Using artificial neural network for the diagnosis of an asynchronous motor rotor eccentricity

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Abstract. Traditionally, the most numerous class of alternating current electric machines in power generation and industrial production are asynchronous motors (AM). As the practice of AM operation shows, about half of them operate for a long time with static rotor eccentricity. Such an operation does not usually cause immediate AM breakdown, but it is accompanied by considerable deterioration of its performance. A method is proposed for diagnosing asynchronous motor rotor eccentricity using artificial neural network. Experimental data show that the method proposed can identify presence of AM rotor eccentricity with acceptable level of accuracy.

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Introduction

For diagnostics of rotor eccentricity, one of additional harmonics of AM stator current, internal or external magnetic field is often used as diagnostic characteristic [1-10]. This additional harmonic is detected, e.g., by means of numerical decomposition into a Fourier series [6-10]. However, as it is shown by numerous experiments on AM's of different types, values of additional harmonics with fixed value of the eccentricity is not constant in time, and eccentricity increase is not always accompanied by growth thereof. All this is caused by fluctuation of grid frequency, AM vibrations and uneven modulus of resistance of its load as well as inaccuracy of choice of transformation period in course of defining values of these additional harmonics using the Fourier transformation.

Particularly this defines absence of a simple and reliable method for obtaining and processing information on order to detect presence of AM rotor eccentricity with indirectly changing parameters of diagnostics characteristics.

Main part

In order to solve these problems, the following is proposed:

1) To diagnose AM in two stages, i.e. in adjustment and diagnostic modes. In adjustment mode, spectrogram is obtained and stored in form of instrument converter's EMF $e_{ic}(t)$ proportional to phase current of an AM in good order, and diagnostic symptoms of rotor eccentricity are formed. The spectrogram obtained is later used for reference. In the diagnostic mode, this AM's spectrogram is obtained and diagnostic symptoms obtained from it are compared to the reference value. By results of comparison, presence and value of rotor eccentricity is defined, and a decision is made about further operation of the AM.

2) To receive the $e_{ic}(t)$ signal in the idle mode for a long period. This will reduce the effect of AM vibrations, unevenness of moment of resistance of its load, grid frequency oscillations, and errors in defining the transformation period T_{calc} on accuracy of spectrograms in Fourier transformation of $e_{ic}(t)$.

3) To use, in order to form diagnostic features of rotor eccentricity, not only all additional harmonic EMF E_ν with frequency $f_\nu = f_1 / p[p\nu \pm 1)]$ [3], but also adjacent EMF $E_{\nu\pm1}$ in the spectrogram with frequencies $f_\nu + \Delta f_\nu$, whereas f_1 is main frequency; p is the number of pole pairs; ν= 1, 2 ... is the number of grid harmonic; Δf_ν is frequency transformation step. This will make it possible to determine diagnostic features of rotor eccentricity in form of $E_{av,m} = (E_{\nu-1} + E_\nu + E_{\nu+1})/3$, where m can take values from one to infinity. It also reduces the effect on parameters of the diagnostic feature of grid frequency oscillations and inaccurate definition of T_{calc}.

In practice, m should be limited due to the fact that growth of ν is accompanied by a sharp decrease in the value $E_{av,m}$, which at m>5-10 becomes comparable with measurement error.

4) To use, for the purpose of diagnosing rotor displacement, several diagnostic features $E_{av,m}$, and apply artificial neural network (ANN) for recognition of AM rotor eccentricity image.

Dependence of additional harmonics of phase current with frequencies f_ν on the value of rotor eccentricity

$\varepsilon = d/\delta_n$ can be estimated by figure 1 and table data, where δ_n and d are AM nominal air gap and offset of one of the rotor bearings; Δf_v = 0.2 Hz. It is evident that growth of rotor eccentricity does not always lead to increasing the value of additional harmonics with frequencies f_v.

It should be also mentioned that data E_v in Figure 1 and Table 1 are given in units of the oscilloscope based on a personal computer with "Elena 2012" software. In this case, the AM phase current of 4.2 A corresponds to 7600 units of EMF by the scale of this oscilloscope.

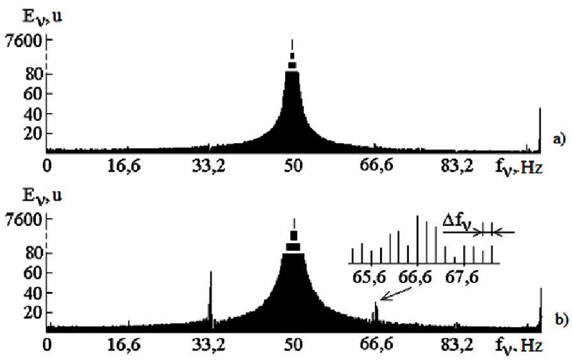

Figure 1. Spectrograms of AM phase current AO-41-6 in idle mode without (a) and with (b) rotor eccentricity

Table 1. Dependence of $E_{av,m}$ on eccentricity value

ε, p.u.	Diagnostic features $E_{av,m} = (E_{\nu-1} + E_{\nu} + E_{\nu+1})/3$		
	$E_{av,1}$ (16.6 Hz), units	$E_{av,2}$ (33.3 Hz), units	$E_{av,3}$ (66.6 Hz), units
0	$\frac{4,2+4,1+4,0}{3} = 4,1$	$\frac{10,0+3,0+5,5}{3} = 6,17$	$\frac{4,0+9,8+8,1}{3} = 7,3$
0.25	$\frac{5,1+5,5+4,5}{3} = 5,03$	$\frac{2,4+22,5+12,4}{3} - 12,4$	$\frac{9,8+16+9,5}{3} - 11,77$
0.5	$\frac{4,3+3,9+4,7}{3} - 4,3$	$\frac{12,4+33+14,6}{3} - 20$	$\frac{13,6+34+9,8}{3} - 19,13$
0.75	$\frac{6,6+7,1+7,0}{3} = 6,9$	$\frac{28+44+11}{3} = 27,67$	$\frac{7+31+9}{3} = 15,67$
1.00	$\frac{5,8+7,4+6,0}{3} = 6,4$	$\frac{46+63+17}{3} = 42$	$\frac{12+30,4+26,4}{3} = 22,9$

For rotor eccentricity image recognition with implicitly changing features, most suitable is Rumelhart's Multilayer Perceptron model [12, 13].

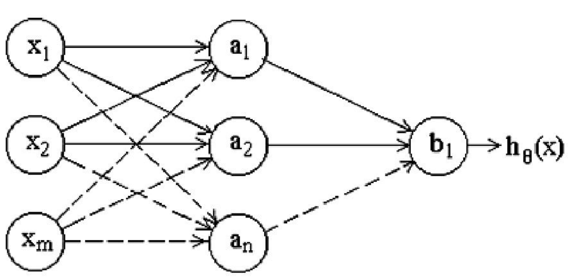

Figure 2. Sample structure of an ANN with one output

Multilayer Perceptron model is shown in Figure 2. It consists of an input layer formed by neurons $x_1 \div x_m$, a hidden layer with neurons $a_1 \div a_n$, and output layer with a single neuron b_1. The number of input neurons is determined by the number of diagnostic features, i.e., the value m. Neurons in the input and hidden layers are interconnected by unidirectional links with coefficients $\theta_{nm}^{(1)}$, where n are the numbers of neurons in the hidden layer. Neurons of the hidden and output layers are interconnected with similar links with coefficients $\theta_{1n}^{(2)}$.

Diagnosing AM rotor eccentricity using ANN is made using the following provisions:

1. Presence of AM rotor eccentricity is determined by value

$$\Delta b = b_{1d} - b_{1a}, \qquad (1)$$

whereas b_{1a} and b_{1d} are values of output layer neuron in the modes of adjustment and diagnostics.

2. First layer $\theta_{nm}^{(1)}$ coupling coefficients are equal, and their value is chosen based on the maximum change b_1 at a fixed $x_1 \div x_m$ change.

3. Second layer coupling coefficients $\theta_{1n}^{(2)}$ are defined in a similar way.

4. To ensure the same sensitivity to neurons $x_1 \div x_m$ changes in adjustment mode, their values are considered equal to unity. The difference between neuron value in adjustment and diagnostic modes is accounted for by reduction ratio k_m, which is defined as:

$$k_m = 1 / E_{av,m} \qquad (2)$$

As a result, in the diagnostic mode, values of input neurons are

$$x_m = k_m \; E_{av,m} \qquad (3)$$

In adjustment and diagnostic modes, values of the hidden layer neurons are determined from mathematical expressions

$a_1 = g(z_1^{(1)})$, and , $a_2 = g(z_2^{(1)})$

$$a_n = g(z_n^{(1)}) \quad (4)$$

and the value of the output neuron is defined as

$$b_1 = h_\theta(x) = g(z_1^{(2)}), \quad (5)$$

whereas g(z) is activation function.

According to [13], in similar problems, sigmoid transformation is used. However, in view of (3), an activation function is preferred for a specific task in the following form:

$$g(z) = k_z z, \quad (6)$$

whereas $k_z = g / z = 0{,}1$.

In expressions (4), activation function arguments are defined as

$$z_1^{(1)} = \theta_{11}^{(1)} x_1 + \theta_{12}^{(1)} x_2 + \cdots + \theta_{1m}^{(1)} x_m;$$
$$z_2^{(1)} = \theta_{21}^{(1)} x_1 + \theta_{22}^{(1)} x_2 + \cdots + \theta_{2m}^{(1)} x_m; \quad (7)$$
$$\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots$$
$$z_n^{(1)} = \theta_{n1}^{(1)} x_1 + \theta_{n2}^{(1)} x_2 + \cdots + \theta_{nm}^{(1)} x_m,$$

and for expression (5)

$$z_1^{(2)} = \theta_{11}^{(2)} a_1 + \theta_{12}^{(2)} a_2 + \cdots + \theta_{1n}^{(2)} a_n \quad (8)$$

In diagnostic system adjustment mode, values k_m, $\theta_{nm}^{(1)}$, $\theta_{1n}^{(2)}$ and b_{1a} are saved. The AM is diagnosed after a certain period or in case of emergency. In case of diagnosing using obtained EMF $E_{av,m}$ values and previously saved parameters k_m, $\theta_{nm}^{(1)}$, $\theta_{1n}^{(2)}$, b_{1a} value b_{1d} is defined, as well as $\Delta b = b_{1d} - b_{1a}$ by the magnitude of which AM rotor eccentricity is evaluated.

Experimental verification of ANN usage peculiarities in order to identify the eccentricity with implicit diagnostic features was performed on type AO-41-6 AM in idle mode. Data from the table were used as diagnostic features.

Detection and definition of value of experimental AM rotor eccentricity was made with an ANN with three input, three hidden and one output neurons. Coupling coefficients $\theta_{nm}^{(1)}$ and $\theta_{1n}^{(2)}$ of the first and the second layers were taken equal to forty. In adjustment mode, neurons $x_1 \div x_m$ were considered equal to unity. In the diagnostic mode, they were determined by expression (3). The value of AM rotor eccentricity was found as the difference in output layer neuron value in diagnostic and adjustment modes, i.e., like Δb.

ANN dependencies Δb(ε) in case of change of one of diagnostic features $x_1 \div x_3$ in the table in the form of lines 1÷3 are shown in Figure 3. So, line 1 in it is built with $x_1(\varepsilon) = k_1 E_{av,1}$, and $x_2 = x_3 = 1$. Lines 2 and 3 were built in a similar way. Line 4 was obtained when all diagnostic features changed simultaneously.

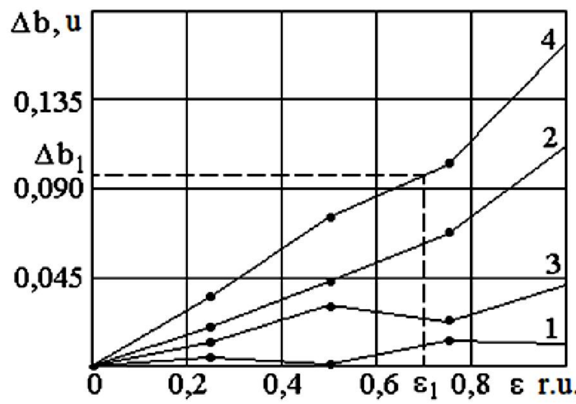

Figure 3. Dependence of signal magnitude at ANN output on AO-41-6 AM rotor eccentricity

Analysis of Δb(ε) simulation results in Figure 3 shows that rotor eccentricity can be identified by one diagnostic feature as well. To do so, for example, in AO-41-6, one should use the second diagnostic feature represented by line 2. However, it will remain unclear, which diagnostic feature should be used for which AM. At the same time, simultaneous use of all of them almost always makes it possible to reliable detect rotor eccentricity.

The value of rotor eccentricity can be determined by the value Δb obtained from diagnostics and known dependency Δb(ε) for this type of AM, as shown in Figure 3. The figure shows that difference Δb_1 corresponds to rotor eccentricity ε_1. Dependencies Δb(ε) for various types of asynchronous motors are obtained by calculation or by experiment.

Besides, use of Artificial Neural Network with constant coupling coefficients θ and linear activation function $g(z) = k_z z$ showed that one can detect and define magnitude of AM rotor eccentricity by an algebraic criterion as well that represents weighted sum of selected diagnostic features.

Conclusions:

1. Increase in rotor eccentricity is not always accompanied by increase in additional harmonics with frequencies $f_\nu = f_1 / p[p\nu \pm 1)]$ in phase currents or AM magnetic fields due to electromechanical properties of the machine and load, as well as due to the signal processing method.

2. Artificial neural network makes it possible to detect and identify, with sufficient accuracy, the magnitude of AM rotor eccentricity by measuring several additional EMF harmonics.

3. Use of Artificial Neural Network with constant coupling coefficients θ and linear activation function $g(z) = k_z z$ showed that one can detect and define magnitude of AM rotor eccentricity by using weighted sum of selected diagnostic features.

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