MCSA and SVM for gear wear monitoring in lifting cranes

Raymond Ghandour[1], Fahed Abdallah[1] and Mario Eltabach[2]

[1]Laboratoire HEUDIASYC, UMR CNRS 7253,
Université de Technologie de Compiègne, Centre de Recherche de Royallieu
BP 20529, 60205 Compiègne Cedex, France
[2]Centre Technique des Industries Mécaniques, CETIM
52 av Félix Louat, BP 80067, 60304 Senlis Cedex, France
{raymond.ghandour, fahed.abdallah}@hds.utc.fr; Mario.eltabach@cetim.fr}

Abstract

In recent years, Motor Current Signature Analysis (MCSA) were explored to diagnose common mechanical faults of the overall kinematic chain of induction machines such as bearing faults, shaft misalignment, and gears faults. In fact, current signals are known to be most representative of the machine torque which can easily distinguish between the healthy and defected operational mode. In addition the electric signals are easily acquired; related sensors are not expensive and can be mounted in a non-intrusive manner.

The aim of this work is to look at failure predictions in three-phase line-operated induction machines through statistical and spectral analysis of electric current signals, validated by the use of classical classification techniques, namely the two-class Support Vector Machine (SVM) and the One Class Support Vector Machine (OCSVM). The SVM based classification methods are able to exploit several indicators at once in order to identify more precisely faulty operational modes when they appear. These methods are applied using data from a lifting crane with an Accelerated Life Time (ALT) test. The lifetime test began on September 2008 and finished on July 2012 after gear degradation has been revealed by oil analysis and inspection.

1 Introduction

In many industry sectors, unexpected machinery failures can lead to significant damage of material. The early detection of these failures is an essential maintenance task so that the necessary repairs can be carried out before the effective date of the failure.

Research into induction motor behaviors under abnormal conditions caused by the presence of mechanical faults, as well as into possibilities for diagnosis, has been a challenging area leading to number of studies.

Many condition monitoring methods can be found in the literature. They are usually based on vibration monitoring, thermal monitoring or acoustic emission monitoring. They require expensive sensors or specialized tools, whereas current monitoring does not require costly sensors [1].

Motor Current Signature Analysis (MCSA) -based methods are used to diagnose faults that commonly occur in induction machines, such as gears faults [2], bearing faults [3], air-gap eccentricity and load faults [4]. MCSA techniques usually analyze and compare the magnitude of the fault frequency components in the Amplitude or Frequency current spectrum or in the demodulated signal, where the magnitude tends to increase as the severity of the fault increases.

In this paper, two types of MCSA techniques are investigated. The first is based on statistical indicators, whereas the second is based on spectral indicators. The Support Vector Machine (SVM) is discussed in this paper as a means of providing accurate and efficient failure diagnostics [5]. Both faulty and healthy signals from the lifting machine are used in two-class SVM and one-class SVM (OCSVM) scenarios. This paper is organized as follows: In section 2 some of the MCSA diagnosis methods are presented. The SVM-based classification methods are detailed in section 3. Section 4 describes the benchmark from which the data was acquired and used to apply the methods presented in section 2 and 3 and to test their effectiveness in detecting problems of gear wear. Finally, experimental results are presented is section 5.

2 MCSA Diagnosis Methods

2.1 Condition monitoring method in the time domain

This condition monitoring is based on the supervision of the raw time current signal. The associated indicators are based on the comparison of the statistical techniques. The indicators used in this work are the:

- ✓ RMS: the standard deviation of the signal.
- ✓ The energy in a specific frequency band: expressed as the average power (mean of the squared values) in a pass band filtered signal.

2.2 Condition monitoring method in the spectral domain

The main frequency analysis methods are based on the application of Fast Fourier Transform (FFT) or on the calculation of the power spectral density (PSD) of the measured or demodulated electric signals.
Many fault indicators are more effective when applied to the demodulated current signal. The demodulation technique using Hilbert transform is done in several steps [6] as illustrated in Figure 1**:**

1. Band pass filtering of the signal around the main current frequency (by a real filter).
2. Extraction of the associated modulation functions.

The extraction of the amplitude and frequency modulation functions is done from the complex analytic signal $\boldsymbol{I_{a1}(t)}$. The amplitude modulation function AMF corresponds to the modulus of the analytic signal, while the phase modulation function PMF corresponds to the argument of the signal. The frequency modulation function FMF is obtained from the PMF by the relationship:

$$FMF = \frac{1}{2\Pi} \frac{dPMF\ (t)}{dt} \tag{1}$$

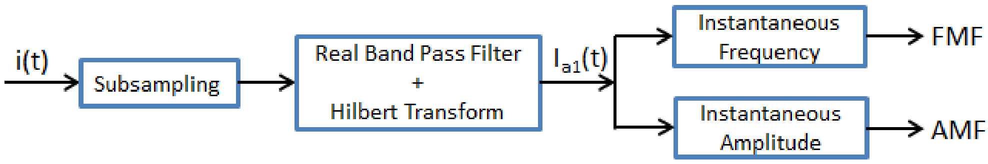

Figure 1: Extraction technique of the modulation functions AMF and FMF.

The condition monitoring indicators corresponding to AMF and FMF are the amplitude modulation rate and the frequency modulation rate defined by equations (2 and 3).

$$AMR = \frac{FMA_{PK-PK}}{2I_{01}} \qquad AMR_{rms} = \frac{FMA_{rms}}{2I_{01\,rms}} \tag{2}$$

$$FMR = \frac{FMF_{PK-PK}}{2f_0} \qquad FMR_{rms} = \frac{FMF_{rms}}{f_0} \tag{3}$$

Where $\boldsymbol{rms\ and\ PK-PK}$ denote respectively the root mean square and the peak-to-peak values. I_{01} is the maximum value of the simple current.

3 SVM Classification Methods

In this paper, two-class SVM and One-Class SVM (OCSVM) are used. Two-class SVM is a classification technique used for binary classification problems where data from two classes are available. It enables a classifier to be trained using positive (first class) and negative (second class) vectors or observations. In our case, positive examples may be generated from the first signals acquired where we are sure about the healthy state of the machine. Negative examples may be obtained from the last signals acquired after a degradation of the state of the lifting machine. In OCSVM, only data from one class are available. It makes training a classifier possible in the absence of any negative example data.

3.1 Two-class SVM

SVM is a machine learning technique based on Vapnik's Statistical Learning Theory [7]. Two-class support vector machines learn to distinguish between two classes, given a training data set, by fitting a hyperplane that maximally divides the two classes.

Given data inputs $\boldsymbol{x_i}$ ($i = 1, 2 \ldots M$), M is the number of samples. The samples belong to either of two classes, namely positive and negative, with labels $\boldsymbol{y_i}$ = 1 for the positive class and $\boldsymbol{y_i}$ = -1 for the negative class, respectively. In the case of linearly separable dare, it is possible to determine the hyperplane $h(x)$ = 0 that separates the given data.

$$\boldsymbol{h(x) = w^T x + b = \sum_{j=1}^{M} w_j x_j + b = 0} \tag{4}$$

Where $\boldsymbol{w}$ is the M-dimensional vector and b is a scalar used to define the separating hyperplane. The decision function is made using sign $h(x)$ in order to classify input data into either the positive or the negative class. A distinct separating hyperplane should satisfy the constraints:

$$\begin{aligned} \boldsymbol{h(x_i)} &\geq \boldsymbol{1} \quad \boldsymbol{if\ \ y_i = 1} \\ \boldsymbol{h(x_i)} &\leq \boldsymbol{-1} \quad \boldsymbol{if\ \ y_i = -1} \end{aligned} \tag{5}$$

3.2 One-class SVM

The idea of OCSVM is to define a boundary between the majority of the positive data points and outliers. OCSVM may be viewed as a regular two-class SVM where all the training data belongs to the first class, and the origin is taken as the only member of the second class. Solving the OCSVM optimization problem is equivalent to solving the following dual quadratic programming problem [8]:

$$\boldsymbol{\min_{\alpha} \frac{1}{2} \sum_{i,j}^{M} \alpha_i \alpha_j K(x_i\,, x_j)} \tag{6}$$

subject to

$$\boldsymbol{0 \leq \alpha_i \leq 1/\nu l, \quad and \quad \sum_{i=1}^{M} \alpha_i = 1} \tag{7}$$

Where $\boldsymbol{\alpha_i}$ is a Lagrange multiplier, $\boldsymbol{\nu}$ is a trade-off hyper-parameter that defines the ratio between the number of samples in the data class and the outlier class, l is the number of points in the training dataset, and $\boldsymbol{K(x_i, x_j)}$ is the kernel function.

4 The Benchmark

Figure 2a shows a global view of the lifting crane used in an accelerated lifetime test. Several types of signals are acquired from this benchmark. The electric signals of the lifting crane are acquired using three clamps for motor supply current measurements (Figure 2b) and three differential probes for motor voltage measurements (Figure 2c).

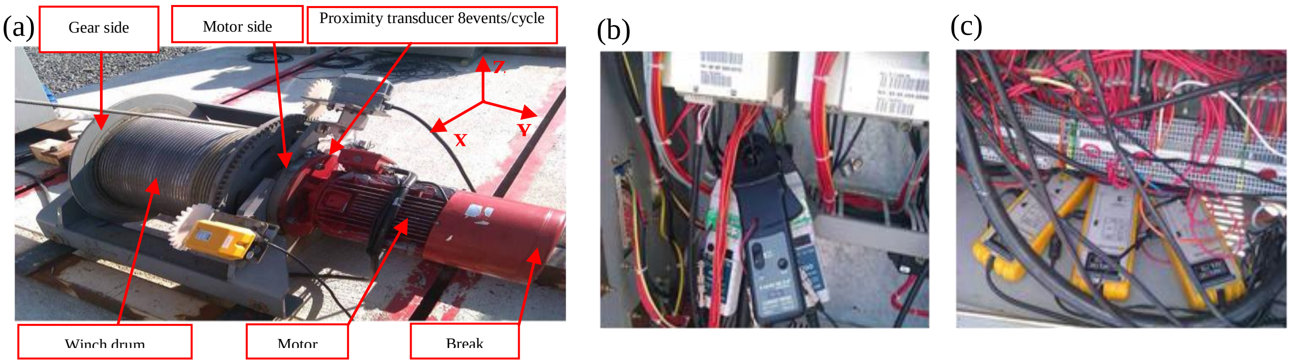

Figure 2: Benchmark of the lifting crane ‘Accelerated Lifetime Test’: (a) General view; (b) The clamps for motor supply currents measurement, (c) The differential probes for motor voltages measurements

The load level applied to the winch during the test period is relatively high. The lifetime test began on September 2008, and a gear oil analysis carried out in February 2012 revealed excessive metal debris. This detection was performed using emission spectroscopy to gauge the amount of each metal element present in the oil in the two stage planetary gear.

5 Diagnosis Results

5.1 Indicator trend analysis

The analysis of the indicators and their trends throughout the operation period of the crane is performed to examine their relevance in the representation of how mechanical faults progress.

5.1.1 Monitoring indicators for a raw current signal

These indicators are applied to the raw current signal selected cycles throughout the period of the two modes of operation of the crane ("up" and "down"). The reference cycle is cycle 5500. The change in each indicator is represented by the ratio between the value of this indicator for different cycles and the reference value obtained from cycle 5500. Figure 3 shows the changes in indicators applied to the raw current signal in the "down" operating cycle.

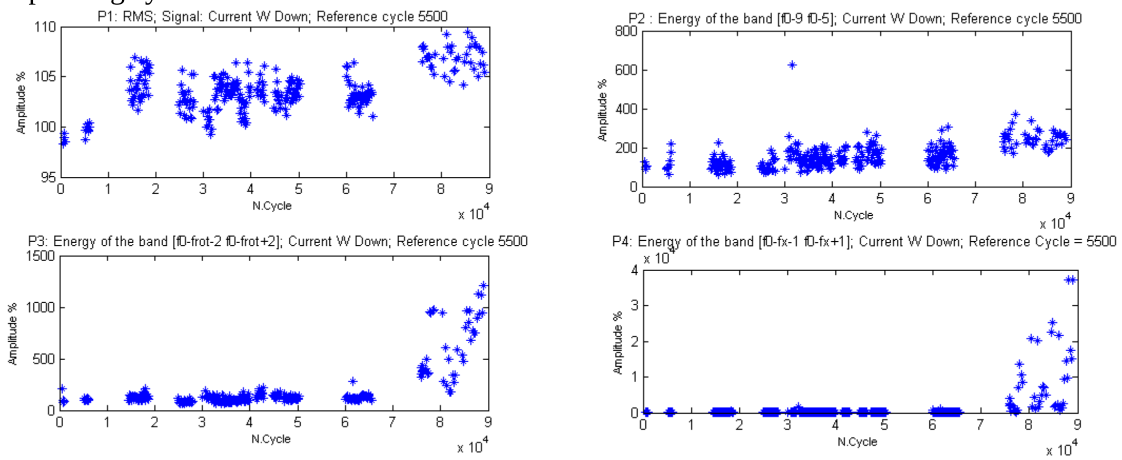

Figure 3: Monitoring indicators evolution (P1, P2, P3, P4) applied to the raw current signal in the down operation mode

We notice three different types of indicator trends:

- ✓ A random movement according to the cycle number.
- ✓ A quasi-linear movement according to the cycle number.
- ✓ A sudden trend change during given periods of operation.

The various proposed indicators for monitoring the raw current signal, and their type of evolution as a function of gear degradation, are given in Table 1(f_0 is the supply frequency, f_{rot} is the rotational frequency and fx is the planet carrier frequency of the first train of the planetary gear).

Monitoring indicators applied to raw current signal		Evolution	
Name	**Description**	**Down**	**Up**
P1	RMS of the overall signal		
P2	Energy of the band [f0-9 f0-5] Hz		
P3	Energy of the band [f0-frot-2 f0-frot+2] Hz		
P4	Energy of the band [f0-fx-1 f0-fx+1]		

Linear trend Fluctuations Nonlinear trend

Table 1: Relevance of different monitoring indicators applied to the raw current signal.

5.1.2 Monitoring indicators for the modulation functions AMF and FMF

Some similar indicators are applied to the AMF signal for both modes of operation. Among the most relevant indicators we should mention the RMS value of the AMF, the average power of the [4-7] Hz band for the "up" cycles and the [5-9] Hz for the "down" operation modes. These bands represent a cover for the fault characteristic. The monitoring indicators, as well as their kind of changes, are presented in Table 2 and Table 3.

Monitoring indicators applied to AMF		Evolution	
Name	**Description**	**AMF Down**	**AMF Up**
P5	RMS of the overall signal		
P6	Energy of the band [0 ; 45]Hz		
P7	Energy of the band [4 ; 7]Hz (Up), [5;9]Hz (Down)		
P8	RMS modulation rate indicator		

Linear trend Fluctuations Nonlinear trend

Table 2: Relevance of different indicators proposed for monitoring from the amplitude modulation function AMF

Monitoring indicators applied to FMF		Evolution	
Name	**Description**	**FMF Down**	**FMF Up**
P9	RMS of the overall signal		
P10	Energy of the band [4 ;7]Hz (Up), [5;9]Hz (Down)		

Linear trend Fluctuations Nonlinear trend

Table 3: Relevance of different indicators proposed for monitoring from the frequency modulation function FMF

5.2 SVM-based algorithms applied to fault detection

In this section, we present the application of the two-class SVM and the OCSVM methods in the fault monitoring of the lifting crane.

5.2.1 Training dataset construction

The training dataset for two-class SVM chosen consist of a set of characteristic vectors of cycles of two classes (healthy and faulty):

- ✓ 40 cycles randomly chosen from the first 50 (cycle number <20000) to represent the healthy state
- ✓ 60 cycles randomly selected from the last 80 (cycle number> 60500) to represent the faulty state.

5.2.2 Two-class SVM diagnosis results

The classification method is applied to a characteristic vector of "up" cycle indicators, "down" cycle indicators and indicators from both cycles.

Figure 4 presents the results of the classification of cycles by numerical indices (-1 for a healthy state and 1 for a faulty state). These results show that the degradation state of the winch began around cycle 30000. From cycle 40000 onwards the winch is considered to be in a completely faulty condition.

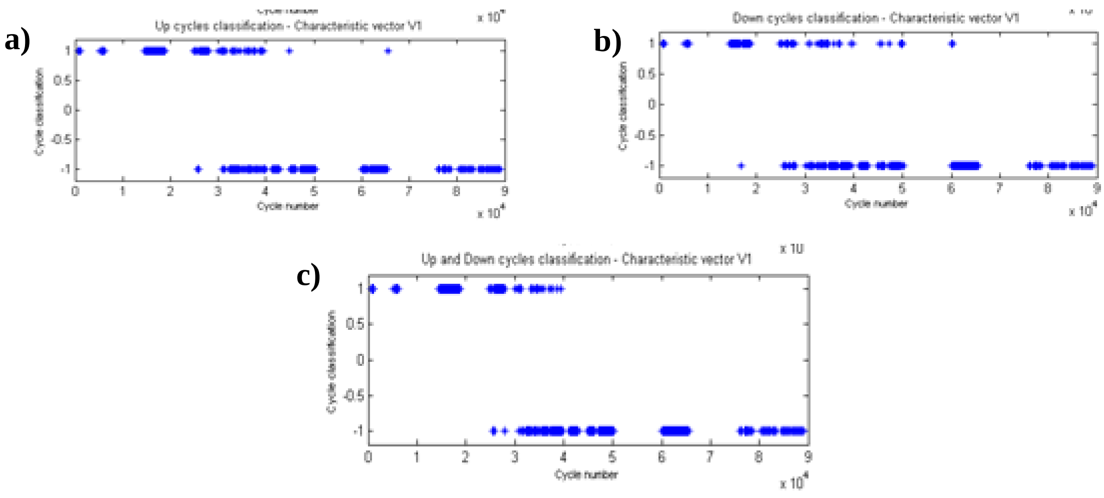

Figure 4: Classification cycles results aaplied to different operations modes: a) Up, b) Down, c) both

5.3 Applying OCSVM to fault detection

Training vectors for OCSVM are built just like in conventional SVM classification, with a set of points all belonging to the same positive class. For our needs, we chose a set consisting of the first 45 cycles assumed to be normal operating cycles for the winch and they represent a healthy state of the machine. Classification is performed using different attributes and with respect to the two modes in combination. The figure below shows the results of OCSVM classification using vector V1.

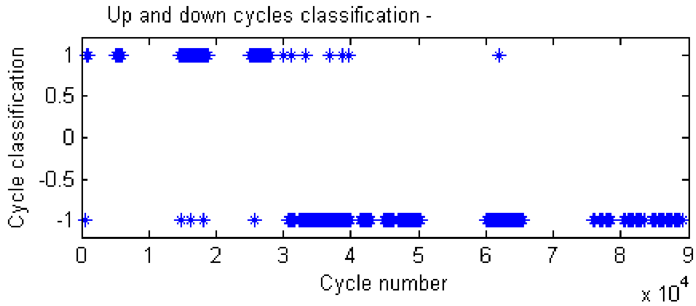

Figure 5: OCSVM classification cycles results applied to up and down cycles of V1 characteristic vector

It can clearly be seen that the degradation of the state of the lifting machine starts around cycle 30000, as was established by applying two-class SVM.

6 Conclusion

In this paper, we show that a diagnosis of the state of a lifting crane can be made based on current signals, using classical classification methods applied to statistical and spectral indicators. First, a spectral analysis of the raw supply current signal and its amplitude and frequency modulation functions (AMF and FMF) is performed. We then propose a set of monitoring indicators based on the extraction of general statistical information from three signals (raw current signal, AMF and FMF) and the extraction of energy information for fault characteristic frequency bands in the spectra of these signals. The application of these monitoring indicators to the lifting crane signals reveals different trends. We, then perform a classification of the different operating cycles between healthy state operation class and defective condition operation class. The classification is performed using two different techniques (two-class SVM and OCSVM). The results of the classification techniques reveal the importance of these classification techniques to detect the beginning of the degradation phase in an accelerated life time test of the winch.

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