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Intelligent Valve Fault Diagnosis Approach for Reciprocating Compressor Based on Acoustic Signals

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Abstract

Reciprocating compressor is one of the critical components in petrochemical, process and gas storage /transportation industry. Due to the dynamic operating conditions, valve failures of the compressors are one of the most frequent failures that causes around 36% of the unplanned shutdowns for reciprocating compressors. For reliable operations of the compressor, a condition-based fault diagnosis model is proposed in this study. Majority of the existing studies are based on vibration, pressure and other intrusive sensors, which interferes with the system dynamics. Hence, non-intrusive acoustic sensor-based signal analysis technique is tested in this study. Due to the non-stationary nature of the acoustic signal obtained from the working compressor, it is quite difficult to extract fault-specific information. Hence, Minimum Entropy Deconvolution Adjusted (MEDA)-Empirical Mode Decomposition (EMD) approach is proposed for valve-fault diagnosis of reciprocating compressor. After enhancing the impulsiveness of the raw signals with the help of MEDA, a set of IMFs is obtained through EMD method. From this IMF-set, information rich IMF is selected based on the kurtosis value. For extraction of fault related information, two time-domain features (RMS and sample entropy) are used. The results show that MEDA can enhance the signal features effectively which is critical for fault detection. Compared to EMD method, the proposed methodology has shown promising results for inlet and outlet valve-fault diagnosis of reciprocating compressor.

Keywords: *Condition based health monitoring, Fault diagnosis, Reciprocating compressor, Minimum Entropy Deconvolution Adjusted (MEDA), Empirical Mode Decomposition (EMD)*

I. Introduction

In petrochemical, gas transportation and process industries, reciprocating compressor are considered to be one of the most heavily used equipment for fluid compression. In order to fulfil industrial demands economically, reciprocating compressors are run at its maximum capacity and without any backup in many cases. Hence, its reliability is critical to avoid unscheduled production shutdowns. However, due to its complex structure and dynamic nature of operation, even with advanced designs and materials, failure is inevitable. With the advent of industry 4.0 associated technologies, organizations are interested in adopting automated technical systems to monitor critical equipment. Such automated condition monitoring systems can help in reducing the on-site inspection risks as well as labor costs.

Condition based health monitoring and fault diagnosis has attracted much attention due to its unparallel benefits with Internet of Things (IoT) and sensor technology. This helps in understanding system behavior and taking preventive steps to avoid progression of early faults to system failure. For monitoring system health state various physical properties, such as vibration, pressure, current, temperature, are measured via different types of sensors. Selection of appropriate sensor is of importance for accurate diagnosis respective fault. In case of reciprocating compressor, around 36% of unscheduled maintenance are caused due to suction and discharge valve failure, which is the most common reason [1]. According to [2], observations from real case study of reciprocating compressor, likely reasons for valve are dynamic operating conditions, improper valve installation, incorrect choice of valve parameters and pressure pulsations in transportation tubes. It is crucial to diagnose a valve failure as it can cause exhaust pressure drop which can eventually lead to functional failure.

Several condition-based health monitoring studies addressing the valve failure detection have been proposed. Due to the non-stationary nature of the signals collected from reciprocating compressor [3], many signal processing techniques employing vibration analysis [4–7], temperature [8], pressure-volume analysis [9], angular speed based analysis [10] and acoustic analysis [11–13] have been employed for fault diagnosis. In [14], a basis pursuit based denoising approach and wave-matching based feature extraction approach is proposed to diagnose reciprocating compressor faults. Vibration, current and pressure signals of reciprocating compressor were analyzed through Teager-Kaizer Energy operator (TKEO) based feature extraction approach in [15] for valve fault diagnosis. Furthermore, for non-stationary signal analysis, Empirical Mode Decomposition (EMD) [3,16], Short-Time Fourier Transform [17,18], wavelet transform [19–22], and Wigner-Ville distribution [23,24] are some of the most popular techniques for feature extraction. For fault diagnosis of reciprocating compressor used in refrigerators, Yang et al. [25] employed wavelet transform for vibration signal denoising and feature extraction. Although wavelet analysis can extract useful features from the non-stationary signals, for effective results optimal wavelet basis and number of layers for signal decomposition needs to be selected beforehand [26]. These parameter values are critical as quality of decomposition depends on it [27]. However, the problem of parameter selection can be avoided in EMD technique as it is self-adaptive analysis method that uses intrinsic characteristics of signal [28]. It has been successfully applied for compressor fault detection in combination with autocorrelation function [29]. Later, EMD coherence based fault diagnosis approach was proposed by the same authors in [30] for eliminating the cylinder signal interference. In [31], proposed rational Hermite interpolation based EMD technique to diagnose valve failure.

Most of these studies requires the sensors to be mounted in contact with the system for data acquisition. Due to such intrusive nature of these sensors, researchers find it inconvenient. To avoid this problem, several studies have employed non-intrusive acoustic sensors for fault diagnosis of reciprocating compressor. In [11], statistical features are extracted to diagnose valve failure. For varying pressure conditions, fault diagnosis approach is proposed in [32] based on acoustic emission signals. Effects of gas and fluid leakage through types of valve are studied based on acoustic emission variations in [33,34]. Moreover, for pipeline leakage detection also acoustic analysis has found to be effective [35,36]. Unlike rotary systems such as bearings and gearboxes, reciprocating compressors has rotary as well as reciprocating components which resonates huge background noise in acoustic signals [37]. Hence, extraction of efficient and characteristic features for fault diagnosis of reciprocating compressor poses a great challenge. Verma et al. [13] has conducted an extensive study on reciprocating compressor fault diagnosis based on acoustic signals. This study has employed wavelet-based feature extraction approach and used different feature selection approach (such as mutual information, Bhattacharya distance and principal component analysis) to input optimal features for SVM variant-based fault diagnosis approach. However, it is to be noted that the acoustic signals collected from reciprocating compressors have periodic impulses generated by valve opening and closing. In case of valve failure, non-linearity and randomized periodic impulses generates harmonic components in the signal. The traditional feature extraction techniques (such as wavelet transform) are not efficient enough to extract characteristic features from the signal containing high background noise. Hence, it is imperative to propose an advanced fault diagnosis approach for identifying valve faults of reciprocating compressor.

In this paper, Minimum Entropy Deconvolution Adjusted (MEDA)-EMD based fault diagnosis approach is proposed for detection of valve fault in reciprocating compressor. First, raw signal is preprocessed through MEDA technique. Then the deconvolved signal is decomposed into intrinsic mode functions (IMFs) with the help of EMD to extract significant frequency components for fault diagnosis. Condition Indicators (CI) are extracted from the selected IMF to separate the healthy and fault state of the system. The rest of the paper is structured as: Section II briefly discusses the theoretical background of MEDA and EMD techniques and proposed methodology. The following section presents the proposed methodology. The adopted dataset of reciprocating compressor is discussed the next section. Section IV provides discussion on the obtained results and analyses it. In the following conclusion section, summary of the paper is presented.

II. Methods

It is critical to figure out fault features from the acquired raw signal. In order to preprocess the non-stationary acoustic signals, MEDA and EMD techniques are employed in this paper. This section discusses both the signal processing techniques, MEDA and EMD, and CIs used for fault detection in brief.

I. Minimum Entropy Deconvolution Adjusted (MEDA)

MED technique is designed to enhance the spike-like features and localize the impulse response frequencies closer to the cause of original impulse [38]. This technique has yielded promising results for seismic signal- [39], machinery fault diagnosis [40–42]. However, convolution definition assumption in MED technique generated discontinuity in output results for rotating machinery [43]. To mitigate the discontinuity effects, Auto Regressive model based preprocessing was proposed by Endo H. et al. [41] before applying MED to rotary machine signals. Another, solution, by adjusting the convolution definition, was proposed in [43] to tackle this limitation. The MEDA approach is as follows:

For measured raw signal $\vec{x}$, finite length filter $\vec{f}$ is found out in order to enhance the source fault impulse (having higher kurtosis values) and undermine the noise and system dynamics (having lower kurtosis values). $\vec{y}$ is filtered output signal of length N datapoints.

$$\vec{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix} \qquad \vec{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix} \qquad \vec{f} = \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_N \end{bmatrix} \tag{1}$$

$$\vec{y} = \vec{f} * \vec{x} \tag{2}$$

$$Y_k = \sum_l^L f_l x_{k+L-l}, \qquad k=1, 2, \dots, N-L+1 \tag{3}$$

Matrix form of above expressions (1-3) is presented in expression (4):

$$\vec{y} = X_0^T \vec{f} \tag{4}$$

$$\text{Where, } X_0 = \begin{bmatrix} x_1 & x_{L+1} & x_{L+2} & \cdots & x_N \\ x_{L-1} & x_L & x_{L+1} & \cdots & x_{N-1} \\ x_{L-2} & x_{L-1} & x_L & \cdots & x_{N-2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_1 & x_2 & x_3 & \cdots & x_{N-L+1} \end{bmatrix}_{L\ by\ N-L+1}$$

Iterative selection of MEDA results into expression (5).

$$\vec{f} = \frac{\sum_{n=1}^{N-L} y_n^2}{\sum_{n=1}^{N-L} y_n^4} (X_0 X_0^T)^{-1} X_0 \, [y_1^3\ y_2^3\ y_3^3\ \dots\ y_{N-L}^3]^T \tag{5}$$

Initially $\vec{f}$ is assigned [0, …, 0, 1, -1, 0, …, 0] and iteratively find out $\vec{y}$ from the above equations for new filters in every iteration.

In previous studies, MED based approaches have been successfully applied for early fault detection of bearing [44] and compressor system [42]. Inspired from the efficacy of the technique, MEDA is employed in this study for signal processing. The performance of MEDA technique is presented in the results section IV.

II. Empirical Mode Decomposition (EMD)

EMD is an adaptive signal decomposition technique that works on the basis of oscillatory components [45]. For identifying the fault information, EMD does not necessitates signal stationarity, periodicity or linearity information beforehand. EMD is used to decompose multi-component signal into mono-component Intrinsic Mode Functions (IMFs) [46]. IMFs are a set of frequency bands that constitute the multi-component signal. As per the assumptions on the basis of which EMD is developed, any non-stationary signal can be expressed as sum of IMFs and residual component. It can be expressed in mathematical form as following (equation (6)):

$$x(t) = \sum_{n=1}^{N} IMF_n(t) + res(t) \tag{6}$$

Where, $IMF_n(t)$ and res(t) denotes n^{th} IMF and residual component. It is to be noted that, to qualify as an IMF, a constituent function (extracted from raw signal) must satisfy the following two conditions: (i) the count of extrema and zero-crossings should be equal or defer by one at most. (ii) mean value of envelope developed by maxima and minima must be zero at any point. The steps of EMD technique are as follows:

(1) Detect all minima and maxima points of original signal x(t).

(2) Build lower envelope (E_{lower}(t)) and upper envelope (E_{upper}(t)) by using cubic spline interpolation technique for minima and maxima data points.

(3) Calculate mean envelope by using the equation: $E_{mean}(t) = (E_{lower}(t) + E_{upper}(t))/2$.

(4) Compute $s(t) = x(t) - E_{mean}(t)$.

(5) Verify the two conditions for s(t) if is qualified to be an IMF.

(6) If s(t) is qualified to be an IMF, then $IMF_n(t) = s(t)$ and repeat the procedure from step (1) for residual signal $res(t) = x(t) - s(t)$.

Else, replace x(t) with s(t) and repeat the procedure.

(7) Repeat steps (1-6) until monotonic res(t) is obtained.

The set of $IMF_n(t)$ contains frequency components such that $IMF_1(t)$ represents highest frequency component and subsequent IMFs express lower frequency components.

III. Condition Indicators

In order to extract fault information from the IMFs, various feature extraction approaches have been developed. Root mean square (RMS) and entropy are one of the most commonly used condition indicators (features) for compressor faults [42,47]. A short description on these condition indicators, used in this study, is presented below.

(1) Root Mean Square (RMS):

RMS is the square root value of the mean of the sum of squares of signal. It is generally used to evaluate the signal amplitude and signal energy in time domain [48]. Formula to calculate is presented as equation (7).

$$\text{RMS} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(x(t))^2} \tag{7}$$

(2) Sample entropy:

Sample entropy is used for evaluation of signal complexity that reflects the probability of novel pattern generation in accordance with the signal variation [49]. This method was proposed by Richman and Moorman [50] to overcome the limitations of approximate entropy and it has been quite popular since [27]. Sample entropy is independent of data length (which adversely affected the performance of approximate entropy) and it could tackle the signal noise effectively. Steps to calculate sample entropy are as follows:

For a given time series signal {z(t), t=1, 2, ..., N}, at time i and dimensional vector m can be expressed as (equation (8)):

$$Z_t^m = \{z(t), z(t+1\}, \ldots, z(t+(m-1))\}, \quad t = 1, 2, \ldots, N-(m-1) \tag{8}$$

Where, Z_t^m represents new time series, τ denotes time delay and m is embedding dimension.

(1) Compute $d_{ij} = \max_{0\le k\le m-1} |x(t+k) - x(j+k)|$, $1 \le t, j \le N-m+1$;

(2) Calculate $C_t^m(r) = \frac{Num(d_{ij} \le r)}{N-m-1}$ for all x(t). Here, r is tolerance value and $Num\big(d_{ij} \le r\big)$ is count of distances qualifying the $d_{ij} \le$ r constraint.

(3) Compute $B^m(r) = \frac{1}{N-m}\sum_{t=1}^{N-m} \ln\left(C_t^m(r)\right)$

(4) Take embedded dimension as m+1, and repeat steps (1-3) to compute $B^{m+1}(r)$.

(5) Obtain sample entropy: SampE (m, r, N) = $-\ln\frac{B^{m+1}(r)}{B^m(r)}$.

III. Proposed Methodology

Flowchart of the proposed fault diagnosis algorithm is illustrated below in Figure 1. First, machinery signals are extracted through sensitive and accurate sensors. The details of sensor type and data acquisition is discussed in detail with experimental setup in Section 4. After acquiring raw signal dataset, MEDA is applied to the raw signal for enhancement of signal. It is to be noted that selection of filter size is reflected on the results obtained by MEDA. Hence, after careful investigations of different filter size cases, it is selected as 10 for this study. The filtered signal is decomposed by EMD method and IMFs are obtained. From the set of IMFs, IMF with rich fault information is selected on the basis of kurtosis value. Next, for capturing the fault dynamics condition indicators, RMS and sample entropy, are extracted from the selected IMFs. The difference in these condition indicators is used for fault diagnosis of the system.

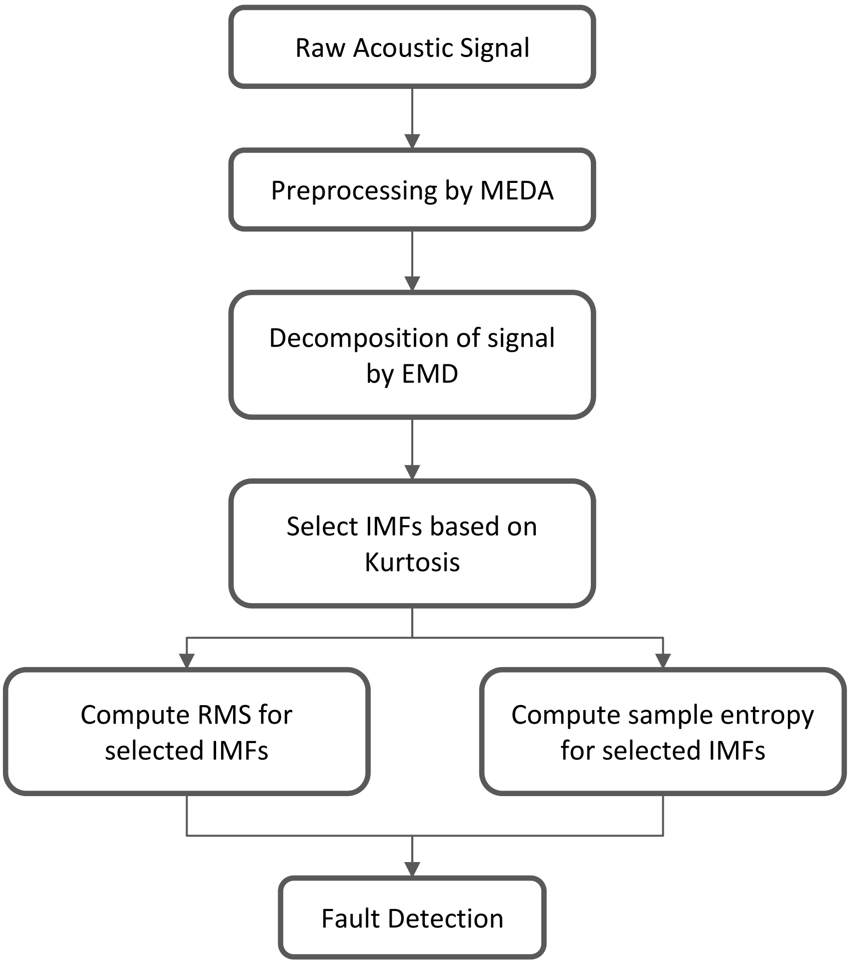

Figure 1: *Steps of Proposed Methodology*

VI. Experimental results and discussion

In order to validate to test the proposed methodology, a single stage reciprocating compressor dataset is used. This study is validated with the same dataset used in [13]. The compressor used for the experiments was run by 5HP-1440 rpm (415V, 50 Hz, 5 amp) induction motor and had air pressure range of 0-35 kg/cm^2. The pressure switch used in the experiment was of Type PR-15 with pressure range of 100-213 psi. Acoustic sensor readings for healthy state and two faults (Leakage in Inlet Valve (LIV) and Leakage in Outlet Valve (LOV)) are acquired. The dataset was collected at sampling frequency of 50 kHz.

For testing the effectiveness of the proposed algorithm, traditional EMD method and proposed method are applied to the raw acoustic signal. In order to visualise the effectiveness of signal enhancement, the raw signals and MEDA-filtered signals are illustrated in Figure 2.

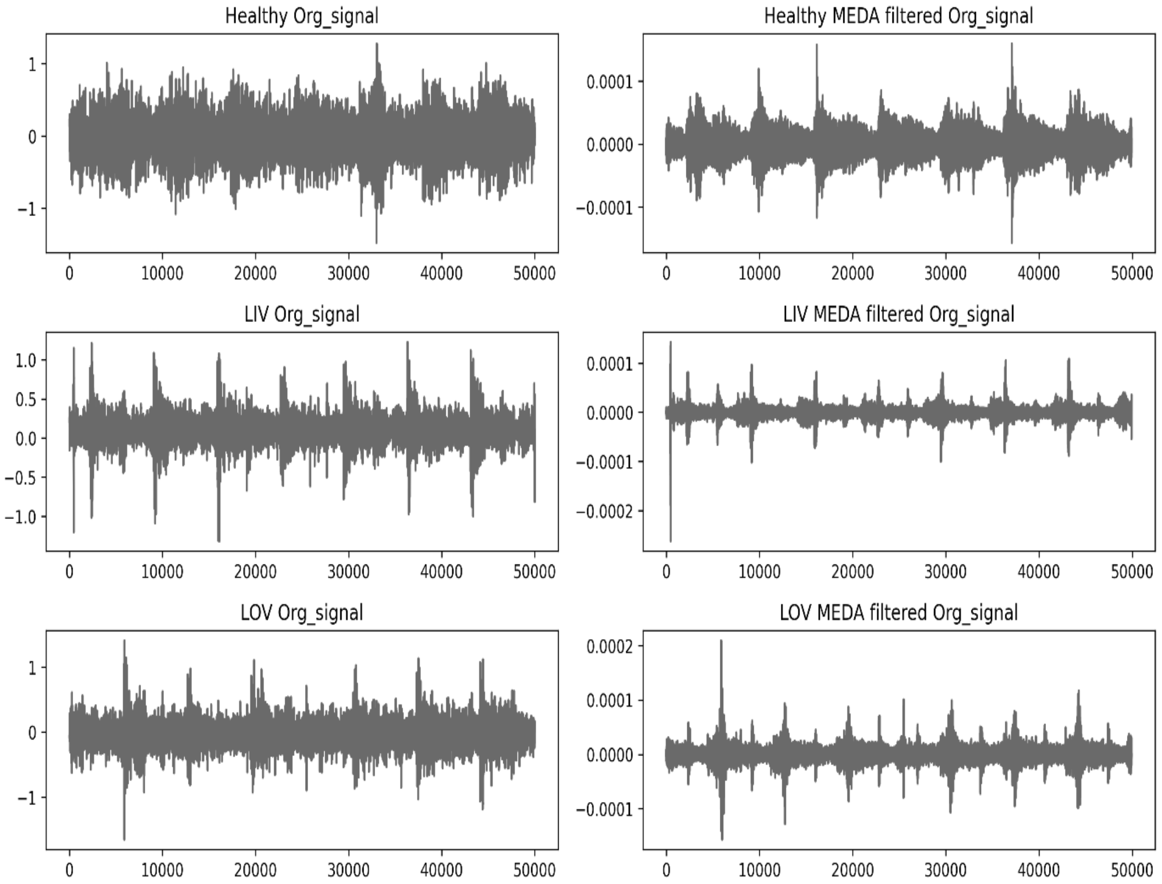

Figure 2: *Raw and MEDA filtered acoustic signals for healthy, LIV and LOV states*

From the Figure 2, it can be observed that the transient spikes (impulsiveness) for each state are clearly enhanced, as compared to the raw noisy signal, by MEDA method. Next, the filtered signals are used as input signal for EMD method and decomposed into set of IMFs. From the set of IMFs, fault-information rich components are selected on the basis of higher kurtosis value. Table 1, depicts kurtosis value for first 6 IMFs of EMD and MEDA-EMD signals. It can be observed that IMF2 has higher frequency of highest kurtosis values. Hence, for acoustic signal analysis, the condition indicators (RMS and sample entropy) are extracted from IMF2 for healthy as well as fault signals.

Table 1: *Kurtosis value of IMF 1-7 extracted with EMD and MEDA-EMD method for healthy, LIV and LOV states*

Kurtosis	Healthy		LIV		LOV	
	EMD	MEDA_EMD	EMD	MEDA_EMD	EMD	MEDA_EMD
IMF1	1.10885	1220.009	8.957949	**804.0393**	4.750699	9.917119
IMF2	1.305557	**1832.79**	**21.37063**	759.5153	**6.21626**	6.779707
IMF3	**2.50234**	249.2484	6.87206	408.9886	1.95156	15.593

	1		6		7	
IMF4	1.023759	57.10541	4.540992	203.2668	2.27516	3.154513
IMF5	0.418795	27.10442	1.869759	153.5696	1.589103	9.239799
IMF6	1.266586	49.32549	4.829074	21.73766	5.573468	10.38324
IMF7	1.205461	73.24571	3.114345	30.11287	0.659162	14.50046

Figure 3 depicts the RMS values of IMF2 obtained by EMD and MEDA-EMD method for healthy, LIV fault and LOV fault signal. From the Figure 3(a), it can be noticed that healthy state of compressor is clearly distinguished from fault signals. However, this condition indicator can not separate LIV and LOV fault by EMD approach. Figure 3(b), shows that MEDA-EMD method can differentiate each state of compressor. It is to be noted that RMS value for EMD processed IMF is quite higher than that for MEDA-EMD processed IMF.

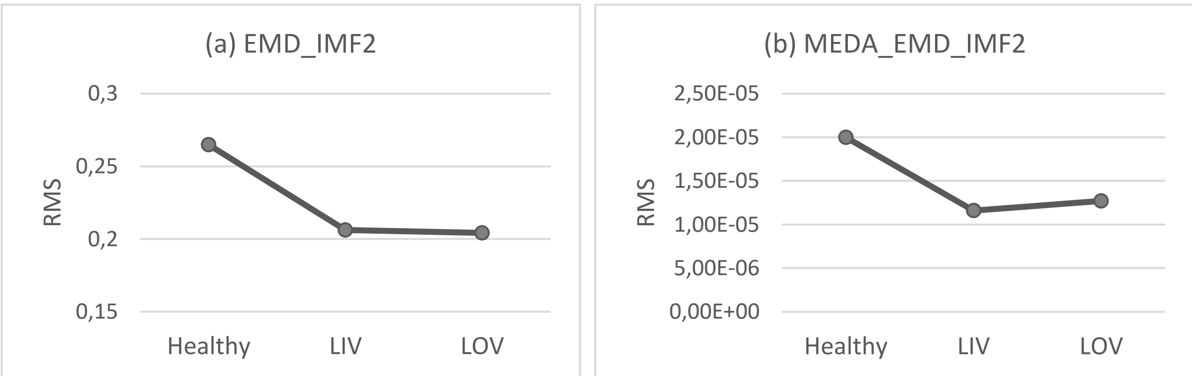

Figure 2: *RMS value of IMF2 extracted with (a) EMD and (b) MEDA-EMD method for healthy, LIV and LOV states*

Figure 4 and Figure 5 illustrates the sample entropy feature for IMF2 component obtained through EMD and MEDA-EMD technique respectively. Figure 4 shows that sample entropy values for LIV and LOV fault conditions are almost overlapping each other. Hence, it can be noted that EMD-sample entropy approach is not as effective in differentiating the LIV and LOV faults from each other as it is for differentiating the healthy from valve-fault (LIV and LOV) conditions of reciprocating compressor.

However, as shown in Figure 5, the MEDA-EMD-sample entropy approach has clearly

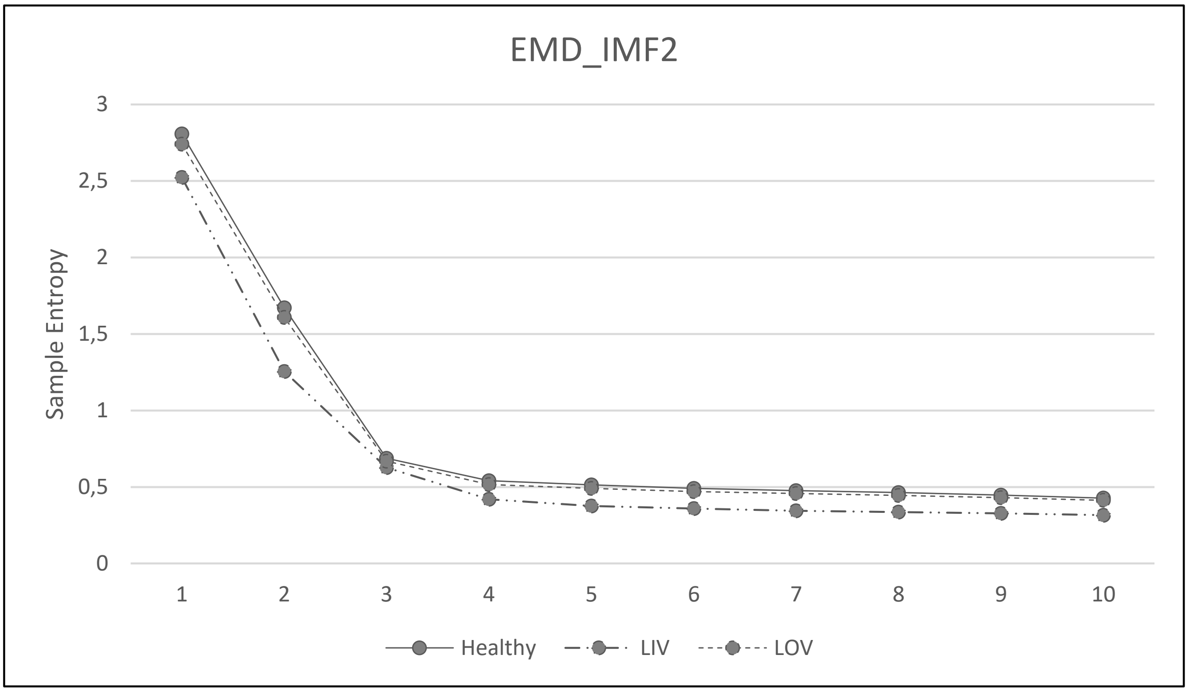

Figure 4: *Sample entropy of IMF2 extracted with EMD method for healthy, LIV and LOV states*

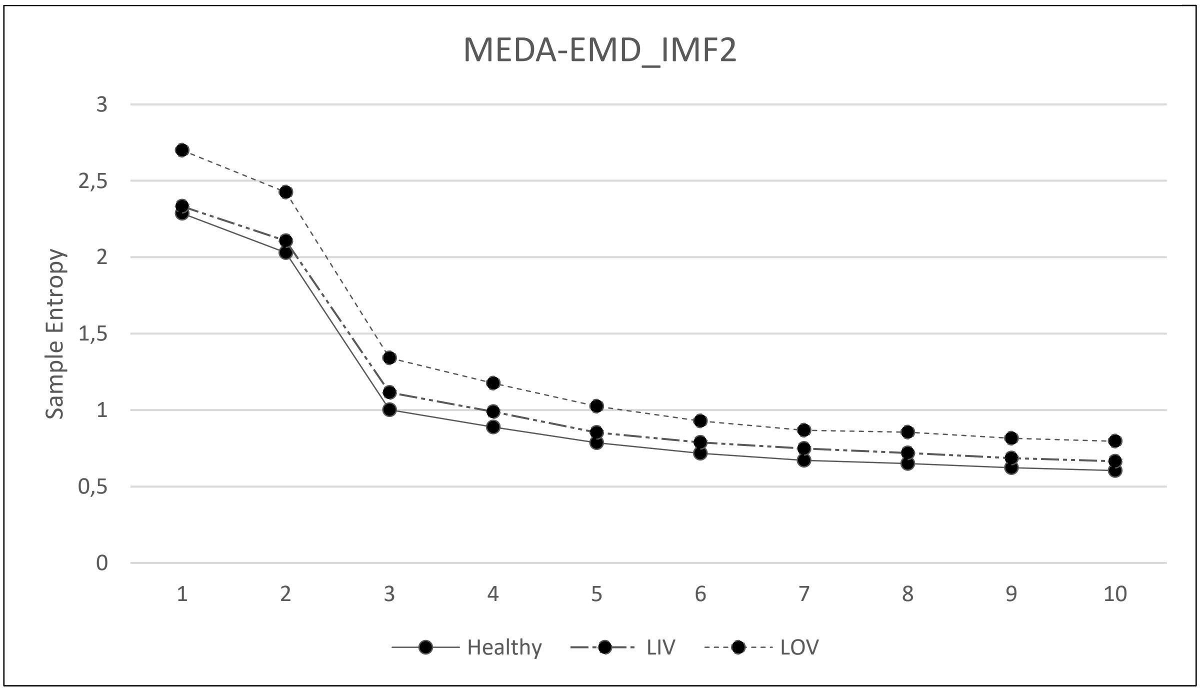

Figure 3: *Sample entropy of IMF2 extracted with MEDA-EMD method for healthy, LIV and LOV states*

identified the healthy, LIV and LOV states of the compressor. The results demonstrate the effectiveness of the MEDA-EMD approach for valve-fault diagnosis of reciprocating compressor based on acoustic signals.

V. Conclusion

In petrochemical, process and gas storage and transportation industries, reciprocating compressors plays a crucial role. For reliable operation of the compressor, it is imperative to develop a condition-based health monitoring and fault diagnosis model that can accurately detect faults. Among compressor faults, valve failure is critical as it causes most frequent unscheduled maintenance shutdowns. Hence, to address the problem, a MEDA-EMD based fault diagnosis approach is proposed in this study. For this purpose, unlike other signal analysis techniques that are commonly based on signals obtained from vibration, pressure and other intrusive sensors, non-intrusive acoustic signal-based signal analysis technique is employed in this study. After applying the MEDA-EMD technique, IMF with highest kurtosis value is selected as it contains higher fault-information compared to others. In order to quantify the fault information, time-domain based RMS and sample entropy features are extracted from the selected IMF. To validate the proposed approach, acoustic signals of healthy and inlet-outlet valve faults (LIV and LOV) are analysed. From the presented results, it can be concluded that compared to self-adaptive EMD method, MEDA-EMD based approach is more effective. Although EMD can separate the healthy and valve-fault conditions, it fails to differentiate the LIV and LOV. However, RMS and sample entropy features obtained after applying the MEDA-EMD method can clearly identify healthy, LIV and LOV states of the compressor from each other. It is to be noted that the applicability of the proposed methodology is validated, in this study, for acoustic signals of the mentioned states of the compressor only. Nonetheless, the results of this study shows that potential of this approach is promising as fault diagnosis model for other faults of compressor as well as other rotary or reciprocating systems.

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Declaration of Conflicting Interests:
The Authors declare that there is no conflict of interest.

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