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NEURAL NETWORKS FOR THE PREDICTION OF MINE-INDUCED VIBRATIONS TRANSMISSION FROM THE GROUND TO BUILDING FOUNDATION

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Keywords: Mining tremors, Neural Networks, Transmission of Ground Vibrations, Acceleration of Vibrations, Response Spectra, Building Foundation Vibrations.

Abstract. *This paper deals with the application of neural networks for the prediction of the transmission of mine-induced accelerations of ground vibrations to the foundations of apartment buildings. Results from measurements in situ at the same time on the ground level and on the building foundation were used as the neural networks training and testing patterns. Rockbursts in Legnica-Glogow Copperfield (LGC), the most seismically active mining region in Poland with surface horizontal vibrations reaching 0,2 acceleration of gravity (g) and vertical components reaching 0,3g, were the sources of vibrations. The mining tremors are not subject to human control and they are random events in view of their time, place and magnitude, similarly as earthquakes. Full-scale tests were carried out many times in a period of a few years. Comparison of a huge number of records of vibrations measured at the same time on the ground and on the building foundation level leads to conclusion that they differ generally significantly. However the more precise estimation of harmfulness of the mine-induced vibrations to actual buildings can be performed on the basis of the foundation vibrations. Therefore the prediction of foundation vibrations is necessary if the measured ground vibrations are accessible only. Reduction of maximal values of accelerations of horizontal vibrations as well as differences between non-dimensional ground and foundation acceleration response spectra were taken into account in this paper. Various pre-processing of the experimental data (compression, linguistic variables introduction, scaling of input and output data) is proposed. The influence of some mining tremors as well as ground vibrations parameters (e.g. energy, epicentral distance, direction of wave propagation, direction of vibrations parallel to the transverse or longitudinal axis of the building, values of accelerations of the ground vibrations) on the transmission is considered in the input vectors. The main advantage of the neural approach is that the prediction of the parameters of vibrations of building foundation can be performed on the basis of ground vibrations taken from experimental data. The obtained results show that application of relatively simple neural networks enables us providing for building foundation vibrations based on ground vibrations with satisfactory accuracy.*

1 INTRODUCTION

Soil-structure interaction involves a lot of very difficult problems in the dynamic analysis of structures. Estimation of the way of ground vibrations transmission to building foundations is one of the most important issue among them.

Such problems are mainly analysed with respect to earthquakes. However the ground motion can be induced not only by earthquakes, but also by the so-called paraseismic sources, for instance mining tremors. Although these tremors are strictly connected with human activity, they differ considerably from other paraseismic vibrations. They are not subject to human control and they are random events in view of their time, place and magnitude, similarly as earthquakes whereas some parameters of such ground vibrations (for instance: dominating frequencies, duration) are different from earthquake-induced ground vibrations [11].

Mine-induced seismicity has been recorded in many countries in mining areas with underground exploitation of coal, copper, gold. In Poland, mining tremors resulted from underground raw mineral material exploitations induce the surface horizontal vibrations reaching even 0,2 acceleration of gravity (g) and vertical components reaching 0,3g. Such large values of the peak accelerations are comparable with the peak accelerations of the surface vibrations excited by some weak and shallow earthquakes. It is worth mention that the mining works are run under highly urbanized and heavily populated areas, so the harmful effects of mining seismicity may affect many buildings and people on the surface.

A great number of published papers deal with dynamic soil-structure interaction. The most of them are of theoretical character. A lot of computational models are discussed, cf. e.g. [1, 4, 8, 9, 10, 12]. In spite of extensive development of computational methods (first of all the Finite Element Method) and progress in computer software and hardware, the analysis of soil-structure interaction problems is still far from satisfactory from the structural engineering point of view. That is why there are attempts to explore non-standard, co-disciplinary approaches in the analysis of the dynamic problems. From this point of view artificial neural networks seem to be a tool, very prospective for solving the problems [5, 7].

The comparison of maximal values (amplitudes) of vibrations (accelerations, velocities, displacements) recorded at the same time on the ground and on the foundation level is the simplest and very often employed way of estimation of the vibrations transmission from the ground to the building. The more general way of evaluation the differences between vibrations recorded at the same time on the ground and on the foundation level is the comparison of response spectra from both the vibrations.

This paper deals with the application of neural networks for the prediction of the transmission of mine-induced accelerations of ground vibrations to the foundations of apartment buildings. Rockbursts in Legnica-Glogow Copperfield (LGC), the most seismically active mining region in Poland, were the sources of vibrations. Results from measurements *in situ* at the same time on the ground level and on the building foundation were used as the neural networks training and testing patterns. Reduction of maximal values of accelerations of horizontal vibrations as well as differences between non-dimensional ground and foundation acceleration response spectra were taken into account in this paper. Various pre-processing of the experimental data (compression to principal components by the Principal Component Analysis method – PCA, linguistic variables introduction, scaling of input and output data) is proposed. The influence of some mining tremors as well as ground vibrations parameters (energy, epicentral distance, direction of wave propagation, direction of vibrations parallel to the transverse or longitudinal axis of the building, values of accelerations of the ground vibrations, dominating frequency of ground vibrations) on the transmission is considered in the neural network input vectors. Types of problems analysed with neural networks application are synthetically presented in Table 1. The information about the components of the neural network input and output vectors and variants of the experimental data pre-processing methods is given in the table.

Neural network		Variants of actual data pre-processing
input	output	
- maximal value (amplitude) of ground vibrations - other parameters 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	- scaling - introduction of the linguistic variables (fuzzy inputs)
- 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	- scaling - compression using PCA
- response spectrum from the ground vibrations	response spectrum from the building foundation vibrations	- scaling

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

2 EXPERIMENTAL DATA

Mining tremors in the most seismically active mining region in Poland with underground copper ore exploitation – Legnica-Glogow Copperfield (LGC), were the sources of ground and buildings vibrations. Full-scale tests were carried out many times in a period of a lot of years. Measurements come from the surface and building seismological measurement stations. The accelerometers were installed on the ground in the front of the building (in six meters distance), at the foundation level in the building and on some floors of the building. The results of long-term experimental monitoring of ground and actual building vibrations were synthetically collected. Simultaneously recorded ground and building foundation accelerograms are useful in the determination of the way of vibration transmission from ground to buildings. The main attention was devoted to measurements of the horizontal vibration components in the directions parallel to the transverse (x) and longitudinal (y) axis of the considered buildings. In this paper two types of typical prefabricated (with load bearing walls) actual buildings were taken into account – medium-height (five-storey) and tall (twelve-storey) buildings founded directly on the ground using concrete strip foundations.

At a contact between the ground and a building foundation, accelerations undergo changes. The building works, to a certain degree, as a low-pass filter for ground accelerations, first of all, with high frequencies. The degree of the acceleration modification depends on the characteristics of the ground accelerograms, intensity of vibrations and the type of the building on which vibrations are transmitted [2, 6].

Comparison of a huge number of records of vibrations measured at the same time on the ground and on the building foundation level leads to conclusion that they differ generally significantly. The similar effect in the corresponding response spectra can be observed. It is the result of soil-structure interaction, which is visible in the transmission of ground vibrations to building foundations. Therefore the responses of buildings determined on the basis of vibrations recorded on the ground may be different than the responses obtained with application of vibrations recorded on the foundation level of the buildings.

Examples which illustrate these significant differences between the simultaneously recorded horizontal components of ground and building foundation accelerations of vibrations in case of medium-height and tall buildings are shown in Fig. 1. Fig. 2 presents the examples of trajectories of the ends of the resultant acceleration vectors at the same time of mine-induced ground and medium-height building foundation vibrations. In Fig. 3 comparisons of non-dimensional acceleration spectra (β) from simultaneously measured ground and foundation vibrations in case of medium-height as well as tall building are performed. With regard to the determined damping, the response spectra are computed with damping ratio ξ = 3%. All these illustrative vibrations were induced by the mining tremors in LGC region with energies (*En*) and epicentral distances (*re*) given below the figures.

a)

b)

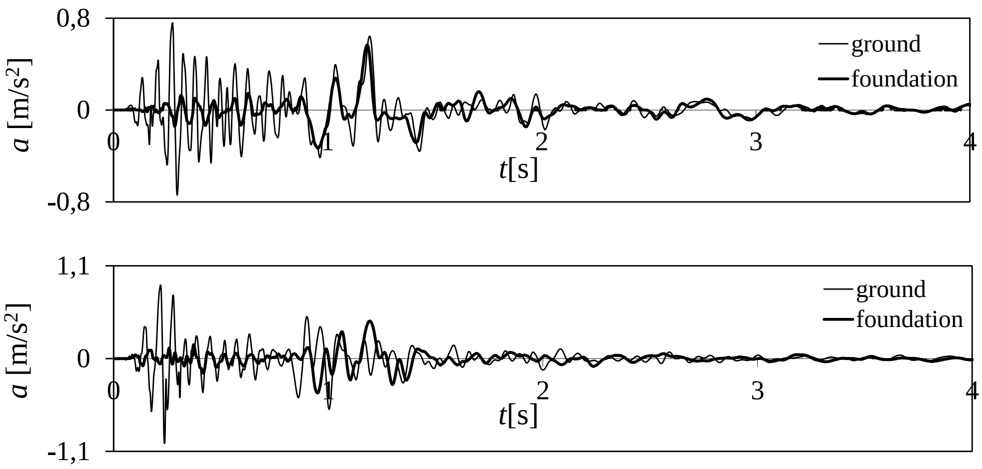


Figure 1: Records of horizontal components of vibrations (accelerations):
a) medium-height building, mining tremor – En = $1{,}3{\cdot}10^{8}$J, re = 905m, direction x;
b) tall building, mining tremor – En = $1{,}3{\cdot}10^{8}$J, re = 650m, direction y.

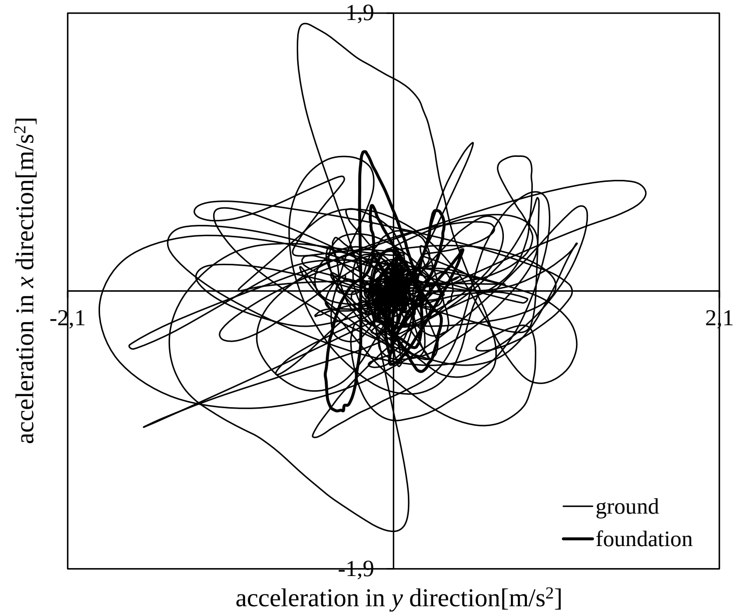
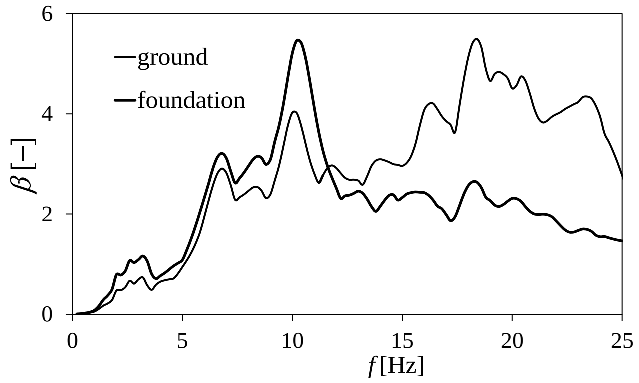


Figure 2: Trajectories of the ends of resultant acceleration vectors at the same time of mine-induced the ground and the medium-height building foundation vibrations: En = $1{,}9{\cdot}10^{9}$J, re = 1267m.

a)



b)

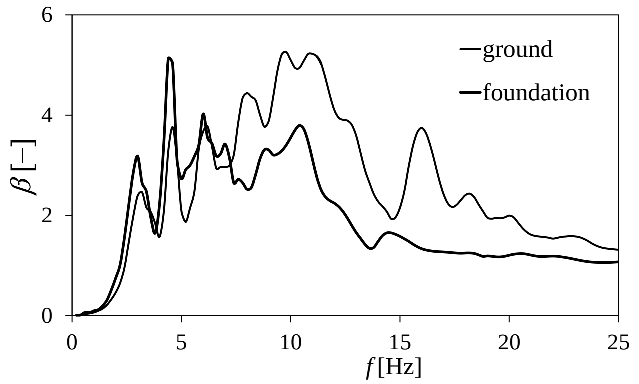


Figure 3: Non-dimension response spectra: a) medium-height building, mining tremor – $En = 8{,}3\cdot10^6$J, re = 1569m, direction y; b) tall building, mining tremor – $En = 3{,}5\cdot10^7$J, re = 964m, direction x.

The influence of rockbursts parameters as mining tremor energy, epicentral distance, wave propagation direction as well as ground vibrations parameters (amplitude, direction of vibrations, dominating frequency) on the soil-structure interaction effect can be observed. However the prediction of the relation between ground and foundation records of accelerations and the mine-induced vibrations transmission from the ground to the building foundation is very difficult.

3 NEURAL NETWORKS APPLICATION RESULTS

3.1 Introductory remarks

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

The database created of the results of long-term experimental monitoring of ground and actual structure vibrations makes it possible to use them as the patterns to design the neural network analysers for considerations of the transmission of ground vibration accelerations induced by mining tremors to building foundation. Pre-processing methods of the experimental data are applied: scaling, introduction of the linguistic variables (fuzzy inputs) and compression.

Back-propagation neural networks (BPNNs) were trained and tested on the basis of experimental data. The results of neural network analysis and the results of experiments were compared. The accuracy of the network approximation was evaluated by the mean-square-error $MSE(Q)$, the standard error st$\varepsilon(Q)$ and the relative errors ep, eQ_{avr}:

$$MSE(Q) = \frac{1}{Q}\sum_{p=1}^{Q}(z^{(p)} - y^{(p)})^2 , \tag{1}$$

$$\mathrm{st}\varepsilon(Q) = \sqrt{\frac{1}{Q}\sum_{p=1}^{Q}(z^{(p)} - y^{(p)})^2} , \tag{2}$$

$$ep \ = |1 - y^{(p)}/z^{(p)}| \cdot 100\% , \tag{3}$$

$$eQ_{\mathrm{avr}} = \frac{1}{Q}\sum_{p=1}^{Q} ep , \tag{4}$$

where: $z^{(p)}$, $y^{(p)}$– target and neurally computed outputs for p-th pattern, $Q = L, V, T, P$ – number of the learning (L), validating (V), testing (T) and all (P) patterns respectively.

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

3.2 Prediction of the maximum accelerations of foundation vibrations based on maximal value (amplitude) of ground vibrations, other parameters of ground vibrations and mining tremors parameters

The first proposition deals with the application of neural networks for the estimation of the way of vibrations transmission from the ground to the building foundation by the evaluation of the reduction of maximal values of the accelerations. Therefore the comparison of maximal values (amplitudes) of accelerations recorded at the same time on the ground (a_{gmax} in x or y directions, respectively) and on the foundation level (a_{fmax}) was necessary. For this purpose the ratios $r = a_{\mathrm{fmax}}/ a_{\mathrm{gmax}}$ were computed. The value of ratio r was proposed as the output of the corresponding neural network.

The aim of this approach is to apply neural networks for the prediction of ratios r based on the corresponding mining tremor and ground vibration parameters. The following neural network input parameters were taken into consideration: a_{gmax} - maximal value (amplitude) of accelerations recorded on the ground in the case of vibrations in x or y directions, k - parameter related to direction of vibrations (values k = 0,4 and k = 0,7 were arbitrarily assumed for the transverse direction x and longitudinal direction y, respectively in order to differentiate the directions), En - mining tremor energy, re - epicentral distance, X and Y - local seismological coordinates, fg - dominating ground vibration (acceleration) frequency. Variant neural network input vectors were analysed taking into account the various combinations of input parameters. Parameters of the neural network pairs of input-output vectors, the neural network structures and the errors corresponding to the networks training, validating and testing processes for selected neural networks designed in case of the ground vibrations transmission to the medium-height building foundation are given in Table 2.

Neural network number	Input parameters	Neural network structure	$MSE(Q)$		
			L	V	T
NN1	$a_{g\max}$, *En*, *re*	3-25-1	0,0194	0,0237	0,0220
NN2	$a_{g\max}$, *En*, X,Y	4-5-1	0,0212	0,0232	0,0236
NN3	$a_{g\max}$, *En*, *re*, *fg*	4-22-1	0,0153	0,0157	0,0166
NN4	$a_{g\max}$, *En*, *re*, *k*	4-7-1	0,0150	0,0148	0,0143
NN5	$a_{g\max}$, *En*, X,Y, *fg*	5-4-1	0,0167	0,0175	0,0175
NN6	$a_{g\max}$, *En*, X,Y, *k*	5-10-1	0,0137	0,0148	0,0140
NN7	$a_{g\max}$, *En*, *re*, *fg*, *k*	5-15-1	0,0095	0,0115	0,0114
NN8	$a_{g\max}$, *En*, *re*, X, Y	5-7-1	0,0229	0,0250	0,0228
NN9	$a_{g\max}$, *En*, X, Y, *fg*, *k*	6-15-1	0,0079	0,0095	0,0104
NN10	$a_{g\max}$, *En*, *re*, X, Y, *fg*	6-5-1	0,0184	0,0174	0,0184
NN11	$a_{g\max}$, *En*, *re*, X, Y, *fg*, *k*	7-4-1	0,0129	0,0120	0,0103

Table 2: BPNNs input parameters, structures and training, validating and testing errors (medium-height building).

The influence of various input parameters on the neural network approximation accuracy is visible. It was stated that certainly the more precise prognosis of ratios *r* is obtained for the richer neural network input information. Moreover an application of neural networks enables to evaluate the influence importance of some mining tremors and ground vibrations parameters on the reduction of maximal foundation acceleration of vibrations vs. maximal ground acceleration of vibrations.

The neural network input parameters, mining tremor energy and epicentral distance among others, are estimated as approximate values found experimentally. The energy of mining tremor and epicentral distance are calculated by the seismologists on the basis of vibrations simultaneously recorded in time of this tremor on a few measuring stations in the underground mine. Then the found experimentally values of *En* and *re* have an approximate character and the ranges of small, medium and large mining tremors energies as well as the ranges of small, medium and large epicentral distances can be defined. This is in fact the introduction of the linguistic variables associated with the fuzzy character of the mining tremor energy {*Enl*} and epicentral distance {*rel*} instead of crisp values *En* and *re*, respectively.Therefore the linguistic variables associated with the fuzzy character of the parameters are introduced in the neural network analysis.

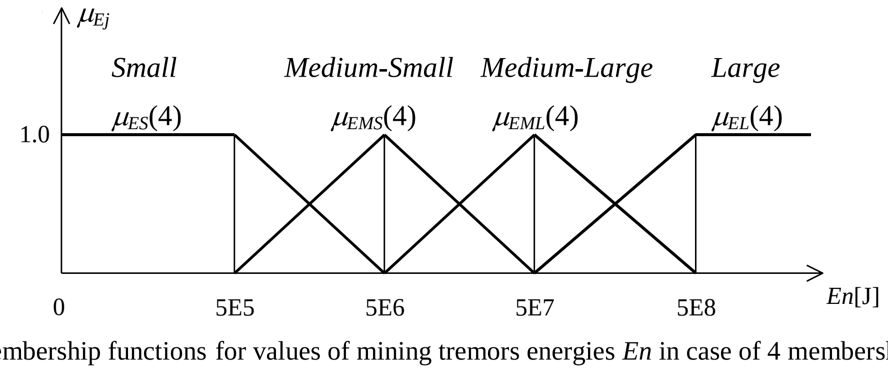


Figure 4: Membership functions for values of mining tremors energies *En* in case of 4 membership functions.

Triangular and trapezoid membership functions are adopted. Then instead of the crisp value of *re* the linguistic variable {*rel*} is introduced in the neural network input vector: {*rel*} = {μ_{rS}, μ_{rM}, μ_{rL}}, where: μ_{rS}, μ_{rM}, μ_{rL} – values of membership functions for small, medium and large epicentral distance, respectively, corresponding to membership functions. Taking into account the wide range of values of energies, three variants of the number of membership functions in case of mining tremors energies are analyzed: three (3), four (4) and five (5) membership functions. These functions adopted in case of four (4) membership functions are shown in Fig. 4 as the example.

Thus eight, nine or ten components in the input vector occur respectively, as the result of introducing the linguistic variables {*rel*} and {*Enl*(3)}, {*Enl*(4)} or {*Enl*(5)} instead of crisp parameters in the neural network input vector composed of parameters: $a_{g\max}$, *En*, *re*, *k*. The errors related to these neural networks in case of the high building are collected in Table 3.

Input parameters	BPNN	*MSE*(*Q*)		eQ_{avr}			st ε	*R*(*P*)
		L	*T*	*L*	*T*	*P*		
$a_{g\max}$, *En*, *re*, *k*	4-5-1	0,00895	0,01900	18,1	33,8	25,9	0,118	0,677
$a_{g\max}$,{*Enl*(3)},{*rel*}, *k*	8-6-1	0,01303	0,01622	22,5	32,5	27,5	0,121	0,639
$a_{g\max}$,{*Enl*(4)},{*rel*}, *k*	9-7-1	0,00599	0,01870	13,3	29,1	21,2	0,111	0,725
$a_{g\max}$,{*Enl*(5)},{*rel*}, *k*	10-7-1	0,00365	0,02131	11,2	34,3	22,7	0,112	0,717

Table 3: BPNNs input crisp and linguistic parameters, structures and errors (tall building).

Additionally, Fig. 5 presents the success ratio *SR* for the neural prediction of the transmission of accelerations of ground vibrations to building foundation obtained using the above-mentioned BPNN: 4-5-1 and BPNN: 10-7-1.

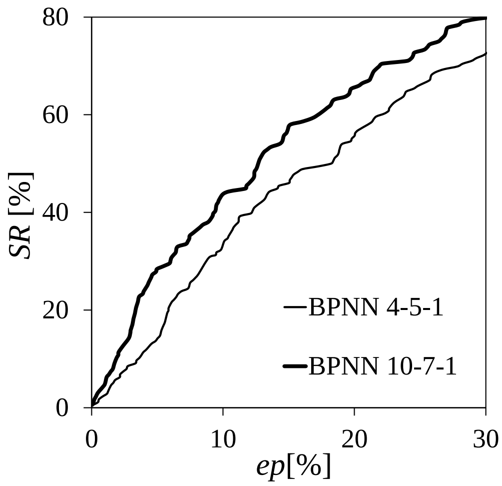


Figure 5: Success ratio *SR* for the neural prediction of the transmission of accelerations of ground vibrations to building foundation in cases of BPNN: 4-5-1 and BPNN: 10-7-1 (tall building).

It can be concluded that the introduction of linguistic variables can lead to a better accuracy of neural identification than that by means of crisp values of epicentral distance and mining tremor energy. These results can also be explained by the increase of the number of network parameters but with no increase of physically interpreted input variables. Three membership functions are not sufficient for describing such large (wide) range of mining tremors energies.

It is visible that the accuracy of network with such linguistic variable is not better than in case of network with crisp values in the input vector.

3.3 Prediction of the maximum accelerations of foundation vibrations based on compressed record of ground vibrations and mining tremors parameters

The aim of the next approach is to apply neural network for the prediction of the ratio *r* on the basis of the corresponding mining tremor parameters and the compressed ground vibration record instead of maximal value of ground acceleration. Compression of the data to principal components by the Principal Component Analysis method (PCA) [3] is proposed.

The carried out analysis leads to conclusion that the introduction of the principal component analysis method enables us to compress vibration data corresponding to the ground records of accelerations. Because of the strong correlation of the successive values of accelerations, the full ground acceleration vibrations in time domain could be compressed to the first principal components only. Hence the design of considerably smaller neural networks than those without data compression for the prediction of building foundation vibrations on the basis of ground vibrations taken from measurements is possible. It results in the reduction of number of network parameters and improvement of the network generalization properties.

The following neural network input parameters were taken into consideration: cag_1, *En*, *re*, *k*, where cag_1 – record of ground acceleration vibrations compressed to the first principal component and *En* – mining tremor energy, *re* – epicentral distance, *k* – parameter related to the direction of vibrations as in chapter 3.2.

The neural network of structure 4 – 6 – 4 – 1 was accepted for the practical applications in case of medium-height building 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 the all patterns: $SR(30\%) = 88\%$. The comparison of results obtained using neural network with experimental ones is shown in Fig. 6. In this figure the bounds of relative errors $ep = 30\%$ are marked. The following values of the neural network errors were computed: $MSE(L) = 0{,}0035$, $eL_{avr} = 13{,}5\%$, $R(L) = 0{,}941$ in case of learning; $MSE(T) = 0{,}0053$, $eT_{avr} = 18{,}9\%$, $R(T) = 0{,}883$ in case of testing. It should be noted that very simple network with the compressed ground vibration record instead of the maximal value (amplitude) of vibrations causes an increase of accuracy of obtained results.

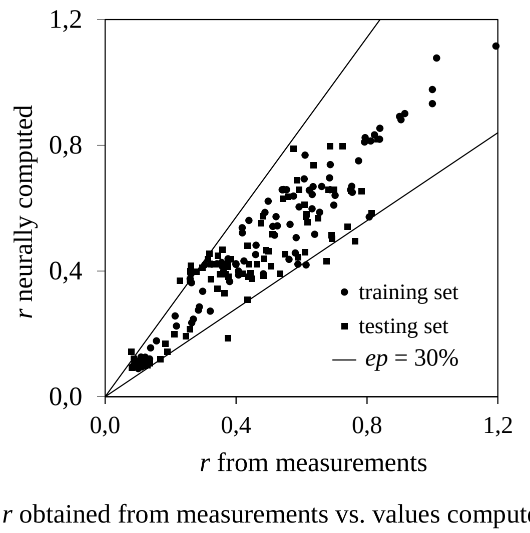


Figure 6: Values of ratio *r* obtained from measurements vs. values computed by the neural network (medium-height building).

3.4 Mapping of response spectra from the ground vibrations into response spectra from foundation vibrations

In the third way of the analysis of the vibrations transmission the acceleration response spectra were considered. The subpicture idea from picture transmission is also adapted for the mapping of response spectra from ground vibrations to response spectra from foundation vibrations of the buildings. Then in the input vector six elements were proposed: $\beta_g(f_{i-2})$, $\beta_g(f_{i-1})$, $\beta_g(f_i)$, $\beta_g(f_{i+1})$, $\beta_g(f_{i+2})$, f_i, where f_{i-2}, f_{i-1}, f_i, f_{i+1}, f_{i+2} – successive vibration frequencies, β_g – non-dimensional acceleration spectrum from ground vibrations. The corresponding value of non-dimensional acceleration spectrum from the vibrations recorded at the foundation level of building $\beta_f(f_i)$ was taken as the output of this neural network. The neural networks of structure 6 – 5 – 1 in case of the medium-height building as well as 6 – 10 – 1 in case of the tall building were formulated after a number of numerical experiments.

The errors corresponding to the training and testing processes of the network applied in case of the medium-height building are put together in Table 4 and the example of comparison of computed on the basis of recorded vibrations and neurally predicted non-dimensional acceleration response spectra from foundation is shown in Fig. 7.

$MSE(L)$	$MSE(T)$	eQ_{avr} [%]			stε (P)	$R(P)$
		L	T	P		
0,00283	0,01385	9,4	15,9	12,7	0,091	0,766

Table 4: Errors of the training and testing processes of the network applied for mapping of response spectra from the ground vibrations into spectra from foundation vibrations in case of the medium-height building.

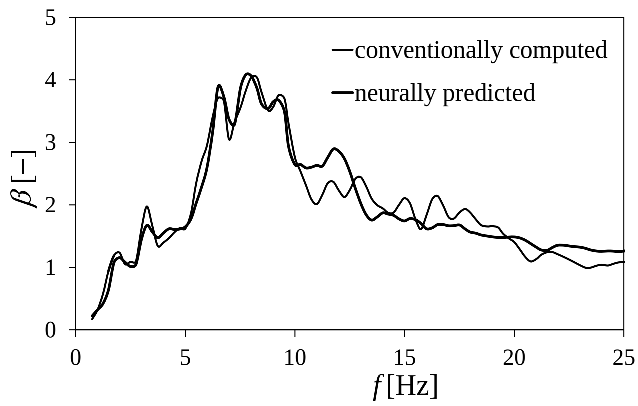


Figure 7: Comparison of computed on the basis of recorded vibrations and neurally predicted non-dimensional acceleration response spectra from foundation vibrations in case of the medium-height building.

Application of simple neural networks enables us to predict the acceleration response spectra from building foundation vibrations with satisfactory accuracy. That is the result of neural mapping of response spectra from ground vibrations to response spectra from foundation vibrations of buildings.

4 CONCLUSIONS

Because of the significant differences of mine-induced ground and building foundation vibrations simultaneously measured and the fact that the more precise estimation of harmfulness of the mine-induced vibrations to actual buildings can be performed on the basis of the foundation vibrations, the prediction of foundation vibrations is necessary if the measured ground vibrations are accessible only (for instance in the design procedure of new structures).

Looking at the difficulties in prognosis of differences between ground and foundation vibrations it is visible from the results obtained that the effects of the transmission of mine-induced ground vibrations to building foundation may be successfully analyzed using neural networks.

The main advantage of the neural approach is that the prediction of the parameters of vibrations of building foundation can be performed on the basis of ground vibrations taken from experimental data. The obtained results show that application of relatively simple neural networks enables us providing for building foundation vibrations based on accelerations of ground vibrations with satisfactory accuracy.

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