Artificial neural networks for non destructive testing of concrete structures

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Abstract

In this paper, the determination of defects in concrete structures using an ultrasound technique is discussed. A diagnostic model for concrete pillars by means of Multi Layer Perceptron neural networks is developed to locate and classify the defects. Finite Elements numerical techniques have been used to model a concrete pillar of specified size (i.e., rectangular cross section and 2 meters in span) affected by defects of different position and size. The numerical analyses enable to obtain several received signals containing the fault information. These signals have been processed by a feature extractor system, whose purpose is to reduce the data dimensionality and to compute suitable features. Results showed good accuracy in the identification of the position and entity of the faults.

1. Introduction

Evaluating the integrity of a masonry structure and locating the potential defects is a recurrent issue. Non Destructive Testing (NDT) allows one to implement a control over the material at different stages of its evolution and permits to safeguard the integrity of the structure during the analysis.

Several methods have been proposed that use the propagation of ultrasonic waves for NDT tasks [1-12]. In fact, the wave velocity, amplitude and frequency content clearly depend on the state of the material.

By applying a point impact on the surface of the structure under test, a stress pulse propagates into the concrete as compressional, shear and surface waves. The compressional and shear waves are partly reflected by any internal interface or discontinuity such as reinforcements, ducts, defects, delaminations. These waves are almost completely reflected if the second material is air, such as in the presence of a void or at the external boundaries of the element under investigation.

The principle of *impact echo* testing is based on multiple reflections of the wave between the surface and any internal reflector. These reflected waves are picked up by a transducer at the receiver position - just besides the impactor - so that compressional wave arrivals will be dominant [1].

In the *transparency* testing that requires access to two surfaces, the receiver is in the opposite surface of the transmitter. The first pulse that arrives at the receiving transducer will be diffracted around the periphery of the eventual defect [1].

Compared to the application of elastic waves for NDT of metals, NDT in civil engineering is a very challenging task. This is due to the strong heterogeneity of typical materials like concrete, leading to multiple scattering modifying the velocity and the attenuation of the received ultrasonic waves.

Literature reports different approaches to concrete strength estimation based on the correlation between physical parameters and concrete strength [2,3] and its correlation with the compression strength is a classical technique that can be applied to each concrete after a calibration campaign. These measurements can be performed on cores extracted from the structure; thus, they are representative of a region with limited and supposedly homogeneous size. In [4] the authors analysed the longitudinal speeds of propagation of ultrasound in various samples of concrete, confirming the exponential relationship with the samples' compressive strength characteristics as evaluated during destructive testing.

Imaging and interpretation of the waves in the time domain as well as in the frequency domain can be used for thickness and defect location measurements.

In [5] acoustic parameters obtained from received signals generated by impact on concrete surface are analysed to estimate defect sizes.

The attenuation of the transmitted [6] or backscattered waves [7], the spectrum degeneration [8,9] or the evolution of the signal energy [10] are useful ultrasonic indicators of the damaging evolution.

Generally speaking, in wave propagation based methods, the user must interpret the recorded signals. Qualitative interpretation requires a user experienced in waveform recognition.

Artificial intelligence techniques such as neural networks, seem to be particularly suitable to automate ultrasonic signals interpretation for their ability of self-learning and generalization. In [11] a Multi Layer Perceptron neural network is trained to recognize three damage conditions in a reinforced concrete beam. The beam is divided in eight regions as diagnosis location and the damage is simulated by the reduction of the material strength.

In [12] a concrete undamaged detection system is built using fuzzy neural networks to obtain the concrete strength, processing the rebounding value and the carbonation depth.

At the author's knowledge of the literature in this area, nothing has been recorded about the prediction of position and entity of the damage.

In this paper, a Multi Layer Perceptron (MLP) neural network is trained to assess the dimensions and location of defects in a concrete pillar. The experimental test pillar is modeled using finite elements methods. Numerical analysis of a pillar of rectangular cross section is performed to generate training and testing samples for neural network assessing task. In particular, the wave source is due to the impact of a force in the pillar surface. The received signal, recorded in the opposite face of the pillar, is used to feed the network after a suitable preprocessing.

The paper is organised as follows: section II describes the data set generation, the adopted feature extraction technique and the neural model; in section III the results are presented and section IV reports the conclusions.

2. Proposed Diagnostic Method

The applied diagnostic technique is based on the propagation of ultrasonic waves in the test structure. In fact, the received wave's velocity, amplitude and frequency content clearly depend on the state of concrete. In particular, in the transparency technique a mechanical impact is applied on the surface of the concrete element and a receiver is located in the opposite surface of the structure. The technique is based on the detection of elastic waves and their conversion into electrical signals. This is accomplished by directly coupling piezoelectric transducers (accelerometers) on the surfaces of the structure under test. Sensors are coupled to the structure by means of a fluid couplant and can be secured with tape, adhesive bonds or magnetic hold downs.

Usually, the applied excitation frequency ranges from 15 to 75 kHz, and its propagation velocity in a mean is a function of the elastic characteristics of the mean itself (Young modulus, and Poisson coefficient) and of its density.

Dishomogeneities in the structures (cracks, degraded regions, etc.) produce variation of the propagation velocity; reflections, refractions, partial absorption and attenuation of the wave. The analysis of such phenomena can be useful to evaluate the presence of such dishomogeneities.

Fig. 1 shows an experimental set up to apply the transparency technique.

2.1. Data Set

The propagation of an elastic wave through a concrete pillar has been simulated by means of the Finite Element Method (FEM), using LS-DYNA module of ANSYS [13].

The numerical analyses have been carried out simulating an advanced multi-channel acquisition system.

The instrument is based on piezoelectric transducers technology, and it can be arranged to generate and detect sonic and ultrasonic waves in the masonry structures under test. In the examined cases, the instrument has been simulated as made up of one excitation transducer and 7 receiving transducers located in the front and back sides of a pillar, as shown in Fig. 2 and Fig. 3. The acquisitions are repeated for each position of the excitation.

The excitation is a force characterized by a triangular shape, lasting 50μs, and whose amplitude is equal to 10^3 kN [5]. The excitation signal is shown in Fig. 4.

The generated wave propagates in the pillar until it is received by the transducers in the opposite side.

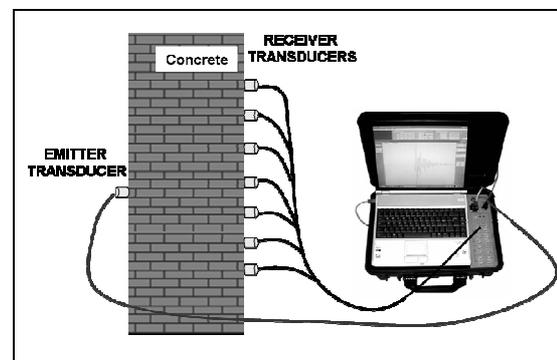In the following, a detailed description of the three-

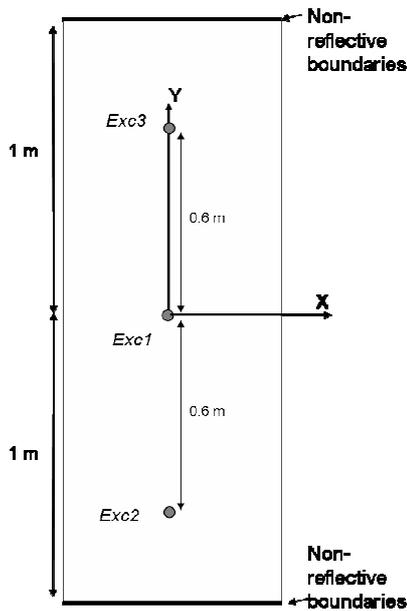**Figure 1. Experimental set up**

Figure 2. Front view of the pillar and excitation points

dimensional model used to generate the synthetic data is reported.

Data have been generated by simulating propagation and scattering of elastic waves in the concrete structure with defects having different geometrical dimensions. The transient numerical analysis has been carried out
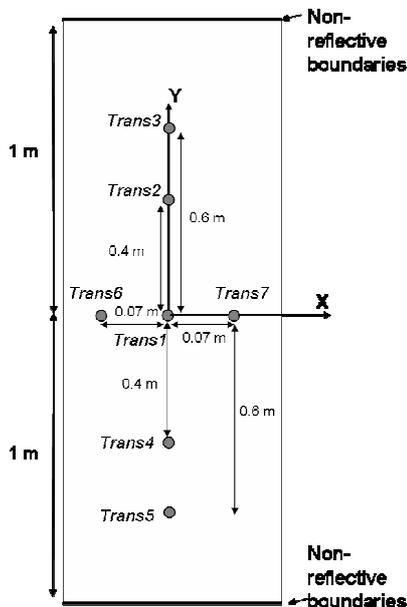

Figure 3. Back view of the pillar and observing points
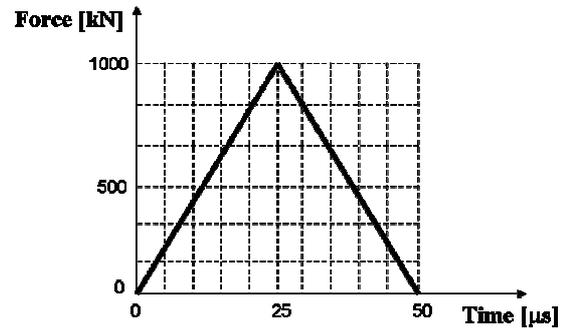

Figure 4. Excitation signal

by the finite element method. The general principle consists of defining a homogeneous medium equivalent to that of concrete and with the same acoustic characteristics.

The geometrical dimensions and the characteristics of the pillar are shown in Table I.

Table I - Geometrical dimensions and material properties of the concrete pillar

High [m]	2
Width [m]	0.3
Depth [m]	0.3
Young's modulus [GN/m^2]	33
Poisson's coefficient	0.300
Density [kg/m^3]	2300

An analysis of the pillar model without defects has been firstly performed. The purpose of this test is to set the simulation parameters, i.e., the dimensions of the elements in the FEM model, and the sampling time.

The FEM model of the concrete pillar is reported in Fig. 5, while the dimensions of the elements in the FEM model, and the sampling time are shown in Table II.

Non reflecting boundaries have been imposed on the upper and on the bottom surfaces of the pillar in order to simulate an infinite boundary. These constraints are typically used to limit the size of the model and to prevent artificial wave reflections at the boundary.

In a second phase, the same pillar has been considered, which presents different defects. Varying the location and the dimensions of the defect, several simulations have been performed. The defects are modelled by simply varying the characteristics of a set of elements inside the pillar, in order to simulate air regions.

Figure 5. 3-D FEM model of the concrete pillar

Table II – Model parameters

Number of x-axes subdivisions	30
Number of y-axes subdivisions	100
Number of z-axes subdivisions	30
Sampling time [µs]	5
Excitation frequency [kHz]	50

The defect geometrical and physical characteristics are reported in Table III and Table IV.

The resulting data set is composed by 82 defect cases plus the fault free case. The limited number of simulations is due to the high CPU time required for each of them.

The three components aggregate, cement, and pores constitute concrete as a heterogeneous material. In order to take it into account the wave propagation on a heterogeneous pillar in presence of a defect has been simulated. The heterogeneity has been modelled varying the characteristics of a set of elements inside the pillar, in order to simulate small air regions.

The three examples of heterogeneous pillar have been used as test set in order to evaluate network robustness.

Table III – Geometrical Defect characteristics

Defect x-axis barycentre position [m]	0÷0.12
Defect y-axis barycentre position [m]	0÷0.2
Defect z-axis barycentre position [m]	±0.08
Defect high [m]	0.02÷0.1
Defect width [m]	0.02÷0.1
Defect depth [m]	0.04÷0.12

Table IV – Physical Defect characteristics

Young's modulus [GN/m$^{2]}$]	$1.5 \cdot 10^{-4}$
Poisson's coefficient	0.1
Density [kg/m^3]	1.3

For each defect, the used signals are the waves measured in the 7 observing points.

In order to reduce the data dimensionality, the acquired waves obtained from the numerical simulations have been surveyed only during prefixed time windows. In particular, a time window of 0.005 seconds has been chosen. This time window contains 1000 samples. In Fig. 6, the received signals corresponding to pillar without and with a defect respectively, are reported, in the corresponding time windows.

In general, if D is the number of simulations (D = 83 in the present paper), S is the number of samples in the chosen temporal window (S = 1000 in the present paper), and N is the number of receiving transducers (N = 7), 3×D different matrices of dimension S×N can be built. Let M_d, d=1,…D, be the matrix of dimension [S×(N×3)] characterizing a particular defective pillar or the pillar without defect. Each matrix M_d, which represents the pattern describing the corresponding defect, has been processed (as detailed in the following) in order to generate input patterns suitable to feed the NN classifier. The corresponding output pattern will be constructed associating to the input pattern the corresponding coding of the defect, i.e., the barycentre position and the dimensions.
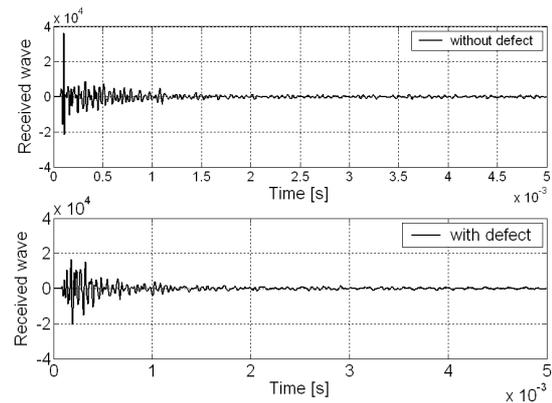

Figure 6. Transmitted waves corresponding to pillar without and with defect.

As outlined, some post processing is necessary on the $\mathbf{M_d}$ matrices, in order to extract the significant features and to reduce the data dimensionality.

2.2. Feature Extraction and Data Reduction

A two-dimensional Fast Fourier Transform (FFT-2D) has been applied to each of the $\mathbf{M_d}$ matrices, obtaining D new couples of matrices, $\mathbf{A_d}$ and $\mathbf{P_d}$, containing the amplitude and the phase components of the FFT-2D respectively. In fact, it has been verified that the defect thickness influences the FFT amplitude, while the defect axial length influences the shape of the waves, and, consequently, the FFT phase [14,15].

To reduce the data dimensionality, a subset of K amplitude components has been selected from each $\mathbf{A_d}$. The K selected components are those whose amplitude is greater than the 75% of the maximum value of the matrix elements, i.e.,

$$a_{ij} \geq 0.75 \cdot \max_{s=1,\ldots S; n=1,\ldots N} \left(a_{sn} \right)$$

The coefficient 0.75 has been chosen with a trial and error procedure.

The selected K amplitude components of all the D matrices have been stored in a unique matrix of dimension $K \times D$, and the corresponding phase components have been stored in another matrix of the same dimension.

In the present case, K is equal to 32.

These two matrices have been normalized so that they have mean equal to zero and standard deviation equal to 1.

2.3. Neural Network NDT System

The use of model free approaches for NDT, such as neural networks, is justified by the difficulty of finding a proper solution to this problem by using analytical methods. The most widely used neural classifier is the Multi-Layer Perceptron. An MLP neural network is constituted by an input layer, one or more hidden layers, and one output layer of neurons. The neurons of each layer are connected with all the neurons of the previous layer. The connection weights are the free parameters of a learning process. They are determined by presenting to the network a set of actual input-output values (the training set) and searching the minimum of a suitable error function, which depends on the connections weights.

Due to the exiguity of data set, leave-one-out cross-validation on 70 examples is applied to evaluate the network performances. In leave-one-out cross-validation the network is trained several times, each time leaving out one of the samples from training, but using only the omitted sample to compute the error [16]. The resulting estimates of the generalization error is used for choosing among network architectures with a different number of hidden neurons. The chosen architecture has been trained by using the 70 examples. Network performance has been evaluated on an independent test set.

It can be noted that, if the number of examples in the training set is limited, as in the present problem, the network size (i.e., the number of connection weights) has to be limited, in order to avoid the overfitting of the network. This can be done by limiting the number of hidden layers, or the number of neurons in the hidden layers, or by reducing the number of input neurons. Since the number of input neurons has to be chosen according to the number of independent variables, i.e., the number of features used to describe the wave reflected by the defect, the feature extraction and selection procedure is crucial to limit the network size.

The following MLP architecture has been used to predict the defect position and dimension :

- 32 input nodes;
- one hidden layer with 10 nodes and hyperbolic tangent activation function;
- 6 output nodes corresponding to the dimension of the defect and the position of the barycentre. The output nodes activation functions are linear.

The network has been trained using the Levenberg-Marquard learning algorithm.

3. Results

The following results refer to the classification errors evaluated on an independent test set consisting of 13 examples, not used during the training procedure.

Figures from 7 to 12 show the actual values of the position of the barycentre and the defect dimensions and the corresponding values predicted by the neural classifier.

As can be noted, the classifier is able to detect both the defect position and size with high accuracy in the majority of the tested configurations.

The last three examples correspond to the case of heterogeneous pillar with small air regions in random position. Results show that the network is able to identify the defects with a sufficient accuracy even in case of input signals perturbed with respect to the training examples.
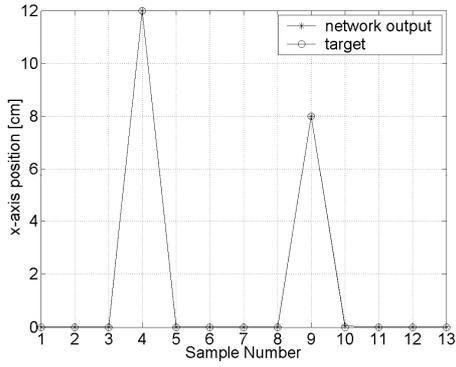
Figure 7. Position of the barycentre in the x axis: actual and predicted values.
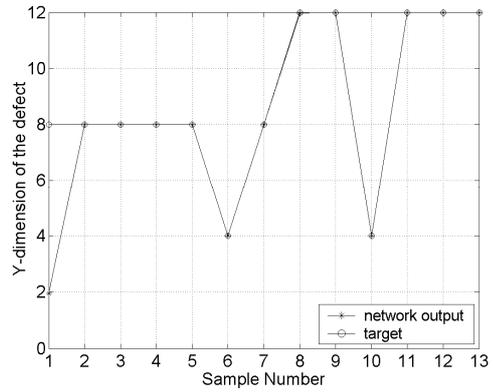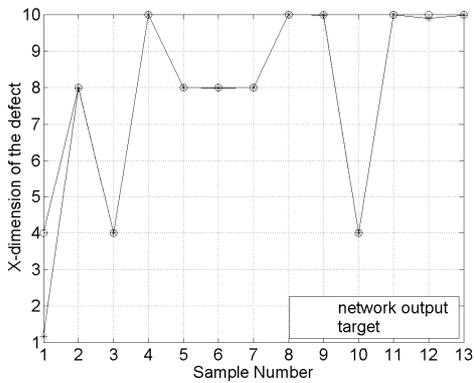

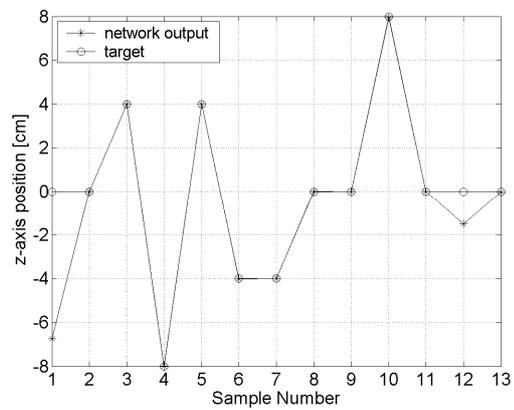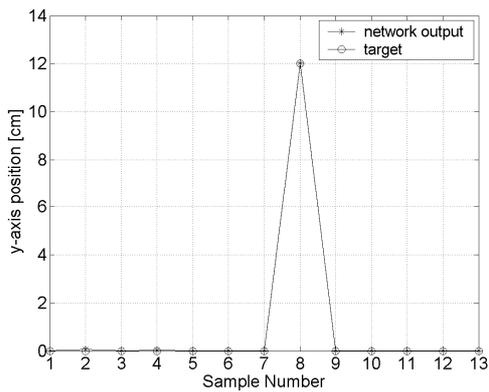**Figure 8. X-dimension of the defect: actual and predicted values .**

Figure 9. Position of the barycentre in the y axis: actual and predicted values.

Figure 10. Y-dimension of the defect: actual and predicted values.

Figure 11. Position of the barycentre in the z axis: actual and predicted values.
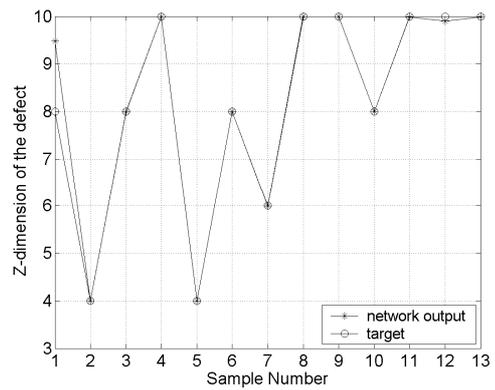

Figure 12. Z-dimension of the defect: actual and predicted values .

4. Conclusion

In the present paper a neural model for non destructive evaluation of concrete's damaging by using ultrasound technology is proposed. The results show that the proposed technique can be efficient for the diagnosis purpose.

Future research will investigate the method applicability using a more realistic model of the pillar including the interaction of the ultrasonic wave with the scatterers. Moreover, test on a real world pillar will be performed.

5. Acknowledgment

6. References

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