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THE APPLICATION OF A NEURAL NETWORK TO CLASSIFY THE ACOUSTIC EMISSION WAVEFORMS EMITTED BY THE CONCRETE UNDER THERMAL STRESS

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In this article Acoustic Emission (AE) measurement results for five different compositions differing in compression strength are presented. Thermal stresses occuring in concrete samples during their cooling after heating up to 150°C in controlled conditions have been the source of AE signals. The influence of structure of frequency spectra of recorded AE signals is described. An automatic recognition procedure of the recorded AE waveforms using neural network is discussed and the details of the learning process of the neural network are shown.

1. Introduction

The thermal working in low-pressure steam environment is in Poland wide introduced technological treatment during production of prefabricated elements [1]. The heating period may usual vary from single to several hours while the hydratation processes in concrete matrix are improving and the presence of hardened regions in the material are formed. The internal stresses occurring in the fast hardening material are the drawback of the described technology, caused by the local temperature gradients and different volume changes of the concrete ingredients. For example the linear thermal expanding rate of the gravel aggregates may be five times smaller than the same parameter of the concrete matrix. The increasing stress concentration in the structure under thermal processing may result in some internal defects as microcracks and porosity increase.

In the following paper the correlation between frequency spectra of the AE signals registered during thermal stress relaxation processes and the compression strength of the different concrete compositions is discussed. The occurrence of the maxima on the spectral pattern of the registered AE waveforms have been used to characterise the certain concrete composition and to determine its strength to be fed into automatic recognition procedure, the spectral patterns were digitised as it is shown in the further sections of this work.

2. Experimental materials and methods

Five concrete compositions, similar to used in [2], are indicated in Table 1. The cement of Grade "35" was used. The specimen were 140 millimeters long, 40

Table 1. Physical and structural parameters of the compositions used for the investigation

Set number	seeming density $[Tm^{-3}]$	specific density $[Tm^{-3}]$	porosity [%]	water to cement ratio	aggregate to cement ratio	sand to cement ratio	compressive strength [MPa]
0	1.20	1.67	34.2	0.4	0	0	48.0
I	2.129	2.559	16.8	0.4	0.45	2.2	43.0
II	2.096	2.560	18.12	0.5	0.33	3.0	37.5
III	2.075	2.564	19.07	0.6	0.23	4.3	23.0
IV	2.054	2.565	19.92	0.65	0.20	5.0	21.8

millimeters wide and 40 millimeters thick. The set labelled "0" was made of mortar while the other sets were made of standard, medium plasticity concrete. All the samples were heated in the oven with controlled temperature gradient. They were left in the temperature 150°C for two hours. Then, after removing from the oven the sample were cooled with use of a fan. The first 20 minutes of the cooling process were used to register the AE signals. Then the inner temperature of the samples came to the ambient value. The temperature sensor was fixed to the sample 50 millimeters from its colder end and 30 millimeters from the same end the wideband AE sensor was mounted. The sensor, type WD SN954 made in Physical Acoustic Corporation performs flat (+/−20 dB) response to the AE signals within the frequency band 50−800 kHz when matched to the block of concrete. The AE signals were amplified and high-pass-filtered (over 25 kHz) with the use of EA200 Acoustic Emission Processor, made in Institute of Fundamental Technological Research. The IWATSU DS 6612C storage oscilloscope was connected to the output of AE processor to capture the AE waveforms. When the amplitude of the AE signal (after 80 dB amplification) was greater than 100 mV, the trigger of the oscilloscope enabled the capturing of 500 microsecond of the AE signal at a sampling rate of 2 MHz. Several hundreds of such waveforms caused by the thermal stresses in the concrete samples under test were stored in the disk of logged — in PC computer with the application of the procedure described above.

3. Spectral characteristic of measured concrete samples

The averaging of 100 AE waveforms for each of 5 tested sets of samples, differing in compression strength was made for the purpose of further processing using neural network. The examples of averaged spectra calculated for the sets labelled as "0", "II" and "IV" are presented in Fig. 1−3. The distinct patterns of presented spectra

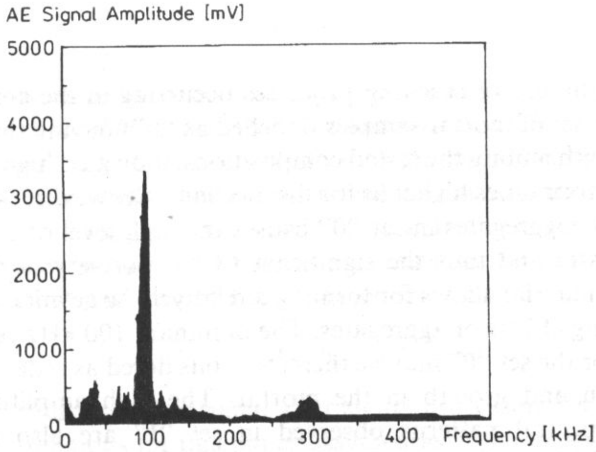

Fig. 1. Averaged spectrum of concrete composition "0", constructed in linear scale. The amplitude of the AE signals was measured after 40 dB amplification.

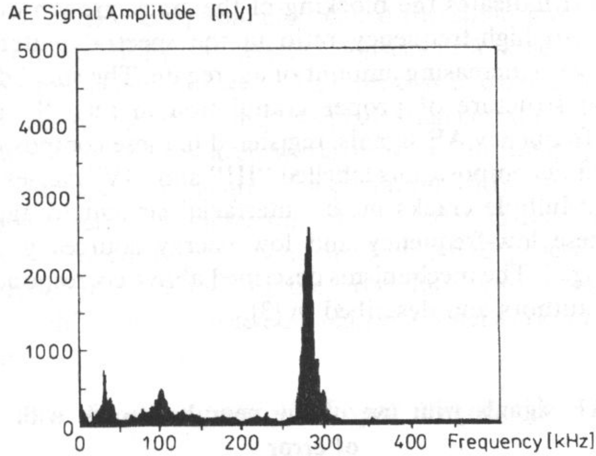

Fig. 2. Averaged spectrum of concrete composition "II", constructed in linear scale. The amplitude of the AE signals was measured after 40 dB amplification.

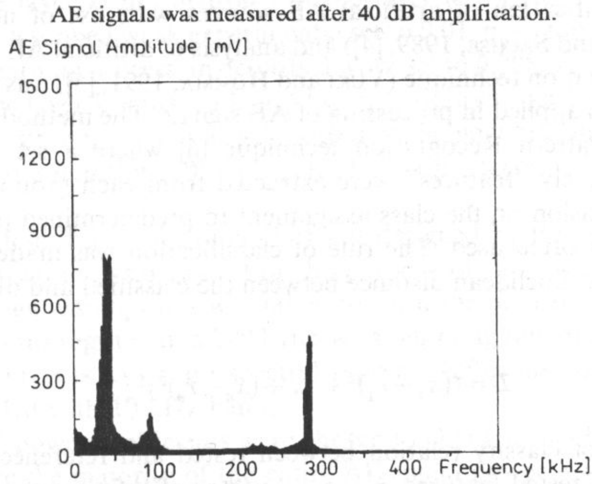

Fig. 3. Averaged spectrum of concrete composition "IV", constructed in linear scale. The amplitude of the AE signals was measured after 40 dB amplification.

are related to the nature of cracking processes occurring in the compositions under investigation. The set of mortar samples (labelled as "0") having the highest value of compressive strength among the tested compositions, indicated high — amplitude EA pulses — approx. four times higher as for the mechanically weakest set, labelled "IV". The absence of the aggregates in set "0" causes the high level of contraction during fabrication processes and thus the significant (34%) porosity of the material. The structure of such material allows for forming a relatively large microcracks due to the lack of the blocking effects of aggregates. The dominant 100 kHz components of the spectral pattern for the set "0" may be therefore considered as reflecting the processes of crack initiation and growth in the mortar. The high amplitudes of 100 kHz components of spectral patterns observed in set "I" are also related with the mechanism described for the pure mortar. The low contents of aggregates for this set let us suppose that the dominant effects here are appears in the spectral pattern of set "I". The latter effect indicates the blocking of the crack growth due to aggregates. The different low- to high-frequency ratio in the spectral patterns is present in samples composed with increasing amount of aggregate. The small dimensions of the cracks, blocked on structure of proper granulation in sets "I" and "II" enable generation of high frequency AE signals, registered in these compositions. More sand and aggregates used in compositions labelled "III" and "IV" causes the compression strength decrease. Multiple cracks in the interfacial cement to aggregate zone are observed here. These low-frequency and low energy sources produce a spectral pattern shown in Fig. 3. The mechanisms described above correspond with the results obtained by other authors and described in [3].

4. Processing of AE signals with use of the neural network with backpropagation of error

Since an identification of artificial AE sources with use of neural associative memory (Grabec and Sachse, 1989, [4]) and analysis of artificial AE waveforms using neural backpropagation technique (Yuki and Homma, 1991, [5]) was made, the neural network analysis is applied in processing of AE signals. The method has replaced the previously used Pattern Recognition technique [6] where a set of characteristic measurements, namely "features" were extracted from each grouping of measured data. To make decision on the class assignment to predetermined pattern the linear classifier was most often used. The rule of classification was made on the basis of finding the minimal Euclidean distance between the classified and different reference sets of features:

$$D=((x_1-r_1)^2+\dots+(x_n-r_n)^2)^{1/2}. \tag{4.1}$$

Here: D distance of classify relation between tested and reference set of features, $x_1 \dots x_n$ — vector of tested features, $r_1 \dots r_n$ — vector of reference features.

The described above linear classifier seemed to be insufficient to determine within the class of *linear non separable vectors* (MINSKY and PAPPERT, 1969 [7]). The non-linear neural backpropagation algorithm is able to solve the problem. Neural networks are computer models of circuits composed of multi-input vs. angle output elements (neurons) connected in serveral chains called layers. Each neuron output (except the output layer) is connected with all the neurons, consisting the next layer. The relation between element input and output signal can be expressed as:

$$y_j(t+1)=\theta(\Sigma_j w_{ij}x_j(t)-\mu_i). \tag{4.2}$$

Here: $y_i(t+1)$ — neuron output signal after signal processing cycle, θ — one of the neural activation functions [in this paper assumed as $1/(1+\exp(-x))$], w_{ij} — called a weighting coefficient a synaptic weight which expresses the bonding strength, between connected neurons labelled j and i, $x_j(t)$ — neuron input signal before signal processing cycle, μ_i — process parameter, called threshold level.

The computer model of neural network consists of a table of weight coefficients, being modified in the *learning process*. This process is carried out to vary synaptic weights to obtain desired network output signal when certain signal is fed to input of the network. The aim of the research work presented in this paper was to form the network output signal as a measure of association with one of the five averaged acoustic emission spectra characterising the tested concrete compositions. Each weight was changed according to wide used iterative procedure called "backpropagation of error" [8]. The idea of the procedure is to make a weight changes proportional to the difference between the temporary network output and the desired (optimal) output:

$$\Delta w_{ij}{}^{(k)}=\eta_1(d\theta(E_i)/dE)\,x_j\,\delta_i{}^{(k)}+\eta_2 m_{ij}{}^{(k+1)}. \tag{4.3}$$

Here: θ — activation function, $\Delta w_{ij}{}^{(k)}$ — weighting coefficient between neuron labelled i in the layer k and neuron j in the layer $(k-1)$, η_1 — parameter called learning rate, in described work experimental set to 0.01, η_2—momentum, parameter optimising the learning process, in described work set to 0.008, E_i— total excitation of j-th neuron in the layer k, equal to $\Sigma_j w_{ij}{}^{(k)}x_j$, z_i —desired signal at i-th output of the network, y_i — temporary signal at i-th output of the network, m_{ij} — weight change used in the previous iteration, $\delta_i^{(k)}-z_i-y_i$ for the output layer or $\Sigma_1 w_{1i}{}^{(k)}\,\delta_1^{(k+1)}$ for the other layers.

Algorithm, described as formula (3.3) was designed by P.J. Werbos in 1974 but was wider practised ten years ago. For the purpose of the research work described here, the following assumptions was taken to form the data processing procedure:

- AE waveforms registered in 200 bytes with sampling rate of 2 MHz were used in averaging process to obtain spectral power coefficients while each coefficient corresponded with 10 kHz band,
- 31 spectral power coefficients were chosen to characterise the range of 30–310 kHz, where the majority of the entire AE signal power is included,

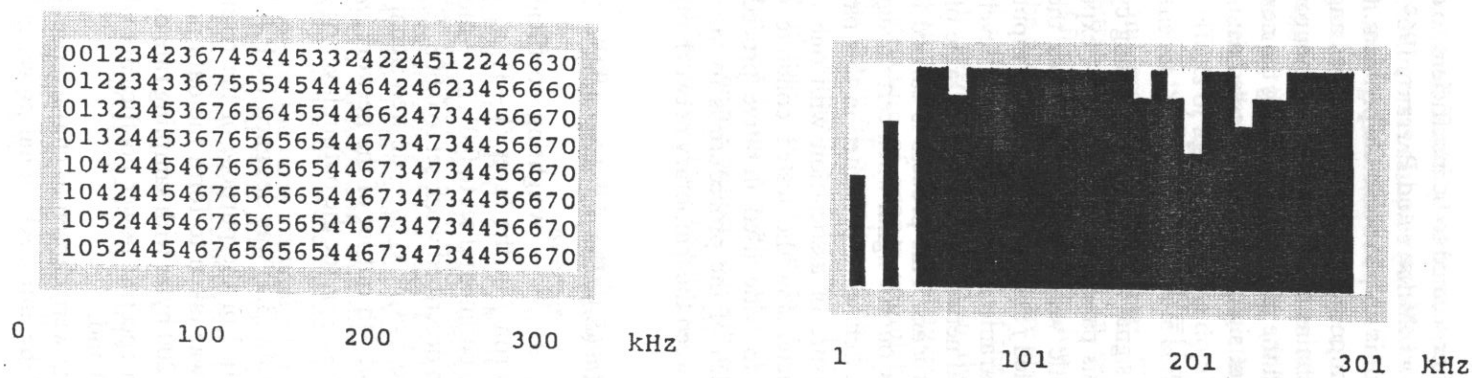

Fig. 4: Number of the occurrences of certain patterns elements for waveforms registered in composition labelled "0" (left). The averaged pattern for these waveforms (right).

- the used neural network was able to analyze 8 signal levels of the values of discretized spectral power coefficients (the discretization was set up every 6 dB of the signal level),
- this spectral modelling scheme required 31 times 8 binary inputs to the network, connected to 62 neural units used in the first layer,
- the second layer consisted of five neurons to generate five output signals due to association between the input signals and five learned patterns.

The following procedure was used to prepare the five spectral patterns representative for five tested concrete compositions. Seven most typical AE waveforms were chosen for each composition and their discrete spectral patterns were combined at one graph. The left side of the Fig. 4 presents the numbers proportional to the occurrences of certain pattern elements in seven waveforms registered for composition labelled "0". The pattern element was used in the learning process if it was present in not less than in three waveforms used to compare. The averaged pattern for composition labelled "0" is shown at the right side of Fig. 4. The Fig. 5 and 6 present the averaged patterns obtained for the compositions labelled "II" and "IV".

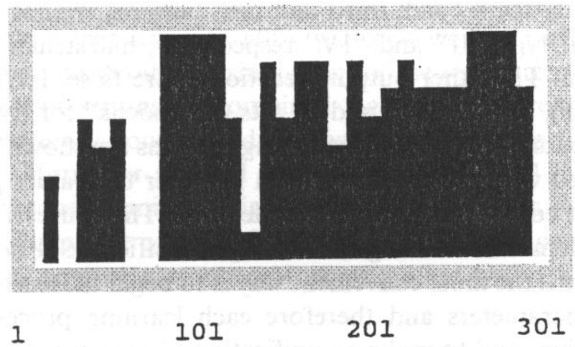

Fig. 5. The averaged pattern constructed for the waveforms registered in composition labelled "II".

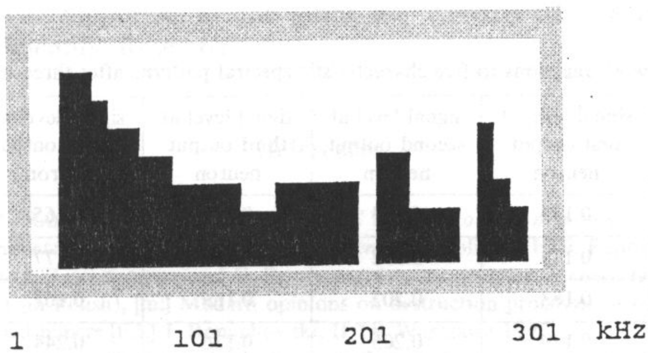

Fig. 6. The averaged pattern constructed for the waveforms registered in composition labelled "IV".

5. Process of learning the neural network

The main shortcoming of the backpropagation method of learning the network is longer period of the iterative process when comparing to other methods. The advantage of backpropagation is its algorithm — simple and therefore easy to modify the size of processed binary pattern. The important point is that time required for the single iteration step is proportional to the number of the network interconnections. Such iteration step called "epoch" lasted aporox. 0.3 s for the network configuration described in Section 3 when executed on PC 486 DX/40 MHz computer. 800 sets of repetitions had to be run to complete the learning process. The operation of comparing the learned pattern and test signal took approx. 1 s. The procedure of learning the network consisted of several steps. Five spectral patterns, corresponding to five concrete compositions were presented in controlled order to overcome the effect of gradual disappearing of previously formed associations when the new associations were formed. After the three series of learning steps (400, 300 and 50 sets of "epochs" for each pattern) the network was able to produce the signals at its outputs as it is shown in Table 2. The values presented in five consecutive rows of the table correspond with the network reactions to presentation of five characteristic spectral patterns. Only the second, third and fifth outputs, trained to be associated with compositions of type "II" and "IV" respectively, had achieved the ability of proper determination. The other outputs reactions were false. In the next part the three series of learning steps (25, 20 and 15 sets of "epochs" for five patterns) were performed. The outputs obtained for five testing patterns are shown in Table 3. Each output was associated with the proper pattern however the values generated as the reaction for different compositions were not identical. The cause of this effect is the influence of the random initial setting of the weight coefficients. For large sets of the neural interconnections the most convenient way is to begin the learning process with randomised initial parameters and therefore each learning process comes to the unique final equilibrium and to make an unification of output signals the additional signal processing is required.

Table 2. Network reactions to five characteristic spectral patterns after three series of learning

pattern symbol	signal level at first output neuron	signal level at second output neuron	signal level at third output neuron	signal level at fourth output neuron	signal level at fifth output neuron
0	0.179	0.184	0.140	0.165	0.114
I	0.179	0.212	0.154	0.177	0.125
II	0.183	0.202	0.169	0.167	0.126
III	0.179	0.205	0.136	0.244	0.135
IV	0.175	0.200	0.137	0.224	0.139

Table 3. Network reactions to five characteristic spectral patterns after six series of learning

pattern symbol	signal level at first output neuron	signal level at second output neuron	signal level at third output neuron	signal level at fourth output neuron	signal level at fifth output neuron
0	0.195	0.236	0.263	0.119	0.211
I	0.186	0.277	0.275	0.130	0.223
II	0.192	0.259	0.311	0.120	0.220
III	0.182	0.202	0.161	0.219	0.221
IV	0.174	0.238	0.210	0.216	0.254

6. Conclusions

After completion of learning process where the averaged spectral patterns were used, reactions of the network for real signal patterns presentation were tested. The proper outputs for the patterns of type "III" was observed in 67% of all cases however for other types approx. 60% patterns were classified right. It can be explained with the considerable dissimilarities of the real patterns and the occurrence of sample signals representing the combined character of more than one spectral type. Considering these limitations the adaptative algorithm able to determine different categories of waveforms or spectral patterns may be useful in practise to examine large records of acoustic emission signals. The collected sets of data concerning the different standard concrete compositions can be used to compare with tested samples during the routine compression strength investigation.

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