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Induction Motor Bearings Diagnostic Indicators Based on MCSA and Normalized Triple Covariance

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***Abstract*—Induction motors are one of the most widely used electrical machines. Statistics of bearing failures of induction motors indicate, that they constitute more than 40% of induction motor damage. Therefore, bearing diagnosis is so important for trouble-free work of induction motors. The most common methods of bearing diagnosis are based on vibration signal analysis. The main disadvantage of those methods is the need for physical access to the diagnosed machine, which is not always possible. Methods based on motor current signature analysis are free of this disadvantage. Preliminary studies have shown that motor current signature analysis based normalized triple covariance is a very good diagnostic indicator for induction motor bearings. This paper presents an attempt to find a more accurate diagnostic indicator based on normalized triple covariance. In this paper the author verifies how many diagnostic features (normalized triple covariances) included in diagnostic indicator can give better separation between healthy and unhealthy cases.**

Keywords—induction motor, motor current signature analysis (MCSA), motor diagnosis, bearing diagnosis, signal processing, normalized triple covariance.

I. Introduction

Induction motor (IM) is currently the most widely used machine in electrical drivelines. Simplicity of IM construction causes that bearings are the most damageable elements. According to statistics of IM breakdowns, bearings damage constitute more than 40% of all IM breakdowns [1]. Therefore, proper diagnostic of bearings is crucial in IM maintenance. Early detection of bearing damage can prevent failures of other parts of IM, which may consequently lead to a complete destruction of the machine.

Bearing damage generates diagnostic symptoms, observation of which can carry valuable diagnostic information. Bearing damage can cause symptoms such as: increased vibration, increased noise levels, increased work temperature, efficiency loss, additional components in instantaneous power or current spectrum. There are many methods of IM bearings diagnostic based on the measurement of various physical quantities e.g. vibration [2] [3], supply current [3] [4] [5] [6] [7], magnetic flux [8], acoustic emission [9], temperature [10] or power of supply [11]. Currently, the most commonly used methods of bearings diagnostic use the measurement of vibration on the bearing housing [12]. However, vibration based methods have a fundamental disadvantage – they require direct access to the machine for sensors installation. In cases of limited access to the diagnosed drive, vibration measurement implementation can be very difficult and costly. Diagnostic methods based on Motor Current Signature Analysis (MCSA) are successfully used for detecting stator [13] [14] and rotor [15] [16] [17] faults. Therefore, the development of effective methods of IM bearings diagnostic based on MCSA would allow implementation of the whole engine diagnostic with the measurement of only one physical quantity. This solution would be very convenient and economically efficient because it would lead to cost reduction of the IM diagnosis. For this reasons new MCSA based methods of IM bearings diagnostic are being developed.

In literature [4] [8] [18] on MCSA based bearing diagnostic methods the authors usually focus on proving the effectiveness of the method in a single case. Introduced damage is usually high (e.g. a hole drilled trough the outer ring of the bearing [18]) and consequently easy to detect. Present literature also lacks information on the accuracy of diagnoses for presented methods. So far, there is no MCSA based method which accuracy would allow for industrial application. Therefore, the authors of papers [4] [8] use measurements of additional physical quantities such as efficiency [4] or electromagnetic flux [8] to improve MCSA diagnostic properities. However, even the additional features do not give full information on the type and depth of damage.

In previously mentioned works on IM bearings diagnostic based on MCSA the authors assumed that amplitudes of additional current components caused by bearings damage do not vary significantly in time and their level may be a good diagnostic indicator (DI). According to this assumption seeking of additional components of motor current in averaged current spectrum seemed reasonable. This approach gives positive results only for IM with significantly damaged bearings. However, the concept of diagnostic is to detect faults in the early stages of development to prevent secondary damage of other parts of the motor. The Normalized Triple Covariance (NTC) method is based on opposite assumption that amplitudes of additional current components with frequencies associated with bearing damages may significantly vary in time. NTC detects nonlinear amplitude changes common for three diagnostic current components. This method has already been described in [19] [20] [21] [22].

According to mentioned woks, NTC approach seems to be more effective especially for bearings in early stages of damage.

II. NTC

The author of this paper proposed a new method of IM bearings diagnostic based on MCSA which is NTC given by (1).

$$NTC = \frac{\frac{1}{n}\sum_{i=1}^{n}((X_i(f_1) - E(X(f_1)))\cdot(X_i(f_2) - E(X(f_2)))\cdot\overline{(X_i(f_3) - E(X(f_3)))})}{\sqrt{\sigma^2(X(f_1))\cdot\sigma^2(X(f_2))\cdot\sigma^2(X(f_3))}} \quad (1)$$

where:
n – number of time segments
$X_i(f_1)$ – Fourier series coefficient from signal for i-th time segment for frequency f_1
$E(X(f_1))$ – mean value of Fourier series coefficients for frequency f_1 in all time segments
$\sigma^2(X(f_1))$ – variance of Fourier series coefficients for frequency f_1 in all time segments

The first step to calculate NTC is to cut the discreet time domain signal into segments. In this experiment, authors used 10 s segments in order to get 0.1 Hz spectrum resolution. Tests were performed on 64 s three phase IM supply current signals with sampling frequency 65536 Hz. To get more time segments, cutting was done with 60% overlap. The next step was to perform FFT with Blackman window for each time segment. Shaft rotation frequency f_r and supply grid frequency f_g were designated from obtained spectrum for each segment. Values of these frequencies are necessary to calculate the characteristic frequencies for bearing damage. The next step is to get complex amplitude values from spectra for three characteristic frequencies in each segment. The following step is to use (1) to calculate NTC. Last operation is to calculate mean value of NTC for three phases of motor current. The author of this paper proposes to use NTC as a diagnostic feature (DF) for IM bearings diagnostic. Experimental studies have confirmed that the variability of diagnostic components amplitudes represented by NTC value can be successfully used as a DF for a variety of bearing defects in IM.

Preliminary research on IM bearing diagnostic with NTC [21] confirmed great capabilities of NTC, but it is important to improve this method for better results. DI efficiency in this method depends on several parameters such as measurement time, spectrum resolution, frequencies of components used to calculate NTC or number of DF included in DI. This research aim is to examine how does the number of DF used for DI calculation affects accuracy of diagnoses and separation between damaged and undamaged cases.

III. Experiment Methodology

Previous research on MSCA based IM bearings diagnostic showed a dependency between bearings condition and occurrences of current components in specific frequencies. According to literature [23] there are 32 additional current components most sensitive to the bearing damage. Frequencies of this components are listed in Table 1.

TABLE I. FREQUENCIES OF COMPONENTS

Component number	**Frequency of component**	**Component number**	**Frequency of component**
1.	f_g+f_{def}	17.	$f_g+3\cdot f_r+f_{def}$
2.	$\lvert f_g-f_{def}\rvert$	18.	$\lvert f_g+3\cdot f_r-f_{def}\rvert$
3.	$3\cdot f_g+f_{def}$	19.	$\lvert 3\cdot f_g-f_r+f_{def}\rvert$
4.	$\lvert 3\cdot f_g-f_{def}\rvert$	20.	$\lvert 3\cdot f_g-f_r-f_{def}\rvert$
5.	$5\cdot f_g+f_{def}$	21.	$3\cdot f_g+f_r+f_{def}$
6.	$\lvert 5\cdot f_g-f_{def}\rvert$	22.	$\lvert 3\cdot f_g+f_r-f_{def}\rvert$
7.	$\lvert f_g-f_r+f_{def}\rvert$	23.	$\lvert 3\cdot f_g-2\cdot f_r+f_{def}\rvert$
8.	$\lvert f_g-f_r-f_{def}\rvert$	24.	$\lvert 3\cdot f_g-2\cdot f_r-f_{def}\rvert$
9.	$f_g+f_r+f_{def}$	25.	$3\cdot f_g+2\cdot f_r+f_{def}$
10.	$\lvert f_g+f_r-f_{def}\rvert$	26.	$\lvert 3\cdot f_g+2\cdot f_r-f_{def}\rvert$
11.	$\lvert f_g-2\cdot f_r+f_{def}\rvert$	27.	$\lvert 5\cdot f_g-f_r+f_{def}\rvert$
12.	$\lvert f_g-2\cdot f_r-f_{def}\rvert$	28.	$\lvert 5\cdot f_g-f_r-f_{def}\rvert$
13.	$f_g+2\cdot f_r+f_{def}$	29.	$5\cdot f_g+f_r+f_{def}$
14.	$\lvert f_g+2\cdot f_r-f_{def}\rvert$	30.	$\lvert 5\cdot f_g+f_r-f_{def}\rvert$
15.	$\lvert f_g-3\cdot f_r\rvert+f_{def}$	31.	$\lvert 5\cdot f_g-2\cdot f_r+f_{def}\rvert$
16.	$\lvert\lvert f_g-3\cdot f_r\rvert-f_{def}\rvert$	32.	$\lvert 5\cdot f_g-2\cdot f_r-f_{def}\rvert$

where:
f_g – frequency of supply grid;
f_r – frequency of shaft rotation;
f_{def} – frequency of bearing defect.

The proposed algorithm requires exactly three components to calculate NTC. Previous research did not distinguish clearly which of the components are best for use with NTC. Therefore, the author of this paper assumes that NTC calculated for each combination of 3 out of 32 components is a potential DF for IM bearings diagnosis. Considering the 32 components and including the fact that switching places of the first and second component does not affect the value of NTC, one can get 14880 different combinations of 3 out of 32 components. NTC calculated for different components combinations reveals different properties. Therefore NTC calculated for different components combinations can work better with some bearings cases but not so well for other cases. The author proposes to use the sum of n NTCs calculated for different components combinations as a DI to make this DI more reliable. The choice of components is very important from the point of view of separation between damaged and undamaged cases. It is not possible to distinguish which components combination has better properties on a theoretical basis, so the author calculated NTC for all possible components combinations. The next step was to calculate Fisher's criterion given by (2), with NTCs calculated for all 14880 components combinations on a random set of bearings.

$$F = \frac{|m_1 - m_2|^2}{\sigma^2{}_1 + \sigma^2{}_2} \quad (2)$$

where:
m_1 – mean value of NTC for undamaged bearings cases;
m_2 – mean value of NTC for damaged bearings cases;
$\sigma^2{}_1$– variance of NTC for undamaged bearings cases;
$\sigma^2{}_2$– variance of NTC for damaged bearings cases.

The author assumed that the separation between damaged and undamaged cases is better when the value of Fisher's criterion is greater. DI is defined as sum of n NTCs with the highest Fisher's criterion achieved on a random set of bearings. Rest of bearings not included in the learning set is diagnosed with DI obtained this way to validate achieved DI. Author set the border between healthy and unhealthy cases in the middle between mean DI value for damaged cases and mean DI value for undamaged cases.

In previous research, the author used DI consisted of 1 [22], 3 [19] or 5 [20] [21] DFs. The goal of this research is to examine how does the number of DFs included in DI affects Fisher's criterion and accuracy of diagnoses.

IV. Results

Squirrel cage IM used for the tests was Sh 80X-4C, with 1,1 kW nominal power. Bearings type in this motor is 6204. The motor was supplied directly from 50 Hz three phase supply grid. Current measurements used in this research were taken under full load conditions.

The presented experiment was performed on 10 damaged bearings (numbers 1 to 10) and 32 undamaged bearings (numbers from 11 to 42). Bearings used in this experiment were mechanically damaged. Damaged bearings are listed in Table 2 with full description of introduced damages. All introduced damages in this experiment were outer race damages. Simultaneously with motor current measurement a vibration measurement was taken. Vibration measurement results were used to validate bearings condition. For this purpose the DREAM vibration diagnostic system was used. Results obtained from this system are also listed in Table 2. According to DREAM those results should be interpreted as a depth of damage.

TABLE II. BEARINGS USED FOR EXPERIMENT

Bearing number	Introduced damage in outer race	DREAM result for outer race
1.	pit damage diameter=1.0 mm and depth=0.5 mm	17%
2.	pit damage diameter=1.5 mm and depth=0.7 mm	17%
3.	pit damage diameter=2.0 mm and depth=1.0 mm	80%
4.	scratch along the rolling direction length=3 mm, depth=0.5 mm, width=1 mm.	14%
5.	scratch along the rolling direction length=3 mm, depth=0.7 mm, width=1 mm.	36%
6.	scratch along the rolling direction length=3 mm, depth=1.0 mm, width=1 mm.	80%
7.	scratch along the rolling direction length=6 mm, depth=0.7 mm, width=1 mm.	32%
8.	scratch across the rolling direction length=3 mm, depth=0.5 mm, width=1 mm.	59%
9.	scratch across the rolling direction length=3 mm, depth=0.7 mm, width=1 mm.	80%
10.	scratch across the rolling direction length=3 mm, depth=1.0 mm, width=1 mm.	80%
11. to 42.	bearings not damaged	<5%

For this experiment the author randomly selected three sets of bearings for learning. Each set contains 5 bearings with damaged outer race and 16 bearings with undamaged outer race. Bearings used for learning were:

Set 1: Damaged: 2, 4, 6, 7, 9
Undamaged: 12, 14, 18, 25, 26, 27, 29, 30, 31, 33, 35, 36, 38, 40, 41, 42

Set 2: Damaged: 2, 4, 5, 7, 8
Undamaged: 11, 14, 15, 16, 19, 21, 22, 23, 24, 27, 29, 35, 36, 38, 39, 40

Set 3: Damaged: 2, 5, 7, 8, 9
Undamaged: 11, 12, 13, 17, 21, 22, 24, 25, 26, 29, 31, 33, 36, 37, 39, 41

The rest of the bearings not listed in sets above were diagnosed with DI obtained with bearings listed in sets above. For this sets the author performed the analysis on how does the number of DF (n) included in DI affects the accuracy of diagnosis and the Fisher's criterion value. The author defined accuracy of diagnoses as a ratio of proper diagnoses compared to all, multiplied by 100%.

Fig. 1 a) shows the overall tendency of Fisher's criterion value. The most interesting part is Fig 1 b) where the value of Fisher's criterion is low for using single DI in each of examined sets. For set 1, the Fisher's criterion value has local maximum for n=3 and a global maximum for n=6. For set 2 maximum value of Fisher's criterion is for n=6 and for set 3 for n=3. For n>6 value of Fisher's criterion drops in each analyzed set.

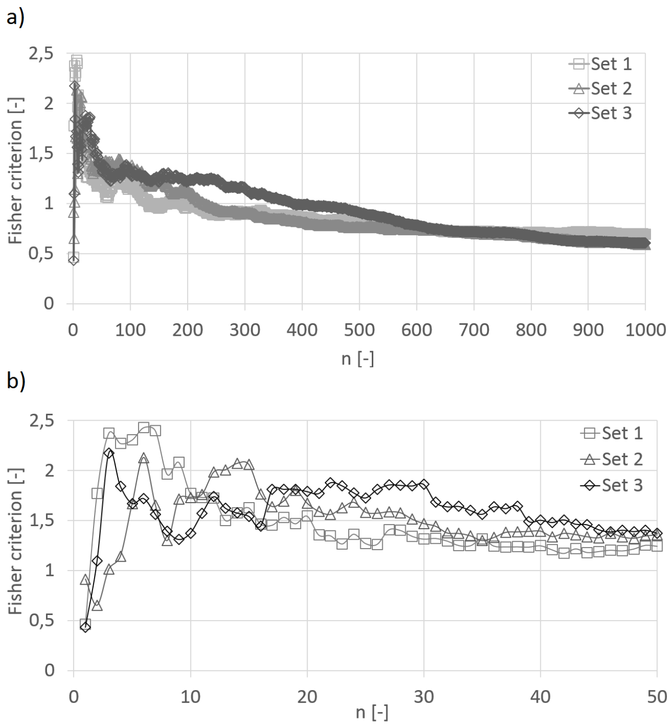

Fig. 1. Graphs of Fisher's criterion value.

Fig. 2 shows accuracy of diagnoses for damaged bearings. In each analyzed set, the accuracy of damaged bearings reaches the highest value of 80%, which means that 4 out of 5 damaged bearings were diagnosed correctly. For set 1 the highest values are for *n*=3 and for *n* in range from 5 to 14. For set 2 the highest values are for *n*=3 and *n*=6. For set 3 *n*=3, *n*=6 and for *n* in range from 11 to 18. For *n*=3 all examined sets reach 80%, it is the only maximum common for all sets.

Fig. 3 shows accuracy of diagnoses for undamaged bearings. For set 1 the maximum value is 94% for *n*=3. Maximum value for other sets is 88%. For *n*=5 all examined sets reached accuracy of diagnoses equal to 88%.

Fig. 4 shows accuracy of diagnoses for all bearings. For set 1 maximum value is 90% for *n*=3. Maximum accuracy of diagnoses for all bearings for other sets is 86%. Set 2 reaches maximum only for *n*=6. Set 3 reaches maximum for *n*=3, *n*=8 and *n* in range from 11 to 18.

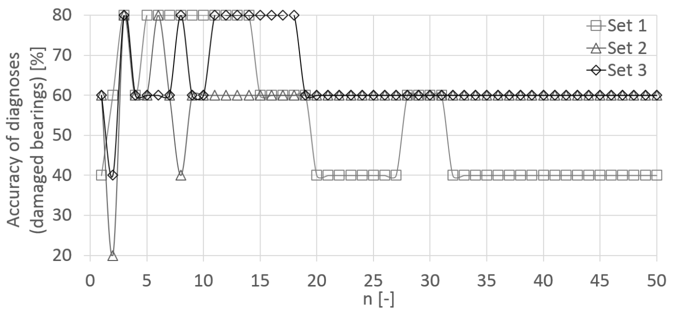

Fig. 2. Graph of accuracy of diagnoses for damaged bearings.

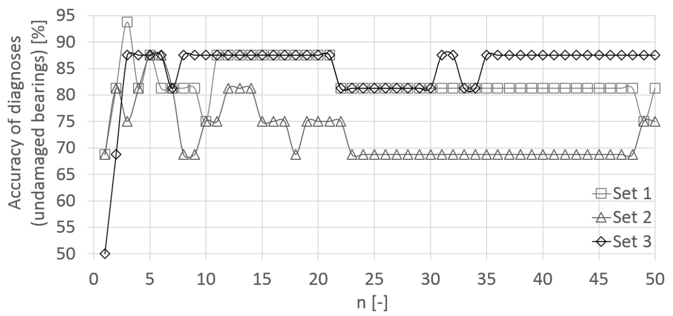

Fig. 3. Graph of accuracy of diagnoses for undamaged bearings.

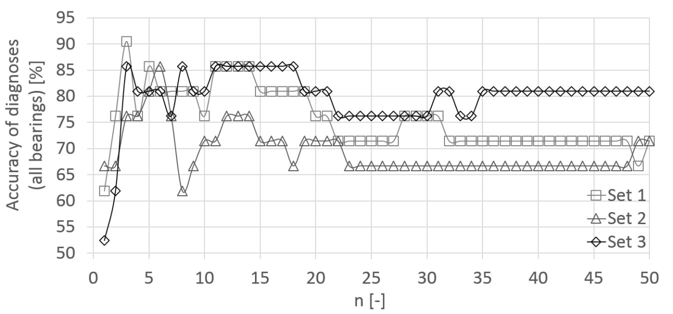

Fig. 4. Graph of accuracy of diagnoses for all bearings.

V. Conclusion

The presented research confirmed very good diagnostic properties of MCSA with NTC for diagnosis of IM bearings. Accuracy of diagnoses for all bearings reached 90% for set 1 and 86% for other sets. These values are comparable with accuracies of vibration based methods for bearings diagnostic.

Conducted research has shown that in the presented method, increasing the number of DFs included in DI does not always improve the achieved results. For all analyzed data the best solution was achieved for *n* in range from 3 to 8.

Considering accuracy of diagnoses for all bearings as the most important value, for sets 1 and 3 the best solution was for *n*=3 and for set 2 for *n*=6. Considering Fisher's criterion value as the most important, the best solution is for *n*=6 for sets 1 and 2 and for *n*=3 for set 3.

On the basis of analyzed data it is not certain that *n*=3 or *n*=6 is always the best solution. However, this research clearly shows that in most cases the best solution is for *n* in range from 3 to 8. From the practical point of view, a lot of DFs included in DI would significantly increase computation time needed for NTC calculations.

Fig. 1. a) clearly shows that in further research on this topic there is no need of making analysis for *n*>50. Further research on this topic should focus on investigating the presented dependencies in a narrower range of *n* but on a significantly larger group of test sets.

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