A Comparative Experimental Study on the Use of Machine Learning Approaches for Automated Valve Monitoring Based on Acoustic Emission Parameters

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Abstract. Acoustic emission (AE) analysis has become a vital tool for initiating the maintenance tasks in many industries. However, the analysis process and interpretation has been found to be highly dependent on the experts. Therefore, an automated monitoring method would be required to reduce the cost and time consumed in the interpretation of AE signal. This paper investigates the application of two of the most common machine learning approaches namely artificial neural network (ANN) and support vector machine (SVM) to automate the diagnosis of valve faults in reciprocating compressor based on AE signal parameters. Since the accuracy is an essential factor in any automated diagnostic system, this paper also provides a comparative study based on predictive performance of ANN and SVM. AE parameters data was acquired from single stage reciprocating air compressor with different operational and valve conditions. ANN and SVM diagnosis models were subsequently devised by combining AE parameters of different conditions. Results demonstrate that ANN and SVM models have the same results in term of prediction accuracy. However, SVM model is recommended to automate diagnose the valve condition due to the ability of handling a high number of input features with low sampling data sets.

Keywords: Faults diagnosis; Acoustic emission; Signal analysis; Machine learning; SVM; ANN.
1. Introduction
Reciprocating compressors are one of the most essential machines in many industries, for instance in power plants, gas transmission and storage, petrochemical industry and many other applications. The ongoing growth in these sectors, have increased the demand of reciprocating compressors worldwide and the demand is expected to grow more in the next couple of years [1]. The compressor reliability is an essential factor required by customers who are expecting a reduction of unscheduled shutdowns and extending the critical components lifetime. This drives the challenge among rival firms in term of design development and employing advanced materials in the compressors manufacturing. However, fatigue failure in some compressor components cannot be avoided. Compressors valves are one of the critical components that play a significant role on both efficiency and reliability of reciprocating compressor. Due to repetitive pressure loads, valves failures are accounted by 29% of unscheduled shutdowns in reciprocating compressor [2]. This issue drives the consideration of effective valves monitoring methods to enable scheduling maintenance shutdown according to the valve condition.

Many methods have been proposed for valve fault detection in reciprocating compressor. Ren et al. [3] detected valve faults using extracted features of vibration signal and SVM. Tran et al. [4] attempted to use three signals including pressure, vibration and current of the induction motor to diagnose valve condition in reciprocating compressor. They extracted the Teager-Kaiser energy from the acquired signals then they employed the deep belief networks (DBN) to diagnose the valve condition. Manepatil et al. [5, 6] investigated the fault detection in reciprocating compressor based on modelling and simulation study of pressure signal. Tiwari and Yadav [7] proposed a method to quantify the valve leakage percentage by analyzing the acquired pressure pulsation using artificial neural network (ANN). Some of the previous studies have analyzed the acquired signal using the same machine learning approaches that are proposed in this paper, for instance [3, 7]. However, they did not consider the variation of speeds and loads during compressor operation which is necessary for any automated system to cope with this fact. In addition, vibration is not the most sensitive method to detect the fault at incipient stage and the pressure measurements are not preferred for issues related to intrusiveness into the compressor operation.

The feasibility of using AE for reciprocating compressor valve condition monitoring has been investigated by some researchers. Gill et al. [8] revealed the advantage of using the AE technique for valve faults detection in a reciprocating compressor. They further concluded that vibration analysis is less sensitive to the higher-frequency noise emitted by fluid-mechanical motion. El-Ghamry et al. [9] suggested a method based on AE statistical feature isolation to diagnose several reciprocating machinery faults. Wang et al. [10, 11] proposed a diagnosis method for reciprocating compressor valve condition by comparing the AE waveforms for normal and faulty valves in simulated valve motion. Unfortunately, limited operational conditions have been used and some faults could not be identified. Sim et al. [12] proposed a valve fault detection method by analysing the AE signal. The authors employed wavelet packet transform (WPT) to decompose the acquired AE signals to different frequency ranges then they used statistical analysis to detect the valve fault based on RMS value. Although the AE could detect the valve’s faults but the analysis was complicated and not practical to use in the industry.

AE signal analysis based on artificial intelligence (AI) has been reviewed in [13, 14]. The research revealed a potential for use AI in automated machinery fault detection. Moreover, AE features extractions have been investigated in our previous research using statistical analysis [15]. This paper aims to automate valve fault detection for reciprocating compressor based on the most common machine learning approaches ANN and SVM with selected AE signal parameters. Moreover, this paper investigates the performance of selected AI methods. The paper structure presented as follows. Section 1 reviews the state of the art the techniques used in valve fault detection and the shortcomings of the existing AE analysis methods. Section 2 briefly describes the theoretical background, including AE parameters, ANN and SVM. Section 3 explains the research methodology, including the test rig, instrumentation and experimental procedure. Section 4 illustrates the modelling results and models validation. Section 5 concludes the paper.
2. Theoretical Background

2.1. AE Signal Parameters

Acoustic emission refers to the generation of transient elastic waves produced by a rapid release of energy from a localized source within the surface of material, as reported by the American Society for Testing and Materials (ASTM) [16]. In this paper, AE is defined as transient elastic waves produced by the impact of one surface on another in a reciprocating motion. In other words, the transient elastic waves produced by the impingement of the plates inside the valve with the upper and lower plate housing during the reciprocating compressor operation. AE hit has specific parameters related to the signal event. The interpretations of AE parameters often related to the machine condition [17]. In this study, AE parameters have been extracted from the acquired AE hits include amplitude, counts, duration, energy, absolute energy, ASL and signal strength. See Fig. 1 and Table 1.

![AE Signal Parameters Diagram](image)

**Fig. 1:** AE signal parameters.

| AE Signal Parameters | Description                                                                 | Units          |
|----------------------|-----------------------------------------------------------------------------|----------------|
| Amplitude            | The greatest measured voltage in a waveform.                                | Volt           |
| Counts               | The number of times the AE signal exceeds a preset threshold during an event. | Counts         |
| Duration             | The time between AE signal start and AE signal end.                         | μsec           |
| Energy               | The mean area under the rectified signal envelope.                          | MARSE          |
| Absolute energy      | The real amounts of AE signal energy.                                       | Attojoule (aJ) |
| ASL                  | The average signal level of the AE amplitude.                               | db             |
| Signal strength      | The integral of the rectified voltage signal over the duration of the AE waveform packet | V.sec          |

Table 1: AE main parameters according to ASTM E1316-05 standard.
2.2. Support Vector Machine

Support vector machine is a supervised machine learning method that relies on statistical learning theory with an ability to handle high input features with low sampling data sets [18]. This learning technique uses input vectors for pattern classification. During the training process, SVM creates a hyperplane that allocates the majority points of the same class in the same side, while maximizing the distance between the two classes to this hyperplane [2]. See Fig. 2.

![SVM's decision boundary](image)

This hyperplane could be either linear or non-linear, which is also relevant to the kernel function [19]. SVM training seeks a globally optimized solution and avoids over-fitting so that it can deal with a large number of features. A comprehensive description, limitations and drawbacks of SVM method are available in [20, 21]. In the linearly separable case, there exists a separating hyperplane whose function:

$$w \cdot x + b = 0 \quad (1)$$

Where:
- $w$: weight
- $x$: input factor
- $b$: bias

which implies:

$$y_i (w \cdot x + b = 0) \geq 1, i = 1, ..., N \quad (2)$$

Where:
- $y_i$: the labels of the training samples
- $N$: number of samples
The SVM algorithm tries to determine a distinctive separating hyperplane with minimizing \( \|w\| \) which represents the Euclidean norm of \( w \); the distance between the hyperplane, by adjusting the data points of each category using \( 2/\|w\| \). When Lagrange multipliers \( \alpha_i \) introduced, the SVM training process is to solve a convex quadratic problem (QP). The solution employs the following equation:

\[
w = \sum_{i=1}^{N} \alpha_i y_i x_i
\]  

(3)

Where:

\( \alpha_i \): Lagrange multipliers

Only if corresponding \( \alpha_i > 0 \), this \( x_i \) is known as support vectors. During the model training process, the decision function is represented by:

\[
f(x) = \text{sign} \left( \sum_{i=1}^{N} \alpha_i y_i (x \cdot x_i) + b \right)
\]  

(4)

In this study, the SVM tries to place a margin between the faulty-healthy data and adjusts it in a way to keep the distance between the data points and the margin as maximal in each group. The nearest data points are used to define the margin and are known as support vectors. However, in most cases the patterns are not linearly separable; therefore, a kernel function is used to perform the transformation. Hsu et al. [22] proposed RBF kernel function to be the first try kernel function for an SVM model. Chen et al. [23] found that RBF kernel gives a better test accuracy compared to the polynomial kernel. Therefore, SVM with RBF kernel function was deployed in this study.

2.3. Artificial Neural Network

Artificial neural networks (ANNs) are a family of statistical learning models inspired by biological neural networks of human brain. The ANN may don’t have exact precision and of the traditional computing approach; yet, they are sufficient to get close approximations to the system that we have inadequate information to make a suitable solution [24]. ANNs are generally presented as systems of interconnected "Neurons" which exchange messages between each other. A neuron often received several inputs \( x_i \). Each input should multiply by a value of weight \( w_i \) and then compile with a bias \( b \). Thus the neuron’s activation \( z \) will calculate as a result. The activation function to calculate as following:

\[
z = \sum_{i=1}^{p} w_i x_i + b
\]  

(5)

When the activation \( z \) is obtained by the neurons, it is then ready to calculate the activation function \( f(z) \). There are many types of activations functions and the selection depends on the network application and ANN architect choice. However, the most used activation functions include linear, threshold and sigmoid function. Thus the output of an activation function is the output of certain
neuron. Moreover, the ANN consists of interconnection for all neurons that they are arranged in form of layers. The most common ANN includes three layers (input layer, hidden or interactive layer and output layer). In this study, feed forward network was employed. The neurons in each layer are connected to the next layer in one direction. See Fig.3.

![Fig. 3: A simple three layered ANN.](image)

In this study, the network was trained to receive 9 inputs (duration, count, amplitude, ASL, signal strength, energy, absolute energy, speed and flow rate) and 2 output (healthy and faulty). The data were divided randomly into three groups: 70% as the training set, 15% as the validation set and 15% as the testing set [25]. Training and validation samples were used to develop the model, whilst the testing samples were held out and then applied to the developed model to evaluate the model performance. Once training is complete, a relationship between input and output data can be established. In training stage, the node weighting is adjusted till the value get close to the real value of all available inputs. However, if over fitting is identified, the computational processing will stop. Over fitting takes place when the model is performed well during training; then it starts to decline when tested with hidden data.

Two error values: mean squared error (MSE) and the percent error (%E) were used to check the network during training, validation and testing process. MSE is defined as the average squared difference among outputs and targets. The lower values of MSE are better (when MSE = 0, means no error). The percent error defined as a fraction of samples which are misclassified by ANN (when %E = 0, indicates that no misclassifications happened by the network. While a value of 100 indicates maximum misclassifications). Feed forward supervised network was used to classify the inputs according to targeted classes. Scaled conjugate gradient back propagation (TRAINSCG) was utilized as training algorithm. See Fig. 4. Thus, training will stop when validation data set MSE has increased more than maximum fail times; set to be 6 times, to avoid over fitting [26, 27]. Further, hyperbolic tangent sigmoid (TANSIG) has been employed as a transfer function. Thus, the network process input of both negative and positive values in fast time [28]. Equation 6 presented the TANSIG transfer function:

\[
f(z) = \frac{e^{2x} - 1}{e^{2x} + 1}
\]

The number of neurons in the hidden layer was optimized through changing the number of neurons and trains the network until the highest accuracy and MSE of the network was achieved.
3. Experimental Study

3.1. Test Rig and Instrumentation

The test rig employed in this study consists of a single-stage, two-cylinder air-cooled reciprocating compressor with a 1.5 kW/2 hp motor that can provide a maximum speed of 820 rpm. The compressor consists of two plate valves mounted over each cylinder. The valve consists of two parts, suction and discharge. Each part includes one plate, and both plates are move up and down opposite to each other during the compressor cycle for the suction and discharge process. During the opposite movement of the valve plates (up and down), the plates will impact the upper and lower valve housing. This impact is a rapid release of energy that generates a transient elastic wave, which moves through the valve up into the valve/cylinder cover and is detected by the AE sensor. See Fig.5.

A digital laser tachometer was used to show the compressor speed and to record the compressor cycle. The tachometer was installed near to the compressor flywheel to receive a pulse from a reflective tape attached to the flywheel. An AE sensor (model: PKWDI) was used to acquire the signal in this research. The sensor was placed at the centre of the valve/cylinder cover (the left cylinder of the reciprocating compressor) and fixed firmly to the surface by super glue. A single channel AE data acquisition (DAQ) system (model: USB AE Node) used for AE signal collection. AEwin™ software was used for recording AE hits and extracting AE parameters. The AE signal for valve faults diagnosis is less than 250 kHz [29], the AE signals were acquired at a sampling rate of 500 kHz. The signal was recognized perfectly at a threshold level of 55 dB. The AE signals was digitized and conditioned by the DAQ device before transmission to a computer for further analysis.
3.2. Experimental Procedure

The experiment began by acquiring the AE signal (baseline signals) from the compressor with the valve in a healthy condition. The experiments were conducted in various operational conditions in terms of speed and airflow rate. Thirteen operational speeds ranging from 200-800 rpm (with incremental increasing by 50 rpm) and three flow rates (0%, 50% and 100%) were employed. Speeds were controlled by the speed controller, whilst the flow rates were controlled using a flow metre at the compressor outlet. Next, the experiment was repeated with the same operational conditions but emulated two types of actual faults, corrosion and clogged, individually at the compressor valve (including both the suction and discharge parts). Corrosion was introduced into the valve plates, whilst clogs were introduced into the valve body. Each fault was simulated with different severity levels to simulate progressive fault deterioration. Table 2 illustrates the types of defects with their severities. Fig.6 and Fig.7 illustrates the defects simulation.

| Valve Condition | Defect Type | Defect Severity       | Defect Symbol | Defect Size     |
|-----------------|-------------|-----------------------|---------------|----------------|
| Healthy Condition | No defect   | No defect              | ND            | No defect      |
| Corrosion Defect | Very small corrosion | VSC       | 37.07 mm²   |
|                  | Small corrosion    | SC     | 56.57 mm²   |
|                  | Medium corrosion   | MC     | 79.63 mm²   |
|                  | Large corrosion    | LC     | 106.27 mm²  |
|                  | Very large corrosion | VLC   | 136.48 mm²  |
| Clogged Defect   | Moderate clogged   | MCL    | 40 %        |
|                  | Intense clogged    | ICL    | 80 %        |

All defects in the experimental specimens (spare valves) were simulated in advance. Next, the first defective valve was configured inside the reciprocating compressor. The first AE signal was acquired when the test rig was operated at the first speed and flow rate. The test was repeated for the other speeds and flow rate conditions until the signal was acquired for all the operational conditions. Then, the test rig was shut down, and the valve was replaced with the second specimen with another fault severity. The procedure was repeated, and another set of AE signals was recorded.
Fig. 6: The valves corrosion severity simulation (a) ND, (b) VSC, (c) SC, (d) MC, (e) LC and (f) VLC.
To complete the experimental procedure, the test-rig was operated for 39 different operational conditions (13 speeds × 3 flow rates = 39) and sixteen valve conditions (8 valve conditions ×2 fault locations = 16) for a total of 624 tests. Each test was conducted for 30 sec and repeated 3 times, and the average was calculated. All experiments were conducted at laboratory temperature range between 25-30°C and standard atmospheric pressure. According to hold and train method [25], the data were divided randomly into two groups: 85% as the training set and 15% as the validation set. Training samples were used to develop the model, whilst the validation samples were held out and then applied to the developed model to evaluate the model performance.

4. Results and Discussions

4.1. Artificial Neural Network Model

The best network was selected according to the network highest classification accuracy and minimum MSE through changing the number of neurons in the hidden layer and trains the network until the highest accuracy and minimum MSE was achieved. Twelve attempts of changing the number of neurons have been investigated to select the network. The MSE value shows a significant decrease when the number of neurons increases until it has achieved a minimum value < 0.01 at the network with 40 neurons in the hidden layer. Next, any try to increase the number of neurons for more than 40...
was resulted in increasing the value of MSE. Likewise, the network observed to achieve the highest accuracy when the proposed number of neurons in the hidden layer was 40 with dramatic decrease after that. Accordingly, the ANN with 9-40-2 configuration (Input layer: 9 neurons, Hidden layer: 40 neurons and output layer: 2 neurons) has been selected as the best network to classify the valve condition into healthy/faulty with an accuracy of 99.4% and minimum MSE of 0.0053. See Fig.8 and Fig. 9.

![Image](image1.png)

**Fig. 8:** Mean Squared Error versus Number of Neurons.

![Image](image2.png)

**Fig. 9:** The Overall ANN Accuracy versus Number of Neurons.

4.2. Support Vector Machine Model

SVM algorithms (svmtrain) and (svmclassify) were used in to train and classify the AE data. In this method, the SVM model was generated as follows: first, map the inputs vectors nonlinearly into one features space. Then, within the feature space from the first step, seek an optimized boundary division, that is, construct a hyperplane which separates the two classes of faulty/healthy. Thus, SVM training seeks a global optimized solution and avoid over-fitting. Table 3 illustrates the summary of SVM model based on 85% of training samples.
Table 3: SVM model structure based on training samples.

| Output Arguments         | Value                                                                 |
|--------------------------|-----------------------------------------------------------------------|
| Support vectors          | range: -7.69 to 7.47 for 3511 samples                                |
| Alpha                    | range: -0.74 to 1.53                                                  |
| Bias                     | 0.0829                                                               |
| Kernel function          | RBF kernel                                                           |
| Group names              | 120823 samples                                                       |
| Support vector indices   | range: 5 to 120492                                                    |
| Scale shift              | range: -4.07 to -0.22                                                 |
| Scale factor             | range: 1.76 to 6.42                                                   |

Table 3 shows the output arguments for SVM model, the support vectors are the range of data points with each row after normalization has been applied. Alpha are the weights values for the support vectors. The sign of the weight is positive for support vectors belonging to the first group (healthy) while negative for the second group (faulty). Bias refers to the intercept of the hyper plane that separates the two groups. RBF kernel has been used as a kernel function. Group names refer to the total data samples. Support vector indices refer to the training data that were selected as support vectors after the data was normalized. Shift refers to the negative of the mean across an observation in training while scale factor refers to 1 divided by the standard deviation of an observation in training. Based on the training data, the overall accuracy for SVM model was 99.4%.

4.3. ANN and SVM Models Performance

The ANN and SVM models were validated using 15% validation samples which were separated randomly from the original acquired data set. This method allows the fitted models to predict the valve condition from validation samples. The process was performed many times to obtain distribution of the predictive performance for each model. Thus, if the models classify the data correctly, then the usability of the model in other contexts can be assured. A lack of fit is possible if the model is unable to classify the data. In addition, receiver operating characteristic curves (ROC) is another comparable method to determine models classification ability [30]. The ROC curve is created by plotting the true positive rate (sensitivity) and false positive rate (one minus the specificity). The point on the curve that is nearest to the upper left corner corresponds to maximum sensitivity and specificity of model classification. The classification accuracy for ANN and SVM model are illustrated in Table 4 and Table 5 respectively. Fig. 11 shows the ROC curve for both models.

Table 4: ANN model classification based on validation samples.

| Observed | Predicted | Total | Predicted Correctly |
|----------|-----------|-------|---------------------|
|          | Healthy   | Faulty|                    |
| Healthy  | 6796      | 62    | 6862                | 99.1%               |
| Faulty   | 73        | 14374 | 14350               | 99.5%               |
| Total    | 21212     |       |                     | 99.4%               |
Table 5: SVM model classification based on validation samples.

| Observed | Predicted | Total | Predicted Correctly |
|----------|-----------|-------|---------------------|
|          | Healthy   | Faulty|                    |
| Healthy  | 6842      | 97    | 6939               | 98.60% |
| Faulty   | 20        | 14253 | 14273              | 99.90% |
| Total    | 21212     |       |                     | 99.4%  |

Table 4 and Table 5 clearly show that both ANN and SVM model have the same prediction accuracy of 99.4%. However, the models found slightly different in term of sensitivity and specificity. By using the measure of percentage in the validation data that predicted correctly, ANN model could classify 99.1% from the healthy as healthy (true positive rate or sensitivity) and 99.5% from the faulty data as faulty (false positive rate or specificity) while the SVM model could classify 98.60% from the healthy as healthy and 99.90% from the faulty data as faulty. See Fig. 10.

![Fig. 10: A comparison between ANN and SVM performance.](image1)

Moreover, the ROC curve shows that both models were able to discriminate between healthy and faulty valve condition maximum sensitivity and specificity as both curves observed to be near to the upper left corner corresponding to maximum sensitivity and specificity of model classification.

![Fig. 11: ROC curve based on validation samples (a) ANN model and (b) SVM model.](image2)
5. Conclusion

The performance two machine learning approaches ANN and SVM models has been evaluated for detection valve fault in single stage reciprocating compressor based on AE signal. The experimental procedure was conducted by inducing two typical valve faults with different severity to acquire the combination of healthy/faulty AE signal during different speed and flow rate conditions. Same data sets, operational condition and AE parameters are used in constructing both models. ANN and SVM models have been train and evaluated based on hold and train method by using Matlab. In evaluating the results we consider the total accuracy of the detection and the ease of the model building. ANN and SVM models demonstrated slightly different in term of sensitivity and specificity, while they have same ability to detect the valve condition with accuracy of 99.4%. Since, ANN accuracy is highly dependent on the neural networks structure such as number of nodes and hidden layers. While SVM has an excellent ability of handling a high number of input features with low sampling data sets [31]. SVM model is recommended for automate diagnose the valve condition in single stage reciprocating compressor.

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