UDC 004.9: 621.313.3

Informatics and Mathematical Methods in Simulation
Vol. 4 (2014), No. 2, pp. 111-119

WAVELET-NEURAL ANALYSIS FOR INDUCTION MOTOR FAULTS DETECTION

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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 confirmed 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.

Keywords: induction motor drive, wavelet transformation, network learning rule.

Introduction

Diagnostics of electromechanical processes is involved in the recognition of undesirable changes of their states, which will be presented in the form of a series of intentional actions executed in a fixed time by the determined set of machines and devices with specified and 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.

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 analysis of these signals in different fields, e.g. simultaneously in the fields of time and frequency, simpler interpretation of meanings and different features of these signals is possible. Thus, there is also a simpler interpretation of attributes assigned to different undesirable states of the system.

Classification of signals simultaneously in the field of time and frequency is possible by use 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.

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. Obtained in this way set of basic 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 transformed 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.

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.

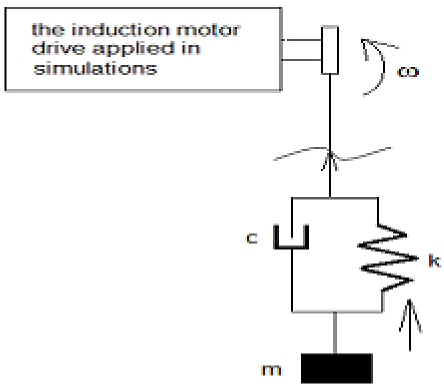
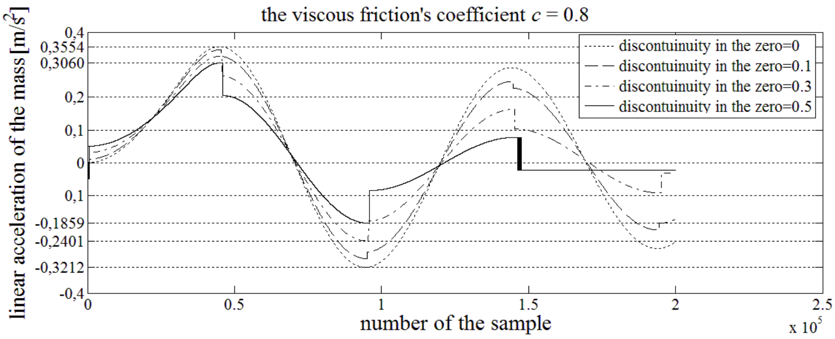


Fig. 1. Diagram of the dynamic mass-absorbing-resilient element which was connected to the induction motor drive applied in simulations.

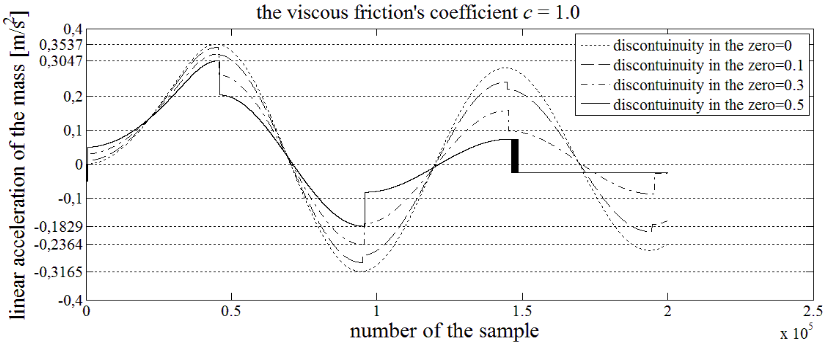
The simulation model of the induction motor drive was realised in the environment MATLAB/Simulink. The following parameters of induction motor drive were fixed in executed simulations (applied induction motor drive is the substitute diagram and the following parameters are expressed in the relative units): $r_s = 0.059$, $r_w = 0.048$, $x_s = 1.92$, $x_w = 1.92$, $x_m = 1.82$, $w = x_s x_w - x_m^2 = 0.374$, $T_m = 0.86$ [s].

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

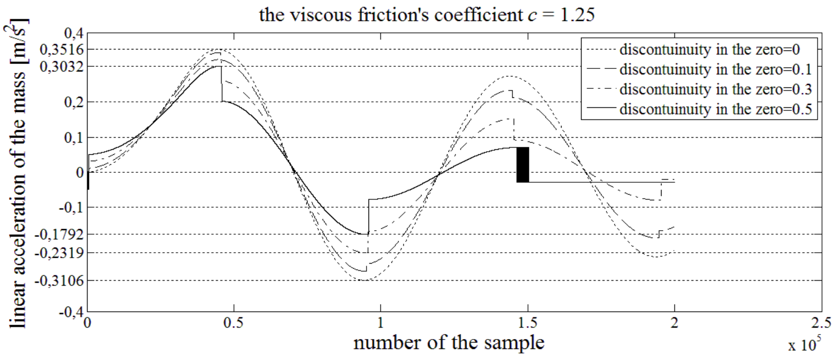
For all tests (in four groups of simulations) there were fixed the same values: (the coefficient of springiness) $k = 100$ [N/m], radius $r = 0.15$ [m], $m = 10$ [kg]. In the next groups of simulations value of the viscous friction's coefficient c was fixed: $c = 0.8$ [Ns/m], $c = 1.0$ [Ns/m], $c = 1.25$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



a



b



c

Fig. 2. Waveforms of characteristics of linear acceleration of the dynamic mass-absorbing-resilient element‘s mass: a – viscous friction’s coefficient $c = 0.8$; b – viscous friction’s coefficient $c = 1.0$; c – viscous friction’s coefficient $c = 1.25$

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. 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 $\delta = 0.5$;
- value of the first neural network's 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 network's learning coefficient l_k from 0.3 to 0.95.

It is necessary to state on the basis of 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 numbers 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 a 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 a more profitable effect of improvement of the identification of fault's number. The process of identification of the 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:

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

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 good induction motor drive);

$M_{(j)}$ – matrix registered for stator's resistance r_s of good 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 i_s, 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 $\varepsilon_1 = 1$, however in case angle speed's coefficients ω is fixed $\varepsilon_1 = 100$;

j – number of the index of chosen sample with matrix M.

Otherwise the process of identification of the fault will be finished.

The idea of diagnostic algorithm consists of indication of the occurrence of fault's number. This number is determined by means of calculating the smallest values of matrices: Mse_1 and Mse_2. The 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.

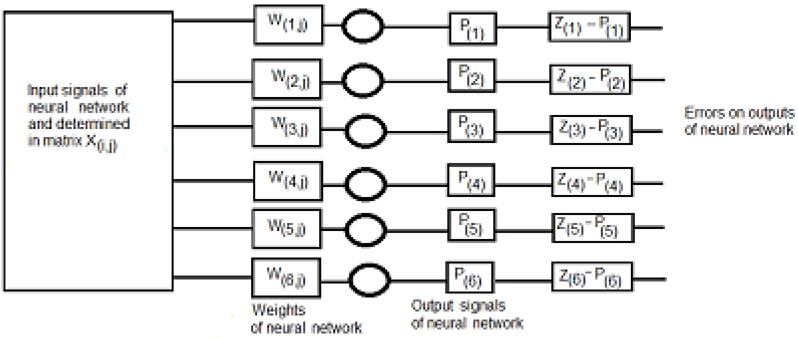


Fig. 3. Diagram of the applied neural network with supervised learning according to the rule delta. The presented circles represent neurons in neural network.

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

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

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 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 the correct identification of fault's number.

Advantage of this neural network is a 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 a set of 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:

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

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:

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

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:

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

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:

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

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 i_s, angle speed ω and linear acceleration A,

ε_2 – coefficient fixed in simulations, in the of case the coefficients stator's current i_s and linear acceleration A is fixed, $\varepsilon_2 = 1$, however in case angle speed's coefficients ω is fixed $\varepsilon_2 = 10$,

i – 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 good induction motor drive. Determination of the 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

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

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 the learning pattern correction of weight will follow as a result of earlier weight correction about the 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 rule delta according to the formula:

$$W_{(i,j)} = \mathop{\forall}_{\substack{i=1,2...6 \\ j=1,2...750}} W_{(i,j)} + l\,X_{(i,j)}\,E_{(i)}\,, \tag{8}$$

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 the neural network 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

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

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

$$RMS < \delta\,, \tag{10}$$

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 confirmed that the occurrence of small step changes of stator's resistance r_s decreased in percentage terms into the bottom her nominal value at sampling frequency 50 kHz 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 the case of correct selection of the wave kind and its order referring to transitory course's shape of the tested physical quantity.

The results of executed simulations confirmed 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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ВЕЙВЛЕТ-НЕЙРОННИЙ АНАЛІЗ ДЛЯ ВИЯВЛЕННЯ ДЕФЕКТІВ АСИНХРОННОГО ДВИГУНА

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У статті представлено метод ідентифікації дефектів приводу з асинхронним двигуном, використовуючи вейвлет-аналіз досліджуваних сигналів і модель нейронної мережі. Наведено модель нейронної мережі, перетворюваної на чергових наступних етапах на підставі алгоритму, за допомогою якого вносяться істотні зміни параметрів цієї мережі. На основі проведених досліджень для трьох важливих змінних стану, які описують фізичні величини обраної моделі асинхронного електроприводу, підтверджено придатність запропонованого методу для проведення діагностики, що дає змогу ідентифікувати характер пошкоджень в даному приводі на початковій стадії виникнення.

Симуляцію моделі асинхронного двигуна здійснено в середовищі Matlab Simulink. В подальшому виконано моделювання на основі нейронних мереж, підтримуючи вейвлет-розкладання для трьох змінних стану. За допомогою цих змінних стану описано такі фізичні величини: струм ротора, кутову швидкість, лінійне прискорення. Всі результати, отримані на базі обчислень за допомогою нейронної мережі, надалі збережено у відповідній матриці.

Для реалізації алгоритму діагностики застосовано нейронну мережу, що має один шар нейронів. Нейронні мережі навчено згідно з прийнятим алгоритмом для знаходження найменшого значення матриці. Доведено, що отримане найменше значення матриці є корисним для правильної діагностики випробуваного двигуна. Результатами проведеної симуляції підтверджено, що модельований асинхронний двигун можна здіагнозувати щодо джерел дефектів в двигуні на підставі вейвлет-розкладання та інформації, зібраної під час аналізу із застосуванням нейронних мереж.

Ключові слова: асинхронний двигун, вейвлет-перетворення, правило мережевого навчання.

ВЕЙВЛЕТ-НЕЙРОННИЙ АНАЛИЗ ДЛЯ ВЫЯВЛЕНИЯ ДЕФЕКТОВ АСИНХРОННОГО ДВИГАТЕЛЯ

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В статье представлен метод идентификации дефектов привода с асинхронным двигателем, используя вейвлет-анализ для исследуемых сигналов и модель нейронной сети. Приведена модель нейронной сети, преобразованной на очередных последующих этапах на основании алгоритма, при помощи которого вносятся существенные изменения параметров этой сети. На основе проведенных исследований для трех важных переменных состояния, которые описывают физические величины выбранной модели асинхронного электропривода, подтверждена пригодность предложенного метода для проведения диагностики, что дает возможность идентифицировать характер повреждений в данном приводе на начальной стадии возникновения.

Симуляция модели асинхронного двигателя осуществлена в среде Matlab Simulink. В дальнейшем выполнено моделирование на основе нейронных сетей, поддерживая вейвлет-разложение для трех переменных состояния. С помощью этих переменных состояния описаны такие физические величины: ток ротора, угловую скорость, линейное ускорение. Все результаты, полученные на базе вычислений с помощью нейронной сети, в дальнейшем сохранены в соответствующей матрице.

Для реализации алгоритма диагностики применена нейронная сеть, которая имеет один слой нейронов. Нейронные сети обучены согласно принятому алгоритму для нахождения наименьшего значения матрицы. Доказано, что полученное наименьшее значение матрицы является полезным для правильной диагностики испытуемого двигателя. Результатами проведенной симуляции подтверждено, что моделируемый асинхронный двигатель можно сдиагнозировать относительно источников дефектов в двигателе на основании вейвлет-разложения и информации, собранной во время анализа с применением нейронных сетей.

Ключевые слова: асинхронный двигатель, вейвлет-преобразование, правило сетевого обучения.