Development of a software package for acoustic emission control data analysis

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Abstract—The following article addresses a software package developed for working with data obtained during monitoring the detection of material defects via the acoustic emission (AE) method. Timely detection of cracks allows to prevent contingencies and accidents at early stages. This paper describes the architecture of this software, as well as the used calculation methods, provides visualized results of their work, and compares them with other analysis methods. The innovation of this work is the use of the moving window method for AE data analysis. Obtained results indicate the practical importance and relevance of our research in this area.

I. Introduction

Evaluation of the current condition of varying industrial and infrastructural objects is one of actual problems of modern material science. These objects include, but are not limited to the oil and gas and chemical industry equipment, thermal and nuclear power equipment, aerospace equipment, pipeline and railway transportation, bridge constructions, and concrete and reinforced concrete structures. The risks of equipment failure increase substantially after it has been in use for a long time under mechanical and thermal loads. The development of methods that allow to study the physical nature of material degradation processes is an important task within the field of technical diagnostics. Acoustic emission testing is prominent among these methods. It allows to identify the coordinates and estimate the danger level of defect-associated acoustic emission sources that appear in a loaded object.

In this work we present a software package intended for analyzing a large volume of specific data that is being studied by a considerable number of researchers all around the world. Our software is designed for analyzing different impulse responses of AE signals (amplitude, energy, length, etc) with the use of the moving window method. By employing this method, the software identifies the change dynamics of the arithmetic mean, median, standard deviation, and b-value of these responses.

II. Acoustic emission method

Acoustic emission testing is an efficient method of nondestructive testing. It is based on detecting elastic waves during deformation of stressed material. These waves travel from the source to sensors that transform them into electrical signals. From the standpoint of the AE method, a defect can produce its own signal [1]. The AE testing devices measure these signals, and then display data used for evaluating the condition and behavior of the entire structure of the tested object. The sensitivity of this method is sufficient to register even microscopic crack growth (by 0.001 mm), which allows to detect cracks in time. The AE method can be employed for testing of a wide variety of technological processes, as well as processes of changes in properties and condition of materials. This broad spectrum of tasks and the variety of control objects requires constant improvement of data processing tools.

III. Overview of existing solutions

There are several acoustic emission systems made by different manufacturers. A review of the characteristics of their software, technical parameters, capacity of their AE equipment, and certain abilities for the analysis of registered data is presented in study [2]. Unfortunately, the post-experimental analysis capabilities of reviewed systems are limited — mostly to creation of standard plots. For example, in AMSY-5, it is easy to create an number of impulses-amplitude histogram or an amplitude-time correlation plot, but it is not always possible to implement a custom user formula [3]. Moreover, the system itself is quite expensive.

Furthermore, a considerable number of studies dedicated to experimental and practical results of using AE exists, for example: [4], [5], [6]. The moving window method is widely applied in different scientific fields, such as economics [7], geophysics [1], social networks analysis [8], audio encryption, and so on.

Our software applies the moving window method to three statistical quantities and one composite parameter specifically during analyzing data of acoustic emission testing of loaded structures. This allows to filter peak values of these quantities and observe the trends in changes of process phases in general.

IV. Software architecture

Currently, our software allows to build the trend of a time series. We employ moving averaging for trend determination. The calculations are performed on impulse responses of acoustic signals — mainly amplitude values. This parameter is one of the most informative, because it indicates the detectability of a signal, which is why it is frequently used during AE testing. For example, in [9], the average amplitude of events is used for forming the P(R) criterion used for determining the necessity of additional testing of detected areas of AE activity.

This software is written in C#. It accepts an input of a file containing data from a certain time interval. Every line of this file contains data collected from a single sensor, in particular, registration time (up to a microsecond), sensor number, and the value of the parameter chosen for processing, e.g., amplitude. The user can set up the parameters required for their research. The software allows to select the sensor whose data will be analyzed to localize the process, indicate whether the analysis will be performed with respect to the number of signals or time, designate the calculation method for one of the four statistical indicators (arithmetic mean, median, standard deviation or b-value). The selection of the window size adjusts the accuracy grade of data evaluation and resolves the problems associated with the possible non-uniformity of data distribution in the time domain.

V. Experiments

In this study we use the data collected during two experiments designed to model the use of real-life constructions with different load types. In the first experiment (strength load) we have used steel-reinforced concrete beam samples which were being bent according to a 3-point scheme. The total volume of AE testing data we have obtained is quite significant. Thus, in some figures we have only plotted the data of sensor 2 (Fig. 1, 3, 5, 7, 10), and in others we have used the data of all four sensors (Fig. 9, 8).

In the second experiment (strength-thermal load), we have monitored a large-sized object contained in a cylindrical concrete construction. During the experiment, the control object was uniformly heated to 400°. The data were being registered by ten sensors. Fig. 2, 4, 6, 11.

VI. Processing methods

The developed analysis system provides the ability to average the processed parameter by calculating three indicators: arithmetic mean, median, and standard deviation. All of them are calculated with the use of the moving window method. This method can be explained as follows: the calculations are performed on same length sets of consecutively registered data, which are shifted by one value relatively to each other during consecutive scanning of the entire measurement interval. The data set size (moving window size) is determined by the user.

A. Simple moving average

Simple moving average (or arithmetic mean) is calculated as follows:

$$\sigma_t = \frac{\sum_{i=1}^{n} x_i(t)}{n} \tag{1}$$

where t is the time interval; n is the smoothing interval; $x_i(t)$ is the time series.

Fig. 1 and 2 present the plots of the simple moving average. The smaller the size of the window, the faster the moving window method identifies the new trend, but with that, the final plot contains more false vibrations. If the size is too large, then the trend will be identified slower, however, there will be fewer false vibrations as well.

Fig. 1-6 display the plots of the moving average for the first experiment (destructive testing of steel-reinforced concrete beams), where the optimal window size is 100. This size has been identified via the possibility of real-time adjustment of program parameters.

Hereinafter in this section, all plots are built with the window size set to 100 signals, for time windows this size is set to 100 milliseconds, used data slice — the entire duration of the experiment.

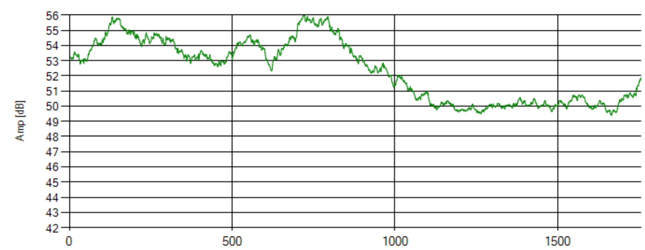

Figure 1. Simple moving average. X-axis indicates the number of signals, Y-axis indicates amplitude.

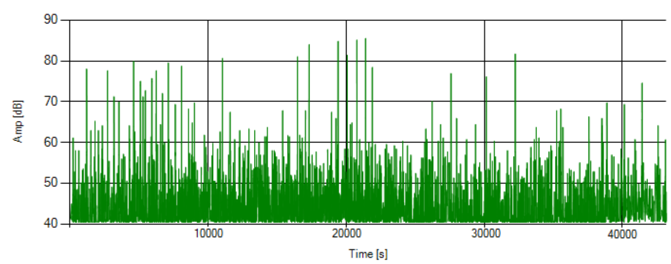

Figure 2. Simple moving average. X-axis indicates time (in milliseconds), Y-axis indicates amplitude.

B. Statistical median

Statistical median is the middle element of an ordered sample. We use the following algorithm to determine the median values: enumerate all values from 0 to N in an ascending order, then the median values are the elements indexed 0.5N and (0.5N+1) for an even N, and 0.5(N+1) for an odd N. Fig. 3 and 4 display the plots of the medians.

C. Standard deviation

Standard deviation is calculated as follows:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n} (x_i(t) - \overline{x}(t))^2}{n}} \tag{2}$$

where x(t) is the time series, $\overline{x}(t)$ is the arithmetic mean, and n is the size of the moving window.

A larger standard deviation value indicates a larger scatter in the presented sample. A smaller value points

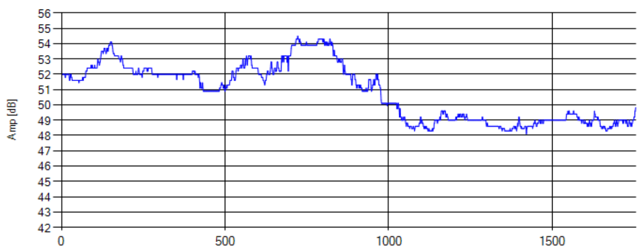

Figure 3. Statistical median. X-axis indicates the number of signals, Y-axis indicates amplitude.

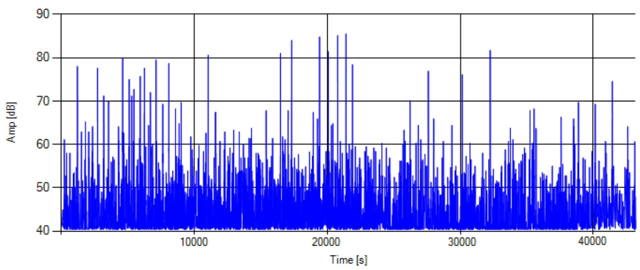

Figure 4. Statistical median. X-axis indicates time (in milliseconds), Y-axis indicates amplitude.

to set values being aggregated around the mean (Fig. 5 и Fig. 6). Standard deviation can be calculated in a different way if variance, which is equal to the radicand in formula 2, has been found previously.

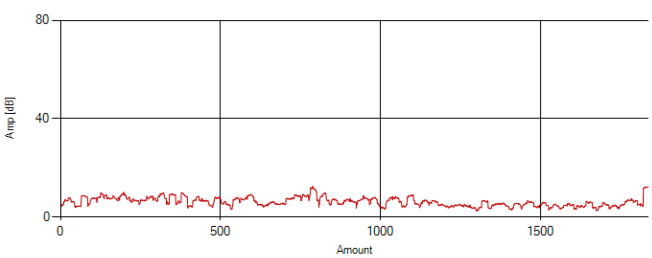

Figure 5. Standard deviation. X-axis indicates the number of signals, Y-axis indicates amplitude.

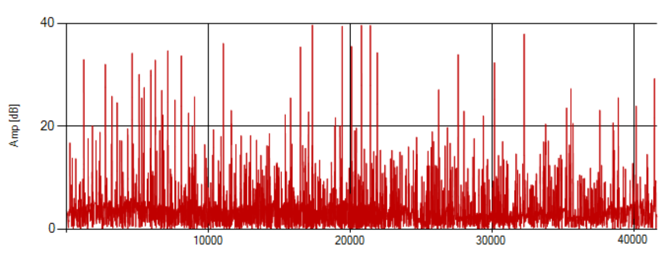

Figure 6. Standard deviation. X-axis indicates time (in milliseconds), Y-axis indicates the calculated indicator.

VII. Plot analysis

In the beam destruction experiment, the plots of the simple moving average and the statistical median are virtually the same. This is correct for both the time scale of the entire experiment (Fig. 2 and 3) and smaller time scales (Fig. 7). Our analysis has revealed that standard deviation is the least significant parameter out of all three. Although it is of theoretical interest, statistical median and simple average have turned out to be more informative in practice. These parameters help to trace the dynamics of crack formation. According to the study [6], during static loading of metal with a crack there is no increasing trend in the time domain of AE signal amplitude, but there are individual AE signals whose amplitude exceeds the average by 45 dB. We observe a similar situation in the beam loading experiment. This change of trend can be observed on the resulting plots: in Fig. 7, which represents the phase of active formation of main cracks, the averaged amplitude values do not increase uniformly. Furthermore, the increases of amplitude of certain signals are filtered via the moving window method which allows to see the whole picture of trend change.

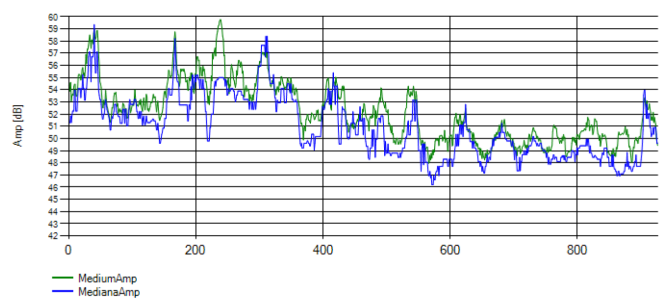

Figure 7. Statistical median and simple average for a shorter time slice. Windows size is set to 20.

The selection of an optimal size of the moving window is important. Our software allows the user to make this choice empirically for the whole duration of the experiment, and then change this value proportionally to the total number of signals in a particular smaller data slice. For example, in the beam experiment, one sensor has registered 1700 events. The clearest picture was obtained with the size of the window L = 100 events. Thus, for the macrocrack formation period that contains 305 events, L was set to $305*100/1700 \approx 18$ (Fig. 7). Sometimes, it is reasonable to reduce the window size, for example, to avoid missing the registration of relatively rare events such as macrocrack formation.

Consider Fig. 8. In this figure, arrows denote the moments of crack formation that were registered directly (visually) during the experiment. It is interesting that this plot also contains similar decline peaks at different time points. It is highly likely that those points correspond to internal cracks in the structure that could not be identified visually.

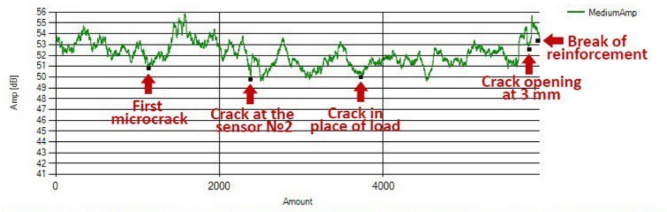

Figure 8. Simple moving average for different stages of beam destruction. X-axis indicates the number of signals, Y-axis indicates amplitude.

VIII. b-value analysis

It is possible to use the Gutenberg-Richter law (widely applied in seismology [1]) to study the scaling of the amplitude distribution of AE signals that appear during crack formation. In AE terms, this formula can be written as follows:

$$log_{10}N = a – b * A_{max}dB \tag{3}$$

where $A_{max}dB$ is the maximum amplitude in the window (in decibels), a is an empirical constant value set to 4.8, b is a value obtained from this equation and then multiplied by 20 to be comparable to the value used in seismology[14]. The b-value is used for identifying the predominate destruction type and determining trends in construction damage development.

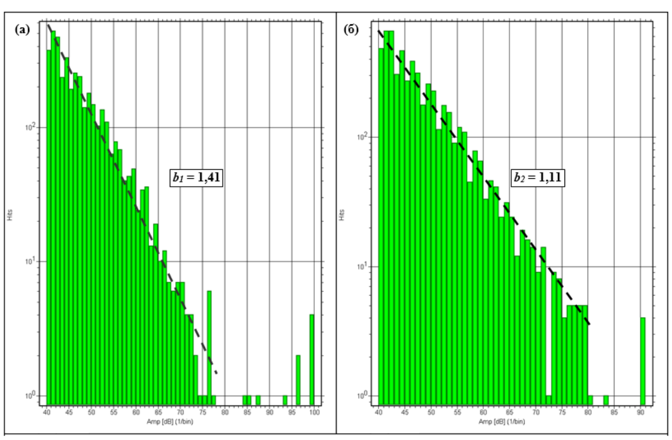

Figure 9. Plots of amplitude distributions for different stages of beam destruction and their b-values

Fig. 9 provides an example of express analysis for b-value estimation for the experiment conducted by non-destructive testing specialists during test destruction of a reinforced concrete construction. In this analysis, the angle of inclination of a line (which is build via the least squares method) determines the b-value. Fig. 9, (a) shows the amplitude distribution for the stage that directly precedes the destruction of reinforcement metal; at this stage, macrocracks have already formed, the main material has unloaded, and microcracks were forming intensively on the last loaded area in the vicinity of the reinforcement metal. Fig. 9, (b) displays the data for the stage of main macrocrack formation. The obtained results correspond with the notions of b-value evolution associated with the change of the predominant destruction type that were presented in the following studies: [13], [15], [16], [17].

We have implemented the ability to calculate the b-value in our software package. In some cases, it turns out to be a more informative evaluation parameter for crack formation dynamics than other statistical indicators. For example, in experiments with thermal or composite (strength-thermal) loading of a large-size reinforced concrete structure, the change of b-value trends in regards to the defect formation stage are more pronounced in comparison to the experiments with strength loading of small samples. Fig. 10 and Fig. 11 show the b-value plotted by the system during analyzing the results of the strength and thermal load experiments respectively.

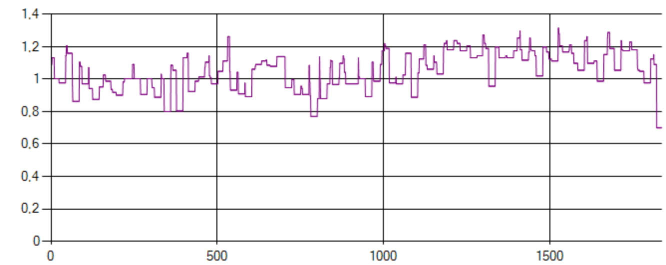

Figure 10. Dependency of b-value on the number of signals. Strength load experiment.

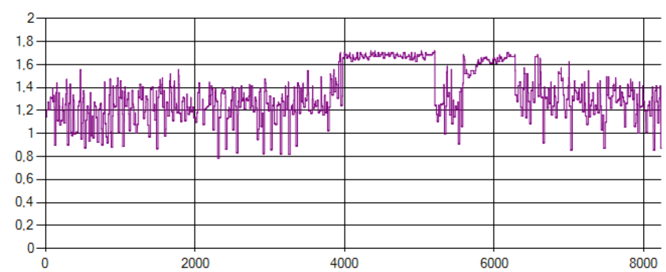

Figure 11. Dependency of b-value on the number of signals. Thermal load experiment.

The resulting plots demonstrate the b-value fluctuating in a significantly wider range for the second structure type. However, its use is sufficiently informative for the objects of the first type as well. It can be seen that destruction processes of different intensity are being considered, which is confirmed by the presented dependencies.

Analyzing these kinds of dependencies allows AE testing specialists and material scientists to obtain useful and, sometimes, unexpected information on the behavior of materials under the influence of different kinds of loads [18].

IX. Results and conclusions

The following results have been obtained:

1) We have developed a software package that enhances an AE control analysis system with several data analysis methods designed to increase the informativeness of testing. This

software was tested on real experimental data.

2) The correctness of the employed algorithms is confirmed by the obtained results matching the previously known facts on the development of defect formation.

3) Employing this software package allowed the AE testing specialists to perform a more accurate and detailed analysis of data, which substantially increased the informativeness of testing.

In this paper, we have presented elements of analysis of data collected during both a laboratory experiment of loading and destruction of reinforced concrete beams and real-world testing of a large-size reinforced concrete construction. The conditions of conducting the first type of experiments have made it possible for us to observe certain key phases of the sample destruction process and identify them with the corresponding AE testing data. Software algorithms have performed well in these experiments: the type of obtained dependencies corresponds to the real-world processes that occurred in control objects according to the known facts about the mechanics of destruction of this type of materials. Thus, the proposed algorithms were tested successfully.

During our research, we have corrected the moving window size with respect to estimating the maximum informativeness of this parameter during the destruction stage. The resulting estimates are employed for the moving window method in the developed software for both the described experiment and other situations in which crack formation (deformation or other internal destruction) processes are obscured and occur inside of the object. In this kind of experiments, the value of such analysis increases due to the inability to visually observe material structure degradation processes and having to resort to evaluating them by indirect indicators.

The second kind of structure that was considered in this study is an object of this type. The results of additional examination of material structure via destructive methods confirmed the correctness of conclusions that were made during the AE testing with the use of our software.

The software of existing AE systems is generally limited to a set of standard plots used for a formal representation of testing results. It usually lacks advanced tools of data analysis. This is typical even for the most modern AE testing systems, such as AMSY-5 (developed in Germany) [3], which was employed during the discussed experiments.

X. Conclusion

In this work we have developed a software package intended for analyzing acoustic emission testing data. We have shown that it can be successfully employed for both laboratory experiments and large-size construction testing. We should note that this kind of analysis requires determining the optimal size of the moving window. All of the required estimates of this value for the arithmetic mean, median and standard deviation were obtained. Using these estimates, we have performed the calculations on data of impulse responses of acoustic signals. The final results indicate the efficiency of the suggested moving averaging methods in the task of analyzing acoustic emission testing data and the practicability of using the considered software.

In our further research we plan to perform the analysis of data obtained in experiments with composite loads and then generalize the results.

The development of methods for detecting signals associated with defect growth with the use of information theory methods could be a fruitful area for further work as well.

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