Rotor bar fault diagnosis of induction motor based on single-class SVM

Abstract. The paper presents a new automatic method of the cage diagnosis of the asynchronous electrical engine by applying the 1-class Support Vector Machine (SVM). The diagnosis is made on the basis of phase current of the engine. The important point in this solution is the generation of the diagnostic features, on the basis of which the recognition of the state of the object will be done. In this approach we normalize the time series of the phase current which makes the method universal and applicable without retraining for wide range of engines. The recognition of fault is done by the 1-class SVM network on the basis of the harmonic components corresponding to twice slip of the motor. The results of testing the system on a series of 24 engines have proved high accuracy of the performance.

Streszczenie. Praca poświęcona jest opracowaniu nieinwazyjnej metody diagnostyki prętów klatki wirnika maszyny indukcyjnej, pracującej w trybie online. Diagnostyka prętów klatki wirnika polega na wykryciu uszkodzeń w formie uszkodzenia rurań prętów. Zależy ona na podstawie informacji o czestotliwości pośilu silnika indukcyjnego generowane są cechy diagnostyczne wprowadzone następnie na klasifikator neuronowy, który określa stan prętów wirnika.

Keywords: induction motor diagnosis, broken bars, broken bars detection, single class SVM
Słowa kluczowe: diagnostyka wirnika, diagnostyka silnika klatkowego, jednklasowa sieć SVM, cechy diagnostyczne

Introduction
The well-known engineering problem in the industry is the maintenance of the induction motor in a non-invasive way. Actually applied approach is an invasive one based on visual inspection of disassembled engine. To reduce the maintenance cost and prevent unscheduled shutdowns of the motor there is a need of the non-invasive and on-line diagnostic system.

The paper presents the new automatic method of the cage diagnosis of the asynchronous electrical engine by applying the 1-class Support Vector Machine (SVM).

The principal reason of the cage damage is usually the first broken bar in the cage. In relatively short period of time it causes avalanche damage of the bars on the back side of the cage. The obvious fact is that the motor can still work for some (rather short) period of time but after that the next bars are damaged and finally a machine stops.

There are few principal faults in induction motors such as rotor bars fault, stator windings fault and damage of bearings. This paper describes the non-invasive and on-line rotor bars diagnostic method relying on detection at least one broken bar in the rotor cage.

It’s very important to catch the moment when only one or at least few bars are broken (the beginning of the avalanche process) because the repairing cost of induction motor in this stage is relatively low, comparing to the faults at dozen bars breaken. The most difficult thing is to catch the moment of the first bar broken. In the first stage of the cage damage, there aren’t any symptoms of faults that could be discovered visually. Hence, it’s important to create a non-invasive and on-line method, which would be able to recognize the state of the induction motor cage in its first phase of damage.

On the basis of observation of the phase current of the machine with broken bars we have found the peaks in frequency characteristics of the current, appearing on both sides of the fundamental frequency of 50Hz. These peaks are strictly correlated with the slip of the motor. The relative magnitude of the peaks with respect to the neighbouring values can lead to the generation of the diagnostic features, used by SVM classifier to recognize the fault.

In the proposed solution we will use the classifier in the form of 1-class SVM network, trained on the data information drawn from the phase current, registered only at the normal state of the cage. This is quite important since in practice it is difficult to create sufficiently large data base concerning the damage of the bars. The 1-class classifier is trained to recognize the normal state of the motor with some a’priori assumed tolerance, formed automatically in the learning process. In the retrieval phase, after supplying the actual data corresponding to the fault of the bars the 1-class classifier will indicate the disagreement with the learned data and this disagreement will be associated with the fault of the cage.

The most important problem for the efficient performance of the neural classifier is generating suitable features, which for the classifier to distinguish correctly between the normal and the faulty state of the motor. In this approach we normalize the phase current to be on the basis of the harmonic components corresponding to the slip of the motor.

The diagnostic method presented in this paper is based on current and rotor speed measurements. First of all the current time series should be normalized and then transformed to the frequency domain using FFT.

A lot of information can be obtained from the current frequency characteristics. The most important from our point of view are the frequencies associated with the slip frequency of the rotor. On the basis of them we generate the set of diagnostic features used by 1-class SVM in the recognition process.

The numerical experiments have been performed on the data set created for various cage asynchronous engines of different parameters and at various loading, including the engines with healthy and faulty cages. The results of these experiments will be presented and discussed in the paper.

Current time series registration and normalization
The diagnosis of the bars of the cage induction motor, will apply time series registration regarding the phase current. The registration is done by using the on-line acquisition card (USB-3110) at the sampling frequency $f_s = 20\text{KHz}$. For every engine 10s registration of the phase current has been made. The acquired time series of current should be normalized to make the recognition independent on the power of the engine and its actual
loading. The normalization applied in the paper can be described in the following form [5].

\( x_n(t) = \frac{x(t) - x_{\text{mean}}}{x_{\text{std}}} \)

In this expression \( x(t) \) means the real measured values of current and \( x_n(t) \) - the normalized values. The \( x_{\text{mean}} \) is the mean value of current and \( x_{\text{std}} \) - the standard deviation.

Feature generation

The most important part of each classifier system is the set of diagnostic features, well characterizing the process under recognition [1, 2]. To generate the proper set of them we have to understand the process and try to find the measures well characterizing different states of it, called classes.

First of all need to know some basic information concerning of the engine. The most important one include:

- \( N_s \) - the synchronous speed (constant value),
- \( N_r \) - the rotor speed (value changing with time),
- \( f_1 \) - supply frequency (in our country it is 50Hz).

The induction motor slip is described by the relation:

\( s = \frac{N_r - N_s}{N_s} \)

The bar diagnostic features are associated with the twice slip frequency placed on both sides of fundamental supply frequency \( f_1 \).

\( f_{sb} = f_1(1 \pm 2s) \)

Above equation defines \( 2sf_1 \) sideband frequencies around the supply frequency \( f_1 \) [10,11,12]. They appear as a result of the broken rotor bars.

To find these frequencies there is a need of rotor slip measurement. It is done with some tolerance and this may introduce some errors in determination of twice slip frequency components.

To prevent such problems we are searching the maximum points of frequency characteristics in the range of \( \pm 1\%f_1 \) around calculated \( f_{sb} \). It means that we are looking for the frequencies satisfying the conditions:

\( f_{sb\_low} = \max\{x_n(f_1(1-2s) \pm 1\%f_1)\} \)

\( f_{sb\_high} = \max\{x_n(f_1(1+2s) \pm 1\%f_1)\} \)

Based on the equation (4) we can generate two harmonic components determined at \( f_{sb\_low} \) (left sideband \( f_1 \)) and at \( f_{sb\_high} \) (the right sideband).

The relationship between the cage induction motor state and the slip frequency components is quite simple. If the magnitude of the peek for twice slip frequency components is unambiguously exposed it means that the bar/bars are broken. So we conclude that the cage is damaged. In the other hand rotor cage is healthy.

We have have elaborated the features which characterize how much the magnitude of the peek for mentioned components is exposed with regard to the baseline. These feature are defined by the following equations.
The parameter denoting the asymptotic fraction of outliers allowed, and approach [4,6,8] by introducing the Lagrange multipliers learning samples. Here a hyperplane. The primary problem of learning is defined in function and then maximally separated from the origin using data is first mapped to the feature space using the kernel used in training of the classifier. In 1-class formulation the belonging to the normal state of the cage forms the baseline the novelty detection using 1-class SVM [6]. The data as accurate as possible we have applied the approach of (7)

\[ (6a) \min \left( \frac{1}{2}\|w\|^2 + \frac{1}{2}p \sum_{i=1}^{p} \xi_i^2 - \rho \right) \]

subject to

\[ (6b) \quad \langle w, \Phi(x_i) \rangle \geq \rho - \xi_i \]

with \( \xi_i \geq 0 \) for \( i = 1, 2, ..., p \), where \( p \) is the number of learning samples. Here \( \Phi \) is the map from the input space to feature space, \( w \) and \( \rho \) are hyperplane parameters, \( v \) is the parameter denoting the asymptotic fraction of outliers allowed, and \( \xi \) is the slack variable. The solution of this primary problem is obtained in an identical way as in SVM approach [4,6,8] by introducing the Lagrange multipliers \( \alpha_i \) and transforming the task to the dual problem, that is finally solved using quadratic programming algorithms [6]. As a result of solving this problem the decision function can be expressed in the form of the kernel expansion [6]

\[ y = f(x) = \text{sgn} \left( \sum_i \alpha_i K(x_i, x) - \rho \right) \]

with \( K(x, x) \) the kernel function, defined on the basis of \( \Phi \),

\[ K(x, x) = \Phi(x) \Phi(x) \]. To apply this approach we have to define the type of kernel function, kernel parameters, separating point in the feature space and the outlier fraction. The kernel function should encode the prior knowledge about the problem [7]. Here we will apply the Gaussian kernel \( K(x, x) = \exp \left(-v|x-x|^2\right) \), the most universal kernel function used in support vector machine research of only one hyperparameter \( v \). The outlier fraction should incorporate the prior knowledge regarding the frequency of novelty occurrences. We have applied here \( v=0.01 \), indicating that approximately 1% or less of the entire data may be estimated to be novel. The Scholkopf formulation [6] of the separation problem of the multidimensional data samples from the origin of the coordinate system, defined in the feature space has been implemented using the Matlab platform [9].

The results of numerical experiments

The numerical experiments checking the performance of the system have been performed for 24 engines of different series and parameters (power, current and number of bars). Some of them were quite new and some used for many years in companies (Warsaw metro, Tramwaje Warszawskie).

Table I presents the comparison of the basic data of these machines, including power and nominal slip.

<table>
<thead>
<tr>
<th>Type</th>
<th>( P ) [kW]</th>
<th>slip</th>
</tr>
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<tbody>
<tr>
<td>1 Sg132S-6</td>
<td>2.5</td>
<td>0.03</td>
</tr>
<tr>
<td>2 Sg132S-4</td>
<td>3.5</td>
<td>0.04</td>
</tr>
<tr>
<td>3 SUDI 112M-4B</td>
<td>3</td>
<td>0.06</td>
</tr>
<tr>
<td>4 SUDI 112M-4B</td>
<td>4.4</td>
<td>0.06</td>
</tr>
<tr>
<td>5 SZJe 34 b</td>
<td>4</td>
<td>0.04</td>
</tr>
<tr>
<td>6 SI 132</td>
<td>5.5</td>
<td>0.03</td>
</tr>
<tr>
<td>7 SZcd 44p</td>
<td>1.7</td>
<td>0.05</td>
</tr>
<tr>
<td>8 SE Mg 80-2b</td>
<td>0.75</td>
<td>0.05</td>
</tr>
<tr>
<td>9 SF e 90-L4</td>
<td>1.1</td>
<td>0.02</td>
</tr>
<tr>
<td>10 Sg132M-6B-S</td>
<td>5.5</td>
<td>0.105</td>
</tr>
<tr>
<td>11 Ventilator 1</td>
<td>75</td>
<td>0.05</td>
</tr>
<tr>
<td>12 Ventilator 2</td>
<td>55</td>
<td>0.02</td>
</tr>
<tr>
<td>13 Ventilator 3</td>
<td>55</td>
<td>0.02</td>
</tr>
<tr>
<td>14 Lift 1</td>
<td>2</td>
<td>0.04</td>
</tr>
<tr>
<td>15 Lift 2</td>
<td>2</td>
<td>0.04</td>
</tr>
<tr>
<td>16 Lift 3</td>
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<tr>
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</tr>
<tr>
<td>18 Ventilator 4</td>
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<td>0.03</td>
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<tr>
<td>19 Ventilator 5</td>
<td>10</td>
<td>0.03</td>
</tr>
<tr>
<td>20 Ventilator 6</td>
<td>10</td>
<td>0.03</td>
</tr>
<tr>
<td>21 Ventilator 7</td>
<td>10</td>
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<tr>
<td>22 Ventilator 8</td>
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<tr>
<td>23 Ventilator 9</td>
<td>10</td>
<td>0.03</td>
</tr>
<tr>
<td>24 Ventilator 10</td>
<td>10</td>
<td>0.03</td>
</tr>
</tbody>
</table>

Table I. Details of induction motors parameters used in experiments

The engines have been working at the nominal or close to nominal conditions.

The data of the broken bar engines has been acquired from specially prepared induction motor (Sg132M-6B-S) equipped in the additional head ring with screw connection to each bar of the squirrel cage. This construction change has enabled us to simulate different stages of the damage, as well as the number of broken bars in the induction motor. The modified engine had 33 bars in the squirrel cage. The simulation of the damage of any bar was possible by simple unscrewing it.

To get the sufficiently large set of learning samples we have made the experiments of the machines at different load states, registering the phase current waveforms. The operation of machine has been registered for faulty bars at one, two, three, four, five and six bars broken. In the simulations we have taken into account different positions of the broken bars in the rotor.

For the engines presented in table I we have performed the registration of phase current at their normal operation. The data set obtained in this way contained the samples used for the learning neural classifier and for the testing it. Learning data set consisted of 72 healthy induction motor samples and the testing set consisted of 385 samples corresponding to different cage induction motor state (healthy and broken bars).

Only the data corresponding to the normal operation of the engine has been applied in learning. The 1-class SVM classifier of radial Gaussian function was trained on the set

![Fig.2. An example of current spectrum for the unhealthy induction motor with a) one bar broken, b) three broken bars.](image-url)
of learning data. The hypersparameter used in learning were as following: $\nu=0.01$, the constant $\gamma$ of the Gaussian function $\gamma=0.1$.

Table II presents the statistical results of these experiments depicting the relative errors for learning and testing data.

<table>
<thead>
<tr>
<th></th>
<th>Learning data (healthy cases)</th>
<th>Testing data (broken bars)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative error</td>
<td>2%</td>
<td>4%</td>
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<tr>
<td></td>
<td>0%</td>
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</tr>
</tbody>
</table>

The results confirm good quality of solution. The recognition of the faulty state of the machine was perfect (no errors). The recognition of the normal state of the bars was not ideal, but the error was negligible (below 4%) and acceptable in practical applications. The nonideality of recognition follows from different states of the bars in old machines. Some of them were probably on the border between healthy and broken bars.

**Conclusion**

The paper has presented the diagnostic system of the cage induction motor applying the 1-class Support Vector Machine. On the basis of many performed experiments we may conclude that application of the SVM based classifier combined with the proper feature selection, relying on twice slip frequency harmonics, provides the recognition of the motor fault with good, acceptable in practice accuracy.

The important advantage of this approach is its universality. Thanks to the current time series normalization it is applicable without retraining to wide range of power of engines. It performs well, irrespective of the actual speed and loading. The other point worth of mention is the fact that SVM classifier is trained on the data corresponding to the healthy engines only, which are widely accessible for data acquisition. The system may be retrained any time after gathering new set of measurements. Application of SVM network as the classifier enables to establish soft margin between the healthy and broken bar states.

**References**


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