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**DIAGNOSIS OF THE INDUCTION MOTOR ROLLING BEARINGS USING NEURAL NETWORKS**

In the paper results of bearing fault detection for the induction motor using two neural network types are presented. Feedforward and Kohonen networks were trained using pre-processed measurements of mechanical vibrations and stator currents of the induction motor. The stator current spectra as well as vibration spectra were used for the development of neural network detectors for bearing failure classification. Preparations of training patterns as well as training procedures were described. The usefulness of these neural detectors was determined based on experimental tests.

1. **INTRODUCTION**

Recently a wide interest is observed in the development of condition monitoring and diagnosis systems for the induction motor drives. It is caused by the wide introducing of the induction motor drives to the industrial and commercial installation and thus by the requirement of more reliable drive system design.

Bearing faults are one of the most common faults in electrical machines and represent approximately 40% of all motor failures [1]. This causes that known bearing diagnosis methods are still developed and new solutions are proposed. The application of methods based on artificial intelligence, like neural networks or fuzzy logic is the most recent trend in new attempt to these problems [2]-[8]. In this paper results of bearing fault detection of the induction motor using two neural network types are presented. Feedforward and Kohonen networks were trained using pre-processed measurements of mechanical vibrations and stator currents of the induction motor and NN detectors were developed.

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2. METHODOLOGY ASPECTS FOR NEURAL DETECTORS OF MOTOR BEARINGS

2.1. GENERAL REMARKS

Bearing failures are caused by different stresses of electrical or mechanical nature. Many subjects can deteriorate bearing mechanism, like contaminated lubrication, improper application, misalignment, excessive loading, ageing of the motor, shaft-to-ground currents, etc. Bearing fault cause the specific harmonics in the vibration spectrum of the motor [1], which frequency depends on bearing geometry and kinematics.

Fundamental frequencies, at which defects of rolling bearings appear, can be obtained by simple calculations:
- for a train defect:

\[
\begin{align*}
    f_{b^1} &= \frac{1}{2} \cdot f_r \left(1 - \frac{BD}{PD} \cos \beta \right) \\
\end{align*}
\]

(1)

- for a ball defect:

\[
\begin{align*}
    f_{b^2} &= \frac{PD}{BD} \cdot f_r \left(1 - \left(\frac{BD}{PD} \cos \beta \right)^2 \right) \\
\end{align*}
\]

(2)

- for an outer bearing race defect:

\[
\begin{align*}
    f_{b^3} &= \frac{n}{2} \cdot f_r \left(1 - \frac{BD}{PD} \cos \beta \right) \\
\end{align*}
\]

(3)

- for an inner bearing race defect:

\[
\begin{align*}
    f_{b^4} &= \frac{n}{2} \cdot f_r \left(1 + \frac{BD}{PD} \cos \beta \right) \\
\end{align*}
\]

(4)

where: 
- \( n \) - the number of rolling elements,
- \( f_r \) - the rotational frequency,
- \( \beta \) - the contact angle of the ball,
- \( BD \) - the ball diameter,
- \( PD \) - the ball pitch diameter.
The specific spectral peaks depend on the type of fault, the rotational speed and the bearing geometry. Many publications have discussed the use of these frequencies to identify defects in a bearing assembly [1], [5], [6], [8]. It should be emphasised, that if the defective area is large, harmonics \( f_{bv}^k \) will be present as an indication of the severity of the defects. The vibration spectrum must be measured in a frequency range that includes all the relevant components (typically 10-20000 kHz). Since most bearing vibrations are periodical movements, it is easy to extract vibration features from the frequency domain, using FFT techniques. Thus many publications have studied the frequency features of rolling bearing vibrations [2], [7], [9].

Motor current spectrum contains also harmonics specific for different types of bearing faults [4], [5]. So these symptoms could be used for monitoring and diagnostics of bearing failure with help of neural networks trained on the base of harmonics content of these spectra.

The relationship of the bearing vibration to the stator current spectra can be determined by remembering that any air-gap eccentricity produces anomalies in the air-gap flux. Since ball bearings support the rotor, any bearing defect will produce a radial motion between the rotor and stator of the machine. The mechanical displacement resulting from damaged bearing causes the machine air-gap to vary in a manner that can be described by combination of rotating eccentricities moving in both directions. The air-gap geometry is then disturbed leading to a modulation of the stator current. Thus the stator current frequencies will be generated due to the bearing fault:

\[
f_{bc} = \left| f_s \pm mf_{bv}^k \right|,
\]

where: 
- \( f_s \) – motor supply frequency,
- \( f_{bv}^k \) – one of the characteristic vibration frequencies (1)-(4),
- \( m = 1,2,3... \)

It should be noted that the current spectrum will also contain other components, which are caused by e.g. broken rotor bars, air-gap eccentricity, winding distribution etc., and the frequency components caused by bearing damage are relatively small, compared to the other components. So the sufficient spectral resolution is necessary to use the above calculation for the bearing diagnosis purposes. These specific vibration and/or current harmonics can be used for training of neural networks and design the neural fault detector.

2.2. DESCRIPTION OF PERFORMED EXPERIMENTS

Neural fault detector should realise the task of system states detection, which is classical picture recognition problem. Each picture used for NN training contains a set
of specially chosen input data and suitable output data. Application of NN for diagnosis purposes requires the following actions:
- definition of failures list,
- determination and choice of typical pictures suitable for particular faults and normal state of the object,
- choice of NN structure and training algorithm,
- training procedure,
- NN testing for different object’s conditions.

In this work experiments were performed for rolling bearing of 1.5 kW induction motor. Special series of measurement were realised for obtaining sets of data for training and testing procedures of different neural networks. The following measured samples were acquired:
- stator current spectrum and vibration spectrum for the induction motor loaded with nominal torque,
- vibration spectrum for the unloaded induction motor.
Addingtionally the supply asymmetry of the motor was taken into account in the case of neural fault classifier.

Tested bearings were divided into two groups:
a) bearings with *a priori* known failures, assigned for training procedure of neural network: healthy bearing, train defect, outer bearing race defect, bearing with damaged rolling element;
b) bearings assigned for testing procedure of neural network: two damaged bearings with unknown failures and one healthy bearing.

The main part of the experimental benchmark was multianalyser PULSE 3560 (Brüel&Kjær). The accelerometer 4397 of Brüel&Kjær was mounted on the motor frame and used as vibration sensor.

The designed bearing fault detector was supposed to recognise the bearing state and its classification to one of the following groups: healthy or damaged bearings.

Two NN types were used for this purpose:
- feedforward multilayer network trained with back propagation algorithm,
- self-organising Kohonen network with two-dimensional feature map.

For the feedforward network four types of classifiers were developed:
- the one-output detector for determination of bearing condition (good–bad) based on the vibration spectrum,
- the one-output detector for determination of bearing condition (good–bad) based on the current spectrum,
- the one-output detector for determination of bearing condition (good–bad) based on the vibration and current spectra,
- the three-output detector for determination of bearing condition (good–bad) as well as supply asymmetry based on the vibration spectrum.
In the case of feedforward NN training it is necessary to present not only input vectors but also target output. For the one-output detectors these outputs are following:
- 0 - for healthy bearing,
- 1 - for damaged bearing.

The bearing condition or supply asymmetry is represented by the output state of neurons in the output layer of feedforward neural detector. In the case of three-output detector, each output of NN represents the different condition of the motor: the first output represents healthy bearing, the second – damaged bearing and the third – supply asymmetry.

For the Kohonen network vibration and current spectra were used in the training and testing vectors. Two-dimensional feature map was used and the distribution of responses on the output nodes was analysed for the classification of specific failures.

The training of neural networks with real data sets was performed using Matlab and Neural Network Toolbox. Feedforward neural networks with one or two hidden layers were trained by using Levenberg-Marquardt algorithm [10]. The activation functions at the hidden layer and the output layer were respectively:
- for the one-hidden-layer network: sigmoidal and linear function;
- for the two-hidden-layer network: sigmoidal, tangensoidal (hyperbolical) and linear function.

The different numbers of hidden neurons were tested by trial and error. All inputs were normalised. The best results of training procedures were obtained for one-hidden layer networks, in the case of learning algorithm with variable learning rate, with momentum factor.

3. CHOSEN EXPERIMENTAL RESULTS

Testing results of the developed NN detectors based on feedforward networks trained using vibration spectrum are presented in the Table 1 and Table 2, for one and three-output detectors, respectively. In these tables the incorrect answers of neural detectors were marked by bold numbers.

In the case of testing of healthy and damaged bearings only three bad responses of neural networks were obtained, what gives 85% accuracy of neural detector presented in the Table 1. For the second detector the results are presented for three bearings only (one healthy and two damaged bearings), to have better transparency of the table. Additionally, the Table 2 presents the responses of the network for two cases of supply asymmetry. In this case the accuracy of the neuron detector was about 93%. It should be mentioned that in these examples very simple structures of NN were taken into account. For bigger number of neurons in the hidden layer even better results were obtained. But simplicity of NN is the main condition of practical realisation of such neural detectors using digital signal processors.
Table 1: Responses of the feedforward NN with 5 neurons in hidden layer for the one-output NN detector (vibration spectrum used in training): a) healthy bearings, b) damaged bearings

<table>
<thead>
<tr>
<th>Bearing No.</th>
<th>Healthy bearings</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1    2    3    4    5    6    7    8    9    10</td>
</tr>
<tr>
<td>Actual output</td>
<td>0.03  0.08  0.09  0.04  0.15  0.55  0.32  0.29  0.07  0.12</td>
</tr>
<tr>
<td>Target output</td>
<td>0     0     0     0     0     1     0     0     0     0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Bearing No.</th>
<th>Damaged bearings</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1    2    3    4    5    6    7    8    9    10</td>
</tr>
<tr>
<td>Actual output</td>
<td>0.99  0.87  0.72  0.95  1.04  0.38  1.12  0.91  0.46  0.69</td>
</tr>
<tr>
<td>Target output</td>
<td>1     1     1     1     1     0     1     1     0     1</td>
</tr>
</tbody>
</table>

Table 2: Responses of the feedforward NN with 4 neurons in hidden layer for the three-output NN detector (vibration spectrum used in training)

<table>
<thead>
<tr>
<th>Neuron</th>
<th>Healthy bearing</th>
<th>Damaged bearing 1</th>
<th>Damaged bearing 2</th>
<th>Supply asymmetry 8%</th>
<th>Supply asymmetry 20%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neuron 1</td>
<td>Actual output</td>
<td>0.9463</td>
<td>0.0398</td>
<td>0.4503</td>
<td>0.0196</td>
</tr>
<tr>
<td>Target output</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Neuron 2</td>
<td>Actual output</td>
<td>0.1067</td>
<td>1.0280</td>
<td>0.9239</td>
<td>0.0403</td>
</tr>
<tr>
<td>Target output</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Neuron 3</td>
<td>Actual output</td>
<td>0.1537</td>
<td>0.0739</td>
<td>0.3441</td>
<td>0.9348</td>
</tr>
<tr>
<td>Target output</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

The stator current spectrum was also used for training of NN detectors. In the Table 3 an example of results obtained for the feedforward one-output detector are presented. In this case responses of the NN are also good. The obtained accuracy was about 85%.
In the Table 4 results obtained for feedforward one-output detector, trained using the current and vibration spectra simultaneously, are demonstrated. The neural network in all cases has answered properly, so the obtained accuracy was 100%.

Table 3: Responses of the feedforward NN with 3 neurons in hidden layer for the one-output NN detector (stator current spectrum used in training): a) healthy bearings, b) damaged bearings

<table>
<thead>
<tr>
<th>Bearing No.</th>
<th>Healthy bearings</th>
<th>Damaged bearings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual output</td>
<td>0.01 0.03 0.19 0.56 0.23 0.09 0.41 0.04 0.06 0.18</td>
<td>0.98 1.10 0.42 1.02 1.24 0.39 1.17 0.90 0.56 0.88</td>
</tr>
<tr>
<td>Target output</td>
<td>0 0 0 1 0 0 0 0 0 0</td>
<td>1 1 0 1 1 0 1 1 1 1</td>
</tr>
</tbody>
</table>

Table 4: Responses of the feedforward NN with 9 neurons in hidden layer for the one-output NN detector (stator current and vibration spectra used in training)

<table>
<thead>
<tr>
<th>Bearing No.</th>
<th>Healthy bearings</th>
<th>Damaged bearings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual output</td>
<td>0.12 0.23 0.14 0.06 0.24 0.21 0.38 0.08 0.03 0.13</td>
<td>0.12 0.23 0.14 0.06 0.24 0.21 0.38 0.08 0.03 0.13</td>
</tr>
<tr>
<td>Target output</td>
<td>0 0 0 0 0 0 0 0 0 0</td>
<td>0 0 0 0 0 0 0 0 0 0</td>
</tr>
</tbody>
</table>
Moreover, the possibility of the damage classification was tested, using unsupervised, self-organising neural network. The simple Kohonen two-dimensional feature map was used for bearings failures and supply asymmetry recognition. The results obtained for this neural classifier are presented in Fig. 2, in the case when NN was trained and tested using the same vibration spectra as in the case of the three-output feedforward detector.

<table>
<thead>
<tr>
<th>Actual output</th>
<th>0.89</th>
<th>1.13</th>
<th>0.72</th>
<th>1.32</th>
<th>1.04</th>
<th>0.59</th>
<th>1.06</th>
<th>0.92</th>
<th>0.68</th>
<th>0.98</th>
</tr>
</thead>
<tbody>
<tr>
<td>Target output</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

In Fig. 2 the following notation was used:
- ▲ △ - neuron response for training and testing samples for healthy bearings,
- ● ○ - neuron response for training and testing samples for supply asymmetry,
- ■ □ - neuron response for training and testing samples for damaged bearings.

The specific location of responses, suitable for healthy bearings as well as stator supply asymmetry and for damaged bearings, in a different region of Kohonen map is observed respectively.

It can be seen that the network has well separated the various characteristic regions and thus such network can be used as a preprocessor in the diagnostic system for clustering of various faults. Then, based on this classification, the other NN, of perceptron type, can be used for the failure evaluation in the automatic diagnostic system.

4. CONCLUSION
Neural networks have been used for motor bearing faults monitoring, based on the vibration and current spectra. Bearing frequency spectra collected on the real drive system were used for training and testing of neural networks. Two kinds of NN (feed-forward and Kohonen) were tested for the detection and classification of bearing faults.

The neural detector based on the feedforward network has perfectly discriminated the healthy and damaged bearings, especially in the case, when the network was trained simultaneously by the current and vibration spectra. The simple structures of neural detectors were obtained (small number of neurons in the one hidden layer only).

From tests performed with Kohonen networks it is seen that this kind of network has clustered the various faults in distinct regions and the three clusters are well separated. This clustering can be used as a preprocessing diagnostic stage which could be followed by the feedforward network which then evaluates the fault severities.

Results of experimental tests show that neural networks can be effectively used in the monitoring of motor bearing faults through appropriate measurement and interpretation of motor bearing vibration and stator current signals.

REFERENCES


DIAGNOSTYKA ŁOŻYSK SILNIKA INDUKCYJNEGO PRZY ZASTOSOWANIU SIECI NEURONOWYCH

W artykule przedstawiono wyniki detekcji uszkodzeń łożysk tocznych silnika indukcyjnego przy zastosowaniu sieci neuronowych. Sieci jednokierunkowe i sieci Kohonena były trenowane za pomocą odpowiednio przetworzonych sygnałów drgań mechanicznych wirnika oraz prądu stojącego silnika. Widma prądu stojącego i drgań mechanicznych były stosowane jako sygnały wejściowe neuronowych detektorów i klasyfikatorów uszkodek łożysk. Opisano sposób przygotowania wektorów uczących dla sieci neuronowych. Przydatność opracowanych detektorów oceniono na podstawie testów eksperymentalnych.