A review on the artificial neural network approach to analysis and prediction of seismic damage in infrastructure

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A Review on the Artificial Neural Network Approach to Analysis and Prediction of Seismic Damage in Infrastructure

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Abstract: Natural disasters are capable of extending disastrous consequences and effects on the functionality of infrastructure systems and result in intense systemic and socio-economic losses. According to financial restrictions, it is essential to optimize decisions regarding mitigation, preparedness, response, and recovery practices for these systems. This necessitates accurate and efficient measures to assess the infrastructure system reliability. Machine learning has been the focus of attention in recent decades, and the influence of the Artificial Neural Networks (ANN) is definitely notable as the most extensively used models of machine learning in the assessment of infrastructure. This review provides damage detection assessment of seismic performance of reinforced concrete (RC) bridges by using machine learning methods. A multi-layered perceptron (MLP) with a back-propagation (BP) algorithm neural network was implemented to predict the seismic performances of the designated bridges. ANN models were developed, trained and tested in a MATLAB and Python program. A training set and a validation set of bridges were produced from the dynamic response of different RC bridges. The method is performed on the collected feature measurements on a railway RC bridge during the dynamic response of bridge structures, which were brought together in a numerical experiment using a three dimensional finite element model for this study. Thus, the next step consists of the design and unsupervised training of Artificial Neural Networks that are used as the mentioned input data. The results indicate that the proposed method is productive and capable of capturing physical complexities for the dynamic damage detection force on the RC bridge prediction task. Therefore, the results will be compared to analytical and exact deflection. The outcomes revealed that an appropriately trained neural network could consistently predict permanent earthquake-induced seismic deformation of the RC bridges. The bridges fragility analysis to calculate failure probability was another achievement that was created by using nonlinear analysis (NA) and ANNs. Nonlinear response history analysis was achieved in order to calculate the seismic performances of the bridges. The consequences of this study demonstrate that ANNs are suitable tools for predicting damage detection of seismic performances of RC bridges. It was also shown that efficiency stresses of the reinforcements are one of the important sources of uncertainty in fragility analysis of RC bridges. It is evident from this evaluation that ANNs have been successfully applied to many infrastructure engineering areas like prediction, risk analysis, decision-making, resources optimization, classification, and selection, etc. The neural network based approach demonstrates signs of being highly successful in verifying the response of bridges and buildings subjected to seismic evaluation. Based on the results of case studies, it is evident that ANNs perform better than those similar to conventional methods.

Keywords: Seismic evaluation, Dynamic analysis, RC bridge, Artificial Neural Network, FEM, Deep Learning, Damage detection

I. INTRODUCTION

Many recently built buildings might need strengthening in order to have high performance while being exposed to close-fault ground motions. Fiber Reinforced Polymers are believed to be sustainable replacement, since they can be quite an easy option and quickly installed. In addition, they contain nearly zero maintenance demand and minimum life cycle costs. The target of this research is to measure and evaluated the efficiency of Artificial Neural Networks (ANN) in determining the three dimensional dynamic response of FRP strengthened RC buildings under near-fault ground motions. In order to reach this aim, an ANNs model is offered and prepared to evaluate the base shear force, base bending moments and roof displacement of buildings in two directions. The FEA analysis results of the dynamic response of RC buildings under near-fault earthquakes yield a training set of 168 and a validation set of 21 buildings. We have attempted to demonstrate that the neural network based approach is extremely successful in determining the response [1]. The seismic response of a structural building system is linked to a number of factors such as its configuration, dynamic features and the features of the applied ground motion.

It is compulsory to replicate these factors to make them as similar to reality as possible, so vividly and correctly vividly and correctly foreseeing the seismic performance or vulnerability of a given structural system using experimental or analytical techniques is a possibility. Seismic responses of reinforced concrete structures have been investigated using various methodologies which conclude a vast intricacy specifically in analyzing the real building on account of the deficiencies of complete data related to excitation, creation of a theoretical model, modeling the dynamic loads, carrying out an analysis and inferring the hypotheses to the actual system [2]. Civil engineering structures are on their way out and put to use after their life expectancy, simultaneously enduring heavier traffic loads as a result of the enlarging claims of transportation amplitude. Bridges are a crucial link in modern transport networks, making it the right opportunity to develop vigorous and dependable structural damage detection systems that can certify the bridges operate in secure conditions. The method is performed on the collected feature measurements on a railway RC bridge during the dynamic response of bridge structures, which were collected in a numerical experiment implementing a three dimensional finite element model. Furthermore, the next step consists of the design and unsupervised training of Artificial Neural Networks which are being used as the mentioned input data [3].

Recently, Artificial Neural Network (ANN) models have been become widely obligatory for numerous relevant civil engineering realms including geotechnical engineering, water resources and structural engineering. With due consideration of almost every single case, an ANNs is a versatile system that is able to change its structure based on inner and outer information that overflows throughout the network. This can be arranged to obtain different patterns in data or to archetype the multiplex relationships between inputs and outputs. The main objective of the inquiry is to evolve a complex relationship among the design parameters for punching shear strength of the flat plate based on a developed Back-Propagation Neural (BPN) network algorithm [4]. Over the past few years, ANNs have been manipulated favorably to model almost all dimensions of geotechnical engineering problems and were extensively used in pavement engineering to discover the patterns between the input data and the output outcome. As indicated in the literature, ANNs have been immensely utilized to predict the axial and lateral load capacities in the compression and uplift of pile foundations [5]. In order to investigate the compound stringent pavements structure, finite element analysis will provide the most precise solution. The finite element methods have reached protrusion in complex structures such as rigid pavements due to their ability to efficiently model different axle configurations and complex boundary conditions. However, in order to obtain the mechanistic empirical design purpose, the design requires numerous iterations and analyses for multiple axle loads, which necessitates a long duration to reach the optimum design. This issue can be solved by developing and training an artificial neural network that would immediately foretell the rigid pavement responses to axle loads in a short duration [6]. During the last decades, neural networks in structural dynamic and earthquake engineering problems have experienced great advancements, which can be considered for applying neural networks in determining the static and dynamic parameters of structures[7].

ABAQUS, which is an example of general finite element programs, has also been wielded impressively for the analysis of pavement structure [8]. In applying the finite element method, selecting the correct form of elements might have a significant impact on the desired accuracy. The finite element method can have the highest efficiency in the modeling of those systems with specific dimensions since we propose the layered method with the assumption of the infinity of layers in the radial direction. The finite element method for the nonlinear analysis of pavement has many advantages to the programs based on layered system theory. ANNs is a kind of mathematical tool, which creates a mapping between a set of input numbers and output numbers. Generally, the highest ranked use of the artificial neural network method is to analyze rigid pavements [9]. One of the most terrifying concerns of civil engineering is the prediction and assessment of dynamic seismic responses of infrastructures (bridges or structures) linked and related to earthquakes. Seismic dynamic responses of R/C structures have been examined using various methodologies, and many complication in the analysis of real buildings appear as result of deficiencies in incomplete data related to excitation, creating an idealized model, modeling the dynamic load, performing an analysis and extrapolating the predictions to the real system. Considering reasoning and interpretative experience from the analyst, the new generation of programs inclined to capture the knowledge or experience of expert analysts that is necessarily required for these situations. Thus, the prediction and evaluation of seismic responses of structures necessitated substantial knowledge of conceptual design, structural details, mathematical models and analysis presumptions. Despite the extensively developing computational methods, the dynamic analysis of structures in 3D is far from acceptable level from a structural engineering point of view. Hence, a new methodology is required to defeat these barriers. ANNs has been applied as an alternative method for more realistic estimation of seismic behavior of reinforced concrete (RC) plane frame structures. ANN is an enhanced data modeling able to capture and represent multifaceted relationships between inputs and outputs. It seems to provide a means of coping with many multi-variety problems in which an accurate analytical model does not exist or at least was extremely demanding and would take a lot of time to advance. ANN is also an alternative method and a tool for modeling complex phenomena in different areas of research and engineering practice[10].

Here, ANN-based metamodels are used to estimate the reaction of a comprehensive FEM to appraise the conjecture put forth by making use of the ANN metamodels in substituting the details [11]. FEM Artificial Neural Network (ANN) empirical regression models are implemented as fast-running surrogates of the Finite Element Models (FEMs) that are usually chosen for the simulation of the system structural response.

II. BACKGROUND & LITERACTURE REVIEW

The seismic vulnerability assessment of current reinforced concrete (r/c) buildings is one crucial issues in infrastructures like bridges. As a result, it has been the subject of prevalent research worldwide. The outcome of this extensive research is the advancement of methods, used to assess the assessment the seismic vulnerability of existing buildings, in addition to estimating their seismic damage condition as a result of future earthquakes. The existing methods implemented for the solution of the two problems previously mentioned can be categorized into two general groups: (a) methods that can approximate the seismic performance of individual buildings and (b) methods that can quickly assess the seismic vulnerability of groups of buildings with typical structural features [12]. The approaches of the first class are related to linear and nonlinear analytical procedures adequate for specific buildings for which initial investigations assert a detailed assessment of their seismic susceptibility assessment or their pre-seismic strengthening or post-seismic retrofitting is necessary. As a result of their innate complicated nature, these methods are time consuming but undoubtedly required for buildings reckoned to be seismically vulnerable buildings which have suffered seismic damages or old bridges considered without the supplies of seismic codes or for buildings thought to be significant. The first category includes method which are mainly based on the Finite Element Method (FEM)) having been adopted and explained in modern seismic codes[13].

Any reduction in sustainability, inflexibility and magnitude that has adverse functional impact on the structures or contains affections that might cause damage to serviceability and safety and possibly result in failure is designated as damage in structural systems. We classify the damage into four different and at the same time mutual-based definitions: identification consisting of determining of the presence of damage in the structure, determination of the severity of damage and calculation the remaining service life of the structure. ANNs are considered to be a strong method in structural dynamism and are also powerful tools used to solve many real life problems that are inspired by the human brain, which has been applied to damage identification. Natural frequencies and mode forms were applied as inputs to the ANN for damage identification. Applicability and efficiency of the ANN in determining the extremity and locating damage of the joints in truss bridges was proven in this study. Park proposed a sequential methodology for damage detection in beam by making use of time-modal features and ANNs[14]. In this research study, the first natural frequency of a cracked column under different compression loads was estimated by an analytical method and applied as inputs and the crack size, crack location and compression load of the column were selected as outputs of the ANNs. Given the results of testing designs on a numerical sample of a trained ANNs, the authors found that BPNN is a beneficial tool used to predict the practical compressive force to the column, and the crack size-location on the cracked column. Natural frequencies were used to identify the location and depth of cracks in a clamped-free beam and a clamped-clamped plane frame by Suh, who presented a technique of combining the neural network with a genetic algorithm for dynamic damage calculation[15]. Damage assessment of a bridge structure was investigated based on the estimated modal parameters using ANN [16]. As inputs to the neural networks, the ratios of the resonant frequencies were used and after damage and the mode shapes were used after damage. It was found that the predicted damage locations and severities compared fine with the imposed deflection on the infrastructures. In addition, many other research studies have attempted to apply ANNs in identifying structural engineering damages[17][18][19]. This research focus on the numerical modal analysis based on a finite element simulation used to generate modal parameter data to train ANNs for the aim of predicting damage severity. This study presents the finite element modeling of a bridge girder structure using DIANA as a robust and efficient software package [20]. A number of damaged scenarios are developed and the numerically obtained natural frequencies of the undamaged and damaged bridge model first five modes have been adequately used as the training samples for the ANNs. Mousavi (year) has focused on ANFIS, MLP, WNN, EPS, DT, RF, CART, and ANNs as some of the most popular ML modeling methods for flood prediction. The major ML methods used for flood prediction and the number of related articles in the literature over the past 100 year are given in Figure 1. This figure was designed to notify which ML methods gained popularity among hydrologists for civil engineering within the past decade[21].

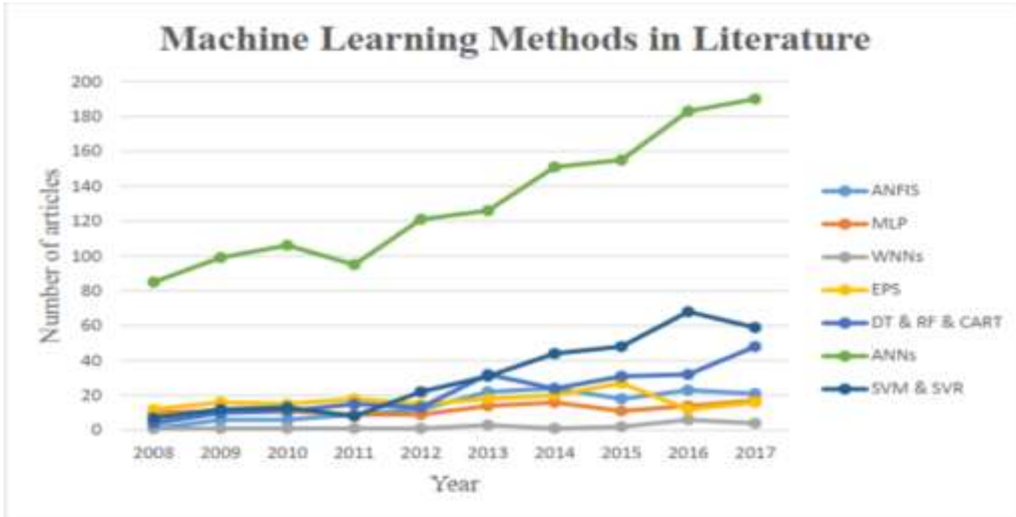

Figure 1. Major ML methods used in Civil Engineering [21].

III. CHARACTERISTICS AND DATABASE OF DYNAMIC LOADS STRUCTURE

We have witnessed great efforts made for predicting the wave characteristics by physical modeling and using traditional engineering methods in the past few years, including complicated deterministic equations. In this research, ANNs technology has been adopted to assist in the prediction of wave characteristics. This study aims at establishing an alternative approach for the prediction of seismic characteristics (Dynamic response & Deflection period) which is the ANNs. The database was generated using numerical models.

The following goals have been set for this study:

- Examining the accuracy of various structured ANNs for the prediction of seismic damages characteristics predicted by numerical methods.
- Recommending the most effective and acceptable ANNs model for the bridges engineering practice
- Incorporating the written program to an existing 3-D finite element program (FEM)

Definition of the Computational Problem

Description of the mathematical formulation of R/C bridges and buildings' seismic response problem:

- *Models which simulate the R/C bridges buildings and their seismic damage level*
- *Parameters which have used for the assessment of the influence of Earthquakes and Vibration on b*
- *Computational methods which are used for R/C bridges' seismic damage assessment*

↓

First Approach to Definition of the problem Data

Initial selection of the parameters which will be utilized for the definition and solution of the problem of R/C bridges and infrastructures damage assessment using ANN :

- *Input Parameters: Generally are classified to structural, seismic and soil parameters*
- *Output Parameters: Describes the seismic damage state [Damage Index (DI)]*

↓

ANNs ' Training Data

Formation of the set of input and vectors on the basis of the initially selected input and output parameters conducting the following steps:

- *Selection of characteristic types of R/C bridges ("actual" buildings) and ground motions*
- *Criterion: Coverage of a wide range for the values of the selected structural, seismic, soil parameters*
- *Evaluating and making use of of the selected bridges (following the provisions of pre-selected seismic codes)*
- *Calculation of the seismic Damage Index of the selected buildings due to the selected ground motions (Performing static or dynamic nonlinear analyses)*
- *Assessement of the seismic Damage Index of the selected bridges due to the selected ground motions (Performing static or dynamic nonlinear analyses)*
- *processing of the extracted consequences Formation of the set of input and target vectors*

Fig. 2. Steps for designing training data set.

The first five natural frequencies are proposed to act as the inputs of the ANNs to predict damage severity. Finite element analysis was performed with different damage scenarios to determine the natural frequencies as dynamic properties of the bridge girder. Numerical modeling was performed using an undamaged bridge girder to obtain the modal frequencies in the first stage. Then, the introduction of different severities of damage at various locations along the bridge girder has lead to the creation of various damage scenarios. Later on, the results of the numerical modal analysis will be applied as training data for the ANNs algorithm. The ANNs will be capable of giving outputs in terms rigorous damage using the first five natural frequencies only and only by incorporating the training data [22].

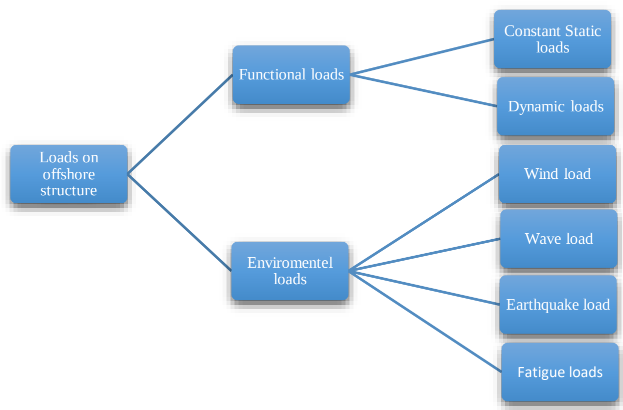

Figure 3. The important loads act on Infrastructures

The FEM software ABAQUS was used to develop a numerical 3D model of a single-track railway bridge [23]. The structure includes a concrete deck, two steel girder beams that support the deck and steel cross bracings used to link the girders. The deck and girder beams were modeled as shell elements and the cross bracings were modeled as truss elements. All the elements of the bridge are presumed to be rigidly connected to each other. If two different incidents are considered, then we will be able to replicate the damage in the bridge: in damage case 1, a section of the bottom flange of one girder beam is eliminated in an endeavor to show a damage situation in which a fatigue crack exists. The cut out section includes of dimension of longitudinal length l by the flange width, indicating a scenario in which a propagating crack has come to its critical depth (about 30% of the flange's width or less) causing a sudden rupture through the whole flange width. In damage case 2, one bracing is removed which is in equal agreement with reducing its elastic modulus in the model to approximately zero. Considering that girder beam and bracings are connected by high-tension bolts, this can reflect a situation where there is looseness in the bolted connection [24]. Resulting in bracing functioning to become inadequate. The locations of the accelerometers that are installed on the top of the bridge deck are represented by Figures 1 to 6: three aligned with the train track and three aligned with the girder beam in which damage takes place in DC1. The method proposed for structural assessment is meant to identify current damage from the measured vibration of the bridge. Dynamic loads typically come from traffic, which is expected to be continuous while the bridge is in service. In the numerical model, traffic induced vibration was simulated by means of the passage of a train with a fixed configuration, crossing the bridge with a speed in the range of [70–100] km/h, and increments of 0.1 km/h. Overall, simulation of 300 different train passages was carried out and the related measurement data sets were collected and saved. The moving axle loads were modeled as a series of constant moving forces with short time steps adhering to vehicle motion.

IV. Artificial Neural Network

Artificial Neural Network (ANN) is a technique that uses existing experimental data to foretell the behavior of similar material under various testing conditions. The ANNs has appeared as a beneficial concept from the field of artificial intelligence, and has been successfully used in modeling engineering problems over the past decade, specifically those related to the mechanism behavior of composite materials. Neural networks can be used as a powerful regression tool. They are highly nonlinear and can capture complex interactions among input/output variables in a system without any prior knowledge about the nature of these interactions [25]. ANNs was originally introduced as simplified models of brain-function [26]. The human brain is composed of billions of interconnected neurons. These are cells having specialized members that permit the transmission of singles to neighboring neurons [23]. The concept of neurons, transfer functions and connections are the fundamental elements that ANNs are based on. The uniformity of different structures of ANNs can be found in various research studies [27]. The majority of the variation stems from various learning rules, as well as how these rules modify a network's typical topology. Generally, most applications of ANNs can be divided into the following four categories:

- **Prediction**: Uses input values to predict some output. The backpropagation network model is mostly used for engineering predictions [28]. This is a powerful mechanism for establishing nonlinear transfer functions between a number of continuous valued inputs and one or more continuously valued outputs. Essentially, the network uses multi-layer perception architecture and obtains its name from the way it processes errors while training [29]. In the present study, we also build an ANN model to predict wave characteristics based on this model.

- **Classification**: Uses input values to determine the classification. This model is generally used for pattern recognition [30].
- **Data association**: Used simulation for the classification, while also recognizing data that contains errors [31].
- **Data filtering**: Analyzes input data and makes it smooth for the output [32].

A neural network is characterized by 3 different main actions, which are listed as [33]:

(1) Its pattern of connections between the neurons

(2) Its method of determining the weights on connections

(3) Its activation function.

Among the applied neural networks, the feed forward neural networks (FFNN) are the most common used method in resolving several engineering restrictions. The FFNN method contains of a layer being fully linked to the preceding layer by weights [34]. Fig. 4 illustrates the common three-layer feed forward type of an artificial neural network.

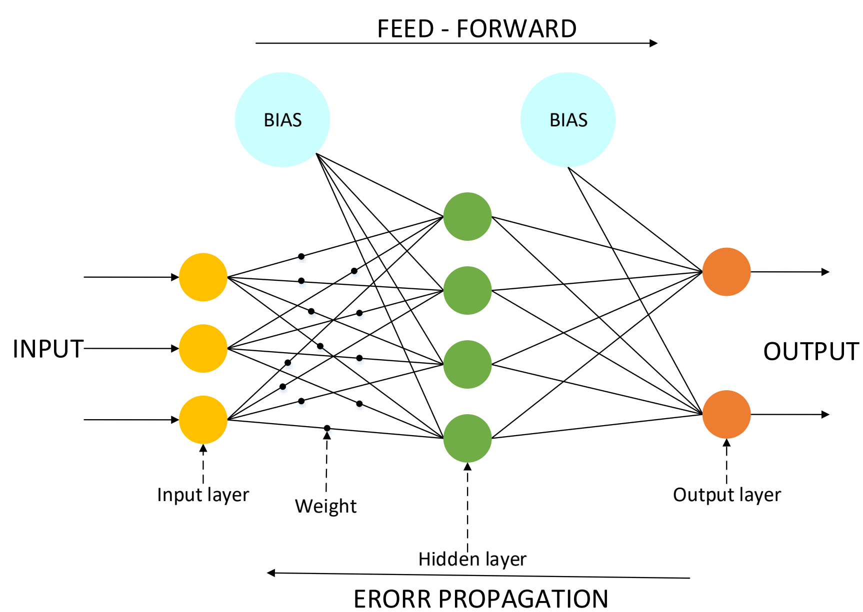

Fig. 4. Schematic representation of three-layer feed forward artificial neural network

At the present time, this interactive network developed of backpropagation architecture has become popular, valuable, and simple to learn even for complicated models, such as multi-layered networks. The greatest strength of ANNs is in its dealing with nonlinear solutions to indefinite problems. The professional back-propagation network has an input layer, an output layer, and at least one hidden layer [35].

The BP algorithm is one of the most popular ANNs algorithms. It is claimed that BP algorithm could be packed up to four major steps. Once the weights are chosen computation, of the required corrections is done by the back propagation algorithm. The algorithm can be conveyed in the following four steps:

- Computation of feed-forward
- Back propagation to the output layer
- Propagation to the hidden layer
- Weight updates

V. ANNs for Seismic & Dynamic Analysis

Finite Element Analysis (FEA) was used to produce the training and testing set of ANN models. A training and validation data set of RC bridges will be derived from the results of FEA analysis results of the dynamic response of RC bridges by shifting parameters (the input parameters of ANNs) including accelerations and axle loads, concrete compressive strength, reinforcement ratio, size of column, column shape, width of slab, effective depth of tension reinforcement, slab shape, peak acceleration, shear wall, story height, max width of bay in X, Y direction and etc., under the near-fault earthquakes. On the other hand, the output will be a dimensional dynamic response in terms of roof displacement, base shear forces and base bending moments, precisely when compared with the results of conventional methods like FEA [36]. The ANNs implemented in this research is a Multilayer Perceptron (MLP), with an architecture based on an alignment of nodes existing in one hidden layer and one output layer. The input layer transfer information from the outside into the first hidden layer and the process goes forth until reaching the output layer. While elements in the same layer are not interconnected, each unit in a layer is connected to all the nodes of the next layer. It is a feed-forward ANNs since the signals only circulate in the direction moving from the input into the one hidden layer and then to the output layer. With regard to the learning rule, a back propagation algorithm with a sigmoid transfer function was used as a first stage to investigate the power of the ANNs [37]. Since the damage condition is not seriously influenced by the bearing factor, the remaining three groups are employed to train the neural network. Hence, these factors are: the superstructure, piers and foundations, and seismicity. The categorization of the superstructure, in addition to piers and foundations, are put forth in Tables 1 and 2. The incidental numbering after each item listed in the tables will be put to use for the neural network input nodes [22].

Table 1: Superstructure Specifications

Classification		**Element**		**Seismic condition**
Superstructure	Bridge type	bridge Characteristics	I Prestress beam (I)	F: Collapsed superstructure
			B Box beams	A: Intense Dynamic Seismic Bridges’s Concrete: Substantial spalling or falling concrete
		Rigid frame bridge		Girder
		Truss bridge		Steel bridge: Broking truss
		Arch bridge		Broking bottom flange or buckling
		Cable bridge		
		Suspension bridge		
	Support Type	Simple support Continued		B: Middle Dynamic Seismic Bridges’s Concrete: large cracking on a concretes superstructure
	Materials	R RC R PC S Steel		Steel bridge: Deformation shapes of truss or other members Deformed bottom flange
	Plan shape	L Line bridge G curved bridge		C: Small Dynamic seismic
	Vertical Configuration	$Slope \leq 2\%$ $2\% < Slope \leq 6\% (2)$ $6\% < Slope$		Concrete bridge: Minor cracking on a concrete girder Steel bridge: Localized light deformation or buckling of a member

	slope	$A\ 75 < \theta \leq 90(1)$ $B\ 60 < \theta \leq 75(2)$ $C\ \theta \leq 60$	D: No Dynamic seismic No damage

Table 2: Foundation Specification

Classification			**Seismic condition**
	Pier type	W Wall column S Single column M Multiple column N No pier	F: Disintegrate columns, piers A: Big hazard Concrete: Cracked and deformation of columns or piers Overturned or tiled abutments Steel: Fracture or Crack
	Abutment	Gravity Abutment Cantilever Abutment Wall-type	B: Middle Dynamic Seismic Concrete: Deformation of members(Building od Bridges) Partial bulging out of reinforcements and spalling of cover concrete
Piers and Foundation	Materials	R Rc S Steel	Massive fracture on abutments Steel: Remaining deflection be less 0.03Lb
	Shape	C Circular R Rectangular E Ellipse P Polygon	C: Small Dynamic Seismic Concrete: Horizontal cracks that effects to Colums
	Body	Solid Hollow	Steel: Remaining deflection be than 0.01Lb. D: There is not any deflection
	Height	A 20m<h B 10m<h<20m C h<10m	

Table 3: Inputs characteristics X and Y direction

No.	Inputs	Symbol
1	bridge Length	L_b
2	bridge Width	W_b
3	No. of columns	N_c
4	No. of beams	N_B
5	Minimum dimension of column along X direction	W_{cmin}
6	Maximum dimension of column along X direction	W_{cmax}
7	bridge Height	H_b
8	Story Height	H_s
9	No. floors	N_f

No.	Inputs	Symbol
1	bridge Length	L
2	bridge Width	W
3	No. of bridges columns	N_c
4	No. of bridges beams	N_B
5	Minimum dimension of column in Y direction	D_{cmin}
6	Maximum dimension of column in Y direction	D_{cmax}
7	bridge Height	H
8	Story Height	H
9	No. of floor	N_f

The ANNs implemented in this study is a Multilayer Perceptron (MLP) constructed on the basis of an arrangement of nodes in one hidden layer and one output layer. The input layer transfer data from the outside into the first hidden layer and the process goes forth until reaching until the output layer. Each unit in a layer is linked to all the nodes of the next layer, while elements in the similar layer are not interconnected; i.e., it is a feed-forward ANNs since the signals only spread in the direction moving from the input into the one hidden layer and then to the output layer. Considering the learning rule, a back propagation was used to explore the power of the ANNs with a sigmoid transfer function as an initial stage.

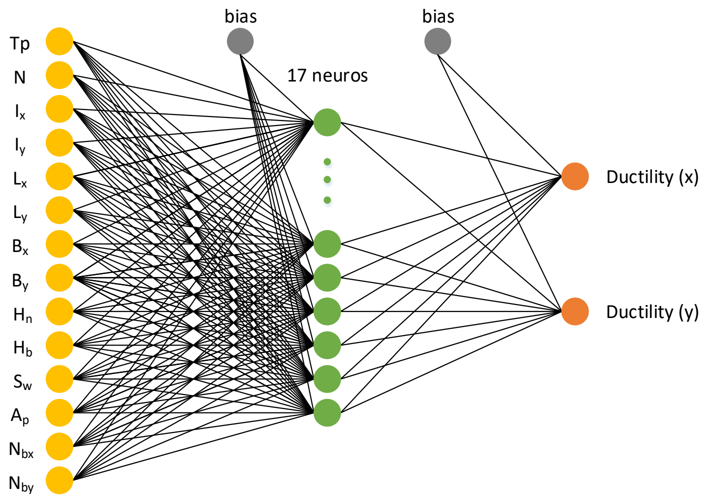

Fig. 5 Schematic shape of ANN model

An adequately trained ANNs necessitates that the phenomenon to be modeled is recognized as well as possible, in order to accurately choose the parameters that clarify it or have an impact on it. It is also very notable to have an efficient database that contains as many characteristic cases of the phenomenon being considered also involving the defining parameters a. An ANNs model was generated for simulating the ductility as shown in Fig. 3. Inputs of ANNs models include of 14 data sets in terms of general properties of buildings and earthquakes.

Table 4: Inputs Features for buildings during ANN Models

Symbolizations	Inputs
A_p	Peak acceleration
S_w	Shear wall
I_x	Total moment of inertia (in x direction)
I_y	Total moment of inertia (in y direction)
H_n	Story height

H_b	Story height of base floor
L_x	Max width of bay in x direction
L_y	Max width of bay in y direction
B_x	Widths of building in plan in x direction
B_y	Widths of building in plan in y direction
N	Number of stories
N_{bx}	Number of bay in x direction
N_{by}	Number of bay in y direction
T_p	Pulse period

VI. CONCLUSION AND DISCUSSION

The current study summarizes various ANNs models used for predicting the strength of concrete. The various software used for devising the ANNs model and the complementary theories to ANNs are reviewed. This paper gives a thorough insight of ANNs model applicability to predict the strength of concrete. Changes in dynamics properties are due to deterioration and reduction in structural stiffness such as the natural frequencies and mode shapes. During the research, neural networks make used to deduce knowledge from the natural frequencies of damaged structures at various points. Details of the study were described using ANNs to prediction of damage severity in a model steel girder bridge. The dynamic tests carried out on the damaged and undamaged test structure indicated that a decrease in stiffness during the damage resulted in a decrease in natural frequencies for various modes. The numerically generated natural frequencies of the first five modes of the undamaged and damaged bridge model were successfully applied as the training samples for the ANNs. According to the results, the ANNs was able to predict the damage severity with an average percentage error of 6.8 % and 8.25%, respectively for training and testing. In addition, the results indicate a particularly satisfactory coefficient of correlation between the identified and numerical data and generated that the developed ANNs model can be implemented as efficient tool to identify the severity of damage in the bridge girder model. Therefore, it can be inferred that ANNs trained with only natural frequencies derived from a numerical modal analysis as inputs can be adequately applied to evaluate the extent of damage in a structure [22].

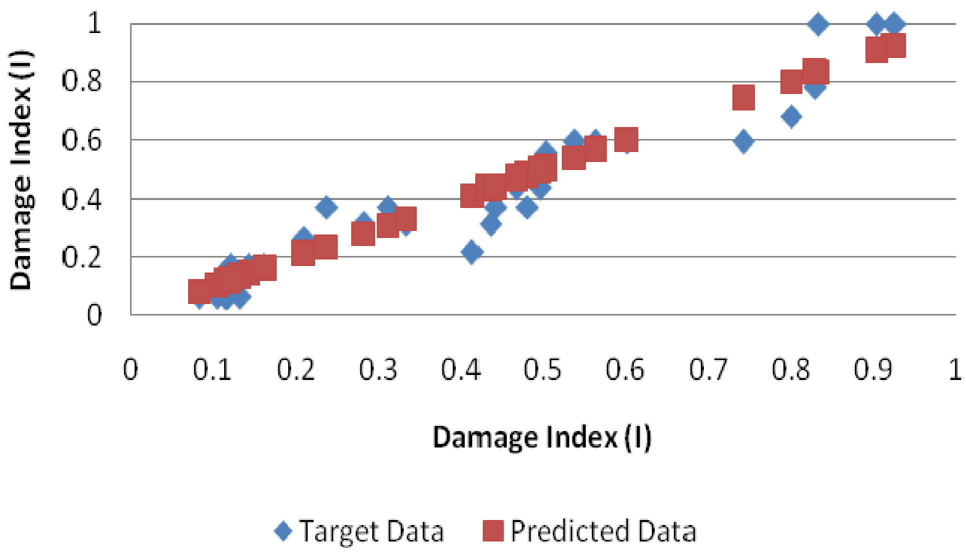

Fig. 6 Damage Index identified with ANN & target data [22].

As confirmed by a statistical values, the proposed ANNs model is adequate for predicting the dynamic response of buildings, considering the roof displacement, base shear forces and base bending moments, precisely comparison to the results of FEA. The results for R2 are 0.999689, 0.99057, 0.97895 and 0.942561 for the periods, roof displacements, base shear force and base bending moment respectively and indicate an acceptable correlation. As ANNs requires no simplifying assumption, preliminary modeling or calibration, its advantages to FE analysis are now relatively clear [1].

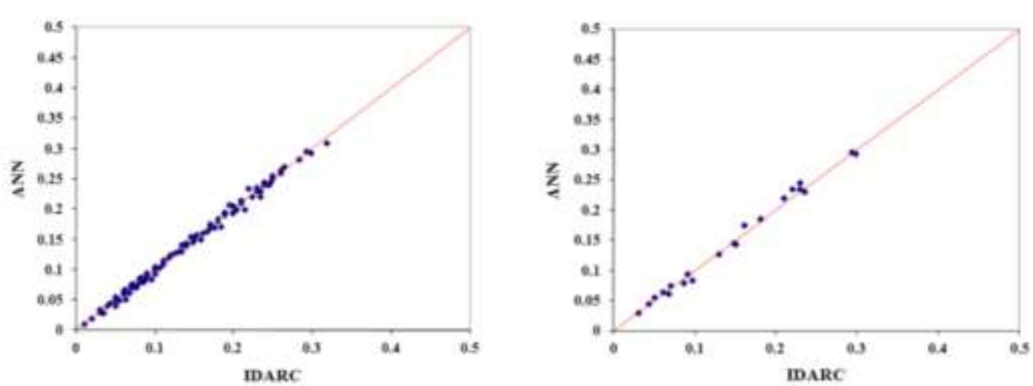

Fig. 4 Accuracy of ANN method for training and testing set by IDARC and ANN [1].

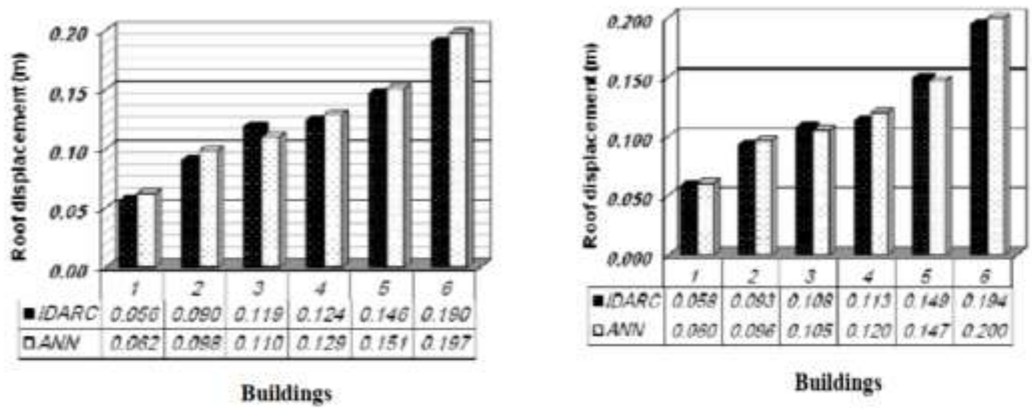

Fig. 5 Assessments of displacement for roof during two directions; x , y by IDARC and ANN [1].

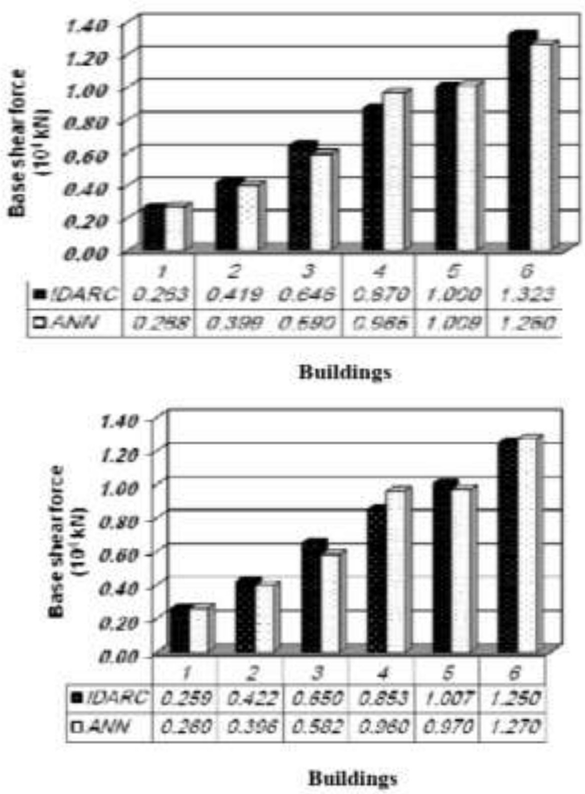

Fig. 6 shear stress during two directions; x, y by IDARC and ANN [1].

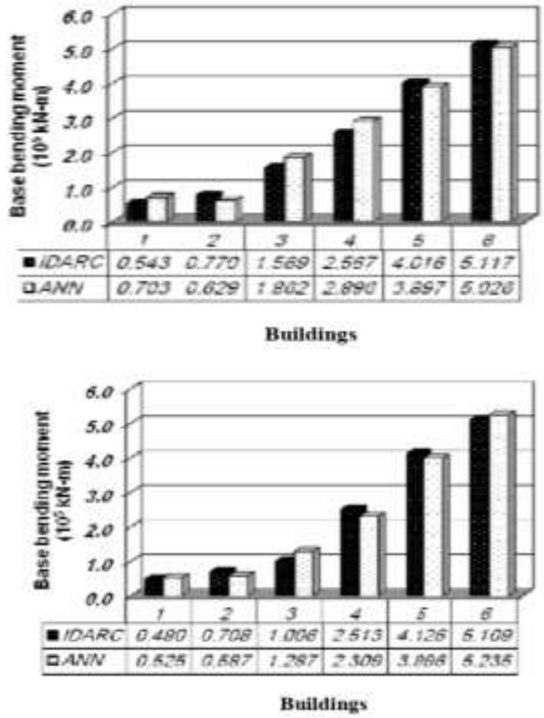

Fig. 7 Illustration bending stress during in two directions; x, y by IDARC and ANN [1].

306 bridge-earthquakes were considered in the final stage. The MLP neural networks considered in this study consist of input layer vectors, hidden layers and an output vector. 70% of the numerical results have been selected and the remaining 30% are employed to test reliability and validation of ANNs in order to train them. To obtain efficient and effective neural networks, numerous structures of MLP neural networks were analyzed. After obtaining the best structure of a neural network, the one selected was used for generating new data. A total number of 600 new bridge-earthquake cases were generated based on neural simulation. Finally, probabilistic seismic safety analyses were conducted. Therefore, the bridges fragility analysis was generated using numerical results, neural predictions and a combination of numerical and neural data [4].

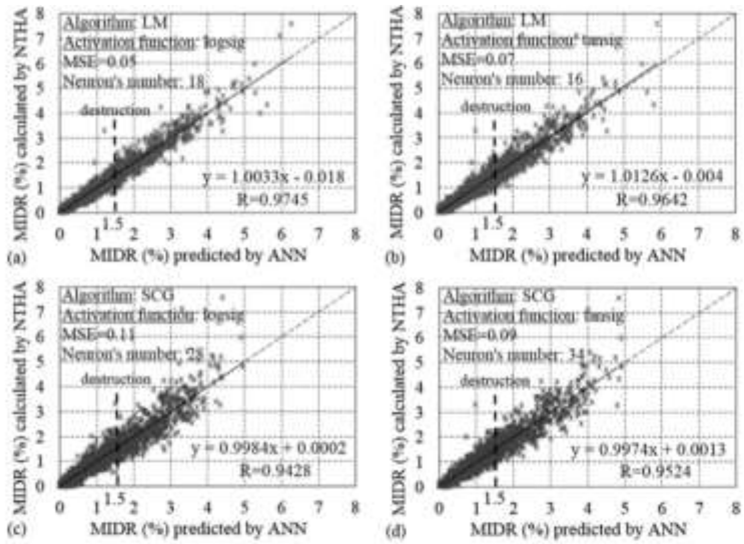

Fig. 8. Illustration the damage assessments by NTHA & trained Artificial Neural Network[12].

Fig. 8 depicts the predictability of the optimum networks when the criterion of min (MSE) is chosen for the testing sub-set. More precisely, the diagrams of this figure are concerned with the four optimum networks that are related to the four evaluated combinations of training algorithms and activation functions of the neurons of the hidden layer. In these diagrams, the MIDR (Maximum Interstorey Drift Ratio) values that were estimated using NTHA (Nonlinear modeling and analysis) are plotted against the MIDR values predicted by the optimum networks for all samples of the entire data set. The main conclusion is depicted in Fig. 8, that is, the network which has 18 neurons with the logsig activation function in the hidden layer and was trained using the LM algorithm (henceforth “N1LM-log/lin-18” network) yields the best predictions about the expected MIDR values (Fig. 8a). Specifically, the “N1-LM-log/lin-18” network extracts MIDRANN values, which are the best associated with relative MIDRNTHA values (R=0.9745). Another notable conclusion obtained from Fig. 8 is that the correlation between MIDRNTHA and MIDRANN values is more acceptable in the range (MIDR=0–1.5%). All points of the data set in this range with slight deviations, extremely near the straight diagonal reference line [12].

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