International Journal of Automotive and Mechanical Engineering (IJAME)
ISSN: 2229-8649 (Print); ISSN: 2180-1606 (Online);
Volume 13, Issue 3 pp. 3584 - 3598, December 2016

DOI: https://doi.org/10.15282/ijame.13.3.2016.5.0295

Fatigue damage monitoring using un-supervised clustering method of acoustic emission signal on SAE 1045 steel

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ABSTRACT

This paper described the capability of acoustic emission (AE) technique in monitoring the fatigue damage level using unsupervised clustering technique. As fatigue damage is being a major contributing factor to component failure, it is essential to evaluate the level of damage caused by fatigue load in order to prevent the catastrophic failure of the structure. It is a concern in this study to differentiate the AE signals according to the fatigue damage stages by implementing an unsupervised clustering technique. In this study, the AE signals were collected on specimens made of medium carbon steel SAE 1045 that underwent the axial fatigue testing. The test was run at three loading values of 600, 640 and 680 MPa. The pattern behaviour of AE signals was recorded using a piezoelectric sensor in a form of time domain history signal. Later, the AE signals collected were analysed and clustered using K-means technique. Five clusters of *K1*, *K2*, *K3*, *K4*, and *K5* have been found for the specimens subjected to stress value of 600-680 MPa. The optimum numbers of *K* clusters were determined using the smallest objective function in their group which ranges between 2.6 to 3.0. This pilot investigation shows that it may be useful to estimate the remaining life for a component before it fails.

Keywords: AE; clustering; fatigue; K-means and medium carbon steel.

INTRODUCTION

Acoustic emission (AE) technique has a capability of detecting high frequency wave ranging of 20 KHz-2 MHz deep inside the material. At very high frequency, AE can detect the incipient damage that just happens in the material [1] . AE technique is part of non-destructive technique (NDT) which can evaluate the damage without disturbing the machine operation. The progression of fatigue crack in aluminium specimen monitored using AE shows that this technique is suitable for monitoring the crack growth in the material [2]. AE offers promising NDT technique as it can offer on-line inspection of the running structures or components which cannot be offered by other methods. Therefore, the application of this technique is quite popular to detect and monitor failures on steel bridges, pressure vessel, pipelines, boiler etc [3].

The engineering components are exposed to fatigue failure that occurs suddenly before maintenance could be carried out. Even at very low stress, the cyclic load will contribute the fatigue to occur and break the component without any warning. Many research has been conduct to detect, monitor, as well as to predict the fatigue life of mechanical structures or components [4]. It covers all types of materials such as steel, aluminium, composites, as well as biomaterial metallic [5]. Apart of many techniques such as locating the strain gauge at the expected crack sources, dye penetrating, and ultrasonic and the finite element analysis [6, 7], the AE technique also has been widely used in evaluating the fatigue damage mechanism. It can locate the crack location, monitor the crack propagation, and come up with a solution to predict the fatigue life [8]. Comparing to other non-destructive testing technoques (NDT), AE is favourable as it can detect in-situ damage and the monitoring can be done while the component or structure is running. Recently, a group of researchers used AE signal to evaluate the fracture resistance in an endodontically treated tooth and short glass fibre reinforced (SGFR) under the fatigue testing by AE monitoring technique [9]. Similarly, a group of researchers that found the AE technique can predict the remaining life of composite structures under fatigue loading [10]. In addition, other novel work has been carried out to detect the fatigue crack propagation on the reinforced masonry walls [11], as well as to monitor the fatigue damage for carbon fibre reinforced concrete [12]. As for steel, AE technique has been used to characterise the fatigue crack growth of RAFM steel latest in 2016 [13]. Other than that, the application of AE has been also applied to the aluminium alloys [2], various types of composites [14] and bio-medical implants [15].

As AE signals are huge noisy data produced during the fatigue test, it is essential to differentiate between the real data or the noise coming from the machine or environment during the test. Although the chances to eliminate the noise have been done during setting up the threshold value, there might be a slim chance that the unwanted noise still encounter in the signals collected during the test by the specimen slippage, hydraulic error, or machine start/stop. To minimise the problem, the pattern recognition approach such as clustering (unsupervised classification) and classification (supervised) method can be used to classify and group the useful AE data to whatever basic parameter desired. For supervised (classification), either the parametric model or model of the data that is known while in clustering (unsupervised classification), the labels of input pattern are unknown and the classifier needs to determine the cluster structure. In AE application, this technique is widely used to monitor and group the damage level of a component. Principle component analysis (PCA), K-means, and artificial neural network (ANN) are the most favourable techniques used in clustering and classification the AE data [16]. Unsupervised pattern recognition using Mahalanobis-like distance method was used to successfully classify the damage level of the polymer-composite that experiences the fatigue test through the AE technique [17]. In other research, the unsupervised classification i.e., Principle component analysis (PCA) and K-means has been used to identify the source mechanism involved at high temperature of ceramic matric composites (CMC) during the fatigue test [18]. Besides that, the unsupervised AE data clustering using PCA and fuzzy c-means clustering has been used to tackle out the analysis of damage mechanisms in glass/polyester composites. The researchers conclude that this method provides an effective tool to discriminate the damage mechanism of the material [19].

From the previous study, it seems that composite is the favourable materials that have been chosen to be analysed via pattern recognition methods. Therefore, the present study uses the unsupervised clustering method in analysing the AE data. The aim of this work is to enhance the capability of the method to steel component that is used widely in automobile as well as pipes industries. The group or clusters that will contribute through the AE data, taken from the cyclic fatigue test, will establish the baseline data for preventive maintenance to avoid sudden breakdown while the component in operation. The results obtained may guide to a comprehensive research to predict the fatigue life of the material.

METHODS AND MATERIALS

K-means clustering method

The K-means technique was used to cluster and group the signals to determine the damage severity of the specimen. In K-means, the continuous reassignment of objects is performed until different cluster (*K* cluster) is determined. The distance within the cluster is minimised and the centroid of every cluster is determined. Using the iterative algorithm, the minimum sum of point-to-centroid distances over the entire *K* cluster was determined [20]. Eq. (1) shows the formula for the objective functions for K-means:

$$J_h = \sum_{j=1}^{k} \sum_{i}^{c} \left\| x_i^{(j)} - c_j \right\|^2 \tag{1}$$

where $\left\| x_i^{(j)} - c_j \right\|^2$ is the distance between point $x_i^{(j)}$ and the means of point c_j .

K-means has been used widely in assessing and monitoring many types of mechanical failure in components as well as mechanical structures. K-means has been used by Moevus et al. [21] to differentiate the damage mechanism of matrix cracking of SiCf/[Si-B-C] composites that exhibit different tensile behaviours using AE signals. Other research using K-means technique to identify the fretting fatigue crack propagation also has been using the AE approach [22].

Experimental Set up

The AE signals were collected during the axial fatigue test. Both tensile and fatigue tests were run according to respective ASTM standards that will be mentioned in next section. Basic parameters of AE such as rise time and amplitude were extracted from the signals and used as the input parameter for the clustering method (Figure 1).

Specimen Preparation

The material used in this research is the SAE 1045 medium carbon steel. Table 1 shows the typical chemical composition of this material [23]. It has been chosen due to its availability and a wide range of application such as automotive, power plants, and piping system. Due to its high carbon content, this type of steel also can be employed as a replacement for tool steels in structural application [24]. The material has been cut to a flat specimen according to ASTM E8 standard, as the geometry shown in Figure 2 (a and b). Following the ASTM E3-11 standard, the specimens has been polished using several grades (400, 800, 1000, 1200, and 2000) of silicon carbide abrasives papers to produce the mirror-like surface finish before the specimens undergo both the tensile and cyclic fatigue test as shows in Figure 3 (c and d). This aims to ensure that the surface scales left as well as the residual stress caused by the machining process are removed [25].

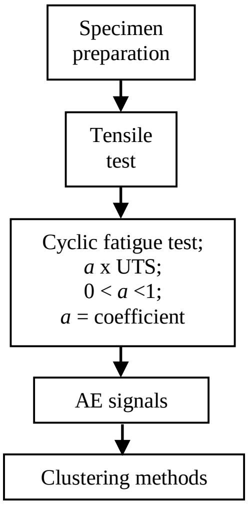
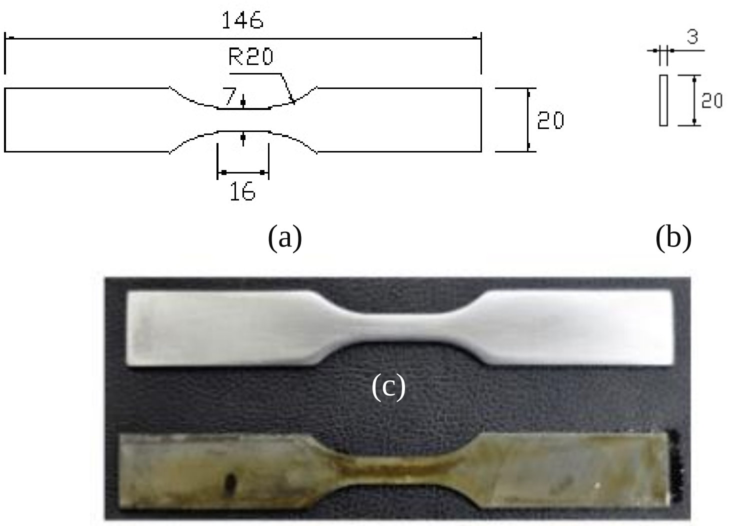


Figure 1. Process flow throughout the research.



(d)

Figure 2. Geometry (unit in mm) and image of specimen images (a) top view; (b) side view; (c) after; (d) before polishing process.

Table 1. Chemical composition of carbon steel 1045 (wt%) [44].

C	Mn	Si	P	S	Fe
0.43	0.52	0.11	<0.02	0.011	Balance

Testing procedure

The tensile test was carried out to get the monotonic properties of the material such as the ultimate tensile strength (σ_u), yield stress (σ_y), and Young modulus (E). The test was performed according to the ASTM E8 standard using the 100 kN universal testing machine (UTM) at the cross-speed rate of 1.2 mm/min. The ultimate tensile strength acquired from the test will be the input stress for the cyclic test. The cyclic test was performed at 75 %, 80 %, and 85 % of the σ_u value. The cyclic test was performed according to ASTM 466-96; *Standard Practice for Conducting Force Controlled*

Constant Amplitude Axial Fatigue Tests of Metallic Materials procedure using the 25 kN table top servo hydraulic machine as shown in Figure 3. The hydraulic machine was controlled and calibrated by the *Instron WaveGuide Matrix Software* before the tests were run. The specimens were controlled by the displacement of the specimens that has been setup in the program. It has been run using the stress ratio, R = -1. During the test, a piezoelectric sensor has been attached to collect the AE signals.

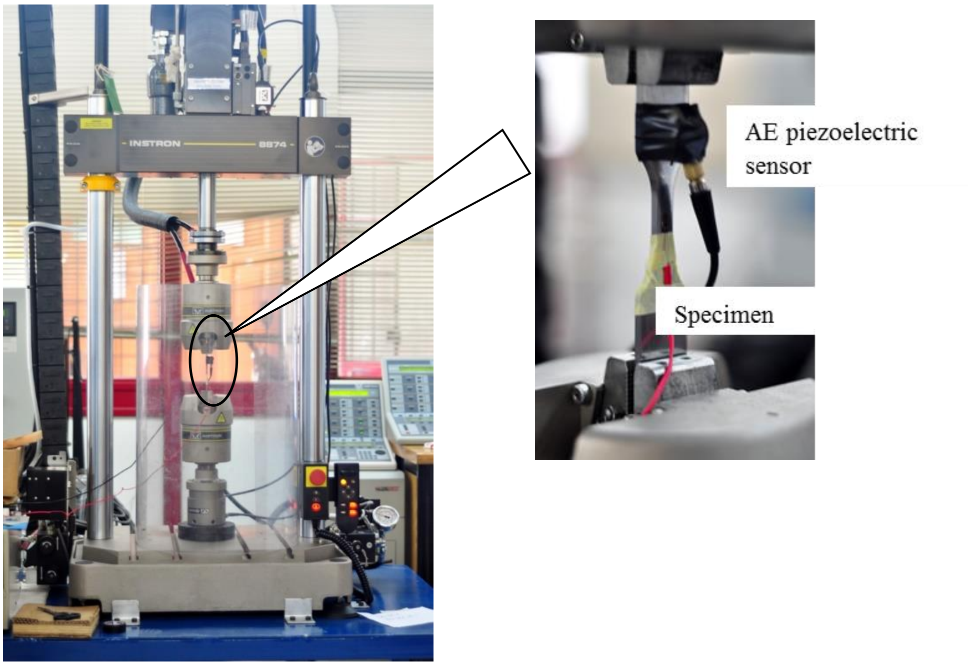


Figure 3. Axial fatigue test set-up (a) 25 kN servo hydraulic machine, (b) Location of AE piezoelectric sensor on the specimen during the fatigue test.

AE Data Acquisition Procedure

In this study, a four channel of Vallen Systeme data acquisition system with the sampling frequency of 5000 kHz and 40 dB pre-amplification were used to record the signals. The piezoelectric sensor of range 100-2000 kHz was attached using silicon grease on the specimen during the test to collect the AE signals. The sampling frequency needs to be greater than twice of the sensor capabilities to avoid signal distortion called alias [26]. Before each test, the pencil lead procedure was carried out to calibrate the data acquisition system in order to estimate the attenuation and the velocity of the signal, as well as to make sure that the sensor was attached correctly [27].

Signal Analysis

The typical AE signal has some descriptors known as amplitude, rise time, duration, counts, and energy, while the entire signal in one activity is called an event. Only the amplitude is measured real time by the data acquisition system, whereas the other descriptors are defined from the waveform and threshold dependent. In this research the feature extraction of AE signal that has been used is the rise time and amplitude, since these parameters have been used widely in assessing the material damage [21]. Figure 4 shows the flowchart of K-means algorithm.

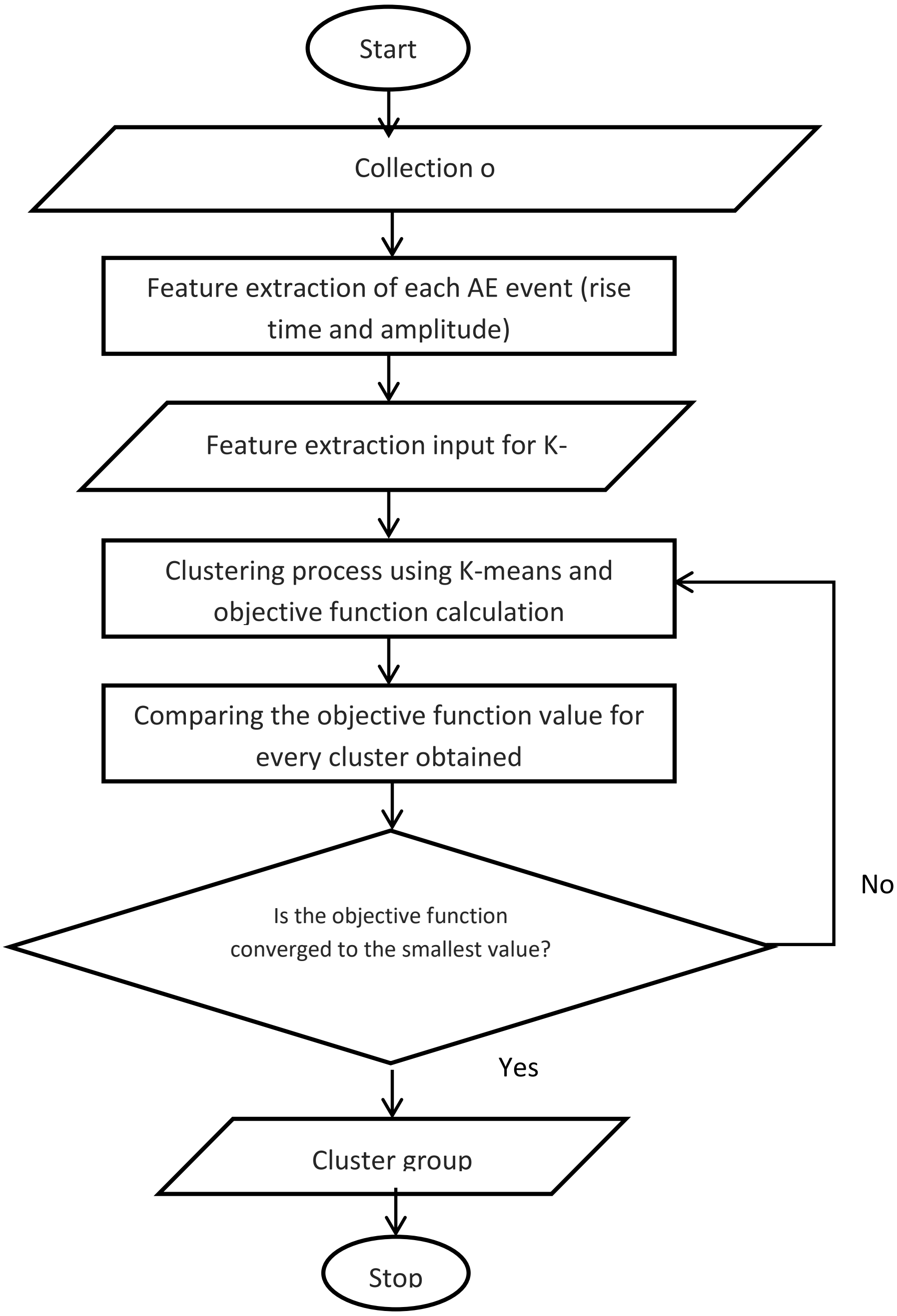


Figure 4. Flowchart for K-means clustering technique

RESULTS AND DISCUSSION

The specimens made of SAE 1045 carbon steel underwent the tensile test to get the monotonic properties of the material as shown in Figure 5. The values from the curve were then tabulated in Table 2. The ultimate tensile strength, σ_u of this material is 798 MPa with 414 MPa of yield stress and 196 GPa of Young modulus. As mentioned in the earlier section, the input values of stresses for the cyclic fatigue test were based from the value of the σ_u.. Table 3 shows the stress values to be used in the cyclic test. It shows that, the test was carried out at three different loading conditions i.e.; 600 MPa, 640 MPa, and 680 MPa where it is at 75 % σ_u, 80 % σ_u and 85 % σ_u respectively. The loading was selected based on the machine capability and the failure period of the specimens. Pilot test on the specimen and machine shows that applied stress more than 680 MPa will vibrate the machine, while applied stress below 600 MPa will take more than one day for the specimen to break.

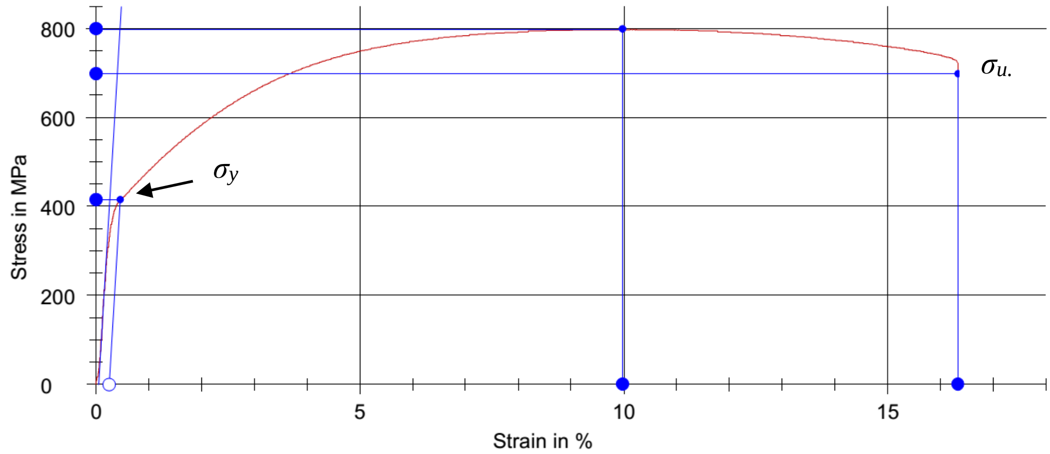


Figure 5. The stress-strain (σ-ε) curve for SAE 1045 at room temperature.

Table 2. Monotonic properties for SAE 1045.

Properties	Value
Ultimate Tensile Stress, σ_u	798 MPa
Yield Stress, σ_y	414 MPa
Young Modulus, E	196 GPa

Table 3. Applied stress for the cyclic test.

Percentage of σ_u (%)	Stress Value
70	600 MPa
80	640 MPa
85	680 MPa

The overall AE events for three different stress values are shown in Figure 6 (a, b, and c). The signals were collected throughout the test until the specimen fracture. Every dot in the event is called a hit. Every hit has its own waveform and characterised by their own descriptors as shown in Figure 6 (d). Many research used AE basic descriptors in their analysis. A group of researchers monitored of crack propagation in the pressure vessel, where they used the counts, duration, amplitude, and rise time to detect various stages of damage of heat affected zone (HAZ) and welded steel [28]. Latest, all the basic descriptors ie., hit, count, rise time, and amplitude were used to localise and identify the fatigue matrix cracking and delamination in the carbon fibre panel [29]. In this work, amplitude and rise time were used as the feature extraction for every signal.

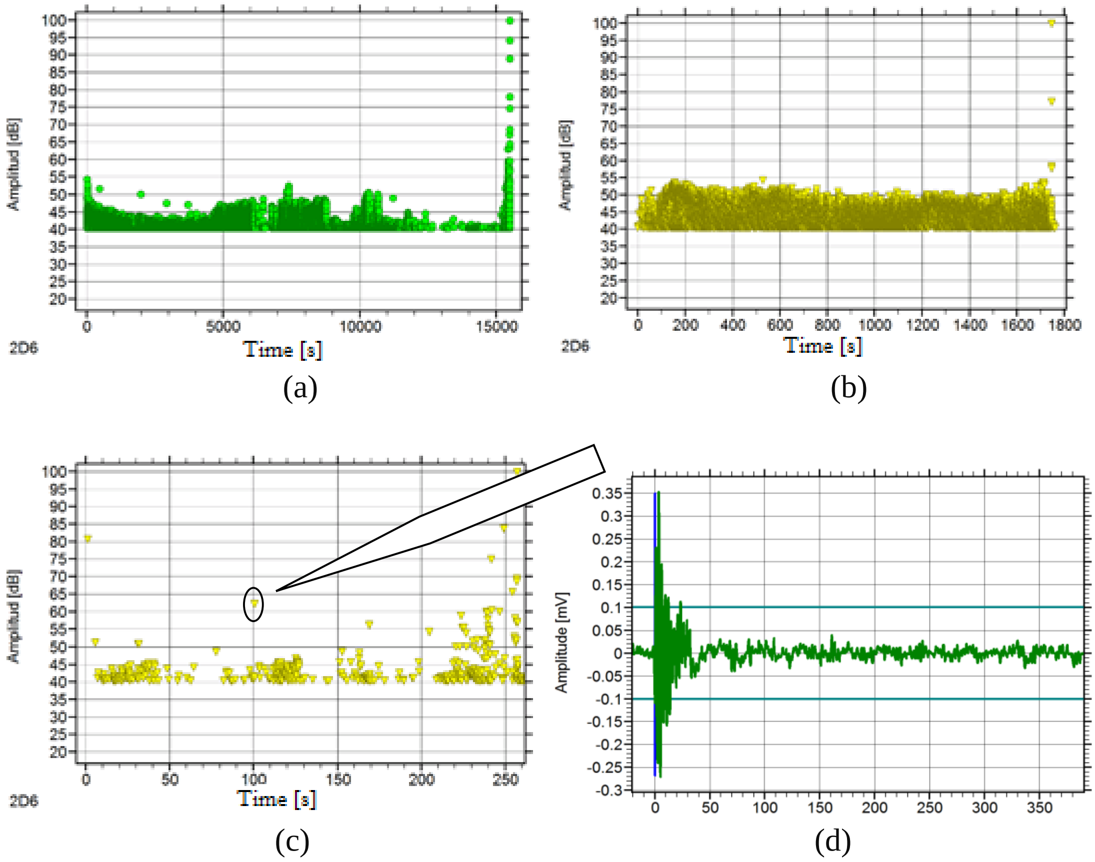
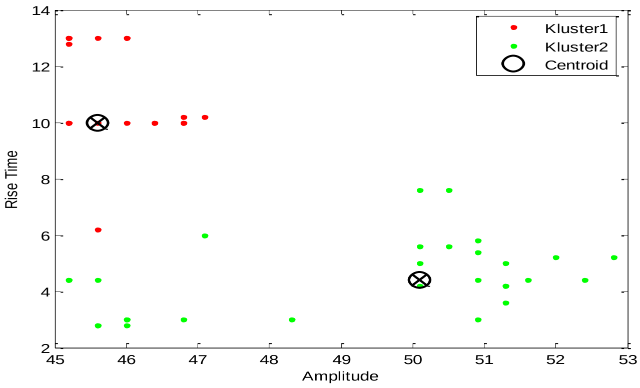
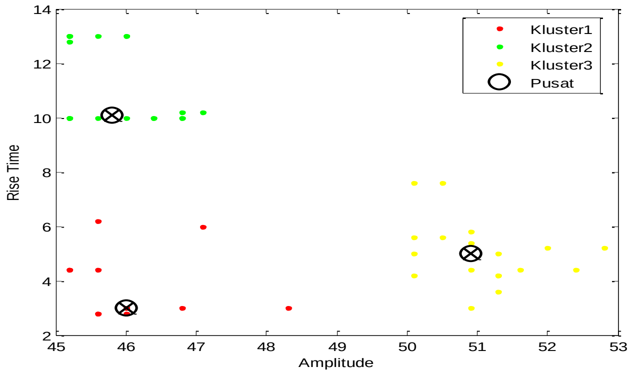


Figure 6. Original time history AE event at (a) 600 MPa; (b) 640 MPa; (c) 680 MPa; (d) a typical burst waveform of an AE hit at high amplitude hit

The amplitude and rise time of the hits were extracted from the AE event to be the input value in the clustering process. In AE application, clustering analysis has been used widely to differentiate the damage level in a material. K-means clustering technique has been used to identify the damage mechanism under fatigue loading condition on an E-glass/epoxy laminates [30]. Meanwhile, fuzzy C-means clustering associated with principle component analysis (PCA) has been used to correlate the damage mechanism of the polymer – based composite materials [27]. In this research, the K-means clustering analysis was used to show the damage level experience by the specimens. Figure 7 shows the K-means centroid of rise time and amplitude for stress loading of 600 MPa. In this work, every cluster shows the scatter pattern of data consisting of two-centroid cluster until five-centroid cluster. Clusters in every set of data were determined based on the centroid calculated. Every set of data will be run from two-centroid cluster to five centroid cluster. Figure 7(a) shows only two-centroid cluster. It is a very weak cluster as it can be seen that all the maximum and minimum values of data are mixed because the centroid points were used randomly [31]. Then, three-centroid and four-centroid clusters were run and the cluster is scattered in Figure 7 (b) and (c). As for three-centroid, a yellow cluster was formed but the data were still split with a range of distance. Moreover, the four-centroid cluster looks more convincing as data were closed to the centroid accordingly. Some data were found as outlier in this cluster and this means that the cluster is not optimum enough to represent the whole data.



(a)



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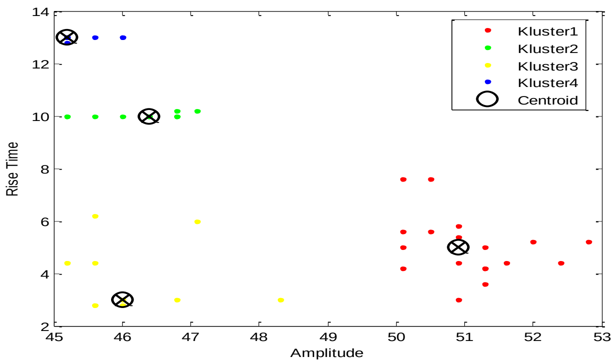

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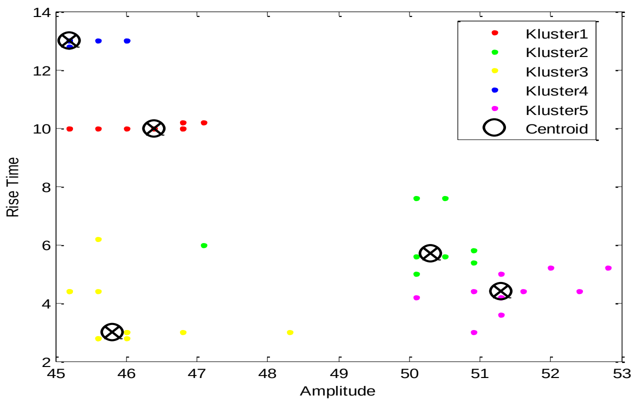


(d)

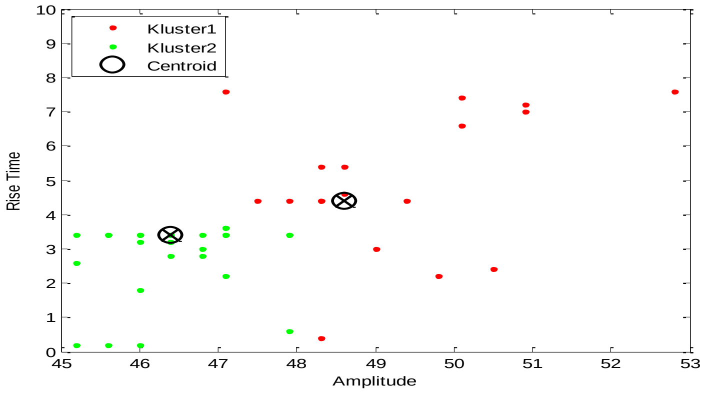
Figure 7. The K-means cluster for data 600 MPa (a) two-centroi; (b) three-centroid; (c) four-centroid; (d) five-centroid

In fatigue an outlier data cannot be ignored as it may represent a negative effect of overall data [32]. The five-centroid cluster was shows that the data were nicely grouped according to the nearest centroid. Some of the outliers found their own cluster. The data were clustered accordingly to the value of the rise time and amplitude. In this case cluster five can be the fracture stage as the amplitude of the signals was high. In AE, when the specimens were about to break or fail, the rise time became very short with high amplitude magnitude. It is also shown in some other researchers' studies that carried out the fatigue test to laminate material [30].

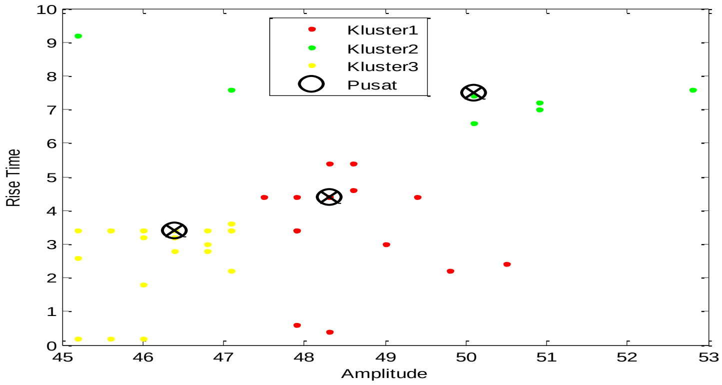
Figure 8 shows the clusters built for specimen that was given 640 MPa stress load. As before, the two-centroid cluster contains mixed data. Three-centroid cluster seems to have too many outliers that can be grouped to another cluster. The best cluster is with five-centroid that is split between lower and higher amplitude data corresponding to their own rise time value. In this case the breaking part happens in cluster one with the one in red colour. Data with high amplitude definitely show that the cluster is approaching the fracture stage, but in this case the rise time value is also high. According to some reseachers, the AE activity in intergranullar will increase during the fracture stage [33]. The cluster for specimen at 680 MPa is shown in Figure 9, in which the best cluster is five-centroid cluster. Cluster five in pink is the fracture stage of the specimen with high amplitude and low rise time, similar to what has been found for specimen that has given 600 MPa stress load. The data scattered nearby the centroid show the closeness between the data and centroid. From this analysis, the failure of this material can be predicted by the grouping or cluster found for every stress given to the component. To make sure that the cluster has been assigned correctly for every case of data, the objective function needs to be determined. Objective function is the average distance between data points in the entire centroid cluster. For instance, the objective function for all data has been tabulated in Table 4, where the smallest objective function has been circled for all data groups. All data show that the minimum value of objective function is found at the cluster five or five-centroid cluster. It also means that when more clusters are created in the signal, the data distributions are more focused on the centroid and automatically decrease the distance to the centroid. Other than that, smaller numbers of objective function show that the data are closer to the centroid. To determine the optimum numbers of clusters in the data, the lowest value of objective function has to be achieved [20].

Table 4. Objective function values.

Cluster group	Value of objective function 600 MPa	640 MPa	680 MPa
K=2	4.2	4.4	4.4
K=3	4.0	4.0	3.4
K=4	3.6	4.0	3.3
K=5	2.6	3.2	3.0



(a)



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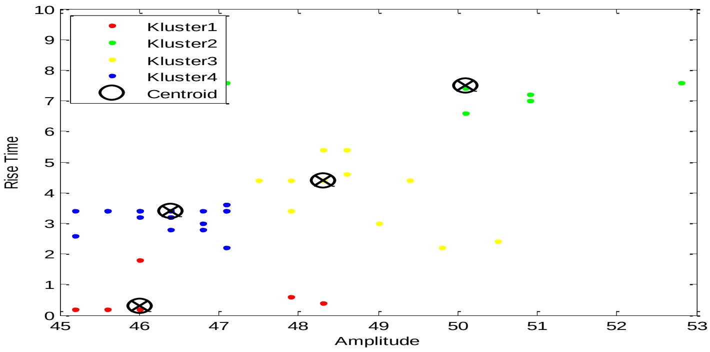

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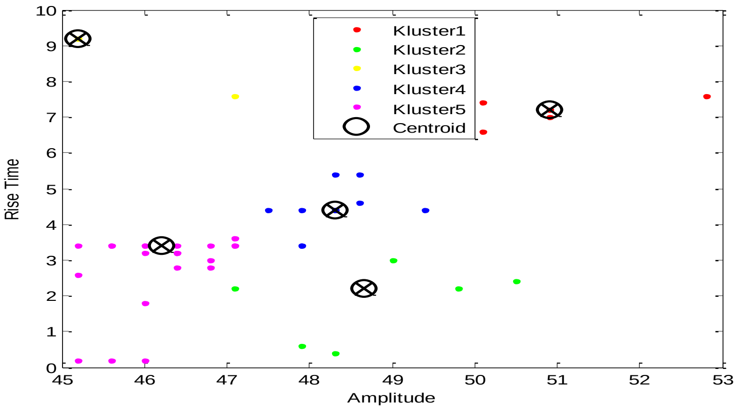

(d)

Figure 8. The K-means cluster for data 640 MPa (a) two-centroid; (b) three-centroid; (c) four-centroid; (d) five-centroid.

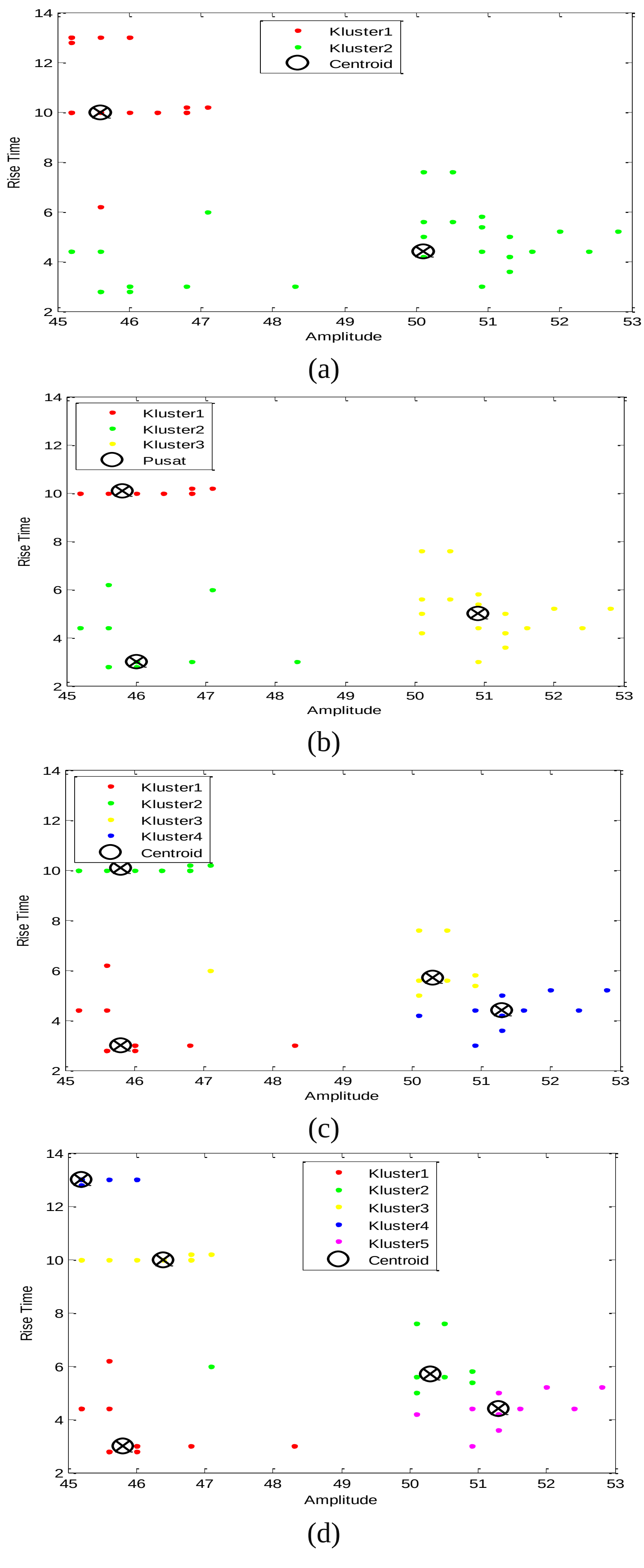

Figure 9. The K-means cluster for data 680 MPa (a) two-centroid; (b) three-centroid; (c) four-centroid; (d) five-centroid

CONCLUSIONS

The behaviour of AE signals under fatigue damage condition can be monitored and clustered using the K-means analysis in this paper. By using the K-Means clustering analysis plots, the grouping of the damage level experienced by the specimen was done based on the number of centroid points. For specimens that experienced stress levels at 600, 640, and 680 MPa, the best clusters were found for five centroid points with the smallest objection function value of 2.6, 3.2, and 3.0 for 600, 640, and 680 MPa respectively. From this analysis, the failure can be predicted using the clusters or groups that have been assigned to every case. Thus, it can be a good benchmark in designing a structure using this type of material to prevent sudden breakdown from happening.

ACKNOWLEDGMENTS

The author gratefully acknowledges funding by Universiti Teknologi MARA (UiTM), Malaysia, especially from the Geran Dana Pembudayaan Penyelidikan (RAGS/1/2015/TK0/UITM/03/7).

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