WOUND ROTOR INDUCTION MACHINE'S ROTOR FAULTS DETECTION METHOD BASED ON WAVELET TRANSFORM

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Abstract: Early detection and diagnosis of the electrical machine's incipient faults is desirable for advanced condition assessment, product quality assurance and improved operational efficiency. In this paper some results on non-invasive detection of rotor faults in wound rotor induction motors are presented. The applied diagnosis method is the motor current signature analysis (MCSA), which utilises the results of the line current's spectral analysis. Usually the FFT (Fast Fourier Transform) is used to obtain the power density vs. frequency plots to be analysed. In this paper a novel versatile tool of harmonic analysis, the wavelet transform will be applied for processing the data obtained via the motor current signature analysis. The proposed wavelet based detection method shows a good sensitivity, short detection time and can be easily applied also for on-line fault detection. The theoretical basis of the method is proved by laboratory tests.

1. INTRODUCTION

The early diagnosis of a developing fault is necessary to allow maintenance personnel to schedule repairs prior to an actual failure. Therefore is much interest in early fault detection and diagnosis techniques for use in condition based maintenance. In contrast to preventive maintenance, in condition based maintenance one does not schedule maintenance or machine replacement based on previous records or statistical estimates of machine failure. Rather, one relies on information provided by condition monitoring systems assessing system condition. This allows better utilisation of equipment and components, leading to considerable reduction of downtime and maintenance costs. The key for the success of condition based maintenance is the fault diagnosis [1].

Induction motors are widely used in many industrial processes because they are cost effective and mechanically robust. They are one of the critical components in many commercially available equipment and industrial processes.

Therefore these machines play an important role in the safe and efficient operation of industrial plants. The squirrel cage variants are the most widely used induction motors, but, especially where hard starting conditions exist, also the wound rotor induction motors are frequently utilised. Usually these machines are designed for 30 years fault-free lifetime, but most of them are not available at all times.

Many of the wound rotor induction machine's components are susceptible to failures. The stator or rotor windings are subject to insulation break-down caused by mechanical stress and vibration, excessive heat, age, damage during installation, carbon dust, etc. Excessive heat can result from operation on continuous overload, motor stall, and too many starts in succession without adequate cool down combined with excessive accelerating time.

Mechanical stress failures are generally due to repetitive centrifugal loading on the coil extensions, or coil end-arm vibration, especially when the motor is subjected to frequent starts. One of the most common causes of winding faults in a wound rotor induction machine is from winding contamination from carbon or graphite dust from the brushes. The fine powder permeates all of the stator and rotor windings and can create a path between conductors or between conductors to ground. Machine bearings are subject to excessive wear and damage caused by inadequate lubrication, asymmetric loading, or misalignment. The brushes or the slip ring of the motor also can also damage.

In many applications these failures of the electrical machines can shut down an entire industrial process. The unplanned machine shut downs cost both time and money that could be avoided if an early warning system is available against impending failures. Such a system could also improve process safety, a key factor in many industrial environments.

Fault detection and diagnosis schemes are intended to provide advanced warnings of incipient faults, so that corrective action can be taken without detrimental interruption to processes [2].

Fault diagnosis of electrical machines, as a critical part of a condition based maintenance program therefore can lead to greater plant availability, extended plant life, higher quality products, and smoother plant operations.

Numerous fault detection methods have been proposed to identify the faults of electrical machines. The fault detection methods involve several different types of fields of science and technology and they are generally performed by mechanical and/or electrical monitoring.

The most frequent used detection methods are [3]:

- motor current signature analysis (MCSA),
- acoustic noise measurements,
- model, artificial intelligence and neural network based techniques,
- noise and vibration monitoring,
- electromagnetic field monitoring using search coils, or coils wound around motor shafts (axial flux related detection),
- temperature measurements,
- infrared recognition,
- radio frequency (RF) emissions monitoring,
- chemical analysis, etc.

In this paper results of the detection of the wound rotor induction motor's rotor faults are presented based on the motor current signature analysis method [4, 5].

2. THE WAVELET TRANSFORM

In several scientific applications the frequency spectrum of a time-domain signal is required. The frequency spectrum of a signal is basically the frequency components (spectral components) of that signal. This shows what frequencies exist in the signal. Several transformations from time-domain to frequency-domain can be applied. The Fourier transform (FT) is probably by far the most popular and widely used one, especially in electrical engineering.

The Fourier series allows a periodic function to be represented as an infinite sum of harmonic oscillations at definite frequencies equal to the multiples of the fundamental. The frequency analysis methods were dramatically improved since the development of the fast Fourier transform algorithm (FFT) in 1965. The Fourier transform decomposes a signal to complex exponential functions of different frequencies. The way it does this, is defined by the following equation:

$$X(f) = \int_{-\infty}^{+\infty} x(t)\, e^{-2j\pi ft}\, dt \qquad (1)$$

where t is the time, f the frequency and x denotes the analysed signal.

Hence using the FT a non-periodic function can be expressed as an integral sum over a continuous range of frequencies. Therefore the FT gives the frequency information of the signal (how much of each frequency exists in the signal). But it does not mark when in time these frequency components exist, e.g. the standard FT does not tell us when a non-stationary event (as a fault in a dynamic system) occurred [6].

For non-stationary analysis the short-time Fourier transform (STFT) can be applied. Upon this method the signal is divided into small enough segments, where these segments (portions) of the signal can be assumed to be stationary. For this purpose, a window function is chosen. The width of this window must be equal to the segment of the signal where its stationarity is valid. The window is shifted along the time axis.

The definition of the STFT is the following:

$$\begin{aligned} STFT_X^{\omega(t)}(t,f) &= \\ &= \int_t [x(t)\,\omega^*(t-t')]\, e^{-j2\pi ft}\, dt \end{aligned} \qquad (2)$$

where $\omega(t)$ is the window function, and * marks the complex conjugate. As you can see from equation (2), the STFT of the signal is nothing but the Fourier transform of the signal multiplied by a window function [7].

For fast varying signals in order to obtain the stationarity, the window must be taken as short as the signal within to be stationary. The narrower window means better time resolution and better assumption of stationarity, but the frequency resolution is poorer. A wide window means good frequency resolution, but poor time resolution and furthermore, the condition of stationarity may be violated.

Another data processing approach is by using the wavelet transforms (WT) developed by J. Morlet in 1987, a French geophysicist, to aid seismic analysis. WT can be considered as the localised equivalent of FT and work on the principle that all signals can be reconstructed from sets of local signals of varying scale and amplitude, but constant shape [6].

The discrete wavelet transform (DWT) is an easy and fast to implement data processing method. Using DWT a time-scale representation of a digital signal can be obtained using digital filtering techniques. Filters of different cutoff frequencies are used to analyse the signal at different scales. The signal is passed through a series of high pass filters to analyse the high frequencies, and it is passed through a series of low pass filters to analyse the low frequencies.

The DWT analyses the signal at different frequency bands with different resolutions by decomposing the signal into a coarse approximation and detail information. DWT employs two sets of functions, called scaling functions and wavelet functions, which are associated with low pass and highpass filters, respectively.

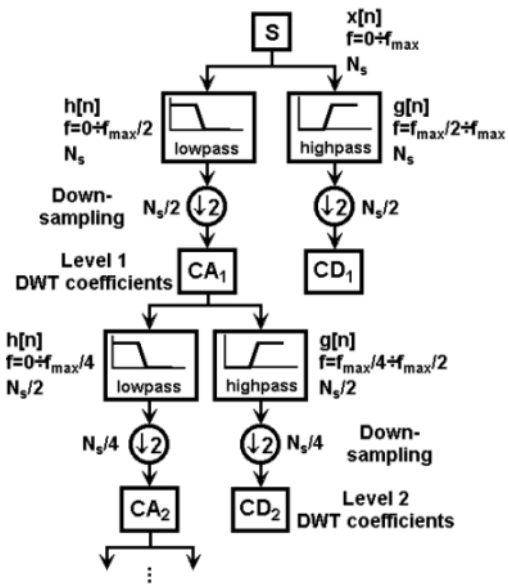


Fig. 1. The DWT decomposition of a signal

The decomposition of the signal into different frequency bands (see Fig. 1) is simply obtained as it was stated out previously by successive highpass and lowpass filtering of the time domain signal. The original signal $x[n]$ is first passed through a halfband highpass filter $g[n]$ and a lowpass filter $h[n]$.

After the filtering, half of the samples can be eliminated according to the Nyquist's rule. Simply discarding every other sample will subsample the signal by two, and the signal will then have half the number of points.

The scale of the signal is now doubled. Note that the filtering removes a part of the frequency information (changing the resolution of the signal), but leaves the scale unchanged. Only the subsampling process changes the scale [7].

The above procedure constitutes one level of decomposition, and is also known as the subband coding. It can be repeated for further decomposition. At every level, the filtering and subsampling will result in half the number of samples (and hence half the time resolution) and half the frequency band spanned (and hence double the frequency resolution). This process can continue until only two samples are left.

The frequencies that are most prominent in the original signal will appear as high amplitudes in that region of the DWT signal that includes those particular frequencies.

The difference of this transform from the Fourier transform is that the time localisation of these frequencies will not be lost. This procedure in effect offers a good time resolution at high frequencies, and good frequency resolution at low frequencies.

3. THE MEASUREMENTS CARRIED OUT

The required measurements were performed on a special test bench set up in the Electrical Machines Laboratory of the Department of Electrical Machines of the Technical University of Cluj (see Fig. 2.).

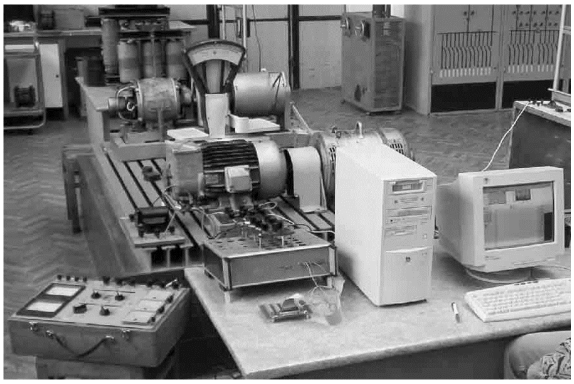


Fig. 2. The laboratory setup

The test bench consists of two mechanically coupled electric motors, a dc motor for breaking and loading purposes and the wound rotor induction motor to be tested. Voltage and current sensors give signals to the data acquisition board.

The measurement part of the bench is based on a usual Pentium processor based PC having a AT-MIO-16XE-10 type (National Instruments Inc.) acquisition board. This delivers high performance and reliable data acquisition capabilities, having 1.25 MS/s sampling rate, 16 single-ended analogue inputs. The acquisition board features both analogue and digital triggering capability, as well as two 12-bit analogue outputs, two 24-bit, 20 MHz counter/timers and eight digital I/O lines.

The electrical signals generated by the transducers are optimised for the input range of the DAQ board. The SCXI 1140 type signal conditioning accessory amplifies the low-level signals, and then isolates and filters them for more accurate measurements [8].

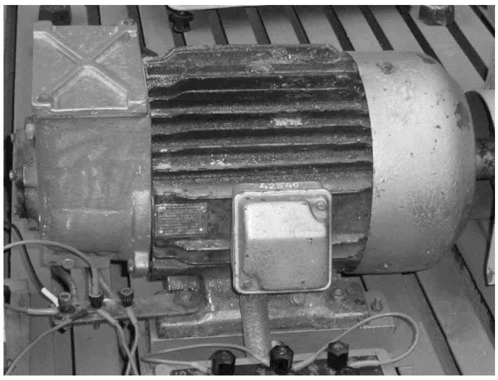


Fig. 3. The tested machine

The wound rotor induction motor used for testing (its picture being given in Fig. 3) is of M2-3/6 type and has the following main data:

- Rated power: 3 kW
- Rated voltage: 220/380 V (Δ/Y)
- Rated current: 13,9/8 A (Δ/Y)
- Rated speed: 920 r/min.

The above presented test bench can be used also for testing other types of electrical machines.

Several special programs, so called virtual instruments (VIs) were built up for testing the machine and for data processing purposes in LabVIEW 6i graphic programming environment. For example the diagram panel of a used Vi is given in Fig. 4.

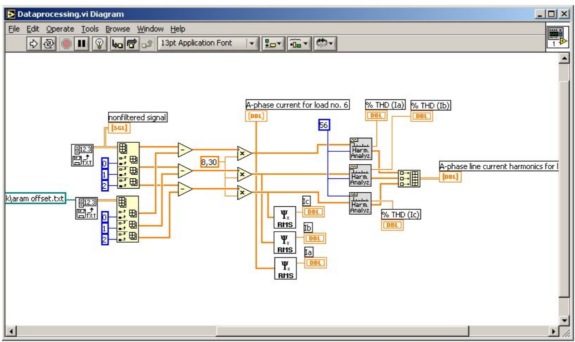


Fig. 4. The data processing VI's diagram

All of them were simply made by assembling using drag-and-drop methods software objects from the various libraries of the program package.

The acquired data also was stored in simple ASCII-type text files in order to be easy imported in any other programming environment.

4. RESULTS OF DATA PROCESSING

Several measurements were performed using the above described test bench and computer programs.

The wound rotor induction machine was tested when it was considered healthy and with a provoked rotor fault. The rotor fault was simulated by interrupting a rotor phase.

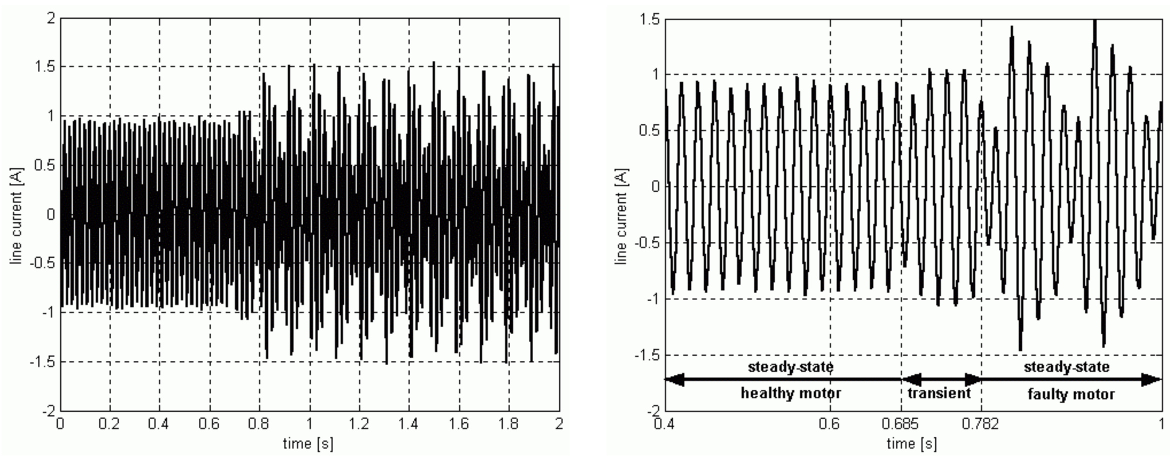
The sample frequency for the data acquisition was set to a high value (2^{16}=65.536 samples/seconds).

The results of the measurements performed with the healthy and with the faulty motor were presented in detail in [9]. In this paper we will study the results of measurement obtained during the occurrence of the rotor fault.

The measured line current plotted versus time is given in Fig. 5.

It can be clearly distinguished the steady-state regime before and after the rotor fault was produced. Due to the interruption of the rotor winding the line currents become greater and they begin to fluctuate.

In Fig. 5b, where only the variation of the line current during the transition from the healthy condition to the faulty one is given, the transition period from one to the other



a) the whole measured period b) a zoom on the transient regime

Fig. 5. The measured line currents

steady-state can be seen. This transition period is about 0.1 s long.

The measured and saved values of the line currents were exported in MATLAB for further data processing.

The functions of the Wavelet Toolbox are well suited for the required DWT method based data analysis [10].

In order to obtain the components of the measured signal in a band near the fundamental harmonic (of 50 Hz) an 11 level one-dimensional discrete wavelet analysis was performed using the *wavedec* function. The *db3* type wavelet from the Daubechies family was selected. The used 11 level wavelet decomposition tree is given in Fig. 6.

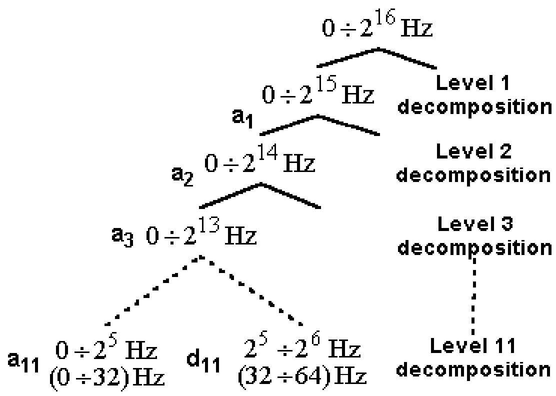


Fig. 6. The wavelet decomposition tree

As it was stated out in [9] the difference signal at the 11th level of decomposition (d_{11}) can be used for fault detection of the wound rotor induction machine, because its frequency band is between 32 and 64 Hz, where all the sideband components of interest are [11].

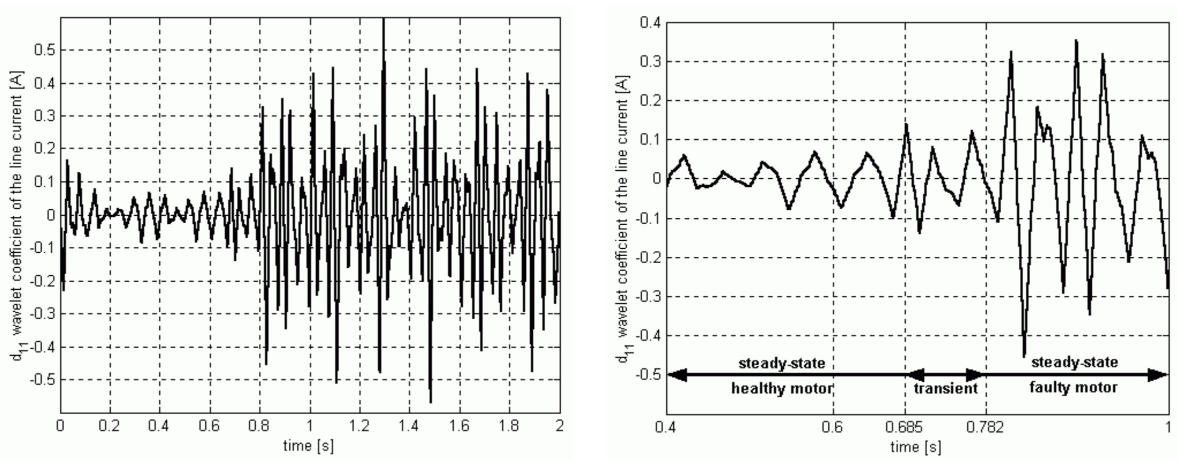
As only a single branch of the decomposition tree is required for the fault analysis of the wound rotor induction machine the d_{11} coefficient of the one-dimensional line current signal was reconstructed using the *wrcoef* function of the same MATLAB toolbox.

In Fig. 7 the obtained d_{11} wavelet coefficient's variation versus time are given for the measured line current given in Fig. 5.

As it was presented in the above-mentioned previous study [9] from the d_{11} wavelet coefficient's value the electrical machines condition can be easily determined. In order to emphasise the effects of the fault independently of the load, the ratio of the root-mean-square (RMS) of the d_{11} wavelet coefficient and of the line current can be computed:

$$k = \frac{(I)_{RMS}}{(d_{11})_{RMS}} \tag{3}$$

This factor is not proportional with the measured line current's values, and therefore neither with the load. Hence as it was demonstrated this can be used to estimate the condition of a wound rotor induction machine. The threshold value of factor k in the case of the wound rotor induction machine having a rotor phase interrupted was found to be 0.09. If the computed d_{11} wavelet



a) the whole measured period b) a zoom on the transient regime

Fig. 7. The d_{11} wavelet coefficient's variation

coefficient's RMS value is above this threshold it means that the motor is faulty [9].

The variation of the d_{11} wavelet coefficient's RMS during the transient regime from the healthy state to the faulty one is given in Fig. 8. In the figure with an interrupted red line is marked the threshold value of the *k* factor.

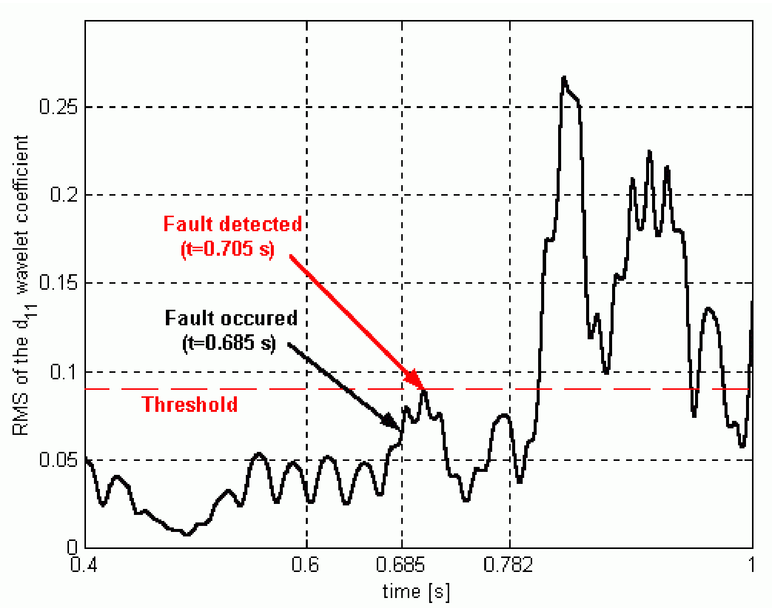


Fig. 8. The variation of the d_{11} wavelet coefficient's RMS during the transient regime

As it can be seen, this threshold value is reached very fast (at *t*=0.705 s) after the fault occurred (at *t*=0.685 s), much before the end of the transient regime. Only 20 ms (a period of the 50 Hz signal) were requested to sense the appearance of the fault!

5. CONCLUSIONS

Finally it can be concluded that the wavelet analysis of the measured line current can be used successfully for the rotor fault detection of wound rotor induction machines.

The difference signal at the 11^{th} level of the one-dimensional discrete wavelet analysis wavelet decomposition tree (d_{11}) was used for the rotor fault detection of the wound rotor induction machine. Practically the ratio of the root-mean-square (RMS) of the d_{11} wavelet coefficient and of the line current was observed in order to compare it with a well-determined threshold value. It was demonstrated that the described method could be applied when the fault occurred during the measurements, hence the method can be used also for on-line detection of the rotor faults.

In further works the above-described method will be extended also to the rotor fault detection of the squirrel cage induction machine, and also for the diagnosis of the all the other faults that can be detected by the motor current signature analysis (rotor eccentricity, etc.).

Also other wavelet transform methods (for example the continuous wavelet transform) will be studied to be applied in electrical machines fault diagnosis.

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