DETECTION OF FAULTS USING ARTIFICIAL NEURAL NETWORKS IN PIPELINES FOR TRANSPORT OF PETROLEUM AND GAS

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Abstract. *The condition monitoring and diagnostic of structural faults in pipelines are an important problem for the petroleum's industry, being necessary to develop supervisory systems for detection, prediction and evaluation of a fault in the pipelines to avoid environmental damages and financial losses. Among the several techniques for detection of structural faults available actually, the analysis based on the change of the dynamic behavior presents good results. In these analysis, physical and geometric properties the of structures submitted to forces and external excitations can to cause relative variations and used as condition indicators.*
In this work, three types of Artificial Neural Networks (ANNs) are reviewed and used to detect and locate a fault in a simulated pipe. The simulated pipe was modeled through the Finite Elements Method. For the Neural Networks' analysis, the first six natural frequencies of the pipe are used as inputs in the networks. The used ANNs were the Multi-Layer Perceptron Network with backpropagation, the Probabilistic Neural Network and the Generalized Regression Neural Network. After the analysis, it was concluded that the ANNs are a good computational tool for problems of faults detection in pipelines with a greater precision. In the localization of the faults, numerical error smaller than 5% were verified..

Keywords: *Finite Element Methods, Modeling of Faults, Artificial Neural Networks, Pipelines*

1. Introduction

The petroleum is the energy source most used by the man. The way to transport petroleum (and gas) more used is by pipelines. The pipes used in the petroleum's industry are fabricated of many materials and has various diameters and thickness. However all they have something in common: the need of an appropriate maintenance to eliminate the risk of leaks during transport of the oil and gas.

Similarly to others mechanical structures, the pipelines are susceptible to deterioration as a function of the time, as well the local where are localized and the substance that are transporting. Due to the deterioration and applied loads the pipelines can fail. Those faults generally begin with a small crack that is increasing, reducing the structural integrity of the pipe, carrying it to the limit of resistance and to the consequent leak. Knowing the damages that a leak can cause, it is of common interest that systems of detection and prediction of faults are developed for pipelines.

However, some techniques for inspection and monitoring pipelines are very established (pigs, acoustic emission) and generally possess an high cost. This limitation encourages the researchers to develop techniques that combine high efficiency with a low cost (Rodrigues *et al*, 2002).

Among the several techniques for detection of structural faults actually available, the analysis based on the change of the dynamic behavior can presents good results. In this analysis, the physical and geometric properties of structures submitted to forces and external excitations can has relative variations (mass, stiffness, natural frequencies, damping, mode shapes, etc.) and used as condition indicator (McConnell, 1995). Hartnett (2000) and Mangal *et al* (2001) concluded that the natural frequencies as important tool for the monitoring and diagnostic of faults in offshore structures.

Recently, the search for a tool to realize a fast identification of faults before it causes the structure's collapse, has taking many researchers to verify the efficiency of Artificial Neural Networks (ANNs). A Neural Network can be defined as a massive and parallel distributed processor constituted of units of simple processing (neurons) able to store experimental knowledge and to turn it available for future use (Haykin, 1999). Several publications about the application of ANNs in the detection and diagnostic of faults are found in the literature (Wu *et al*, 1992; Alves Jr. *et al*, 2001; Santiago *et al*, 2002), being ANNs recommended to on-line monitoring (Lopes *et al*, 1998), especially of offshore platforms' (Mangal *et al*, 1996).

The goal this work is investigate the effects of the position and length of fault, introduced artificially, on the natural frequencies of a simulated pipe, modeled by the Finite Elements Method. Associated to the modal analysis, three types of neural networks are used to identify the fault location, establishing a comparative of the efficiency of each one of these ANNs. In this work the following types of ANNs are analyzed: the Multi-layer Perceptron (MLP) Neural Network with Backpropagation, the Probabilistic Neural network (PNN) and the Generalized Regression Neural Network (GRNN).

2. Artificial Neural Networks

2.1. Review

The Artificial Neural Networks (ANNs) are systems constituted of simple computational elements that are united for links with variable weights. According Kaminski and Alves (2001), the Multi-Layer Perceptron neural networks (MLP) are the most commonly used actually. These systems have the learning capacity starting from a group of information, and were developed initially as a model of the nervous cells proposed by McCulloch and Pitts (1943). this model was divided in two main parts, that were the *input connections*, where each entrance x_i, was associated to a weight w_i and the *implementation of the transfer's function* of the neuron, being this the function "step". For this network, if the total inputs (values of the inputs multiplied by weights and later added) is larger than a certain value, then the neuron activates and it produces an output equal to one, otherwise, equal to zero. In the course of time, ANNs went being developed, until arriving in the model developed by Rosemblatt, that proposed the perceptrons and the training algorithm to the network that consists of determining the weights of the neural network relating the input data and the expected output. The new developments in training algorithms came with ADALINE, proposed by Widrow and Hoff (1960) based on the Delta Rule, whose function is to optimize values of the weights that it minimizes the quadratic error among the expected and calculated outputs, realizing a supervised learning. To establish these weights, however, it is necessary to have training data composed for inputs and expected outputs. Actually, other tendencies for the development of ANNs are the transfer's functions. The most used are the sigmoid functions, for example, the hyperbolic tangent function, and the main advantage of this function is to help the network to control small and big entrances at the same time.

Generally, the use of neural network is applied to patterns recognition due the learning potential of the system functions. One great advantages in relation to other analysis techniques is its capacity to treat complex systems without the need of using a complex algorithm, being needed just a group of examples for it "to learn" how to associate those data.

2.2. Multi-Layer Perceptron Neural Networks

This type of ANN is usually constituted of three classes of neuron's layers: the input layer, the hidden layers and the output layer. In the MLP networks just the hidden and output layers are processors of data, and the input layer just distributes the data for the first hidden layer.

The representation of a Multi-layer Perceptron Neural Network is presented in Fig. (1).

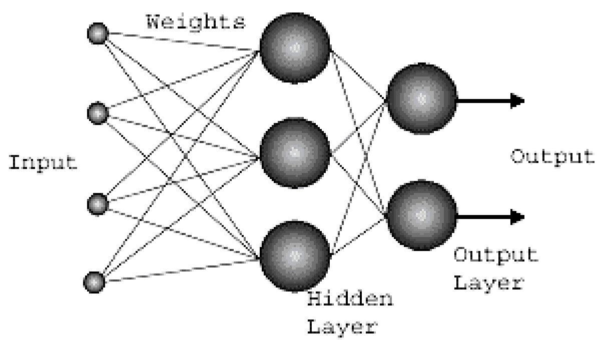

Figure 1. Representation of a MLP Neural Network.

The smallest unit of a MLP Network is a processor neuron that is composed by a scalar, called of synaptic weight, and for a transfer's function. The Fig. (2) shows a processor Neuron.

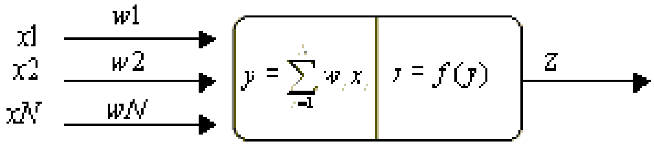

Figure 2. Neuron's diagram (Padovese, 2002).

Each processor layer of the neural network is constituted by a group of processors neurons, being then the Multi-Layer Perceptron Network the totality formed by the interconnection of the neurons of adjacent layers. If the neuron belongs to the hidden layer, it will receive *N* values distributed by the input nodes, where *N* is the dimension of the input vector. Each one of these values is multiplied by a weight w_i, and a pondered sum of them results in y that is supplied in the entrance of the neuron. This value is used by transfer's function to calculate the output value. Therefore, a MLP Neural Network is formed by neurons interconnected to each other, where each neuron has its own group of weights and the neurons of a same layer has a same transfer's function.

According to Padovese (2002), the traditional algorithm of training for the MLP Neural Network is called "Error Backpropagation". In this algorithm, each vector of the group of training data is taken to the input neurons, that as they move forward in the network, its values are modified in agreement with the weights and transfer's function and in the output layer it will be available a vector that is compared with the target vector through a error function selected previously.

In this work, 15 architectures of MLP Networks were used. After the training and test of these networks, it was verified which obtained the best performance in order to compare its efficiency with the efficiency of the other types of ANNs. Those architectures were divided in two groups: networks with a hidden layer (denominated 6xYx1, where Y is the number of neurons) and networks with two hidden layers (denominated 6xYxZx1, where Y is the number of neurons in the 1st hidden layer and Z is the number of neurons in the 2nd hidden layer).

The MLP Networks used possesses the following parameters:

- ✓ The hidden layers are activated by the *Tan-sigmoid function*;
- ✓ The output layer is activated by the *Linear function*;
- ✓ The optimization's method used is the *method of Levenberg-Marquardt*;
- ✓ The maximum number of epochs used is *3500 Epochs*;
- ✓ The acceptable total error: *1e-8*.

2.3. Probabilistic Neural Network

The Probabilistic Neural Network (PNN) is an adaptation of the rule of statistical Bayesian decision. Padovese (2002) defends that while a MLP Neural Network tends to follow a real model of the human brain working, the origins of PNN are based on a statistical model of classification. Specht (1988) discovered that could dispose the classifier of Bayes-Parzen in the form of a neural network, because if enough information is available in a classification problem, the strategy of decision of Bayes-Parzen permits to classify a new example with a maximum success probability.

Padovese (2002) still exemplifies saying that if a group classification problem exists, with its space dimension amostral M, the Baye's classifier requests that the Probability Density Functions (PDF) are calculated of each class in which the problem divides. The PDF present a problem because they are strangers, what took Parzem in 1962 to estimate the probability density functions through ponder functions.

The PNN structure is composed by an input layer, whose dimension N is function of the dimension of the input vector. This layer distributes the input vector to all the neurons of the following layer, whose dimension is equal to the number of examples in the training group, and it is called patterns' layer because is formed by the neurons processors that contain the ponder functions. The third layer is called addition layer that is the number of classes contained in the problem, whose function is to sum the values came of the patterns' layer, and it can still exist another optional layer call of output layer, that supplies the number of the class that possesses the biggest value in the addition layer (the class for which the input vector had the biggest probability density).

Kaminski and Alves (2001) trace a comparative between the PNN and the MLP, concluding that PNN offers the following advantages:

- ✓ it is faster and doesn't need training;
- ✓ if the training data are appropriate, it is possible to guarantee that PNN will converge for the Bayesian classifier independent of the complexity of the relation among patterns;
- ✓ the output of PNN is probability of a classification, and this fact doesn't happen for the Backpropagation's ANN.

2.4. Generalized Regression Neural Networks

This type of ANN is usually used like an approximation function and it belongs to the group of the neural networks with *radial basis functions*. Giving the appropriated number of neurons in the intermediary layer, is possible to demonstrate that the Generalized Regression Neural Network (GRNN) are able to approach a continuous function with appropriated precision (Wasserman, 1993).

This network is based on the theory of the non-linear regression and it permits that an appropriated form of the probability density function be obtained experimentally, starting from a training database. During the processing phase it is necessary to normalize the scale of the input vector so that have the same limits and variations, and an exact scale is not necessary and besides another scale is not necessary when new data are added. Equally to PNN, the input vector of GRNN possesses the number of neurons equal to the number of training vectors and not to the number of data of the training vector. The main attributes of a net GRNN, according to Cabral (1999) are:

- ✓ It possesses fast learning and convergence when the number of data is relatively high;
- ✓ An interactive procedure is not necessary;
- ✓ It possesses a great amount of procedures during the classification phase.

3. Modeling of the Structure

The structure that was considered in this study consists of a simulated pipe of steel fixed as a cantilever beam. None external load is applied in the simulated pipe and nor a pressures field in your interior. This pipe possesses 1000mm of length (L), 114.3mm of diameter (D), 5mm of thickness (t). This pipe is shown in the Fig. (3).

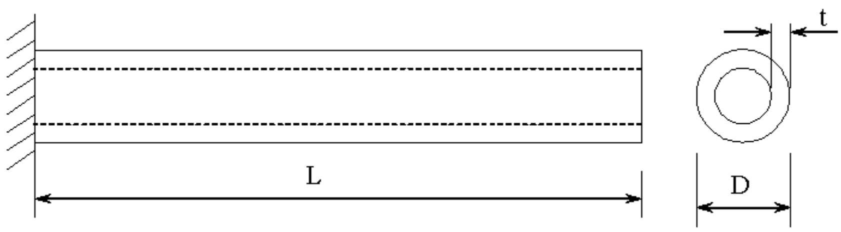

Figure 3. Scheme of the simulated pipe in study.

This pipe possesses the following attributes:

- ✓ Density – ρ = 7860 kg/m^3.
- ✓ Young's Module – E = 210.0×10^9 N/m^2;
- ✓ Poisson Coefficient – ν = 0.3;

This pipe was modeled through the finite elements method using the software ADINA System 7.4.0 900 Nodes® (Licensed from ADINA R&D, Inc.), adopting an one-dimensional model, using tube elements. A mesh was used with 897 elements, and each element has 1.11mm of length.

The introduction of the fault in this model was realized considering a reduction in the cross-section of the pipe, showed in the Fig. (4). This fault was simulated by an element with the thickness of cross-section different (smaller) of the remaining of the pipe.

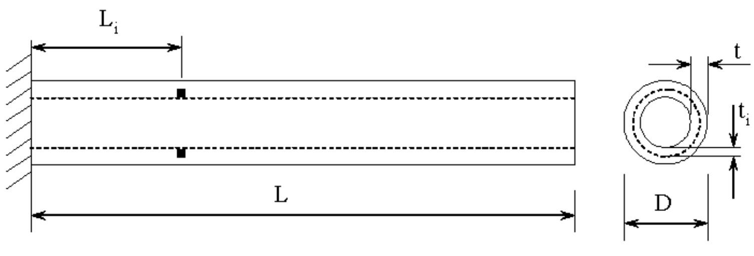

Figure 4. Illustrative scheme of the simulated pipe with the fault.

The faults were simulated for several positions and depths. With that each fault is identified by two numeric values. The relative positions are described by the Eq. (1) and the relative depths by the Eq. (2). The values of the Eq. (2) represent the relative percentages of reduction of the cross-section.

$$\frac{L_i}{L} = \{0.05;\ 0.10;\ 0.15;\ 0.20;\ 0.25;\ 0.30;\ 0.35;\ 0.40;\ 0.45;\ 0.50\} \tag{1}$$

$$\frac{t_i}{t} = \{0.1;\ 0.2;\ 0.3;\ 0.4;\ 0.5;\ 0.6;\ 0.7\} \tag{2}$$

where L is the pipe's length;

L_i is the distance between the fault and the fixed side of the pipe;

t is the thickness of the cross-section; and

t_i is the thickness reduction of the faulted cross-section.

In the analysis was used the Neural Network Toolbox of the Software Matlab 6.0® (The MathWorks, Inc) to realize the processing of the data to obtain the fault location, here considered as a reduction of cross-section in a small part of the pipe. The input parameter of the networks used for identification of the fault position was based in parameters associated to the natural frequency variations.

After elaboration of the model, the simulations were realized, obtained from the first six natural frequencies of the pipe without fault and of the pipe with each simulate fault, totalized 71 simulations. These frequencies were stored in a database. The Fig. (5) shows the natural frequencies normalized by the natural frequencies of the pipe without fault obtained in the faulty pipe fixing a same depth for all the positions of the fault. It is observed that the natural frequencies are influenced by the presence and position of the fault.

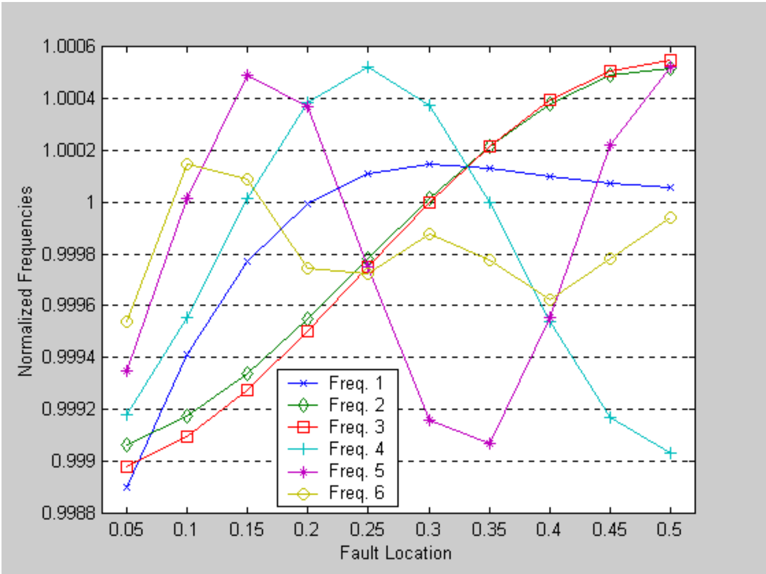

Figure 5. Variation of the natural frequencies of the simulated pipe with the position of the fault.

The plotted curves in the Figure 5, is the normalized natural frequencies of the pipe for the different positions of the fault and they illustrate the sensibility of the frequencies changing with the fault location. It can be observed that the first natural frequency doesn't has sensibility in the position 0.20, nor the second nor the third frequency in the position 0.30, nor the fourth frequency in the position 0.15 as well the fifth frequency in the position 0.10. The sensibility of a natural frequency is low when the position of the fault is very close to one of the nodal points in the mode shape corresponding to this frequency. This behavior justifies the fact of some natural frequencies be not influenced by the presence of the fault in certain positions of the structure (Craig Jr., 1981). Moreover, several natural frequencies are used in the same analysis, because it is practically null the probability of all the used frequencies possess a low sensibility in a same point.

3.1. Pre-processing of the Data

The use of the natural frequencies directly in the ANN is not recommended, because it can take the saturation problems in the training process of the network. To eliminate this inconvenient, a pre-processing of the data should be realized to adjust them to the characteristics of ANN.

Starting from the natural frequencies of the system, Alves (1997) propose a pre-processing creating two more effective parameters for identify the location and diagnostic the faults. The first parameter was denominated of nfr_i and it consists of the average pondered among the natural frequencies of the structure without and with fault. According to Alves, this parameter depends on the fault location and of the stiffness variation that it causes. Eq. (3) gives this parameter.

$$nfr_i = \frac{\omega_{0i} - \omega_i}{\omega_{0i}} \tag{3}$$

where, ω_{0i} is the natural frequency of the structure without fault and ω_i is the natural frequency of the structure with the fault.

The second parameter was denominated of $nfrn_i$ and consists in normalization of the parameter nfr_i. Kaminski (1995) showed that the parameter $nfrn_i$ only depends of the fault location. Eq. (4) gives this parameter.

$$\mathrm{nfrn}_i = \frac{\mathrm{nfr}_i}{\sum_i \mathrm{nfr}_i} \qquad (4)$$

The parameter used in our analysis was the $nfrn_i$. So, it was generated a new database that is the bench of the pre-processed data composed by the $nfrn_i$ of the 70 simulations of faults realized.

To use the ANN was necessary to divide the bench of the pre-processed data in two new benchs: the training bench and the test bench. The test bench is composed for 15 simulations retired arbitrarily of the bench of the pre-processed data and the training bench is composed by the 55 remained simulations.

4. Results and Discussions

Several architectures of MLP Networks were appraised, modifying the number of hidden layers and the number of neurons per layer, to determine which is the MLP network configuration most adequate for the problem of the fault localization. A total of 15 configurations of nets MLP was used. After the simulations, the medium quadratic error (MQE) it was calculated to evaluate which was the most efficient configuration in the determination of the fault position in the pipe. These results are presented in the Tab. (1) with the maximum error that was obtained in each net.

Table 1. Architectures of the used MLP Networks, MQE and maximum errors obtained.

Architecture of the MLP Networks	Medium Quadratic Error	Maximum Error (%)
6x8x1	3.6018e-4	3.4546
6x10x1	1.0969e-4	2.3491
6x12x1	1.4945e-4	2.7264
6x16x1	1.2020e-4	2.6229
6x20x1	1.5516e-4	2.6459
6x8x4x1	1.0943e-4	1.8501
6x8x6x1	3.0971e-5	1.3160
6x8x8x1	1.4965e-4	2.8032
6x10x6x1	6.6195e-5	1.3469
6x10x8x1	1.1488e-4	2.6725
6x10x10x1	5.2597e-5	2.0856
6x20x6x1	8.4463e-5	1.5467
6x20x8x1	7.2845e-5	1.7773
6x20x10x1	1.3372e-4	2.2384
6x20x20x1	9.9235e-5	2.1747

It can be observed that the MLP Network of better performance in the localization of the fault was the network designated by 6x8x6x1, in blue in the tab. (1), presenting a maximum error of 1.32% in the determination of the fault position. This is the architecture of MLP Network that will have its performance compared with the other ANNs' types.

Other two ANNs' types were used: the Probabilistic Neural Network (PNN) and the Generalized Regression Neural Network (GRNN). The Tab. (2) presents the results for the three used ANNs' types.

Table 2 - Performance of the three ANNs' types in the tests

Expected Output	Output of MLP with architecture 6x8x6x1	PNN's Output	GRNN's Output
0.0500	0.0433	0.0500	0.0500
0.3000	0.3132	0.3000	0.3009
0.5000	0.4932	0.5000	0.4500
0.2500	0.2551	0.2500	0.2500
0.1000	0.1071	0.1000	0.1000
0.1500	0.1517	0.1500	0.1500
0.5000	0.4920	0.4500	0.4500
0.2000	0.1982	0.2000	0.2000
0.2000	0.1982	0.2000	0.2000
0.3000	0.3020	0.3000	0.3000
0.1000	0.1028	0.1000	0.1000
0.3000	0.3024	0.3000	0.3000
0.2500	0.2497	0.2500	0.2500
0.1000	0.1055	0.1000	0.1000
0.2500	0.2513	0.2500	0.2500
Medium Quadratic Error	3.0971e-5	1.6667e-4	3.3322e-4
Time of Operation (s)	6.54	0.99	0.55

It can be observed that the network of better performance the fault localization was the MLP Network, which obtained the smallest medium quadratic error (3.0971e-5). Soon after comes the PNN and the GRNN was the one of weaker performance. It is useful to emphasize that in spite of MLP's good performance, the use of another MLP's architectures that were not tested, other values in the Network's parameters, other Transfer's Functions and a larger training bench can still take to more accurate results.

With regard to the time of operation, as already expected, the network of better performance was the GRNN that stretch out at the result in 0.55 seconds. The PNN needed 0.99 seconds and MLP needed 6.54 seconds. In spite of the MLP to have taken more time than the others, its performance was excellent, because it was expected that it carried of very more time. The literature indicates that it can be much slower than the PNN, could get to be slower 104 times, (Specht, 1990), but, in our case, the difference of the necessary times was of just 6.6 times.

The Fig. (6) shows a comparative among the performances of the networks through the medium quadratic errors and times of operation, normalized by the weakest performances, because these two parameters are the most important in the classification process through neural networks. In this work we stand out for the precision of the results and consequently for the network that presented smaller medium quadratic error.

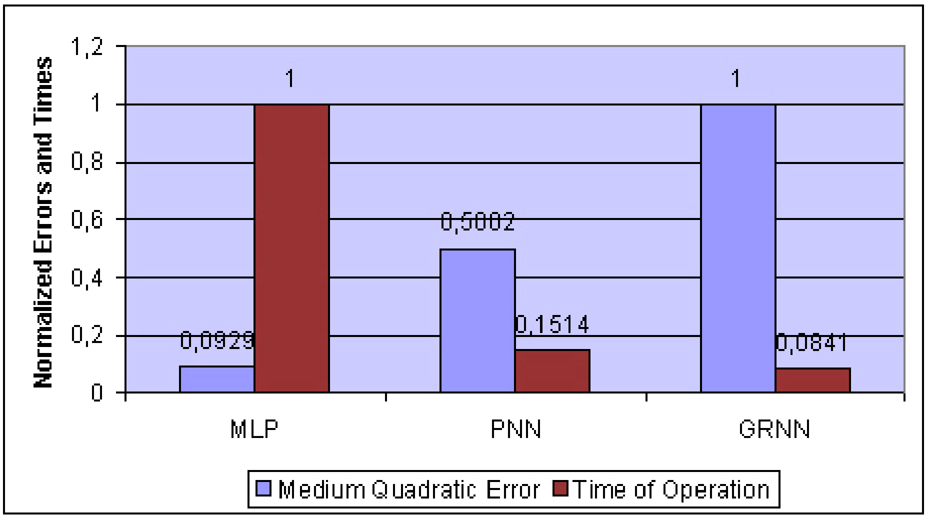

Figure 6. Comparison of the quadratic errors and the operation times of the ANNs' types.

Seeking better to understand the networks' performance, the Fig. (7) shows the obtained output of each network and the expected output. The blue curve is the value waited for the neural networks and the symbols are the answers of the three ANNs' types (MLP, PNN and GRNN). It is possible to observe that for some of the elements of the test bench, the PNN and GRNN showed the exact fault position, even so they are dispersed a lot in the identification of others, while the MLP gave good approaches in all the elements, and therefore it presented a greater precision. The good concordance between the results of the networks' output and the data of the test bench can be verified, permits to conclude that they were shown efficient for identification of the position fault and proving that the utilization of Artificial Neural Networks can permit a technical quite promising in the analysis of structural integrity, in real physical systems.

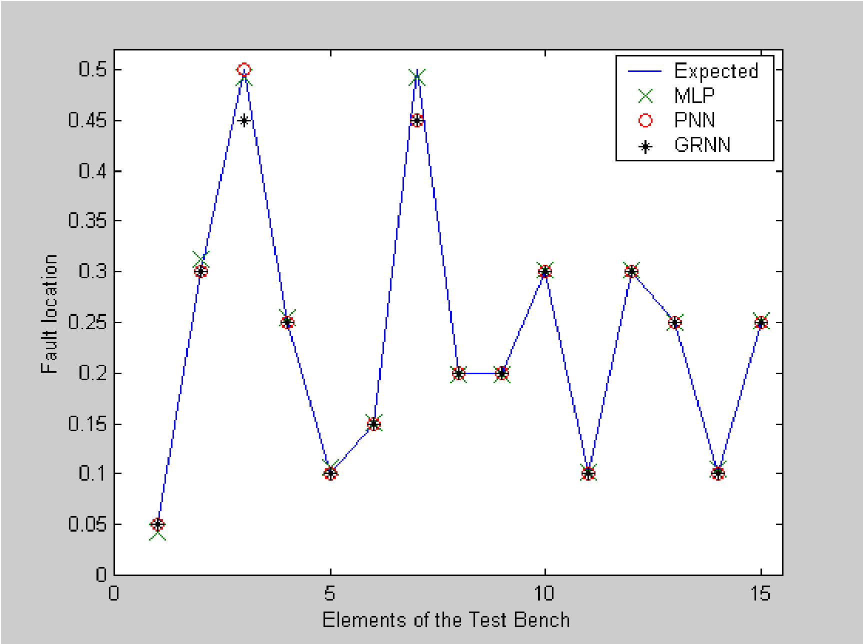

Figure 7. Comparative of MLP, PNN and GRNN's performances.

5. Conclusions

The objective of this work was to establish a comparison among the efficiencies of some ANNs' types in the detection of faults in a simulated pipe. For this purpose were used the MLP, PNN and GRNN Networks. From the obtained results it is possible to affirm that the Artificial Neural Networks demonstrate to be a good computational tool in relation to other identification methods, based on the variations of the natural frequencies of structures, for the faults detection placed in the same ones, according to Alves (1997).

Among the MLP's architectures evaluated in this work was obtained more satisfactory results with the architecture 6x8x6x1. This MLP's architecture with two hidden layers presented quite small relative errors, of the order of 1,32%, what takes to conclude that presents good generalization capacity.

For the others ANNs' types (PNN and GRNN), can be observed that these reached more exact results than the MLP's results for most of the tests, even so less precise than this, due to presence of isolated errors that affected its medium quadratic errors were superiors to the from the MLP.

For the MLP Network, this it was shown more exact than those, because in spite of being less exact, its results were always very close of the expected, indicating a larger reliability in the results of this network.

In relation to the time of operation, the PNN was about 6.6 times faster than the MLP Network while the GRNN was about 12 times faster than the same. In spite of this, the time of operation of MLP can be considered low because it is included the training's time of the network, operation non necessary for the others networks, and that won't also need to be repeated, because the MLP is already trained. In this case, ANN's MLP was the most efficient of the analyzed ANNs.

Experimental studies about the use of the Artificial Neural Networks in real pipes are foreseen, seeking to validate the developed model. Studies seeking the analysis of the structural integrity to simulated models and experimental studies concerning others structures presents in the Petroleum's Industry also foreseen to be investigated.

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