

Detection of the Propagation of Defects in Pressurized Pipes through the Acoustic Emission Technique Using Artificial Neural Networks

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Abstract. The acoustic emission test has distinguished relevance among the non-destructive testing and, therefore, existing research abound at present aiming at the improvement of the reliability of their results. In this work, the methodologies and the results obtained in a study performed are presented to implement pattern classifiers by using artificial neural networks, aiming at the propagation of existing defects in pressurized pipes by means of the Acoustic Emission testing (AE). Parameters that are characteristic of the AE signals were used as input data for the classifiers. Several tests were performed and the classification performances were in the range of 92% for most of the instances analyzed. Studies of parameter relevance were also performed and showed that only a few of the parameters are actually important for the separation of the classes of signals corresponding to *No Propagation* (NP) of defects and *Propagation* (P) of defects. The results obtained are pioneering in this type of research and encouraged the present publication.

1. INTRODUCTION

In the development of the non-destructive testing, the tools for the pattern recognition and signals modeling are increasingly present, being used for the development of automatic or semi-automatic systems of detection and classification of existing defects in equipment through ultrasonic signals (Pulse-echo and Time of Flight Diffraction (TOFD)), eddy current and digital radiography [1-3].

Taking into consideration the importance of the Acoustic Emission testing (AE) among the non-destructive testing used in the inspection of equipment, the main objective of the present work is to describe the methodologies and the results obtained in a study carried out to evaluate the possibility of application of pattern recognition techniques in EA signals, aiming at the detection of the propagation or not of defects in pressurized pipes. These techniques can be used in the implementation of an automatic system for the detection of unstable growth of defects in this equipment.

For this purpose, the development of nonlinear pattern classifiers implemented by artificial neural networks was made use of. As input data for the pattern classifiers, parameters of the AE signals were used. The separation of the signals into the classes *No Propagation* of Defect (NP) and *Propagation* (P) was carried out based on the follow-up of the increase of the defects by means by ultra-sound testing, carried out simultaneously with

the hydrostatic and AE testing. Besides, the separation of the classes by means of J critical integral value was carried out. Several relevant studies of the parameters of the signals were executed to verify which ones were really important in the detection of the propagation of defects.

The classification results were quite satisfactory, showing that it is possible to reach high performance in the detection of the propagation of defects in pressurized pipes. It is important to enhance that this study is innovative in this area of equipment inspection.

2. METHODOLOGIES

2.1. Materials

The specimens were built of API XL Grade 60 steel, with 20 inches in diameter and 14 mm in thickness. The specimens were welded at their extremities in order to form a closed volume and in such a manner that would allow them to be pressurized. An external crack of 7 mm in depth by 140 mm in length was previously created to the pressure in the specimen testing. Figure 1 displays a photograph of the specimens used.



Figure 1: Photograph of the specimens used.

2.2. Hydrostatic Test

The extensions of the pipe were tested hydrostatically up to the propagation of the defect and subsequent failure of the specimen. The chart in Figure 2 represents the evolution of the pressure of the testing as time goes by.

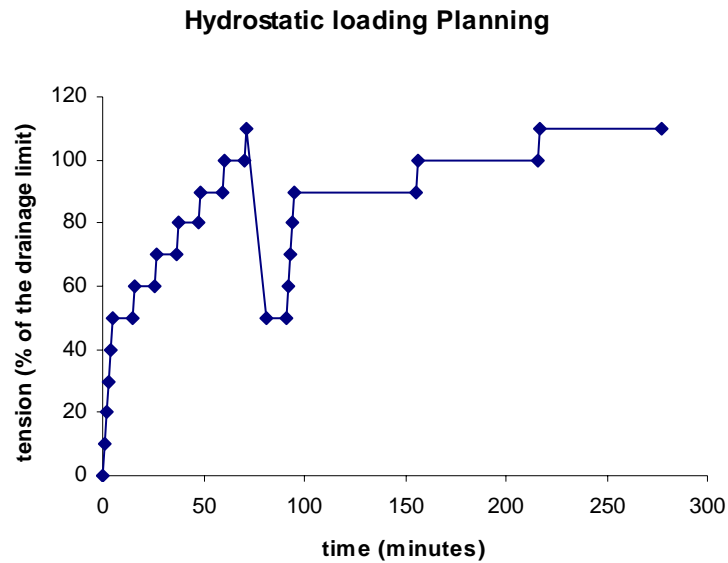


Figure 2: Evolution of the loading of the hydrostatic testing as compared with the testing time.

2.3. Acquisition of the Parameters of the Acoustic Emission Signals

Figure 3 below illustrates a typical form of an Acoustic Emission signal and some parameters that can be extracted to characterize the signal.

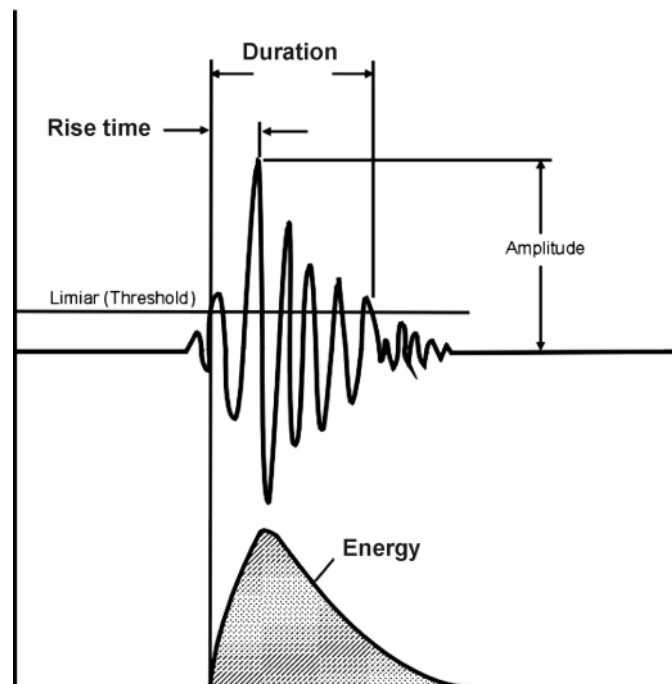


Figure 3: Parameters commonly extracted from the acoustic emission signals.

In the present work, the following parameters were previously selected from the AE signals obtained: testing time, channel, rise time, counts, energy, duration, amplitude, mean frequency, RMS (Root Mean Square) and ASL (Average Signal Level).

2.4. Monitoring of the Increase of the Defects

The increase monitoring of the crack was carried out by means of ultrasonic testing with angular beam. A transducer of 70° was placed sidelong to the crack according to Figure 4. From the distance of the emission point of the transducer up to the defect (L) and sound path (S), it was possible to determine the depth of the defect (P).

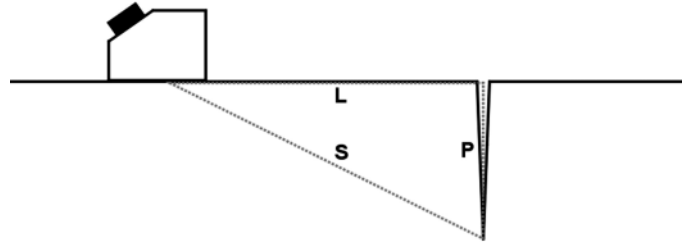


Figure 4: Configuration of the angular ultra-sound testing for determining the depth of the defect. 70° angular transducer.

2.5. Pattern Nonlinear Classifiers

The nonlinear classifiers were implemented using artificial neural network of double layer of neurons of the hyperbolic tangent type and with feed forward. The optimal parameters of the classifiers, neural synapses and bias were estimated through the training algorithm by retro-propagation of errors [4, 5].

In order to estimate the best number of neurons to be used in the intermediate layer of the classifier, the amount of neurons used in each training was variable. The number of neurons, which provided the best results with the test set was used in the evaluation of the classification improvement.

2.6. Selection of Characteristics

In patter recognition, as well as in signal processing areas, quite often the reduction of the dimensionality of input data is advisable due to several reasons: reduction of computer costs of the classifiers, increase of the robustness of the classification systems and reduction of the possibility of data overtraining in the evaluation of the classifier parameters. In this work, a few techniques of characteristic selection were used, which will be briefly described below since they have been used in other works, in which details of the issue can be found [6, 7].

2.6.1. Linear Correlation

The coefficient of linear correlation between two variables can be used to verify the linear correlation among the characteristics of a classification system, as well as the existing correlation among the characteristics and the classes under study. The calculation of the correlation coefficient is done according to the equation [6]:

$$C(x, y) = \frac{1}{n} \sum_{i=1}^n \left(\frac{x_i - \bar{x}}{\sigma_x} \right) \left(\frac{y_i - \bar{y}}{\sigma_y} \right) \quad (1)$$

$C(x, y)$: linear correlation between x and y variables.

\bar{x} and \bar{y} : expected values of x and y variables, respectively.

σ_x and σ_y : standard deviations x and y variables, respectively.

To verify the correlation reliability among the characteristics or between the characteristics and classes of defects, the confidence interval of 95% was used. The correlation coefficients are shown in matrixes whose columns represent the sum of the characteristics including the classes, and the lines represent the characteristics.

2.6.2. Criterion of Relevance

Another technique to evaluate how the performance of a classifier depends on a given characteristics is calculated by means of the equation (2) described by Seixas [8]:

$$R(x_i) = \frac{1}{N} \sum_{j=1}^N \|\underline{\tilde{y}}(x_j) - \underline{\tilde{y}}(\underline{x}_{ji})\|^2 \quad (2),$$

$R(x_i)$: relevance of the x_i component of the \underline{x} input vectors;

N : number of patterns (training or testing);

$\underline{\tilde{y}}(x_j)$: input vector of the neural network for each x_j input pattern presented;

\underline{x}_{ji} : \underline{x}_j input vector, in which the i component has been replaced by its average value calculated over all input vectors;

$\underline{\tilde{y}}(\underline{x}_{ji})$: network output for \underline{x}_{ji} input.

In this work, the relevance criterion was carried out by means of a nonlinear classifier.

2.6.3. Fisher Criterion

Fisher's linear discriminant is based on the attainment of the discrimination main directions of a group of classes [5], based on the fact that the main direction in the discrimination of the classes is the one in which the maximal separation among the averages of data projected in this direction takes place, as well as the minimum scattering among the classes. In other words, in a simple example with two classes, the objective function is described by the equation (3):

$$D(\underline{w}) = \frac{|\tilde{m}_1 - \tilde{m}_2|^2}{\tilde{s}_1 + \tilde{s}_2} \quad (3),$$

where \underline{w} is the discrimination main direction of the two classes, in which the distance between \tilde{m}_1 and \tilde{m}_2 is maximal and the intra-class scatter is minimal, measured by the sum of the variance of each class, \tilde{s}_1 e \tilde{s}_2 [5. 7]. In order to evaluate the relevance of a characteristic in a multivariate distribution, the matrixes of S_W intra-class covariance and S_B intra-class were defined by means of the equations (4) and (7):

$$S_W = \sum_{x \in D_i} (\underline{x} - \underline{m}_i)(\underline{x} - \underline{m}_i)^t \quad (4),$$

where,

$$\underline{m}_i = \frac{1}{n_i} \sum_{x \in D_i} \underline{x} \quad (5),$$

being \underline{x} the characteristics vector and n_i the samples of an i class. For a class C case, the S_{WT} total intra-class scatter matrix will be:

$$S_{WT} = \sum_{i=1}^C S_i \quad (6),$$

The interclass covariance matrix is defined by:

$$S_B = (\underline{m}_1 - \underline{m}_2)(\underline{m}_1 - \underline{m}_2)^t \quad (7),$$

being \underline{m}_1 and \underline{m}_2 the average vectors of the two classes. For a C class case, the total intra-class scatter will be calculated by the equation (8):

$$S_{BT} = \sum_{i=1}^C n_i (\underline{m}_i - \underline{m})(\underline{m}_i - \underline{m})^t \quad (8).$$

In this project, the D value for each parameter of the acoustic emission signal was calculated between the equations (4) and (7).

3. RESULTS

3.1. Separation of the AE Signals in the Classes No Propagation (NP) and Propagation (P)

The separation of the signals in the classes No Propagation of Defect (NP) and Propagation (P) was carried out based on the follow-up of the increase of the defect by means of ultrasound testing, carried out simultaneously with the hydrostatic and AE testing. In order to separate the AE signals into the NP and P classes, firstly, the variation of the pressure of the testing with time for data acquisition was made use of, as well as the follow-up of the crack propagation analyzed by ultrasonic testing with pressure variation. In this case, the division of classes was based on the significant change of propagation of the crack (depth (mm)) shown in the chart of Figure 5 (the sound path is also shown), gathering the classes with the time, as per Table 1.

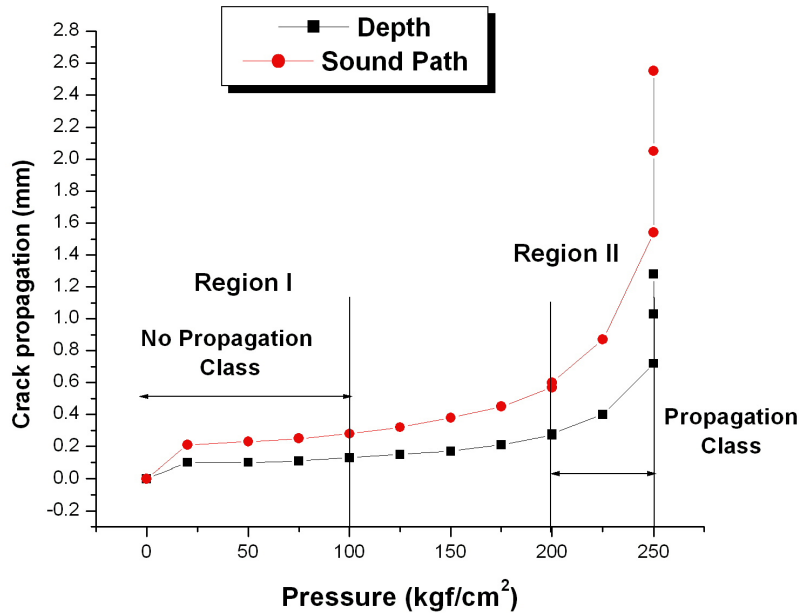


Figure 5: Definition regions of the classes.

Table 1: Data division for formation of the classes.

<i>Classes</i>	<i>Pressure (kgf/cm²)</i>	<i>Time (s)</i>
No Propagation (NP)	0-100	0-4710
Propagation (P)	200-250	9419-20667

Regions I and II of the chart in Figure 5 were also defined with other pressure variation ranges to verify the changes caused in the performance of the classifiers, which will be described thereafter.

Besides the separation of the classes by following-up the increase of the defect by means of ultrasonic testing, taking into consideration that this is not usually done in the operation field of these tubes, the separation of the signals in the NP and P classes by the J critical integral value of this material was also carried out, as will be discussed later on in the text of this work.

3.2. Nonlinear Classifiers

With the separation of the classes carried out according to item 3.1, the set of input of the neural network was formed by 8049 samples of NP and 7697 samples of P. Initially, seven parameters of the signals were used: channel, rise time, Counts, Energy, duration, amplitude and ASL (Average Signal Level) collected directly from the AE apparatus. In this case, the output set was constituted by 15746 lines and seven columns. The output set corresponding to the training of the neural network included 15746 lines and only one column, as long as it is a case of only two classes of standards.

Firstly, since it is known that nonlinear classifiers are implemented in neural networks with two layers, an intermediate layer and an output layer, an evaluation of the number of optimal neurons was carried out in the intermediate layer in order to obtain the best possible performance with the testing samples, characterizing the generalization of the classifiers and the non-occurrence of data overtraining. It must be highlighted that all neurons used were of the hyperbolic tangent type.

In order to optimize the number of neurons in the intermediate layer, initially a random raffle of 20% of each class data for formation of the test set was carried out. This way, it was ensured that the two classes (NP and P), even when including an amount of different samples, had similar relative percentages of samples raffled for test. The data remaining (80%) were used in the formation of the training set. Afterwards, several training sessions and tests were carried out in these raffled samples varying the number of neurons in the intermediate layer on a two-by-two basis, using batch training up to 3000 epochs, with moment ($\beta=0.9$) and variable learning rate (α) [4, 5], parameters that empirically had demonstrated to be the best for fast convergence of the training error. The training sessions and tests were carried out with a minimum of five neurons and a maximum of 25 neurons. Table 2 shows the results obtained with the training and test sets for each situation.

Table 2: Optimization of the number of neurons in the intermediate layer.
SP up to 100kgf/cm², P from 200 kgf/cm²

Number of neurons in the intermediate layer	Training (%)*	Test (%)*
5	87.70	88.86
7	87.95	87.84
9	87.88	88.41
11	87.83	88.00
13	87.92	87.62
15	87.86	87.75
17	87.72	88.38
19	88.07	87.56
21	87.86	88.32
23	88.10	87.43
25	87.98	87.62

*Results for the same pair of training/test sets.

 Maximum
 Minimum

As per the table, it can be verified that with five neurons the best (maximum) performance was obtained with the test set (88.86%), a result slightly better than the one obtained by the training set (87.70%). With the results obtained, it is evident that a high number of neurons are not necessary to increase the performance significantly. Since the smaller the quantity of neurons used in the intermediate layer, the smaller will be the probability of occurrence of overtraining of the network parameters (synapses and bias) [4], the number of neurons in the intermediate layer was established at five for the following training procedures of the classifiers.

3.3. Classification Accuracy

In order to calculate the classification accuracy of nonlinear classifiers, ten training sets and ten test sets were formed by means random raffle from the preliminary data (15746 data), being 80% of the data for training and the remaining 20% for test. The average of the performance obtained for the test sets provides an estimate of the classification accuracy for the signals under study [9]. In addition, to calculate the general classification accuracy, the rates of False Positive (FP) were also determined (signals characterizing *No Propagation* of defect which were indicated as *Propagation*), as well as False Negative (FN) (signals characterizing *Propagation* of defect which were indicated as *No Propagation*), for each training and test set. Table 3 shows all rates obtained for training and test and the average values as well as standard deviations.

Table 3: Performance obtained with ten training and test sets with the nonlinear classifier, as well as the results of False Positive (FP) and False Negative (FN).
NP up to 100kgf/cm², P from 200kgf/cm²

Sets	Performance		Training		Test	
	Training (%)	Test (%)	FP (%)	FN (%)	FP (%)	FN (%)
1	87.81	88.20	7.61	16.94	8.70	15.23
2	88.02	87.70	7.68	16.51	7.12	17.62
3	87.93	87.65	7.60	16.77	7.13	17.76
4	88.05	87.81	7.45	16.65	7.56	17.16
5	87.93	87.87	7.85	16.48	6.98	17.58
6	87.86	88.45	7.65	16.83	8.30	15.07
7	88.03	87.65	7.43	16.74	8.70	16.21
8	87.70	88.76	7.80	16.98	7.15	15.68
9	88.05	87.40	7.94	16.15	8.15	17.28
10	87.90	88.20	7.82	16.65	6.88	16.82
Average	87.92	87.97	7.70	16.67	7.67	16.66
Standard Deviation	0.12	0.42	0.17	0.25	0.73	1.03

As per Table 3, it is verified that the accuracy of the classifier with test data was of 87.97% (average). Since no expressive difference between the performance of the training and test sets occurred, the generalization of the nonlinear classifiers was proven, even without the use of a criterion of advance interruption to avoid the overtraining, as for instance the use of a validation set during the training [4].

The rates of False Positive (FP) concerning the test samples resulted in an average of 7.67% that proves that there were a low number of signals concerning the Non-Propagation of defect, which were indicated as Propagation. However, the indications of False Negative (FN) resulted in an average of 16.66% that proves that there was a greater number of signals concerning the Propagation (P) of defects, classified as No Propagation (NP), certainly the most critical situation from the point of view of equipment failure.

The generalization of the nonlinear classifier for the classification of data under this study is fully proven by the existing similarity between the results obtained with the training and test data, either for the performance or for the FP and FN rates, as can be seen in Table 3. It is also highlighted by the results that the resulting standard deviations can be considered low due to the number of sets used.

3.3.1. Redefinition of the SP and P Classes

The next step in the test was to diminish regions I and II on the chart of Figure 5, defining the SP class up to 25 kgf/cm² and the P class from 250 kgf/cm² (from 15758s). Under this condition, the total set was constituted by 1298 samples of NP and 1253 samples of P; in this case, there was a small difference between the amounts of samples of the two classes. Table 4 includes the performance with the training and test sets in the execution of the study concerning the number of neurons in the intermediate layer. For this situation, with seven neurons, the best percentage of performance with these signals (93.53%) was obtained, although with only three neurons a very close rate had already been obtained (93.34%).

Table 4: Study of the number of neurons in the intermediate layer.
NP up to 25kgf/cm², P from 250kgf/cm²

Number of Neurons	Training (%)	Test (%)
1	87.71	87.65
3	93.88	93.34
5	93.88	93.34
7	93.68	93.53
9	93.98	93.34
11	94.03	93.53
13	93.83	93.53
15	93.88	93.34

Table 5 shows 10 pairs of results between the training and test sets that were raffled from the original set, in this case constituted by 2551 samples (80% for training and 20% for testing). Under this condition, a percentage of 93.64% of average performance for training and test was reached, a rate considerably better than the approximately 88.00% obtained by the first tests (Table 3). The values of standard deviation obtained are small, demonstrating the small variability of the results. With this, it can be inferred that the redefinition of the P class (propagation) for pressures above 250 kgf/cm² was responsible for the increase of the performance, which could be expected due to fact that the False Negative (FN) rates were greater than the False Positive ones (see table 3), being class P "responsible" for the higher rates concerning the classification of errors, which is worsened if we increase region II on the chart of Figure 5, removing a larger amount of signals from the "confusion" region between the two classes. The similarity between the training and tests results confirms the generalization of the classifier, even if a control with the validation set has not been carried out.

Table 5: Performance obtained by ten training and test sets
 (Nonlinear classifier).
NP up to 25kgf/cm², P from de 250kgf/cm²

Sets	Performance	
	Training (%)	Test (%)
1	93.54	94.12
2	93.73	93.14
3	93.10	95.90
4	93.60	93.93
5	93.50	94.12
6	93.68	92.55
7	93.60	93.93
8	94.17	92.36
9	93.73	92.55
10	93.68	93.73
Average	93.64	93.64
Standard Deviation	0.27	1.06

3.4. Elimination of the Irrelevant Parameters

In the pattern recognition, as Duda [5] stands out, the ideal is that the smallest possible amount of parameters describing the classes be used and that these parameters not be

correlated, which facilitates the trainings of the parameters that form the classifiers and benefits their generalization. Although in terms of generalization of the nonlinear classifiers, the results obtained have shown the generalization of these classifiers, studies of relevance of the parameters were carried out for the possible dismissal of less relevant parameters in the discrimination of classes with data with the new definition of classes (table 5).

Firstly, the coefficients of linear correlation were calculated for a confidence interval of 95% [6], as per Equation 1, and are presented in Table 6 below. Later, the criterion of relevance (Equation 2) was made use of, calculated with the nonlinear classifier. Table 7 lists the results obtained in terms of relevance.

Table 6: Matrix with the coefficients of linear correlation for seven preliminary parameters, but with the new definition of classes (up to 25kgf/cm² – SP, and from 250kgf/cm² – P).

Parameters	Channel	Rise Time	Count	Energy	Duration	Amp.	ASL	Class
<i>2/√n Ratio for determining the correlation limit : 0.040 (n = 2551)</i>								
Channel	1	-0.038	0.035	0.033	0.036	0.08	-0.08	0.136
Rise Time	-0.038	1	0.368	0.232	0.383	0.302	0.193	-0.068
Score	0.035	0.368	1	0.624	0.863	0.66	0.172	0.058
Power	0.033	0.232	0.624	1	0.689	0.468	0.147	0.05
Duration	0.036	0.383	0.863	0.689	1	0.66	0.169	0.019
Amplitude	0.08	0.302	0.66	0.468	0.66	1	0.029	0.267
ASL	-0.08	0.193	0.172	0.147	0.169	0.029	1	-0.42

Table 7: Relevance values obtained by the nonlinear classifier.

Parameters	Relevance
Channel	0.020
Rise Time	0.135
Score	0.061
Power	0.003
Duration	0.003
Amplitude	0.145
ASL	0.757

As per Table 6, it is clear that all seven parameters present correlation amongst themselves, because they exceed the limit of 0.040. However, the correlation is even more evident between parameters Counts and Energy; Counts and Duration; Energy and Duration; and Energy and Amplitude, which is explained by the technique of acoustic emission itself.

Almost all parameters presented linear correlation with the classes (only one column is presented because if a parameter is relevant to discriminate a class, obviously it will be for the other). However, parameters ASL and Amplitude were highlighted in linear correlation with classes, showing to be the most relevant ones under the analysis of correlation coefficient.

In order to conclude the relevance studies of the parameters, values *D* of Fischer's criterion (Equation 3) were calculated for the seven parameters. The chart in Figure 6

shows **the J values** obtained. Ratifying the results obtained by the other two techniques, once again, the ASL and Amplitude parameters present greater comparative relevance to the other parameters, except for the parameter Channel that presents similar relevance to the parameter Amplitude, as per this technique. By Fisher's criterion, there is also no expressive difference among the parameters Duration, Energy, Count and Rise Time. Although there are no negative values of D , because the value in module of the difference among the averages of each class (Equation 3) is considered, the axis of the chart was moved to negative values in order to facilitate the visualization of the difference among the parameters.

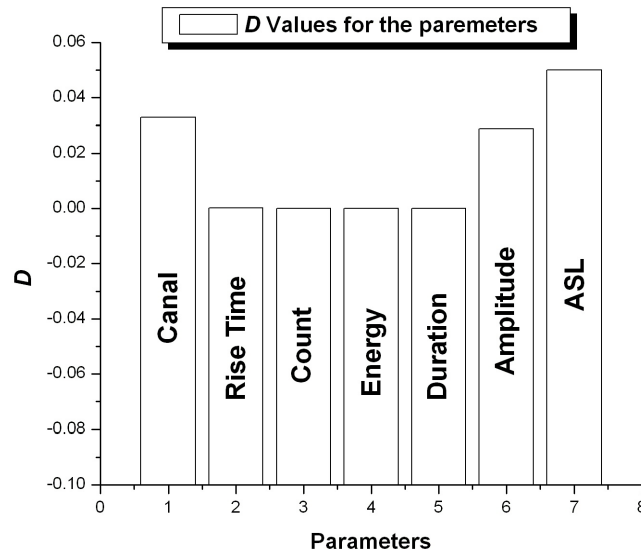


Figure 6: Relevance values for the parameters according to Fisher's criterion.

Analyzing the results of the parameter relevance calculations, it was proven that the parameters ASL and Amplitude are in fact the most relevant ones in the discrimination of the NP and P classes of AE signals. From Tables 6 and 7, it is also verified that the parameters Channel, Rise Time and Count are the three other most important parameters for class separation. It is important to highlight that the use of parameter Channel is not recommended because of the amount of channels used, and because their position in the testing equipment varies in each testing. In such a manner, the next procedure was to test the nonlinear classifier using an input including only parameters: ASL, Amplitude, Count and Rise Time. In this case, the same number of neurons in the intermediate layer of the classifier of Table 4 (seven neurons) was repeated, but new ten pairs of training and test sets were formed. Table 8 shows the results obtained.

Table 8: Performances obtained using ten training and test sets with four parameters: ASL, Amplitude, Count and Rise Time.

SP up to 25kgf/cm², P from 250kgf/cm²

Sets	Performance	
	Training (%)	Test (%)
1	92.80	92.36
2	93.20	93.53
3	92.61	90.40
4	92.85	95.10
5	93.34	92.36
6	93.10	91.38
7	92.85	93.53
8	93.05	91.57
9	93.05	92.16
10	92.66	93.34
Average	92.96	92.58
Deviation	0.23	1.28

The averages obtained in this classification situation, 92.95% with training sets and 92.57% with test sets, are lower than the averages obtained using seven parameters, as per Table 5, which confirms that the dismissal of three parameters, Channel, Energy and Duration, causes a small decrease in the performance of the classifier. However, the decrease of about only 1% of adjustment with testing data really showed that the four parameters used are the most relevant ones in the discrimination of NP and P classes and the use of a reduced number of parameters is possible with no great classification loss.

It is important to stand out that other combinations of parameters can be tested in order to check the performance with the nonlinear classifier. However, due to the results already obtained, it is evident that the variation of the performance is small between the training and test sets, and that about 92/93% of the correct classification found can be considered satisfactory in view of the small number of parameters used for the characterization of the signals concerning the classes NP and P.

3.5. Classification by means of J initiation values (critical J)

In practical terms, in field work, it is known that the monitoring of the defect increase in pressurized tubes is not performed; therefore, the final tests of this project were carried out based on J initiation integral values, at which time, under a date pressure, a stable propagation of the defect takes place. In this case, classes NP (No Propagation) and P (Propagation) are now defined based on J initiation integral value for this material (steel API XL grade 60).

In order to find the J initiation value and the concerning pressure, respectively, the chart on Figure 7 was used below. It was stipulated (according to ASTM E1820 [10]) that J initiation happens for the depth variation range of defect of 0.2mm in depth ($\Delta a = 0.2\text{mm}$). From the chart of Δa (mm) versus J (kJ/m^2), Figure 7 below, drawing a parallel straight line to the tangent of the curve in the origin (after an approximate extrapolation), it is observed that for the point where $\Delta a = 0.2\text{mm}$, the J initiation value is in the range of 2000Kj/m^2 . From this result, now analyzing the chart on Figure 8 [11], this J value for the external crack defect of 7 mm in depth (initial value of a) and 140 mm in length, is located between the third and the fourth measure from the superior part of the curve (J integral versus crack

depth). As per Table 9 presented below, it was verified that for this variation range of the crack (between the third and the fourth measure of fracture propagation), the J initiation value happens for pressure values between 225 kgf/cm², in a more conservative consideration, and 250 kgf/cm², in a less conservative consideration.

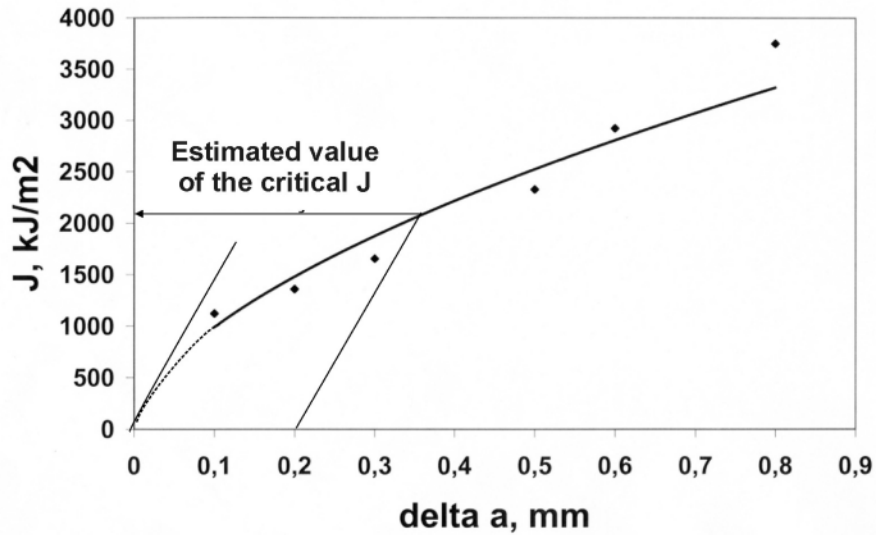


Figure 7: Delta curve a (mm) versus J (kJ/m²).

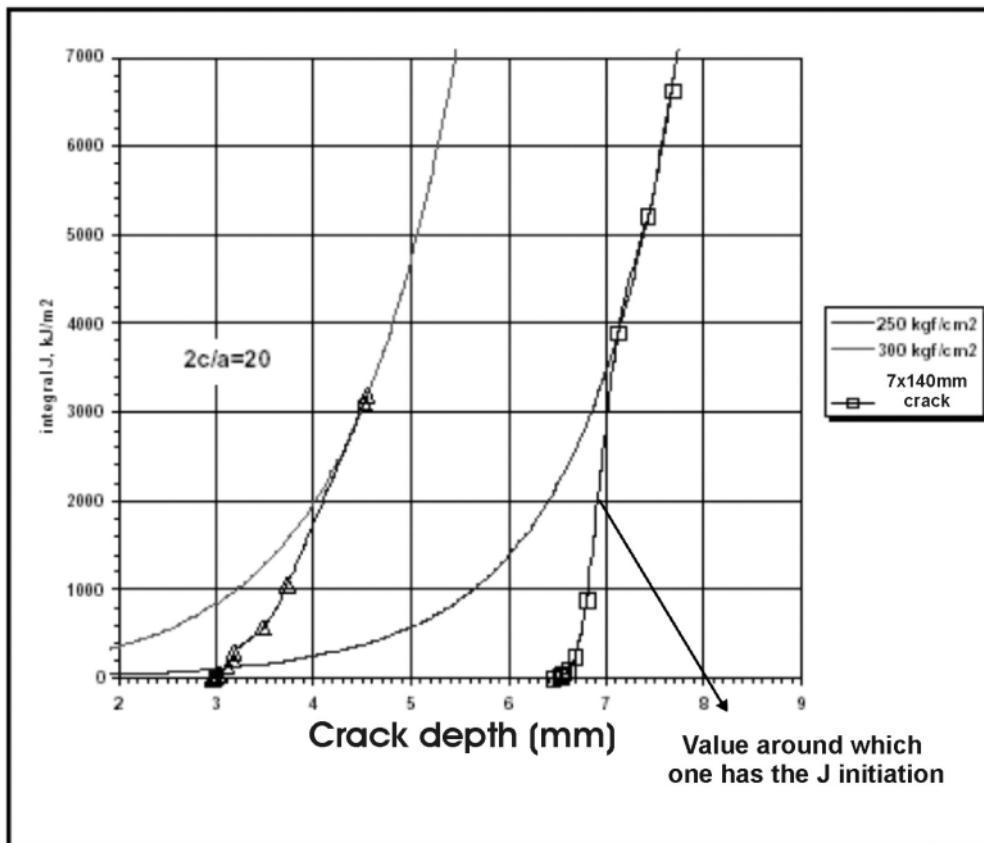


Figure 8: J resistance curves [11].

Table 9: Testing pressure variation with crack propagation.

Pressure (kgf/cm ²)	Depth (mm)	Sound path (mm)
0	0.00	0.00
20	0.10	0.21
50	0.10	0.23
75	0.11	0.25
100	0.13	0.28
125	0.15	0.32
150	0.17	0.38
175	0.21	0.45
200	0.27	0.57
200	0.28	0.60
225	0.40	0.87
250	0.72	1.54
250	1.03	2.05
250	1.28	2.55

For the pressure of 250 kgf/cm² (less conservative situation in terms of tube fracture), the testing were carried out (Table 8). Therefore, new test were carried out now with NP and P classes defined as: NP up to 25 kgf/cm² and P from 225 kgf/cm². In this case, once again, the number of optimal neurons to be used in the intermediate layer of the nonlinear classifier was studied; being this implemented exactly like the others already described. Table 10 below shows the training adjustment rates (80% of the original set) and test (20%) varying the number of neurons.

Table 10: Optimization of the number of neurons in the intermediate layer of the nonlinear classifier. *NP up to 225 kgf/cm² and P from 225 kgf/cm² (Separation for J initiation)*

Number of Neurons	Training (%)	Testing (%)
1	89.61	89.68
3	92.39	91.76
5	92.66	92.56
7	92.66	92.44
9	92.69	92.66
11	89.81	89.98
13	92.66	92.66

While analyzing Table 10, the best result obtained with the test set happened with nine neurons in the intermediate layer (92.66%). Later, a raffle of ten random sets of training and tests was carried out, just like the one that has been carried out until the present time of the project, aiming at the evaluation of the classification accuracy for this situation. The rates obtained can be found in Table 11, as well as the accuracy and the respective standard deviations for training and test.

Table 11: Performance obtained with ten sets of training and test.
SP up to 25 kgf/cm² and P from 225 kgf/cm² (Separation for J critical)

Sets	Performance	
	Training (%)	Test (%)
1	89.78	89.38
2	92.56	90.17
3	89.81	90.37
4	89.73	89.88
5	92.64	90.97
6	92.59	92.76
7	92.66	91.76
8	90.13	88.10
9	92.70	92.67
10	89.83	88.78
Average	91.24	90.50
Standard Deviation	1.40	1.50

The accuracy of 90.50% obtained for the test data can be considered quite satisfactory, first because once again the generalization of the classifier is ensured in view of the small difference between this rate and the one for training (91.24%), second because it differs only 2% for the less conservative situation of J initiation integral value (250 kgf/cm², 92.58% - table 8).

4. Conclusion

In general terms, the results of accuracy classification, or simply, expected performance (average) of the pattern classifiers were considerably satisfactory and promising, because they presented values in the range of 90% up to 93% of performance of the classes of signals, No Propagation and Propagation, in most of the situations studied during the work. The reliability of these results is supported by the similarity of the rates obtained with the training and test sets, proving the generalization of the classifiers.

It can also be inferred that the tools for analyzing the relevance of the parameters used in the project allowed to verify that not all characteristic parameters of the AE signals are in fact relevant for the discrimination of the standard classes involved.

Taking into consideration the last results concerning the J initiation integral values, it was possible to confirm that the performance are also high, allowing a separation of the signals and indication of defect occurrence based on the pressure information that the pipe is suffering, which in practical terms enables the construction of an automatic or semi-automatic system to identify the propagation of defects in similar materials reserved for loading on pressure, a main reason for the development of the present project. Evidently, many studies can and must be carried out aiming at attaining other results and increase even more the reliability of the results already obtained, which will permit addressing the research of the project to the actual construction of these systems.

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