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Evaluation of Acoustic Emission Signal Parameters for Identifying the Propagation of Defects in Pressurized Tubes

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ABSTRACT

Acoustic emission tests are highly relevant among nondestructive tests applied in equipment for the petroleum industry. This paper presents methodologies for the classification of acoustic emission patterns obtained in tests to identify propagation of defects in pressurized tubes. This work is a continuation of previous research. However, to estimate the accuracy of the classification and give greater reliability to previous results use is made of new signals with a greater number of parameters, and some new methodologies not used in the previous paper are presented. The new results show the efficiency of the pattern classification methods implemented and encourage the present publication.

1 - Introduction

Acoustic emission is a very important test among nondestructive tests, and it has been applied for the detection of failures in various types of equipment in the petroleum industry, such as pressure vessels, tanks and pipelines. Their main functions are to detect and localize faults that present a risk of unstable propagation that can lead to catastrophic fracture of the equipment (1).

This paper presents new results obtained to identify, through the use of pattern classifiers developed by neuronal networks, the propagation of defects in pressurized tubes monitored by acoustic emission. The main objective is to provide continuity to previously done and published research (2), either checking the accuracy of the classifiers through the use of new signals (new tests were made on specimens similar to the previous ones), as well as evaluating the relevance of new parameters obtained during the tests carried out on the test bodies. The objectives developed in this paper can be decribed as follows:

1°) Development of the pattern classsifiers by artificial neural networks (optimizing the number of neurons in the intermediate layer, confirming the best index attained with samples of the set of tests) (3,4).

2°) Calculation of the accuracy of the classifiers by random selection of test training sets, as well as the False Positive (FP) and False Negative (FN) indices.

3°) Evaluation of the relevance of the new parameters (not evaluated previously) of the signals in the discrimination of the classes No Propagation (NP) and Propagation (P) of the defect.

4°) Test of the classifiers only with the parameters shown as the most relevant for the discrimination of the NP and P classes.

5°) Construction of an ROC (*Receiver Operating Characteristic*) curve to estimate the reliability of the detection of the propagation of defects in the AE signals.

2. Materials, Tests and Methods

2.1. Materials

The specimens used were built from tubes sections made of API XL Grau 60 steel 20 inches in diameter and 14.5 mm thick. These sections were welded at their ends to form a closed volume that could be pressurized. On these specimens, four external elliptic cracks 7.25 mm deep (a) with an aspect ratio 2c/a equal to 10 or 20 were machined, two of them close to the weld seam and two on the base metal. Figure 1 below shows a schematic design of the positions of the cracks on the specimens.

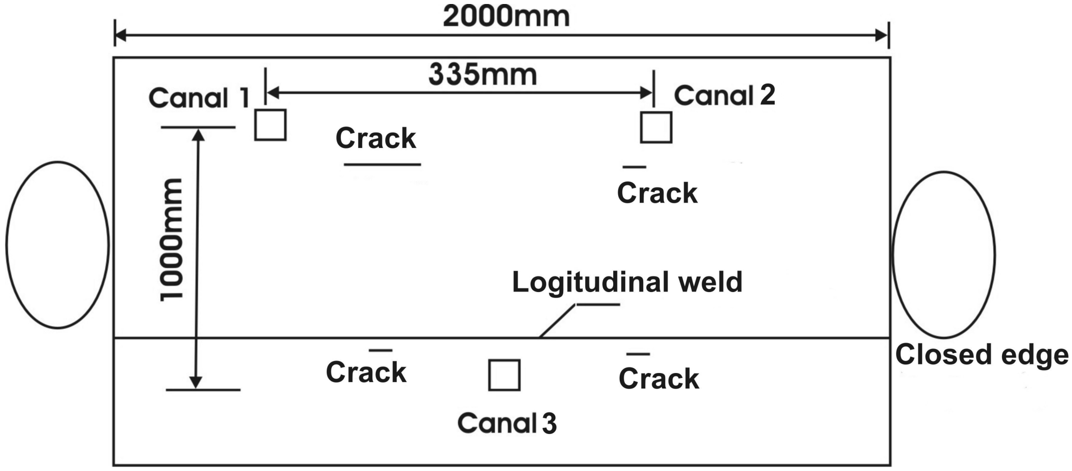

Figure 1: Schematic diagram of the specimens with the locations of the machined cracks and the positions of some channels.

2.2. Hydrostatic Test

The specimens were subjected to a hydrostatic test up to the pressures that would cause stable or unstable defect propagation, being the pressure velocity desired between 3 and 5 bar per minute.

2.3. Acquisition of the Acoustic Emission Signals

Acquisition of the AE signals was made with the three sensors positioned as in Figure 1 for the first test (first set of signals), and with eight channels in the other test (signal sets two).

2.4 Monitoring of defect growth

Monitoring of the crack increase was carried out by means of an ultra-sound test with an angular beam. A 70° transducer was placed sidelong to the crack according to Figure 2. From the distance of the emission point of the transducer to the defect (L) and the sound path (S), it was possible to determine the depth of the defect (P).

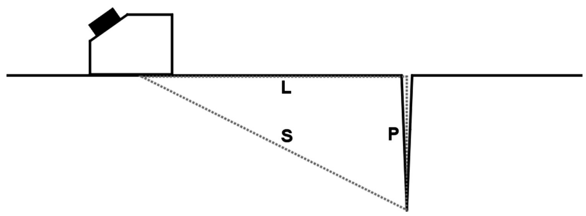

Figure 2: Configuration of the angular ultrasound test for determining the depth of the defect. 70° angular transducer.

2.5 Sincronization of the acoustic emission, pressure, and defect growth signals (TOFD).

With the monitoring of the pressurization and of the defect growth, in addition to the acoustic emission signals, a procedure was established for synchronizing them, since the acoustic emission activity is related to the imposed load and to the propagation of the defect. After synchronizing the files, the acoustic emission events were divided into Propagation (P) and No Propagation (NP) classes as a function of the pressures associated with the growth of the defects.

2.6. Analysis of the relevance of the acoustic emission parameters

Using the same methodologies that had been used with the signals in the previous paper (2), which gave good results, to analyze the parameters of the acoustic emission signals trying to determine which are the most relevant parameters to discriminate the kinds of signals, use was made of the calculation of the linear correlation coefficients, which are measured according to the equation:

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

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

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

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

To verify the reliability of the correlation between the signals' features or between the features and classes of defects, the confidence interval of 95% was used. The correlation coefficients are shown in matrices whose columns represent the sum of the features including the classes, and the rows represent the features.

2.7. Development and evaluation of the classifiers

The pattern classifiers were implemented using artificial neural networks. Training of the network parameters was done by means of the backpropagation of error algorithm (4), and some configurations of training parameters were studied to allow the best possible result for distinguishing the classes. Let us point out, however, that we will not describe the training of the neural networks because that is well known in science and can be found in the literature (3, 4). We will only mention the adopted network architecture and the adjusted configuration values.

2.8. Estimation of the accuracy of the classifiers

In pattern recognition, one of the most controversial questions is to know the real accuracy of the classifiers (5), i.e., which is the expected degree of success for any set of signals/data tested in the classification. Just as was done in the first stage of the project (2), several sets of training, testing and validation data were selected randomly without replacing data with the purpose of estimating the accuracy for identifying signals with Propagation (P) and No Propagation (NP) of defects.

2.9. ROC (Receiver Operating Characteristic) Curves

In this new work, in addition to the correct mean calculated as in the first paper (2), an estimation of the ROC curve is also presented to evaluate the reliability of the classification of the signals by means of the true positive (TP) and false positive (FP) values (3).

3. Results

3.1. First set of signals

For the first set of data, the test took a total time of 19334 seconds with a pressure between 2 and 270 bar (1 bar = 0.980 kgf/cm^2). Follow-up of the propagation of the cracks with the ultrasonic test was made every second of the test. Analyzing the graph of Figure 3, it is seen that there was significant growth of the defect only for the larger crack of the base metal at a pressure of around 248 bar. Since this pressure was reached after 10840 s of the test, the separation of the signals into the classes NP (up to 10840 s) and P (signals acquired after 10840 s) took place in this test time. In this case, the classes had 2072 and 2697 signals for NP and P, respectively.

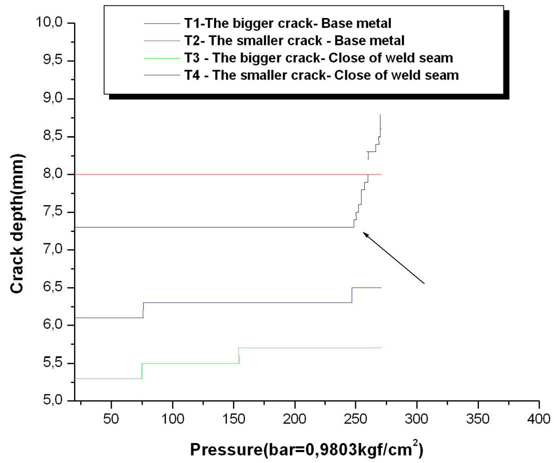

Figure 3: Stress (pressure in bar) against depth graph of the cracks in the specimen tested for the acquisition of the signals of set 1.

Continuing with the line of research of the relevance of the parameters used for discriminating between the classes of signal patterns (NP and P) (2), linear correlation coefficients between the parameters and between the parameters and the classes were calculated, forming a matrix with the results shown in Table 1 (a detailed description of the use of this methodology can be found in references (2) and (5). From the table it is seen that there is good correlation between the parameters (coefficients above the limit of 0.03), and that the parameters Count and Amplitude are the most relevant, since their correlation coefficientes with the classes exceeds this limiting value for a confidence interval of 95% (5). The same as with the results of our previous project, the Amplitude parameter was confirmed as one of the most relevant for discriminating between the two classes of signals. It should be pointed out that the ASL (*Average Signal Level*) parameter, more relevant in the previous tests (2), was not included among the parameters of the first set because it was not acquired at the time of the acoustic emission test (probably because the operator was not aware of its relevance for these evaluations).

Table 1: Linear correlation between parameters and classes for set 1.

Parameters	**Rise time**	**Count**	**Energy**	**Duration**	**Amplitude**	**Class**
	$2/\sqrt{N} = 0.03$					
Rise time	1	0.18	0.08	0.27	0.32	-0.10
Count	0.18	1	0.88	0.98	0.63	0.05
Energy	0.08	0.88	1	0.86	0.43	0.016
Duration	0.27	0.98	0.86	1	0.70	0.03
Amplitude	0.32	0.63	0.43	0.70	1	0.18

In spite of the lack of the ASL parameter, the classification tests with that set were carried out. In the first place, a study was made of the number of neurons in the intermediate layer of the classifier. For that purpose some training and test sets were chosen randomly among the original data of each class, in the proportion of 80% for training data and the remaining 20% for tests. Under these conditions, the training set had 1658 NP data and 2158 P data, and the test set had 414 NP data and 539 P data. Table 2 shows the results of correct classification with the number of neurons varying two by two up to 45 neurons in the intermediate layer. Analyzing Table 2, it is seen that there is no significant difference in agreement by increasing the number of neurons in the intermediate layer, showing that in this case it is not necessary to use a large number of neurons to implement the nonlinear classifier. On the other hand, the correctness indices of about 60% are considerably lower than the close to 90% reached with the signals of the first project. This shows, definitely, that the ASL parameter is extremely significant for the characterization of the acoustic emission events, and that whenever possible it must not be disregarded. For that reason the research with that set of signals was closed, to continue with new sets of EA signals (from new tests).

Table 2: Results of the study of the number of neurons in the intermedite layer (first set of signals).

Number of neurons in the intermediate layer	Training(%)	Test (%)
1	59.57	62.02
3	60.04	61.81
5	59.91	62.23
7	59.96	60.03
9	61.25	59.82
11	58.57	59.30
13	60.70	61.91
15	59.83	62.23
17	58.73	60.45
19	60.78	62.12
21	61.35	62.12
23	60.93	62.54
25	61.35	61.60
27	60.64	61.91
29	60.64	62.23
31	61.40	61.60
33	61.10	62.23
35	61.04	62.02
37	60.80	61.08
39	60.62	62.23
41	60.85	61.60
43	61.22	61.81
45	61.70	62.02

3. 2. Second set of signals

The second set of data studied came from an acoustic emission test applied to a test body identical to the one used for the first set of data, but in this test eight signal acquisition channels were be used. Total test time was 7801 s, resulting in 37921 data.

The same as in the generating test of set 1, the propagation of the cracks took place by the ultrasonic test with the TOFD technique. During that time interval the hydrostatic pressure varied from 0.1 bar to about 233 bar.

Once again, making the correlation between the increase in depth of the cracks registered for the TOFD tests, pressure and test time, it was found that the fast growth starts occurring from 200 bar (this time the graph is not shown because it similar to that of Figure 3). Therefore, that instant was chosen for an initial separation between NP classes (No Propagation) and P (Propagation). With that class separation situation, corresponding to the instant of 5362 s of the test, class NP ended with 11812 data and class P with 26109 data.

Considering the large amount of data, which would certainly turn the process of training the neural network quite slow even on a fast computer, as well as the sharp data inequality between the classes (P with more than twice the data than NP), a sampling was made every two NP data and every four P data. That way the NP and P classes ended with 5906 and 6528 data, respectively, in that way keeping an optimum amount of data for implementing the classifiers and verifying the accuracy, besides decreasing the inequallity of data between the classes.

In this second set of signals, 18 parameters of the signals were acquired during the acoustic emission test. They are Rise Time, Count, Energy, Duration, Amplitude, ASL (Average Signal Level), PCNTS (number of count until the maximum amplitude is achieved), R-FRQ, I-FRQ, SIG (measure of signal energy), STRNGTH (measure of signal energy), ABS-Energy (measure of signal energy), FREQ PP1, FREQ PP2, FREQ PP3, FREQ PP4 (these four last parameters are measured by dividing the total spectro of frequency in four segments), C-FRQ (central frequency) and A-Freq (final frequency) (6). Considering that for pattern recognition the ideal is to use signal or image characterization parameters that are really relevant in the discrimination of the classes of patterns involved, and not only to decrease computing costs and also because of problems of classification generalization (3,4), a new study of the linear correlation coefficient was made. The matrix of Table 3 shows the results obtained.

Evaluating correlation Table 3, it is seen that only four parameters do not present correlation coefficients above the limit of 0.010 (limit for a 95% confidence interval), and they are Energy, R-FRQ, SIG and STRNG (in the gray cells of the last column). For that reason, with the purpose of reducing the initial data size, they were excluded a priori from data set 2. There are, however, four parameters that, although above the 0.010 limit, have coefficient values comparatively smaller than the 10 remaining parameters. Three of these four parameters (Count, PCNTS, I-FRQ – blank cells of the last column) will be excluded, retaining only the Amplitude parameter in the data set because it showed relevance in all the tests carried out so far in the research. In this case, set 2 ended with 11 parameters (dark gray cells of the last column of Table 3).

Table 3: Linear correlation between the eleven parameters and classes for set 2.

Rise time	Count	Energy	Duration	Amplitude	ASL	PCNTS	R-FRQ	I-FRQ	SIG	STRNG.	ABS.	FRQ PP1	FRQ PP2	FRQ PP3	FRQ PP4	C-FREQ	A-FREQ	Class
Confidence interval of 95%: $2/\sqrt{N} = 0{,}010$																		
1,00	0.325	0.234	0.461	0.275	0.223	0.525	-0.032	-0.122	0.122	0.107	0.038	-0.006	-0.028	-0.076	-0.005	0.017	-0.115	**0.1**
0.325	1,00	0.641	0.806	0.476	0.223	0.492	0.005	-0.024	0.515	0.472	0.06	0.091	0.003	-0.055	0.064	0.116	-0.022	-0.07
0.234	0.641	1,00	0.454	0.273	0.172	0.391	0.005	-0.012	0.807	0.788	0.029	0.029	-0.003	-0.017	0.023	0.026	-0.005	-0.001
0.461	0.806	0.454	1,00	0.467	0.191	0.474	-0.05	-0.066	0.301	0.262	0.142	0.121	0.018	-0.056	0.121	0.164	-0.126	**-0.158**
0.275	0.476	0.273	0.467	1,00	0.309	0.273	-0.011	-0.046	0.147	0.128	0.044	0.103	-0.054	-0.221	0.016	0.185	-0.145	**0.031**
0.223	0.223	0.172	0.191	0.309	1,00	0.165	-0.021	-0.092	0.106	0.097	-0.156	-0.329	-0.285	-0.419	-0.379	-0.209	-0.147	**0.598**
0.525	0.492	0.391	0.474	0.273	0.165	1,00	-0.003	-0.019	0.168	0.149	0.026	0.036	0.005	-0.04	0.025	0.049	-0.019	0.024
-0.032	0.005	0.005	-0.05	-0.011	-0.021	-0.003	1,00	0.015	0.005	0.005	-0.027	0.034	0.016	0.029	0.014	0.007	0.366	-0.002
-0.122	-0.024	-0.012	-0.066	-0.046	-0.092	-0.019	0.015	1,00	-0.006	-0.005	-0.002	0.086	0.048	0.071	0.067	0.031	0.178	-0.077
0.122	0.515	0.807	0.301	0.147	0.106	0.168	0.005	-0.006	1,00	0.997	0.012	0.014	-0.003	-0.007	0.011	0.003	0.002	0.007
0.107	0.472	0.788	0.262	0.128	0.097	0.149	0.005	-0.005	0.997	1,00	0.009	0.011	-0.002	-0.005	0.008	-0.001	0.003	0.009
0.038	0.06	0.029	0.142	0.044	-0.156	0.026	-0.027	-0.002	0.012	0.009	1,00	0.362	0.031	0.163	0.75	0.314	0.006	**-0.346**
-0.006	0.091	0.029	0.121	0.103	-0.329	0.036	0.034	0.086	0.014	0.011	0.362	1,00	0.357	0.353	0.823	0.62	0.095	**-0.48**
-0.028	0.003	-0.003	0.018	-0.054	-0.285	0.005	0.016	0.048	-0.003	-0.002	0.031	0.357	1,00	0.806	0.497	0.435	0.055	**-0.337**
-0.076	-0.055	-0.017	-0.056	-0.221	-0.419	-0.04	0.029	0.071	-0.007	-0.005	0.163	0.353	0.806	1,00	0.553	0.356	0.187	**-0.418**
-0.005	0.064	0.023	0.121	0.016	-0.379	0.025	0.014	0.067	0.011	0.008	0.75	0.823	0.497	0.553	1,00	0.598	0.1	**-0.557**
0.017	0.116	0.026	0.164	0.185	-0.209	0.049	0.007	0.031	0.003	-0.001	0.314	0.62	0.435	0.356	0.598	1,00	0.017	**-0.346**
-0.115	-0.022	-0.005	-0.126	-0.145	-0.147	-0.019	0.366	0.178	0.002	0.003	0.006	0.095	0.055	0.187	0.1	0.017	1,00	**-0.103**
0.1	-0.07	-0.001	-0.158	0.031	0.598	0.024	-0.002	-0.077	0.007	0.009	-0.346	-0.48	-0.337	-0.418	-0.557	-0.346	-0.103	1.00

Starting from the fact that with this second set of data there are more relevant parameters than in all the tests made so far in that research line, the first step was to check the possibility of classifying with a linear classifier. To train and test this classifier, five pairs of training and testing sets were selected randomly, following a methodology of separate selection of the classes: first, 80% of the data for training each class were selected, producing 4725 data for NP and 5223 data for P (9948 data for training); then the remaining 20% of each class, producing 1,181 data for NP and 1,305 data for P, were used for the construction of the test sets (with a total of 2486 data in each set). This procedure was repeated to produce five pairs of sets.

The implementation of the linear classifiers was made with a network of only one neuron with an activation function of the hyperbolic tangent type. For the training, use was made of the variable learning rate parameters and constant moment of 0.9, total number of 3000 training periods (after which the training error was stabilized). Since it is a linear classifier, therefore without overtraining problems, in this case resort was not made of the cross-validation criterion (3,4).

Table 4 shows the results obtained for both the number of correctly classified data and for the percentage agreement. The indices of training agreement of the test reached values close to 100.0%, with a classification accuracy (mean of the agreements of the test sets) of 99.8%. The False Negative (signals referring to the propagation of defects classified as NP) and False Positive (signals referring to no propagation of defects classified as P) indices were quite low. In this situation, only five sets were used for estimating the accurcy, because when getting the results of the first sets it was found that the deviation of the mean was rather low, not requiring ten sets as in the previous project (2).

The accuracy obtained (99.8%) can be considered excellent, and it is much higher than that of set 1 (close to 62%), and also higher than the 92% obtained with the previous tests with the first signals used in the first project. This can be accounted for not only by the reuse of the ASL parameter, but also by the introduction of new relevant parameters like ABS, FRQ PP1, FRQ PP2, FRQ PP3, FRQ PP4, C-FREQ and A-FREQ.

Table 4: Results of the linear classifier with five sets chosen randomly from set 2.

Sets	Training (%)	Test (%)	False Negative (%)	False Positive (%)
1	9929/99.81	2477/99.64	0.32	0.04
2	9928/99.8	2483/99.88	0.08	0.04
3	9929/99.81	2482/99.84	0.12	0.04
4	9931/99.83	2481/99.8	0.16	0.04
5	9930/99.81	2482/99.84	0.08	0.08
Mean	99.82	99.8	0.15	0.05
Standard deviation	0.02	0.10	0.10	0.02

The False Positive (FP), values of NP (No Propagation) that were indicated as P (Propagation), and True Positive (TP), values of P indicated correctly as P, were calculated for each of the five test sets of Table 4, keeping in mind the estimation of the ROC curve (3), which can be used as another way of estimating the reliability of the detection of defect propagation by the EA test, besides the estimation of the accuracy of agreement already given by the test mean (second column of the table). The FP indices, represented on the graph as the x axis, are the ratios of the number of NP data that were indicated by the classifier as P and the total number of data of this class, in this case 1181 (according to the second report). The TP indices (1 minus the values of FP of the third column of the table), represented on the graph as the y axis, are the correct indications of class P, the number of P data indicated as P over the total number of data in this class (in this case, 1305). The five pairs of points available for the estimation of the ROC curve were: (0.04; 0.9968), (0.04; 0.9992), (0.04; 0.9988), (0.04; 0.9984) and (0.04; 0.9992). Points (1;1) and (0;0), even though they had not been obtained, were introduced in the graph only to facilitate the estimation of the curve. The curve was estimated by making an interpolation of 60 points, a figure found empirically, on the points found for FP and TP. The area above the curve gives the reliability of the detection system of defect propagation in the specimen (3). In this case, the area was calculated simply as the integral of the estimated curve. The values of TP and FP are also known as *Sensitivity and 1-Specificity* (3). Figure 5 shows an estimated ROC curve, and the area found below the curve was equal to approximately 0.979, indicating a 97.9% probability of detection of the propagation of the crack. This index is lower than the accuracy estimated by the mean (99.8% in Table 4), but it is seen that the values are quite close and confirm the efficiency and reliability of the classifiers of signal patterns implemented by neural networks for the identification of propagation.

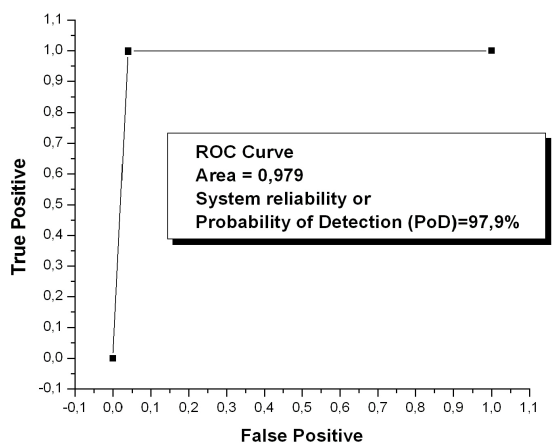

Figure 5: ROC curve for the test results of Table 4.

Continuing the idea of using the smallest possible number of parameters without affecting the classification indices, an idea that is justified by the fact of decreasing computer calculations and problems like classifier generalization (4), some more tests were made excluding some parameters of the 11 used before. The question that was asked at that point of the tests was: Which parameters should be excluded from the 11 main ones, since all appeared to be relevant as shown by the correlation matrix of Table 3?

In this case, since the FREQ PP1 (*Parcial Power*), FREQ PP2, FREQ PP3 and FREQ PP4 parameters are not normally acquired during the acoustic emission tests, as well as to compare with the old results of the first project (2) when six parameters were used (Rise Time, Count, Energy, Duration, Amplitude, and ASL), they were excluded from the five pairs of training and testing sets that gave the results of Table 5, therefore leaving seven parameters (Rise Time, Duration, Amplitude, ASL, ABS-Energy, C-Freq and A-Freq).

In the same way as using the 11 parameters for comparison purposes, the linear classifiers for the five pairs of training and test sets were implemented, and the results are shown in Table 5. It is evident that the indices of agreement will be drastically reduced to mean of about 84%, quite lower than the 99.8% accuracy obtained with the 11 parameters. This shows that the four parameters removed are really relevant for the identification of crack propagation in acoustic emission signals and cannot be discarded when making use of a linear classifier.

Table 5: Results of the linear classifier with five sets chosen randomly from set 2, however without parameters FREQ PP1, PP2, PP3 and PP4.

Sets	Training (%)	Test (%)
1	8833/88.80	2077/83.55
2	8807/88.54	2096/84.32
3	8826/88.73	2073/83.40
4	8811/88.58	2112/84.96
5	8803/88.50	2064/83.03
Mean	88.63	83.86
Standard Deviation	0.13	0.78

To verify if with a nonlinear classifier it would be possible to achieve correct classification indices similar to those obtained with 11 parameters and using only a linear classifier, use was made of the study of the number of neurons in the intermediate layer as had been done until this stage of the project, except using only the seven parameters that were used for the results of Table 5.

For that purpose, the number of neurons was varied two at a time in the intermediate layer of the classifier, as described above. With the random selection of 20% for test data and 80% for training, a pair of training and test sets was formed that was used to estimate the optimum number of neurons, keeping in mind that in this case the data of the less favored NP class were duplicated randomly to reach the number of data of class P after the selection. The idea of this methodology is to make both classes have the same number of samples, so that none of them is favored in the training of the neural network, since this is done by minimization of the total mean square error, even though the variance of each class remains the same. More details of the use of this technique can be found in Silva (7). The results are given in Table 6, showing that even with a large number of neurons in the intermediate layer of the classifier, correct indices better than 92/93% are not obtained, which is a worse result than when the 11 main parameters were used, even using only one linear classifier. This shows once more that it is not advisable to discard the FREQ PP2, FREQ PP3 and FREQ PP4 parameters because the correct classification of the NP and P signals would be affected.

Table 6: Results of the study of the number of neurons in the intermediate layer (second set of duplicated data and with seven parameters).

Number of neurons in the intermediate layer	Training (%)	Test (%)
1	91.72	91.72
3	92.26	92.44
5	92.26	92.56
7	92.45	92.76
9	92.32	92.40
11	92.53	92.70
13	92.32	92.44
15	92.56	92.57

In relation to this second test, after cutting the material and analyzing the specimen in the region of the crack that was propagated, it was verified that there was an error in the project, because it was created with a rectangular and not an elliptic shape, as it should have been. With absolute certainty, that was the reason for its having propagated in an unstable way leading the to fracture, facilitating the discrimination between the NP and P signals.

4. Discussion and final conclusions of the results of this second stage of the research

In this second stage of the research on the possibility of identifying automatically the propagation of defects in equipment monitored by acoustic emission, satisfactory results were obtained on the relevance of some parameters of the EA signals characteristic of propagation, in addition to confirming results obtained in the first work [2] on the viability of classifying these signals by the techniques used. In fact, some characteristic parameters of the EA signals are much more relevant than others to characterize a signal of fault growth in the material.

The application of pattern recognition techniques in nondestructive tests is beeing increasingly known and reported (8-13). Therefore, considering the application of neural networks in acoustic emission signals with the methodologies described in this and in the previous paper, the authors are not aware of similar work by other authors. For that reason no comparison was made with other papers.

5. Future work

In the face of the success of the research made so far (we are not talking of success in terms of always positive results, but rather of showing that the techniques used can be efficient to develop a system that supports more precise monitoring of fault growth in this kind of equipment, together with the fact of the importance of EA in that equipment in the petroleum industry), a new set of tests will be made in a project foreseen to last two years.

In this way, several tests will be carried out for the acquisition of more sets of EA signals in a manner similar to that of the finished projects. Meanwhile, evaluations will be made of the possibility of classifying three classes of signals: No Propagation, Stable Propagation, and Unstable Propagation of the fault. Also new estimations of the accuracy of signal pattern classification, evaluations of parameters, etc., will be made.

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