Noesis - Advanced Data Analysis, Pattern Recognition & Neural Networks Software for Acoustic Emission Applications

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Abstract. The complexity of Acoustic Emission (AE) can be overwhelming, if the appropriate tools are not available to the analyst. The main tool used for AE data analysis has traditionally been feature correlation graphs. These have allowed experienced users to investigate the data structure, decide on the origin of the data, apply appropriate filters and investigate the validity of the result. This task is very difficult and time consuming especially in novel applications. The NOESIS™ is a software application for advanced Acoustic Emission data analysis, pattern recognition & neural networks. It offers powerful tools to aid and improve data analysis, ranging from drastically improved graphics with numerous options to view the data in new and different ways, to mathematical algorithms for signal processing, event location, data discrimination, classification and manipulation after or during acquisition. All NOESIS™ functions are available to the user in a friendly way resulting in the most time effective means of treating AE data for any application. Noesis™, has been recognized by industry and research institutions, as the most advanced tool for AE data analysis and it is currently used in a large number of AE applications world-wide, from industrial inspections to aerospace research. It provides all the tools an analyst would like to use in industrial applications as well as for research purposes with its very advanced data manipulation functions. NOESIS™ successfully solved many challenging and innovative applications like granulation end point prediction of pharmaceutical products, crack detection of high noise areas in roller coasters, in-flight helicopter gear boxes and gas turbine stator cracking.

Introduction

The complexity of Acoustic Emission (AE) (and in fact of any data) can, at times, be overwhelming, if the appropriate tools are not available to the analyst. The main tool used for AE data analysis has traditionally been feature correlation graphs. These have allowed experienced users to investigate the data structure, decide on the origin of the data, apply appropriate filters and investigate the validity of the result. Noesis™, is an Advanced Data Analysis software featuring Pattern Recognition and Neural Networks, with powerful tools to aid and improve data analysis, ranging from drastically improved graphics with numerous options to view the data in new and different ways, to mathematical algorithms for signal/data discrimination and data classification and manipulation during acquisition.

Noesis™ is a data visualization and handling software with very advanced Pattern Recognition functions and extensive viewing, filtering and handling capabilities. It is designed for use with Acoustic Emission data (hit and time driven data) and waveforms and it includes a large array of functions and commands allowing users to manipulate data in any manner. In addition, Noesis™ is available for data classification and processing after or during acquisition (real-time). Noesis™ offers unique advantages when analysing AE data as it has been specifically designed for this purpose. Noesis™ Pattern recognition option (both Unsupervised and Supervised) provide very powerful data discrimination algorithms (effectively separating similar data into groups).

1. Main Features of the Software

1.1 Data support

Noesis™ offers full support for Physical Acoustics (DTA and TDA) acoustic emission data files from Spartan, Mistras, DiSP, Samos, PCI-2, Express-8, Pocket-AE and USB Node systems, with save and export capabilities. Also, it supports AE Wave Streaming Data (WFS) from PCI-2 and Express-8 systems, with save and export capabilities. Additional, Noesis™ offers text Files import and export support for hits, time driven and waveform data. Supplementary, Noesis™ supports Audio Files (wav) with import and export for waveform data.

1.2 Advanced Data Viewing

Noesis™ uses an advanced page creation and graph arranging method. Each page can support graphs (scatter, density, bar, cumulative, line, 3D etc.) with unique customization options. In addition, statistics, data tables, waveforms, FFT, RMS, Autocorrelation and many more data views can be on screen simultaneously. The graphs and other views are active in the sense that the user can zoom and pan to closely view the data, apply graphical filtering to each graph individually, select data with the mouse or user defined functions and view the selection in all other graphs (hit correspondence) and do much more. These functions alone render Noesis™ a superior analysis tool as the user gets a new and deeper look into the data. The simplicity and user friendliness that such complex data viewing is achieved can be compared to typing a text document.

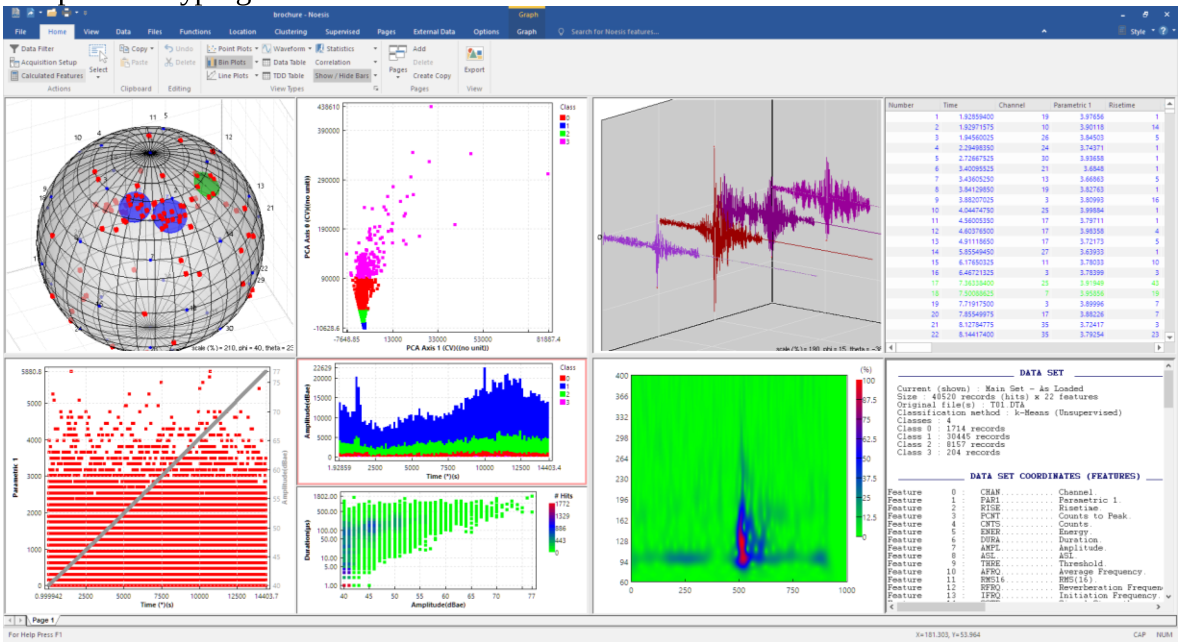

Fig. 1. Typical Noesis view containing different types of data representation.

The general Noesis™ View can contain the following types of graphs (see typical example above in Figure 1):

- Plot (e.g. scatter, bar), including also background plots
- Text (e.g. statistics),
- Waveform/DSP (e.g. waveform, FFT).
- HDD Table (data view).
- TDD Table (data view).
- Periodic Statistics
- Hierarchical and Parallel Coordinates diagrams

1.3 Data Grouping & Multi-Dimensional Sorting

A Cluster or Class is a group of signals/data, which can be selected and defined by the user, according to their similarity or correspondence to physical phenomena, so as to distinguish from other data. Creating data clusters drastically enhances the way the user can view the data. Different clusters can have different color and symbol so that they can easily be distinguished in any graph or other view (tables, waveforms, etc.). The user can get separate statistics for each cluster (class), compare clusters, view cluster comparative and evolution statistics etc. The user can simply drag the mouse over a plot and select some data from multiple plots with logical AND/OR operations, or apply advanced multi-dimensional filtering. As data are usually grouped according to their similarity Noesis™ offers much more than manual, user defined, selections and clustering (which are limited to the user's observation capabilities in 2D or 3D space), although these tools alone can provide great power, ease, confidence and speed in data analysis.

1.4 Other Advanced Tools

Data viewing is only the beginning in Noesis™. The data structure can be investigated using advanced statistics (e.g. feature discriminant, class discriminant etc.), feature correlation matrices and dendrograms (to investigate feature correlation – see Figure 2), principal component analysis and data projections (to investigate the data in a mathematically defined space), feature extraction from waveforms (to get new unique signal features and use them in the analysis), calculated features (to get computed features from the existing ones) and other small functions that will make data analysis a new process.

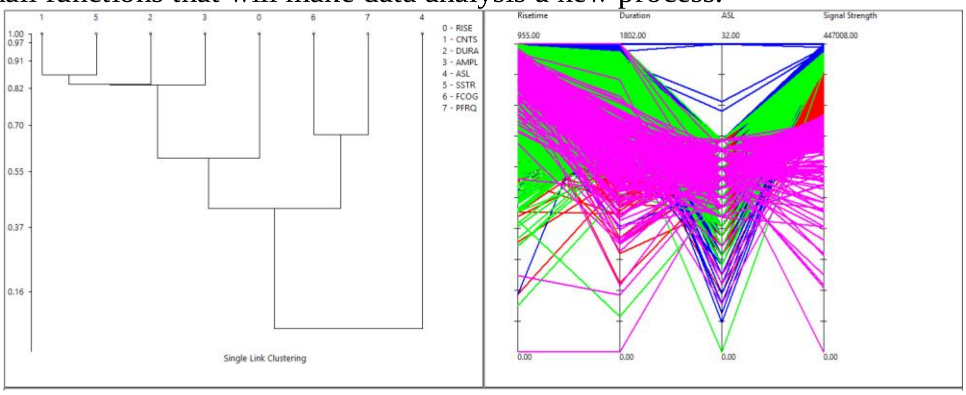

Fig. 2. Typical Dendrogram of Features and Parallel Coordinates Diagram.

1.5 Feature Extraction

This function allows the user to extract features for records with waveforms in the data file(s). The user can either use the original settings, as these apply to each file and channel, or use a custom, global, setup for all files and channels having control over certain extraction parameters. In total, the user could extract up to 51 features that listed in the Table 1.

Table 1. Feature Extraction Options.

Feature Name	Description	Feature Name	Description
Amplitude (dBae)	Signal Max Amplitude in dBae	**Frequency Centroid**	Measures the average frequency weighted by amplitude
Amplitude (mV)	Signal Max Amplitude in mV	**Partial Powers**	There are up to 8 Partial Powers. Any number of which can be used. They represent the percentage of energy contained in a certain frequency range.
Duration (µsec)	Signal Duration	**Peak Frequency**	Maximum frequency determined from FFT Power Spectrum
Rise Time (µsec)	Time from signal start to max amplitude	**Peak Power**	Maximum power determined from FFT Power Spectrum
Counts to Peak (#)	Cycles from start to max ampl.	**Threshold**	Fixed or dynamic threshold determined from peak amplitude.
Counts (#)	Cycles from start to end	**RA Value**	The ratio between Rise Time and Amplitude
Rise Angle (rad)	Angle from start to max ampl.	**STFFT Max**	Max. magnitude of Short Time FFT
Decay Angle (rad)	Angle from end to max ampl.	**STFFT Max Time (µsec)**	Time of max. magnitude of Short Time FFT
Energy (EC#)	Energy Counts	**STFFT Max Frequency (kHz)**	Frequency of max. magnitude of Short Time FFT
Signal Strength (pVsec)	Area under signal envelope		
Absolute Energy (aJ)	Signal Energy	**DWT Max**	Max. magnitude of Discrete Wavelet
Average Frequency (kHz)	Average Frequency	**DWT Max Time (µsec)**	Time of max. magnitude of Discrete Wavelet
Initiation Frequency (kHz)	Average frequency from start to max ampl.	**DWT Max Wavelet Scale**	Scale (base 2) of max. magnitude of Discrete Wavelet
Reverberation Frequency (kHz)	Average frequency from max ampl. to end	**CWT Max**	Max. magnitude of Continuous Wavelet
Non-Dimensional Amplitude (-)	Ratio of Max to Mean signal amplitude	**CWT Max Time (µsec)**	Time of max. magnitude of Continuous Wavelet.
Zero Crossings (#)	Zero crossings from start to end	**Second Peak Frequency (kHz)**	The frequency of the second peak value of the FFT Magnitude
Zero Crossings Frequency (kHz)	Av. Freq. Based on Zero Crossings	**Third Peak Frequency (kHz)**	The frequency of the third peak value of the FFT Magnitude
FFT Amplitude (V/Hz or Vrms)	Max. amplitude of the Amplitude Spectrum magnitude	**Wave Onset Time (µsec)**	The onset time of the waveform
FFT Width at 10% max ampl. (kHz)	Band width over 10% max amplitude	**Amp Onset Time (µsec)**	The time of the first peak value after the onset time
FFT Width at 30% max ampl. (kHz)	Band width over 30% max amplitude	**Amp Onset Value (V)**	The amplitude of the first peak value after the onset time
FFT Crossings at 30% max ampl. (kHz)	FFT magnitude 30% max ampl. crossings		

For AE Wave Streaming Data (WFS), Noesis™ offers the option to extract features and arrival times of multiple transient signals in a streamed waveform, based on threshold or length. See a typical example in the Figure 3 below.

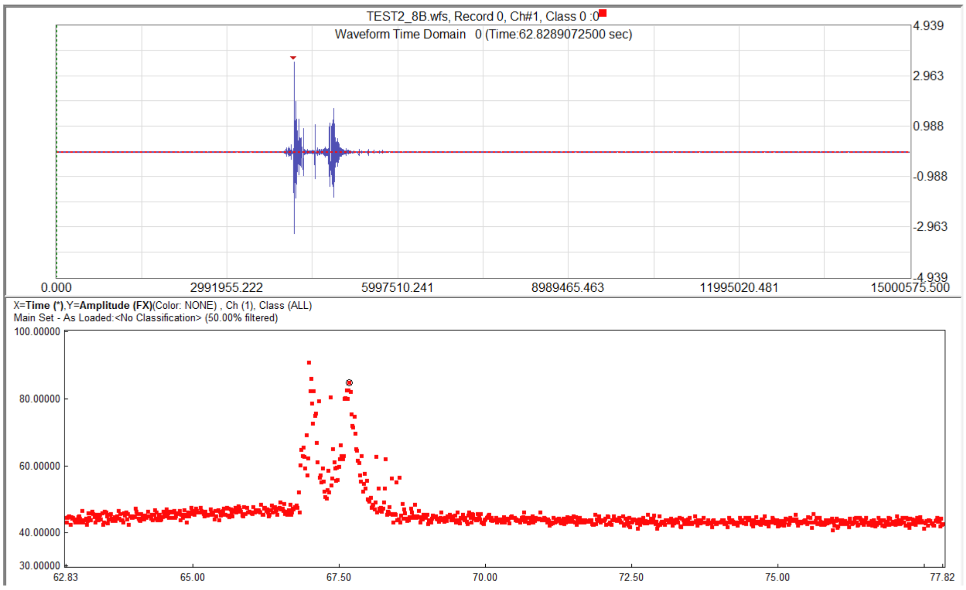

Fig. 3. Feature Extractions for AE Wave Streaming Data (WFS).

1.6 Interactive Advanced Data Clustering

Apart from manual clustering ™ offers a number of algorithms to automatically classify data. The Interactive Advanced Data Clustering is known as Unsupervised Pattern Recognition (UPR) and incorporates mathematical algorithms and Neural Networks. As its name suggests this process investigates the data to find and Recognize Patterns in the data and group them accordingly. These algorithms provide the user with an interactive way to classify data according to their similarity. Traditional analysis of 2D or 3D graphs has limited analysts. Unsupervised Pattern Recognition lets the user set a limited number of parameters and get an automatic classification based on these parameters. The results of the classification will depend on user input (e.g. features to be used, desired clusters, algorithm used etc.) but most importantly they will depend on the quality of the data. Thus, Noesis™ allows signal/data similarity to be compared on Multi-Dimensional space (can be 10D or 20D even) that an analyst could not even begin to imagine due to the complexity of the problem. The results of any classification of data will be immediately visible on all graphs and views as different colors for each class (group of data) are automatically assigned. The data structure can then be further investigated using graphs, tables, statistics, correlation plots and all the tools available in Noesis™.

1.7 Fully Automated Advanced Data Classification

Unsupervised Pattern Recognition is a process requiring some user input to allow data grouping in some unknown data. The Fully Automated Data Classification functions, known as Supervised Pattern Recognition (SPR), incorporates mathematical algorithms and Neural Networks that can be trained from known data or data clustered by UPR (see Interactive Advanced Data Clustering) and then automatically classify similar unknown data, even during acquisition! The user needs some data and decide on their classification (data groups). Once this is finalized an SPR algorithm can be trained to recognize the defined patterns in the data. The algorithm can then be applied to unknown data and it will classify the signals into the predefined groups (classes).

1.8 Dynamic Interface between Unsupervised and Supervised algorithms

In the Figure 4 (see below), the Overall Strategy for clustering of data using Unsupervised and Supervised algorithms is presented:

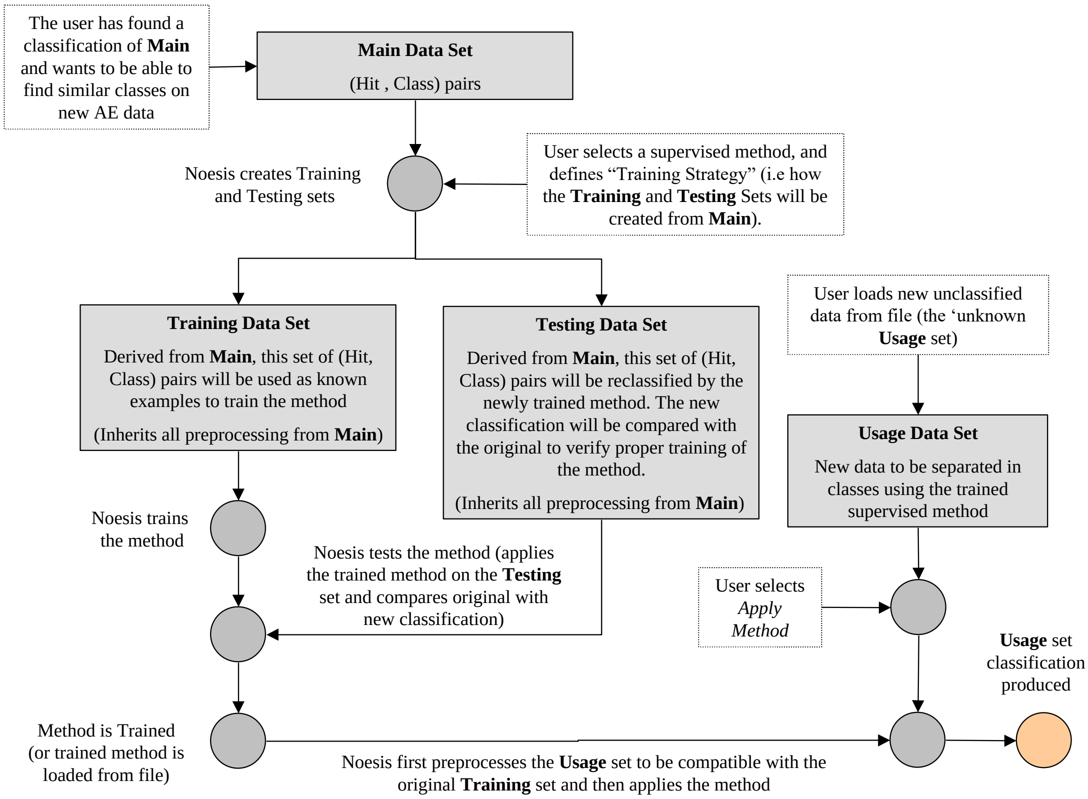

Fig. 4. Overall Strategy for Cluster Analysis.

1.9 Classification during Acquisition

Noesis™ offers the option to apply Supervised Classification during acquisition. When this option is used, Noesis allows real-time feature extraction and classification of data from DTA or WFS files with graphs, statistics and all other Noesis™ functions. In this case, a very useful functionality is the Periodic Statistics. This function allows the user to monitor various statistics relating to clusters and to other classification parameters and features. These can be set-up and run during a Live-SPR session to provide real-time information about clustering and will provide information about the evolution of the data acquisition and clustering process. In general, Periodic Statistics use two classes and measure distances and class evolution (e.g. velocity and class size) between them. To achieve this there is a reference class, which is the measurement's origin, and a target class which is the point to measure to. Periodic data are shown on graphs with the color and symbol of the target class.

2. Use of Noesis in Applications

NOESIS™ successfully solved many challenging and innovative applications. There are more than 1000 active users worldwide that they use Noesis in different areas of Acoustic Emission. A representative list of applications using Noesis™ capabilities is listed below:

- In the work of Etiemble at al. [1], "On the Use of the Acoustic Emission Technique for In-situ Monitoring of the Pulverization of Battery Electrodes", the Acoustic emission coupled with electrochemical measurements have been successfully applied for the in situ monitoring of the cracking upon cycling of metal hydride electrodes for Ni-MH batteries and Si-based electrode for Li-ion batteries. Noesis™ used for classification of the AE signals. The analysis of the AE signals made by Noesis™ which had identify the most discriminate acoustic parameter which in this case was the peak frequency.

- In the work of Kalicka [2], "Acoustic Emission as a Monitoring Method in Prestressed Concrete Bridges Health Condition Evaluation", an acoustic emission (AE) monitoring technique has been used for monitoring of prestressed and post-tensioned concrete bridges. Noesis™ used for classification of different AE sources corresponding to the level of damage severity.
- In the work of Ramadan et al. [3], "Contribution of Acoustic Emission to Evaluate Cable Stress Corrosion Cracking in Simulated Concrete Pore Solution", the applicability of acoustic emission (AE) technique for evaluation and detection of stress-corrosion cracking and localized corrosion of steel cables in simulated concrete-pore solution was studied. Noesis™ used for AE data clustering by applying principal component analysis (PCA) and separation of AE signals released during corrosion stages (localized corrosion and SCC) on steel surfaces by the K-mean clustering algorithm.
- In the work of Sause et al. [4], "Acoustic Emission Investigation of Coating Fracture and Delamination in Hybrid Carbon Fiber Reinforced Plastic Structures", Nickel-copper-coated and uncoated carbon-fiber reinforced plastic specimens were investigated by acoustic emission (AE) analysis during four-point bending tests and subsequently characterized by scanning electron microscopy. The combination of pattern recognition techniques and advanced frequency-spectrum analysis used to distinguish between different failure mechanisms. Noesis™ used for data reduction and application of unsupervised pattern recognition techniques to separate the AE of different failure mechanisms.
- In the work of Anastasopoulos [5], "Pattern Recognition Techniques for Acoustic Emission Based Condition Assessment of Unfired Pressure Vessels", the basic principles of supervised and unsupervised pattern recognition (PR) techniques for classification of acoustic emission (AE) data were successful applied for AE condition-assessment of unfired pressure vessels. Noesis™ used for data pre-processing, features selection and application of unsupervised and supervised pattern recognition techniques identify, separate and validate the AE of different data sources (simulated and real).
- In the work of Zacharias et al. [6], "Signature Analysis of Acoustic Emission Data Obtained during Proof Pressure Test of 15CDV6 Pressure Vessel", they present the details on the analysis carried out on AE data obtained during the proof pressure testing of 15CDV6 steel alloy pressure vessels. In this work, Noesis™ was used extensively. Pattern recognition based on clustering methods was applied on the AE data was found beneficial in noise filtering of internally resin coated pressure tanks. AE features of five case studies are compiled to find the range AE features form epoxy resin coating. Supervised method can effectively separate signals of different sources and can be effectively used to filter the noise signals due to the micro cracking internally coated of epoxy resin to aid in real time structural integrity assessment.
- In the work of Didem et al. [6], "Damage Assessment of Gearbox Operating in High Noisy Environment using Waveform Streaming Approach", the application of waveform streaming used on detecting corrosion pitting on gear teeth under a high background noise environment. The Noesis™ software used, in the first stage, for his option to extract features and arrival times of multiple transient signals in a streamed waveform, based on threshold or length and in a second stage for the option to apply Digital Filters in the transient signals. In the next, Feature Extraction was applied and in the result dataset was

applied data pre-processing, features selection and application of unsupervised pattern recognition techniques identify, separate and validate the AE of different data sources.

- In the work of Kostopoulos et al. [8], “Fracture behavior and damage mechanisms identification of SiC/glass ceramic composites using AE monitoring”, Ceramic glass matrix composites was investigated by using DEN specimens under tensile loading conditions with in situ Acoustic Emission monitoring. The AE data were successfully classified using Noesis™ Unsupervised Pattern Recognition Algorithms and the resulted clusters were correlated to the dominant damage mechanisms of the material.
- In the work of Bollas et al. [9], “Acoustic Emission Inspection of Rail Wheels”, extensive acoustic emission (AE) measurements have been performed on various trains and trams. Noesis™ used for Waveform processing, Feature Extraction and Unsupervised Pattern Recognition.

References

[1] Aurélien Etiemble, Hassane Idrissi and Lionel Roué, On the Use of the Acoustic Emission Technique for In-situ Monitoring of the Pulverization of Battery Electrodes, J. Acoustic Emission, 30 (2012), p. 54-63.

[2] Małgorzata Kalicka, Acoustic Emission as a Monitoring Method in Prestressed Concrete Bridges Health Condition Evaluation, J. Acoustic Emission, 27 (2009), p. 18-26.

[3] S. Ramadan, L. Gaillet, C. Tessier and H. Idrissi, Contribution of Acoustic Emission to Evaluate Cable Stress Corrosion Cracking in Simulated Concrete Pore Solution, J. Acoustic Emission, 27 (2009), p. 254-262.

[4] Markus G. R. Sause, Daniel Schultheiß and Siegfried Horn, Acoustic Emission Investigation of Coating Fracture and Delamination in Hybrid Carbon Fiber Reinforced Plastic Structures, J. Acoustic Emission, 26 (2008), p. 1-13.

[5] Athanasios Anastasopoulos, Pattern Recognition Techniques for Acoustic Emission Based Condition Assessment of Unfired Pressure Vessels, J. Acoustic Emission, 23 (2005), p. 318-330.

[6] Anto Zacharias, Jeby Philip, Toney Varghese and Amal Jyothi, Signature Analysis of Acoustic Emission Data Obtained during Proof Pressure Test of 15CDV6 Pressure Vessel, International Journal of Science, Engineering and Technology Research (IJSETR), Volume 3, Issue 10, October 2014, p. 2855-2860.

[7] Didem Ozevin, Jason Dong, Valery Godinez and Mark Carlos, Damage Assessment of Gearbox Operating in High Noisy Environment using Waveform Streaming Approach, J. Acoustic Emission, 25 (2007), p. 355-363.

[8] V. Kostopoulos, T. Loutas and K. Dassios, Fracture behavior and damage mechanisms identification of SiC/glass ceramic composites using AE monitoring, Composites Science and Technology 67 (2007) p. 1740–1746.

[9] K. Bollas, D. Papasalouros, D. Kourousis and A. Anastasopoulos, Acoustic Emission Inspection of Rail Wheels, J. Acoustic Emission, 28 (2010), p. 215-228.