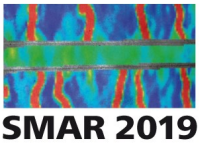
SMAR 2019 – Fifth Conference on Smart Monitoring,
Assessment and Rehabilitation of Civil Structures



Reinforced Masonry Retention Wall Model Using Artificial Neural Networks

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ABSTRACT: The use of reinforced masonry retention walls has become widely spread in South America as a fast-built and relatively economical construction technique. Nevertheless, there exists no much information related to the behavioral characterization of this type of elements. Experimental results exhibit both a highly nonlinear behavior and large dispersion of results since fragile masonry cells are filled with flowable concrete of low resistance and their reinforcement is basically composed of small-diameter steel bars. In the framework of an experimental program, a set of reinforced masonry-wall strips were tested under flexure for different steel reinforcement ratios. The experimental results obtained were numerically simulated using an inelastic-spring for the representation of plastic displacements and lumped damage with a nonlinear kinematic hardening model. The characterization performed through these numerical simulations allowed the training and validation of artificial neural network (ANN) model to obtain damage patterns and fragility curves. The ANN methodology is used as a partial surrogate model that seeks to consider an irreducible dispersion in the experimental data, and for the stochastic prediction of the structural parameters of the physical-based constitutive model (nonlinear spring). These structural parameters, which have a physical meaning (stiffness, damage, permanent displacement), help improving the understanding of the nonlinear material behavior. It is evident that the ANN must be trained with experimental reliable data of good quality.

1 INTRODUCTION

Reinforced masonry, a structural system widely used in Latin America for soil retaining walls, is a fast-built and relatively economical construction technique when compared to its reinforced concrete counterpart. A reinforced masonry wall is composed of concrete masonry cell units (CMU) joined by a mortar. These CMUs are filled with a flowable concrete mixture that provides an adequate level of workability that ensures a perfect engagement between the mortar and reinforced masonry wall [Gallegos et al. (2018)]. The metallic reinforcement usually consists of 13-mm diameter reinforcing bars. However, some studies have indicated that smaller diameters can ensure a more ductile performance [Castillo (2009)]. Being a very heterogeneous material, the structural response of an RMU walls present a considerable dispersion in the parameters that characterize its flexural behavior such as (1) rigidity; (2) yield strength; (3) ultimate load; and (4) ultimate displacement. Several models have been reported to characterize the plasticity and degradation of flexural elements in the literature [Do et al. (2018)]. For the study reported herein, an implementation of artificial neural networks (ANN) was conducted to

investigate the structural response of strips of RMU walls given the outstanding associated memory capacity exhibited by this technique [Hurtado (2002)].

ANN can work as a partial surrogate model that seeks to consider an irreducible dispersion in this composite material (reinforced masonry). Furthermore, ANN have proved to handle several type of engineering problems that demand complex response models [e.g., Douma et al. (2017, Abu Yaman et al. (2017)]. The main principle underlying this technique consists of emulating the learning and inference capacity of the biological neurons that constitute the human brain. This is achieved by following computational algorithms that simulate the information-transmission phenomenon throughout neurons (synapse) using weighting functions that are readjusted for different input parameters. The algorithm requires the training of the ANN (i.e., adjusting of the synaptic weights) by relating a set of known inputs with a set of outputs to be determined as depicted by Nunes-Silva et al. (2017).

The present work aimed at characterizing the process of plasticity and degradation of reinforced masonry strips (RMS) [Vergara (2012)]. To attain this objective the ANNs were trained [Barreto (2016)] with data obtained from a degradable elasto-plastic, physical-based constitutive model [Cipollina et al. (1995, Inglessis et al. (2002)] that was calibrated with experimental data recorded from tests conducted on the aforementioned RMS. The purpose of the study was to showcase the outstanding feature of ANNs to detect underlying patterns (degradation and plasticity) in the partial substitution of complex structural models that do not consider the randomness of the data given its deterministic nature. The elasto-plastic model was used to obtain a larger number of points of the force-displacement curve additional to those obtained from lab experiments.

2 PROBLEM FORMULATION

A set of RMS was designed using different configurations of metallic reinforcement and was tested under flexural monotonic cycles (load and unloads) as reported by Vergara (2012). The ANN approach was used due to the dispersion of the force-displacement curves. Subsequently, the tests were simulated with a computational program based on the damage model proposed by Flórez-López et al. (2014). This model is based on the concept of plastic behavior combined with the methods of continuous damage mechanics and assumes the inelastic phenomena (plasticity and degradation) are concentrated in an inelastic hinge with flexural plastic rotation and axial plastic elongation. For this model, a frame element is an assembly of a beam-column element with elasto-plastic behavior and the mentioned inelastic lumped hinge. The response of a cantilever retention wall with nonlinear behavior at the base or the simply supported RMS carrying loads applied at their center line, evaluated on this study, may be simulated by using a modified version of the model proposed by Flórez-López et al. (2014). This is done by assuming no flexural hinge is formed at the center line of the simply supported wall and using an equivalent single degree of freedom (SDOF) system instead. The equivalent SDOF system consists of a nonlinear elasto-plastic spring with damage and axial rigidity equivalent to the flexural stiffness of the strip. The state of energy dissipation is characterized by two variables: plastic displacement and damage index that takes values in the interval [0, 1]. A damage index value of zero corresponds to an intact, non-cracked strip, and an index value of one corresponds to a totally damaged strip. Note that the equivalent spring is an indirect way to consider the lumped inelastic hinge.

The few unload cycles of the tests (from 3 to 5 unloads per test), were used to calibrate the numerical nonlinear spring models; then a greater number of unloads were simulated to obtain enough values of damage and permanent displacement. This new information was used to train and validate an ANN software [Barreto (2016)] designed to predict the degradation process of reinforced masonry walls (RMW). The next sections describe (1) the laboratory flexural tests; (2) the degradable elasto-plastic

model for an equivalent axial spring; and (3) the ANN model. For the last two procedures (2 and 3), computational subroutines were developed to characterize the RMS behavior. Since the present work employs a physical-based constitutive law model, ANN was used as a partial surrogate model that seeks to consider an irreducible dispersion in the experimental data by monitoring the dissipation variables of the constitutive model. These variables, which have a physical meaning (stiffness, damage, and permanent displacement), help improving the understanding of the nonlinear material behavior. It worth mentioning that the successful ANN must be trained with data of good quality and reliability.

2.1 Experimental Program

A set of 80 RMS was fabricated using different diameters and locations of the metallic reinforcement (Vergara 2012). The RMS consisted of rows fabricated with five concrete masonry cell units (CMU) with a height of 200 mm. The height of an RMS was 1000 mm [Figure 1(a)]. The CMU were connected by a cement mortar joint (using a 3 to 1 sand-cement ratio and a 3 to 4 water-cement proportion). The cross section of the blocks was 150 mm by 400 mm [Figure 1(b)]. Inside the empty cells of the strips, metallic bars and very flowable concrete were placed [with an average compressive strength of 15.7 MPa]. Strength tests were performed on the CMU, mortar, flowable filling concrete and rebars. RMS were subjected to a line load applied at the midspan of the specimen [Figure 1(b)]. The load pattern consisted of a displacement–control test recording the history of force and displacement every millimeter until the collapse of the specimen was reached. For each test, a total of three to five cycles were conducted. Figure 1(c) shows the force-displacement relationship for two identical specimens showing a different response. The red line corresponds to a specimen that failed due to the adherence of the metal bars, and the blue line shows the response of a specimen that showed a ductile failure.

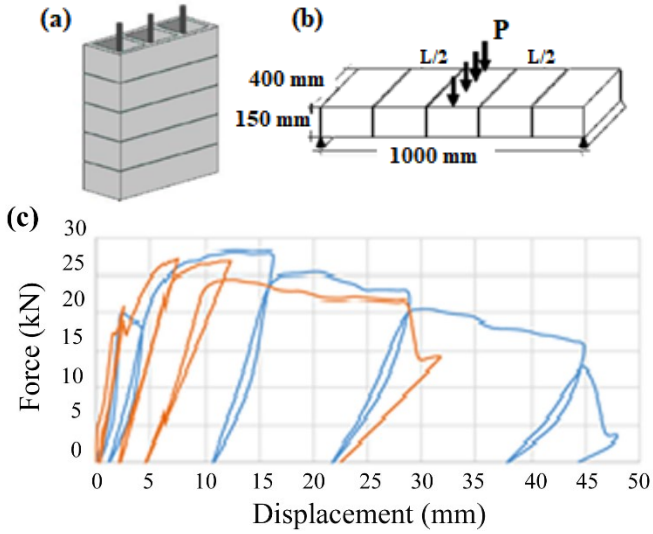

Figure 1. Experimental program details. (a) RMS specimen; (b) load pattern; and (c) force-displacement curve of two tests. Conversion factors: 1 m = 1000 mm.

2.2 Elasto-plastic Spring Model Coupled with Damage and Nonlinear Hardening (EPDM)

The simply supported masonry strips can be modeled as a one-degree of freedom system by using a nonlinear spring whose axial rigidity is equivalent to the flexural rigidity of the strips. The concept of inelastic bending hinge is avoided for modeling purposes. The main difficulty of the mathematical representation of the elasto-plastic model is that an infinite number of forces can correspond to a given

value of the displacement. In the elasto-plastic model coupled with damage [Flórez-López et al. (2014)], it is necessary to introduce "internal variables". For the present work, these variables are the vertical permanent displacement, Δ_p, and the damage, D. The external applied force, P, is determined using Equation (1).

$$P = (1 - D)K_0(\Delta - \Delta_p) \tag{1}$$

where K_0 represents the initial flexural stiffness of the strip, and Δ is the total displacement. The damage variable can take values between zero (intact material) and one (completely damage material). Equation (1) cannot be considered as a constitutive equation since the permanent displacement (Δ_p) and the damage (D) are unknown. In addition, these two variables depend on the history of total displacement. It is necessary to introduce additional relationships that allow the determination of these unknown variables. These equations are called *evolution laws* for the permanent displacement and damage. For plastic models, the *evolution laws* are expressed by means of a "yield function". In the case of elasto-plastic model coupled with damage, a yield function, f, is defined by Equation (2):

$$f(P, D) = \left|\frac{P}{(1 - D)} - X\right| - P_y \leq 0 \tag{2}$$

where P_y is the yielding force corresponding to the first permanent displacement Δ_p*; and* X is the kinematic hardening force that considers the position of the center of the elastic domain; for nonlinear kinematic hardening models, X is given by Equation (3):

$$X(\Delta_p) = (P_u - P_y)(1 - e^{\alpha\Delta_p}) \tag{3}$$

where P_u is the maximum limit imposed to the force and α is a material´s constant that define the strain hardening path [i.e., α is a parameter that represents the slope of the resulting line in a plot of $ln(P_u - P_y)$ vs. Δ_p]. The softening deformation behavior is not considering in the present model. The evolution law for permanent displacements are differential equations given by Equations (4) and (5):

$$d\Delta_p = 0 \; if \; f(P, D) < 0 \;\; or \;\; df(P, D) < 0 \tag{4}$$

$$d\Delta_p \neq 0 \; if \; f(P, D) = 0 \;\; and \;\; df(P, D) = 0 \tag{5}$$

Equation (4) has two conditions that characterize the elastic behavior. The force is lower than the yielding force, or elastic unload occurs regardless of the force value. Equation (5) represents the elastic-plastic behavior (i.e., permanent displacements are only possible if the force is equal to the yield force, and no elastic unload process occurs). In Equation (1), the term $(1 - D) K_0$ is known as the effective stiffness $\bar{K}$. Solving for the damage, D, an indirect measurement of the damage from the elastic unload is defined by Equation (6):

$$D = 1 - \bar{K}/K_0 \tag{6}$$

In Equation (6), each of these damage measurements is associated to a given Δ_p and an effective stiffness $\bar{K}$. In this manner, a relationship can be found being the damage a function of permanent displacement (evolution law or ductile damage) as described by Equation (7):

$$D = m(\Delta_p - \Delta_{cr}) \tag{7}$$

where m is the slope of the straight line in the graph D vs Δ_p; Δ_{cr} is the permanent displacement corresponding to the beginning of damage. Note that a linear relation between internal variables is imposed. In addition, it must be highlighted that in Equation (2) both the damage and hardening variables [given by Equations (3) and (7)] are functions of the permanent displacement because the model represents a ductile damage phenomenon. Equations (1), (4) and (5) represent the constitutive model for an elasto-plastic axial nonlinear spring coupled to damage and considering nonlinear kinematic hardening, representing simply supported masonry strips.

2.3 Artificial Neural Networks (ANN)

An ANN is inspired by biological neural networks simulating a series of characteristics of the human brain such as (1) learning based on experience; (2) generalization of the experience; and (3) extraction of the main features of a series of data (hidden patterns). An artificial neuron combines several inputs by basic addition operations. The sum of the entries is modified by a transfer function and its result is transmitted. These outputs are connected to the inputs of other neurons through weighted connections or weights (synapses). The network consists of an input layer, hidden layers and an output layer. Learning of a network, in artificial intelligence context, consists basically in the adaptation of the synaptic weights. During the training phase, weights gradually converge towards the values that make each input produce a desired output vector. This learning is called “supervised” if the training is controlled by modifying the weights to get an approximation to a desired output, so the network does not need to find the features, regularities, correlations or categories between the input data. The training stops when the quadratic error of the data reaches a minimum or when for each of the given examples a pre-established threshold is reached. Once the learning is finished, the weights will not be modified again. The next phase of validation corresponds to checking if the neural network can solve new problems of the general type for which it has been trained. A new data set (inputs and outputs) is used but the network will not change the synaptic weights. Then, the expected solution (validation data) is compared with the solution of the network.

In the present work, a backpropagation network was used. For this type of ANN, the error propagates backwards from the output layer, allowing the synaptic weights of the hidden layers to change during training. This type of ANN is characterized by its generic ability to map patterns that have a supervised training method. A correlated pair pattern is introduced (i.e., an input pattern with a desired output pattern), and the weights are adjusted to minimize the error between the desired output and the network response. Learning can be slow due to the difficult to determining the number of neurons and layers needed. Moreover, learning is unable to detect new patterns, only those that are the same or like the used in training. Convergence is obtained by minimizing the error, usually by means of first-order derivatives in the optimization process. In the present investigation, a back-propagation algorithm based on the Levenbert-Mardquardt method, which is based on second order derivatives (Nunes 2017), was used. This algorithm combines back propagation error and Newton's method. Therefore, subroutines were elaborated to predict the nonlinear behavior of the samples through ANN. The network was trained with several loads and unloads simulated by the degradable elasto-plastic numerical models described in section 2.2 that were previously calibrated with the experimental data of the RMS described in section 2.1. This model allowed to obtain continuous load data, total displacement, permanent displacement and damage that were used for training and validation. Within the training phase, all the possible combinations for input and output with the representative variables were used. The one that corresponds to the damage represented the only output with the best results. The data of all the specimens were randomly separated into training, validation and test groups (70% training, 15% validation, 15% test). The linear regression adjustments for the data (training, validation and test) resulted with a coefficient of determination of 0.99.

3 ANALYSIS OF RESULTS

The experimental force-displacement curves showed different behavior that varied from those with (1) similar envelopes but different values of the permanent displacement and damage; (2) different ductility; (3) different type of failure (bond failure versus ductile behavior); (4) constructive defects creating changes of the boundary conditions of the specimens during the test; and (5) different degree of strain softening as shown in the force-displacement curves [Figure 1 (c)]. An initial analysis of the ANNs was performed using the entire data partitioned into different groups for the training, validation and testing phases (70%, 15%, 15%). Preliminary results demonstrated the difficulty of the algorithm for learning due to an exaggerated dispersion of training data [Figure 2 (a)].

3.1 Artificial Neural Network (ANN) Trained with the Nonlinear Spring Model (EPDM)

In a first phase, results were discriminated for those tests with exaggerated disturbing behavior (i.e., case of bond failure tests) allowing a second phase for the training. No classification machine learning procedure were used for this purpose. Figure 2(b) shows force-displacement curves simulation for a group of specimens used in the training. Plastic softening was not considered. A test strip is modeled by ANN (red line) and compared with the result obtained by the numerical model (blue line). In Figure 2(c), the damage obtained by the ANN and that obtained with the numerical model show an excellent fit. The model of plasticity and damage (EPDM) allowed to simulate many unloads data (used for training) that would hardly be obtained in an experimental test.

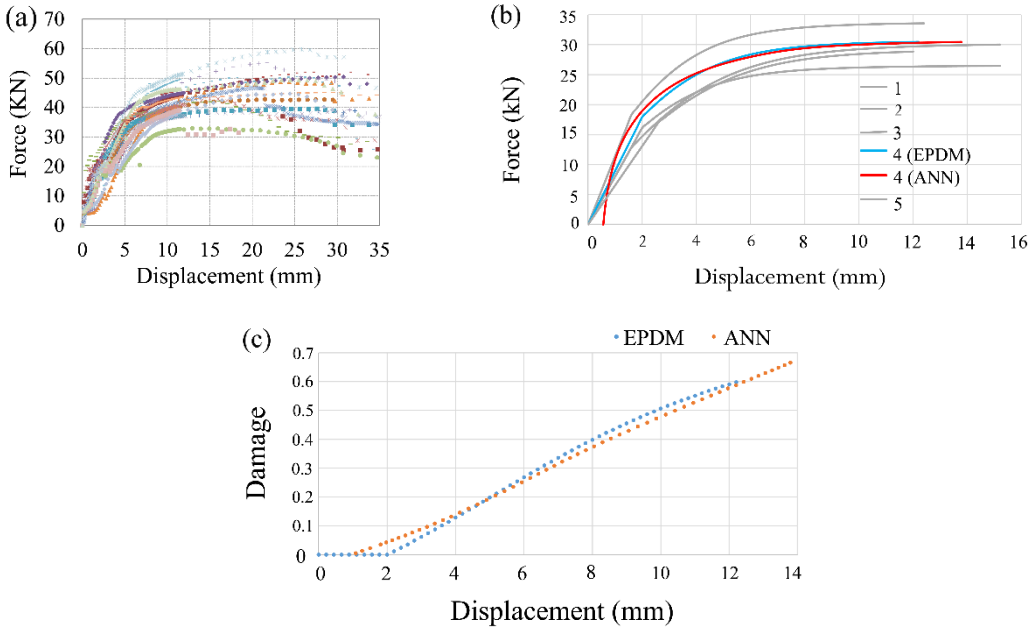

Figure 2. Results. (a) RMS tests' data; (b) test and simulation results; (c) damage vs. permanent displacement. Conversion factors: Conversion factors: 1 cm = 10 mm; 1 kgf = 9.8 N.

3.2 Model of ANN using experimental data

Neural networks were trained with only experimental data, corresponding to three elastic unloads per specimen test. That is, only three permanent displacement values and their corresponding damage values. Therefore, force and displacement values belonging to these unloads were used (unlike the procedure

described in section 3.1, where data was taken from simulations with the numerical EPDM model). After preliminary trial-and-error attempts, ten nodes were used for the hidden layer, leaving the architecture of input-hidden layer-output as [4, 10, 1] Once trained, we proceeded to test the ANN for 4 unknown unloads of the same specimen. The damage values obtained were compared with those simulated by the EPDM model obtaining a negligible error, however, the number of iterations was 246; moreover, the amount of force and displacement values that had to be used for the training was considerably much greater than that of section 3.1.

The linear correlation, *R*, of the expected data (targets) and those estimated by the network (output) was one during the training, validation and proof phases. This confirms that the network is perfectly trained if the data behavior during the learning phase is not too different. In this case, the network was trained for only a layer. When several strips were used, the network was not capable of obtaining acceptable values. It might have been possible that network was not capable of making a distinction due to the high density of the cloud of points [Figure 2(a)]. Consequently, this could lead to the incapacity of the network to find the adequate relationship between the permanent deformation and damage, especially for those cases where the damage increment is not physically acceptable.

3.3 Artificial neural network used to construct fragility curves

Damage indexes were estimated using the ANN approach for different force values adjusted to a lognormal probability distribution. The log-normal distribution has been widely employed to build fragility curves [Bonett (2003)]. Once the best fit of the probability distribution was known, the cumulative distribution functions were obtained [Sanchez (2015)]. These cumulative functions were classified for values of damage that ranged from slight (less than 0.1), smooth (0.1–0.2), moderate (0.2–0.3), and strong (0.3–0.4). The points of intersection with the vertical axis represent the exceedance probability for the four damage segments defined previously. The fragility curves represent exceedance probability of a damage state as function of the actions that cause it (i.e., external applied load in this case). The exceedance probability was estimated as *PE = (1 – CDF)*. Figure 3 shows the fragility curve damage obtained using ANN on the external applied load.

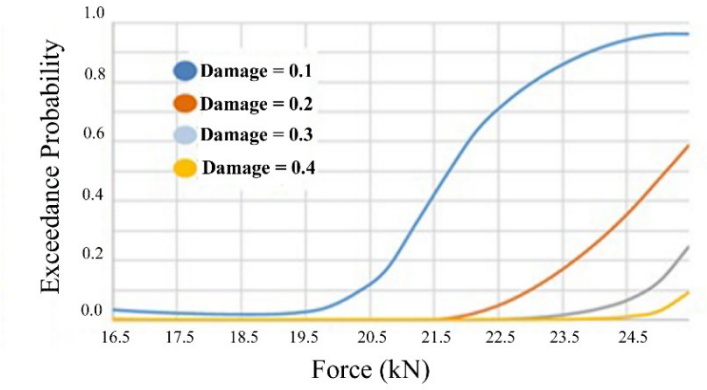

Figure 3. Fragility curves of strip sets

4 CONCLUSIONS

Artificial neural networks have demonstrated to be a powerful alternative technique to handle complex engineering problems such as nonlinear behavior with certain degree of dispersion of the input data. This

ANN technique allows to train an algorithm with a small amount of experimental data, or a combination of experimental and numerical simulation data to predict new input data problems. The main feature of ANN is its ability to find underlying patterns from the data. However, reliable information with enough quality must be available. The response of neural networks is very sensitive to the characteristics and statistical patterns of the data used for training. The experimental training data obtained for masonry strips is highly sensitive to variables such as (1) construction quality; (2) specimen's support conditions; and (3) failure due to steel debonding. An important goal of the design process is the estimation of a balanced number of neurons of the hidden layers to ensure an efficient prediction of output data. In the present work, the ANN methodology was used as partial surrogate model that seeks to consider an irreducible dispersion in the experimental data because a physical-based constitutive model (nonlinear spring) was used. The ANN found a good relation that fitted with the experimental data. The stochastic prediction of the structural parameters, having physical meaning (stiffness, damage, and permanent displacement), helped improving the understanding of the nonlinear behavior of the reinforced masonry strips (RMS). However, it is worth to mention that the quality and reliability of the training data is a critical issue. The use of ANN methods based on physical model can result in a significant reduction of time and cost savings. Moreover, as increasing computational efficiency and convergency in many structural engineering tasks. In contrast, ANN based on non-physical models do not require complex mathematical formulation based on its ability to find hidden patterns during the training phase. However, since ANN works as a black box, it fails to improve the understanding of the nature of the problem under study.

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