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Predicting the impact of traffic–induced vibrations on buildings using artificial neural networks

Anna Jakubczyk-Gałczyńska[1,*]

[1]Gdańsk University of Technology, Faculty of Civil and Environmental Engineering, Narutowicza 11/12, 80-233 Gdańsk, Poland

Abstract. Traffic–induced vibrations may constitute a considerable load to a building, cause cracking of plaster, cracks in load–bearing elements or even a global structural collapse of the whole structure [1-4]. Vibrations measurements of real structures are costly and laborious, not justified in all cases. The aim of the paper is to create an original algorithm, to predict the negative dynamic impact on the examined residential building with a high probability. The model to forecast the impact of vibrations on buildings is based on artificial neural networks [5]. The author's own field studies carried out according to the Polish standard [6] and literature examples [7-10] have been used to create the algorithms. The results of the conducted analysis show that an artificial neural network can be considered a good tool to predict the impact of traffic–induced vibrations on residential buildings, with a sufficiently high reliability.

1 Introduction

The problem of traffic-induced vibrations is important because more and more areas are urbanized. New roads are being built, both in cities, on suburbs. In rural areas more buildings are being built near roads. Areas that are well communicated are readily built and inhabited. As a result, vibrations in buildings caused by vehicles concern both existing as well designed houses.

Taking into account the impact of traffic-induced vibrations caused on buildings, they can be unnoticeable or even causing a structural failure. Vibrations may cause cracking of plaster, cracks in load-bearing elements or even collapse of the structures [11, 12]. The impact of vibrations of the building is affected by many factors related to the road on which vehicles pass. The dynamic parameters of the building are also important. Measurements of vibrations on real constructions are labor-intensive and costly tests, and importantly, not justified in every case. It may be economically unprofitable to carry out such tests for all buildings located near the road. Modern, still growing technology brings a lot of possibilities to solve such as problems (for example see [13-15]). Therefore, there is a need to develop effective methods for forecasting the impact of traffic-induced vibrations on residential buildings. Thus the aim is to create an expert system, which it is possible to

* Corresponding author: annjakub@pg.gda.pl

predict with a certain probability the threat of negative dynamic impact on the tested building, without performing labor-intensive measurements. There are many methods for forecasting various types of phenomena. An example here are Artificial Neural Networks (ANN).

2 Traffic-induced vibrations

2.1 Definition and factors affecting the size of interaction

Vibrations are a phenomenon of the movement of building structure molecules most frequently caused by waves propagating in the subsoil and reaching to the foundations [16]. Vibrations transmitted through the ground can be divided into: seismic (independent of human activity, caused by earthquakes, see [17-23]) and paraseismic caused by human activity (see, for example [1-4]). Traffic-induced vibrations are a subset of paraseismic effects and are caused by the passage of wheeled and rail vehicles (also underground). The subject of the research in the paper are vibrations caused by road traffic.

The size of vibration depends on many factors, are associated with the following [16]:

- distance of the object from the source of vibrations (the range of dynamic effect is usually about 25 m from the egde of the road),
- soil: ground water, partitions, wells, absorption of soil,
- vehicles: shape, weight, technical condition, speed, number of vehicles passing at once, starting, stopping,
- surface: type, technical condition, unevenness (damage, protruding sumps causing a change in the trajectory of the vehicle, vertical and horizontal hit of wheels, which increases the emission of waves propagating in the ground),
- building: type, construction, foundation, technical condition, damping.

These factors depend on the intensity of the transmitted vibrations to the building. The more vibrations are transmitted to the building, the greater damage can occur.

2.2 Measurement methodology

In Poland, each building, should be carried out a detailed standard analysis according to [6]. Acceleration values recorded during the measurements are analyzed in one-third octave frequency bands. As a result, the amplitude values are obtained for all the centre frequencies in the range of 1-100 Hz. Then, peak values are selected and plotted on Dynamic Influence Scale (DIS) (see Fig. 1). The standard [6] concerns residential buildings, which have been divided into two groups:

- densely-shaped brick buildings, vertical projection of which should not exceed 15 meters, th building should not exceed two floors and its height must not exceed the measurement of the projection (assessment by DIS I),
- buildings of maximum 5 floors, their height being lower than doubled width (assessment by DIS II).

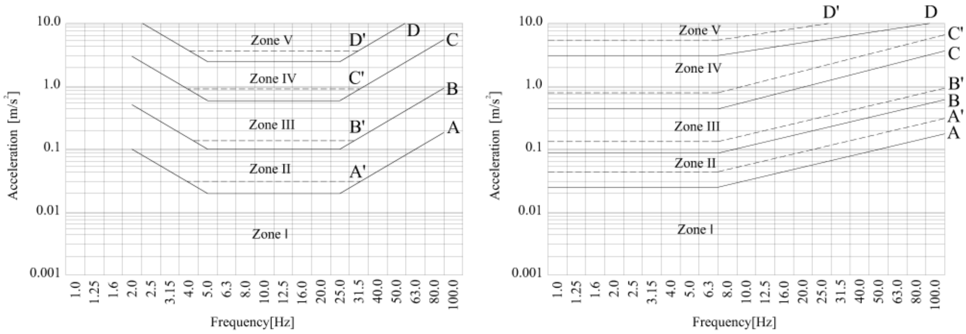

Fig. 1. Dynamic Influence Scale (DIS I on the left, DIS II on the right) [6].

The size of the impact and possible effects are described in [6]:
- Zone I: no impact of vibrations on building;
- Zone II: vibrations are noticeable but do not pose a threat to the structure;
- Zone III: the overall load bearing capacity of building may be weakened;
- Zone IV: vibrations have major influence on building, the amplitudes are high enough to cause various objects in the apartments to tremble, there is a risk for health of inhabitants;
- Zone V: The load bearing capacity is dysfunctional as a result of large amplitudes of vibrations what may lead to a major malfunction or even total collapse of the structure.

3 Experimental research

The measurements were made using specialist equipment (see Fig. 2). Piezoelectric acceleration sensors were connected to the measuring apparatus in their assigned sockets, which were previously configured (accordingly). During the tests 6 sensors were used mounted on the foundation wall of a building parallel to the street, just above ground level according to [6]. After connecting the sensors and setting the apparatus, calibration was carried out. On the computer connected to the measuring apparatus, the time histories shall be performed during passing of various types of vehicles (two-axle buses, vans and trucks with a total weight up to 10 t and for buses and trucks weighing over 10 t and have more than 2 axles.

Fig. 2. Specialized measuring equipment and piezoelectric accelerometers mounted on the wall of the tested building.

The measurements for 11 buildings were analyzed, filtering each measurement in 21 third bands (in each measurement independent values for several sensors were obtained, but ultimately the sensor that showed the highest amplitudes was selected), receiving 693 time history. An extreme acceleration was determined for each of the mid-frequencies one-third octave bands and the results were plotted on DIS graphs. They were data for artificial neural networks.

4 Artificial neural networks

4.1 Definition of artificial neural networks

Artificial neural network (ANN) is a machine learning algorithm based on the principle of the human brain's prosperity [5]. The human brain consists of about 10^{10} nerve cells, called neurons, and performs even 10^{18} operations per second. The neuron consists of a body called somme and spikes. The core element of the soma is the nucleus, in which all processes essential for the functioning of the neuron occur [24]. The spikes are divided into dendrites (there can be thousands of them) introducing information to the neuron and axon - one projection leading information from the soma. In order to create an algorithm it is necessary to build an artificial neuron (Fig. 3). The information is given, processed, saved and even corrected by the system. The process of building network consists of three basic steps: learning, validation and testing.

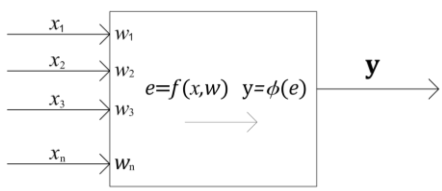

Fig. 3. Model of artificial neuron (perceptron): x_i– input signals; y – output vector (signal); w_i– weight; e – internal processing function; ϕ – activation function [5].

In classification problems, the most common types of ANN are Multilayer Perceptrons. These are basic neural networks, based on the principle: input – internal processing and activation functions - output [25]. This is a global approximation. Another tool is Radial Basis Functions that allow local type approximation. In the hidden layer, the neuron is subjected to functions that change radially around the selected center c.

4.2 Created algorithm of ANN

This subchapter presents the classification problem defined in such a way that the ANN algorithm (on the basis of several parameters given by the user) will be able to make a predict of the impact of traffic-induced vibrations on the building with a satisfactory probability. The network was built on the basis of principles described in the literature [5, 24-26]. The first step was to create a database necessary to start the builiding of the algorithm, i.e. to perform vibration measurements on the buildings. 63 samples were collected, including 33 samples of input data, performing their own measurements and 30 samples based on measurements of other researchers [7-10].

The input neurons were assumed to be factors (independent variables) determined during measurements based on standard [6] and book [16]:

- B_{TC} – technical condition of the building;
- D_{BR} – distance of the building from the edge of the road;
- S_A – absorption of soil;
- R_S – type of road surface;
- R_{STC} – technical condition of the road surface;

- V – vehicle type.

Input vectors for subsequent network adopted at random, in the form of:
- ANN no. I: $\mathbf{x}_{(6x1)} = \{B_{TC}, D_{BR}, S_A, R_S, R_{STC}, V\}$;
- ANN no. II: $\mathbf{x}_{(5x1)} = \{B_{TC}, D_{BR}, S_A, R_{STC}, V\}$;
- ANN no. III: $\mathbf{x}_{(4x1)} = \{B_{TC}, D_{BR}, S_A, R_{STC}\}$;
- ANN no. IV: $\mathbf{x}_{(4x1)} = \{B_{TC}, D_{BR}, R_S, V\}$;
- ANN no. V: $\mathbf{x}_{(4x1)} = \{D_{BR}, S_A, R_{STC}, V\}$.

As an output signal, a neuron with possible values was determined:
- 0 – no impact on building – zone I according to standard [6];
- 1 – possible impact on building – zone II or above according to standard [6].

All samples were randomly divided into 3 sets, i.e. learning, verification and testing set. Two variants of division were made:
- 1st variant: 44 samples were allocated randomly to the learning set (69.84% of all samples), 10 cases assigned to the verifying collection (15.87% of all cases) and 9 samples for the testing set (14.29% of the total);
- 2nd variant: 30 samples were allocated randomly to the learning set (47.62% of all samples), 16 cases were assigned to the verification set (25.40% of all cases) and 17 samples for the testing set (26.98% of the total).

Depending on the type of ANN, the BFGS learning algorithm was used, a strong second-order algorithm with fast convergence, local extremes of functions were found [26]. In the case of radial networks, Radial Basic Functions were used in the learning process. In the created algorithms, the activation functions given in [24].

4.3 Results

Five different network characteristics have been created. A summary of the results of the reliability of all networks is presented in Table 1. The general reliability of the ANN was calculated as a weighted average, taking into account the size of the learning, verification and testing sets.

Table 1. Summary of reliability of the analyzed artificial neural networks.

NETWORK No.	VARIANT OF DIVISION	RELIABILITY [%]			
		LEARNING SAMPLES	VERIFICATION SAMPLES	TESTING SAMPLES	GENERAL
ANN I	1	81.82	90.00	77.78	82.54
	2	76.67	81.25	88.24	80.96
ANN II	1	88.64	100.00	88.89	90.48
	2	96.67	87.50	82.35	90.48
ANN III	1	86.36	60.00	66.67	79.36
	2	76.67	68.75	88.24	77.78
ANN IV	1	88.64	70.00	66.67	82.54
	2	83.33	81.25	88.24	84.13
ANN V	1	86.36	90.00	88.89	87.30
	2	83.33	87.50	88.24	85.71

Taking into account all the combinations of the factors in different variants, it can be concluded that the best prediction, with a general reliability of 90.48%, was achieved by network No. II, in which the input vector has the form: $\mathbf{x}_{(5x1)} = \{B_{TC}, D_{BR}, S_A, R_{STC}, V\}$. This means that the best combination of input factors for the analyzed cases of vibration prediction is: technical condition of the building, distance of the building from the edge of the road, absorption of soil, technical condition of the road surface and vehicle type.

Network no. II, both in the first and in the second variant of the division into samples, reached very good results. In the first case-division variant, the reliability for the learning sample was 88.64%, the verification samples reached 100.00% correctness, while for the testing cases, the algorithm received 88.89% correct results. On the other hand, in the second variant the distribution of the cases, the credibility of the learning sample was 96.67%, for the verification sample obtained 87.50% accuracy, for the testing cases for algorithm obtained 82.35% correct results. Obtaining the best prediction results for the network no. II means that the type of surface is the least important for the analyzed cases. After performing sensitivity analysis for the testing samples (i.e., cases not used to build the algorithm or to validate it), it can be determined that the condition of the road surface is the most important issue.

5 Conclusions

The conclusion of results is that ANNs is suggested to be a relevant tool to predict the impact of traffic-induced vibrations on residential buildings with a relatively high probability. In addition, the presented algorithm can be applied both to existing and designed buildings, while the source of vibration is already present or may appear in the future.

The author's method may be helpful when user must decide about the location of the proposed investment and, in the case of existing buildings provides the basis for specialized vibration measurements to confirm or exclude risks.

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