Detection of inter-turn short-circuit at start-up of induction machine based on torque analysis

Abstract: Recently, interest in new diagnostics methods in a field of induction machines was observed. Research presented in the paper shows the diagnostics of induction machine based on torque pulsation, under inter-turn short-circuit, during start-up of a machine. In the paper three numerical techniques were used: finite element analysis, signal analysis and artificial neural networks (ANN). The elaborated numerical model of faulty machine consists of field, circuit and motion equations. Voltage excited supply allowed to determine the torque waveform during start-up. The inter-turn short-circuit was treated as a galvanic connection between two points of the stator winding. The waveforms were calculated for different amounts of shorted-turns from 0 to 55. Due to the non-stationary waveforms a wavelet packet decomposition was used to perform an analysis of the torque. The obtained results of analysis were used as input vector for ANN. The response of the neural network was the number of shorted-turns in the stator winding. Special attention was paid to compare response of general regression neural network (GRNN) and multi-layer perceptron neural network (MLP). Based on the results of the research, the efficiency of the developed algorithm can be inferred.

Keywords: Wavelet Transform, Induction machine, Fault analysis, Finite element method, Artificial neural networks

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1 Introduction

One of the most common requirements in modern industrial applications is to minimize costs associated with repair and exploitation. Recently, in the industrial processes, induction motors are most often used as drive systems. Therefore, providing them continues and failure-free work is closely linked to the aforementioned cost minimization. The development of electronics as well as low cost of production will increase the number of induction motors which are used in industrial applications [1]. The use of semiconductor devices to control induction motors makes it easy to adjust the system and thus greatly improves its flexibility. With the variety of uses of induction motors, the importance of fault diagnostics is also increased. Diagnosis of faults has to ensure reliable and continuous operation of the motors [2]. One of the most common damage of induction motors are damage of the stator circuit. Stator circuit damage accounts for about 36% of damages [3, 4]. Damage to the stator circuit is very often triggered by inter-turn short-circuits [3, 5]. Inter-turn short-circuits are caused by insulation damage between the single windings of coil and this can lead to spread short-circuit to the whole coil and even between adjacent coils. Damage to the insulation may be associated with mechanical stress, over-current or thermal impact. In addition, inter-turn short-circuits may cause asymmetry of the magnetic field that can lead to the generation of vibration and the occurrence of higher harmonics in a torque waveform, which can significantly affect the reduction of system performance. As a result of the process described above, it may be possible to stop the motor which can involve high costs of a production process.

Current trends in the field of diagnostics of electrical machines focuses on early and non-invasive failure detection. Most common non-invasive diagnostic techniques use such methods as Discrete Variation Transform (DFT) or Fast Fourier Transform (FFT). The input signal to the above mentioned methods is usually the current, the pulsation of the torque or the machine vibrations. One of the most popular methods is motor current signature analysis (MCSA). The MCSA method allows to monitor the state of machine
without the use of additional sensors and thus does not interfere with its operation [2, 6]. Another example of a diagnostic method related to inter-turn short-circuit is a method that is similar to the MCSA method which involves analysis of back-electromotive force (emf) in the frequency domain. This method is more fully described in [7]. The above mentioned methods, apart from numerous advantages, also have disadvantages, frequency analysis can be used only for stationary signals. Analysis of non-periodic signals that occur, for example, during start-up of a motor, it is necessary to use another method which allows analysis of non-stationary signals such a method is based on wavelet transform. Furthermore, modern diagnostic systems use artificial neural networks as decision support systems to automate the diagnostic process [8–10].

In the paper, a finite element method (FEM) which is shown, among others, in the paper [11–15] and a field-circuit model were used. The use of a field-circuit model of the machine makes it unlike the circuit model to take into account such electromagnetic phenomena as for example: eddy currents or a saturation of magnetic core. For the field-circuit model equations of motion, supply system and magnetic field were formulated. These equations allow to describe the magnetic fields distribution as well as description of stator connection with power supply. As mentioned earlier, the finite element method was used. The FEM is one of the most popular methods used in the analysis of electrical machines. The advantage of FEM is the ability to determine in a simple way mechanical and electrical parameters or response of the motor. Another method for using FEM was the simplicity that it gives with modelling of motor faults. Other methods are, for example: winding function theory (WFT), magnetic equivalent circuit (MEC) or dq0 conversion method [16].

The paper focuses on the analysis of torque pulsation of an induction motor. The presented results concern two cases: the first in which the machine is unloaded and the second when the load is equal to 15 Nm. Moreover, the paper describes the effect of inter-turn short-circuit on torque pulsations in transient state. Furthermore, results of the learning process of two types of neuronal networks were presented: the first GRNN and the second MLP. This paper presents an extension of the methods described in article [17].

2 Modeling of inter-turn short-circuit

The result of the inter-turn short circuit in a phase winding is a division of the phase winding into two parts (Figure 1).

In the Figure 1, the phase stator windings are highlighted as follows: phase A is highlighted in red, phase B in green, and phase C in blue. However, the part of phase A winding, which has been shorted is in yellow. The red part denotes the faulty phase winding with the number of turns equal to \( N_{Af} \), the resistance \( R_{Af} \) and the inductance \( L_{Af} \). Theyellowpartrepresentsshortedturnshasanumber of turns equal to \( N_{f} \), the resistance \( R_{f} \) and the inductance \( L_{f} \). The short circuit has been treated as a metal-metal connection. Therefore, there is no additional resistance in the shorted circuit.

3 Wavelet analysis of torque waveforms

3.1 The torque waveforms during the start of the machine

Calculations were made for a squirrel cage induction machine. Its rated parameters were: the power was 2.2 kW, the speed was 1410 rpm, the supply voltage was 400 V (stator windings connected in a star configuration), and the frequency of supply system was 50 Hz. The machine had 24 stator slots, and 22 rotor slots. The number of coils per phase winding was 4, the number of turns per winding was 220. The rotor cage was made of aluminum. The nonlinear B-H curve of the stator and rotor core was taken into account. The skewing of the rotor was included into the field-circuit model. It was assumed that the supply voltage was sinusoidal, symmetrically and mutually displaced by the angle of \( 2/3\pi \). On the basis of the technical documentation of the tested machine, the FEM model of a machine was developed.

Simulations were performed for two cases: the first at no-load test \((T_L = 0 \, \text{Nm})\) and the second at rated load \((T_L = 15 \, \text{Nm})\). In the first step, the torque waveforms for a healthy motor was calculated. In the second step, the torque waveforms for a faulty motor were calculated. The
Calculations were performed for a set of selected numbers of shorted turns from \( N_f = 0 \) turns to \( N_f = 55 \) turns. The obtained waveforms as results of calculations in case of \( T_L = 0 \) Nm and \( T_L = 15 \) Nm are presented in Figure 2a and Figure 2b, respectively. The amplitudes of the torque waveforms are presented in Table 1. The calculations were carried out in Maxwell computing software.

### Table 1: Amplitudes of the torque during start-up.

<table>
<thead>
<tr>
<th>( N_f )</th>
<th>( T_L = 0 ) Nm</th>
<th>( T_L = 15 ) Nm</th>
</tr>
</thead>
<tbody>
<tr>
<td>55</td>
<td>90.589</td>
<td>99.471</td>
</tr>
<tr>
<td>50</td>
<td>90.365</td>
<td>99.702</td>
</tr>
<tr>
<td>40</td>
<td>89.148</td>
<td>99.567</td>
</tr>
<tr>
<td>30</td>
<td>87.410</td>
<td>98.583</td>
</tr>
<tr>
<td>20</td>
<td>91.727</td>
<td>96.986</td>
</tr>
<tr>
<td>10</td>
<td>92.689</td>
<td>95.689</td>
</tr>
<tr>
<td>3</td>
<td>91.938</td>
<td>97.009</td>
</tr>
<tr>
<td>2</td>
<td>92.076</td>
<td>97.286</td>
</tr>
<tr>
<td>1</td>
<td>92.220</td>
<td>97.599</td>
</tr>
<tr>
<td>0</td>
<td>92.305</td>
<td>97.974</td>
</tr>
</tbody>
</table>

The obtained waveforms of torque have been analysed using wavelet transform. In this analysis, the Discrete Wavelet Transform using the wavelet Daubechies “db3” was used [18]. The analysis relies upon a decomposition process which split the signal (torque waveform) into approximation and detail. The calculations were performed up to the 5th level of the decomposition tree (Figure 3). The results of decomposition, i.e. approximation “A” and detail “D”, for number of shorted turns equal to 55 at no-load and nominal load, are presented in Figure 4 and Figure 5, respectively.

#### 3.2 Wavelet analysis torque waveforms

The numerical technique in signal analysis, classification problems and deduction is a difficult task. The artificial neural network could be very helpful and stand in for this task.

In this paper a generalized regression neural network (GRNN) was developed. The GRNN consist of two-layers and two types of activation function (Figure 6a). A radial basis function was used as an activation function for neurons in the first layer of network. Neurons in the second layer were activated using a linear function. The radial basis function of neurons of the first layer is defined as:

\[
\phi(x, c_i) = e^{-\|x - c_i\|^2 / 2\sigma^2}
\]

where \( c_i \) is the center, and \( \sigma_i \) is the spread.

An issue related to the classification of faults in a machine as the number of shorted turns through the neural network was based on a sum of radial basis functions...
which can be described by following formula:

\[
f(x) = \sum_{i=1}^{n} w_i \phi(||x - c_i||)
\]

where \(\phi\) is the activation function and \(w_i\) is the weight.

Expected value of a number of shorted turns as well as the answer of GRNN and MLP in cases of \(T_L = 0\) Nm and \(T_L = 15\) Nm are shown in Figure 7. The multilayer perceptron network (MLP) was chosen as the reference for performance of GRNN. The structure of MLP was as follows: ten neurons with a sigmoid activation function in the first layer and one neuron with a linear activation function in the second layer of network (Figure 6b). The elaborated MLP network was trained using Levenberg-Marquardt algorithm.

The process of training an artificial neural network consists in modifying network parameters such as weights and biases. The learning process ends when the objective function reaches its minimum value. The objective function can be describe by following formula:

\[
E = \sum_{i=1}^{p} \left[ \sum_{j=1}^{n} w_j \phi(||x - c_i||) - d_i \right]^2
\]

where \(d_i\) is the target value.

The performance of ANN (GRNN, MLP) was determined by the answer error. The error was calculated as a relative difference between the answer of the ANN and the expected value in the following form:

\[
\varepsilon = \frac{N_f - N_{ANN}}{N_f} \times 100\%
\]

where \(N_f\) is expected value, \(N_{ANN}\) is answer of ANN (GRNN, MLP).

This error indicates how well the ANN has been trained. The goal of training process it to get the lowest
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(a) Structure of ANN: a) generalized regression (GRNN) b) multi-layer perceptron (MLP)

(b) Figure 6: Structure of ANN: a) generalized regression (GRNN) b) multi-layer perceptron (MLP)

Figure 8: Error of answer of ANN (GRNN, MLP), at $T_L = 0$ Nm and $T_L = 15$ Nm

Figure 7: The expected value, the answer of GRNN and the answer of MLP: a) $T_L = 0$ Nm, b) $T_L = 15$ Nm

Figure 9: The error of GRNN for the selected number of shorted turns as a function of the spread.
value of the error. The results of training process are presented in Figure 8.

One of parameters of GRNN which can be modified is a spread $\sigma$ (1). Therefore, the results of error of GRNN answer are presented as a function of spread in case of selected number of shorted turns (Figure 9).

5 Summary

In the paper, the analysis of the torque of the squirrel cage induction motor with use of DFT and ANN was shown. Torque waveforms were obtained from finite element analysis for two cases: first one when induction motor was loaded by rated torque equal of 15 Nm and second for a load equal 0 Nm. The wavelet decomposition of torque waveforms was made up to 5th level of decomposition tree. Results presented in Figure 7. i.e. answer of ANN in relation to expected value, show advantage GRNN over MLP. It should be noted that in the case in which motor is loaded by rated torque, the error of MLP is lower than in the case of an unloaded motor. Furthermore, one can observe that the biggest error of answer is in case of few shorted turns at rated torque. Regardless of the load of the motor, MLP generates larger errors than GRNN which is shown on Figure 8. Moreover, it should be noticed that for GRNN influence of spread on mean square error (mse) is significant only for small number of shorted turns. Increasing the number of shorted turns reduces the effect of the spread parameter on the mse.

References