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Application of a wavelet neural network approach to detect stator winding short circuits in asynchronous machines

Introduction. *Nowadays, fault diagnosis of induction machines plays an important role in industrial fields. In this paper, Artificial Neural Network (ANN) model has been proposed for automatic fault diagnosis of an induction machine. The* ***aim*** *of this research study is to design a neural network model that allows generating a large database. This database can cover maximum possible of the stator faults. The fault considered in this study take into account a short circuit with large variations in the machine load. Moreover, the objective is to automate the diagnosis algorithm by using ANN classifier.* ***Method****. The database used for the ANN is based on indicators which are obtained from wavelet analysis of the machine stator current of one phase. The developed neural model allows to taking in consideration imbalances which are generated by short circuits in the machine stator. The implemented mathematical model in the expert system is based on a three-phase model. The mathematical parameters considered in this model are calculated online. The characteristic vector of the ANN model is formed by decomposition of stator current signal using wavelet discrete technique.* ***Obtained results*** *show that this technique allows to ensure more detection with clear evaluation of turn number in short circuit. Also, the developed expert system for the taken configurations is characterized by high precision.* References 18, tables 5, figures 4.

Key words: **discrete wavelet transform, induction machine, three-phase model, multilayer perceptron neural network.**

Вступ*. Нині діагностика несправностей асинхронних машин відіграє значну роль у промисловості. У цій статті запропоновано модель штучної нейронної мережі для автоматичної діагностики несправностей асинхронної машини.* ***Метою*** *цього дослідження є розробка моделі нейронної мережі, що дозволяє генерувати велику базу даних. Ця база може охоплювати максимально можливі несправності статора. Несправності, розглянуті у цьому дослідженні, враховують коротке замикання при великих коливаннях навантаження машини. Крім того, мета полягає в тому, щоб автоматизувати алгоритм діагностики за допомогою класифікатора штучної нейронної мережі.* ***Метод****. База даних, що використовується для штучної нейронної мережі, заснована на показниках, отриманих в результаті вейвлет-аналізу струму статора машини однієї фази. Розроблена нейронна модель дозволяє враховувати дисбаланси, що виникають при коротких замиканнях у статорі машини. Реалізована математична модель в експертній системі ґрунтується на трифазній моделі. Математичні параметри, що враховуються в цій моделі, розраховуються онлайн. Характеристичний вектор моделі штучної нейронної мережі формується шляхом розкладання сигналу струму статора з використанням вейвлет-дискретного методу.* ***Отримані результати*** *показують, що дана методика дозволяє забезпечити більше виявлення з чіткою оцінкою числа витків при короткому замиканні. Також розроблена експертна система для конфігурацій, що приймаються, відрізняється високою точністю.* Бібл. 18, табл. 5, рис. 4.

Ключові слова: **дискретне вейвлет-перетворення, асинхронна машина, трифазна модель, багатошарова персептронна нейронна мережа.**

Introduction. The application of the discrete wavelet transform (DWT) technique demonstrates significant results in terms of fault diagnosis [1, 2]. The discrete decomposition of the stator current to multilevel gives a real image about stator fault of the induction machine. Detection of non-stationary produced by the stator current during a short circuit is obtained by using multilevel decomposition. Diagnosis by using wavelet techniques for discrete and continuous signals has been presented in [1-3]. Fault diagnosis methods that based on the fast Fourier transform approach are more efficient for stationary signals or permanent regime. Furthermore, these methods are largely used for fault detection and isolation scheme of induction machines [2]. However, the fast Fourier transform approach is not efficient and has drawbacks for no-stationary signals [1, 4]. To resolve these drawbacks the DWT technique has been proposed. This last is not only used for fault detection and localization in the machine stator (such as short circuit), but also it allows extracting their frequency. The frequency extraction is performed based on decomposition of the stator current to multilevels.

The proposed technique offers a powerful analysis of signals. In signal processing field this technique is considered as an important tool of diagnosis for the induction machines [5, 6]. So, to ameliorate the diagnosis procedure for induction machine a novel approach has been proposed. This approach is hybridization between neural networks (NNs) and the DWT technique. The principal of the proposed approach is given as follow: first by using the DWT technique three parameters (energy, Kurtosis and singular values), which are associated to a stator fault are calculated. These three parameters must be extracted for each level of the current stator. The obtained results demonstrate the effectiveness of the proposed approach for fault detection and isolation in induction machines.

Automatic fault detection and localization using NNs for the three-phase model of the induction machine, is considered more realistic «Xianrong Chang model» [7]. Intern faults which are studied in this work are short circuits between turns of the same stator phase. This model allows taking into account disequilibrium in the stator. This disequilibrium can generate a short circuit between turns.

Several methods have been developed in literature. These methods are based on NNs [7-9], shape recognition [1, 10], fuzzy logic [11], genetic algorithms [12], time-frequency representations. All these methods are used to automate the diagnosis process basing on data acquisition from the machine for without intervention of an expert.

NNs represent a preferred solution for diagnosis problems using automatic classification of signals and shapes. In this context, many applications of NNs are distinguished for fault diagnosis and especially for electrical machines [13].

In fact, NNs are largely exploited in the field of classification and shape recognition. Their outputs allow approximating the inputs to different classes; which means that a NN can work as an optimal classifier [14]. NNs are characterized by a mathematical structure, and able to generate behavioral model from input-output data of dynamic systems. Recently, NNs have known large use in modeling, controlling and supervision of industrial systems. Using NN models for measuring, observing and diagnosis can solve many problems of classical modeling. These models allow global monitoring for complex systems, and offer the possibility of fault isolation with necessary decisions [15].

Following the obtained results given in [1] and taking into consideration the results of [2, 3, 16], it is possible to select as an input vector for the NN model the stored energy [17], the Kurtosis and the singular values decomposition (SVD) of each level (D_3, D_4, D_5, D_6, D_7) and the resistant torque value. The designed NN model has three layers. Many tests of classification have been realized to determine the optimal structures of the NN model. The NN model used for discrimination of the stator fault is described as follow:

- 16 neural for the input layer;
- 10 neural for the hidden layer;
- 4 neural for the output layer.

The **main objective** of this research work is to present developments by applying NNs in fault diagnosis. Methods of diagnosis based on a black box model type (NNs with supervised learning) have been adopted. This research work is subdivided in two steps:

- The first step concerns a formulation of an input vector based on the Kurtosis values, SVD and the stored energy values in each level D_3, D_4, D_5, D_6, D_7 with variations in short circuit percentage between 0 to 15 %. This formulation is applied for the phase A, B and C respectively in different operating regime from 0 to 7 N·m with a variation step of 0.25.
- The second step concerns the classifier conception to classify the operating modes of the induction machine. So, different classes are distinguished, three classes are used for fault cases and one class is used for normal case.

Three-phase equivalent model of unbalanced asynchronous machine (X. Chang model). The present paper shows an induction machine model taking into account a short circuit in the three-phases of the machine. To extract electrical faults signature, the stator currents of the phases are used. First, to detect effectively the presence of the signatures related to the stator currents of three-phase model, sophisticated techniques have been proposed. Furthermore, the obtained results using numerical simulation demonstrate that excellent performances have been obtained using the proposed method. Finally, in last section, many comments and explanations are highlighted. The model used in this work is the X. Chang model which equivalent three-phase model having the following properties:

- all parameters of the model are computable online;
- this model is derived directly from the equivalent three-phase model, no additional assumptions required;
- the mutual inductances no longer depend on the relative position between the stator and the rotor, the value of this position is unknown in practice;
- the model is verified by comparing the simulation data to the experimental data obtained on a test rig (Poitiers LAII Laboratory, France) in the time domain.

The motor model [6] in the presence of short circuit fault is obtained from electric and magnetic equations of asynchronous machine. X. Chang et al, have proposed a transformation matrix T to transform the rotor variables into new variables having the same angular stator frequency. Equations (1) – (4) represent the new three-phase model in which all parameters can be computed on-line [8, 9]:

$$[U_s]=[R_s]\times[I_s]+[P\,\Psi_s]; \qquad (1)$$

$$[0]=[R_r]\times\left[I_r^s\right]+(1-g)\Omega\left[K_{rs}^{sp}\right]\left[\Psi_r^s\right]+P\left[\Psi_r^s\right]; \qquad (2)$$

$$[\Psi_s]=[M_s]\times[I_s]+\left[M_{sr}^s\right]\times\left[I_r^s\right]; \qquad (3)$$

$$\left[\Psi_r^s\right]=\left[M_{sr}^s\right]\times[I_s]+\left[M_r^s\right]\times\left[I_r^s\right]; \qquad (4)$$

where P is the differential operator d/dt.

- stator variables are:

$$[U_s]=[u_{sa}\quad u_{sb}\quad u_{sc}]^T; \qquad (5)$$

$$[I_s]=[I_{sa}\quad I_{sb}\quad I_{sc}]^T; \qquad (6)$$

$$[\Psi_s]=[\Psi_{sa}\quad \Psi_{sb}\quad \Psi_{sc}]^T; \qquad (7)$$

$$[U_r]=[0\quad 0\quad 0]^T; \qquad (8)$$

- rotor variables are:

$$[I_r]=[I_{ra}\quad I_{rb}\quad I_{rc}]^T; \qquad (9)$$

$$[\Psi_r]=[\Psi_{ra}\quad \Psi_{rb}\quad \Psi_{rc}]^T; \qquad (10)$$

$$\left[\Psi_r^s\right]=[T]\times[\Psi_r]; \qquad (11)$$

$$\left[I_r^s\right]=[T]\times[I_r]; \qquad (12)$$

$$\left[M_{rs}^s\right]=[T]\times[M_{rs}]; \qquad (13)$$

$$\left[M_r^s\right]=[T]\times[M_r]\times[T]^{-1}; \qquad (14)$$

It is important to note that the matrixes $[R_s]$, $[R_r]$, $[L_{s\sigma}]$, $[L_{r\sigma}]$, $[M_{ss}]$, and $[M_{rr}]$ are constant matrixes. The parameters values depend on the number of considered coils turns. The matrixes $[M_{sr}]$ and $[M_{rs}]$ are with coefficients varying over time. Thus, the coefficients are in function of the relative position θ between the stator and the rotor. This position is defined as follows: θ is the angle between the stator phase A and the rotor phase A, thus the following expressions are obtained:

$$\begin{cases}\theta\cong\int\Omega'\mathrm{d}t;\\ \Omega'\cong(1-g)\Omega;\\ g\cong(\Omega-\Omega')/\Omega,\end{cases}$$

where g is the slip coefficient; Ω is the rotating field speed; Ω' is the rotor mechanical speed.

If the rotor is balanced, the following equations are deduced:

$$[R_r]=\begin{bmatrix}R_r & 0 & 0\\ 0 & R_r & 0\\ 0 & 0 & R_r\end{bmatrix}; \qquad (15)$$

$$[L_{r\sigma}]=\begin{bmatrix}L_{r\sigma} & 0 & 0\\ 0 & L_{r\sigma} & 0\\ 0 & 0 & L_{r\sigma}\end{bmatrix}; \qquad (16)$$

$$[M_{rr}]=\begin{bmatrix}M_r & -M_r/2 & -M_r/2\\ -M_r/2 & M_r & -M_r/2\\ -M_r/2 & -M_r/2 & M_r\end{bmatrix}. \qquad (17)$$

The following coefficients are defined as:

$f_{sa}^* = 1 - f_{sa}$; $f_{sb}^* = 1 - f_{sb}$; $f_{sc}^* = 1 - f_{sc}$, where f_{sa}, f_{sb} and f_{sc} are the percentages of turns number reduction in stator 3 phases A, B and C.

The matrixes $[R_s]$, $[L_{s\sigma}]$, $[M_{ss}]$, $[M_{sr}]$ and $[M_{rs}]$ depend on 3 coefficients f_{sa}^*, f_{sb}^* and f_{sc}^*:

$$[R_s] = R_s \begin{bmatrix} f_{sa}^* & 0 & 0 \\ 0 & f_{sb}^* & 0 \\ 0 & 0 & f_{sc}^* \end{bmatrix}; \tag{18}$$

$$[L_{s\sigma}] = R_s \begin{bmatrix} f_{sa}^{*2} L_{s\sigma} & L_0 & L_0 \\ L_0 & f_{sb}^{*2} L_{s\sigma} & L_0 \\ L_0 & L_0 & f_{sc}^{*2} L_{s\sigma} \end{bmatrix}; \tag{19}$$

$$[M_{ss}] = M_s \begin{bmatrix} f_{sa}^{*2} & \frac{-f_{sa}^* f_{sb}^*}{2} & \frac{-f_{sa}^* f_{sc}^*}{2} \\ \frac{-f_{sa}^* f_{sb}^*}{2} & f_{sb}^{*2} & \frac{-f_{sb}^* f_{sc}^*}{2} \\ \frac{-f_{sa}^* f_{sc}^*}{2} & \frac{-f_{sb}^* f_{sc}^*}{2} & f_{sc}^{*2} \end{bmatrix}; \tag{20}$$

$$[M_{sr}] = M \begin{bmatrix} f_{sa}^* \cos(\theta) & f_{sa}^* \cos\left(\theta + \frac{2\pi}{3}\right) & f_{sa}^* \cos\left(\theta - \frac{2\pi}{3}\right) \\ f_{sb}^* \cos\left(\theta - \frac{2\pi}{3}\right) & f_{sb}^* \cos(\theta) & f_{sb}^* \cos\left(\theta + \frac{2\pi}{3}\right) \\ f_{sc}^* \cos\left(\theta + \frac{2\pi}{3}\right) & f_{sc}^* \cos\left(\theta - \frac{2\pi}{3}\right) & f_{sc}^* \cos(\theta) \end{bmatrix}; \tag{21}$$

where:

$$[M_{sr}] = [M_{rs}]^T. \tag{22}$$

The transformation matrix T:

$$T = \frac{2}{3} \begin{bmatrix} \cos(\theta) + \frac{1}{2} & \cos(\theta + \frac{2\pi}{3}) + \frac{1}{2} & \cos(\theta - \frac{2\pi}{3}) + \frac{1}{2} \\ \cos(\theta - \frac{2\pi}{3}) + \frac{1}{2} & \cos(\theta) + \frac{1}{2} & \cos(\theta + \frac{2\pi}{3}) + \frac{1}{2} \\ \cos(\theta + \frac{2\pi}{3}) + \frac{1}{2} & \cos(\theta - \frac{2\pi}{3}) + \frac{1}{2} & \cos(\theta) + \frac{1}{2} \end{bmatrix}, \tag{23}$$

where:

$$[T]^{-1} = [T]^T. \tag{24}$$

From (1)–(4), the new model is rewritten in the following form:

$$P\left[\Psi_r^s\right] = [R_r] \times \left[M_r^s\right]^{-1} \times \left[M_{rs}^s\right] \times [I_s] - \\ -\left(\left[R_r\right] \times \left[M_r^s\right]^{-1} + (1-g)\Omega\left[K_{rs}^{sp}\right]\right) \times \left[\Psi_r^s\right]; \tag{25}$$

$$P[I_s] = \\ = \Gamma^{-1}\left(\left[U_s\right] - \left(\left[R_s\right] + \left[M_{rs}^s\right] \times \left[M_r^s\right]^{-1}\left[R_r\right]\left[M_r^s\right]^{-1}\left[M_{rs}^s\right]\right)\left[I_s\right]\right) + \\ + \Gamma^{-1}\left[M_{rs}^s\right]\left[M_r^s\right]^{-1}\left(\left[R_r\right] \times \left[M_r^s\right]^{-1} + (1-g)\Omega\left[K_{rs}^{sp}\right]\right)\left[\Psi_r^s\right], \tag{26}$$

where:

$$\Gamma = \left(\left[M_s\right] - \left[M_{sr}^s\right] \times \left[M_r^s\right]^{-1}\left[M_{rs}^s\right]\right). \tag{27}$$

The obtained equations are nonlinear; thus, a numerical method must be implemented to reach a solution and the classical 4th order Runge Kutta method is chosen:

$$\left[K_{rs}^{sp}\right] = \begin{bmatrix} 0 & \sqrt{3}/3 & -\sqrt{3}/3 \\ -\sqrt{3}/3 & 0 & \sqrt{3}/3 \\ \sqrt{3}/3 & -\sqrt{3}/3 & 0 \end{bmatrix}. \tag{28}$$

Mechanical equations. According to [10] if we consider the current and flux in three-phase frame, the following expression is obtained:

$$C_{em} = \frac{P}{\sqrt{3}} \begin{pmatrix} \Psi_{sb} I_{sa} - \Psi_{sc} I_{sa} - \Psi_{sa} I_{sb} + \\ + \Psi_{sc} I_{sb} - \Psi_{sa} I_{sc} - \Psi_{sb} I_{sc} \end{pmatrix}. \tag{29}$$

In the case of three-phase source without neutral:

$$\begin{cases} I_{sa} = -I_{sb} - I_{sc}; \\ \Psi_{sa} = -\Psi_{sb} - \Psi_{sc}. \end{cases} \tag{30}$$

From this, the equation presented below is obtained:

$$C_{em} = \sqrt{3} P (\Psi_{sc} I_{sb} - \Psi_{sb} I_{sc}). \tag{31}$$

Automatic detection steps of stator faults. DWT application for diagnosis. The three-phase model of the synchronous machine is called X. Chang, which take into account a disequilibrium mode in the stator turns [1]. This model has ability to study many phenomena more than a short circuit fault in synchronous machines, which allows to select an efficient diagnosis method. For this reason, the DWT technique has been used [1]. This technique has proved significant results in terms of short circuit faults. In addition, it facilitates the X. Chang model use in real time to diagnosis and control of machines.

Analysis of wavelets is performed in order to study the spectral behavior, elaborate reliable spectral signatures, characterize short circuit fault between turns, and estimate in real time the phase currents (I_A, I_B and I_C).

In order to study the effect of turn number in short circuit (f_{sa}, f_{sb} and f_{sc}) on one of the three stators phase the nominal load C is fixed to 7 N·m, with variation in turn number between 0 % and 15 %. The experiment tests have been realized under variation of load between 0 and 7 N·m with a sampling step equals to 0.25. The obtained results in [1] show that the application of the wavelet technique is largely used for fault diagnosis. In fact, this technique allows decomposing the stator signal for a non-stationary current during a short circuit. The direct decomposition of the stator signal to multilevels generates a real image about the induction machine stator faults.

In the research work [1], it is also remarked that the coefficient amplitudes of signals which are obtained after decomposition are augmented comparing to healthy mode of the machine.

This augmentation is interpreted by the variation of the relative stored energy associated to each level of decomposition. It is observed that, the wavelet technique is used to extract and locate the no-stationary point in signals, which allows to select the stored energy as an important fault indicator. The fault indicator is considered as a parameter to formulate input vector of the artificial neural network (ANN). So, to detect automatically the differential state between the faulty and the healthy machine an ANN is designed.

In order to analyze the no-stationary generated in the stator current during a short-cut of a phase, or in transitional mode, the decomposition of the stator current signal of a specific phase has been performed (Table 1). The decomposition test is realized by using the DWT on the phase A «Daubechies (by 40 dB)». The decomposition level n depends on the sampling frequency f_e and the supply frequency f_s and can be calculated using the equation presented below [18]:

$$n > \frac{\log(f_e / f_s)}{\log 2} + 1 , \quad (32)$$

where sampling frequency f_e = 2000 samples/s; supply frequency f_s = 50 Hz.

Table 1

Frequency bands for wavelet signal

Levels	Approximations		Details
Level 1	A1	0-1000 Hz	1000-2000 Hz
Level 2	A2	0-500 Hz	500-1000 Hz
Level 3	A3	0.250 Hz	250-500 Hz
Level 4	A4	0-125 Hz	125-250 Hz
Level 5	A5	0-62.5 Hz	62.5-125 Hz
Level 6	A6	0-31.25 Hz	31.25-62.5 Hz
Level 7	A7	0-15.625 Hz	15.625-31.25 Hz

Architecture of the automatic diagnosis system. By using the NN technique, it is possible to detect a short-cut in a stator phase during the operating of the induction machine. However, the localization of the fault represents a big problem. So, in this work the problem of localization is solved by considering specific indicators for the NN input. These indicators are used for classification and learning of the NN. The short circuit fault on the three stator phases is evident from the wavelet decomposition of stator current signal I_A, the results of the expertise carried out in our work showed that the best performance of the localization of the short circuit fault phase is the stored energy (E_j), the Kurtosis value (KT), the singular value decomposition (SVD) of each level D_3, D_4, D_5, D_6 and D$_7$:

- the proper value of the stored energy (E_j) in each band of frequency is defined by the following formulation:

$$E_j = \sum_{k=1}^{k=n} D_{j,k}^2(n). \quad (33)$$

- Several facts on Kurtosis are transformed into the one for discrete time system as:

$$KT = \frac{\int_{-\infty}^{+\infty} x^4 p(x)\mathrm{d}x}{\left[\int_{-\infty}^{+\infty} x^2 p(x)\mathrm{d}x\right]^2} = \lim_{N\to\infty} \frac{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - x')^4}{\left\{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - x')^2\right\}^2} , \quad (34)$$

where x_i: i = 1, 2, ... , N represents the discrete signal data; x' is an average of $\{x_i\}$ and given as follow:

$$x' = \frac{1}{N}\sum_{i=1}^{N} x_i , \quad (35)$$

- the decomposition to singular values (SVD) allows to extract principal components of a matrix. In the case of signals, these principal components are linked to data which maximize the energy of signal. For example, the SVD of a matrix that composes of vibratory measures in different points allows under certain conditions to extract specific dominant proper modes [4].

In Tables 2–4 among 1334 experiments examples of experiences are presented. For each experiment, the value of load is fixed and the short-cut percentage varies between 0 % and 15 % in the phase A. So, an experiment is repeated for each value of load. The load values considered in the simulation are 0, 3.5 and 7 N·m.

Table 2

Stored energy evolution (E_j) in levels D_3, D_4, D_5, D_6 and D_7 in function to short circuit in phase A

Short circuit, %	E_3	E_4	E_5	E_6	E_7	Torque C_r, N·m
0	0.00032867	0.13039	12.185	0.10273	0.090117	
1	0.00033862	0.13235	12.846	0.10392	0.089307	
5	0.00039182	0.14131	16.095	0.10922	0.086439	0
10	0.00049887	0.15584	21.936	0.11727	0.084027	
15	0.00067368	0.17576	30.673	0.12749	0.083692	
0	0.00052029	0.14211	18.863	0.11242	0.098359	
1	0.00054522	0.14478	19.988	0.11424	0.098125	
5	0.00066619	0.15701	25.356	0.12237	0.097866	3.5
10	0.00087918	0.17681	34.567	0.13490	0.099550	
15	0.00119040	0.20373	47.724	0.15096	0.104510	
0	0.00210290	0.30525	121.46	0.19438	0.196270	
1	0.00218110	0.31311	126.18	0.19935	0.199820	
5	0.00253800	0.34828	147.43	0.22160	0.216480	7
10	0.00310670	0.40248	180.55	0.25584	0.244090	
15	0.00385850	0.47173	223.27	0.29941	0.281750	

Table 3

SVD evolution in levels D_3, D_4, D_5, D_6 and D_7 in function to short circuit in phase A

Short circuit, %	SVD_3	SVD_4	SVD_5	SVD_6	SVD_7	Torque C_r, N·m
0	0.81076	16.149	156.11	14.334	13.425	
1	0.82224	16.270	160.29	14.417	13.365	
5	0.88524	16.812	179.42	14.780	13.148	0
10	0.99887	17.655	209.46	15.315	12.964	
15	1.16080	18.749	247.68	15.968	12.938	
0	1.02010	16.859	194.23	14.995	14.026	
1	1.04420	17.016	199.94	15.116	14.009	
5	1.15430	17.720	225.19	15.644	13.990	3.5
10	1.32600	18.805	262.93	16.426	14.110	
15	1.54300	20.186	308.95	17.376	14.457	
0	2.05080	24.708	492.88	19.717	19.813	
1	2.08860	25.024	502.35	19.968	19.991	
5	2.25300	26.392	543.01	21.052	20.808	7
10	2.49270	28.372	600.92	22.620	22.095	
15	2.77790	30.716	668.24	24.471	23.738	

Table 4

KT evolution in levels D_3, D_4, D_5, D_6 and D_7 in function to short circuit in phase A

Short circuit, %	KT_3	KT_4	KT_5	KT_6	KT_7	Torque C_r, N·m
0	193.16	28.635	12.3050	63.194	71.722	
1	188.78	27.614	11.9410	63.637	71.495	
5	169.47	23.783	10.391	64.755	69.782	0
10	149.21	19.579	8.4478	64.377	65.305	
15	142.86	16.032	6.7193	61.632	57.558	
0	195.95	24.129	5.4852	53.033	60.318	
1	199.08	23.101	5.2977	52.963	59.372	
5	214.10	19.302	4.6081	52.059	54.801	3.5
10	236.47	15.270	3.8850	49.466	47.383	
15	259.73	12.022	3.3069	45.319	38.634	
0	449.87	6.6108	1.7489	25.888	22.014	
1	455.70	6.3101	1.7480	25.802	21.521	
5	477.96	5.2501	1.7434	25.385	19.834	7
10	503.00	4.2131	1.7362	24.768	18.421	
15	524.31	3.4466	1.7271	24.176	17.789	

Following Tables 2–4, the stored energy (E_j), the Kurtosis value (KT) and the singular value decomposition (SVD) of different levels (D_3, D_4, D_5, D_6 and D_7) are considered efficient indicators for diagnosis of the induction machine in terms of short-cut fault.

ANN for diagnosis. The present research work focuses on the use of an artificial NN model. This model allows to estimate automatically the state of the induction machine in healthy and fault modes basing on the input indicators. Diagnosis using learning and recognition algorithms is considered as a powerful tool comparing to conventional techniques. However, training of an ANN requires a large database to attain high precision. In this sense, the three phases model of the induction machine is used (X. Chang). This model takes into account all possible situations of short circuit percentage for each stator phase.

Stator fault diagnosis by NN. The purpose of the proposed fault diagnosis system is to detect and locate short circuits on the stator windings of a three phase induction motor using ANN. The motor fault diagnosis process is shown in [1]. It is composed of four parts: data acquisition, feature extraction, fault detection and post-processing as shown in Fig. 1. The design of the ANN based fault diagnosis system can be decomposed in the following four steps [2]:

- preparation of a training data set for the ANN;
- selection of the ANN architecture;
- training of the ANN model;
- evaluation of the trained model on test dataset.

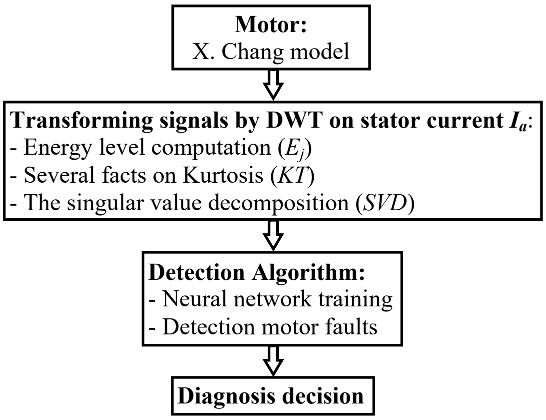

Fig. 1. Flowchart of proposed motor fault diagnosis

Preparation of the training dataset for NN. The dataset consists of examples where each example is couple of the input vector and the output default to train the classifier. Input data was collected through simulations using X. Chang's three-phase mathematical model. To locate the faulty phase of an induction motor very efficiently, since the model is practically validated in the NANTE Laboratory, the training data must cover the entire range of operating conditions, including all possible fault phenomena, even healthy cases.

The input matrix X_{train} and the output matrix Y_{train} have been used as database to train the ANN model. Equations (25), (26) and (29) are used to formulate the X_{train} matrix. The experiment tests have been realized under variation of load between 0 and 7 N·m with a sampling step equals to 0.25, which corresponds to the following different operating cases of the induction motor: healthy (29 samples) and fault of an odd number of shorted turns (with variation in turn number between 0 % and 15 %) on each stator phase [(435 = 29·15) samples]. Thus, a total of 1334 (1334 = 435·3 + 29) samples have been collected and applied as the inputs to the NNs for stator inter-turn fault diagnosis.

The desired outputs (S_i) of the NN are chosen as follows:

1) S_1 = 1 for a short circuit at phase As; otherwise, S_1 = 0;
2) S_2 = 1 for a short circuit at phase Bs; otherwise, S_2= 0;
3) S_3 = 1 for a short circuit at phase Cs; otherwise, S_3 = 0.

Therefore, the output states of the NNs are set as the following (Table 5):

[1; 0; 0; 0] – healthy mode;
[0; 1; 0; 0] – a defect has occurred on phase A;
[0; 0; 1; 0] – a defect has occurred on phase B;
[0; 0; 0; 1] – a defect has occurred on phase C.

Table 5

The output states of the NNs

Type of fault	Symbol	S1	S2	S3	S4
Healthy mode	C1	1	0	0	0
Fault occurred on phase A	C2	0	1	0	0
Fault occurred on phase B	C3	0	0	1	0
Fault occurred on phase C	C4	0	0	0	1

The ANN paradigm used in the proposed fault diagnosis system is a feed forward multilayer perceptron NN trained by a back propagation and gradient descent algorithm. The number of input units of ANN is determined by the size of the input vector. However, the number of neurons in the output layer is determined by the number of faults to be diagnosed.

The input vector values are: the stored energy eigenvalues (E_j), the Kurtosis value (KT) and the singular value decomposition (SVD) of each level D_3, D_4, D_5, D_6 and D_7. The outputs of the ANN represent the fault classes, which are the 3 phases of the induction motor, respectively, and one hidden layer with 10 neurons. The activation functions of the hidden and output layers are «tansig» and «logsig», respectively.

Training of the NN. Multilayered perceptron NNs are trained using a supervised learning algorithm known as backpropagation. Backpropagation combined with descent gradient raining is the used training algorithm. It attempts to reduce global error by updating the weights in the direction of the gradient, thereby improving the performance of the ANN.

In this paper, the error is expressed as mean square error (MSE). The training performance is shown in Fig. 2, where a low training MSE is achieved after 334 epochs ($2.6377 \cdot 10^{-7}$). The training output and error from the NN are shown in Fig. 3. From Fig. 4 it is clear that the NN is well trained and reproduces the desired output correctly with few errors.

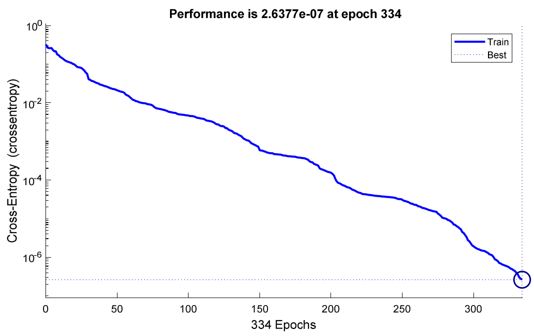

Fig. 2. Training performances of the NN

Simulation results. The performance of a NN on the test dataset is its capacity for generalization. This data set is divided into 2 parts. One set is used for training and the other set is used for testing. In fact, the trained ANN classifier performs well on both training and test data. The test procedure is carried out on an independent test dataset from the training dataset to assess the generalizability of the trained model.

The test data set is presented to the NNs under 14 load torques (0.25, 0.75, 1.25, 1.75, 2.25, 2.75, 3.25, 3.75, 4.25, 4.75, 5.25, 5.75, 6.25, and 6.75 N·m) and corresponds to the following different operating cases of the induction motor: healthy (14 samples) and fault of an even number of shorted turns (1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, and 15) on each stator phase [210 samples]. Thus, a total of 224 test samples were collected to test each phase stator inter-turn fault.

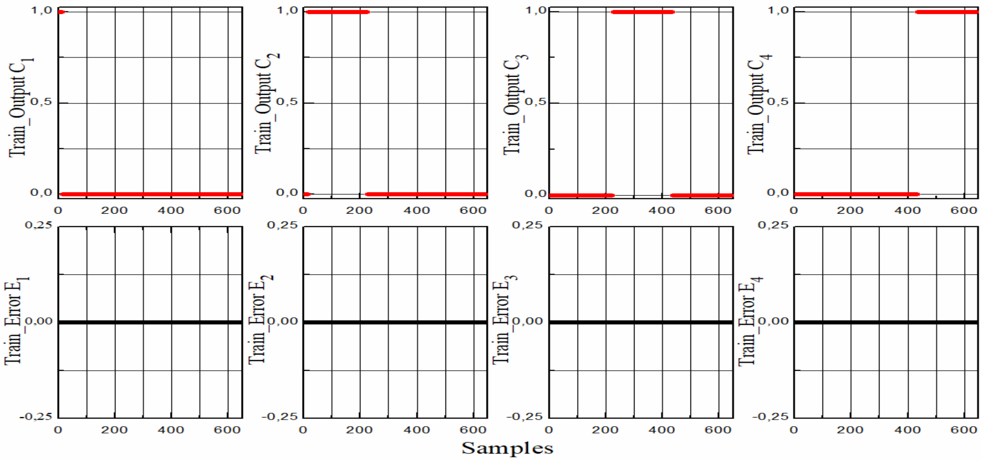

Fig. 3. Training outputs and errors of NN

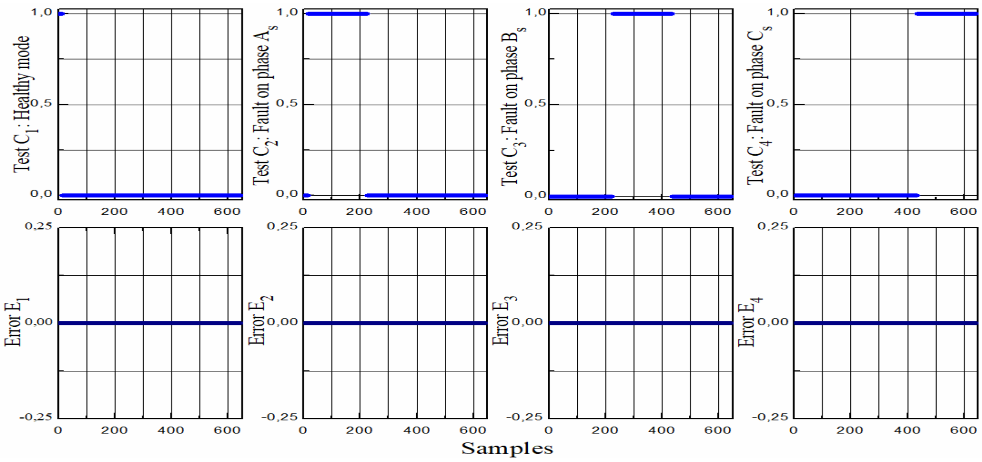

Fig. 4. Test outputs and errors for fault on phase As, Bs and Cs

Figure 4 shows the NN test outputs and their errors for faults on the As, Bs and Cs phases. The test output of the NN (C1, C2, C3, C4) is equal to (1, 0, 0, 0), (0, 1, 0, 0), (0, 0, 1, 0) and (0, 0, 0, 1) with good accuracy. This means that the NN is able to correctly locate the fault occurring on the faulty phase, As phase, Bs phase and Cs phase respectively. The test error for this case is very small. We conclude that the NN is able to correctly locate the stator inter turn short circuit fault occurring on one of the phases.

Conclusions. This article presents a technique of detection and localization of short circuit defects of turn-by-turn in induction motors, chosen as a condition model, the three-phase model of X. Chang because it takes into account the case of imbalance in the stator winding. This choice is based on the nature of the fault to be studied (short circuit) and in addition the ease of use of this model for diagnosis and monitoring. In this work, the use of two analytical methods for diagnosing and detecting defects in the machine is based on two techniques, one being discrete wavelet transform and the other on neural network fault classification techniques. The discrete wavelet transform application of the stator current in phase A is used to determine the three parameters that are sensitive to the short circuit fault: energy, kurtosis and decomposition into singular values of each level D_3, D_4, D_5, D_6 and D_7. These values are then used as inputs for classifier neural network. The information provided by this input on the detection and localization of defects makes it a reliable indicator of the short circuit defects between coils in the stator windings of induction motors. The results obtained are outstanding, and the proposed technique is capable of automatically detecting and locating short circuit failures. As another area of this paper, we can expand our research to determine the number of short circuits on a faulty phase, allowing for a complete diagnostic procedure.

Conflict of interest. The authors declare no conflict of interest.

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