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# A NOVEL SIGNAL PROCESSING APPROACH FOR VALVE HEALTH CONDITION CLASSIFICATION OF A RECIPROCATING COMPRESSOR WITH SEEDED FAULTS CONSIDERING TIME-FREQUENCY PARTITIONS

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Keywords: automated condition classification, reciprocating compressor, time-frequency analysis.


## ABSTRACT

This study deals with a novel signal processing approach for automated valve condition classification of a reciprocating compressor with seeded faults. The classification system consists of a front end time-frequency analysis platform for the vibration signal measured, fault feature vectors for making the formidable amount of time-frequency data manageable, and a probabilistic neural network for automatic classification without the intervention of human experts. Rather than representing each time-frequency data set with one single feature vector comprising three indices, namely time, frequency, and amplitude, the time-frequency plane is further partitioned into an appropriate number of sub-regions to enhance the characteristics representation of the time-frequency data. This study shows that a flawless classification can be realized by using the proposed approach with appropriate selections of index modification method and number of time-frequency sub-regions without resorting to the removal of similar fault cases.


## I. INTRODUCTION

Condition monitoring and classification of machinery state is of vital importance to provide early warning for the deterioration of the machine health condition so that timely maintenance can be made to prevent catastrophic breakdown. Research efforts on fault detection and classification of commonly used machine components, such as bearings [9, 11, 16, 17, 20, 22 ], gears [12, 13, 24], and valves [3, 14, 15, 21, 23] have been reported. In a recent article reported by the authors of the present paper [14], it was shown to be feasible to classify the valve conditions of a reciprocating compressor using the time-frequency analysis and the artificial neural network. The study showed the classification error can be greatly reduced from approximately 80% down to approximately 20% for the 15 fault cases by using proper modification indices, as opposed to the original indices. Further enhancement for correct condition classification could be realized if the similar fault cases were removed. However, the inability to differentiate the minute difference of the fault cases hinders the realization of the ability to provide early warning of the machine's health conditions, which may possess indiscernible variation as compared to the intact condition of the machine concerned. In this work, we propose a new strategy to tackle the challenge of similar fault cases which failed the automatic condition classification system. The proposed novel approach does not require the removal of the fault cases with minute differences. Both the time and frequency partitions are considered to reveal more features of the time-frequency data sets while still maintaining the original simplicity in using a simple fault feature vector comprising the time, frequency, and amplitude indices for the formidable amount of data being analyzed. A comprehensive examination of the characteristics of the time-frequency partitioning strategy will be presented for the proposed approach.

In the following sections, the formulation rationale will be introduced first in order to describe the procedure for dealing with non-stationary vibration measured from the valve cover seat of the reciprocating compressor. The time-frequency analysis techniques applied will be briefly reviewed. The fault feature vector extracted from the formidable amount of time-frequency data to facilitate later processing using an artificial neural network is thereafter addressed. Modification of the fault feature vector for better performance is subsequently reported. Numerical results and discussions are given to accentuate the unique achievement for the remarkable 100% correct classification of the 15 fault cases without removing the similar ones.

## II. FORMULATION RATIONALE

The feasibility for valve condition classification of reciprocating compressors using the time-frequency analysis technique and the artificial neural network has been demonstrated [14, 15]. Fifteen seeded faults are presented in this work based on practical observation of the valve flaws, such as misplace-

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ment between the valve and the spring plates, incorrect valve seat or valve cover tightness, softening of the spring plate, cracked or broken valve plate/spring plate. The seeded faults are tabulated in Table A.1, as shown in Appendix A. An accelerometer was mounted on the valve cover for vibration monitoring with a remote optical sensor used to track the cycle events, such as opening or closing of the suction/discharge valves of the reciprocating compressor. Three time-frequency analysis techniques, i.e. the short time Fourier transform (STFT), the smoothed pseudo-Wigner–Ville distribution (SPWVD), and the reassigned smoothed pseudo-Wigner–Ville distribution (RSPWVD), were applied to extract the time-frequency characteristics of the compressor considering the time-varying nature of its vibration.

The STFT of the vibration signal measured can be written as [5, 6, 10]:

$$STFT_x^{(\gamma)}(t, f) = \int_{t'} [x(t')r^*(t'-t)]e^{-j2\pi ft'}\mathrm{d}t' \tag{1}$$

where $x(t')$ is the time domain signal and $r^*(t)$ is the complex conjugate of the window function. The SPWVD of the vibration signal measured can be described as [5, 6, 8, 10]:

$$\begin{aligned} SPWVD_s^{(g,\eta)}(t,f) &= \int_\tau \left[ \int_{t'} g(t-t')s(t'+\frac{\tau}{2})s^*(t'-\frac{\tau}{2})\mathrm{d}t' \right] \eta(\frac{\tau}{2})\eta^*(-\frac{\tau}{2})e^{-j2\pi f\tau}\mathrm{d}\tau \\ &= \int_{t'} h(\tau)\int_{t'} g(t-t')WVD_s(t, f')\mathrm{d}t'\mathrm{d}\tau \\ &= \int_{t'}\int_{f'} g(t-t')H(f-f')WVD_s(t, f')\mathrm{d}t'\mathrm{d}f' \end{aligned} \tag{2}$$

where *s(t)* and $g(t)$ are the signal to be analyzed and the smoothing time window, respectively. $H(f)$ is the Fourier transform of the smoothing window $h(\tau)$ along the frequency axis. The RSPWVD of the vibration signal measured can be used to re-allocate the centers of the time and frequency for improving the interference, as shown below [1, 2, 4, 7]:

$$\hat{t}(x;t,f) = \frac{\iint t'\psi_t(t-t', f-f')W_x(t', f')\ \mathrm{d}t'\mathrm{d}f}{\iint \psi_t(t-t', f-f')W_x(t', f')\ \mathrm{d}t'\mathrm{d}f} \tag{3}$$

$$\hat{f}(x;t,f) = \frac{\iint f'\psi_t(t-t', f-f')W_x(t', f')\ \mathrm{d}t'\mathrm{d}f}{\iint \psi_t(t-t', f-f')W_x(t', f')\ \mathrm{d}t'\mathrm{d}f} \tag{4}$$

To facilitate automatic condition classification of the valve faults, the probabilistic neural network (PNN) [18, 19] is implemented so that no human experts are required to make judgment of the fault type. The manual inspection would be futile because of the complexity of the system considered. The amount of the time-frequency data is formidable to be processed by the PNN and an appropriate data reduction strategy is crucial. The fault features are extracted from the original data sets by considering three indices, namely time, frequency, and amplitude of each time-frequency vibration data. For better conditioning of the data to be processed in PNN, three modification methods are considered. They are the mean variation method, the min/max method, and the unit STD method, which are summarized in Appendix B for completeness. To improve the classification accuracy for a system with minute differences between the fault cases, a novel approach by considering time/frequency partitions is proposed in this work. The analysis steps for the proposed automated classification system can be summarized below:

1. Measure the vibration data at the valve cover for each cycle event of the reciprocating compressor.
2. Perform the time-frequency analysis of the measured vibration signal for each fault case.
3. Extract the fault feature vector from the time-frequency data obtained in step 2 for each fault case. The time-frequency data can be further partitioned to provide additional fault feature vectors for each fault case for better representation of system characteristics.
4. Train and test the artificial neural network using the extracted fault feature vectors for each fault case.

## III. NUMERICAL RESULTS AND DISCUSSIONS

Typical analysis results for the number of misclassification using two partitions in both the frequency and the time axes with the STFT considered for the 15, 11, and 7 fault cases are shown in Tables 1-3 respectively. Twenty samples are used for both the training and testing for each case and the numbers in parentheses denote the results without any time/frequency partition. As can be seen, a drastic improvement in classification accuracy is evident with use of the proposed approach considering the time/frequency partition. For instance, the number of misclassification can be reduced from approximately 25% to below 3% for the 15 fault cases, and from approximately 9% to below 1% for the 11 fault cases. A flawless classification can be achieved for the 7 fault cases using any of the three modification indices. Note that minute differences in nature between the fault cases are present for the 15 fault cases. It is difficult to differentiate the fault cases with minute differences by the automated classification system.

To further examine the characteristics and performances of the time/frequency partition approach, a systematic analysis has been conducted for classification of the 15 fault cases. Figures 1-3 depict the misclassification versus the number of partitions on the frequency axis when the STFT is considered. The effect of partition on the time axes is also illustrated. As can be seen in Fig. 1, the use of time/frequency partition when using the mean variation method appreciably reduces misclassification initially, but the classification accuracy declines when more partitions are considered.

Significantly better performances can be observed when using the two other modification indices, the min/max method and the unit STD method, as illustrated in Figs. 2 and 3. A striking 100% correct classification can be achieved when using these methods. A similar trend can be observed in Figs 4-6 and 7-9, which show the classification results when the SPWVD and the RSPWVD are considered.

**Table 1. The number of misclassification for the 15 fault cases with two**

**partitions on both the frequency and the time axes using STFT with training / testing samples:20/20 for each case (numbers in parenthesis denoting the results without any time/frequency partition)**

| | mean variation method | min/max Method | unit STD method |
|---|---|---|---|
| Case 1 | 1 (6) | 0 (7) | 0 (7) |
| Case 2 | 2 (3) | 3 (4) | 0 (4) |
| Case 3 | 1 (2) | 3 (7) | 2 (8) |
| Case 4 | 0 (3) | 0 (2) | 0 (2) |
| Case 5 | 3 (7) | 3 (20) | 2 (20) |
| Case 6 | 2 (11) | 1 (11) | 1 (11) |
| Case 7 | 2 (3) | 1 (3) | 1 (3) |
| Case 8 | 1 (3) | 2 (6) | 1 (6) |
| Case 9 | 0 (3) | 0 (3) | 0 (3) |
| Case 10 | 0 (2) | 0 (1) | 1 (1) |
| Case 11 | 2 (3) | 0 (6) | 0 (5) |
| Case 12 | 0 (7) | 0 (2) | 0 (3) |
| Case 13 | 0 (2) | 0 (1) | 0 (1) |
| Case 14 | 0 (0) | 0 (0) | 0 (0) |
| Case 15 | 0 (0) | 0 (0) | 0 (0) |
| Total Misclassification | **14** (55) | **13** (73) | **8** (74) |
| Error (%) | **4.67** (18.33) | **4.33** (24.33) | **2.67** (24.67) |

**Table 2. The number of misclassification for the 11 fault cases with two partitions on both the frequency and the time axes using STFT with training / testing samples:20/20 for each case (numbers in parenthesis denoting the results without any time/frequency partition)**

| | mean variation method | min/max Method | unit STD method |
|---|---|---|---|
| Case1 | 0 (0) | 0 (1) | 0 (1) |
| Case2 | 2 (1) | 3 (4) | 0 (4) |
| Case4 | 0 (1) | 0 (1) | 0 (1) |
| Case7 | 1 (2) | 1 (1) | 1 (2) |
| Case9 | 0 (3) | 0 (3) | 0 (3) |
| Case10 | 0 (0) | 0 (0) | 0 (0) |
| Case11 | 1 (3) | 0 (6) | 0 (5) |
| Case12 | 0 (5) | 0 (2) | 0 (3) |
| Case13 | 0 (1) | 0 (1) | 0 (1) |
| Case14 | 0 (0) | 0 (0) | 0 (0) |
| Case15 | 0 (0) | 0 (0) | 0 (0) |
| Total Misclassification | **4** (16) | **4** (19) | **1** (20) |
| Error (%) | **1.82** (7.27) | **1.82** (8.64) | **0.45** (9.09) |

**Table 3. The number of misclassification for the 7 fault cases with two partitions on both the frequency and the time axes using STFT with training / testing samples:20/20 for each case (numbers in parenthesis denoting the results without any time/frequency partition)**

| | mean variation method | min/max Method | unit STD method |
|---|---|---|---|
| Case1 | 0 (0) | 0 (1) | 0 (1) |
| Case4 | 0 (1) | 0 (1) | 0 (1) |
| Case9 | 0 (3) | 0 (3) | 0 (3) |
| Case10 | 0 (0) | 0 (0) | 0 (0) |
| Case12 | 0 (5) | 0 (2) | 0 (6) |
| Case13 | 0 (0) | 0 (0) | 0 (0) |
| Case14 | 0 (0) | 0 (0) | 0 (0) |
| Total Misclassification | **0** (9) | **0** (7) | **0** (11) |
| Error (%) | **0** (6.43) | **0** (5) | **0** (7.86) |

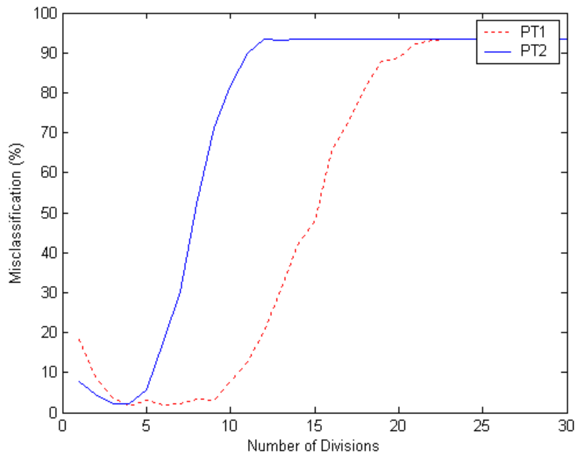


**Fig. 1. Misclassification versus the number of partitions on the frequency axis for the 15 fault cases with the STFT and the mean variation method being used. PT1 (No. of Partitions on the Time Axis: 1), PT2 (No. of Partitions on the Time Axis: 2)**

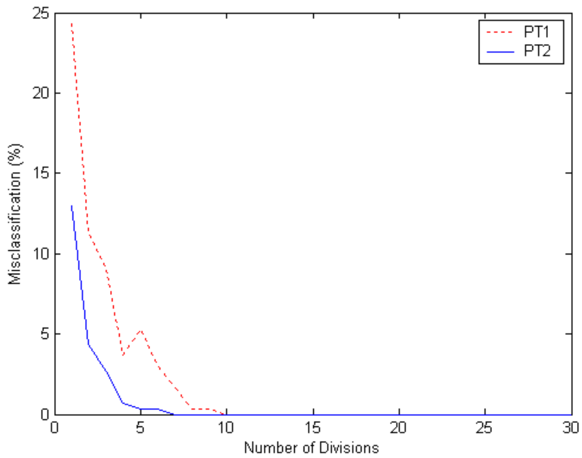


**Fig. 2. Misclassification versus the number of partitions on the frequency axis for the 15 fault cases with the STFT and the min/max method being used.**

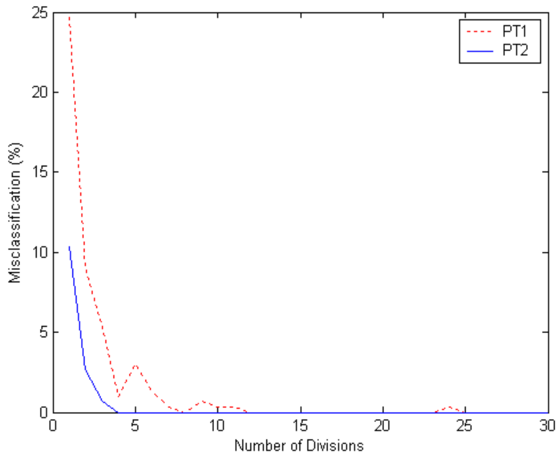


**Fig. 3. Misclassification versus the number of partitions on the frequency axis for the 15 fault cases with the STFT and the unit STD method being used.**

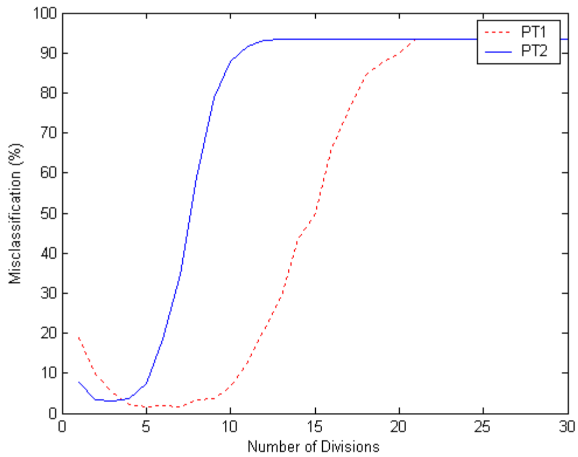


**Fig. 4. Misclassification versus the number of partitions on the frequency axis for the 15 fault cases with the SPWVD and the mean variation method being used.**

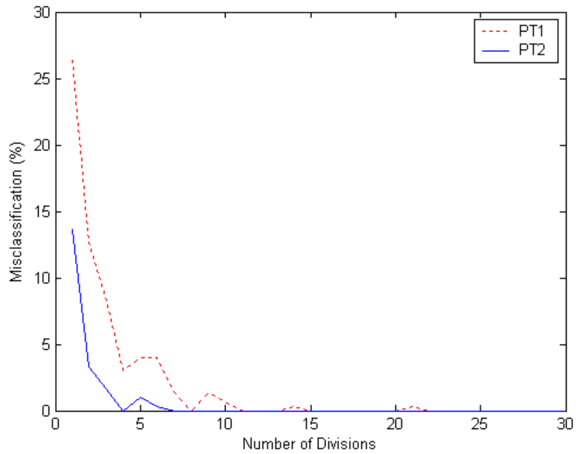


**Fig. 5. Misclassification versus the number of partitions on the frequency axis for the 15 fault cases with the SPWVD and the min/max method being used.**

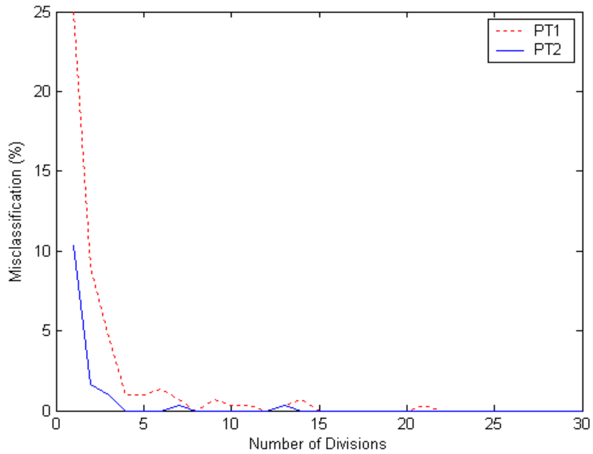


**Fig. 6. Misclassification versus the number of partitions on the frequency axis for the 15 fault cases with the SPWVD and the unit STD method being used.**

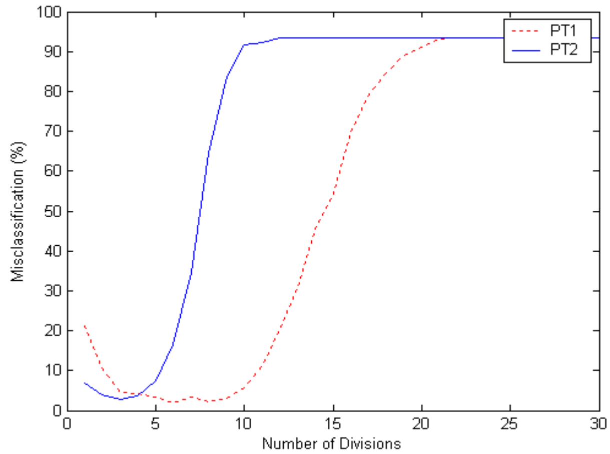


**Fig. 7. Misclassification versus the number of partitions on the frequency axis for the 15 fault cases with the RSPWVD and the mean variation method being used.**

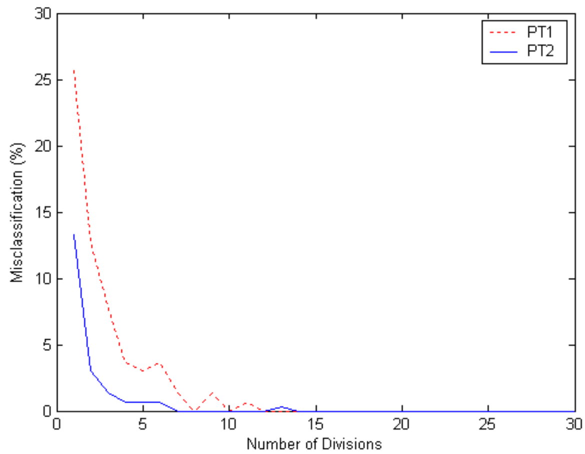


**Fig. 8. Misclassification versus the number of partitions on the frequency axis for the 15 fault cases with the RSPWVD and the min/max method being used.**

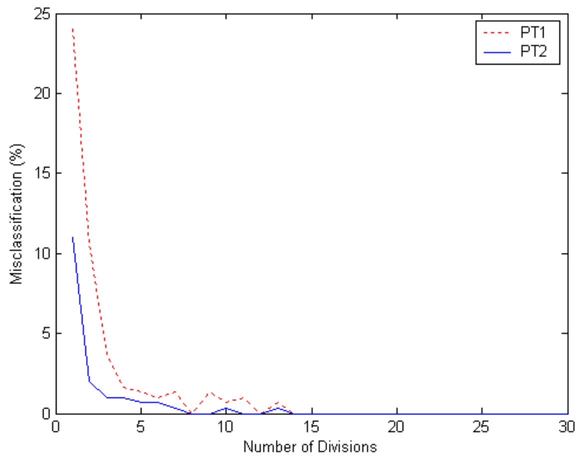


**Fig. 9. Misclassification versus the number of partitions on the frequency axis for the 15 fault cases with the RSPWVD and the unit STD method being used**

It is worth noting that the use of too many time/frequency partitions may be unfavorable, especially for the mean variation method. Figures 10 and 11 illustrate the data reduction scheme to represent the original formidable amount of time-frequency data with three and ten partitions on the frequency axes, respectively. Two partitions on the time axes are considered. The centroids are represented by enlarged bold dots. Figure 10 shows a proper time/frequency partition, whereas the use of too many partitions, as shown in Fig. 11, may create indiscernible regions among the fault cases, such as those highlighted with elliptical marks. This is attributed to the fact that finer partitioning increases the possibility of information-sparse regions.

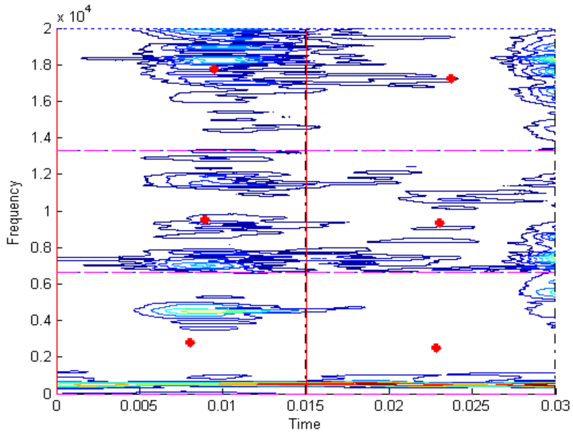


**Fig. 10. The centroid locations for three partitions on the frequency axes and two partitions on the time axes of the STFT time-frequency representation.**

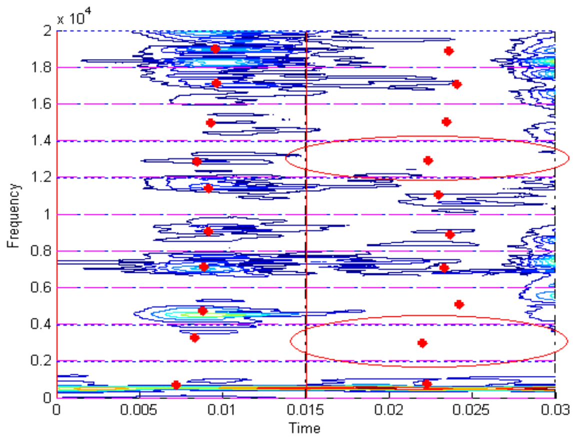


**Fig. 11. The centroid locations for ten partitions on the frequency axes and two partitions on the time axes of the STFT time-frequency representation.**

The minute activities in these regions may incur misclassification due to their similarities. The mean variation method appears to be highly susceptible due to its nature in considering the mean and variation of the time-frequency data. Table 4 shows the achievable minimal misclassification considering time/frequency partitions. As can be seen, a flawless 100% correct fault classification can be realized using either the min/max or the unit STD method. For instance, fascinating classification results without any error can be achieved with the use of 12 partitions on the frequency axis and no partition on the time axis when the STFT and the unit STD method are applied. To achieve the same perfection in fault classification, only four

partitions on the frequency axis is required if the time axis is partitioned into two parts.

**Table 4. Achievable minimal misclassification considering time/frequency partitions (numbers in parenthesis denoting the results without any time/frequency partition)**

| | | Mean Variation Method | | Min/max Method | | Unit STD Method | |
|---|---|---|---|---|---|---|---|
| | | No. of Frequency Partitions | % Error | No. of Frequency Partitions | % Error | No. of Frequency Partitions | % Error |
| STFT | PT1 | 4 | 1.67 (18.33) | 10 | 0 (24.33) | 12 | 0 (24.67) |
| | PT2 | 3 | 2.337 (18.33) | 7 | 0 (24.33) | 4 | 0 (24.67) |
| SPWVD | PT1 | 5 | 1.67 (19) | 15 | 0 (26.33) | 15 | 0 (25) |
| | PT2 | 3 | 3 (19) | 7 | 0 (26.33) | 8 | 0 (25) |
| RSPWVD | PT1 | 6 | 2 (21.33) | 12 | 0 (25.67) | 14 | 0 (24) |
| | PT2 | 3 | 2.67 (21.33) | 14 | 0 (25.67) | 14 | 0 (24) |

PT1 (number of partitions on the time zxis: 1)
PT2 (number of partitions on the time axis: 2)

It is worth noting that the use of STFT outperforms the other two more complex time-frequency analysis techniques, the SPWVD and the RSPWVD, for the valve condition classification of a reciprocating compressor considered in this study. Either the SPWVD or the RSPWVD yields significantly better localization properties than the STFT, at the expense of requiring more than 30 times in computation time in the analysis case of 2048 samples (sampling frequency: 51200 Hz). For the problem examined in this work, it can be seen to be futile to pursue better localization properties of the original time-frequency characteristics. The use of the proposed feature vector to represent the time-frequency data and the application of the STFT make the automated valve condition classification system remarkably appealing in view of the attainable accuracy and the required computation expenditure.

## IV. CONCLUSIONS

A novel strategy has been reported in this work to further enhance the accuracy of a valve condition classification system without removing the disturbing similar fault cases which deteriorate the performance of the classification system. It can be observed that 100% correct classification can be accomplished without removing similar fault cases. This perfection in classification is realized by considering improved representation of the time-frequency characteristics with an appropriate partitioning in the time-frequency plane and selection of index modification method. As can be seen from the analysis results, the use of four partitions on the frequency axis with two partitions along the time axis, resulting in a total of eight sub-regions, can render nil misclassification of all fault cases considered in this work when the STFT and the unit STD method are applied. This study demonstrates that the indiscernible minute difference can be successfully classified and early warning of the machine's health condition can be accomplished by the proposed automated valve fault classification system.


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## APPENDIX A

Table A.1 shows the seeded faults which reflect the typical problems the valve system commonly encounters in practice.

**Table A.1 The seeded fault cases under investigation.**

| | Valve cover torque (N·m) | Valve seat torque (N·m) | Valve Plate | Spring Plate (SP) | Notes |
|---|---|---|---|---|---|
| Case 1 | 19.62 | 19.62 | VP 1 | SP 4 | Normal condition ($K$ = 5306.35 N/m) |
| Case 2 | 19.62 | 19.62 | VP 1 | SP 4 | Misplacement of the valve and spring plates |
| Case 3 | 19.62 | 24.53 | VP 1 | SP 4 | Over-tightening of the valve seat |
| Case 4 | 19.62 | 14.72 | VP 1 | SP 4 | Moderately inadequate tightening of the valve seat |
| Case 5 | 19.62 | 9.81 | VP 1 | SP 4 | Inadequate tightening of the valve seat |
| Case 6 | 14.72 | 19.62 | VP 1 | SP 4 | Moderately inadequate tightening of the valve cover |
| Case 7 | 9.81 | 19.62 | VP 1 | SP 4 | Inadequate tightening of the valve cover |
| Case 8 | 19.62 | 19.62 | VP 1 | SP 1 | Softening of the spring plate ($K$ = 4054.65 N/m) |
| Case 9 | 19.62 | 19.62 | VP 1 | SP 2 | Softening of the spring plate ($K$ = 4329.15 N/m) |
| Case 10 | 19.62 | 19.62 | VP 1 | SP 3 | Softening of the spring plate ($K$ = 2886.25 N/m) |
| Case 11 | 19.62 | 19.62 | VP 1 | SP 5 | Cracked spring plate |
| Case 12 | 19.62 | 19.62 | VP 2 | SP 4 | Cracked valve plate |
| Case 13 | 19.62 | 19.62 | VP 1 | SP 6 | Spring plate with the inner end broken |
| Case 14 | 19.62 | 19.62 | VP 3 | SP 4 | Valve plate with the inner end broken |
| Case 15 | 19.62 | 19.62 | VP 4 | SP 4 | Valve plate with the outer end broken |

## APPENDIX B

Three fault features, namely, the time index $T_i$, the frequency index $F_i$, and the amplitude index $P_i$ are considered here, as shown below:

$$T_i = \frac{\int_{t_1}^{t_2} t \cdot TFD_s(t, f)\mathrm{d}t}{\int_{t_1}^{t_2} TFD_s(t, f)\mathrm{d}t}$$
$$F_i = \frac{\int_{f_1}^{f_2} f \cdot TFD_s(t, f)\mathrm{d}f}{\int_{f_1}^{f_2} \cdot TFD_s(t, f)\mathrm{d}f} \tag{B.1}$$
$$P_i = E\left[TFD_s(t, f)\right]$$

Modification of indices for better performance in fault classification is considered in this work. The variance $\sigma_z{}^2$ can be expressed as

$$\sigma_z{}^2 = E\left[(z - \bar{z})^2\right] \tag{B.2}$$

where $\bar{z}$ is the mean of $z$ and $\sigma_z$ is the standard deviation. Three modified indices methods are considered in this work, namely, the mean variation method, the min/max method, and the unit STD method. The mean variation method defines the three indices as

$$t_{i1} = (T_i - \bar{T}^e) / \bar{T}^e \times 100,$$
$$f_{i1} = (F_i - \bar{F}^e) / \bar{F}^e \times 100 \tag{B.3}$$
$$p_{i1} = (P_i - \bar{P}^e) / \bar{P}^e \times 100$$

where the superscript '$e$' refers to the expected value. The min/max method modifies the original data set to fall in the range [-1, 1]:

$$t_{i2} = 2 \times (T_i - T_{\min}) / (T_{\max} - T_{\min}) - 1$$
$$p_{i2} = 2 \times (P_i - P_{\min}) / (P_{\max} - P_{\min}) - 1 \tag{B.4}$$
$$f_{i2} = 2 \times (F_i - F_{\min}) / (F_{\max} - F_{\min}) - 1$$

where the subscripts 'max' and 'min' refer to the maximum and minimum, respectively, of the corresponding indices. The unit STD method normalizes a given data set so that the inputs and targets will have means of zero and standard deviations of unity:

$$t_{i3} = (T_i - \bar{T}^e) / \sigma_{T_i} \times 100$$
$$f_{i3} = (F_i - \bar{F}^e) / \sigma_{F_i} \times 100 \tag{B.5}$$
$$p_{i3} = (P_i - \bar{P}^e) / \sigma_{P_i} \times 100$$

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