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SIMPLE METHOD FOR ROTOR FAILURE DETECTION BASED ON QUANTUM ENTROPY

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Abstract: In this paper the diagnosis of high voltage induction motors (HVIM) with the enhanced and simplified method originated from detection of the change in the "behavior" of the (time series) signal and motor current signature analysis (MCSA) is introduced. The MCSA is one of the most efficient techniques for the detection and the localization of electrical and mechanical failures, in which faults become apparent by side band harmonic components around the supply frequency and higer harmonics [1-9]. But, extensive recording and preprocessing is necessary in each particular case. From that, in plant time consuming approach arises the need for a simple method for detection of the change in the "behavior" of the (time series) signal, based on recently proposed probabilistic method. The proposed method is based on two of the major concepts in quantum physics – a density matrix and the Born rule. As an example we will show how this method could be used in detection of the high voltage asynhronous motor rotor failure detection. Method is based on the on-line calculation of Tsallis entropy of the first derivative of the sampled stator current. The major contribution of this work is to prove the efficiency of Tsallis entropy based diagnosis methodology to detect multiple faults simultaneously. The results illustrate good agreement between both simulated and experimental results.

Key Words: *MV motor/broken rotor bar /Tsallis entropy*

1. INTRODUCTION

The problem under scope is how to make a very simple and cheap device for rotor failure detection in large induction motors in an early stage, in order to increase production availability through reduced downtime and by minimizing the repair cost. That simple and cheap device should be connected to each induction motor under surveillance. The main problem is how to detect the first sign of rotor failure during normal operation. The main focus of the paper is to develop method and means how indicate accurate and simply enough the need for further, more sophisticated and time consuming signal processing and more detailed problem identification. The more detailed failure identification, as: how to make a difference between rotor failure, bearings failure and other problems related to mechanical power transmission, while still in an early phase is out of the paper scope.

The common approach in solving this problem is periodical monitoring of mechanical vibrations, radio noise, stray magnetic field or input current in order to detect some signal spectrum irregularities. Usually, a quantity or quantities under consideration are recorded in the regular time intervals and then analyzed on a computer. It is very convenient to make measurements while the motor is running under load, despite the fact that the more accurate data can be obtained by the off-line machine testing. The analysis of the current spectrum is very popular, due to an easy way of recording the stator input current while the motor is loaded. This widely accepted approach is based on the fact that in the case of broken rotor bars it is possible to detect the side bands in the spectrum around the fundamental frequency and side bands around higher order harmonics [1] ,[2]. Another reported approach is monitoring the spectra of processed signals, as it is the spectra of stator current inverse components or instant power spectra [3].

The problems associated with the previously mentioned methods are:

- misidentification of failure due to noise,
- poor differential diagnosis between different types of failure,
- the need for easy on-line signal conditioning and processing in order to get the accurate diagnosis without involving expert people,
- a majority of reported data are correlated with the medium size low voltage induction motors, despite the fact that high voltage induction motors are more important in industry.

To overcome the previously defined problems, a new approach is introduced to increase the MCSA method sensitivity and to suppress unwanted disturbances [10].

Here we propose a very simple method for detection of the change in "behaviour" of the stator current that could indicate possible rotor failure. Method is based of the main concepts in quantum physics and it is going to be explained in the following sections.

2. QUANTUM PROBABILITY MODEL AND THE BORN RULE

In this section, a short recapitulation of the quantum probability model and the Born rule is given, based on a similar section in [12, 11].

The quantum probability model takes place in a Hilbert space H of finite or infinite dimension. A state is represented by a positive semidefinite linear mapping (a matrix $\boldsymbol{\rho}$) from this space to itself, with a trace of 1, i.e. $\forall \boldsymbol{\Psi} \in$ H $\boldsymbol{\Psi}^T\boldsymbol{\rho}\boldsymbol{\Psi}\geq 0$, $\mathrm{Tr}(\boldsymbol{\rho}) =1$. Such $\boldsymbol{\rho}$ is self adjoint and is called a density matrix.

Since $\boldsymbol{\rho}$ is self adjoint, its eigenvectors $\boldsymbol{\Phi}_i$ are orthonormal, and since it is positive semidefinite, its eigenvalues p_i are real and nonnegative $p_i \geq 0$. The trace of a matrix is equal to the sum of its eigenvalues, therefore $\sum_i p_i =1$.

The equation $\boldsymbol{\rho}=\sum_i p_i\, \boldsymbol{\Phi}_i\, \boldsymbol{\Phi}_i^T$ is interpreted as "the system is in state $\boldsymbol{\Phi}_i$ with probability p_i". The state $\boldsymbol{\rho}$ is called the pure state if $\exists i$ s.t. $p_i =1$. In this case, $\boldsymbol{\rho}=\boldsymbol{\Psi}\boldsymbol{\Psi}^T$ for some normalized state vector $\boldsymbol{\Psi}$, and the system is said to be in state $\boldsymbol{\Psi}$. So, the most general density operator is in the form $\boldsymbol{\rho}=\sum_k p_k\, \boldsymbol{\Psi}_k\, \boldsymbol{\Psi}_k^T$ where the coefficients p_k are nonnegative and add up to one, and $\boldsymbol{\Psi}_k$ represent pure states. We can see that this decomposition is not unique.

A measurement M with an outcome $\boldsymbol{z}$ in some set $\boldsymbol{Z}$ is represented by a collection of positive definite matrices $\{\boldsymbol{m}_z\}_{z\in \boldsymbol{Z}}$ such that $\sum_{z\in \boldsymbol{Z}} \boldsymbol{m}_z = \mathbf{1}$($\mathbf{1}$ is being the identity matrix in H). Applying measurement M to state $\boldsymbol{\rho}$ produces the outcome $\boldsymbol{z}$ with probability

$$p_z(\boldsymbol{\rho})=\mathrm{trace}(\boldsymbol{\rho}\boldsymbol{m}_z). \quad (1)$$

This is the Born rule. Most quantum models deal with a more restrictive type of measurement called the von Neumann measurement, which involves a set of projection operators $\boldsymbol{m}_a=\boldsymbol{a}\boldsymbol{a}^T$, for which $\boldsymbol{a}^T\boldsymbol{a}'=\delta_{aa'}$. In a modern language, von Neumann's measurement is a conditional expectation onto a maximal Abelian subalgebra of the algebra of all bounded operators acting on the given Hilbert space. As before, $\sum_{a\in M} \boldsymbol{a}\, \boldsymbol{a}^T =\mathbf{1}$. For this type of measurement, the Born rule takes a simpler form: $p_a(\boldsymbol{\rho})=\boldsymbol{a}^T\boldsymbol{\rho}\boldsymbol{a}$. Assuming $\boldsymbol{\rho}$ is a pure state this can be simplified further to

$$p_a(\boldsymbol{\rho}) = (\boldsymbol{a}^T\boldsymbol{\Psi})^2. \quad (2)$$

So, we can see that, if the state is $\boldsymbol{\rho}$, the probability of the outcome of the measurement will be $\boldsymbol{a}$, which is actually defined by the cosine square of the angle between vectors $\boldsymbol{a}$ and $\boldsymbol{\Psi}$, or $p_a(\boldsymbol{\rho})=\cos^2(\boldsymbol{a},\boldsymbol{\Psi})$.

Now, without loss of generality, let's assume that we are dealing with a random variable $\boldsymbol{x}$ that takes realizations from a set of observed K-dimensional zero-mean data vectors $\{\boldsymbol{x}_k\}$, $k \in\{1, \ldots, N_{\mathrm{sample}}\}$, which are sampled from some distribution in time instants $t = kT$ where k is already defined and T represents the sampling period. Then, we can define $p(\boldsymbol{x}=\boldsymbol{x}_k \mid t=kT)$ as

$$p(\boldsymbol{x}_k) \overset{def}{=} \frac{\|\boldsymbol{x}_k\|^2}{\sum_{i=1}^{N_{sample}} \|\boldsymbol{x}_i\|^2} \quad (3)$$

where N_{sample} represents the overall number of samples that are going to be analyzed. It is interesting to note that the only thing that we can conclude about the $p(\boldsymbol{x}_k)$ is that it is proportional to $\|\boldsymbol{x}_k\|^2$. The sum in the denominator represents the energy of samples that are going to be analyzed – we actually do not know the value of that sum in any, but the final moment. However, we know that it represents some constant. We can easily see that the adopted probability measure fulfils the two conditions that are required for the probability function $f(z)$ (in our case $p(z)$) to be considered as a modified generalized probability measure [13]:

1. For each z, $0 \leq f(z) \leq 1$,
2. $\sum_i f(z_i) = 1$.

3. ROTOR CAGE FAULT

The most common indicators for rotor faults (broken bars or end-rings) in squirrel cage motors are excessive vibration noise during motor starting. Such secondary effects become noticeable only when the incipient fault has grown enough to involve several broken bars. Increased vibration and noise can be caused by a multitude of other defects, making the identification of rotor faults at an early stage difficult. If left undetected, the occurrence of incipient fault will eventually degenerate into a full motor failure. Example of total rotor failure (several cracked and broken rotor bars) on motor is shown on Fig.1.

Fig. 1. *The faulty cage with several cracked and broken rotor bars*

The "faulty" magnetic field around the broken bar has a fundamental component that is always two-pole; however, due to the abrupt nature of its air-gap component, it is also rich in harmonics. The magnetic flux anomaly rotates at the mechanical frequency of the rotor since it is attached to the broken bar. The rotating current and flux are pulsating at the slip frequency. While the presence of broken bars based solely on the low frequency spectra cannot be reliably established, the high frequency content of such disturbance provides an opportunity for an unambiguous detection. Similar but smoother spatial distributions of the air gap flux result from magnetic anisotropy and bearings damage. Also, the other mechanical problems due to power transmission generate harmonics in stator current at lower band frequencies, which can be easily misinterpreted as rotor cage fault originated [3], or gone undetected

Here we propose that the measure of the "behavior" of the motor current is Tsallis' entropy of the recorded samples in the sliding window of the proper size. The Tsallis' entropy is defined by the following equation:

$$E_{TS} = \left(\frac{1 - \sum_{k=1}^{K} p(x_k)^q}{q-1} \right),$$

where q is usually taken in the range 6-12 for the case of interest, and x_k represents samples of the derivatives of the stator current and $p(x_k)$ is defined by equation (3). The measure M of the current "behavior" is actually defined by the following equation

$$\mathrm{M} = \mathrm{E}\left(\sum_{k=1}^{K} p(x_k)^q \right) = \mathrm{E}\left(1 - (q-1)E_{TS}\right),$$

where E stands for expectation. In order to improve the method sensitivity, the derivatives of the stator current are used for numerical processing, from the reason that detection of the rotor failure could be detected by the presence of the spectral components close to the 5^{th} and 7^{th} harmonic, which are much more "visible" in the derivative of the stator current then in the stator current itself. On the following figure we can see the sinusoidal signal with 1% presence of 5^{th} harmonic, on upper figure and corresponding derivative shown on lower figure.

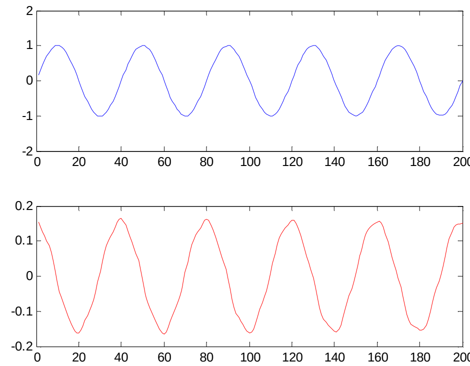

Fig. 2.*Sinusoidal signal with 1% presence of 5^{th} harmonic (upper plot) and its derivative (lower plot)*

By calculating the factor M for the case without presence of the component close to 5^{th} harmonic and with its 1% presence, change of the M of the stator current is just 20%, while the change of M of the derivative is close to 300% (for q=6).

In the case that it is necessary to target some specific frequency "region", it is possible to condition signal with appropriate band-pass filter and, again it is possible to use M as a measure of the change of the "behavior".

This method is particularly efficient if the several motors of same size are in the similar working conditions. In that case results could be compared between which further increase robustness of the method (like in the case explained in [14]).

In case study, two HVIM rated 3,15 MW 6 kW used as main circulating pump drives in steam power plant were tested under the same water flow (100 ton/h). The corresponding stator currents are recorded (4 kSample per second, 20 seconds time window) and processed using FFT and Hanning window. So derived spectral contence around fundametal frequency is shown in Fig. 3 for healthy rotor cage and in Fig. 4 for faulted rotor cage.

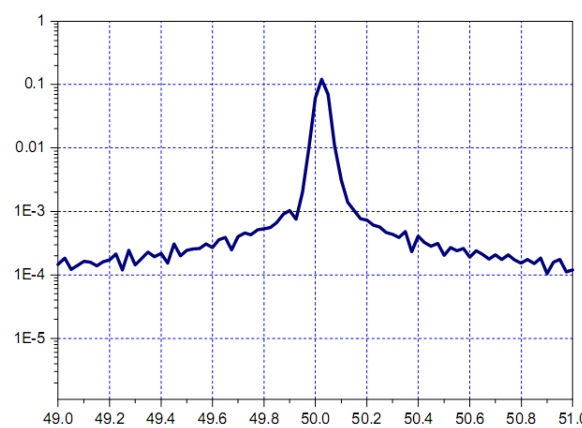

Fig. 3. *The healthy cage current spectrum(relative amplitude versus frequency) around fundamental frequency (50 Hz)*

Fig. 4. *The faulty cage with several cracked and broken rotor bars, cage current spectrum (relative amplitude versus frequency) around fundamental frequency (50 Hz)*

The calculated Tsallis' entropy ratio between damaged and healthy rotor cage case is around 8, what is considered to be a significant difference.

4. CONCLUSION

We proposed very simple method (cheap for realization) for detection of the point of change of "behavior" of derivative of asynchronous motor stator current, in order to diagnose rotor failure. Method shows good results in the cases that were analyzed, especially where direct comparison is possible. Method could be further refined by implementation of the preconditioning by appropriate band-pass filters of the current signal.

5.ACKNOWLEDGEMENT

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