Structural Engineering and Mechanics, *Vol. 71, No. 5 (2019) 545-552*
DOI: https://doi.org/10.12989/sem.2019.71.5.545

Using a feed forward ANN to model the inelastic behaviour of confined sandwich panels

María E. Marante[1a], Wilmer J. Barreto[1,2b] and Ricardo A. Picón[*1,2]

[1]*Laboratory of Structural Mechanics, Lisandro Alvarado University, Barquisimeto, Venezuela*
[2]*Departamento de Obras Civiles y Geología, Facultad de Ingeniería, Universidad Católica de Temuco, Temuco, Chile*

(Received February 8, 2019, Revised April 10, 2019, Accepted April 17, 2019)

Abstract. The analysis and design of complex structures like sandwich-panel elements are difficult; the use of finite element method for the analysis is complicated and time consuming when non-linear effects are considered. On the other hand, artificial neural network (ANN) models can capture the non-linear effects and its application requires lesser computational demand. Two ANN models were trained, tested and validated to compute the force for a given displacement of a sandwich-type roof element; 2555 force and element deformation pairs were used for training the ANN models. For the models trained without considering the damping effect, there were two values in the input layer: maximum displacement and current displacement, and for the model considering damping, displacement from the previous step was used as an additional input. Totally, 400 ANN models were trained. Results show that there is a good agreement between the experimental and simulated data, and the models showed a good performance with a mean square error value of 4548.85. Both the ANN models could simulate the inelastic behaviour, loss of rigidity, and evolution of permanent displacements. The models could also interpolate and extrapolate, which enables them to be used as an analysis and design tool for such complex elements.

Keywords: Artificial Neural Networks; inelastic behavior; composed panels; non-traditional structures; permanent displacement

1. Introduction

There are various structural systems and numerical tools to analyse structures for understanding the variation of stresses and deformations in each of its element. The structural systems can be classified as traditional and non-traditional systems. There are several numerical tools used for structural analysis; the finite element method (FEM) is one such numerical analysis tool. For traditional structures, which are made of homogeneous materials and have regular dimensions, the FEM is the preferred analysis tool. In contrast, non-traditional structures are made of elements that combine different types of materials and have cross sections made of heterogeneous materials; therefore, defining the cross-sectional mechanical properties of these elements is difficult. Hence, the use of FEM to numerically analyse this type of non-traditional structures is complicated (Perera *et al*. 2010, Hashemi *et al*. 2018). Currently, researchers are trying to model the inelastic behaviour of homogeneous and non-homogeneous materials using FEM (Picon-Rodriguez, Quintero-Febres and Florez-Lopez 2007, Guerrero *et al*. 2007, Perdomo *et al*. 2013). However, these models are not suitable when the structural elements are highly complex and heterogeneous (Pendharkar Chaudhary and Nagpal 2011), such as sandwich panels, requiring a complex 3D-FEM analysis (Yoon, Kim and Lee 2017).

Sandwich systems, which are non-traditional systems, are quick and easy to construct, can withstand external loads and possess good mechanical behaviour (Mohamed *et al*. 2016, Poluraju and Rao 2014). The shear walls of a sandwich system may exhibit a good behaviour when subjected to lateral loads (De Matteis and Landolfo 1999). The behaviour under impact forces have also been evaluated experimentally for these structures (Rotaru *et al*. 2016). The cross section of a sandwich panel consists of different materials, which makes them difficult to model using the FEM.

New techniques based on machine learning are emerging for structural analysis (Taffese and Sistonen 2017, Reuter, Sultan and Reischl 2018); one such technique is the artificial neural network (ANN). ANNs are capable of modelling complex systems and inelastic behaviour (Akbas 2006, Ramnavas *et al*. 2017). ANN models are being used to predict the shear stress in reinforced concrete (RC) beams (Mansour *et al*. 2004, Amani and Moeini 2012, Yavuz 2016) and the moment capacity of RC slabs (Erdem 2017). However, there is little research regarding the modelling of inelastic behaviour of composite structural elements under cyclic loads.

In this paper, an ANN model is built based on the experimental data to model the inelastic behaviour of a

*Corresponding author, Ph.D.
E-mail: rpicon@uct.cl
[a] Ph.D.
E-mail: emarante@ucla.edu.ve
[b] Ph.D.
E-mail: wbarreto@uct.cl

http://www.techno-press.com/journals/sem&subpage=7
ISSN: 1225-4568 (Print), 1598-6217 (Online)

sandwich panel subjected to pure bending under cyclic loads. An inelastic behaviour is visualised for the roof slab by observing the evolution of permanent deformations and the drop in the initial stiffness. Another phenomenon in the experimental curve is the dissipation of energy due to the damping effect of the constituent materials (Darendeli 2001). This damping effect occurs when the path of unloading is different from the path of reloading the element.

The ANN facilitates numerical analyses based on the experimental data used for its training. A main advantage of ANN is that to solve a problem, each neural network needs to solve only a simple and efficient equation set, unlike the conventional methods that use a more complex set of equations (Hadi 2003, Zopf and Kaliske 2017). This ANN method can also be applied in geotechnics and nanotechnology, in addition to structural analysis (Haj-Ali *et al*. 2008, Freitag *et al*. 2018). Also ANNs have proven to be less complicated and time-consuming (Azqandi Nooredin and Ghoddosian 2018) and capable to deal with structural damages (Mariani, Venini and Nascimbene 2003). This article demonstrates the training of two ANN models using experimental data. The first one represents the flexural behaviour of a sandwich-type roof slab without considering the damping effect and the second model simulates the damping effect in the sandwich panel.

2. Experimental design and materials

A set of confined sandwich panels was made and a few results are showed in this paper. Each panel is a basic element of a roof plate and is experimentally analysed under bending stress. The experiments were conducted in the Laboratory of Structural Mechanics of "Lisandro Alvarado University", Venezuela. The confined sandwich panel is a non-traditional composite element.

2.1 Specifications of roof plate panel

The roof plate consists of several interconnected individual panels of size 300 cm x 40 cm x 10 cm (Fig. 1a). These panels are sandwich-type structures made of two thin, high-resistance, RC elements of thickness 14 mm located on the top and bottom, separated by Expanded Polystyrene material (EPS), and confined by cold-bent steel sheet of a special shape (Fig. 1b, c).

2.2 Mechanical properties of panel materials

The concrete plates have a thickness of 14 mm, and a carbon-fibre mesh is provided in the middle as reinforcement. The concrete resistance reached a value of 30 MPa. The cold-bent steel sheet was subjected to single tension test, and the value obtained for ultimate stress was 283 MPa.

2.3 Implementation of the experiment

The test panels of complex cross sections were experimentally analysed under pure bending stress to obtain the behaviour curve and maximum capacity. The roof panel was placed on two simple supports, and point loads were applied at L/3 locations on the panel (ASTM E72-15 2015, ASTM E564-06 2018), as shown in Fig. 2.

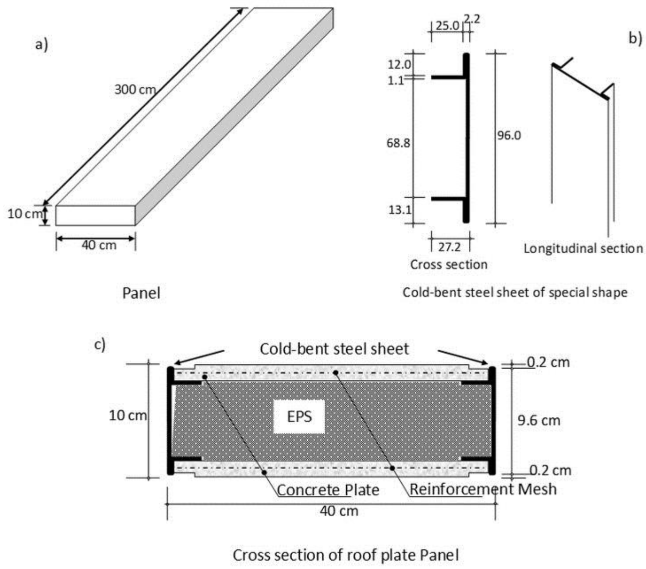


Fig. 1 a) Dimensions of the panel b) cross section of the steel sheet c) cross section of roof plate panel

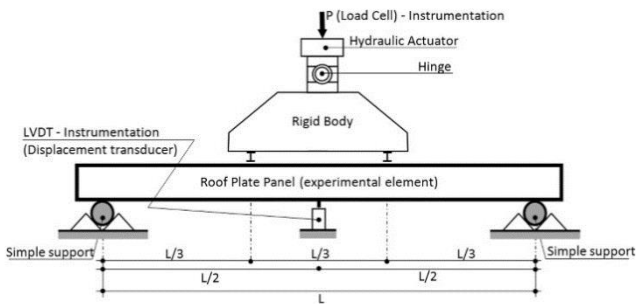


Fig. 2 Scheme and instrumentation of pure bending tests

The roof-plate panels were subjected to a positive cyclic displacement history with unloading (see Fig. 3). The control variable was the displacement, and it was applied with a hydraulic actuator. During unloading, the displacement was controlled until the load reached zero. The displacement was measured at the centre of the panel opening. A displacement transducer (LVDT) was used to measure the displacement, see Fig. 4a and 4b

2.4 Analysis of experimental results

The experimental results of the tested panels are presented in this section. The global behaviour curves (force vs. displacement) of the panels are shown in Fig. 5; the ultimate force and the corresponding displacement can be observed from these curves. Further, the permanent displacements in each load cycle can also be observed (Fig. 6).

The first deformation detected was the buckling of the steel plate (Fig. 7a), followed by a brittle failure due to the cracking of concrete (Fig. 7b).

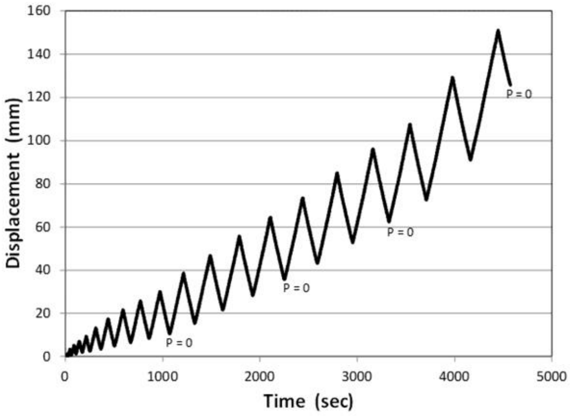
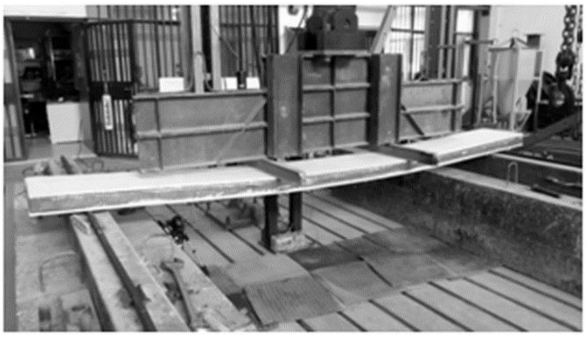
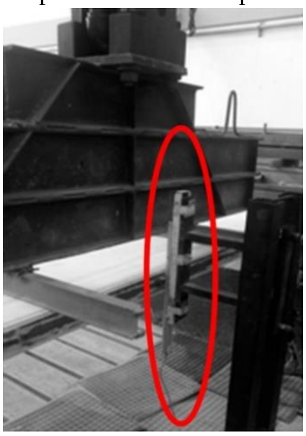


Fig. 3 Displacement History



(a) Implementation of experiment



(b) LVDT placed at the centre of panel opening

Fig. 4 Experimental test

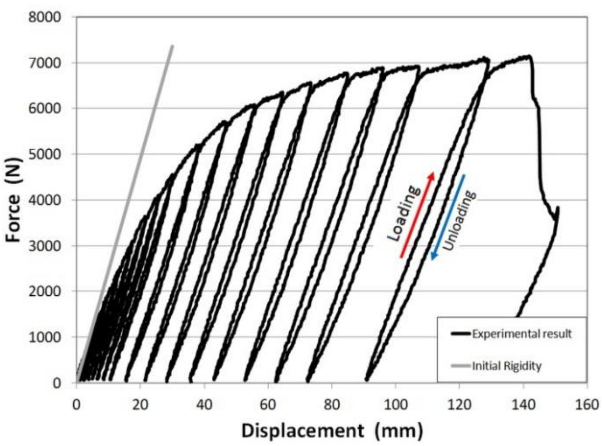


Fig. 5 Behaviour curve (force vs. displacement)

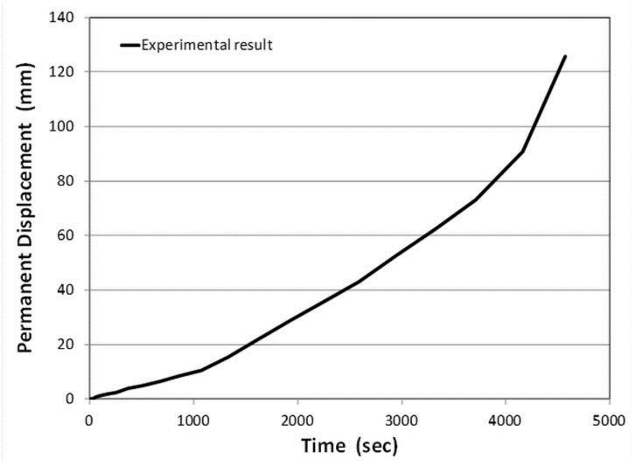
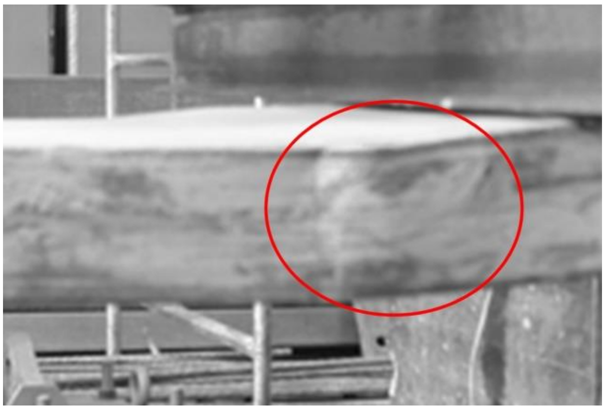
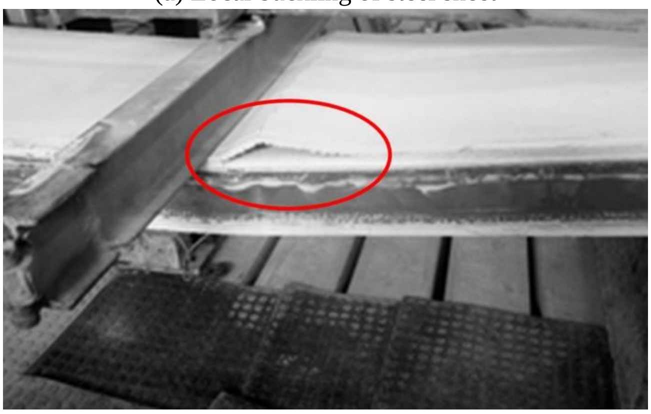


Fig. 6 Permanent displacement history



(a) Local buckling of steel sheet



(b) Fragile failure, crack on the top concrete plate

Fig. 7 Failure types

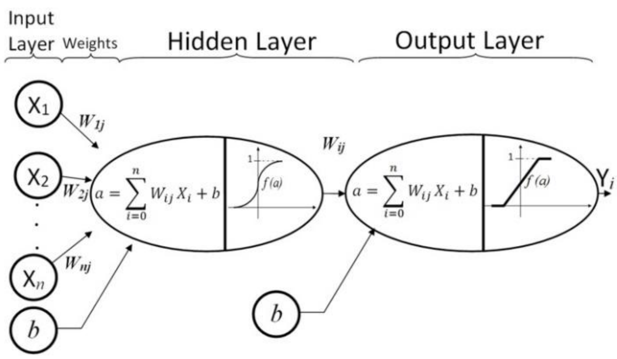


Fig. 8 ANN Structure: input, hidden and output layers

3. Artificial Neural Networks

Artificial neural network (ANN) is a technique derived from the biological brain behaviour and developed for machine learning applications. The neuron is the basic unit of the brain, and its function is mimicked using a perceptron (Rosenblatt 1958). The perceptron was initially introduced by Rosenblatt, and was improved by years of research to evolve into a complex perceptron's network. The ANNs are composed primarily of three layers: a vector input layer, one or more hidden layers, and a vector output layer, as shown in Fig. 8.

The most recognised and widely used ANN is the feed forward network; such a network is commonly trained using a back-propagation algorithm. The input layer is connected to the hidden layer with weights; the result of the scalar product of the inputs and weights is passed to a transfer function to activate the output layer. These output results are compared to a target set during the training phase, and the errors are computed and corrected by changing the value of the weights using an optimisation algorithm.

In this study, the raw data were processed before the construction of the ANN model to eliminate the noise introduced in the data acquired from electronic equipment. These values were smoothened using moving average with a frame of 100 data values for deflection and force. The data collected after the failure of the structural element were removed from the training set. The ANN model was trained using these pre-processed data. Totally, 2555 pairs of force and deformation values were used for the training process. The Levenberg-Marquardt backpropagation learning algorithm was used and the initial "mu" parameter was set to 0,001.

3.1 Implementation of ANN Models with and without damping effect

The training of the ANN was done by dividing the pre-processed data into three sets: One set (70%) for training, second set (15%) for cross validation, and the rest (15%) for verification of the trained network. The mean square error (MSE) was selected as the performance indicator. The value of MSE was computed for the training and cross validation sets as the stopping criterion.

Fig. 5 shows the raw measured data; it can be observed that there are two branches for each loading and unloading cycle. The branch to the left corresponds to the loading cycle, and the branch to right corresponds to the unloading cycle. This effect is due to the damping coefficient of the element and the energy absorption capacity. Due to the occurrence of damping effect, it was decided to build two models: one with damping and the other without damping.

The instantiated ANN models differ in the input layer; both models are built to obtain the force (F) for a given vertical deformation (δ). The input layer for the model without damping has two entries: the vertical deformation (δ_i) and the maximum vertical deformation (δ_{MAX}) applied to the structural element. The model with damping has the vertical deformation computed in a previous step (δ_{i-1}) as an entry in addition to those mentioned above.

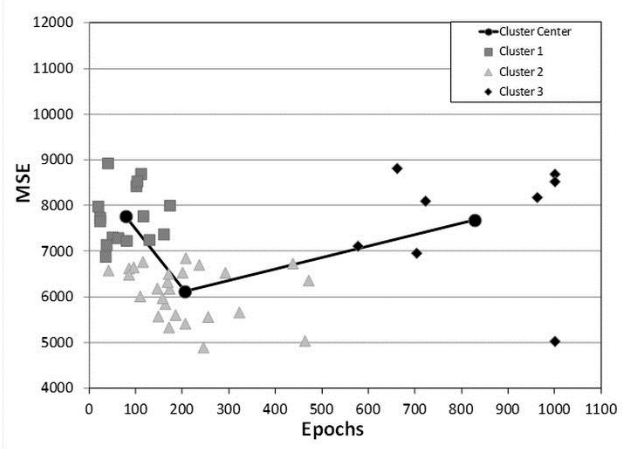


Fig. 9 Cluster centres for a model with 1 hidden node

The feed forward network was trained using a back-propagation algorithm. A script was written for training the network. This script trained 50 artificial neural networks by changing the initial seed to obtain various models with different weights and performances (MSE). These 50 models were grouped by a k-mean clustering algorithm based on the number of epochs and MSEs. After some trials and errors in the clustering process; it was conclude that the best number of cluster is three. The cluster centres indicate the optimum number of epoch to be used for the network training and the associated performance.

The procedure described in the precedent paragraph is repeated for 1, 2, 3 and 4 nodes in the hidden layer. Totally 400 models were instantiated. From this set, the best models were selected, one without damping and the other with damping. Each model was tested using a synthetic history of displacement to observe the performance of the models under data that was not used for training or validation. Two tests were carried out; the first was conducted to check the model behaviour under interpolation, and the second to check the extrapolation capabilities.

3.2 Training of ANN Models

The process of clustering helps to identify the best set of training parameters. Fig. 9-12 show the clustering results of the model with damping, for 1, 2, 3 and 4 nodes in the hidden layer, respectively. By comparing the figures, it can be observed that the model shows improves performance (MSE) when the number of nodes in the hidden layer increases. This can be attributed to the better learning capacity of the ANN model with more number of nodes.

It can be observed that the performance of the cluster centres is low when the number of epochs is low (less than 150 epochs), improves for a range between 150-500 epochs, and again deteriorates for values greater than 500 epochs. The behaviour seen in Fig. 9-12, regarding the number of epochs, indicates the generalisation capacity of the ANN model.

The cluster centres with the best performance for 1, 2, 3 and 4 hidden nodes are shown in Table 1. The number of epochs with the best performance ranges between 200-250; this is independent of the number of hidden nodes. The

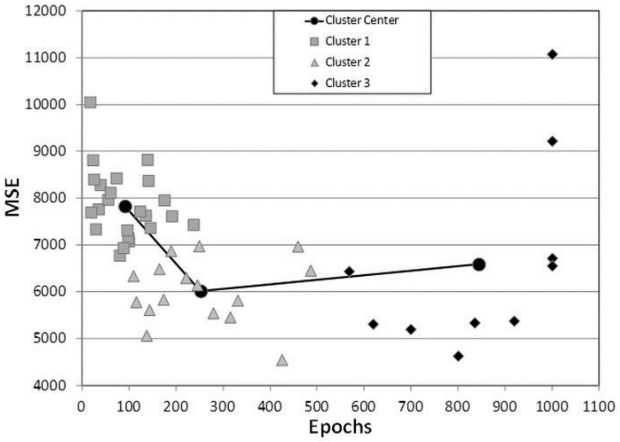


Fig. 10 Cluster centres for a model with 2 hidden nodes

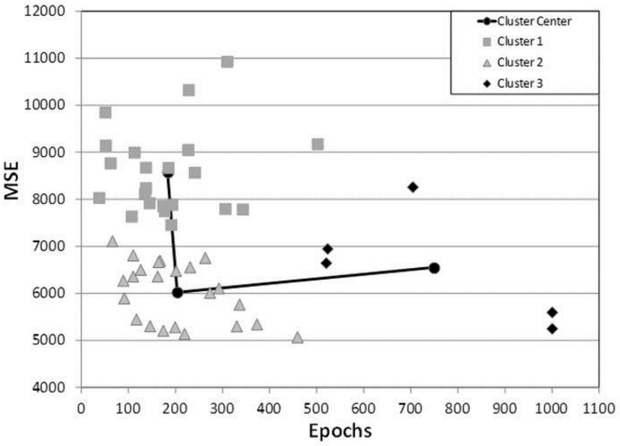


Fig. 11 Cluster centres for a model with 3 hidden nodes

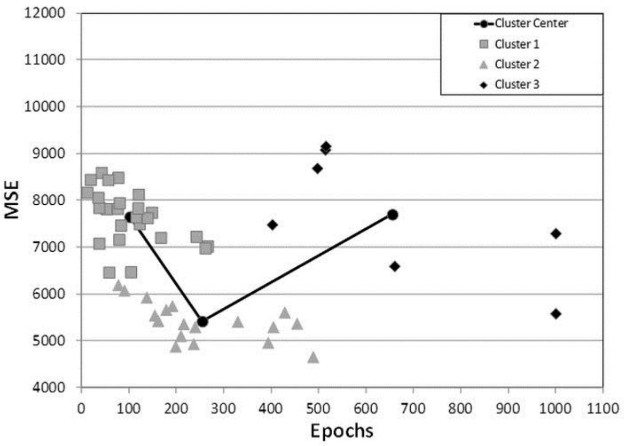


Fig. 12 Cluster centres for a model with 4 hidden nodes

Table 1 Cluster centre and best model performance

Model	Best Models		Cluster Centre	
	Epochs	MSE	Epochs	MSE
1 Hidden Node	245.00	4899.43	205.54	6117.32
2 Hidden Nodes	425.00	4548.85	252.50	6015.32
3 Hidden Nodes	459.00	5073.43	204.26	6023.58
4 Hidden Nodes	488.00	4654.68	254.50	5411.47

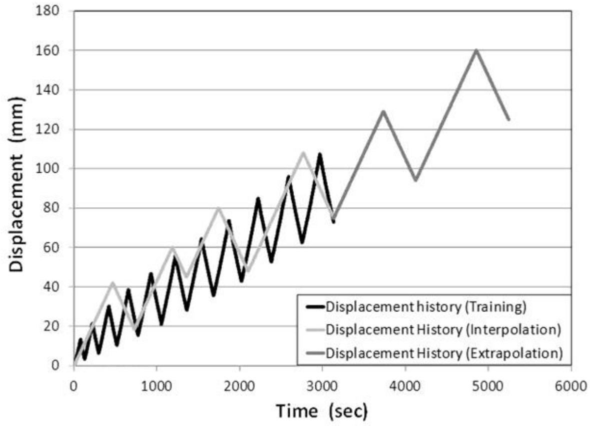


Fig. 13 Displacement history used for ANN training

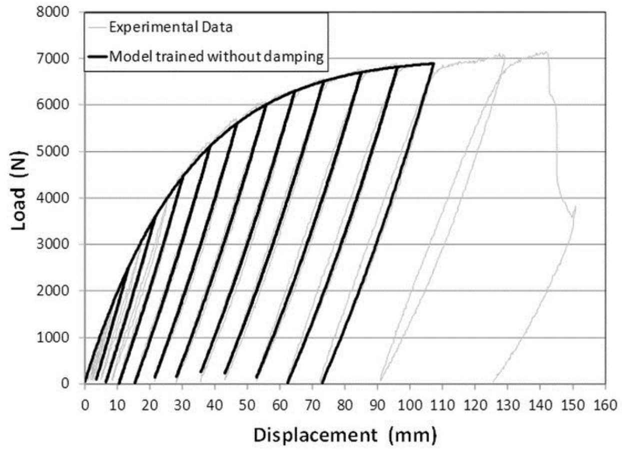


Fig. 14 Model results vs. measured data (without damping)

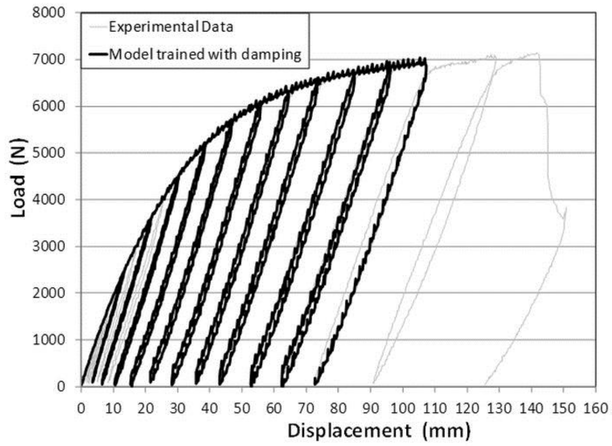


Fig. 15 Model results vs. measured data (with damping)

model with 4 hidden nodes has the lowest MSE for the best average performance. The best individual models for 1, 2, 3 and 4 hidden nodes are shown in Table 1. The best individual model is the one with 2 hidden nodes; it has an MSE value of 4548.85, obtained for 425 epochs.

The results show that the best average performance is observed for the models with 4 hidden nodes. However, these models lose generalisation when the number of epochs increases because of the increase in the degrees of

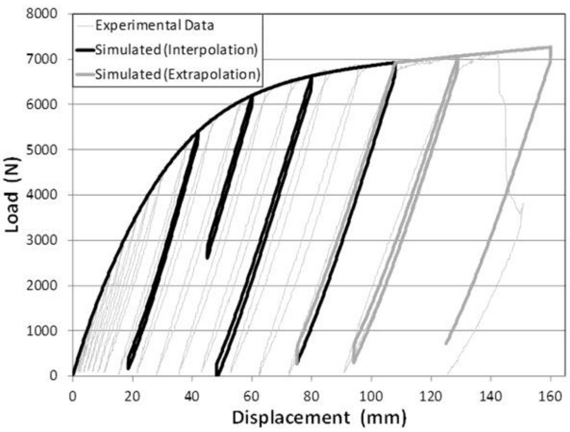


Fig. 16 Interpolation and extrapolation of model with damping

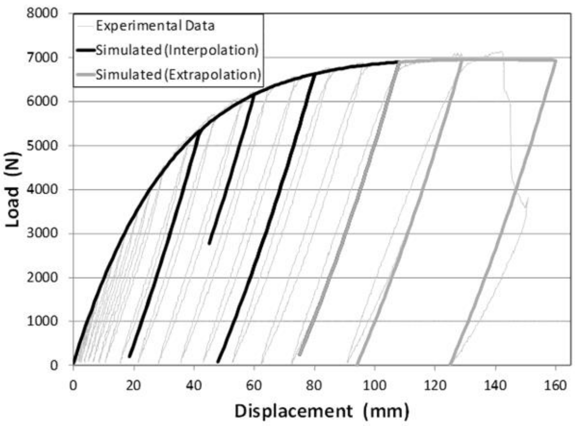


Fig. 17 Interpolation and extrapolation of model without damping

freedom in the model. The models with 2 and 3 hidden nodes show similar average performances and generalisation; however, the models with 2 hidden nodes have better individual performance. A similar behaviour was observed in the models without damping. Finally, the selected models, with and without damping, were the models with 2 hidden nodes. They were observed to have the best performance and training generalisation.

4. Validation of ANN Models

In order to validate and test the two selected models, three tests were conducted for each model. The first test dealt with the training process of the ANN model. Once the model was selected, the criteria explained in the preceding paragraphs were employed to confront with the whole data set. Fig. 13 shows the displacement history input to the model for training. It can be seen that the models, with and without damping, can reproduce the measured data with accuracy (see Fig. 14 and 15). The model with damping was able to learn with more precision than the model without damping.

The second test was aimed to verify the capacity of the ANN model for interpolation. This is a complementary test to verify if the model obtained a good generalisation. The model was subjected to a new pattern of displacements; the pattern was selected such that they were not used previously for training, test, or verification of the ANN model, see Fig. 13. The final test was to check the extrapolation ability of the model. Similar to interpolation, extrapolation is a method to verify the generalisation in the training of the ANN.

Fig. 16 and 17 show the graphical results of interpolation and extrapolation for the model with and without damping, respectively. It can be seen that both the models can deal with interpolation and extrapolation. The model with damping could extrapolate 20% beyond the range used for training with a good precision, while the model without damping could extrapolate the same 20%, but with lesser precision. In the model without damping, the curve becomes approximately horizontal during extrapolation; whereas, the model with damping has a more logical behavior.

These results verify that the Artificial Neural Network can mimic the inelastic behaviour of the force-displacement curve. It can be observed that when the model is subjected to a cycle of loading and unloading, it does not return to its initial deformation. This verifies that the model can replicate the permanent deformations produced by the damage and plastic deformations of the material. It can be deduced that the model has "memory" of the previous loads and deformations to which the element was subjected.

The excellent performance of both models demonstrates the feasibility to use ANN models for structural calculations and design of complex structural elements. However, further research is required regarding the incorporation of other variables, such as the resistance of the mortar, the reinforcement mesh, and the steel profile; these will help to improve the behaviour of the model. These variables will also help to use the model not only for simulation, but also for design. Due to the high performance obtained, it can be argued that a model for more complex structures or hybrid models can be built by this method; such hybrid models can combine numerical schemes and ANNs to improve modelling in terms of non-linearity and save computational time.

5. Conclusions

Two ANN models have been successfully instantiated, tested and validated; they calculate the applied force for a given maximum displacement of a complex structural element, and vice versa. The instantiated models are able to simulate the inelastic behaviour produced in the materials due to plastic deformations in the steel and the cracks in the reinforced mortar. Furthermore, the models can simulate the residual deformation that occurs during the unloading of the element.

The application of clustering algorithms helps to determine the number of hidden layers and epochs required for the best training of the ANN. The best average performance (MSE) is obtained for ANNs with 2 hidden nodes and 200-250 epochs in both the models; these values imply a good generalisation in these models.

The model considering the internal damping of materials has a slightly better performance than the model that does not consider the damping (MSE of 4548.85). It could reproduce the looped branches, implying that the model considers the energy dissipation in materials. Finally, the most important feature was that the models could interpolate and extrapolate; this proves that the ANN models have a remarkable generalisation and it is possible to elaborate complex models. For instance, hybrid models can be created by combining the ANN models with FEM or numerical models to incorporate the modelling of inelastic behaviour.

Acknowledgments

The results presented in this paper were obtained in the course of an investigation sponsored by SISTEMA MODULAR IC and CDCHT-UCLA (004-IC-2014).

References

Akbas, B. (2006), "A neural network model to assess the hysteretic energy demand in steel moment resisting frames", *Struct. Eng. Mech.*, **23**(2), 177-193. https://doi.org/10.12989/sem.2006.23.2.177.

Amani, J. and Moeini, R. (2012), "Prediction of shear strength of reinforced concrete beams using adaptive neuro-fuzzy inference system and artificial neural network", *Scientia Iranica*, **19**(2), 242-248. https://doi.org/10.1016/j.scient.2012.02.009.

ASTM E564-06 (2018), *Standard Practice for Static Load Test for Shear Resistance of Framed Walls for Buildings*, ASTM International, West Conshohocken, PA, USA.

ASTM E72-15 (2015), *Standard Test Methods of Conducting Strength Tests of Panels for Building Construction*, ASTM International, West Conshohocken, PA, USA.

Azqandi, M., Nooredin, N. and Ghoddosian, A. (2018), "Optimization of spring back in U-die bending process of sheet metal using ANN and ICA", *Struct. Eng. Mech.*, **65**(4), 447-452. https://doi.org/10.12989/sem.2018.65.4.447.

Darendeli, M.B. (2001), "Development of a new family of normalized modulus reduction and material damping curves", Ph.D. Dissertation, The University of Texas at Austin, USA. http://hdl.handle.net/2152/10396.

Erdem, H. (2017), "Predicting the moment capacity of RC slabs with insulation materials exposed to fire by ANN", *Struct. Eng. Mech.*, **64**(3), 339-346. https://doi.org/10.12989/sem.2017.64.3.339.

Freitag, S., Cao, B.T., Ninić, J. and Meschke, G. (2018), "Recurrent neural networks and proper orthogonal decomposition with interval data for real-time predictions of mechanised tunnelling processes", *Comput. Struct.*, **207**, 258-273. https://doi.org/10.1016/j.compstruc.2017.03.020.

Guerrero, N., Marante, M.E., Picón, R. and Flórez-López, J. (2007), "Model of local buckling in steel hollow structural elements subjected to biaxial bending", *J. Consruct. Steel Res.*, **63**(6), 779-790. https://doi.org/10.1016/j.jcsr.2006.08.006.

Hadi, M.N.S. (2003), "Neural networks applications in concrete structures", *Comput. Struct.*, **81**(6), 373-381. https://doi.org/10.1016/S0045-7949(02)00451-0.

Haj-Ali, R., Kim, H.K., Koh, S.W., Saxena, A. and Tummala, R. (2008), "Nonlinear constitutive models from nanoindentation tests using artificial neural networks", *J. Plasticity*, **24**(3), 371-396. https://doi.org/10.1016/j.ijplas.2007.02.001.

Hashemi, S.J., Razzaghi, J., Moghadam, A.S. and Lourenço, P.B. (2018), "Cyclic testing of steel frames infilled with concrete sandwich panels", *Archives Civil Mech. Eng.*, **18**(2), 557-572. https://doi.org/10.1016/j.acme.2017.10.007.

Mansour, M.Y., Dicleli, M., Lee, J.Y. and Zhang, J. (2004), "Predicting the shear strength of reinforced concrete beams using artificial neural networks", *Eng. Struct.*, **26**(6), 781-799. https://doi.org/10.1016/j.engstruct.2004.01.011.

Mariani, C., Venini, P. and Nascimbene, R. (2003), "Neural networks in computational damage mechanics", *Comput. Fluid Solid Mech.*, 426-428. https://doi.org/10.1016/B978-008044046-0.50105-6.

De Matteis, G. and Landolfo, R. (1999), "Structural behaviour of sandwich panel shear walls: An experimental analysis", *Mater. Struct.*, **32**(5), 331-341. https://doi.org/10.1007/BF02479624.

Mohamed, M., Hussein, R., Abutunis, A., Huo, Z., Chandrashekhara, K. and Sneed, L. (2016), "Manufacturing and evaluation of polyurethane composite structural insulated panels", *J. Sandwich Struct. Mater.*, **18**(6), 769-789. https://doi.org/10.1177/1099636215626597.

Pendharkar, U., Chaudhary, S. and Nagpal, A.K. (2011), "Prediction of moments in composite frames considering cracking and time effects using neural network models", *Struct. Eng. Mech.*, **39**(2), 267-285. https://doi.org/10.12989/sem.2011.39.2.267.

Perdomo, M. E., Picón, R., Marante, M. E., Hild, F., Roux, S. and Flórez-López, J. (2013), "Experimental analysis and mathematical modeling of fracture in RC elements with any aspect ratio", *Eng. Struct.*, **46**, 407-416. https://doi.org/10.1016/j.engstruct.2012.07.005.

Perera, R., Barchín, M., Arteaga, A. and Diego, A. De. (2010), "Prediction of the ultimate strength of reinforced concrete beams FRP-strengthened in shear using neural networks", *Compos. Part B*, **41**(4), 287-298. https://doi.org/10.1016/j.compositesb.2010.03.003.

Picon-Rodriguez, R., Quintero-Febres, C. and Florez-Lopez, J. (2007), "Modeling of cyclic bond deterioration in RC beam-column connections", *Struct. Eng. Mech.*, **26**(5), 569-589. https://doi.org/10.12989/sem.2007.26.5.569.

Poluraju, P. and Rao, G.A. (2014), "Behaviour of 3D-panels for structural applications under general loading: A state-of-the-art", *IJRET*, **3**(16), 173-181.

Ramnavas, M.P., Patel, K.A., Chaudhary, S. and Nagpal, A.K. (2017), "Explicit expressions for inelastic design quantities in composite frames considering effects of nearby columns and floors", *Struct. Eng. Mech.*, **64**(4), 437-447. https://doi.org/10.12989/sem.2017.64.4.437.

Reuter, U., Sultan, A. and Reischl, D.S. (2018), "A comparative study of machine learning approaches for modeling concrete failure surfaces", *Adv. Eng. Software*, **116**, 67-79. https://doi.org/10.1016/j.advengsoft.2017.11.006.

Rosenblatt, F. (1958), "The perceptron: A probabilistic model for information storage and organization in the brain", *Psychological Rev.*, **65**(6), 386-408. http://dx.doi.org/10.1037/h0042519.

Rotaru, F., Rosculet, R., Chirica, I. and Beznea, E.F. (2016), "Experimental Analysis of the Sandwich Composites Loaded to Mechanical Impact", *Adv. Compos. Mater. Eng.*, 198-203. http://hdl.handle.net/123456789/2147.

Taffese, W.Z. and Sistonen, E. (2017), "Machine learning for durability and service-life assessment of reinforced concrete structures: Recent advances and future directions", *Automat. Construct.*, **77**, 1-14. https://doi.org/10.1016/j.autcon.2017.01.016.

Yavuz, G. (2016), "Shear strength estimation of RC deep beams using the ANN and strut-and-tie approaches", *Struct. Eng. Mech.*, **57**(4), 657-680. https://doi.org/10.12989/sem.2016.57.4.657.

Yoon, K., Kim, D.N. and Lee, P.S. (2017), "Nonlinear torsional analysis of 3D composite beams using the extended St. Venant solution", *Struct*. *Eng*. *Mech*., **62**(1), 33-42. https://doi.org/10.12989/sem.2017.62.1.033.

Zopf, C. and Kaliske, M. (2017), "Numerical characterisation of uncured elastomers by a neural network based approach", *Comput. Struct*., **182**, 504-525. https://doi.org/10.1016/j.compstruc.2016.12.012.

PL