On Detection and Classification of State Changes in Physical Processes by Signal Processing Techniques

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Abstract: The paper presents a comparation of some methods based on signal processing, for detection and classification of the changes in the states of physical processes. The investigated processes generate mechanical vibrations, which are properly managed for computer-based processing. As a case study, the incipient faults in bearings are considered. Five signal processing methods are promoted, which are based on statistical processing, signal modelling, spectral analysis, time-frequency image processing, and information modelling. Statistical processing method considers ten features based on statistical moments of various orders. The method of signal modelling involves models with parameters estimated by an Kalman estimator. The method of spectral analysis considers the power spectrum of the vibration's signals. The method based on time-frequency analysis considers the short-time Fourier transform and Choi-Williams transform for feature extraction. The information-based method is based on information source identification and processing. The classifier is based on similarity comparation using a distance-based classifiers. The novelty/contribution of the paper is the evaluation of the methods for change detection and diagnosis, all based on signal processing paradigm. Each of the considered method has advantages and disadvantages and depends on available data. The involved techniques could be applied also in process monitoring and conditioning.

1 INTRODUCTION

In the operation of production processes, defects in various elements of the components may occur. Their incipient detection and limitation of interruptions in production are of major importance in engineering practice. Fault detection refers to such problems/defects in the context of physical and – very often – industrial processes. However, the use of this expression may be limiting or inappropriate, as possibly giving rise to mis interpretation in certain cases. For example, changing the state of a variable in the process can also be achieved without being defective, by changing the regime and/or the load in the process under study.

Change detection based on the recording and processing of a single signal, in the simplest case, is done by checking the "dynamic" range of the signal (peak-peak value) or, in more complex cases, on the extraction of features and the application of change detection methods.

By detecting the change of a state is meant the activity of sensing/ identifying the change of a state (usually undesirable) in the operation of a system. The processed signals are taken from the process or are obtained from the use of a model, through simulation. Such signals can be vibration signals, sound waves of different frequencies (e.g., audio, ultrasonic), and even electrical signals from the investigated system.

There are processes in which harmonic signals are available (by measurements) and affected by a greater or lesser number of noises, so they have a random behavior. If the changes in these signals correspond to defects in action elements, process or sensors, methods based on signal-model-based can be applied. A representative example is the vibration monitoring application which allows, by measuring position, speed or acceleration, the detection of non-equilibrium or defective bearings.

An example of a complex process, in which the detection of change and the detection of defects and diagnosis are important activities are the case of a

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wind turbine, where faults can be in the mechanical part (external blades, reducer box) or in the electrical part (generator, converter, transformer, etc.). Another case is of a rolling mill, where the mechanical part is important in the quality of the product and is the part dominated in the generation of defects, sources of vibration signals, (Precup et al., 2015), (Seeliger et al., 2002).

In the field of Change Detection and Diagnosis (CDD) methods, two categories are important, (Zhang & Jiang, 2008). The methods based on model, process and/or measured signals, and methods based on measured data. From the various available methods, in this work it will be considered the analytical method, based on the processing of the vibration signals. Other examples and details are available through the references (Isermann, 2006), (Patton, et al, 1989), (Venkatasubramanian, et al, 2008), (Ypma, 2001), (Zhang, 2010).

The structure of the detection method by analyzing the signal model assumes a mathematical model for the signal, one can calculate specific parameters such as: amplitudes, phases, frequency spectra and correlation functions, for the frequency of the signal. By comparison with the features observed in normal function, analytical syndromes are generated. Signal models can be parametric (amplitudes for certain frequencies or specific type models) or nonparametric (frequency spectra or statistical correlation functions), (Iserman, 2006).

The detection of the changes by methods of processing their signatures can be solved by several methods, some of which are direct (i.e. the signal is processed directly and the processed values have physical significance) or indirect (values are processed transformed into different spaces from the original ones, where the processed data may or may not have physical significance, (Timusk, et al, 2008). In direct methods, the observed values are directly calculated by calculating statistical quantities (most often) or gradient-based criteria. These methods are often applied in process monitoring applications by processing vibrations and audio signals. The methods are simple to understand and simple to implement, sometimes with very good results, but less good in the case of non-stationary signals or time-varying or interdependent events (defects).

Indirect methods, based on transformations, are more complex, but the calculations for decision making in the new spaces of observations are simpler. Compared to direct methods, indirect methods give better results. The following types of transformations can be exemplified here: time-frequency transformations and entropic transformations (based on the evolution of entropy).

The signals can be processed in the time domain, in the frequency domain or in the combined/mixed time-frequency domain. Each of these areas has advantages and disadvantages, so a robust solution involves a combination of methods from the fields presented, (Popescu et al, 2017).

The paper is organized in five sections. The next section presents the general structure of the methods used for data processing and a short analysis of data used in the testing stage. Section 3 presents the principles of the promoted methods. Section 4 presents some results of the computer-based experiments. Finnally, the conclusion section ends the paper.

2 THE STRUCTURE OF THE METHODS

The problem of change detection and classification of faults in bearings is considered. The data used for experiments are from (CWR, 2022). There are four classes of signals, associated to four states/cases/faults: F0- free of faults, F1- fault in ball, F2 – fault in inner ring, and F4-fault in outer ring. For each state/fault, a record of 200,000 samples is available, which corresponds to an observation interval of ten [s]. The motor speed is 1797 rpm, and the working conditions are without mechanical load.

A test vector is considered with frames of 5,000 samples for each record, which is explored with a sliding window of length *w*, variable from 100 to 5,000 samples, depending on the performance of the detection. The bigger window the less precise is the point change detection.

The structure of the data processing is presented in Fig.1. Data are pre-processed by filtering and scaling to [-1,1] interval. The next block computes the features, and the classifier estimates the state/fault. The input waveforms are quite similar, so the most important block is the feature selector. A primary frequency analysis shows an overlapping in frequency domain, which will generate difficulties for a right classification. This is a reason to explore more than a method for CDD, as in the case of the present paper, and to promote combination of methods from the same domain or from different domains.

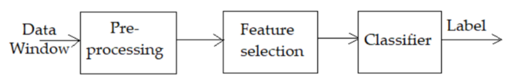

Figure 1: The structure of data processing.

3 THE METHODS

Five methods are considered for this work. Some are used as references, e.g., statistical method, and others are based on advanced processing techniques, as those based on time-frequency techniques.

3.1 The Statistical Method

The basic theory and the computation of the statistical moments are presented in (Gustafson, 2007), (Shanmugan and Breipohl, 1988), and (Barkat, 2005). Examples of the method under various simulation scenarios are presented in (Basseville, 1997), (Aiordachioaie, 2013).

Ten statistical features are used: the mean, the dynamic range, the median, the variance, the mean of the absolute values, the root mean squares, the peak value, the crest factor, the skewness, and the kurtosis.

Fig. 2 presents the evolution of the feature set, for an observation window with 500 samples. The evolution of the features indicates the moment of change. The process diagnosis depends on the performance of the classifier.

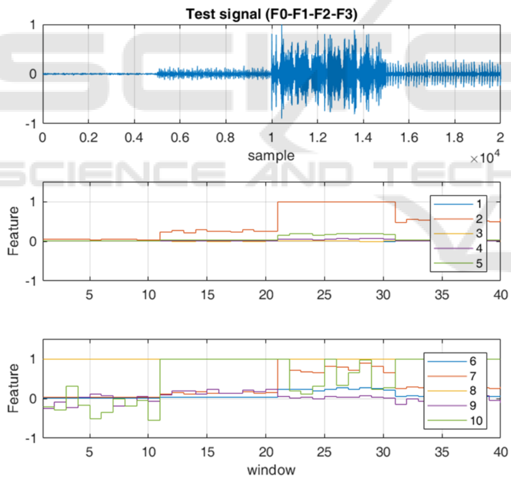

Figure 2: Features of the statistical method.

3.2 The Signal Modelling Method

The principle of the method is to design an autoregressive moving average (ARMA) signal model, (Kay, 1993), (Poor, 1994), (Bozic, 2021) and to estimate its parameters in each observation window. A change in one or more parameters indicates a change in the structure of the process.

The equation of the ARMA (*Ma, Mb*) model is

$$y(n) + \sum_{k=1}^{M_a} a_k(n) y(n-k) = \sum_{j=1}^{M_b} b_j(n) v(n-j) + v(n) \tag{1}$$

where *y(n)* is the modelled signal, and *v(n)* is Gaussian white noise. A Kalman estimator is used for the estimation of the parameters, (Haykin, 2002).

Fig. 3 presents an example of the first five parameters of the ARMA(5,5) model, during the test with windows (of length 500 sample). More details of the used method are available in (Aiordachioaie, 2014).

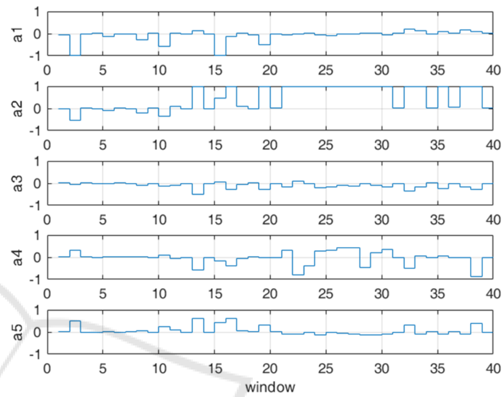

Figure 3: Features of the signal model-based method.

3.3 The Spectral Analysis Method

For each sliding data window, a power spectrum is computed and analysed. The features vector is composed of eight features: the mean and the variance in frequency, the third and fourth order centred statistical moments, the median, the energy in frequency domain, and the mean and the variance over the amplitude values. The basic equations are presented in (Aiordachioaie, 2022a).

Fig. 4 presents the evolution of the feature set, over a test vector composed of 40 windows. The evolution allows the detection of the changes in the test vector.

The method based on the features of power spectra is called SF (Spectral Features) and the method based on power spectra only is referred a SD (Spectral Direct) in Table 1. In the case of SD method, the spectral lines could be labelled as direct features. The SD method needs a higher resolution than SF.

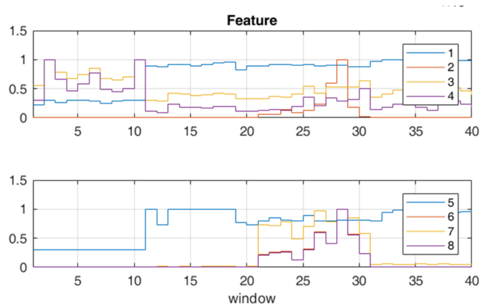

Figure 4: Evolution of the features in frequency domain.

3.4 Time-Frequency Analysis Method

The methods based on time-frequency transforms (TFT) represent effective solutions for the detection of change of in vibratory processes, since it is detected the change in the frequency domain and the moment of change in time domain, when they have occurred. The approach is indicated for intermittent and dynamic faults. Time-frequency analysis covers a major area related to the non-stationary signals (including transient ones) by the ability to detect and to locate them.

Three most used methods are based on the short-time Fourier transform (STFT), quadratic time-frequency transform (e.g., Wigner transform) and wavelet transform (WT). Some good references are (Auger, 1991), (Boashash, *et al*, 2014), and (Cohen, 1989).

Let consider a signal $x(t)$ and a sliding observation window $w(t)$. By discretization, a time-frequency matrix is generated. The basic equations for the above transforms are

$$X(n,f) = \sum_{k=-\infty}^{\infty} x(k)w(k-n)e^{-j2\pi fk} \qquad (2)$$

for STFT, and

$$W(n,f) = \sum_{k=-\infty}^{\infty} x(k)x^{*}(n+k)\, e^{-j2\pi fk} \qquad (3)$$

for Wigner transform. In experiments, the Choi-Williams transform (CWT) is used to decrease the interference terms, (Barry, 1992), (Flandrin, *et al*, 1996). In the case of WT, the signal $x(t)$ is decomposed following the mother wavelet φ, and the coefficients a_{lk} define the matrix of interest, (Mallat, 1989), and (Daubechies, 1992).

An efficient approach is to consider the coefficients of the TFT as elements of a digital image, and thus to obtain a time-frequency image (TFI). Each observation window generates a TFI, which is a matrix or a 2D signal.

Seven features are considered for an image as: the mean, the variance, the skewness, the kurtosis, the coefficient of variations, the spectral flux, the frequency of the maximum amplitude. The computation expressions are available in (Aiordachioaie, 2022b).

Fig. 5 presents a set of TFI based on STFT. It is about windows 1, 13, 27 and 39 from the set of 40. On the *x* axis the index of the window is presented, and on *y* axis the frequency in Hz. The size of the TFI is 6001x50 pixel.

Fig. 6 shows a set of four TFI based on CWT for the same set of windows. The time variable is considered on the *x* axis. The size of the TFI is 500x500 pixel. This approach has a higher precision referred to the previous one. By analysing and classifying the content of the image, the change and diagnosis could be easily solved.

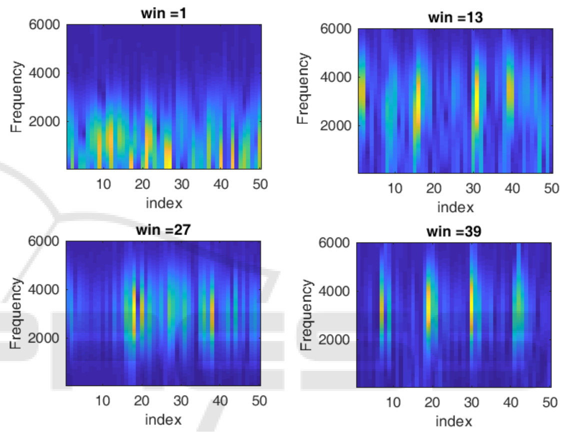

Figure 5: Time-frequency images for STFT.

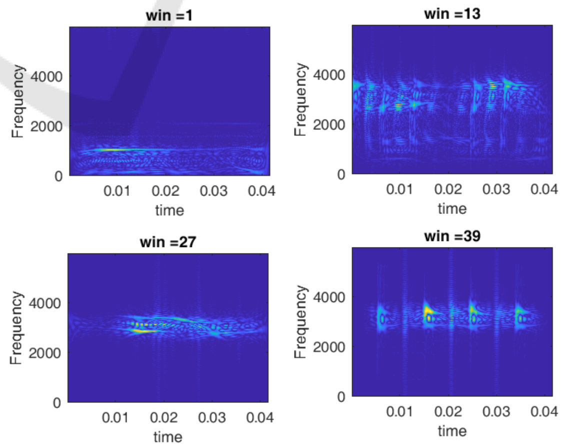

Figure 6: Time-frequency images for CWT.

The Fig.7 and 8 presents the evolution of some features for the methods of time-frequency approaches. A change in the signal is detected by one or more changes of the selected features.

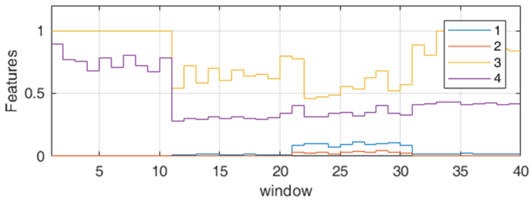

Figure 7: Feature evolution for STFT based method.

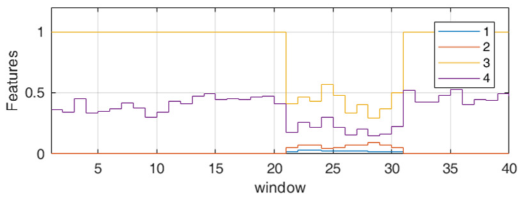

Figure 8: First four features for CWT based method.

3.5 The Information Processing Method

Functions based on entropies is used for each data window, e.g., Renyi entropy. A source identification process is necessary before computation of the entropies, to estimate the probabilities of the basic elements. The approach can be applied directly to the vibration signals (1D signals) or to time-frequency images (2D signals) as in the present approach.

The set of the features has the Shannon entropy, the Renyi entropy of order 2 and 3, (Baraniuk, 2001), the multiscale entropy, (Humeau-Heurtier, 2016), the crest factor, the variance of the probabilities, the maximum amplitude of data, and the Lempel-Ziv complexity (Aiordachioaie & Popescu, 2020), (Karmeshu, 2003), and (Aiordachioaie, 2021).

The most used entropy is the Renyi entropy of order α, defined as

$$HR_{\alpha}(X) = \frac{1}{1-\alpha} log_2 \sum_{i=1}^{n} P_i^{\alpha}, \alpha \neq 1 \qquad (5)$$

where P_i are the probabilities of the samples from the set X. For an image $\boldsymbol{I}$, a normalized expression is used for Renyi entropy as

$$HR_{\alpha}(\boldsymbol{I}) = \frac{1}{1-\alpha} log \sum_n \sum_k \left(\frac{I[n,k]}{\sum \sum I[n',k']} \right)^{\alpha} \qquad (6)$$

Fig. 9 presents the first four features obtained by using information-based approach. This method is called “Info” in Table 1. The challenge is to properly design the change detection criteria, in a trade-off between the change point detection and computational resource and complexity.

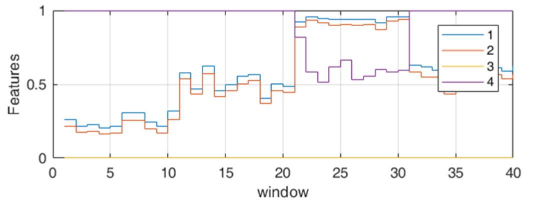

Figure 9: The information-based features.

4 EXPERIMENTS RESULTS

The above methods were evaluated with a vector composed from four segments, one for a state/fault, each of 5,000 samples.

The results of the classification/recognition rates (RR) are presented in Table 1, for both used distances, Euclidean and Manhattan. Three values of the length *w* of the observation window were considered, i.e., 500, 2,500 and 5,000 samples. The number of the used features *nf* is also presented.

The low values of some methods are explained by the non-stationarities of the test signals. The highest values of classification rates were obtained by the ARMA method, which needs at least 5,000 samples to properly estimate the parameters of the model.

Table 1: Results of the classification.

		RR [%]			
No.	*Type*	*Euclidean*	*Manhattan*	*w*	*nf*
1.	Stat	72.50	47.50	500	10
2.	ARMA	67.50	52.50	500	10
3.	SF	70.00	75.00	500	8
4.	SD	80.00	**90.00**	500	*w*
5.	STFT	75.00	50.00	500	7
6.	CWT	40.00	40.00	500	7
7.	Info	47.50	45.00	500	8
8.	Stat	75.00	50.00	2500	10
9.	ARMA	87.50	62.50	2500	10
10.	SF	75.00	75.00	2500	8
11.	SD	**100**	62.50	2500	*w*
12.	STFT	50.00	50.00	2500	7
13.	CWT	50.00	50.00	2500	7
14.	Info	50.00	50.00	2500	8
15.	Stat	75.00	50.00	5000	10
16.	ARMA	**100**	50.00	5000	10
17.	SF	75.00	75.00	5000	8
18.	SD	75.00	50.00	5000	*w*
19.	STFT	50.00	50.00	5000	7
20.	CWT	50.00	50.00	5000	7
21.	Info	50.00	50.00	5000	8

5 CONCLUSIONS

The main objective of the work was to present a set of CDD methods based on signal modelling paradigm. The basic structure of the data processing has two blocks: one for the computation of the features and another one for classification, based on distance functions. The block of feature selection based, e.g., on feature variance and on the sensitivity of CDD criterion is not considered here. The complexity of the methods is not considered here.

Five methods were considered. Each method has pros and cons, and a good approach is to combine them to obtain the highest recognition rate.

A special attention was paid to time-frequency representations, by developing and adapting features from time or frequency domains.

The computer-based experiments indicate a need to select the region of interest before computing the features for CDD. This will be the next research step to follow.

REFERENCES

Aiordachioaie, D., 2022a. On change detection and process diagnosis based on information and frequency domain models, *AIP Conference Proceedings*, 2570, 040020.

Aiordachioaie, D., 2022b. On Feature Selection from Time-Frequency Images, *14th Int. Conf. on Electr., Comp. and AI* (ECAI), pp. 1-4.

Aiordachioaie, D., 2021. Industrial Process Diagnosis based on Information and Time Domain Models, *13th Int. Conf. on Electr., Comp. and AI* (ECAI), pp. 1-4.

Aiordachioaie, D. and Popescu, Th.D., 2020, Aspects of Time Series Anal. with Entropies and Complexity Measures, *Int. Symp. on Electr. & Tc* (ISETC), pp. 1-4.

Aiordachioaie, D., 2014. On quick-change detection based on process adaptive modelling and identification, *Int. Conf. on Develop. and Appl. Syst.* (DAS), pp. 25-28.

Aiordachioaie, D., 2013. Signal Segmentation Based on Direct Use of Statistical Moments and Renyi Entropy, *10th Int. Conf. on Electr., Computer and Computation* (ICECCO), Istanbul, Turkey, pp. 359-362.

Auger, F., 1991. *Representations Temps-Frequence Des Signaux Nonstationnaires: Synthese et Contributions*, PhD thesis, Ecole Centrale de Nantes, France.

Bozic, S.M., 1996. Digital and Kalman Filtering. An introduction to discrete time-filtering and optimum linear estimation, *Halsted Pr*., 2nd Edition.

Basseville, M., 1997. Statistical approaches to industrial monitoring problems - Fault detection and isolation, *Proc. Of the SYSID'97*, Kitakyushu, Japan.

Boashash, B., Azemi, G., and Khan, N.A., 2014. Principles of time–frequency feature extraction for change detection in nonstationary signals: appl. to newborn EEG abnormality detection, *PR*, pp. 616-627.

Baraniuk, R.G., et al, 2001. Measuring time–frequency information content using the Rényi entropies, *IEEE Trans. on IT*, 47(4), pp. 1391-1409.

Barry, T. 1992. Fast calculation of the Choi-Williams time-frequency distribution, *IEEE Trans. on SP*, 40(2), pp. 450-455.

Barkat, M., 2005. *Signal Detection and Estimation*, 2nd Edition, Artec House.

CWR, Case Western Reserve Univ. Bearing Data Center, 2022. https://engineering.case.edu/bearingdatacenter.

Cohen, L., 1989. Time-Frequency Distributions - A Review, *Proceedings of the IEEE*, 77(7), pp. 941–980.

Daubechies, I., 1992. Ten lectures on wavelets, CBMS-NSF Conf. series in applied mathematics. *SIAM* Ed.

Flandrin, A.P.; Gonçalvès, P.; Lemoine, O., 1996. *Time-Frequency Toolbox for Use with MATLAB,* CNRS (France) / Rice Univ. (USA).

Gustafson, F., 2007. *Statistical Signal Processing Approaches to Fault Detection*, ARC, 31, pp.41–54.

Haykin, S. 2002. *Adaptive Filter Theory*, 4th Edition, Prentice Hall.

Humeau-Heurtier, A., (Editor) 2016. *Multiscale Entropy Approaches and Their Applications*, MDPI Entropy.

Isermann, R. 2006. *Fault detection with signal models. In: Fault-Diagnosis Systems*. Springer, Berlin, Heidelberg.

Karmeshu, J., 2003. (Ed.). *Entropy measures, maximum entropy principle and emerging applications*, New York: Springer-Verlag.

Kay, S.M., 1993. *Fundamentals of Statistical Signal Processing: Estimation Theory*, Prentice Hall.

Seeliger, A., Mackel, J., and Georges, D., 2002. Measurement and Diagnosis of Process-Disturbing Oscillations in High-Speed Rolling Plants, *IMEKO* 2002, Tampere, Finland

Shanmugan, K.S. and Breipohl, A.M., 1988. *Random Signals: Detection, Estimation and Data Analysis*, John Wiley & Sons, NY.

Timusk, M.; Lipsett, M.; Mechefske, C.K., 2008. Fault detection using transient machine signals, *Mechanical Systems & SP*, Vol. 22, pp. 1724-1749.

Patton, R.J.; Frank, P; Clark, R., 1989. *Fault Diagnosis in Dynamic Syst. – Theory and Application*, Prentice Hall.

Precup, R.E., et al, 2015. An overview on fault diagnosis and nature-inspired optimal control of industrial process appl., *Computers in Ind.*, 74, pp. 75-94.

Popescu, Th.D, Aiordachioaie D., and Manolescu, M., 2017. Change detection in vibration analysis — A review of problems and solutions, *Proc of the ISEEE*, Galati, Romania, pp. 1-6.

Poor, H.V., 1994. *An introduction to signal detection and estimation,* Springer.

Mallat, S., 1989. A theory for multiresolution signal decomposition: the wavelet representation, *IEEE Pattern Anal. and Machine Intell.*, 11(7), pp 674–693.

Venkatasubramanian, V., Rengaswamy, R; Yin, K.; Kavuri, S. N., 2008. A review of process fault detection and diagnosis, *Comp. & Chem. Eng.,* 27, pp. 293-311.

Ypma, A., 2001. *Learning Methods for Machine Vibration Analysis and Health Monitoring*, PhDThesis, TU Delft.

Zhang, W., 2010. *Fault detection*, In-Tech.