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Experimental diagnosis of inter-turns stator fault and unbalanced voltage supply in induction motor using MCSA and DWER

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ABSTRACT

This paper presents a comparative study between two techniques of signal processing to diagnose both faults the inter-turn short circuit (ITSC) in stator windings and the unbalanced voltage supply (UVS) in induction motors. The first is considered a classical technique called Motor Current Signature Analysis (MCSA) which is based on the processing of the stator current by the Fast Fourier Transform (FFT). The second is anadvanced technique based on a Discrete Wavelet Energy Ratio (DWER) of three stator currents. The aim objective of this paper is to compare the ability and effectiveness of both techniques to detect the ITSC fault and the UVS in induction motors, and distinguishing between them. An experimental implementation tests the two diagnosis techniques.The results obtained show that the MCAS technique by the FFT analysis has a difficult to discriminate between the current harmonics due to the provide voltage unbalance and those originated by ITSC faults. Unlike the DWERtechnique, which has high sensitivity and exceptional ability to detect and distinguish between the two faults that lead to the reliability of the diagnosis system. To demonstrate that the DWER is an accurate and robust diagnosis approach are used the neural network (NN) as a tool to classify the faults (ITSC and USV) where using DWER indicators as NN input. The results obtained of combination between the DWER and NN are effective and proved its ability to detect both faults under different load conditions and distinguish between them accurately with low error (10^{-5}).

Keywords: *Induction motor, diagnosis, inter-turn short circuit(ITSC), unbalanced voltage supply (UVS), FFT, DWT*

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Acronyms

ITSC	Inter Turn Short Circuit
UVS	Unbalanced Voltage Supply
DWER	Discrete Wavelet Energy Ratio
MCSA	Motor Current Signature Analysis
FFT	Fast Fourier Transform
NN	Neural Network
EPRI	Electric Power Research Institute

1. **Introduction**

Nowadays, almost 70% of the machines used in industries are three-phase induction motors (IM) because they are simple, robust, and low cost. The malfunction of IM can cause damage to the environment, human beings, or make a significant financial loss. For that, it has become essential to diagnose faults at their very inception. The protection and the fault diagnosis are outdated as the machines themselves. The constructor and users of electrical devices initially relied on simple protection on,for example, over current, over-voltage, earth-fault ... to ensure safe and reliable operation. However, as the tasks performed by these motor became more complex, improvements were also sought in the domain of fault diagnosis. Early detection and correct diagnosis of incipient faults could allow preventive maintenance to be performed and provide sufficient time for the controlled shutdown of the affected process.

The stator winding faults are considered as an essential type of fault in the IM. It approximately contributes 28 % to 36% of the IM failures, as per the review of IEEE and EPR [1]. The common stator winding faults are turn-to-turn fault, coil to coil fault, phase to phase fault, a short circuit between turns of all three phases, and coil to ground fault. Causes of stator winding faults are different stresses, namely electrical stress, thermal stress, environmental stress, and mechanical stress [2].These stressful conditions cause the deterioration and breakdown of the winding insulation which leads to ITSC faults, and it can develop into more severe faults, resulting in irreversible damage to the stator winding and core[3]. Furthermore, the unbalanced voltage supply(UVS) rises the stator and rotor temperature, and it can cause detrimental effects, such as, vibration, reduction in output torque, and overheating that lead to a decrease in insulation life of the IM[4]. There are a lot of reasons for the supply unbalancing such as generators terminal voltages, the impedance of the electricity, fault operations, load currents, power factor correction equipment, and voltage regulators in the utility distribution lines[5].

Various fault detection approaches for IM are classified into three categories: a model-based, signal processing based, and artificial intelligence approaches.

- Model-based approach use system mathematical models.However, it is difficult to achieve a precise mathematical model of a physical system. Typically, the parameters of the system can vary with time, and the features of the faults and noises cannot be accurately modelled. Therefore,there is always a deficiency of congruence between the actual system (motor) and its mathematical model under no-fault conditions. Such conflicts cause problems with fault detection and condition monitoring applications and can act as sources of false alarms.
- Many efforts have been made by researchers about the implementation of artificial intelligence (AI) in motor monitoring and fault diagnosis. Different AI tools have been developed and applied in the monitoring processes of faults, among them, the Artificial Neural Network (ANN), Fuzzy Logic (FL), and Support Vector Machines (SVM). Typically, expert systems are trained using a database that correlates measurement and corresponding fault. In practical applications, the severity levels of faults may vary and not exactly match the database used for training. It can lead to false diagnosis.
- Thanks to recent technological developments in the field of digital signal processing, motor failure diagnostics can be performed in real-time based on minimal motor signals, e.g. current on the stator line or vibration signals. It facilitates accurate and inexpensive motor faults detection.

In this paper, the diagnostic approaches are used based on signal processing because it has the advantages as, efficiency, simplicity, and the low-cost to detect the IM faults.Among the most critical signal processing tools used in IM fault diagnosis literature: Fast Fourier Transform (FFT), Short-time Fourier Transform (STFT), Wavelet transform (WT) [6, 7] and Empirical Mode Decomposition (EMD) [8]. Generally,the FFT analysis converts a signal into a frequency domain from the time domain. It is a good technique for the IM faults detection in the steady-state and is easy to implement. However, the application of this technique has limitations especially for the signal whose characteristic changes with time [9]. For this reason, a short-time Fourier transform (STFT) has been used to analyze transient signals. STFT uses a constant-sized window to analyze all frequencies which lead to poor frequency resolution, to overcome, this limitation, researchers utilized wavelet transform (WT) both in discrete and continuous form for detection of the motor fault. The WT can be applied to the multi-scale analysis of a signal through dilation and translation. Thus, it can effectively identify a time-frequency feature of a signal.

Moreover, WT has efficient advantages in the analysis of non-stationary signals[10]. Many researchers have applied the WT to detect the IM faults, as stated in[11-15].According to robustness and higher efficiency of digital processing techniques, in this research work, two fault diagnosis approaches are proposed based on respectively: the FFT and Discrete wavelet transform (DWT) of stator currents of the IM for diagnosis the ITSC and UVS faults.

The fault of the stator winding creates unbalance in the line current like the faults are caused by unbalancing voltage supplyin the IM. The diagnosis of both defects (ITSC and UVS) and distinguishing between them have posed a significant challenge for the researchers in the faults diagnosis field of the IM. Some researchers haveinterested in studyinga diagnosis of each defect separately. Also, some haveconsidered them together,which have focused on the detection of faults and distinction between them. Therefore, a lot of researches have been done for this purpose in the diagnosis literature. The authors have done a study about the diagnosis of both faults, ITSC, and UVS in the IM [16]. They have used the three-phase shift between the line currents and their voltages as indicators to detect the faults, and they considered it as inputs data for the neural network (NN) to classify the faults and to distinguish between them. This approach has given good results but, it is practically expensive because it has required three current sensors and three voltages sensors for implementing it.

Furthermore, in [17] authors have presented a diagnosis method based on spectral analysis, via the FFT analysis of the Park's vector modulus computed from the analytical signals of the three phases currents which are obtained by HT, for detecting the ITSC faults in IM. Moreover, authors in [18] have presented a diagnosis method based on discrete wavelet transform (DWT) and NN. They have processed the stator current by DWT then calculating their energy which has used as fault feature and considered it as inputs of the NN others in[3]have represented an analytical and experimental study to diagnose the balanced and unbalanced voltage supply faults in IM,based on the spectral analysis of magneto-motive force (MMF).Furthermore, in Ref. [19], the authors have presented a problem in difficulty to distinguish between current harmonics due to the UVS and originated by ITSC faultsbecause they have provided with the same components of harmonics which can lead to errors in the task of diagnosis.

This paper aims to present a comparative study between two diagnostic methods for diagnosis the ITSC and UVS faults of the IM. The first is the MCAS method that is based on processing the stator current by FFT. The second is the DWER method which is based on the DWT and the ratio of the discrete wavelet energy of three stator currents. Results will be examined by an experimental implementation that shows the ability and efficiency of each method to diagnose and distinguish between both faults.The NN is used for classifying the faults (ITSC and UVS) where are considered the DWER as fault indicator and NN inputs,to confirm the robustness and efficiency of this approach in diagnosis.

2. Background of the two diagnosis approaches proposed

This study will introduce two approaches to diagnose the ITSC faults and the unbalanced voltage supply (UVS) in IM. It is the first. It is based on the FFT, called the motor current signature analysis (MCSA) and the second is based on discrete wavelet energy ratio (DWER)of the three stator current.

2.1. Motor current signature analysis (MCSA)

The MCSA is one of the most commonly u0sed approaches to diagnose of IM faults. This approach applies FFT to process the stator current for extracting the spectrums that concerning the faults, as shown in Figure1. Practically, It requires only one current sensorand speed sensor, which is used to calculate the slip (s). Researches in [17, 20, 21] are cited that the appearance ofthe ITSC faultgenerates harmonics in the stator currents with frequencies given by equation (1)[17]:

$$\boldsymbol{f_{ITSC}} = (\boldsymbol{m f_s} \pm \frac{\boldsymbol{k(1-s)}}{\boldsymbol{p}} \boldsymbol{f_s}) \tag{1}$$

Where:$f_s$is the fundamental frequency of the power supply, $\boldsymbol{s}$ is the slip, $\boldsymbol{m}$ = 1,3,5…..is the time-harmonic order, and $\boldsymbol{k}$ = 1,2,3…an integer.

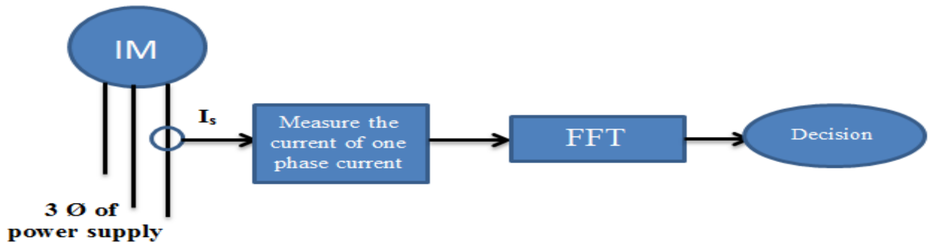


Figure 1. Motor current signature analysis

2.2. The discrete wavelet energy ratio (DWER)

The Wavelet Transform (WT) is considered as a powerful and advanced signal processing technique that offers time and frequency knowledge for a signal by decomposing it into different scales at various resolution levels by changing the time widths to the frequencies of a single prototype function called a mother wavelet. The WT is split into two categories: Continuous Wavelets Transform (CWT), and Discrete Wavelets Transform (DWT). The CWT works on every possible scale and position (continuous dilation and translation). However, the DWT utilizes a particular subset of scale and positional values which are less complex in computation and require less time to calculate compared to CWT[1]. For this reason, the DWT is used in this study.The DWT is calculated by a series of low-pass and high-pass filters as represented in Figure 2, which are known as MallatorMallat decomposition tree. In Figure 2, the signal is indicated by x[n], where n is an integer. The low pass filter is indicated by LP while; the high-pass filter is indicated by HP. For each level of decomposition, a high-pass filter generates a detail signal D, while the low pass filter computes the approximations signal A[1, 22].

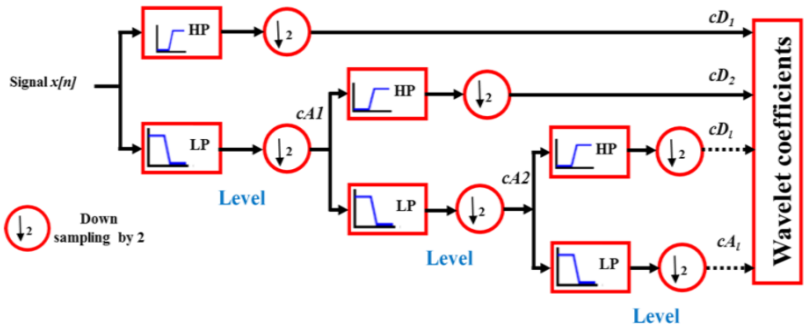


Figure 2. DWT signal decomposition

- **Discrete Wavelet Energy (DWE)**

The Discrete Wavelet Energy (DWE) related to the decomposed signal for each detail and approximation coefficients Ed_j, Ea_jcan be computed by equations2 and 3[12, 23]. Such as j is the level of decomposition.

$$Ed_j = \sum_{k=1}^{k=n} \left| D_{jk}(n) \right|^2 \tag{2}$$

$$Ea_j = \sum_{k=1}^{k=n} \left| A_{jk}(n) \right|^2 \tag{3}$$

The DWE of stator current has been used as indicator to diagnose faults in the IM, as it is in[11]. Although the results obtained are good in this work,there are drawbacks represented in the DWE decompositions values where they are changed according to the length of the current signal time interval, which is analyzed by DWT leads to finding the same case has more than one energy value. Furthermore, their values are somewhat big and consume more storage space in memory. As a solution to these problems, this paper presents a simplified

and efficient fault indicator based on the Discrete Wavelet Energy Ratio(DWER) of three stator currents to detect the ITSC and UVS faults and distinguish between them.
The DWER is computed by dividing the energy values of three stator current indirect order as follows:

$$(Ed_{ias} / Ed_{ibs}), (Ed_{ibs} / Edi_{cs}), (Ed_{ics} / Ed_{ias}).$$

The general framework of the proposed diagnosis methodology is shown in Figure 3. The three stator currents signals (I_{as},I_{bs}, and I_{cs}) under different test conditions are first acquired. Next, we processed them via DWT,which extracts the detail and approximation decompositions signals of the currents. Then, the DWE is calculated for each decompositionchoosing the highest value.Finally,the DWER is computed for the high decomposition level by dividing the energy values in direct order as follows: (Ed_{7as} / Ed_{7bs}), (Ed_{7bs} / Ed_{7cs}), and (Ed_{7cs} / Ed_{7as}).The DWER values are selected as faults feature.

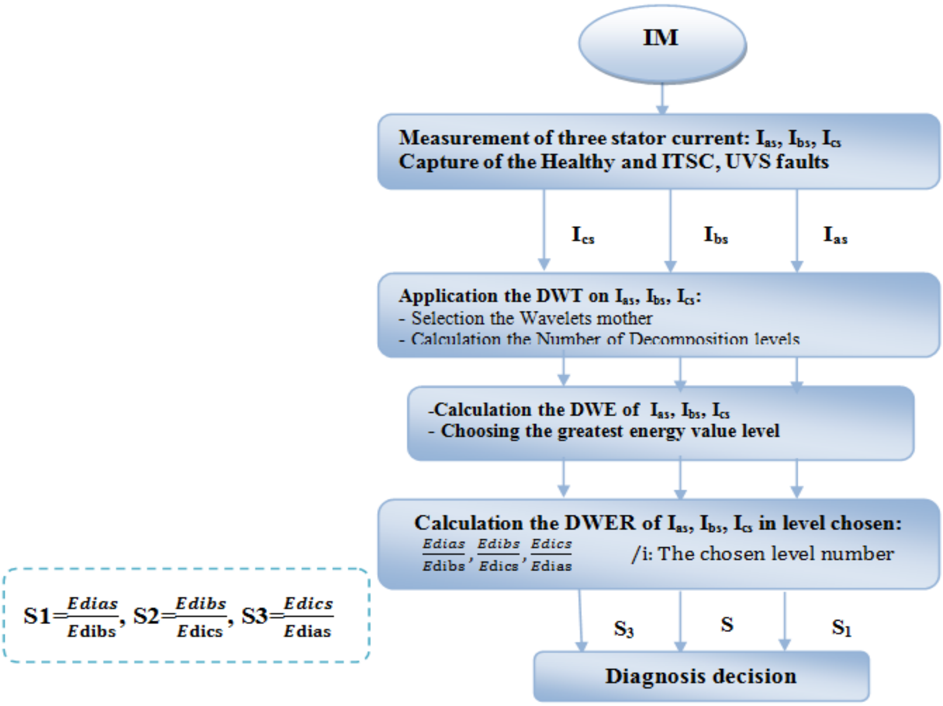


Figure 3. Flowchart for the DWER-baseddiagnosis methodology

3. Unbalanced voltage supply(UVS) definitions

Unbalanced voltage exists almost everywhere electrical systems, being one of the most common disturbances [24]. According to a different standard, there are three general definitions for measuring the unbalance voltage [25, 26], By National Electrical Manufacturer Association (NEMA): The NEMA describes the unbalanced voltage by the Line Voltage Unbalance Rate (LVUR), which is given by equation (5):

$$LVUR(\%) = \frac{\text{Max voltage deviation from avg. line voltage}}{\text{Average line voltage}} X100 \tag{5}$$

By Institute of Electrical and Electronics Engineers (IEEE): The unbalance voltage is defined by The IEEE through the phase voltage unbalance rate (PVUR), which is given by equation (6):

$$PVUR(\%) = \frac{\text{Max voltage deviation from avg. phase voltage}}{\text{Average phase voltage}} X100 \tag{6}$$

By the International Electrotechnical Commission (IEC): The IEC has explained the imbalance voltage as the ratio between the reverse voltage component and the positive voltage component. The percentage of Voltage Unbalance Factor (VUF) is given by equation (7):

$$VUF(\%) = \frac{\text{Negative Sequence voltage component}}{\text{Positive Sequence voltage component}} X100 \tag{7}$$

4. Experimental setup

The experimentalsetup used in tests is shown in Figure 4. It is composed of (1): A squirrel-cage IM 1.1 kW. (2): DC generator with resistive load. (3): External box enables introducing ITSC with a different number of turns in three phases. (4): DSpace DS 1104 with 5 control desk software plugged in personnel computer. (5): current sensors. (6): Auto-transformer (0-450V) to fed the IM directly by (50-Hz,Y connection, Un=400v). (7): incremental encoder (position and speed sensor). The stator winding specially rewound so that each percentage of the number of turns of a phase winding is returned to an external connection box. This way, you can make the ITSC default externally easily. To make the unbalanced voltage of 4% in the amplitude, we put up a resistance in phase **a**,at the feed inlet of the motor. By current sensor connecting in the interface of the **DSpace card** record the data on the PC**.** The sampling frequency of the data acquisition of stator currents were 10Kilo Sample/sec in the all experimental result of the test.

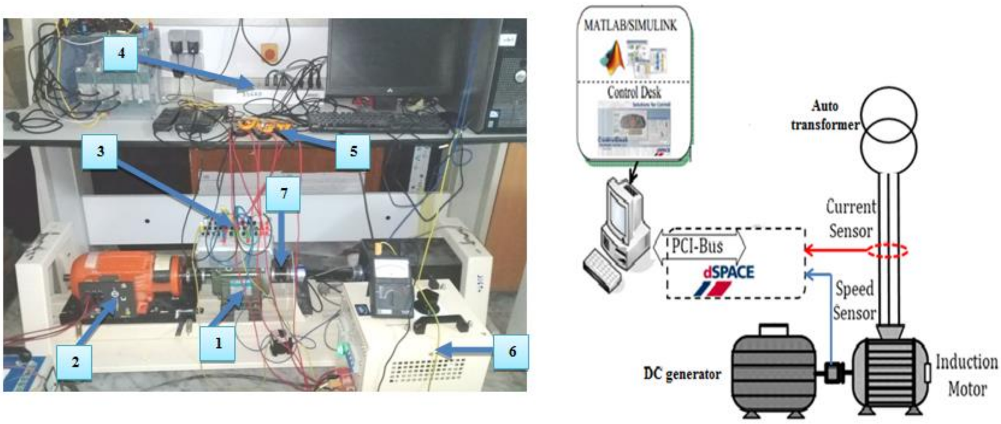


Figure 4. Experiment setupused in tests

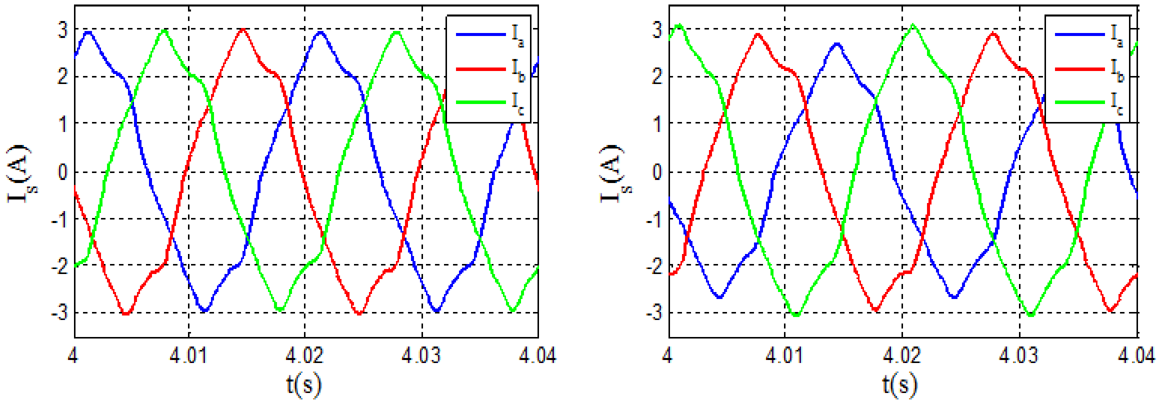
Table 1. Parameters of IM used in the experimental result

P_n: Output power	1.1KW
V_s: Nominal stator voltage	400/230V
I_s: Nominal current	2.5/4.3A
N_n: Nominal speed	1450 rpm
f_s: Stator frequency	50Hz
P: Number of Pole pairs	2
n_b: Number of rotor bars	46
n_s: Number of turn per stator phase	396

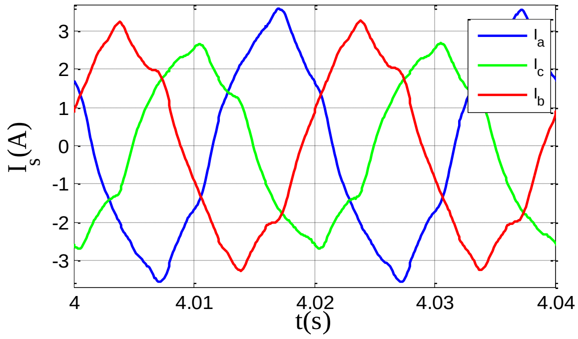
5. Experimental results and discussion

Figure 5 shows the experimental results of the three currents absorbed by the stator winding under average load in the states: (a) healthy motor, (b) Unbalanced voltage supply of 4%, and (c) ITSC fault with 20 turns shorted in phase a. The parameters of this motor are grouped in the Table1. Compared to the three states of stator currents in Figure 5,it is noted that in the ITSC state (Figure 5. c), an interesting increase in the amplitude of the phase where the fault has occurred (phase a) and a relative height that is lower for the other phases.

Furthermore, an imbalance in the phase shifts is there.However, in the UVS state in Figure 5.b, it is clear that there was a slight decrease in amplitude of the current in phase **a**, where the unbalanced voltage (4%) has occurred, and the two others did not notice a significant change.



(a- Healthy state) **(b -** Unbalanced voltage supply**)**



(c - ITSC fault**)**

Figure 5. Stator current of IMin :(a) Healthy state, (b) Unbalanced voltage supply (UVS),(c)ITSC fault (20 turns shorted)

5.1. Applied the MCSA approach

➢ **Current analysis by FFT**

The experimental data of one phase stator current were analyzed by the FFT which is carried out by a Hanning type windowing in steady state, for the cases healthy and with two defects. ITSC fault with 20 turns shorted in phase A and unbalance on power supply voltages of 4% in the amplitude of phase A, under average load (3.5 N.m). Figure 6 shows that the ITSC fault has amplified significantly the amplitudes of harmonics which corresponds to Equation (1), especially the:$(3f_s - f_r)$=125Hz,$(3f_s + f_r)$=174Hz $(5f_s - f_r)$=225Hz and $(5f_s + f_r)$=274Hz. Moreover, it has increased the amplitude of those harmonics related to mixed eccentricity faults:$(f_s - f_r)$=25Hz, $(f_s + f_r)$=74Hz and the time harmonics: $3f_s$=150Hz,$5f_s$=250Hz which we notice was mainly present in the healthy state(bleu) of the IM.

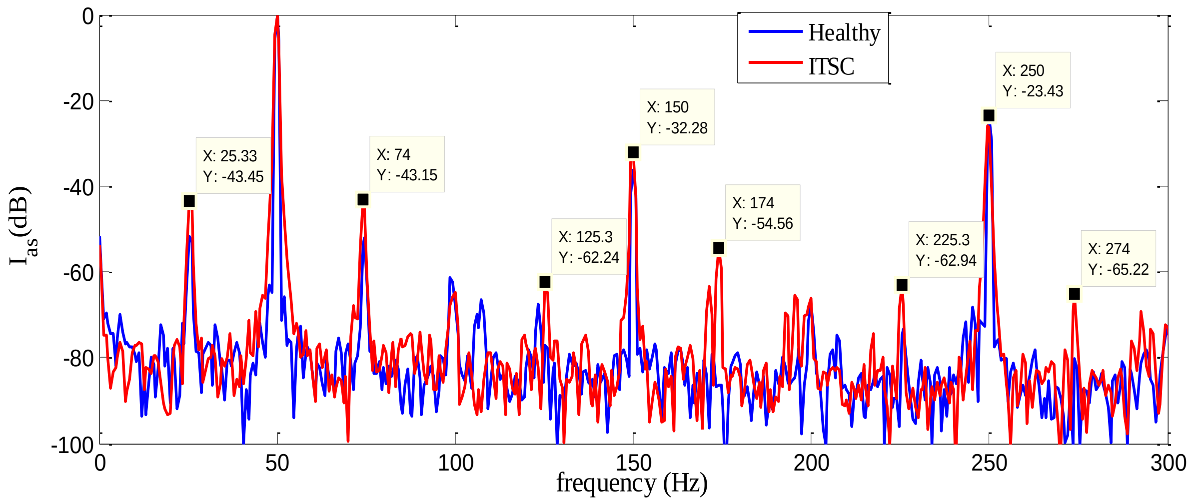


Figure 6. Stator current spectrum of healthy (blue) and ITSC fault "20 turns shorted"(red) motor at average

Figure 7 presents the spectrums of stator current in healthy (blue) and unbalance on power supply voltages of 4% in the amplitude of phase A (green). The same harmonics that appeared in the ITSC state are observed with only different amplitudes. The difference between the two last results is just in the amplitude of harmonics that previously mentioned. The similarity between the two defects signatures through FFT can occur errors in the diagnosis process. So, this requires the use of other technologies for a more accurate diagnosis.

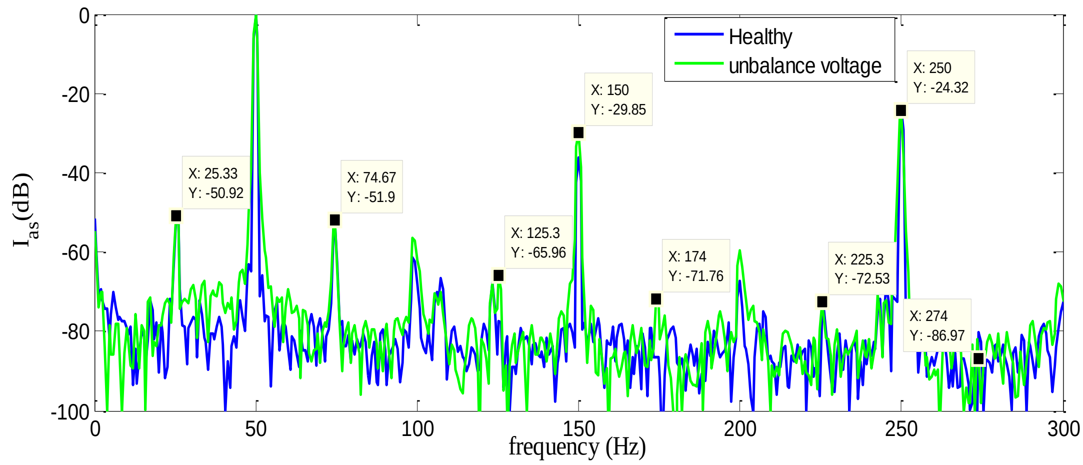


Figure 7. Stator current spectrum of healthy (blue)and unbalanced voltage supply 4% (green) under average load

5.2. Applied the DWER approach

- **Current analysis by DWT**

In this study, a multi-resolution decomposition of DWT based on wavelet mother "Daubechies (db44)" which useful to achieve better frequency resolution compared to other types of wavelets. The number of decomposition levels is computed by equation (8).In this work, the number of decompositions equals' 9. The frequency range of the decomposition is presented in Table 2.

$$n_{ls} \succ \text{int}\left(\frac{\log\left(\frac{f_e}{f_s}\right)}{\log(2)}\right)+1 \tag{8}$$

Where: n_{ls}: number of decomposition level, f_e=10 kHz: the sampling frequency of the current signal being analyzed, and $\boldsymbol{f_s}$= 50 Hz is the fundamental frequency of the current signal.

Table 2. Frequency bands of DWT decomposition

Coefficient	frequency bandwidth (Hz)
D1	2500-5000
D2	1250-2500
D3	625-1250
D4	312.5-625
D5	156.25-312.5
D6	78.125-156.25
D7	39.0625-78.125
D8	19.531-39.0625
D9	9.765-19.531
A9	0-9.765

Figure 8 represents the experimental results of DWT decompositions of the stator current in phase **as**. The details and approximations decompositions are obtained by wavelet mother "db44", for the cases healthy and both faults: ITSC fault with 20 turns shorted and UVS in the amplitude by 4% under average load (3.5 Nm) on the motor. It is noted different disturbances in the wavelet coefficients in the decompositions signals (D6, D7, D8, D9 and A9) for the three cases: healthy and both faults (ITSC and supply voltage unbalance). The decomposition at level 7 (D7) represents the largest one where it is analogous to the original signal of the current because it contains the fundamental frequency 50Hz, as shown in Table 2.

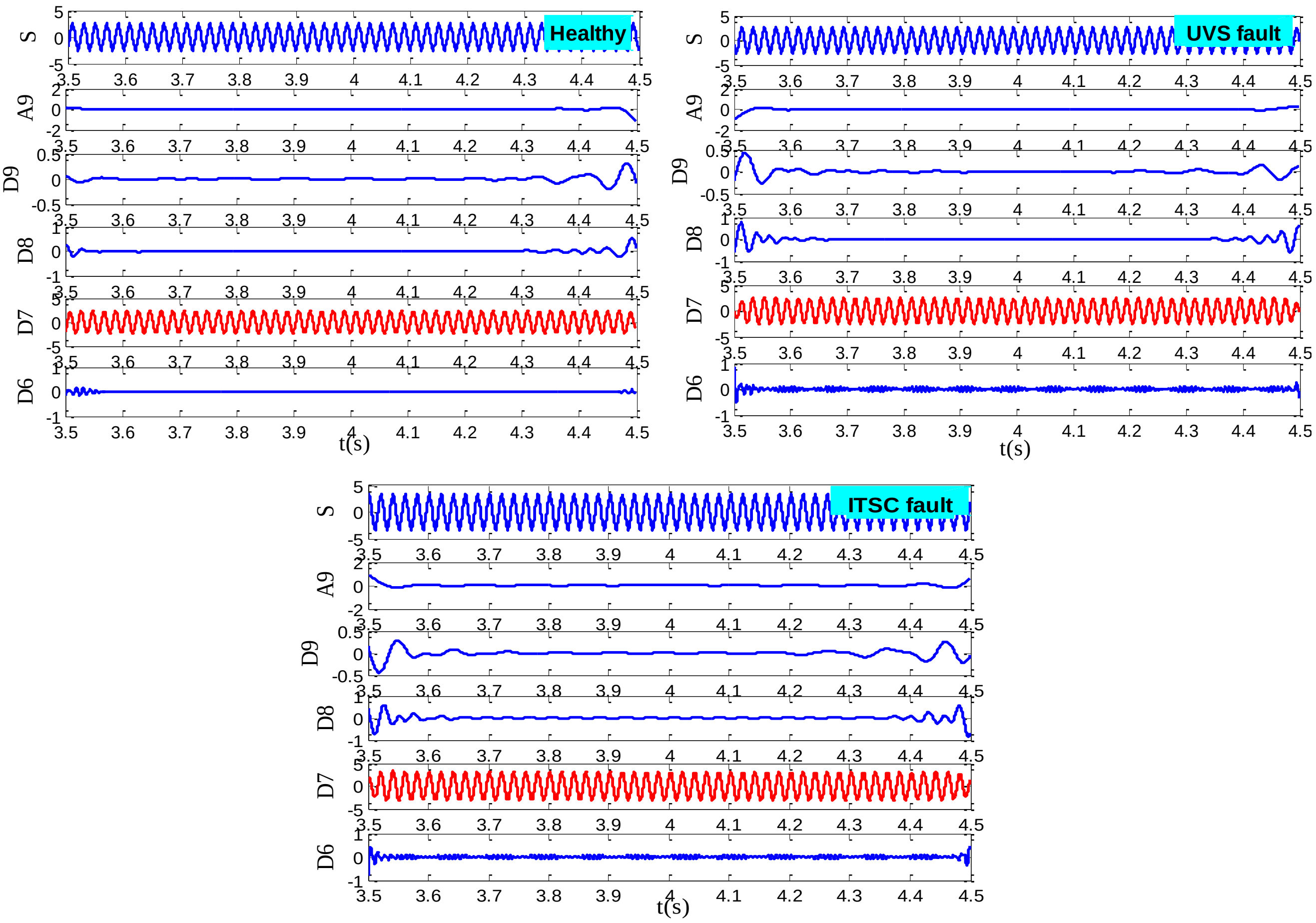
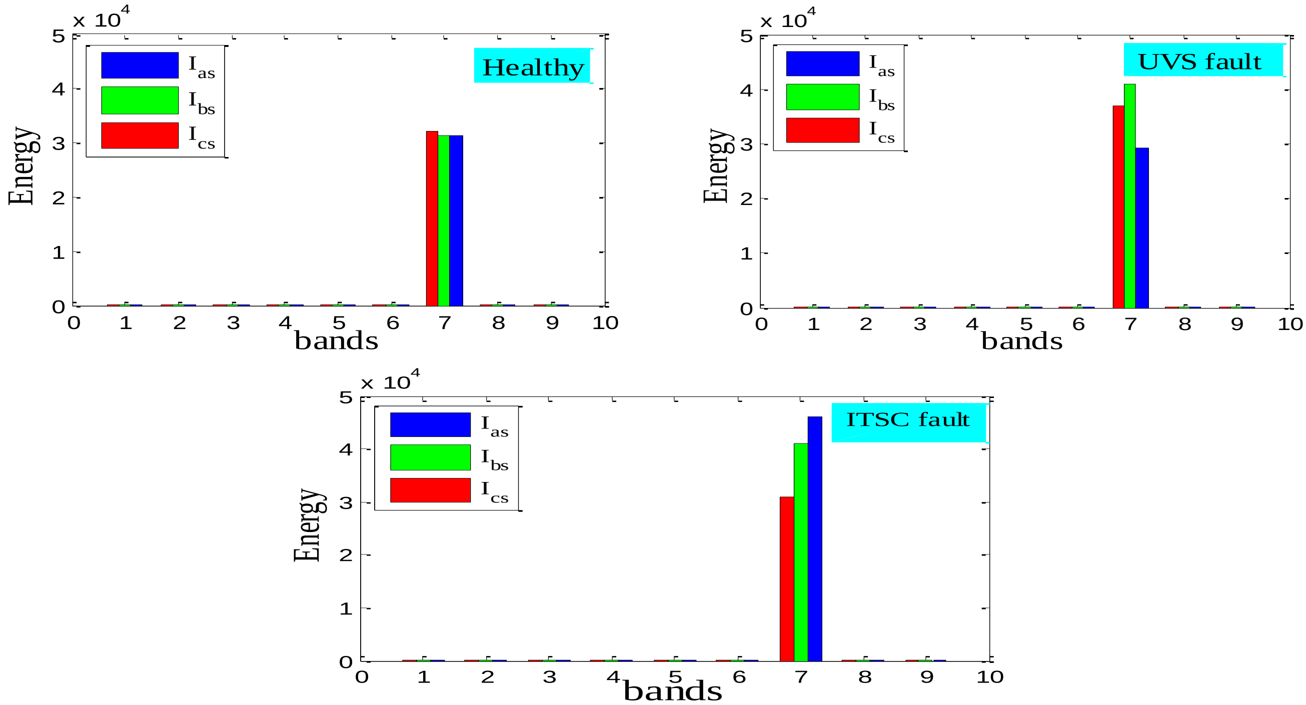


Figure 8. DWT decompositions of stator current for Healthy state, ITSC fault and UVS fault.

Figure 9 represents the DWE values of the detail decomposition of three stator currents (I_{as}, I_{bs} and I_{cs}) under average load (3.5Nm) for three cases: healthy state, ITSC fault by 20 turns shorted in phase as and UVS fault of 4% in the amplitude of phase as. It is noted that the energy stored in Ed7 represents the greatest one because it found at the frequency margin [39.0625-78.125], which contains the fundamental frequency, as shown in Table2. The behavior of Ed7 values can be tracked in the diagnosis without having to track all the amounts of energy levels.



Figre 9. Energy variation for several levels of DWT decomposition of three stator currents in Healthy state and UVS, ITSC faults

Figure 10shows the experimental results of DWER of three phases currents (E_{d7as}/E_{d7bs}, E_{d7bs}/E_{d7cs} and E_{d7cs}/E_{d7as}), obtained for the three stator currents, at level 7 in healthy and faulty states: ITSC fault by 20 turns shorted and UVS fault of 4%, under average load in the phase as. It is noted that in a healthy state, the values of three ratios are equal to 1, unlike in faulty states, the values of the three ratios vary according to the type of the fault, with these indexes, the faults can be easily detected.

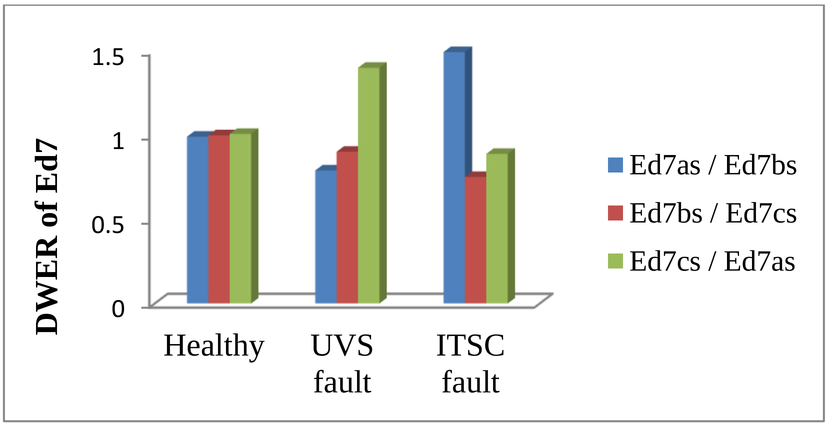


Figure 10. Discrete wavelet energy Ratio in E_{d7}

Table 3 represents a comparison between MCSA and DWER approaches.The comparison showed that the DWER approach more efficient and effective than MCSA in diagnosis the ITSC and USV faults. To demonstrate that the DWER is an accurate and robust diagnosis approach will be used the neural network (NN) method to classify the faults (ITSC and USV) where using DWER indictor as NN input.

Table3. Comparison between MCSA and DWER approaches

MCSA approach	**DWER approach**
• Classical approach	• Advanced approach
• Based on FFT	• Based on DWT
• Used in the stationary regime	• Used in the stationary and non-stationaryregime
• Ineffective in the detection of both faults ITSC and UVS in IM, because it cannot distinguish between them	• Effective and accurate in the detection of both faults ITSC and UVS in the IM.
• Easy to implement	• Easy to implement
• requiring one current sensor and speed sensor	• required three current sensors
• low-cost	• low-cost

5.3. Neural network faults diagnosis

There are several kinds of NN architecturein the literature feed-forward award multi-layer perception (MLP) Neural Network type is the most useful structure in the classification field. For this reason, it is selected for the classification of motor faults. The fundamental training algorithm feed-forward multi-layer network is the Back-Propagation (BP) algorithm. This algorithm is a gradient descent algorithm with an adaptive earning rate to improve the NN performanceby reducing the error between the desired output and the actual output of the network, on changing the weights along its gradient. That is so-called the mean squared error (MSE).For the classification of healthy and faulty (ITSC and UVS) states using NN, the MLP structure has been envisaged. It consists of an input layer with three neurons which are $Ed7_{as}/Ed7_{bs}$, $Ed7_{bs}/Ed7_{cs}$, and $Ed7_{cs}/Ed7_{as}$ respectively, one hidden layer contains 10 neurons with a sigmoid activation transfer function, and finally, an output layer which contains a tow neuron, with linear transfer function. Figure 11 shows the envisaged MLP structure.After determining the inputs, outputs and the network structure, the next step consists in acquiring data from experimental tests of the IM. These data are treated and classified in a record called database. The learning database must be represented in terms of the quality and quantity of the different modes of motor operation. The NN task is searching to couple each of the input data to the mode of operation (healthy, or faulty).

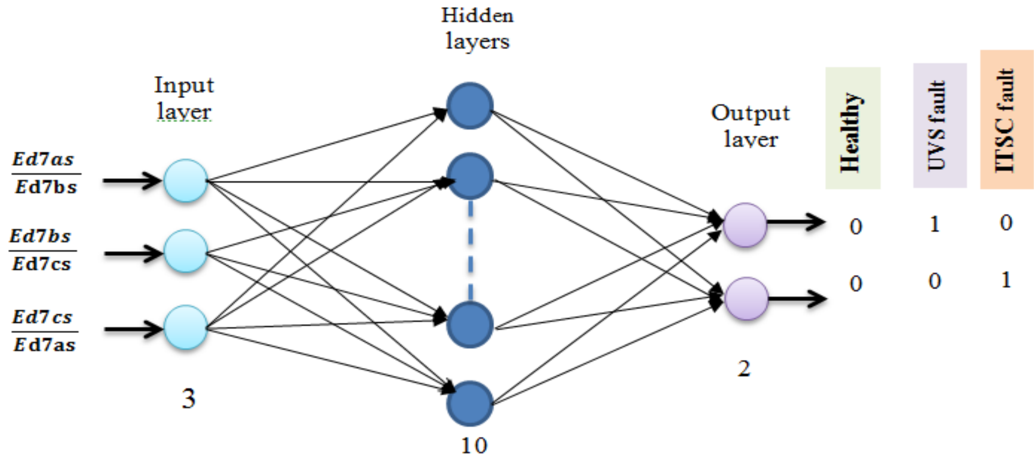


Figure 11. MLP Structure

a) **Training results**

Figure 12 represents the training input data of the NN, which constituted by a successive sequence of examples extracted from the experimental tests of the IM. The training data composed of the input vectors:

$[E_{d7as}/E_{d7bs}\ E_{d7bs}/E_{d7cs}\ E_{d7cs}/E_{d7as}]$.

The input data in Figure 12 is constituted by a successive series of examples (64 samples) divided into three parts, as follows:

- **Part.1:**8 samples for the healthy state of the motor under 8 loads (no-load, 10%, 20%, 40%, 60%, 70%, 90% and 100% of the rated load).
- **Part.2:**8 samples UVS of 4% fault states under 8 loads (no-load, 10%, 20%, 40%, 60%, 70%, 90% and 100% of the rated load).
- **Part.3:**48samples for the ITSC faults states of the (8-13-14-15-20-30) shorted turns under 8 loads (no-load, 10%, 20%, 40%, 60%, 70%, 90% and 100% of the rated load).

The desired outputs vector O_i=[O_1; O_2] of the NN are formed as the following:

- O_1= 1 for an UVS fault; otherwise, O_1= 0;
- O_2= 1 for an ITSC; otherwise, O_2= 0;

Thus, the output states of the NN are set as below:

- [0; 0] no-fault (healthy mode);
- [1; 0] UVS fault;
- [0; 1] ITSC fault;

Figure13 shows the training outputs and errors of NN, which has perfectly learned the input data, as presented in the previous examples and given correctly desired output with low errors ($e_1=10^{-5}$, $e_2=10^{-5}$).

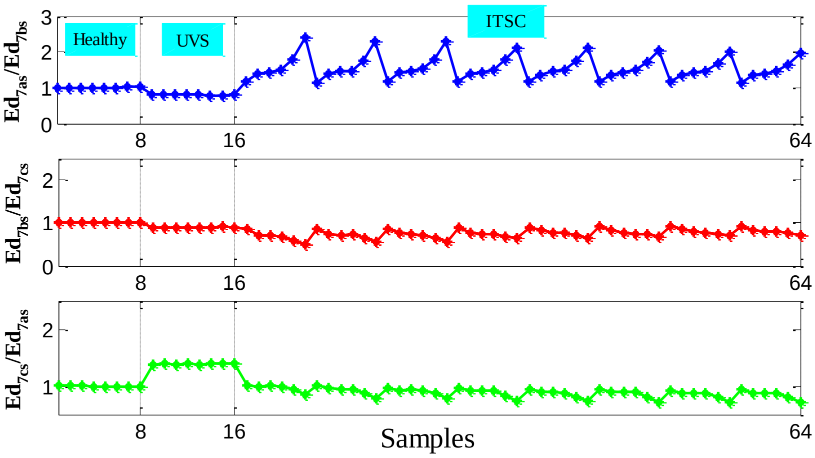


Figure 12. Experimental training data set input

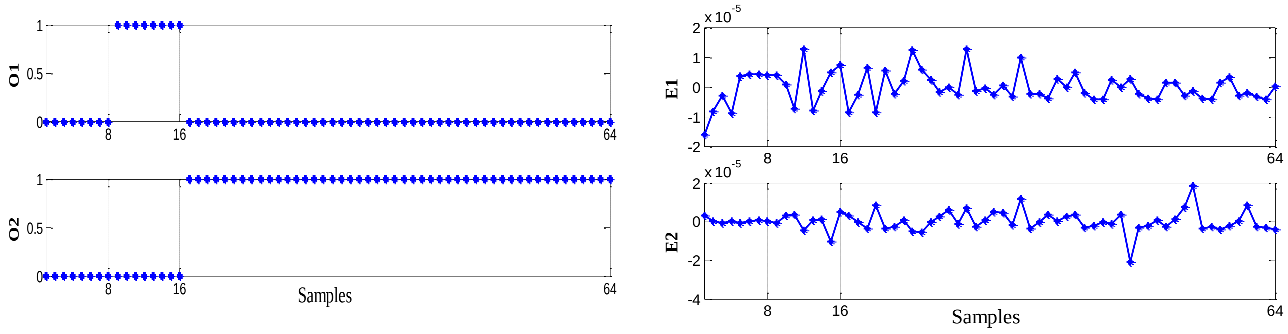


Figure 13. Experimental training outputs and errors of NN

b) Testing results

In order to evaluate the NN ability to generalize; the network must be supplied with a data test set composed of examples that are different from the one in training. The various test results for a simple fault under three load torques (30,50%and 80% of the rated load) are distributed as follows:

Healthy states (3 samples), UVS fault of 4% (3 samples), and ITSC fault with (18-25) shorted turns (6samples).Figure14 represents the test output and error. According to the neglected errors of the test (about 10−5), it is apparent that the NN can correctly detect and identify the ITSC and the UVS faults in IM, and distinguishing between them accurately.

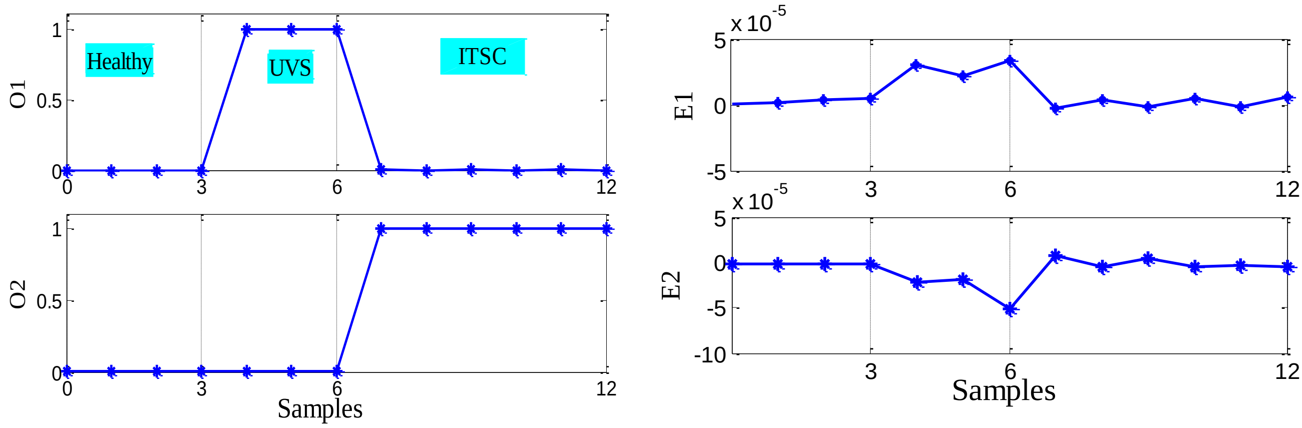


Figure 14. Experimental test outputs and errors

6. Conclusion

The main objective of this study is to know the accuracy and effectiveness of each technique on the early detection of the faults (ITSC and UVS) and their ability to distinguish between them clearly. In summary, the study unveils the followings:

- The MCSA-FFT approach using spectrums extracted from the stator current to diagnose ITSC and UVS faults gave the same harmonics, the difference between the two results being just in the amplitude of the harmonics. The similarity between the two fault signatures by FFT can lead to a false diagnosis.
- The DWER approach, which was based on the DWT and the ratio of the discrete wavelet energy of three stator currents were effective and accurate to detect both faults even in different conditions of the motor. Furthermore, it could distinguish between both faults.
- The DWER features include information concerning the ITSC and UVS faults, which allows them to be good and reliable indicators for detecting the faults easily, in the IM.
- To confirm the effectiveness and robustness of this approach (DWER) to diagnose, the NN was used for classifying and auto-detection the faults in different loads conditions of the motor in the cases: healthy and ITSC, UVS faults,where considering the DWER indicators as the NN input.The results obtained of combination between the DWER and NN are effective and proved its ability to detect both faults under different load conditions and distinguish between them accurately with low error (10-5). It gave to the proposed approach strength and accuracy in fault diagnosis.

As the further scope, we can improve the research by using advanced artificial intelligence tools like neuro-fuzzy networks SVM …, where can the DWER indicators detection and localization automatically the faults?

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