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STUDY OF ARTIFICIAL NEURAL NETWORKS BASED METHODS FOR THE RAPID ESTIMATION OF R/C BUILDINGS' SEISMIC DAMAGE

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ABSTRACT

In the present paper the investigation of the problem of reinforced concrete (r/c) buildings' seismic damage prediction utilizing Artificial Neural Networks (ANN) is exhibited. More specifically, the problem is formulated and solved in terms of the Function Approximation (FA) problem as well as of the Pattern Recognition (PR) problem using Multilayer Feedforward Perceptron Networks (MFP) and Radial-Basis Function (RBF) networks. The required ANNs' training data-set is created by means of Nonlinear Time History Analyses (NTHA) of 30 r/c buildings which are subjected to 65 earthquakes. The selected buildings have different heights, structural systems and structural eccentricities, and are designed on the basis of the provisions of Eurocodes. The seismic damage index which is used to describe the seismic damage state of buildings is the Maximum Interstorey Drift Ratio (MIDR). The influence of the parameters which are used for the configuration and the training of MFP and RBF networks on the reliability of their predictions (i.e. number of the hidden layers, the number of neurons in the hidden layers, the training algorithms, as well as the neurons' activation functions in the case of the MFP networks and the width parameter of the radial basis function in the case of the RBF networks) is investigated. The generalization ability of the best configured ANNs is examined by means of seismic scenarios. The most significant conclusion that turned out is that the trained ANNs can reliably and rapidly classify the r/c buildings into pre-defined damage classes provided they are appropriately configured.

Keywords: Seismic Damage Prediction; Artificial Neural Networks; Existing R/C Buildings; Structural Vulnerability Assessment; Seismic Response of Buildings

1. INTRODUCTION

The capability of rapid estimation of numerous buildings' seismic damage level instantly after a strong earthquake which strikes big cities or metropolitan areas constitutes a very significant parameter for the optimum prioritization of the essential post-seismic actions. This capability leads to a more effective coordination of the departments of civil protection agencies, because it provides instant information about the most stricken cities' regions. The accumulated experience of the problems which were resulted during the handling efforts of the earthquakes' consequences is a continuous research object for the international earthquake engineering research community since many decades. The corresponding research efforts led, among others, to the development of methods for the instant (but approximate) seismic vulnerability assessment as well as the estimation of the expected seismic damage state of various classes of buildings with common structural materials and/or structural systems. Well-documented methods of this category are the seismic vulnerability curves, the damage probability matrices and the procedures of rapid visual screening of structures (e.g. Kappos et al. 2006, ATC 1985, FEMA-154 2002).
The significant increase of the computational power of computers in the recent decades, as well as the demand for the improvement of the rapid seismic damage estimation methods' reliability led to research efforts, among others, for the introduction of artificial intelligence-based methods. Methods of this class are the artificial neural networks-based methods. The Artificial Neural Networks (ANNs) are complex computational structures (e.g. Haykin 2009) which are capable (after a training using appropriate algorithms) to approach the solution of problems using the general rules of the human brain functions (e.g. memory,

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training etc.). Thus, utilizing ANNs it is feasible to approximate the solution of problems such as pattern recognition, classification and the function approximation problem. The ability of ANNs to embed and deploy results of problems which have known input data in order to extract predictions for the solution of same type's problems with unknown input data instantly, led to the thought to use them for the estimation of existing buildings' seismic damage state in real time after an earthquake (e.g. Molas and Yamazaki 1995, Latour and Omenzetter 2009, Rofooei et al. 2011, Vafaei et al. 2013).
In the present paper the results of the study of ANNs' ability for rapid and reliable estimation of seismic damage state of numerous r/c buildings are presented. More specifically, two different types of ANNs were utilized (and were compared) for this purpose: the Multilayer Feedforward Perceptron (MFP) networks and the Radial-Basis Function (RBF) networks. Moreover, the problem of the rapid estimation of r/c buildings' seismic damage state was formulated and solved as a problem of approximation of an unknown function (i.e. the approximation of the r/c buildings' seismic damage function, FA problem), as well as a pattern recognition problem (i.e. the classification of r/c buildings into pre-defined damage classes, PR problem). For the creation of the required ANNs' training data set 30 r/c buildings with different structural parameters (the total height, the structural eccentricity, and the ratio of base shear received by r/c walls (if they exist) along the two orthogonal construction axes) were selected and designed. These buildings were analyzed for 65 selected actual ground motions using Nonlinear Time History Analyses (NTHA). As seismic input parameters 14 parameters widely used in literature were chosen (e.g. Kramer 1996). The well-documented Maximum Interstorey Drift Ratio (MIDR) was utilized as the damage index of the r/c buildings (e.g. Naeim 2011). The influence of the parameters which are used for the configuration and the training of networks on the reliability of their predictions was investigated. These parameters in the case of the MFP networks are the number of the hidden layers, the number of neurons in the hidden layers, the training algorithms, as well as the neurons' activation functions. In the case of the RBF networks the influence of the radial basis function's width parameter was studied. This investigation led to the optimum configured networks on the basis of the optimization of the corresponding performance evaluation parameters. The generalization ability of the optimum configured and trained networks (i.e. the ability of ANNs to extract reliable predictions for r/c buildings subjected to earthquakes which are both unknown to them) was examined by means of seismic scenarios. In these scenarios, earthquakes and buildings which were not utilized in the creation of the training data set were used. The most significant conclusion that turned out is that the ANNs can reliably classify the r/c buildings into pre-defined damage classes in real time provided they are appropriately configured.

2. THE ARIFICIAL NEURAL NETWORKS

The Artificial Neural Networks (ANNs) are complex computational structures which are capable to solve problems using the general rules of the human brain functions (see e.g. Haykin 2009). Thus, the ANNs are capable to handle problems such as the Pattern Recognition (e.g. Ripley 1996) and the Function Approximation problem. To this end the ANNs must be trained using a set of input vectors and outputs (target) vectors which correspond to known solutions of the problem, and a mathematical procedure which is called "training algorithm". During the training procedure the networks are adapted (as regards the values of their internal parameters) in order to optimize the output errors (Haykin 2009). Several types of ANNs have been introduced during the past decades. Between these types of ANNs are the Multilayer Feedforward Perceptron (MFP) networks and the Radial-Basis Function (RBF) networks, which are utilized in the present study. Both the types of ANNs constitute basis of the continuous real-valued functions. For this reason, these networks can approximate precisely unknown continuous real-valued functions (Hornik et al. 1989, Park and Sandberg 1991). In the following sub-sections, the differences between the MFP and RBF networks will be presented.

2.1 The Multilayer Feedforward Perceptron (MFP) networks

The MFP networks' function is based on the combined action of interconnected processing units (artificial neurons). The artificial neurons receive input signals and transform them to an output signal through the use of an adder (which adds the products of the input signals by the respective synaptic weights of neuron's synapses), and the use of an activation function (Figure 1a). The typical configuration of MFP networks with four layers of neurons (input layer, 2 hidden layers and output layer) is presented in Figure 1c.

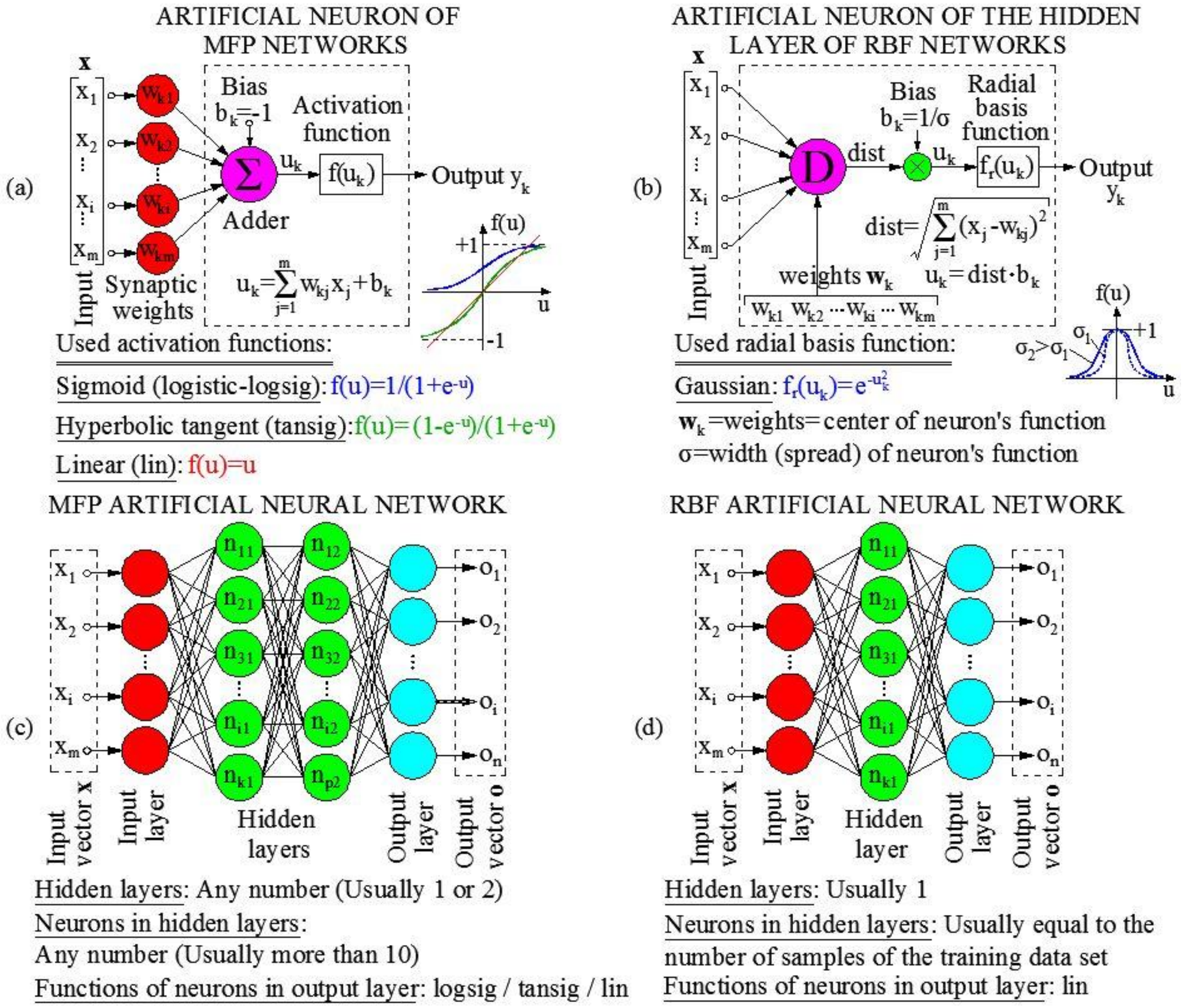


Figure 1. The artificial neuron of (a) MFP networks, (b) RBF networks. General form of MFP (c) and RBF networks (d)

In MFP networks, the neurons in any layer are connected to all neurons in the adjacent layer (fully connected ANNs). During the training procedure, the training vectors **x** are introduced successively to the network's input layer. The output vectors **o**, which are produced by the network, are compared with the corresponding target vectors **d.** Then, the vector of error **e** (which is a function of the synaptic weights **w**) is calculated: **e**(**w**)=**d**-**o**(**w**). The training algorithm successively updates the values of the synaptic weights up till the minimization of the error **e**. More details about the MFP networks can be found in the literature (e.g. Haykin 2009).

2.2 The Radial Basis Function (RBF) networks

The RBF networks have specific similarities and basic differences with the MFP networks (Haykin 2009). The basic similarity concerns their general structure which is consisted of input, hidden and output neurons' layers (Figure 1d). Nevertheless, the RBF networks have usually one hidden layer. Moreover, the RBF networks are fully connected ANNs. As regard the differences the most significant of them are the structure and the function of the hidden layer's neurons (Figure 1b), the order of magnitude of the number of hidden layer's neurons and the rationale of the used training algorithms. The function of the RBFs' neurons in the hidden layer is based on radial functions. These functions have the following general form:

$$f(\boldsymbol{x}) = f\left(\|\boldsymbol{x}-\boldsymbol{c}\|, \sigma\right) \tag{1}$$

In the above equation $\boldsymbol{x}$ is the input vector of neuron (i.e. the argument of the function) and $\boldsymbol{c}$ is the centroid (or center) of the function. The value of f (i.e. the output of neurons) is depended on the (Euclidean) distance (dist=$\|\boldsymbol{x}-\boldsymbol{c}\|$) of the input vector $\boldsymbol{x}$ from the center $\boldsymbol{c}$ and on a parameter which is called width parameter σ (Figure 1b). The width σ is a parameter which defines the function values' rate of degrease bilateral to the center (greater values of σ lead to lesser rate of degrease of function values bilateral to the center and vise-versa, Figure 1b). A common used type of radial function is the gaussian function (Figure 1b).
In contrast to the MFP networks the number of hidden layer's neurons of the RBF networks can be equal to the number of the samples of the training data-set. In this case every sample of the training data set corresponds to a neuron of the hidden layer. Thus, every hidden layer's neuron i is a center c_i and has its width σ_i. It is also permissible to select certain samples of training data set as centers. The above two different choices define the target of the RBF networks' training procedure. The training of the RBF networks is divided into two stages: first the weights from the input to hidden layer and then the weights from the hidden to output layer are determined. Generally, the target of the hidden layer's neurons training procedure is the optimum determination of the radial basis functions' centers and of their widths. In this case only a percentage of the training data set's samples (randomly selected) is used as centers, and the training procedure's target is the optimum selection of these samples. If all samples of the training data set are used as centers (i.e. the number of hidden layer's neurons is equal to the training data set samples' number) no need for the optimum determination of centers exists. In this case, the training procedure is concentrated on the optimum determination of the widths of the neurons' radial basis functions σ. Often, common value for all neurons' width parameter is selected. The training procedure for the determination of the weights from the hidden to output layer is based on the Least Mean Square estimation.

3. FORMULATION OF THE PROBLEM BY MEANS OF TERMS COMPATIBLE TO ANNS

In the current section the procedure for the FA and PR problems' formulation in terms compatible to MFP and RBF networks' philosophy is presented.

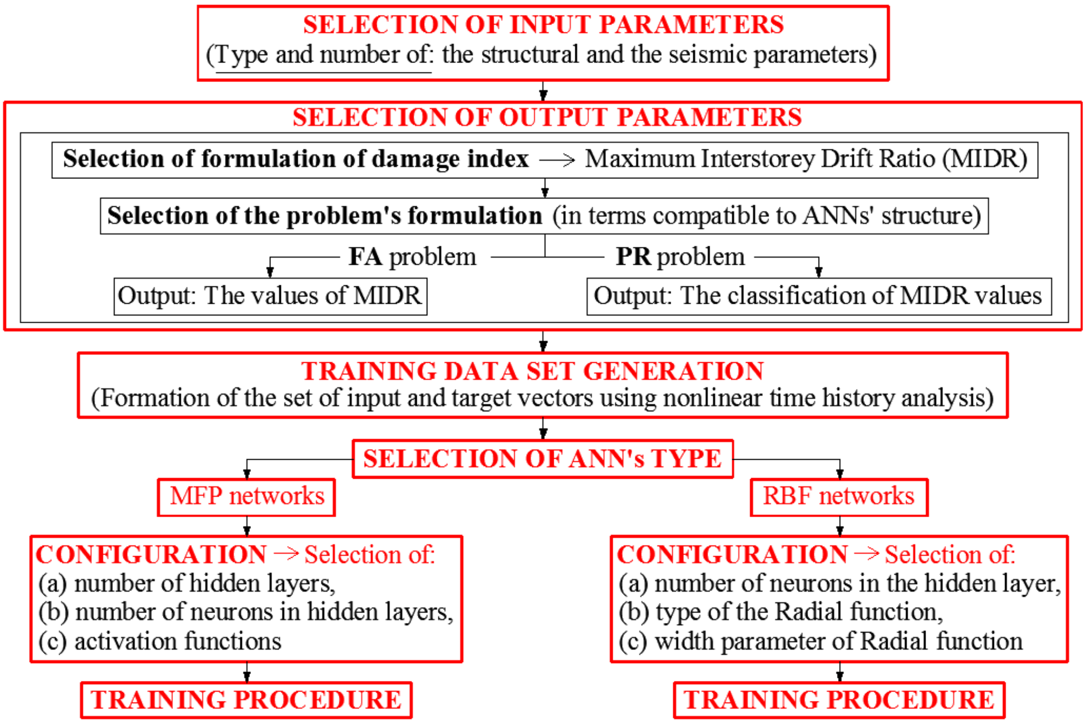


Figure 2. Procedure for the formulation of the investigated problem in terms compatible to the ANNs' structure

The steps which are required for this formulation are briefly illustrated in Figure 2. In this figure the choices which were made for some of the problem's parameters in the current investigation are also presented.

Detailed description of all selected parameters will be given in the following subsections.

3.1 Selection of the input and the output parameters

The input parameters which describe the problem of the prediction of the seismic damage of r/c buildings are structural parameters and seismic parameters. As regards the structural parameters, in the case of the vulnerability assessment of existing r/c buildings, the widespread methods such as the fragility curves method (e.g. Kappos et al. 2006) utilize macroscopic characteristics which are related to the geometric morphology and the structural system. In the present paper 4 structural parameters were selected: the total height of buildings H_{tot}, the ratio of the base shear that is received by r/c walls (if exist) along two perpendicular directions x and y (ratio n_{vx} and ratio n_{vy}), and the structural eccentricity e_0. As regards the seismic parameters which are used to describe the seismic excitations and their impact to structures, there are many definitions which are resulted from the accelerograms records. For the study conducted in the present paper, the 14 seismic parameters presented in Table 1 have been chosen (e.g. Kramer 1996).

Table 1. The selected seismic (ground motion) parameters.

	Seismic parameter		Seismic parameter
1	Peak Ground Acceleration: **PGA**	8	Housner Intensity: **HI**
2	Peak Ground Velocity: **PGV**	9	Arias Intensity: $\mathbf{I_a}$
3	Peak Ground Displacement: **PGD**	10	V_{max}/A_{max} (**PGV/ PGA**)
4	Effective Peak Acceleration: **EPA**	11	Predominant Period: **PP**
5	Specific Energy Density: **SED**	12	Uniform Duration: **UD**
6	Acceleration Spectrum Intensity: **ASI**	13	Bracketed Duration: **BD**
7	Cumulative Absolute Velocity: **CAV**	14	Significant Duration: **SD**

Thus, in the present study, 18 input parameters (4 structural and 14 seismic) were utilized. Therefore, the input vectors of networks **x** (18x1) have the general form which is given by Equation 2:

$$\begin{aligned} \mathbf{x} &= \left[\mathbf{x}_{seism} \,|\, \mathbf{x}_{struct}\right]^T \\ \mathbf{x}_{seism} &= \left[PGA \,\vdots\, PGV \,\vdots\, PGD \,\vdots\, I_a \,\vdots\, SED \,\vdots\, CAV \,\vdots\, ASI \,\vdots\, HI \,\vdots\, EPA \,\vdots\, PGV/PGA \,\vdots\, PP \,\vdots\, UD \,\vdots\, BD \,\vdots\, SD\right]^T \\ \mathbf{x}_{struct} &= \left[H_{tot} \,\vdots\, e_0 \,\vdots\, n_{vx} \,\vdots\, n_{vy}\right]^T \end{aligned} \tag{2}$$

According to Figure 2 the procedure for the selection of output parameters requires two steps. The first step concerns the choice of an appropriate damage index. In the present study, the seismic damage of r/c buildings was expressed in terms of the Maximum Interstorey Drift Ratio (MIDR), (e.g. Naeim 2011). The second step of the procedure entails the choice of the problem's formulation. This choice is necessary in order to define the shape of ANNs' output vectors.

In the present study the problem is formulated as FA problem and as PR problem. As regards the FA problem, the formulation is based on the approximation of values of an unknown real-valued function f(**x**) for which a set of known pairs (**x**, f(**x**)) is available. The vector **x** is given by the Equation 2, whereas the f(**x**) is the unknown real-valued function which correlates the structural and seismic parameters with the buildings' seismic damage. Thus, in the case of the formulation of the FA problem the output parameter must be a real number i.e. in the case of the present study, the value of seismic damage index MIDR (f(**x**)=MIDR). The formulation of the PR problem requires the definition of classes into which a r/c building can be classified on the basis of its seismic damage level. To this end, in the present study three damage states were defined using specific limit values of MIDR. These damage states are presented in the Table 2. The number of the damage classes (three) was selected in order to be compatible to the common used rationale of seismic damage classification in slight (green), moderate (yellow) and heavy (red) damage states which are utilized in the case of r/c buildings' rapid seismic assessment after strong events. The choice of the limit MIDR values of the three damage classes was based on the fusion of the two lower as well as the two higher damage classes of a well-known MIDR-based damage classification of r/c buildings (Masi et al. 2011).

Table 2. Relation between MIDR and damage state.

MIDR (%)	0.0-0.50	0.50-1.00	>1.00
Degree of damage	Slight (No damages or repairable slight damages)	Moderate (Significant but repairable damages)	Heavy (non-repairable damages)

Thus, the output vectors as well as the target vectors must have dimension (3x1). In other words, the number of outputs of ANNs in the present case is three. The general form of the output vectors is given (using an example) in Figure 3.

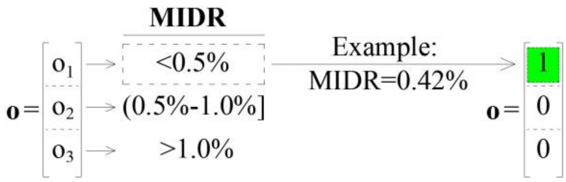


Figure 3. General form of output vectors **o**

As it emerges from Figure 3, each element of a vector **o** represents one of the three classes/damage states of Table 2 and attains value equal to 1 if the corresponding MIDR belongs to the interval of values which define the specific damage state. Otherwise, it attains value equal to 0.

3.2 Generation of the training data set

The next step of the procedure for the problem's formulation (Figure 2) is the generation of the training data set i.e. the generation of a set which consists of input and target vectors for the networks' training. To this end, we must first select characteristic types of r/c buildings which cover a wide range of the utilized structural parameters (in the present study: H_{tot}, e_0, n_{vx}, n_{vy}). Thus, 30 different types of r/c buildings were selected. These types cover the following ranges of the selected input parameters' values: H_{tot}=9.6m-22.4m, e_0=0.0m-6.73m, n_{Vx}=0.0%-77%, n_{Vy}=0.0%-80% (Morfidis and Kostinakis 2017). The selected buildings (rectangular in plan and regular in elevation according to the criteria set by EN1998-1) were modeled and designed according to the provisions of EN1992-1-1 and EN1998-1. In this point it must be stressed that the choice of buildings which were designed on the basis of the provisions of EN1992-1-1 and EN1998-1 does not deprive the generality of the proposed neural networks based methods because it is possible to generate additional training data sets comprising of buildings designed on the basis of provisions of other (or older) codes. These training data sets can be used for the training of networks which can utilized in parallel with the ones presented herein.
The buildings were considered to be fully fixed to the ground and were analyzed using the elastic modal response spectrum method. The buildings' nonlinear behaviour was modeled by means of lumped plasticity models at the column and beam ends, as well as at the base of the walls. The effects of the axial load-biaxial bending moments (P-M_1-M_2) interaction at column and wall hinges were taken into account by using appropriate P-M_1-M_2 interaction diagrams. After the nonlinear modeling, the selected buildings were analyzed by means of NTHA for each one of the 65 earthquake ground motion pairs which were obtained from the PEER (2003) and the European strong-Motion (2003) databases. Thus, a total of 1950 NTHA (30 buildings x 65 earthquake records) were performed. For each one of the 1950 analyses, the required data for the MIDR calculation were exported. Thus, 1950 training vectors which are given in Equation 2, and the corresponding 1950 target vectors were formed. The shape of the target vectors depends on the problem's formulation. In particular:
(i) In the case of the FA problem, the target vectors are in fact scalar-real values (the values of MIDR).
(ii) In the case of the PR problem, the target vectors have the form which is presented in Figure 3.

3.3 Selection of ANNs' types, configuration and training procedures

Since the training data set is created, the last step of the problem's formulation according to Figure 2 is the selection of the utilized ANNs' types, their configuration and the training procedure. In the framework of the present study MFP as well as RBF networks were selected. As regards the configuration of the MFP networks in the present study the optimum combination of the following parameters was investigated: (a) the number of hidden layers, (b) the number of neurons in each hidden layer and (c) the activation functions of neurons. The choice of the other parameters which influence the MFP networks' function (the performance evaluation parameters, the normalization functions of the input values, and the method for partitioning the data set in training, validation and testing data sub-sets) are summarized in Table 3.

Table 3. Configuration parameters of MFP networks

PARAMETERS OF MFP NETWORKS	FA problem	PR problem
Number of hidden layers	1	1 or 2
Number of neurons in hidden layer(s)	10÷60	10÷60
Activation functions in hidden layer(s)	logsig or tansig	logsig or tansig
Activation functions in output layer	linear	logsig or tansig
Performance parameters	• Mean Square Error (MSE) • Correlation Factor R between analytically calculated and neurally predicted MIDRs	Confusion Matrix (CM) (for details see e.g. Theodoridis and Koutroumbas 2008)
Partition ratios of randomly composed data sub-sets (training/testing/validation)	70%/15%/15%	70%/15%/15%
Normalization functions of input values	in the range [-1,1]	in the range [-1,1]
Training algorithm	Levenberg-Marquardt (LM)	Resilient Backpropagation (RP)

The corresponding configuration of the utilized RBF networks in the present study regards the choice of (a) the number of neurons in the hidden layer, (b) the type of the used radial function and (c) the value of the width parameter of the selected radial function (the type of the other parameters which control the RBF networks' performance is identical to the corresponding parameters of the MFP networks). The number of the neurons in the hidden layer was chosen to be equal to the number of training data-set's samples, whereas the gaussian function was selected as networks' radial function. The value of the width parameter was the objective of parametric investigation in order to estimate its optimum value. All configuration parameters of the RBF networks which were chosen in the present study are summarized in Table 4. More details about the investigation of the optimum configuration of MFP and RBF networks in the framework of FA problem's and of PR problem's solution will be given in the next section.

Table 4. Configuration parameters of RBF networks

PARAMETERS OF RBF NETWORKS	FA problem	PR problem
Number of hidden layers	1	1
Number of neurons in hidden layer	Equal to the number of training samples (1365=1950x0.7)	Equal to the number of training samples (1365=1950x0.7)
Radial functions in hidden layer	Gaussian	Gaussian
Activation functions in output layer	linear	linear
Performance parameters	• Mean Square Error (MSE) • Correlation Factor R	Confusion Matrix (CM)
Partition ratios of randomly composed data sub-sets (training/testing/validation)	70%/15%/15%	70%/15%/15%
Normalization functions of input values	in the range [-1,1]	in the range [-1,1]
Training procedure	Investigation of the optimum value of the width parameter	Investigation of the optimum value of the width parameter

4. PARAMETRIC INVESTIGATION OF THE OPTIMUM ANNS' CONFIGURATIONS

4.1 Investigation of the optimum performance for FA problem's solution

In the case of the FA problem's solution using MFP ANNs, networks with one hidden layer ("N1" networks) were utilized. As it emerges from Table 3, two classes of MFP networks were configured. The networks of the first class have activation functions tansig for neurons of the hidden layer, whereas the networks of the second class have logsig functions. More specifically, 51 different versions of MFP networks as regards the number of neurons (10÷60) in the hidden layer were configured for each one of the two network classes. All networks of the two classes were trained 75 times (using the Levenberg-Marquardt (LM) algorithm (Marquardt 1963)). This was done because differences in ANNs' performance are caused by synaptic weights' and biases' initial values (e.g. Latour and Omenzetter 2009), and also by the random composition of the three sub-sets of the total data set (Matlab 2013). From the 75 trainings of each one of the 51 of configured ANNs of two classes the optimum ones were detected. More specifically, the trainings which yielded the optimum values of the performance parameters MSE and R-factor on the basis of the testing sub-set were detected. Thus, from the 7650(=51x75x2) trainings 102(=2x51) optimum trained ANNs were emerged taking into consideration the criterion of min(MSE) and 102(=2x51) optimum trained ANNs were emerged taking into consideration the criterion of max(R) for the testing sub-set (i.e. for a set which consists of 1950x0.15=293 samples). It must be noted that the choice of the testing sub-set for the performance assessment of ANNs is based on the fact that this sub-set is used for the evaluation of ANNs' ability to extract reliable results for data which were not used for their training (generalization ability). The results of the above described procedure are given in Figure 4.

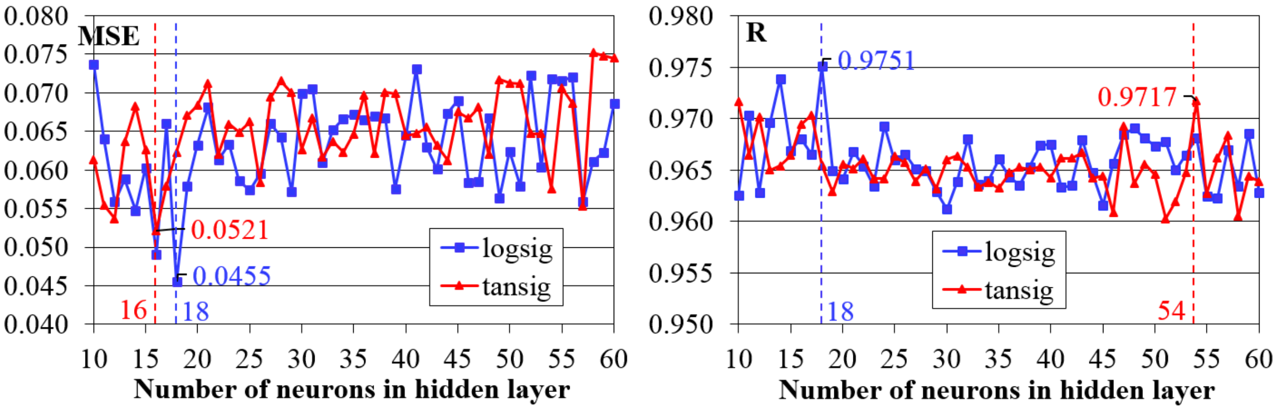


Figure 4. Results of investigation for the optimum configuration of the MFP networks – FA problem

The conclusions which arise from Figure 4 are the following:

- The MFP networks export generally reliable MIDR values (the optimum values of the performance parameters MSE and R can be considered as acceptable (minMSE=0.0455 and maxR=0.9751)).
- The networks with activation function logsig in the hidden layer are more efficient than the networks with activation function tansig since they export results with better performance parameters' values.
- As regards the optimum number of neurons in the hidden layer, it generally depends on the utilized performance criterion and it is not defined uniquely.

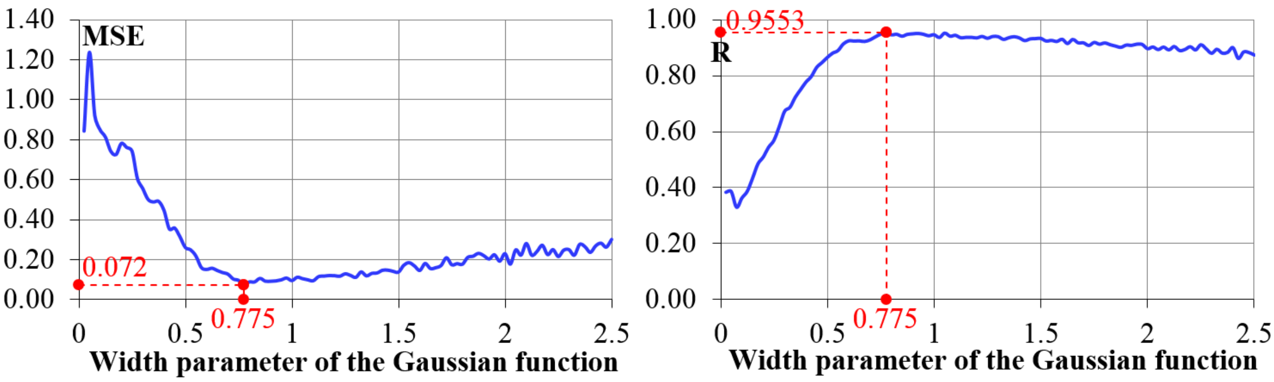


Figure 5. Investigation for the optimum definition of the RBF networks' functions' width parameter – FA problem

The procedure for the FA problem's solution using RBF networks was performed through the investigation of the gaussian function's width parameter's value which lead to the performance parameters' MSE and R optimum values for the testing sub-set. To this end, 100 different RBF networks were formed. In these networks the values of the gaussian functions' width parameter fluctuate between 0.1 and 2.5. Each one of the 100 RBF networks was trained 150 times using the 1365(=0.7x1950) samples of the training data sub-set which were randomly chosen in every training procedure. From these 150 trainings the ones which export results with optimum values for parameters MSE and R were detected. Thus, 100 best trained networks (one for every value of the gaussian functions' width parameter) on the basis of the minimum value of the MSE were detected. Similarly, 100 best trained networks on the basis of the maximum value of the R were also founded. The results of the above described procedure are presented in Figure 5. The conclusion which arise from this figure is that the RBF networks are capable to export MIDR values which can be considered as reliable but not so as the MIDR values which are extracted from MFP networks. This conclusion is based on the comparison of the MSE and R parameters' values of the Figures 4 and 5.

4.2 Investigation of the optimum performance for PR problem's solution

In the case of the PR problem's solution using MFP ANNs, networks with one and two hidden layers ("N2" networks) were utilized. Eight different types of networks with one hidden layer and sixteen different types of networks with two hidden layers were formed (Table 3). More specifically a total of 204(=4 combinations of activation functions x 51 different numbers of neurons (between 10 and 60) in the hidden layer) MFP networks with one hidden layer and 20808(=8 combinations of activation functions x 51 different numbers of neurons (between 10 and 60) in the first hidden layer x 51 different numbers of neurons (between 10 and 60) in the second hidden layer) networks with two hidden layers were configured. For MFP networks' training the Resilient Backpropagation (RP) algorithm was utilized (Riedmiller and Braun 1993). As performance "generalized" parameter for the networks' evaluation the Confusion Matrices (CMs) were chosen. These matrices give an overall evaluation of the classifications' quality which the networks can perform (see e.g. Theodoridis and Koutroumbas 2008). In Figure 6 the CMs of the classifications made by the best trained ANNs with one and two hidden layers for the 293(=1950x0.15) samples of the testing sub-set are illustrated. In the blue colored cells of these matrices the "Overall Accuracy" (OA) index values which represent the total percentage of the correct networks' classifications are also presented.

ANNs' classification

True class	1	2	3	Recall%
1	**82**	3	0	96.5%
2	3	**46**	9	79.3%
3	0	5	**145**	96.7%
Precision%	96.5%	85.2%	94.2%	***93.2%***

(a) MFP network with 1 hidden layer

ANNs' classification

True class	1	2	3	Recall%
1	**92**	6	0	93.9%
2	2	**48**	1	94.1%
3	0	8	**136**	94.4%
Precision%	97.9%	77.4%	99.3%	***94.2%***

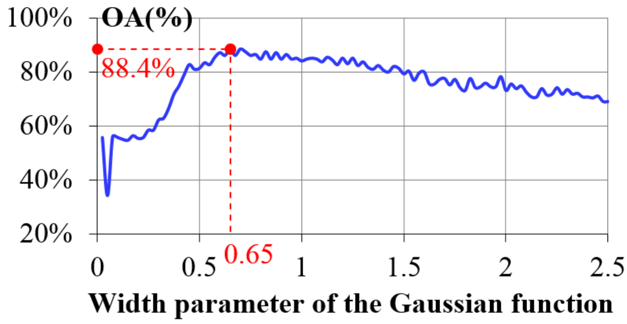
(b) MFP network with 2 hidden layers

Figure 6. CMs of the MFP networks with (a) one hidden layer and (b) with two hidden layers – PR problem

The conclusions which arise from Figure 6 are the following:

- The MFP networks export generally reliable classifications for the r/c buildings' damage state (the optimum values of the OA parameter is significantly high (OA=93.2% (i.e 93.2% of the tested samples were classified in the correct damage category) for the networks with one hidden layer and OA=94.2% for the networks with two hidden layers).
- All classifications which are presented in Figure 6 are in the correct classes (green colored cells) or in classes adjacent to them (yellow colored cells). Thus, no classifications in categories which are not adjacent to the correct category are exported. This means that the general conclusions which are extracted from the study of the CMs are reliable and give instantly a correct approach of the real damage's level.
- The use of two hidden layers increases the effectiveness of networks but not significantly. The increase of the OA value due to the introduction of the second hidden layer is about 1.0%.

The procedure for the PR problem's solution using RBF networks is exactly the same as the corresponding procedure for the solution of the FA problem which was presented in the sub-section 4.1. The only difference is the utilization of the total percentage of correct classifications (OA parameter) as performance parameter. The results of this procedure are presented in Figure 7.



(a)

ANNs' classification

True class

	1	2	3	Recall%
1	**76**	3	0	96.2%
2	7	**51**	7	78.5%
3	1	16	**132**	88.6%
Precision%	90.5%	72.9%	95.0%	***88.4%***

CM matrix for the results of RBF network with width parameter's value equal to 0.65

(b)

Figure 7. Results of PR problem's solution using RBF networks: (a) Optimum value of width parameter, (b) Best CM

From the combined study of figures 6 and 7 it can be concluded that the RBF networks with number of neurons in hidden layer equal to the number of training sub-set's samples and the utilization of gaussian functions with common value for their width parameter extract generally acceptable results (OA=88.4%) but no better than the results which are extracted by the MFP networks.
In the following Table 5 the configuration parameters of the MFP and RBF networks which export the optimum results of the FA and PR problems' solutions are summarized. These networks are utilized for the assessment of ANNs' generalization ability which will be presented in the section 5.

Table 5. Configuration parameters of the optimum MFP and RBF networks

CONFIGURATION PARAMETERS	FA problem		PR problem	
	MFP ANN	**RBF ANN**	**MFP ANN**	**RBF ANN**
Number of hidden layers	1	1	2	1
Number of neurons in hidden layer(s)	18	1365	1st: 44 /2nd: 50	1365
Activation functions in hidden layer(s)	logsig	-	1st: tansig / 2nd: logsig	-
Radial function (rf) in hidden layer	-	gaussian	-	gaussian
Activation functions in output layer	linear	linear	tansig	linear
Width parameter's value of rf	-	0.775	-	0.65
ANNs' names	MFP-N1-log-18	RBF-N1-0775	MFP-N2-tan/log/tan-44/50	RBF-N1-065

5. EVALUATION OF GENERALIZATION ABILITY OF THE OPTIMUM CONFIGURED ANNS

In the current section the prediction ability of networks presented in Table 5 is investigated through the predictions of the seismic damage level for a set of samples which are not included to the training data-set. To this end, three new testing r/c buildings were selected. The structural parameters of these buildings are (H_{tot1}=9.6m / e_{01}=0.0m / n_{Vx1}=62% / n_{Vy1}=0.0%), (H_{tot2}=16.0m / e_{02}=0.0m / n_{Vx2}=60% / n_{Vy2}=0.0%) and (H_{tot3}=25.6m / e_{03}=0.0m / n_{Vx3}=58% / n_{Vy3}=0.0%). Moreover, 15 new testing seismic excitations were chosen from the PEER and the European strong-Motion databases. Then, following the same procedure as the one which is conducted for the generation of the training data set (section 3.2), a new testing data set was generated. This data set consists of 45(=3x15) samples. As in the cases of the training data set, two types of target vectors were formed: one type compatible to the formulation of the FA problem (Equation 2) and one type compatible to the formulation of the PR problem (section 3.1). The input vectors of the new testing data set were introduced to the most efficient networks of Table 5 in order to predict the seismic damage state for the 45 testing samples.
Figure 8 illustrates the predictions of the networks "MFP-N1-log-18" and "RBF-N1-0775". This figure concerns the predictions which arise from the approach of the FA problem's solution. Figure 9 illustrates the

predictions of the networks “MFP-N2-tan/log/tan-44/50” and “RBF-N1-065” which arise from the approach of the PR problem’s solution.

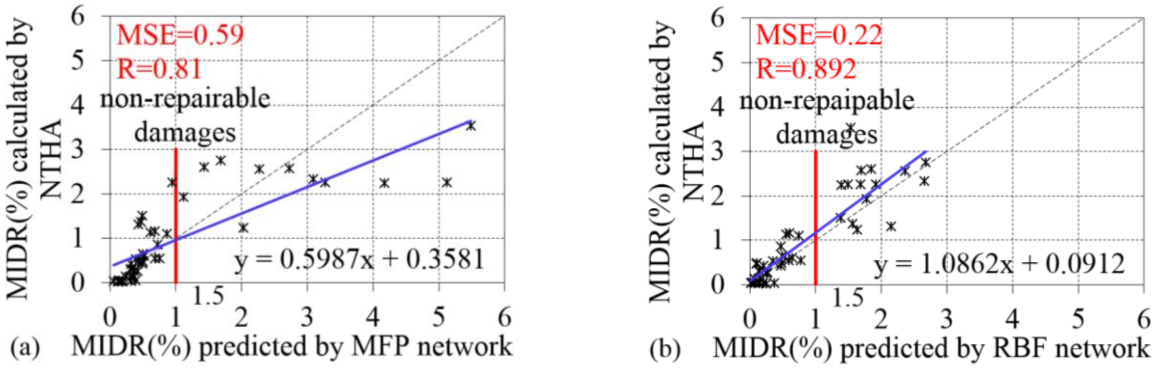


Figure 8. Comparison of MIDR values predicted by NTHA and networks (a) “MFP-N1-log-18”, (b) “RBF-N1-0775”

As emerges from the study of Figure 8, both examined networks extract predictions of a similar level of accuracy as regards the value of the R-factor. On the contrary the “RBF-N1-0775” network extracts results with significantly lower MSE value. However, the MSE value is relatively high in both cases. These high MSE values could be attributed mainly to the insufficiency of networks to adequately approach high MIDR values (higher than 1.0%) calculated by NTHA. This insufficiency is not of great importance since for MIDR values larger than 1.0% the buildings suffer heavy (and practically non-repairable) damages. Thus, the precision of the predicted MIDR values in these cases is not critical. By contrast, the ability for the reliable prediction of the order of magnitude of MIDR values is significant.

ANNs' classification

True class	1	2	3	Recall%
1	19	2	0	90.5%
2	2	4	2	50.0%
3	0	0	16	100.0%
Precision%	90.5%	66.7%	88.9%	***86.7%***

(a) "MFP-N2-tan/log/tan-44/50" network

ANNs' classification

True class	1	2	3	Recall%
1	20	2	0	90.9%
2	1	4	3	50.0%
3	0	0	15	100.0%
Precision%	95.2%	66.7%	83.3%	***86.7%***

(b) "RBF-N1-065" network

Figure 9. CMs of the new testing samples’ damage state classifications made by the most efficient networks

The main conclusion which is extracted from Figure 9 is the high quality of classifications of both the examined networks (OA values equal to 86.7%). More specifically, besides the high value of the OA index the percentages of correct classifications to individual classes are also acceptable. Furthermore, it must be stressed that none of the examined samples is classified by both networks to classes not adjacent to the correct ones. Finally, a very significant conclusion which is extracted from the combined study of Figures 8 and 9 is that the predictions of the most efficient networks are more reliable when they are extracted on the basis of the PR problem’s solution.

6. CONCLUSIONS

The aim of the present study is the investigation of the Artificial Neural Networks’ (ANN) ability for rapid and reliable estimation of seismic damage state of numerous r/c buildings. For this purpose, two different types of ANNs were utilized: the Multilayer Feedforward Perceptron (MFP) networks and the Radial-Basis Function (RBF) networks. The examined problem was formulated and solved as a problem of approximation of an unknown function (Function Approximation (FA) problem), as well as a pattern recognition problem (PR problem). The influence of the networks’ configuration parameters on the reliability of their predictions was also examined. This investigation led to the best configured MFP and RBF networks on the basis of the optimization of their predictions. The generalization ability of these networks was examined using seismic scenarios. The main conclusions of the above described investigation procedure are the following:

- The MFP and RBF networks export generally significantly reliable predictions for the r/c buildings' damage state when the problem is formulated as PR problem. These predictions are achieved in the case of MFP networks when two hidden layers of neurons are introduced.
- The performance of MFP and RBF networks in the case of FA problem's solution is not such high as in the case of the corresponding solution of the PR problem. More specifically the for MIDR values in the range 0.0%-1.0% the performance of networks is acceptable. For MIDR values higher than 1.0% (which correspond to practically non-repairable damages) the accuracy of the networks' predictions is reduced (mainly in the case of MFP networks). However, for MIDR>1.0% the accuracy of numerical values is not so significant.
- In general, the generalization ability of RBF networks is slightly better than the corresponding MFP networks' ability. However, this conclusion arises from the specific training data set. Thus, the more robust conclusion of the current study is that the methods which are based on Artificial Intelligence (as the ANNs) are very promising methods for rapid and reliable estimation of numerous r/c buildings' seismic damage.

7. REFERENCES

ATC (1985). Earthquake Damage Evaluation Data for California, ATC-13 Report. Redwood City, CA: Applied Technology Council.

European Strong-Motion Database (2003). http://www.isesd.hi.is/ESD_Local/frameset.htm

FEMA-154 (2002). Rapid visual screening of buildings for potential seismic hazards: A Handbook (FEMA-154). 2nd Edition, Washington, DC.

Haykin S (2009). Neural Networks and Learning Machines. 3rd edition, Prentice Hall.

Hornik K, Stinchcombe M, White H (1989). Multilayer Feedforward Networks are Universal Approximators. *Neural Networks*, 2(5): 359-366.

Kappos AJ, Panagopoulos G, Panagiotopoulos Ch, Penelis Gr (2006). A Hybrid Method for the vulnerability assessment of R/C and URM buildings. *Bulletin of Earthquake Engineering*, 4(4): 391-413.

Kramer SL (1996). Geotechnical Earthquake Engineering, Prentice-Hall.

Lautour OR, Omenzetter P (2009). Prediction of seismic-induced structural damage using artificial neural networks. *Engineering Structures*, 31: 600-606.

Marquardt DW (1963). An algorithm for least squares estimation of non-linear parameters. *Journal of Society for Industrial and Applied Mathematics*, 11(2): 431–441.

Masi A, Vona M, Mucciarelli M (2011). Selection of Natural and Synthetic Accelerograms for Seismic Vulnerability Studies on Reinforced Concrete Frames. *J. Struct. Eng.*, 137: 367-378.

Matlab (2013). Neural networks toolbox user guide.

Molas G, Yamazaki F (1995). Neural Networks for quick Earthquake Damage Estimation. *Earthquake Engineering and Structural Dynamics*, 24: 505-516.

Morfidis K, Kostinakis K (2017). Seismic parameters' combinations for the optimum prediction of the damage state of R/C buildings using neural networks. *Advances in Engineering Software*, 106: 1-16.

Naeim F (2011). The seismic design handbook, 2nd edition, Kluwer Academic, Boston.

Park J, Sandberg IW (1991). Universal Approximation Using Radial-Basis-Function Networks. *Neural Computation*, 3(2): 246-257.

PEER (2003). Strong Motion Database. http://peer.berkeley.edu/smcat/

Riedmiller M, Braun H (1993). A Direct Adaptive Method for Faster Backpropagation Learning: The RPROP Algorithm. Proceedings of IEEE, San Francisco 1993: 586-591.

Ripley BD (1996). Pattern Recognition and Neural Networks, Cambridge University Press.

Rofooei FR, Kaveh A, Farahani FM (2011). Estimating the vulnerability of the concrete moment resisting frame structures using Artificial Neural Networks. *International Journal of Optimization in Civil Engineering*, 3: 433-448.

Theodoridis S, Koutroumbas K (2008). Pattern Recognition, 4th edition, Elsevier.

Vafaei M, Adnan AB, Rahman ABA (2013). Real-time Seismic Damage Detection of Concrete Shear Walls Using Artificial Neural Networks. *Journal of Earthquake Engineering*, 17: 137-154.