BULGARIAN ACADEMY OF SCIENCES

CYBERNETICS AND INFORMATION TECHNOLOGIES • Volume **16**, No 1
Sofia • 2016 Print ISSN: 1311-9702; Online ISSN: 1314-4081
DOI: 10.1515/cait-2016-0009

Optimizing Signal De-Noising Algorithm for Acoustic Emission Leakage of Wavelet

Wang Xin-Hua[1, 2]*, Jiao Yu-Lin*[2]*, Niu Yong-Chao*[3]*, Yang Jie*[1]

[1]*Wuhan University of Technology, Wuhan 430063, China*
[2]*Shangqiu Vocational and Technical College, Shangqiu 476000, China*
[3]*Shangqiu Jinpeng Industrial Co., Ltd., Shangqiu 476000, China*
Email: gyxxwxh@163.com

Abstract: *Traditional wavelet denoising method cannot eliminate complex high-pressure pipe signals effectively. In the updated wavelet adaptive algorithm, this thesis defines the constraints in order to reconstruct the signals accurately. According to the minimum mean square error criterion, the results predict the weight coefficient and get the optimal linear predictive value. Adopting the improved algorithm under the same condition, this thesis concluded that Db6 increased the complexity of wavelet algorithm by 50% by comparative experiments. It will be more conducive to the realization of hardware and the feasibility of real-time denoising. Dual adaptive wavelet denoising method improved SNR by 50%. This denoising method will play a key role in the detection rate of high-pressure pipe in the online leakage detection system.*

Keywords: *acoustic emission, wavelet de-noising, leakage detection, wavelet analysis, acoustic emission signal.*

1. Introduction

In the acoustic emission leak detection of heater in power plants, the acoustic emission signal contains abundant of information related to defect nature and various types of interference and noises simultaneously. It has long been a technical problem to identify the weak defect signal from the background noise. The impulse interference noise caused by occasional factors can be wiped off easily through amplitude limiting filter method, median filter method and arithmetic method [1-5]. But for complicated and special testing materials, it is difficult to detect defect for the randomly distributed background noise which is generated internally, especially in some noise material application such as carbon fiber composite, welded joint and laminate material. This noise has a similar frequency distribution feature to acoustic emission wave in the reflection inside the material due to the internal structure of these materials. Thus it is hard to use the mentioned methods above to isolate the background noise from the frequency domain or time domain. Besides, noises are very easy to be brought in every links of the acoustic emission wave propagation. The noises include loop noise caused by detection system and other causes. And the electronic noise caused by pre-amplifier and the frictional noise caused by relative mechanical sliding in the loading procedure is more serious. These complicated noises have severer effects on acoustic emission signals. SNR deterioration is more prominent. Due to all this, the false drop rate and omission rate in acoustic emission detection increase. This has already been one of the key factors that influence the improvement of the reliability in acoustic emission detecting and evaluating technologies [5-8]. Therefore, acoustic emission signal de-noising is one important step of acoustic emission signal processing. It is helpful to adopt effective denoising pretreatment technology to increase SNR in order to improve the accuracy of subsequent acoustic emission signal processing.

2. De-noising principle for acoustic emission signal based on wavelet analysis

There are many methods to conduct the de-noising of digital signals which can be classified as time domain method, frequency domain method and time-frequency domain method. Every method has different range of application and application effect. For stable signal, frequency domain analysis is generally adopted. The frequency feature of signals is extracted through Fourier transform [9], and for unstable signal, wavelet analysis method is adopted in most situations [10-12].

Acoustic emission signal is featured with unstable randomness and it belongs to one-dimensional signals. The de-noising model of one-dimensional signals proposed by Fujita, Morikazu and Shintani [13] is as follows:

(1) $$x(n) = s(n) + \sigma \cdot u(n),$$

where $x(n)$ is the observed signal with noise, and $s(n)$ is the true signal; $u(n)$ is the Gaussian white noise signal, while σ is the noise intensity; signal de-noising means to acquire the optimum value of assessment $\hat{s}(n)$ of the original signal $s(n)$ from the observed signal $x(n)$.

This thesis adopts wavelet threshold value noise method to deal with the acoustic emission signal processing. Through scatter binary row wavelet transformation, conducted to acoustic emission signal and then wavelet threshold value de-noising method is also conducted to the acoustic emission signal de-noising. The specific processes are: 1) confirm a wavelet basic function, conduct wavelet decomposition to signals at the appropriate decomposition dimension, calculate the wavelet decomposition coefficient of noise signal at this dimension; 2) estimate the noise level of high-frequency coefficients at each dimension and then set up a threshold value, use the threshold value method to modify relevant wavelet coefficient; 3) conduct wavelet inverse transformation and signal reconstruction to low-frequency coefficients and the modified high-frequency coefficients and thereafter gain the signal estimated value after de-noising process.

3. The lifting algorithm of wavelet denoising

Since the construction of wavelet in time domain is directly realized, the complexity of lifting algorithm is only half of the original convolution method. The structure of the algorithm is simple and the calculation is speedy. Thus, the lifting method has become mainstream method of calculating scatter wavelet transformation [14-16]. The traditional wavelet transformation algorithm (Mallat algorithm) adopts a method of convoluting input signal and high plus low pass filters to realize separation of high frequency and low frequency information. However, the coefficients of wavelet filter are all decimals. Some results are decimals and upon taking the integer of decimals, tons of information will be lost and the re-construction and de-composition will be irreversible. Consequently, reconstruction cannot be realized accurately. But in the lifting scheme, integer transformation is operable and it will not affect accurate reconstruction.

Due to all these advantages mentioned above regarding the lifting algorithm and existing problems of acoustic emission wavelet de-noising method, this chapter proposed a de-noising algorithm based on lifting acoustic emission signal of wavelet. The steps are as follows:

(1) Confirm the lifting frame type and lifting steps of signals, conduct lifting wavelet decomposition to the observed data;

(2) Extract low frequency smooth signal and high frequency detail signal coefficient at each step, which is to acquire new approximate dimension coefficient and wavelet coefficient and then conduct condition analysis to wavelet coefficient which is to estimate noises of high-frequency coefficients at each step;

(3) According to the noise estimation, combine the threshold value algorithm adopted, set up threshold value and modify high-frequency coefficients at each step;

(4) Conduct lifting inverse calculation to low-frequency coefficients and modified high-frequency coefficients. The reconstructed signals include estimated values of noise signal.

The process of acoustic emission signal lifting wavelet de-noising is as shown in Fig. 1. During the de-noising processes, selecting the proper framework type and optimizing the threshold value are two important factors in determining the de-noising effect, like traditional scatter wavelet de-noising. During the de-noising process, picking threshold value and optimizing the threshold value are very important links. The selection of threshold form needs not only to remove the noise effectively, but also to protect useful signals from being harmed. This thesis adopts medium-soft threshold value method. This method can dispose wavelet coefficient with hard threshold value or soft threshold value respectively according to the practical acoustic emission data features.

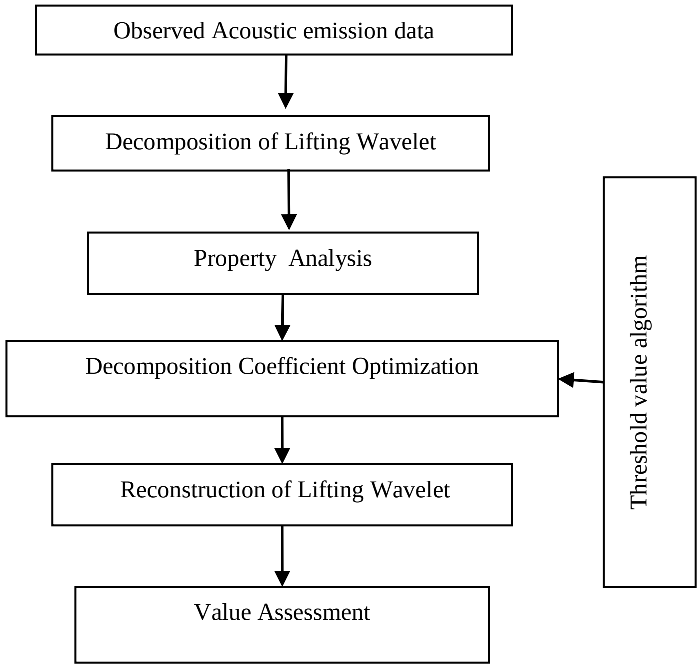

Fig. 1. De-noising process based on lifting wavelet acoustic emission signal

Besides, lifting steps also need to be considered comprehensively. During the lifting calculation process, the length of signal coefficient will be halved gradually as the lifting process goes on. After a certain number of steps, the number of signal coefficient declines to 1. So the number of steps should not be too large. And in the noise estimation of decomposition coefficient at each level, the length of signal should not be too short; otherwise the noise level would not be estimated correctly. Moreover, the number of lifting steps cannot be too small.

Every framework structure in the lifting wavelet transform is like the wavelet basis function in the traditional wavelet analysis. Different framework structure will generate different results in the signal de-noising. Thus, the lifting frame should also be optimized when conducting wavelet de-noising. During this process, the number of lifting steps is three, and they all need the same threshold value calculation method.

4. Dual self-adaptive lifting wavelet de-noising algorithm

For one-dimensional acoustic emission signal, signals in different region have different features because of the diversity of its generation mechanism. For example, carbon fiber composite acoustic emission signal which needs to be disposed of in this thesis is unstable random signal. It has two models: bending wave and spreading wave. It includes smooth region and mutational region. Therefore, the selection of decision criterion should be appropriate. The forecasted weighting coefficient should be adjusted to make weighting coefficient match feature region self-adaptively.

Self-adaptive lifting algorithm first analyzes the signal sequence, selecting corresponding updating operator and prediction operator according to the sequence's local features. After that it disposes the signals. It is thus clear that this transformation method thinks completely from the perspective of signal, self-adaptively choosing different filters according to signal features in de-noising processes. This method can conduct a complete reconstruction to the signals so that it can finish de-noising disposal to the signals effectively. Researches of Zhou Donghua et al. [18] have proven this point and given an updated self-adaptive algorithm.

In practical application, for some signals of fixed features, two methods can be adopted to realize the self-adaptive filtering to signals. The first one is the combination of fixed predictive filter and updated self-adaptive algorithm and the second one is the combination method of fixed updated algorithm and self-adaptive prediction filtering. The acoustic emission signal studied in this thesis shows non-stationary characteristics vary with the change of time. The sampled signal in every experiment demonstrates a feature of randomness. So in order to acquire better de-noising effects, a dual self-adaptive lifting wavelet transformation algorithm is adopted to conduct de-noising processing which is to adopt self-adaptive filtering method in both updating link and predicting link [19].

4.1. Updated self-adaptive algorithm

The principle structure of the updated self-adaptive algorithm is demonstrated in Fig. 2.

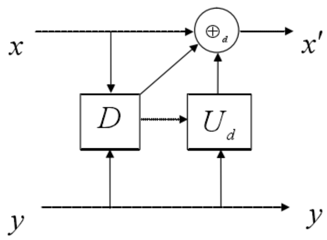

Fig. 2. Self-adaptive updating principle

In Fig. 2, x, y and x', y are low-frequency coefficients and high-frequency coefficients respectively before and after updating; *D* is decision function; U_d is update operator; $\oplus_d$ is generalized additive operator. Being different from the updating process of standard lifting method, update operator U_d here and additive operator are not fixed. They are picked self-adaptively by the discrimination function *D* on the basis of information of odd-even sequence. Under this condition, the low-frequency coefficient is

(2) $$x'[n] = x[n] \oplus_d U_d \{y(n)\},$$

(3) $$d_n = D(x, y)[n].$$

Here d_n is the discriminant function value at n point. The definition of discrimination function $D(x,y)$ is

(4) $$D(x,y)[n]=\begin{cases}-1 & \text{if} \quad |x[n]-y[n-1]|<|x[n]-y[n]|,\\ 0 & \text{if} \quad |x[n]-y[n-1]|=|x[n]-y[n]|,\\ 1 & \text{if} \quad |x[n]-y[n-1]|<|x[n]-y[n]|.\end{cases}$$

Then the expression of update operator is

(5) $$U_d(y[n])=\begin{cases} y[n-1] \quad \text{if} \quad d=-1,\\ \frac{1}{2}(y[n-1]+y[n]) \quad \text{if} \quad d=0,\\ y(n) \quad \text{if} \quad d=1.\end{cases}$$

From (4), it can be seen that the symbol of d_n is determined by the value of equation $\left|x\left[n\right]-y\left[n-1\right]\right|<\left|x\left[n\right]-y\left[n\right]\right|$. The derivation from this is that the discrimination function is determined by the following gradient vectors:

(6) $$\left(x\left[n\right],w\left[n\right]\right)=\left(x\left[n\right]-y\left[n-1\right],y\left[n\right]-x\left[n\right]\right).$$

Then

(7) $$D\left(x,y\right)\left[n\right]=d\left(v\left[n\right],w\left[n\right]\right)=d\left(x\left[n\right]-y\left[n-1\right],y\left[n\right]-x\left[n\right]\right),$$

where d represents mapping function, and different discrimination principles reflect different gradient values.

Update operator U_d is defined as

(8) $$U_d(y\left[n\right])=\delta_d(y\left[n-1\right])+\varphi_d(y\left[n\right]).$$

Additive operator $\oplus_d$ is defined as

(9) $$x\left[n\right]\oplus_d U_d(y\left[n\right])=\alpha_d(x\left[n\right]\oplus U_d(y\left[n\right])).$$

Low-frequency coefficients are obtained according to Equations (2), (8) and (9):

(10) $$x^{'}\left[n\right]=\alpha_d x\left[n\right]+\beta_d y\left[n-1\right]+\gamma_d y\left[n\right].$$

Here define $\alpha_d+\beta_d+\gamma_d=1$,

(11) $$d(|v(n)|+|w(n)|)=\begin{cases}0 & \text{if} \quad |v(n)|+|w(n)|\le T,\\ 1 & \text{if} \quad |v(n)|+|w(n)|>T.\end{cases}$$

The constraint conditions of equation (11) can ensure that the signals can be reconstructed accurately.

4.2. Self-adaptive forecasting algorithm

Forecasting algorithm predicts signal odd sequence through signal even sequence. The more accurate the forecasting is, the smaller are the high-frequency coefficients acquired and then the better is the forecasting effect. This method adopted in this thesis conducts updating first and then forecasting. The process of forecasting does not have any effects on the updating process. So the accuracy of this algorithm can be improved on.

The specific forecasting algorithm is

(12) $$D[n] = x[2n+1]\Theta P\{x[2n]\},$$

where $D(n)$ represents high-frequency coefficients in the lifting method. The definitions of operators P and Θ are:

(13) $$P(x[2n]) = \delta(x[2n+1]) + \varphi(x[2n]),$$

(14) $$x[2n+1]\Theta P(x[2n]) = x[2n+1] - P(x[2n]).$$

By substituting Equations (13) and (14) into Equation (12), the linear prediction equation is acquired as below:

(15) $$D(n) = x[2n+1] - \delta x[2n+2] - \varphi x[2n].$$

From the forecasting equation, the key to construct linear prediction filter is to calculate the values of prediction weighting coefficients δ and φ. To make sure that the forecast error is the least and then the high-frequency coefficients in the lifting algorithm are the least, so the odd sequence prediction must be accurate. According to the minimum mean square error principle, the optimized linear prediction value can be acquired. The follow should be satisfied:

(16) $$E\{x[2n+1] - (\delta x[2n+2]) + \varphi x[2n]x[n])\} = 0.$$

From (16), the prediction weighting coefficients δ and φ can be calculated.

To dispose acoustic emission signal, the absolute value of difference value between two adjacent sampling points are picked to be a criterion in this paper. The signal sequence is divided into smooth and mutational regions. Minimum mean square error calculation is conducted to the signal samplings in two regions respectively. Then the prediction weighting coefficients in these two regions are calculated as well. At last, the self-adaptive forecasting is realized.

5. Simulation experiment and analysis

In order to verify the effectiveness of the algorithm, traditional wavelet (Db6), lifting algorithm constructed wavelet (Db6) and dual self-adaptive lifting wavelet are adopted respectively to conduct de-noising experiments for the broken lead acoustic emission signal based on the acoustic emission signal de-noising steps discussed above in the paper. Table 1 and Fig. 3 give different wavelet de-noising algorithm results.

Table1. Performance of different de-noising algorithms

De-noising algorithm	SNR	RMSE
Traditional wavelet (Db6)	8.9762	3.5182
Lifting wavelet (Db6)	9.5485	2.6936
Dual self-adaptive lifting wavelet	18.998	2.7853

From the data in Table 1, the signal to noise ratios of de-noising signals of noisy acoustic emission signal in traditional wavelet transformation and lifting algorithm (Db6) wavelet transformation are basically close, being 8.9762dB and 9.5485dB respectively. The signal to noise ratio of signal de-noised by dual self-adaptive lifting method is 18.998dB, being enhanced considerably. That proves that the dual self-adaptive lifting method has better de-noising effects than the other two methods.

From Fig. 3, it can be seen that based on the combination method of lifting wavelet and medium-soft threshold value de-noising retains the peak value feature of composite acoustic emission signal effectively. The method also demonstrates good smooth feature in the process of tending to be steady.

For wavelet basis function (Db6) of the same kind, adopting lifting algorithm wavelet and traditional wavelet have no obvious differences in enhancing signal to noise ratio. However, the complexity of lifting algorithm is only half of that of the Mallat algorithm. So, the lifting wavelet de-noising algorithm introduced in this thesis has advantages in calculation speed and storage space. It is in favor of hardware implementation.

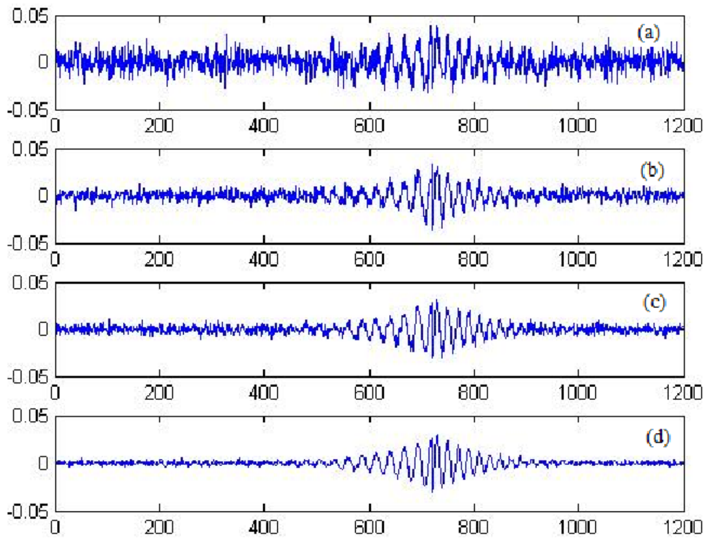

Fig. 3. De-noising results of different acoustic emission signals of wavelet: Original signal (a); de-noising of traditional wavelet Db6 (b); de-noising of lifting wavelet Db6 (c); de-noising of self-adaptive wavelet (d)

6. Conclusion

This paper conducted a deep research to wavelet de-noising methods of acoustic emission signal which analyze the selection of threshold value function and optimization of threshold value in de-noising processes. It also analysed the key technologies such as confirmation of wavelet basis function and evaluation standards of de-noising effects. Moreover, it proposed a de-noising method for acoustic emission based on lifting method to deal with problems that traditional wavelet de-noising method cannot. And considering the features of acoustic emission signal, the paper also proposed a combination method of least square method and wavelet de-noising to improve de-noising algorithm for acoustic emission signal of wavelet and adopted dual self-adaptive lifting algorithm to conduct de-noising of acoustic emission signal. Due to the flexibility of lifting algorithm, this de-noising algorithm is not constrained by the integral construction of signal but designs different wave filters to deal with features of different parts of signals during the signal disposal processes. In comparison with traditional wavelet transformation method, this method not only enhances signal to noise ratio effectively but also has advantageous features. The structure is simple; the calculation is fast. These features are good for the hardware implementation and are beneficial for the real-time online application in heater leakage fault detection. At the end of paper, the broken lead analogy simulation experiment has verified this analysis conclusion.

Acknowledgements**:** Foundation item: Nature Science Foundation of Henan Science and Technology Bureau (141008 and 141080); Major science and technology research plan project in Henan province (142102110028).

References

1. Heo, G., S. K. Lee. Internal Leakage Detection for Feedwater Haters in Power Plants Using Neural Networks. – Expert Systems with Applications, Vol. **39**, April 2012, Issue 5, pp. 5078-5086.
2. Eaton, M. J., R. Pullin, K. M. Holford. Acoustic Emission Source Location in Composite Materials Using Delta T Mapping. – Composites Part A: Applied Science and Manufacturing, Vol. **43**, June 2012, Issue 6, pp. 856-863.
3. Shao, H., S. Jiang, L. Wang, Z. Wu. King Factor of the Strata Overlying the Gob and a Three-Dimensional Numerical Simulation of the Air Leakage Flow Field. – Mining Science and Technology (China), Vol. **21**, March 2011, Issue 2, pp. 261-266.
4. Ghosh, S., D. Mukhopadhyay, S. K. Saha. An Experimental Analysis of Subcooled Leakage Flow through Slits from High Pressure High Temperature Pipelines. – International Journal of Pressure Vessels and Piping, Vol. **88**, August-September 2011, Issues 8-9, pp. 281-289.
5. Ghertner, D. A., M. Fripp. Ding Away Damage: Quantifying Environmental Leakage through Consumption-Based, Life-Cycle Analysis. – Ecological Economics, Vol. **63**, 1 August 2007, Issues 2-3, pp. 563-577.
6. Chambers, W. M., N. J. Mc C. Mortensen. Toperative Leakage and Abscess Formation after Colorectal Surgery. – Best Practice & Research Clinical Gastroenterology, Vol. **18**, October 2004, Issue 5, pp. 865-880.
7. Keum, C.-M., J.-H. Bae, M.-H. Kim, W. Choi, S.-D. Lee. Ution-Processed Low Leakage Organic Field-Effect Transistors with Self-Pattern Registration Based on Patterned Dielectric Barrier. – Organic Electronics, Vol. **13**, May 2012, Issue 5, pp. 778-783.
8. Roetzel, W., D. W. Lee. Effect of Baffle/Shell Leakage Flow on Heat Transfer in Shell-and-Tube Heat Exchangers. – Experimental Thermal and Fluid Science, Vol. **8**, January 1994, Issue 1, pp. 10-20.
9. M. F. El-Amin, H. Kanayama. Boundary Layer Theory Approach to the Concentration Layer Adjacent to a Ceiling Wall at Impinging Region of a Hydrogen Leakage. – International Journal of Hydrogen Energy, Vol. **33**, November 2008, Issue 21, pp. 6393-6400.

10. O r, S. W., H. L. W. C h a n, C. L. C h o y. P(VDF-TrFE) Copolymer Acoustic Emission Sensors. – Sensors and Actuators A: Physical, Vol. **80**, 15 March 2000, Issue 3, pp. 237-241.
11. W u, X., S. K a n e k o. Linear and Nonlinear Analyses of Sheet Flutter Induced by Leakage Flow. – Journal of Fluids and Structures, Vol. **20**, October 2005, Issue 7, pp. 927-948.
12. G e, C., G. W a n g, H. Y e. Analysis of the Smallest Detectable Leakage Flow Rate of Negative Pressure Wave-Based Leak Detection Systems for Liquid Pipelines. – Computers & Chemical Engineering, Vol. **32**, 22 August 2008, Issue 8, pp. 1669-1680.
13. F u j i t a, K., H. M o r i k a z u, A. S h i n t a n i. A Consideration on Pre- and Post-Instability of an Axisymmetric Elastic Beam Subjected to Axial Leakage Flow. – Journal of Fluids and Structures, Vol. **23**, April 2007, Issue 3, pp. 463-478.
14. A b b a s i o n, S., A. R a f s a n j a n i, A. F a r s h i d i a n f a r, N. I r a n i. Rolling Element Bearings Multi-Fault Classification Based on the Wavelet Denoising and Support Vector Machine. – Mechanical Systems and Signal Processing, Vol. **21**, October 2007, Issue 7, pp. 2933-2945.
15. M e s i a r, R., A. M e s i a r o v á. Fuzzy Integrals and Linearity. – International Journal of Approximate Reasoning, Vol. **47**, March 2008, Issue 3, pp. 352-358.
16. R o m á n-F l o r e s, H., A. F l o r e s-F r a n u l i č, Y. C h a l c o-C a n o. Fuzzy Integrals. – Applied Mathematics and Computation, Vol. **204**, 1 October 2008, Issue 1, pp. 178-183.
17. L e i, C., P. Z o u. Application of Neural Network in Heating Network Leakage Fault Diagnosis. – Journal of Southeast University, Vol. **26**, 2010, No 2, pp. 173-176.
18. Z h o u, D. H., X. H e, Z. W a n g, G.-P. L i u, Y. D. J i. Leakage Fault Diagnosis for an Internet-Based Three-Tank System: An Experimental Study. – In: Proc. of IEEE Transactions on Control Systems Technology, June 13, 2011.
19. T u n c a y, E., Y. O b a r a. Comparison of Stresses Obtained from Acoustic Emission and Compact Conical-Ended Borehole Overcoring Techniques and an Evaluation of the Kaiser Effect Level. – Bulletin of Engineering Geology and the Environment, Vol. **71**, 2012, No 2, pp. 367-377.
20. D a i, Q., K. N g, J. Z h o u, E. L. K r e i g e r, T. M. A h l b o r n. Damage Investigation of Single-Edge Notched Beam Tests with Normal Strength Concrete and Ultra-High Performance Concrete Specimens Using Acoustic Emission Techniques. – Construction and Building Materials, Vol. **31**, June 2012, pp. 231-242.