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Automated valve fault detection based on acoustic emission parameters and support vector machine

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Abstract Reciprocating compressors are one of the most used types of compressors with wide applications in industry. The most common failure in reciprocating compressors is always related to the valves. Therefore, a reliable condition monitoring method is required to avoid the unplanned shutdown in this category of machines. Acoustic emission (AE) technique is one of the effective recent methods in the field of valve condition monitoring. However, a major challenge is related to the analysis of AE signal which perhaps only depends on the experience and knowledge of technicians. This paper proposes automated fault detection method using support vector machine (SVM) and AE parameters in an attempt to reduce human intervention in the process. Experiments were conducted on a single stage reciprocating air compressor by combining healthy and faulty valve conditions to acquire the AE signals. Valve functioning was identified through AE waveform analysis. SVM faults detection model was subsequently devised and validated based on training and testing samples respectively. The results demonstrated automatic valve fault detection model with accuracy exceeding 98%. It is believed that valve faults can be detected efficiently without human intervention by employing the proposed model for a single stage reciprocating compressor.

1. Introduction

Reciprocating compressors are often one of the most critical machines in gas transmission, petrochemical plants, refineries and many other industries which deserve special attention. The efficiency and the reliability of a particular reciprocating compressor highly depend on the performance of its valves. Therefore, valve design optimization and improving valve materials have been studied and proposed to extend valves lifetime [1]. Valve failures had been recognized as the most frequent malfunction in reciprocating compressor with high maintenance costs [2,3]. According to an industrial survey by Prognost Systems, 29% of unplanned shutdowns for reciprocating compressors were related to valve faults [4]. This issue drives the consideration of effective and accurate valves' fault diagnostic methodologies to ensure maximum productivity and minimize maintenance costs for reciprocating compressor.

Over the last past decade, various condition monitoring methods have been proposed to diagnose reciprocating compressor valves. For instance, Elhaj et al. [5,6] proposed a method based on the dynamic cylinder pressure and crankshaft instantaneous angular speed (IAS) to detect valve faults in reciprocating compressor. Zhenggang and Fengtao [7]

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proposed a method to monitor the valve condition using the variation of cylinder pressure. Pichler et al. [8] and Wang et al. [9] proposed pressure-volume (PV) measurements for valve condition monitoring in a reciprocating compressor. Then they used support vector machine (SVM) to classify the valve faults. However, the pressure curve is not the most direct way to show valve conditions [10]. Besides, intrusiveness into machine operation and required to fix the sensor into the compressor cylinder in a permanent way. Therefore, pressure measurement is not preferred in industry.

Vibration and acoustic emission based condition monitoring is often considered practical because both measurements are non-intrusive to machine operation. However, many scholars reported the effectiveness of the AE signal measurement compared to the conventional vibration signal analysis method for early fault detection in machinery condition monitoring [11–13]. In addition, AE signal could clearly describe the valve function when it employs for reciprocating compressor condition monitoring. Subsequently, many experimental studies have been carried out to investigate the use of AE for reciprocating compressor valve condition monitoring. For instance, Gill et al. [14] 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. [15] developed a technique based on AE statistical feature isolation to diagnose several reciprocating machinery faults. Wang et al. [10,16] proposed a diagnosis method for reciprocating compressor valve faults 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. Compared with the AE full waveform analysis, parameter analysis using simplified waveform parameters is a powerful method in the AE signal processing field [17,18]. However, few efforts have been published using AE parameters for reciprocating compressor valve fault detection. For example, Sim et al. [19] 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 faults, the analysis was complicated and not practical to be used in the industry. Besides, wavelet transform (WT) has no standard rules for function selection with constant multi-resolution and adding more complexity.

Many analysis methods have been employed for machinery condition monitoring based on AE signals [20,21]. These methods have shown special advances in rapid signal processing due to the development of computers. For example, Phillips et al. [22] developed a condition classification model for heavy mining truck engines based on oil samples and binary logistic regression (LR). The study provides a comparison of the methods used with the SVM and ANN methods. The authors concluded that logistic regression performs better than other classification methods regarding prediction for healthy/not healthy engines. However, the analysis required additional effort to interpret the results of the LR model. Widodo et al. [23] used relevance vector machine (RVM) and SVM for low speed machine fault diagnosis. Despite the analysis revealed promising results and potential for use SVM in automated machinery fault diagnosis, no published work can be found employing this method to analyse AE parameters for reciprocating compressor valve condition monitoring. This paper will investigate the performance of support vector machine to detect valve condition in reciprocating compressor based on acoustic emission signal parameters. It should be noted that this work doesn't aim to generate an interface for valve fault detection but to employ the SVM for AE parameters analysis in an attempt to reduce human intervention in the analysis process. The paper structure is presented as follows. Section 1 reviews the state of the art methods used in valve fault detection. Section 2 briefly describes the theoretical background, including AE parameters and SVM. Section 3 explains the research methodology, including the research test rig, instrumentation and experimental procedure. Section 4 illustrates modelling results and 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) [24]. 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 are 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 are often related to the machine condition [25]. 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.

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. 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. This hyperplane could be either linear or nonlinear, which is also relevant to the kernel function [23]. 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 [26,27]. In the linearly separable case, there exists a separating hyperplane whose functions are:

$$\mathbf{w} \cdot \mathbf{x} + b = 0 \tag{1}$$

where
w: weight
x: input factor
b: bias

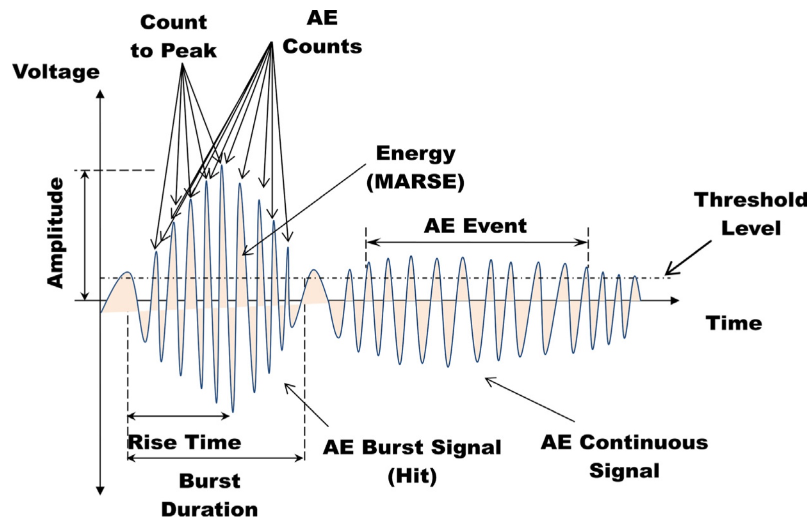

Figure 1 AE signal parameters.

Table 1 AE signal parameters according to ASTM E1316-05 standard.

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

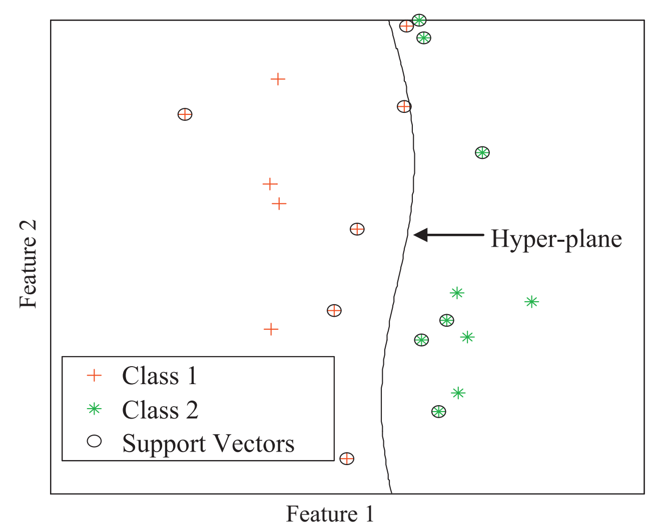

Figure 2 SVM's decision boundary.

which implies

$$y_i(\mathbf{w}\cdot\mathbf{x}+b=0)\geqslant 1, i=1,\ldots,N \tag{2}$$

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 $\|\mathbf{w}\|$ which represents the Euclidean norm of $\mathbf{w}$: the distance between the hyperplane, by adjusting the data points of each category using $2/\|\mathbf{w}\|$. When Lagrange multipliers $\boldsymbol{\alpha}_\mathbf{i}$ introduced, the SVM training process is to solve a convex quadratic problem (QP). The solution employs the following equation:

$$w=\sum_i^N \alpha_i y_i \mathbf{x_i} \tag{3}$$

where

$\boldsymbol{\alpha}_\mathbf{i}$: Lagrange multipliers

Only if corresponding $\alpha_i > 0$, this $\mathbf{x}_i$ is known as support vectors. During the model training process, the decision function is representing by the following:

$$f(\mathbf{x})=\operatorname{sign}\left(\sum_{i=1}^N \alpha_i y_i(\mathbf{x}\cdot\mathbf{x}_i)+b\right) \tag{4}$$

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. [28] proposed RBF kernel function to be the first try kernel function for an SVM model. Chen et al. [29] 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.

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 moving 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. 3.

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) with operating frequency range of 200–850 kHz 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) with 18-bit resolution providing a full AE hit and time-based features was used for AE signal collection. AEwin™ software was used for recording AE hits and extracting AE parameters. The AE signals were acquired at a sampling rate of 500 kHz, for a total of 2048 data points per acquisition (data file). The signal was recognized perfectly at a threshold level of 55 dB. The AE signals were 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 regarding speed and airflow rate. Thirteen operational speeds ranging from 200 to 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, while the flow rates were controlled using a flow metre at the compressor outlet. Next, the experiment was repeated with the same operational conditions but emulating two types of real faults, corrosion and clogged, individually at the compressor valve (including both the suction and discharge parts). Corrosion was introduced into the valve plates, while clogged was introduced into the valve body. The simulation of the corrosion defect involved making a hole with an oval shape at the centre of the plate by using a drilling machine. On the other hand the clogged defect was simulated by sealing some of the valve outlet holes using welding to emulate the condition of a valve clogged due to excessive dirt. Each fault was simulated with different severity levels to simulate progressive fault deterioration. Table 2 illustrates the types of defects with their severities.

All defects in the experimental specimens (spare valves) were simulated in advance. Thus, 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 shutdown, 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.

To acquire the AE signal, the test-rig was operated with 39 different operational conditions (13 speeds × 3 flow rates = 39) and sixteen valve conditions (8 valve conditions × 2 fault locations = 16) with a total of 624 tests. Each test was conducted for 30 s and repeated three times, and the average was calculated. All experiments were conducted at

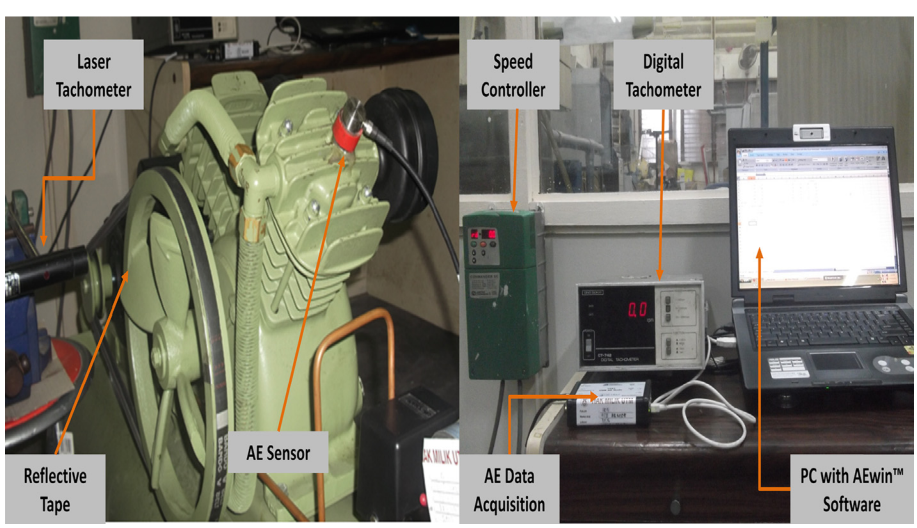

Figure 3 Test rig and data acquisition setup.

Table 2 Types of defects and defects severities.

Valve condition	Defect type	Defect severity	Defect symbol	Defect size
Healthy condition	No defect	No defect	ND	No defect
Faulty condition	Corrosion defect	Very small corrosion	VSC	37.07 mm^2
		Small corrosion	SC	56.57 mm^2
		Medium corrosion	MC	79.63 mm^2
		Large corrosion	LC	106.27 mm^2
		Very large corrosion	VLC	136.48 mm^2
	Clogged defect	Moderate clogged	MCL	40%
		Intense clogged	ICL	80%

laboratory temperature range between 25 and 30 °C and standard atmospheric pressure. Thus, a total of 142,035 data samples for AE signal statistical parameters were obtained from the experimental tests. According to hold and train method [30], the data were divided randomly into two groups: 85% as the training set, including 120,823 data samples, and 15% as the validation set, including 21,212 data samples. Training samples were used to develop the model, while the validation samples were held out and then applied to the developed model to evaluate the model performance.

4. Results and discussions

4.1. AE waveform analysis

The main purpose of waveform analysis was to investigate the AE source. For this reason, a pre-test was performed with the valve in a healthy condition. The test consists of acquiring the AE signal simultaneously with the compressor cycle, using a digital laser tachometer at a speed of 820 rpm and without a 100% flow rate. The compressor valve must both open and close within one cycle. It was envisioned that the AE bursts would be detected along the waveform with a rate equivalent to the plate movement frequency per cycle, representing the valve open-close function. Therefore, the acquired AE waveform signal was drafted with the reciprocating compressor cycles. See Fig. 4.

The AE waveform contains a sequence of intermittent spikes dominant along the acquired signal. Besides, these spikes are in a sequence of differentiated amplitudes during the same period. By comparing these spikes with the compressor cycle signal, which is represented by the pulse waveform signal with each two pulses equal to 1 cycle, there appear to be two AE spikes in each compressor cycle. Consequently, the period between any identical amplitude is found to be the same time as one compressor cycle, which is 0.07 s when the speed is 820 rpm. See Fig. 4.

As a result, the spikes in the AE waveform are directly associated with the compressor valve and indicate the valve open-close function. However, the reason for the divergence in the spikes amplitude is the difference in air pressure inside and outside the compressor. In other words, when the valve is opening, the air is sucked from low pressure (atmosphere pressure), and thus the impact of the valve plates with the plates housing will release a slight elastic energy. In contrast, when the valve is closing, the air will compress under higher pressure; therefore, the impact of the valve plate with the plate housing will release a higher elastic energy. Indeed, this result is similar to the observations of AE waveforms produced by reciprocating compressors in previous studies [6,10]. The transient waveform of AE activity associated with the valve movement has been reported.

4.2. Support vector machine model

SVM algorithms namely (svmtrain) and (svmclassify) were used to train and classify the AE data. In this method, the SVM model was generated by mapping the inputs data nonlinearly according to the input features. Next, the model will seek for optimized margin division for these features that construct a hyperplane to split the features into faulty and healthy. Table 3 illustrates the summary of SVM model based on 85% training samples.

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 is the weight 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 hyperplane that are separated into 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 were 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 observation in training. Based on the training data, the overall accuracy for SVM model was 99.4%.

4.3. SVM model validation

The SVM models were validated using 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 check the predictive performance of the SVM model. Thus, when the model classifies the data correctly, 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. Therefore, receiver operating characteristic curves (ROC) was employed to determine model's classification ability [31]. The ROC curve usually sketched in a two-dimensional diagram by plotting the sensitivity (the data that are originally healthy and predicted healthy by the model) versus the one minus specificity (the data that are originally healthy and predicted faulty by the model). When the curve

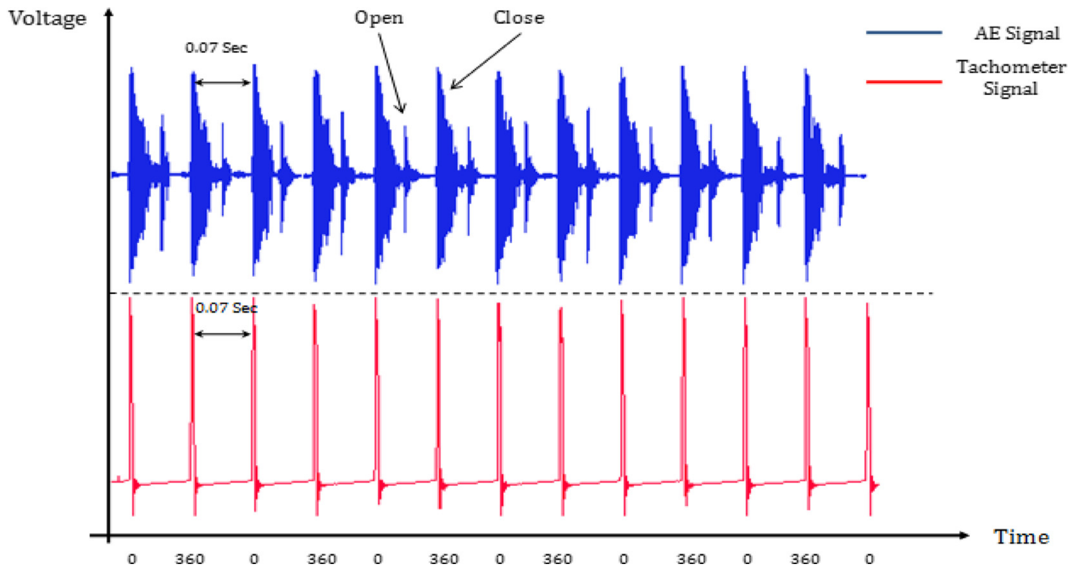

Figure 4 AE waveform versus the reciprocating compressor cycles.

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	120,823 samples
Support vector indices	Range: 5–120,492
Scale shift	Range: −4.07 to −0.22
Scale factor	Range: 1.76–6.42

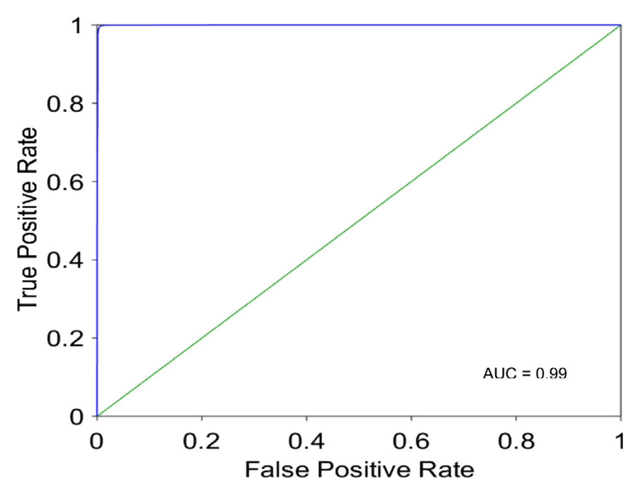

Figure 5 ROC curve based on validation samples for SVM Model.

appeared close to the upper left corner that is mean the model has a maximum sensitivity and maximum specificity for classifying the data. Moreover, model discrimination can be further checked by calculating the area under the curve (AUC) (If AUC = 0.5 means the model cannot discriminate between the two classes of data while if AUC > 0.8 means the model has an excellent discrimination ability) [32]. Table 4 illustrates the classification accuracy for SVM model and Fig. 5 shows the ROC curve for SVM model.

By using the measure of percentage in the validation data that were predicted correctly, Table 4 clearly shows that the SVM model could classify 98.60% from the healthy as healthy and 99.90% from the faulty data as faulty. The overall prediction accuracy of SVM was 99.4%. Moreover, ROC curve shows that SVM was able to discriminate between healthy and faulty valve condition with AUC of 0.99. That indicates a maximum sensitivity and specificity of SVM model. The SVM model performance was found to be reliable and accurate for automated diagnosis of the valve condition in a single stage reciprocating compressor. See Table 5.

Table 4 SVM model classification based on validation samples.

Observed	Predicted		Total	Predicted correctly (%)
	Healthy	Faulty		
Healthy	6842	97	6939	98.60
Faulty	20	14,253	14,273	99.90
Total			21,212	99.4

Table 5 SVM model accuracy details.

	SVM
AUC	0.99
Sensitivity	98.6%
Specificity	99.9%
Overall accuracy	99.4%

5. Conclusion

This study proposed automated diagnosis the valve condition using support vector machine based on AE parameters. An experimental procedure was conducted on a single stage industrial reciprocating air compressor and consisted of inducing two typical valve faults in the compressor with different severity. Data were tabulated according to the valve condition and then SVM model was developed based on training samples of the AE signal parameters. The model was validated by using other validation samples never train the model. Based on predictive accuracy and the ROC curve, the results demonstrated that the SVM model could classify 99.4% of valve condition correctly. Moreover, ROC curves illustrate maximum sensitivity and specificity by the SVM model. It is concluded that the proposed SVM model can be used with utmost accuracy to diagnosis valve condition in a single stage reciprocating compressor.

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