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Neural network identification of building natural periods with various splitting up of the patterns into training and testing sets

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The paper deals with an application of neural networks for computation of fundamental natural periods of buildings with load-bearing walls. The identification problem is formulated as a relation between structural and soil parameters and the fundamental period of building. The patterns are based on long-term tests performed on actual structures. Various splitting up of the set of patterns into training and testing sets are considered in the analysis. The carried out analysis leads to conclusion that, even in "the worst" case of randomly selected testing patterns, the natural periods of vibrations of buildings are obtained with accuracy quite satisfactory for engineering practice.

1. Introduction

Estimation of the periods of natural vibrations is usually necessary in the dynamic analysis of buildings. The basic approach is related to full-scale measurements of dynamic characteristics of structures. There are, of course, many problems associated with planning, carrying out and analysis of measurements. But in many cases this experimentally supported analysis is superior to theoretical methods, which require some well known problems and difficulties resolving to create a satisfactory model of very complex structures as buildings are, in particular — prefabricated buildings. In the paper, on the basis of the results from full-scale dynamic tests of actual structures, neural networks are used for computation of the fundamental natural periods of vibrations of medium height, residential, prefabricated buildings (five-story buildings) with load bearing concrete walls. Back-Propagation Neural Networks (BPNNs) and networks with Radial Basis Functions (RBF) are applied in the analysis. The paper is a continuation of the research originated in [3, 4].

2. Results of experimental tests on analysed buildings

Measurements were carried out on thirteen typical residential, prefabricated, with load-bearing walls, five-story buildings. Ten of the buildings were erected in large panel technology, three buildings — in large block technology. Full-scale tests were performed many times during a period of a few years [1, 5]. Vibrations of actual buildings were excited by explosions in nearby quarries, mining tremors, wind gusts, rhythmic swinging of people on the upper floor, impact of weights falling down onto the ground near the buildings. The tests included measurements of horizontal vibration components in two mutually perpendicular directions, parallel to the transverse and longitudinal axis of the buildings. In Fig. 1 the selected example of considered structures with the measurement points is shown. Because of very small damping in the analysed buildings, the differences between the free frequencies and the eigenfrequencies were considered negligible. In order to determine the fundamental periods of vibrations various methods of records processing were used — especially

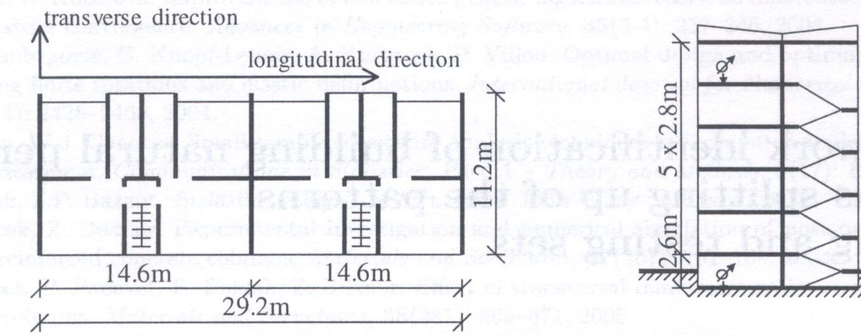

Fig. 1. Plane and vertical section of the building WK-70

Table 1. Experimentally evaluated fundamental natural periods of analysed buildings

Building		Direction	Pattern number	T_1 [sec] measured
1		2	3	4
DOMINO-68 (I)		transverse	1	0.256
		longitudinal	2	0.230
DOMINO-68 (II)		transverse	3	0.256
		longitudinal	4	0.230
WUF-T-67-SA/V		transverse	5	0.253
		longitudinal	6	0.204
WUF-GT 84 (I)	seg. I	transverse	7	0.175
		longitudinal	8	0.185
	seg. II	transverse	9	0.180
		longitudinal	10	0.169
WUF-GT 84 (II)	seg. I	transverse	11	0.157
		longitudinal	–	–
	seg. II	transverse	12	0.180
		longitudinal	13	0.177
C/MBY/V (I)		transverse	14	0.172
		longitudinal	15	0.192
C/MBY/V (II)		transverse	16	0.185
		longitudinal	17	0.213
C/MBY/V (III)		transverse	18	0.227
		longitudinal	19	0.233
BSK (I)	seg. I	transverse	20	0.155
		longitudinal	21	0.233
	seg. II	transverse	22	0.155
		longitudinal	23	0.233
BSK (II)	seg. I	transverse	–	–
		longitudinal	–	–
	seg. II	transverse	24	0.156
		longitudinal	25	0.233
WWP		transverse	26	0.270
		longitudinal	27	0.294
WBL		transverse	28	0.294
		longitudinal	29	0.263
WK-70		transverse	30	0.256
		longitudinal	31	0.227

FFT and spectral analysis. In column 4 of Table 1 the experimentally evaluated fundamental natural periods of analysed buildings are collected.

3. Application of neural networks for building natural periods identification

In the paper neural networks are used for computation of the fundamental natural periods of vibration of medium height (five-story) prefabricated, residential buildings with load-bearing walls. The analysis is based on the results of measurements on actual buildings and the main problem associated with neural network identification is a proper selection of input variables.

The identification problem is formulated as a relation between structural and soil parameters, and the fundamental period of building. In the light of full-scale tests of the analysed buildings it can be stated [5] that the soil-structure interaction plays an important role in vibrations of medium height buildings. The foundation flexibility is expressed by the coefficient of an elastic uniform vertical deflection of the subgrade 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 a cross-sectional area of the i-th wall in the building plan, a — length of building. These parameters were taken as input vectors $\mathbf{x}$ of neural networks and the building fundamental natural period T_1 was the output t of the network [3],

$$\mathbf{x}_{(4\times1)} = \{C_z, b, s, r\}, \qquad t = T_1. \tag{1}$$

The sets of training and testing patterns were formulated on the basis of the results from full-scale tests. $P = 31$ patterns from the experimental data were collected. The numbers of patterns are placed in column 3 of Table 1. It is necessary to split up the patterns into training (learning) and testing sets.

4. Influence of splitting up of the patterns into training and testing sets on the results obtained

The neural network is learned using a training set and the main goal of the learning process is to memorize by the network the rules which constitute the relationship between the input and output data. The learned network should have generalization properties, i.e. the network trained on the learning set should well operate on other patterns. In order to verify the generalization properties of the network it is tested on the set of testing patterns. Thus, the correct choice of testing patterns is very important in the neural network analysis.

Having a very small set of patterns a network was designed applying a modification of the multifold cross-validation procedure [2]. From the total number of $P = 31$ patterns, $T = 5$ patterns for testing set were randomly selected, whereas the remaining $L = 26$ patterns were assigned as a learning set. This procedure was repeated one hundred times. BPNNs of structure 4–4–1 with Resilient back-propagation learning method and sigmoid activation function corresponding to the input and output (1) considered above were formulated for each one from the one hundred cases. Stuttgart Neural Network Simulator (SNNS) package [6] was used. As a result one hundred pairs of Mean Square Errors (MSE) for the training and testing processes were obtained and analysed,

$$MSE(V) = \frac{1}{V}\sum_{p=1}^{V}(t_p - z_p)^2, \tag{2}$$

where: $V = L, T$ — number of patterns in the training (L) and testing (T) sets, t_p and z_p — computed on the basis of experimental data and neurally predicted values of p-th pattern, respectively.

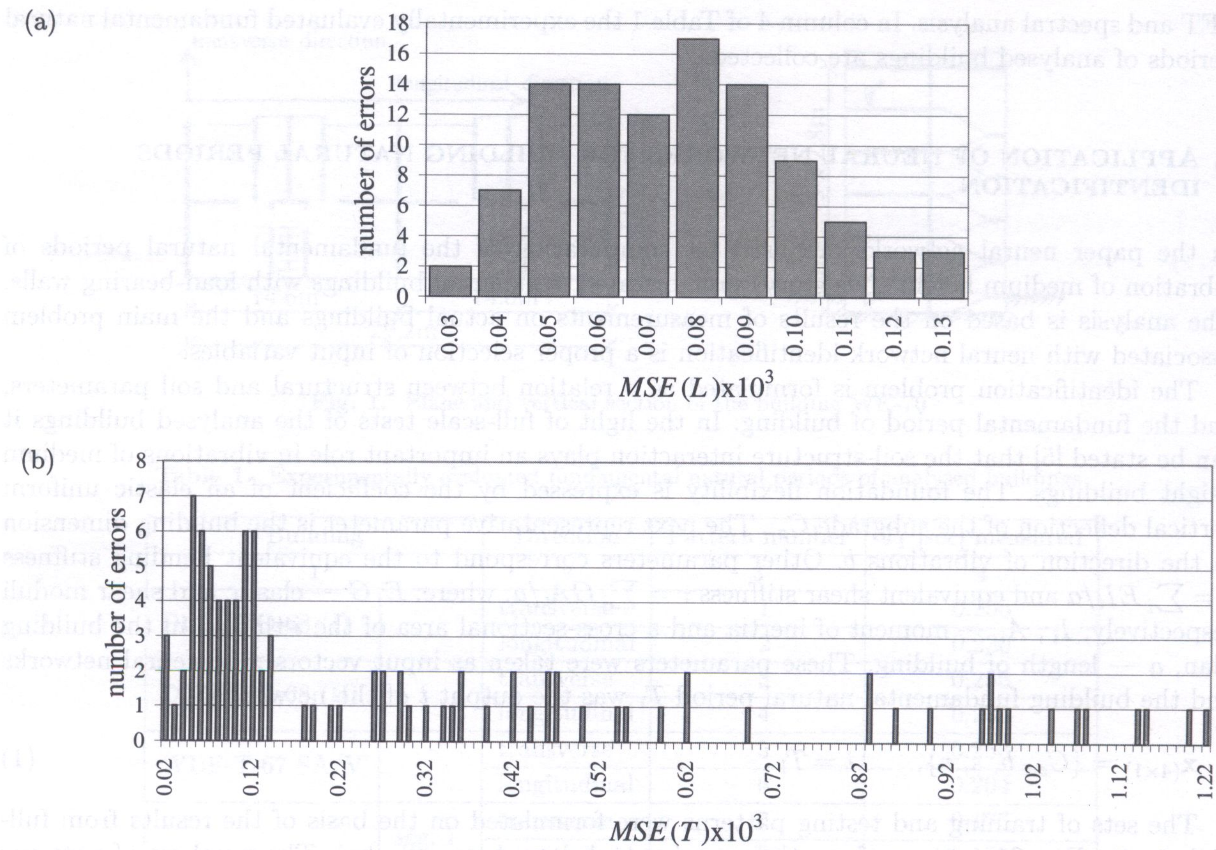

Fig. 2. Histograms for (a) $MSE(L)$ and (b) $MSE(T)$

In Fig. 2, the histograms of Mean Square Error for training processes $MSE(L)$ and for testing processes $MSE(T)$, obtained during the multifold cross-validation process, are shown.

The average values of Mean Square Errors for the training and testing processes for various groups of the sampling numbers are shown in Fig. 3. In Fig. 3a there are the errors for the five groups with twenty successive random selections in every group. In Fig. 3b the errors for twenty, forty, sixty, eighty and all (that is one hundred) successive random selections are presented, respectively.

Looking at these average errors presented in Fig. 3 it is visible that the average Mean Square Error values for learning process are nearly the same regardless of the group of sampling. The differences between the corresponding testing errors are little higher. The average values of the total one hundred training and testing errors were: $MSE(L) = 0.000075$ and $MSE(T) = 0.000327$, respectively.

Besides the network errors $MSE(L)$ and $MSE(T)$ the accuracy of the networks training and testing was estimated also by relative errors (ep_i, ep, eV_{avr}) and standard error ($\text{st}\,\varepsilon$),

$$ep_i = \left(1 - \frac{z_p}{t_p}\right) \cdot 100\% \tag{3}$$

$$ep = |ep_i|, \tag{4}$$

$$eV_{\text{avr}} = \frac{1}{V}\sum_{p=1}^{V} ep, \tag{5}$$

$$\text{st}\,\varepsilon = \sqrt{\frac{1}{P}\sum_{p=1}^{P}(t_p - z_p)^2}, \tag{6}$$

where: $V = L, T, P$ — number of the training, testing and all patterns, respectively.

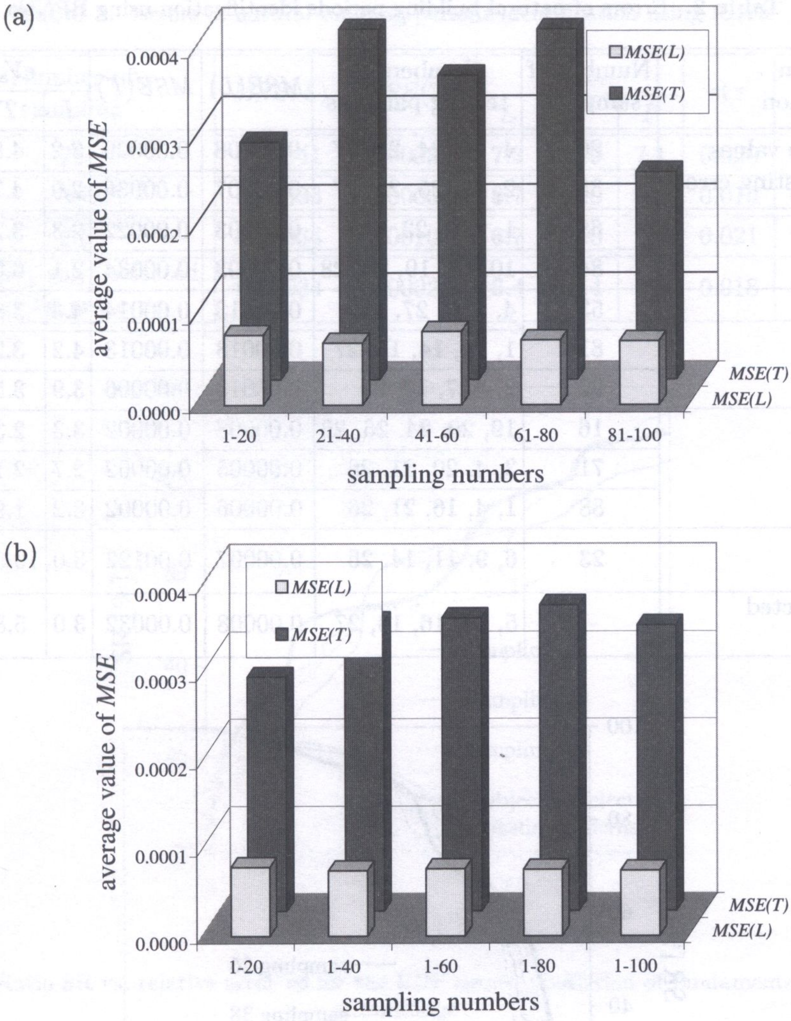

Fig. 3. Average values of Mean Square Errors (*MSE*) for various groups of the sampling numbers

The coefficient of a linear correlation $r(P)$ is also computed for every set of all pairs $\{t_p, z_p\}$.

The cases with training and testing errors nearest to average values of the total one hundred, with the minimal Mean Square Error for training process, with the maximal Mean Square Error for training process, with the minimal Mean Square Error for testing process and with the maximal Mean Square Error for testing process are taken in detail under consideration from the one hundred randomly selected pairs of training and testing sets.

The errors corresponding to the training and testing processes for the above mentioned BPNNs: 4–4–1 are shown in Table 2. In the last row of the Table 2 the results for "subjective" selection of testing patterns are also presented. The "subjectively" selected testing patterns represent different buildings and different directions. Therefore, from the engineering point of view, it is quite good choice.

Figure 4 shows a comparison of Success Ratio SR for the prediction of fundamental natural periods of prefabricated medium height buildings obtained using the analysed BPNNs for some cases of randomly selected testing patterns — sampling number 26, 38, 23 and "subjective" selection. The Success Ratio as the function SR(ep) [%] enables us to evaluate what percentage of patterns (SR) gives the neural prediction with the error not greater than ep [%]. In sampling number 26 and 38 the values of training errors $MSE(L)$ and testing errors $MSE(T)$ are the nearest to average values of the total one hundred cases whereas in sampling number 23 the testing error $MSE(T)$ is maximal.

Table 2. Errors of natural building periods identification using BPNNs

Criterion for selection	Number of sampling	Numbers of testing patterns	$MSE(L)$	$MSE(T)$	eV_{avr}			st ε	$r(P)$
					L	T	P		
nearest to average values of training and testing errors	26	4, 10, 24, 25, 27	0.00008	0.00029	3.2	4.8	3.4	0.011	0.968
	38	2, 12, 25, 26, 27	0.00007	0.00036	2.9	4.7	3.2	0.011	0.966
minimal training error	68	1, 7, 9, 23, 28	0.00003	0.00022	2.3	3.2	2.4	0.008	0.982
	84	10, 11, 19, 20, 28	0.00003	0.00034	2.1	6.0	2.7	0.009	0.978
maximal training error	53	4, 5, 9, 27, 30	0.00013	0.00014	4.3	3.8	4.2	0.011	0.960
	81	1, 10, 14, 15, 27	0.00013	0.00013	4.2	3.2	4.0	0.011	0.961
	92	2, 4, 7, 16, 29	0.00013	0.00006	3.9	3.5	3.8	0.011	0.965
minimal testing error	16	19, 20, 24, 26, 29	0.00008	0.00002	3.3	2.3	3.1	0.008	0.981
	71	3, 4, 20, 21, 26	0.00005	0.00002	2.7	2.1	2.6	0.007	0.985
	88	1, 4, 16, 21, 26	0.00006	0.00002	3.2	1.9	3.0	0.007	0.983
maximal testing error	23	6, 9, 11, 14, 26	0.00007	0.00122	3.0	10.9	4.3	0.016	0.927
"subjectively" selected testing patterns	–	5, 10, 16, 18, 27	0.00008	0.00032	3.0	5.8	3.5	0.011	0.964

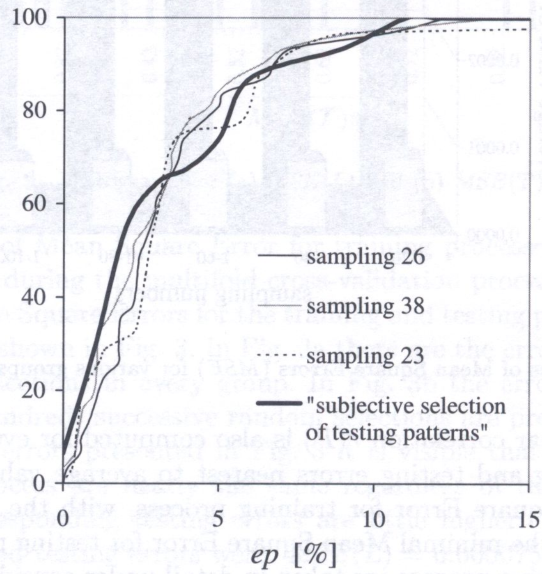

Fig. 4. Success Ratio SR vs. relative error *ep* for the BP neural prediction of fundamental natural periods of buildings

Looking at the errors corresponding to the training and testing processes of the considered BPNNs put together in Table 2 and SR (ep) in Fig. 4 it is clear that the accuracy of the considered BPNNs of architecture 4–4–1 is satisfactory from the engineering point of view. The carried out analysis leads to conclusion, that even in "the worst" case of randomly selected testing patterns when the $MSE(T)$ is maximal, the natural periods of vibrations of buildings are obtained with accuracy quite satisfactory for engineering practice. It is necessary to pay attention to the fact that at least 97% of patterns have relative errors not greater than 10% (cf. Fig. 4) in all cases of division of patterns into training and testing sets.

Besides of BPNNs application the estimation of fundamental natural periods was performed by another type of neural networks: neural networks of architecture 4–5–1 with Radial Basis Functions (RBF). These computations employed the same cases of patterns selection as for BPNNs.

Table 3. Errors of natural building periods identification using RBFs

Number of sampling	$MSE(L)$	$MSE(T)$	eV_{avr} L	eV_{avr} T	eV_{avr} P	st ε	$r(P)$
26	0.00041	0.00036	7.2	6.9	7.1	0.020	0.876
38	0.00036	0.00034	6.7	6.0	6.6	0.019	0.890
23	0.00034	0.00108	6.7	14.0	7.9	0.021	0.864
"subjectively" selected testing patterns	0.00034	0.00028	6.4	6.4	6.4	0.018	0.899

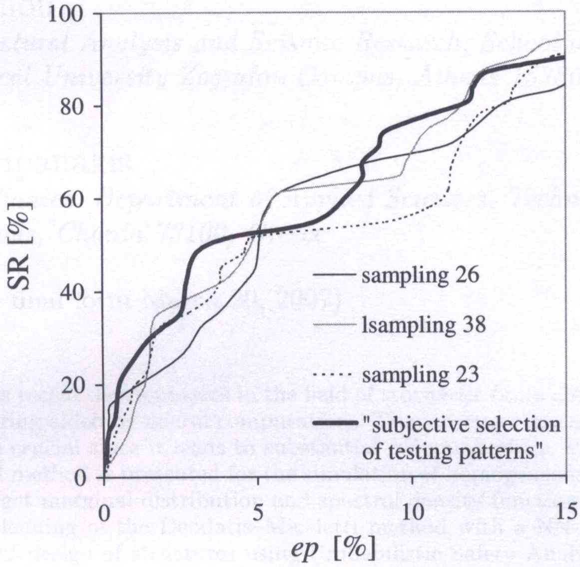

Fig. 5. Success Ratio SR vs. relative error *ep* for the RBF neural prediction of fundamental natural periods of buildings

All the RBF neural networks considered in the paper are trained by means of a SNNS computer simulator [6]. The RBF hidden neurons are associated with Gaussian RB function and each of RBF networks has linear output. The results achieved for some of the RBF networks are shown in Table 3 and in Fig. 5.

Comparing the errors for BPNNs from Table 2 with the errors for RBF networks from Table 3 as well as Success Ratio SR(ep) in Figs. 4 and 5, it is clear that the RBF networks give the worse accuracy of the obtained results.

5. Conclusions

The carried out analysis leads to conclusion that the application of all proposed BPNNs enables us to identify the natural periods of the buildings with accuracy quite satisfactory for engineering practice. Even in "the worst" case of randomly selected testing patterns, when the $MSE(T)$ is maximal, the neurally predicted natural periods of vibrations of buildings are very close to experimentally obtained. The RBF networks give the worse accuracy than BPNNs.

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