International Journal of Electronic and Electrical Engineering.
ISSN 0974-2174 Volume 4, Number 1 (2011), pp.95-106

http://www.irphouse.com

Monitoring & Diagnosis of Induction Motor for Stator Voltage Unbalance

***Anjali U. Jawadekar, Shilpa V. Deshmukh, G.M. Dhole, Sudhir Paraskar and Mirza Ansar Beg**

Department of Electrical Engineering, S.S.G.M. College of Engineering, Shegaon. (M.S.), India
**Corresponding Author E-mail: anjali_jawadekar@ rediffmail.com*

Abstract

Induction motors are mostly used in industrial, commercial and residential sectors because of enormous merits of these over other types of available electric motors. These motors work under various operating stresses, which deteriorate their motor operating conditions giving rise to faults. Deficiencies like unbalanced voltages in the voltage source could result in problems like excessive losses, over voltages, mechanical oscillations. The early detection of these conditions in incipient phase and its removal or correction is very necessary for prevention of failure of induction motor.

Artificial Neural Network techniques easy for fault detection of induction motor. These networks can be applied when information about the system is obtained from measurements which later can be used in training procedures of neural network.

In present paper, voltage unbalance in induction motor is diagnosed by Park's Vector Approach. Stator currents Park's vector patterns are first learned using ANN and then used to discern between healthy and faulty induction motor. Induction motor under unbalanced voltage condition is simulated using Matlab/Simulink

Keywords: Artificial neural networks, Diagnosis, Induction Motor, Open phase, Park's vector approach, Voltage Unbalance.

Introduction
Power quality problems and surveys have been reported in many publications. The unbalanced Voltage gives a bad influence for power quality problems. If unbalanced power is applied to electric apparatus it gives difficult problems to them especially

electric motors [15]. Amongst the various strategies that can be followed to assess the operating conditions of induction motors Motor Current Signature Analysis (MCSA) is widely used to diagnosis tool for fault detection. Regular inspection and processing of input voltages and currents allow one to predict possible deterioration and to schedule the motor shutdown if a prefixed rate is exceeded [2]–[6].

There have been various traditional fault detection techniques based on sensors and parameter estimation approach. These approaches, sometimes, are not able to give accurate indication about incipient faults because of their limitations. Force and vibration based techniques for monitoring of induction motors are also used by researchers. Further these techniques are quite expensive too. [16]-[18].Induction motor fault detection technique based on virtual instrumentation method uses the high-frequency carrier-signal injection technique i.e. virtual instrumentation to obtain information about faults from the machine.

Recent development in diagnosis system makes extensive use of ANN. ANN based techniques are being used extensively for incipient fault detection because of various merits of techniques over other traditional and parameter estimation techniques. A lot of work has been reported in literature for ANN based techniques for induction motor fault identification. Researchers have extensively used multilayer ANN structure and back propagation algorithms for online fault detection of induction motors. Self organizing map (SOM) technique has also been tried in the past.

For the inputs to the ANN most of the researchers have gone for RMS values of three phase voltages and current quantities.ANN techniques are easy to extend and modify.[6]-[14].In the present paper the instantaneous values of three phase voltages and currents have been utilized for the inputs to the ANN.

Further the Park's Transform is most popular transform used in vector control algorithm .Stator current Park's vector pattern are first learned using ANN and then used to discern between healthy and faulty conditions.

Effects of Voltage Unbalance and Single Phasing on Three Phase Induction Motor

Unbalance Voltage Effects

Voltage unbalance of a 3-ph system is expressed as a percentage value, and is often defined as the maximum deviation from the average of the 3-ph voltages divided by the average of the 3-ph voltages [6].

Phase voltage unbalance ratio PVUR(%) is defined as

$$PVUR(\%) = \frac{\text{Maximum phase voltage deviation from average phase voltage magnitude}}{\text{Average phase voltage magnitude}}$$

$$= \frac{\text{Max}\,[|Va-Vavg|, |Vb-Vavg|, |Vc-Vavg|]}{Vavg} \times 100\% \tag{1}$$

$$V_{avg} = \frac{Va+Vb+Vc}{3}$$

Voltage unbalance in induction motor induces negative sequence current which in turn produces a backward rotating field in addition to forward rotating field produced by positive sequence one. Interactions of these fields produces pulsating electromagnetic torque and velocity disturbance resulting in increase losses, stresses and noise in machine.[14]

Even if unbalanced voltage applied to motor is small enough, large unbalanced motor current can flow because of relatively low negative sequence impedance. Large unbalanced current makes difficult problems in induction motor applications such as heat problems, increase of losses, vibrations, shortening of life, decrease of rotating torque. The percentage increase in temperature of the winding is approximately two times the square of the voltage unbalance. These higher temperatures soon result in degradation of the motor insulation and shortened motor life. This additional rotor heat can exist for a considerable time period and since the rotor and shaft are continuous metallic structure, the heat transfer to the shaft ends can reduce the bearing failure.[19]

Single-phasing effects

If single phasing occurs when the motor is rotating, the torque produced by the remaining two positive rotating fields continues to rotate the motor and develop the torque demanded by the load. The negatively rotating field i.e. the field associated with the lost phase produces currents in the inductive loads resulting in voltages at the faulted leg of the 3-ph supply. These voltages may be nearly equal to the phase voltage that was lost. Three-ph motor may continue to run, but they are not capable of starting on single-phasing. Even though the motor will continue to operate in this condition, the motor will heat up quickly, and it is essential that the motor be removed from service.

The effects of single phasing are similar to the unbalanced voltages, since the single phasing represents the worst case of an unbalanced voltage condition. An additional effect is the remaining phase windings experience excessive overheating, thereby creating a greater potential for stator winding failure.

Park's Vector Approach

In three-phase induction motors, the connection to the mains does not usually use the neutral. Therefore, the mains current has no homopolar component so a two dimensional representation can be used to for describing three phase induction motor. Park's transform reduces the number of current components and makes calculation easier.

As a function of mains phase variables (ia, ib, ic) the current Park's vector components (id, iq) are

$$i_d = \sqrt{2/3}\, i_a - 1/\sqrt{6} i_b - 1/\sqrt{6} i_c \qquad (2)$$

$$i_q = 1/\sqrt{2}\, i_b - 1/\sqrt{2} i_c \quad (3)$$

Under ideal conditions, three-phase currents lead to a Park's vector with the following components

$$i_d = \sqrt{6}/2\ I \sin wt \quad (4)$$

$$i_q = \sqrt{6}/2\ I (\sin wt - \pi/2) \quad (5)$$

where

I- maximum value of the supply phase current

w_{s-} supply frequency;

t -time variable

Artificial Neural Network

ANNs are highly interconnected processing units inspired in the human brain and its actual learning process. Interconnections between units have weights that multiply the values which go through them. Also, units normally have a fixed input called bias. Each of these units forms a weighted sum of its inputs, to which the bias is added. This sum is then passed through a transfer function.

Prediction with NNs involves two steps: training and learning. Training of FFNNs is normally performed in a supervised manner. The success of training is greatly affected by proper selection of inputs. In the learning process, a neural network constructs an input–output mapping, adjusting the weights and biases at each iteration based on the minimization or optimization of some error measure between the output produced and the desired output. This process is repeated until an acceptable criterion for convergence is reached. The most common learning algorithm is the back propagation (BP) algorithm, in which the input is passed layer through layer until the final output is calculated, and it is compared to the real output to find the error. The error is then propagated back to the input adjusting the weights and biases in each layer. The standard BP learning algorithm is a steepest descent algorithm that minimizes the sum of square errors. In order to accelerate the learning process, two parameters of the BP algorithm can be adjusted: the learning rate and the momentum. The learning rate is the proportion of error gradient by which the weights should be adjusted. Larger values can give a faster convergence to the minimum. The momentum determines the proportion of the change of past weights that should be used in the calculation of the new weights.

In this paper, the fully-connected multilayer FFNNs is used and trained for discriminating healthy and faulty condition with a supervised BP learning algorithm. The FFNN consists of an input layer representing the input data to the network, hidden layers and an output layer representing the response of the network. Each layer consists of a certain number of neurons; each neuron is connected to other neurons of the previous layer through adaptable synaptic weights ***w*** and biases ***b***, as shown in Fig.1 (a) and Fig.1 (b).

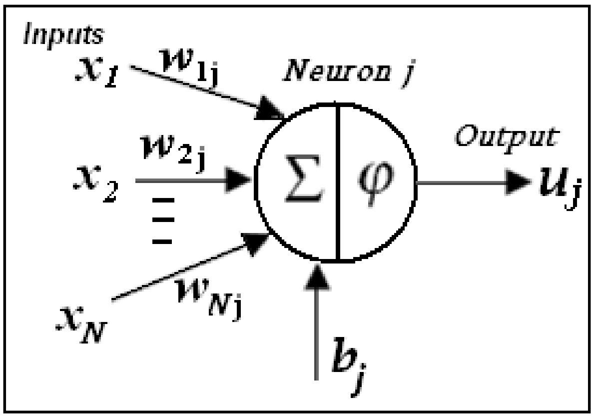

Figure 1(a): Information processing in a ANN.

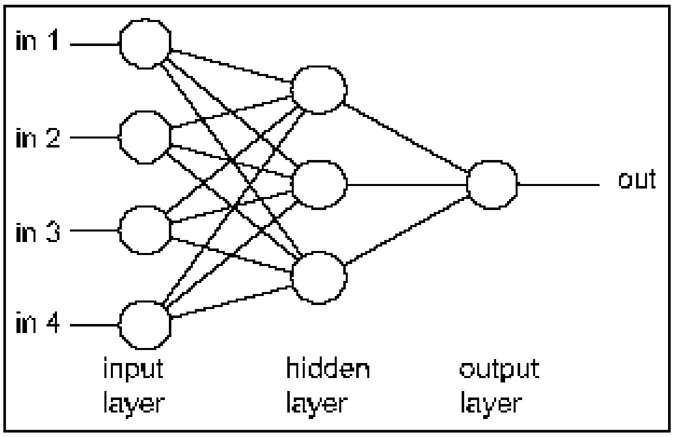

Figure 1 (b): Architecture of ANN.

If the inputs of neuron j are the variables $x_1, x_2, \ldots, x_i, \ldots, x_N$, the output u_j of neuron *j* is obtained as

$$u_j = \varphi\left(\sum_{i=1}^{N} w_{ij} x_i + b_j\right) \tag{6}$$

where w_{ij} is the weight of the connection between neuron *j* and *i*-th input; b_j is the bias of neuron *j* and φ is the transfer (activation) function of neuron *j*.

An FFNN of three layers (one hidden layer) is considered with N, M and Q neurons for the input, hidden and output layers, respectively. The input patterns of the ANN represented by a vector of variables $x = x_1, x_2, \ldots, x_i, \ldots, x_N)$ submitted to the NN by the input layer are transferred to the hidden layer. Using the weight of the connection between the input and the hidden layer and the bias of the hidden layer, the output vector $u = (u_1, u_2, \ldots, u_j, \ldots, u_M)$ of the hidden layer is determined.

The output u_j of neuron j is obtained as

$$u_j = \varphi hid\left(\sum_{i=1}^{N} w_{ij}^{hid}\ x_i + b_j^{hid}\right) \tag{7}$$

where w_{ij}^{hid} is the weight of connection between neuron *j* in the hidden layer and the *i*-th neuron of the input layer, b_j^{hid} represents the bias of neuron *j* and φhid is the activation function of the hidden layer.

The values of the vector *u* of the hidden layer are transferred to the output layer. Using the weight of the connection between the hidden and output layers and the bias of the output layer, the output vector $y = (y_1, y_2, \ldots, y_k, \ldots, y_Q)$ of the output layer is determined.

The output y_k of neuron *k* (of the output layer) is obtained as

$$y_k = \varphi out\left(\sum_{j=1}^{M} w_{jk}^{out}\ u_j + b_k^{out}\right) \tag{8}$$

where w_{jk}^{out} is the weight of the connection between neuron *k* in the output layer and the *j*-th neuron of the hidden layer, b_k^{out} is the bias of neuron *k* and $\boldsymbol{\varphi out}$ is the activation function of the output layer.

The output y_k is compared with the desired output (target value) y_k^d . The error E in the output layer between y_k and y_k^d ($y_k^d - y_k$) is minimized using the mean square error at the output layer (which is composed of *Q* output neurons), defined by

$$E = \frac{1}{2}\sum_{k=1}^{Q}(y_k^d - y_k)^2 \tag{9}$$

Training is the process of adjusting connection weights *w* and biases *b*. In the first step, the network outputs and the difference between the actual (obtained) output and the desired (target) output (i.e., the error) is calculated for the initialized weights and biases (arbitrary values). In the second stage, the initialized weights in all links and biases in all neurons are adjusted to minimize the error by propagating the error backwards (the BP algorithm). The network outputs and the error are calculated again with the adapted weights and biases, and this training process is repeated at each epoch until a satisfied output y_k is obtained corresponding with minimum error. This is by adjusting the weights and biases of the BP algorithm to minimize the total mean square error and is computed as

$$\Delta w = w^{new} - w^{old} = -\eta\frac{\partial E}{\partial w} \tag{10a}$$

$$\Delta b = b^{new} - b^{old} = -\eta\frac{\partial E}{\partial b} \tag{10b}$$

where η is the learning rate. Equation (10) reflects the generic rule used by the BP algorithm. Equations (11) and (12) illustrate this generic rule of adjusting the weights and biases. For the output layer, we have,

$$\Delta w_{jk}^{new} = \alpha \Delta w_{jk}^{old} + \eta \delta_k y_k \quad , \tag{11a}$$

$$\Delta b_k^{new} = \alpha \Delta b_k^{old} + \eta \delta_k \quad , \tag{11b}$$

where $\propto$ is the momentum factor (a constant between 0 and 1) and $\delta_k = y_k^d - y_k$

For the hidden layer, we get,

$$\Delta w_{ij}^{new} = \alpha \Delta w_{ij}^{old} + \eta \delta_j y_j \tag{12a}$$

$$\Delta b_j^{new} = \alpha \Delta b_j^{old} + \eta \delta_j \tag{12b}$$

where

$$\delta_j = \Sigma_k^Q \delta_k w_{jk} \quad \text{and} \quad \delta_k = y_k^d - y_k$$

Simulink Implementation of Induction Motor

Sim Power System toolbox is a useful software package to develop simulation models for power system applications in Matlab/Simulink environment. A 2 H.P Induction motor was simulated using Matlab/Simulink (Fig 2) in healthy condition to determine reference current Park's vector pattern as shown in Fig(3). After that machine was simulated for two conditions, first for 50% unbalance and second for single phasing. Stator current vector pattern corresponding to these faulty conditions are shown in Fig (4.a) and Fig (4.b) respectively. These two patterns deviate from healthy pattern.

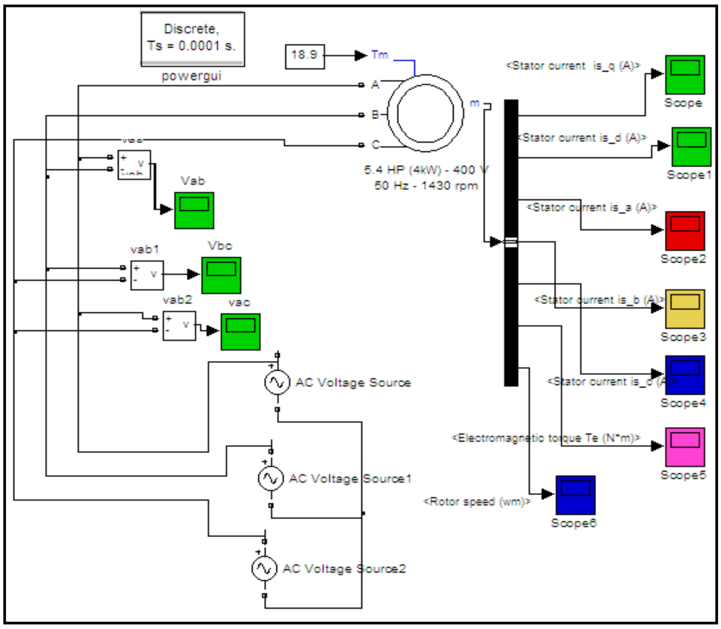

Figure 2: Simulation model of Induction Motor.

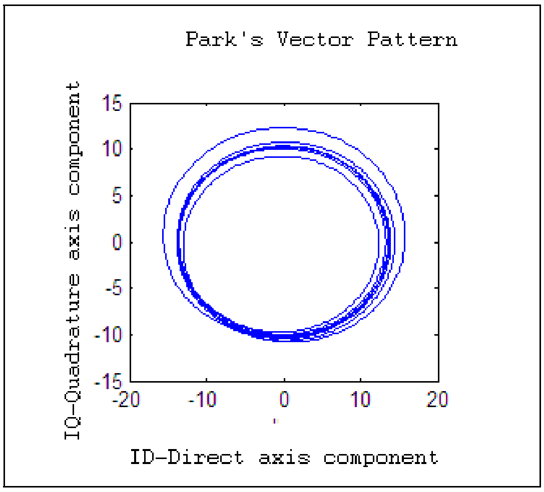

Figure 3: Park's Vector Pattern for Healthy Motor.

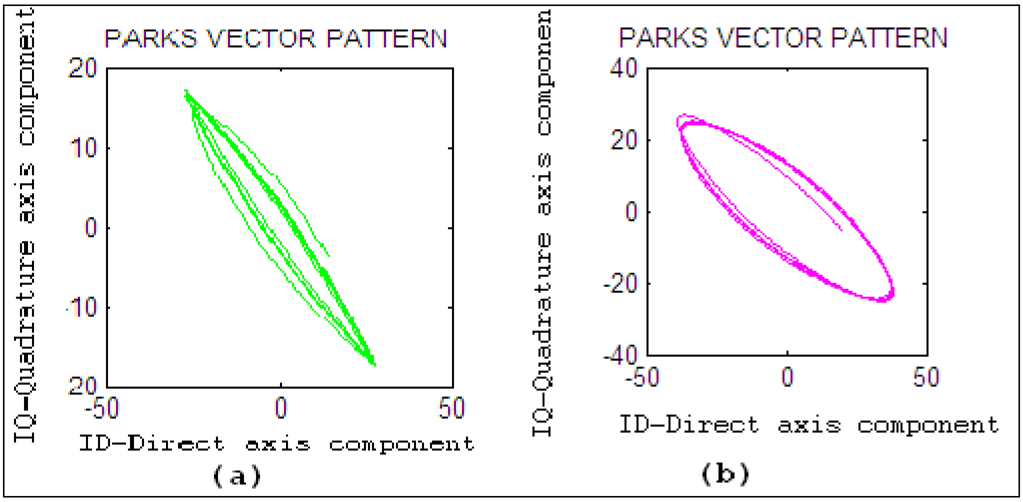

Figure 4: (a) and Fig4 (b) Park's Vector Pattern for Voltage Unbalance condition and for single phasing.

ANN based Fault Classification

Feed Forward Artificial Neural Network is widely accepted classifier .The success of FFANN to distinguish between healthy and faulty induction motor is strongly related to the success in the preprocessing of its input data. The inputs should contain lot of information for the network to properly classify the events.

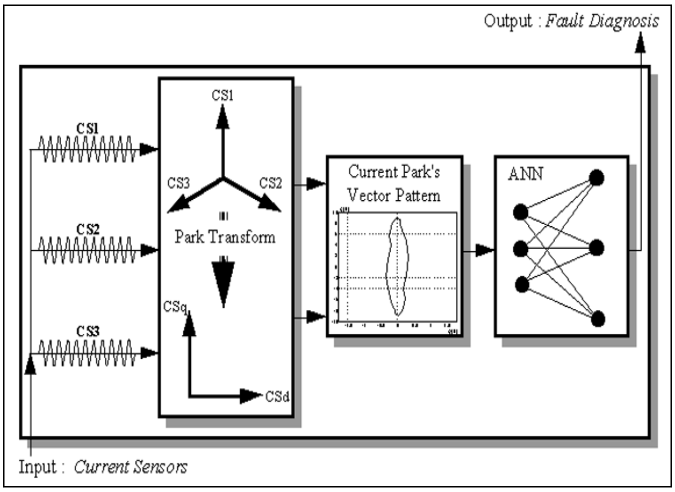

Figure 5: Schematic architecture of the NN faults detection system.

In this paper three layers fully connected FFANN is used and trained with a supervised learning algorithm called back propagation .FFANN consists of one input layer, one hidden layer and one output layer. Input layer consists of two neurons. Total 5000 D and 5000 Q stator currents are computed by simulating induction motor for healthy and faulty conditions in Matlab environment using Simulink toolbox which are provided as inputs to neurons. Output layer consists of three neurons representing healthy, voltage unbalance and single phasing conditions.

Levenberg Marquardt back propagation method is used for training the network and average minimum MSE on training and testing data is obtained. For this training method it is assumed that learning rate LR=0.8, momentum MM=0.7, data used for training purpose TR= 60 %, for cross validation CV = 10% and for testing purpose TS= 30%. With these assumptions the variation of average minimum square error (MSE) and percent accuracy of classification for healthy, voltage unbalance and single phasing conditions of induction motor with respect to number of processing elements in the hidden layer is obtained.

Fig (6.a and 6.b) respectively shows variations of average minimum square error (MSE) and variations of percentage accuracy with respect to number of processing elements in hidden layer.

It is observed that for seven processing elements in hidden layer MSE is 0.00458 and percentage accuracy is 100% for healthy, 99% for voltage unbalance and 98% for single phasing.

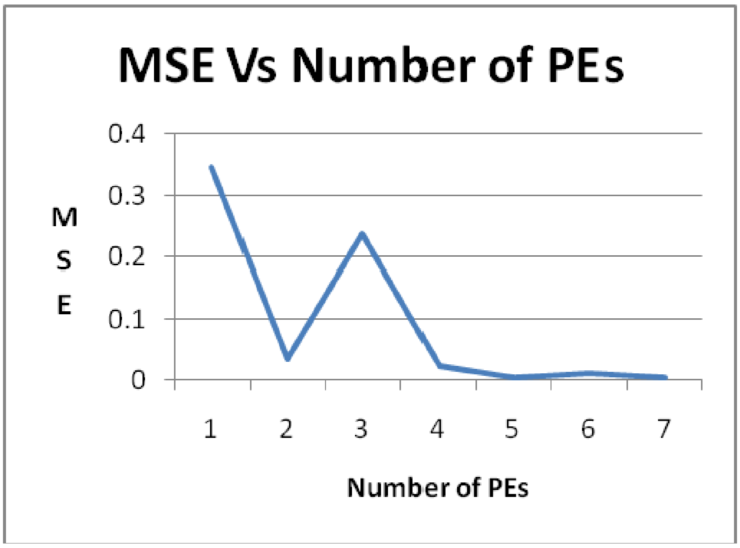

Figure 6.a: Mean Square Error V/S Number of PE's in the hidden layer.

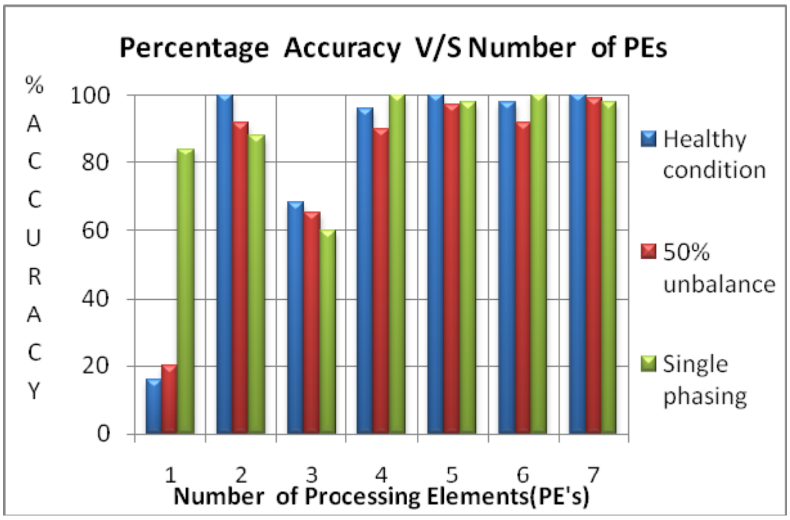

Figure 6.b: Percentage Accuracy Vs Number of PE's in the hidden layer.

Conclusion
On line induction motor diagnosis is very useful tool. This paper has presented a specific application of Park's Transform for fault detection and diagnosis in induction motor. Park's Transform allows a new approach to the fault detection by simple analysis of DQ components. This paper proposes a new diagnostic tool that can be used in vector control applications. This transform has been coupled to ANN to automate the detection and diagnosis process. The purpose of this method is to facilitate a satisfactory distributed implementation of new types of faults to the initial Neural Network monitoring system. The generality of the proposed methodology is tested by simulating the induction motor under fault conditions.

References

[1] Hamid Nejjari and Mohamed El Hachemi Benbouzid, Monitoring and Diagnosis of Induction Motors Electrical Faults Using a Current Park's Vector Pattern Learning Approach IEEE TRANSACTIONS ON NDUSTRY APPLICATIONS, VOL. 36, NO. 3, MAY/JUNE 2000

[2] M. E. H. Benbouzid et al., "Induction motors faults detection and localization using stator current advanced signal processing techniques," IEEE Trans. Power Electron., vol. 14, pp. 14–22, Jan. 1999.

[3] G. B. Kliman et al., "Recent developments in on-line motor diagnostics,"in Proc. 1998 Int. Conf. Electrical Machines, vol. 1, Istanbul, Turkey, pp.471–475.

[4] M. E. H. Benbouzid, "A review of induction motors signature analysis as a medium for faults detection," in Proc. IEEE IECON'98, vol. 4,Aachen, Germany, 1998, pp. 1950–1955.

[5] G. B. Kliman et al., "Sensorless online motor diagnostics," IEEE Comput. Applicat. Power, vol. 10, pp. 39–43, Apr. 1997.

[6] N. M. Burstein et al., "Case histories of rotating equipment condition assessment by electric signal analysis," P/PM Technol., pp. 36–39, Dec.1996.

[7] M. E. H. Benbouzid et al., "A decentralized neural network-based architecture for induction motor faults detection," in Proc. 1998 Int. Conf. Electrical Machines, vol. 3, Istanbul, Turkey, pp. 1855–1860.

[8] F. Filippetti et al., "AI techniques in induction machines diagnosis including the speed ripple effect," IEEE Trans. Ind. Applicat., vol. 34, pp.98–108, Jan./Feb. 1998.

[9] M. Y. Chow, "Intelligent motor fault detection," in Intelligent Techniques in Industry, L. C. Jain, Ed. Boca Raton, FL: CRC Press, 1998.

[10] M. E. H. Benbouzid et al., "Induction motor interturn short-circuit and bearing wear detection using artificial neural networks," Electromotion, vol. 5, no. 1, pp. 15–20, Jan./June 1998.

[11] M. Y. Chow, "Motor fault detection and diagnosis," IEEE Ind. Electron. Soc. Newslett., vol. 42, pp. 4–7, Dec. 1997.

[12] R. R. Schoen et al., "An unsupervised, on-line system for induction motor fault detection using stator current monitoring," IEEE Trans. Ind. Applicat., vol. 31, pp. 1280–1286, Nov./Dec. 1995.

[13] E. Alguindigue et al., "Monitoring and diagnosis of rolling element bearings using artificial neural networks," IEEE Trans. Ind. Electron., vol. 40, pp. 209–217, Apr. 1993.

[14] Annette von Jouanne, Senior Member, IEEE and Basudeb (Ben) Banerjee," Assessment of Voltage Unbalance IEEE TRANSACTIONS ON POWER DELIVERY, VOL. 16, NO. 4, OCTOBER 2001

[15] Davar Mirabbasi, Ghodratollah Seifossadat, Mehrdad Heidari, Effect of Unbalanced Voltage on Operation of Induction Motors and Its Detection

[16] Tanver, P.J. and Penman, J. Condition Monitoring of Electrical Machines, Research Studies Press Ltd., 1987.

[17] Lau, Neural Network: Theoretical Foundations and Analysis, IEEE Press, New York, 1992.
[18] Vas, P. Parameter Estimation, Condition Monitoring, and Diagnosis ofE1ectricol Machines, Clarendon Press, Oxford,1993
[19] Mrs. M. SUIDHA', Dr. P. ANBALAGAN,"A Novel Protecting Method for Induction Motor Against Faults Due to Voltage Unbalance and Single Phasing" The 33rd Annual Conference of the IEEE Industrial Electronics society (IECON) Nov. 5-8, 2007, Taipei, Taiwan.