DETECTION FAULTS AND DIAGNOSIS PROBLEMS IN INDUCTION MOTORS USING HYBRID TECHNIQUES OF PREDICTIVE MAINTENANCE

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Abstract. *The paper deals with detection faults and diagnosis problems in induction motors using hybrid techniques of predictive maintenance (vibration analysis, current analysis and artificial neural network). Two kinds of faults have been studied: mechanical faults (unbalance, misalignment and mechanical looseness) and electric faults (single phase and broken bars) beyond the normal condition (motor signature). The signals have been acquired in the both sides of the motor (radial and axial directions) through UltraSpec 8000 device, manufactured by the CSI - Computation System Incorporated. The MPN (Multilayer Perceptron Networks) and RBF (Radial Basis Function) have been trained and have been tested using Matlab program. A selective filter has been used to reduce the number of parameters in order to represent the signals of excitations during the 36 artificial neural networks training. The results obtained confirmed the efficiency of the hybrid techniques and their relevance to detect and diagnose faults in induction motors. In this way its possible to include it in a maintenance programs.*

Keywords: *Fault diagnosis, Induction motors, Artificial neural networks, Predictive maintenance.*

1. INTRODUCTION

Modern technological processes are characterized by the application of more and more complicated equipment including modern electrical drives. An electrical motor together with a load machine as well as supply and control systems are run to risk of various failures which are independent of the usage of elements and materials characterized by high reliability.

Long time disturbances in technological processes cause big economic loses. The importance of incipient fault detection is a method of cost saving which is realized by detecting potential motor failures before they occur. Currently, motors require to be protected by circuit breakers or fuses that interrupt instantaneous fault currents. However, these devices are intended only as safety devices and they may protect the motor and nearby personnel from injury due to a fault, but will not warn of potential faults before they occur. Incipient fault detection, on the other hand, allows preventative maintenance to be scheduled for machines that might not ordinarily be due for service and may also prevent an extended period of downtime caused by extensive motor failure. For this reason, the problem of fast fault detection and location as well as the problem of technical state evaluation are very significant in the industrial practice (Eisenmann *et al*., 1997; Vas, 1999). Brito (2001), has been developed a hybrid neural/expert system to diagnose faults in induction motors.

Vibration analysis continues to be one of the most versatile and informative tools available for on-line monitoring and problem analysis. Vibration analysis is often required to identify faults from mechanical sources. Its deterministic frequencies are the rotational frequency and its harmonics (1 x f_r, 2 x f_r, 3 x f_r and 4 x f_r), (Brito *et al*., 1999; Brito *et al*., 2001[a]). Faults from electrical source (phase unbalances and broken bars) can also be identified by vibration analysis. The vibration spectra has been plotted in dB. The broken rotor bars have been identified when sidebands of the slip frequency (2 x f_s) are visible about rotational frequency (1 x f_r), (Brito *et al.,* 2001[b]). The vibration spectra of phase unbalance have been identified when sidebands of the rotational frequency (2 x f_r) are visible about line frequency (2 x f_l), (Baccarini *et al.*, 2001).

Diagnostic systems use different procedures in a diagnostic process, starting from heuristic knowledge, through mathematical models to the artificial intelligence methods. The diagnosis of the industrial processes can be performed using different elements of knowledge based on analytical methods, expert systems, artificial neural networks (ANN) or fuzzy logic reasoning.

Faults detection using analytical method is not always possible because it requires perfect knowledge of a process model. In the case of a not adequate or imprecise mathematical model false alarms can occur due to estimation errors of the systems state variables or process parameters (Vas, 1993; 1999).

Human knowledge and experience are used in the case of the application of the heuristic expert system and during the interpretation of measured signals acquired on-line in the diagnosed plant. This solution is much easier and more useful in comparison with analytical methods. On the other hand it is difficult for automatic implementation.

On the contrary, the application of artificial intelligence methods, like neural networks is rather easy to develop and to perform (Filippetti *et al.*, 1997). Neural networks can be applied when the information about the process is obtained by measurements, which later can be used in the training procedures of neural nets. The main advantage of such solution is obtaining on-line information about the kind and the "size" of a fault without developing very complicated mathematical models. Neural detectors can be designed using the data acquired from simulation or experimental tests (Filippetti *et al*., 1997; Schoen, 1995; Vas, 1999).

The paper deals with detection faults and diagnosis problems in induction motors using hybrid techniques of predictive maintenance (vibration analysis, current analysis and artificial neural network). Two kinds of faults have been studied: mechanical faults (unbalance, misalignment and mechanical looseness) and electric faults (single phase and broken bars) beyond the normal condition (motor signature). The MPN (Multilayer Perceptron Networks) and RBF (Radial Basis Function) have been trained and have been tested using Matlab program. A selective filter has been used to reduce the number of parameters in order to represent the signals of excitations during the 36 artificial neural networks training.

2. BASIC PROBLEMS OF THE INDUCTION MOTOR FAULTS

During the operation of induction motors (which at present make about 90% of all electrical motors used in the world) different faults of the electrical and mechanical parts of stator and rotor occur as well as some faults of a loading machine together with coupling devices. The possibility of incipient fault detection of electrical, magnetic and mechanical parts of the a motor has recently become one of the most important problems of induction motors exploitation (Yuen, 1997; Einsenmann et al (1997);

There are three main kinds of faults of induction motors: winding faults (short-circuits of stator windings, short-circuits of rotor windings, broken rotor bars and broken rings of the rotor); faults of the magnetic circuit (air-gap asymmetry and stacking clearance) and faults of the motor mechanical system (mainly bearing failures).

All these faults are connected with some particular phenomena: electrical, magnetic and vibroacoustic ones. The fault statistics of high- and low-voltage induction motors has been changing within the last few years. There is a significant increase of mechanical failures in comparison with electrical and magnetic circuits' failures. Figure (1) shows the percentage of all motor faults, according to Thomson (1997).

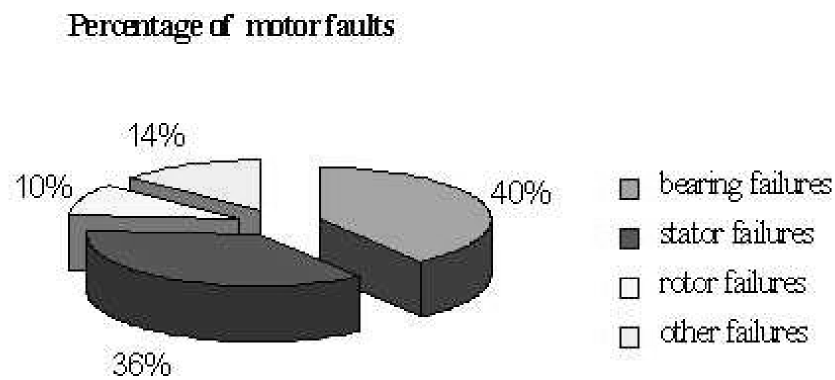

Figure 1 - Percentage of motor faults

Condition monitoring schemes have concentrated on sensing specific failure modes in one of three main induction machine components: the stator, the rotor or the bearings

3. EXPERIMENT SETUP

The experiments setup of the present work have been carried out in the Energy's Laboratory of the UFSJ (Federal University of São João del Rei). Figure (2) shows the instrumented test desk, which includes: [1] UltraSpec 8000 manufactured by CSI - Computation System Incorporated; [2] notebook; [3] induction motor (squirrel-cage rotor, 5 HP, 220V, 60 Hp, 4 poles, 44 bars, 36 slots, 1730 rpm nominal rotation); [4] CC generator; [5] resistance bench; [6] flexible linking; [7] voltmeter ENGRO- 600; [8] current digital clipper DAWER- CM-600; [9] Optho Tako tachometer; [10] CC generator field current and [11] acelerometer A0720GP SN6714.

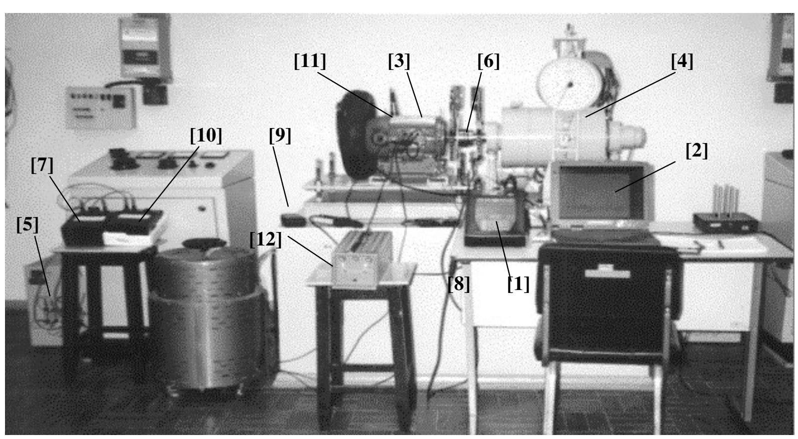

Figure 2. Experimental Setup

4. VIBRATION DATA

The vibration signals have been taken from the accelerometer at vertical, horizontal and axial positions in both sides of fan and motor linking, respectively. Hamming window with 3200 lines and 10 averages of samples have been used for a frequency width from 0 to 400 Hz and amplitude measured in speed (mm/s). It will be show the vibration spectra for vertical position for each type of excitation plotted at the same scale in order to compare the level of amplitude.

The vibration spectrum for normal working condition (motor signature) is shown in Fig. (3). It can be seen from this spectrum that there are no peaks at these deterministic frequencies and that the peaks showed have amplitude level bellow 0.5 mm/s (maximal level for normal motor working condition).

The instrumented test desk has been adjusted for the normal working condition before introducing a new fault. When necessary the test desk has been laser aligned and precision balanced. This procedure guaranteed that the faults signatures have been well defined for all tests. The vibration spectra for mechanical faults (unbalance) is shown in Fig. (4).

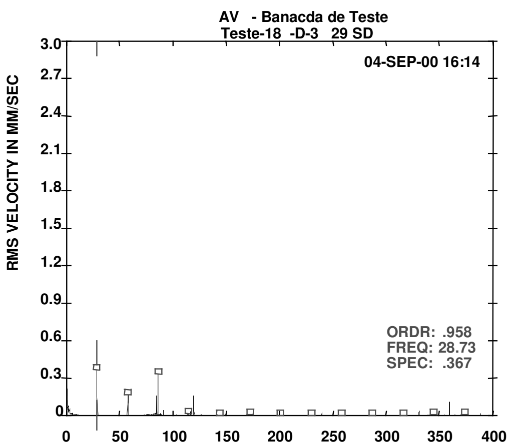

Figure 3. Vibration specrum for normal working condition.

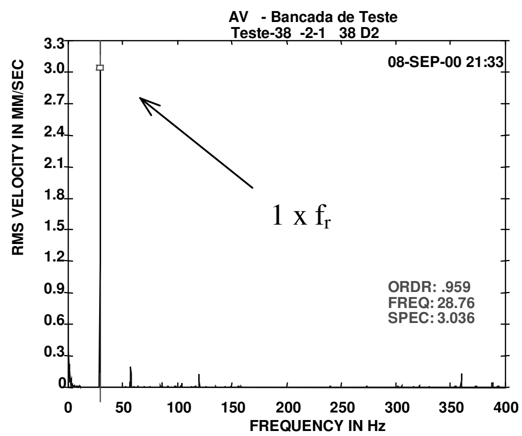

Figure 4. Vibration spectrum for Unbalance 35,1g.

The vibrations spectral for mechanical faults (misalignment and mechanical looseness) are shown in Fig. (5) and (6), respectively

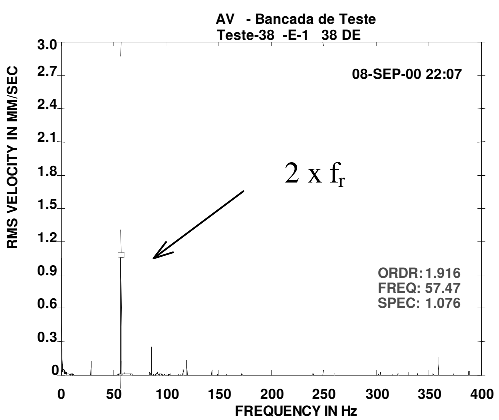

Figure 5. Vibration spectrum for Misalignment

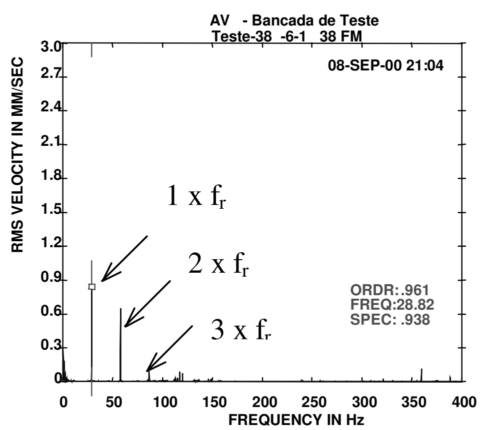

Figure 6. Vibration spectrum for Mechanical looseness

The vibration spectra for broken rotor bar (*BRB*) and single phase are shown in Fig. (7) and (8), respectively

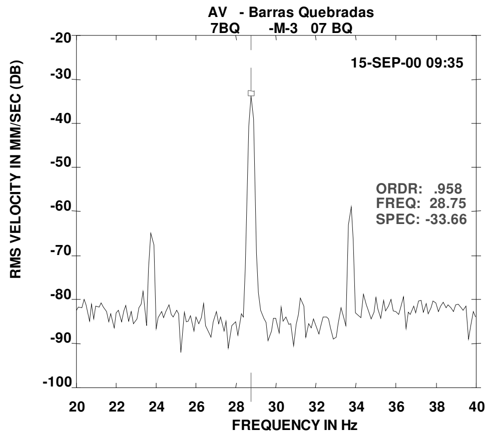

Figure 7. Spectra for 7 broken rotor bars

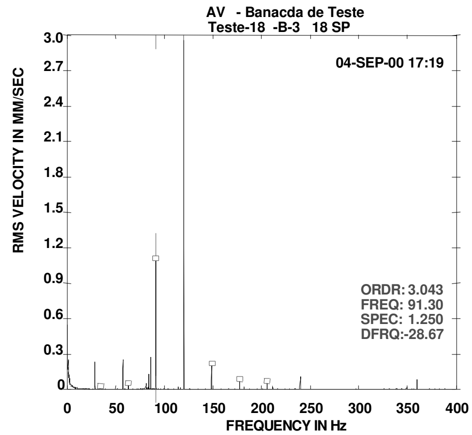

Figure 8. Spectra for Single phase

In the present work, these time-frequency data were processed to extract the peaks deterministic frequencies features for using as inputs to ANNs.

5. NEURAL NETWORKS APPLICATION IN DIAGNOSTIC AND FAULT PROBLEMS

The ability of the human brain to think, remember, and problem solve inspired many researchers to develop artificial models whose basic learning process are similar to that of a biological neuron. And as a result, artificial neural networks (ANN) have been developed, which are simplified artifcial models based on the biological learning process of the human brain.

In this section, basic principles of two neural network have been employed in this paper will be discussed.

5.1. Multilayer Perceptron networks

The multi-layer perceptron neural network model consists of a network of processing elements or nodes arranged in layers. Typically it requires three or more layers of processing nodes: an input layer which accepts the input variables (e.g. vibration spectra for mechanical faults, spectra eletric faults, etc.) used in the classification procedure, one or more hidden layers, and an output layer with one node per class (Figure 9). The principle of the network is that when data from an input pattern is presented at the input layer the network nodes perform calculations in the successive layers until an output value is computed at each of the output nodes.

This output signal should indicate which is the appropriate class for the input data i.e. we expect to have a high output value on the correct class node and a low output value on all the rest (Haykin, 1999).

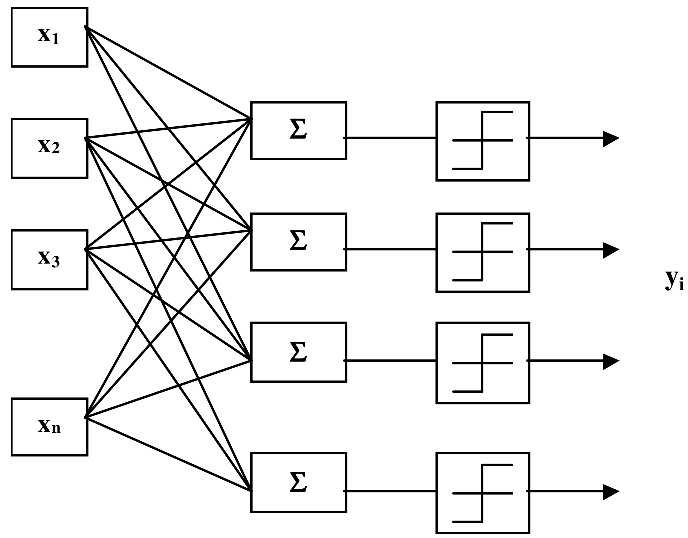

Figure 9. MPL with many inputs and many outputs

5.2 Radial Basis Function (RBF) Network

A Radial Basis Function (RBF) ANN is basically a structure that represent the idea just showed in Fig. (10). It may have however more than one output. The RBF ANN can be seen hence as another type of feed-forward ANN. Additionally, it uses the technology of ANN training to identify the values of the mentioned parameters, and a clustering algorithm to identify positions of centers. Typically in an RBF network, there are three layers: one input, one hidden and one output layer. The hidden layer uses Gaussian transfer function instead of the sigmoid function. In RBF networks, one major advantage is that if the number of input variables is not too high, so the learning is much faster than in other types of networks. However, the required number of the hidden units increases geometrically with the number of the input variables. It becomes practically impossible to use this network for a large number of input variables (Haykin, 1999).

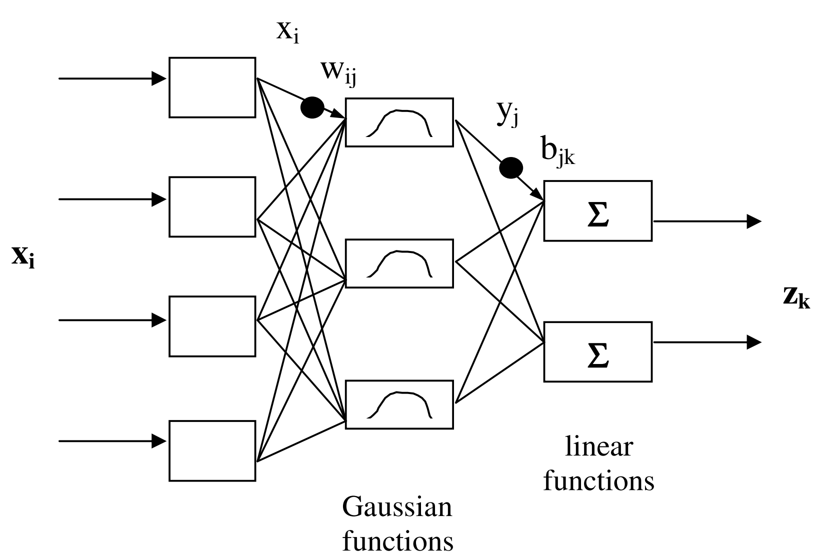

Figure 10. RBF neural network with four inputs and two outputs

5.3 ANN for Identifying Induction Motor Faults

In order to use ANN for identifying induction motor fault and normal conditions, it is necessary to select proper inputs and outputs of the network, structure of the network, and train it with appropriate data. In this study, inputs have been implemented trough the selective filter in order to pick up only the deterministic frequencies of interest. This procedure reduced significantly the number of information to send to neural networks removing noises, redundancies and improving the quality of data training. Therefore, there are seven input neurons. There are six outputs corresponding to five faults described before and normal condition. The output goes to 1 if that particular condition exits, otherwise it is zero. Therefore, there are eight output neurons. There is one middle layer, and the number of neurons in that layer is varied during training. Figure (11) shows the inputs and outputs of the ANN.

To train the network, simulated mechanical and electric faults representing the five different faults and normal condition are considered.

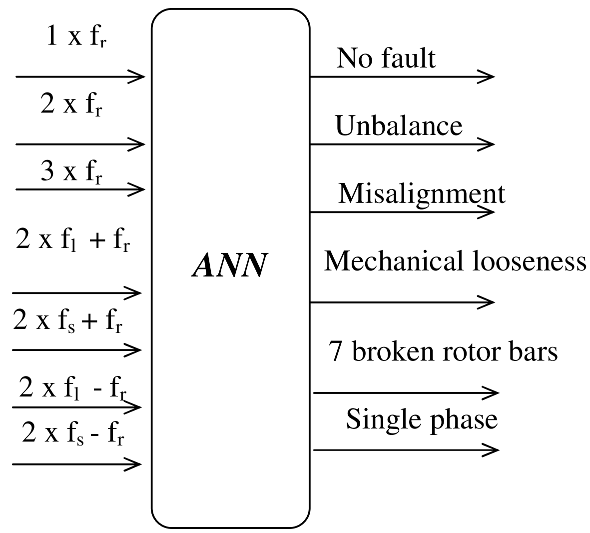

Fig. 11. ANN to identify induction motor fault conditions

The inputs are one of the most important topics and have strongly influence on data convergence. If the base of data isn't well constructed the artificial neural network can present convergence problems. The tests procedures have been planned in detail in order to minimize ambiguity and mistakes during data acquisition. The data have been acquired randomly on the vertical, axial and horizontal directions, side of the fan and side of the motor linking. The vibration analysis has been chosen because it is a non invasive technology and has more information on the spectra belonging fault identification from mechanical and electrical sources. The domain of frequency has been chosen because it is easier to diagnose faults.

6. RESULTS TRAINING OF ARTIFICIAL NEURAL NETWORK

The network has been trained using the back propagation algorithm by Toolbox Matlab®. In the network training, learning coefficient (η) and the momentum coefficient (α) have been chosen with different values each time. It has been built one artificial neural network to detect each of the six excitations for each six positions of the sensors, in a total of thirty-six artificial neural networks. This procedure permits smaller architectures that are easier to train. Networks architecture with 7-11-8, 7-12-8 and 7-13-8 input, middle and output layer neurons are trained. Training has been processed through error convergence criteria, Anon (1993). The 7-13-8 network architecture produced the best convergence. For this network, the error convergence used is 0.01, learning coefficient (η) used is 0.8 and the momentum coefficient (α) used is 0.6.

During the test of validation each excitation has been passed in all thirty-six artificial neural network and the condition of detected and undetected excitation has been considered. When one excitation has been presented for a specific artificial neural network the result has been considered detected for output values > 0,5 mm/s (1 mm/s is the ideal value) and ≤ 0.5 mm/s for the others (0 is the ideal value).

Figure (12) shows expected output for ANN's RBF for position of the sensor (P-1). The answer showed values greater than 0,5 mm/s that means the artificial neural network was capable to identify seven broken rotor bars correctly.

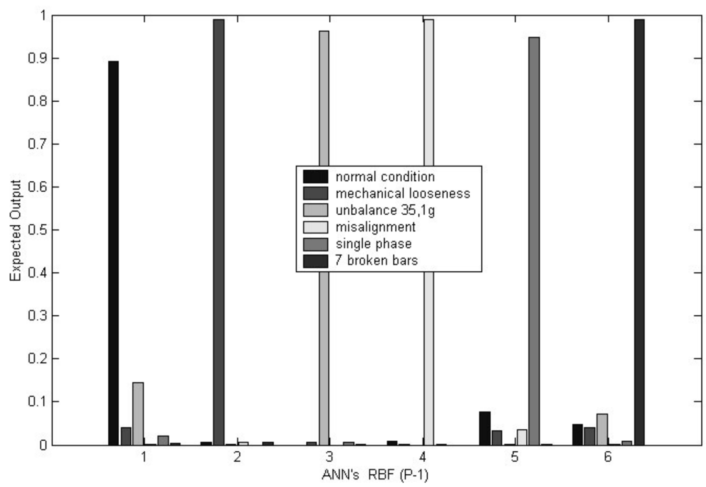

Figure 12. Expected Output for ANN's RBF for position of the sensor (P-1)

It is clear from Figure 12 that the ANN identified the faults. The output of the ANN for a particular fault is close to 1.0 while the other outputs are close to 0.0 when that fault is present. Though the results are satisfactory for the all positions of the sensors: P-1 (vertical direction, side of the fan); P-2 (axial direction, side of the fan); P-3 (horizontal direction, side of the fan); P-4 (vertical direction, side of the motor linking); P-5 (axial direction, side of the motor linking); P-6 (horizontal direction, side of the motor linking), further improvements can be obtained if more data points are used in training. For each series of ten tests it was separated randomly six series for training (total of 1.080 spectra), four series for neural network validation (total of 666 spectra). Data inputs are generally compacted in order to reduce computational time and neural network's efficiency. In this way it was implemented the selective filter in order to pick up only the deterministic frequencies of interest. This procedure reduced significantly the number of information to send to neural networks removing noises, redundancies ant improving the quality of data training. Table (1) shows the ratio of accuracy for the MLP and RBF artificial neural networks. The sensor (P-1) shows the expected output.

Table 1. Ratio of accuracy for the MLP and RBF artificial neural networks

TEST OF VALIDATION	**MLP NETWORKS**						**RBF NETWORK**					
SENSORS POSITIONS	**P-1**	**P-2**	**P-3**	**P-4**	**P-5**	**P-6**	**P-1**	**P-2**	**P-3**	**P-4**	**P-5**	**P-6**
Normal condition	82,30	90,70	80,3	98,55	70,14	86,35	88,52	94,46	89,83	96,05	76,44	88,3
Unbalance 35,1g	97,25	90,00	94,25	93,76	92,68	97,74	95,32	91,50	95,75	95,67	94,08	96,57
Mechanical looseness	96,00	97,75	98,45	95,35	98,90	95,76	97,10	99,25	96,05	96,35	96,35	96,66
Misalignment	97,68	96,90	96,77	98,78	97,39	90,25	98,15	97,00	98,25	97,18	99,86	93,68
Single phase	98,33	96,34	98,43	99,35	99,76	97,75	97,48	98,16	99,00	97,00	100	99,85
7 broken bars	96,31	97,51	100	96,34	98,98	98,25	95,74	98,09	99,87	100	100	100

The training time requirement for the ANN is on the order of training time requirements of Multilayer Perceptron and RBF networks in general as presented in Tab. (1). In all cases, the difference in the training time requirements between feedforward and RBF is relatively small. Here it's possible to see that RBF networks present a great variation when compared with Multilayer Perceptron, indicating good generalization. Generalization is a models ability to predict an new unseen pattern. Statistically the generalization is a combination of the probability of a pattern and the conditioned probability of the size of the error with that pattern. A fundamental observation with neural network is that the *costfunction minimum* for a finite training set is *not* the *minimum for the generalization error*. This is due to *overfitting*: where the model has fitted the noise in the training set, or has made an extraordinary complex model. Even though any new training hasn't been performed for the thirty-six artificial neural networks, the sensors showed high level of accuracy.

7. CONCLUSIONS

In this paper, we have discussed an hybrid method to detect and diagnose problems in induction motors from mechanical sources (unbalance, misalignment and mechanical looseness) and electrical sources (phase unbalances and broken bars) beyond normal condition (motor signature).

A multilayer perceptron and RBF ANN structure has been used and has been trained using the back-propagation algorithm. Although others have found that RBF networks generally give better results than MLP networks fault diagnosis and detection, they may not be using the RBF network to the best of its ability. In general, the RBF network is more resilient against a bad training set than an MLP and, hence, provides better results. However, an RBF system can provide even better results with a suitable training set. For a good training set, a significant improvement would be expected for an RBF network relative to an MLP, whereas a poor training set will not show much improvement.

7. Acknowledgement

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