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Wavelet-neural detection of induction motor drive's faults

***Abstract**. This paper presents a method of fault identification of induction motor drive by means of the application of wavelet analysis of a tested signal and a model of neural network with supervised learning, and also a model of neural network processed in the next epochs by means of algorithm making essential changes of parameters of this network. The tests which were executed on three important state variables, describing physical quantities of the chosen induction motor drive model indicated the usefulness of the method used for diagnostic purposes, allowing the identification of the fault type occurring in the induction motor drive in the initial phase of formation.*

Streszczenie.** W artykule przedstawiono metodę identyfikacji uszkodzeń napędu z silnikiem indukcyjnym przy zastosowaniu analizy falkowej badanych sygnałów i modelu sieci neuronowej. Ukazany został model sieci neuronowej przetwarzanej w kolejnych stadiach za pomocą algorytmu dokonującego istotnych zmian parametrów tej sieci. Badania przeprowadzone na trzech istotnych zmiennych stanu opisujących wielkości fizyczne wybranego modelu napędu z silnikiem indukcyjnym potwierdziły przydatność zastosowanej metody do celów diagnostycznych umożliwiając identyfikację rodzaju uszkodzenia występującego w napędzie z silnikiem indukcyjnym w jego początkowej fazie powstawania. **Metoda identyfikacji uszkodzeń napędu z silnikiem indukcyjnym przy zastosowaniu analizy falkowej

Keywords: induction motor drive, wavelet transformation, network learning rule, epochs.
Słowa kluczowe: silnik indukcyjny, transformata falkowa, sieci neuronowe.

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Introduction

Diagnostics of electromechanical processes is involved in the recognition of undesirable changes their states, which will be presented in the form of a series of intentional action executed in a fixed time by the determined set of machines and devices with specified available resources. Faults and other destructive events can be caused by changes of these states. The diagnostic system should as soon as possible detect and identify occurring faults already in their initial formation phase. The destructive events resulting from an increasing time of exploitation and use are recognized as some kind of faults, which must be detected and identified after exceeding some value [3].

Currently, methods of modeling of the faults and their identification, designed on the basis of artificial intelligence techniques, are being applied intensively in diagnostics of industrial processes.

The signals of electromechanical systems contain some information which is the basis of diagnostic analysis. Therefore, attention should be focused on extraction and use of the information contained in those signals. As a result of an analysis of these signals in different fields, e.g. simultaneously in the field of the time and the frequency, simpler interpretation of the meanings of the different features of these signals is possible. Thus, there is also a simpler interpretation of attributes assigned to different undesirable states of system.

Classification of signals simultaneously in the field of time and frequency is possible by using of transformation methods allowing research of his spectral properties. Tested signal is presented as a linear combination of some basic orthogonal signals. This method minimizes the signal model. In order to minimize the set of relevant decomposition's coefficients shapes of the basis function must be adapted to the analysed signal [3].

The wavelet analysis is one of the popular and more often used methods of spectral analysis. This analysis contrary to the Fourier analysis does not express analysed functions by polynomials built on harmonic functions but by special functions - waves, which are made with the function of the so-called mother wave designed for this purpose. Created wavelet functions are put to multiple translations. The obtained in this way set of basis functions of the transformation has many important, scalable properties, which can be related to the time as well as the frequency, analyzing relationships between the tested function and its transform coefficients.

As a result of localization of wavelets in time and frequency domains, the wavelet signal processing in comparison to sinusoids is suitable for those signals whose spectral content changes over time. The adaptive time-frequency resolution of wavelet signal processing allows us to perform multiresolution analysis [4].

Methodology and simulations of diagnostic algorithm of fault's identification

Simulations were executed for nominal conditions of asynchronous induction motor drive, whose model was built in the stationary system of coordinates referring to stator (model α, β, 0). The induction motor drive was burdened by the working machine, with the character of the dynamic mass-absorbing-resilient element. Figure 1 shows the connection of the working machine with the induction motor drive.

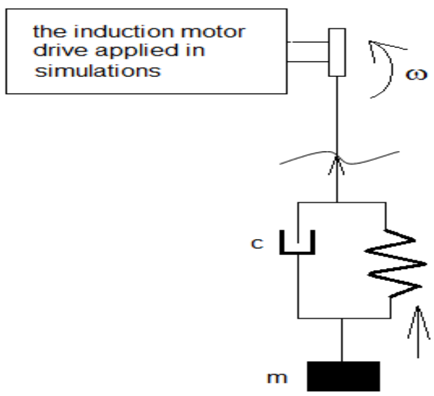


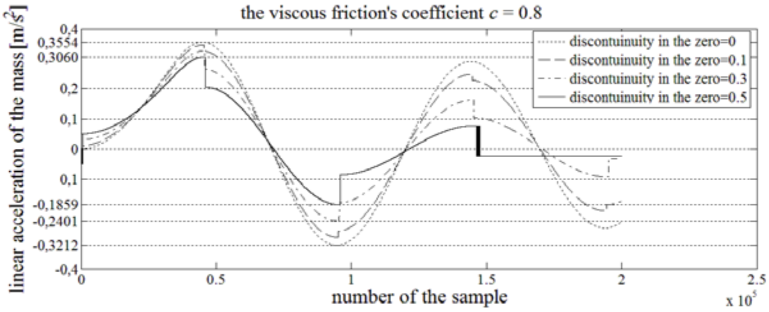
Fig.1. Diagram of the dynamic mass-absorbing-resilient element which was connected to the induction motor drive applied in simulations.

The simulation model of induction motor drive was realised in the environment MATLAB/Simulink. The following parameters of induction motor drive were fixed in simulations (applied induction motor drive is the substitute diagram and the following parameters are expressed in the relative units): r_s = 0.059, r_w = 0.048, x_s = 1.92, x_w = 1.92, x_m = 1.82. $w = x_s * x_w - x_m * x_m$ = 0,374, T_m = 0,86 [s].

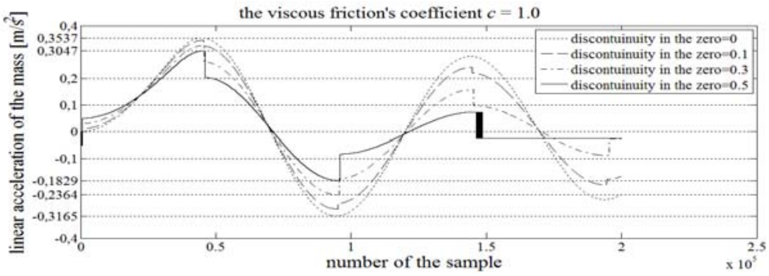
Simulations were executed on two neural networks for wavelet decomposition's coefficients of three state variables describing physical quantities: stator's current *is*, angle speed ω and linear acceleration *A*. The results of simulations for every physical quantity were written in matrix *M* [3].

For all tests (in four groups of simulations) there were fixed the same values: (the coefficient of springiness) k=100[N/m], radius r = 0.15 [m], m = 10 [kg]. In the next groups of simulations value of the viscous friction's coefficient *c* was fixed: c = 0.8 [Ns/m], c=1.0[Ns/m], c = 1.25 [Ns/m] and c = 1.5 [Ns/m].

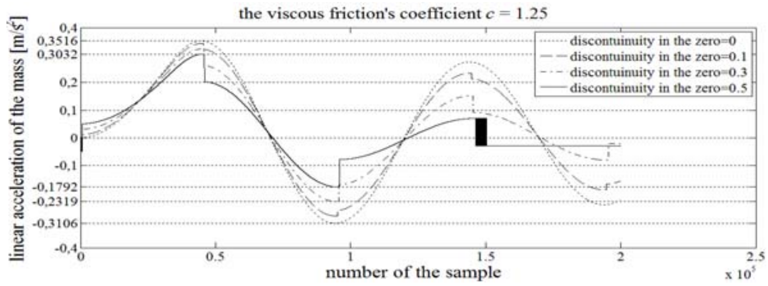
a)



b)



c)



c)

During the execution of tests in each of these groups of simulations the coefficient of discontinuity in the zero was changed (the Coulomb's friction): 0.0, 0.1, 0.2, 0.3, 0.4 and 0.5. The noticeable influence of increasing the viscous friction's coefficient *c* on the decrease of discontinuity's zone in the zero as well as on the decrease of the linear acceleration of the mass value is visible on Fig. 2.

Characteristics (presented in figure 1) of the linear acceleration of the mass show that the smallest values of this acceleration as well as the smallest values of discontinuity's zone in the zero were obtained for viscous friction's coefficient value c =1.25.

Characteristics presented on Fig. 2 related to fault of stator's resistance=15%. The time of every test's duration in executed and the time of the sampling was fixed equal $2*10^{-5}$ [s]. Stator's resistance r_s for healthy induction motor drive was equal: r_s =0.059.

Fig.2. Waveforms of characteristics of linear acceleration of the dynamic mass-absorbing-resilient element's mass: viscous friction's coefficient c=0.8 (a); viscous friction's coefficient c=1.0 (b); and viscous friction's coefficient c= 1.25 (c).

Results of simulation of fault's identification

On the basis of exemplary results with complex done simulations of state variables, it is possible to notice that the obtained results of correct minimal value in the matrix Mse_2 are bigger in comparison to the results obtained in matrix Mae_1 and Mse_1 for the correct fault's identification [3].

Besides this it is necessary to state on the basis bad exemplary results that minimal values of matrix Mse_1 repeats in results for the same simulation. In such cases identification of fault's number is possible only by means of minimal value of matrix Mse_2.

In executed simulations the fixed value of the second neural network's learning coefficient l_k = 0.3 caused bad identification of occurring fault's number.

Most of the good results of identification of fault's number were obtained for the following parameters:
- value of the stopping condition of the first neural network's learning δ = 0.5;
- value of the first neural net learning coefficient l = 0.9;
- increasing of number epochs of the second neural network's processing from 3 to 12;
- increasing of the second neural net learning coefficient l_k from 0.3 to 0.95.

It is necessary to state on the basis the exemplary good results of minimal values of matrices Mse_1 and Mse_2 that the next increase of the number of epochs in the second neural network from value 6 as well as the next increase of the learning coefficient l_k from value 0.6 does not cause the change of the final result of identification of fault's number for wavelet decomposition's tested coefficients of the chosen state variables describing physical quantities in the experiment. From the results it has been possible to notice that small value of learning coefficient l_k and big value δ does not assure the correct fault's identification even with an increase of the number of epochs in the second neural network.

As a result of the decreasing value δ and the increase of the number of epochs in the second neural network, it has been possible to notice the more profitable effect of improvement of the identification of fault's number. The process of identification of fault begins in a moment when the expression determined in the left part of following inequality is bigger than insensibility's zone determined in the right part of this inequality:

$$(1)\quad \sum_{j=1}^{750} \varepsilon_1 \left| M_{1(j)} - M_{(1,j)} \right| > \sum_{j=1}^{750} \varepsilon_2 \left| M_{2(j)} - M_{(1,j)} \right| ,$$

where:

$M_{1(j)}$ - matrix registered for the unknown fault of stator's resistance from wavelet decomposition's tested coefficients of state variables describing three physical quantities in experiment: stator's current i_s, angle speed ω and linear acceleration *A;*

$M_{(1,j)}$ - matrix registered from wavelet decomposition's tested coefficients of state variables describing three physical quantities in experiment: stator's current i_s, angle speed ω and linear acceleration *A* (1- the number of the index in matrix *M* and concerns healthy induction motor drive);

$M_{(j)}$ - matrix registered for stator's resistance r_s of healthy induction motor decreased about 0,25% her nominal value into the bottom from wavelet decomposition's coefficients of three state variables describing physical quantities in the experiment: stator's current *is*, angle speed ω and linear acceleration A.

ε_1 - coefficient fixed in simulations, in the case coefficients of stator's current i_s and linear acceleration *A* is fixed ε_1 = 1, however in case angle speed's coefficients ω *is* fixed ε_1 = 100;

j - number of the index of chosen sample with matrix *M*. Otherwise the process of identification of the fault will be finished.

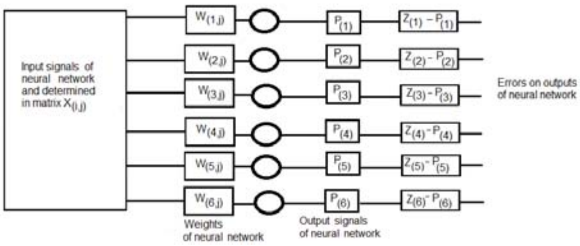


Fig.3. Diagram of the applied neural network with supervised learning according to the Delta rule. The presented circles represent neurons in neural network

The idea of diagnostic algorithm consists of indication of the occurrence of fault's number. This number is determined by means of the calculated smallest values of matrices: Mse_1 and Mse_2. Values of matrices Mse_1 and Mse_2 were calculated by means of parameters obtained as a result of training of neural network with supervising learning, and also a model of neural network processed in next epochs by means of algorithm making essential changes of parameters of this network.

This neural network has one layer of neurons. The diagram of this neural network is presented on Figure 3.

It was fixed that input signals of neural network *X* were calculated according to the formula:

$$(2) \qquad X_{(i,j)} = \underset{i=1,2...6}{\forall} \sum_{j=1}^{750} \varepsilon_1 \left| M_{1(j)} - M_{(1,j)} \right| ,$$

where: $M_{1(j)}$ – matrix is described by the formula (1), $M_{(1,j)}$ – matrix is described by the formula (1), ε_1 – coefficient is described by the formula (1), *I* – a number of neural network's neuron.

The aim of this training is to find values of neural network's output signals *P*, for which values of weights *W* are the best for obtainment of the appropriate smallest value of matrix Mse_2 necessary for correct identification of fault's number.

Advantage of this neural network is linear layer in which each neuron has such same the set of input signals *X* as well as such same initial values of matrix of weights *W*.

Additionally adoption of such same of set input signals *X* for each neuron causes faster finishing of this neural network's learning. The initial values of matrix's $W_{(i,j)}$ were calculated according to the formula [3]:

$$(3) \qquad W_{(i,j)} = \underset{\substack{i=1,2...6 \\ j=1,2...750}}{\forall} \left(M_{(1,j)} - mean \right)^2 ,$$

where: $M_{(1,j)}$ – matrix is described by the formula (1), *Mean* – the arithmetic mean of matrix $M_{(1,j)}$, *I* – number of neuron and is described by the formula.

The arithmetic mean of matrix $M_{(1,j)}$ was calculated according to the formula [3]:

$$(4) \qquad mean = \frac{\sum_{j=1}^{750} M_{(1,j)}}{750} .$$

In the purpose of proper assurance of learning's process, weights *W* must be selected, so that output signals *P* like the most correspond to determined target values *Z* on neural network's outputs in moment of finishing of neural network's learning.

Output signals of neural network *P* were calculated according to the formula [3]:

$$(5) \qquad P_{(i)} = \underset{i=1,2...6}{\forall} \sum_{j=1}^{750} W_{(i,j)} X_{(i,j)} ,$$

where: $X_{(i,j}$ – matrix is described by the formula (2), $W_{(i,j)}$ – matrix of neural network's weights and is described by the formula (3).

The learning pattern of this network contains two components: input data *X* and target values *Z* for these input data and is always presented in next epochs of neural network's learning.

Appropriate determination of the neural network's target signals *Z* decide about faster finishing of this neural network's learning with the obtainment of the best results for identification of fault's number.

The target values on neural network's outputs *Z* were calculated according to the formula [5]:

$$(6) \qquad Z_{(i)} = \underset{\substack{i,l=1,2...6 \\ k=1,2...7}}{\forall} \varepsilon_2 \sum_{j=1}^{750} \left| M_{(l+1,j)} - M_{(k,j)} \right| ,$$

where: $M_{(l,j)}$, $M_{(k,j)}$ – matrices registered for all possible cases of faults stator's resistance decreased about 1% to 20 % into the bottom of its nominal value for wave-let decomposition's tested coefficients of state variables describing three physical quantities in experiment: stator's current *is*, angle speed ω and linear acceleration *A*, ε_2 – coefficient fixed in simulations, in case coefficients of stator's current *is* and linear acceleration *A* is fixed ε_2 = 1, however in case angle speed's coefficients ω *is* fixed ε_2 = 10, *l* – number of neurons and is described by the formula (2), *k,l* – numbers of the index of matrix *M*.

Index *k* =1 in matrix $M_{(k,j)}$ represents case for healthy induction motor drive. Determination of neural network's target values *Z* and input signals *X* as well as correction of weights *W* is necessary for calculation of errors on neurons *E*. This calculation follows always after presentation the learning pattern in next epochs of the learning process of this neural network. Values of errors on neurons *E* were calculated according to the formula [5]:

$$E_{(i)} = \underset{i=1,2\ldots 6}{\forall}\left(Z_{(i)} - P_{(i)}\right), \quad (7)$$

where: $P_{(i)}$ – matrix is described by the formula (5), $Z_{(i)}$ – matrix is described by the formula (6).

In learning process of neural network is possible to find iteratively appropriate for purposes of fault's identification values of matrix *W*. Updating of weights of this neural network is possible after each presentation of one learning pattern and according to the adopted rule of changing their. According to this rule, after presentation of learning pattern correction of weight will follow as a result of earlier weight's correction about product of difference between target value on output *Z*, and obtained value on neuron's output *P* and also input's value *X*, from which this weight is associated. Additionally in the adopted rule values of input signals *X* are decreased as a result of multiplication of their with experimentally selected neural network's learning coefficient *l*. Correction of weights in the next epochs of neural network's learning was calculated on the basis of the well-known Delta rule according to the formula [5]:

$$W_{(i,j)} = \underset{\substack{i=1,2\ldots 6\\ j=1,2\ldots 750}}{\forall} W_{(i,j)} + l\, X_{(i,j)}\, E_{(i)}, \quad (8)$$

where: $E_{(i,j)}$ – matrix is described by the formula (7), $W_{(i,j)}$ – matrix is described by the formula (3), $X_{(i,j)}$ – matrix is described by the formula (2), *l* – learning coefficient of neural network is fixed in range from 0 to 1.

A commonly used cost is the *Root-Mean Squared* error *RMS*, which after presentation of the learning pattern in next epochs of neural network's learning tries to minimize the error *E* between the output values *P* and the target values *Z* over all the exemplary pairs *X* and *W* in the purpose of the obtainment of the smallest value of matrix Mse_2.

Advantage of this neural network is speed of obtainment of stopping condition of neural network's learning despite of necessity and difficulties resulting with adoption of values of input signals *X* and target values *Z*.

The *Root-Mean Squared* error RMS was calculated according to the formula [5]:

$$RMS = \sqrt{\frac{\sum_{i=1}^{6}(E_{(i)})^2}{6}}, \quad (9)$$

where $E_{(i,j)}$ is a matrix described by the formula (7).

It was fixed that neural network was learnt in a moment of condition's obtainment [3]:

$$RMS < \delta, \quad (10)$$

where δ is a value fixed experimentally in executed simulations for the necessity of stopping of applied neural network's.

Conclusions

Simulations presented in this work indicated that the occurrence of small step changes of stator's resistance r_s (caused by short circuit Interturns) decreased in percentage terms into the bottom of it's nominal value. At sampling frequency 50 kHz it gives in the determined conditions a noticeable effect in the form of changes of wavelet decomposition's tested coefficients of state variables describing physical quantities: linear acceleration on circuit of motive wheel of rotor *A,* stator's current i_s and also angle speed of rotor ω.

This effect is more noticeable in case of correct selection of the wave's kind and its order referring to transitory course's shape of the tested physical quantity.

The results of executed simulations indicated that for a model induction motor drive, which usually is described by nonlinear characteristics of elements, information contained in wavelet decomposition's coefficients can be used in the process of reasoning the kind and localization of fault's occurring of this model's elements.

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