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DIAGNOSTICS OF INDUCTION MOTOR BASED ON SPECTRAL ANALYSIS OF STATOR CURRENT WITH APPLICATION OF BACKPROPAGATION NEURAL NETWORK

DIAGNOSTYKA SILNIKA INDUKCYJNEGO OPARTA NA ANALIZIE PRĄDU STOJANA Z ZASTOSOWANIEM SIECI NEURONOWEJ Z ALGORYTMEM WSTECZNEJ PROPAGACJI BŁĘDÓW

Nowadays PC computers make possible the signal characteristics by calculation. The paper presents an automatic computerized system for the diagnosis of the rotor bars of the induction motor by applying spectral analysis and backpropagation neural network. Software to recognize the current of induction motor was implemented. System of current recognition is based on a study of the frequency spectrum of stator current. The studies were conducted for two conditions of induction motor. The results of the numerical experiments are presented and discussed in the paper. The researches show that the system can be useful for protection of the engines and metallurgical equipment.
Keywords: Diagnostics, Recognition, Current, FFT, induction motor

Obecnie komputery osobiste pozwalają na wyznaczenie charakterystyk sygnałów. W artykule przedstawiono automatyczny, skomputeryzowany system diagnozowania prętów wirnika silnika indukcyjnego przy zastosowaniu analizy widmowej i sieci neuronowej opartej na algorytmie wstecznej propagacji błędów. Zaimplementowano oprogramowanie do rozpoznawania prądu silnika indukcyjnego. System rozpoznawania prądu oparty jest na badaniu widma częstotliwości prądu stojana. Przeprowadzono badania dla dwóch stanów silnika indukcyjnego. Wyniki eksperymentów numerycznych są przedstawione i omówione w artykule. Badania pokazują, że system może być opłacalny do zabezpieczania maszyn i sprzętu hutniczego.

1. Introduction

Condition monitoring and diagnostic systems are developed in order to improve human diagnostic knowledge. A human is good at diagnosing whether things are going well or wrong. Hence the idea to study imminent failure conditions of electrical machine. There has been a lot of research reported over the past years devoted to the development of various monitoring techniques. Most of them use Fourier transformation of the stator current in a steady state. Some apply more sophisticated method of wavelet analysis of stator current in transient state. There are also solutions relying on the analysis of the magnetic field, thermovision and image recognition. All these methods of preprocessing are combined with different tools of analysis, forming the classification stage. Among them, we can mention statistical approach, artificial neural networks, fuzzy logic and genetic algorithms. These algorithms are responsible for data classification [1].

Steel is made by dissolving carbon into iron. Pure iron melts at an extremely high temperature, 1538°C and at such temperatures carbon readily dissolves into the molten iron. Steel elements are very important for industry. Electrical machines contains steel elements. Diagnostic methods of electrical machines are investigated in the literature [2-12]. In this paper research focuses on current signals of selected induction motor. The results of these studies can be used to improve the diagnostics of electrical motors.

2. Process of current recognition of induction motor

The process of current recognition of induction motor contains pattern creation process and identification process (Fig. 1).

At the beginning of pattern creation process an electrical signal is sent to the data acquisition card, then to the computer for recording. After that system divides data. Next signals are sampled, normalized and filtrated. Afterwards data are converted through the Hamming window. Next data are converted through the FFT algorithm. FFT algorithm creates feature vectors. Feature vectors are used in training of neural network. Afterwards identification process is executed. The signal is sampled, normalized and filtrated. After that Hamming window and FFT algorithm are used. Last step is classification. Neural network identifies the current signal.

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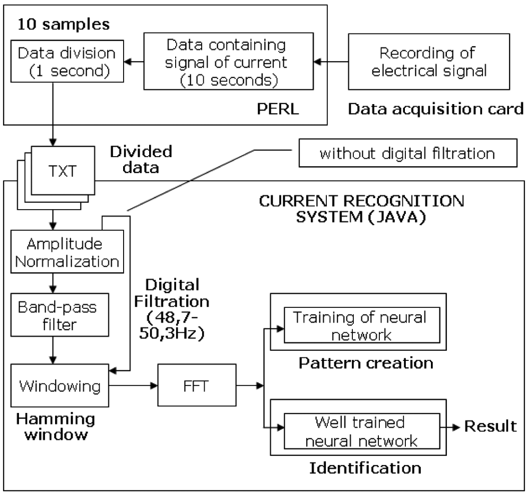

Fig. 1. Process of recognition of current

Current recognition system uses the measuring set-up and algorithms of data processing. The measuring set-up consisted of antialiasing filter, data acquisition card, and personal computer. The data were recorded with the following parameters: sampling frequency was 819 Hz, number of bits was 16, number of channels was 1 (Fig. 2, 3).

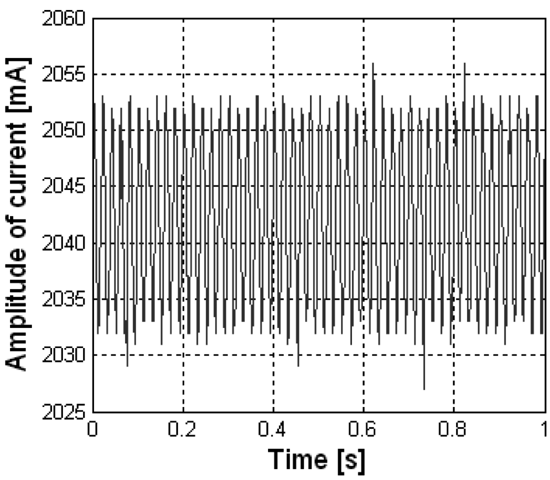

Fig. 2. Signal of current of stator of faultless induction motor (1.0 s.)

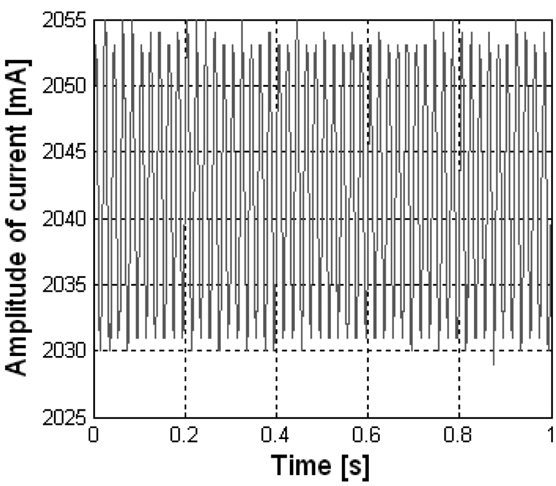

Fig. 3. Signal of current of stator of induction motor with one faulty rotor bar (1.0 s.)

2.1. Fast Fourier Transform

Discrete Fourier Transform converts signals from a time domain to a frequency domain. Given N samples $x_0, x_1, x_2, \ldots, x_{N-1}$, the Fourier transform of them are the N complex numbers $y_0, y_1, y_2, \ldots, y_{N-1}$ given by

$$y_j = \sum_{k=0}^{N-1} x_k e^{-i2\pi kj/N}, \text{ for } j = 0, 1, \ldots, N-1, (1) \qquad (1)$$

where k – number of sample, N – number of all samples.

This complex numbers represent the magnitude and phase of the various frequencies present in the x_k. Given N input points, the Fast Fourier Transform (FFT) computes Discrete Fourier Transform in O(Nlog$N$) steps [13]. FFT is applied instead of discrete Fourier Transform because of shorter time of calculations. It takes a window of size 2^k and returns a complex array of coefficients (harmonics). These coefficients create feature vectors which are used in calculations (Fig. 4).

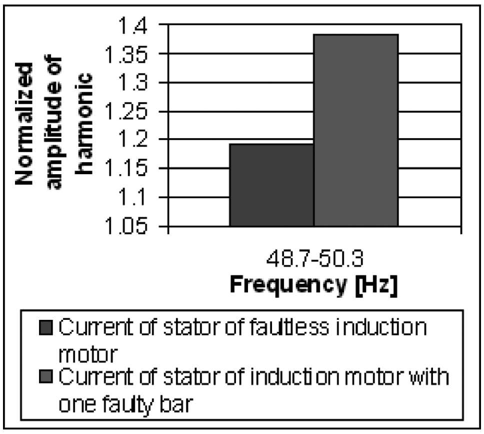

Fig. 4. Frequency spectrum of current of stator of induction motor in range of 48.7-50.3 Hz

2.2. Neural network with backpropagation algorithm

A lot of classification algorithms have been designed and implemented [14-24]. In this section the neural network with backpropagation is discussed. Neural network consists of many neurons connected by synapses. This algorithm is based on two phases. In the forward phase, the output of each neuron in each layer and the errors between the actual outputs from the output layer and the target outputs are computed, in the backward phase, weights are modified by the back-propagation errors that occurred in each layer of the network. After that the neural network identifies feature vectors. Structure of back-propagation neural network is shown in Fig. 5.

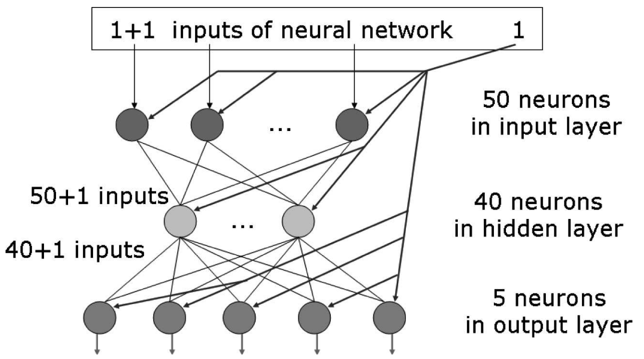

Fig. 5. Structure of backpropagation neural network in current recognition system

3. Results of current recognition

Measurements were made by data acquisition card and computer software. Researches were conducted for two induction motors with power 500W. Categories of current were specified as follows:

– current of stator of faultless induction motor,

– current of stator of induction motor with one faulty rotor bar (Fig. 6).

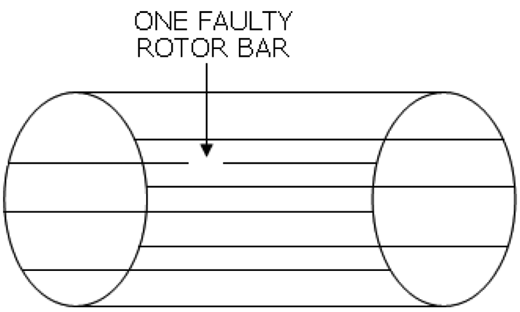

Fig. 6. Squirrel cage of induction motor with one faulty rotor bar

Moreover, the number of channels was 1, one sample contained 16384 values, the period of sampling was 1221μs, power supply was 220V, $n_N = 1400$ rpm. Diagram of diagnostics of induction motor with application of spectral analysis of stator current is shown in Fig. 7.

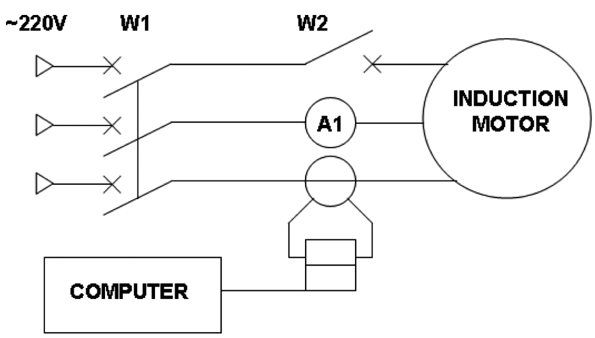

Fig. 7. Diagnostics of induction motor with application of spectral analysis of stator current

Training set contained two one-second samples. Pattern creation process used training set. Identification set had 38 one-second samples, 16 two-second samples, 10 three-second samples. This set was used by identification process.

Efficiency of current recognition was expressed by formula:

$$S = \frac{N_1}{N} \cdot 100\% \tag{2}$$

where: S – efficiency of current recognition, N_1 – number of correctly identified samples, N – number of all samples.

The best recognition results were obtained using the normalization of the amplitude and the filter that passed frequencies from 48.7 Hz to 50.3 Hz. Efficiency of current recognition of faultless induction motor was 100%. Efficiency of current recognition of induction motor with one faulty rotor bar was 100% (Fig. 8).

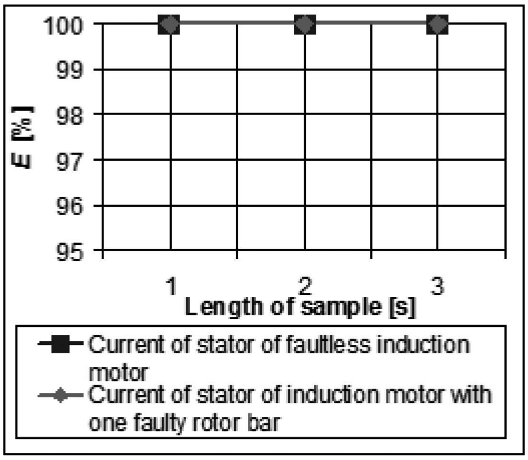

Fig. 8. Efficiency of current recognition of induction motor depending on length of sample

4. Conclusions

Condition monitoring of induction motor is a difficult task for the engineers. Current monitoring techniques are usually applied to detect the various types of induction motors faults such as rotor fault, short winding fault, air gap eccentricity fault, bearing fault, load fault. In this paper diagnostics of rotor faults was considered. In this aim current recognition system was designed and implemented for induction motor. Results of current recognition were good for FFT and backpropagation neural network. The proposed methods in these researches allow tracking of various types of faults in induction motors. The best result was obtained for filter that passed frequencies from 48.7 Hz to 50.3 Hz. Efficiency of current recognition of induction motor was 100%. Time of performance of identification process of one-second sample was 0.25 s for Intel Pentium M 730 processor. Time of performance of identification process of three-second sample was 0.28 s.

In metallurgy squirrel-cage induction electric motors are commonly used to power the mechanical devices. Current recognition system can be useful for detecting failures of the engines. In the future, the current recognition system of induction motor can be applied with other effective data processing algorithms.

Acknowledgements

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