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Using neural networks to model and predict amplitude dependent damping in buildings

Q.S. Li†, D.K. Liu‡, J.Q. Fang‡, A.P. Jeary‡† and C.K. Wong‡‡

Department of Building and Construction, City University of Hong Kong, Tat Chee Avenue, Kowloon, Hong Kong

Abstract. In this paper, artificial neural networks, a new kind of intelligent method, are employed to model and predict amplitude dependent damping in buildings based on our full-scale measurements of buildings. The modelling method and procedure using neural networks to model the damping are studied. Comparative analysis of different neural network models of damping, which includes multi-layer perception network (MLP), recurrent neural network, and general regression neural network (GRNN), is performed and discussed in detail. The performances of the models are evaluated and discussed by tests and predictions including self-test, "one-lag" prediction and "multi-lag" prediction of the damping values at high amplitude levels. The established models of damping are used to predict the damping in the following three ways : (1) the model is established by part of the data measured from one building and is used to predict the another part of damping values which are always difficult to obtain from field measurements : the values at the high amplitude level. (2) The model is established by the damping data measured from one building and is used to predict the variation curve of damping for another building. And (3) the model is established by the data measured from more than one buildings and is used to predict the variation curve of damping for another building. The prediction results are discussed.

Key words: full-scale measurement; amplitude dependent damping; artificial neural networks; general regression network, prediction.

1. Introduction

Damping in structures, which is a practical measure of the efficiency of a system to dissipate the energy that it acquires in its attempt to return to quiescent conditions, is recognised as one of the important parameters for assessing structural response at the design stage. The importance of damping is becoming increasingly significant as buildings are become taller and relatively more flexible. However, in most cases, the design value of the damping ratio is generally set at a fixed value for special structures. For example in Japan, the design value of the damping ratio is generally set at 2% and 3% for steel structures and reinforced concrete structures, respectively (Tamura *et al.* 1994). This is not completely consistent with the practical cases, and the design values of damping could be quite different from actual values. Unlike the mass and stiffness

† Assistant Professor
‡ Research Fellow
‡† Professor
‡‡ Laboratory Manager

characteristics of a structural system, damping does not relate to a unique physical phenomenon. The estimation of damping in buildings poses most difficult problems. Over the years, there has been considerable research work in pursuit of descriptions of inherent damping of structures. Several investigations have shown that the damping of steel and concrete structures increases with the amplitude of vibration. For example, based on a significant full scale measurement data base, Jeary (1986) investigated the mechanism for the amplitude dependent damping in buildings, and applied a random decrement technique (RDT) to evaluate damping in buildings. A RDT ranked by peak amplitude was proposed by Tamura and Suganuma (1996) for directly and effectively evaluating the amplitude dependence of dynamic phenomena, and was applied to the wind-induced response data of three towers. The results were compared with those of the traditional techniques. Kareem and Gurley (1996) presented the estimation of damping by the RDT in detail and analysed the implications of the uncertainty of damping on system responses in terms of a perturbation technique, second-moment analysis and Monte Carlo simulation. Li *et al.* (1996a, 1996b) and Fang *et al.* (1998a) investigated the effects of random factors on the damping values in the different amplitude regions, and established an AR model of damping in a building and predicted the damping values at higher amplitude levels. Because of the complexity of the damping in buildings and the needs to aid designers in estimating damping ratios precisely, some simple forecast models of damping have been established over the years. These models are based on theoretical considerations and statistical analyses carried out based on a wide and reliable experimental database. The forecast of structural damping is currently entrusted to two classes of procedures : empirical methods and semi-empirical methods. The former methods are general proposed by standards and consist of assuming constant values to the damping, eventually differentiated in accordance with the building type and the structural material (Haviland 1976). The latter methods use relationships based on the statistical analysis of experimental data from full-scale tests. The formulae proposed are often qualitatively supported by theoretical considerations that sometimes justify their use outside the experimentally investigated dominion. The model proposed by Davenport and Hill Caroll (1986) and those by Jeary (1986) which is presented in Section 2 in this paper represent the most important examples.

At present, these forecast formulae of damping in buildings give a deterministic value for a building, they can not give the changing process of the damping with the increase of amplitude, especially in the high amplitude plateau of the curve. The amplitude dependent damping in buildings can be described as shown in Fig. 1 (Jeary 1986). The changing curve of damping with amplitude will help researchers and engineers to analyse the dynamic response of buildings, and to design the passive and active damper for control of the structural response under the excitation of external loading such as strong wind and earthquake actions. Therefore, it is important and useable to forecast the variation of damping with amplitude, especially in the high amplitude plateau in which the values of damping can not be obtained easily in full-scale measurements. The main purpose of this paper is to propose effective methods to model and forecast the variation curve of damping of tall buildings with amplitude.

From Fig. 2 it can be seen that the variation curve of damping with amplitude takes on distinct non-linearity. And it can be also see from the figure that the amplitude dependent damping data obtained from full-scale measurements shows that the damping has distinct time series properties (here the time series is the amplitude series), i.e., the past damping values in the series may influence the future damping values. In order to predict the variation of

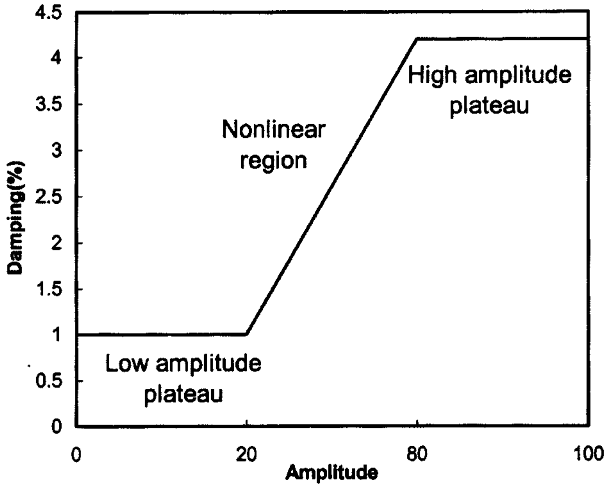


Fig. 1 Generalised damping characteristic

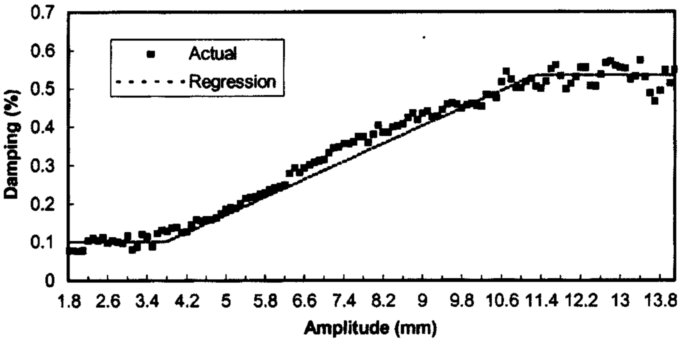


Fig. 2 Damping curve measured from building 1

damping with amplitude effectively, it is necessary to establish an accurate model of damping. But at present, there is no widely accepted method available for modelling the damping in buildings. A traditional statistical treatment of time series would include a test for randomness, analysis of series into component parts, seasonal adjustments, smoothing, and the class of autoregressive forecasting. However, direct test for randomness can be fraught with problems. Techniques in non-linear modelling have been developed, particularly in control theory and engineering. But most of these techniques rely on polynomial series. For general problems that are not polynomial in nature, high orders of the polynomial are required, and the method may become unwieldy as the number of coefficient increases. Currently, there is a new challenger for these methodologies-artificial neural networks (ANNs).

ANNs may be considered as a data processing technique that maps, or relates, some type of input stream of information to an output stream of data, and thus they belong to the class of data-driven approaches, as opposed to model-driven approaches. Neural networks encompass many desirable features as a data analysis tool. The most important advantages of neural networks may be generalisation, flexibility and non-linear modelling. Thus, they have strong capability to construct non-linear relationships between the input data and the target output. In recent years, a number of publications which concern forecasting and modelling problems have appeared in the literature (e.g., Tiao *et al.* 1989, Harvey 1989, Chakraborty *et al.* 1992, Refenes *et al.* 1993, Hill *et al.* 1994, Gorr *et al.* 1994, Azoff 1994, Pham *et al.* 1995). ANNs and traditional time series techniques have been compared and studied. The results of these research works show that neural networks have several potential advantages over statistical methods in modelling and prediction. These advantages include (1) ANNs can be mathematically shown to be universal function approximators (Hornik *et al.* 1989), which means that they can automatically approximate whatever functional form best characterises the data. (2) ANNs are also inherently non-linear (Rumelhart and McClelland 1986), which means not only can they estimate non-linear functions well, but they can also extract any residual non-linear elements from the data after linear terms are removed. (3) With ANNs using one or more hidden layers, the networks can partition the sample space automatically and build different functions in different portions of that space. This means that ANNs have a modest capability for buildings piece-wise non-linear models. On the other hand, although the future looks bright for ANNs applications in forecasting and decision-making, it is still necessary to rigorously evaluate these applications in many fields.

Non-stationary nonlinear time series are more suitable for analysis by the general nonlinear mapping provided by a neural network, than by linear based autoregressive models. The ability and the advantages of neural networks to model and forecast non-linear data makes them a good candidate to model the amplitude dependent damping in buildings. In this paper, artificial neural networks are employed to model the amplitude dependent damping in buildings. The modelling method, modelling procedure and modelling parameters using neural networks to model the damping are studied. Comparative analysis of different neural network models of damping, which includes multi-layer perception network (MLP), recurrent neural network, and general regression neural network (GRNN), is performed and discussed in detail. The performances of the models are evaluated through tests and predictions. The established models of damping are used to predict the damping in the following three ways : (1) the model is established by part of the data measured from one building and is used to predict the another part of damping values, the values in the high amplitude level. (2) The model is established by the damping data measured from one building and is used to predict the variation curve of damping for another building. And (3) the model is established by the data measured from more than one buildings and is used to predict the variation curve of damping for another building. The prediction results are discussed.

2. Damping in buildings

Based on a significant full scale measurement data base, Jeary (1986) suggested that the amplitude dependent damping in buildings can be described, as shown in Fig. 1 and pointed out that damping values can be estimated by the following expression :

$$\zeta_a = \zeta_0 + \zeta_1 [X_1]/H \tag{1}$$

where ζ_0 is the low-amplitude damping, ζ_1 is a rate of increase of damping with amplitude, ζ_a is the absolute value of damping at amplitude X_1, H is the height of the building. The data presented in Fig. 2 were measured from a 120 metres steel building (building 1) with rectangular shape. Two accelerometers were placed orthogonally at one corner on the top of the roof, one was placed along the longer side (direction 1) with the other along the shorter side (direction 2). A record of the response of the building was continuously acquired and digitized at 30 Hz and was amplified and low pass filtered at 5 Hz before the digitization. The spectra of acceleration responses demonstrate that the wind-induced vibration of building is mainly dominated by the first natural frequency (Li *et al.* 1996b, Fang *et al.* 1998b). In order to obtain the damping estimates, the fundamental mode of the response was then band-pass filtered with an 8 pole filter and a random decrement process was performed with 200 threshold levels. The selection method for this particular test was chosen at response peak only. The random decrement signature on the graph is based on a 30 days accumulation of results with minimum 1000 averages so that each point of the curve converges before performing a curve filtering.

3. Neural network models of damping for building 1

3.1. Neural networks and their structures

Multilayer perception neural network (MLP) may be perhaps the best known feedfoward network, which has been deeply studied and widely used in many fields. But in fact, MLP has some shortcomings due to its learning process. In the past few years, many advanced neural network architectures and learning algorithms have emerged and have been successfully applied to practical problems. Examples are recurrent neural network (RNN), probabilistic neural network (PNN) (Specht 1990), general regression neural network (GRNN) (Specht 1991), etc. PNN and GRNN perform stochastic modelling, but they do not operate in a probabilistic manner, as in the case of the Boltmann Machine. The networks are constructed through the addition of inner-layer nodes that represent the statistical properties of the training patterns. PNN is based on concepts used in classical pattern recognition problems, it learns complex decision boundaries for category classification tasks. The GRNN, on the other hand, learns the regression function relationship (linear or nonlinear) between the dependent and independent variables. Thus, in order to investigate the application of neural networks to modelling the damping, three kinds of neural networks are used in this study : MLP network, recurrent network and general regression neural network (GRNN).

Fig. 3(a) shows a time-delay MLP neural network architecture with three layers : an input layer, an output layer and an intermediate or hidden layer. The input vectors are $D \in R^n$, $D = (d_0, d_1, \cdots, d_{n-1})^T$; the outputs of q neurons in the hidden layer, $Z \in R^q$, $Z = (z_0, z_1, \cdots, z_{n-1})^T$; and the outputs of the output layer are $Y \in R^m$, $Y = (y_0, y_1, \cdots, y_{n-1})^T$. Assuming that the weight and the threshold between the input layer and the hidden layer is w_{ij} and θ_j, respectively, and the weight and the threshold between the hidden layer and output layer is w_{jk} and θ_k, respectively, the outputs of each neuron in a hidden layer and output layer are :

$$z_j = f\left(\sum_{i=1}^{n} w_{ji}\, d_i - \theta_j\right) \tag{2}$$

$$y_k = f\left(\sum_{j=1}^{q} w_{kj}\, z_j - \theta_k\right) \tag{3}$$

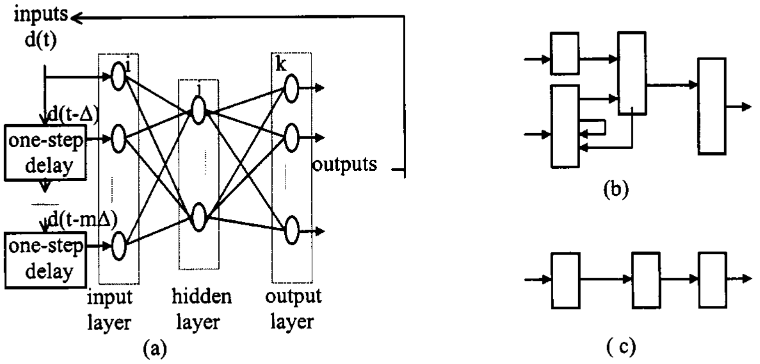


Fig. 3 The structures of neural networks (a) time-delay feedforward neural network (MLP), (b) recurrent network, (c) general regression neural network (GRNN)

where $f(\,)$ is transfer function, which is the rule for mapping the neuron's summed input to its output, and by a suitable choice, is a means of introducing a non-linearity into the network design. The backpropagation (BP) training process requires that the activation functions be bounded, differentiable functions. A range of possible active functions may be utilised such as Sigmoid function, hyperbolic tangent, sine and cosine function, etc. In practice the functions are also chosen to be monotonic and to saturate at the two extremes of [0, 1] or [-1, 1]. One of the most commonly used functions satisfying these requirements is the Sigmoid function, and it is monotonic increasing and ranges from 0 to 1 which is consistent with the range of the damping values. Thus, the Sigmoid function is chosen for the active function.

$$f(x) = 1/(1+\exp(-\beta x)) \tag{4}$$

where β is a constant that determines the steepness of the S Shape curve; x is the input to the transfer function, being the part in brackets of the above Eq. (2) and Eq. (3).

The second network investigated in this paper is recurrent network. Differing from the feedforward networks, in a recurrent network, the outputs of some neurons are fed back to the same neurons or to the neurons in preceding layers. Thus, signals can flow in both forward and backward directions. An example is the Hopfield network. Recurrent networks have a dynamic memory : their outputs at a given instant reflect the current input as well as previous inputs and outputs, and thus they have been successfully used in predicting financial markets. Because recurrent networks can learn sequences, they are excellent for time series data. In terms of network training, recurrent networks are trained in the same way as a standard backpropagation network, except that patterns must always be presented in the same order. There are three types of recurrent networks : input layer fed back into the input layer, hidden layer fed back into the input layer and output layer fed back into the input layer. In this paper, the second type of recurrent network is used.

The third network used in this paper is the general regression neural networks (GRNN) (Specht 1991), which is a three-layer network where there must be one hidden neuron for each training pattern. There is no training parameter such as a learning rate and momentum as in backpropagation, but there is a smoothing factor that is applied after the network is trained. GRNN works by measuring how far a given sample pattern is from patterns in the training set in

N dimensional space, where *N* is the number of inputs to the problem. When a new pattern is presented to the network, that input pattern is compared in *N* dimensional space with all of the patterns in the training set to determine how much it deviates from those patterns. The output that is predicted by the network is a proportional amount of all the outputs in the training set. The proportion is based upon how far the new pattern is from the given patterns in the training set. GRNN is known for the ability to train quickly with sparse data sets.

3.2. Design of training data set, test data set and the structures of neural networks

The design stage of working with neural networks involves a number of aspects : (1) designing the network structure; (2) Selecting neuron transfer functions; (3) A method for updating the weights and (4) A training cessation scheme. Before doing this, determination of the input vectors is the most important step since it will strongly affect the design of the networks, and may even affect the performance of the neural network models. For modelling a time series, the previous data will affect the current value, thus it is necessary to determine the optimum number of input units and this must be investigated by experiments for some cases. In this paper, two different numbers of input units are used and a comparative analysis of their results is performed. The first uses 2 input units, which predicts the current value of damping d(k) using the past two values d (k-1) and d(k-2), and the second uses 4 input units to predict the d(k) using the previous 4 values d(k-1), d(k-2), d(k-3) and d(k-4), where k is the step number in the data series. After determining the input units, the network structure can be evaluated by the estimation software according to the minimum acceptable training error, maximum number of iterations and the training data set.

Momentum coefficient and "learning rate" are the principal parameters in BP learning algorithm, which roughly describe the relative importance given to the current and past error values in modifying connection strengths. In our analysis, we have chosen the initial learning rate to be 0.2 and an associated momentum term to be 0.7. According to the different number of inputs, two structures, 2-13-1 and 4-13-1, of MLP network are adopted corresponding to the 2 inputs and 4 inputs, respectively. In the recurrent network, the structure of the hidden layer feeding back into the input layer is adopted, as shown in Fig. 3(b). The number of units in each layer is 4-13-1, and the transfer function of the neurons is Sigmoid function. The architecture of general regression neural network is shown in Fig. 3(c), and a structure of 4-115-1 is adopted, this notation signifies that there are 4 units, 115 units and 1 unit in the input, hidden and output layer, respectively.

The training data set and the test data set are arranged as follows : training data set consists of 115 input patterns which corresponds to the range of amplitude from 1.8 mm to 13.3 mm. The test data set is composed of 8 patterns, which corresponds to the range of amplitude from 13.4 mm to 14.1 mm. Each pattern is generated based on the format : "d(k-2) d(k-1) d(k)" or "d (k-4) d(k-3) d(k-2) d(k-1) d(k)" for the 2 inputs or 4 inputs, respectively. The training results of the three networks are tabulated in Table 1.

3.3 Test and analysis of ANNs models of damping

In order to test the trained neural networks, three testing strategies were adopted in this paper : self-test, "one-lag" prediction and "multi-lag" prediction. The results of self-test which

Table 1 Network structures and parameters, as well as training and test values

	MLP network	MLP network	Recurrent network	GRNN
Structure	4-13-1	2-13-1	4-13/13-1	4-115-1
Training parameters	learning rate : 0.2 momentum : 0.7	learning rate : 0.2 momentum : 0.7	learning rate : 0.2 momentum : 0.7	smoothing : 0.3
Training patterns	117	117	117	117
Test patterns	8	8	8	8
Training time	4'50"	4'40"	1'45"	1'
MSE	0.34E-03	0.37E-03	0.57E-03	0.5E-04
Mean absolute error	0.0148	0.016	0.0196	0.0038
Min/max absolute error	0.0002/0.0484	0.0002/0.046	0.0005/0.0484	0.00001/0.0456

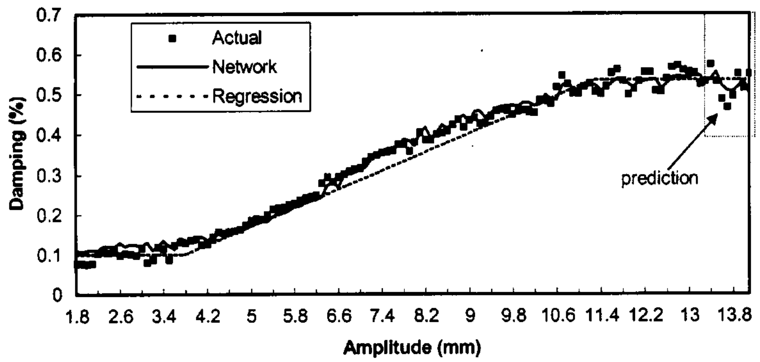


Fig. 4 Actual, test and prediction curve of damping using MLP network (4-13-1)

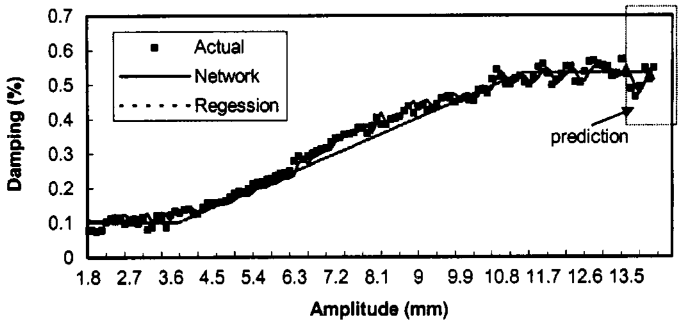


Fig. 5 Actual, test and prediction curve of damping using MLP network (2-13-1)

uses the training input data set as the test set are shown in Fig. 4~Fig. 7. The part of these curves from 1.8 mm to 13.3 mm of amplitude is the result of the self-test. From these figures it can be seen that there is little error between the outputs of the network and the actual target values in the input training data. The values of errors are listed in Table 1.

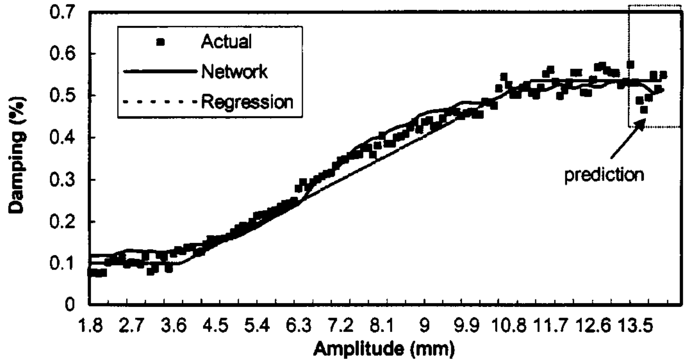


Fig. 6 Actual, test and prediction curve of damping using recurrent network (4-13-1)

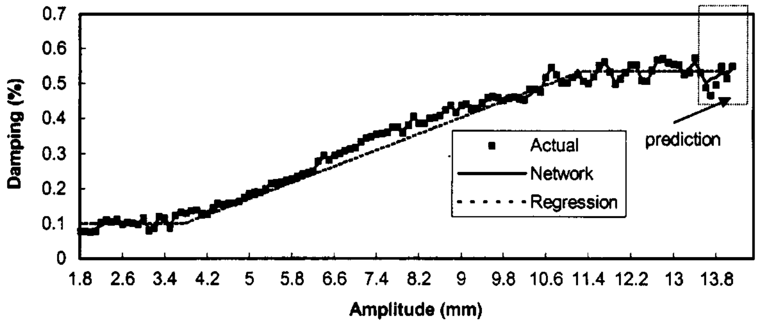
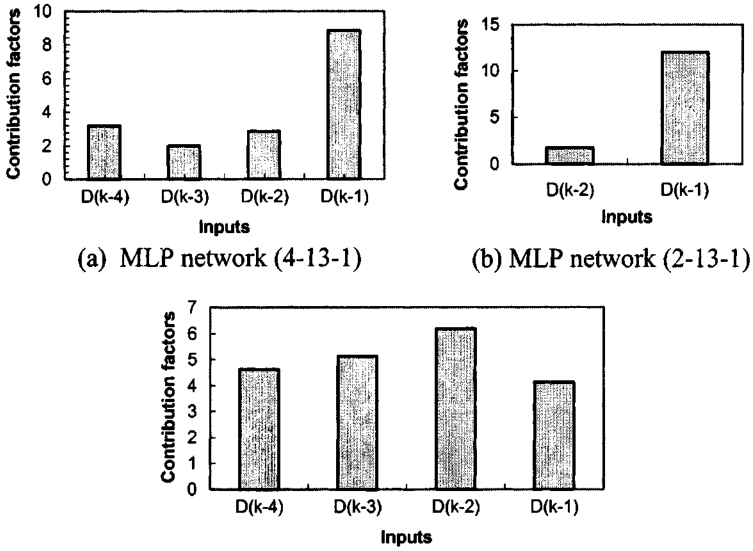


Fig. 7 Actual, test and prediction curve of damping using GRNN (4-115-1)

The results of the self-test can only confirm the performance with which the network maps the input data, but is not by itself enough to illustrate the abilities of the network. The ultimate purpose of using neural networks is to solve new problems using the trained network, and thus, the test of the performance of the network to predict the new data is an important task. The second stage of testing the network is carried out by using the test data set which is not included in the training data set. In this stage, both "one-lag" and "multi-lag" (Chakraborty *et al.* 1992, Pham *et al.* 1995) output predictions for the test samples are carried out with the given models. In the one-lag prediction, the inputs to the network are historical values obtained from the field measurements, and the network is expected to predict a new value. In the multi-lag prediction, on the other hand, the predicted values, which are the output of the network, are appended to the input database and these values are used to predict future values. For instance, if the network is used to predict a value d'(k) from real measurement data d(k-4), d(k-3), d(k-2) and d(k-1), then the next network prediction d'(k+1) is made using inputs data d(k-3), d(k-2), d(k-1) and d'(k). In both cases, the one-lag prediction provides short-term forecasts and the multi-lag prediction provides long-term forecasts. The results of prediction using the one-lag method and the real target value are shown in Fig. 4~Fig. 7 and in Tables 1 and 2. From these curves and data it can be seen that the maximum error of prediction using MLP with 4 inputs MLP with 2 inputs, recurrent network and GRNN network is 0.0484, 0.046, 0.0484 and 0.0456, respectively, and the mean square error (MSE) is 0.34E-03, 0.37E-03, 0.57E-03 and 0.5E-04, respectively. It



(a) MLP network (4-13-1) (b) MLP network (2-13-1)

(c) Recurrent network (4-13-1)

Fig. 8 Contribution factors of inputs

Table 2 Predictor at high amplitude of damping (building 1)

		Prediction values of damping (%)				
Amplitude (mm)	Actual damping (%)	MLP network (4-13-1)	MLP network (2-13-1)	Recurrent network	GRNN (one-lag)	GRNN (multi-lag)
13.4	0.574	0.5368	0.528	0.5256	0.5614	0.5626
13.5	0.531	0.5536	0.5535	0.5269	0.5329	0.5643
13.6	0.488	0.5202	0.5247	0.5267	0.5003	0.5403
13.7	0.466	0.5072	0.4928	0.5227	0.5116	0.5693
13.8	0.495	0.5066	0.4752	0.5143	0.5178	0.5456
13.9	0.549	0.5179	0.503	0.5045	0.53	0.55
14.0	0.515	0.5342	0.5406	0.5074	0.525	0.555
14.1	0.549	0.5006	0.5142	0.5127	0.5419	0.5256

can be also seen that the prediction curve is consistent with the actual damping curve, and the error between these two curves is small.

Comparing the results shown in Fig. 4, Fig. 5, Fig. 8(a), Fig. 8(b), Table 1 and Table 2, which were obtained form the 4 input MLP network and the 2 input MLP network, respectively, it is interesting to observe that the 2 input MLP network obtains a little better results than the 4 input MLP network in the prediction of damping under the same learning rate and momentum coefficient. This illustrates that the 4 input network (4-13-1) is oversized for the given damping data set, the 2 input network is more suitable for the modelling and prediction of damping than the 4 input network. This can be verified by observation of Fig. 8(a) and Fig. 8(b), from which it can be seen that the contribution factor of the nearest input d(k-1) is much larger than the other inputs, such as d(k-2), d(k-3) and d(k-4), and that every output in the series is strongly dependent on the past two values. This result gives us a useful indicator for the modelling of the amplitude

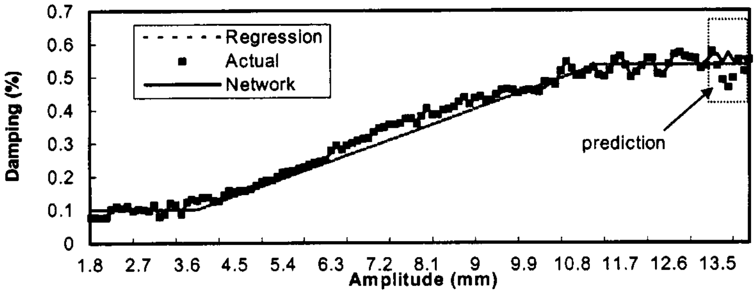


Fig. 9 "Multi-lag" prediction curve of damping using GRNN (4-115-1)

dependent damping in buildings. However, this is not the case for the recurrent network, as shown in Fig. 8(c), in which there is no distinct difference among the 4 inputs. This suggests that different networks should use their corresponding training data structures. In a wide range of application of neural networks to time series, four inputs are adequate. In the training and testing of recurrent network and GRNN, four inputs are also used.

From Fig. 7, and from Tables 1 and 2, it can be seen that the mean square error of the GRNN is 0.5E-04, and the network output curve (one-lag prediction) closely approximates the actual target curve. Comparing with the other networks, it can be concluded that the performance of the GRNN is better than the MLP network and the recurrent network for modelling the damping in buildings, which can be seen from Fig. 4~Fig. 7 and Table 1.

The results obtained by the GRNN for the multi-lag prediction test are presented in Fig. 9 and Table 2. Both the one-lag prediction and multi-lag prediction results for the trained GRNN reflect their ability to predict damping using new data. However, in the multi-lag prediction, the predicted results of damping deviated from the actual values, and the error becomes larger than the one-lag prediction as the prediction process proceeds. The maximum absolute error value reached to 0.1033. Furthermore, from the first step to the last step of the prediction, corresponding to the range of amplitude from 13.4 mm to 14.1 mm, the MSE steeply increases from 0.4E-04 to 0.18E-03. It can be seen from Fig. 9 that the performance of multi-lag prediction is not as good as that of the one-lag prediction.

4. Neural network model of damping for building 2

The building 2 is also a steel building with 68 stories, the structural form is similar with the building 1. Two accelerometers were installed at the top floor to provide the measurement of accelerations. The accelerometers are placed orthogonally along the major axes of this building at one corner. Acceleration responses are continuously acquired and digitized at 20 Hz and were amplified and low pass filtered at 10 Hz before digitization. The spectra of acceleration responses demonstrate that the wind-induced vibration of building is primarily dominated by the first natural frequency (Fang *et al.* 1998b). In order to obtain the damping estimates, the fundamental mode responses were band-passed with a 4096 pole filter before processing the random decrement. The random decrement signature on each graph represents a one-month accumulation of results with minimum 1000 averages. The damping estimates for the two channels were obtained from September 1995 to January 1998.

Table 3 The prediction results of neural network model of damping (building 2)

Amplitude (mm)	Actual damping (%)	Network output (%)	Δ=Actual-Network
19.1	0.505	0.496	0.009
19.2	0.446	0.447	-0.001
19.3	0.421	0.443	-0.021
19.4	0.441	0.43	0.011
19.5	0.495	0.445	0.05
19.6	0.422	0.437	-0.015
19.7	0.493	0.483	0.01
19.8	0.461	0.445	0.016
19.9	0.492	0.504	-0.012
20.0	0.463	0.42	0.043

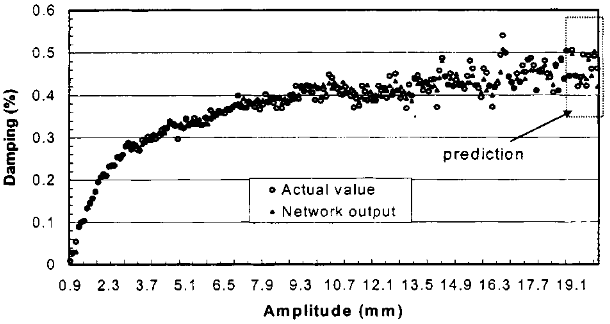


Fig. 10 Actual damping curve measured from building 2 and neural network prediction curve

Based on the results obtained in Section 3, the GRNN is also used to model the damping of the tall building. 4 input units have been used to predict the d(k) using the previous 4 values d(k-1), d(k-2), d(k-3) and d(k-4). The network structure can be determined based on the criteria set by the minimum acceptable training error, the maximum number of iterations and the training data set. The network structure of GRNN was determined as 4-182-1, that is, there are 4 units, 182 units and 1 unit in the input layer, hidden layer and output layer, respectively. There are 192 input vectors in the data set, and from these the first 182 vectors were used as a training set and the remaining 10 vectors were used as a test set. This corresponds to an amplitude range from 0.9 mm to 19.0 mm and from 19.1 mm to 20.0 mm, respectively. The test results of the trained GRNN are listed in Table 3 and showed in Fig. 10. From the test results and curves it can be seen that the maximum absolute error of prediction value is 0.05, the mean absolute error of prediction is less than 0.011. From these results it can be seen that the output of the neural network model of damping is closely consistent with the actual damping value.

5. Prediction of amplitude dependent damping in buildings

As presented above, the neural network models of damping established using part of the damping data measured from one building is capable of predicting the damping values in the high amplitude level which are not included in the training data set. The following part of this paper will investigate the prediction function of the established damping model. Two cases will be investigated: the first case is to predict the damping curve of building 1 using the damping model established based on the measured data from building 2; the second case is to predict the damping curve of building 1 using the model established based on two buildings' damping data (buildings 2 and 3).

5.1. Predicting the damping values for building 1 using the neural network model of damping established based on the measured data from building 2

In order to test the modelling methods and the performance of the established models of amplitude dependent damping in buildings, the damping model established in Section 4 for building 2 was used to predict the variation curve of damping for building 1. In this case, the damping data of building 1 were not included in the training data set and the test data set. The prediction results are shown in Fig. 11 and Table 4. From these results it can be seen that there are relatively large errors between the actual damping data and the prediction values comparing with the errors in Table 2. But from Fig. 11 it can be seen that the variation trend of the damping values with amplitude coincides with the actual measurements of damping, and in the low amplitude plateau and non-linear region the variation trend of prediction curve

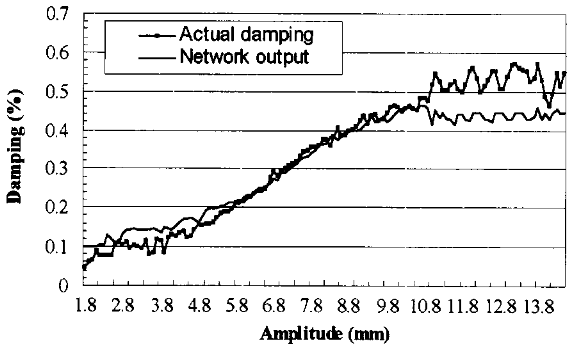


Fig. 11 Prediction curve of damping for building 1 using the damping model established based on building 2

Table 4 Part of the preduction values of damping for building 1 obtained from the application of damping model established based on building 2

Amplitude(mm)	Actual damping(%)	Network output(%)	Error
13.4	0.574	0.459	0.115
13.5	0.531	0.431	0.1
13.6	0.488	0.443	0.045
13.7	0.466	0.429	0.037
13.8	0.495	0.443	0.052
13.9	0.549	0.457	0.092
14	0.515	0.446	0.069
14.1	0.549	0.443	0.106

is coincident closely with the actual damping curve. As for the relatively large errors in the high amplitude plateau, the main reason is that the training data set is quite small (only the damping data of one building).

5.2. Predicting the damping values of building 1 using the damping model established based on building 2 and 3

The neural network model of damping is established based on two buildings : building 2 and building 3. The building 3 is a 30-storey steel building with the similar structural form as the building 1. The variation of damping with amplitude is shown in Fig. 12. The model of damping is established using the same method as described for building 2, but the training

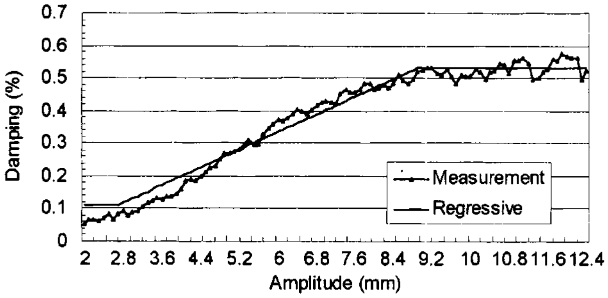


Fig. 12 Damping curve measured from building 3

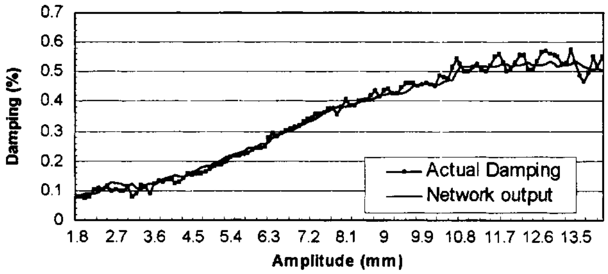


Fig. 13 Prediction curve of damping in building 1 using the damping model established based on the damping data of buildings 2 and 3

Table 5 Part of the prediction values of damping in building 1 obtained from the application of the damping model established based on buildings 2 and 3

Amplitude(mm)	Actual damping(%)	Network output(%)	Error
13.4	0.574	0.524	0.05
13.5	0.531	0.537	-0.006
13.6	0.488	0.525	-0.037
13.7	0.466	0.517	-0.051
13.8	0.495	0.511	-0.016
13.9	0.549	0.506	0.043
14	0.515	0.512	0.003
14.1	0.549	0.506	0.043

damping data are consisted of the building 2 and the building 3. The established damping model is used to predict the damping curve of the building 1, the prediction results are shown in Fig. 13. The errors between the actual values and prediction values are listed in Table 5, the maximum and mean absolute error is 0.103 and 0.015, respectively. From these results it can be seen that the prediction curve is consistent with actual damping curve, and the prediction error is small.

6. Discussion

Comparing the results in 5.1 with those in 5.2 it can be seen that the error in the later case is much smaller than that in the former case. This can be explained from the following two reasons: the first and the most important reason is that neural networks learn from examples, the performance of neural network model of damping strongly depends on the quality and number of examples. The more the examples are, the less the prediction error. Second, the building 3 is similar with the building 1 in the structural form and material, thus their damping curves are similar under the similar external excitation and measurement conditions. When the damping data measured from the building 3 is used to model the damping model, and the established model is used to predict the damping curve for the building 1, the error should be small.

Many factors may affect the damping of buildings, in this paper, the structural form and material of the three buildings are similar, and so there exist comparable conditions which reduce the complexity of establishing the damping model. For a more general or wider problem of damping modelling, the results obtained in this paper are still feasible. And then, there are two approaches may be considered in the future studies : one way is that the damping models are established based on different classes of buildings, each class corresponds to a damping model. In this way, buildings must be classified as different classes according to some conditions such as structural systems, building material, building height and foundation conditions etc. The another way is that a model is established based on damping data measured from many buildings. For this case, the measurement data as well as the structural parameters such as material, structural form and so on are all used as the input parameters of neural networks.

7. Conclusions

A neural network approach has been presented for modelling and predicting the amplitude dependent damping in buildings. Field measurements of damping made by the authors have been used to train and test the neural networks. Remarkable success has been achieved in training the networks to learn the variation curves of damping with the amplitude of vibration, and thereby to make accurate damping predictions, including the prediction of damping values in high amplitude level and damping curve for new building. The results show that neural network is an effective approach to modelling non-linear relationships between damping and vibration amplitude. Additionally in the techniques and methods using neural network to establish damping models, it has been found that the 2 inputs of the time series of damping is good enough to model the field data of damping using an MLP network model. It has been also found that the general regression neural network is more suitable for modelling the damping than the MLP network and the recurrent network.

References

Azoff, E.M. (1994), *Neural Network Time Series Forecasting of Financial Markets*, John Wiley & Sons.

Chakraborty, Kanad, *et al.* (1992), "Forecasting the behaviour of multivariate time series using neural networks", *Neural Networks*, **5**, 961-970.

Davenport, A.G. and Hill Caroll, P. (1986), "Damping in tall buildings : Its variability and treatment in design", *Proc. of ASCE Spring Convention*, Seattle, USA.

Fang, J.Q., Jeary, A.P., Li, Q.S. and Wong, C.K. (1998a), "Random damping in buildings and its AR model", *Journal of Wind Engineering & Industrial Aerodynamics*, **79**, 159-167.

Fang, J.Q., Li, Q.S., Jeary, A.P. and Wong, K.C. (1998b), "Full scale measurements of damping in a 78-storey tall building", *Advances in Structural Engineering*, **2**(1), 41-48.

Gorr, W.L., Nagin, D. and Szczypula, J. (1994), "Comparative study of artificial neural network and statistical models for predicting student grade point averages", *International Journal of Forecasting*, **10**, 17-34.

Harvey, A.C. (1989), *Forecasting, Time Series Models and Kalman Filter*, U.K. : Cambridge University Press.

Haviland, R.A. (1976), "A study of the uncertainties in the fundamental translational periods and damping values for real buildings", *MIT Research Reports* No 56, Pub. No R76-12, Department of Civil Engineering, Cambridge, Mass.

Hill, T., Marquez, L., O'Connor, M. and Remus, W. (1994), "Artificial neural networks models for forecasting and decision-making", *International Journal of Forecasting*, **10**, 5-15.

Hornik, K., Stinchcombe, M., and White, H. (1989), "Multilayer feedforward networks are universal approximators", *Neural Networks*, **2**(5), 359-366.

Jeary, A.P. (1986), "Damping in tall building – A mechanism and a predictor", *Earthquake Engineering and Structural Dynamics*, **14**, 733-750.

Kareem, A. and Gurley, K. (1996), "Damping in structures : Its evaluation and treatment of uncertainty", *Journal of Winding Engineering and Industrial Aerodynamics*, **59**, 131-158.

Li, Q.S., Fang, J.Q., Jeary, A.P., Wong, C.K. (1996a), "Full scale measurements of wind effects on a tall building in Hong Kong, Part I : Probability Distributions", *Structural Dynamics Research Centre Report, BC-SDRC/96/09*, Dept. of Building & Construction, City University of Hong Kong.

Li, Q.S., Fang, J.Q., Jeary, A.P., Wong, C.K. (1996b), "Full scale measurements of wind effects on a tall building in Hong Kong, Part II : Spectral Analysis", *Structural Dynamics Research Centre Report, BC-SDRC/96/10*, Dept. of Building & Construction, City University of Hong Kong.

Pham, D.T., Liu, X. (1995), "Neural networks for identification, prediction and control", Springer.

Refenes, A.N., Azema-Barac, M., Chen, L., and Karoussos, S.A. (1993), "Currency exchange rate prediction and neural network design strategies", *Neural Computing and Applications*, **1**(1), 46-58.

Rumelhart, D. and McClelland, J. (1986), "Parallel distributed processing", MIT Press, Cambridge.

Specht, D. (1990), "Probabilistic neural network", *Neural Networks*, **3**, 109-118.

Specht, D. (1991), "A general regression neural network", *IEEE Trans. on Neural Networks*, **2**(6), 568-576.

Tamura, Y., Yamada, M. and Yokota, H. (1994), "Estimation of structural damping of buildings", *ASCE Structures Congress and the IASS International Symposium*, Atlanta, Georgia, April 24-28, 1994.

Tamura, Y., Suganuma, S. (1996), "Evaluation of amplitude-dependent damping and natural frequency of buildings during strong winds", *Journal of Winding Engineering and Industrial Aerodynamics*, **59**, 115-130.

Tiao, G.C., and Tsay, R.S. (1989), "Model specification in multivariate time series", *Journal of the Royal Statistical Society*, **B51**, 157-213.

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