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# Artificial neural network and discrete wavelet transform for inter-turn short circuit and broken rotor bars faults diagnosis under various operating conditions

***Introduction.*** *This work presents a methodology for detecting inter-turn short circuit (ITSC) and broken rotor bars (BRB) fault in variable speed induction machine controlled by field oriented control. If any of these faults are not detected at an early stage, it may cause an unexpected shutdown of the industrial processes and significant financial losses.* ***Purpose.*** *For these reasons, it is important to develop a new diagnostic system to detect in a precautionary way the ITSC and BRB at various load condition. We propose the application of discrete wavelet transform to overcome the limitation of traditional technique for no-stationary signals.* ***The novelty*** *of the work consists in developing a diagnosis system that combines the advantages of both the discrete wavelet transform (DWT) and artificial neural network (ANN) to identify and diagnose defects, related to both ITSC and BRB faults.* ***Methods.*** *The suggested method involves analyzing the electromagnetic torque signal using DWT to calculate the stored energy at each level of decomposition. Then, this energy is applied to train neural network classifier. The accuracy of ANN based on DWT, was improved by testing different orthogonal wavelet functions on simulated signal. The selection process identified 5 pertinent wavelet energies, concluding that, Daubechies44 (db44) is the best suitable mother wavelet function for effectively detecting and classifying failures in machines.* ***Results.*** *We applied numerical simulations by MATLAB/Simulink software to demonstrate the validity of the suggested techniques in a closed loop induction motor drive. The obtained results prove that this method can identify and classify these types of faults under various loads of the machine.* References 31, table 1, figures 9.

*Key words:* **diagnosis, short circuit, broken bars, induction motor, discrete wavelet transform, artificial neural network, indirect field oriented control.**

***Вступ.*** *У цій роботі представлена методологія виявлення міжвиткового короткого замикання (ITSC) та несправності стрижнів ротора (BRB) в асинхронних машинах з регульованою швидкістю, керованих полеорієнтованим керуванням. Якщо будь-яка з цих несправностей не буде виявлена на ранній стадії, це може призвести до несподіваної зупинки виробничих процесів та значних фінансових втрат.* ***Мета.*** *З цих причин важливо розробити нову діагностичну систему для профілактичного виявлення ITSC та BRB за різних умов навантаження. Ми пропонуємо застосувати дискретне вейвлет перетворення, щоб подолати обмеження традиційної техніки для нестаціонарних сигналів.* ***Новизна*** *роботи полягає в розробці системи діагностики, що поєднує в собі як переваги дискретного вейвлет перетворення (DWT), так і штучної нейронної мережі (ANN) для виявлення та діагностики дефектів, пов'язаних як з несправностями ITSC, так і з BRB.* ***Методи.*** *Пропонований метод включає аналіз сигналу електромагнітного моменту, що крутить, з використанням DWT для розрахунку запасеної енергії на кожному рівні розкладання. Потім ця енергія застосовується на навчання класифікатора нейронної мережі. Точність ANN, заснованої на DWT, була підвищена за рахунок тестування різних ортогональних вейвлет функцій на сигналі, що моделюється. У процесі відбору було визначено п'ять відповідних енергій вейвлета, і було зроблено висновок, що Daubechies44 (db44) є найбільш підходящою материнською вейвлет функцією ефективного виявлення і класифікації відмов у машинах.* ***Результати.*** *Ми застосували чисельне моделювання за допомогою програмного забезпечення MATLAB/Simulink, щоб продемонструвати ефективність запропонованих методів приводу асинхронного двигуна із замкнутим контуром. Отримані результати доводять, що цей метод дозволяє виявити та класифікувати дані види несправностей при різних навантаженнях машини.* Бібл. 31, табл. 1, рис. 9.

*Ключові слова:* **діагностика, коротке замикання, обрив стрижнів, асинхронний двигун, дискретне вейвлет перетворення, штучна нейронна мережа, непряме полеорієнтоване керування.**

**Introduction.** The squirrel cage induction motor (IM) by its robustness, simplicity and relatively low cost, plays a most significant role in applications requiring high power in industrial applications, particularly for constant or variable speed applications. Despite these great benefits, various stresses may occur, during operating conditions. For these reasons, early recognition of abnormalities is important to identify any faults at an incipient stage can help to avoid catastrophic failure and global damage. Literature has reports that electrical faults are principal causes [1-3], inter-turn short circuit (ITSC) have a significant share with approximately 30 % to 40 % and broken rotor bars (BRB) which represent 5-10 % of all the IM faults. These faults are caused by several forms of stress such as thermal, electrical, mechanical and environmental.

Several publications have focused on stator winding defects. In [2] a mathematical model of an IM based on coupled magnetic circuit theory is presented. This model allows detection of short circuit (SC) faults in stator winding and predicts it before it grows and damages the machine completely. In [3], a thermal model analysis of IM relies on finite elements method used to identify how ITSC faults of different severity affect the temperature of the IM. However, this method needs times after starting the motor to estimate the failure severity. Another useful technique was proposed in [4], combines the genetic algorithm and simulated annealing method to identify ITSC in IM during load current variations. In [5] Least Squares Support Vector Machine technique is proposed for fault detection and classification of the short circuit in the stator phases of an IM using information provided by the stator current. Moreover In [6], the estimations of rotor and stator resistances parameters based on Model Reference Adaptive System technique. Work [7] proposes axial stray flux based on analysis of flux signals collected by sensor. The pattern obtained from two-phase quantities is observed to be circular in nature for healthy case and elliptical nature for stator malfunctions. However, it is costly and challenging to install a sensor on the inside of the machine. Also in [8], an off line signal processing techniques called the Fortescue transform is applied to obtain the zero sequence of the current and the Fast Fourier Transform (FFT) is applied to detect the occurrence of the ITSC from the current and voltage signals of synchronous reluctance motor. Other work [9] use the three-phase stator voltages of IM as inputs, and by using the short-time least square Prony's method, to extract phases and magnitudes of the fundamental harmonics to calculate indicator called zero voltage factor that allows a rapid ITSC fault detection. However, this method is susceptible to load variation and the presence of unbalanced supply voltage. In [10], the residuals current between the estimated currents provided by the Extended Kalman Filter and the actual ones using FFT and Short-Time Fourier transform approaches are used for ITSC fault diagnosis and identification. The Artificial Neural Network (ANN) and Discrete Wavelet Transform (DWT) are proposed in [11], for ITSC fault diagnosis of IM. Three parameters (energy, Kurtosis and singular values) of DWT technique are computed under load variation and used as the input for the ANN classifier, using a single wavelet function db40. In [12], continuous and discrete wavelet methods are applied to study the stator current, at the start-up to identify BRB fault. But the limitation is that it is not always feasible to frequently restart the motor to capture starting current. The detection of BRB faults are detected by DWT based on harmonics characteristic, using vibration signal decomposition and ANN is presented in [13].The detection and classification of BRB fault in the IM, based a combination of the DWT, the slip and the ANN algorithm to solve the problem of low load has been discussed in [14]. Similarly, in [15, 16] the multiple signal processing tools using Hilbert Transform and ANN, are proposed for BRB fault diagnosis. In [17] suggests a hybrid combining a new electrical-time synchronous-averaging, DWT and fuzzy logic techniques was employed for dealing with the early identification of an incipient defect occurring at the rotor bar and classification of the severity of this defect.

**Problem definition.** Generally, diagnostic methods used for open-loop machine operation are not efficient when the control structure becomes more complex, particularly, in closed-loop drives. It's necessary to employ different analysis to interpret the acquired signals for the detection process. The FFT approach is widely applied and proven to be effective for stationary signals. However, this approach is not efficient and has limitations for non-stationary signals. In this context, to ameliorate the diagnosis procedure taking into account different faults of IM, a combination of DWT and ANN technique becomes our main focus to resolve these drawbacks for processing non-stationary, low load and over load. However, different types of the wavelet function can be used for early fault detection based electromechanical signal decomposition in closed loop operation. The comparison between the proposed methodology and the previously used methods is made based on the faults severity, operating mode, different load torques, and fault diagnosis methods. The work [18] focuses on the analysis of BRB faults in open-loop asynchronous machines powered by electrical network. The study utilized a single db40 wavelet function, and the acquisition of three current sensors for phases ($I_a$, $I_b$, $I_c$), the calculated energy of three-phase ($E_{7a}$, $E_{7b}$, $E_{7c}$), are employed as input of ANN to determine the faulty phases ($a_s$, $b_s$, $c_s$). However this work deals with the diagnosis of both short circuit faults and BRB at speeds, with a reference speed set to 100 rad/s controlled by Indirect Field Oriented Control (IFOC) technique. Various wavelet functions are used to compare the best suitable function such as BiorSplines, ReverseBior, Symlet, Coiflet, and Daubechies are used for diagnosis. Only one acquisition signal is used, which is the torque signal to differentiate between stator and rotor faults. The energy calculation of the electromagnetic torque signal involves selecting the pertinent energy, resulting 5 energies ($E_1$, $E_2$, $E_6$, $E_7$, $E_8$), after that these energies are used as input of ANN. The wavelet function db44 was found to be the best function to identify these faults. The application of this work is used in the first step to determine which fault occurs ITSC or BRB after that we use the method from [18], to locate the faulty phases. This study presents an effectiveness percentage of 98 %, taking into account both different severity levels of short circuited turns, 1, 2 and 3 BRB with different mechanical load levels (ranging from 1 to 7 N·m), in contrast to other works reviewed in [19-21], which analyze levels of fault and different operating conditions or different levels of fault and a constant load operating condition in open loop machine. Whereas, works [22-24] introduced a signal transformation and several nonlinear indices is required, along with an expert to interpret the obtained results. Other works [25-27] have good accuracy in diagnosing the highly incipient faults based fuzzy logic method but using number of fuzzy rules causes significant computation time, which is always longer

**The goal of the paper** is to identify ITSC and BRB fault when the IM operates in a closed-loop drive to preserve high performance. The used method for the fault detection combines DWT and ANN method to provide intelligent methodology for the diagnosis system.

**Subject of investigations.** This approach used DWT of electromechanical torque signal at steady state to compute the stored energy at each level of decomposition. Then, this energy is applied as input for the Neural Network (NN) classifier. Many test of orthogonal wavelet function are evaluated with ANN to find the best classification and lowest Root Mean Square Error (RMSE), and justified that db44 is the best suited mother wavelet function to detect and identify different severity for both the ITSC and BRB faults under various loads operation of IM.

**IM mathematical model.** An accurate model including a fault is needed to test fault diagnosis strategies in IM. The equivalent circuit diagram of the IM, in the reference frame (*d-q*) is considered, taking into account ITSC and BRB fault. Additionally, the following non-linear system equations are developed to validate IM performance [18]:

$$\begin{cases} \dot{X}(t) = A(\omega)X(t) + Bu(t); \\ Y(t) = CX(t) + Du(t), \end{cases} \quad (1)$$

where

$$X = \begin{bmatrix} i_{ds} & i_{qs} & \phi_{dr} & \phi_{qr} \end{bmatrix}^T, u = \begin{bmatrix} U_{ds} \\ U_{qs} \end{bmatrix}^T, Y = \begin{bmatrix} i_{ds} \\ i_{qs} \end{bmatrix}.$$

The expression of equivalent rotor resistance is:

$$R_{eq} = R_r \cdot I + \frac{\alpha}{1+\alpha} K(\theta_0) R_r; \quad \alpha = \frac{2}{3}\eta; \quad \eta = \frac{3N_{bc}}{N_b}; \quad (2)$$

$$K(\theta_0) = \begin{bmatrix} \cos(\theta_0)^2 & \cos(\theta_0)\sin(\theta_0) \\ \cos(\theta_0)\sin(\theta_0) & \sin(\theta_0)^2 \end{bmatrix}, \quad (3)$$

where $N_b$, $N_{bc}$, $R_r$, $R_{eq}$ are the total number of bars in the rotor, the number of BRB, the rotor resistance and the equivalent resistance of rotor, respectively; $\theta_0$ is the initial phase of the rotor.

By adding the mechanical equation to the system equation, we obtain the complete model of the machine taking account the ITSC and BRB in the Park coordinate system. The mechanical speed $\omega$ is the solution of the equation:

$$J\frac{\mathrm{d}\omega_r}{\mathrm{d}t}=T_e-T_l-f_v\omega\,, \tag{4}$$

and the electromagnetic torque in the Park coordinate system is given by the expression:

$$T_e=p(i_{qs}\phi_{dr}-i_{ds}\phi_{qr})\,, \tag{5}$$

where $T_e$ is the electromagnetic torque; $T_l$ is the load torque; $J$ is inertia moment; $f_v$ is friction coefficient.

**Indirect field oriented control.** The most significant aspect of field oriented control of the IM is transformation that converts a three-phase system into 2 components, which used to generate both the magnetizing flux and the electromagnetic torque [16, 24]. This transformation simplifies the structure of IM similar that of a DC machine as shown in Fig. 1. It implies that the 2 stator current components would be aligned as input references: the flux component (aligned with the $d$ coordinate) and the torque component (aligned with the $q$ coordinate).

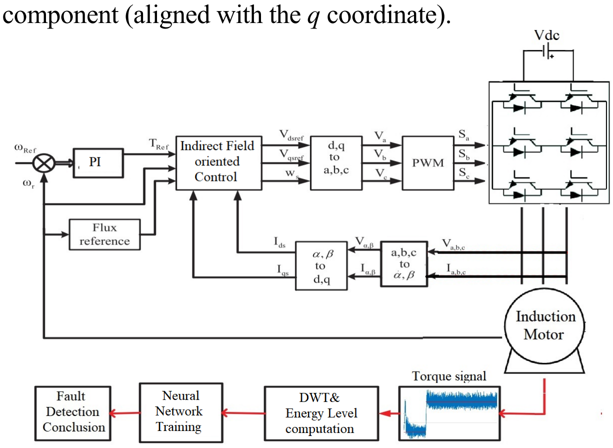

Fig. 1. Block diagram of the diagnosis system

The IFOC technique is known for its simplicity of implementation and high effectiveness what makes it widely used in industry applications. The flux component is aligned in the direction of rotor flux $\phi_r$ to achieve field orientation along the rotor flux direction:

$$\phi_{dr}=\phi_r\,,\quad \phi_{qr}=0,\quad V_{dr}=0,\quad V_{qr}=0\,. \tag{6}$$

The advantage of using a reference linked to the rotating field frame is to have constant magnitudes. The control is then made easier by relying on the variables of direct axis current $i_{ds}$ and the quadrature axis current $i_{qs}$. The magnitudes of flux $\phi_r$ and torque $T_e$ are independent controlled is assumed as [16, 24]. The calculated rotor flux, given by:

$$\phi_r=\frac{L_{sm}\cdot i_{ds}}{1+s\dfrac{L_r}{R_r}}\,, \tag{7}$$

where $L_r$, $L_{sm}$ are the rotor and mutual inductance; $s$ is the Laplace transform. The slip frequency is expressed by:

$$\omega_{sl}=\frac{L_{sm}i_{qs}}{T_r\phi_r}\,, \tag{8}$$

where $T_r = L_r / R_r$ is the rotor time constant.

The equation of the electromagnetic torque can be given by:

$$T_e=\frac{pL_{sm}i_{qs}\phi_r}{L_r}=K'i_{qs}\,, \tag{9}$$

where $p$ is the number poles pairs; $\phi_r$ is the rotor flux. Therefore, the relation with DC motor is clearly demonstrated by holding the flux constant.

The two components magnetizing flux $\phi_r$ and electromagnetic torque $T_e$ can independently controlled by acting on each variable separately, establishing the high performance of a DC machine. The simulation results of IFOC control IM drive in cases of healthy and faulty motors demonstrated through simulation in MATLAB/Simulink.

Figures 2-4 show the dynamic performance of speed, stator current and electromagnetic torque in healthy and when a fault appears in stator or rotor bars fault with reference speed set to 100 rad/s. After reaching the set value of motor speed, the step change of load torque (from 1 to 7 N·m) at the moment $t$ = 0.6 s. It is evident that, the actual speed accurately follows the reference speed in healthy and faulty state, which be explain by the fact that the PI speed controller minimize the effects of ITSC and BRB faults on the speed (Fig. 2).

Figure 3 depicts the stator currents that are sinusoidal and have the same amplitude. But in the occurrence of the fault, there will be an imbalance at the level of the stator currents which increase in term of amplitude.

Similarly, we observe the influence of ITSC and BRB in the electromagnetic torque. During a fault condition, motor suffers from oscillations. The amplitude of these oscillations increases when the severity of fault increases (Fig. 4).

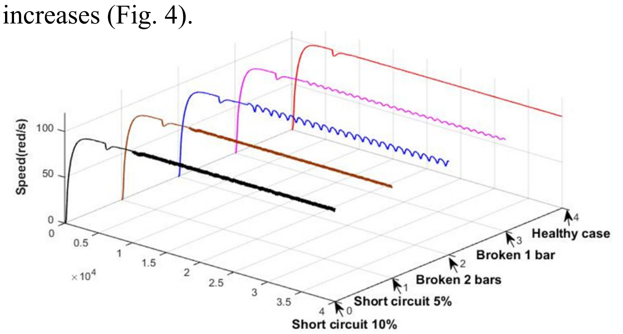

Fig. 2. Actual speed at full load

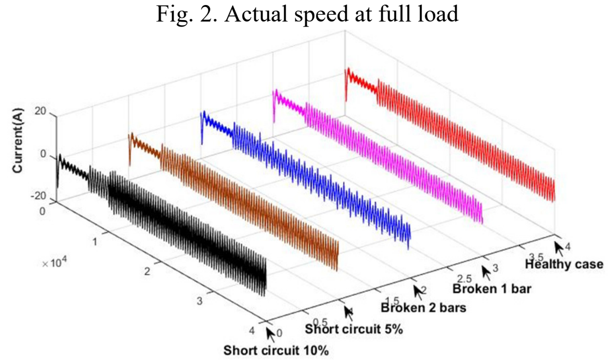

Fig. 3. Evolution of stator currents under full load

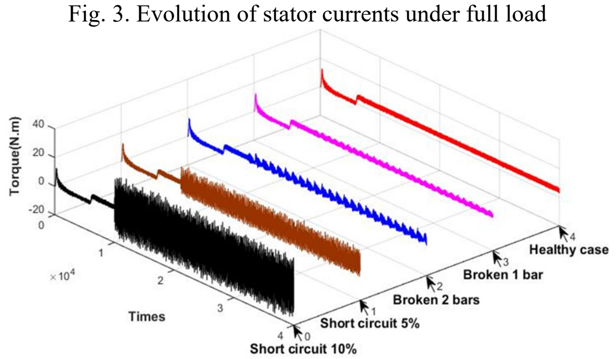

Fig. 4. Electromagnetic torque at full load

**Discrete Wavelet Transform (DWT).** The wavelet transform is an effective method for acquiring time-frequency information in both stationary and non-stationary signal processing, with the intention to solve the limitations of Fourier transform. This signal processing tool, characterized by robust time and frequency localization, is divided into Continuous Wavelet Transforms (CWT) and DWT. Adopting a mother wavelet $\Psi(t)$, the CWT of a function $x(t)$ can be expressed as:

$$CWT(a,\tau)=\frac{1}{\sqrt{|a|}}\int_{-\infty}^{+\infty}x(t)\psi^{*}\left(\frac{t-\tau}{a}\right)\mathrm{d}t\,, \tag{10}$$

where $\psi(t)^{*}$ is the complex conjugates form; $\tau$ is the time parameter; $a$ is the scale factor; $\sqrt{|a|}$ is the energy normalization.

The translation and the expansion transform the signal into another timescale. The high-frequency components correspond to the smallest scales [28, 29].

A more computationally efficient form of the CWT which gives optimal accuracy at low frequency and non-stationary state is the DWT given by [20, 22]:

$$DWT(J,k)=\frac{1}{\sqrt{2^{J}}}\int_{-\infty}^{+\infty}x(t)\psi^{*}\left(\frac{t-k\cdot 2^{J}}{2^{J}}\right)\mathrm{d}t=2^{\frac{-J}{2}}\psi(2^{-J}\cdot t-k)\,. \tag{11}$$

The DWT decompose a given signal into its constituent level (scales), each one representing that part of the original signal occurring at particular time and frequency band. DWT is performed by a sequential operation using a high-pass filters $H$ (details) and through a series of low-pass filters $L$ (approximations).

The original signals $x(t)$ is divided into 2 parts high frequency part, and low frequency part used to decompose and reconstruct a signal (Fig. 5) [18-20].

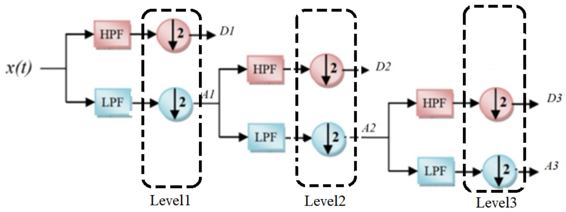


Fig. 5. DWT decomposition process of the signal at level 3

The low frequency part called approximations ($A_j$) contains the low-frequency information of the original signal belong to $[0,\ f_s\cdot 2^{-(j+1)}]$. The high-frequency part called detail ($D_j$) contain high frequency information included in the interval $[f_s\cdot 2^{-(j+1)},\ f_s\cdot 2^{-j}]$. Practically, the DWT decomposition at level $N$ of signal $x(t)$, giving rise to one approximation coefficient vector $A_N$ and $N$ detail coefficient vectors $D_j$ are expressed by [29, 30]:

$$x(t)=A_N(t)+\sum_{j=1}^{N}D_j(t)\,. \tag{12}$$

It can be shown that the approximation and detail coefficients can be recursively calculated by:

$$A_{j,k}=\sqrt{2}\sum_{-\infty}^{+\infty}L[n]A_{j-1,\,2k+n};$$
$$D_{j,k}=\sqrt{2}\sum_{-\infty}^{+\infty}H[n]A_{j-1,\,2k+n}. \tag{13}$$

The effectiveness of DWT relies on the careful choice of the wavelet function. Different types of mother wavelets exist, such as: Meyer, Coiflets, Symlets and Daubechies.

Preliminary step before selecting the wavelet function involves judiciously choosing the number of levels in order to cover the whole range of frequencies approximation and detail, given by the relationship:

$$\frac{f_s}{2^{N+1}}\le f_e\,, \tag{14}$$

where $f_e$ is the fundamental frequency of the signal, $f_e$ = 22 Hz; $f_s$ is the sampling frequency, $f_s$ = 10 kHz; $N$ is the number of decomposition levels.

**Wavelet energy.** The consumed energy at each level of decomposition is calculated, to identify and validate the frequency bands containing the defect frequency for both faulty and healthy cases under different load conditions. For this purpose, the energy linked to each $D_j$ detail signal of the torque signal is expressed as follow:

$$E_j=\sum_{k=1}^{n}D^{2}{}_{j,k}(n)\,, \tag{15}$$

where $j$ is the decomposition level ($j\in[1,\ N]$); $E_j$ is the detail energy; $D_{j,k}$ is the magnitude of the coefficient in corresponding level $j$; $n$ is the DWT decomposition time.

The energy extracted from the torque signal through wavelet transformation, using db44 under different load and faults severity. The number of decomposition levels $N$ depends on the sampling frequency $f_s$ of the signal were performed up to the 10th level of the decomposition. By computing associated coefficient at each decomposition levels of the torque signal. The results of detail energy $D_j$ for various instances of shorted turns and broken 1 bar and 2 bars under different loads are depicted in Fig. 6.

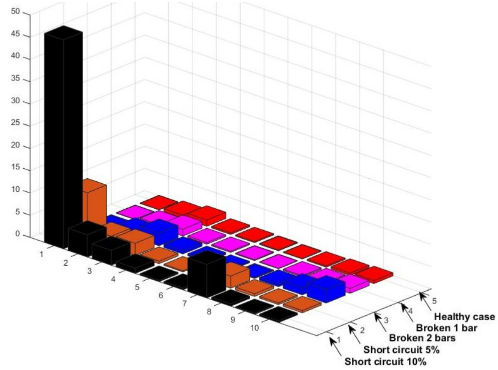


Fig. 6. The comparison of total energy

**Artificial Neural Networks** are complex intelligent structures inspired by biological neurons, have demonstrated remarkable performances to solve analytically challenging problems and the automation of the monitoring process. The most frequently used NN for classification purposes is feed forward multilayer perceptron NN, known for its simple structure making it easily implementable. Hence, it was chosen for the developing of the monitoring process. The training function used was Levenberg–Marquardt trained by back propagation algorithm and training results are used to attain the minimum Mean Square Errors (MSE) [28, 29]. Typically, an ANN consists of an input layer, hidden layers and an output layer, where each layer connected to other layer, with weights assigned to the connections. The activation function used for the hidden layer is tangent sigmoid «tansig», while the activation function for the output layer is Logsigmoid «logsig» [30, 31].

The inputs are the pertinent wavelet energy value and outputs are the fault class of IM, respectively.

The training performance and parameters related to the training algorithm are illustrated in Fig. 7. After 85 epochs, a low training MSE of $2.3561 \cdot 10^{-11}$ is achieved, indicating suitability for accurately classifying the test set.

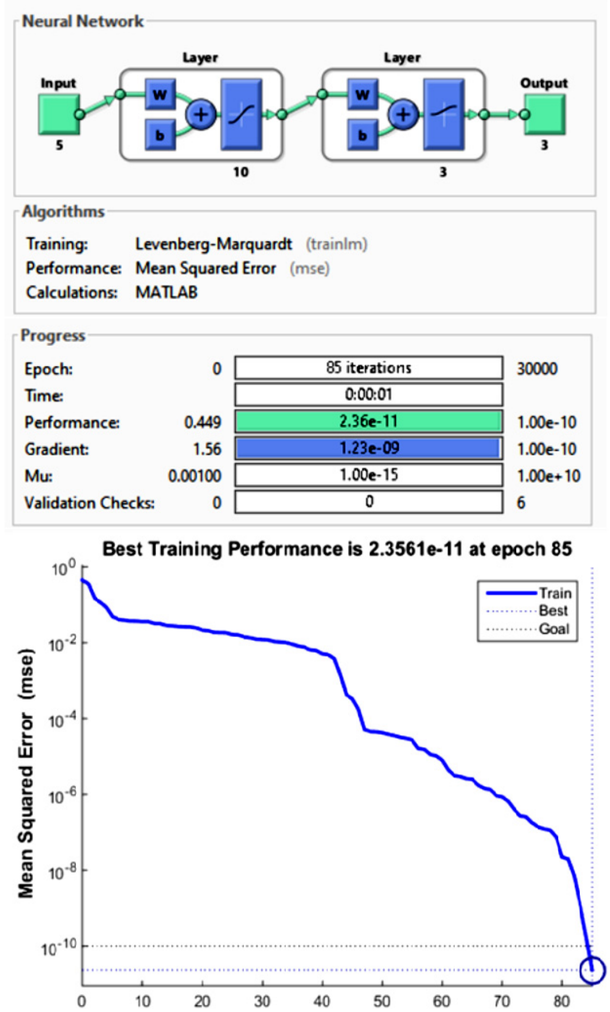


Fig. 7. Neural network performance

**Preparation of training data.** The NN is trained using a dataset comprising input and output sets. The number of input units in the ANN corresponds to the fault indicators, while the output units are determined by the number of faulty states. The inputs represent the pertinent stored energy calculated from the torque signal, which found the best value are 5 energies ($E_1$, $E_2$, $E_6$, $E_7$, $E_8$) and the outputs signify the fault classes: healthy case, short circuit and BRB fault. For an optimal compromise between complexity and accuracy, one hidden layer with 10 neurons is chosen. Input data are gathered through simulations under various loading conditions and fault severities, ranging from no load to full load. The NN is exposed to examples under 7 load torques (1–7 N·m), representing different operating conditions, including healthy states (7 samples), faults with an even number of shorted turns (2, 4, 6, 8, 10), and faults with single and 2 BRB. This results in a total of 56 cases ((7 healthy) + (7×5 shorted turns with different loads and severities) + (7×2 BRB with different loads)), as shown in Fig. 8. Consequently, the dimension of the training vector inputs for the NN is 5×56.

The target data required for supervised learning in the NN are defined accordingly:

T1 = [1; 0; 0] – healthy case;

T2 = [0; 1; 0] – short circuit fault;

T3 = [0; 0; 1] – BRB.

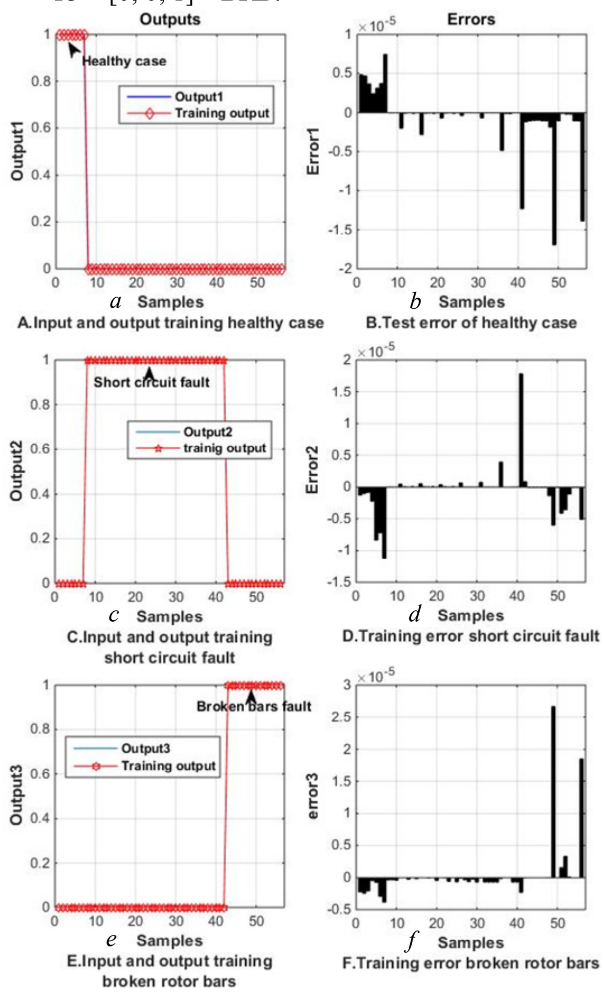


Fig. 8. Training and classification errors of the NN

**Simulation results.** The NN ability to generalize is assessed through its performance on the testing dataset. To evaluate classification effectiveness, 2 distinct datasets are compiled, representing both healthy and faulty cases. Various tests are conducted to determine the optimal structure and outcomes. The results indicate that the selected ANN model has achieved significant success in detecting and classifying these faults.

The dataset is divided into 2 parts, with 1 set applied for training while another for testing. An effective NN is expected to perform well on both training and testing data, showcasing its generalization capacity. The testing process involves a dataset separate from the one used for training, providing an assessment of the network's ability to generalize to new, unseen data.

Figure 9 depicts the test data set of the system under different operating cases of IM: healthy case (7 samples), fault of shorted turns (1, 3, 5, 7, 9), and fault for 1 and 2 BRB, are obtained under 7 load torques (0.5, 1.5, 2.5, 3.5, 4.5, 5.5 and 6.5 N·m).

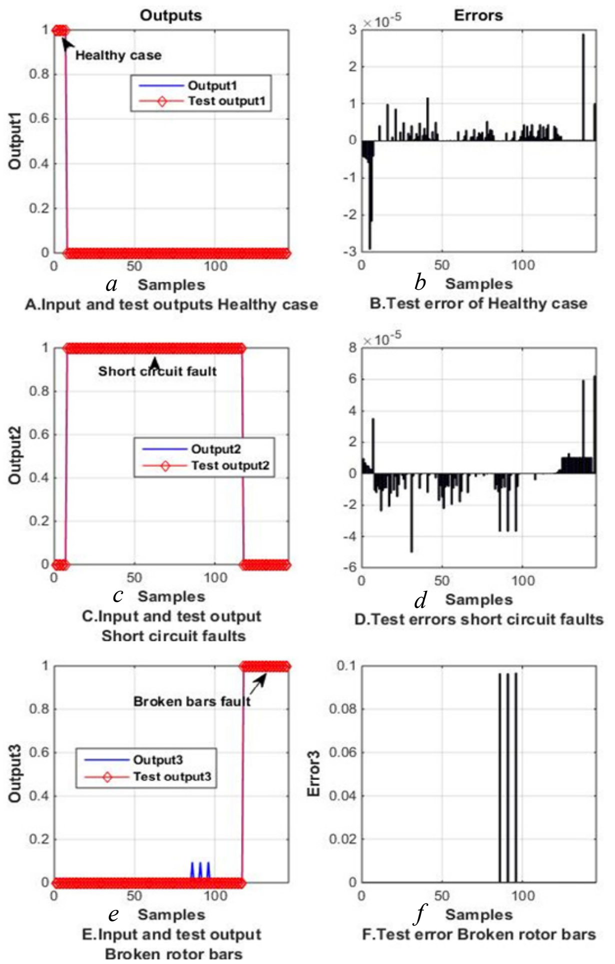


Fig. 9. Test and classification errors of the NN

As a result, the total number of combinations of load variation, shorted turn and BRB was 143 ((7 healthy) + (7×5 load of different severities of ITSC) + (7×5 different load of ITSC) + (7×5 different load and severities of ITSC) + (7×2 different load of BRB) + (7×2 different load + 3 BRB)).

The test output of the NN (T1, T2, T3) is accurately equal to (1, 0, 0), (0, 1, 0), and (0, 0, 1). The NN test outputs and classification errors for faults of ITSC and BRB, respectively is shown in Fig. 9. The test output of NN from (Fig. 9,*a*,*b*) is accurately identical to (1, 0, 0) in healthy state and classification error is very low. The NN output in (Fig. 9,*c*,*d*) give the output (0, 1, 0), with minimal amount of testing error in short circuit faults. As a result, the ITSC can be accurately located by the NN. According to (Fig. 9,*e*,*f*), the NN accurately gives the outputs (0, 0, 1) for the BRB indicating the occurrence of small errors. Therefore, we can observe that the NN can accurately identify the ITSC and BRB faults.

Table 1 shows a comparison of the performance of a simulated model. In this study, the accuracy of ANN is evaluated using the RMSE with the expression given by:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{m}(x_i - x_i^*)^2}{m}}, \qquad (16)$$

where $x_i$ and $x_i^*$ represent respectively the measured and desired outputs; $m$ is the total number of input sets.

The test data are simulated under various wavelet functions, using BiorSplines (bior6.8), ReverseBior (rbior6.8), Symlet (sym8), Coiflet (coif5) and Daubechies (db44) wavelet families. The input of NN are chosen by selecting the pertinent energy, we found 5 energies ($E_1$, $E_2$, $E_6$, $E_7$, $E_8$) identified as the most effective. Subsequently, the best classification and the minimum classification error are achieved using Daubechies44 (db44) which found better than any other wavelet transform. The achieved results clearly demonstrate that the db44 of the electromechanical torque signal can used as an effective indicator for stator and rotor condition monitoring.

Table 1

Performance of different wavelets functions with 5 energies ($E_1$, $E_2$, $E_6$, $E_7$, $E_8$)

| Wavelet mother | bior6.8 | rbior 6.8 | sym8 | coif5 | db44 |
|---|---|---|---|---|---|
| ANN-RMSE (test) | 0.0235 | 0.0164 | 0.0339 | 0.0308 | 0.0011 |
| Classification accuracy, % | 97.24 | 98.16 | 96.32 | 97.24 | 98.62 |

**Conclusions.** This paper introduces a precise method for diagnosing inter-turn short circuit (ITSC) and broken rotor bars (BRB) in variable speed drives using discrete wavelet transform (DWT) and artificial neural network (ANN). The proposed approach involves analyzing the electromechanical torque signal of a squirrel cage induction motor (IM) through DWT. This analysis computes the stored energy at each level of decomposition, which then serves as input for an ANN classifier.

The proposed technique has been applied for fault detection under various loads, instances of ITSC, and different occurrences of BRB in the IM. The results obtained are highly significant, demonstrating the ability to automatically detect and locate faults related to BRB and ITSC. The best result is achieved through the application of 5 pertinent energies, particularly using db44. According to the test results, DWT and ANN prove to be a powerful method for diagnosis, offering a means to automatically identify faults under variable load conditions. Future research could further develop this work to determine the specific number of short circuits and BRB, enabling continuous and real-time monitoring.

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

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