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Discrimination of Faults in induction machine based on pattern recognition and Neural Networks techniques

***Abstract**. The work presented in this paper is a contribution in the theme of monitoring and diagnosing of faults in the three-phase squirrel cage induction machine. The proposed approach is based on the pattern recognition methods and the artificial intelligence techniques. For so doing, measurements of the stator currents are carried out on a machine subject to various faults such as: short-circuit in the stator windings, bar breakage, bearing failure and eccentricity fault. These acquisitions are classified in databases in order to process them and calculate their Power Spectral Density (PSD). Then, another database is formed of the digital data of the PSD images of the currents associated with the type of fault. After that, a process of learning and classification by artificial neural networks was developed. The test results show the efficiency, robustness and correctness of the proposed approach for the discrimination of faults of electrical or mechanical origin affecting the machine*.

***Streszczenie.** Praca przedstawiona w tym artykule stanowi wkład w temat monitorowania i diagnozowania uszkodzeń w trójfazowej maszynie indukcyjnej klatkowej. Proponowane podejście opiera się na metodach rozpoznawania wzorców i technikach sztucznej inteligencji. W tym celu pomiary prądów stojana są przeprowadzane na maszynie podlegającej różnym usterkom, takim jak: zwarcie w uzwojeniach stojana, pęknięcie pręta, uszkodzenie łożyska i błąd mimośrodowości. Przejęcia te są klasyfikowane w bazach danych w celu ich przetworzenia i obliczenia ich gęstości widmowej mocy (PSD). Następnie tworzona jest kolejna baza danych z cyfrowymi danymi obrazów PSD prądów związanych z rodzajem uszkodzenia. Następnie opracowano proces uczenia się i klasyfikacji przez sztuczne sieci neuronowe. Wyniki testu pokazują skuteczność, niezawodność i poprawność proponowanego podejścia do rozróżnienia wad pochodzenia elektrycznego lub mechanicznego mających wpływ na maszynę. (**Dyskryminacja błędów w maszynie indukcyjnej na podstawie rozpoznawania wzorców i technik sieci neuronowych**).*

Keywords: *Induction machine, diagnosis, pattern recognition, neural network, discrimination.*
Słowa kluczowe: *Maszyna indukcyjna, diagnoza, rozpoznawanie wzorów, sieć neuronowa, dyskryminacja.*

Introduction

The induction machine is the most robust and cheapest machine on the market. Its multiple qualities make it a machine particularly appreciated in an industrial environment. Although these machines are reliable, they are subject to unexpected faults, which can be classified as follows[1],[2]:

- Electrical faults at the stator level, which are manifested by the opening of a phase or a short circuit within the same phase, between two phases or between a phase and the stator cylinder.
- Electrical faults at the rotor level, which include an opening or a short-circuit of the turns for machines with a wound rotor and breaking of the bars or rings for machines with a cage.
- Mechanical faults in the stator, or in the rotor such as Bearing, eccentricity and alignment faults.

To ensure reliability, efficiency and security of the induction machines, the integration of a fault detection and diagnosis system should be performed. Proper diagnosis and early detection of faults can minimize downtime and maintenance time for the process where the machine is included. They also make it possible to avoid the harmful consequences of faults, as well as to reduce financial losses.

The diagnosis of faults in electrical machines has benefited to a lot of research work in recent years, because of its considerable influence on the operational continuity of many industrial processes. However, the solutions give, very rarely, the location and the estimation of the degree of severity of the faults, which does not allow prioritizing actions for improving maintenance[3]. In addition, the majority of diagnostic means are not adaptive to other machine ranges. Manny works on the study of vibrations, acoustics, temperatures, rotational speed, electromagnetic torque, fluxes and currents of the induction machine has performed for this purpose. Their common point is the use of artificial intelligence techniques with more or less complexity. However, the use of stator currents constitutes the vast majority of works[4].

Among the diagnostic methods are those based on signature recognition. The fault signatures obtained by modelling or by measurement, are generally classified in a database. The analysis is performed by interpretation of the signal characteristics or by an expert system. The approaches based on the analysis of the spectral signature are the most commonly encountered to detect machine faults. The main problem with spectral analysis is the sensitivity to the quality of measurement, as well to the sampling frequency and the number of samples. To extract precisely the information relating to faults, research was particularly directed towards the spectrum of stator currents for two reasons. Currents are easy to measure; they provide information on many faults.

Pattern recognition method proposed is aimed at identifying the pattern data of currents spectrums of in order to make a decision about the fault assigned to this pattern. It uses the artificial intelligence that makes use of machine learning techniques. The artificial intelligence techniques are used more and more in the field of supervision and diagnosis of electric machines. It has made it possible to increase the efficiency and reliability of diagnosis. These methods are interesting even if they require an initial learning phase which is critical for optimal functioning. The learning phase requires a large set of examples as it can be misleading or can produce results limited to a set of systems. Once the learning phase is complete, these techniques prove to be effective and simple, and they can be successfully adopted for diagnosing system faults[5],[6].

The work presented in this paper uses pattern recognition of PSD of stator currents based on neural network technique for discrimination between faults affecting the induction machine such as: Inter-turn short-circuit fault (ITSCF), Bearing fault (BF), eccentricity fault (EF) and broken bar fault(BBF). For that, the paper is structured in four sections. After having mentioned the importance of diagnosis and the faults affecting the induction machine, a presentation of the faults taken into consideration in our work and their effects on the PSDs of stator currents was carried out in the second part. Then, the third section gives detailed description of the proposed approach and explains the process of shape recognition by neural networks adopted. The results obtained are presented in the fourth section. And finally a conclusion which summarizes all the remarks and the results obtained[7],[8].

Current signature of faulty induction machine

Induction machines are subject to many types of faults. These can be classified according to their origins into two main families: electrical faults and mechanical faults[2],[9]. Figure.1 gives the classification of principal faults affecting induction machine according to their origins.

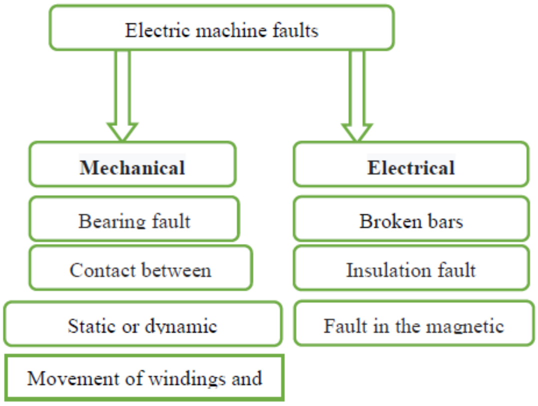


Fig. 1. Classification of IM faults according to their origins.

Electrical faults

a - Short circuit fault

The stator faults manifest in the form of an inter-turn short circuit, a short circuit between two phases or a short circuit between a phase and the machine housing[10],[11],[12]. It is schematized by the straightforward connection between two points of the winding (figure .2).

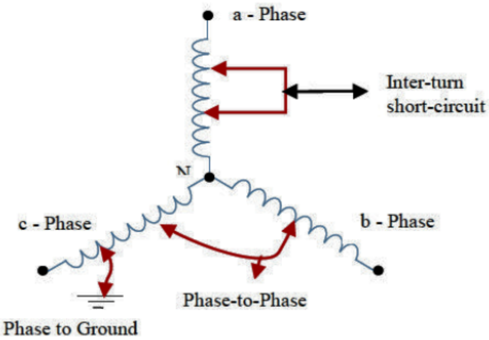


Fig. 2. Representation of IM windings containing short-circuit faults.

Generally, short-circuits between phases appear in the coil heads. Short-circuits between turns of the same phase can appear either at the level of the coil heads or in the notches, which leads to a reduction in the number of effective turns of the winding.

The frequency components linked to inter-turns short-circuit faults can be expressed by the presence of the third harmonics in the spectrum of the stator current. The figures below show the stator current signals and their PSD that have used in the detection of inter-turns short-circuit faults.

b - Broken bar fault

For a cage rotor, the breaking of bars or the breaking of rings can be due, for example, to a mechanical overload (frequent starts…), to excessive local heating or to a manufacturing defect (air bubbles or bad welds)[13],[14],[15]. Figure .3 shows a rotor cage with broken bar and broken ring.

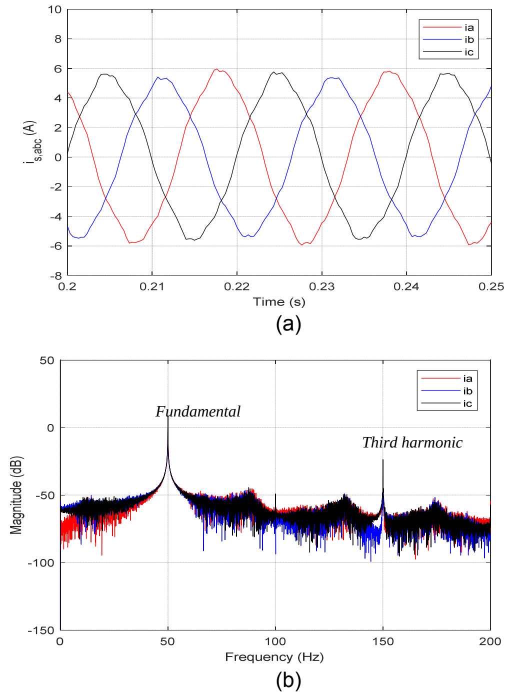


Fig. 3. Stator currents and their PSD of IM under ITSC faults

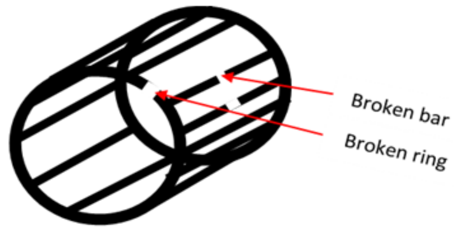


Fig. 4. Representation of IM rotor containing a Broken bar and ring fault.

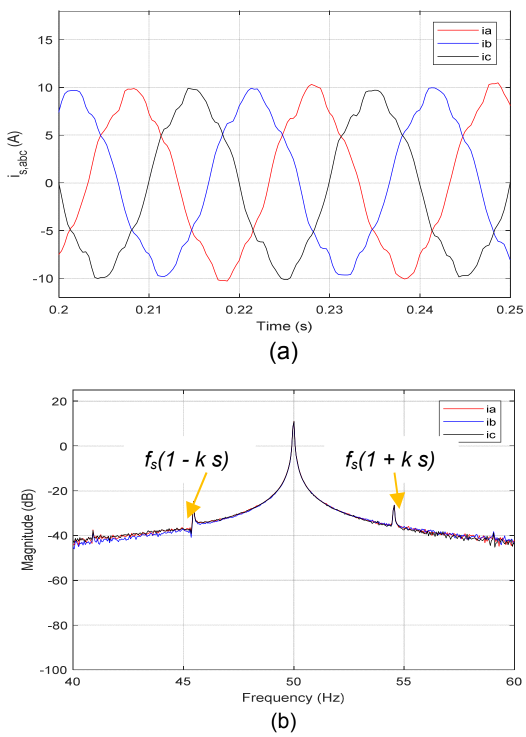


Fig. 5.Stator currents and their PSD of IM under broken bar fault

The frequency components linked to the broken bar fault can be expressed by the relation:

(1) $$f_{broken-bar}(Hz)=f_s\left(1\pm 2ks\right) \quad , k=1, 2, 3...$$

With: f_s: Source frequency, s: slip,

The figures 5 show the stator current signals and their PSD, which have used in the detection of a broken bar fault.

Mechanic faults

a - Bearing fault

The ball bearing is one of the most important components of electric machines[16],[17]. This bearing mainly consists of an outer ring, an inner ring, balls and a cage, which ensures equidistance between the balls as shown in

Figure 6.

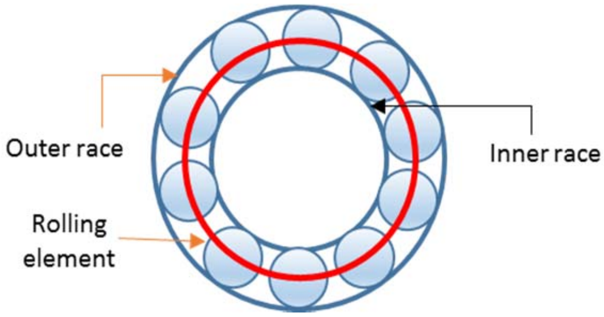


Fig. 6. Representation of bearing.

Bearing faults can appear under stresses related to the fatigue of the material, or environmental causing vibrations of the machine. The frequency components linked to bearing faults can be expressed by the relationships[17],[18],[19]:

(2) $$f_{\mathrm{bearing}}(Hz)=f_{rot}\left|f_s \mp k.f_v\right| \quad ,k=1, 2, 3..$$

With:
f_v is one of the vibration frequencies characterizing the failing element defined by equations (3), (4), (5) and (6), that is to say:

(3) $$f_{cage}(Hz)=\frac{1}{2}f_{rot}\left[1-\left(\frac{D_b}{D_p}\cos(\beta)\right)\right]$$

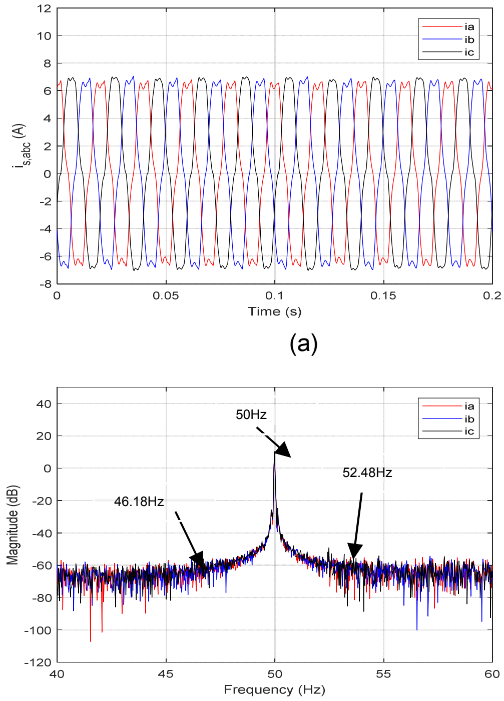
(4) $$f_{outer-ring}(Hz)=\frac{N_b}{2}f_{rot}\left[1-\left(\frac{D_b}{D_p}\cos(\beta)\right)\right]$$

(5) $$f_{inner-ring}(Hz)=\frac{N_b}{2}f_{rot}\left[1+\left(\frac{D_b}{D_p}\cos(\beta)\right)\right]$$

(6) $$f_{ball}(Hz)=\frac{D_b}{2D_p}f_{rot}\left[1-\left(\frac{D_b}{D_p}\cos(\beta)\right)^2\right]$$

With: f_{rot}: rotating shaft frequency, D_b: ball diameter, D_p: pitch diameter, N_b: Number of bearing elements, β: Ball contact angle

The figures 7 show the stator current signals and their PSD, which have used for detection of bearing faults.



(a)

(b)

Fig. 7.Stator currents and their PSD of IM under Bearing fault.

b - Bearing fault

The consequences of mechanical faults generally appear at the air gap by: static, dynamic or mixed eccentricity faults,[20],[21] (figure .8):

-The static eccentricity fault is generally due to a misalignment of the rotation axis of the rotor with the stator axis.

- The dynamic eccentricity fault can be caused by deformation of rotor cylinder, deformation of stator cylinder or deterioration of ball bearings.

- The most frequent is the mixed eccentricity which is the combination of the static eccentricity and the dynamic eccentricity

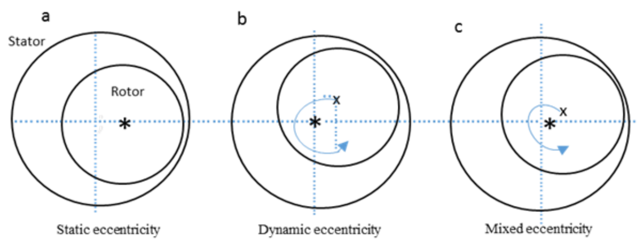


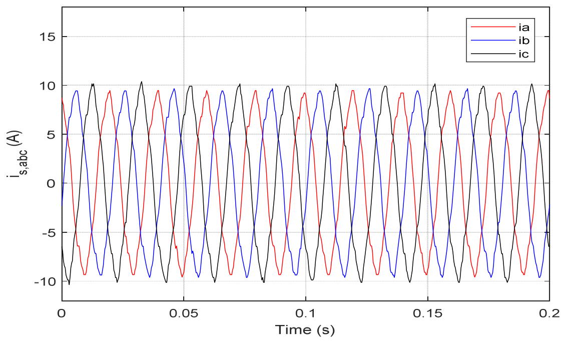
Fig. 8. Representation of the types of eccentricity faults.

The frequency components linked to static, dynamic and mixed eccentricity faults can be expressed by the relation:

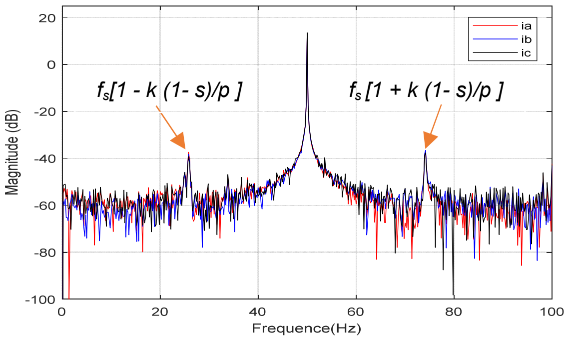
(7) $$f_{exc}(Hz)=f_s\left[1\pm k\,\frac{(1-s)}{p}\right] \quad , \mathrm{k}=1, 2, 3...$$

With: p: Number of pole pair.

The figures 9 show the stator current signals and their PSD, which have used in the detection of eccentricity faults.



(a)



(b)

Fig. 9.Stator currents and their PSD of IM under static eccentricity fault .

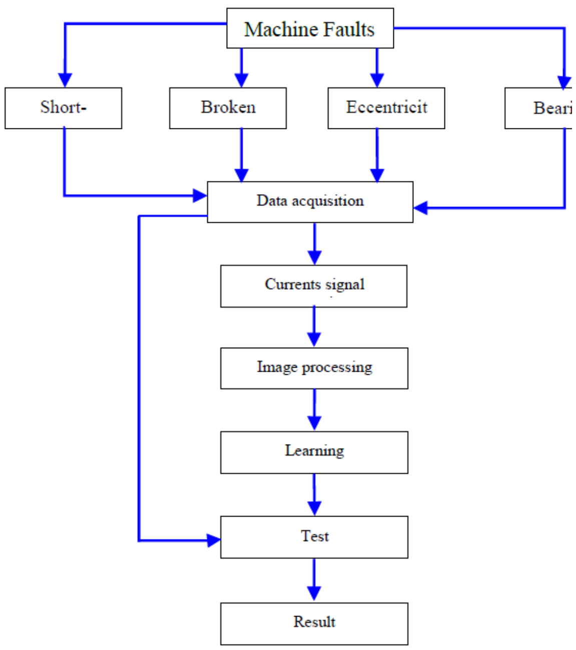


Fig. 10. Flowchart of the proposed method for discriminating faults affecting IM.

Proposed method

Our method is based on neural networks and pattern recognition. It automates the diagnostic process from the acquisition of data on the machine to decision-making without the intervention of an expert. It uses the parameters from the stator current signal. These parameters constitute the characteristic signature of the fault. A learning base integrating fault signatures in different operating modes is used[22],[12],[23],[24].

The characteristic signature of the fault has extracted from each of the measurements performed on the machine. The decision rules used made it possible to classify the observations described by the shape vector, in relation to the various known operating modes with or without fault.

The majority of Pattern Recognition systems have the following operating procedure[25],[26],[27].

- Data preparation
- Learning:
- Classification

This flowchart clearly describes the steps followed in the proposed method for discriminating faults affecting the induction machine.

a - Data preparation

a-a – Data acquisition

The measurement workbench realised uses three current sensors (Fluck i30s) to measure the stator currents. All these signals have digitized at the same time using a 08-type acquisition card (NI USB-6229). All the acquisitions have made in steady state with a rotation speed of 1410 rpm. The acquisition parameters chosen are respectively: an acquisition time of 10 seconds and a sampling frequency of 3 KHz.

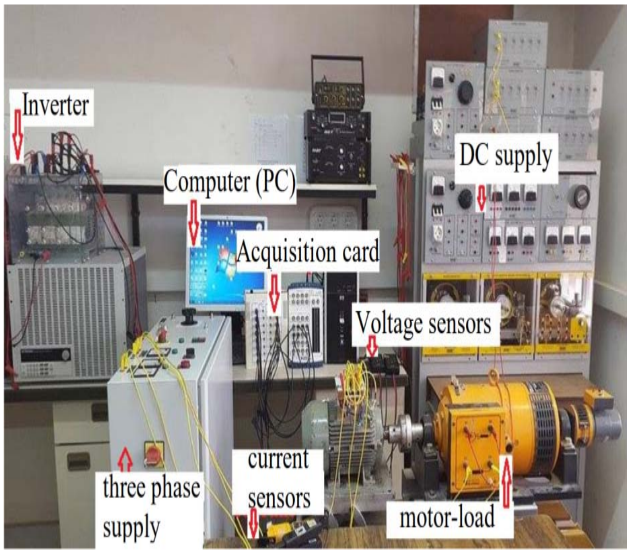


Fig. 11. Currents acquisition Workbench.

a-b- Data processing

The diagnosis of fault most often requires the use of signatures. This approach uses signal processing techniques. In our application, the characteristic vector, used as the input of the neural network, has extracted from the power spectrum of the stator current signals. The calculation of the PSD $\hat{P}(f)$of the sampled current $i_s(n)$ has carried out with the relation[28],[29],[30]:

$$\hat{P}_{is}(f) = \frac{1}{N}\left|\sum_{n=0}^{n-1} i_s(n)e^{-j2\pi fn}\right|^2 \quad (8)$$

For better visualization of the components of the frequency spectrum, we use so-called weighting windows. The expression of the PSD has given by the following equation:

$$\hat{P}_{is}(f) = \frac{1}{N}\left|\sum_{n=0}^{n-1} \omega(n)\, i_s(n)e^{-j2\pi fn}\right|^2 \quad (9)$$

With: ω (n): represents the mathematical expression of the chosen weighting window.

The best-known weighting windows are hamming, Hanning, and Blackmann. Each of them allows you to choose the desired ratio between the width of the main lobe and the attenuation of the height of the secondary lobe of the frequency spectrum[22],[31],[32].

The Hamming window has optimized to minimize the nearest side lobe. It reduces the ripple on either side of the peak. Consequently, it give a more accurate idea of the original signal's frequency spectrum. For that, it has chosen for our application. An example of currents PSD pattern after introducing the Hamming windows has presented in the below figure.

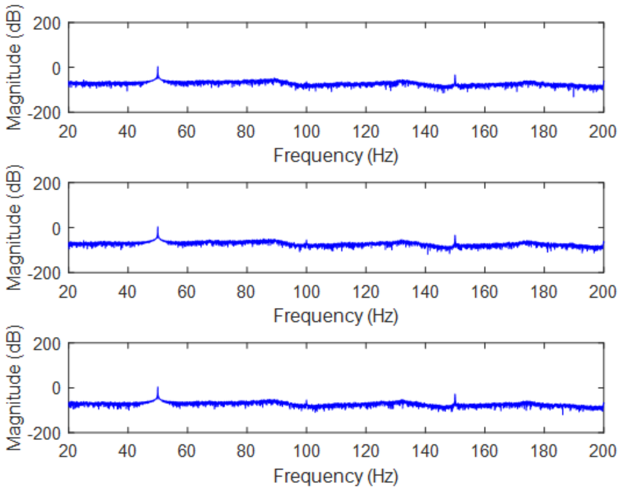


Fig. 12. Currents PSD with hamming window.

a-c- Signature digitization

To be able to use in the neural network learning process for pattern recognition, the PSD of the currents has considered as images. Each pixel coordinates (Ix, Iy) have given as follows:

$$\begin{cases} I_x = \dfrac{[fix(f-\min(F))]}{K_x} + 1 \\ I_y = \dfrac{[fix(p-\min(P))]}{K_y} + 1 \end{cases} \qquad (10)$$

With:

$$\begin{cases} K_x = \dfrac{(\max(F)-\min(F))}{L_x-1} \\ K_y = \dfrac{(\max(P)-\min(P))}{L_y-1} \end{cases} \qquad (11)$$

F and P are the frequency and Currents PSD vector respectively.

f and p are the element of the vectors F and P respectively

L_x and L_y are the pixel numbers belong (x) and (y) axis of the image. in our case, we choose: $L_x = L_y = 100$.

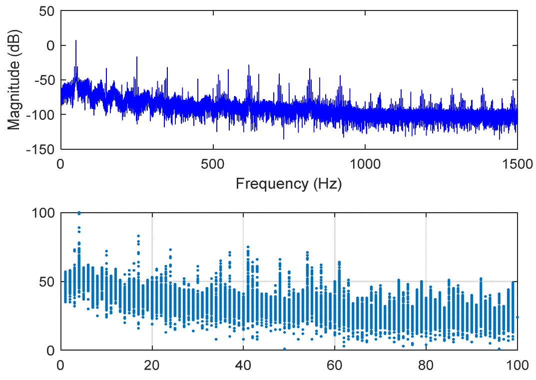
In the digitized image, we consider the foreground pixels (object pixels) I (xi, yi) = 1, the other pixels are the background pixels I (xi, yi) = 0.

a-d- Database organisation

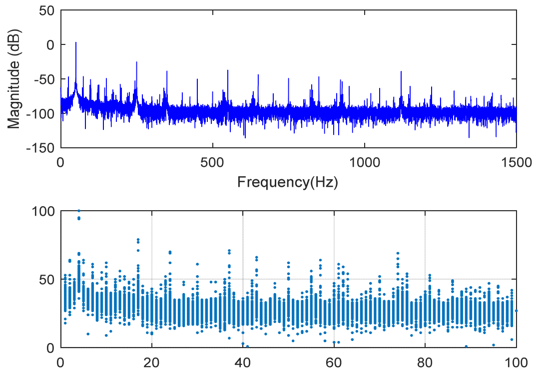
For a multilayer perceptron model, the learning database has created using 320 samples of the digitized image vectors in input layer and their equivalent vectors in the output layer.

The digitized image vectors of the stator currents PSDs have the size of 30,000 elements, which regroup the image vector of the three-stator currents respectively. The output vectors have four binary elements. Each elements represent the presence of a class of fault.

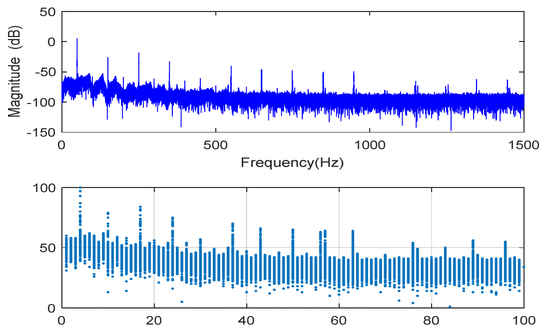
a) Short circuit fault



b) Broken bar fault



c) Bearing fault



d) Eccentricity fault

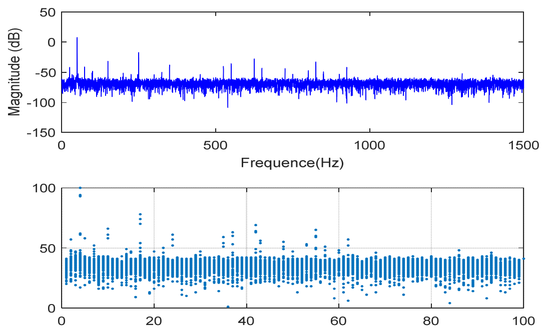


Fig. 13. Digitized fault signatures.

The input vectors and the target vectors have divided into three sets, as follows:

- 70% for training.
- 15% to validation
- 15% for test

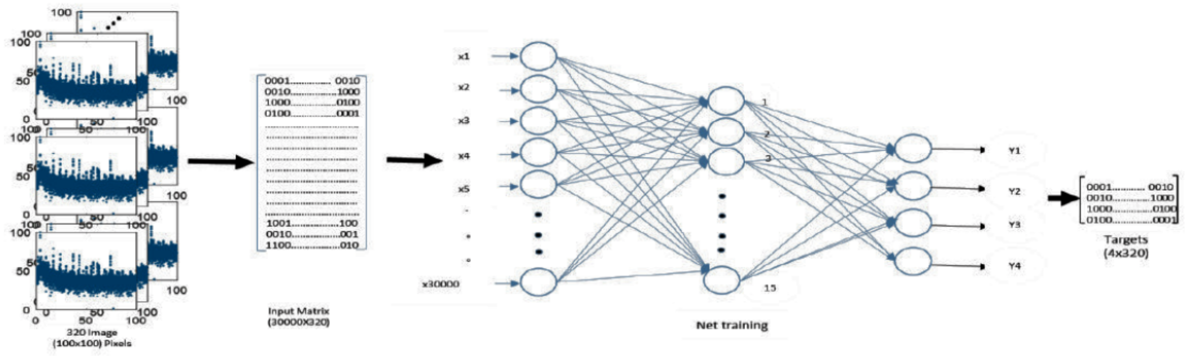


Fig.14. Block diagram of the proposed method

b – Learning

The network used for pattern recognition is a standard three-layer anticipation network: Input layers, hidden layers and output layers. The input represented by the input signals. The neurons in the hidden layer behave like characteristic detectors. While, the neurons in the output layer present the conclusions obtained by the network (Fig.14). A sigmoid transfer function in the masked layer and a softmax transfer function in the output layer are used.

C – Classification Test

To evaluate the capacity of our ANN and generalized the method, we did test it in the healthy case and in the faulty cases. The performance of this test has illustrated in figure 15 and 16, where we can see that the ANN developed shows a good accuracy. It is able to identify accurately the state of the machine.

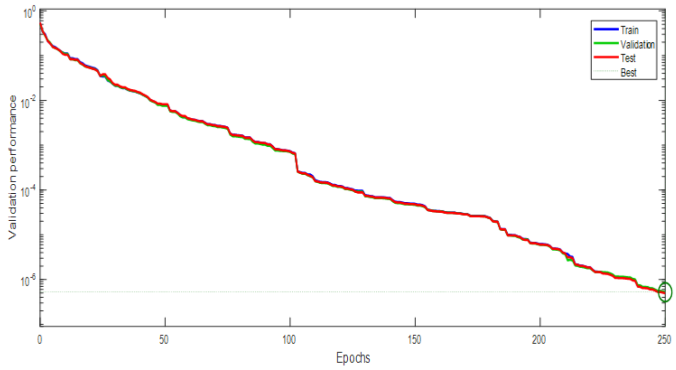


Fig. 14. Validation performance

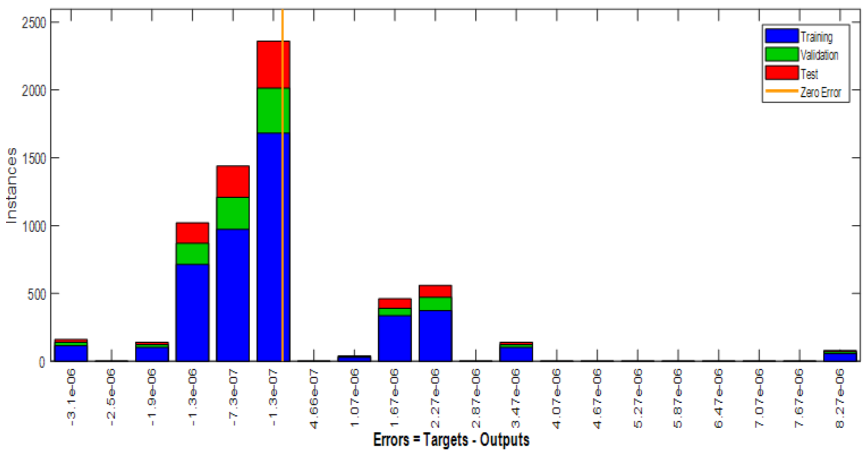


Fig. 15. Error histogram.

Conclusion

The work presented in this article contributes to the development of monitoring system based on pattern recognition methods to the diagnosis of faults in induction machines. We considered certain faults created in the stator and the rotor, specifically: broken bars in the rotor, bearing fault, stator short circuit and eccentricity fault. The approach used consists in exploiting the PSD representation of the stator currents. Based on this signature, we then built a database classified by type of fault. Based on neural networks technique, a learning process has carried out then. The results presented in this paper clearly show the effectiveness and robustness of the proposed approach. This approach allows classification with an almost zero error rate. It is flexible and easy to implement. Therefore, this method lends itself well for online diagnosis.

Appendix

Table 1. Motor parameters

Description	Value	Units
Nominal power	3	kW
Supply frequency	50	Hz
Rotation speed	1410	tr/mn
Resistance of a stator phase	5.5	Ω
Stator leakage inductance	0.063.	H
Resistance of a rotor bar	150	μΩ
Resistance of a short-circuit ring	1.59	μΩ
Leakage inductance of a rotor bar	0.603	nH
Short circuit ring leakage inductance	2	nH
Moment of inertia	0.058	kgm^2
Number of pairs of pole	2	-

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REFERENCES

[1] M. B. Abdelkader LAKROUT Noureddine HENINI, "Detection of Inter Turn Short Circuit Fault in Induction Motor Using Artificial Neural Network Approach," presented at the Conference on Electrical Engineering (CEE 2019), 2019.
[2] S. Bazine and J. C. Trigeassou, "Les défauts des machines électriques et leur diagnostic," 2010.
[3] D. M. Sonje, P. Kundu, and A. Chowdhury, "Detection and discrimination of simultaneous stator inter-turn and broken rotor bar faults in induction motor," presented at the 2015 International Conference on Condition Assessment Techniques in Electrical Systems (CATCON), 2015, pp. 133–138.
[4] A. Lakrout, M. Bendjebbar, and N. Henini, "Electric Stator Faults Detection in Induction Motor based on Fuzzy Logic Technique," presented at the 2018 International Conference on Applied Smart Systems (ICASS), 2018, pp. 1–5.
[5] P. A. Panagiotou, I. Arvanitakis, N. Lophitis, J. A. Antonino-Daviu, and K. N. Gyftakis, "A new approach for broken rotor bar detection in induction motors using frequency extraction in stray flux signals," *IEEE Transactions on Industry Applications*, vol. 55, no. 4, pp. 3501–3511, 2019.
[6] A. Boum, N. Y. J. Maurice, L. N. Nneme, and L. M. Mbumda, "Fault diagnosis of an induction motor based on fuzzy logic, artificial neural network and hybrid system," *Int J Control*, vol. 8, no. 2, pp. 42–51, 2018.
[7] S. S. Refaat, H. Abu-Rub, and A. Iqbal, "ANN-based system for a discrimination between unbalanced supply voltage and phase loss in induction motors," 2014.
[8] S. S. Refaat and H. Abu-Rub, "ANN-based diagnosis of incipient stator winding turn faults for three-phase induction motors in the presence of unbalanced supply voltage," presented at the IECON 2015-41st Annual Conference of the IEEE Industrial Electronics Society, 2015, pp. 005328–005334.
[9] M. Harir and A. Bendiabdellah, "Stator current spectral content of an induction motor taking into account saturation effect," *Przegląd Elektrotechniczny*, vol. 94, 2018.
[10] N. Lashkari and J. Poshtan, "Detection and discrimination of stator interturn fault and unbalanced supply voltage fault in induction motor using neural network," presented at the The 6th Power Electronics, Drive Systems & Technologies Conference (PEDSTC2015), 2015, pp. 275–280.
[11] L. Maraaba, Z. Al-Hamouz, and M. Abido, "An efficient stator inter-turn fault diagnosis tool for induction motors," *Energies*, vol. 11, no. 3, p. 653, 2018.
[12] F. Jia, Y. Lei, J. Lin, X. Zhou, and N. Lu, "Deep neural networks: A promising tool for fault characteristic mining and intelligent diagnosis of rotating machinery with massive data," *Mechanical Systems and Signal Processing*, vol. 72, pp. 303–315, 2016.
[13] M. E. Iglesias-Martínez, P. F. de Córdoba, J. A. Antonino-Daviu, and J. A. Conejero, "Detection of bar breakages in induction motor via spectral subtraction of stray flux signals," presented at the 2018 XIII International Conference on Electrical Machines (ICEM), 2018, pp. 1796–1802.
[14] M. O. Mustafa, D. Varagnolo, G. Nikolakopoulos, and T. Gustafsson, "Detecting broken rotor bars in induction motors with model-based support vector classifiers," *Control Engineering Practice*, vol. 52, pp. 15–23, 2016.
[15] A. S. Al-Mashakbeh, D. Mamchur, A. Kalinov, and M. Zagirnyak, "A diagnostic of induction motors supplied using frequency converter basing on current and power signal analysis," *Przegląd Elektrotechniczny*, vol. 92, no. 12, pp. 5–8, 2016.
[16] M.-N. Saadi, M. Boukhenaf, A. Redjati, and N. Guersi, "Bearing failures detection in induction motors using the stator current analysis based on Hilbert Huang transform," presented at the 2017 European Conference on Electrical Engineering and Computer Science (EECS), 2017, pp. 101–106.
[17] M. B. KOURA and A. H. BOUDINAR, "Comparaison entre la Technique Vibratoire et la Technique des Courants Statoriques: Application au Diagnostic des Roulements à Billes," presented at the 2018 International Conference on Electrical Sciences and Technologies in Maghreb (CISTEM), 2018, pp. 1–6.
[18] H. Shao, H. Jiang, H. Zhao, and F. Wang, "A novel deep autoencoder feature learning method for rotating machinery fault diagnosis," *Mechanical Systems and Signal Processing*, vol. 95, pp. 187–204, 2017.
[19] I. Ishkova and O. Vítek, "Detection and classification of faults in induction motor by means of motor current signature analysis and stray flux monitoring," *Przegląd Elektrotechniczny*, vol. 92, no. 4, pp. 166–170, 2016.
[20] P. S. Puhan and S. Behera, "Application of soft computing methods to detect fault in AC motor," presented at the 2017 International Conference on Advances in Computing, Communication and Control (ICAC3), 2017, pp. 1–5.
[21] J. Sun, C. Yan, and J. Wen, "Intelligent bearing fault diagnosis method combining compressed data acquisition and deep learning," *IEEE Transactions on Instrumentation and Measurement*, vol. 67, no. 1, pp. 185–195, 2017.
[22] M. He and D. He, "Deep learning based approach for bearing fault diagnosis," *IEEE Transactions on Industry Applications*, vol. 53, no. 3, pp. 3057–3065, 2017.
[23] A. Khiam, M. Ouassaid, and N. Ngote, "A Hybrid TSA-Neural Network Approach for Induction Motor Faults Diagnosis," presented at the 2017 International Renewable and Sustainable Energy Conference (IRSEC), 2017, pp. 1–6.
[24] B. Wangngon, N. Sittisrijan, and S. Ruangsinchaiwanich, "Fault detection technique for identifying broken rotor bars by artificial neural network method," presented at the 2014 17th International Conference on Electrical Machines and Systems (ICEMS), 2014, pp. 3436–3440.
[25] V. Sreeram and M. Supriya, "Fault current discrimination during induction motor starting," presented at the 2016 IEEE 6th International Conference on Power Systems (ICPS), 2016, pp. 1–4.
[26] M. Subha, N. S. Kumar, and K. K. Veni, "Artificial Intelligence Based Stator Winding Fault Estimation in Three Phase Induction Motor," presented at the 2018 Second International Conference on Electronics, Communication and Aerospace Technology (ICECA), 2018, pp. 1929–1933.
[27] M. WOLKIEWICZ and G. TARCHAŁA, "Diagnostyka uszkodzeń elektrycznych silnika indukcyjnego zasilanego z przemiennika częstotliwości w zamkniętej strukturze sterowania," *Przegląd Elektrotechniczny*, vol. 94, 2018.
[28] J. Bulla, A. D. Orjuela-Cañón, and O. D. Flórez, "Feature extraction analysis using filter banks for faults classification in induction motors," presented at the 2018 International Joint Conference on Neural Networks (IJCNN), 2018, pp. 1–6.
[29] R. A. Patel and B. Bhalja, "Induction motor rotor fault detection using artificial neural network," presented at the 2015 International Conference on Energy Systems and Applications, 2015, pp. 45–50.
[30] R. Chehda, N. Benouzza, and N. Kada-Belghitri, "Stator current spectrum analysis applied on short-circuit fault diagnosis of SRM," *Przegląd Elektrotechniczny*, vol. 95, 2019.
[31] N. R. Devi, D. S. Sarma, and P. R. Rao, "Detection and identification of stator inter-turn faults in three-phase induction motor in presence of supply unbalance condition," presented at the 2014 IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES), 2014, pp. 1–4.
[32] K. URBAŃSKI and D. MAJCHRZAK, "Faults detection in PMSM drive using Artificial Neural Network," *Przegląd Elektrotechniczny*, vol. 93, 2017.