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Creep Predicting Model in Masonry Structure Utilizing Dynamic Neural Network

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Abstract: Problem statement: When the loads are applied to a brickwork structure, visco-elastic behavior upon their stress-strain relationships is exhibited, where the response can be classified into two separate parts: an instantaneous elastic strains and time-dependent creep strains. The creep strain represents the non- instantaneous strain that happens with time when the stress is sustained. Through the previous century, along with the alter in brickwork construction, A chain of creep tests on brickwork has shown that creep in brickwork be able to result in deformation that rise gradually with the way of time. Brickwork has considerable creep strain that is complicated to predict because of its reliance on several unrestrained parameters (e.g., relative humidity, time of load application, stress level). Dependable and precise prediction models for the long term, time-dependent creep deformation of brickwork structures are required. Artificial Neural Network (ANN) models have been determined useful and efficient especially in such problems for which the characteristics of the processes are difficult to describe using numerical models. **Approach:** This study introduces a creep prediction model based Focused Time-Delay Neural Network (FTDNN) which could detect and consider within its architecture the time dependency which is major factor in creep deformation in brickwork structure. **Results:** Performance of the proposed FTDNN model was examined with experimental creep data from brickwork assemblages collected over the last 15 years. Results showed that the FTDNN model has a relatively small prediction error compared to the other models with the error less than 15%. **Conclusion:** The results showed that the FTDNN model outperformed the existing ANN models and significantly enhance the accuracy of creep prediction.

Key words: Dynamic neural network, creep predicting, masonry

INTRODUCTION

When the load is applied on a quasi-brittle materials (e.g., concrete and masonry), the quasi-brittle materials shows elastic deformation/strain, then followed by a slow additional increase of deformation with time. This slow increase of deformation is known as creep, which was discovered in 1907 by Hatt (1907). However, when the load is applied, an instantaneous elastic strain $\varepsilon(t_0)$ occurs at the time of load application t_0, can be defined in this equation:

$$\varepsilon(t_0) = \frac{\sigma}{E(t_0)} \quad (1)$$

Where:
σ = The applied stress
$E(t_0)$ = The modulus of material at the time of load application, then the creep strain $\varepsilon_{cr}(t, t_0)$ occurs between the load application time t_0 and the time t

The ratio of the creep strain to the elastic strain is called the creep coefficient $\phi(t, t_0)$:

$$\phi(t, t_0) = \frac{\varepsilon_{cr}(t, t_0)}{\varepsilon(t_0)} \quad (2)$$

Moreover, creep strain (at any time) can be separated into a basic creep and drying creep component. The basic creep occurs if the creep strain under sealed conditions or if there is no moisture exchange with the ambient medium, while drying creep is the additional creep experienced when the material is allowed to dry while under sustained load, drying creep also called the Pickett (1942) effect. The sum of basic and drying creep is referred to as total creep. The creep of quasi-brittle materials (e.g., concrete and masonry) under load has been studied intensively during the past century and many theories have been advanced to

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explain the basic physical process which causes creep and relate the creep strains to the microstructure of quasi-brittle materials, examples of these theories: The mechanical deformation theory, the visco-elastic flow theory, the solid solution theory and the seepage theory (Hannant, 1968; Morgan, 1974; Neville *et al*., 1983). These theories established the bases for accurate modeling of creep.

Neville *et al*. (1983) defined three basic stages of creep: primary creep, secondary creep and tertiary creep. Primary and secondary creep are those commonly observed creep in structures under service load, tertiary creep may only happen when the stress levels are greater than service load stresses (above 40% of the material strength).

The issue of creep modeling of masonry structures attracted much attention in the research community after the collapse of the civic tower of pavia in Italy (Binda *et al*.,1989) without any warning signal, which was attributed to local overstressing of structural components as a result of combined creep and microcraching effects (Binda *et al*., 1992), the tower of pavia is not a secluded case and quite a few other famous examples can be referred, such as the collapse of San Nicolo Cathedral of Noto in Italy (1996), the collapse of the St. Magdalena bell-tower in Goch, Germany (1993) and the harsh damage exhibited by the bell-tower of the Monza Cathedral in Italy. Also other case in the past are comparatively well documented, for example the collapse of the spire of Chichester Cathedral in UK (1861).

However, it is well recognized that creep deformations in brickwork masonry structures are substantial and could result in significant stress redistribution in the structure during its life time (Harvey and Lenczner, 1993; Hamilton and Badger, 2000). Shrive and England (1981) showed that creep redistribution of stresses in brickwork wall will result in reducing the stress on the vertical mortar joint and increasing it on the horizontal bed joint. It has also been demonstrated that different creep rates in the materials of grouted masonry walls might result in a decrease and then an increase in the stress in the masonry brick itself. Such stress variation could be detrimental if combined with stiffness degradation as a result of aging or fatigue (Shrive and Taha, 2003). Masonry creep also results in losing more than 20 of the pre-stressing force in post-tensioned brickwork (Shrive, 1988). Therefore, accurate modeling of creep in masonry structures is required for efficient structural design of new structures (Schultz and Scolforo, 1992) and for a pragmatic evaluation and monitoring of historical structures (Anzani *et al*., 2000; Zijl, 1999).

Conventional creep predicting models: Conventionally, several empirical models have been utilized in the last 60 years for creep predicting using functional mapping mathematics (Brooks and Neville, 1978; Gardner and Zhao, 1993; Lenczner, 1986). Most of these models utilize curve-fitting techniques derived for specific experimental data sets and achieved by methods of linear and non-linear regression analysis. Usually, four typical prediction models used in predicting creep in quasi-brittle materials (Neville *et al*., 1983), these models are: the logarithmic, the power, the hyperbolic and the exponential mathematical models. The functional mapping models have limited accuracy attributed to the large number of uncertain and inter-related parameters that affect the prediction process and the need for a comparatively large database to establish a dependable model.

On the other hand, models based on rheological models have been developed over the last few decades to represent elastic and creep deformations in concrete and masonry structures. Where the rheological models are mechanical models that contain a group of connected spring and dashpots connected in series or parallel. Three basic rheological models usually used to represent elastic and creep deformations in concrete and masonry structures, these models are: Maxwell model, Kelvin model and Burgers model, further details are provided elsewhere (Neville *et al*., 1983).

Yet, accurate creep prediction models for masonry structures are uncommon due to most of the masonry design cods worldwide use empirical formula to predict creep deformations (Sayed-Ahmed *et al*., 1998). Moreover, most of the presently available models are sensitive to changes in the input parameters that considerably affect their dependability for structural design. Comparisons of some code creep prediction models to experimental results showed that most code models undervalue the creep strain (Zijl, 1999).

Artificial neural network: Artificial Neural Network ANN are networks of many simple processors (neurons) operating in parallel, each probably having a small amount of local memory. The smallest network unit (the neuron) receives its input through a connection that multiplies its strength by a scalar weight and adds a bias. The sum of the weighted inputs and their weights and biases is the argument for a transfer function that produces the neuron output. Neural networks can be classified into dynamic and static categories. Static (feed-forward) networks have no feedback elements and contain no delays; the output is calculated directly from the input through feed-forward connections. In dynamic networks, the output depends not only on the current input to the network, but also on the previous inputs, outputs, or states of the network. Dynamic networks can also be divided into two categories: Those that have only feed-forward connections and those that have feedback, or recurrent connections.

Two important characteristics of ANN that make them valuable for predicting time-series relationships such as creep are:

- The ability to learn from examples without prior knowledge of the regularities in data
- The ability to generalize from a previous state to a new one by modifying their behavior in response to new information. Therefore, they can be suitable for time-varying pattern modeling. The advantages of ANN based creep prediction modeling against the conventional methods have been discussed (Taha *et al*., 2003). Recently, a Recurrent Neural Network (RNN) has been developed as a modeling technique for predicting creep deformation in masonry structures and showed high accurate prediction when compared with conventional creep models (El-Shafie *et al*., 2009). This study takes masonry creep modeling on step further by focusing on a class of ANN known as Focused Time-Delay Neural Networks (FTDNN)

Problem statement: Several empirical models have been developed within the last few decades to predict creep deformation in masonry structures. Unfortunately, most of the present conventional creep models techniques have not shown sufficient performance in predicting creep with acceptable accuracy. The aim of this research is to investigate the potential of using Focused Time Delay Neural Network (FTDNN) in predicting creep deformations of masonry structures. The benefit of this model is that the trains of the network faster than other dynamic networks, this is because the tapped delay line appears only at the input of the network and contains no feedback loops or adjustable parameters. Moreover, it has been reported that this networks is well suited to time-series prediction (Demuth *et al*., 2009).

Dynamic neural networks:

Focused Time Delay Neural Network (FTDNN): Focused Time Delay Neural Network (FTDNN) is a straight forward dynamic network, which consist of a feed forward network with a tapped delay line at the input layer. This is part of a general class of dynamic networks, called focused networks, in which the dynamic appear only at the input layer of a static multilayer feed forward network.

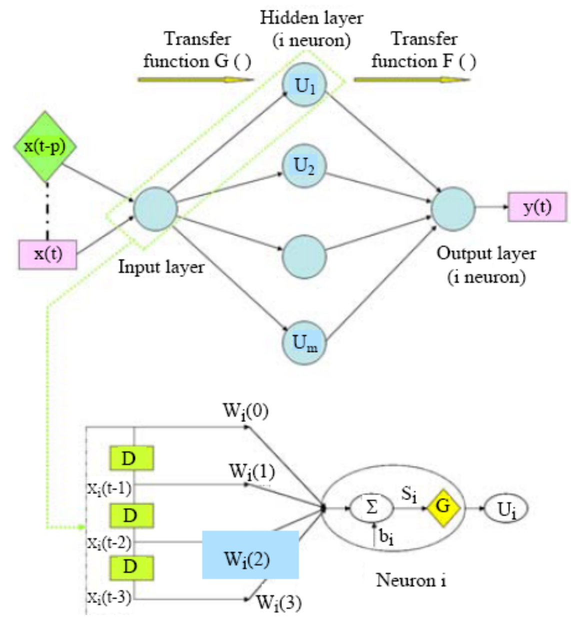

Fig. 1: General architecture of FTDNN and single neuron calculations

The basic FTDNN consist of two components: A memory structure and non linear associator. The memory structure is a time delay line which containing the p most recent inputs generated by the delay element represented by the operator D, while the associator is the conventional feed-forward network. The memory structure hold on the relevant past information and the associator uses the memory to predict future occasions. A particular feature of the FTDNN is that the memory structure is focused on the input layer; this makes it different from the general Time Delay Neural Network (TDNN). A major advantage of the FTDNN is that is less complex than the conventional TDNN and has the same temporal patterns processing capability. Furthermore, the FTDNN can be trained even with the standard back-propagation algorithm (Haykin, 1994). Figure 1 depicts the general architecture of a FTDNN in addition to zooming on the internal structure of a single neuron. The case shown in Fig. 1 considers a tapped delay line that involves the p most recent inputs. This example shows three delay elements represented by the operator D. For a case of p delay elements and an input variable x(t), the network processes x(t), x(t-1), x(t-2),… and x(t-p), where p is known as the tapped delay line memory length. Therefore, the input signal $S_i(t)$ to the neuron i (Fig. 1) is given as:

$$S_i(t) = \sum_{k=0}^{p} w_i(k)x(t-k) + b_i \quad (3)$$

Where:
$w_i(k)$ = The synaptic weight for neuron i
b_i = Its bias

Then the output of this neuron (U_i) is obtained by processing $S_i(t)$ by the non-linear activation function G( ), which is the most often used form of the sigmoid activation function for neuron i:

$$U_i = G\left(\sum_{k=0}^{p} w_i(k)x(t-k) + b_i\right) \quad (4)$$

$$G(S_i(t)) = \frac{1}{1+e^{-S_i(t)}} \quad (5)$$

The output of the FTDNN, assuming that it has one output neuron j, a single hidden layer with m hidden neurons and one input variable as shown in Fig. 1, is given by:

$$y_j(t) = F\left(\sum_{i=1}^{m} w_{ji} U_i + \alpha_j\right) \quad (6)$$

Where:
F ( ) = The transfer activation function of the output neuron j (which can be chosen to be sigmoid or a linear function)
α_j = Its bias
w_{ji} = The weight between the neurons of the hidden layer and the neuron of the output layer

FTDNN is well suited to time-series prediction. One nice feature of the FTDNN is that it does not require dynamic back-propagation to compute the network gradient. This is because the tapped delay line appears only at the input of the network and contains no feedback loops or adjustable parameters. For this reason, this network trains faster than other dynamic networks. However, the major property of the model relies on input delay elements at the input layer so that the output of the network depends here not only on the connection weights and the current input signal, but also on the previous states of the network. Therefore, the FTDNN may be suit the creep prediction task, where in order to predict the current state; previous states have to be considered.

MATERIALS AND MATHODS

An experimental program to examine masonry creep has been carried out at The University of Calgary for the last 15 years. In this program, the creep deformation of masonry prisms subjected to different stress levels and the environmental conditions have been monitored. The experimental results of one type of bricks only are analyzed here for examining the potential use of ANN in predicting creep performance of masonry structures.

Experimental data analysis: The test apparatus as shown in Fig. 2 consist of two prisms held between two steel plates with hydraulic ram loading the top plate. A steel ball is used to prevent load eccentricity and Dywidag bars are used to contain the apparatus. Seven fixed DEMEC points are marked on each prism creating four gauge length used to measure the creep deformation. The gauge lengths are 250, 250, 50 and 50 mm, respectively. A series of unloaded prisms subjected to similar environmental conditions to their counterpart-loaded prisms were also measured at the same time intervals. The use of unloaded prisms allows accounting for shrinkage and thermal changes. Twelve testing groups were included. All the groups have similar types of brick and mortar. The brick was a standard 190×90×45 mm brick with 2-20 mm circular holes two square 40×40 holes. Standard type N mortar was used. All masonry prisms were constructed from 90×190×57 mm standard clay bricks with standard type N mortar (1 Portland cement: 1 Lime: 6 Sand). The specimens were kept under two environmental conditions; the first group was sealed and kept continuously wet by providing an outer source of water to the specimens (RH = 100%), while the second group was kept at the room humidity (RM = 40%).

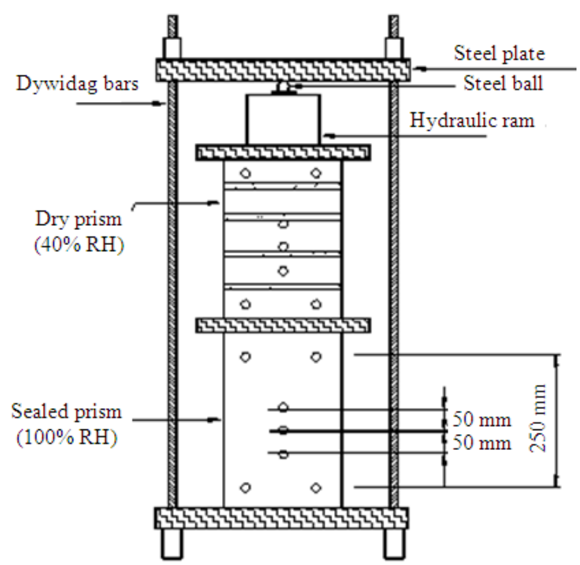

Fig. 2: Masonry creep testing apparatus

Table 1: Summary of experimental data used for training the network

Group	A1	A2	A3	A4	A5	A6	A7	A8	A9
σ	2.4	4.8	4.8	4.8	1.2	2.4	4.8	2.4	3.6
t	7.0	7.0	14.0	14.0	28.0	28.0	28.0	28.0	28.0
RH	40.0	100.0	40.0	100.0	40.0	40.0	40.0	100.0	100.0

Table 2: Summary of experimental data for establishing the model

Group	B1	B2	B3	B4
σ	4.8	2.4	1.2	3.6
t	7.0	14.0	28.0	28.0
RH	100.0	40.0	100.0	40.0

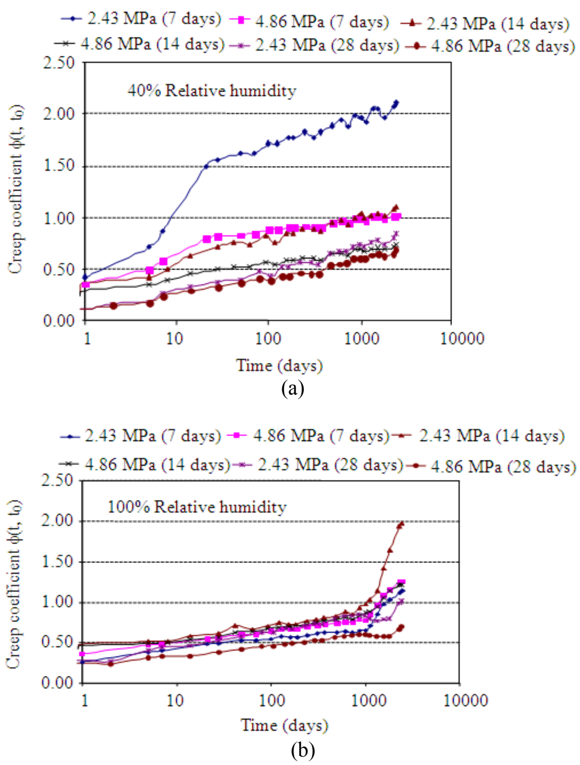

Fig. 3: Creep coefficients versus time for different age of loading and stress level (a) relative humidity =100%; (b) relative humidity = 40%

All specimens were kept in the laboratory at a temperature of 20±2°C. The prisms were subjected to different stress levels (1.21, 2.43, 3.61 and 4.86 MPa) representing approximately (12, 24, 36 and 48%) the prisms compressive strength, respectively. To compensate the effect of shrinkage and minor thermal effects, strains of unloaded prisms that were subjected to similar environmental conditions to their counterpart-loaded prisms were also recorded.

The creep coefficient $\phi(t, t_0)$ is determined from the testing data using Eq. 1 and 2. Figure 3 shows the change of the creep coefficient with time for the different groups for the tow different Relative Humidity (RH) 100 and 40% respectively.

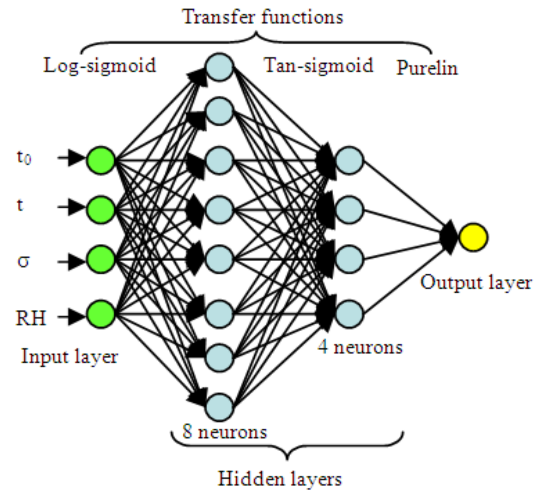

Fig. 4: Schematic representation of the FTDNN used for modeling creep

The creep data extracted from experiment on structural masonry prisms collected continuously in the last 15 years by Shrive and Tilleman (1995) have been used for providing the training and testing data sets needed for the development of the FTDNN for predicting creep. Thirteen experimental testing groups were used for training and testing the network as presented in Table 1 (9 training groups) and Table 2 (4 testing groups). As all the experiments were performed on specimens of the same size, four parameters only were considered for modeling creep: The applied stress level (σ), the Relative Humidity (RH), the age of loading (t_0) and the time at which creep is measured (t).

The effect of temperature on creep was not examined here. Also, the surface area to volume ratio was not considered as a changing parameter, being constant for all tests. Preliminary investigations proved that the inclusion of constant values representing the surface area and the temperature would not have any effect on the performance of the ANN.

FTDNN training: The FTDNN for modeling creep deformations of structural masonry was developed. The network consists of an input layer with four neurons, two hidden layers with eight, four neurons respectively and an output layer with one neuron. The number of hidden layers and neurons for the network are given in Fig. 4. One delay for each input has been used meaning initially the network would like to see 1 (delay) + 1 (input) before computing its associated output in the respect time series. That is mean, the first layer has weights coming from the input with the specified input delay, each subsequent layer has a weight coming from the previous layer, all layers have biases and the last layer is the network output. This process continues in a sequential manner until the entire pulse train is run over. The transfer functions used in each layer of the network are shown in Fig. 4. The Levenberg-Marquardt training criterion was utilized during the learning process of the network with a training goal of achieving a mean square error MSE of 0.0001 (Haykin, 1994). The Levenberg-Marquardt is a quasi-Newton method in which the error gradient vector g as presented in Eq. 7 is computed approximately to speed up the training process of the of the network:

$$g = J^T E \tag{7}$$

where, J is the jacobian matrix including the network gradient error and the network error vector E. A learning matrix including 47 training sample drawn from 10 training groups was used in training the network.

In order to achieve fast training convergence to the target MSE of 0.0001, the input and output data were normalized with respect to the corresponding maximum values in the input vectors using linear normalization functions. The iterative procedure stops after achieving a certain objective mean square error MSE, which is normally chosen to be the sum of squares of the error between the network output (Y_P) and the desired response (Y_O) on the training data set defined as:

$$MSE = \frac{1}{2}\sum_{i=1}^{n}(Y_{oi} - Y_{Pi})^2 \tag{8}$$

The network successfully achieved the target MSE. The structure of the network, transfer functions and the number of tapped delay line clearly affect the number of iterations needed during the training procedure of the network to achieve the target MSE. Several learning algorithms have been proposed for training FTDNN. In practice, Levenberg-Marquardt is faster and finds better optima for a variety of problem than other methods for training. The FTDNN model successfully achieved the target MSE after 48 iterations. The number of iterations also represents the time needed for the network training.

RESULTS

The FTDNN was tested using a matrix of 80 samples drawn from the four testing groups presented in Table 2. These groups were not used in training the network. The FTDNN model was used to predict the creep coefficient $\phi(t, t_0)$. Comparison of the creep coefficient as predicted by the FTDNN model versus the creep coefficient determined experimentally is presented in Fig. 5. To assess the efficiency of the FTDNN model, the predicted creep compliance $J(t, t_0)$

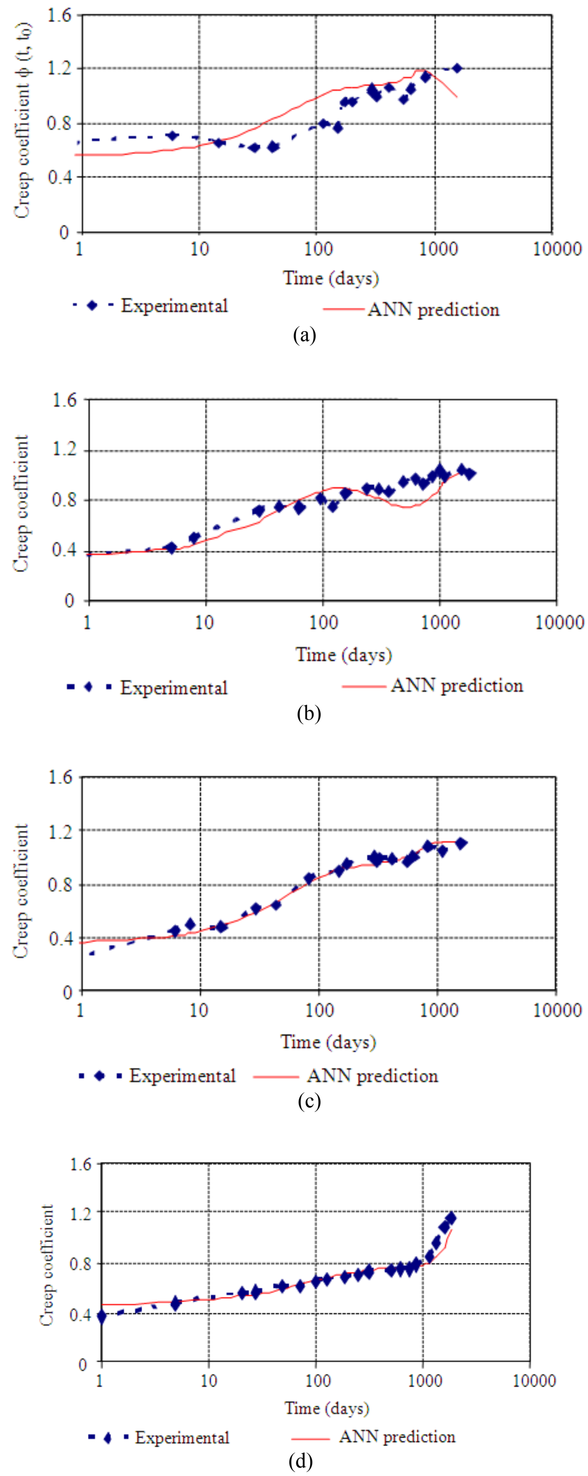

Fig. 5: Samples of creep prediction using FTDNN model versus measured creep coefficient $\phi(t, t_0)$, (a) testing Group 1; (b) testing Group 2; (c) testing Group 3 and (d) testing Group 4

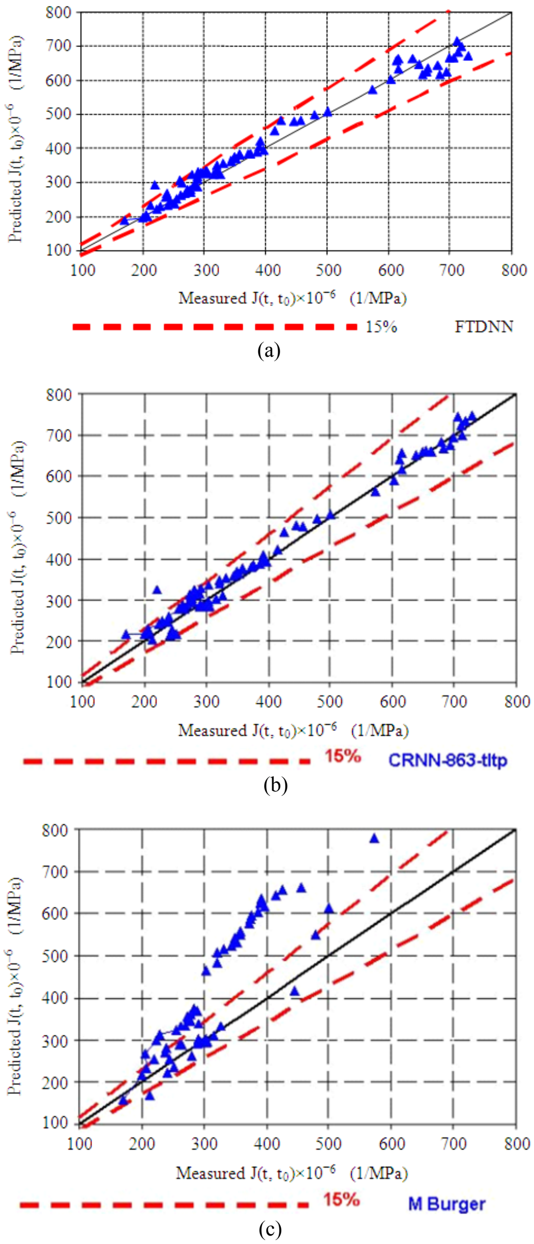

Fig. 6: FTDNN, RNN and M. Burger models for predicting creep compliance

Was calculated and was compared to the measured creep compliance. Comparison between the predicted versus measured creep compliance are visually presented using the 45° line of graph and to deviation lines the ±15% deviation from the 45° lines as shown in Fig. 6. The network with prediction falling between the dashed lines represents prediction accuracy within 15%. To examine the difference between FTDNN model, RNN model and creep prediction models developed using curve-fitting technique, the experimentally measured creep was also compared to the modified Burgers model as presented in Eq. 9 and 10:

$$\phi(t, t_0) = R\, t^{0.3} + (1 - e^{-Rt}) \quad (9)$$

$$R = 0.112 - 3.35 * 10^{-6} * E(t_0) \quad (10)$$

It can be observed from Fig. 6a that the FTDNN model was able to predict creep compliance within ±15%, while the modified Burgers model was not able to achieve similar level of accuracy as shown in Fig. 6c. The accuracy of creep compliance prediction of the FTDNN model was also compared to the accuracy of creep compliance prediction using RNN model (El-Shafie *et al*., 2009). The RNN model used for comparison includes feedback connections from its hidden layers neurons back to its input (Elman RNN), in addition to the feed-forward network includes three hidden layers that have 8 neurons in the first hidden layer, 6 neurons in the second hidden layer and 3 neurons in the third hidden layer. Creep prediction using RNN model for the same input data is shown in Fig. 6b.

DISCUSSION

The results showed that the use of FTDNN significantly improves the accuracy of creep prediction. This might be attributed to the architecture of FTDNN which can detect and consider the time dependency which is major factor in creep deformation in masonry structure. The performance of the RNN model was comparable to that of the FTDNN model, where both models having much butter accuracy than the conventional functional mapping models. However, FTDNN model still has the advantage of faster training process that makes it more robust and reliable than RNN model.

Statistical analyses: The statistical comparisons between predicted and measured creep for the three models were performed by determining the Prediction Error (PE) which measures the average squared error between the predicted creep obtained from the model and the factual measured creep. The Prediction Error (PE) is determined as shown in Eq. 11:

$$PE = \frac{1}{m}\sum_{i=1}^{m}(y_{ti} - y_{pi}) \quad (11)$$

Where:

y_{pi} = The predicted value
y_{ti} = The experimentally measures value
m = Represents the number of samples in each testing group

Table 3: Prediction Error (PE) between predicted and experimentally measured creep

Model	Prediction Error			
	Group 1	Group 2	Group 3	Group 4
FTDNN	0.03	0.012	0.002	0.067
RNN	0.117	0.051	0.195	0.092
M.Burger	0.133	0.699	0.509	0.748

Prediction errors for the FTDNN model, the RNN model and the modified Burgers model are listed in Table 3. It is obvious from Table 3 that creep predictions models using ANN have a smaller prediction error and consequently higher accuracy than classical creep prediction models using conventional regression analysis (modified Burgers model). More particularly, the accuracy of the FTDNN model is obviously higher than that one developed using RNN.

CONCLUSION

While accurate prediction of creep deformations is required to increase the level of confidence in serviceability analysis, it is obvious that high level of accuracy cannot be achieved with classical curve-fitting techniques because of the large uncertainty in the analysis. Therefore, the use of artificial intelligence is necessary to increase the level of accuracy in predicting creep. A model to predict creep deformations of brickwork structures using artificial intelligence has been developed. The model utilizes Focused Time Delay Neural Network (FTDNN). The model capability to predict creep of masonry is compared with other model utilizes Recurrent Neural Network (RNN), includes feedback connections from its hidden layers neurons back to its input in addition to the feed-forward network, recently developed by the co-authors (El-Shafie *et al*., 2009). The Statistical analysis of the FTDNN model showed that the model has a comparatively small prediction error compared to the RNN model and M. Burger model.

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