. To do this, a floating threshold value [17] that is higher than the AE mean signal level is defined. Any part of the signal crossing this value is considered transient and is removed from the continuous AE signal. Values below the floating point gives information about tool wear and are used in the analysis. This process causes discontinuities in the signal because of the "clipping" effect. This would have an adverse effect on the feature extraction step if spectral features were to be used since discontinuities in the spectrum correspond to an infinite spread of the signal in the time domain. However, in this work we use statistical features.

2.3. Feature extraction and selection

Sensory signals patterns are related at the end to the state of the tool. Therefore, it is important to build a relationship between signal patterns and tool wear. It is clear that the collected signals will have a certain level of redundancy and randomness that bear no useful information about the classification of the signal. In this sense it is important to create a system which is able to extract features that are concise and representative of the relevant information in the signal. This task in tool wear monitoring is crucial and challenging. Different signal processing techniques can be used to extract features from the sensory signal. Two major domains are used in feature extraction: time domain and frequency domain. Most commonly used are time series analysis, fast Fourier transform (FFT) [18], and wavelet transform [19,20]. Time series analysis is used in this work. Previous studies have shown that statistical features can be indicative of tool wear [21,22]. The following statistical features are extracted from a sensory signal: mean, standard deviation, variance, kurtosis, and skewness. Principal components analysis (PCA) [9] is used extensively in feature dimensionality reduction for the purpose of eliminating redundant and irrelevant information [23–26]. Transforming high dimensional and correlated data set to new coordinate system produces a new set of uncorrelated and smaller size variables [27]. This new set represents the principal components that retain the variation in the original data as much as possible. In order to predict tool wear, relevant features from cutting force and acoustic emission signals must be extracted. Among all extracted statistical features, mean and standard deviation of AE signal [10] and the maximum value of the three force components are the most highly correlated with tool wear. The remaining features demonstrated no potential correlation with tool wear. The AE statistical features are used in PCA in the following order: mean, standard deviation, variance, kurtosis, and skew to generate coefficients for five principal components. Accordingly, the original data is mapped into the new coordinate

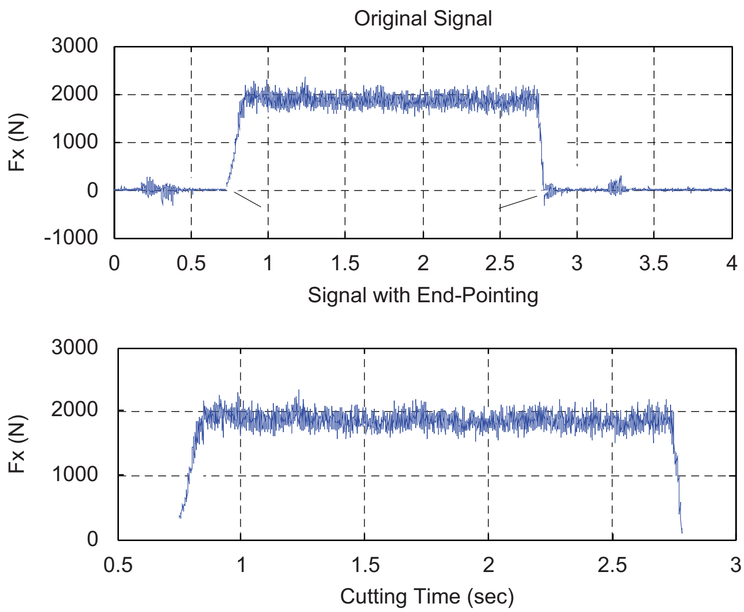

Fig. 2. Force signal pre-treatment.

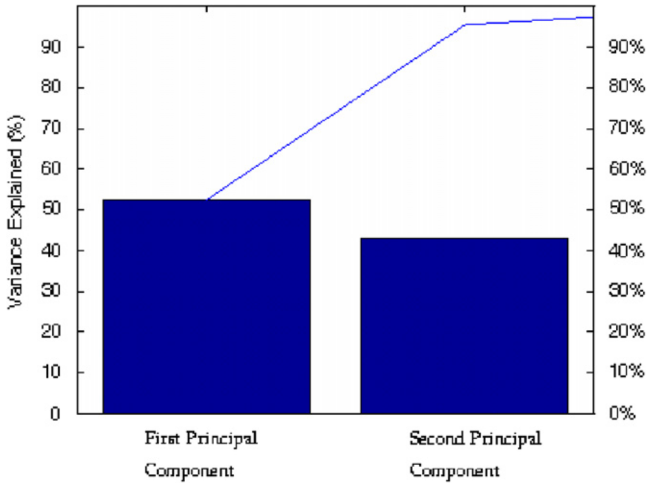

Fig. 3. Contribution of the first two AE principal components.

system defined by the principal components. The mapped data is the same size as the input data matrix, the AE features in this case.

It can be observed from Fig. 3 that the first two principal components explain roughly more than 90% of the total variability in the standardized ratings. The remaining principal components carry insignificant information related to tool wear. Therefore, it is reasonable to reduce the statistical data of the AE signal to two-dimensional data which also make it possible to visualize the data.

In the same way, seven cutting force statistical features are used in PCA in the following order: max, mean, median, standard deviation, variance, kurtosis, and skew to generate coefficients for seven principal components. It can be shown, see Fig. 4, that the first two principal components explain roughly more than 80% of the total variability in the standardized ratings, and hence might be a reasonable way to reduce the dimensions in order to visualize the data. We decided to use the first three components because they cover almost 90% of the total data.

2.4. Feature combinations and score fusion

As mentioned above, features are extracted from three different sources: cutting conditions, cutting forces, and acoustic emission. Different schemes can be deployed for combining these three different feature sets. A straightforward method would be by concatenating all of them or a subset of each set together to form one feature vector that is passed to a single classifier. Table 1 presents the features used from machining parameters $\{X\}$, cutting force $\{F\}$ and acoustic emission $\{AE\}$. Features are grouped into six sets as follows:

- $S1$ includes all machining parameters, all cutting forces, and all acoustic emissions:
  $S1 = [X1, X2, X3, F1, F2, F3, F4, F5, F6, F7, AE1, AE2, AE3, AE4, AE5]$;
- $S2$ includes all machining parameters and all cutting forces:
  $S2 = [X1, X2, X3, F1, F2, F3, F4, F5, F6, F7]$;
- $S3$ includes all machining parameters and all acoustic emissions:
  $S3 = [X1, X2, X3, AE1, AE2, AE3, AE4, AE5]$;
- $S4$ includes all machining parameters, the best cutting force, and the best acoustic emission:
  $S4 = [X1, X2, X3, F1, AE1, AE2]$;
- $S5$ includes all machining parameters and the best cutting force: $S5 = [X1, X2, X3, F1]$;
- $S6$ includes all machining parameters and the best acoustic emission:
  $S6 = [X1, X2, X3, AE1, AE2]$.

The machining parameters are an essential part among all feature sets. Among the six feature sets, $S1$ included all extracted features, in addition to the machining parameters, from force and AE signals, and $S2$ and $S3$ are separated features of force and AE signals, respectively. Finally, $S4$, $S5$, and $S6$ are the reduced feature sets produced by PCA technique. The eliminated features $S4$, $S5$, and $S6$ are the ones with very low corresponding PCA parameters. However, this elimination must be verified by corresponding testing sets of the six feature sets, and the testing accuracy provides an indicator of features contribution.

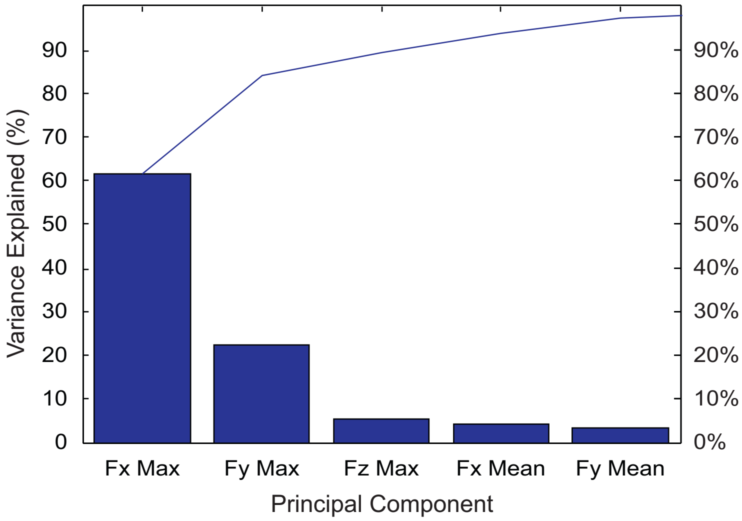

Fig. 4. Contribution of cutting forces' principal components.

Table 1
Feature list.

Index	Description	Index	Description
*X*1	Cutting speed	*F*6	Force kurtosis
*X*2	Feed rate	*F*7	Force skewness
*X*3	Machining time	*AE*1	Acoustic emission mean value
*F*1	Force maximum value	*AE*2	Acoustic emission standard deviation
*F*2	Force median value	*AE*3	Acoustic emission variance
*F*3	Force mean value	*AE*4	Acoustic emission kurtosis
*F*4	Force standard deviation	*AE*5	Acoustic emission skewness
*F*5	Force variance		

Alternatively, they can be used separately to train three separate classifiers whose outputs (scores) are fused together as shown in Fig. 5. The fusion of the scores is done in a supervised manner to minimize the error between the actual measured tool wear values and the output of the fusion system for all the training data. The weights of the score fusion $\{w_1, w_2, w_3\}$ are obtained by least-squares method.

2.5. *Prediction and classification*

2.5.1. *Neural networks*

Among different architectural models of ANNs, feed-forward back-propagation type is most used [15,28]. Such ANNs consist of three layers; namely, input layer, hidden layer, and output layer. Fig. 6 shows the structure of a 3-layer feed-forward neural network (FFNN) where each layer is composed of a number of nodes (neurons) interconnected by a set of weights. Fig. 7 zooms in the details of one node (neuron).

2.5.2. *Polynomial classifiers*

Polynomial classifiers are considered, e.g., the powerful pattern recognition and matching techniques that have been used in several pattern recognition and system modeling applications such as voice recognition [29] and fetal ECG signal extraction [30]. In this work we consider modeling a multi-input single-output (MISO) system via polynomial classifiers. The modeling here involves finding the system parameters that best map the multidimensional input sequence (training feature vectors) to the corresponding one-dimensional output sequence (target).

In our case the training data consists of a set of N d-dimensional feature vectors, $\mathbf{X}$, with its corresponding set of N *one-*dimensional targets, $\mathbf{t}_x$. Targets $\mathbf{t}_x$ depend on the problem that is being solved. For instance, in classification problems, t_x represents the class labels of the training feature vectors; typically, *ones* are used as labels for the in-class feature vectors and *zeros* for the out-of-class feature vectors in a way that targets are arranged in neural networks. On the other hand, for prediction problems like the one being encountered, targets $\mathbf{t}_x$ are set to the actual values of tool wear measurements.

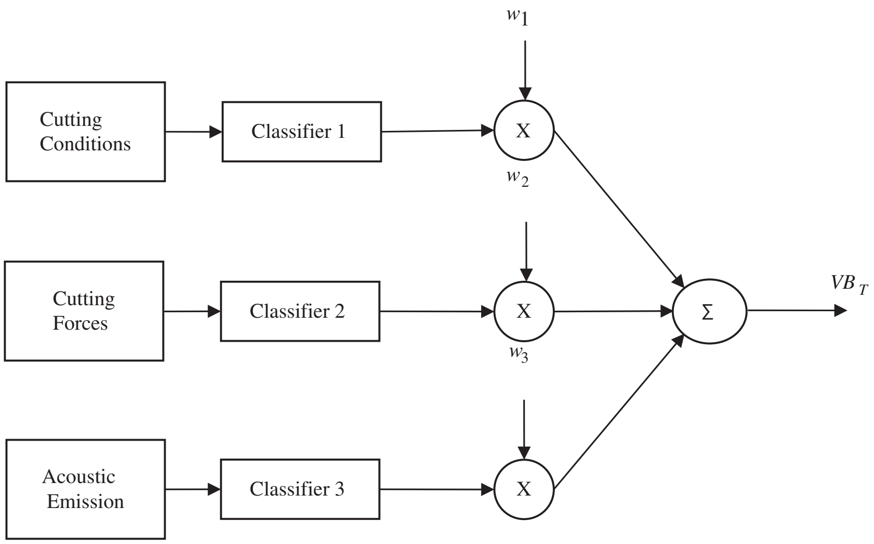

Fig. 5. Prediction tool wear using score fusion.

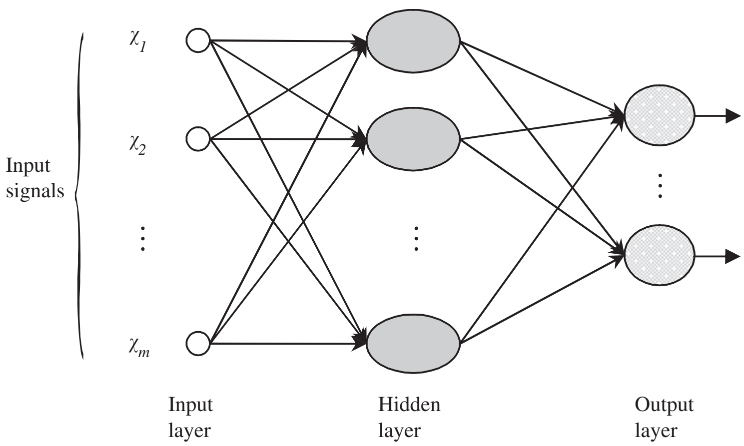

Fig. 6. Structure of a FFNN.

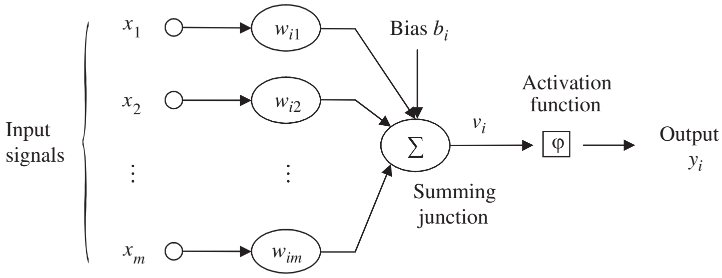

Fig. 7. Model of a neuron.

The basic embodiment of a Kth-order polynomial classifier consists of several parts. In the training phase, the elements of each training feature vector, $\mathbf{x} = [x_1, x_2, \ldots, x_d]$, are combined with multipliers to form a set of basis functions, $\boldsymbol{p}(\mathbf{x})$. The elements of $\boldsymbol{p}(\mathbf{x})$ are the monomials of the form $\prod_{j=1}^{d} x_j^{k_j}$, where k_j is a positive integer and $0 \leqslant \sum_{j=1}^{d} k_j \leqslant K$.

The Kth-order polynomial expansion of a d-dimensional vector $\mathbf{x}$ generates a higher dimensional vector $\mathbf{p}(\mathbf{x})$ whose dimensionality is a function of both d and K.

Once the training feature vectors, $\mathbf{X}$, are expanded into their polynomial basis terms, $\mathbf{M}$, the polynomial classifier is trained to approximate the ideal output (target) using mean-squared error as the objective criterion. The training problem reduces to finding an optimum set of weights (model parameters), $\mathbf{w}^{opt}$, that minimizes the distance between the ideal outputs and a linear combination of the polynomial expansion of the training data such that

$$\mathbf{w}^{opt} = \arg\min_{\mathbf{w}} ||\mathbf{M}\mathbf{w} - \mathbf{t}_x||^2 \tag{1}$$

The weights (models) $\mathbf{w}^{opt}$ can be obtained explicitly by applying the normal equations method [31] to obtain the optimal weight vector

$$\mathbf{w}^{opt} = (\mathbf{M}^T\mathbf{M})^{-1}\mathbf{M}^T\mathbf{t}_x \tag{2}$$

In the recognition stage when an unknown feature vector, z, is presented to the trained model in order to obtain its corresponding target t_z, the vector is expanded into its polynomial terms $p(z)$ (similar to what was done in the training phase) and the target is estimated:

$$\hat{t}_z = \mathbf{w}^{opt}\mathbf{p}(z) \tag{3}$$

2.5.3. Leave one out

In classification algorithm, it is important to use as much training data as possible in order to get accurate and statistically significant results [10]. In pattern recognition, the data are divided into training set and testing set. This means that part of the collected data is not utilized in the training and testing process. It also biases the results according to the partitioning of the data into training and testing. To alleviate these problems, Leave One Out (LOO) or Round Robin method is used. Training in LOO is done using all but one data point, which is used for the testing. If our data consists of N feature vectors the LOO scheme avails N opportunities to train and test the classifier. LOO is applied for both ANNs and PC to predict and to classify the status of the tool after machining. The deployment of the LOO strategy in training and evaluating the system generates more accurate models of the data than those generated by dividing the data into two parts (e.g. 50% for training and 50% for testing). Moreover, LOO offers more statistically significant predication results than those obtained by the classical division of the data into training and testing parts.

3. Results and discussion

A clear variation in both sensor outputs is observed as cutting conditions changed. The features extracted from processing the force and acoustic emission output influence most the neural network and polynomial classifier performance. The measurement of performance of both classifiers consisted simply of the percentage error of the prediction compared with the actual wear value. The average percentage error at each wear level is selected as the final performance measure.

3.1. Using artificial neural networks

To compare the learning ability of different feature sets, Tables 2–4 show the training and testing results for prediction and classification of tool wear, of three different cutting conditions and of six trials under the feature sets. It also shows the time required for the training in seconds using Matlab running on a Pentium 4 Personal Computer.

In Tables 2–4, among the six feature sets $S1$ shows always the highest prediction accuracy. Thus, it can be concluded that the redundant features, which are eliminated by PCA, may still provide some useful information. However, $S1$ requires more training time compared to others. The overall accuracy of the results is in the range of high 80 s and low 90 s. Using $S6$, in contrast to $S1$, yields the lowest accuracy. The last column presents the system capability in classifying the tool state. The tool is identified as fresh or worn. The tool flank wear of 0.3 mm, which is suggested by ISO 3685, is used as a criterion to identify tool state. Flank wear in the fresh tool state is overestimated sometimes by approximately 0.3 mm. Over all the system achieves a successful classification percentage of 100% for all worn states.

Table 2
NN trial 1 ($v = 130$ m/min, $f = 0.15$ mm/rev).

Feature set	Training time (s)	Prediction accuracy (%)	Classification accuracy (%)
$S1$	–	87.2	100
$S2$	945	86.77	100
$S3$	174	86.09	90
$S4$	–	85.83	90
$S5$	155	84.75	100
$S6$	126	84.63	100

Table 3
NN trial 2 ($v = 170$ m/min, $f = 0.2$ mm/rev).

Feature set	Training time (s)	Prediction accuracy (%)	Classification accuracy (%)
*S*1	–	88.13	100
*S*2	945	87.6	100
*S*3	174	78.74	100
*S*4	–	77.25	100
*S*5	155	76.07	100
*S*6	126	75.89	100

Table 4
NN trial 3 ($v = 190$ m/min, $f = 0.15$ mm/rev).

Feature set	Training time (s)	Prediction accuracy (%)	Classification accuracy (%)
*S*1	–	93.87	100
*S*2	945	93.73	100
*S*3	174	90.35	84
*S*4	–	91.27	84
*S*5	155	91.01	100
*S*6	126	89.44	100

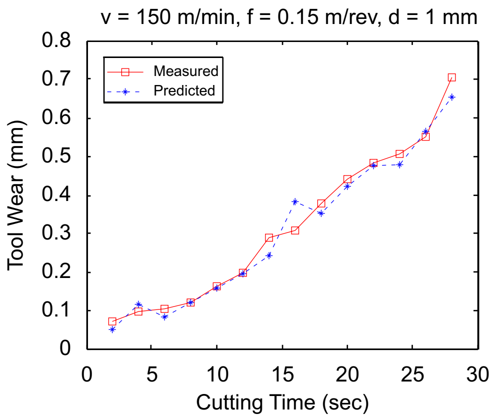

Fig. 8. Measured and predicted tool wear using *S*1 feature set and neural networks.

Figs. 8 and 9 show measured and predicted amount of tool wears. Fig. 8 presents the results using *S*1 set as inputs. A good matching between measured and predicted values is noticed. Cutting speed $v = 150$ m/min, feed rate $f = 0.15$ m/rev, and depth of cut $d = 1$ mm. Average accuracy is 92.04%. Fig. 9 presents tool wear prediction using *S*4 set. Cutting speed $v = 170$ m/min, feed rate $f = 0.15$ m/rev, and depth of cut $d = 1$ mm. Average accuracy is 89.02%. Computation times are more than 15 and 4 min, respectively.

3.2. *Prediction using polynomial classifiers*

Experiments performed for neural network are individually selected to be repeated using the new decision-making model. The same feature sets and data partitioning schemes applied in the previous section to train neural network are used here to compare the two models.

Tables 5–7 present the result obtained using the polynomial classifier for the same machining parameters used in the previous section.

In Tables 5–7, the first-order model is used. All the sets give almost the same performance accuracy, i.e. redundant values do not affect the polynomial classifier adversely in terms of performance. In all experiments, the computational decision-making time, is dramatically low, less than 2 s. It should be point out that the reduced features sets in cutting force and *AE* requires 70% less computational time compared to the full features sets. In terms of overall classification

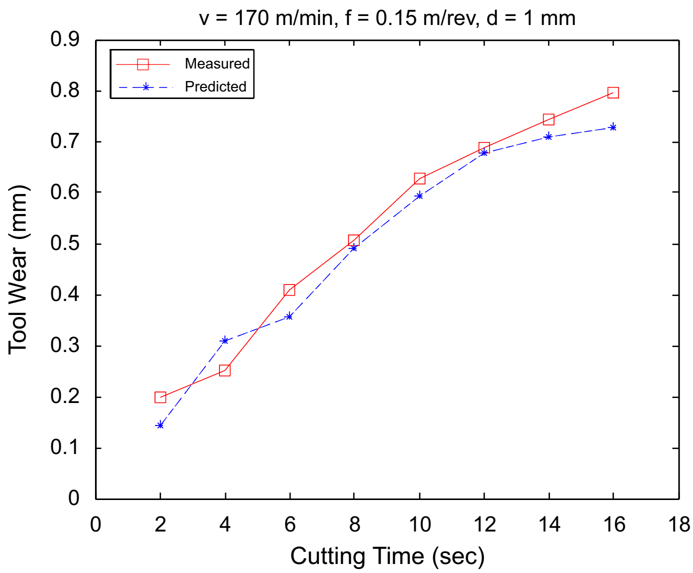

Fig. 9. Measured and predicted tool wear using *S*4 feature set and neural networks.

Table 5
PC trial 1 ($v = 130\,\text{m/min}$, $f = 0.15\,\text{mm/rev}$).

Feature set	Training time (s)	Prediction accuracy (%)	Classification accuracy (%)
*S*1	–	77.58	100
*S*2	1.490337	77.60	100
*S*3	0.768242	76.47	100
*S*4	–	85.28	100
*S*5	0.472064	73.07	100
*S*6	0.259504	77.26	100

Table 6
PC trial 2 ($v = 170\,\text{m/min}$, $f = 0.2\,\text{mm/rev}$).

Feature set	Training time (s)	Prediction accuracy (%)	Classification accuracy (%)
*S*1	–	90.44	100
*S*2	1.490337	90.41	100
*S*3	0.768242	90.67	100
*S*4	–	89.98	100
*S*5	0.472064	91.41	100
*S*6	0.259504	90.62	100

Table 7
PC trial 3 ($v = 190\,\text{m/min}$, $f = 0.15\,\text{mm/rev}$).

Feature set	Training time (s)	Prediction accuracy (%)	Classification accuracy (%)
*S*1	–	96.82	100
*S*2	1.490337	96.83	100
*S*3	0.768242	95.34	100
*S*4	–	95.08	100
*S*5	0.472064	95.24	100
*S*6	0.259504	95.29	100

performance, the polynomial classifier shows a great ability at the rate of 100% in identifying worn out tools. Flank wear in the fresh tool state is overestimated sometimes by approximately almost 0.2 mm.

The following figures presents measured and predicted amount of tool wear through LOOPC, using the above sets.

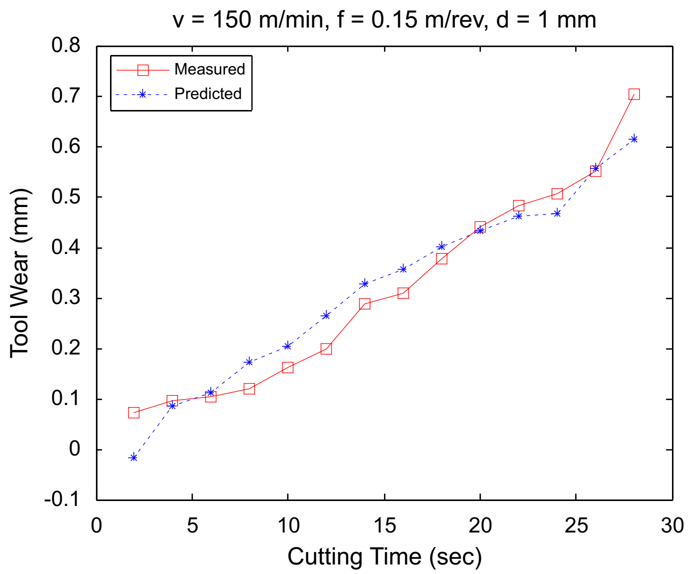

Fig. 10. Measured and predicted tool wear using *S*1 feature set and the polynomial classifier.

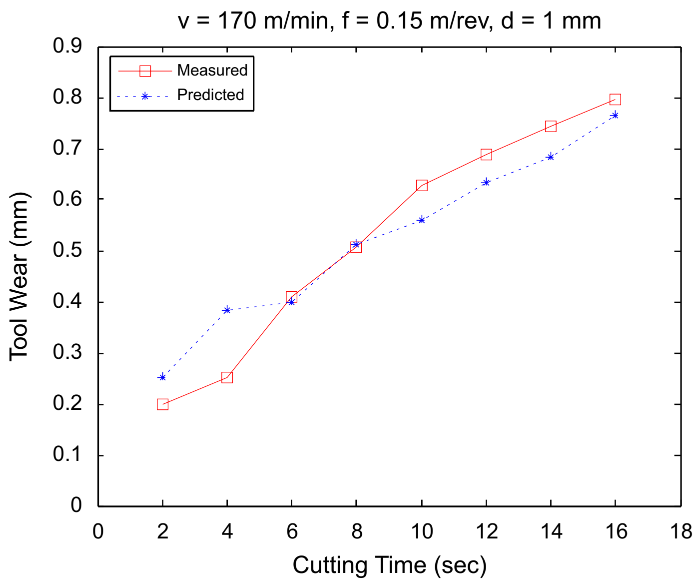

Fig. 11. Measured and predicted tool wear using *S*4 feature set and the polynomial classifier.

Fig. 10 presents tool wear prediction using $S1$ set. Cutting speed $v = 150\,\mathrm{m/min}$, feed rate $f = 0.15\,\mathrm{m/rev}$, and depth of cut $d = 1\,\mathrm{mm}$. Average accuracy is 78.01%. Fig. 11 presents tool wear prediction using $S1$ set. Cutting speed $v = 170\,\mathrm{m/min}$, feed rate $f = 0.15\,\mathrm{m/rev}$, and depth of cut $d = 1\,\mathrm{mm}$. Average accuracy is 85.78%. Computation times are less than 2 and 0.3 s, respectively.

Based on the above results, both BPNN and PC, each acting alone, have a large capability to classify and predict the development of tool wear. The training time has a large effect on the performance of the system. The content of the data used in training the system has a potential effect on the prediction error. BPNN shows better results when more features are used, with the consequence of more training time being required, which results in very slow prediction. On the contrary, more data do not add to PC, neither extra information nor better significant prediction is achieved. It should be pointed out that the slowest training time in PC is less than 2 s, while BPNN need at least 2 min even for the fastest training.

4. Conclusion

In this paper a method for predicting tool wear is presented. The presented methodology involves an experimental setup for collecting cutting force and acoustic emission signals while machining mild steel workpiece. Feed-forward neural networks and polynomial classifiers have been used to predict and classify different tool wear states based on statistical features extracted from sensory information. The effectiveness of both proposed decisions-making models has been demonstrated in experimental trials. The experimental test results indicate that the proposed methodology results in a good agreement between the predicted and measured tool wear. The prediction accuracies of the two approaches are comparable. However, polynomial classifiers show improvement in the training time over neural networks. Experiments showed that polynomial classifiers require a maximum of 2 s for training compared to few minutes required by neural networks. Finally, results showed that the sensory signal acquired from low-cost sensor and easy to mount (i.e. the *AE* sensor) correlate very well with tool wear. Further analysis is worthwhile in order to build an online intelligent monitoring system for turning using the proposed approaches.

Acknowledgements

The authors acknowledge the financial support from the American University of Sharjah through research Grant FRG07_17257.

References

[1] K.B. Kim, D.J. Yoon, J.C. Jeong, S.S. Lee, Determining the stress intensity factor of a material with an artificial neural network from acoustic emission measurements, NDT and E International 37 (6) (2004) 423–429.
[2] K. Jemielniak, L. Kwiatkowski, P. Wrzosek, Diagnosis of tool wear based on cutting forces and acoustic emission measures as inputs to a neural network, Journal of Intelligent Manufacturing 9 (5) (1998) 447–455.
[3] R. Du, M.A. Elbestawi, S.M. Wu, Automated monitoring of manufacturing processes, Part 2: Applications, Journal of Engineering for Industry, Transactions of the ASME 117 (2) (1995) 133–141.
[4] G.S. Hong, M. Rahman, Q. Zhou, Using neural network for tool condition monitoring based on wavelet decomposition, International Journal of Machine Tools and Manufacture 36 (5) (1996) 551–566.
[5] R.J. Kuo, Multi-sensor integration for on-line tool wear estimation through artificial neural networks and fuzzy neural network, vol. 13, June 2000, pp. 249–261.
[6] M. Balazinski, E. Czogala, K. Jemielniak, J. Leski, Tool condition monitoring using artificial intelligence methods, Engineering Applications of Artificial Intelligence 15 (1) (2002) 73–80.
[7] D.E. Dimla Sr., P.M. Lister, On-line metal cutting tool condition monitoring. II: Tool-state classification using multi layer perceptron neural networks, International Journal of Machine Tools and Manufacture 40 (5) (2000) 769–781.
[8] R.G. Silva, S.J. Wilcox, R.L. Reuben, Development of a system for monitoring tool wear using artificial intelligence techniques, in: ASME International Mechanical Engineering Congress and Exposition, Proceedings, vol. 2, November, 2001, pp. 1003–1010.
[9] D. Shi, N. Gindy, Tool wear predictive model based on least squares support vector machines, Mechanical Systems and Signal Processing 21 (4) (2007) 1799–1814.
[10] J. Sun, G.S. Hong, M. Rahman, Y.S. Wong, Identification of feature set for effective tool condition monitoring by acoustic emission sensing, International Journal of Production Research 42 (5) (2004) 901–918.
[12] V. Astakhov, The assessment of cutting tool wear, International Journal of Machine Tools and Manufacture 44 (6) (2004) 637–647.
[13] X. Li, A brief review: acoustic emission method for tool wear monitoring during turning, International Journal of Machine Tools and Manufacture 42 (2) (2002) 157–165.
[14] M. Lu, E. Kannatey-Asibu Jr., Analysis of sound signal generation due to flank wear in turning, Journal of Manufacturing Science and Engineering, Transactions of the ASME 124 (4) (2002) 799–808.
[15] B. Sick, On-line and indirect tool wear monitoring in turning with artificial neural networks: a review of more than a decade of research, Mechanical Systems and Signal Processing 16 (4) (2002) 487–546.
[16] J. Roget, P. Souquet, N. Gsib, Application of acoustic emission to the automatic monitoring of tool condition during machining, Materials Evaluation 46 (2) (1988) 225–229.
[17] Y. Yao, X. Li, Z. Yuan, Tool wear detection with fuzzy classification and wavelet fuzzy neural network, International Journal of Machine Tools and Manufacture 39 (10) (1999) 1525–1538.
[18] Jae-Seob Ha Kwak, Man-Kyung Neural network approach for diagnosis of grinding operation by acoustic emission and power signals, Journal of Materials Processing Technology 147 (1) (2004) 65–71.
[19] Ya. Wu, R. Du, Feature extraction and assessment using wavelet packets for monitoring of machining processes, Mechanical Systems and Signal Processing 10 (1) (1996) 29–53.
[20] C. Scheffer, P.S. Heyns, Wear monitoring in turning operations using vibration and strain measurement, Mechanical Systems and Signal Processing 15 (6) (2001) 1185–1202.
[21] K. Jemielniak, O. Otman, Tool failure detection based on analysis of acoustic emission signals, Journal of Materials Processing Technology 76 (1–3) (1998) 192–197.
[22] E. Kannatey-Asibu Jr., D.A. Dornfeld, Study of tool wear using statistical analysis of metal-cutting acoustic emission, Wear 76 (2) (1982) 247–261.
[23] R. Sun, F. Tsung, L. Qu, Evolving kernel principal component analysis for fault diagnosis, Computers and Industrial Engineering 53 (2) (2007) 361–371 Selected Papers from the 27th International Conference on Computers and Industrial Engineering—Part 2, September 2007.
[24] K.I. Kim, K. Jung, H.J. Kim, Face recognition using kernel principal component analysis, IEEE Signal Processing Letters 9 (2) (2002) 40–42.
[25] K.K. Dong, S.K. Nam, Rapid speaker adaptation using probabilistic principal component analysis, IEEE Signal Processing Letters 8 (6) (2001) 180–183.
[26] C.J. Twining, C.J. Taylor, The use of kernel principal component analysis to model data distributions, Pattern Recognition 36 (1) (2003) 217–227.
[27] I.T. Jolliffe, Principal Component Analysis, Springer-Verlag New York, Incorporated, Secaucus, NJ, USA, 2002, p. 1.
[28] B. Sick, Tool wear monitoring in turning: a neural network application, Measurement and Control 34 (7) (2001), 207–211+222.
[29] W.M. Campbell, Assaleh Khaled, C. Broun Charles, Speaker recognition with polynomial classifiers, IEEE Transactions on Speech and Audio Processing 10 (4) (2002).
[30] Khaled Assaleh, Hasan Al-Nashash, A novel technique for the extraction of fetal ECG using polynomial networks, IEEE Transactions on Biomedical Engineering 52 (6) (2005) 1148–1152.
[31] G.H. Golub, C.F. Van Loan, Matrix Computations, John Hopkins, 1989.