



# Sensor fusion and the application of artificial intelligence to identify tool wear in turning operations

A. Al-Azmi<sup>1</sup> · Amin Al-Habaibeh<sup>2</sup> · Jabbar Abbas<sup>3</sup>

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## Abstract

This paper aims to develop an effective sensor fusion model for turning processes for the detection of tool wear. Fusion of sensors' data combined with novelty detection algorithm and learning vector quantisation (LVQ) neural networks is used to detect tool wear and present diagnostic and prognostic information. To reduce the number of sensors required in the monitoring system and support sensor fusion, the ASPS approach (Automated Sensor and Signal Processing Selection System) is used to select the most appropriate sensors and signal processing methods for the design of the condition monitoring system. The experimental results show that the proposed approach has demonstrated its efficacy in the implementation of an effective solution for the monitoring tool wear in turning. The results prove that the fusion of sensitive sensory characteristic features and the use of AI methods have been successful for the detection and prediction of the tool wear in turning processes and show the capability of the proposed approach to reduce the complexity of the design of condition monitoring systems and the development of a sensor fusion system using a self-learning method.

**Keywords** Artificial intelligence · Sensor fusion · Neural networks · Novelty · Machining · Self-learning · Turning

## 1 Introduction

The drive to increase productivity and reduce energy consumption is attracting manufacturers into adopting Industry 4.0, artificial intelligence, 5G and the Internet of Things (IoT) in their facilities to increase flexibility, reduce waste and enhance efficiency. Machining operations are considered one of the most complex operations in manufacturing due to its variability. And the reliability of cutting tools in machining influences the whole manufacturing efficiency. However, tool wear and tool conditions are probabilistic in

nature making it difficult to correctly estimate the remaining life of a tool; and hence, a real-time determination system of tool conditions is needed. Condition monitoring systems of manufacturing processes could provide a means to offer prognosis and diagnosis of tools' life and status. Tool wear is an important limitation in machining productivity. Tool wear is difficult to predict due to a large number of influencing variables and tool-to-tool performance variation. As a result, empirical models or physics-based models require experimentation to calibrate model coefficients, which are infeasible in an industrial setting due to large number of tool-material combinations [1]. Therefore, it is important to develop a reliable and inexpensive intelligent monitoring system for cutting processes with self-learning from experience. A successful monitoring system can effectively maintain the health of machine tools, cutting tools and workpieces in cutting processes. Various methods have been studied to detect tool wear states, and a large variety of sensors can be used for tool wear condition monitoring. Unfortunately, the performance of monitoring systems is still behind the expectations due to its high cost/performance ratio [2]. Successful condition monitoring is becoming extremely dependent on the ability to interpret multi-sensor data based on advanced signal processing methods [3]. Sensor fusion has already

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✉ Amin Al-Habaibeh  
Amin.Al-Habaibeh@ntu.ac.uk

A. Al-Azmi  
afalmea@collegeofaviation.com

Jabbar Abbas  
jabbarkabbas@scrdiraq.gov.iq

<sup>1</sup> Kuwait Aviation and Technology College, Abu Halifa, Kuwait

<sup>2</sup> Product Innovation Centre, Nottingham Trent University, Nottingham, UK

<sup>3</sup> Ministry of Higher Education, Baghdad, Iraq

been widely used in various applications in which multiple sources of presented information are combined to provide improved and robust estimates.

In manufacturing process, the stability of cutting state is especially important for machining quality. Monitoring cutting forces has been the focus of researchers for many years. Research has seen the development of a wide range of sensors for the use in machining operations [4]. However, the limiting factors have been on the use of artificial intelligence in providing efficient monitoring systems. With the rise in using digital technology of computers, the last decade has witnessed the development of several artificial intelligence methods to the area of condition monitoring systems [5]. Artificial intelligence (AI) is used to apply knowledge, reasoning, self-learning and decision-making to enable machines to function with the capability and intelligence of human beings. Generally, artificial intelligence may be separated into two groups: symbolic intelligence contains expert systems, knowledge-based systems, case-based reasoning, etc.; and the second is computational intelligence which contains artificial neural networks (ANN) [6]. Many artificial intelligence techniques which have been developed for manufacturing systems have been found reasonably successful [7]. However, pattern recognition techniques described in the literature have their own limitations. Measurements have to be made on the healthy system to store the healthy response [8] and in most cases, the information contained in the data is not comprehensive to cover all possible scenarios [9]. Reference [10] suggested an online scheme for tool wear monitoring using artificial neural networks (ANNs) by giving the cutting velocity, feed, cutting force and machining time as inputs to the ANN, and the flank wear is estimated using the ANN. Despite the success of the suggested approach, the probabilistic nature of the machining process would still provide indeterministic results. Reference [11] presented two experimental cases including rolling bearing fault and rotor system fault to evaluate the proposed scheme of using neural networks; the results demonstrate a better comprehensive performance in the number of best features, training time and testing accuracy, when compared with some previous research work. A mathematical analysis [12] is used to select the most significant intrinsic mode functions (IMFs); therefore, the selected features are used to train an artificial neural network (ANN) to classify bearings defects. Experimental results showed that constantly evaluating the condition of the monitored bearing could support detecting the severity of the defect successfully; the results showed the potential application of ANN as effective tool for automatic machining performance degradation assessment without human intervention.

In pattern recognition techniques [13], the response of some parameters is recorded and monitored to detect abnormalities. Intelligent fault diagnosis of rotating machinery is

essentially a pattern recognition problem. Reference [14] proposed a knowledge-based system and feature selection to enhance the design of condition monitoring systems. However, the knowledge-based system requires feature understanding to enable the development of the knowledge.

Tool state monitoring is a key technology in intelligent manufacturing. But it is still in a research stage in many cases and lacks general adaptability for different machining conditions. To overcome this limitation, reference [15] has investigated an intelligent, real-time, and visible tool state monitoring through adopting integrated theories and technologies, i.e. using distinctively designed experimental technique with comprehensive consideration of cutting parameters and tool wear values as variables. Bisensor fusion for simultaneous measurements of low and high frequency signals, for performing dual feature extraction and feature dimension reduction to achieve more accurate state identification using neural network, has been investigated. The results show a recognition rate of neural network model after training to be 92.59%, which could provide uncertainty during factory operations.

Significant research has been done in literature to develop smart tools and model machining processes. In previous research, smart tools, including force-based, temperature-based, fast tool servo and smart collets/fixtures for ultra-precision machining purposes, have been presented in [16]. Adaptive control has been used to maintain a constant cutting force with varied depths of cut particularly for components made from hybrid materials or structures [16]. The findings show the positive impact of the suggested methodology. In reference [17], a novel cutting force modelling approach in diamond turning is suggested by employing a specific cutting force level and the corresponding quantitative analysis of the dynamic cutting process in order to accurately model the dynamic cutting behaviour. Moreover, a detailed discussion of tool wear monitoring in turning processes is presented in [18]. Flank wear, crater wear and corner/nose wear are found to be the most common types of wear in turning processes [18].

The above discussion shows that there is still a gap in the area of self-learning intelligent condition monitoring systems, and more research is still needed to develop a systematic approach in condition monitoring of machining operations such as turning processes and the application of artificial intelligence towards the establishment of Industry 4.0 applications.

## 2 The proposed method

Considering the above discussion, it is evident that more work is still needed to address the self-learning process to monitor machining operations. Hence, this paper provides a new perspective for fault information extraction and fault

classification of machining operations. In this paper, two unsupervised approaches have been selected, namely, novelty detection (ND) and learning vector quantisation (LVQ). This should allow the automated process of diagnostic or prognostic without the need to develop a knowledge-based system or full understanding of the actual fault mechanisms.

Novelty detection [19] requires no comparison between healthy and unhealthy signals. Only normal conditions are needed to characterise the normal process. Any deviation from normal conditions will be identified as novel. Novelty detection [19] is a classification technique that recognises a presented data as novel or non-novel. The training data for the novelty detection algorithm consists of only the normal class which is often much easier to obtain than data for multiple classes. Since a degree of overlap is normally expected between different classes, classification problems have a probabilistic nature. Novelty detection involves estimating the probability density function (PDF) of a normal class from the training information and then estimating the probability that a new set of data belongs to the same class. The accuracy of novelty detection classification is dependent on the accuracy of the modelled density functions. Three main methods are normally used to model the PDF: parametric methods, non-parametric methods and semi-parametric methods [19]. The parametric methods assume sufficient statistical information about the training data set which is not normally available. In non-parametric methods, no assumptions are made regarding the underlying density functions, and they depend on the training data to find the probability density function for a new input. Reference [20] classifies such methods as being kernel-based techniques and K-nearest neighbour techniques. The K-nearest neighbour method depends on the probability that K number of data points of a vector fall within a specific volume. The kernel-based technique calculates the volume by defining width parameters for a number of known probability distribution functions (kernels) to provide a general model for the training set. However, non-parametric methods require long computations for every input vector. Semi-parametric density estimation is used in this research for novelty detection because it combines the advantage of both parametric and non-parametric techniques and does not require extensive computational effort. Semi parametric methods use fewer numbers of kernels. In this research, a Gaussian mixture model (GMM) is used to estimate the PDF. Unlike non-parametric methods, the training data are used only during the process of construction of the density model and are not needed for calculation of the PDF for new vectors.

Neural networks are selected in this paper as another AI technique. Learning vector quantisation neural network (LVQ) is suggested in this paper. It implements competitive neural network as an unsupervised neural network which uses associative learning rules which allow the network to

learn the association between the inputs and the outputs in response to the data presented to them. Effective assessment of the rate of tool wear increases the efficiency of the process and makes it possible to replace the tool before catastrophic wear occurs.

Neural networks has been widely used for the prediction of tool wear; see, for example [21].

Recent papers have included significant work in image-based tool condition monitoring [22, 23]. Deep learning for tool condition monitoring has been well articulated in [24]. And knowledge graph has been successfully suggested by [25] with final results showing evidence for monitoring machine tool structure; but it was not tested for cutting tools. Tool life prediction of milling tools using deep transfer reinforcement learning based on long short-term memory networks have been presented in [26], the prediction results demonstrate that the proposed method has relatively high accuracy. Topological feature vectors for chatter detection in turning have been presented by [27] which shows an accuracy of up to 97%.

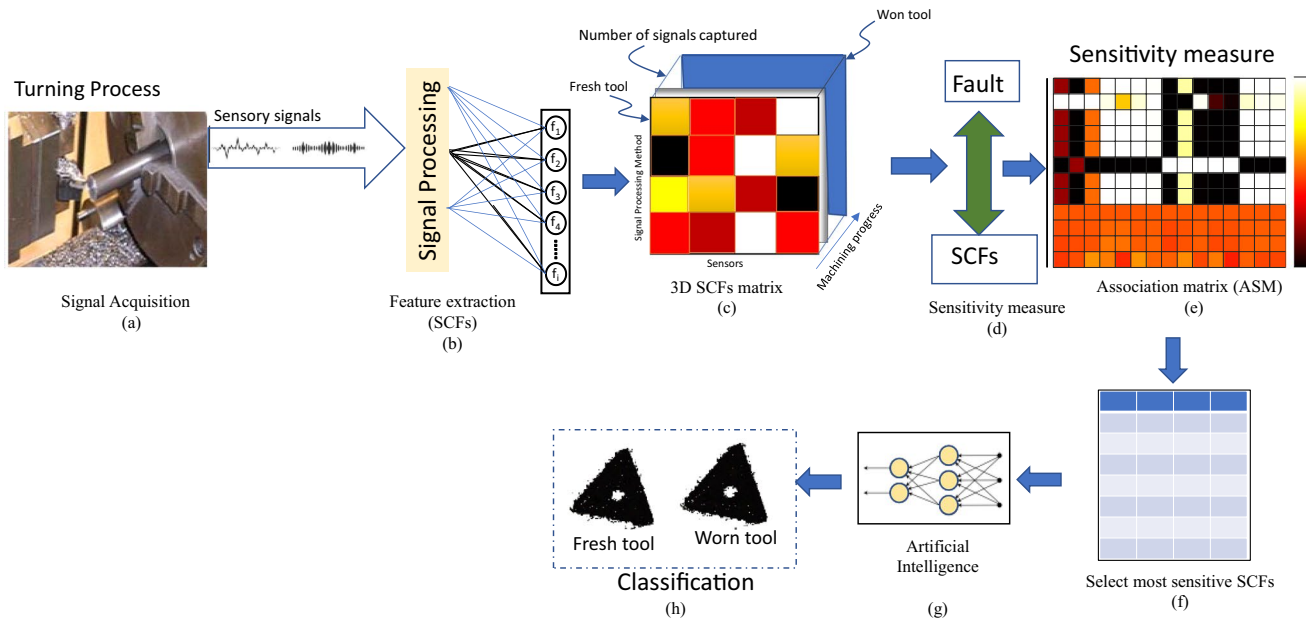
But for turning processes, an automated and self-learning system is still needed. Hence, in addition to the above, to enhance the quality of the input data to novelty detection and the LVQ neural networks, a novel method, called ASPS (Automated Sensor and Signal Processing Selection System) has been presented in [28]. It has been found to enhance the quality of data fed into the AI techniques. The (ASPS) approach is implemented and tested to determine the sensitivity of the sensory signals to the fault or machining characteristics [29] in milling operations.

This paper modifies and develops the approach for turning and defines a new Automated Sensor and Signal Processing Selection System for Turning (ASPS-T) approach which deals with turning processes. Therefore, the domain of this paper is in implementing the ASPS approach in selecting the sensors and signal processing techniques essential for monitoring turning processes and conditions. The use of the decision-making stage is to confirm and assess this method for selecting sensors and signal processing methods.

To design a condition monitoring system for turning processes using an automated simple procedure to detect the sensory characteristic features (SCF) which are most sensitive to the process states, the ASPS-T approach is based on conducting studies to prove that there is a dependency between a measured sensory value (SCF) and the monitored state or physical phenomenon or fault [28, 29].

## 2.1 The ASPS-T approach

The implemented approach is named ASPS-T (Automated Sensor and Signal Processing Selection System for Turning). Figure 1 presents the basic principle of the ASPS-T generic approach. It systematically relates the sensory



**Fig. 1** The generic basic structure of the ASPS-T approach

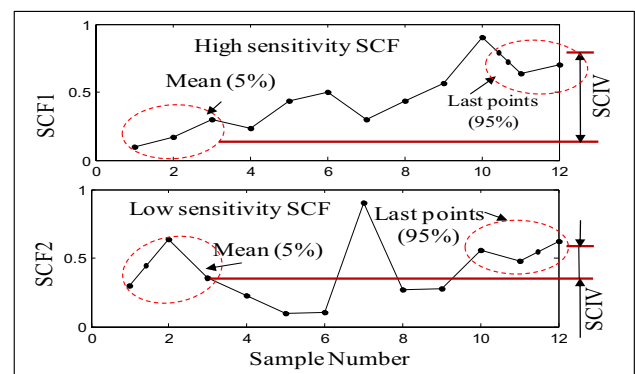
signal and the signal processing methods used to the state or the physical phenomenon (fault) which needs to be detected or evaluated. The ASPS-T approach starts by defining the operation to be monitored and its states (e.g. healthy or faulty condition) as illustrated in Fig. 1. Then, a wide range of sensors are installed for process monitoring to produce sensory signals that contain information about the process. The following stage of the proposed approach is for extracting sensory characteristic features (SCFs) obtained from the sensory signals using a wide range of signal processing methods and then discovering the sensitivity of such features on the investigated process state. If a specific feature from a specific sensor shows high sensitivity to the fault, this means this sensory characteristic feature is useful in detecting or evaluating that fault. A particular number of sensitive sensors and signal processing methods are then selected as the best and most sensitive monitoring system. Figure 1-a presents the turning process and the sensory signals extracted.

Figure 1-b presented the extraction of sensory characteristic features (SCFs) from all the sensors and signal processing methods to construct a 3D matrix of the features, given that the 3rd dimension is time (or number of tests). Based on the SCFs, a correlation or sensitivity measure will be used to quantify the sensitivity of each SCFs (Fig. 1-d); and that sensitivity values will be allocated in an Association Matrix (ASM) (Fig. 1-e). Based on the ASM's sensitivity values, the SCFs in the 3D matrix (Fig. 1-c) will be arranged, and the SCFs with maximum sensitivities will be selected as data to be fed into the artificial intelligence stage for classification of the turning process or tool health.

For the stage in Fig. 1-d, the sensitivity of the features in this paper will be identified using a novel method, namely Sudden Change In Value (SCIV), which is utilised to measure sensitivity for a group of SCFs, and a comparison between a group of SCFs with high average sensitivity with a group of SCFs with low average sensitivity.

## 2.2 Sudden Change In Value (SCIV)

The Sudden Change In Value (SCIV) statistical method is used in this research to find the average difference between the first group of points and the last points in the monitored sensory data. The first variable is the average value of the first (5%) of the data values. While the second variable is the maximum value of the last (95%) of the data



**Fig. 2** Examples of SCFs using Sudden Change In Value (SCIV)

values as shown in Fig. 2. Mathematically, the last variable can be described as:

$$Lv = \max\{x_i\}_{i = \lceil 0.95lp \rceil}^{lp} \tag{1}$$

where  $Lv$  is the Last variable and it is defined as the maximum value within the last 95% of the vector values;  $lp$  is the length of the vector, and  $x_i$  is the value of the vector at location  $i$ , where  $\lceil 0.95lp \rceil$  is the nearest integer value of  $0.95lp$ . The first variable can be described mathematically as:

$$Fv = \text{mean}\{x_i\}_{i = 1}^{\lceil 0.05lp \rceil} \tag{2}$$

where  $Fv$  is the first variable which is the average of the first 5% group of points and  $\lceil 0.05lp \rceil$  is the nearest integer value of  $0.05lp$ . Hence, as shown in Fig. 2, the Sudden Change In Value (SCIV) can be expressed as:

$$SCIV = Lv - Fv \tag{3}$$

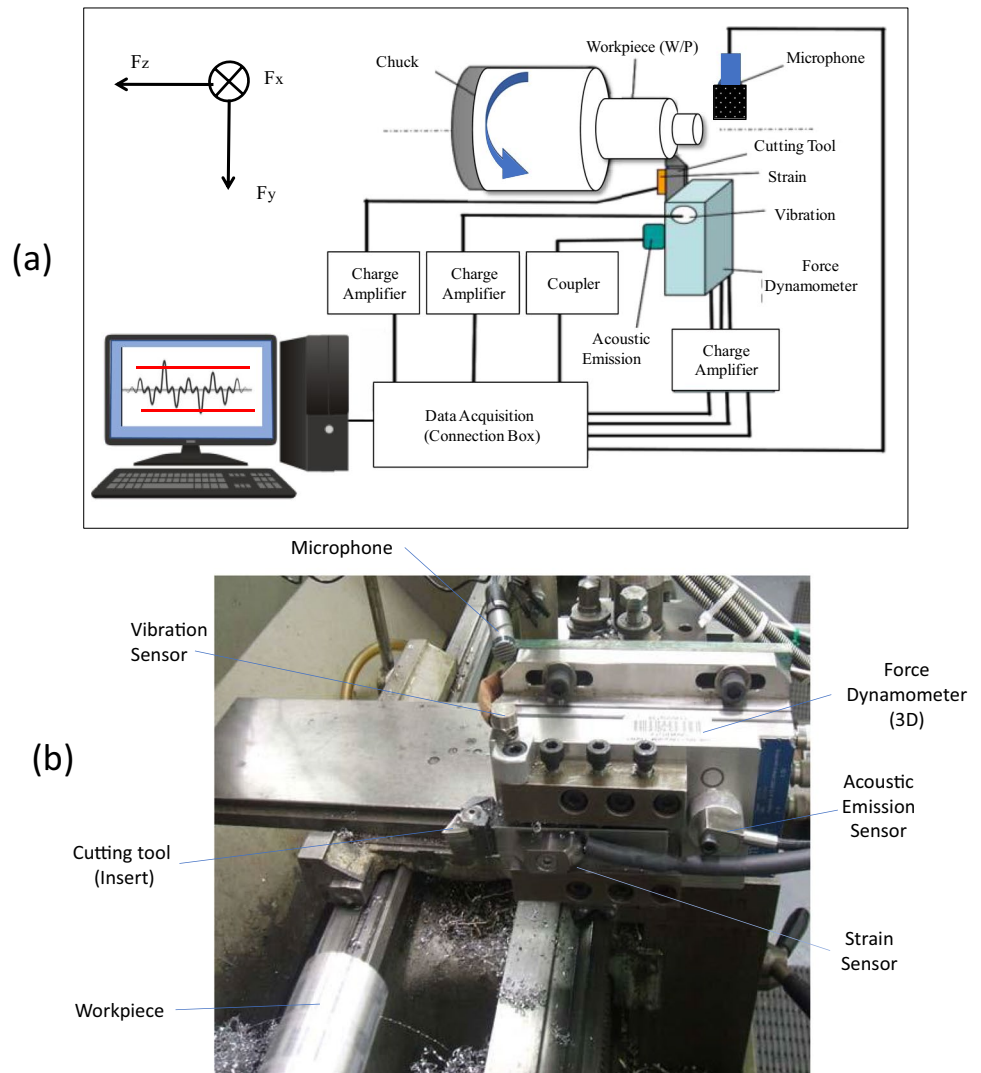
In the current investigation, Sudden Change In Value (SCIV) is used to define the pattern regression of the features (i.e. the sensitivity of features to fault generation). Furthermore, novelty detection and learning vector quantisation neural networks (LVQ) are used to confirm the results. Consequently, the above suggested approach should provide a sensor fusion and a selection process of the most sensitive sensors and signal processing methods to detect tool wear or deterioration in a turning process.

### 3 Experimental work

#### 3.1 Hardware setup

The experimental work is performed on a lathe machine tool, as shown in Fig. 3. It includes a turning process of stainless

**Fig. 3** Schematic diagram of the complete monitoring system (a) and a photo of the setup (b)



steel workpiece using cemented carbide inserts (Sandvik Coro-mant P25). The chosen process parameters monitored are the cutting forces (three axes), strain, vibration, acoustic emission (RMS and AE signal) and sound. The force signals are monitored using a 3-component dynamometer (Kistler 9257A). The force dynamometer is coupled to a 3-channel charge amplifier (Kistler 5001). The machining parameters are selected to resemble industrial practice. The signals are monitored using a National Instrument NI PCI-6070E and a specially designed software using NI LabWindows/CVI. The sampling rate is 1 K sample/s, and turning process is performed at 1000 RPM spindle speed and 0.05 mm/revolution feed rate. The steel work-piece had a diameter of 30 mm. The experimental cutting conditions are chosen to cover the manufacturer’s recommended interval for insert type. Figure 3 presents the complete diagram of the experimental setup of this paper.

### 3.2 Signal processing methods

The signal processing and feature extraction methods are selected based on the previous research in condition monitoring of machining operations. However, any other methods of signal processing and features extraction can be applied

provided that they produce real numbers. The key objective of these processes is to simplify the resulted complex signals from turning processes for analysis. The feature extraction methods used in the time domain are standard deviations, average, maximum, minimum, range, kurtosis, skewness and power. In frequency domain, fast Fourier transformation (FFT) and wavelet analysis are used, as presented in Table 1.

**Fourier transformation** Fourier transformation can be used to transform a signal  $x(t)$  with length ( $N$ ) from the time domain into a signal in frequency domain  $x(f)$  which is defined in mathematical form as follows:

$$X(f) = \sum_{i=0}^{N-1} x(i)W_n^{ih} ; \text{where } W_N = e^{-j2\pi/N} \tag{4}$$

for  $h=0, 1, 2, \dots, N-1$ , where  $j = \sqrt{-1}$

Breaking down the signal into its frequency spectrum allows to assess the presence of certain frequencies. Fast Fourier transformation (FFT) is used to transfer digital signals from time domain into the frequency domain. In this paper, the FFT of each signal is divided into 12 different ranges of frequencies, and then the average value is used for the ASPS-T approach; see Table 1.

**Table 1** The implemented signal processing methods

<i>Symbol</i>	Equation/description
<i>STD</i>	$TD_1 = \sqrt{\frac{\sum_{i=1}^N (x_i - TD_2)^2}{N-1}}$
<i>Average</i>	$TD_2 = \frac{1}{N} \sum_{i=1}^N x_i$
<i>Abs (max)</i>	$TD_{53} = \max x_i $
<i>Abs (min)</i>	$TD_4 = \min x_i $
<i>Range</i>	$TD_5 = \max(x) - \min(x)$
<i>Kurtosis</i>	$TD_7 = \frac{\sum_{i=1}^N (x_i - \bar{x})^4}{(N-1)TD_2^4}$
<i>Skewness</i>	$TD_6 = \frac{\sum_{i=1}^N (x_i - TD_2)^3}{(N-1)TD_2^3}$
<i>Power</i>	$TD_7 = \sqrt{\frac{\sum_{i=1}^N (x_i)^2}{N}}$
<i>FFT (f1, f2)</i> = average value of the FFT between frequencies $f_1$ and $f_2$	
FFT1	Average of [FFT (20 Hz, 200 Hz)]
FFT2	Average of [FFT (200 Hz, 400 Hz)]
FFT3	Average of [FFT (400 Hz, 600 Hz)]
FFT4	Average of [FFT (600 Hz, 800 kHz)]
FFT5	Average of [FFT (800 kHz, 1 kHz)]
FFT6	Average of [FFT (1 kHz, 1.2 kHz)]
FFT7	Average of [FFT (1.2 kHz, 1.4 kHz)]
FFT8	Average of [FFT (1.4 kHz, 1.6 kHz)]
FFT9	Average of [FFT (1.6 kHz, 1.8 kHz)]
FFT10	Average of [FFT (1.8 kHz, 2 kHz)]
FFT11	Average of [FFT (2 kHz, 2.2 kHz)]
FFT12	Average of [FFT (2.2 kHz, 2.5 kHz)]
Wav_ $i$ = standard deviations of the $i$ th level of the wavelet analysis, where $1 \leq i \leq 13$	

**Wavelet signal processing** Fourier transformation has an important disadvantage, where the transformation process from the time domain to frequency domain removes the time contents. Hence, when looking at a frequency spectrum, it is not possible to know when an exact event has occurred. Wavelet signal processing provides an alternative technique of breaking a signal down into sub-signals or levels with different frequencies which carry the time information. In wavelet analysis, the length of the signal determines how many wavelet levels there will be in the decomposition of the original signal. In general, for a signal of length  $N$ , where  $N = 2^n$ , there are  $n + 1$  wavelet levels. The shape of the wavelet levels depends on the mother wavelet signal which is employed to build these levels. Wavelet analysis involves breaking the signal into sub-signals, each of which is generated from a combination of shifted and scaled wavelet signals. The dilation equation is used to define the basic scaling function  $\varphi(x)$  from which the D4 discrete wavelet original signal is calculated as follows:

$$\varphi(x) = \sum_{j=0}^3 c(j)\varphi(2x - j); \tag{5}$$

where  $c(j)$  represents the wavelet coefficient and  $j$  the index.

The primary wavelet signal is computed from the scaling function which is expressed as follows:

$$\Psi(x) = \sum_{i=0}^3 (-1)^i c(i + 1)\varphi(2x - i) \tag{6}$$

The four coefficients for D4 wavelets are as follows:

$$\begin{aligned} C(0) &= \frac{1}{4}(1 + \sqrt{3}) & C(1) &= \frac{1}{4}(3 + \sqrt{3}) \\ C(2) &= \frac{1}{4}(3 - \sqrt{3}) & C(3) &= -\frac{1}{4}(\sqrt{3} + 1) \end{aligned} \tag{7}$$

For discrete D4 wavelets transformation, the original function can be reconstructed from the equation:

$$x = \sum_{l=-\infty}^{\infty} c_{\varphi} \varphi_n(x - 1) + \sum_{i=0}^{\infty} \sum_{h=-\infty}^{\infty} C_{h,l} \Psi(2^h - 1) \tag{8}$$

The standard deviations (STD) of the wavelets are used as features (SCFs) for the proposed monitoring system. A total of 13 wavelets were produced, and hence, 13 SCFs were used for the suggested approach in relation to wavelet analysis. For further information, please see [29–32].

## 4 Results and the implementation of the ASPS-T approach

The machining process would start with a fresh tool, and the machining will continue until a worn status or fully damaged tool is created; see Fig. 4. Figure 5a and b show examples of

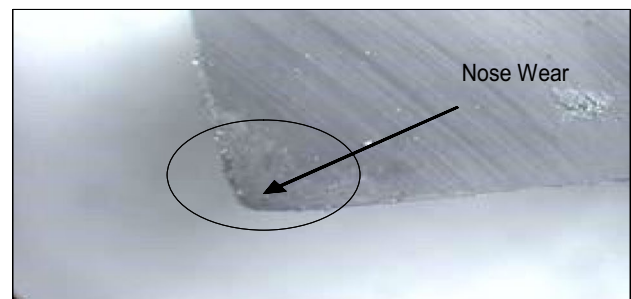
the machining signals obtained from the signals for the fresh and worn tool, respectively. It is extremely different from such complex signals to develop a sensor fusion model or to integrate artificial intelligence into the condition monitoring system.

### 4.1 Signal simplifications

The Association Matrix (ASM) for this test has a size of  $8 \times 33$  (8 signals and 33 signal processing methods) and embodies 264 features, or simply SCFs. These features are divided into 26 different systems; each system contains 10 features (i.e. each 10 SCFs form a suggested monitoring system). The level of tool wear is visually monitored in this experimental work, and it shows that wear increases with machining time, compared with the results of the automated AI system. All features have been normalised between 0.1 and 0.9 to allow a relative and accurate comparison; see Fig. 6.

### 4.2 Sensitivity detection

As discussed above, in order to automate the sensitivity detection of the systems and to keep the automated measurements simple for a complex machining process such as turning, it has been found that the SCIV method is a substantial method to be used in this research as a sensitivity evaluation method to tool wear. Figure 6 presents examples of four SCFs, two high sensitivity (Fig. 6a), and two with low sensitivity (Fig. 6b). SCIV is used on the normalised features between 0.1 and 0.9 as a relative measure of sensitivity to tool wear. Figure 6b shows the result of using the Sudden Change In Value (SCIV) method. It can be noticed that the SCFs of (strain, wavelet\_8) and (Fx, wavelet\_3) are not sensitive to tool wear. Meanwhile, it is noticed that when utilising the Sudden Change In Value (SCIV) method, it indicates that both have low sensitivity as indicated manually. In addition, looking at Fig. 6a, it can be observed that



**Fig. 4** An example of tool wear (nose/corner wear) during the experimental work

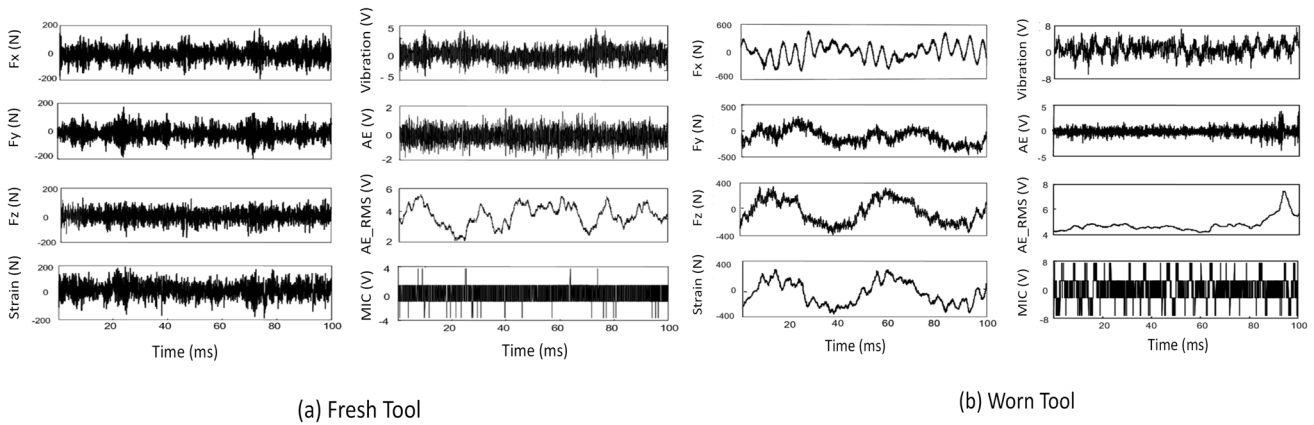


Fig. 5 Machining signals

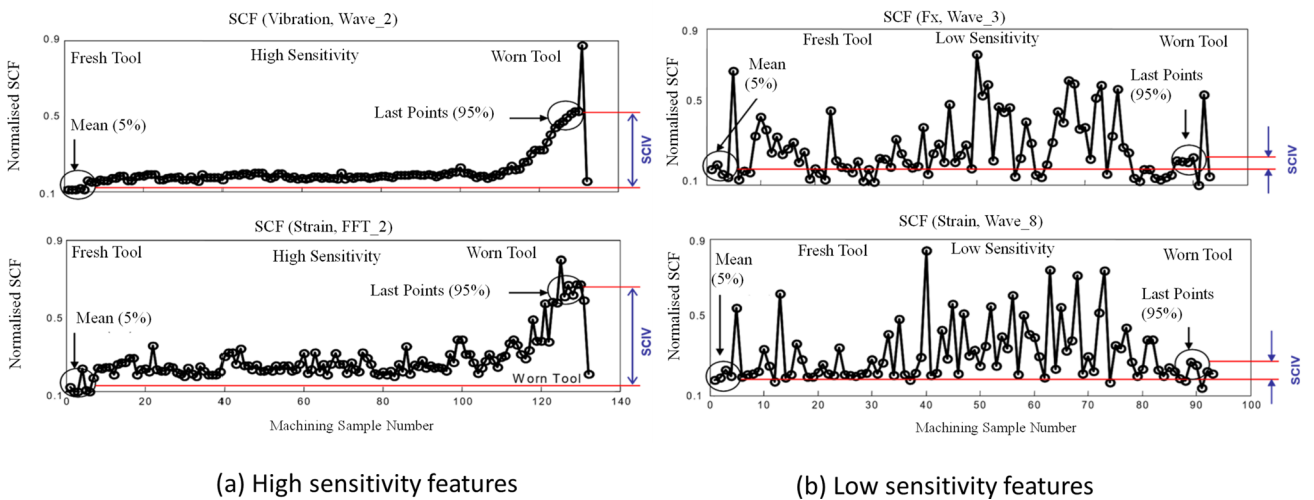


Fig. 6 Example of two features with high sensitivity using SCIV (a) and two features with low sensitivity using SCIV (b)

the SCFs of (AE\_RMS, FTT\_2) and (vibration, wavelet\_2) are sensitive to tool wear with high sensitivity measure.

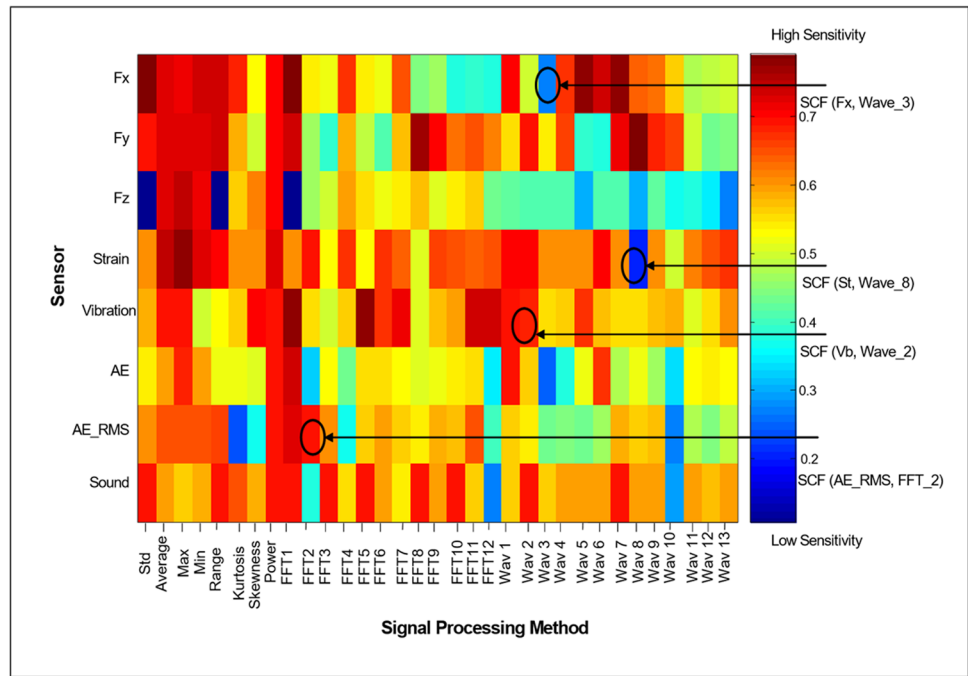
Therefore, the Sudden Change In Value (SCIV) method is an appropriate method to use as an automated detection method with the ASPS-T approach. In general, it is concluded that the Sudden Change In Value (SCIV) method is a good indicator of the automated sensitivity detection. Figure 7 presents the ASM matrix for this particular tool wear test where sensitivity values are the Sudden Change In Value (SCIV) of the normalised values. You can notice that the SCFs presented in Fig. 6 are indicated in colours that represents the sensitivity within the Association Matrix (ASM) in Fig. 7. Figure 7 presents a suitable way to visualise the best sensors and signal processing methods. Based on the ASM, the features are arranged in descending order so that the system number 1 is containing the features of maximum sensitivity as predicted by the ASPS-T approach as in Fig. 1, while system number 26 contains the feature

of minimum sensitivity. The suggested number of features in every system, 10, is based on previous implementation of the ASPS in end milling [28]. However, any other number could be used based on the applications and error assessment.

In addition, the SCIV method indicates the same result when it is used as an automated sensitivity detection method and gives accurate result when it is applied to the massive data of the SCFs. Therefore, the Sudden Change In Value (SCIV) method is an excellent method to detect sensitivity and to keep measurement automated and simple, which has been well presented in the ASM matrix of Fig. 7. The first system which includes the most sensitive 10 features is shown in Table 2. The first system is found to have relative sensitivity (SCIV average of 0.7797) which is more than the average sensitivity of the second (0.7372). In addition, system number 26 is found to have the lowest sensitivity for the detection of the tool wear (0.2210); Fig. 8 presents the



**Fig. 7** The ASM (Association Matrix) example of the result for all the SCFs for one tool using SCIV as a sensitivity measure



**Table 2** First system with the SCFs sensitivity

Sensory signal	Signal processing methods	Sensitivity (SCIV)
Fy	Wavelet_3	0.79668
Fy	Wavelet_4	0.79635
Strain	Wavelet_1	0.78646
Fx	Power	0.78141
Vibration	Wavelet_5	0.78058
Fy	Power	0.77813
Vibration	Wavelet_1	0.77648
Fy	Minimum	0.77532
Fy	Average	0.77365
Vibration	Kurtosis	0.75149
<b>The average value of sensitivity (SCIV)</b>		<b>0.7797</b>

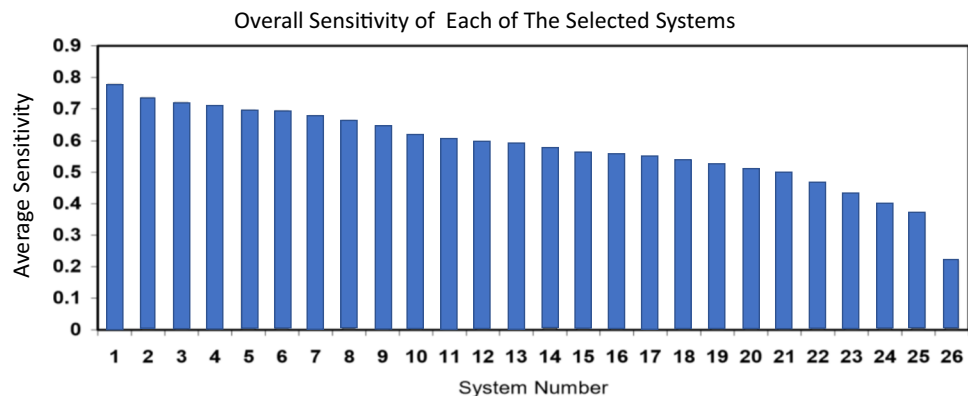
The last line is the average value of the lines above

average sensitivity of the 27 suggested system (each has 10 SCFs).

### 4.3 The performance of the pattern recognition systems

The sensitivity of a sensory characteristics feature to detect tool wear in turning processes for all the tools is investigated automatically using the automated Sudden Change In Value (SCIV) sensitivity detection method for the 8 sensors and 33 signal processing methods which represent the 264 SCFs. A total of 5 tools are tested from fresh to totally worn. Two tools are selected arbitrarily for the training of pattern recognition systems, and then the full 5 tools are tested. In order for the ASPS-T approach to be a useful method, the sensory characteristics features which are assumed to have a higher sensitivity to tool wear should result in better

**Fig. 8** A comparison between the 26 systems according to their sensitivity



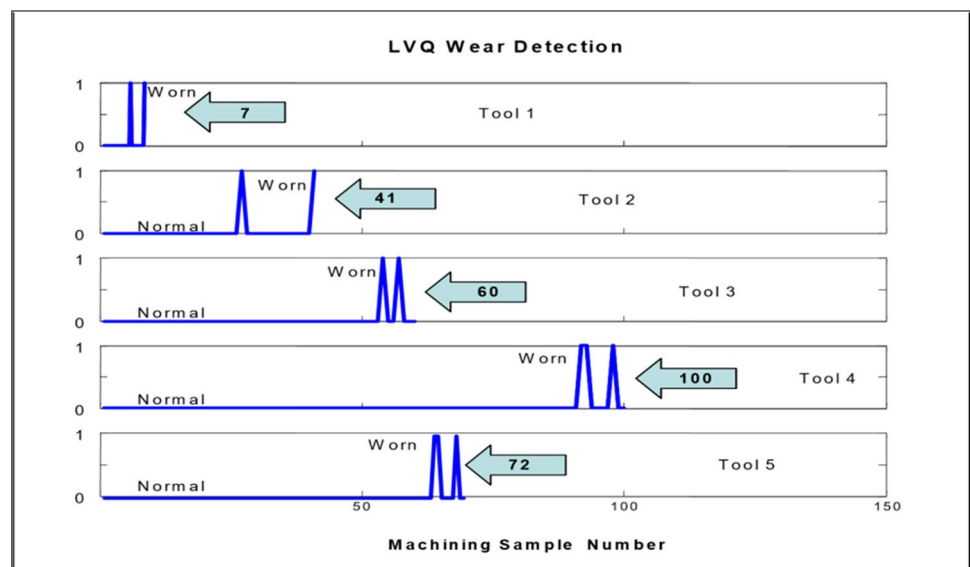
identification when it is tested by a pattern recognition system. On the other hand, the sensory characteristics features which are assumed to have a lower sensitivity to tool wear should result in poorer identification when they are tested by a pattern recognition system. For this purpose, two pattern recognitions are used to test the system as discussed above: Learning vector quantisation (LVQ) and novelty detection algorithm. The parameters used in both pattern recognitions, LVQ and Novelty Detection, are selected to give a practical response. Nevertheless, it is significant to note that neither pattern recognitions are optimised for this application since the target here is to evaluate the systems to select the most suitable sensor and signal processing method. The implemented LVQ and novelty detection systems used in this research are programmed using MATLAB.

### 4.3.1 Learning vector quantisation (LVQ)

The advantage of using LVQ is that it learns to classify input vectors into target classes chosen by the user. However, the learning rules are done according to the competitive layers depending on the distance between the input vectors and the weight and, unlike back propagation neural networks, not according to the error between the output and the target. Hence, there is no mechanism in the network to dictate whether or not any two input vectors belong to the same category. LVQ has an input layer, a competitive layer, and a linear output layer. The competitive layer learns to classify the input vectors to subclasses, while the output linear layer transforms the competitive subclasses into the desired target classes. The parameters used are a learning rate 0.05, hidden layer size 50, training iteration 500 and bias time constant 0.99.

The parameters are chosen in order to give a reasonable response. However, it is important to point out that the neural networks are not optimised for this application since the objective in this research is to compare systems in order to select the most appropriate sensors and signal processing methods. Two tools are selected arbitrarily to train the LVQ neural networks, and the total 5 tools are selected for testing. The SCFs from the 5 tools are fed to the neural networks for testing. Figure 9 presents the results of using the LVQ for detecting tool wear using the 10 features of system 1 which has been identified as the most sensitive system. In Fig. 9, the arrows show the maximum number of cuts for each tool (i.e. tool life) until complete wear or failure. The number 0 means that the tool is in normal condition, while the number 1 means that the tool is in worn condition. For example, for tool 2, the LVQ neural networks has identified that cut/sample 27 is the start of tool failure. However, the actual tool failure happened at 40 cuts/samples. For tool 3, the maximum number of cuts is 60, and failure is identified at sample 59. The number of cuts/samples needed to produce a worn tool is significantly different for each tool. This proves that using statistical methods is not a suitable option. Also the system is successful in detecting tool wear before the end of life of the tool. The ASPS-T approach has been found successful in detecting tool wear. However, for tool 2, there has been early warning regarding the end of its life. When examining the signals, it has been found that there is less stability on the nature of the signal for tool 2. In addition, when examining the insert, this explains the early warning. In some cases, unexpected wear or tool breakage does occur. However, the subsequent machining cuts could re-sharpen the tool

**Fig. 9** The result of the LVQ to detect tool wear (tools 1–5) for high sensitivity SCFs (system 1)



and extend its life for a specific period before total failure. Because this approach presented in this work uses the ‘black box’ concept (i.e. looking at the process signals and outputs without studying the intermediate tool conditions), it is difficult to confirm the conditions of the tool at every stage of the process.

Looking at Fig. 9, it can be noticed that system 1 with high sensitivity levels produce high-level identification of tool wear. It also produces prognosis of nd of life just before the complete wear or damage (i.e. the two spikes of the signal). Therefore, the ASPS-T approach is found very useful in predicting the behaviour of condition monitoring systems when using system 1 with high sensitivity SCFa using SCIV as a sensitivity measure. Figure 10 presents system 26, the system with low sensitivity values as suggested by the method. You can observe in this case the false warning during the normal operation of the tool. This indicates that the proposed ASPS-T method is capable to identify the most suitable sensors and signal processing methods for the design of the condition monitoring system.

### 4.3.2 Novelty detection

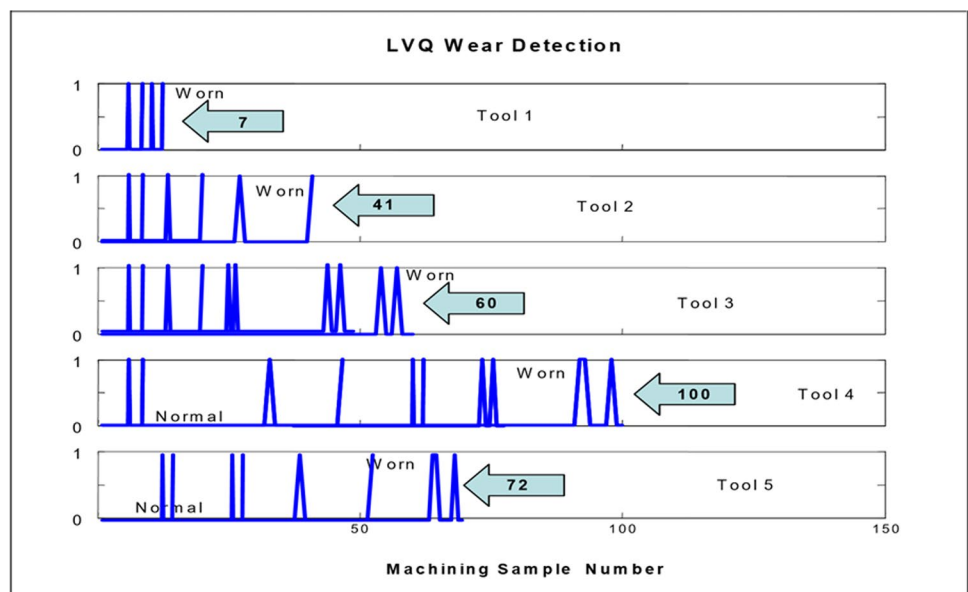
Novelty detection is used in this work as a self-learning approach to characterise the ‘fresh’ or normal state of the cutter. Novelty detection is a classification technique that recognises the presented data as novel (i.e. new) or non-novel (i.e. normal). The SCFs of all the 5 tools are then fed into a novelty detection algorithm to investigate the capability of the ASPS-T approach and the complete monitoring system. NETLAB software is used for the implementation of the novelty detection. The response of the

Gaussian kernels  $\varphi_j$  is defined by a covariance matrix (a spherical matrix in this case) and a centre (i.e. the centroid of the input clusters). A single variance parameter for each Gaussian component is calculated using 6 centres in the mixture which has been found to be a suitable structure that gives a relatively quick learning process and consistent results. Figure 11 shows the novelty detection result for the 5 tools. The novelty detection has been found successful. However, for tool 2, it can be seen that there is an early warning before tool wear detected. By comparing this with the results from the LVQ and SCFs of tool 2, it can be seen that both systems show same detections. This proves that the utilisation of the SCIV automated method in ASPS-T approach is successful regardless of the AI technique used. By selecting a suitable threshold value for the novelty detection, the success of the novelty detection algorithms is found to be 100%. Moreover, the threshold value could be selected for efficient wear prediction before the actual tool wear occurs. Figure 12 shows the novelty detection for system 26 with low sensitivity features. We can notice in this case the high levels of error in predicting the conditions of the tools.

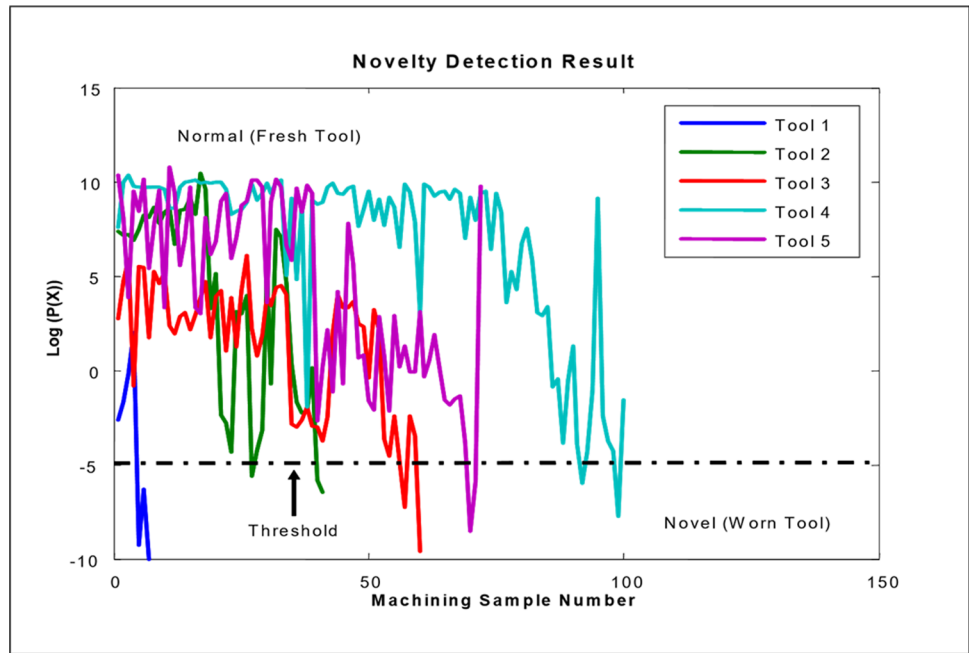
### 4.4 System evaluation and cost analysis

The ASPS-T approach can also be used to evaluate the average effectiveness of all the sensors and signal processing methods by averaging the rows and columns of the Association Matrix (ASM) of Fig. 7. Figure 13 presents the average sensitivity of all the sensors used. We can observe that Fz has the least sensitivity which is expected as the direction of Fz is perpendicular to the motion of the tool. The highest two sensors are found to be strain and vibration. Also sound

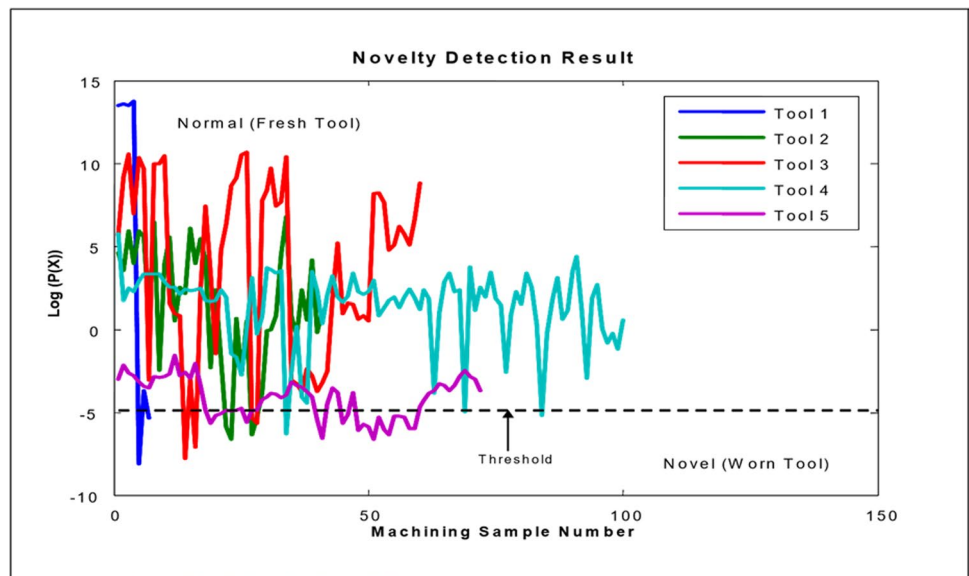
**Fig. 10** The result of the LVQ to detect tool wear (tools 1–5) with low sensitivity SCFs (system 26)



**Fig. 11** The result of the novelty detection (tools 1–5) for high sensitivity SCFs (system 1)

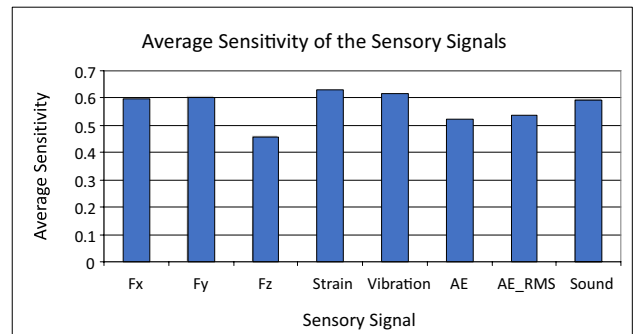


**Fig. 12** The result of the novelty detection for tools (1–5), for low sensitivity SCFs (system 26)



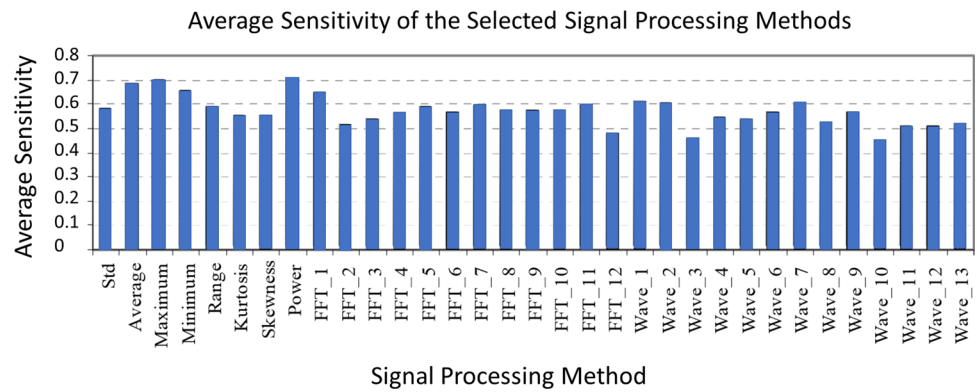
signals of the microphone have been found to be reasonably sensitive. When considering the relative cost of the sensors, it can be argued that the microphone will be at much lower cost than force signals or the acoustic emission. Hence, the ASPS-T can also provide further information about the cost analysis vs sensitivity.

Figure 14 presents the average sensitivity of the signal processing methods. The power of the signal and FFT1 has been found to be on average the most sensitive signal processing methods. However, system 1 might not include the expected maximum average sensors or signal processing methods. As in Table 2, Fy and vibration are found the most



**Fig. 13** As values for the sensory signals

**Fig. 14** The average sensitivity for the signal processing methods



common sensors, while power and Wavelet\_1 are found to be the most common signal processing method.

In addition to the above, the ASM of Fig. 7 can be employed to evaluate and compare the sensitivity of the monitoring system compared with other similar monitoring systems, using the sensitivity values as a relative comparison.

## 5 Conclusion

This paper has indicated the full capability of the proposed ASPS-T approach which is implemented to design an effective system to monitor tool wear in turning processes. The presented work has included using a lathe machine to detect wear in cutting tools when machining stainless steel workpiece. A wide range of sensor (i.e. vibration, dynamometer, sound, strain and AE) and signal processing method applications has been presented to evaluate the proposed approach for turning processes. Based on the novel Sudden Change In Value (SCIV) analysis, the Associate Matrix (ASM) is constructed of the sensory characteristic features (SCFs) to choose the most sensitive sensory characteristic features to detect tool wear. Neural networks (LVQ) and novelty detection algorithm have been used as artificial intelligence (AI) and decision-making techniques. The results of the LVQ neural networks and novelty detection algorithm have proven that high sensitivity means better information and low sensitivity means worse information for the AI system. In general, the behaviour of LVQ neural networks and novelty detection has shown similar results for the tested cutting tools for wear for both high and low sensitivity. The results prove that the combination of sensitive sensory characteristic features and both of AI methods have been successful for the detection and prediction of the tool wear in turning process and show the capability of the proposed approach to reduce the complexity of the design of condition monitoring systems and the development of a sensor fusion system using a self-learning method.

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**Author contribution** • Dr. Abdulrahman Al-Azmi

Credit role: conceptualisation; data curation; formal analysis; methodology; mathematical modelling; software; investigation; visualisation; roles/writing—original draft

• Professor Amin Al-Habaibeh

Credit role: conceptualisation; methodology; project administration; resources; supervision; validation; visualisation; writing—review and editing

• Dr. Jabbar Abbas

Credit role: validation; writing—review and editing

**Data availability** Data will be provided upon request.

**Code availability** LVQ neural network are based on MATLAB Toolbox, and novelty detection is based on NETLAB software. The original ASPS code is proprietary code by Amin Al-Habaibeh and written using MATLAB programming language. The modified ASPS-T code of this paper is proprietary code written in MATLAB programming language.

## Declarations

**Ethics approval** Not applicable

**Consent to participate** Not applicable

**Consent for publication** The authors consent for the publication of the accepted paper in *The International Journal of Advanced Manufacturing Technology*.

**Conflict of interest** The authors declare no competing interests.

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