Introduce Applicability of Multi-Layer Perceptron to Predict the Behaviour of Semi-Interlocking Masonry Panel

O. Zarrin, M. Ramezanshirazi

***Abstract*—**The Semi Interlocking Masonry (SIM) system has been developed in Masonry Research Group at the University of Newcastle, Australia. The main purpose of this system is to enhance the seismic resistance of framed structures with masonry panels. In this system, SIM panels dissipate energy through the sliding friction between rows of SIM units during earthquake excitation. This paper aimed to find the applicability of artificial neural network (ANN) to predict the displacement behaviour of the SIM panel under out-of-plane loading. The general concept of ANN needs to be trained by related force-displacement data of SIM panel. The overall data to train and test the network are 70 increments of force-displacement from three tests, which comprise of none input nodes. The input data contain height and length of panels, height, length and width of the brick and friction and geometry angle of brick along the compressive strength of the brick with the lateral load applied to the panel. The aim of designed network is prediction displacement of the SIM panel by Multi-Layer Perceptron (MLP). The mean square error (MSE) of network was 0.00042 and the coefficient of determination (R2) values showed the 0.91. The result revealed that the ANN has significant agreement to predict the SIM panel behaviour.

***Keywords*—**Semi interlocking masonry, artificial neural network, ANN, multi-layer perceptron, MLP, displacement, prediction.

I. Introduction

ONE of the most important behaviours of the mortarless wall is out-of-plane performance that received little attention. Developing of wall-diaphragm connections has always been assumed a practical alternative for out-of-plane strengthening. Flexible performance can be the key factor of masonry panel subjected to the large displacement. The other aspect of this issue is related to the existing buildings and historical buildings, which need to retrofit the connection of wall-diaphragm. In this case, it should be ensured that all of the elements behave in elastic limits, especially in out-of-plane direction and strongly avoid the non-linear behaviour. According to Derakhshan's results [1], the initial cracks in the mortarless panels do not have serious dangers and cannot threat the human's life. Researchers have revealed that this kind of panels can tolerant the post-cracking stress and absorb energy as rocking system without collapsing [1]. Doherty et al. and Griffith et al. had new investigation on out-of-plane by considering the effective secant stiffness. This method has used the average displacement, which approximate easily the linear wall behaviour from nonlinearity behaviour [2], [3]. Simsir had experimental study on single-story house by flexible roof. During the test, Simsir has used concrete blocks and reinforced the out-of-plane with different flexibility of roof to examine the out-of-plane behaviour [4]. The results revealed that the out-of-plane response was affected by the frequency of the flexible diaphragm, "and in some cases, the out-of-plane vibration amplitude was amplified by as much as five times" [4].

During the last decades, engineers have been working on a solution to decrease the earthquake damage and invented several different devices, which can convert and dissipate the earthquake excitation energy to different type of energy such as thermal. Most of these devices were modelled to add on buildings such as damper, which apply on braces or base isolation that place between structures and foundation. All of the mentioned devices have same problem; need skillful worker, are expensive and in most cases, cannot be added to an exciting building. By changing some parameters of masonry construction, the brittle behaviour of masonry panels can be converted to flexible with high dissipating energy capability. Traditional masonry wall has some limitation to use in the seismic region due to its inherent negative characteristics in tension. In fact, high rigidity of the masonry wall leads to brittle behaviour and during earthquake excitation this phenomena absorb more energy and initiate cracks [5]. The other negative point of masonry wall is high mass feature with low shear and tensile strength [6]. To overcome this effect, masonry panel has been reinforced by different materials and methods [5]. Frame structure becomes a popular method of construction, which has been used by reinforced concrete or steel frame with masonry wall as infill panel [7]. Nevertheless, the negative point of this structure appears in the seismic region due to brittle behaviour of infill panel and high absorbing energy characteristic [8]-[11]. To improve the masonry inherent weakness in seismic region, a new masonry system without interlayer mortar is invented. Based on this novelty, the frame and mortarless panel work together and this system would be able to dissipate energy (more than the traditional masonry wall) because of the relative in-plane sliding and high flexibility [5].

Accordingly, a masonry system is developed in the Masonry Research Group at the University of Newcastle, and named as SIM panel [3]. The main characteristics of these bricks are being mortarless and specific geometry, which led

O. Zarrin is with Centre for Infrastructure Performance and Reliability, The University of Newcastle Newcastle, Australia (corresponding author, phone: +612450627180; e-mail: orod.zarrin@ uon.edu.au).

M Ramezanshirazi was with Sapienza University of Rome, Italy, (e-mail: mohsen.ramezanshirazi@uniroma1.it.).

to a flexible panel. The interlocking of these bricks can speed up the construction time without skilled worker [12]. In the recent years, researchers tried to find out different aspects of interlocking bricks and building semi-interlocking bricks, which can dissipate forces just in one direction (in plane). Semi-interlocking bricks move freely in-plane direction and prevent the out-of-plane movements [13], [14]. Significant behaviour of the mortarless panel is the out-of-plane performance that has received less attention. Numerical modelling of masonry panel is a common method to predict the panel behaviour and can be verified by an experimental test. Totally, the laboratory test is always time consuming and expensive. The researchers in artificial intelligence can predict different aspects of a complicate project by gathering the result and different characteristics of tests. Recently, many researchers have found different algorithms of prediction based on neural network process [15]-[23]. In fact, the process of prediction is taken from the neuron in the brain with several simple calculations arranged in the network layers [19]. The first step of neural network developing is training network by input data, which are the main factors of test behaviour. These factors contain the relevant information of material and the result of experimental test, which present the sufficient characteristic of sample. Therefore, the ability of trained network to reproduce the results of input data is based on generalization capability [17].

In this paper, we tried to use ANN to predict the displacement behaviour of the SIM panel in the out-of-plane loading. The overall data to train and test the network are 70 specimens of force-displacement containing none of the principal input nodes. The ANN modelled by MATLAB software and by MLP network predicted the displacement of the SIM panel. The MSE of network was 0.00042 and the coefficient of determination (R2) values showed the 0.91. The result revealed that the ANN has significant accuracy to predict the SIM panel behaviour.

II. Artificial Neural Networks

Over the last two decades, with rapid urbanization, combined with fast improvement in standards of living, construction demand has increased rapidly. At the same time with development of construction, the genius of mathematical model speeded up the process of development. ANNs are intelligent and complex models, which are considered for many number of practical engineering projects. The structure of biological neuron has developed a nonlinear system as shown in Fig. 1.

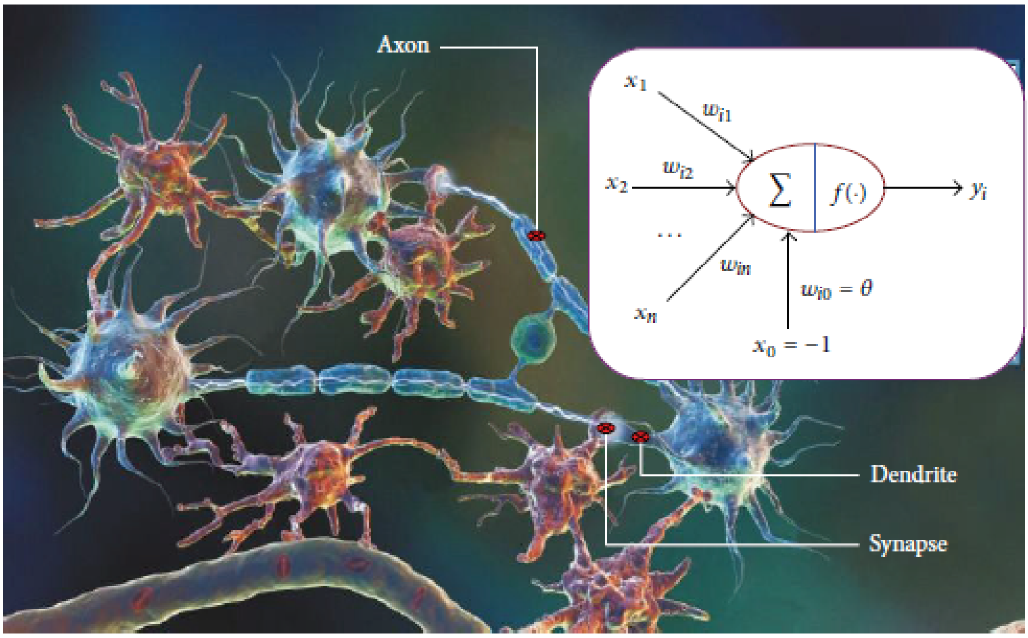

Fig. 1 The neuron system [17]

ANN depends on parameters such as, input data, output data, networks neuron, topologies of networks, and connection weights and threshold limit (bias factor b) [28]. The position of each factor is different and related to duty of parameter. Therefore, ANN consists of three main layers, input, output and hidden layers. According to the problem scale and topology of designed network, every layer needs to process and approximate desired data by fixed neuron.

A. Topology

The ANN transfers the latent information in associated with input data to the network by processing the input. [24], [25]. One of the important features of ANN appears in the process of error or incomplete part, generalization and learning ability. Nowadays, artificial intelligence neurocomputing support all the process of physical hardware or software, which play important role to solve the massive problems. Back Propagation algorithm is one of the simplest ways for training input data in networks. Total behaviour of network consists of five senses:

- scrutiny of database
- design structure
- learning process
- training of the networks
- Test and generalization of network

The error acquired during the training can be expressed as MSE and calculated by (1) [26]:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\widehat{Y_i} - Y_i)^2 \quad (1)$$

Furthermore, coefficient of determination (R2) is calculated by

$$R^2 = 1 - \left(\frac{\sum_j (Y_j - \hat{Y}_j)^2}{\sum_j (Y_j - \bar{Y}_j)^2}\right) \quad (2)$$

where, Y is the target value of network, $\bar{Y}$ is the data average and $\hat{Y}$ is the output value.

B. MLP Applications in General

The application areas of multiple layered neural network include a wide variety of fields, involving estimation problems, prediction problems as well as pattern recognition/ classification. Prediction models are used to find an underlying trend depending on the input features, which varies over time and can be useful if the network is designed and trained perfectly. The estimation problems deal with investigating the linear correlations as well as non-linear relationship between the input variables to approximate the output function.

C. Training a MLP (the Back-Propagation Algorithm)

During the ANN training process, the weights are considered as the sole variables affecting the estimation errors. For simplicity's sake, hereafter we try to limit the structure of the neural network with only two weights. The error in estimation is simply summation of all the squared differences between the estimated outputs versus the real values.. The error plot in each trial of training phase is shown in Fig. 2. The plot in 3D is often called the error surface, which should be as small as possible. The minimum point of the error surface corresponds to the weights in the network that minimizes the estimation error.

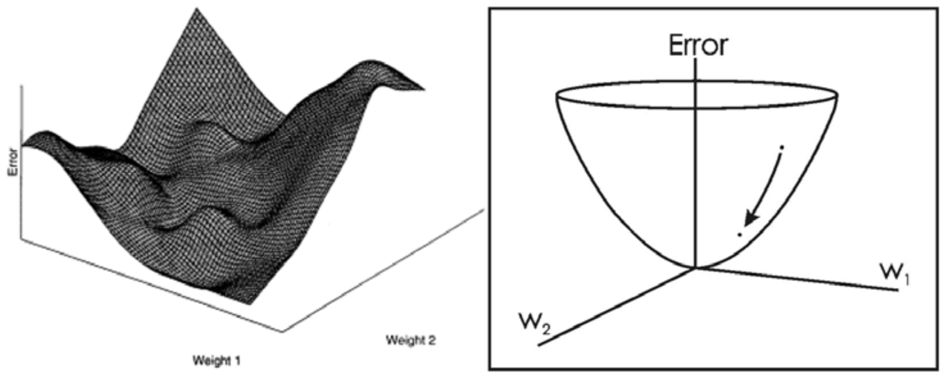

Fig. 2 An error surface for a simple MLP containing only two weights

Gradient descent is a common method to minimize the error index in MLP network. The transferring information process between layers in reverse direction, i.e., from the output layer to the first layer of neurons, is backpropagation. During the backpropagation, the weights are adjusted according to the derivatives of the activation function and the error index to find the set of weights minimizing the estimation error. The backpropagation is among the most popular methods of training a neural network [27]. The backpropagation algorithm works quite well with multiple layered neural network models. The backpropagation is used to minimize the set of weights in neural networks and it does not refer to any new additional network in artificial intelligence. During the process, a set of randomly generated weights are used initially for the feed-forward process. Once the weights are used to estimate the output, then the difference between the approximated output and their real value is taken as the error of the network. From this stage on, the backpropagation starts by computing the derivatives and using the gradient descent method to find the global minimum of the network. The learning parameter is set adequately to a small value and the weights will eventually converge to a minimum, and since the error index function is a convex function, it definitely has a global minimum. The summery of backpropagation is listed below:

- assume a random set of weights;
- put the input variables' values into the neurons of the first layer;
- take the feed-forward process to estimate the outputs;
- compute the error index;
- use the backpropagation process to step back in the network;
- justify the weights to that minimize the error index; and
- repeat steps 2-7 until the error index falls below a user-defined threshold.

The algorithm presented above is often known as the "on-line" or "batch" algorithm of training since the weights will not be updated in the network unless all the weights are adjusted which are fully discussed. In some cases, although thousands or even millions of iterations cannot minimize the error index of an ANN, the network might have reached a satisfactory estimation way before than such high number of iterations. This happens when the backpropagation is trapped into a local minimum and thus there is the need for a change in the learning parameter of the algorithm. Fig. 2 shows the case where the error function has a local minimum. The greater the learning parameter, the greater speed in convergence can be obtained at the cost of higher chance being trapped in a local minimum. Additional parameter is the momentum term, which rescues the gradient descent algorithm from local minimum. Fig. 2 shows an error surface with more than one minimum. By adding a slight change into the weights of the network, it is possible to escape from the local minimum.

III. Datasets

Data are assembled from the experimental project in Masonry Research Group at the University of Newcastle, Australia. The Masonry Research Group focuses on mortarless panel with topological bricks (Fig. 3). Due to the special shape of bricks, which are locked inside the upper bricks, the entire panel resists without mortar. The required data to train the neural network comprise nine input nodes as height and length of panels, height, thickness, and length of brick, geometry angle, friction angle, and compressive strength of brick and applied force. The input data range has seven parameters, and total sample for training the network is 70 samples.

TABLE I
INPUT PARAMETERS

Input parameters	Minimum	Maximum
Height of Brick (mm)	73	76
Thickness of Brick (mm)	110	110
Length of Brick	220	220
Geometry Angle of Brick	8	12
Friction Angle of Brick	37.95	40
Compressive Strength (MPa)	33.35	38.01
Force (KPa)	0	40.1
Length of Panel (mm)	1980	2400
Height of Panel (mm)	2025	2400

Fig. 2 Topological brick

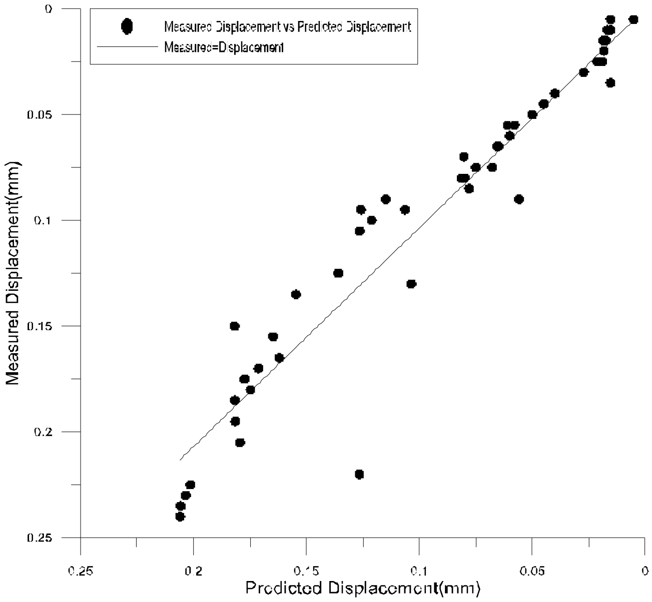

Fig. 4 Results of Used Optimal Network for Training Phase

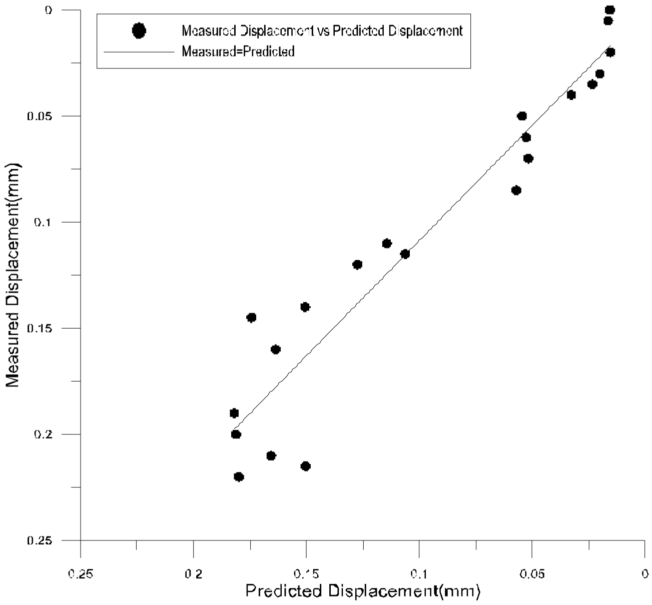

Fig. 5 Results of Used Optimal Network for Testing Phase

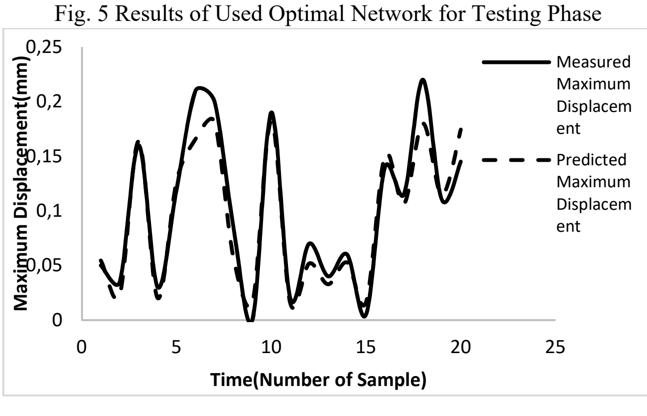

Fig. 6 Results of compression of measured and predicted relation displacement in Testing Phase used optimal network for testing phase

IV. Analysis of Results

Due to the important advances in engineering application and appearance of complex mathematical tools such as neural networks, this study tried to introduce ANN to optimize time and human resource to predict the behaviour of masonry wall. Based on the results from Figs. 4 and 5 in two phases of training and testing, applicability of RBF network for prediction of maximum displacement has been proved. Figs. 4, 5 show the good performance in learning and testing part due to the fitting value of R2. Moreover, there is a good agreement between desired displacement and predicted displacement based on R2. With respect to the number of data and the result of designing network, prediction of maximum displacement with MLP networks is achievable. Fig. 6 plotted the result of testing phase by optimal network to compare the desired and predicted displacement. As can be seen in Fig. 6, the predicted displacement has close relation to the desired data, which show the correct training and testing of the network.

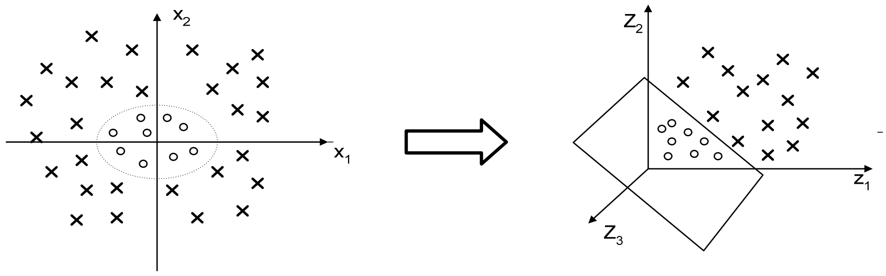

Fig. 7 Mapping nonlinear data to a higher dimensional feature space

V. Conclusion

In this study, the ANN is developed to predict the behaviour of SIM panel. The important characteristic of SIM panel is mortarless joint and the connection between bricks supply by specific shape of bricks and locked inside each other. ANN networks have strong capability to predict the behavior of linear problem. In this paper, by using MLP network, the panels' displacement has trained to network and the results showed a close expectation to the experimental test. In fact, testing the SIM panels is time consuming and expensive, and needs an appropriate laboratory to test the correct behavior. ANN revealed a reliable result to predict the wall displacement in very short time. The MLP network has good performance in learning and the coefficient of determination showed 0.95% of alignment, which is acceptable learning range. Furthermore, the close relation between desired and predicted displacement based on 0.91% of coefficient of determination led that MLP has an acceptable capability of prediction. Finally, with respect to important limitation of this tool such as data base preparation for learning part, this paper could be useful and recommended for applying on real experimental project to optimize time and human resource.

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