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ORIGINAL ARTICLE

Support vector machine for fault diagnosis of the broken rotor bars of squirrel-cage induction motor

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Abstract The paper presents an automatic computerized system for the diagnosis of the rotor bars of the induction electrical motor by applying the support vector machine. Two solutions of diagnostic system have been elaborated. The first one, called fault detection, discovers only the case of the fault occurrence. The second one (complex diagnosis) is able to find which bars have been damaged. The most important problem is concerned with the generation and selection of the diagnostic features, on the basis of which the recognition of the state of the rotor bars is done. In our approach, we use the spectral information of the motor current, voltage and shaft field of one phase registered in an instantaneous form. The selected features form the input vector applied to the support vector machine, used as the classifier. The results of the numerical experiments are presented and discussed in the paper.

Keywords Bar fault detection · Squirrel-cage induction motor · Support vector machine · Signal processing

1 Introduction

The problem of non-invasive diagnosis of the faults of rotor bars in the induction motor belongs to difficult problems [5, 7]. Motor with this type of damage is still functioning but such work causes increased currents at both sides of the broken bar. This causes the damage of the next bars. The result of this avalanche process is the damage of all bars, and finally the machine stops functioning. Thus, the most important problem is to catch the moment when only one or at most few bars are broken (the beginning of the avalanche process).

There has been a lot of research reported over the past years devoted to the development of various steady state condition monitoring techniques. Most of them use Fourier transformation of the stator current in a steady state [4, 14, 19]. Some apply more sophisticated method of wavelet analysis of stator current in transient state [18]. There are also solutions relying on the analysis of the magnetic field space vector orientation [13]. All these methods of current preprocessing are combined with different tools of analysis of the results of this preprocessing stage, forming the final classification stage. Among them, we can mention the statistical approach to classification [4, 6, 8], the artificial neural networks [5, 9, 17] or support vector machine [1, 3, 10]. They are responsible for the automatic recognition of fault.

The observation of motors working in the normal state or at faulty conditions of the bars allows to point out some typical symptoms indicating the bar faults [4–6]. To the most important belong changes of the harmonic spectrum in the phase currents and voltages, change of the shaft flux, increased vibration and noise of the machine [4, 7, 8, 17]. These symptoms let us create a diagnostic model of the machine, responsible for early estimation of the technical bar fault of the motor.

The important point in this task is to develop the mechanism of association of the changes of the observed harmonic spectrum with the actual condition of the rotor

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bars. Different approaches to this problem have been developed in the past. In [16], the unsupervised neural network using clusterization technique has been used. In [6], the Bayes decision theory and Bayes minimum error classifier have been applied. Some papers present the application of the multi-layer perceptron, performing the role of classifier [9, 17]. Recently, there is a lot of papers proving the superiority of support vector machine (SVM) in the classification tasks [12], including diagnosis of the bars in the machine [1, 3, 10]. This paper will develop the fault detection model based on the application of SVM. In distinction to the other solutions, we propose to use special type of SVM, called single-class SVM.

This type of classifier is ideally suited for the fault detection, since in the learning stage, it needs only the data belonging to one class, corresponding to the normal operation of machine (so called "healthy" bars). This is quite important, since in the industrial practice, most machines under operation are in normal state of bars. Thanks to this, there will be no problems with learning data acquisition. In the process of discovering the potential fault in an online operation, the trained single-class SVM compares the actual input signals with the learned prototype, corresponding to the "healthy" bars. When this difference is beyond the learned tolerance limit, the classifier treats it as a fault.

Two solutions of the diagnostic system have been elaborated and presented in this work. The first detection system discovers only the fact of fault occurrence. The second one (complex diagnosis) is able to find how many bars have been damaged. The important point in diagnosis is the definition of diagnostic features, on the basis of which the classifier will be able to recognize the fault. In this work, we have defined special features relying on the FFT analysis of the registered instantaneous forms of the phase current, voltage and shaft field in a steady state. As a recognizing and classifying tool, we have used the Gaussian kernel support vector machine, known from its very good generalization ability [15].

Two kinds of SVM networks have been used. For the fault detection, we apply the single-class SVM. The use of this type of classifier for the bar fault detection was never reported before. In the case of complex diagnosis, we have applied the ordinary two-class SVM, combined with a sophisticated procedure of feature selection. Thanks to such solution, we were able to recognize many different types of faults, never considered in the previous publications. The numerical experiments using Matlab [11] have been performed at the measurements done on a specially prepared machine platform, enabling to emulate the typical faults of the of rotor bars. The results presented in the paper show high efficiency of the proposed approach.

2 The experimental set up description

The experimental data were gathered using the real measuring system, built in the laboratory of the Institute of the Electrical Machines of Warsaw University of Technology [10]. All registrations have been done by using the data acquisition card USB-6251 of the sampling frequency equal 10 kHz. To perform highly specific measurements, we have used specially prepared induction motor equipped with the additional head ring and screw connection to each bar of the squirrel cage (Fig. 1).

This construction change has enabled us to emulate the broken bars in the induction motor. In our case, the induction motor had 33 bars in the squirrel cage. The nominal parameters of the Sg132M-6B-S electrical machine were the following: the nominal voltage: $U_N = 3 \times 400$ V, frequency: $f = 50$ Hz, nominal power: $P_N = 5.5$ kW, nominal current: $I_N = 12.1$ A, $\cos \phi_N = 0.83$, efficiency: $\eta_N = 79\%$, speed: $n_N = 895$ rev/min.

The diagnostic measurements of the machine have been done at the load changing from the nominal to half of the nominal value and at practically symmetrical 3-phase system of supply (the real industrial system). All registered data have been normalized. Thanks to the normalization of data, the size and power of the machine (and to some degree also the load) has no influence on the performance of the elaborated diagnostic system.

3 Fault detection system

Our first diagnostic system is responsible only for detection of the occurrence of bar faults. We have to decide only whether the motor bars are healthy or not. For this simplified task, we have proposed the solution based on the

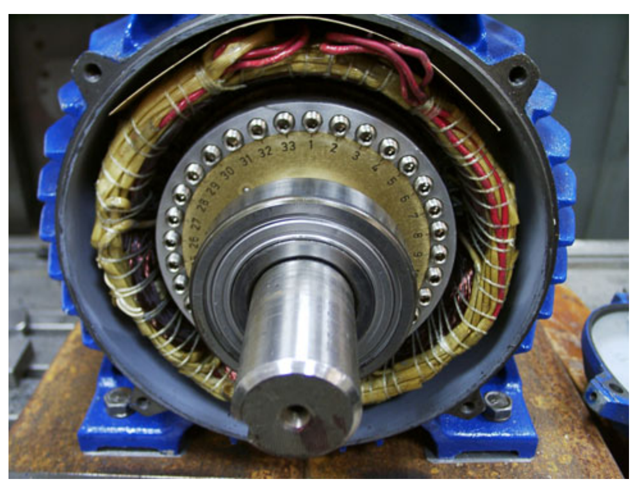

Fig. 1 The view on the head ring with a screw connection to each bar of the squirrel cage

single-class SVM classifier [15]. This type of SVM developed by Scholkopf and Smola [15] is trained using the data information drawn from the stator current, registered only at the normal state of the bars. This is quite important advantage of the solution, since in practice, it is difficult to create sufficiently large data base concerning the damage of the bars. On the other hand, it is easy to acquire data corresponding to "healthy" bar motors (most of motors actually operating in industry).

The single-class classifier is trained to recognize the normal state of the rotor bars 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 single-class classifier will indicate the disagreement with the learned data and this disagreement will be associated with the fault of the bars.

3.1 Diagnostic features

The most important point in this approach is development of the diagnostic features, well characterizing the considered faults of the bars [2, 9]. The 3-phase symmetrical stator winding fed from a symmetrical supply of the frequency f_s will produce a resultant forward rotating magnetic field. The rotor current in a cage winding produces an effective 3-phase magnetic field with the same number of poles as the stator field but rotating at a slip frequency sf_s. The slip s is defined as the relative difference between the synchronous (Ω_s) and actual (Ω) speed of the motor, i.e., $s = \frac{\Omega_s - \Omega}{\Omega_s}$. With a symmetrical cage winding, only a forward rotating field exists. At rotor asymmetry, caused by the bar faults, there will be also a resultant backward rotating field at the slip frequency with respect to the forward rotating rotor. As a result, the backward rotating field with respect to the rotor induces an *emf* and current in the stator winding of the frequency [7]

$$f_p = (1 \pm 2s) f_s \tag{1}$$

These two frequencies $f_{pl} = (1 - 2s) f_s$ and $f_{pu} = (1 + 2s) f_s$ are the classical twice slip frequency sidebands due to the broken bars. Figure 2 presents the frequency spectrums around these two characteristic points for the induction motor at normal state of the bars (Fig. 2a) and after damage of one bars (Fig. 2b), three neighboring bars (Fig. 2c) and six bars placed symmetrically in the rotor (Fig. 2d). It is seen that the damage of any bars of the cage results in an additional harmonic generation, placed at the frequencies defined by (1) and well visible over the harmonic spectrum, typical for the normal operation of the machine. The positions of these two characteristic harmonics are independent on the number of broken bars.

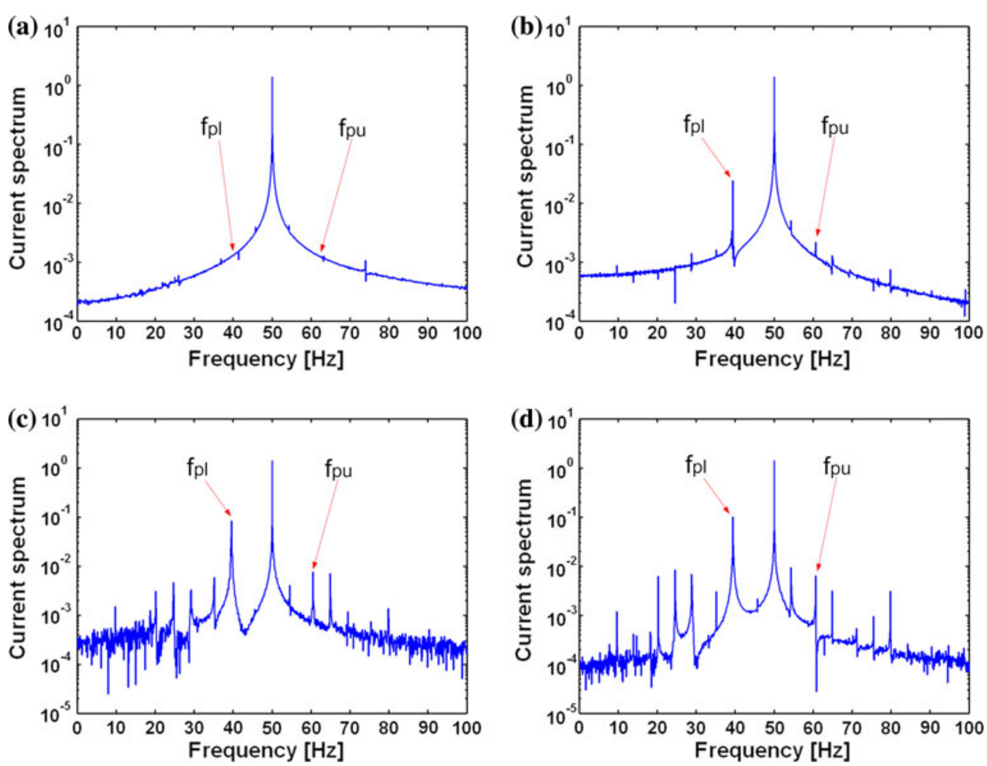

Fig. 2 The stator current spectrum corresponding to *bars* in the normal state (**a**), one *bar* broken (**b**), three broken *bars* (**c**) and pair of three neighboring *bars* placed symmetrically in the cage (**d**)

To define the reliable diagnostic features, we have to take into account some inaccuracy in the speed measurement, and (following from this) the error of determination of f_{pl} and f_{pu}. At the actually measured twice slip frequency sidebands, we have decided to search for the maximum value of the current harmonics in the range of frequencies $f_{\mathrm{p}} \pm 0.01 f_{\mathrm{s}}$. The considered searched range $\Delta f = \pm 0.01 f_{\mathrm{s}}$ allows us to compensate for the limited accuracy of the speed measurements. As a result of such procedure, we get two harmonic currents at precisely determined frequencies f_{pl} and f_{pu}

$$I(f_{\mathrm{pl}}) = \max_f \left\{ I\left(f_{\mathrm{pl}} - 0.01 f_{\mathrm{s}}\right), I\left(f_{\mathrm{pl}} + 0.01 f_{\mathrm{s}}\right) \right\} \quad (2)$$

$$I(f_{\mathrm{pu}}) = \max_f \left\{ I\left(f_{\mathrm{pu}} - 0.01 f_{\mathrm{s}}\right), I\left(f_{\mathrm{pu}} + 0.01 f_{\mathrm{s}}\right) \right\} \quad (3)$$

Two diagnostic features, x_1 and x_2, are then defined as a difference between the peak values of current at f_{pl} (f_{pu}) and their closest neighborhood at the distance of $\pm 0.01 f_{\mathrm{s}}$. To constitute these features, we have applied the following relations

$$x_1 = I(f_{\mathrm{pl}}) - \frac{I(f_{\mathrm{pl}} - 0.01 f_{\mathrm{s}}) + I(f_{\mathrm{pl}} + 0.01 f_{\mathrm{s}})}{2} \quad (4)$$

$$x_2 = I(f_{\mathrm{pu}}) - \frac{I(f_{\mathrm{pu}} - 0.01 f_{\mathrm{s}}) + I(f_{\mathrm{pu}} + 0.01 f_{\mathrm{s}})}{2} \quad (5)$$

These two features form the vector $\mathbf{x} = [x_1, x_2]^{\mathrm{T}}$ put to the input of the single-class SVM, performing the role of final classifier.

3.2 Single-class SVM classifier

Single-class classifier is a very special kind of SVM proposed by Scholkopf and Smola in [15]. The most distinctive fact is that it is trained by using the data belonging to one class only, representing the normal state of the process ("healthy" bars of the motor). These data form the baseline used in training of the classifier. In the single-class SVM formulation of the learning process, the data are first mapped to the feature space using the kernel function and then maximally separated from the origin using a hyperplane. The primary problem of learning is defined in the way [15]

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

subject to

$$\langle \mathbf{w}, \mathbf{\Phi}(\mathbf{x}_i) \rangle \geq \rho - \xi_i \quad (6b)$$

with $\xi_i \geq 0$ for $i = 1, 2, \ldots, p$, where p is the number of learning samples. Here, $\mathbf{\Phi}$ is the map from the input space to the feature space, $\mathbf{w}$ and ρ are hyperplane parameters, ν is the parameter denoting the asymptotic fraction of outliers (the data different from the typical) allowed and ξ is the slack variable. The solution of this primary problem is obtained in an identical way as in a typical two-class SVM [15] by introducing the Lagrange multipliers α_i and transforming the task to the dual problem, which is finally solved using quadratic programing algorithms. As a result, the decision function (the output signal of the classifier) can be expressed in the form of the kernel expansion [15]

$$y(\mathbf{x}) = f(\mathbf{x}) = \operatorname{sgn}\left(\sum_i \alpha_i K(\mathbf{x}_i, \mathbf{x}) - \rho \right) \quad (7)$$

with $K(\mathbf{x}_i, \mathbf{x}) = \mathbf{\Phi}^{\mathrm{T}}(\mathbf{x}_i)\mathbf{\Phi}(\mathbf{x})$ the kernel function. At positive value of $y(\mathbf{x})$, the input data are associated with normal state of the bars, and at its negative value, the data are classified to the opposite class (faulty bars).

The most typical and universal is Gaussian kernel, $K(\mathbf{x}_i, \mathbf{x}) = \exp\left(-\gamma \|\mathbf{x} - \mathbf{x}_i\|^2\right)$ of the adjustable parameter γ. The outlier fraction ν should incorporate the prior knowledge regarding the frequency of novelty occurrences in the learning data. We have applied here $\nu = 0.01$, indicating that approximately 1% or less of the entire learning data are novel (not typical).

3.3 The results of numerical experiments

The experiments have been performed for 31 motors operating in industrial plants at normal state of the bars, and one modified motor mentioned in Sect. 2, enabling to emulate different faults of the bars. The power range of the industrial motors were changing from 0.75 kW to 75 kW. Their years of operation were also different and changed from 2 to 25 years. In the case of the modified machine enabling to simulate the faults of the bars, the number of registrations of the phase current was equal 350 corresponding to different faults of the bars and different loads changing from half nominal to nominal value. The current registrations of the industrial plant motors of the "healthy" bars have been done 5 times for each machine at different load, changing according to the technological processes in which the motor was built in (the measurements have been performed online without breaking the production). At 31 motors, we have created in this way 155 data points used in learning of the SVM. In all cases, the measurement window was equal 10 s, resulting in the frequency resolution of FFT equal 0.1 Hz. To get the reliable results, we have applied special solution of the cross-validation procedure [2]. The available data corresponding to the "healthy" bars have been split randomly into two exchangeable parts: the learning (90% of data points) and testing one (remaining 10% of data points). Observe that only the data corresponding to "healthy" bars have been used in learning of

Table 1 The results of testing the fault detection system

Type of testing data	Mean error of testing	Standard deviation of errors
All data	0.93%	0.62%
Machines with healthy bars only	6.37%	4.22%
Machine with broken bars only	0	0

the single-class SVM. On the other side, the testing data contained both types of data, corresponding to the "healthy" and broken bars. The experiments of learning and testing the SVM networks have been performed 100 times at different contents of the learning and testing data chosen randomly from the proper sets. The final error of recognition was defined as the mean of the recognition errors at all 100 individual runs for the testing data only.

Table 1 presents the average results of testing the trained system at different arrangements of testing data. Three kinds of testing data sets have been tried. In the first case, the testing data belonged to both classes (the row "*All data*" in the table). In the second type of experiments, we have excluded all broken bar data from the testing set, concentrating the experiments only on the healthy cases (the second row "*Machines with healthy bars only*"). The last set of experiments has used in testing only the data corresponding to the broken bars (the last row "*Machine with broken bars only*" of Table 1).

The obtained results show good overall accuracy of recognition. All broken bars have been recognized without errors. Some errors (on a reasonable level) have appeared only at the recognition of data corresponding to the motors with "healthy" bars. The lattermost results are in a strict connection with different state of the bars of the industrial machines taken part in experiments (different age and degree of wear). It is quite probable that some of them resembled the bars in a broken state, since the process of increasing the bar resistance is continuous, not sudden.

4 Complex diagnostic system

The complex diagnostic system aims on discovering not only the case of fault occurrence, but also the type of it (discover the number of faulty bars as well as their location in the rotor). This kind of system requires the learning data set covering the faults that are under recognition (not only the data corresponding to the healthy bars). We have chosen into consideration several essential cases of the bar damage, most often appearing in practice. All of them have been called the classes. The considered cases include:

- class 1—no fault of bars
- class 2—one bar broken
- class 3—two subsequent bars broken
- class 4—three subsequent bars broken
- class 5—the 1st, 2nd, 3th and 16th bars broken
- class 6—the 1st, 2nd, 3th and 16th, 17th bars broken
- class 7—the 1st, 2nd, 3th and 16th, 17th, 18th bars broken
- class 8—the 1st, 2nd and 16th bars broken
- class 9—the 1st, 2nd, 16th and 17th bars broken
- class 10—the 1st and 16th bars broken.

In the experiments with the modified machine, we have registered the instantaneous values of the following variables: the phase current, the phase voltage and shaft flux. Our aim was to find which of these variables are the most essential for the appropriate class recognition. All registrations have been made this time at the nominal speed of the motor by using the same measurement window of the length 10 s. The number of registrations was equal 36 for every case, so it means together 360 measurements.

The registered variables were normalized and established the basis for the detailed diagnosis of the rotor bars. The output of the diagnostic system should indicate what is the actual state of the rotor bars, whether all bars are normal, or discover which of them are damaged. In the case of bar damage, the system should qualify the case to one of nine classes of damages defined earlier. To solve the problem, we have to generate the diagnostic features, on the basis of which the SVM classifier will be able to recognize the proper class. Our features will rely on Fourier representation of the measured data. The extremely important task is to discover which frequencies carry the most important diagnostic information.

4.1 Selection of the diagnostic features

The diagnostic features used in the recognition of the faults will be generated on the basis of the discrete Fourier transform (DFT) of the registered data. Fourier transform results show an averaged frequency distribution contained in the measured signals and contain no time information. In practice, we use its implementation in the form of Fast Fourier Transform (FFT).

Figure 3 presents the frequency spectrum of the phase current of the motor at nominal load in the normal state of the bars (a) and with three broken bars (b). A lot of changes of the distribution of spectra, regarding their contents and the magnitude can be observed. In each case of the broken bars, the contents of the spectra differ, but the difference is difficult to the precise interpretation on the basis of the visual inspection.

To design an automatic system able to recognize different faults on the basis of the frequency spectra, we have to find which of the frequencies differentiate the faulty

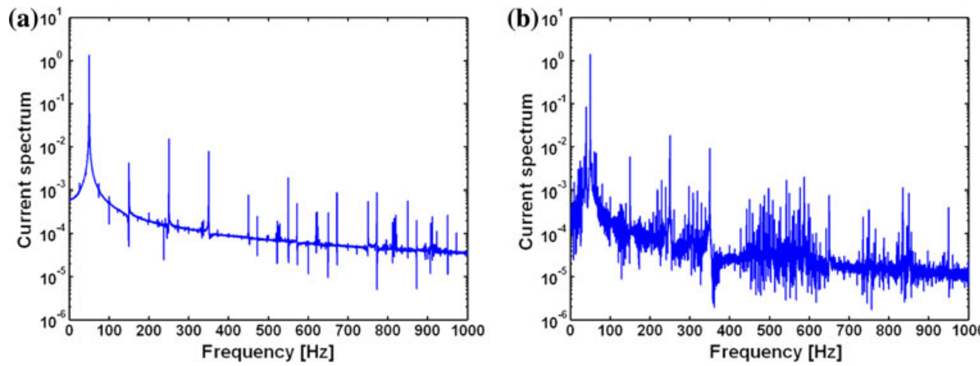

Fig. 3 The induction motor current spectrum: **a** no squirrel-cage fault, **b** motor with three broken *bars*

classes in the most unambiguous way. The visual approach to this problem is inappropriate and we have to develop some automatic method to discover the frequencies differing classes in the most distinctive way.

In our solution, we have applied two step selection method. In the first step, we investigate the change of the differences of the particular feature values corresponding to two classes. The feature suitable for the recognition between these two classes should be characterized by high value of the summed differences over all considered cases. Small value of the summed differences means high diversity of these differences for the subsequent cases and lack of correlation of the feature with a class. Such analysis was performed for each feature at all combinations of two classes. In the second step of selection, we apply the correlation analysis of the features selected in the first stage. This step eliminates the features correlated with each other and leaves only the features of the highest correlation with the recognized classes.

Let us denote by $\mathbf{x}$ and $\mathbf{y}$ the vectors of harmonic distribution of the measured variables (the potential features), belonging to two different classes, generated independently for the current, voltage and flux. Vector $\mathbf{x}$ represents the data of one class and $\mathbf{y}$ the opposite one. We denote by n and m the number of samples of the vectors $\mathbf{x}$ and $\mathbf{y}$, respectively. The resultant ranking measure $d_1(f)$ is calculated for each harmonic of the frequency f using the expression

$$d_1(f) = \sum_{i=1}^{n} \sum_{j=1}^{m} (x_i(f) - y_j(f)) \tag{8}$$

As a result, we get the set of values of $d_1(f_i)$ characterizing the importance of each frequency f_i for two considered classes. High value of $d_1(f_i)$ means high influence of this particular frequency for recognition between classes represented by the vectors $\mathbf{x}$ and $\mathbf{y}$. On the basis of the value of $d_1(f_i)$ for the particular pair of classes, we can sort the frequencies from the most important (the highest value of $d_1(f)$ measure) to the least important (the smallest one). Such sets of frequencies are determined independently for each pair of classes. The definition (8) will be referred further as the differential measure selection algorithm.

Moreover, we have tried also its modified forms $d_2(f)$ defined on the basis of the sign of differences

$$d_2(f) = \sum_{i=1}^{n} \sum_{j=1}^{m} \mathrm{sign}(x_i(f) - y_j(f)) \tag{9}$$

In this modification (Eq. 9), we rely on the signs of the differences between the samples belonging to two different classes for the same frequency f. In the case, when in all samples representing the classes we observe the same tendency (the feature of one class is always higher than in the second class), this feature is valuable and gets higher position in the ranking. In the opposite case, when the samples of both classes are of different tendencies, the signs of differences are changing and partly compensate in (9). In such case, the discriminative measure $d_2(f)$ will assume small value.

As a result of such analysis, we get the set of harmonic frequencies arranged in the decreasing order of their discrimination abilities, independently for the current, flux and voltage for all considered pairs of classes. Putting some threshold on the value of $d_1(f)$ and $d_2(f)$, we are able to reduce the number of these harmonics to small value (say 100) arranged according to their discrimination ability for all pairs of classes. Among them, we search for the harmonics present simultaneously in the sets corresponding to all combinations of two classes. However, among them, there are some harmonics strongly correlated with each other (for example, the neighboring frequencies in the spectrum). The correlated features may dominate over the set of other features and as a result reduce the potential recognition ability of the whole set. To reduce this effect, we have performed the correlation analysis of the selected features (the second step of feature selection) and in this way eliminated the features strongly correlated with others. As a result, we reduce the quantity of harmonics to the size optimal for our recognition problem.

To perform in practice the second step of selection, we have applied the multi-step regressive selection [20]. It combines two sub-steps, repeated many times. One is the forward selection and the second—backward elimination of the features [20]. The main advantage of this solution is the optimal mechanism of elimination of the particular feature from the set on the basis of its low correlation with the class and its possible re-inclusion into the feature set if its correlation changes to the higher value as a result of changing the contents of the actually selected features. The mechanism of this approach automatically eliminates the features strongly correlated with others in the set.

This two step selection procedure was used for the optimal feature selection (independently for the phase current, phase voltage and shaft flux) at application of both ranking measures $d_1(f)$ and $d_2(f)$. The results of such analysis are depicted in Table 2. The quantities of selected harmonics are given independently for current, voltage and flux. It is evident that both measures have produced different sets of harmonics. The efficiency of the selected sets will be verified in the final step of fault recognition by applying the two-class SVM classifiers.

4.2 The two-class SVM classifier

The recognition of ten defined classes representing the state of the rotor bars has been performed at application of different sets of the selected features. This was done by using the ordinary two-class support vector machine of the Gaussian kernel [15], able to recognize two classes of data. The applied SVM is a simple circuit structure of one hidden Gaussian kernel layer and one output linear unit performing the weighted summation. The positive value of output signal is associated with the first class and the negative value with the opposite one. To adapt the parameters of the SVM network, we need now the representatives of both classes under recognition. The learning algorithm of SVM is very efficient and quick, since the learning task is simplified to the solution of the quadratic problem with linear constraints. The details of learning this type of classifiers can be found in the book [15].

At recognition of many classes, we have applied one-against-one approach [15]. In this approach, many SVM networks are trained to recognize between all combinations of two classes of data. At M classes, we have to train $M(M-1)/2$ individual SVM classifiers, each responsible for the recognition of two classes. In the retrieval mode, the vector $\mathbf{x}$ belongs to the class of the highest number of winnings in all combinations of classes. Solution of ten-class problem required to train 45 independent SVM classifiers responsible for recognition of all 45 combinations of classes. The most important advantage of using this approach to multi-class problem is the balanced set of learning samples corresponding to both classes under actual recognition.

From the practical point of view, the most important is the selection of the hyperparameter γ of the Gaussian function and the regularization constant C applied in the experiments. Both have been adjusted by repeating the learning experiments of SVM for the set of their predefined values and choosing the best pair (γ, C) checked on the validation data sets (1/3 of the learning data).

4.3 The numerical results

The results of numerical experiments of recognition of the faulty bars will be presented for ten classes of faults by applying two discussed methods of feature definition. One of them corresponds to the measure $d_1(f)$ and the second to $d_2(f)$. To get the most reliable results of the tests, we have also followed the same type of the cross-validation approach. In this approach, we have performed 200 experiments of learning and testing the Gaussian kernel SVM system using 90% of data for learning and the remaining 10% for testing. The data used in both sets of all trials have been chosen randomly. The final error of the recognition of classes is defined as the average error of testing the system in all trials.

Table 3 presents the testing results of the experiments in the form of the mean relative error of class recognition in 200 trials. Only the results of testing data, not taking part in learning, are presented. The experiments have been performed using independently the features drawn only from the measured current (the second column), the voltage (the third column) and the shaft flux (the fourth column).

It is evident that the voltage features are least efficient and the current features belong to the best. The flux, which is strongly correlated with a current, is only a bit less

Table 2 The quantity of harmonics selected at application of two ranking measures

Ranking measure	The number of selected harmonics of		
	Current	Voltage	Shaft flux
$d_1(f)$	3	3	9
$d_2(f)$	15	12	12

Table 3 The mean relative errors of faulty bars recognition at ten class problem

Selection measure	Current features (%)	Voltage features (%)	Flux features (%)
$d_1(f)$	0.26	9.37	0.87
$d_2(f)$	1.35	3.5	1.78

efficient, but also provides satisfactory accuracy of fault detection. Bad performance of the voltage features is due to the fact that the voltage waveform is rather sensitive to the environmental influences, such as high-frequency noise or other artifacts coming from the electrical devices working nearby. The current and flux of the machine are filtered out of these noisy components thanks to the inductance of the machine. Hence, they are better suited to generate good diagnostic features.

On the basis of these results, it is evident that we can rely the rotor bar diagnosis on the observation of the stator current only. This is very fortunate from the practical point of view, since the registration of phase current of the machine is very easy in the online operation of the machine and does not require any special arrangement connected with stopping the machine at the measurements.

5 Conclusions

The paper has presented the novel approach to the online detection of the bar faults in an induction motor on the basis of the registered stator current in a steady state. Two diagnostic systems of the faults of the cage bars have been presented and discussed in the paper. The first one detects only the fact of fault occurrence, and besides the current registration, it does not need any additional information except the number of poles and actual speed of the motor. This speed does not need to be stable and may vary in experiments from the nominal to the half of the nominal speed. The second (complex) diagnostic system is able to detect also the number end location of the faulty bars. However, it needs the stabilized speed of the motor.

The complete fault detection system applying the support vector machine of two different types (the single-class and two-class SVM) was implemented in the form of computer application and tested on a large data set of machines. After training, the adjusted parameters of SVM have been fixed and the system was ready to detect the faults of the bars in an online operation of the machine on the basis of the actual registration of the stator current.

The results show that support vector machine approach combined with the proper feature selection provides good solution for automatic detection of the bar faults of the induction motor. The paper has shown that the most important diagnostic information is contained in the phase current and this information is sufficient to make diagnostic decision regarding the state of the bars of the squirrel-cage induction motor.

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