Artificial Neural Networks for Diagnosing Stator Induction Motor Faults

Pablo Serrano[1], Antonio Zamarrón[1], Arturo Hernandez[2], and Alberto Ochoa[3]

(1) Instituto Tecnológico de León; Guanajuato México
(2) Centro de Investigación en Matemáticas; Guanajuato, México
(3) Instituto de Ingeniería y Tecnología. Universidad Autónoma de Ciudad Juárez; México
E - mail: *jpsr9@hotmail.com*

Abstract. Stator Winding Fault can be detected by monitoring any abnormality of the Park's spectrum. In this paper is presented a fault-detection performance comparison between the Support Vector Machine (SVM) and backpropagation algorithm (BP) using experimental data for a healthy and faulty case. Support Vector Machine and Backpropagation Algorithm provide environments to develop fault-detection schemes because of their multi-input-processing and its good generalization capability. The training patterns are obtained using motor current signature analysis (MCSA) and using Spectral Park's Vector. The neural networks are evaluated by means of the cross-validation technique to determine easily the diagnosis and severity of turn-to-turn faults.

Keywords: Artificial Neural Networks, Faults Diagnosis, Induction Motor.

1 Introduction

At the present time the induction motor has a multiplicity of applications in the human life. Induction Motors applications are presented in different processes in the industry. However, the induction motors, as other machines, can fault during operation. One of the most important faults presented in induction motors is turn-to-turn short-circuits. Degradation of winding insulation can lead to these faults, starting a process that can progress to severe phase-to-phase or turn-to-ground faults. The investigation presented in this paper promotes induction motor preventive maintenance. This paper is organized as follows. Section II discusses about Artificial Neural Networks particularly backpropagation algorithm and support vector machine. Section III briefly describes the fundamental properties of the Park transformation complex vector. Section IV shows the motor-data specifications and the measurement and analysis data. Section V presents the fault-detection schemes and the experimental results. Conclusions are presented in section VI.

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2 Artificial Neural Networks (Backpropagation Algorithm)

Stator winding fault diagnostic is essentially a classification problem in pattern space. The artificial neural networks (ANN) can be used to classify patterns of a motor in regular and fault condition. The ANN is a massively parallel processor made up of simple processing units, which has a natural propensity for storing experimental knowledge and making it available for use [1]. There are many neural networks models; however the Backpropagation (BP) networks are simple in structure and stable in operation [2]. Neural Networks based on Backpropagation algorithm have been successfully used for pattern recognition and nonlinear mapping. The BP is a supervised learning method, and is an implementation of the Delta Rule; in this algorithm are calculated desired outputs for any given input. The BP network is structured by hide layers which are capable of classifying an arbitrary region of multidimensional space. A three-layer BP networks is presented in the figure 1 where n is the input layer node number as a set of input data ($x_1, x_2, \ldots, x_n$), m is the output layer node number, i is the hidden layer node number pattern number, and w_{ji} are the weights between input layer node and hidden layer node.

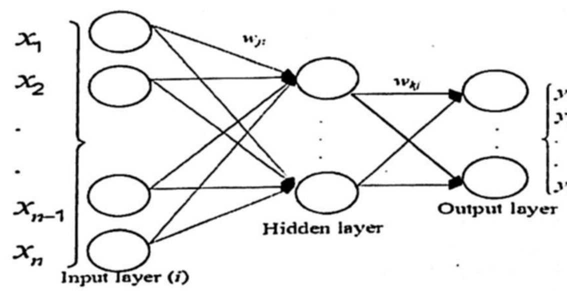


Fig. 1. A three-layer BP networks.

In mathematical terms, the input Net_j is obtained as following:

$$Net_j = \sum_{i=1}^{n} \left(x_i * w_{ji} \right) \tag{1}$$

The output $Output_j$ of layer node input is obtained by the activation function

$$Output_y = f\left(Net_j\right) \tag{2}$$

In this paper was used the bipolar sigmoid function

$$f(x) = \frac{2}{1+e^{-2*x}} - 1 \tag{3}$$

The Mean Square Error (MSE) is used to calculate the total error in training patterns.

$$MSE = \frac{\frac{1}{2}\sum_{n=1}^{N}\sum_{k=1}^{K}(y_{kn} - \hat{y}_{kn})^2}{N \cdot K} \tag{4}$$

where y_{kn} is the target output of the pattern *n*, $\hat{y}_{kn}$ is the actual output of the neuron *k* at output layer for pattern *n*, *N* is the number of patterns, and *K* is the number of output neurons.

3 Support Vector Machine (SVM)

An SVM is a method for separating clouds of data in the feature space *F* using an optimal hyperplane [3]. Considering a training set $D = \{(x_1, y_1), (x_2, y_2), ..., (x_l, y_l)\}$ with input data $x_k \in R^N$ and corresponding binary class label $y_k \in \{+1, -1\}$, the data can be classified by means the SVM classifier. In the general case, the SVM classifier is [4]:

$$f(x) = w^T \Phi(x) + b \tag{5}$$

Where w^T is an m-dimensional vector, $\Phi(x)$ is a nonlinear function, and *b* is a scalar. Data points are mapped by means of a kernel with the purpose of searching a maximal separation between classes. The kernel $K(\cdot, \cdot)$ corresponds to an inner product of vector in the higher dimensional feature space if and only if Mercer's condition is met [3]. In this paper, we used a polynomial kernel, which is described as:

$$K(x,z) = (\langle x,z \rangle)^m \quad \text{With } m \in ¥ \tag{6}$$

An example of the SVM is presented in the figure 2.

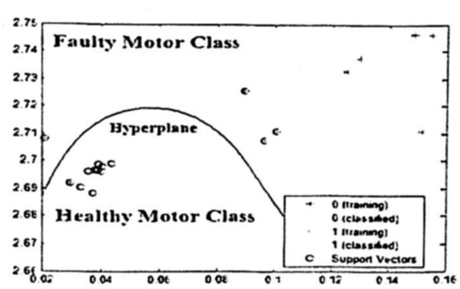


Fig. 2. Example of classification regions of a SVM for a healthy motor and faulty case.

4 Stator Current Complex Vector

Stator current complex vector can be represented as a Park's vector. The Park vector is generally used to carry out a simplified analysis of three-phase stator motor variables. It consists on a two dimensional representation that describes tree-phase induction motor phenomena [3]. In mathematical terms the current complex vector is [3], [4]:

$$\hat{j} = \frac{2}{3}\left\{ i_a + \left(-\frac{1}{2} + j\sqrt{\frac{3}{2}} \right) i_b + \left(-\frac{1}{2} - j\sqrt{\frac{3}{2}} \right) i_c \right\} \tag{7}$$

Where i_a, i_b, i_c are stator currents. Therefore Park's vector has two components which are:

$$i_d = \frac{2}{3} i_a - \frac{1}{3} i_b - \frac{1}{3} i_c \tag{8}$$

$$i_q = \frac{\sqrt{3}}{3}(i_b - i_c) \tag{9}$$

Under ideal conditions, for a healthy motor, Lissajou's curve $i_q = f(i_d)$ has a circular shape, centered at the origin and having a radio equal to the stator current complex vector corresponding to the state of operating of the motor [5]. In case of faulty motor, the Lissajou's curve changes in shape because of the harmonics presence generated by the fault. In this paper, Park's vector complex spectrum is used to detect induction motor faults.

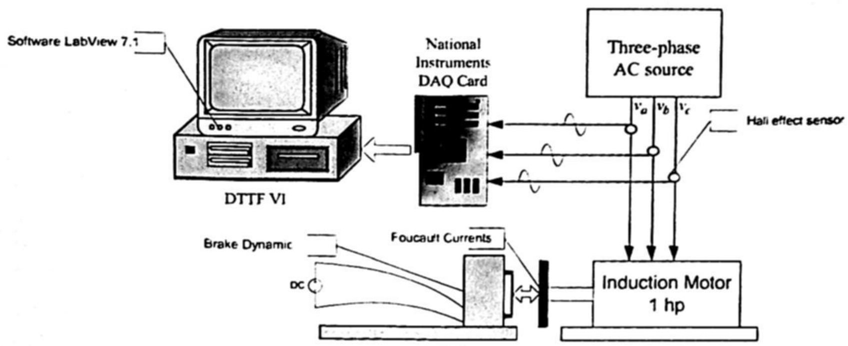
5 Measurement and Analysis Data

We performed invasive experiments on an induction motor to obtain fault data or our analyses. The characteristics of the induction motor used in the experiment are listed in Table 1.

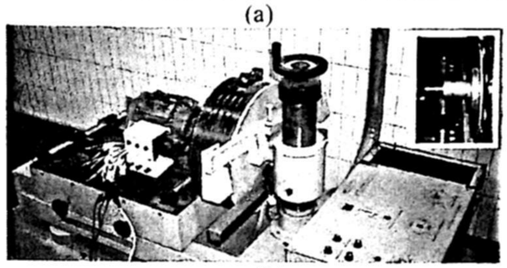
Table 1. Induction motor characteristics

Description	Value
Power.	0.75 kW (1Hp)
Voltage.	220 V
Current.	3.2 A.
Frequency.	60 Hz
Number of Poles.	4
Speed.	1745 rpm

In the figure 3 (a) and 3 (b) is presented the experiment setup. The induction motor was tested in healthy and fault conditions for different speeds and faults. A modified induction motor with shorted adjacent turns was used in the tests carried out. Figure 4 schematically shows the stator winding design, including how turn-to-turn faults can be created. With this machine, a turn-to-turn fault ranging from 1 to 9 turns can be created.

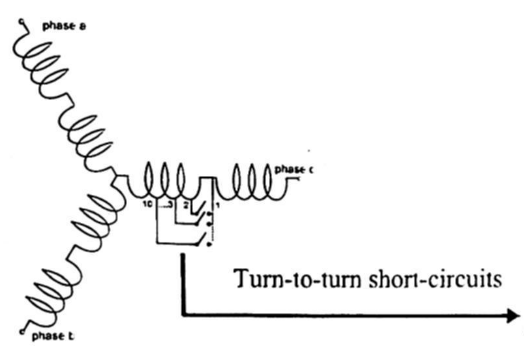


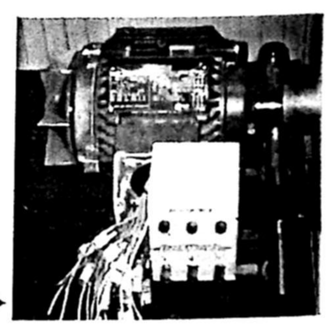
(a)



(b)

Fig. 3. a) Schematic of the experimental setup. b) Actual experiment setup to collect healthy and faulty motor data.





(a) (b)

Fig. 4. a) Schematic of the stator winding design. b) Induction motor tested

Experiment consisted on collecting stator current data at different load motor conditions and faults. The induction machine was tested at 0%, 25%, 50%, 75% and full-load. Three Hall effect based sensors, Data Acquisition Card (National

Instruments DAQ-Card USB-9162), and a computer was used to obtain motor current data. Motor speeds were fixed by a Foucault Currents based break dynamic. Induction motor speed was measured by a tachometer. Figure 5 shows the stator current time evolution for a healthy and a faulty (nine- turn fault) motor respectively.

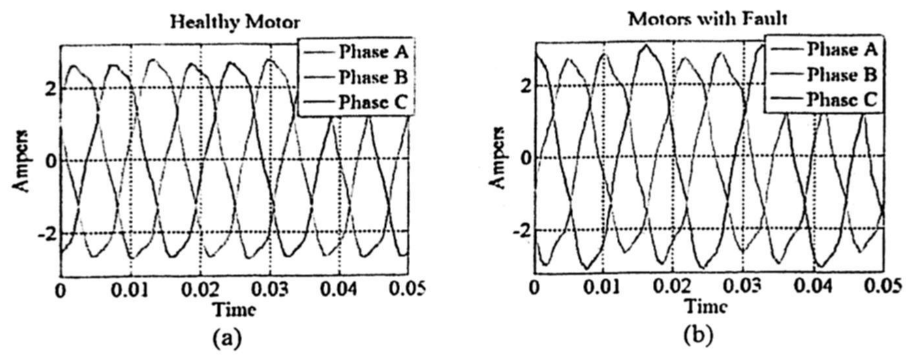


Fig. 5. Stator current time evolution under no load. (a) Healthy motor, (b) Motor with nine-turn short-circuit fault.

In figure 6 is presented the Park's vector trajectory and spectral for two situations: healthy and nine-turn fault. As can be seen in this figure, the magnitude of the harmonic at -60 Hz gives partial information about the fault. Harmonic at -180 Hz is also taken in account for fault detection. Park's vector in different practical situations presents drawbacks like was mentioned previously. For this reason the Park's vector modulus spectrum is proposed to detected abnormalities in the induction motor. The Park's Vector FFT is a power method to detected stator-winding faults. Stator current fault harmonics can be obtained as following [6]:

$$f_{stator} = \left\{ \frac{1}{p}(1-s) \pm k \right\} f_0 \tag{10}$$

Where p is the number of pole pairs of the motor, k = 1, 2, 3..., n is the index harmonic, and f_0 is the fundamental frequency. The equation 10 can be located whether we are doing reference to Motor Current Signature Analysis (MCSA). The slip s is defined as the relative mechanical speed of the motor, n_m, with respect to the motor synchronous speed n_s as [7]:

$$s = \frac{n_s - n_m}{n_s} \tag{11}$$

The motor synchronous speed n_s is related to the line frequency f_0 as:

$$n_s = \frac{120 f_0}{p} \tag{12}$$

Where 120 is a constant used to express the motor synchronous speed n_s in revolutions per minute (r/min) unit.

(a)

(b)

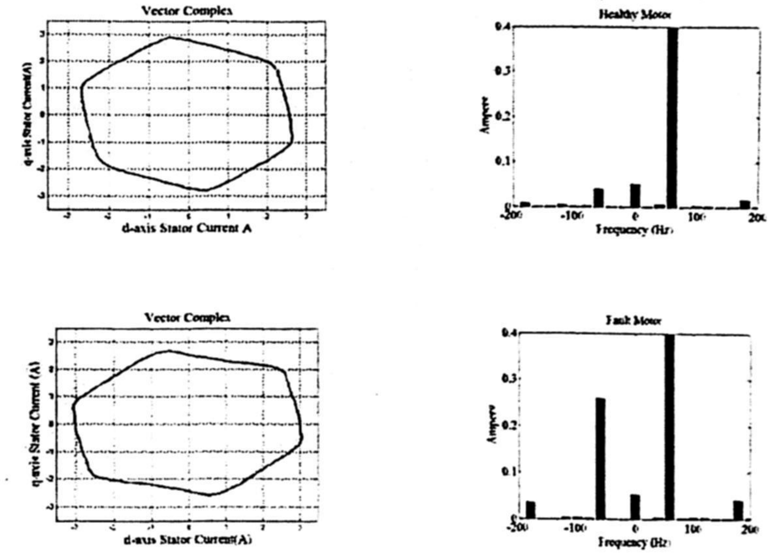


Fig. 6. Park's vector trajectory and spectral for a) Healthy, and b) Faulty condition.

Thus, we can do an analysis of the relation between the magnitude differences of current spectrum versus turn-to-turn fault severity under different load conditions. This relation is presented in the figure 7.

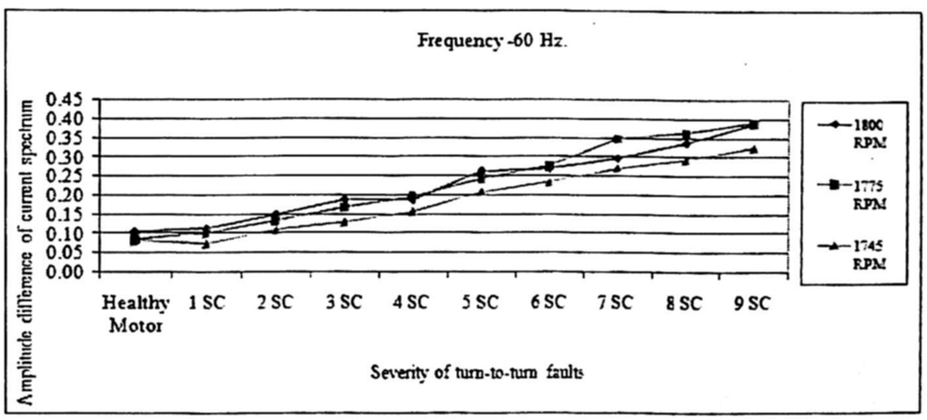


Fig. 7. Magnitude of the harmonic at -60 Hz for several speeds and fault severities.

6 Fault-Detection Schemes and Experimental Results

The experimental data were collected with a sampling frequency of 9.84 KHz for what each motor-current data set contains 9840 samples for duration of 1 s. There are a phase of pre-processing for that the current-data are processed by means of the spectral Park's Vector and using the equation 10 are obtained the training set according the frequency where is presented the stator winding fault. Each training set correspond to two types of condition: Healthy Motor and Faulty Motor under different load conditions. A training pattern is a vector of three columns whose data corresponding to the frequencies of -180 Hz and -60 Hz and 60 Hz of the Park's vector spectral. The experiments were based in two schemes: an artificial neural network with Backpropagation algorithm and a Support Vector Machine. The number of patterns in both schemes was obtained according to the rule of Baum and Haussler (1989) and is determinate for the next condition [11]:

$$P = \frac{W}{e} \tag{13}$$

Where P is the number of training patterns, W is the number of weights in the neural network Backpropagation, and e is the percent of error in the classification on the validation set. Thus, with e = 0.1 and a maxim of 100 weights in the neural network, are obtained 1000 training patterns. These 1000 patterns are divided in two sets that correspond to the training patterns and validation patterns. The dimension of the training set is of 666 patterns and of the validation set is of 333 patterns.

6.1 ANN with Backpropagation Algorithm

The development neural network of this paper is based in the process of Rodvold 2001. This process is composed of five steps ("Network Requirements, Goals, and Constraints", "Data Gathering and Preprocessing". "Training and Testing Loops", "Network Deployment" and "Independent Testing and Verification") [12]. The values of the weights are initialized according to the method of Nguyen-Widrow with the purpose of improvement the learning ability of the hidden units. This method is based on geometrical analysis of the response of the hidden neurons to a single input. First is calculated the scale factor by means of the next equation [11]:

$$\beta = 0.7\,(p)^{\frac{1}{n}} = 0.7\sqrt[n]{p} \tag{14}$$

Where n (n = 3) is the number of input units, p is the number of hidden units. To initialize the weights is necessary to follow the next steps:

1) For each hidden unit, initialize its weights vector v_{ij} that has relation with the inputs units.
2) Firstly, set random number between -0.5 and 0.5 to the weights vector.

(15)

$v_{ij}(old) =$ random number between -0.5 and 0.5

To calculate:

$$\|v_j(old)\| = \sqrt{v_{1j}(old)^2 + v_{2j}(old)^2 + \ldots + v_{nj}(old)} \qquad (16)$$

Reinitialize weights:

$$v_{ij} = \frac{\beta v_{ij}(old)}{\|v_j(old)\|} \qquad (17)$$

3) Finally, set bias v_{oj} random number between $-\beta$ and $+\beta$.

We have two schemes of training for the neural network. The gradient descent is used in both schemes with the next parameters: learning rate is 0.001 and momentum is 0.8. In this paper is used the bipolar sigmoid function.

$$f(x) = \frac{2}{1+e^{-2*x}} - 1 \qquad (18)$$

In case 1, we have stopped training if the network training error reaches a pre-set value, which in our case is set to 0.0005. The training and test results for this second case are shown in Table 2. In this case the ANN only recognizes a motor with fault and without fault. Two output units are codified in this model: 1 for faulty motor and -1 for healthy motor.

Table 2. Training and test results of the neural networks structures

ANN	Units Hidden	Validation Error	%	Test Error.	%
3	10	0.391097	92	0.494273	90
4	15	0.524772	87	0.424829	90
5	20	0.543908	87	0.627349	85
6	40	1.386552	83	1.083323	80
7	60	3.665848	74	3.723645	75
8	80	2.171371	78	3.828273	75
9	100	3.533251	74	4.049451	70

In case 2, we have taken into consideration that we have a large number of units in the hidden layer than the input layer. The gradient descent is used to train the ANN structure. In this case the neural network diagnoses the healthy and faulty condition motor. However, also, diagnose the severity fault since one to nine short-circuits in the stator winding. In the Table 3 are presented the outputs units.

Table 3. Outputs units of the artificial neural network.

Conditions Motor	Outputs Unit 1	2	3	4
Without Fault.	-1	-1	-1	-1
1 short-circuit.	1	-1	-1	-1
2 short-circuits.	-1	1	-1	-1
3 short-circuit.	1	1	-1	-1
4 short-circuit.	-1	-1	1	-1
5 short-circuit.	1	-1	1	-1
6 short-circuit.	-1	1	1	-1
7 short-circuit.	1	1	1	-1
8 short-circuit.	-1	-1	-1	1
9 short-circuit.	1	-1	-1	1

The training and test results are shown in Table 4.

Table 4. Training and test results of the neural networks structures .

ANN	Epochs	Training Error.	Validation Error	Test Error
1	310,000	0.034070	0.14150	0.24350
% Classification Validation/Test				86% / 80%
2	450,001	0.004098	0.05766	0.05966
% Classification Validation/Test				90% / 90%
3	620,001	0.011436	0.05853	0.06150
% Classification Validation/Test				90% / 88%

We applied training stop technique known as "Cross-validation". Cross-Validation is a technique to prevent overtraining which consist in to divide of the data in two disjoints sets. The first data set is the training set, which is used to train the ANN and the second set is used to validate the ANN structure. Thus, the validation error is checked throughout the training process. From Table 4, the absolute errors between the network outputs and the object outputs for all training patterns are less than 0.004098 after 450, 001 iterations. It is shown that the BP networks have the very high diagnosis accuracy and good generalized ability. The figure 9 illustrates the principle of the cross-validation. The figure shows that training stops at the 450,001 epochs. In this figure can be seen the increment of the validation error, the training is stopped to avoid overtraining and most recent weight and the biases are used as the neural networks parameters.

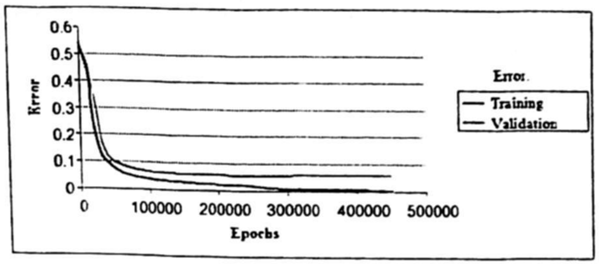


Fig. 9. Training and validation error curves with cross validation technique.

6.2 Support Vector Machine.

The learning samples and the test samples for the SVM are the same that we were used in the neural network with backpropagation algorithm. The polynomial kernel is used to train the SVM. The percent of accuracy rate in the classification, the accuracy rate in the generalization, and the number of support vectors in relation with the grade of the kernel polynomial is presented in the table 5. The percent of the rate of generalization and classification is obtained of the division of the correct number of patterns recognize and the total number of patterns in the set.

Table 5. Training and test results of the neural networks structures .

Polynomial Grade	Rate (%) Classification	Rate (%) Generalization	Number Support Vectors
3	91	87%	21
4	91	87%	15
5	97	90%	18
6	96	91%	15
7	98	91%	15
8	99	96%	21
9	98	96%	12
10	93	90%	9

7 Conclusion

Current spectrum analysis based on vector complex and a neuronal network to diagnose windings faults of an induction motor has been presented. Support Vector Machine and Backpropagation Algorithm were implemented in software to do the diagnostics on line and off line of an induction motor. The system is limited to the diagnostic of stator windings faults. The patterns are obtained by means of the spectral Park's Vector and using the Motor Current Signature Analysis. The MCSA does possible to identify the harmonics that describes the presence of a fault by mean the equation 10. A pattern of behavior is observed in the frequency of -60 Hz of the spectral Park's Vector while the harmonic on 60 Hz can describe a feature about of velocity of the induction motor. A SVM and Backpropagation Algorithm are trained to diagnose faults in an induction motor; however the results suggested that the SVM could be used to develop fault-detection schemes because of their multinput-procesing and its good generalization capability. Cross-Validation technique was used to prevent overtraining and to stop the training of the neural network with backpropagation algorithm.

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