DETECTION OF IMPERFECTIONS IN ROTATING MACHINES THROUGH ARTIFICIAL NEURAL NETWORKS

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Abstract. *The artificial neural networks (ANNs) are mathematical and computational models inspired in the knowledge of the neurosciences. The ANNs is composed of nonlinear elements of parallel processing and is characterized for the capacity of learning through examples. In this work a contribution of the study and characterization of forces of excitement in rotating machines using ANNs trained with experimentall signals of vibration is shown. The developed methodology is used to classify the excitement for four levels of unbalancing beyond the normal condition of functioning. Through a selective filter it is possible to reduce the number of parameters capable to represent the signals used for training of the ANNs. To the results of training through batch method and standard-to-standard method and of qualification for different architectures of networks is shown. The evaluation of sensor's efficiency related with the point of vibration signals acquired is shown too. In this way the goal is to identify which sensors presents the percentage greater of rightness reducing the number of collections.*

Keywords*: Rotating machines, Artificial Neural Networks, Unbalancing, Selective Filter*

1. Introductions

The Predictive Maintenance is a science that uses some types of data to determine the condition of the machine and to predict an imperfection before it occurs. In general, the benefits of the predictive maintenance are to reduce the time of stopping of the machines, to prevent panes, to diminish the maintenance costs and to increase the security and reliability of the components. This component can be small like a transistor or big like a hydroelectric plant, Lin and Wang (1996) and Baillie and Mathew (1996). Currently with the sophistication of the machineries systems, the predictive maintenance has become a viable tool for the accompanying and diagnosis of imperfections. The predictive maintenance depends on investments with specific sensors to monitor the normal and abnormal operations of the machine as well as analyzing these signals comparing them with the levels previously established inside a band of permissible tolerance (alarm levels).

Nowadays there are different types of methods to diagnosis imperfections in rotating machineries: oil analysis, accompanying of pressure and temperature, vibration analysis, etc. For many years, the vibration analysis has been wide accepted as being the most trustworthy method of diagnosis of imperfections in rotating machines. The signals of vibrations have been used for the accompanying of the condition of rotating machines imperfections diagnosis and severity estimation.

The importance of the detention and diagnosis of imperfections in rotating machines grew considerably due to the increase of its complexity and high costs associates to the imperfection and the time of stopping. Normally the recognition of imperfections requires a detailed analysis of the signals of the machines to identify standards of specific imperfections. Traditionally this procedure has been done through visual inspection and for experienced people in spectral analysis or through methods of processing of signals. However, these methods are generally expensive and inefficient in some cases.

Currently techniques of sophisticated vibration analysis are being arranged to be used in the monitoring and in the diagnosis of complex rotating machines. Amongst them have been detailed the Artificial Intelligence techniques as artificial neural networks (ANN's), Fuzzy Logic, expert systems, etc. The artificial neural network is one tool that has been called attention of the researchers in the last years because it has been demonstrating the capability to monitor and to detect faults in rotating machines using an inexpensive, reliable, and noninvasive procedure. Through then it is possible to monitor the machinery on-line aiming at the minimize of the time between the act of receiving of the information and the diagnosis of the problem, Lucifredi *et al.* (2000) and Lopes *et al.* (1998).

Many technical articles have addressed the importance of artificial intelligent techniques in the rotating machines fault detection: Wu *et al.* (1992), Alguindigue *et al.* (1993), Chow *et al.* (1993), Liu *et al.* (1996), Oliveira (1999), Zang and Imregun (2001) Vyas and Satishkumar (2001) and Brito (2002).

In this work a contribution of the study and characterization of excitement forces in rotating machines using ANNs trained with experimentall signals of vibration is shown. The developed methodology is used to classify the excitement for four unbalancing levels beyond the normal functioning condition. Through a selective filter it is possible to reduce the number of parameters capable to represent the signals used for training of the ANNs. To the results of training through batch method and standard-to-standard method and of qualification for different architectures of networks is shown. The sensor’s efficiency evaluation related with the point of vibration signals acquired is shown too. In this way the goal is to identify which sensors presents the percentage greater of rightness reducing the number of collections.

2. Vibration Source - Unbalance

The source of all vibration is less than perfect design and less than perfect manufacturing. In other words, defects are sources of vibration. A perfect machine would generate no vibration when operating. Perfection is not achievable at any cost, and just approaching perfection becomes astronomically expensive. Therefore, we will need always to coexist with defects on this planet. The remaining question is how severe a defect we are willing to tolerate. The answer to that question is rooted in human perception and expectations of machine longevity. General guidelines for severity criteria are contained in standards charts, Wowk (1991).

Every vibration problem is first a problem in identifying and locating source. Identifying the source means to perform a frequency analysis to tag the offensive frequency, and then locate the source by tracking this frequency to its origin. The amplitude is then measured to judge the severity.

Mass unbalance is at the top of the list because it is the most common cause of vibration and the easiest to diagnose. Unbalance is a condition where the center of mass is not coincident with the center of rotating as shown in Fig.1.

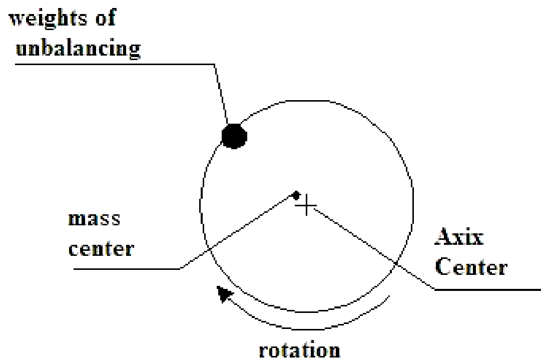

Figure 1. Mass unbalance.

The reason for this is a nonuniform mass distribution about the center of rotation. The vector sum of all the density variables can be combined into a single vector, or single weight at one location (for a thin disk where single-plane balancing applies). This can be viewed as an imaginary heavy spot on the rotor. The heavy spot pulls the rotor and shaft around with it, causing a deflection that is felt at the bearing. The task for the balancer is to find the amount and location of the heavy spot and apply an equal and opposite weight (180^0) to compensate. This will bring the center of mass to be coaxial with the center of rotation, and the result is a smooth running rotor.

The amount of runout, as measured with a dial indicator, is irrelevant to mass balancing. Runout and mass unbalance are independent quantities. A well-balanced rotor can have significantly runout. If the rotor’s mass distribution is compensated for by mass balancing, then a runout condition will not cause significant forces on the bearings, and it can run in this condition indefinitely if there is clearance. The causes of unbalancing are due:

- porosity in casting
- nonuniform density of material
- manufacturing tolerances
- gain or loss of material during operation
- maintenance actions, like changing bearings, or cleaning
- changing bolts
- machining
- loose material moving around, like water in cavities

- keys
- couplings
- anything else that affects the rotation mass distribution.

Unbalance shows up as a vibration frequency exactly equal to the rotation speed (f_r) with an amplitude proportional to the amount of unbalancing, Wowk (1991) and Almeida and Góz (1994).

3. Experiment Setup

The experimental tests have been done in the LASID - Laboratory of Dynamic Systems of the UFSJ - Federal University of São João del Rei. Figure (2) shows the instrumented test desk.

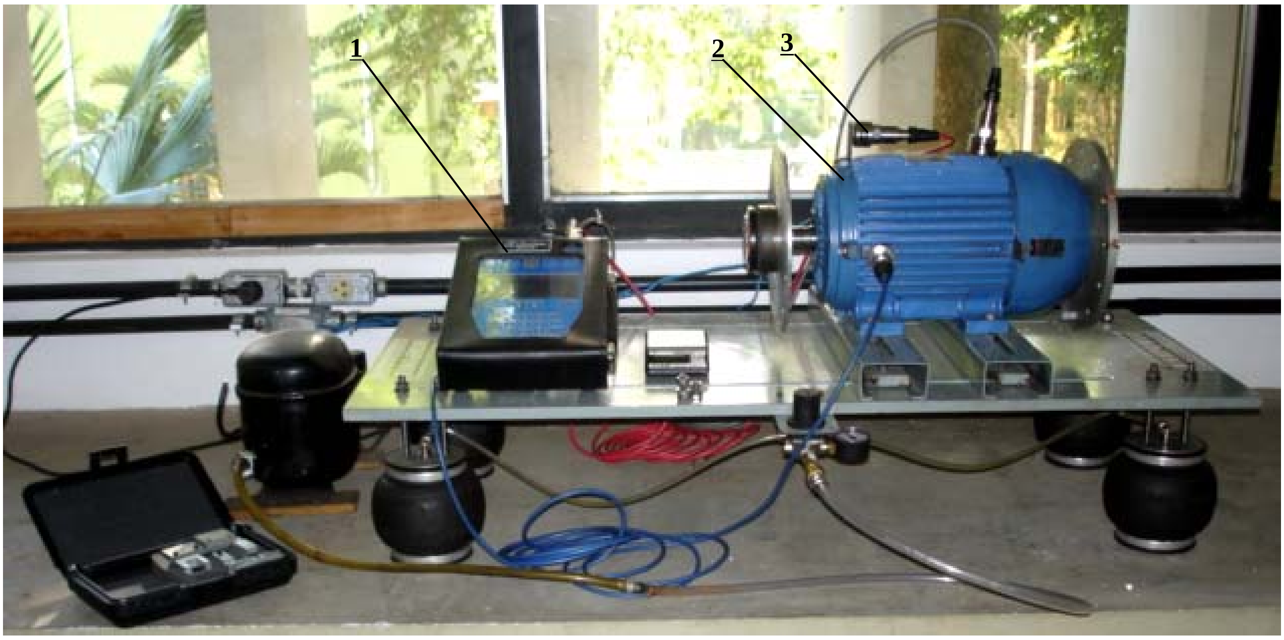

Figure 2. Instrumented test desk.

The equipment UltraSpec 8000 [**1**] manufactured by 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. The last option offers a more comfortable working environment for detailed analysis, technical reports writing and data bank generation.

The three phase, induction motor [**2**], squirrel-cage rotor, 5 HP, 220V, 60 Hp, 4 poles, 44 bars, 36 slots, 1730 rpm nominal rotation, has been powered with unbalance faults beyond the normal condition (motor signature).

Through the UltraSpec 8000 specific firmware the system has been accurate balanced and it has been checked mechanical backlash. 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 x f_r, 2 x f_r and 3 x f_r), Brito *et al*. (1999) and Brito *et al*. (2001).

The accelerometer A0720GP [**3**], SN6714, accuracy of 0.1000 mV has been used for vibration spectra acquisition. Hamming window of 1600 lines and 5 averages of samples has been used for a frequency width from 0 to 1600 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 the electrical motor. 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. 3. It can be seen from this spectrum that there are no peaks at the rotational frequency and its harmonics 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 accurated balanced. This procedure guaranteed that the faults signatures have been well defined for all tests. The vibration spectra for unbalance faults (9,5; 14,5; 20,3 and 32 g.mm) are shown in Fig. (4) to (7).

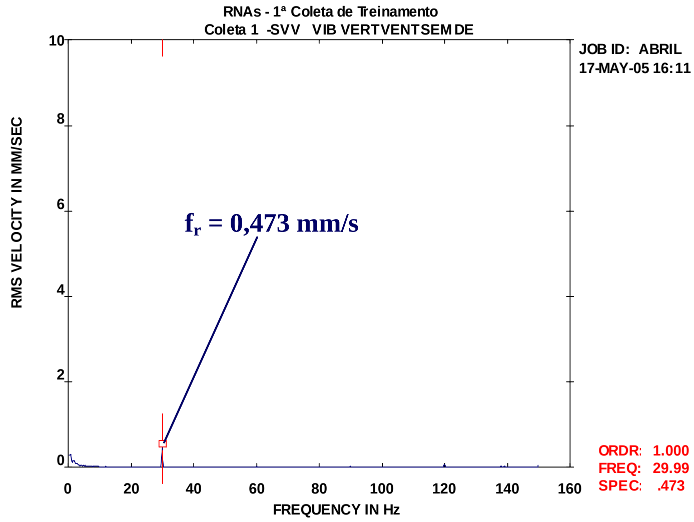

Figure 3. Vibration spectrum for normal condition.

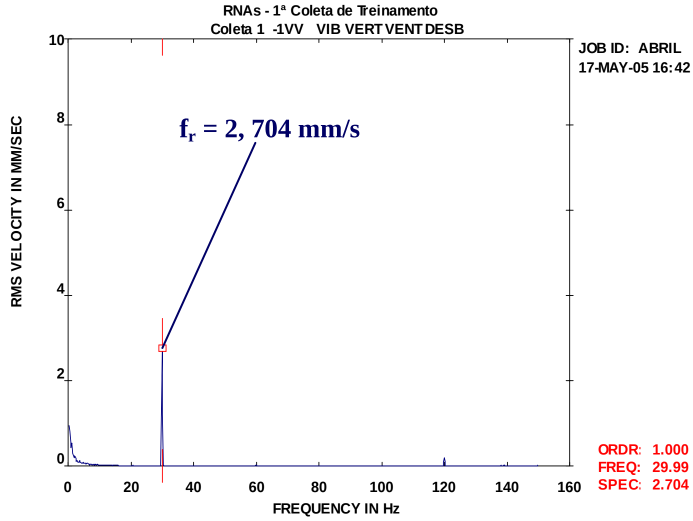

Figure 4. Vibration spectrum for unbalance 9,5 g.mm.

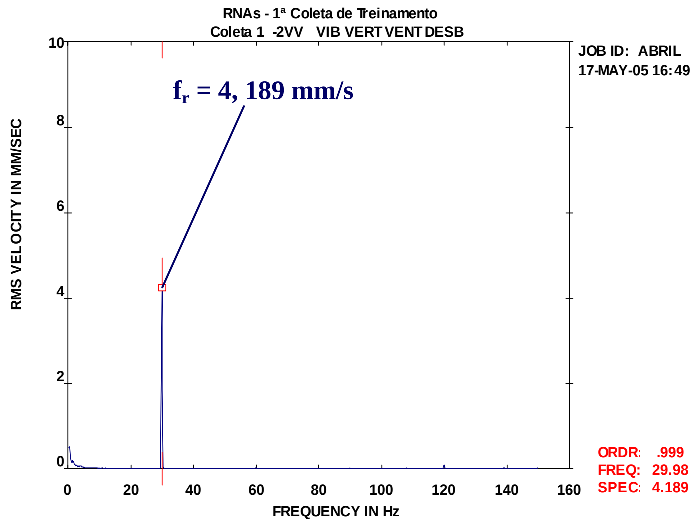

Figure 5. Vibration spectrum for unbalance 14,5 g.mm.

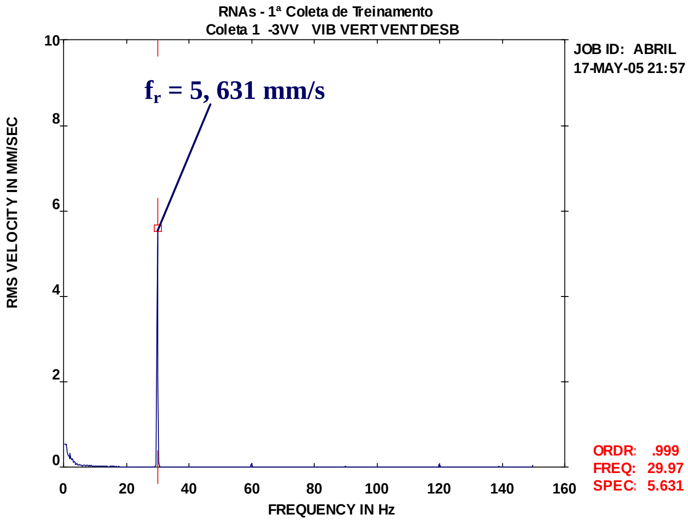

Figure 6. Vibration spectrum for unbalance 20,3 g.mm.

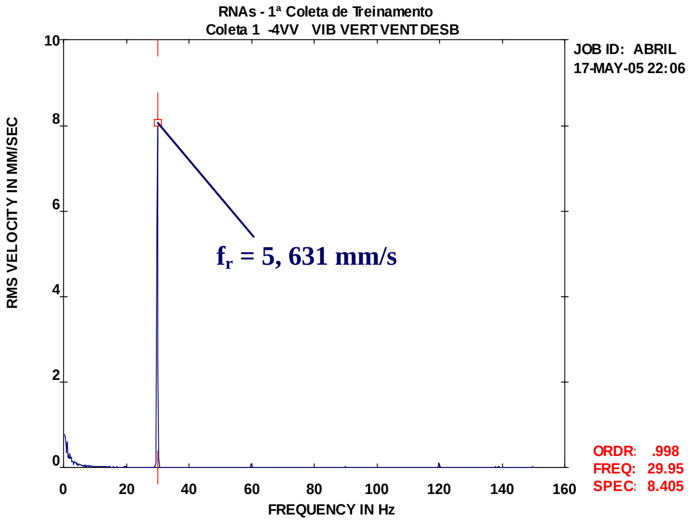

Figure 7. Vibration spectrum for unbalance 32 g.mm.

3. Results Training of Artificial Neural Network

For each series of ten tests (total of 40) it has been separated randomly six series for training (total of 900 spectra) and four series for neural network validation (total of 300 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 have been 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 identified those frequencies which required an exhaustive analysis of all spectra. The frequencies of interest to identify unbalancing faults are (1 x f_r, 2 x f_r and 3 x f_r).

It have been built one artificial neural network to detect each of the five excitations (normal conditions and unbalance - 9,5; 14,5; 20,3 and 32 g.mm) for each six positions of the sensors, in a total of thirty artificial neural networks. This procedure permits smaller architectures that are easier to train. Many tests have been done during the training in order to obtain the best architecture. It had been trained and had been compared the architectures 3x2x3x2, 3x3x3, 3x5x3, 3x5x8 and 9x8x7 for the batch method and standard-to-standard method with desired error equal to 1%, tax of learning equal to 0,01, constant of moment equal to 0,5, random weights initialization and maximum number of epoch equal to 1.000.000.

The accuracy ratio of artificial neural network outputs to validation tests for the five architectures for the batch method and standard-to-standard method is shown in Tab. 1.

Table 1. Accuracy ratio of artificial neural network outputs - Architectures

Architectures	Accuracy Rate [%]	
	Batch Method	Standard-the-Standard Method
3x3x3	89	84
3x5x3	90	83
3x5x8	88	78
9x8x7	91	83
3x2x3x2	93	76

During the test of validation each excitation has been passed in all thirty artificial neural networks and the detected and undetected excitation condition has been considered. When one excitation has been presented for an 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 architecture 3x2x3x2 has been trained in the batch method presented the best result with 93% of rightness. On the other hand, the architecture 3x3x3 have been trained in the standard-to-standard method presented the best result with 84% of rightness. Even though any new training hasn't been performed for the thirty artificial neural networks, the results showed good level of accuracy.

The accuracy ratio of artificial neural network outputs to validation tests for the six sensors for the batch method and standard-to-standard method is shown in Tab. 2.

Table 2. Accuracy ratio of artificial neural network outputs - Individual Sensors

Sensors	Accuracy Rate [%]	
	Batch Method	Standard-the-Standard Method
1 (VV)	97	82
2 (AV)	90	74
3 (HV)	100	85
4 (VA)	99	99
5 (AA)	58	60
6 (HA)	93	83

Base on Tab. 1 and 2 we can verify that the best method of training for the trained architectures is the batch method. The batch method shows approximately 10% more of rightness than the standard-to-standard method as shown in Fig. 8.

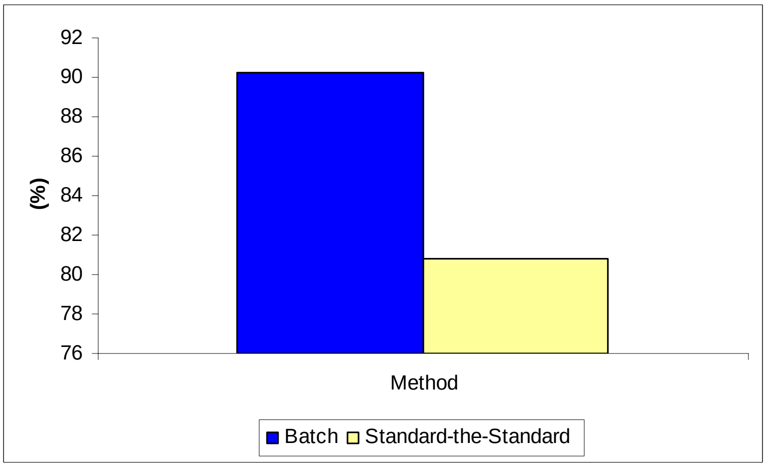

Figure 8. Accuracy ratioof the used methods

The accuracy ratio of artificial neural network outputs to validation tests for the sensor's position for the batch method and standard-to-standard method is shown in Tab. 3.

Table 3. Result of the tree positions of the sensor ones - Sensor's Position

Sensor's Position	Accuracy Rate [%]	
	Batch Method	Standard-the-Standard Method
Vertical (1 e 4)	98	90,5
Horizontal (3 e 6)	84	84
Axial (2 e 5)	74	67

Base on Tab. 3 we can verify that the sensors more efficient have been fixed in the vertical position. The accuracy ratio of the sensor's position for the batch method is shown in Fig. 9. The accuracy ratio of the sensor's position for the standard-to-standard method is shown in Fig. 10.

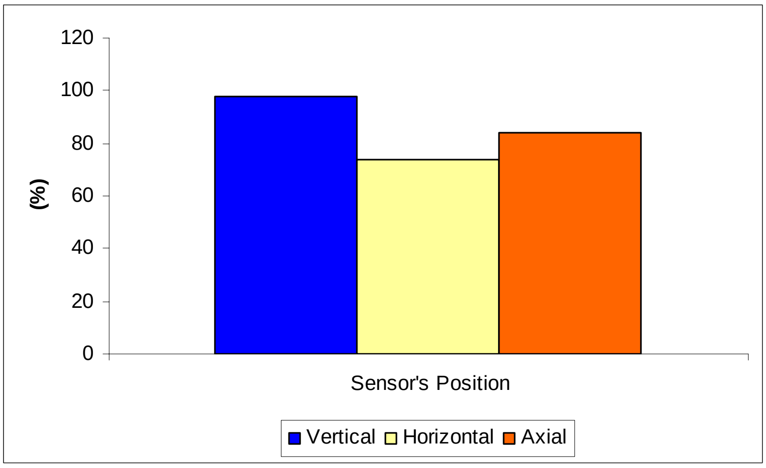

Figure 9. Accuracy of the sensor's position for the batch method

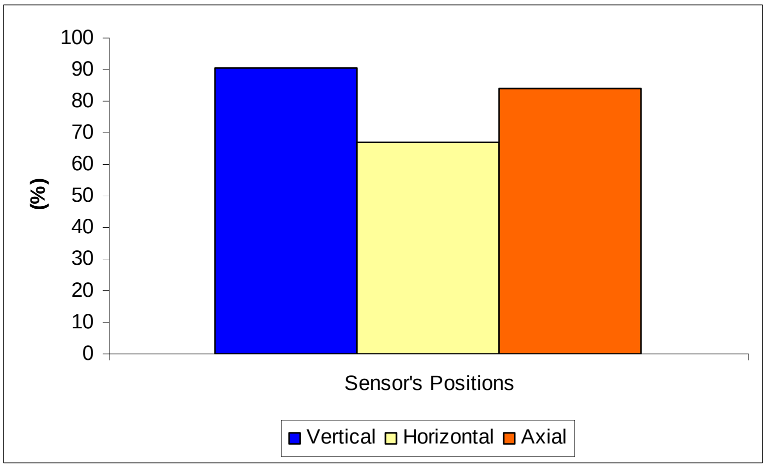

Figure 10. Accuracy of the sensor's position for the standard-to-standard method

4. Conclusion

The artificial neural networks are one of the tools that have been waking great interest of researchers in the last years for being a tool that makes possible the on-line monitoring of the predictive maintenance aiming to minimize of the time between the act of receiving of the information and the diagnosis of the problem.

Amongst many theoretical and practical aspects that they are part of a project of artificial neural networks, the choice of architecture and its training parameters does not follow predefined rules. The knowledge and experience of the designer in relation to the faced problem are more important. The definition phase is delicate because involves the attainment of the set of significant variable for resolution of the problem beyond the choice of the topology of the networks. This attainment involves the removal of not trustworthy variable for the process or which the use is impracticable for reasons economic techniques beyond the identification of the variable that are related with the problem.

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, in the both side of the electric motor. The vibration analysis has been chosen because it is a non invasive technology and has more information on the spectra. The domain of frequency has been chosen because it is easier to diagnose faults.

The results from a real case show the capacity and viability of the application of neural nets as sufficiently efficient tool in the detention and diagnosis of imperfections introduced in a rotating machine.

5. Acknowledgements

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6. References

Alguidingue I. E., Buczak A. L., Uhrig R. E., 1993, "Monitoring and Diagnosis of Rolling Element Bearings Using Artificial Neural Networks", IEEE Transactions on Industrial Electronics, Vol. 40:(2), 209-217, April.

Amand Th., Heyen G., Kalitventzeff B, 2001, "Plant Monitoring and Fault Detection Synergy Between Data Reconciliation and Principal Componen", Computers and Chemical Engineering Vol. 25, pp.501-507.Baillie D. C., Mathew J, 1996, "A Comparison of Autoregressive Modeling Techniques for Fault Diagnosis of Rolling Element Bearing",. Mechanical Systems and Signal Processing, Vol. 10, No. 1, pp.1-17.

Brito J. N., 2002, ''Desenvolvimento de um Sistema Inteligente Híbrido para Diagnóstico de Falhas em Motores de Indução Trifásicos'', Tese de Doutorado, Universidade Estadual de Campinas.

Brito, J. N. Brito, R. R. and Pederiva, R., 2001, "Using neural network to detect fault conditions en electric motors", Proceedings of Sixteen Brazilian Congress of Mechanical Engineering, Vibration and Acoustics, Uberlândia, Brasil, pp.285-294.

Brito, J. N., Baccarini, L. M. R. and Pederiva, R., 1999, "Análisis de vibración y análisis de corriente, herramientas de mantenimiento preditivo aplicadas en la detección de problemas en motores eléctricos", Actas del IV Congreso Iberoamericano de Ingeniería Mecánica, Santiago del Chile, Chile**.**

Chow M.-Y., Sharpe R. N., Hung J. C, 1993, "On The Application and Design of Artificial Neural Networks for Motor Fault Detection – Part II", IEEE Transactions on Industrial Electronics, Vol. 40:(2), 189-196, April.

Lin C.-C., Wang H.-P, 1996 "Performance Analysis of Rotating Machinery Using Enhanced Cerebellar Model Articulation Controller (E-CMAC) Neural Networks", Computers Ind. Engng., Vol 30, No. 2, pp. 227-242.

Liu T. I., Singonahalli J. H., Iyer N. R., 1996 "Detection of Roller Bearing Defects Using Expert System and Fuzzy Logic", Mechanical Systems and Signal Processing, 10:(5), 595-614.

Lopes A. P., Andrade O. P., Vianna A. L., 1998, "Sistemas Inteligentes na Manutenção Predictive", T&N Petróleo, pp. 53-55.

Lucifredi A., Mazzieri C., Rossi M., 2000, "Application of Multiregressive linear Models, Dynamic Kriging Models and Neural Network Models to Predictive Maintenance of Hidroeletric Power Systems", Mechanical Systems and Signal Processing, Vol. 14, No. 3, pp. 471-494.

Vyas N. S., Satishumar D., 2001, "Artificial Neural Network For Fault Identification In a Rotor-Bearing System", Mechanism and Machine Theory, 36, 157-175.

Wowk V.,1991, "Machinery vibration: measurement and analysis", McGraw-Hill. Inc.,358p.

Wu X., Ghaboussi J., Garret-Jr J. H, 1992, "Use of Neural Networks In Detection of Structural Damage", Computers & Structures, 42:(4), 649-659.

Zang C., Imregun M., 2001, "Structural Damage Detection Using Artificial Neural Networks and Measured FRF Data Reduced Via Principal Component Projection", Journal of Sound and Vibration, 242:(5), 813-827.