Discrete Wavelet Transform Based Rotor Faults Detection Method for Induction Machines

Loránd SZABÓ, Jenő Barna DOBAI, Károly Ágoston BIRÓ

Department of Electrical Machines, Marketing and Management
Technical University of Cluj
P.O. Box 358, RO-400750 Cluj, Romania
Lorand.Szabo@mae.utcluj.ro

Abstract – The condition monitoring of the electrical machines can significantly reduce the costs of maintenance by allowing the early detection of faults, which could be expensive to repair. In this paper some results on non-invasive detection of rotor faults in wound rotor induction motors are presented. The applied method is the so-called motor current signature analysis (MCSA), an often cited and investigated diagnosis method. The method utilises the results of spectral analysis of the stator currents. Usually the FFT (Fast Fourier Transform) is used to obtain the power density vs. frequency plots to be analysed. In this paper the use of a novel versatile tool of harmonic analysis, of the wavelet transform will be presented. The proposed wavelet based detection method shows a good sensitivity. The theoretical basis of the method is proved by laboratory tests.

1. Introduction

Induction motors play an important role in the safe and efficient operation of industrial plants. Usually they are designed for 30 years fault-free lifetime, but most of them can fail earlier.

Many of its components are especially susceptible to failures also in the case of wound rotor induction machines. 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 coil 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 [1].

Fault diagnosis of electrical machines can lead to greater plant availability, extended plant life, higher quality products, and smoother plant operations.

Proper implementation of a maintenance program can reduce energy consumption in plants by as much as 10÷14%, while also reducing unplanned production downtime. The average downtime costs can vary between 7.000 $ (in forest products) and 200.000 $ (in the automotive industry) [2].

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.

For the detection of the induction motor's rotor faults here the motor current signature analysis method was applied [4, 5].

2. The Wavelet Transform

In general terms, mathematical transformations are applied to signals to obtain a further information from that signal that is not readily available in the unprocessed signal.

Most of the signals in practice, are time-domain signals in their raw format. That is, whatever that signal is measuring, is a function of time. When time-domain signals are plotted a time-amplitude representation of the signal is obtained. This is not always the best representation of the signal for most signal processing related applications. In many cases, as also in the case of electrical machines diagnosis, the most distinguished information is hidden in the frequency content of the signal.

The frequency spectrum of a signal is basically the frequency components (spectral components) of that signal. The frequency spectrum of a signal shows what frequencies exist in the signal.

There are several transformations that can be applied, among which the Fourier transform is probably by far the most popular. Although this transform is widely used (especially in electrical engineering), it is not the only one, and it have several disadvantages. The Fourier transform gives the frequency information of the signal (how much of each frequency exists in the signal), but it does not marks when in time these frequency components exist.

For better understanding the wavelet transform let take first an overlook on the short time Fourier transform (STFT). There is only a minor difference between it and the Fourier transform.

The Fourier transform decomposes a signal to complex exponential functions of different frequencies. The way it does this, is defined by the following equation:

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

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

In short time Fourier transform (STFT), 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:

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

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.

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.

In electrical machines diagnosis both the continuous and the discrete wavelet transform can be applied.

The continuous wavelet transform (CWT) was developed as an alternative approach to the STFT to overcome its resolution problem. The wavelet analysis is done in a similar way to the STFT analysis, in the sense that the signal is multiplied with a function, with the wavelet, similar to the window function in the STFT, and the transform is computed separately for different segments of the time-domain signal.

The continuous wavelet transform is defined by the following equation:

$$CWT_x^{\psi}(\tau, s) = \Psi_x^{\psi}(\tau, s) = \frac{1}{\sqrt{|s|}} \int x(t)\, \psi^*\left(\frac{t-\tau}{s}\right) dt \tag{3}$$

As it can be seen the transformed signal is a function of two variables (τ and s, the translation and scale parameters), respectively $\psi(t)$ is the transforming function, and it is called the mother wavelet, a prototype for generating the other window functions.

The term translation is used in the same sense as it was used in the STFT; it is related to the location of the window, as the window is shifted through the signal. This term, obviously, corresponds to time information in the transform domain. The parameter scale in the wavelet analysis is similar to the scale used in maps. High scales correspond to a non-detailed global view (of the signal), and low scales correspond to a detailed view. Similarly, in terms of frequency, low frequencies (high scales) correspond to a global information of a signal, whereas high frequencies (low scales) correspond to a detailed information of a hidden pattern in the signal (that usually lasts a relatively short time).

Once the mother wavelet is chosen the CWT computation starts with s=1 The wavelet at this scale then is shifted towards the right by τ amount to the location t=τ, and the equation (3) is computed to get the transform value at t= τ , s=1 in the time-frequency plane. This procedure is repeated until the wavelet reaches the end of the signal. One row of points on the time-scale plane for the scale s=1 is now completed. In this way the continuous wavelet transform is computed for all the imposed values of s.

For the discrete wavelet transform (DWT) the main idea is the same as it is in the case of CWT, but it is considerably easier and faster to implement.

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.

The decomposition of the signal into different frequency bands (see Figure 1) is simply obtained by successive highpass and lowpass filtering of the time domain signal.

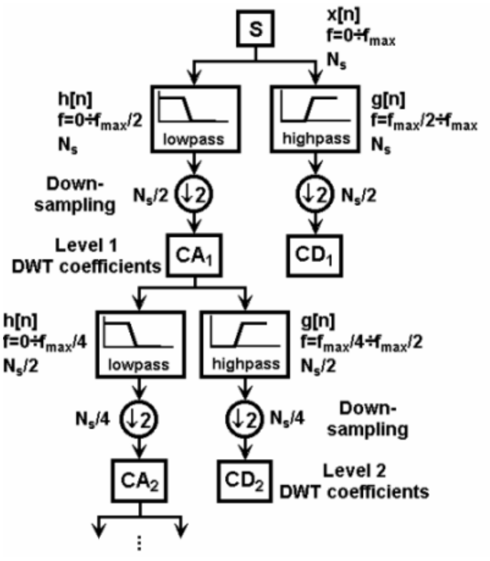


Figure 1. The DWT decomposition of a signal

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.

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 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 [6].

3. The Performed Measurements

In order to perform the required measurements a test bench was set up in the Electrical Machines Laboratory of the Department of Electrical Machines, Marketing and Management, Technical University of Cluj, Romania (see Figure 2.).

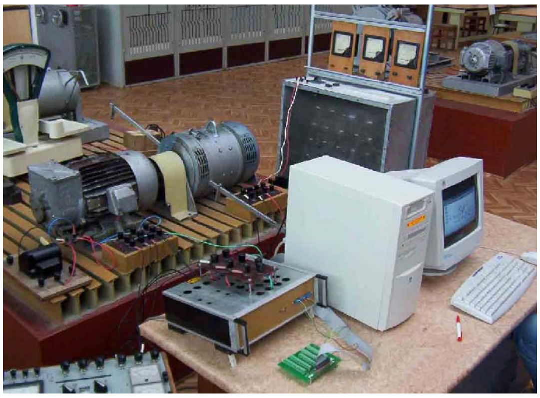


Figure 2. The laboratory setup

The test bench consists of two mechanically coupled electric motors, a dc motor for breaking and loading purposes and the 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 PC having a National Instruments AT-MIO-16XE-10 type acquisition board. This delivers high performance and reliable data acquisition capabilities, having 1.25 MS/s sampling rate and 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 [7].

The tested wound rotor induction motor 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 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 machines and for data processing purposes in LabVIEW graphic programming environment. All of them were simply made by assembling using drag-and-drop methods software objects from the various libraries of the program package.

From the numerous virtual instruments created here only a single one will be presented in Figure 3, which was used for the acquisition of the line currents of the wound rotor induction machine.

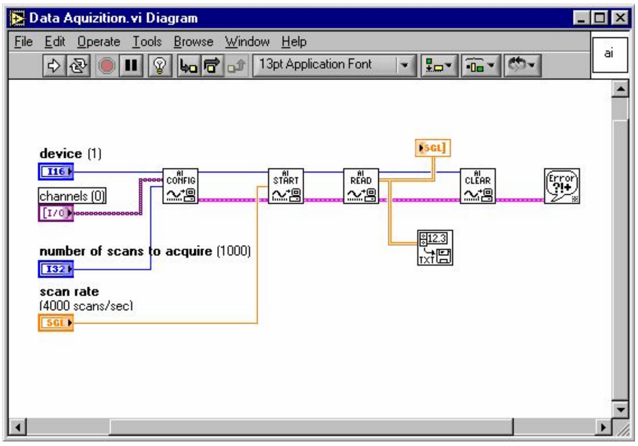


Figure 3. A virtual instrument's block diagram

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

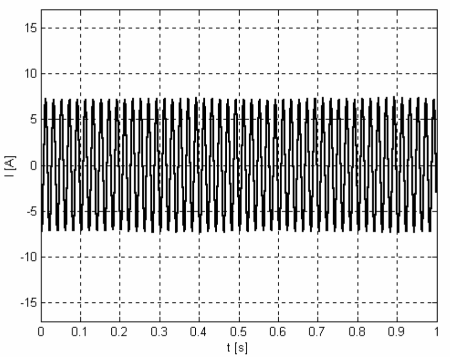
4. Results

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

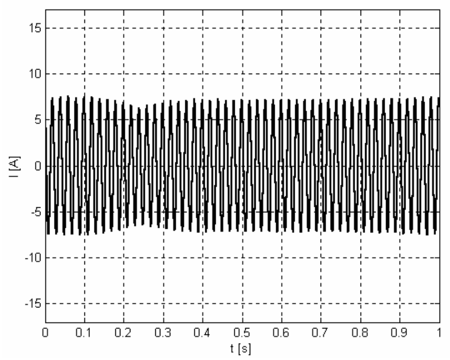
The wound rotor induction machine was tested when it was considered healthy and with a provoked rotor fault. The rotor fault was simulated by interrupting a rotor phase. In both cases the induction motor was tested at no-load condition (having only the unconnected braking machine coupled on its shaft) and at three different loads, inclusive the rated one.

The sample frequency for the data acquisition was set to a high value (2^{16}=65.536 samples/seconds). One second long measurement was performed, which means that on each channel 65.536 values were saved.

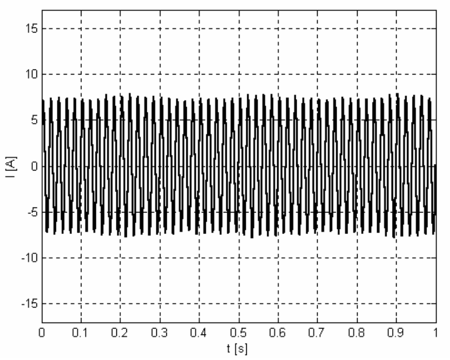
The measured line currents plotted versus time at the four different loads are given in Figure 4.



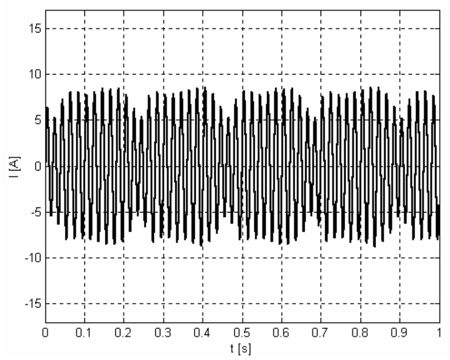
a) Healthy motor, no-load



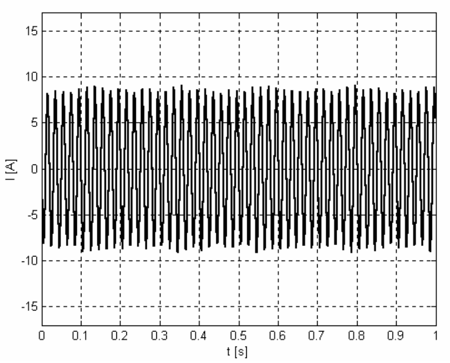
b) Faulty motor, no-load



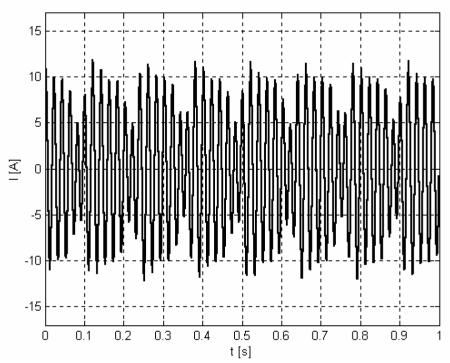
c) Healthy motor, 45% of rated load



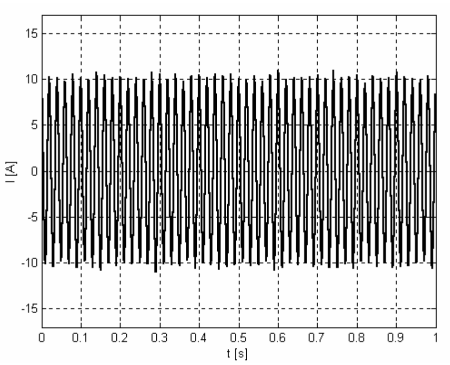
d) Faulty motor, 45% of rated load



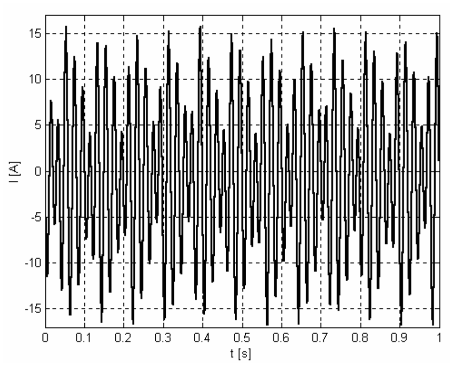
e) Healthy motor, 65% of rated load



f) Faulty motor, 65% of rated load



g) Healthy motor, rated load



h) Faulty motor, rated load

Figure 4. The measured line currents of the healthy and faulty tested motor at four different loads

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 [8]. 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 Figure 5.

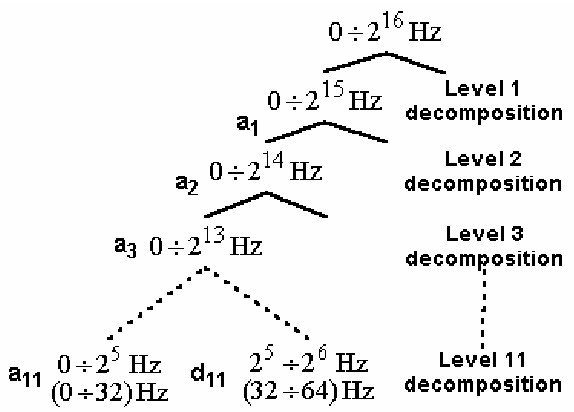


Figure 5. The wavelet decomposition tree

As it will be seen 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 can be found [9].

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.

Next in Figures 6÷9 the obtained d_{11} wavelet coefficient's variation versus time are given for the healthy and faulty induction motor at different loads. For a better comparison in all the four cases the same axis scaling was applied.

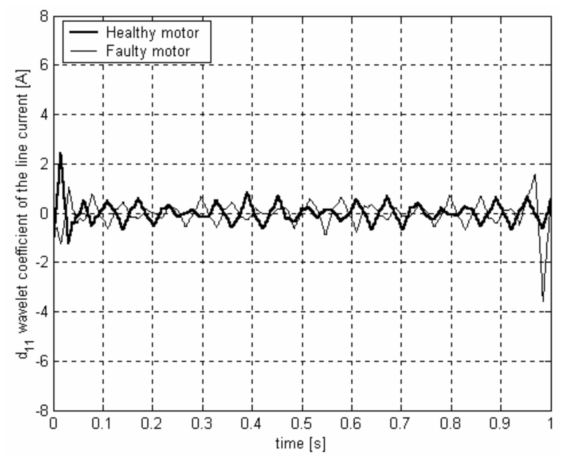


Figure 6. The d_{11} wavelet coefficient's variation at no-load

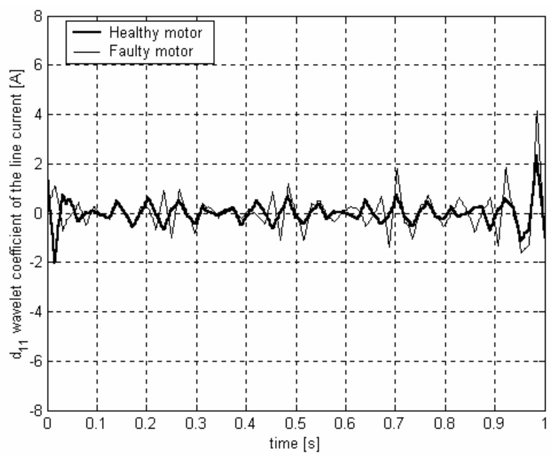


Figure 7. The d_{11} wavelet coefficient's variation at 45% of the rated load

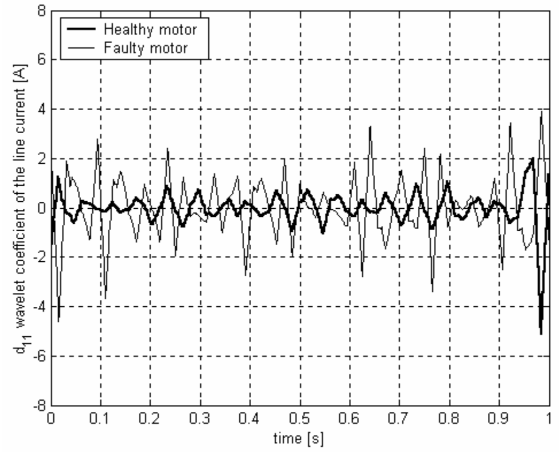


Figure 8. The d_{11} wavelet coefficient's variation at 65% of the rated load

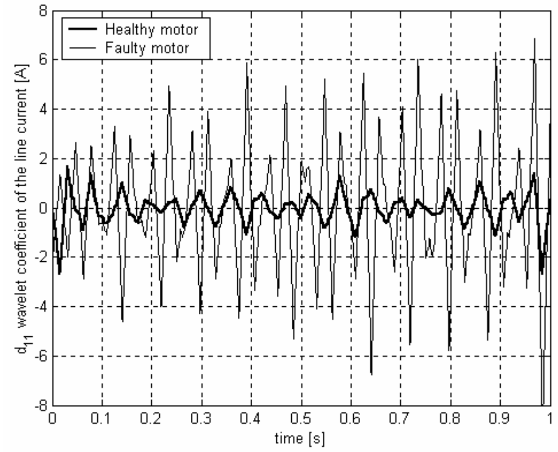


Figure 9. The d_{11} wavelet coefficient's variation at the rated load

As it can be seen very clearly from the above figures, at all the loads the d_{11} wavelet coefficient's variation for the faulty motor has greater magnitude.

As it can be also observed, at no-load the effect of the fault is not so serious as in the case of the rated load, since the currents in the rotor windings are small. Therefore the most eloquent results were obtained at great loads, especially near the rated load.

In order to emphasise the effect 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 will be computed:

$$k = \frac{(d_{11})_{RMS}}{(I)_{RMS}} \tag{4}$$

The obtained RMS values of the measured line currents (I) and of the d_{11} wavelet coefficients, respectively the computed k factor are in Table 1 both for the healthy and for the faulty wound rotor induction motor at all the four studied loads.

Load	**Healthy motor**			**Faulty motor**		
	$(I)_{RMS}$	$(d_{11})_{RMS}$	$k = \frac{(d_{11})_{RMS}}{(I)_{RMS}}$	$(I)_{RMS}$	$(d_{11})_{RMS}$	$k = \frac{(d_{11})_{RMS}}{(I)_{RMS}}$
No-load	5.02	0.36	0.073	5.05	0.474	0.093
45% of rated load	5.22	0.41	0.077	5.43	0.617	0.114
65% of rated load	5.88	0.47	0.079	6.63	1.129	0.171
Rated load	6.97	0.56	0.081	8.25	2.299	0.278

Table 1. Main results of the measurements and of data processing

As it can be seen from Table 1 the computed k factor is not proportional with the measured line current's values, and therefore neither with the load.

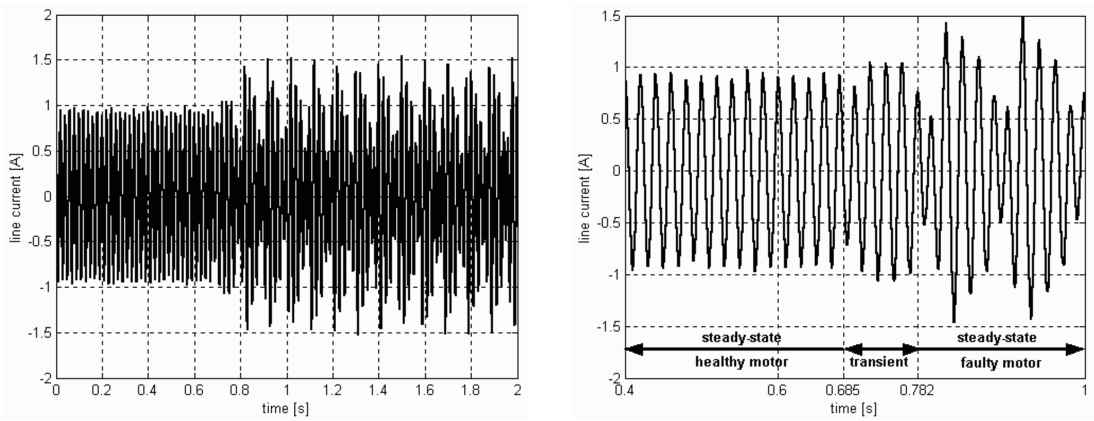
Hence it can be used to estimate the condition of a wound rotor induction machine.

Studying the values of the *k* factor in the case of the healthy and faulty motor it can be stated out that all the values for the healthy induction motor are lower than 0.09, and in the case of the faulty motor are higher than that value.

Therefore it can be seen, that the threshold value of factor *k* in the case of the wound rotor induction machine having a rotor phase interrupted is 0.09.

The above described analysis method can be also applied for on-line condition monitoring.

Next the results of measurements and data analysis obtained during the occurrence of the rotor fault will be presented. The measured line current plotted versus time is given in Figure 10.



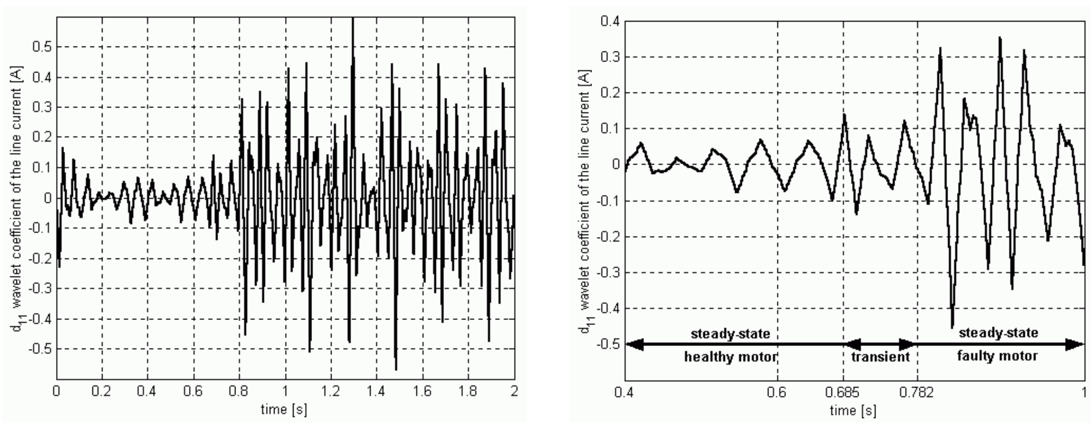
a) the whole measured period b) a zoom on the transient regime

Figure 10. The measured line currents during the occurrence of the rotor fault

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 Figure 10b, 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 steady-state can be seen. This transition period is about 0.1 s long.

The difference signal at the 11th level of decomposition (d_{11}) obtained in this case is given in Figure 11.



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

Figure 11. The d_{11} wavelet coefficient's variation

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 Figure 12. In the figure with an interrupted red line is marked the threshold value of the *k* factor (0.09).

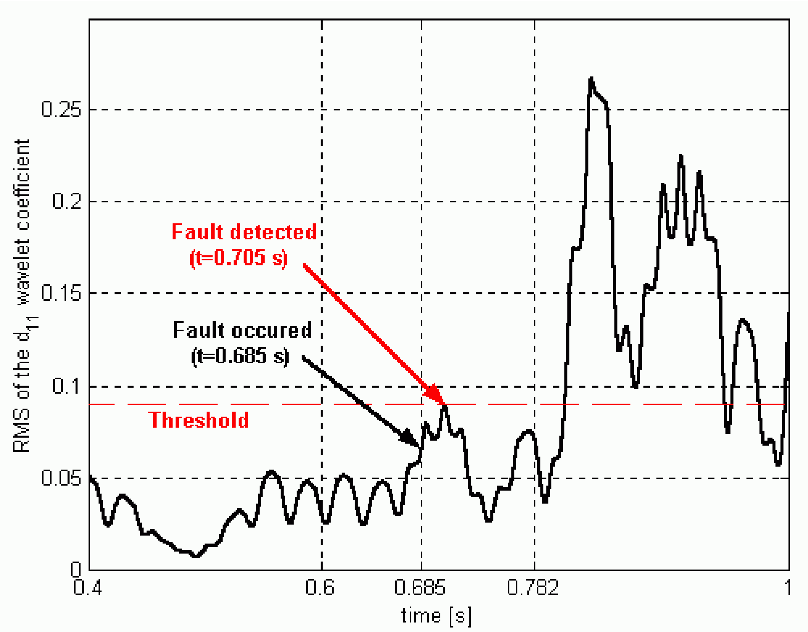


Figure 12 The variation of the d_{11} wavelet coefficient's RMS during the transient regime

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 both off-line and on-line.

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.

Acknowledgements

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About the Authors

Loránd Szabó received Ph.D. degree in electrical engineering from the Technical University of Cluj, Romania in 1995. His main research areas include linear and surface motors, CAD of electrical machines, respectively condition monitoring and diagnosis of electrical machines. He is with the Department of Electrical Machines of Technical University of Cluj since 1990.

Jenő Barna Dobai received the M.S. degree in variable speed electrical drives from the Technical University of Cluj, Romania in 2002. He is a full-time Ph.D. student at the Department of Electrical Machines of Technical University of Cluj since 2001. He is working in the field of condition monitoring and diagnosis of induction machines.

Károly Ágoston Biró received his Ph.D. degree in Electrical Engineering from the Technical University of Timişoara, Romania in 1978. His research interests include parameter determination of electrical machines, electric machines design, modelling of transient behaviour of electrical machines, etc. He is a full professor at Department of Electrical Machines of Technical University of Cluj since 1990. From 1992 he is the head of the Department.