MONITORING PROCESS IN TURNING OPERATIONS FOR CRACKED MATERIAL ALLOY USING STRAIN AND VIBRATION SENSOR WITH NEURAL NETWORK CLASSIFICATION

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ABSTRACT

Surface finish and monitoring tool wear is essential for optimization of machining parameters and performing automated manufacturing systems. There is a very close relationship between tool wear and machining material parameters as surface roughness, shrinkage, cracks, hard particle ... etc. Monitoring of manufacturing processes plays a very important role to avoid dawn time of the machine, or prevent unwanted conditions such as chatter, excessive tool wear or breakage. Feature extraction and decision making is a matter of considerable interest for condition monitoring of complex phenomena with multiple sensors.

In this work, the implementation of a monitoring system utilizing simultaneous vibration and strain measurements on the tool tip is investigated for the shrinkage and crack of cast iron work piece. Machining parameters taken into consideration are cutting speed (116.5 and 136.6) m/min, feed rate (0.17 and 0.23)rev/min respectively and depth of cut (1) mm. Data from the machining processes were recorded with one piezoelectric strain sensor type (PCB 740B02) and an accelerometer type (4370), each coupled to the data acquisition card type (9111 DR). There were 22 features indicative of crack were extracted from the original signal. These include features from the time domain (mean, STD, crest factor, RMS, kurtosis, variance), frequency domains (power spectral density), time-series model coefficient (AR) and four packet features extracted from wavelet packet analysis (RMS, STD, kurtosis, crest factor).

The (2x1) self organizing map neural network was employed to identify the crack and shrinkage effect on the tool state. The program used with this process is MATLAB V.6.5. As a result of the present work, we have an SOM model can classifying the crack with minimal error.

الخلاصة:

تشغيل السطوح ومراقبة بليان أداة القطع ضرورية لتحديد الظروف المثلى لانظمة التصنيع . ان هنالك علاقة بين مراقبة بليان اداه القطع مع ظروف تشغيل سطوح المسبوكات المتشققة، الخشنة، المنكمشة والمحتوية على جسيمات صلدة وما الى . . الخ. مراقبة عمليات التصنيع تَلْعبُ دورمهم جداً لتَجَنُّب صرف وقتِ الماكنةِ، أَو يَمْنعُ شروطَ غير مرغوبةَ مثل الثرثرةِ، التاكل المفرط للاداة أوالكسرِ. إنتزاع وإتّخاذ القرارات مسألة كبيرة الاهميةِ لمراقبة الظواهر المعقّدةِ بالمحسّساتِ المتعدّدةِ.

في هذا العملِ، تطبيق نظام مراقبة يَستعملُ إهتزازاً آنياً ومقاييسَ إجهادِ على رأسِ الأداةَ لتحرّى الإنكماشِ وشَقِّ قطعةِ مِنِ الحديد الصلبِ. أَخذتْ معاملات التشغيل بنظر الإعتبار سرعةَ القطع (١١٦,٥ و١٣٦,٦) م/ دقيقة، نسبة تغذية (٠,١٧ و٠,٢٣) دورة /دقيقة على التوالي وعمق القطعِ (١) مليمتر. البياناتِ مِنْ عملياتِ التشغيل سُجّلتْ بنوعِ محسّسِ إجهادِ piezoelectric (**PCB 740B02**) ونوع معجّلِ (**4370**)، كُلّ مُزَاوَج إلى بطاقةِ جمعَ البيانات نوع(**9111 DR** **)**. كان هناك ٢٢ ميزّةَ مؤشّر على الشَقِّ إنتزعَ مِنْ الإشارةِ الأصليةِ. تتضمن ميزّات مجالِ الوقتَ (**mean, STD, crest factor, RMS, kurtosis, variance**)،

مجالات ترددِ (كثافة طيف كهربائية)، معامل الزمن النموذجي المتوالي (AR) واربع ميزّات حزم إنتزعتْ مِنْ تحليلِ حزمةِ wavelet (**RMS, STD, kurtosis, crest factor**). ان (**2x1**) يُنظّمُ شبكة عصبيةَ إستخدمتْ لتَمييز الإنكماشَ والشَقَّ على حالة أداة القطع. إنّ البرنامجَ المستخدم بهذه العمليةِ Matlab V.6.5 و كنتيجة للعملِ الحاليِ، حصلنا على نموذجُ SOM يُمْكِنُ أَنْ يُصنّفَ الشَقَّ باقل خطأ ِممكنِ.

KEYWORDS :MONITORING, MEASUREMENT,WEAR,NEURAL NETWORK,CUTTING ,VIBRATION

SURVEY OF MONITORING PROCESS:

(Xiaoli etal 2000):used the wavelet transforms and fuzzy techniques are used to monitor tool breakage and wear conditions in real time according to the measured spindle and feed motor currents , respectively .**(Reuben etal 1998) :** feature extraction and decision – making was a matter of consider interest for condition monitoring of complex phenomena with multiple sensors. **(Kndili etal 2003) :** have studied the outlines of a neural networks based modular tool condition monitoring system for cutting tool wear classification . Multi layer neural network structure was used and data set has been trained off – line using back propagation algorithm, an important variation in mean, RMS, standard deviation of cutting forces and vibration can result in estimation and classification error. **(Scheffer etal 2001):** discussed the implementation of a monitoring system utilizing simultaneous vibration and strain measurement on the tool tip, was investigated for the wear manufacturing of aluminum pistons. Data from the manufacturing process was recorded with two piezoelectric strain sensors and an accelerometer, each coupled to a DSPT analyzer. A large number of features indicative of tool wear automatically extracted from different parts of the original signals (**Nadgir etal 2000):** studied the out line of a neural network based (TCMS) for cutting tool state classification. Orthogonal cutting tests were performed on H13 steel using PCBN inserts and on line cutting force data was acquired with a piezoelectric force dynamometer. Simultaneously flank wear data was measured using a tool makers microscope and along with the processed data were fed a back propagation neural network to be trained .All papers which discussed previously were used different method to measure the tool wear such as using (vibration, strain, acoustic emission and feed current signal), the steel and aluminum material was used in most papers as a work – piece with constant cutting condition. In this work are using monitoring processes to classify the cutting tool wear through using the strain and vibration signal , which measured from piezoelectric strain sensors and accelerometer respectively , after that we extract the feature from the signal to applying it into SOM neural network to have the classification of the amount tool wear . It can be divide in two parts theoretical included: (Time domain, Modeling domain, Frequency domain, Wavelet packet coefficients) from the original signals, and use it in SOM neural network. In addition classifying the cutting tool wear using SOM neural network. And experimental such as: (Machining of Cast Iron shaft with and without crack on the surface work-piece using turning machine with different cutting condition; Measuring the wear of Carbide cutting tool type(SNMG 120412) using microscope; Measuring the signal from piezoelectric strain sensor and accelerometer using Data Acquisition Card).

WEAR IDENTIFICATION AND MONITORING

A conventional method for tool wear and shrinkage appeared at the work piece identification is basically a two-step approach: First, extract features from the signals of a single sensor that is highly sensitive to tool-wear and shrinkage but insensitive to noise; then, a physical model is established to reflect the relationship between the sensor signals and the wear status. This is because a crack model based on information from a single sensor cannot adequately reflect the complexity of a cutting process. Therefore, approaches using sensor integration have been introduced in the area of crack and shrinkage monitoring, and have attracted wide interest in recent years. Cutting force measurement is one of the most commonly employed methods for on-line tool and work piece state monitoring, especially in turning because cutting force values are more sensitive to tool and work piece wear than other measurements such as vibration or acoustic emission. In recent years, intelligent control systems such as, genetic algorithm, fuzzy logic, artificial neural network and hybrid of these methods (fuzzy-neuron) are popular **(Xiaoli 2000)**. Conventional methods are mathematical model based systems, so it is difficult to take the machining parameter into account in such models. But artificial intelligence based methods are less dependent on the machine parameters.

MONITORING STAGES:

The classification of work piece and tool wear is a complex task because wear introduces very small changes in a process with a very wide dynamic range. Furthermore, it is difficult to identify whether a change in a signal is caused by wear or a change in the cutting conditions. The task of wear monitoring can be subdivided into a number of stages (Rueben 1998):

- Sensor selection and deployment.
- Generation of a set of features indicative of wear condition.
- Classification of the collected and processed information as to determine the amount of wear.

Sensors used in Monitoring Systems:

The sensors used for monitoring tool conditions can be divided into Two categories: direct and indirect. Despite their high accuracy, direct sensors are rarely used in real-time industrial applications because of their high cost and difficulty of installation also the direct measurements are not possible in many instances such as drilling and milling. Further, such measurements in most cases involve interruption of the machining process. On the other hand, indirect sensors, which are relatively economical and small, can be used for on-line crack and shrinkage detection if a certain relationship between sensor signals and tool-wear status can be established. A variety of indirect sensing methods have been applied to crack monitoring studies, including cutting force signal detection, cutting temperature detection, electrical resistance measurement, cutting vibration detection, measurement of AE (Kandilli 2003) and electrical signals like spindle motor current and power are also useful sources of information about tool states.

Wavelet Transform in Monitoring Process:

Signal processing is a very important step for (TCM). Recently, wavelet transform has provided a significant new technique in signal processing, because it offers solution in the time-frequency domain and is able to extract more information in the time domain at different frequency band. There have been many research activities in the application WT for tool condition monitoring (Scheffer 2001)

- It uses wavelet transform to decompose measured signals. Acoustic emission signal and RMS value of decomposed signals are taken as tool wear monitoring features.
- It uses wavelet transform to analyze cutting force signals and wavelet transform coefficients are taken as recognition parameters of crack.

Neural Networks in Monitoring Process:

In recent past, neural network models which employ cutting forces for estimation as well as classification of wear have been developed. The present work outlines a neural networks based modular tool condition monitoring system for crack and shrinkage classification. A multi layer neural network structure was used and data set has been trained off-line using SOM algorithm. An important variation in mean, RMS, standard deviation of cutting forces and vibration can result in estimation and classification error.

MONITORING PROCESS STAGES:

Work –Piece and Cutting Tool Materials:

Cemented carbide is composed of carbides tungsten, titanium and tantalum with some percentage of cobalt. The chemical composition of work–piece material are given in **Table** (1) **.**

Table (1) chemical composition of cast Iron work piece .

C%	Mn%	Si%	P%	S%	Cr%	Ni%	M%	Fe
3.31	0.72	3.09	0.65	0.13	0.081	0.062	0.038	balance

Cutting Tool Wear Measurement:

After switching off the turning machine the cutting tool wear measured through the microscope. The process of measuring (sensors signal and cutting tool wear) was repeated for other W.P. that have the same dimensions until the wear level reach the maximum (0.3)mm , the cutting condition of the machine were then changed , and the process was repeated . For each of the above tests, strain and vibration data were obtained in order to be used in wear classification by neural network techniques.

- ♦ Carbide tools: roughing = 0.8 mm.
- ♦ Carbide tools: finishing = 0.35 down to 0.15 mm.

Instrument Used in Monitoring Process:

Different instruments are used for different monitoring process depending on the variable to be measured. In the present work (a piezoelectric strain sensor Model 740B02 used to measure the strain at the tool holder and this gives an indication of cutting force applied to the cutting tool , signal conditioner for strain sensor is used for amplifying and analyzing signals , Accelerometer sensor is used to measure the vibration at the tool holder , The power amplifier is used to amplify the accelerometer signal , Data Acquisition Card type PCI-9111 , used for signal analysis application and process control , Microscope used in the measurement of tool wear , Interface between the instrument and the turning machine) .
The system ready to measure the data , from the turning machine as shown in **Fig** (1) .

Experimental Design of Monitoring Processes:

A set of tool wear cutting data were acquired by machining a bar of Cast Iron under a given set of cutting conditions with a coated cemented carbide tip **Table (2)**. The set of sensors used, were an accelerometer for measuring vertical vibrations, piezoelectric strain sensor on tool holder for force measurement as a strain, in order to find the amount of crack compared with the amount of strain and vibration signal. The specification of the instruments used, listed in **Table** (3)

Table (2): Experimental parameters used in the monitoring process

Components	Description
Lathe	HARRISON 15"
Work piece	Cast iron shaft (D:70mm L:270mm)
Holder type	Sandvik SDJCR 2020K11
Insert type	Carbide tips sintered square SNMG 12041 pattern TP15
Feed rate	0.078 -0.23 mm/rev
Cutting speed	105-165m/min
Depth of cut	1 mm

Table (3) Instruments used in the monitoring process

Sensor	Description	Mounting
Piezoelectric strain sensor	PCB model 740B02	On tool holder
Accelerometer	Type 4370	On tool holder
Signal conditioner	Type PCB 480E09	
Power amplifier	Type 2626	
Data acquisition card	PCI 9111DG	In computer board
Software program	Math lab V6.5	

The turning operation was carried out using (HARRISON 15”) turning machine. The experimental set-up and instrumentation are shown in **Fig (1)**. Most previous work interested in monitoring process for crack found the sampling rate at 10 KS/s enough to represent the analogue signal for cutting force. In this work the analogue signals were sampled with an Ampilicon PCI 9111DR data- acquisition board at a sample rate of 10K Hz per channel for a time period of 25.6 ms, number of samples reading through each stage are 12800 sampling pear channel. Data were acquired at intervals between (1.5~3.5) min depending on cutting conditions at which point crack was also measured, taking into account tool life inserts. The total number of tests is 2 each having different cutting conditions (to construct test and conformation sets). Each data record, of 12800 points acquired at the end of the cut, was processed to generate features used in the classification stage. Each feature vectors were extracted from time domain, wavelet domain, frequency domain, and model domain of all sensors. These features were then passed directly to the neural networks for classification (Silva 2000), with the training data coming from selected tests and the testing data used being from tests that were not used during the training phase. The cutting conditions used during the training experiment see in **Table** (4).

Table (4) Cutting conditions used in machining experiment .

Test No	Diameter of shaft (mm)	Cutting speed m/min	Feed mm/rev	Depth of cut DOC (mm)	Wear land (mm)	Number of components	Tool life for each test (min)
1	58	136.6	0.23	1	0.033-0.21	13	17
2	70	116.5	0.17	1	0.002-0.44	6	13

Test (1 and 2) with constant DOC .

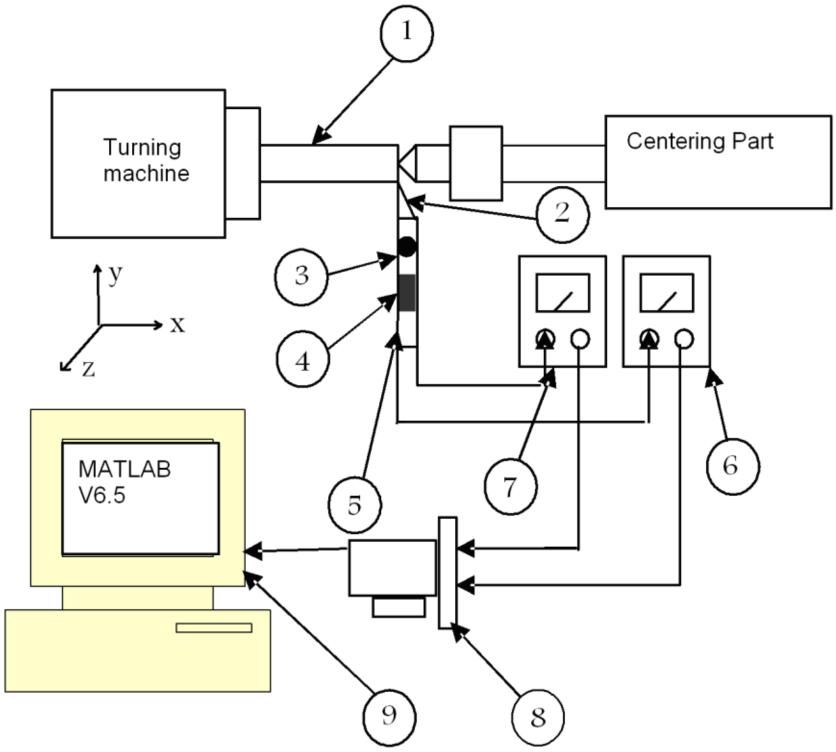


Fig (1) Experimental set-up and Instrumentation

1. Cast iron shaft with dimension (D:70 mm, L:270mm)
2. Square carbide tool
3. Accelerometer
4. Strain sensor
5. Tool holder
6. Power amplifier type 2626
7. Signal conditioner type PCB 480E02
8. DAQ card type 9111DR installed in PC board
9. PC P4 installed MATLAB program

Programming of Monitoring Process :

The flow chart of the programming process is shown in **Fig.(2).**

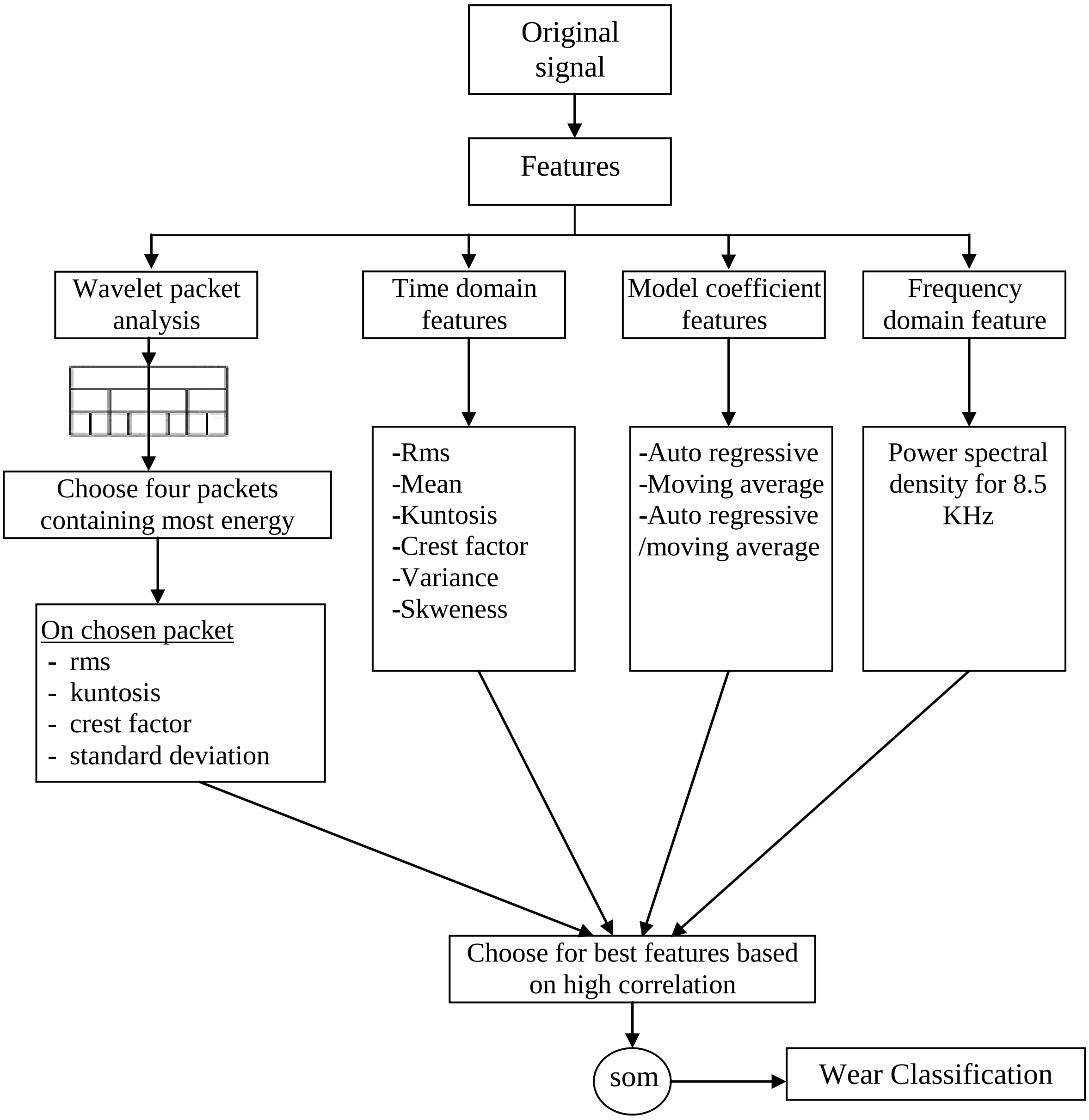


Fig (2) flow chart of the programming process .

Feature Extraction

To increase the reliability of the tool wear monitoring system, in the presented work a monitoring strategy was devised that is based on four type of feature:

- Time and modeling domain feature
- Frequency domain feature
- Wavelet packet analysis feature

The Features of the Time and Modeling Domain:

We can use some time – domain features as descriptors of crack and shrinkage **(Nadgir 2000)**, therefore, the following time-domain features were extracted from each signal: mean, rms, crest factor, standard deviation, skewness and kurtosis. A brief mathematical description of each is given as follows:

1- mean: the mean value of a function x(t) over an interval N is

$$\overline{X} = \frac{1}{N}\sum_{i=1}^{i=N} xi \qquad (1)$$

2- standard deviation (б) :

$$\sigma = \frac{1}{N}\sum_{i=1}^{i=N}[xi-\overline{x}]^2 \qquad (2)$$

3- root mean square (rms) : the rms value Xrms of a function x(t) over an interval of N is :

$$X_{rms} = \sqrt{\frac{1}{N}\sum_{i=0}^{i=N}(x_i)^2} \qquad (3)$$

4- the crest factor CF: is the ratio of the peak level(Xmax) to the RMS level (Xrms)

$$CF = \frac{\text{Xmax}}{\text{Xrms}} \qquad (4)$$

5- the skewness S : is the third statistical moment of a distribution :

$$S = \frac{1}{N\sigma^3}\sum_{i=0}^{i=N}(x_i)^3 \qquad (5)$$

6- the kurtosis K : is the fourth statistical moment of distribution :

$$K = \frac{1}{N\sigma^4}\sum_{i=0}^{i=N}(x_i)^4 \qquad (6)$$

Time-series models of the sensor signals are constructed and the model coefficients are used as features indicative of crack **(Kuo 1999, Ravindra 1997 and Obikawa 1996)**. This is because the model coefficients represent the characteristic behavior of the signal. Depending on the order of the model, a number of model coefficients can be chosen. Normally, only the first model coefficient, or sometimes the first three to four model coefficients are chosen, because they are most descriptive of the signal characteristics of interest. In this case coefficients from (AR) models were considered. A brief discussion of these models follows **(Rueben 1998).**

In a pth-order AR model for a time series x (n), where n is the discrete time index, the current value of the measurement is expressed

as a linear combination of p previous values:

x(n)= a1 x(n-1)+ a2 x(n-2)+……….ap x(n-p) (7)

Where a1, a2, a3… ap are the AR coefficients. The first AR coefficient was chosen as a feature.

Frequency Domain Feature:

The most common frequency domain characteristic in the literature is the spectral energy around the first natural frequency of the tool-work piece system **(Rueben 1998)**. It was established that the fundamental natural frequency for this system lies at about 8.5 kHz. The spectral energy at 8.5 KHz was taken as a feature.

$$\psi_{xb}^{2} = \int_{fl}^{fh} S_X(f)df \qquad (8)$$

With $S_x(f)$ the one-sided PSD function and fl and fh the lower and upper frequencies chosen to reflect the energy in the region of interest.

Wavelet Packet Analysis Feature

The wavelet transform is a relatively new method of signal processing that has been applied to many engineering studies with great success. Fairly recent studies also proved that wavelet analysis could be utilized for monitoring of the machining process **(Jiang 1987)**. The success of the wavelet transform is generally attributed to the natural shape of the wavelet, which is more descriptive of most natural processes than the sine function used in Fourier analysis. Wavelet analysis is capable of revealing aspects of data that other signal analysis techniques miss, like trends, breakdown points, discontinuities in higher derivatives, and self-similarity. In this instance, wavelet packet analysis was used to generate features that may show consistent trends towards tool and work piece wear. Like other wavelet analysis techniques such as (DWT), wavelet packet analysis also requires the construction of a wavelet decomposition tree. Each packet in the decomposition tree contains information on the original signal in the form of wavelet coefficients. The original signal can be reconstructed using any chosen number of the packets on the tree. However, the normal practice is to choose the packets containing the most information on the original signal, and then discarding the packets containing noise or less important information. Usually, an energy-based approach is used to choose the optimal packets. The Shannon entropy formula was used, see equation (9), which is a non-normalized entropy involving the logarithm of the squared value of each signal sample or, more formally **(Obikawa 1996)**,

$$E = -\sum_i S_i^2 \log(S_i^2 \qquad (9)$$

Where *E* is the Shannon entropy and *Si* is the signal sample at instant *i*.

In this study, the method requires that a reliable wavelet packet analysis be established for the given signal. The reliability of the wavelet packet analysis can be investigated in a number of ways, such as assessing the cross-correlation, rms error and cross-coherence between the original signal and the reconstructed signal. A number of packets containing the most energy representative of the original signal must then be chosen. The order of the decomposition tree will determine the maximum number of representative packets that may be chosen.

Wear classification using neural network (SOM):

The self-organizing maps, developed by Kohonen **(Kohonen 1998)**, is a fairly new and effective software crack for data analysis. The SOM has been implemented successfully in numerous applications, in fields such as process analysis, machine perception, control and communication **(Surender 1994)**. The SOM implements the orderly mapping of high-dimensional data onto a regular low-dimensional grid. Thereby the SOM is able to identify hidden relationships between high-dimensional data into simple geometric relationships that can be displayed on a simple figure. The SOM can generally be described as a neutral network with self-organizing capabilities. Most neural networks require information and interaction from the user for classification. Although the SOM was intended as a data visualization tool, it can be used for classification as well. The SOM automatically arranges the data on a two-dimensional grid of neurons where similar observations are placed close to one another and dissimilar ones further away. If the classes of some of the observations are known, certain regions on the grid could be allocated for these classes. The computation of the SOM is a non-parametric, recursive regression process. The incremental-learning SOM algorithm can be described briefly as follows: Regression of an ordered set of model (initialization) vectors mi Є □□Rn into the space of observation vectors xi Є □□Rn is often made by the following processes:

$$m_i(t + 1) = m_i(t) + h_{c(x),i}(x(t) – m_i(t)) \qquad (10)$$

Where t is the index of the regression step, and the regression is performed recursively for each presentation of a sample of x, denoted x (t). The scalar multiplier $h_{c(x),i}$ is called the neighborhoods function, which causes similar observations to be placed in the same region on the map. Its first subscript c = c(x) is defined by the condition

$$\forall_{I,} \ \left\| x(t) - m_c(t) \right\| \le \left\| x(t) - m_i(t) \right\| \qquad (11)$$

which means that mc (t) is the model that matches best with x(t). The neighborhoods function is often taken as the Gaussian function. Note that a batch version of algorithm exist which is computationally much faster.

RESULT AND DISCUSSIONS

Flank Wear Accursed in Machine Cutting Tool due to Crack

The sudden flank wear for tests (1) are shown in **Fig** (3). Certain features of flank wear are identified, first an extreme condition of flank wear often appears on the cutting edge at locations corresponding to the original surface of the work piece it is called (notch wear) .It is accrue because the original work surface is harder and more abrasive than the internal material due to sand particles in the surface from casting or other reason. As a consequence of the harder surface, wear is accelerated at this location. At this level of the tool wears, when the machining process continue the fracture was increased, very high noise appeared and surface roughness of the work piece became very bad **(Surender 1994)**.

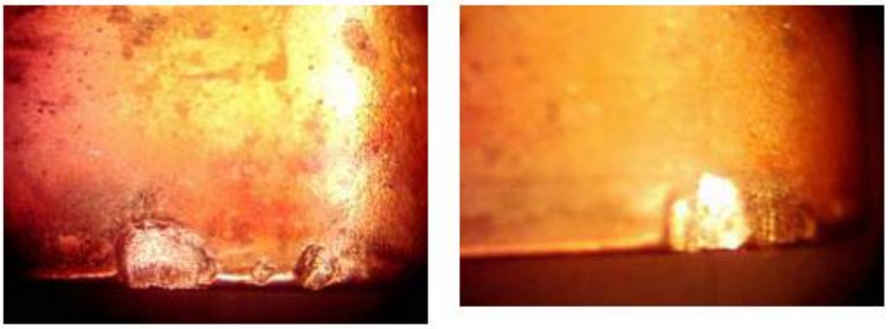


Fig (3) sudden wear at cutting tool due to presenting crack in work piece , wear land (0.33 - 0.2)mm (test1).

Effect of Cutting Condition Tool Life :-

Table (4) represent test with constant D.O.C and different cutting conditions , gave loot life of (13 , 17) min respectively . from these tests it could be seen the tool life decrease with decrease in cutting speed and feed rate . It is occur because the original work surface crack and harder particles in the surface . As a consequence of crack or hard particles , wear is accelerated at this location .

Properties of Signals in Tool Condition Monitoring:

In the metal cutting, the signal from (strain and vibration) sensor is a transient energy spontaneously released in material undergoing deformation or fracture or both. At microscopic level, signal is related to grain size ,dislocation density ,and distribution of the second-phase particles crystal-line form **(Kannatey 1982)** .The signals from (strain and vibration) sensor generator during cutting operation are non stationary and may pass a different magnitude , damping ,frequency and phase **(Stern 1971 and Du 1991)**.

Fig (4) shows the sample of signals for (strain and vibration) sensor. The signal generated from the data sample at 25600 Hz at 1 second contains 25600 data point, for both strain and vibration signal from a turning operation. The continuation of the signal is contributed for by deformation of work piece material at shear zones, the friction at tool work piece and chip –tool contact regions. In **Fig (5)** the approximately constant amplitude signal that run throughout the record, constitute the continuous part of the signals. Superimposed on the continuous part, the transient part of the signal is generated by micro-cracks of the crystal structure of work piece material, nonhomogeneity of work piece material and chip breakage. The high amplitude short –duration signals that appears in all figures are the transient parts of the signal **(Kamarthi 1997)**.

The signal generated from a machining process fundamentally depends on properties of tool and work piece materials applied stress, strain rate and material volume involved in the deformation process. In cutting process, the signal form the function between the tool and

work piece can be distinguished from the signals generated by the chip-breakage and the material deformation process at the share zones this can be shown in **Fig (5)**, where the chip-breakage generated no uniform signal while the material deformation zone make the signal be approximately stable and this can be shown clearly in the feature curves because the chip breakage make the curve flow up or down instantaneously.

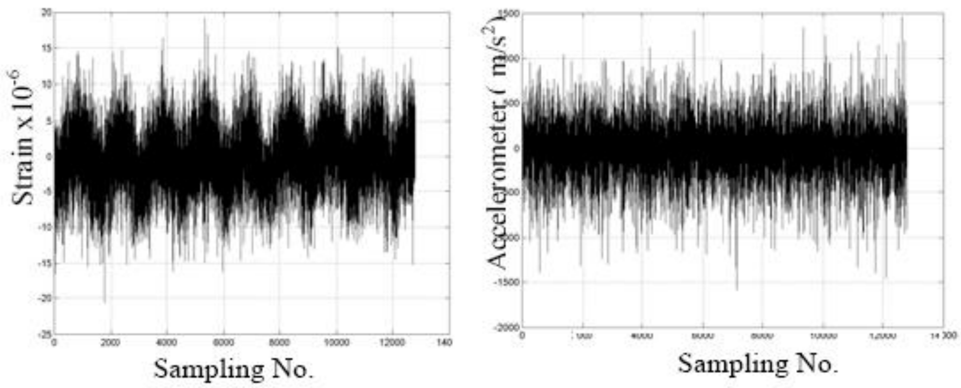


Fig (4) Samples of vibration and strain signals

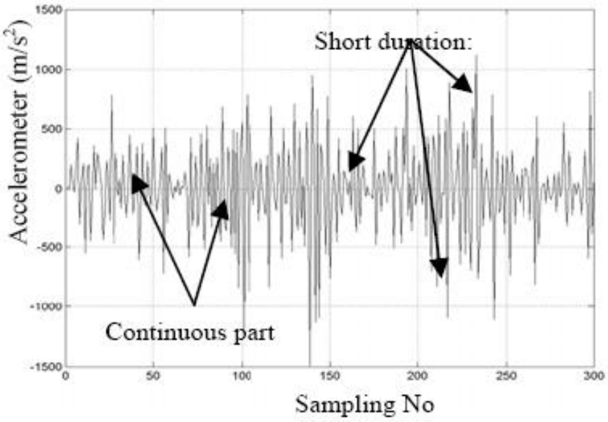
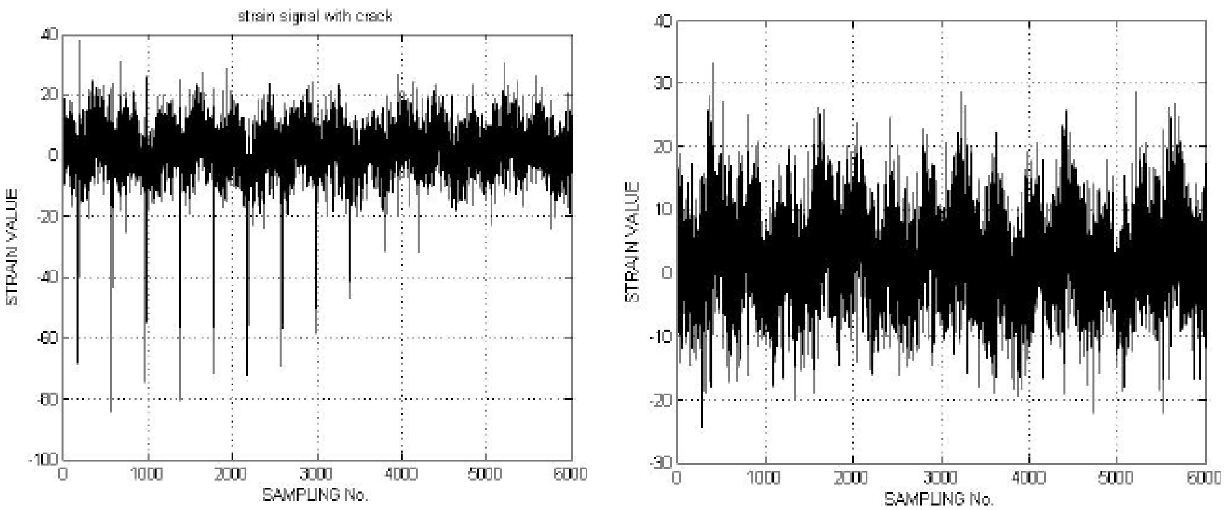


Fig (5) vibration signals for 300 sampling no.

Strain Signals Measured During the Tests and It's Effect of Crack

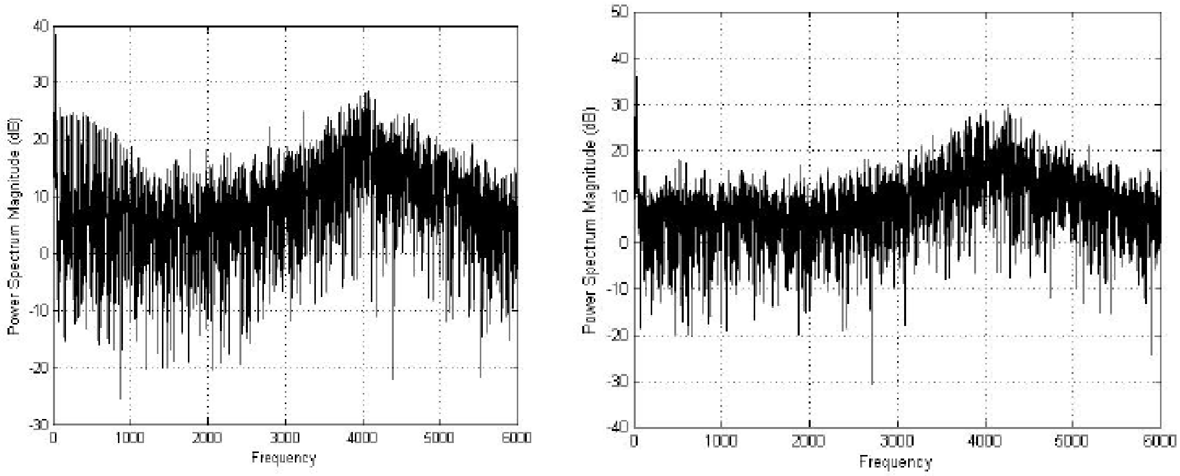
As the signal spectral is sensitive to tool wear and tool fracture, it is possible to use signal for tool condition monitoring, the strain signal as shown in **Fig (4)** is basically sinusoidal in nature. During the course of their propagation, they often undergo considerable changes to scattering by structural defects, multiple reflect at interface and refraction where there is a medium change along the travel path **(Kamarthi 1997)**. **Fig (6)** which show the strain signal measured for cutting tool in test 1 with cutting speed 136.6 mm/sec and feed 0.23 mm/rev when the crack appear on the work piece. Fig(6a) shown clearly that the strain signal have an greatest effect when the crack accurse , where the signal have an negative shoot at the lower frequency of the signal between (1000-3000) Hz. Fig (6b) shows the same signal when the is no crack accursed in work piece where there is no negative shoot in the strain signal. **Fig (7)** shows the power spectral density for the same which shown the signal have a high constricted at the lower frequency when the crack at the work-piece accursed. This produce an indication that when the crack appeared in the work piece the strain signal have an negative shoot indication at the lower frequency of the signal



(a) (b)

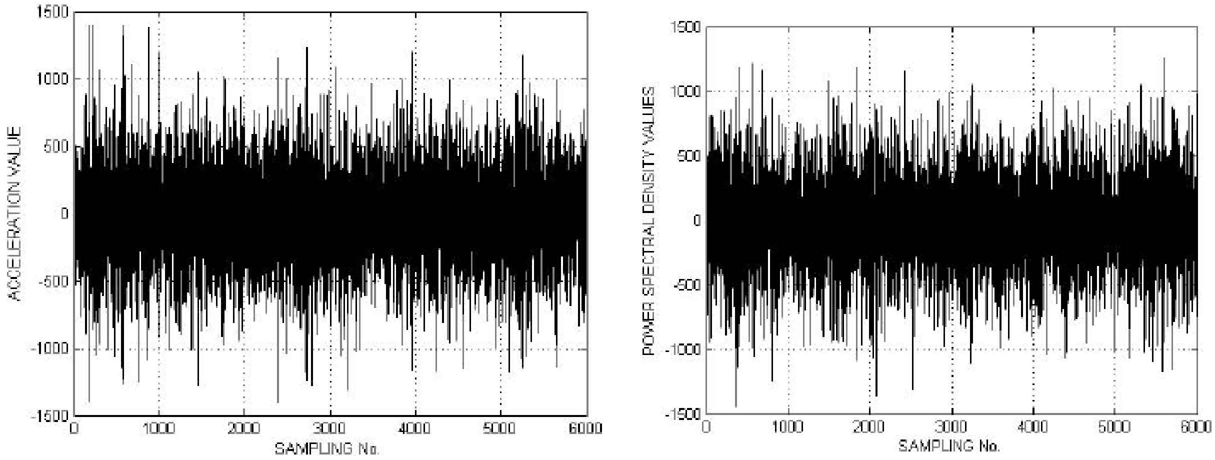
Fig(6) a: strain signal with crack

b: strain signal without crack.



(a) **(b)**

Fig (7) a: PSD for strain signal with crack
b: PSD for strain signal without crack.

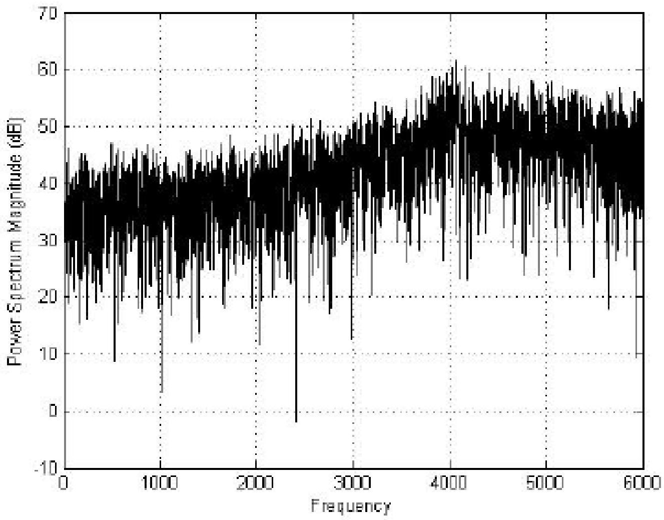


(a) **(b)**

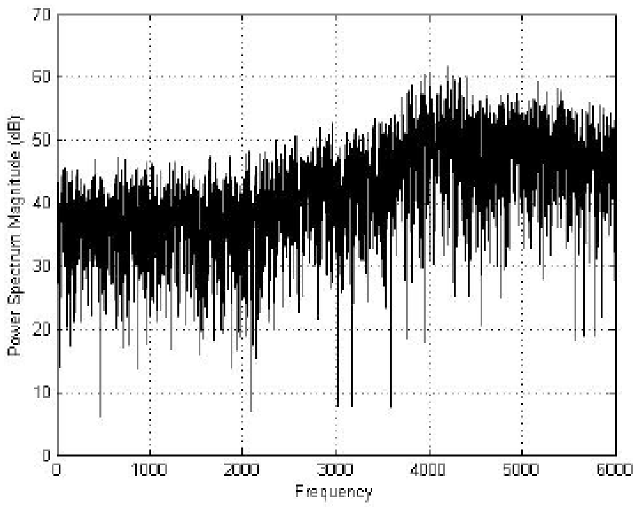
Fig (8) a: vibration signal with crack
b: vibration signal without crack.

Vibration Signals Measured During the Tests and Its Effect of Crack

The vibration signal has a high effect on strain signal during the machining process. As can be show in **Fig (8a)** where the crack appear at the work piece and compare the result with **Fig (8b)** where the crack are not appear we can found there is no trend of vibration signal at the crack of the work piece, this is because the vibration signal result from many external recourses such as gear of cutting machine and other dynamic influence which make the lower frequency not sensitive at the crack in work piece. Also **Fig (9)** which shows the PSD for the vibration signal in both state not give any pure indication towered the crack.



(a)



(b)

Fig (9) a: PSD for vibration signal with crack
b: PSD for vibration signal without crack.

Crack Effects at the Feature Extracted Form Measured Signal

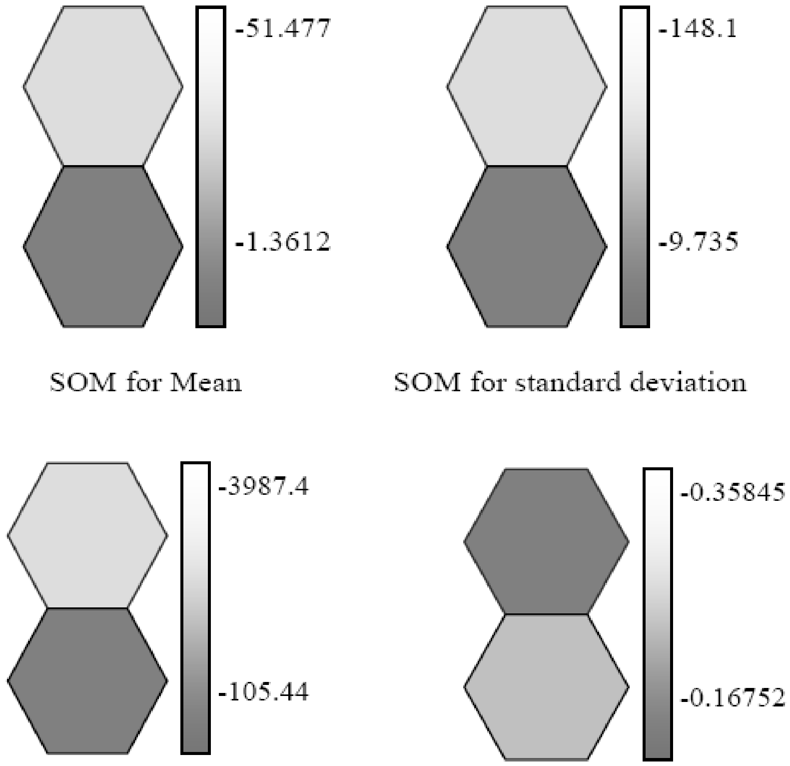
All the feature which are extracted from the measured signals and used to recognized the effect of crack at the strain and vibration signal can be shown in **Table (5)**. When analyzing these feature it can be found that the strain feature has a greatest trend toward crack than the vibration signal. Other that there is a feature has good trend towered crack that others. The time features for strain signal such as (mean, STD, RMS) given a good indication toward crack where it's values when the crack found lower than when the crack disappear. Wavelet packet analysis feature have good indication for crack, such as wavelet packet for (STD, S, K, RMS). In wavelet packet we know it's divide the signal in lower and highest frequency and then select the lower frequency which give good indication for the signal behavior, so in this work we choose the wavelet packet (1 and 3) to represent the effect of crack in wavelet packet domain, in modeling domain feature the auto regressive have good indication towered crack where it's value where the crack happened lower than when the crack disappear. All features for strain signal have the same behavior for crack which it's value with presented the shrinkage and crack are lower than it's value when the crack disappear. For the vibration signal all the feature have lower trend toward crack where it's values with present crack approximately the same without present the crack.

Table (5) features values for strain and vibration signal measured during machining process

features	Strain signal with crack	Strain signal without crack	Vibration signal with crack	Vibration signal without crack
Mean	1.3612	51.477	2.5952	2.8035
STD	9.735	148.1	358.33	351.06
RMS	105.44	3987.4	201.02	217.16
CF	0.35845	0.16752	6.9225	5.801
S	1.0934e+013	8.4593e+013	2.2063e+007	1.1244e+008
K	4.41e+018	6.7478e+019	1.1244e+011	9.8614e+011
WS1	10.146	109.39	175.79	170.09
WS2	9.2921	178.53	475.17	466.55
WS3	13.143	123.92	127.55	129.63
WS4	5.6827	92.217	213.85	202.49
WR1	75.119	2825.5	143.29	154.36
WR2	2.242	87.388	532.37	447.43
WR3	53.92	2007	103.16	109.8
WR4	2.7417	6.0201	46.03	109.99
W1CF	0.31056	0.15768	4.744	5.3746
W2CF	14.862	8.0926	3.238	3.5868
W3CF	0.4681	0.22931	5.193	4.2721
W4CF	15.186	55.881	14.407	6.3551
WK1	2.0635e+062	9.964e+063	1.188e+062	1.3137e+064
WK2	9.9748e+069	3.6012e+065	4.1267e+062	9.5615e+062
WK3	4.1267e+062	1.4139e+064	7.2489e+067	1.866e+062
WK4	1.0767e+064	1.0638e+060	4.6772e+058	5.4921e+062
A(2)	-0.089601	0.37441	0.79146	0.80926

Self Organizing Map for Neural Network:

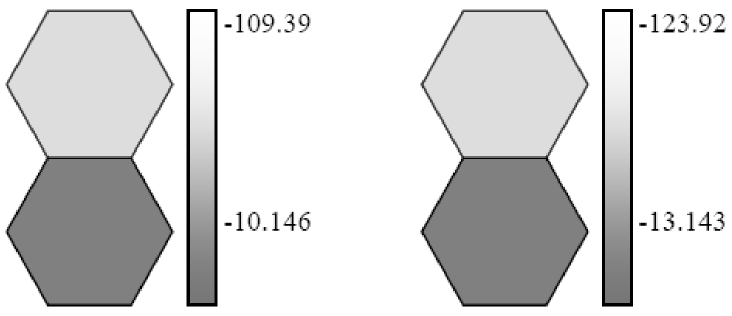
The selected features from the two learning data sets were used to train (2 x 1) SOM with 10000 epoches. **Figs (10-12)** show the feature of SOM neural network for test 1. The SOM layer for specific feature represent the behavior of that feature curve, there is a two specific layer for crack state. The reason why only a small number of neurons are used is because it makes classification easier (although less flexible). In this case, one neuron is used to correspond to no crack present and one neuron refers to crack presented see **Fig (13)**. When more neurons are used in the network, the regions corresponding to a certain classification become larger, and classification becomes more flexible, because when we increase the number of layer in the output the range of each feature to have a specific layer will decrease so the layer have an precise specific feature. For each of the selected features, a (2 x 1) representative SOM for test 1 can be shown in **Figs (10 - 12)**. It is important to note that although a SOM for each feature is available, the SOM is actually a single entity. A view on a selected feature is only the view in the direction of that dimension. The SOM can represent multidimensional data in this manner. This is illustrated in **Figs (10-12)**, where all the selected variables are shown on a single graph. When color coded, such a figure can display how the values of the features correspond among one another. The observations in the (testing) data set were labeled (no crack) and (crack), corresponding to the number of machined components (work piece used in machining process). The best matching units for these data were looked up on the SOM. As shown in **Fig (13)**, it is clear that neurons 1 correspond to a no crack present and neuron 2 to a rack present. The figures show a SOM layer which distributed corresponding to the best matching units of the test data. It is clear that the trajectory moves in time from the (without crack) to the (crack).



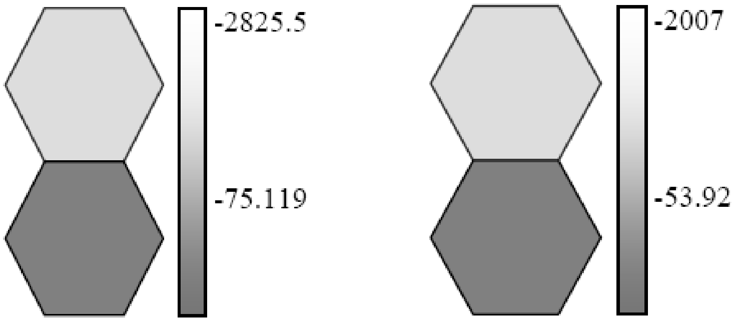
SOM for Mean SOM for standard deviation

SOM for root mean square SOM for crest factor

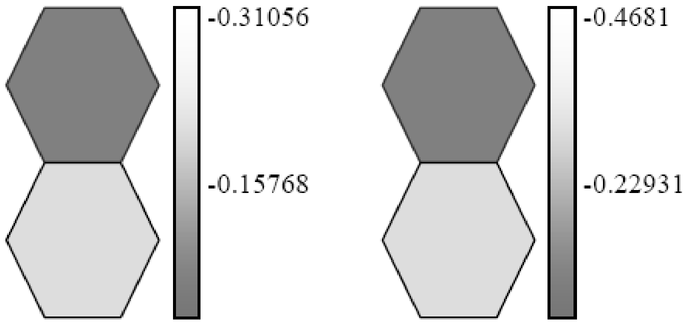
Fig (10) SOM for time domain feature for strain signal test (1).



SOM for STD for Wavelet packet (1) SOM for STD for Wavelet packet (3)



SOM for RMS for Wavelet packet (1)   SOM for RMS for Wavelet packet (3)



SOM for CF for Wavelet packet (1)   SOM for CF for Wavelet packet (3)

Fig (11) SOM for wavelet packet analysis features for strain signal test (1).

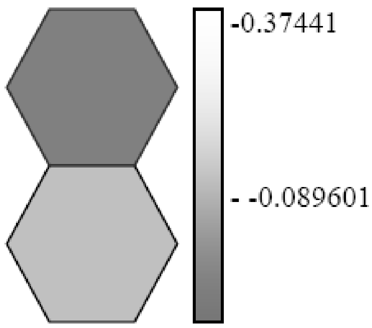


Fig (12) SOM for Auto regressive at strain signal for test (1).

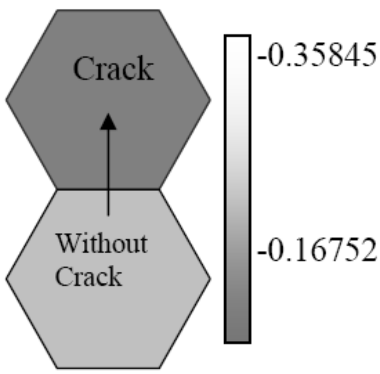


Fig (13) SOM for Crest Factor at strain signal for test (1) with label.

CONCLUSIONS

1- The monitoring system can extract and select features quickly enough to enable the manufacturer to implement an on-line monitoring system.

2- The result we showed that vibration signal has a lower trend toward crack than a strain signal during a machining process.

3- Most features give approximately a behavior toward crack, that when the crack present the features vales became lower values than when the crack not present.

4- RMS, STD, mean, PSD for 8.5 KHz, wavelet features for packet (3), it gives a better indication of tool wear than other features.

5- When using SOM neural network a best correct classification of the tool can be obtained.

6- There are a cutting condition (feed rate & cutting speed)with constant depth of cut in machining process , which give good indication result for tool life and number of work – piece (with and without crack) used.

7- A vibration signal has a high effect on strain signal during a machining process.

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Notification:

A	cross section area of shaft.(mm2)	N	Number of sampling
Ac	alternative current.(A)	n1	Net input in neural network
A/D	analogue to digital converter	Pc	personal computer
AE	acoustic emission	PSD	power spectral density
AR	auto regressive	R	input vector
ARMA	auto regressive moving average		
ANN	adaptive neural network	RMS	Root mean square
Rn	end condition parameter	S	Skew ness function
BPNN	Back propagation neural network		
C	SOM function	SOM	Self organizing map
Cf	crest factor	SOMF	Self organizing map function
DAQ	Data Acquisition Card	T	Time (sec.)
DSPT	Digital signal processing transformer		
DWT	Discrete wavelet transform	TCM	Tool condition monitoring
F	feed rate (mm/min)		
f	frequency function	VB	Vibration signal
(n)	wavelet function	X	Mean value
h(n)	wavelet function		
ICP	Integrate circuit programming		

I.D.D Independent Identification Distribution
K kurtosis function
L length shaft
MA Moving average