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ACOUSTIC EMISSION PARAMETERS EVALUATION IN MACHINERY CONDITION MONITORING BY USING THE CONCEPT OF MULTIVARIATE ANALYSIS

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ABSTRACT

The use of acoustic emission (AE) signal in machinery condition has considerable interest due to AE signal characteristics that can refer to machine condition. However, selecting correct AE parameters playing a pivotal role in machinery condition monitoring. This study proposed a methodology of selecting the best parameters of AE based on multivariate analysis of variance (MANOVA) method. The study aiming at monitoring or modeling enhancement by quantitatively measuring the divergence of AE parameters acquired from 72 operational conditions of industrial reciprocating compressor. In this case, nine out of thirteen AE parameters are selected as the most sensitive parameter to the compressor operational conditions according to MANOVA eta squared (η^2). Eventually, the authors believe that using this method can enhance the monitoring or modelling using AE parameter in the field of machinery condition monitoring.

Keywords: acoustic emission, condition monitoring, reciprocating compressor, multivariate analysis of variance.

INTRODUCTION

The use of AE technology in machinery condition monitoring and fault diagnosisis becoming one of the essential tools in this fielddue to the unique features of AE, which can supply valuable information about the energy sources inside the machine. As a result, AE technology features have been studied, reviewed and well-documented by many researchers (Steel and Reuben 2005, Al-Obaidi, Leong *et al.* 2012, Ali, Rahman *et al.* 2014). Acoustic emission refers to the generation of transient elastic waves produced by a rapid release of energy from a localized source within and/or on the surface of a material according to the definition by the American Society for Testing and Materials (ASTM) (Vahaviolos 1999). In this paper, AE is defined as transient elastic waves produced by the impact of one surface to another in a reciprocating motion. In other words, AE is the transient elastic waves produced by the impingement of the reeds inside the valve with the upper and lower valve housing during the reciprocating compressor operation.

Despite acoustic emissionbeingone of the most recent entries in the field of nondestructive evaluation, AE has rapidly developed and is now used in machinery condition monitoring and fault detection. In the literature, many researchers have reported investigations of the viability of AE as a diagnostic and prognostic tool (Shuib Husin and Hamzah 2010, Ali, Omar *et al.* 2014). The seed defect sizes on a rolling bearing have been estimated by establishing a relationship between the AE signal parameters and the defect size (Al-Dossary, Hamzah *et al.* 2006, Al-Ghamd and Mba 2006, Al-Dossary, Hamzah *et al.* 2009). Seal and blade rubbing has been detected via on line monitoring using AE technology in power turbines (Mba and Hall 2002, Leahy, Mba *et al.* 2006). El-Ghamry *et al.* (El-Ghamry, Reuben *et al.* 2003) developed a statistical feature isolation technique for the diagnosis of faults in reciprocating machines using the AE signal. The technique was used to a selected time window for the AE signal to identify machine faults. It was concluded that this methodology could be applied to the monitoring of many types of reciprocating machines and deferent faults using a variety of sensor data. Valve leakage was detected during reciprocating compressor operation (Gill, Brown *et al.* 1998), and the valve leakage amount was estimated using AE(Kaewwaewnoi, Prateepasen *et al.* 2010). Detection of valve clearance using AE technology was investigated by Elamin *et al.* (Elamin, Fan *et al.* 2010), who foundthat AE is a powerful and reliable method of detection and diagnosis of diesel engines valve faults. Recently Yuefei *et al.* (Wang, Xue *et al.* 2015) presented a methodology for reciprocating compressor valve fault detection by integrating the AE signal with the simulated valve motion. The method could differentiate between the suction and discharge signals, and the proposed method could distinguish between the valve normal condition and a set of valve faults.

Although the previously mentioned studies reported good detection methods for reciprocating compressor valve faults, these methods are still limited in their capabilities, and none of these methods can offer a single comprehensive methodology that can detect, locate, diagnose and estimate the valve faults. In addition, most of these methods ignored the statistical investigation for the acquired data.

This paper investigates the effect of different test-rig operational condition on the main AE parameters value. In addition, the effect of different valve faults with different level of severity on the AE parameters. The main reason for this investigation is to justify that any changing in speeds, flow rate, valve type and valve condition at the test-rig can effect significantly on the AE parameters. Multivariate analysis of variance (MANOVA) with significant level equal to 0.05 was employed to evaluate the main effect of AE parameters versus the change in the test conditions. Thus, according to the MANOVA the most sensitive AE parameterswere selected for further analysis.

THEORETICAL BACKGROUND

AE parameters

Prior using AE method in faults diagnostic assignment or machine integrity assessment, it is necessary to understand the basic of AE signal parameters. Then only relationship between detected AE signal and machine actual condition can be formulated. Baisclly, an acquiredAE signal has special parameters which can describe the AE event. The main AE signal parameters consist ofrise time, duration, count, count to peak, amplitude, RMS, average signal level (ASL), signal strength, average frequency (AF), initial frequency (IF), revarbration frequency (RF), nergy and absolute energy(Grosse and Ohtsu 2008, Al-Obaidi, Leong *et al.* 2012).The hit count is the number oftimes a signal crosses a preset threshold. The rise time isthe interval between the first threshold crossings by the signal and the signal maximum amplitude. The duration is the period of time between the first and last threshold crossings by the AE signal. The hit amplitude is the greatest measured voltage in a waveform. The RMS is the square root of the mean of the squares of AE hits amplitude whilst the ASL is the average of AE signal amplitude. AE Energy is the measured area under the rectified signal envelope (MARSE), with units that usually rely on the AE data acquisition method. In this research, the energy is proportional to voltage and the duration of a signal (energy counts). Absolute energy is measuring the real amount of signal energy by (aJ) attojoule.

Frequency Indicators can be obtain from AE main parameters. Usually use when signal waveforms are practically difficult to be record [6]. These indicators can be determine from the main AE signal parameters by calculate the below equations:

$$\mathrm{AF\ (Hz)} = \frac{\mathrm{Count}}{\mathrm{Hit\ Duration}} \quad (1)$$

$$\mathrm{IF\ (Hz)} = \frac{\mathrm{Count\ to\ Peak}}{\mathrm{Rais\ Time}} \quad (2)$$

$$\mathrm{RF\ (Hz)} = \frac{\mathrm{Count} - \mathrm{Count\ to\ Peak}}{\mathrm{Duration} - \mathrm{Rais\ Time}} \quad (3)$$

These parameters can be related to the machine condition, thus, the interpretations of AE parameters consider a good indicator in condition monitoring and fault diagnoses(Al-Obaidi, Leong *et al.* 2012, Mukhopadhyay, Haneef *et al.* 2014). See Figure-1.

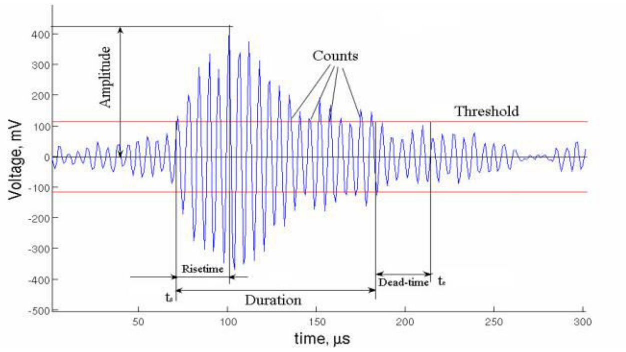

Figure-1. Acoustic emission parameters.

Multivariate analysis of variance

Multivariate analysis of variance (MANOVA) is a statistical technique which used to analyze the influence of qualitative factors on more than one quantitative variable simultaneously. MANOVA is frequently implemented in many statistical software such as MATLAB, Minitab and IBM SPSS software. The main purpose of using MANOVA is to test the research hypothesis and null hypothesis. In addition, MANOVA can test the amount of change (effect size) in each of the AE parameters according to partial eta squared (η^2).

The research hypothesis states that there is a significant difference in the variance of AE parameters when the operational conditions are change. In contrast, the null hypothesis states that there is no significant difference in the variance of AE parameters when operational conditions are changed(Hair, Black *et al.* 2006).

Thus, by performing MANOVA test, AE parameters can be evaluated with significant level equal to 0.05. According to MANOVAtest, the null hypothesis can be either rejected or accepted. Consequently, the most sensitive AE parameter will be determined according to the amount of change in etasquared (η^2). Thus, AE parameter with hight η^2 value will be consider for further analysis while the one with small change can be neglected. The partial eta squared (η^2 measuring the degree of association between the effect and the dependent variables(Brown 2008) as shown in Table-1.

Table-1. Partial eta square interpretation

Size of effect	Partial eta square(η^2)
Small	$0.01 \le \eta^2 < 0.06$
Medium	$0.06 \le \eta^2 < 0.14$
Large	$\eta^2 \ge 0.14$

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METHODOLOGY

Test rig and instrumentation setup

The test rig used in this study consists of a single stage, 2 cylinder, air-cooled industrial reciprocating air compressor (model: SWAN SVP-202) with a 1.5kW / 2 hp motor that can provide a maximum operational speed of 820rpm. A digital laser tachometer is configured and fixed with the test rig to receive a pulse from a piece of reflective tape attached to the flywheel to show the compressor cycle andto record the compressor speed.

The transducer used for AE data acquisition is a piezoelectric type AE sensor (Physical Acoustic Corporation type PKWDI) with an operating frequency range of 200 kHz - 850 kHz; the transducers were placed directly onto the discharge valve housing of the reciprocating compressor and held firmly to the surface by using super glue as an adhesive.

A single-channel AE data acquisition system (model: USB AE Node) with 18-bit resolution provides the full AE hit and time based features, including waveforms, was used for AE signal collection. The AE data acquisition is provided with special software known as AEwin™ for data analysis. The AE data acquisition setup is shown in Figure.2. The data acquisition card provided a sampling rate of up to 20 MHz and a dynamic range of more than 85 dB. In addition, programmable digital filters were built into the data acquisition card. A total of 1024 data points were recorded per acquisition (data file) at a sampling rates of 500 kHz.

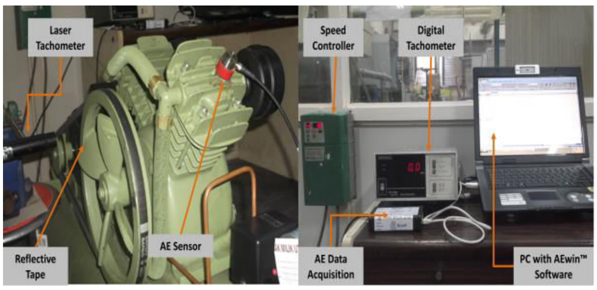

Figure-2. Test rig and data acquisition setup.

Experimental procedure

First of all, the AE baseline signal was recorded for 12 running conditions: four speeds (200, 400, 600 and 800rpm) and three flow rate conditions (0%, 50% and 100%). The speeds were controlled by the speed controller, while the flow rate was simulated by controlling the flow from the compressor outlet usung flow meter. Next, two valve defects; corrosion and clogged, of varying severities were simulated on the discharge and suction valve individually. The test configuration is described and detailed in Table-2.

In an attempt to understand how the valve defects influenced the AE parameters, an incremental procedure for simulating the defects was established. Thus, the simulation of both defects involved starting a sequence on a valve with simulating a small size defect and increasing the area of defect gradually to achieve the maximum size of the possible fault.

Table-2. Test configuration.

Speed		Flow rate	
Symbol	**RPM**	**Symbol**	**Percentage**
S1	200	F1	0%
S2	400	F2	50%
S3	600	F3	100%
S4	800		

The simulation of the corrosion defect involved making a hole with an oval shape; a similar way to the actual defect of the corrosion, using a drilling machine. Thus, five different size of corrosion were simulated. The smallest corrosion size had width of (3mm*10mm) which was labeled as (VSC). Then the size was increased to (7mm*15mm) which was the largest corrosion and labeled as (VC). The clogged defect was conducted by sealing some of the valve outlet holes using welding to emulate the condition of valve clogged due to excessive dirt or from the excessive oil distribution which can make the reed to be stick then to be clogged. The nomenclature used to label all test conditions is described in Table-3.

Experimental tests were performed by first producing the defects of the appropriate size and geometrical shape. After installing the faulty valve inside the compressor, the test rig was run at the first speed and flow rate condition. For accuracy reasons, the base line signal was repeated for 3 times while the faulty signal acquired only for one time due the nature of the fault. The AE data was recorded for 30 sec in each condition. Next, the test rig was shutdown, and then the reed was replaced to simulate another level of fault severity. Thus, the procedure for speed and flow rate was repeated, and then AE data were again recorded. A total of 120 tests were performed for this investigation, and the AE parameters were collected for further analysis using statistical software IBM SPSS (Ver21).

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Table-3. Types of defects and defects severities for suction and discharge valves.

Valve state	Defect type	Defect severity	Defect symbol	Defect ratio (%)
Healthy State	No Defect	Normal Condition	NC	0%
Faulty State	Corrosion Defect	Very Small Corrosion	VSC	15%
		Small Corrosion	SC	30%
		Medium Corrosion	MC	45%
		Large Corrosion	LC	60%
		Very large Corrosion	VLC	75%
	Clogged Defect	Moderate Clogged	MCL	40%
		Intense Clogged	ICL	80%

RESULTS AND CONCLUSIONS

Changes in AE parameters under different speed

The research hypothesis states that there is a significant difference in the variance of AE parameters when speed level is changed. In contrast, the null hypothesis states that there is no significant difference in the variance of AE parameters when speed is changed. Thus, MANOVA was performed to assess if there were differences between different speed level on a linear combination of AE parameters to evaluate the change. According to the result of MANOVA test, overall AE parameters were significantly changed under different speed levels (Wilk's Lambda = 0.069, F = 4682.372, $p < 0.01$, $\eta^2 = 0.591$). On the other hand, the main effects of speed on AE parameters were vary from parameter to another. According to (eta squared η^2) some parameters shoing a high influence and other show less. The effect of speed level on the AE parameters presented in Table-4.

The results of multivariate analysis also indicated that different speed levels are significantly affecting all AE parameters as all the P values are less than 0.05. This indicates that the linear composite of AE parameters is differs for different levels of speed; therefore, null hypothesis must be rejected and the hypothesis is true. However, the tests of between subjects effects table indicates that there are significant main effects of speed on AE parameters and it is vary from medium to large effect sizes according to(etasquaredη^2) accept for rise time, A-freq, R-freq and I-freq which observed to show a small effect size.

Table-4. Effects of AE parameters by speed.

Dependent variable	df	F-value	η^2	P-value
Rise Time	**3**	**1301.41***	**0.085**	**<0.01**
Counts	3	11351.4*	0.448	<0.01
Energy	3	41008.4*	0.746	<0.01
Duration	3	5393.7*	0.278	<0.01
Amplitude	3	959.50*	0.064	<0.01
Average Frequency	3	555.07*	0.038	<0.01
RMS	3	19278.7*	0.58	<0.01
ASL	3	7488.08*	0.349	<0.01
Count to Peak	3	3196.76*	0.186	<0.01
Reverberation Frequency	3	134.02*	0.009	<0.01
Initial Frequency	3	122.48*	0.009	<0.01
Signal Strength	3	41008.4*	0.746	<0.01
Absolute Energy	3	36954.8*	0.726	<0.01

*Significant at 0.05 level

Changes in AE parameters under different flow rate

A multivariate analysis of variance was conducted to assess if there is any differences between different flow rate level on a linear combination of AE parameters. Thus, the research hypothesis states that there is a significant difference in the variance of AE parameters when flow rate level is changed. In contrary, the null hypothesis states that there is no significant difference in the variance of AE parameters when flow rate is changed. According to the result of MANOVA test, overall AE parameters were significantly changed under different flow rate levels (Wilk's Lambda = 0.541, F = 1161.494, $p < 0.01$, $\eta^2 = 0.265$). On the other hand, the main effects of flow rate on AE parameters were vary from parameter to another. According to (eta squared η^2) some parameters shoing a high influence and other show less. The effect of flow rate on the AE parameters presented in Table-5.

Similar to the speed, the results of univariate analysis indicated that different flow levels are significantly affecting all AE parameters as all the P values are less than 0.05. This indicates that the linear composite of AE parameters is differs for different levels of flow rate; therefore, null hypothesis must be rejected and the hypothesis is true. However, the tests of between subjects effects table indicates that there are significant main effects of flow rate on AE parameters and it is vary from small, medium and large effect sizes according to (eta squared η^2) accept for rise time, A-freq, R-freq and I-freq which observed to show extreamly small effect size.

Table-5. Effects of AE parameters by flow rate.

Dependent variable	df	F-value	η^2	P-value
Rise Time	**2**	**351.49***	**0.016**	**<0.01**
Counts	2	3146.24*	0.130	<0.01
Energy	2	11618.2*	0.357	<0.01
Duration	2	1384.49*	0.062	<0.01
Amplitude	2	5.551*	0.000	<0.01
Average Frequency	2	338.13*	0.016	<0.01
RMS	2	644.53*	0.063	<0.01
ASL	2	52.25*	0.002	<0.01
Count to Peak	2	762.32*	0.035	<0.01
Reverberation Frequency	2	4.517*	0.001	<0.01
Initial Frequency	2	48.10*	0.002	<0.01
Signal strength	2	11618*	0.357	<0.01
Absolute Energy	2	12654.6*	0.376	<0.01

* Significant at 0.05 level

Changes in AE parameters under different valve type

To assess whether or not the vlave type; suction and discharge, have significant different of AE parameters values a multivariate analysis of variance was conducted. Thus, the research hypothesis states that there is a significant difference in the variance of AE parameters at different vlave type. In contrary, the null hypothesis states that there is no significant difference in the variance of AE parameters between suction and discharge. According to the result of MANOVA test, overall AE parameters were significantly changed at different vlave type (Wilk's Lambda = 0.359, F = 5756.213, $p < 0.01$, $\eta^2 = 0.641$). On the other hand, the main effects of vlave type on AE parameters were vary from parameter to another. According to (eta squared η^2) some parameters shoing a high influence and other show less. The effect of vlave type on the AE parameters presented in Table-6.

In a similar way to the speed and flow rate, the results of univariate analysis indicated that different vlave types are significantly affecting all AE parameters as all the P values are less than 0.05. This indicates that the linear composite of AE parameters is differs with different vlave types; therefore, null hypothesis must be rejected and the hypothesis is true. However, the tests of between subjects effects table indicates that there are significant main effects of vlave types on AE parameters and it is vary from small, medium and large effect sizes according to (eta squared η^2) accept for A-freq, R-freq and I-freq which observed to show extreamly small effect size.

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Table-6. Effects of AE parameters by valve type.

Dependent variable	df	F-value	η2	P-value
Rise Time	**1**	**9207.25***	**0.180**	**<0.01**
Counts	1	35453.5*	0.458	<0.01
Energy	1	58005.7*	0.580	<0.01
Duration	1	22026.4*	0.344	<0.01
Amplitude	1	8153.22*	0.163	<0.01
Average Frequency	1	5441.4*	0.015	<0.01
RMS	1	2254.74*	0.061	<0.01
ASL	1	3013.64*	0.067	<0.01
Count to Peak	1	12042.4*	0.223	<0.01
Reverberation Frequency	1	56.27*	0.001	<0.01
Initial Frequency	1	55.916*	0.001	<0.01
Signal strength	1	58005.7*	0.580	<0.01
Absolute Energy	1	38187*	0.477	<0.01

* Significant at 0.05 level

Changes in AE parameters under different valve condition

To evaluate if the vlave condition; faulty or healthy, have significant different of AE parameters values, a multivariate analysis of variance was conducted. Thus, the research hypothesis states that there is a significant difference in the variance of AE parameters at different vlave condition. In contrary, the null hypothesis states that there is no significant difference in the variance of AE parameters between faulty and healthy. According to the result of MANOVA test, overall AE parameters were significantly changed at different vlave condition (Wilk's Lambda = 0.214, F = 11820.867, $p < 0.01$, $\eta^2 = 0.786$). Beside, the main effects of vlave condition on AE parameters were vary from parameter to another. According to (eta squared η^2) some parameters shoing a high influence and other show less. The effect of vlave condition on the AE parameters presented in Table-7.

Similarly to the speed, flow rate and valve condition, the results of univariate analysis indicated that different vlave condition are significantly affecting all AE parameters as all the P values are less than 0.05. This indicates that the linear composite of AE parameters is differs with different vlave condition; therefore, null hypothesis must be rejected and the hypothesis is true. However, the tests of between subjects effects table indicates that there are significant main effects of vlave condition on AE parameters and it is vary from small, medium and large effect sizes according to (eta squared η^2) accept for rise time, A-freq, R-freq and I-freq which observed to show extreamly small effect size.

Table-7. Effects of AE parameters by valve condition.

Dependent variable	df	F-value	η^2	P-value
Rise Time	**1**	**53.365***	**0.001**	**<0.01**
Counts	1	14448.3*	0.256	<0.01
Energy	1	81456.3*	0.660	<0.01
Duration	1	5642.42*	0.119	<0.01
Amplitude	1	12135*	0.224	<0.01
Average Frequency	1	4364.75*	0.094	<0.01
RMS	1	94764.5*	0.693	<0.01
ASL	1	26583.1*	0.388	<0.01
Count to Peak	1	1296.34*	0.061	<0.01
Reverberation Frequency	1	125.28*	0.003	<0.01
Initial Frequency	1	2306.09*	0.052	<0.01
Signal strength	1	81456.5*	0.660	<0.01
Absolute Energy	1	96398.4*	0.697	<0.01

* Significant at 0.05 level

The average of eta squared (η^2) for AE parameters at all test condition have been calculated to compare the AE parameters according to their amount of change. Figure-3 presented the comparison amonge all AE parameters. The figure is clearly indicate the sensitive parameter having value of η^2 more than 0.3. In contrary, rise time, A-freq, R-freq and I-freq which observed to show extreamly small effect size at all test condition.

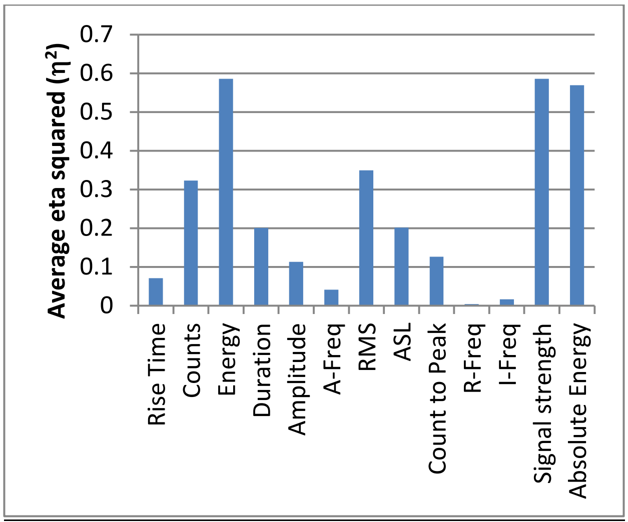

Figure-3. Average eta squared (η^2) for AE parameters at all test condition.

CONCLUSIONS

In summary, the multivariate analysis of variance MANOVA test indicated that changes in the experimental condition effected significantly on the AE paeameters. However, the main effect of valve type, speed and valve condition on AE parameters observe to be more than flow rate.

On the other hand, some AE parameters observe to be more sensitive operational and test condition than other and some showed a not noticeable changes like rise time. In particular, rise time and frequency indicators (initial frequency, reverberation frequency and average frequency), observed to show small changes with the change of operational and test condition.

Therefore, these fourAE parameters will be excluding from further analysis. In contrast, the remain of AE parameters will consider in compressor condition monitoring as well as for the modeling.

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