Fault classification using an Artificial Neural Network based on Vibrations from a Reciprocating Compressor

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ABSTRACT

Reciprocating compressors are widely used in industry for various purposes and faults occurring in them can degrade performance, consume additional energy, and even cause severe damage to the machine. This paper will develop an automated approach to condition classification of a reciprocating compressor based on vibration measurements. Both the time domain and frequency domain techniques have been applied to the vibration signals and a large number of candidate features have been obtained based on previous studies. A subset selection method has then been used to configure a probabilistic neural network (PNN), with high computational efficiency, for effective fault classifications. The results show that a 95.50% correct classification between four different faulty cases is the best result when using a subset of frequency feature, whereas a 93.05% rate is the best for the subset from the time domain.

Keywords: Condition Monitoring, Probabilistic Neural Network, Reciprocating Compressor, Time-domain and Frequency-domain features.

1 INTRODUCTION

Reciprocating compressors are desired in many industrial applications. They have the capability of providing high pressure, applicability for various kinds of gases and inter-stage cooling. However, the compressors expose some serious faults during operation. The cost of maintenance can be several times that of the centrifugal units. So, it is necessary to establish a system to diagnose and monitor reciprocating compressors to minimize unexpected failures and reduce the maintenance.

There have been many attempts made to diagnose and classify earlier faults from reciprocating compressors. Gu and Ball [1] presented the use of a smooth pseudo-Wigner–Ville distribution for interpretation of machinery vibration data. Naid [2] has shown that bispectral analysis of induction motor current has considerable potential as a means of detecting the presence of faults in, say, a driven compressor. However, he also showed that the conventional bispectrum is not sufficiently effective in the analysis of the AM current signals and he introduced the signal kurtosis which was then used to develop a diagnostic method for differentiating valve leakage, intercooler leakage and loose drive belt in a reciprocating compressor. Yang et al [3] presented some classifiers, self organizing feature map (SOFM), learning vector quantization (LVQ), and support vector machine (SVM), for fault features of a small reciprocating compressor.

The vibration of a reciprocating compressor in one service cycle presents non-linear characteristics due to the impacts resulting from the movement of the suction and discharge valves. Features are calculated from the time, frequency and envelope domains to analyze the signals from the sensors to assess the health of the system.

Artificial intelligence (AI) techniques, such as artificial neural networks (ANNs), genetic algorithm (GA), and support vector machine have been employed to analyze the signals for fault classifications and fault diagnosis in reciprocating compressor condition monitoring. Some Research of ANN has been achieved successfully for classifications and fault diagnosis, and the results were promising for complicated situations where the number of features is high with nonlinear characteristics. Orlowska-Kowalska [4] used neural network for induction motor fault diagnosis. Samanta and Al-Balushi [5] applied neural network to diagnose rolling element bearing fault based on time-domain features. We used the Probabilistic Neural Network (PNN) for the condition classification system. The size of the data set is formidable for the operation of a neural network.

2 VIBRATION OF COMPRESSORS

Reciprocating compressors are naturally noisy, vibrating machines, when in operation, are subjected to fatigue, wear and foundation settlement. These effects can cause imbalances in rotors and the misalignment of shafts, which lead to an increase in the levels of vibration produced. Such vibrations are generally symptoms of additional, unbalanced, dynamic loads which may cause breakdown [6]. Excessive vibration on a reciprocating compressor can also be caused by operational problems such as piston slap. Vibration travels easily through a machine structure. Local structural characteristics (such as flexibility and damping) can cause a sympathetic response in one location to a vibration source in an entirely different location. Valve operation in reciprocating compressors generates transient vibrations which are so broad in their frequency range that vibration spectra can be very complicated. Since the vibration of the cylinder head of a reciprocating compressor is the sum of many excitations, including impacts when the valves open and close, it is to be expected that the vibration spectrum will be complex.

2.1 FAULT SIMULATION

In this work, three common faults were separately seeded into a two stage reciprocating compressor: a leaky valve in the high pressure cylinder, a leaky intercooler and a loose drive belt. These faults produce little noticeable influence on the performance of generating pressures but do need to use more electrical energy than that of a healthy compressor. The compressor performance was monitored using one fault at a time. The experimental tests were carried out in the following sequence:

2.1.1 VALVE LEAKAGE SIMULATION

The valve leakage was seeded by drilling a small hole in the valve plate of the second stage discharge valve. Initially the hole was 1mm diameter and then, to allow qualitative comparison of data was subsequently enlarged to 2mm diameter.

2.1.2 LEAK IN INTERCOOLER

Leakages are common in joints in the pipe-work carrying the process gas from the first stage to the second. Here a loose intercooler joint was seeded into a compression joint close to the second cylinder. The pipeline screw nut was loosened to create the leak. A small leakage was achieved by turning the nut through one turn.

2.1.3 LOOSE DRIVE BELT

To model a loose belt arising from belt wear due to friction the separation of the centers of the two pulleys was reduced initially by 1mm and subsequently by 2mm.

Vibration on the two-stage compressor was detected using two accelerometers, Bruel & Kjaer type 4332 with frequency ranges 0-40kHz, and a high temperature capability of up to 250°C. Both accelerometers were located on a cylinder head where the suction and discharge valves are located, one on the 1st cylinder, the other on the 2nd cylinder. This data was then fed, via a data acquisition system, to a computer for further signal conditioning and storage.

One of major concerns for many researchers using signal processing is usually how to extract sensitive time domain features, frequency domain features or time-frequency domain features. However, not all the extracted features are employed in trouble shooting, often on the basis of experience some features are simply disregarded as inappropriate and abandoned [7]. Even for the selected features, not all of them are necessarily used in the most effective way. Often they are used separately and their interaction is not really considered, or is even ignored. Sets of features were obtained based on data pre-processing and feature type. Features were obtained from data taken from all the sensors for the faults previously mentioned, see below:

2.2 STATISTICAL FEATURES

Time domain features were extracted from the statistical measures of Root mean Square (RMS), Peak factor (PF), histogram lower bound (LB), histogram upper bound (UB), Entropy (ENT), Variance (VAR), Skewness (SK), Kurtosis (KT) and Range of Vibration domain for the reciprocating compressor components. All the statics elements mentioned above were computed for high pressure stage and a

36 elements vector with 12 numbers of segments (36 x 12) for each feature. Finally the vector was reduced to form a vector (36 x 1) by taking the last snapshot and merging with other features to make various components. These are defined as follows:

$$RMS = \sqrt{\frac{\sum_{i=1}^{N} Xi}{N}} \tag{1}$$

$$PF = \frac{\mathbf{Peak}}{\mathbf{RMS}} \tag{2}$$

$$LB = \min(x) - \frac{1}{2}\frac{\max(x) - \min(x)}{N-1} \tag{3}$$

$$UB = \max(x) + \frac{1}{2}\frac{\max(x) - \min(x)}{N-1} \tag{4}$$

$$ENT = H(p) = -\sum_{i=1}^{N} p_i \log p_i \tag{5}$$

$$SK = \frac{\frac{1}{N}\sum_{i=1}^{N} x_i^3}{\sigma^3} \tag{6}$$

Where

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (x_i - \text{mean}(X))^2} \tag{7}$$

$$KT = \frac{\frac{1}{N}\sum_{i=1}^{N} x_i^4}{\sigma^4} \tag{8}$$

$$VAR = S^2 = \frac{\sum_{i=1}^{N} (X_i - \bar{x})^2}{N-1} \tag{9}$$

2.3 SPECTRAL FEATURES

The Fast Fourier Transform (FFT) was used to transform the time-domain signal into the frequency-domain. As shown in the spectra of Figure 1, the vibration features a number of discrete components mainly from compressor working frequency 7.6Hz and its harmonics up to 80 orders. Moreover, the amplitudes are different fault cases, but it was difficult to find a simple feature to separate the cases completely. Thus the amplitudes of these components were taken as feature candidates and each trial run used different harmonics. Thus, the resultant data matrix was a (n x *s*) feature matrix for spectral features, where n is number of harmonics and *s* number of sample.

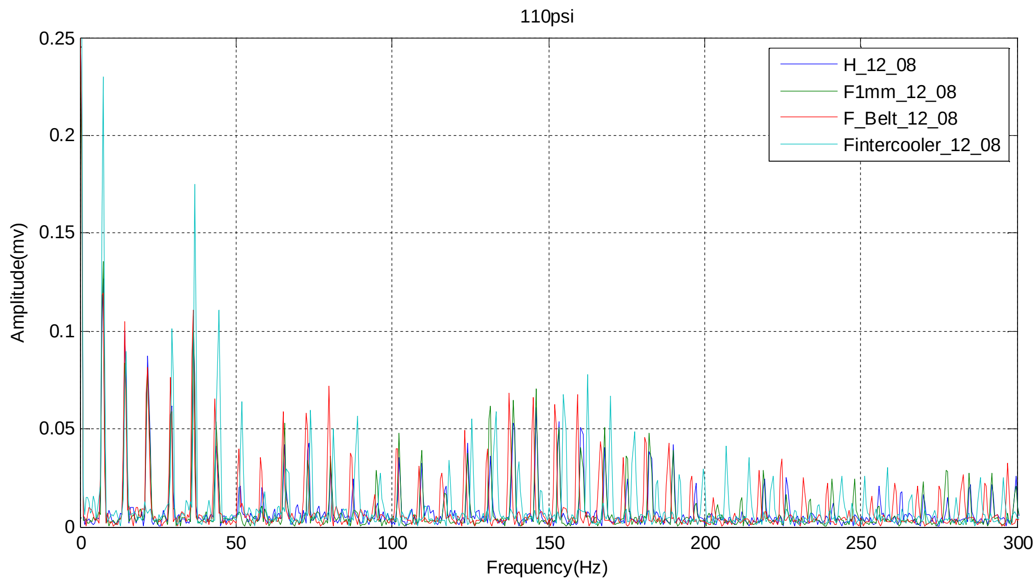

Figure 1 Spectra of vibration for different cases

3 PROBABILISTIC NEURAL NETWORK AND IMPLEMENTATION

The Probabilistic Neural Network (PNN) has been widely used for different fields such as pattern recognition and signal processing. It was first proposed by Specht [8] and is one of the most promising of neural networks because it can be trained to e.g. successfully recognise patterns and evaluate likelihood ratios, and so is now widely used in many real-world problems in the fields of nonlinear mapping, game playing, facial recognition and estimation of the probability that an event is a member of a particular class. That PNNs offer a way to interpret the network's structure in terms of probability-density functions is an important merit of this type of network because it allows the PNN to achieve faster training than Back Propagation of Feed Forward type neural networks. The structure of a PNN algorithm consists of four layers: the input layer, the pattern layer, the summation layer and the output layer. An n-dimensional input vector x is applied to the n input neurons and is passed to the neurons in the pattern layer which is divided into k groups, one for each of the k classes. The i^{th} pattern neuron in the k^{th} group computes its output using a Gaussian Kernel of the form:

$$\mathbf{F_{k,j}(x)} = \frac{1}{(2\pi\sigma^2)^{\frac{n}{2}}}\mathbf{exp}\left(-\frac{\|x-x_{k,j}\|^2}{2\sigma^2}\right) \tag{10}$$

Where, $x_{k,i}$ is the centre of the kernel, and σ is a spread parameter which determines the size of the kernel. The summation layer has one neuron for each class. The summation layer of the network computes the approximation of the conditional class probability function through a combination of the previously computed densities as follows:

$$\mathbf{G_k(x)} = \sum_{i=1}^{M\,k}\boldsymbol{\omega_{ki}}\,\mathbf{F_{ki}}(x), \quad \mathbf{k} \in \{\mathbf{1},\ldots,\mathbf{k}\} \tag{11}$$

Where m_k is the number of pattern neurons of class k, and ω_{ki} are positive coefficients satisfying, $\sum_{i=1}^{M\,k}\omega_{ki} = 1$, pattern vector x belongs to the class that corresponds to the summation unit with maximum output[9] .

The parameter that needs to be determined for optimal PNN performance is the smoothing parameter. One way of determining this parameter is to select an arbitrary set of σ, train the network and test on a validation set. The procedure is repeated to find the set of σ that gives the least misclassification.

In this work, the experiments were carried out using data from a reciprocating compressor test rig and computer implementation was conducted by using MATLAB. Six sets of experiments have been conducted using normal and defective data sets for each parameter. Vibration signals were measured from accelerometers on the high pressure cylinder of a reciprocating compressor, the signals consisting of 24390 samples were obtained using accelerometers In order to facilitate the classification process each data set was divided into 12 segments (bins) of 1024 samples. The application of features from both time-domain analysis and frequency domain analysis in condition monitoring was investigated

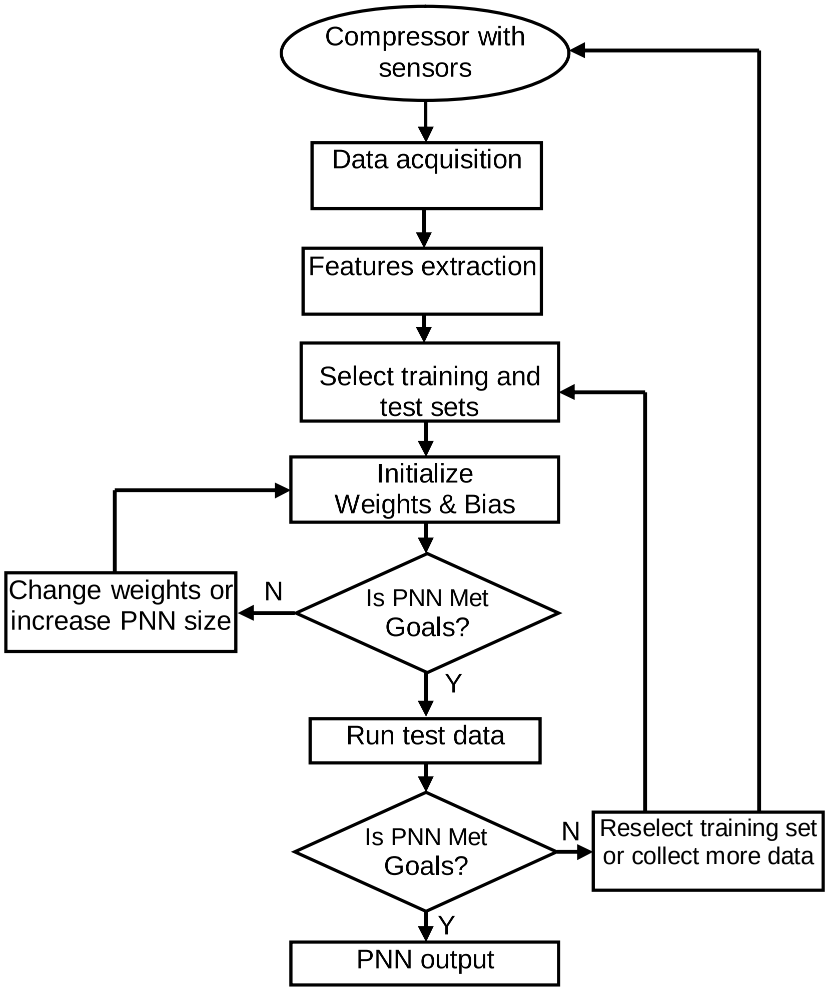

Figure 2 Flow chart of PNN based monitoring

through the approach. Figure 2 shows a flow diagram of the proposed procedure In particular, it was implemented as follows:

- The features were extracted from the data sets of normal conditions to form a healthy feature vector.
- The same features were extracted from the data sets of faulty cases to form a faulty feature vector.
- Both the faulty and healthy vectors were combined into one data vector in which the first part was healthy and the second was faulty.
- A target vector was created the same size as the data vector and values 1, 2, 3 and 4 corresponding to healthy and faulty elements in the data vector.
- Both the data vector and target vector were divided into two subsets of equal size by taking vector values of every other one, of which one was for training PNN and the other for performance evaluation.
- The spread parameter of the PNN was identified by constant value.

4 RESULTS AND DISCUSSION

The data sets obtained when a particular fault was seeded into the compressor were combined to train and test to obtain an optimal classification of features in the time and frequency domains of the particular fault. The overall results of classification performance of our dataset were as shown in the next sections according to time and frequency domain analysis.

Total of combination	Number of input features selection	Features names	Classification rate of PNN
36	2	Skewness, Range	80.55%
84	3	RMS, Variance, Kurtosis	93.05%
126	4	RMS, Peak factor, Variance, Kurtosis	91.66%
126	5	RMS, HUB, Entropy, Variance, Kurtosis	91.66%

Table 1 Performance of PNN classifier in the time domain with different features combination.

Table 1 represents the time-domain performance of the PNN for the evaluation of a fault condition. For example, in the first row, the first cell denotes the total combination of features when the number of input parameters was nine and the two features (Skewness and Range) were extracted. The rate of correct classification rate was 80.55%. In row two, the total combination was 84 when three features (RMS, Variance and Kurtosis) were examined. Here the best classification rate of 93.05% was obtained. With four and five features selected the result was a correct classification rate of 91.66%. Table 2 show results for the frequency-domain of the PNN based on analysis of the number of harmonics and rate of classifications with the seeded faults. The widths (σ) were kept constant at 0.01. In this stage, the best classification rates were 95.50% and 95.45% which were produced with 48 and 65 features. Moreover, with 10 features the correct classification rate was 81.81%.

Number of input features	Classification rate of PNN
10	81.81%
20	87.88%
30	93.94%
48	95.45%
65	95.50%
80	77.50

Table 2 presents the frequency-domain performance of the PNN for the evaluation of a fault condition.

5 CONCLUSION

In this study, a PNN approach has been explored to classify different fault cases from a reciprocating compressor. Both time-domain and frequency-domain analyses have been applied to the vibration signals measured from the cylinder head and result in 9 common statistical parameters: Root mean Square (RMS), Peak factor, histogram lower bound, histogram upper bound, Entropy, Variance, Skewness, Kurtosis and Range in the time domain whereas about 30 features of the rotational frequency and its harmonics in the frequency domain have been studied. A PNN network was trained with a different subset of the features and found that the best results were obtained in a number of subsets. In particular, the subset features from frequency-domain allow a 95.50% successful classification of each of the three faults. In addition, it also found that statistical parameters from the time-domain analysis could achieve a correct rate of 93.05%, which was less frequently performed than that in the frequency domain.

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