ARTIFICIAL NEURAL NETWORK MODEL FOR ANALYSIS OF IN-PLANE SHEAR STRENGTH OF PARTIALLY GROUTED MASONRY SHEAR WALLS

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ABSTRACT

The behaviour of partially grouted masonry (PG) shear walls is complex, due to the inherent anisotropic properties of masonry materials and nonlinear interactions between the mortar, grouted cells, ungrouted cells, and reinforcing steel. Since PG shear walls are often part of lateral force resisting systems in masonry structures, it is crucial that its shear behaviour is well understood, and its shear strength is accurately predicted. This paper presents the development of an ANN model for analyzing the shear strength of PG walls. Artificial neural networks (ANN) have the unique ability to address highly complex problems and the potential to predict accurate results without a defined algorithmic solution. By providing an ANN with a dataset of multiple inputs and a corresponding output, it can be trained to determine the weighted effect of each input parameter and describe nonlinear relationships that may exist among the variables. ANNs have also shown success despite noisy, inconsistent, or imprecise input data. An experimental database of PG shear walls is used as input for the ANN analysis model. Finite element modelling (FEM) is used to address gaps in input values which exist in the database. The effect of previously unaccounted parameters in code-based approaches is discussed, as well as the influence of different types of ANN analysis options and input size on the model predictions. The ANN model results are compared against leading design codes in North America (CSA S304.14) to predict the in-plane shear strength of PG shear walls.

KEYWORDS: *shear strength, partially grouted shear walls, artificial neural network*

INTRODUCTION

Partially grouted (PG) walls are commonly used in many seismic regions as part of lateral force resisting systems in masonry structures. While fully grouted (FG) walls contain grout in all cells, PG walls contain columns of grout exclusively in cells where vertical reinforcement bars are placed. As a result, they offer an economic advantage over FG walls due to reduced material and

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labour costs [1, 2]. However, the behaviour of PG walls under shear loading is not well understood. The current design expressions available for predicting the in-plane shear strength of PG walls have been found to be inaccurate, and in some cases, unconservative [3].

The shear strength and behaviour of PG walls is highly dependent on variables such as the wall geometry, level of axial load (increasing interlocking between masonry units in diagonal cracks), ratio of net/gross area, and distribution of horizontal (increasing ductility and energy dissipation) and vertical reinforcement (resisting shear loading at crack openings) [2, 4]. Under in-plane loading, masonry walls will typically fail in flexure, in shear, or a combination of both. Flexural failure is characterized by bed joint cracking and toe crushing. Shear failure is characterized by diagonal tension cracks, rapidly decreasing the stiffness of the wall and often resulting in brittle failure [3, 5, 6]. This paper focuses on PG walls which are governed by in-plane shear failure.

Under lateral loading, a PG wall's grouted/reinforced cells tend to deform through frame action, while the cracked hollow portions act as an infill with reduced shear stiffness [2]. Unlike FG walls, PG walls do not behave as monolithic walls due to the nonlinear interactions that exist between mortar, grouted cells, ungrouted cells, and reinforcing steel. Instead, the behaviour of PG walls is similar to infilled walls subject to lateral loads [7].

Artificial neural networks (ANNs) are a powerful machine learning tool capable of processing large samples of data. It has great potential in recognizing nonlinear relationships to address complex problems and has demonstrated success in many engineering research applications. Although finite element (FE) models are more robust than ANNs and could be used to investigate the behaviour of PG walls, is often resource heavy and requires significantly more time to prepare models. On the other hand, ANNs are a more efficient alternative to perform analysis through pattern recognition and function approximation.

This paper explores the use of ANNs to predict the in-plane shear strength of PG walls and FE modelling to increase the input training database for ANN analysis. The effects of varying neural network architecture parameters are investigated to produce an improved prediction output by a trained neural network. In addition, the experimental data has been expanded with more results obtained from the literature.

## ACCURACY OF EXISTING SHEAR EXPRESSIONS

Many design codes have adopted a semi-empirical approach to predict shear strength of PG walls. Due to their inherent complex behaviour and the lack of test data, equations to predict the shear strength of PG walls often rely on arbitrary reduction factors to achieve safety levels comparable to those found in the better understood FG walls. However, recent studies have shown that available design expressions currently used in Canada (and other countries) to predict the in-plane shear strength of PG walls are inconsistent and may be unconservative, overestimating the lateral load capacities of PG walls by as much as three to four times [2, 3, 8–11]. The inadequacy of

current design expressions to consistently predict the in-plane shear strength of PG walls has led to the use of alternative analysis techniques, such as ANN analysis models.

NEURAL NETWORKS: GENERAL DESCRIPTION

ANNs are a powerful tool to process large databases of information and recognize underlying patterns which may exist in the data, and especially any nonlinear relationships among variables. Through a process of "learning," an ANN mimics its biological counterpart by adapting synaptic weights with each new piece of information it receives [12]. A well-trained ANN with accurate predictions does not use a physical model of the problem (such as the strut-and-tie formulation), but relies on an optimal arrangement of neurons and its connections [12–14].

Feedforward backpropagation neural networks are a type of multilayer perceptron network that is commonly used for engineering applications. Such neural networks are favourable due to their use of non-linear transformations for function approximations [15]. A simplified schematic of a feedforward backpropagation neural network is illustrated by Figure 1.
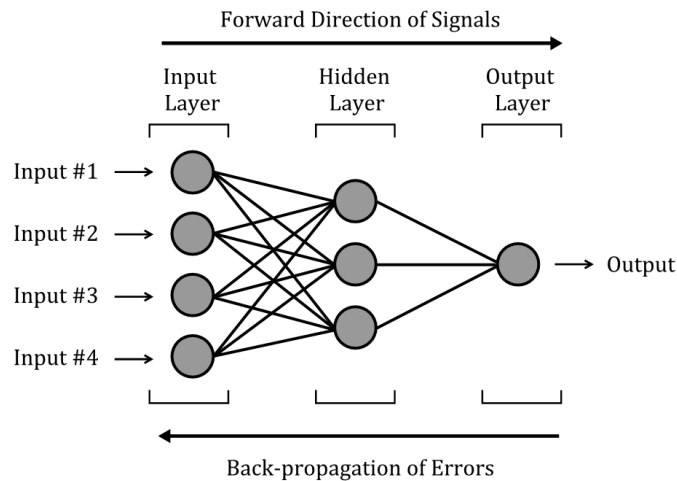

Figure 1: Feedforward backpropagation neural network architecture (Adapted from Plevris and Asteris) [16]

A "neural network" can be described as numerous neurons highly interconnected to one another. The feedforward backpropagation neural network as previously described consists of three layers of neurons: an input layer, a hidden layer, and an output layer. The number of neurons in the input layer is determined by the number of input parameters that are fed into the network. Hidden neurons process the input values by linearly combining them based on a matrix of weights plus a bias. Then, a transfer function is applied to the linear combination computed. The output neuron processes the values input from the hidden layer in a similar manner, computing a single predicted output by the ANN [12, 15, 17–20]. A single neuron process is illustrated in Figure 2.

The matrix of weights and biases of a neural network are initially randomized. With each data point fed into the network, the expected output (experimental value) is compared with the

network's predicted output, and its error is propagated backwards through the network to adjust and fine-tune the weights and biases. In this way, the ANN's capability to predict the output is incrementally improved. The ability of an ANN to be successfully trained is highly dependent on the number of known sets of inputs and outputs that is processed by the network. A trained ANN is only effective in making predictions within the range of input variables that was used for training [12, 15, 17, 21].
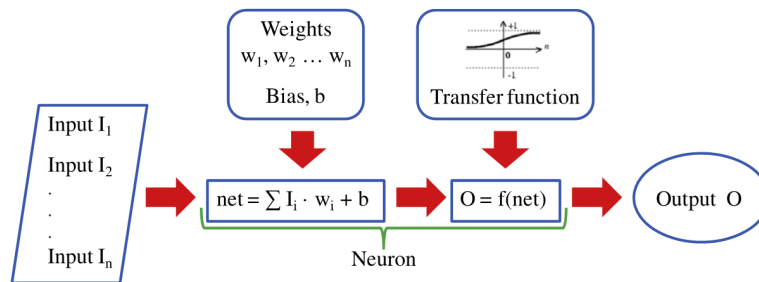
Figure 2: Single neuron work [17]

Hidden Layer & Neurons

Despite several guidelines developed to optimize the number of hidden neurons in the hidden layer of an ANN, no guideline has been universally agreed upon [22–24]. The number of hidden neurons, however, significantly impacts the ANN's performance. While too few hidden neurons will hinder its capacity for pattern recognition, too many hidden neurons in the ANN leads to an overpowered neural network which tends to overfit the data and renders it incapable of generalizing predictions [12, 25].

This brief description of an ANN offers only elementary components of neural networks. Readers interested in more detailed explanations of ANNs may refer to Haykin [12], Tu [14], Basheer and Hajmeer [26], and Svozil et al. [27].

PREVIOUS RESEARCH CONDUCTED WITH NEURAL NETWORKS

ANNs have been successfully developed to address highly complex problems for a wide spectrum of structural engineering applications. Goh [28] demonstrated the ability for a trained ANN to predict the deflection of a cantilevered beam. Plevris and Asteris [16] were successful in training an ANN to predict masonry failure surfaces under biaxial compressive stress.

In a study conducted by Aguilar et al. [20], ANNs were developed to predict the in-plane shear strength of both FG and PG walls. The ANNs were trained with an experimental database of 96 fully grouted concrete block walls, 95 partially grouted concrete block walls, 37 fully grouted ceramic block walls and 57 partially grouted ceramic brick walls. The determination coefficient (R^2) of the correlation, the mean-squared-error, and the mean and standard deviation of experimental to predicted values (V_{exp}/V_n) for each trained ANN are summarized in Table 1. It is seen that the trained ANN for partially grouted concrete block walls did not perform as well as the ANN for the other three types of walls. Ideally, the value of determination coefficient R^2 for a

trained ANN is 0.90 or greater. An insufficient database size, as well as gaps of information in the range of data used for training are possible reasons for the inability of the ANN to predict the in-plane shear strength of CB PG walls [20].

Table 1: ANN results from study performed by Aguilar et al. [20]

Wall Type	R^2	Mean-Squared-Error	Mean V_{exp}/V_n	Std V_{exp}/V_n
Fully Grouted Concrete Block	0.931	0.039	0.997	0.151
Partially Grouted Concrete Block	0.750	0.007	1.013	0.155
Fully Grouted Ceramic Block	0.952	0.024	0.985	0.089
Partially Grouted Ceramic Brick	0.848	0.007	1.005	0.152

EXPERIMENTAL DATABASE

The database for training the ANN is a compiled set of specimens from various experimental studies performed on the in-plane shear strength of PG walls. The database used in this study is summarized in Table 2.

Table 2: PG walls experimental database for ANN training

Source	Specimens	Source	Specimens
Voon [29]	2	Baenziger & Porter [30]	8
Minaie et al. [2]	4	Scrivener [31]	12
Matsumura [32]	29	Ghanem et al. [33]	2
Chen et al. [34]	4	Schultz [35]	6
Yancey and Scribner [36]	10	Elmapruk [37]	6
Schultz et al. [38]	6	Ramirez et al. [39]	10
Oan [40]	66	Maleki et al. [41]	5
Nolph et al. [10]	5	**Total**	**175**

Since the compiled experimental data was recorded by various authors, not all experimental programs were recorded with the same level of detail, resulting in gaps of information such as testing apparatus details and other parameters. Engineering judgement was exercised to complete the database such that there is a data entry for each parameter for each specimen. In addition, a certain level of judgement was used to ensure that only the studies presenting a clear and sound methodology of reporting data were included for ANN analysis, eliminating any unrealistic or unreliable experimental studies from the experimental database.

PROCESSING WITH NEURAL NETWORKS

Network Architecture

The network architecture used in this study is a 9-n-1 feedforward backpropagation neural network multilayer perceptron network: 9 neurons in the input layer, (*n*) neurons in the hidden layer, and 1 neuron in the output layer. A sigmoid transfer function was used for the hidden layer. The

Levenberg-Marquardt algorithm is used to adjust the weights and biases during backpropagation. 80% of the data was used to train, while 10% of the data was used to validate, and 10% used to test the neural network. MATLAB's Neural Network Toolbox was used to generate and train the neural network.

Iterative Approach to Artificial Neural Networks

Each time a neural network is initiated, certain network parameters are randomized: the set in which each data point is assigned (training, validation, or testing), the order in which each data point is fed into the neural network, and the matrix of layer weights and biases. Therefore, each initialization of a neural network results in a uniquely trained ANN [42].

Table 3: Input and output parameters

Parameter		Range	Parameter	Range	
Input 1	H_{eff} (mm)	900-5283	Input 6	f_{grout} (MPa)	10.68-47.54
Input 2	t (mm)	48-200	Input 7	$\rho_v f_{yv}$ (MPa)	0-9.54
Input 3	d_v (mm)	751-3416	Input 8	$\rho_h f_{yh}$ (MPa)	0-1.29
Input 4	A_{net}/A_{gross}	0.35-0.78	Input 9	σ_{gross} (MPa)	0-2.78
Input 5	$f'_{m(g)}$ (MPa)	6.4-24.3	**Output**	$v_{max,gross}$ (MPa)	0.246-2.21

If an infinitely large database is available for training an ANN, then, in theory, it will eventually develop into a successfully trained neural network by adjusting the layer weight matrix with each new data point. However, the availability of large amounts of data is not typical in structural engineering applications. Since a relatively "small" database consisting of only 175 PG walls was compiled in this study, the randomized initial layer weight matrix becomes a critical factor in the ANN's ability to converge and train successfully. Therefore, it is necessary to reinitialize the ANN numerous times to achieve an optimum ANN performance. The trained ANN with the best peformance is then used for predicting the in-plane shear strength of PG walls.
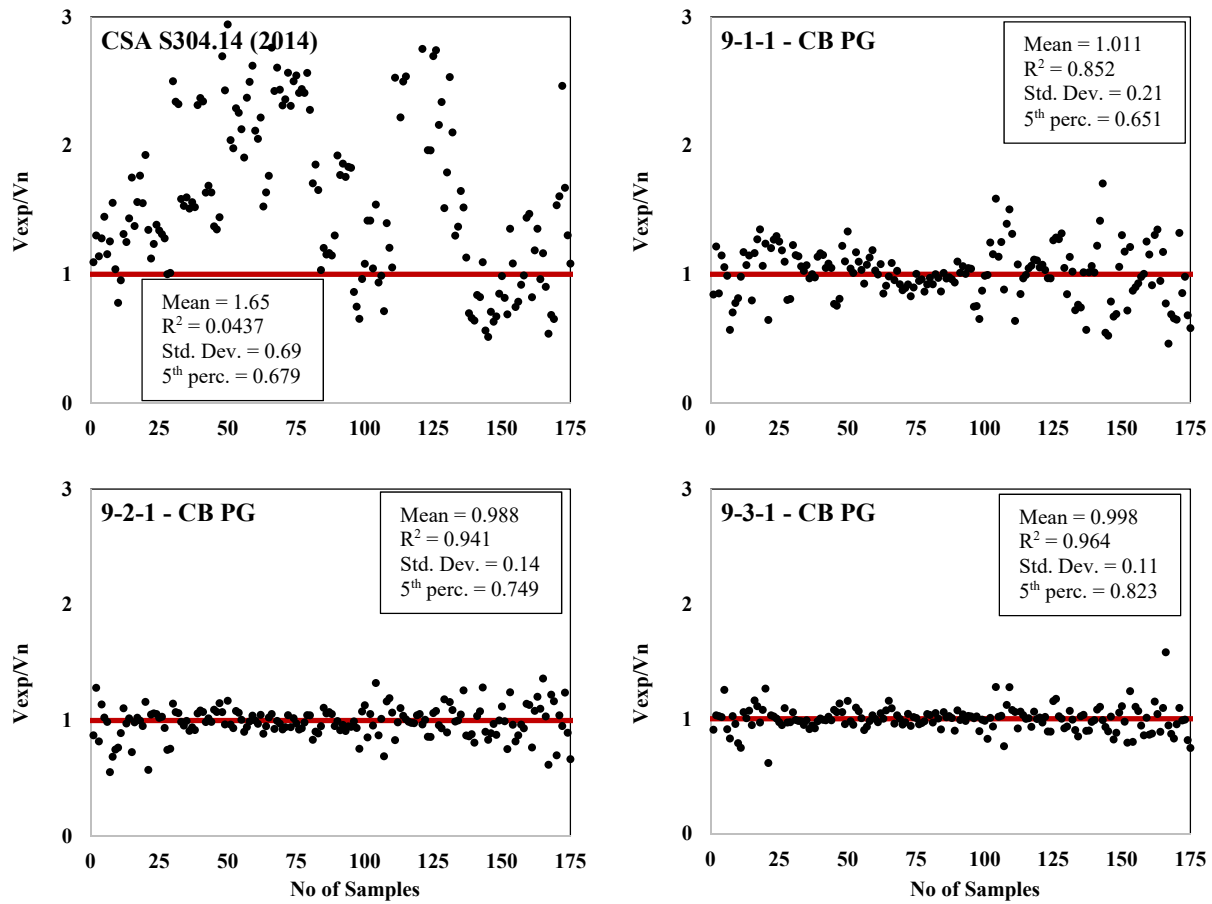
RESULTS

The results from the trained ANNs from this study are compared with the ANNs from Aguilar et al. [20] in Table 4. The iterative approach mentioned in the previous section is used to obtain the ANN with the best performance. It can be observed that the increase of input neurons from 5 to 9 has improved the performance of the ANN.

Table 4: ANN performance from Aguilar et al. [20] and current study

Source	ANN Architecture	MSE	R^2	Mean	Std
Aguilar et al. [20]	5-1-1	0.014	0.504	1.008	0.225
	5-2-1	0.010	0.646	1.012	0.185
	5-3-1	0.007	0.750	1.013	0.155
Current Study	9-1-1	0.020	0.853	1.010	0.208
	9-2-1	0.008	0.941	0.988	0.135
	9-3-1	0.005	0.964	0.998	0.108

As expected, the increase in hidden neurons increases the determination coefficient (R^2) of the correlation. The standard deviation and mean-squared-error also decreases.

The performance of existing design expressions provides a useful benchmark against trained ANNs, as demonstrated in studies such as Aguilar [43] or Naik and Kute [44]. Therefore, the performance of the design expression from CSA Standard S304.14 [45] is shown in Figure 3 on the following page as a benchmark to illustrate the performance the 9-n-1 ANNs from this study.
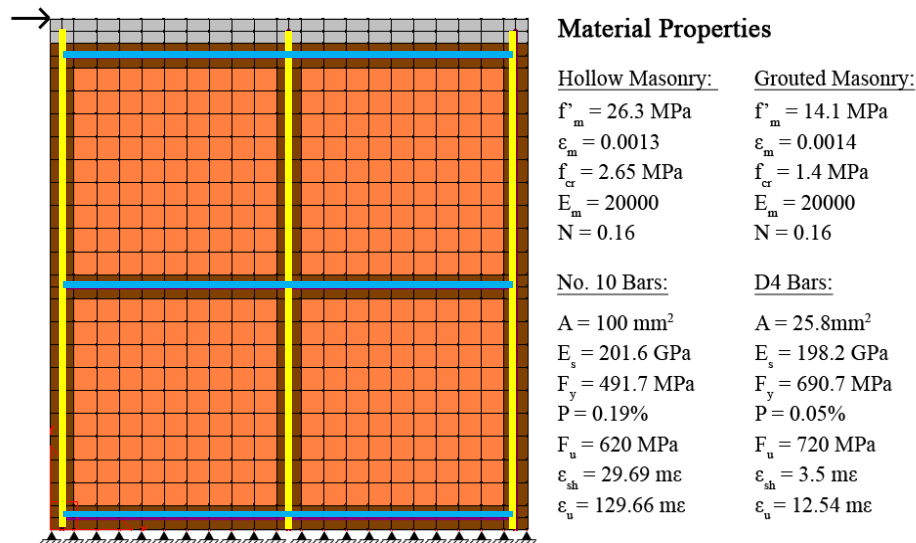

Figure 3: Comparison between existing CSA S304.14 design expression and trained ANNs

FINITE ELEMENT MODELLING OF PG SHEAR WALLS

Although these preliminary results indicate that ANNs are a viable option to predict the in-plane shear strength of masonry walls, there are gaps in the design variables used as input in the database. To address these gaps, a FE analysis validated with experimental results can be used to generate theoretical specimens and enlarge the database. FE program VecTor2 was chosen to conduct the analysis discussed in this section. Studies show that masonry can be modelled as a continuum with average properties where joint failures are smeared across the single element for sufficiently large masonry structures [46]. The tensile behaviour of masonry is modelled as an isotropic linear elastic material and modelled as a continuum that may slip along the head and bed joints even when the material is uncracked [46].

A PG wall specimen tested by Maleki [47] was used to verify the performance of the FE analysis model. The wall is 1800mm x 1800mm x 90mm, (Figure 4). Wall reinforcement consists of three horizontal D4 steel bars and three vertical No. 10 bars. The wall was subject to constant gravity load of 120kN and a cyclic lateral displacement was applied up to 7.2mm.

Material Properties

Hollow Masonry:
- $f'_m = 26.3$ MPa
- $\varepsilon_m = 0.0013$
- $f_{cr} = 2.65$ MPa
- $E_m = 20000$
- $N = 0.16$

Grouted Masonry:
- $f'_m = 14.1$ MPa
- $\varepsilon_m = 0.0014$
- $f_{cr} = 1.4$ MPa
- $E_m = 20000$
- $N = 0.16$

No. 10 Bars:
- $A = 100$ mm^2
- $E_s = 201.6$ GPa
- $F_y = 491.7$ MPa
- $P = 0.19\%$
- $F_u = 620$ MPa
- $\varepsilon_{sh} = 29.69$ mε
- $\varepsilon_u = 129.66$ mε

D4 Bars:
- $A = 25.8$mm^2
- $E_s = 198.2$ GPa
- $F_y = 690.7$ MPa
- $P = 0.05\%$
- $F_u = 720$ MPa
- $\varepsilon_{sh} = 3.5$ mε
- $\varepsilon_u = 12.54$ mε

Figure 4: VecTor2 model of partially grouted shear wall

The material properties of the wall are shown in Figure 4. The test results of the physical wall by Maleki [47] and the VecTor2 model are illustrated in Figure 5 and Table 5 on the following page. The calculated peak load is reasonable close (by 13%) to the measured results. The displacement prediction showed reasonable correspondence as well with the available experimental data.
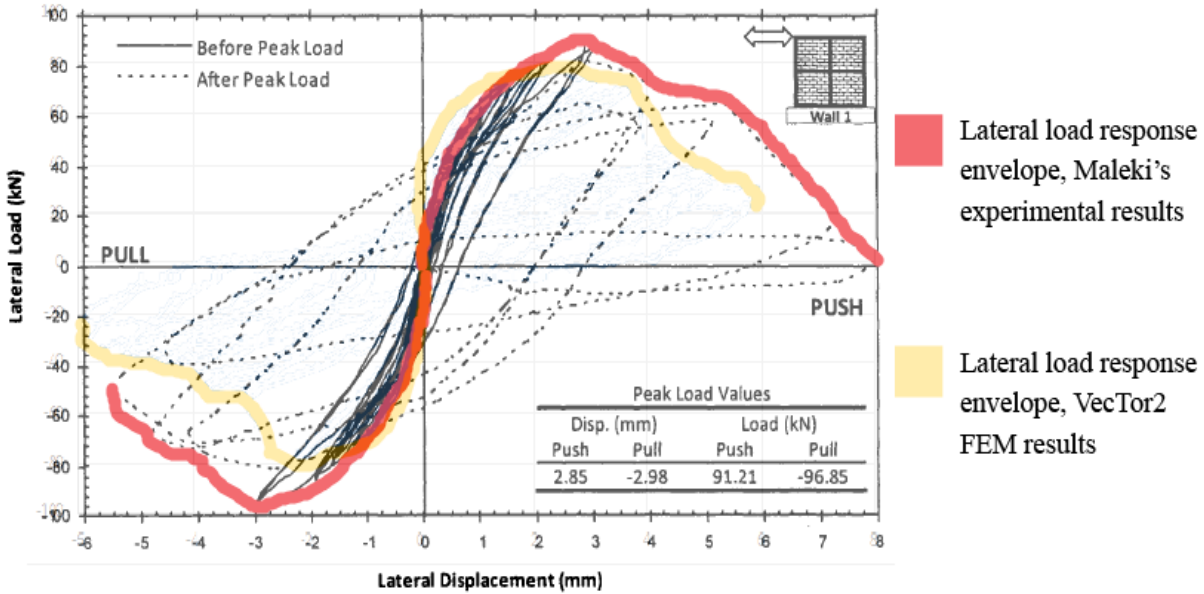
Figure 5: Superimposed graph of real and model walls

The results suggest that a FE analysis model is a practical option for generating additional input data for training the ANN. The relative error between measured and calculated peak strength is within 15-20%. This range of error is typical for FE models with materials similar to masonry, such as reinforced concrete and prestressed concrete structures. Given that the FE model used in this study is a macroscale model, it would be expected that microscale models would be more accurate. Further work on the model is ongoing to refine and validate the FE model, followed by utilizing the model results to increase the ANN training database size.

Table 5: Comparison of experimental vs VecTor 2 results

	Experimental Result		**VecTor2 Result**	
Force Direction	Push	Pull	Push	Pull
Load (KN)	91.2	96.9	78.4	80.4
Displacement (mm)	2.88	2.88	2.45	2.93

FURTHER RESEARCH

Recent research studies evaluating the adequacy of available PG in-plane shear strength expressions have proposed areas for improvement. Despite the presence of wall ratio in several design expressions, Minaie et al. [2] suggests that the area of the wall has a size effect on in-plane shear strength. The vertical and horizontal spacing of grout and reinforcement were also found to be a major factor influencing shear strength. Janaraj and Dhanasekar [11] found that the horizontal reinforcing steel rarely reaches its yield capacity when the wall undergoes shear failure. Thus, Janaraj and Dhanasekar have suggested that the inclusion of horizontal and vertical reinforcing steel in predicting the in-plane shear strength of PG walls is unjustified. Future research is required

to address the unaccounted parameters identified by Minaie et al. and Janaraj and Dhanasekar and investigate their influence on the in-plane shear strength of PG walls.

CONCLUSIONS

The preliminary results presented in this paper demonstrate the potential for utilizing ANNs to address the limitations of current design expressions to predict the in-plane shear strength of PG shear walls. Further research involves expanding the database size to address existing gaps in the database, increasing the ANN's ability to learn and identify patterns, and distilling design equations from the ANN. This can be achieved by a combination of three strategies: *(i)* additional experimental testing, (ii) further literature review to include more shear-critical PG wall specimens, and *(iii)* use of FE analysis models to generate input data that bridges the gaps identified in the design variables.

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