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Neural networks for the analysis of mine-induced building vibrations

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A study of the capabilities of artificial neural networks in respect of selected problems of the analysis of mine-induced building vibrations is presented. Neural network technique was used for the prediction of building fundamental natural period, mapping of mining tremors parameters into response spectra from ground vibrations, soil-structure interaction analysis, simulation of building response to seismic-type excitation. On the basis of the experimental data obtained from the measurements of kinematic excitations and dynamic responses of actual structures, training and testing patterns of neural networks were formulated. The obtained results lead to a conclusion that the neural technique gives possibility of efficient, accurate enough for engineering, analysis of structural dynamics problems related to mine-induced excitations.

Keywords: neural network, neural simulation, data compression, data pre-processing, mining tremors, experimental data.

1. Introduction

Structural vibrations induced by ground motion can be caused not only by earthquakes but also by human activity. Some of the sources of paraseismic excitations such as, for instance, traffic vibrations, industrial explosions and mining tremors in strip mines can be inspected and controlled. On the other hand, mining tremors resulting from underground raw mineral material exploitation are random events. Mine-related underground shocks excite seismic waves that reach the surface of the earth and induce building vibrations. Although these tremors are connected with the human activity and can usually be observed only in mining regions, they differ considerably from other paraseismic vibrations. They are not subject to human control and they are random events with respect to time, place and magnitude likewise earthquakes. However, some parameters of such ground vibrations (e.g. dominating frequencies, duration) are different from earthquake-induced ground vibrations [20].

The evaluation of dynamic properties and dynamic response of a building subjected to mine-induced excitations is a very important issue in structural dynamics. But there are many problems related to full-scale experimental tests on actual buildings. On the other hand, there are a lot of difficulties with material, structural and load modelling in the case of formulation of a model of building in many computational methods (first of all the Finite Element Method).

Neural network technique was used for the prediction of building fundamental natural period, mapping of mining tremors parameters into response spectra from ground vibrations, soil-structure interaction analysis, simulation of building response to seismic-type excitation [6, 15, 19].

Mining tremors in strip mines (measurements were performed by the Institute of Structural Mechanics, Cracow University of Technology) and in the most seismically active mining regions in Poland with underground exploitation – Upper Silesian Coalfield (USC) and Legnica-Glogow Copperfield (LGC) (measurements come from the surface seismological measurement stations) – were the sources of building vibrations. The results of long-term experimental monitoring of actual structures, e.g. [2, 6, 10, 16], were synthetically collected.

The database built of the experimental data obtained from the measurements of kinematic excitations and response building vibrations makes it possible to use them as patterns to design neural network analysers for investigation of building dynamic problems. In some cases pre-processing methods of experimental data are applied: introduction of linguistic variables (fuzzy inputs) and compression. Two methods are proposed for input data compression. In the first approach the back-propagation neural network designed as an auto-associative network – replicator is applied [4, 17]. Compression of data to principal components by the principal component analysis (PCA) is the second method discussed [4, 14].

Types of problems analysed with neural networks application are synthetically presented in Table 1. Additionally, information about the components of the neural network input and output vectors and variants of the experimental data pre-processing methods is also included in the table.

Table 1. Types of problems analysed with neural networks application.

Problem	Neural network		Variants of actual data pre-processing methods
	input	output	
Prediction of building fundamental natural period	– foundation flexibility – parameters corresponding to building stiffness and dimension	fundamental natural period	– without data pre-processing – introduction of the linguistic variables (fuzzy inputs) – compression using PCA
Mapping of mining tremors parameters into response spectra from ground vibrations	mining tremor parameters	normalized acceleration response spectrum from ground vibrations	without data pre-processing
Soil-structure interaction	– maximal value (amplitude) of ground vibrations – mining tremor parameters	comparison of the maximal value (amplitude) of vibrations recorded at the same time on the ground and on the foundation level	without data pre-processing
	– record of ground acceleration vibrations compressed to the first principal component – mining tremor parameters	comparison of the maximal value (amplitude) of vibrations recorded at the same time on the ground and on the foundation level	compression using PCA
	response spectrum from the ground vibrations	response spectrum from the building foundation vibrations	without data pre-processing
Simulation of building response to seismic-type excitation	description of excitation vibrations and information about the dynamic properties of the building	dynamic response of the building	replicator

2. Experimental data and variants of actual data pre-processing methods

Measurements were carried out on thirteen typical apartment medium-height (five-storey) buildings with load-bearing walls. All the buildings are founded directly on the ground on concrete strip foundations. Full-scale tests were performed many times over a period of many years (monitoring) [2, 6, 10, 16]. Explosions in nearby quarries as well as rockbursts in USC and LGC regions with the underground coal (USC) and copper ore (LGC) exploitation were the sources of ground and actual buildings vibrations. Seismographs or accelerometers were installed on the ground in front of the buildings (in six meters distance), on the basement level inside the buildings and on the highest floor of the buildings. Displacements and accelerations were measured. Velocities were obtained by acceleration records integration. The tests included measurements of horizontal vibration components in two mutually perpendicular directions, parallel to the transverse (x) and longitudinal (y) axis of the buildings. Attention was focused on the horizontal vibration components because of their essential role in the responses of surface structures. Figure 1 shows examples of the horizontal components of vibrations in the time domain (accelerations in transverse direction x) recorded at the same time on the ground in front of the building, in the building on the foundation level and on the highest floor level. The vibrations from Fig. 1 were caused by rockburst in LGC region with energy $En = 7.3 \times 10^7$ J and epicentral distance $re = 899$ m.

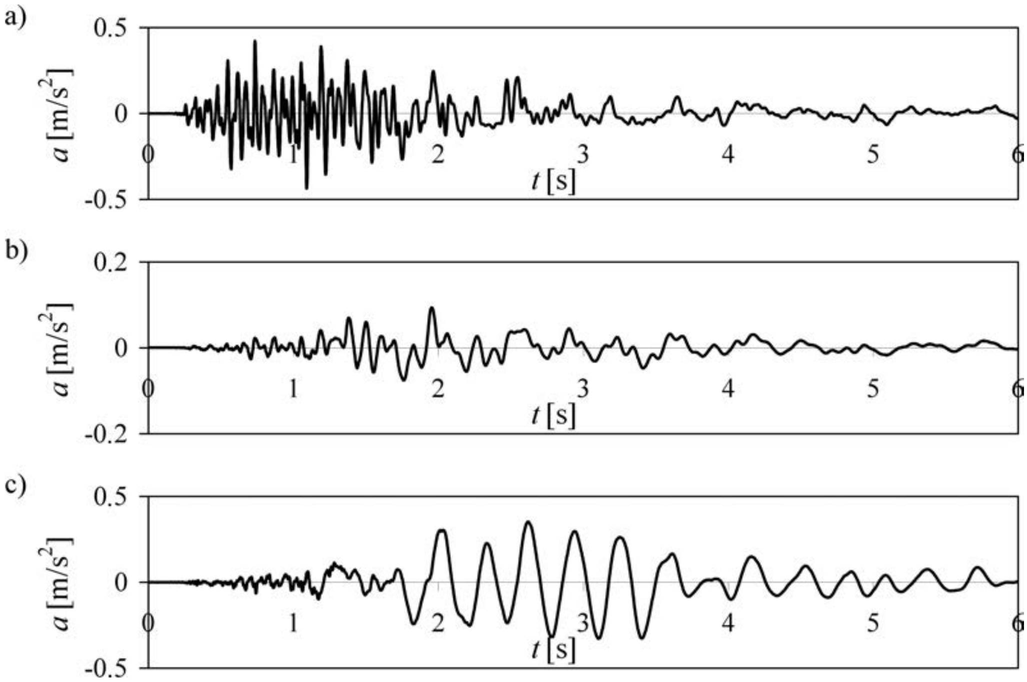

Fig. 1. Records of vibrations induced by mining tremor ($En = 7.3 \times 10^7$ J, $re = 899$ m): a) ground level, b) foundation level, c) the highest floor level.

Some of the parameters used as neural networks input data are estimated as approximate – mean values from the ranges found experimentally. Foundation flexibility expressed by the coefficient of elastic uniform vertical deflection of the ground C_z [MPa/m] is one of them. Soils of small, medium and large stiffness are classified in the Polish code [18]. Therefore the linguistic variables associated with the fuzzy character of such parameters are introduced in the neural network analysis.

Triangular membership functions are adopted. Symmetric triangular membership function can be described as follows:

$$\mu_{\mathrm{F}} = \begin{cases} 1 - \dfrac{|x-c|}{d} & \text{for} \quad x \in |c-d, c+d|, \\ 0 & \text{out of the range.} \end{cases} \tag{1}$$

Next, instead of crisp values, linguistic variables $\{\mu_S,\ \mu_M,\ \mu_L\}$ are introduced, where: μ_S, μ_M, μ_L – values of membership functions for small, medium and large corresponding parameter, respectively. In Fig. 2 the membership functions proposed in case of soil parameters C_z are shown.

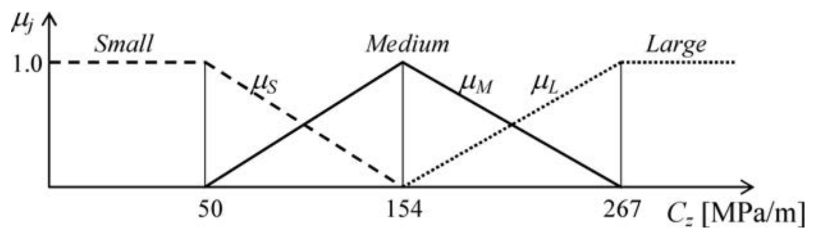

Fig. 2. Triangular membership functions for values of soil parameters C_z.

The application of vibration records in the time domain leads to some computational difficulties related to the "size" of the data. Hence the pre-processing (compression) of the experimental data using as the first way auto-associative network – replicator [4, 17] or principal component analysis (PCA) [1, 4, 14] as the second way is proposed.

The compression of the input as well as output data makes it possible to design much smaller neural networks than those without data compression, i.e. reduction of the number of network parameters and improvement of network generalization properties follow. The basic idea of data compression is to "diminish" the "size" of information with the possibility of data reconstruction (decompression). The advantages of application of the techniques for data compression in case of records of ground and building vibrations (displacements, velocities and accelerations) are shown [7, 12, 13].

Replicator is a back-propagation neural network (BPNN) designed as a network for auto-associative mapping of input vectors into output vectors – the output is replication of input. It can be split into the compressor and decompressor of data. The signals from the hidden layer of the network are used as the components of the compressed input vector. The second part of the network (hidden and output layers) works as the decompressor. It is also possible to design autonomous, additional network for data decompression.

Replicator as a method of reduction of input or output vectors dimensionality was used among others in case of the compression of building responses for the excitations caused by explosions in nearby quarry. The replicator was taken as BPNN: 620–n–620. The number of $N = 620$ inputs/outputs corresponds to parts composed of $N = 620$ successive values of displacements from each record of displacement in time domain $d(t)$ registered on the highest floor of the building, and $n = 9$ neurons were proposed in the hidden layer. Than the compression ratio of building response data was $620/9 = 68.9$. It was stated that 96% of neurons had relative errors less than 5%. The compressed values had to be decoded in order to simulate the displacement records in time domain. Decompression was performed by a part of replicator called decompressor BPNN: 9–620. The process led to the conclusion that the records neurally obtained were very close to the measured records. Figure 3 illustrates one of the experimental and neurally simulated displacement records as an example.

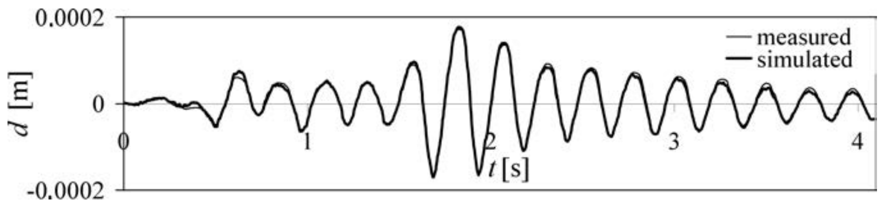

Fig. 3. Measured and neurally simulated (reconstructed using replicator) displacements of highest building floor in case of excitations caused by explosions in nearby quarry.

The PCA method relates to linear transformation of process description in the form of N-elements vector $\mathbf{x}$ into K-elements vector $\mathbf{y}$, using matrix $\mathbf{W} \in R^K \times R^N$. Since $K < N$, the size of vector $\mathbf{y}$ is reduced as compared to $\mathbf{x}$. So the PCA transformation changes the great number of input data into a set of components according to their importance [1, 4]. The reconstruction of vector **x** (with the reconstruction error) is possible on the basis of vector **y** and matrix **W**. Therefore the transformation into principal components enables determination of the correlation between a great number of variables in a data set. If these variables are correlated, only a part of them is sufficient to define the remaining data. So a smaller number of variables could represent the entire data set.

The PCA method was applied, among others, to compression of the ground acceleration and velocity vibration records from mining tremors in LGC region [7]. For this purpose, the fragments (vectors) composed of $N = 1500$ successive values of accelerations as well as velocities from each of the ground records experimentally obtained were taken to account respectively. In the all cases of the records considered (acceleration and velocity records), the relative contributions of the principal components to the total variance of data were computed. Looking at the values distribution it is clear that the first principal component reaches more than 99% part of the total variance of data in all the cases of vibration records experimentally measured. Then the first principal component is predominant. Therefore, considering the records of vibrations (accelerations as well as velocities), it is sufficient to take only the greatest principal components. The other principal components can be neglected, because they do not affect the information substantially. So 1500 successive values of the accelerations in each of the vectors of accelerations as well as 1500 successive values of the velocities in each of the vectors of velocities can be replaced with one parameter only – the first principal component and the "size" of information can be 1500 times smaller. Thus it makes it possible to compress the vector significantly.

Only the first principal components of the records of acceleration and velocity vibrations were taken to reconstruction of the full records of vibrations in time domain. In Fig. 4 examples of the acceleration and velocity ground records from LGC region are compared: the experimental and reconstructed using PCA method. It was stated that for all the patterns of acceleration and velocity vibrations the simulated records were very close to the measured records. They were nearly the same.

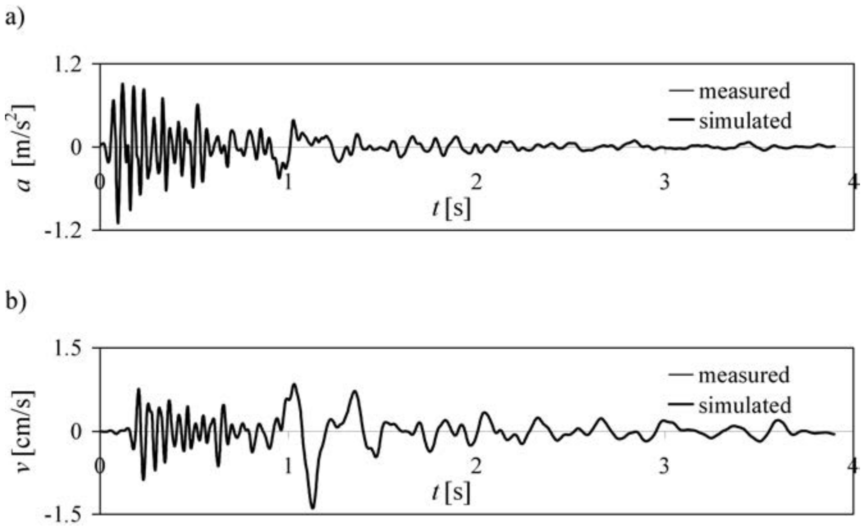

Fig. 4. Comparison of acceleration (a) and velocity (b) ground vibration records measured and simulated (reconstructed) using PCA method in case of mining tremor from LGC region ($En = 5.4 \times 10^7$ J, $re = 920$ m).

3. Analysed problems

3.1. Introductory remarks

Back-propagation neural networks (BPNNs) with the resilient back-propagation learning method and sigmoid activation function [4, 15, 19], networks with radial basis functions (RBFNNs) [4] and fuzzy neural networks of ANFIS type [5] were trained and tested on the basis of experimental data obtained from long-term measurements performed on actual structures. The results of neural network analysis were compared with the results of experiments.

The accuracy of network approximation was evaluated by mean-square-error $MSE(V)$, standard error $st\varepsilon(V)$ and relative errors ep_i, ep, eV_{avr}:

$$MSE(V) = \frac{1}{V \cdot M} \sum_{p=1}^{V} \sum_{i=1}^{M} \left(z_i^{(p)} - y_i^{(p)} \right)^2, \tag{2}$$

$$st\,\varepsilon(V) = \sqrt{\frac{1}{V \cdot M} \sum_{p=1}^{V} \sum_{i=1}^{M} \left(z_i^{(p)} - y_i^{(p)} \right)^2}, \tag{3}$$

$$ep_i = \left(1 - y_i^{(p)}/z_i^{(p)}\right) \cdot 100\%, \qquad |ep_i| = \left|1 - y_i^{(p)}/z_i^{(p)}\right| \cdot 100\%, \qquad ep = \frac{1}{M} \sum_{i=1}^{M} |ep_i|, \tag{4}$$

$$eV_{\mathrm{avr}} = \frac{1}{V \cdot M} \sum_{p=1}^{V} \sum_{i=1}^{M} |ep_i|, \tag{5}$$

where $z_i^{(p)}$, $y_i^{(p)}$ – target and neurally computed i-th outputs for p-th pattern, M – number of outputs, $V = L,\ T,\ P$ – number of learning (L), testing (T) and all (P) patterns, respectively.

Besides, the linear regression coefficient $r(V)$ was computed for every set of pairs $z_i^{(p)}$, $y_i^{(p)}$. The numerical efficiency of the trained network was also evaluated by the success ratio SR. This function enables us to evaluate what percentage of patterns SR [%] gives the neural prediction with the error not greater than ep [%].

3.2. Prediction of building fundamental natural period

Neural networks are used for computation of fundamental natural periods of vibration of thirteen medium height (five-storey) buildings investigated. The identification problem is formulated as a relation between structural and soil parameters, and the fundamental period of building vibrations. In the light of full-scale tests of the analysed buildings it can be stated [16] that the soil-structure interaction plays an important role in vibrations of medium height buildings. Foundation flexibility is expressed by the coefficient of elastic uniform vertical deflection of the ground C_z. The next representative parameter is the building dimension in the direction of vibrations b. Other parameters correspond to the equivalent bending stiffness $s = \sum_i EI_i/a$ and equivalent shear stiffness $r = \sum_i GA_i/a$, where: E, G – elastic and shear moduli, respectively; I_i, A_i – moment of inertia and cross-sectional area of the i-th wall in the building plan, a – length of building.

These parameters were taken as the variables in the input vectors $\mathbf{x}$ of neural networks – in the simplest neural network: $\{C_z,\ b\}$ and in a more extended neural network input vector (with more extended input information): $\{C_z,\ b,\ s,\ r\}$. The building fundamental natural period T_1 was the output of the network [11].

Better accuracy of neural fundamental period prediction and reduction of the number of network training epochs can be obtained as a result of introduction of a linguistic variable $C_l = \{\mu_S,\ \mu_M,\ \mu_L\}$ instead of crisp variable C_z, where: μ_S, μ_M, μ_L – values of membership functions for small, medium and large rigidity of soil, respectively, corresponding to triangular membership functions shown in Fig. 2 [15].

The input data pre-processing associated with the application of PCA is the next proposition in neural identification of fundamental natural building periods [14]. Data compression by decomposition according to principal components deals with the analysis of correlation between the parameter of foundation flexibility – C_z and the three parameters describing building: dimension in the direction of vibrations – b, equivalent bending stiffness – s, equivalent shear stiffness – r. Looking at the values distribution, it is clear that the first principal component is predominant. Therefore, considering the building parameters, it is sufficient to take only the greatest (the first) principal component $y_1(C_z, b, s, r)$. The other principal components can be neglected, because they do not affect the information substantially. So the four parameters in the input vector can be replaced with one parameter only – the first principal component and the "size" of information may be smaller. Thus it makes it possible to compress the input vector.

The errors corresponding to the training and testing processes for the applied neural networks are listed in Table 2. Additionally, Fig. 5 presents a comparison of success ratio *SR* for prediction of building fundamental periods using one type of networks – the BPNNs.

Table 2. Errors of natural building periods identification using different types of neural networks.

Input parameters	Network		$MSE(L)$	$MSE(T)$	eV_{avr}[%]			$r(P)$	$st\,\varepsilon$(P)
					L	T	P		
b, C_z	a	BPNN: 2 – 3 – 1	0.00025	0.00120	6.5	12.5	7.5	0.873	0.020
	b	RBFNN: 2 – 4 – 1	0.00069	0.00084	10.3	11.0	10.4	0.763	0.027
b, μ_S, μ_M, μ_L	a	BPNN: 4 – 3 – 1	0.00014	0.00098	4.9	10.3	5.8	0.916	0.017
	b	RBFNN: 4 – 5 – 1	0.00062	0.00052	9.8	6.7	9.3	0.804	0.025
b, C_z, s, r	a	BPNN: 4 – 4 – 1	0.00008	0.00032	3.0	5.8	3.5	0.964	0.011
	b	RBFNN: 4 – 5 – 1	0.00034	0.00028	6.4	6.4	6.4	0.899	0.018
	c	ANFIS	0.0000001	0.00027	0.15	7.3	1.3	0.987	0.007
$y_1(b, C_z, s, r)$	a	BPNN: 1 – 2 – 1	0.00032	0.00019	7.0	5.3	6.7	0.901	0.017
	b	RBFNN: 1 – 3 – 1	0.00069	0.00036	10.6	7.6	10.1	0.766	0.025
	c	ANFIS	0.00026	0.00019	5.5	5.0	5.4	0.917	0.016

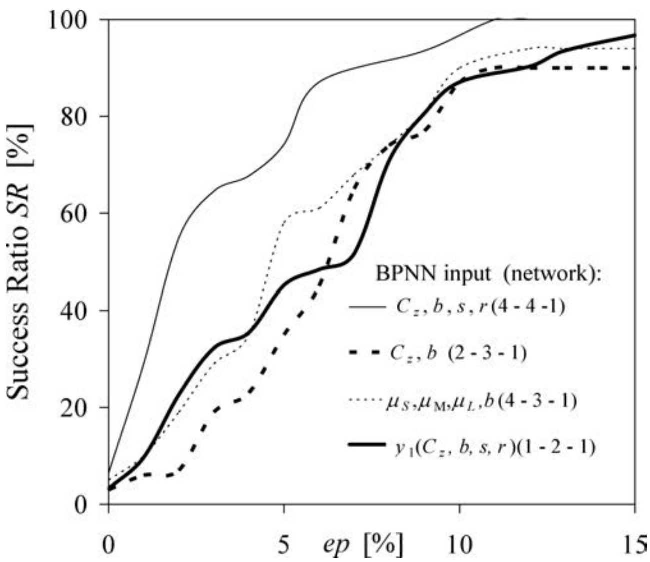

Fig. 5. Comparison of success ratio *SR* for prediction of building fundamental periods using BPNNs.

The analysis performed leads to the conclusion that the application of all the proposed neural networks enables us to identify the natural periods of buildings with accuracy quite satisfactory for engineering practice.

3.3. Mapping of mining tremors parameters into response spectra from ground vibrations

Because of economic and practical reasons, in engineering practice, recording of actual kinematic excitation is not possible for each building in mining regions. Moreover, prediction of real vibration effects of expected mining tremors is very difficult. Therefore the problem was formulated as the neural network evaluation of a relation between mining tremor energies, epicentral distances and acceleration response spectra.

Comparison of many records from both regions leads to the conclusion that typical vibrations in both mining regions differ significantly. So USC and LGC regions are analysed separately. The analysis relates to all the measured mining tremors, regardless of their harmfulness.

All the recorded experimental data in form of accelerations in time domain corresponding to both mining regions (USC and LGC) were first pre-processed. From all the accelerations, the nondimensional acceleration response spectra β were computed ($\beta = S_a/a_{\max}$; where S_a – acceleration response spectrum, $a_{\max}$ – maximum value of acceleration amplitude). They are so-called conventionally computed response spectra. The fraction of critical damping $\xi = 2\%$ was assumed [3].

The following input vector was proposed:

$$\mathbf{x}_{(3\times 1)} = \{En,\ re,\ T_i\}, \tag{6}$$

where En – mining tremor energy, re – epicentral distance, T_i – vibration period.

The corresponding value of nondimensional acceleration response spectrum computed for T_i vibration period was expected as the output of neural network:

$$\mathbf{y}_{(1\times 1)} = \beta(T_i). \tag{7}$$

Additionally, decomposition of the problem was discussed [8]. For this purpose each of the acceleration response spectra was divided into two parts: (a) and (b). It results from the fact that in each of the curves of the nondimensional acceleration spectra from mining tremors in USC and LGC regions, two different parts can be marked out. The first one (a), for $T_i \in [0.02, 0.25]$ s, contains the fragment of the curve of the response spectrum (drawn versus periods of natural vibrations) with a great number of relative extremes. However, the second one (b), for $T_i \in [0.27, 1.3]$ s, is almost smooth, cf. e.g. Fig. 6.

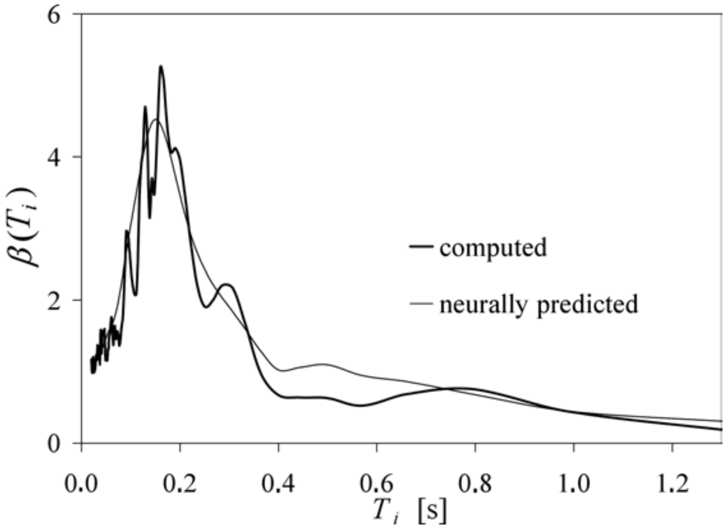

Fig. 6. Comparison of nondimensional acceleration spectra in LGC region ($En = 1.3 \times 10^8$ J, $re = 2633$ m) computed on the basis of measured vibrations and neurally predicted.

The errors corresponding to the training and testing processes for the applied networks for LGC region are listed in Table 3. In Fig. 6 an example of comparison of nondimensional acceleration spectra computed on the basis of measured vibrations and neurally predicted is shown.

Table 3. Errors of neural networks for LGC region.

Neural networks		$MSE(V)$		eV_{avr} [%]			$r(P)$	$st\,\varepsilon(P)$
		$MSE(L)$	$MSE(T)$	L	T	P		
with decomposition	part (a) 3-9-6-1	0.00625	0.00778	21.4	25.1	22.1	0.531	0.081
	part (b) 3-7-1	0.00213	0.00211	18.7	22.7	19.5	0.714	0.046
	(a)+(b)	–	–	21.3	24.9	22.0	0.576	0.079
without decomposition: 3-12-6-1		0.00600	0.00780	21.3	25.6	22.2	0.562	0.080

It was stated that the neurally predicted spectra on the basis of energies and epicentral distances only are very close to the corresponding conventionally computed spectra in case of both USC and LGC regions. The accuracy of the obtained results in case of the two considered neural analyses: without decomposition and with decomposition is nearly the same. But decomposition of the problem makes it possible to reduce the number of neural networks learning epochs and to use much smaller networks for prediction of smooth fragments of response spectra.

The main advantage of the neural approach is that prediction of acceleration response spectra can be performed without recording of surface vibrations. Then the presented way of response spectra computation can be applied to the prognosis of mining tremors influences on structures.

3.4. Soil-structure interaction

Soil-structure interaction plays an important role in the design process of structures subjected to ground motion and is a very important problem from the engineering point of view. Prognosis of structural response to ground vibrations together with estimation of the way of the ground vibration transmissions to basements are indispensable.

Comparison of a huge number of records of vibrations induced by mining tremors (accelerations and velocities) measured at the same time on the ground and on the building foundation level leads to the conclusion that they differ significantly [9, 10]. Additionally, evaluation of mining tremors transmissions to a building is very difficult. The influence of rockburst parameters as mining tremor energy, epicentral distance and the direction of vibrations on the soil-structure interaction effect can be observed. However, prediction of precise relation between ground and foundation records of accelerations and velocities is not possible.

More precise estimation of the harmfulness of mine-induced vibrations to actual buildings can be performed on the basis of building foundation vibrations. In view of the fact that in many cases, for example in design procedure of new structures and in the dynamic analysis of existing buildings, measured ground vibrations are the only accessible, prediction of foundation vibrations is necessary.

Taking into account the difficulties in soil-structure interaction analysis in the case of vibrations induced by mining tremors, the application of neural networks for prediction of building foundation vibrations on the basis of ground vibrations taken from measurements is proposed.

Pre-processing (compression) of the ground vibrations obtained through experimental tests using principal component analysis was carried out, and the influence of mining tremors parameters such as mining tremor energy and epicentral distance on soil-structure interaction effect is also taken into account.

In case of accelerations, the comparison of maximal values (amplitudes) of vibrations recorded at the same time on the ground ($a_{g\,\max}$) and on the foundation ($a_{f\,\max}$) level was the way to estimate vibrations transmission from the ground to the building. For this purpose ratio $ra = a_{f\,\max}/a_{g\,\max}$ was computed.

The aim of the study is to apply neural networks for prediction of ratio ra on the basis of the corresponding mining tremor parameters and compressed ground vibration record.

The following neural network input vector was proposed:

$$\mathbf{x}_{(4\times1)} = \{yag_1,\ En,\ re,\ k\}, \tag{8}$$

where yag_1 – record of ground acceleration vibrations compressed to the first principal component; En – mining tremor energy; re – epicentral distance; k – parameter related to the direction of vibrations, values $k = 0.4$ and $k = 0.7$ were assumed for the transverse direction (x) and longitudinal direction (y), respectively.

The corresponding value of ratio $ra = a_{f\,\max}/a_{g\,\max}$ was expected as the output of the neural network:

$$\mathbf{y}_{(1\times1)} = \{ra\}. \tag{9}$$

Analogous approach was proposed for velocities.

In case of accelerations, the neural network of structure 4 – 6 – 4 – 1 was adopted for practical applications for the sake of the network "size" and good accuracy. Using this network leads to the relative errors less than 30% in the case of 88% of all the patterns: $SR(30\%) = 88\%$. The errors corresponding to this network training and testing processes are given in Table 4. In Fig. 7 a comparison of the results by neural network with the experimental ones is shown. In this figure the bounds of relative errors $ep = 30\%$ are marked.

Table 4. Errors of training and testing processes for network 4 – 6 – 4 – 1.

$MSE(L)$	$MSE(T)$	eV_{avr} [%]		$r(V)$		$st\,\varepsilon(V)$	
		L	T	L	T	L	T
0.00350	0.00533	13.5	18.9	0.941	0.883	0.077	0.095

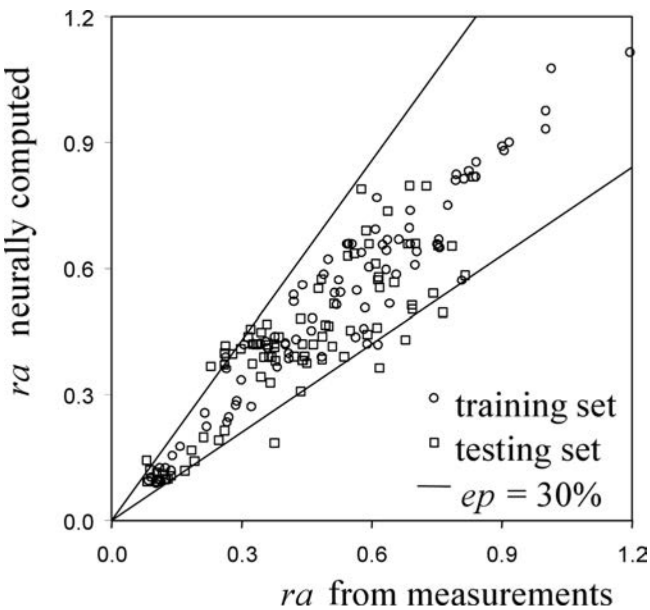

Fig. 7. Values of ratio ra obtained from measurements vs. values of ra computed by neural network adopted.

Very simple networks with maximal value (amplitude) of vibrations only instead of compressed ground vibration record also give good results.

The third way of the analysis of soil-structure interaction is considered using acceleration and displacement response spectra. The subpicture idea from picture transmission is also adapted for mapping of response spectra from ground vibrations to response spectra from basement vibrations of buildings.

In case of the analysis of the recorded vibrations in form of displacements, the following input vector was proposed:

$$\mathbf{x}_{(6\times1)} = \{S_{dg}(T_{i-2}),\ S_{dg}(T_{i-1}),\ S_{dg}(T_i),\ S_{dg}(T_{i+1}),\ S_{dg}(T_{i+2}),\ T_i\}, \tag{10}$$

where $T_{i-2}, T_{i-1}, T_i, T_{i+1}, T_{i+2}$ – successive vibration periods; S_{dg} – displacement response spectrum from ground vibrations.

The corresponding value of displacement response spectrum from the vibrations recorded on the basement level of the building $S_{df}(T_i)$ was expected as the output of neural network:

$$\mathbf{y}_{(1\times1)} = \{S_{df}(T_i)\}. \tag{11}$$

For the analysis of acceleration records, the input vector was proposed in a form analogous to (10):

$$\mathbf{x}_{(6\times1)} = \{\beta_g(T_{i-2}),\ \beta_g(T_{i-1}),\ \beta_g(T_i),\ \beta_g(T_{i+1}),\ \beta_g(T_{i+2}),\ T_i\}, \tag{12}$$

where T_{i-2}, T_{i-1}, T_i, T_{i+1}, T_{i+2} – as in (10); β_g – nondimensional acceleration spectrum from ground vibrations.

Analogous to (11), the corresponding value of nondimensional acceleration spectrum from the vibrations recorded on the basement level of building $\beta_f(T_i)$ was proposed as the output of that neural network:

$$\mathbf{y}_{(1\times1)} = \{\beta_f(T_i)\}. \tag{13}$$

In Fig. 8 an example of a comparison of nondimensional acceleration response spectra from horizontal vibrations of the building basement, computed on the basis of recorded vibrations and neurally predicted is shown.

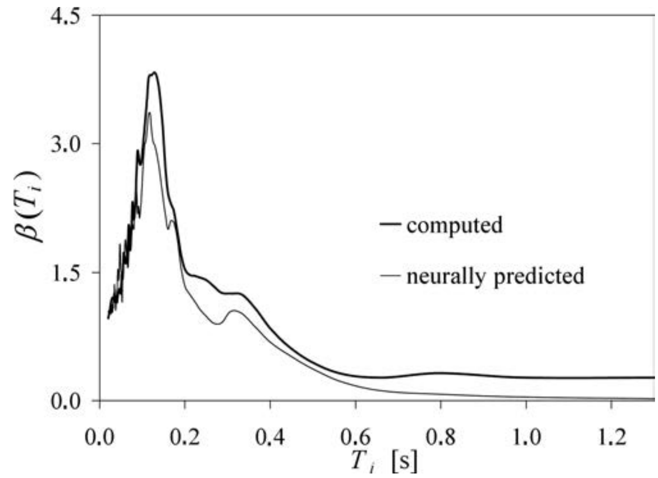

Fig. 8. Comparison of nondimensional acceleration response spectra from horizontal vibrations of the building basement computed on the basis of recorded vibrations and neurally predicted.

From the study of the difficulties in prognosis of differences between the ground and basement vibrations it follows, from the results obtained, that the application of simple neural networks enables us to predict building foundation vibrations with satisfactory accuracy. Thus, the effects of transmission of ground vibrations to building foundation (soil-structure interaction) can be analysed using neural networks.

3.5. Simulation of building response to seismic-type excitation

Prediction of building responses to mine-induced excitations using neural networks was also proposed [6, 12, 13, 15]. In the first case maximal displacement of the building highest floor vibrations was evaluated and in the second case full displacement record in time domain was simulated. In the input vector information about mine-induced excitation and dynamic building properties was included, and the building response was used as the neural network output (Fig. 9).

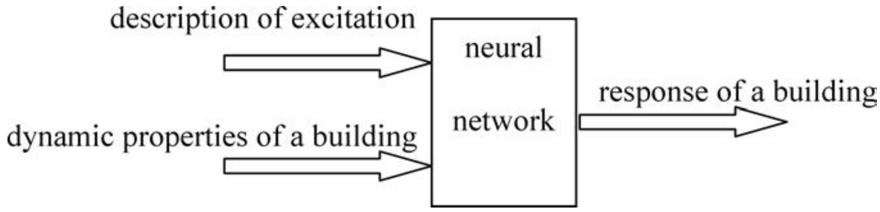

Fig. 9. Scheme of a neural network for prediction of building response.

As an example, Fig. 10 shows a comparison of records of selected building vibrations, experimentally obtained and neurally simulated.

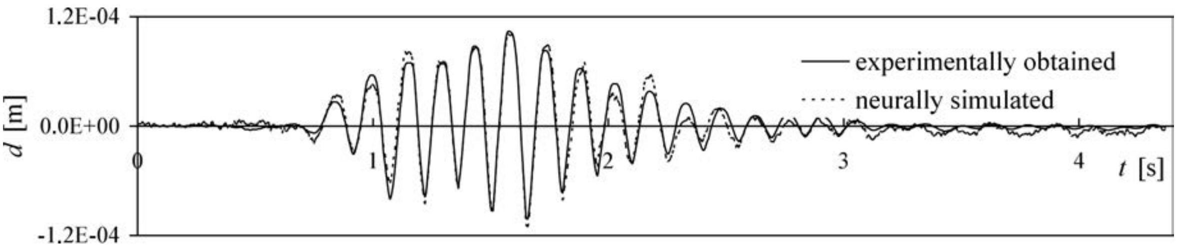

Fig. 10. Comparison of records of selected building vibrations, experimentally obtained and neurally simulated.

Neural networks can be efficiently used for evaluation of the dynamic response of a building from the analysed class of buildings (medium-height buildings) subjected to kinematic excitations. The main advantage of this approach is that the rich database of experimental results from full-scale measurements can be made full use of, and information regarding building dynamic response can be obtained without creating models of such complex structures as buildings and without an analysis of adequate motion equations.

4. Conclusions

The obtained results lead to a conclusion that the neural technique gives a possibility of efficient analysis, accurate enough for engineering, of structural dynamics problems related to mine-induced excitations. Artificial neural networks seem to be a tool that is useful to the analysis of problems with data taken from measurements on actual structures.

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