The growing demand for dependable manufacturing techniques has sped up research into condition monitoring and fault diagnosis of critical motor parts. On the other hand, in modern industry, machine maintenance is becoming increasingly necessary. An insufficient maintenance strategy can result in unnecessarily high downtime or accidental machine failure, resulting in significant financial and even human life losses. Downtime and repair costs rise as a result of failure. Furthermore, developing an online condition monitoring method may be one solution to come up for the problem. Early detection of faults is very vital since they grow quickly and can cause further problems to the motor. This paper proposes an effective strategy for the classification of broken rotor bars (BRBs) for induction motors (IMs) that uses a new approach based on Artificial Neural Network (ANN) and stator current envelope. The stator current envelope is extracted using the cubic spline interpolation process. This is based on the idea that the amplitude-modulated motor current signal can be revealed using the motor current envelope. The stator current envelope is used to select seven features, which will be used as input for the neural network. Five IM conditions were experimentally used in this study, including a part of BRB, 1 BRB, 2 BRBs and 3 BRBs. The new feature extraction and selection approach achieves a higher level of accuracy than the conventional method for motor fault classification, according to the experimental results. Indeed, the results are impressive, and it is capable of detecting the exact number of broken rotor bars under full load conditions

Keywords: classification of broken rotor bars, stator current envelope, neural network, fault detection and diagnosis, induction motors

BROKEN ROTOR BARS FAULT DETECTION IN INDUCTION MOTORS BASED ON CURRENT ENVELOPE AND NEURAL NETWORK

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1. Introduction

In 2011, the overall number of working electrical machines in the world was about 16.1 billion, with a growth of about 50 % in the previous five years [1]. The majority of these machines are IMs. According to many studies, these machines consume approximately 40 % to 50 % of total energy produced in any developed country [2, 3]. IMs are used mainly in industrial applications due to easy maintenance, high performance, low cost. The fault types of an induction motor are bearing, stator, rotor, and unbalances eccentricities. One of the essential components in motors are rotor bars, and faulty rotor bars often seriously decrease the efficiency of operation. In order to ensure the availability of industrial systems and the safety of goods and persons on the site, monitoring and diagnosis of rotor faults are of prime importance. Faults may lead to a system breakdown. To avoid adverse consequences, the primary goal of diagnosis approaches is to detect faults as early as possible [4] and to differentiate between various types of faults [3].

Each sort of IM fault always causes specific frequency components in the current spectrum. That can be utilized as a possible indicator of the type and severity of the fault. The rotor bar faults are caused by thermal, magnetic, residual, dynamic and mechanical stresses [5]. The motor is severely disrupted by a broken rotor bar fault, which results in a substantial drop in overall motor performance and a related rise in operating costs. A broken rotor bar may also damage stator parts during service in extreme cases [6]. Although many researchers have been devoted to the diagnosis of BRBs for many years, there are still some difficulties with regard to the broken bars diagnosis and determination of specific sub-bands with narrow bandwidth without the attendance

of other faults [7]. To alleviate this inconvenience, a stator current envelope has been employed for analysis of the signal obtained from condition monitoring of the machine. The main novelties of the paper are the use of only one current rather than three and the use of multiple features combined with a classifier. The novel fault diagnosis method proposed here is based on a number of features extracted from the current envelope at full load.

2. Literature review and problem statement

Many studies in the literature are focused on fault diagnosis and the operating performance of IM with broken rotor bars, such as voltage, electromagnetic torque, current, vibration and temperature. Among these studies, the motor current signature analysis (MCSA) technique is considered the most promising fault detection method. MCSA [8] does not need IM parameter estimation, it is inexpensive and able to provide the system states without access to the machine, and this machine does not need to be stopped. This technique has significant limitations because of the increased complexity of electric machines and drives. As an example, MCSA is the optimal choice for electrical machines under steady-state conditions and rated load. Moreover, the drawback of MCSA is the inability to get the occurrence time of the signal spectrum.

In this context, numerous works have concentrated on the evaluation of one or multiple BRBs. The work [9] presented the diagnosis of BRBs based on the speed and rotor resistance estimation. The key benefit is that even with an unloaded induction motor, the rotor resistance can be accurately estimated. The thermal variance in the

rotor resistance must be compensated for as part of this calculation procedure. In [10], a classification method is built using a multivariate relevance vector machine with Gaussian kernels and principal component analysis. The paper [11] presents that the pattern recognition and the Support Vector Machine (SVM) approach have recently been found to be surprisingly successful in a variety of real-world applications. The paper [12] presents the results of the SVM, which has been successfully applied to a variety of classification and pattern recognition tasks. The proposed solution reduced the computational expense of the fault diagnosis model by removing redundant data features. The paper [13] shows that the nonlinear classification methods and SVM can be effectively used to map samples from low-dimensional space to high-dimensional space. SVMs have been used to detect rotor bar faults in induction motors. But [14] suggested that in comparison to other approaches, the SVM classifier produces an excellent result that is very quick and easy to implement, and it is a reliable on-line system with high robustness to load variations and changing operating conditions. Furthermore, the research [15] suggested a new approach for measuring the sanity of motors based on SVM. However, the SVM learning efficiency is low, which limits its application. Also, it suffers from difficulties in creating a reliable network, if there are not enough measurements available from all operation states of the process. On the other hand, the paper [16] proposed a model identification in time domain techniques and showed that it could detect and diagnose the broken rotor bars under different load conditions. Moreover, [17] presents a novel technique for detecting and classifying BRB faults, which involves extracting two spectrograms using fixed-width windows and segmenting them using the Otsu algorithm.

Wavelet analysis, according to [18, 19], can be used for fault diagnosis because it allows for stator current analysis during transients. Although these methods improve the reliability of the BRB detection, they cannot avoid the inherent shortcoming of the discrete Fourier transform (DFT). However, these methods still require a long-time data window to obtain good frequency resolution. In fact, using a physical sensor in a motor fault detection device reduces system efficiency as opposed to fault detection systems that do not need additional instrumentation. This is attributable to the sensor's susceptibility to failure, which is compounded by the induction motor's intrinsic susceptibility to failure. One of the oldest monitoring techniques is the analysis of a machine vibration signal [20].

Because of the variation in readings based on sensor position on the system frame and the noise effect of nearby moving and adjacent devices, vibration signal presents some challenges [21]. Artificial intelligence methods, on the other hand, have been implemented in [22]. A large amount of numerical data from the system is also needed for training a neural network. When there aren't enough measurements from all of the process activity states, it is difficult to build a stable network. The paper [23] described model-based fault detection methods for induction machines. This approach was used in [13], which introduced the fault detection problem for IM rotors using parameter estimation methods. Moreover, Set Membership Identification (SMI) in [15] has got a lot of attention recently. Furthermore, it has been thoroughly tested in a number of laboratory studies for the diagnosis of broken rotor bar faults under a variety of fault scenarios and load conditions [15, 16]. The limitation of the

SMI is the need for the healthy data for the induction motor furthermore current signal of the motor. Otherwise, the SMI method cannot work successfully. Moreover, even under full load conditions, a broken rotor bar fault or partially broken rotor bars, which can lead to a larger failure, may be undetectable [18]. As a result, developing condition monitoring techniques to address these issues and allow for earlier detection of rotor faults is critical. Therefore, in the presented work, broken rotor bars of induction motor have been studied and experimentally evaluated successfully based on stator current envelope and neural network.

3. The aim and objectives of the study

The aim of the study is to use a new approach based on a neural network and stator current envelope to classify faults of broken rotor bars (BRBs) for induction motors.

To achieve the aim, the following objectives were set:

– to support and evaluate the proposed approach, the experimental study was considered obtained from a three-phase induction motor operating at full load;

– to extract seven features from the stator current envelope used as inputs to an ANN-based fault diagnosis framework;

– to present a fault diagnosis method for the healthy case, broken part of a bar, one broken bar, two broken bars and three broken bars based on an ANN and current envelope.

4. Materials and methods

4. 1. Features and stator current envelope

The envelope of stator currents ($i_{ev}(t)$) is a smooth curve, which describes a variation in the stator current amplitude. A fault of broken bars affects the form of the stator currents resulting in an envelope [16]. $i_{ev}(t)$ relies on finding the peak values (xi, yi) of one phase of stator current and then using cubic spline interpolation (P_n) to find the current envelope as shown in Fig. 1. A cubic polynomial is used to connect each of the intervals, which are identified by top points respectively, and it is determined as [24]:

$$C_i(x) = a_0 + a_1x + a_2x^2 + a_3x^3. \tag{1}$$

The special form of the linear system of equations that must be solved to obtain a closed-form solution is one of the reasons why cubic splines are one of the most common interpolation schemes. The next task in the proposed fault diagnosis technique is a method of extracting features from a waveform by sampling the envelope values regularly and comparing them to the original waveform ($C = \{C_1, C_2, \ldots, C_N\}$, where the total number of samples is N). To illustrate good features that allow the proposed method to be used, seven features have been developed to obtain good results. This can be deduced from the current envelopes given by the equations below [25].

$$C_{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(C_i)^2}, \tag{2}$$

$$C_{mean} = \bar{C}_i = \frac{1}{N}\sum_{i=1}^{N}C_i, \tag{3}$$

$$C_{Skewness} = \frac{1}{N} \sum_{i=1}^{N} \frac{\left(C_i - \overline{C}_i\right)^3}{C_{Std}}, \qquad (4)$$

$$C_{Kyrtosis} = \frac{1}{N} \sum_{i=1}^{N} \frac{\left(C_i - \overline{C}_i\right)^4}{C_{Std}}, \qquad (5)$$

$$C_{Std} = \frac{1}{N} \sum_{i=1}^{N} \left(C_i - \overline{C}_i\right), \qquad (6)$$

$$C_{Rang} = \min\left(C_i\right) - \max\left(C_i\right), \qquad (7)$$

$$C_{Shape} = \frac{C_{RMS}}{\overline{C}_i}, \qquad (8)$$

$$C_{flact} = 2 * \frac{\min\left(C_i\right) - \max\left(C_i\right)}{\min\left(C_i\right) + \max\left(C_i\right)}, \qquad (9)$$

where $Cskrew$ is skewness, C_{mean}, $C_{kyrtosis}$ is mean value, C_{fluct} is fluctuation, C_{RMS} is root mean square, C_{Std} is standard deviation, C_{Rang} is range factor and C_{Shape} is shape factor. These features are determined for a variety of broken bars and full load condition.

4. 2. Neural network-based classification

Fig. 1 depicts the proposed scheme for broken bar classification based on ANN. It consists of the new patterns of features extracted from the current envelope of the motor under healthy and broken rotor bar conditions, which were used to test the purpose of the neural network.

The motor under consideration is run at full load. Several faults are artificially formed in the rotor and current is collected for each fault successively. Many neural network architectures with different numbers of hidden layers and hidden neurons were used to create suboptimal convolutional neural networks that associated extracted features with the number of broken bars. To train and implement the results of the ANN, the Matlab backpropagation ANN Toolbox was used. The number of features used for classification was used to determine the number of inputs to each neuron.

5. Research results of a new fault classification approach for broken rotor bars (BRBs) for induction motors

5. 1. Experimental setup

In order to examine the efficiency of the proposed fault classification approach, many experimental tests have been carried out, with the following characteristics of a three-phase induction motor: rated voltage 380 V, rated power 1.25 kW, 2 pairs of poles, rated current 2.85 A and load for the IM is a DC generator. The sampling of stator currents were 5 kHz for each case of the healthy and four faulty classes (broken part of a bar, one broken bar, two broken bars and three broken bars). More specifically, Fig. 2 shows a view of the caused complete BRB faults.

In the presented fault detection system, four separate faulty cases were considered and evaluated at full load condition.
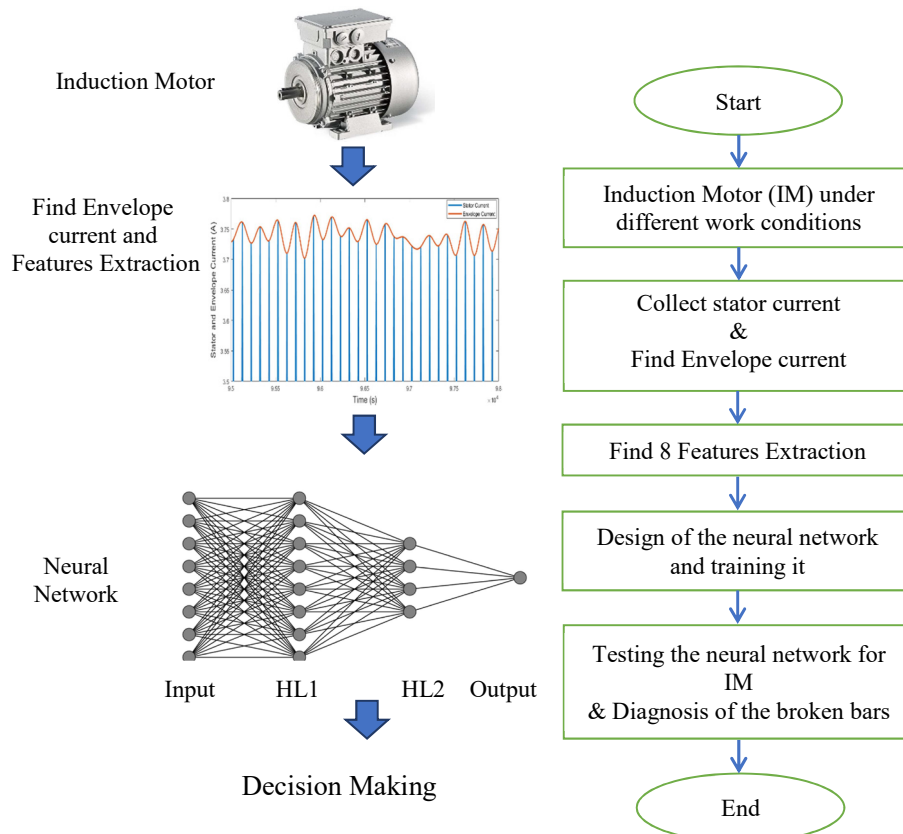

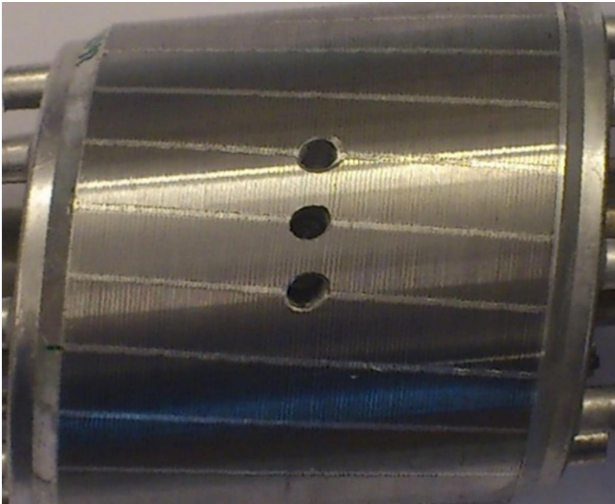Fig. 1. Flow chart for broken rotor bar fault diagnosis technique based on ANN

Fig. 2. Description of the induced broken rotor bar faults
of induction motor

5. 2. Features of stator current

The stator current is significantly changed after the occurrence of the fault, as shown in Fig. 2 for all four evaluated cases for phase A only. Small variations in current are found in the cases of part of BRB, while the amplitude of the currents is strongly changed in the cases of 1BRB, 2BRB, and 3BRB in relation to the number of broken bars. Furthermore, it is important to keep in mind the magnitude of current fluctuation. Moreover, Fig. 3 shows the currents for each of the four faulty cases, as well as the envelopes. Case *a* represents broken part of one bar, case *b* represents one broken bar, case *c* represents two broken bars and case *d* represents three broken bars. It can be seen from the obtained envelopes that in the case of broken bars, the envelope fluctuation will increase in terms of increasing number of BRBs. In Fig. 4, the effect of the broken bar fault on the rotor current is depicted. As can be seen in Fig. 4, when a fault occurs, currents increase, and the explanation for this can be found in the generalized rotating field theory, which states that broken rotor bar faults can generate a backward rotating field. These rotor currents generate a rotor magnetic field, which should interfere with the stator field in order for all of the stator flux to affect each bar equally. Furthermore, all rotor bar currents at rated load should be fairly stable around the rotor radius. However, as shown in Fig. 4, where the fluctuation ratio for each element is plotted against the class label, the fluctuation ratio is ineffective for fully distinguishing between the presented cases, contrary to what was observed in [17].

Furthermore, Fig. 5 shows the relation between the fluctuation ratio and the samples data set. It is clear that current fluctuation will increase with increasing faulty case severity. Moreover, the more continuous broken bars there are, the more significant the rotor faults would be.
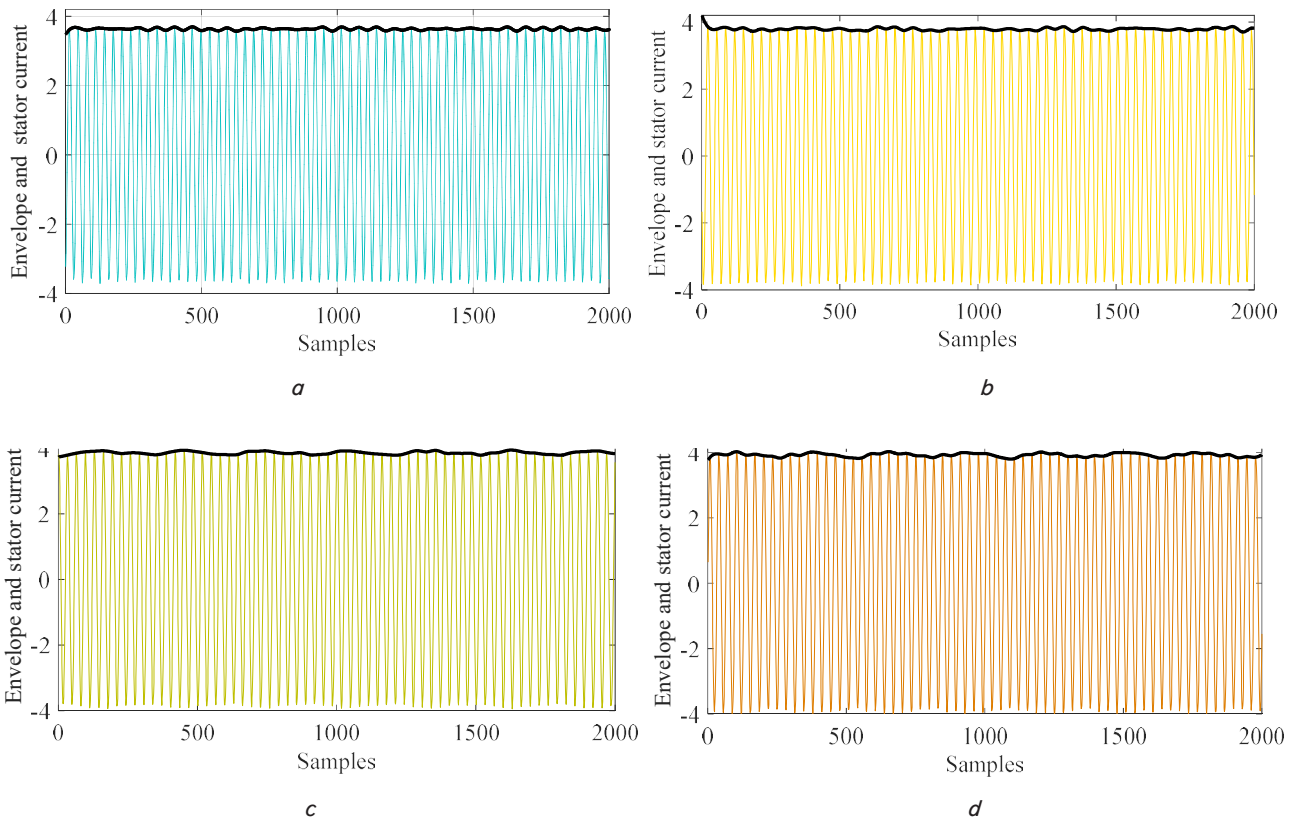

Fig. 3. Envelope and stator current at full load condition for case:
a — broken part of one bar; *b* — one broken bar;
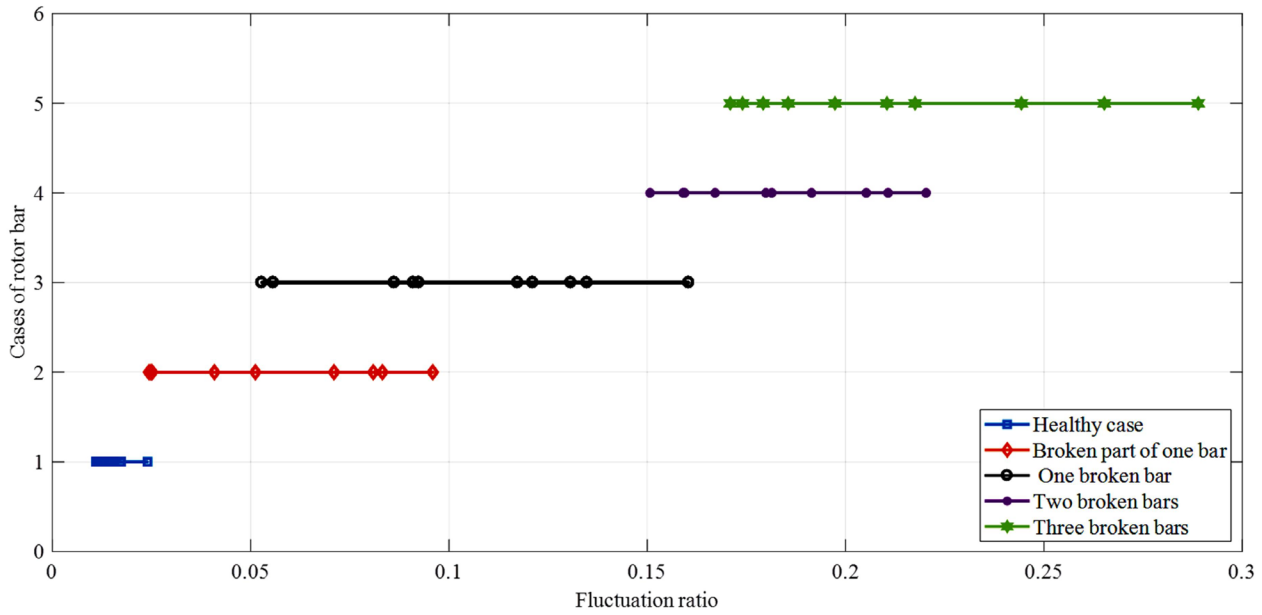*c* — two broken bars;
d — three broken bars

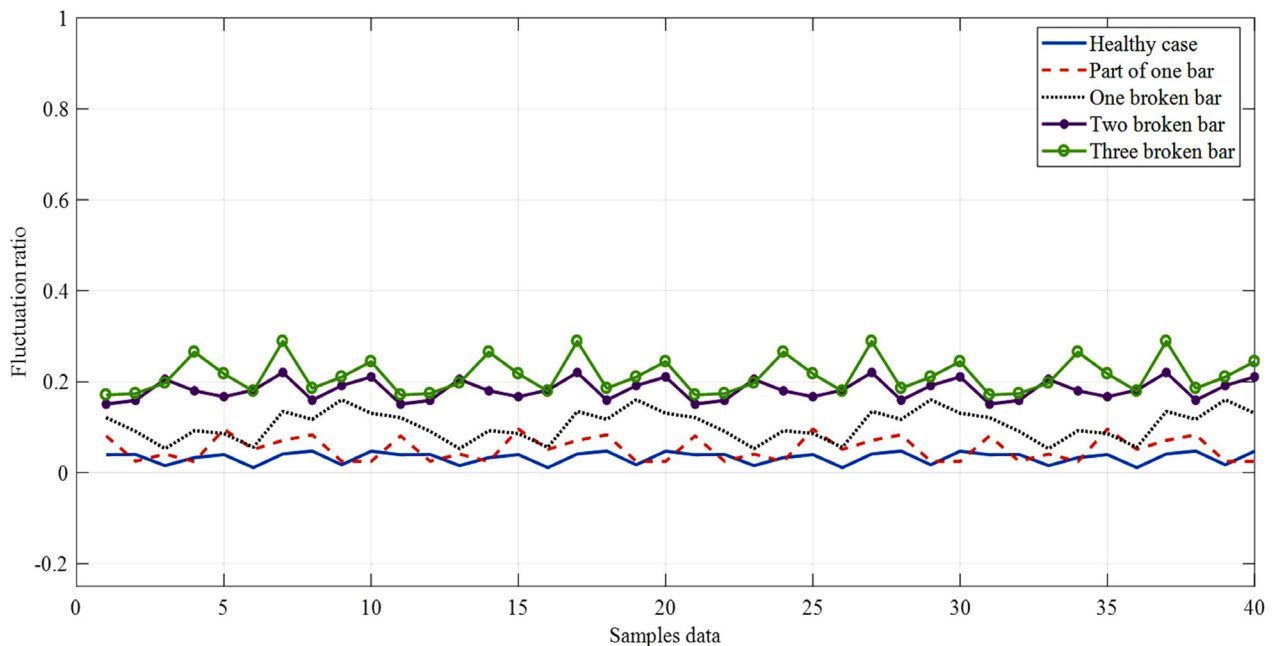Fig. 4. Fluctuation ratio versus healthy and faulty cases

Fig. 5. Fluctuation ratio versus samples data set

5. 3. Neural network-based fault diagnosis

The data set consisted of 200 rows and 7 columns (features) of training and testing data, relating to 40 runs, collected by acquiring stator motor current, i. e. generating 40 samples*5 cases=200 dataset vectors in total. The pattern recognition neural network's output feature matrix was chosen in Table 1.

The input matrix has 110 datasets and it was divided into 2 datasets, one for training (100) and one for testing (10), resulting in 20 training samples and 2 testing samples for 5 cases of induction motor, which include healthy, broken part of one bar, one broken bar, two broken bars and three broken bars. To test the Pattern Net's effectiveness and position for the given classification approach, different numbers of hidden

layer neurons were used to train it. The best result (classification accuracy) was stated after each network was trained and checked ten times with the same dataset. Before providing the input to an ANN for training and testing steps, calculated features were normalized. This method guarantees that all of the present features (ANN inputs) are provided the same weight. A test set for the recall process has been considered to validate the research methodology's generalization characteristics. For evaluating the efficiency of different network implementations, the total number of epochs for better validation performance, classification accuracy for testing dataset, and Mean Square Error (MSE) were chosen and presented in Table 2, which displays the results obtained for several hidden

layers of neurons using scaled conjugate gradient and Levenberg-Marquardt training.

The optimum case was 12 hidden layer and 6 epoch neurons for training algorithms, having the highest testing accuracy, 99.999 % respectively. Furthermore, Fig. 6 shows neural network training and testing performance errors for the optimum case, which includes 12 hidden layer and 6 epoch neurons with the values of MSE ($9*10^{-5}$ and $0.4*10^{-3}$), respectively. While Fig. 7 presents neural network training and testing regression for the optimum case. It is clear that the classified data identical with the target and the accuracy present is almost 100 %.

Table 3 shows the correlation matrix that was obtained. It shows that we have an almost perfect classification between healthy broken bar cases and very relatively high classification rates (100 %, 99.985, 99.99, 100 % and 100 %) using the new features proposed in this work.
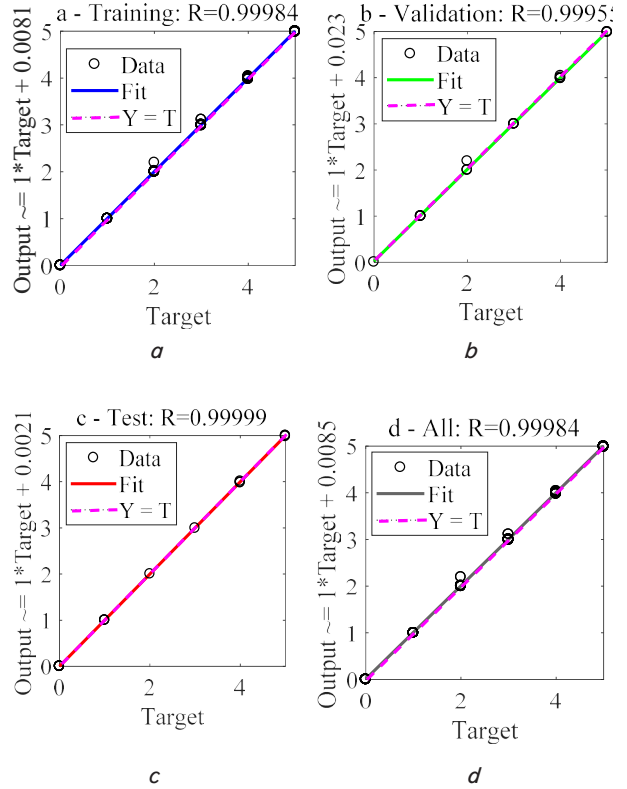
Table 1

Summary of the neural network's output feature matrix

Healthy	0	0	0	0	1
Broken part of a bar	0	0	0	2	0
One broken bar	0	0	3	0	0
Two broken bars	0	4	0	0	0
Three broken bars	5	0	0	0	0

Table 2

Summary of the results with training and testing function

Training samples	Number of hidden layer neurons	Number of epochs	Training performance (MSE)	Testing performance (MSE)	Classification accuracy (%)
10*5	10	14	0.0477	0.246	97
	12	16	0.006	0.1566	98.5
	8	13	0.057	0.32	91.91
	12	12	0.057	0.149	97.07
	8	15	0.0178	0.466	93.59
20*5	20	15	0.006	0.433	98.69
	8	19	0.032	0.0184	99.569
	12	9	0.03	0.238	98.8
	15	13	0.0313	0.0412	99.06
	12	6	$9*10^{-5}$	$0.4*10^{-3}$	99,9999

Fig. 7. Neural network optimum case:
a — training: R=0.999984; b — validation: R=0.99955;
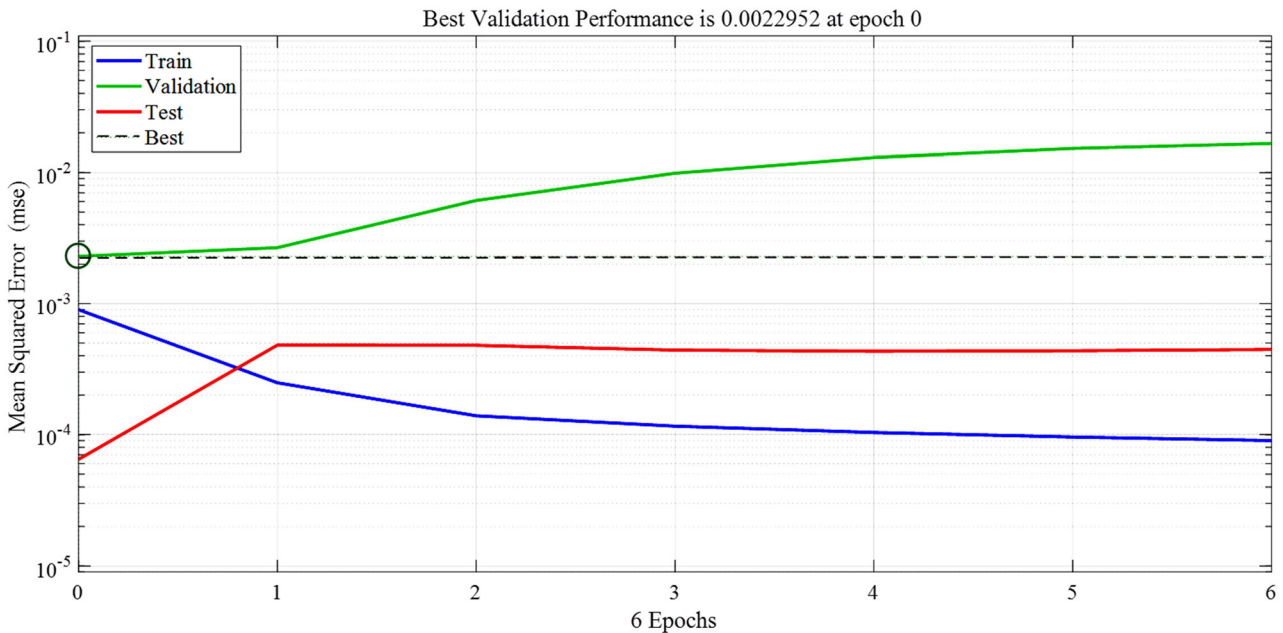c — testing: R=0.99999;
d — all regression: R=0.99984

Fig. 6. Neural network performance errors for the optimum case

Table 3

Correlation matrix for the examined cases

Motor case	Case No.	1	2	3	4	5	Classification percentage
Healthy	1	1	0	0	0	0	100 %
Broken part of a bar	2	0	2.0003	0	0	0	99.9985 %
1 broken bar	3	0	0	3.0001	0	0	99.99 %
2 broken bars	4	0	0	0	4	0	100 %
3 broken bars	5	0	0	0	0	5	100 %

6. Discussion of experimental results

Faults were classified using an adaptive neural algorithm. Neural networks were specifically trained to find the types of faults that occur in IM by using features extracted from the current envelop as neural network inputs. This network has three layers: an input layer, a medium layer, and an output layer, with 300 nodes. The type of BRB faults that occur in the system will be discovered after the training steps. The training error rate was extremely low, and the neural network efficiency in detecting the BRB was satisfactory. The training error rate was MSE=$9*10^{-5}$, and the number of trials was 6 epochs.

The neural network and current envelope for broken rotor bars classification have been presented and experimentally evaluated. Seven features have been extracted from the current envelope and considered as neural network inputs. These seven features are utilized to train the artificial neural network in the Matlab setting. Furthermore, the envelope signals were calculated at full load conditions at the rated speed under a series of faults such as broken part of rotor bar, one broken bar, two broken bars, and three broken bars to estimate the effect of operating conditions on fault classification efficiency. It can be seen from the obtained envelopes that in the case of broken bars, the envelope fluctuation will increase. With a growing number of broken rotor bars, the average value and fluctuation ratio of the current envelope have increased, as has the size of the current envelope fluctuations. However, as shown in Fig. 4, 5, the fluctuation ratio, unlike what was observed in [26], is not capable of fully distinguishing between the four groups of faults. Moreover, the most significant measure for analyzing the existence of overfitting is the difference among training and testing accuracies, a particularly important property to assess if the train-test learning method is robust and accurate. One of the challenges and disadvantages of the neural network is the need for both types of data, that is, it requires healthy and faulty data. In some cases, unavailability of healthy data makes it impossible to use this method. The results show that the approach is very promising, as shown in Table 2, with 100 percent classification accuracy. In addition, the results showed that the number of epochs for the training network decreases with the size of the network. Indeed, the network's stability and convergence are directly proportional to the number of samples in the distinguished features. Furthermore, it was observed that the classification percentages were almost 100 % for all the faulty cases. When comparing the presented work to [19, 22], it is clear that all fault classification results presented in this work have a better effect. Indeed, the obtained experimental results encourage the application of the proposed method in practical systems. Furthermore, the proposed features extended from the stator current envelope have improved the ANN performance accurately. Moreover, the drawbacks of the presented approach stem from the fact that it easily suffers from the time required to implement the presented method will increase as the number of required classification cases increases. Furthermore, in some cases, using this method is not possible if the healthy data are not available. In order to develop this method to be more effective, I suggest studying the detection of broken rotor bars at light loads in the future work. Also in the future, a comparison study with other classification methods, such as kNN and SVM, can be carried out to improve the efficiency of the current work.

7. Conclusions

1. The main takeaways from the presented research are that using a neural network and current envelope for broken rotor bars can be meaningful and the classification method has indeed been successful and accurate, which confirmed the rightness of the proposed approach. The classification percentages clarified in Table 3 were between 99.985 % and 100 %.

2. The feature extraction stages are transformed into good values before being extracted from the current envelope, which were helpful and meaningful for the proposed diagnosis scheme and improved the results of the proposed method. The classification accuracy depends on the features and classification method and the highest testing accuracy was 99.999 %.

3. The results of the research are extremely encouraging. It has a lot of potential for practical systems. For induction motors, envelop current allowed performing condition monitoring and fault diagnosis successfully. Moreover, for the diagnosis of broken rotor bars, a neural network is appropriate and accurate. Furthermore, the methodology carries out the diagnosis method for whatever continuous operation within the specified range. This work leads to the creation of broken rotor bar diagnostic procedures, as well as a high-performance and advanced classification structure.

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