EVALUATION OF ACOUSTIC EMISSION SIGNALS DURING MONITORING OF THICK-WALL VESSELS OPERATING AT ELEVATED TEMPERATURES.

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ABSTRACT

Acoustic Emission testing of thick wall vessels, operating at elevated temperatures is discussed and pattern recognition methodologies for AE data evaluation are presented. Two different types of testing procedures are addressed: Cool Down monitoring and semi-continuous periodic monitoring. In both types of tests, temperature variation is the driving force of AE as opposed to traditional AE testing where controlled pressure variation is used as AE stimulus.

Representative examples of reactors cool down testing as well as in-process vessel monitoring are given. AE activity as a function of temperature and pressure variation is discussed. In addition to the real-time limited criteria application, unsupervised pattern recognition is applied as a post-processing tool for multidimensional sorting, noise discrimination, characterizing defects and/or damage. On the other hand, Supervised Pattern Recognition is used for data classification in repetitive critical tests, leading to an objective quantitative comparison between repeated tests. Results show that damage sustained by the equipment can be described by the plotting the cumulative energy of AE, from critical signal classes, versus temperature. Overall, the proposed methodology can reduce the complexity of AE tests in many cases leading to higher efficiency. The possibility for real time signals classification, during permanent AE installations and continuous monitoring is discussed.

INTRODUCTION

Detecting defects in pressure vessels with Acoustic Emission Testing (AET) is most commonly used in conjunction with a hydro-test or during an on-line over pressurization. Thousands of such AE tests were performed since mid 80s based on ASME[1] code and MONPAC[2] system. In addition to that, On-Stream [3]-[4] AE inspection, is often used for continuous or semi continuous AE monitoring.

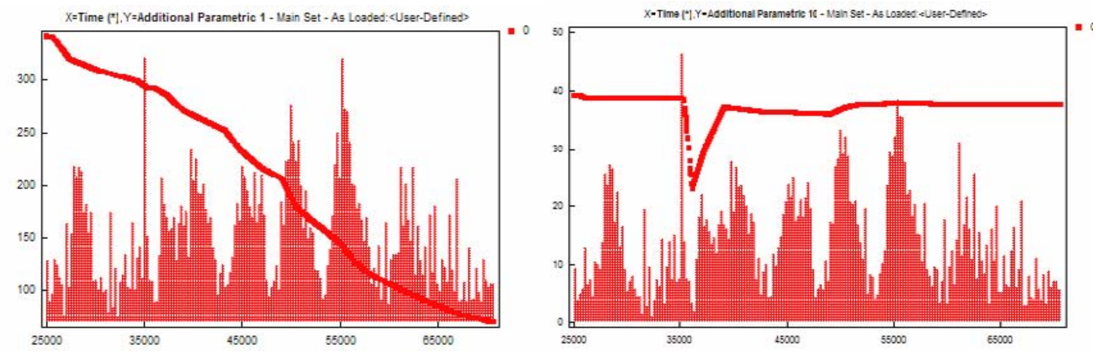
In contrast with pressure vessels operating at near ambient temperatures, thick-wall vessels operating at high-temperature, experience different stress states and damage mechanisms while in operation. In normal pressure vessels AE is produced due to stressing by the application of internal pressure. In high-temperature vessels the most significant parameter and the driving force of AE sources is the temperature variation. More specifically the rate of temperature variation is the most significant factor in the production of AE from the structure as significant thermal gradients can be experienced through the thickness of the material leading to thermal stressing.

On-Stream AE testing of thick wall vessels operating at high temperatures is often based on semi continuous AE monitoring, applied either periodically (as sort time continuous monitoring at time intervals, appropriate for the conditions of the vessel) or during specific conditions e.g. start-up or cool down, introducing highest stresses.

The recorded AE is more complex to analyze for this kind of tests, compared to AE analysis during controlled pressurization. At these conditions the processes/contents of the vessel can produce some AE activity which must be distinguished from material related emission. Thus, more advanced data treatment techniques are needed. In addition the comparative nature of such tests renders the automation or standardization of data treatment (filtering, noise elimination, evaluation, criticality etc) an important part of the test with pattern recognition offering advantages over traditional data analysis. In the present paper modern techniques for data analysis and evaluation will be presented and automated data process sing will be investigated using commercially available software packages.

COOL DOWN MONITORING

Cool down monitoring is typically performed on high energy piping or reactors as they are taken out of service and cooled down for turn-around maintenance and inspection. As the internal temperature drops (the internal pressure is held at the operating. level), a thermal gradient is established through the vessel wall. The effect of temperature and pressure variation during the cool down process is demonstrated in figure 1. It is worth noting that significant pressure variation does not affect AE activity. The higher the cooling rate, the higher the gradient. The thermal gradient gives rise to thermal strains that add to the existing hoop and longitudinal strains. The ideal cool down test is one where, for a given internal pressure, the thermal gradient stays within limits that correspond to 110% and 150% of normal operating load. However deliberate increase in stressing by increasing cooling rate is not recommended as this may actually cause defects.



(a) (b)

Figure 1: Typical response of a reactor vessel during cool-down and related AE activity. (a) - temperature change, (b) significant pressure variation for the same period.

Case study from another reactor is presented in figure 2, showing cumulative AE activity, during cool down (temperature variation superimposed – grey line). Eighteen PAC-R15I AE sensors were mounted on waveguides on a triangular set-up (3X4 attached on the shell and 2X3 on the heads of reactor O.D. =3.3m, L=5.7m, thickness 42mm).

The vessel was monitored with AE for sort periods during normal operation in order to assess background noise. Actual monitoring started before the cool down. Acoustic Emission data evaluated during partial cooling down from 260°C to 170°C (as the reactor was not cooled down to ambient temperature). AE data were originally analyzed by means of standard MONPAC practices.

The results of conventional analysis based on Swanson and further filtering using AE signatures are presented in figure 2 together with temperature variation (decreasing as a function of time – grey line). Among the three cumulative hits lines plotted in figure 2, genuine AE (red line) can be seen well correlated with temperature variation while the remaining two categories not. The green line, active from the beginning of the test, corresponds to friction and mechanical noise as identified mainly by Swanson filter. The light blue line of cumulative hits, corresponds to flow noise at the end of the cool down, as confirmed by the operation department of the plant.

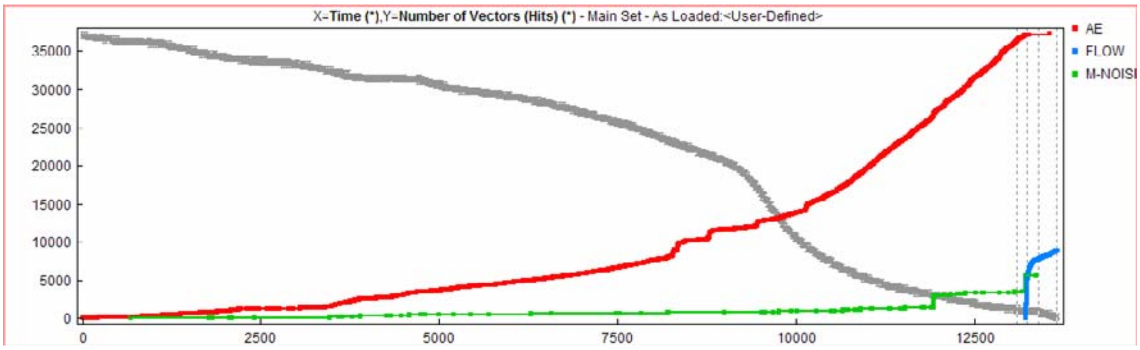


Figure 2: Cumulative AE hits from three different hit categories (genuine AE, friction-mechanical noise and flow noise). Temperature variation superimposed.

In order to investigate the feasibility of automated analysis by means of pattern recognition, the AE data were further analysed using supervised pattern recognition using NOESIS [6] software. During preprocessing stage, additional features were calculated as a combination of measured signal features. Rise angle, initiation and reverberation frequencies were calculated [5] and used as part of the pattern vector.

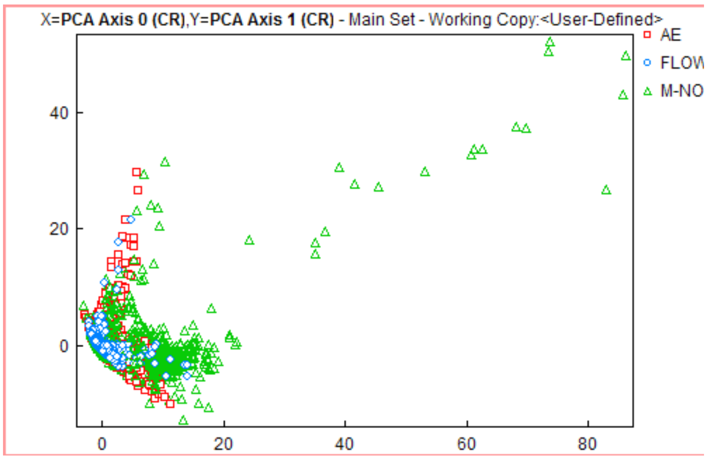


Figure 3: Principal components projection of reactor data (AE, friction-mechanical noise and flow noise)

Principal component projection (typical scatter plot of the 1st and 2nd principal components is presented in figure 3) performed before the training of the k-nearest neighbor classifier. The overall error (misclassified hits over the total number of hits) was bellow 5%. However increase within class error, up to 19%, encountered in some cases, depending on the training and test set used.

In most of the cases of increased within class error, flow noise signals were recognized as genuine AE. Confusion found also between friction and AE where friction and mechanical noise signals were classified as AE. Closer investigation on the classifier performance and the misclassified hits, indicated that the confusion was due to the secondary hits and reverberated signals, since the first hit (as revealed by zonal analysis) were classified successfully).

In order to enhance further the classifier performance two different approaches were followed. In the first one, first hit analysis was applied as a preprocessing step. In this way only the first hits were presented to the classifier resulting in overall error less than 4% and within class error less than 7.5%. As an alternative a two steps classification process established where at first AE and friction data were discriminated from flow noise and during the second step AE data were discriminated from friction and mechanical noise. The classifier performance improved in both cases by more than 50%. Overall the results show that supervised pattern recognition can be applied effectively for the classification of AE data during cool down of thick wall vessels.

SEMI-CONTINUOUS PERIODIC MONITORING

A series of autoclave vessels, serially connected one after the other are used in a production process. A bauxite-soda mixture passes through steam-heated autoclaves operating at elevated temperatures and high pressure. The nature of the contents and operational parameters produce a number of problems with not a single reliable solution in the condition evaluation and repair of such vessels as reported by the operators. Caustic Stress Corrosion or Caustic Embritlement is a common type of failure mechanism encountered in such operating environments [7]-[8].

Autoclaves are inspected and repaired in a cyclic manner (one after the other). This requires the shut-down of the entire process and re-piping the entire line of the reaction process. It was decided to attempt on-line evaluation with AE to determine the possibility of damage evaluation and the level at which various repair methods perform. The autoclave was removed from service and repaired at a number of welds and other areas. Main defect mechanisms were cracks and stress corrosion cracking. Various repairs were attempted by SS lining, SS electrode and normal crack repairs (remove and fill). The autoclave was monitored by AE during Hydrotest. At this point several data were recorded for reference. Data were recorded and evaluated by standard techniques (MONPAC procedure for hydrotest AE monitoring). Several areas were found to have produced AE during the pressurization evaluated as indication of local yielding and stress relieving. Short after the vessel went on-line, semi-continuous AE monitoring was scheduled aiming to record data during normal operation in order to assess the conditions of the vessel and repair effectiveness. Variation of the operating parameters for one of the monitoring periods is presented in Figure 4.

Conventional AE data analysis was originally followed. In addition to that and in an attempt to automate evaluation of the semi-real time periodic monitoring, pattern recognition schemes were investigated. Within this framework, real and artificial AE data were used to produce a representative set which contained the main signal categories of interest which are: 1) AE from cracking of other intense sources, 2) AE from low energy sources such as corrosion, erosion and others, 3) Mechanical type of noise such as impacts, and 4) Process noise.

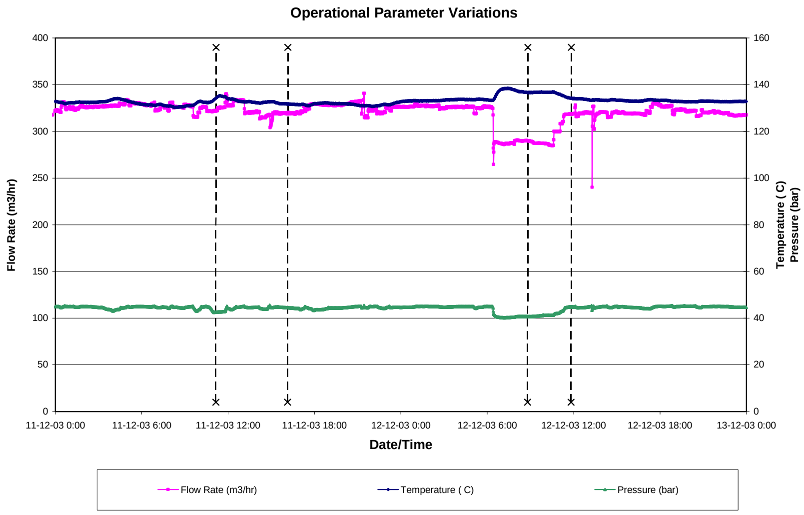


Figure 4: Typical range of operating parameters for the autoclave being monitored.

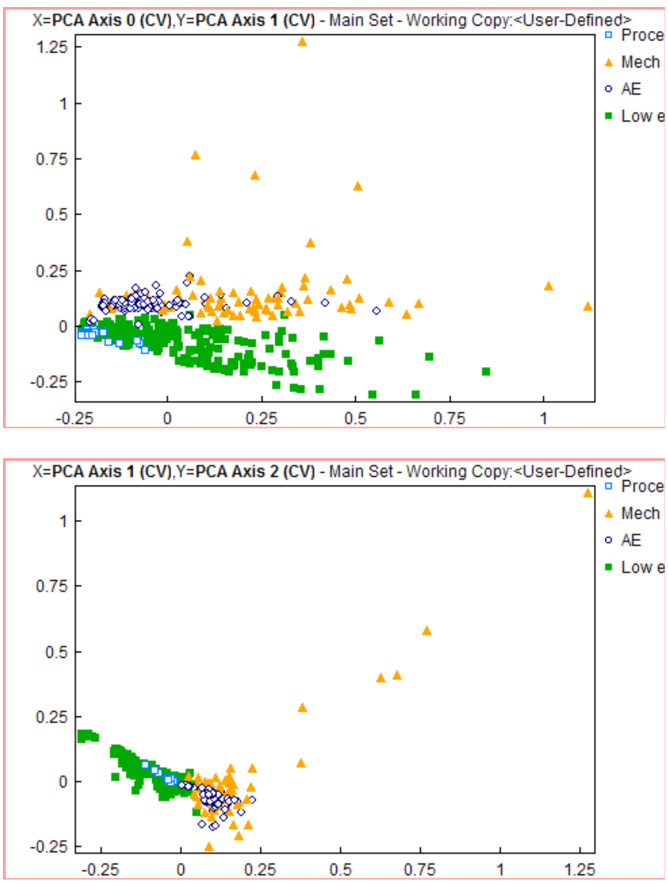


Figure 5: Representative AE data set-Covariance projection.

The representative set of AE data, originally composed of 6 AE features (Rise Time, Counts to Peak, Counts, MARSE, Duration and Amplitude), was automatically processed by Noesis 4.0 AE Pattern Recognition software[6] , using auto pre-processing wizard and principal component covariance projections. (see Figure 5).

A k-Nearest-Neighbour (k-NNC) Supervised Pattern Recognition (SPR) classifier was then trained using the representative data. The training used a random part of the dataset to train and the rest to test the classifier. The stability of the classifier was investigated using different training-test sets. The overall (all classes) test error was in any case below 5%. The best performance was 2.4% error while an average performance from all different trials resulted in 3.56% error.

The algorithm was further tested on data acquired during normal process at a later date and artificial HSU Nielsen sources. The trained classifier successfully recognized the different data categories (see Figure 6). In order to facilitate AE evaluation and correlation of the AE sources with the physical phenomena, the classification results shown in figure 6 are presented in the original AE feature space, using scatter plot of Counts vs. Amplitude, as opposed to the principal components of figure 5. Note that overlapping between signal classes is an artefact of projecting multi-dimensional space to the two dimensional space of counts-amplitude.

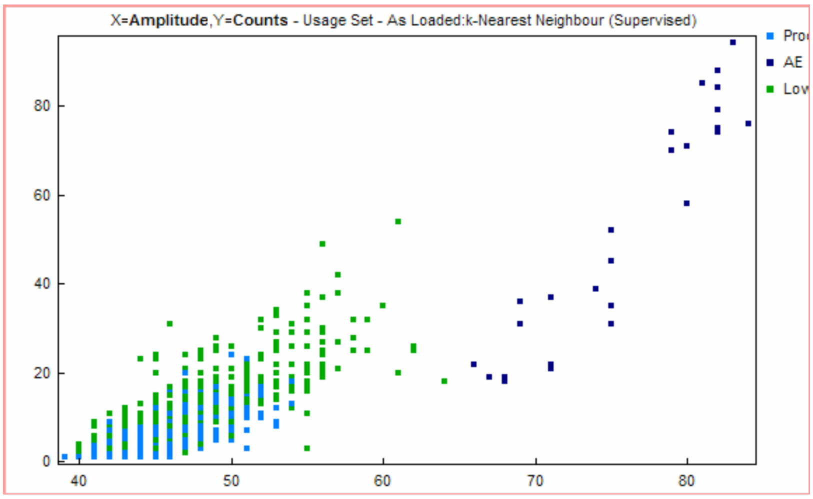


Figure 6: New test data set. The trained classifier successfully recognized the different data categories.

The classifier was then used to investigate data from subsequent AE tests performed during normal operation, to assess the existence of damage mechanisms in the pre-defined categories. The test covered two short periods of monitoring (6-8 hours) over a two day period. The classifier showed that the Mechanical Noise and AE from crack-like sources was almost non-existent (<0.1%). A large portion of the signals were classified as AE from low energy sources (green) (40% of the data) and the rest as process noise (see Figure 7).

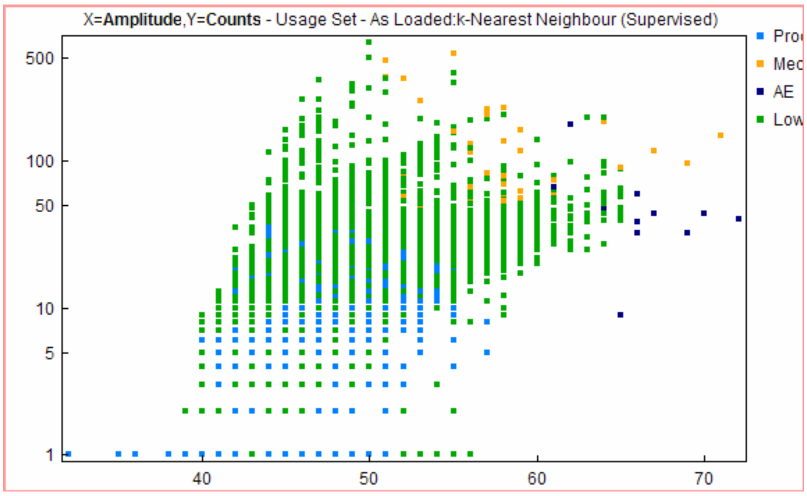


Figure 7: Classifier application to On-Line data acquisition.

Classifier validity was further investigated by means of location analysis from each class of AE data from the previously mentioned set of data. The location plot of figure 8, shows that the Process-Noise class does not produce any location on the vessel. On the contrary, the low energy AE class results in significant and concentrated location at the repairs areas. This first set of data were also analyzed and evaluated by traditional AE methods (graphs, filtering etc) which produced a similar result to the SPR classifier. This is an indication of the classifier being able to produce the desired data separation for in-process monitoring.

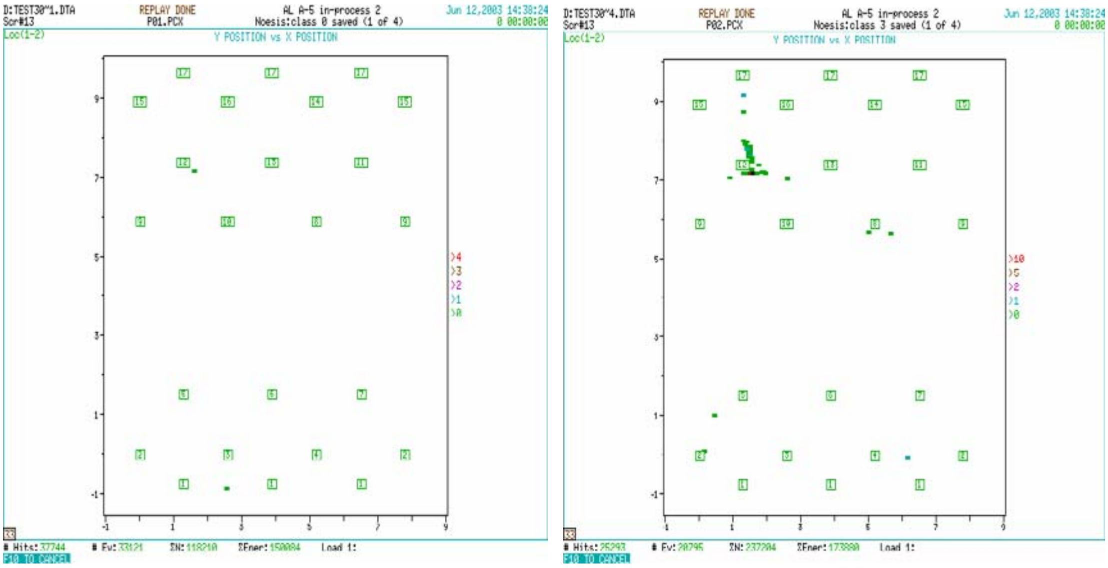


Figure 8: Location from the second monitoring during normal operation: Process class (left) and the low energy AE (right).

Application to another monitoring period (third period) during acquisition also provided similar information. The low energy AE was at 47% of the total data and the Mechanical noise and crack-like AE were practically not present in the data (0.2 and 0.3% respectively). Process noise was again the dominant class in the data.

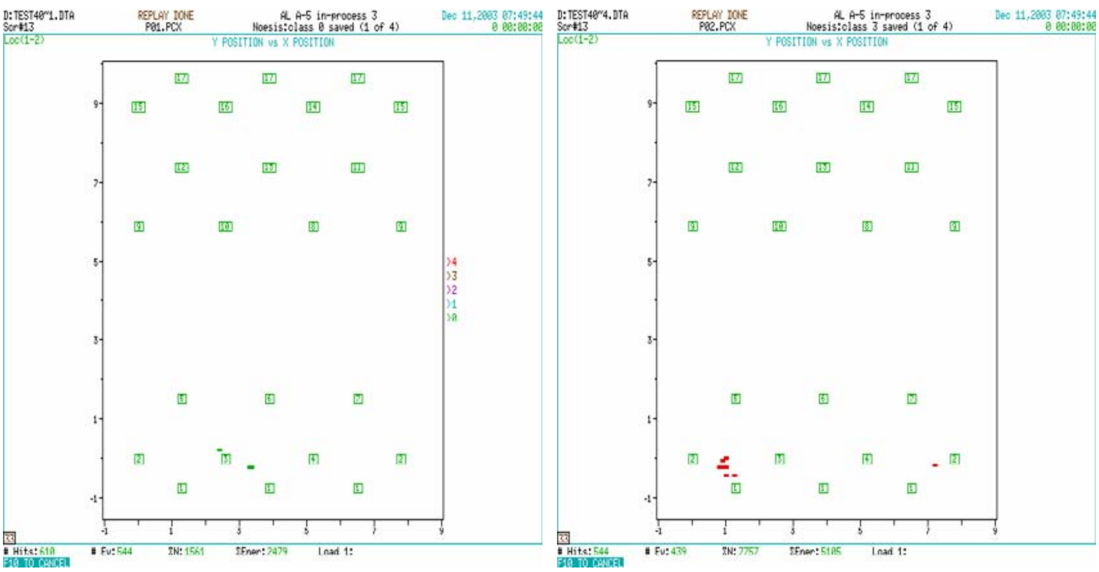


Figure 9: Location from the third monitoring during normal operation: Process class (left) and the low energy AE (right).

AE evaluation and correlation with the conditions that these results appear are being investigated, considering that the location of AE data from genuine AE classes is the first indication of a damage mechanism. The change in AE behaviour (compare figures 8 and 9) of the vessel between the two tests during normal operation depends on a number of parameters that were observed during the tests. More specifically, the operational parameters in the first test had a significant temperature drop at the end of the monitoring period (last 3 hours) when a large number of the data were recorded. The temperature variations in the third test were not so significant and thus any sources are not expected to be as active. However, as the mixture inside the vessel is not known precisely and follow up results by means of metallographic or other analysis are not yet available correlation with damage mechanisms and classifier validity can only be performed based on experience. Classifier validation will be further investigated in future tests.

CONCLUSIONS

The success of the SPR classifier has been proven so far in these pilot tests. Within class error should be considered as an important factor in addition to the overall classification error. Within class error assessment will indicate whether the classification scheme might lead to false alarms (whenever noise is classified as genuine AE) or whether the classification scheme might lead to over filtering of AE data. The use of first hit as opposed to all hits found to improve further the classifier performance. However such type of classifier complicates the subsequent location analysis and source identification.

Overall pattern recognition analysis techniques found suitable AE data analysis from both cool down and semi continuous monitoring tests. Its use and refinement will continue in order to provide a solid, universally applicable method for AE data evaluation for thick wall vessels operating at elevated temperatures. Finally it is worth noting that real time classification investigated during autoclave monitoring using Noesis Live software. The real time classification showed that processing speed of modern AE systems and PCs renders real supervised pattern recognition feasible.

REFERENCES

1. ASME, Section V, Article 12, “Acoustic Emission Examination of Metallic Vessels During Pressure Testing”, 1988
2. T. J. Fowler, J. A. Blessing, P. J. Conlisk and T. L. Swanson, “The MONPAC System”, *Journal of Acoustic Emission,* Volume 8, Number 3, 1989, pp. 1-8.
3. P. T. Cole & S. N. Cautrey, “On Stream monitoring of process plant”, in Emerging Technologies in NDT, A.A. Balkema – ISBN 90 5809 645 9, 2004, pp. 163-166
4. M. F. Carlos et all, “Advanced Acoustic Emission for on-stream inspection of petrochemical vessels”, in Emerging Technologies in NDT, A.A. Balkema – ISBN 90 5809 645 9, 2004, pp. 167-172.
5. A. A. Anastasopoulos, T. P. Philippidis, “Clustering Methodologies for the evaluation of AE from Composites“, J. of Acoustic Emission, Vol. 13, Noa 1/2, *1995*, pp 11-21.
6. NOESIS, “Users Manual”, Envirocoustics S.A. 2003
7. API Recommended Practice 571, “Damage Mechanisms Affecting Fixed Equipment in the Refining Industry”, Dec. 2003.
8. Roach et all, “Caustic Embittlement in the Bayer Industry”, Proceedings of the 6th International Alumina Quality Workshop, 2002, pp. 204-211