A HYBRID NEURAL/EXPERT SYSTEM TO DIAGNOSE PROBLEMS IN INDUCTION MOTORS

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Abstract. *The use of electric motors in industry is extensive and they are exposed to a wide variety of incipient faults. These incipient faults, if left undetected, contribute to the degradation and eventual failure of the motors. With proper monitoring and fault detection schemes, the incipient faults can be detected; thus maintenance and down time expensive can be reduced while also improving safety. The HY_NES, a new approach behind a novel hybrid neural/expert system technologies to solve fault detection from mechanical and electrical sources beyond normal condition, is shown. Those excitations have been obtained through experimental tests repeated fifty times randomly for the same conditions for each failure. The signals have been acquired in the both sides of the motor on the radial and axial directions. It will be also employed a selective filter used to reduce the number of parameters to represent the signals of excitations during the 72 artificial neural networks training. It has been implemented 199 rules in the expert system that can easily provide heuristics reasoning for the artificial neural network outputs. The results obtained confirmed the efficiency of the hybrid system HY_NES and its relevance as a promising approach to diagnose faults in induction motors on-line as well as included in maintenance programs.*

Keywords: *electric motors, incipient faults, artificial neural network, expert system, HY_NES.*

1. Introduction

The use of electric motors in industry is extensive. These motors are exposed to a wide variety of environments and conditions which age of the motor and make it subject to incipient faults. These incipient faults, if left undetected, contribute to the degradation and eventual failure of the motors. With proper monitoring and fault detection schemes, the incipient faults can be detected; thus maintenance and down time expensive can be reduced besides improving safety, Goode and Chow (1995).

There are currently two major classes of motor fault detection techniques: model-based methods and knowledge-based methods (Li *et al*., 1997 and Chow, 1997). The first one, which is based on mathematical model of the system of interest, isn't often robust enough in the presence of noise and other perturbations (Chow and Yee, 1990 and Trutt *et al*., 1993). The goal of the second method is to teach a machine to mimic knowledge and tuition in order to make informed decision.

The knowledge-based method, main interest of this work, is characterized by using artificial intelligence technologies such as artificial neural networks (*ANN*), fuzzy logic (*FL*), expert systems (*ES*) and hybrid systems (*ANN/ES*, *ANN/FL* and *ES/ES*). The application of artificial intelligent techniques on the fault detection can perform the diagnostic with minimal engineer interaction and in a lot of cases can diagnose faults without the help of maintenance specialists. In this way, in the last years, those technologies are replacing the conventional methodologies. The increasing use of artificial intelligent techniques is consequence of the great computational development, the maintenance specialists cost and fast technologic progress.

Many technical articles have addressed the importance of artificial intelligent techniques in the motor fault detection (Li *et al*., 1997; Chow, 1997; Chow and Yee, 1990; Chow and Yee, 1991; Chow *et al*., 1991; Goode and Chow, 1993; Chow and Goode, 1993; Chow *et al*., 1993; Chow, 1994; Goode and Chow, 1995[a]; Goode and Chow, 1995[b]; Schoen *et al*., 1995; Chow *et al*., 1998; Filippetti *et al*., 1998 and Altug and Chow, 1999). A comprehensive list of books, workshops, conferences and journal papers related to induction motors fault detection and diagnosis is presented by Benbouzid *et al.* (1999).

Artificial neural networks have been proposed and have demonstrated the capability to solve the motor monitoring and fault detection problem using an inexpensive, reliable, and noninvasive procedure. However, the major drawback of conventional artificial neural networks fault detection is the inherent black box approach that can provide the correct solution, but does not provide heuristic interpretation of the solution. Engineers prefer the accurate fault detection as well as the heuristic knowledge behind the fault detection process. Expert System is a technology that can easily provide heuristic reasoning while being difficult to provide exact solutions.

The goal of this work is to present the *HY_NES* (Hybrid Neural Expert System), a new approach behind a novel hybrid neural/expert system technologies, to solve fault detection from mechanical (unbalance, misalignment and mechanical looseness) and electrical (phase unbalances and broken bars) sources beyond the normal condition (motor signature).

2. Experimental Tests and Types of Incipient Fault Simulations

The experimental tests have been done in the energy's laboratory of the UFSJ (Federal University of São João del Rei). Figure (1) shows the instrumented test desk.

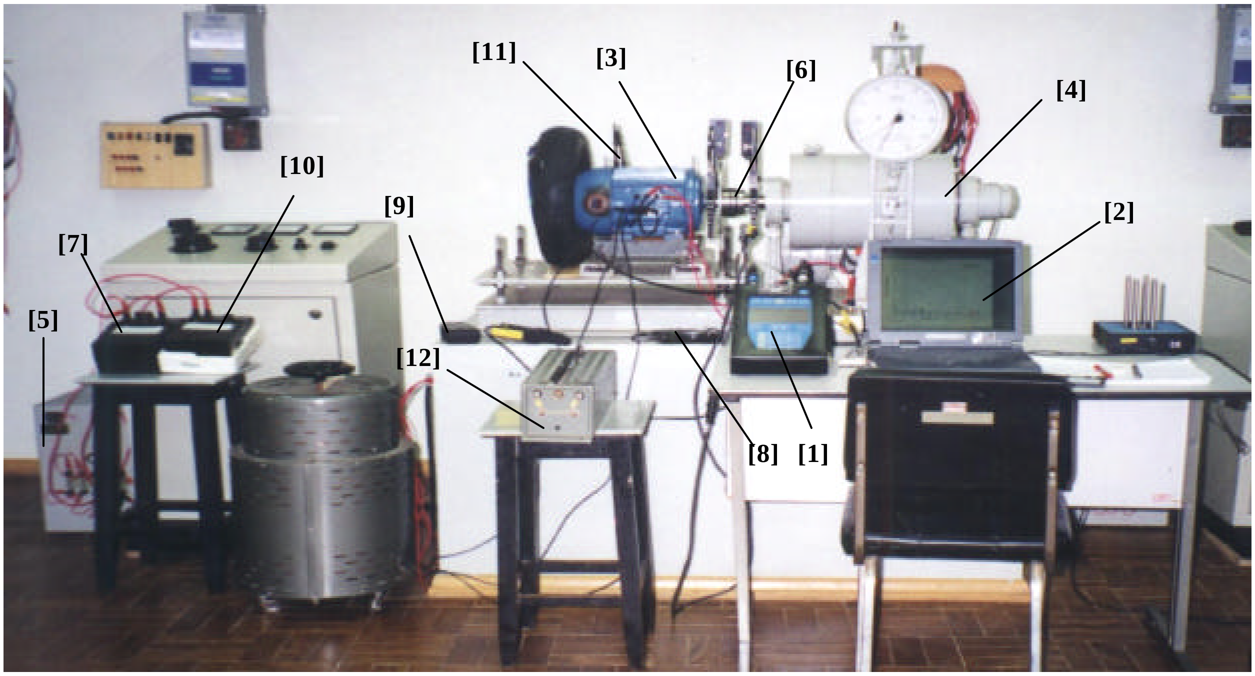

Figure 1. Instrumented test desk.

The equipment UltraSpec 8000 [1] manufactured by the CSI - Computation System Incorporated, has been used for vibration spectra acquisition. It works collecting, memorizing and analyzing signals. Although a computer is not required to use the UltraSpec Analyze, data can be downloaded to UltraManager support software on a computer [2]. The last option offers a more comfortable working environment for detailed analysis, technical reports writing and data bank generation.

The three phase, induction motor [3], squirrel-cage rotor, 5 HP, 220V, 60 Hp, 4 poles, 44 bars, 36 slots, 1730 rpm nominal rotation, has been powered with faults from mechanical (unbalance, misalignment and mechanical looseness) and electrical (phase unbalances and broken bars) sources beyond the normal condition (motor signature). Fifty random tests have been applied in order to analyze the motor behavior.

To simulate load, it has been use a CC generator [4] that power a resistance bench [5] linked to an electrical motor [3] through a flexible linking [6].

The following equipment have been also used for parallel monitoring: high accuracy voltmeter ENGRO-600 [7], current digital clipper DAWER- CM-600 [8] and Optho Tako tachometer [9]. The monitoring aim is to guarantee that the motor is working on the nominal load condition, allowing that the simulated problems to become more visible in the spectra. The voltmeter measures and gives the voltage level information of the three phase motor supply. The motor load is adjusted altering the CC generator field current [10].

Through the UltraSpec 8000 specific firmware, the system (motor plus generator plus load) has been laser aligned and precision balanced and it has been checked mechanical backlash. Dual, visible laser beams and dual built-in inclinometers enable it to monitor the exact position of both shafts during rotation. Measurements are automatic and can be performed with or without cables. This method can determine shaft misalignment with less than one quarter turn of the shaft, making it ideal for application with restricted access. Thus, vibration spectra could be obtained for the system under no failure condition.

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 ($1 \times f_r$, $2 \times f_r$, $3 \times f_r$ and $4 \times f_r$), (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 has been identified when sidebands of the slip frequency ($2 \times f_s$) are visible about rotational frequency ($1 \times f_r$), (Brito *et al*., 2001[b]). The vibration spectra of phase unbalance have been identified when sidebands of the rotational frequency ($2 \times f_r$) are visible about line frequency ($2 \times f_l$), (Baccarini *et al*., 2001).

The accelerometer A0720GP [11], SN6714, accuracy of 0.1000 mV has been used for vibration spectra acquisition. Hamming window of 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). The signals have been taken from the accelerometer at vertical, horizontal and axial positions respectively in both sides of fan and motor linking. It has been showed 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. (2). 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, misalignment and mechanical looseness) are shown in Fig. (3).

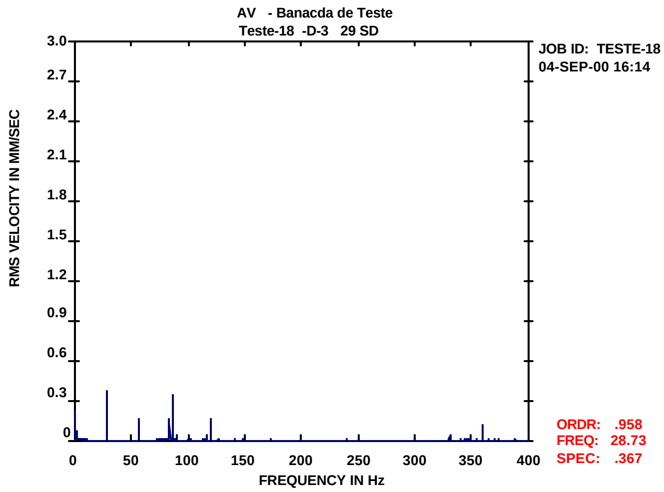

Figure 2. Vibration spectrum for normal condition.

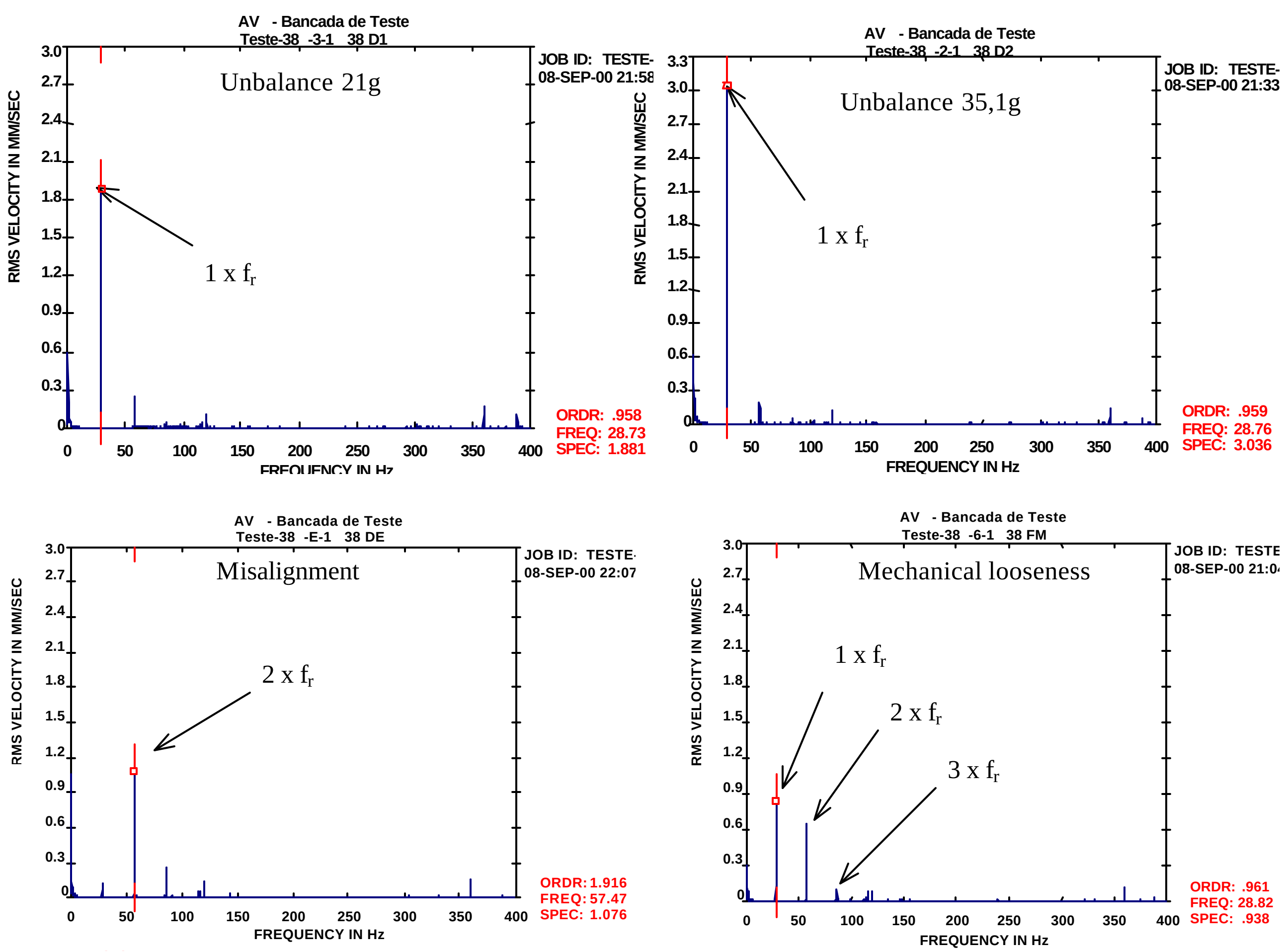

Figure 3. Vibration spectra for mechanical faults (unbalance, misalignment and mechanical looseness).

The vibration spectra for broken rotor bars (*BRB*) are showed in Fig. (4) around 1 x $f_r \pm 2$ x f_s. Unbalance voltages, under phase unbalance DF_1 (V_{AB} = 200 V, V_{BC} = 220 V and V_{CA} = 200 V), phase unbalance DF_2 (V_{AB} = 210 V, V_{BC} = 220 V and V_{CA} = 210 V) and a single phase, are showed in Fig. (5). The phase unbalance DF_1 and DF_2 have been obtained by introducing a variable resistance [12] in one phase of the voltage motor supply resulting in voltage drop in this circuit and a single phase has been obtained by taken off one motor voltage phase.

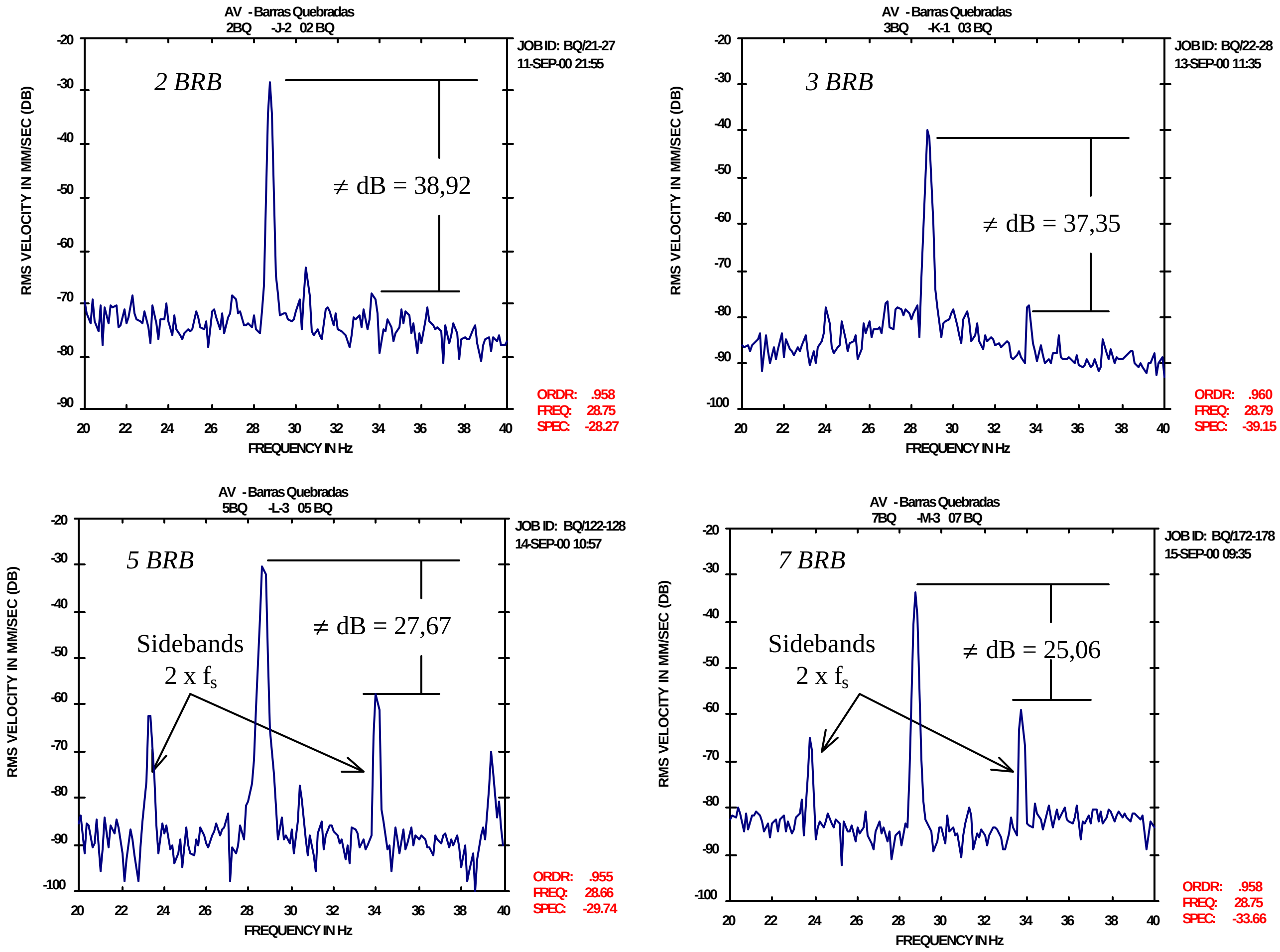

Figure 4. Spectra for broken rotor bars (*2, 3, 5 and 7BRB*).

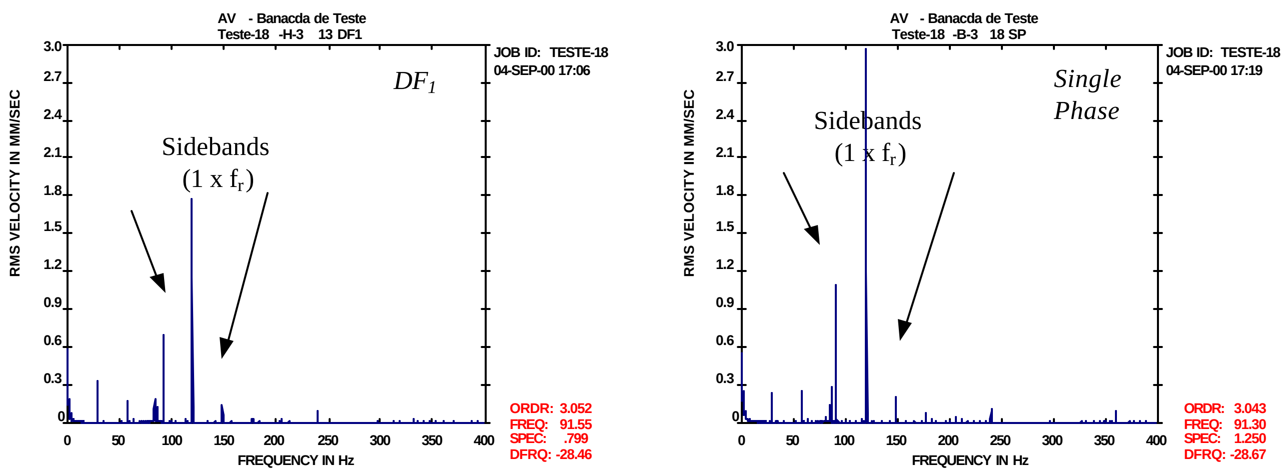

Figure 5. Spectra for unbalance voltages (*DF_1 and single phase*).

3. The Hybrid Neural/Expert System program (***HY_NES***)

The architecture of the *HY_NES* program is shown in Fig. (6). The program has been developed in C^{++} language oriented by object that allows best documentation and future modifications.

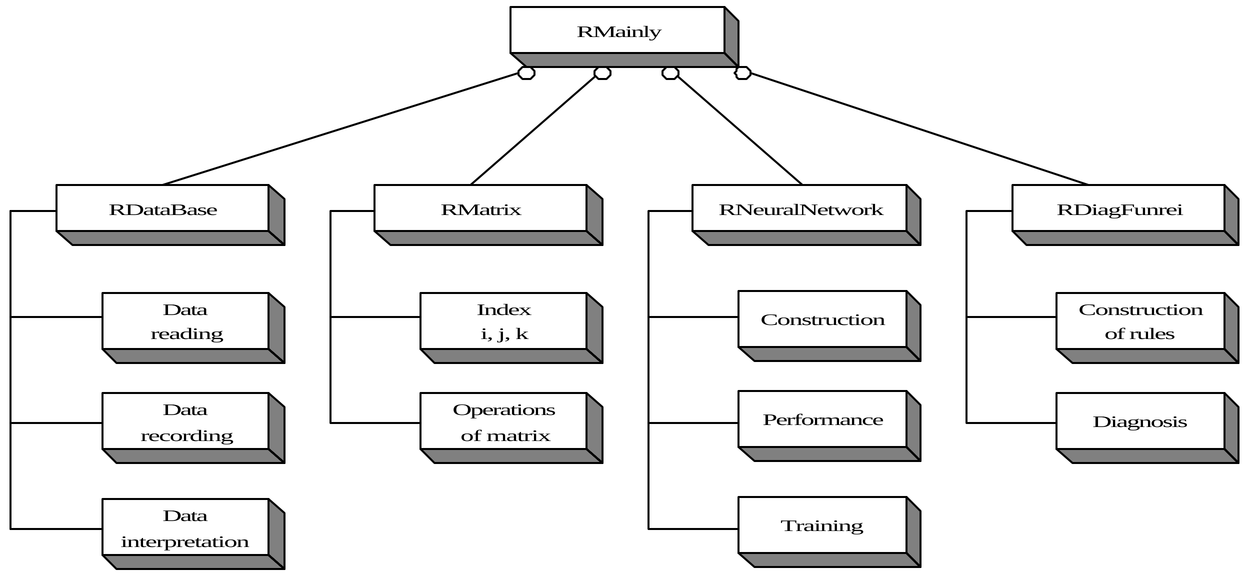

Figure 6. Architecture of the ***HY_NES*** program.

The *RdataBase* module is related to the interface of the program and is responsible for data reading and data recording, type *ASCII*. Those archives are responsible for definition of architecture (for example: number of layers, number of neurons by layers, activation function, weights, bias, training algorithm, learning rate, training error and momentum rate) and data interpretation. The inputs are based on key words that the program performs and can define the network structure. This module also have the option of training or only to perform data archives.

The *Rmatrix* module performs one matrix of three index when operations are processed. The index *i* refers to layer, index *j* refers to neuron and index *k* refers to late neuron or the test that is performing.

The *RneuralNetwork* module is related to neural network strictly speaking. In this module has been implemented several parameters: activation function (*sigmoid*, *sigmoid expanded* and *hyperbolic-tangent*), training algorithm (incremental and batch with and without variation of learning rate) and perform method (*feedforward*). In this module is processed all mathematics operations (error, gradient and variation of learning rate). During training process it is possible to monitoring evolution of the error allowing to stop the program anytime with best performance through threads.

The *RDiagFunrei* module is related to the expert system. In this module it has been implemented 199 rules in order to diagnose incipient faults on the six positions of the sensors.

4. Results of the program *HY_NES*

For each series of ten tests it has been separated randomly six series for training (total of 2.160 spectra), two series for neural network validation (total of 666 spectra) and two series for hybrid system 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 has been 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 and improving the quality of data training.

The great difficulty has been to identify those frequencies, which required an exhaustive analysis of all spectra. The frequencies of interest to identify mechanical faults are (1 x f_r, 2 x f_r, 3 x f_r and 4 x f_r), to identify broken bars are (1 x f_r ± 2 x f_s and 1 x f_r) and to identify phase unbalances are (2 x f_l ± 1 x f_r and 2 x f_l).

It has been built one artificial neural network to detect each of the twelve excitations for each six positions of the sensors, in a total of seventy-two artificial neural networks. This procedure permits smaller architectures that are easier to train. A lot of tests have been done during the training in order to obtain the best architecture (*8x5x3* and *3x3x3*).

For normal working condition it has been used the *8x5x3* architecture and nine inputs (1 x f_r, 2 x f_r, 3 x f_r, 4 x f_r, 1 x f_r ± 2 x f_s, 2 x f_l ± 1 x f_r and 2 x f_l). For mechanical faults it has been used the *8x5x3* architecture and four inputs (1 x f_r, 2 x f_r, 3 x f_r and 4 x f_r). For electrical faults it has been used the *8x5x3* and *3x3x3* architectures and six inputs (1 x f_r ± 2 x f_s, 1 x f_r, 2 x f_l ± 1 x f_r and 2 x f_l).

During the test of validation each excitation has been passed in all seventy-two 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).

The excitations identification is done through the third index of the matrix: for normal condition (1 - 6), mechanical looseness (10 - 15), unbalance 35.1g (20 - 25), unbalance 21g (30 - 35), misalignment (40 - 45), single phase (50 - 55), phase unbalance DF_2 (60 - 65), phase unbalance DF_1 (70 - 75), 2 broken rotor bars (80 - 85), 3 broken rotor bars (90 - 95), 5 broken rotor bars (100 - 105) and 7 broken rotor bars (110 - 115).

The artificial neural network output matrix for the seven broken rotor bars, *7_BRB_8.txt*, is shown on Tab. (1). The answer showed values greater than 0,5 mm/s for index from 110 to 115 that means the artificial neural network has been capable to identify seven broken rotor bars correctly.

Table 1. The neural network output matrix for *7_BRB_8.txt*

Matrix =[	Mt (1 , 1 , 40) = -0.008;	Mt (1 , 1 , 80) = -0.076;
Mt (1 , 1 , 1) = 0.221;	Mt (1 , 1 , 41) = 0.033;	Mt (1 , 1 , 81) = 0.027;
Mt (1 , 1 , 2) = 0.191;	Mt (1 , 1 , 42) = -0.073;	Mt (1 , 1 , 82) = 0.035;
Mt (1 , 1 , 3) = 0.333;	Mt (1 , 1 , 43) = 0.013;	Mt (1 , 1 , 83) = 0.079;
Mt (1 , 1 , 4) = 0.332;	Mt (1 , 1 , 44) = 0.021;	Mt (1 , 1 , 84) = 0.331;
Mt (1 , 1 , 5) = 0.376;	Mt (1 , 1 , 45) = 0.001;	Mt (1 , 1 , 85) = 0.086;
Mt (1 , 1 , 6) = 0.012;	Mt (1 , 1 , 50) = -0.081;	Mt (1 , 1 , 90) = 0.770;
Mt (1 , 1 , 10) = 0.072;	Mt (1 , 1 , 51) = -0.053;	Mt (1 , 1 , 91) = 0.263;
Mt (1 , 1 , 11) = 0.095;	Mt (1 , 1 , 52) = -0.069;	Mt (1 , 1 , 92) = -0.035;
Mt (1 , 1 , 12) = -0.060;	Mt (1 , 1 , 53) = -0.104;	Mt (1 , 1 , 93) = 0.179;
Mt (1 , 1 , 13) = 0.029;	Mt (1 , 1 , 54) = -0.112;	Mt (1 , 1 , 94) = -0.048;
Mt (1 , 1 , 14) = 0.294;	Mt (1 , 1 , 55) = -0.053;	Mt (1 , 1 , 95) = -0.219;
Mt (1 , 1 , 15) = -0.698;	Mt (1 , 1 , 60) = 0.017;	Mt (1 , 1 , 100) = 0.380;
Mt (1 , 1 , 20) = 0.001;	Mt (1 , 1 , 61) = 0.004;	Mt (1 , 1 , 101) = 0.120;
Mt (1 , 1 , 21) = -0.000;	Mt (1 , 1 , 62) = -0.007;	Mt (1 , 1 , 102) = 0.148;
Mt (1 , 1 , 22) = 0.023;	Mt (1 , 1 , 63) = -0.019;	Mt (1 , 1 , 103) = -0.021;
Mt (1 , 1 , 23) = -0.001;	Mt (1 , 1 , 64) = 0.019;	Mt (1 , 1 , 104) = 0.027;
Mt (1 , 1 , 24) = 0.001;	Mt (1 , 1 , 65) = -0.074;	Mt (1 , 1 , 105) = 0.230;
Mt (1 , 1 , 25) = -0.003;	Mt (1 , 1 , 70) = 0.008;	Mt (1 , 1 , 110) = 1.010;
Mt (1 , 1 , 30) = -0.028;	Mt (1 , 1 , 71) = 0.019;	Mt (1 , 1 , 111) = 0.892;
Mt (1 , 1 , 31) = -0.013;	Mt (1 , 1 , 72) = -0.006;	Mt (1 , 1 , 112) = 1.000;
Mt (1 , 1 , 32) = 0.001;	Mt (1 , 1 , 73) = -0.037;	Mt (1 , 1 , 113) = 0.819;
Mt (1 , 1 , 33) = 0.039;	Mt (1 , 1 , 74) = 0.010;	Mt (1 , 1 , 114) = 0.688;
Mt (1 , 1 , 34) = 0.044;	Mt (1 , 1 , 75) = -0.006;	Mt (1 , 1 , 115) = 0.513;]
Mt (1 , 1 , 35) = 0.035;		

The rate of accuracy of artificial neural network outputs to validation tests for the six sensors for all excitations is shown in Tab. (2).

Table 2. Rate of accuracy of artificial neural networks outputs - test of validation

Excitations	P-1 [%]	P-2 [%]	P-3 [%]	P-4 [%]	P-5 [%]	P-6 [%]
normal working condition	88,89	87,50	70,14	71,53	70,14	97,22
mechanical looseness	94,44	93,06	91,67	95,83	95,14	95,83
unbalance 35,1g	98,61	98,61	97,92	98,61	97,92	98,61
unbalance 21g	99,31	97,92	97,92	97,22	94,44	81,94
misalignment	96,53	94,44	100	97,22	98,61	95,83
single phase	98,61	99,31	99,31	100	100	100
phase unbalance DF_2	84,72	92,36	95,83	94,44	95,14	94,44
phase unbalance DF_1	95,83	95,14	96,53	97,22	92,36	96,53
2 broken bars	94,44	94,44	97,92	91,67	80,56	94,44
3 broken bars	93,75	93,06	97,22	93,06	95,14	96,53
5 broken bars	97,92	97,92	97,22	96,53	96,53	95,83
7 broken bars	96,53	99,31	97,22	87,50	98,61	93,75

As some faults have levels of amplitudes close to 0.5 mm/s (maximal level for normal working condition), when these faults have been presented to the normal working condition artificial neural network, they haven't been detected correctly. For this reason, the results for normal working condition showed results in the range 70,14 - 97,22.

Even though any new training hasn't been performed for the seventy-two artificial neural networks, the sensors showed high level of accuracy.

On the expert system subroutine it has been implemented one hundred ninety nine rules to interpretation the outputs of artificial neural networks, that have been built based on artificial neural networks output.

The expert system outputs for the seven broken rotor bars, *7_BRB_8.txt*, is shown on Tab. (3). The rate of accuracy of expert system to validate tests for the six sensors is shown in Tab. (4).

Table 3. Artificial neural networks outputs - test of validation

Position of the sensor *P-1* (vertical direction, side of the fan) Rule 35 Diagnostic: Broken rotor bars (Accuracy percentage = 100%).
Position of the sensor *P-2* (axial direction, side of the fan) Rule 67 Diagnostic: 7 Broken rotor bars (Accuracy percentage = 100%).
Position of the sensor *P-3* (horizontal direction, side of the fan) Rule 100 Diagnostic: 7 Broken rotor bars (Accuracy percentage = 100%).
Position of the sensor *P-4* (vertical direction, side of the motor linking) Rule 131 Diagnostic: 7 Broken rotor bars (Accuracy percentage = 100%).
Position of the sensor *P-5* (axial direction, side of the motor linking) Rule 168 Diagnostic: 7 Broken rotor bars (Accuracy percentage = 100%).
Position of the sensor *P-6* (horizontal direction, side of the motor linking) Rule 199 Diagnostic: 7 Broken rotor bars (Accuracy percentage = 85%).
Diagnostic: Unbalance 21g (Accuracy percentage = 15%).

Table 4. Accuracy of expert system outputs - test of validation

Sensors	Diagnosed fault [%]	Not diagnosed fault [%]	Undefined fault [%]
P-1	83,33	4,17	12,5
P-2	65,63	15,,63	18,75
P-3	89,58	3,13	7,29
P-4	66,67	10,42	22,92
P-5	78,13	3,13	18,75
P-6	70,83	13,54	15,63

The rules have been classified in *diagnosed fault*, *not diagnosed fault* and *undefined fault*. The classification *diagnosed fault* means excitation has been diagnosed correctly. The classification *not diagnosed fault* means excitation has been diagnosed wrongly. Finally the classification *undefined fault* means that there aren't capable rules to identify the excitation. Due to the relative spread of the data and artificial neural networks classifications errors for crossed data, the expert system outputs showed the percentage of accuracy less then to the artificial neural networks outputs, even though these results can be considered goods.

It has been also presented to the *HY_NES* the final test of validation. Those ninety-six tests haven't been used during training and intermediate validation and qualification. The goal of the final test is the identification of excitation through the *HY_NES*, simulating one really application. The data have been used without a new training of the artificial neural networks or even new rule implementation. The main objective of this stage isn't to present optimized final results but to present one methodology that can be used to diagnose faults in induction motors. The global accuracy percentage of *HY_NES* output according to the user's interpretation for each excitation is shown in Tab. (5).

Table 5. Accuracy percentage of the *HY_NES* output according user's interpretation for each excitation

Excitations	Right [%]	Wrong [%]	Undefined [%]
Normal working condition	74	13	13
mechanical looseness	100	-	-
unbalance 35,1g	100	-	-
unbalance 21g	100	-	-
misalignment	75	25	-
single phase	87	13	-
phase unbalance DF_2	49	13	38
phase unbalance DF_1	75	25	-
2 broken bars	87	-	38
3 broken bars	62	38	-
5 broken bars	100	-	-
7 broken bars	100	-	-

The user has the option to see the results for the six sensors through the rules implemented on the expert system subroutine. For the same excitation, e.g. misalignment results from Tab. (2) and Tab. (5) have been showed different accuracy percentage. This is due to the necessity to build and to improve new rules.

Finally, the global accuracy percentage of the *HY_NES* output according to the user's interpretation is shown in Fig. (7).

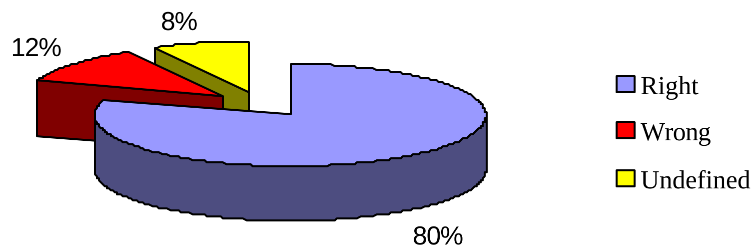

Figure 7. Global accuracy percentage of the *HY_NES* output according to the user's interpretation

5. Conclusions

The hybrid neural expert system *HY_NES* is an approach based on artificial intelligence (artificial neural networks and expert system) developed to diagnose faults from mechanical sources (unbalance, misalignment and mechanical looseness) and electrical sources (phase unbalances and broken bars) beyond normal condition (motor signature).

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.

Normally the data have been separated in two categories: training data and validation data. In this work the data have been separated in three categories: training data, intermediate validation data and final validation data. The *HY_NES* module related to artificial neural networks is a shell that can be used to work with any base of data generated by Analyze Report from UltraManager. The *HY_NES* module related to expert system attends only the simulated excitations and need to be improved in order to become the rules more flexible.

The modular architecture of the hybrid system *HY_NES* allows the inclusion of new sensors, incipient faults, training methods, among others.

It has been introduced some spectra of multiple faults, without a specific artificial neural network training, and the results of the *HY_NES* haven't been good, not indicating clearly the possibilities associated to the introduced combined faults. Also the neural network trained, e.g. unbalance 21g, hasn't been able to detect the case of unbalance 35,1g as a similar fault. The method is based on the pattern recognition and the spread of the data for artificial neural network training are very important in this way. The determination of the spread of the data used for training is a very difficult task and it implies in the capacity of the system to differ from faults and the size of them.

In this work the tests have been controlled in order to verify the viability of the method applied. Even though the results obtained have been very significant, exist strong restrictions related to the identification of the faults that involve patterns not trained. New studies must be done in order to minimize this problem and become the approach more robust to the training patterns variations and its application in a group of different machines. Doing this the hybrid system *HY_NES* could be a promising approach to diagnose faults in induction motors on-line as well as included in Reliability Based Maintenance programs.

6. Acknowledgement

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