Data pre-processing in the neural network identification of the modified walls natural frequencies

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Abstract

Two techniques of neural network input data pre-processing are discussed in the paper: (i) data compression with the application of the principal component analysis method, (ii) various forms of data scaling. Neural networks are applied for the prediction of the first natural frequencies of horizontal vibrations of modified medium height load-bearing walls. The small and the large changes of the wall stiffness and mass resulted from the new door openings size and position are taken into account. The influence of the type of data pre-processing technique on the accuracy of the frequencies neural prediction is discussed.

Keywords: dynamics, neural networks, vibrations

1. Introduction

Various explanations could be given to the role and the need for data pre-processing, especially in case of neural network input data [1, 3, 5, 6, 8]. Although in a lot of cases the pre-processing of neural network data is not needed from the mathematical point of view, it can improve the neural network training process. Moreover, the form of pre-processing applied to the data is very important factor in determining the success of a practical application of neural networks [1, 3, 5].

In the paper the attention is focused on two techniques of neural network input data pre-processing. The first one concerns data compression (reduction of the dimensionality) with the application of the principal component analysis method [1, 4]. The other pre-processing is associated with the various forms of data scaling [5, 8].

The analysed problem is related to the neural prediction of the first natural frequencies of horizontal vibrations of modified medium height load-bearing walls. The small and the large changes of the wall stiffness and mass resulted from the new door openings size and position were taken into account. The influence of the type of data pre-processing technique on the accuracy of the frequencies neural prediction was investigated.

2. The analysed problem

According to the contemporary occupants expectations, the modernization problem appears in many apartment buildings. New door openings or widening of existing door openings in the load-bearing walls are some of the walls modifications. Wall geometrical modifications cause the changes of the wall dynamic properties, among others - natural frequencies of vibrations.

The influence of the modifications (geometrical changes) on the first natural wall frequency was analysed in case of series of door openings one above another on the all storeys (system door openings). The widths of door openings were taken from the range 0.9m-4.8m with step 0.3m. The door openings different positions were considered. They were “shifted” from the wall’s edge with step 0.3m. Typical medium-height reinforced concrete load-bearing walls were considered with 2.7m, 5.4m, 11.7m width and 14m (5 storeys x 2.8m) height, 0.14m thickness.

The relation between geometrical changes and structural parameters, and the first natural frequencies of horizontal vibrations of the modified walls (f_1) was determined using back-propagation neural networks (BPNNs). The following parameters as the input information were considered: p – coordinate of the door openings position, b_1 - door openings width, b_2 – wall width, f_{1S}, f_{2S} – the first and the second natural frequencies of the wall without door openings (cf. Fig. 1). Finite element method [7] was applied to generate neural networks patterns according to the cases of modifications. The fact of symmetry in the cases of door openings positions was taken into consideration and the total number of P=215 patterns were prepared. They were split into three sets: training – L=129 patterns (60%), validating – V=44 patterns (about 20%), testing – T=42 patterns (about 20%). All NNs considered in the paper were trained using Levenberg-Marquadt learning algorithm [2] and sigmoid activation function.

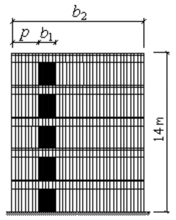

Figure 1: The example of the analysed walls

3. Applied techniques of input data pre-processing

3.1. *Principal component analysis*

The principal component analysis (PCA) is one of the applied methods for the reduction of the neural network input space dimension [4]. The reduction is achieved by transforming the data to a new set of variables, called principal components.

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 $\mathbf{W} \in R^K x R^N$. 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.

Table 1: Neural networks errors of natural wall frequencies identification

NN	Steps of the input data pre-processing	NN structure	*MSE*			*ep* max [%]			*ep* average [%]			r_T
			L	*V*	*T*	*L*	*V*	*T*	*L*	*V*	*T*	
1	without pre-processing	5-5-1	0.00098	0.00795	0.01122	1.38	3.26	4.40	0.29	0.56	0.58	0.9993
2	S1	5-5-1	0.00039	0.00162	0.00107	1.08	2.25	1.63	0.16	0.31	0.25	0.9999
3	S2	5-5-1	0.00146	0.00571	0.00330	2.07	3.29	1.70	0.32	0.58	0.38	0.9998
4	LC	1-3-1	3.48180	3.89550	4.59810	58.26	33.54	59.70	16.9	14.6	18.6	0.6514
5	GC	1-3-1	0.40886	0.87529	0.90390	27.05	25.69	28.58	5.51	6.42	6.32	0.9429
6	S1 – GC – S3(α =4)	1-3-1	0.20809	0.54944	0.55494	18.86	19.94	22.55	3.73	5.25	4.89	0.9653
7	S1 – GC – S4(α =1)	1-3-1	0.30217	0.58572	0.57076	29.73	21.12	22.32	4.73	5.70	5.08	0.9641
8	S2 – GC – S3(α =3)	1-3-1	0.24310	0.50120	0.51222	27.02	19.26	21.57	4.09	5.07	4.68	0.9686
9	S2 – GC – S4(α =1)	1-3-1	0.31102	0.58046	0.55122	30.55	23.33	21.63	4.79	5.88	4.99	0.9650

Two variants of PCA method application were considered: (i) input data transformation into principal components using “the local compression” (LC) and (ii) input data transformation into principal components using “the global compression” (GC). In the first one for each of input vectors the autocorrelation matrix was set up and the linear eigenvalue problem was analysed separately. In the second one only one autocorrelation matrix associated with the all input vectors was computed.

3.2. Scaling of input data

The goal of data scaling is often to transform the data into dimensionless data or into assumed space (range).

A number of input variable transformations by scaling were proposed in the paper. Among others the following formulae were discussed:

S1: $$x_s = \frac{0.9 \cdot (x - x_{\min}) - 0.1 \cdot (x - x_{\max})}{x_{\max} - x_{\min}} \tag{1}$$

S2: $$x_s = \frac{x}{x_{\max}} \tag{2}$$

S3: $$x_s = x^{\alpha} \tag{3}$$

S4: $$x_s = e^{\alpha x} \tag{4}$$

where: x_s – scaled value, x – real value, x_{min} and x_{max} – minimal and maximal values of the real range respectively, α – chosen constant.

4. Numerical results

Looking at the results of GC as well as LC it is clear that the first principal component reaches more than 99% part of the total variance of data in the all considered cases. Then the first principal component is predominant. Figure 2 shows the “difficult” for neural prediction relationship between the first principal components of the modified wall parameters and the wall frequencies.

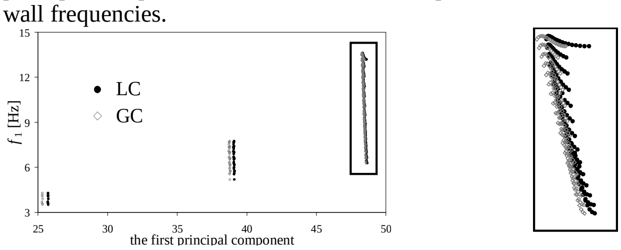

Figure 2: The first principal components of the modified wall parameters vs. wall frequencies

The accuracy of proposed networks with various input data pre-processing was estimated by Mean Square Error (*MSE*), relative errors (*ep*), the coefficient of linear correlation for testing (r_T) and Success Ratio (*SR*). The errors corresponding to the training, validating and testing processes for the demonstration BPNNs are shown in Table 1. Comparison of the distribution of *SR* for testing of some of the above mentioned networks is presented in Fig. 3.

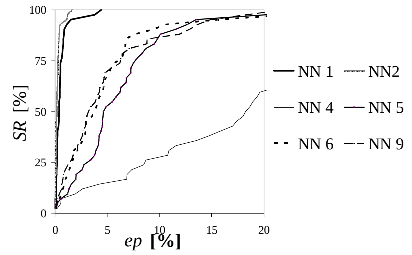

Figure 3: Comparison of the Success Ratio (*SR*) for demonstration neural networks testing

5. Conclusions

The influence of the neural network input data scaling on the accuracy of the neural prediction of the modified wall frequencies could be significant.

The pre-processing using PCA enables us mapping the input data into a space of lower dimensionality. It was stated that in case of considered input vectors (with the same possible values of parameters described different information, e.g. *p*, b_1) GC had given better results than LC.

Because of the obtained special relationship between the first principal components of the modified wall parameters and the wall frequencies, the scaling by rotation (by “stretching”) of the compressed neural network input data was needed.

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