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NEURAL NETWORK TOOL FOR DETERMINATION OF THE FLOOR ECCENTRICITY OF EXISTING BUILDINGS

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ABSTRACT

The effect of torsional and lateral coupling responses of asymmetric buildings is an important aspect in seismic design of buildings. It is common in practice to include the effects of torsion by multiplying floor shear force to the design eccentricity. Often, in cases of strengthening of existing buildings, especially ancient constructions where information on the main structure is lacking or uncertain, the estimate of the total eccentricity is very difficult to evaluate accurately. The aim of this paper is to develop a procedure based on artificial neural networks to locate the actual mass and stiffness centres of a floor using the dynamic responses of two points at its edges. This will enable the determination of the total eccentricity of the floor for seismic calculation and can eventually be used to evaluate the accidental eccentricity for structurally well-defined building.

Moreover, the effect of uneven yielding of structural elements has been investigated and the variation of the eccentricity as well as the apparent eccentricity has been predicted. This is particularly useful for investigating the behaviour of instrumented buildings subjected to real earthquakes in order to assess the effect of the variation of the eccentricity during severe ground motion.

INTRODUCTION

The effect of torsional coupling is an important factor which characterizes the overall seismic behavior of buildings. The seismic codes introduce two torsional moments due to a calculated and accidental eccentricities. In most of these codes, the accidental eccentricity is taken equal to 5% or 10% of the dimension in plan perpendicular to the axis of the seismic excitation for all types of structures. The origin of the accidental eccentricity is related to the uncertainties and errors in evaluating the geometrical and mechanical characteristics of the structural elements, the random rupture of the nonstructural elements, or space variability of the permanents loads, as well as any unfavorable distribution of the live loads or even the torsional vibrations induced by the rotational movement of the foundations. These factors led to a situation where it is almost impossible to evaluate explicitly with a good precision the accidental eccentricity for all types of structures. In this context, several studies have been conducted using different approaches to assess the effect of torsion induced by accidental eccentricity. The torsion induced in nominally symmetric structures due to unexpected variation in the strength of elasto-plastic lateral loads resisting elements have been considered in order to investigate the adequacy of provisions for the accidental eccentricity of the National Building Code of Canada (Pekau and Guimond, 1988). The effects of the rotational component of the earthquake on accidental eccentricity were evaluated in a study that attempted to separate this component relative to other factors and showed that the proposed 0.05b value is not sufficient for buildings design conditions with

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short torsion periods (Shakib and Tohidi, 2002). Another study presented a procedure for the determination of the forces induced by the torsion caused by the accidental eccentricity from records of instrumented buildings in a real seismic loading. The results obtained in this study showed that accidental torsion specified by the UBC is in good agreement with the torsional component of the recorded movements (De la Llera and Chopra, 1992). Based on stochastic analysis of soil-structure interaction of asymmetric buildings, a simple equation for the design eccentricity has been proposed (Shakib, 2004). A different approach based on artificial neural networks (ANN) method was used for the first time to estimate the level of accidental eccentricity in a nominally symmetric building (Bourahla and Boukhamacha, 2005). This method is extended to evaluate the eccentricity level, from only output data in the time domain, when the structure undergoes large nonlinear deformation (Bourahla et al., 2006). In This same trend, another procedure using the same method (ANN) coupled with Monte Carlo simulations has shown its effectiveness in determining the accidental eccentricity of single story structures (Badaoui et al., 2012). The objective of this paper is to locate the mass centre and stiffness centre and therefore quantify the accidental eccentricity of buildings from a dynamic response using an ELMAN type neural network. The second objective is the use of this model for the evaluation of the eccentricity variation from a non-linear dynamic response.

PRINCIPLE AND METHODOLOGY

The main idea of this work is to determine the eccentricity caused by uneven distribution of structural stiffness and mass knowing the displacement dynamic responses of two points situated at the flexible and stiff edges of a floor level.

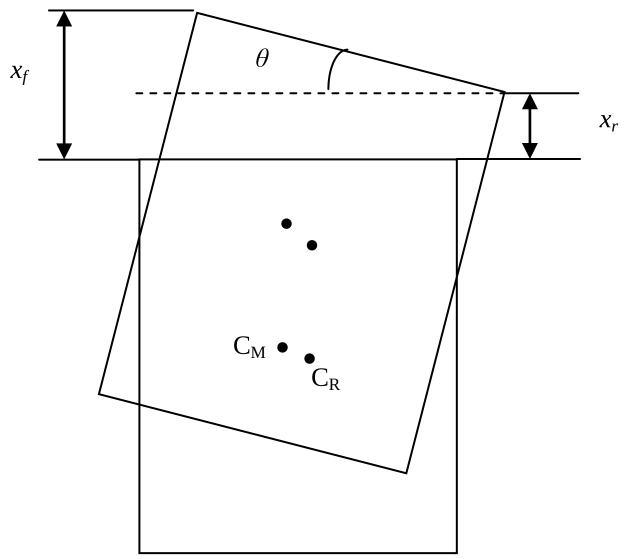

Figure 1. Asymmetric story building system

If we consider an asymmetric floor building represented in Fig.1. Under a seismic excitation and at any time, the rotational displacement of a floor can be expressed as:

$$\theta = \frac{x_f - x_r}{b} \qquad (1)$$

Where θ is the floor rotation time history, x_r and x_f are the displacement time histories of two points on the rigid and flexible side of the floor, respectively and b is the building dimension perpendicular to the direction of the excitation.

Similarly at the mass and stiffness centres (Fig.2.), the rotational displacement can be written as follows:

$$\theta = \frac{x_{CM} - x_{CR}}{e} \qquad (2)$$

From Eq.(1). and Eq.(2). the expression of the eccentricity can be obtained as follows:

$$e = \frac{X_{CM} - X_{CR}}{X_f - X_r} \times b \qquad (3)$$

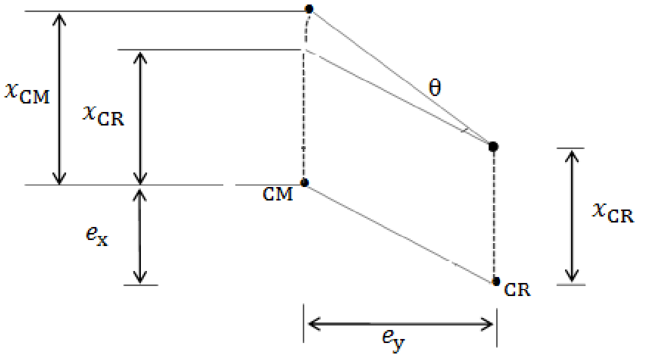

Figure 2. The displacement of mass and stiffness centres in a coupled response

Where, X_{CM} is the displacement of the mass centre along x axis and X_{CR} is the displacement of the stiffness centre along x axis.
To determine the value of the eccentricity e from the above formula, in addition to the x_f and x_r, the displacement of the mass centre and the displacement of the stiffness centre must be known.
x_f and x_r are structural responses that can be measured directly on a floor of building using ambient vibration tests or actual seismic excitations in instrumented buildings. The displacement of the mass and stiffness centres will be determined using the method of artificial neural networks.

NEURAL NETWORKS DESIGN

Based on the literature and particularly the previous work (Bourahla and Boukhamacha, 2005) and (Badaoui et al., 2012), it has been concluded that among the many different types of ANN, the feedforward, multilayered, supervised neural network with the error backpropagation algorithm, the so-called backpropagation (BP) network is most adopted for this application.
Two models of neural networks were built (Figs.3 and 4), one for the prediction of the mass centre displacement, and the second to predict the stiffness centre displacement. For an accurate prediction of the two displacements, we find that the Elman neural network is most appropriate for this work. It has tangential sigmoid transfer functions in the neurons of its hidden (recurrent) layer, and pure linear transfer function in the neurons of its output layer. This combination is special in that two-layer networks with these transfer functions can approximate any function with arbitrary accuracy. The number of nodes in the hidden layer, however, is determined by experiments. It has been found that 21 and 17 neurons for each hidden layers were sufficient for the network to detect the mass centre and the stiffness centre respectively.

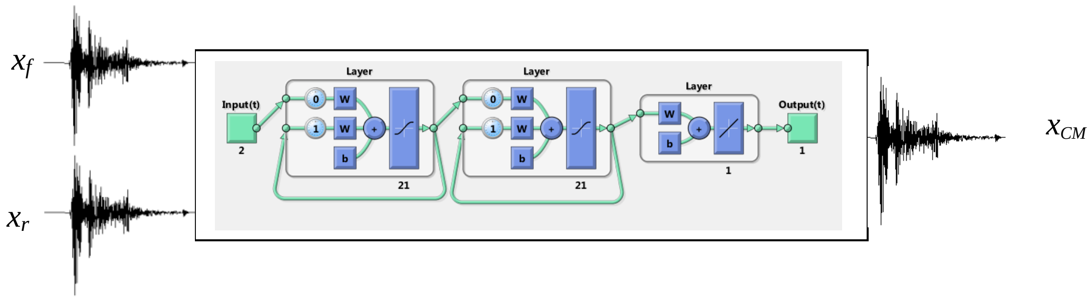

Figure 3. Neural network model to predict the response of the mass centre

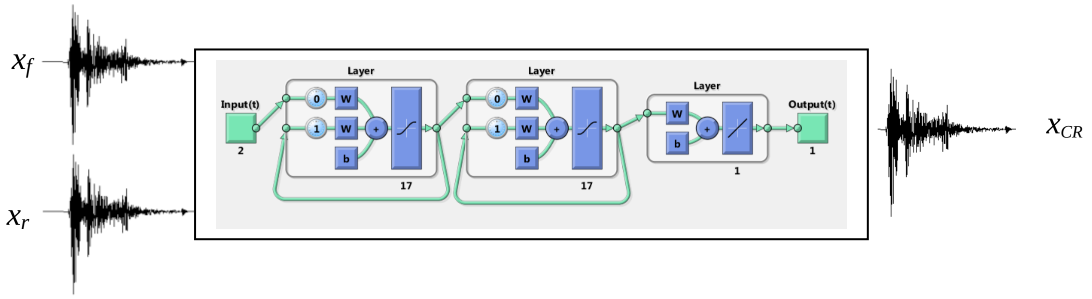

Figure 4. Neural network model to predict the response of the Rigidity (stiffness) centre

DATABASES

The database is divided into two parts, one for the training and another one for the test and validation. For this purpose, a numerical finite element model is used to create the training databases for the two networks. It is a single-story model composed of a 6m x 6m floor resting on four columns. An eccentricity is created by assigning different lumped masses at the two sides of the floor. The model is subjected to an acceleration time history at the base. The resulting displacement responses at the ends of the flexible and rigid sides are used as inputs to the two ANN models. The displacement time history of the mass centre is used as a target (output) for the ANN model that predicts the displacement of the mass centre and the displacement time history of the stiffness centre is used as a target (output) for the ANN model that predicts the displacement of the stiffness centre.

In our networks, the two inputs vectors and the output vector are the discrete signals that contain 5000 points everyone. At each time (point) we have information (displacement of rigid and flexible sides as INPUT and the displacement of the mass or stiffness centre as OUTPUT) which helps us in training networks.

The main problem is to find the minimum size of input and output vectors that ensure the capacity of generalization (extrapolation) of the network. An empirical rule is to have a training corpus 3 times the number of neurons in the network. (Forty neurons would therefore require 120 entries).

We noticed that 100 to 200 points are more than enough for training the networks; it is even possible to go down to 70 points. The only condition is that the segment used should contain varying amplitudes to cover the entire range of interest.

NEURAL NETWORK TRAINING, TESTING AND VALIDATION

The training is a development phase of a neural network during which behaviour of the network is changed until obtaining the desired behaviour. For this particular application where accurate training is required, several test runs were made for different training algorithms available in MATLAB (Beale et al., 2012), and found that Levenberg-Marquardt algorithm has the fastest convergence. The performance function that is used for training the neural network is the mean sum of squares of the network errors (MSE). To avoid an over training of the network, the method of early stopping is used. The entire input sequence is presented to the network, and its outputs are calculated and compared to the target sequence to produce an error order. For each time step the error is backpropagated to find gradients of errors for each weight and bias. This gradient is used to update the weights with the backpropagation training function.

Effectiveness of the proposed neural network model is evaluated on the basis of the capability of the network on simulating accurately the correlation between input and target signals. After the neural network is fully trained for a given set of input-output pairs, it is tested using a signal that does not belong to the training set. For testing the effectiveness of the two neural network models, a database has been built by varying several parameters in numerical finite element models (eccentricity, excitation, structure configuration, positions of the mass and stiffness centres, the number of storeys). 11 numerical models are used for test and validation of the neural networks.

In order to verify the quality of the network predictions, the entire set of data used for validation and testing has been passed through the network to perform linear regression between the network outputs Y and the corresponding targets T.
For networks validation results of mass and stiffness centres displacements prediction (Figs.5; 6; 7 and 8), the fitting lines are practically superposed with the diagonal, and the correlation coefficient is very close to unity, which means that the neural network gives very accurate predictions of the displacements of the mass and the stiffness centres.

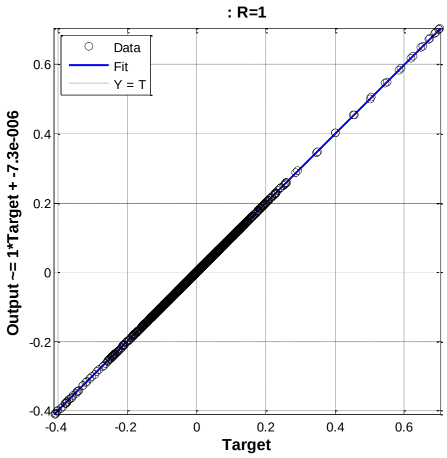

Figure 5. The linear regression between X_{CM} output signal and the model 4 target signal

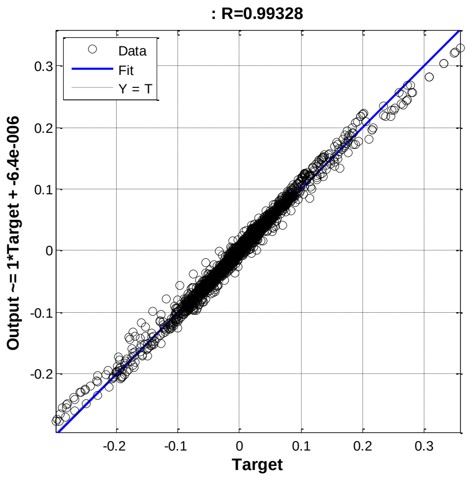

Figure 6. The linear regression between X_{CM} output signal and the model 9 target signal

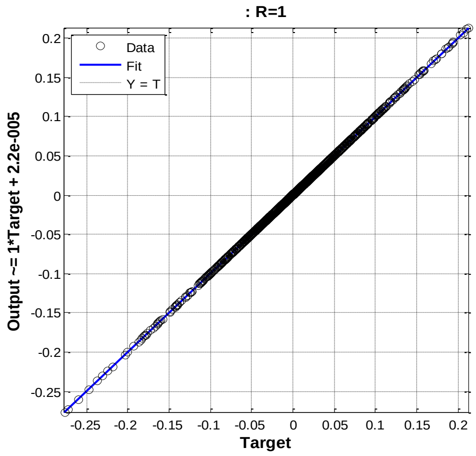

Figure 7. The linear regression between X_{CR} output signal and the model 2 target signal

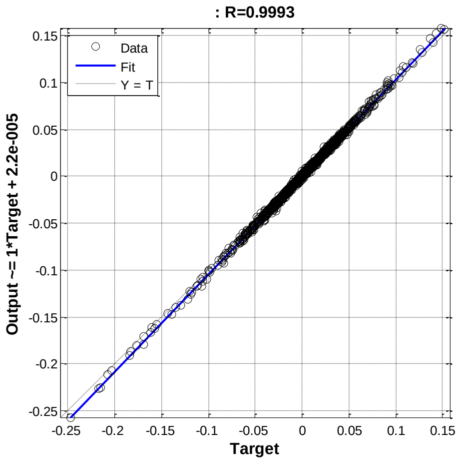

Figure 8. The linear regression between XCR output signal and the model 1 target signal

THE ANN MODEL PERFORMANCE AND ECCENTRICITY PREDICTION

Based on test and validation results, it appears that when the position of mass or stiffness centre in the simulation is closer to the position of mass or stiffness centre in the training, the network accuracy is better. However, the error increases when the position of mass or stiffness centre is very close to the middle of the floor in training, and away from the middle in the simulation. However, when the position of mass or stiffness centre is away from the middle of the floor in training and near the middle in the simulation, the error is less.
It should be noted however that the accuracy of the model is almost insensitive to the number of storeys.

As a result, for a better accuracy when information is available it is proposed to first calculate the ratios of mass and stiffness centre positions P_{CM} and P_{CR} as follows:

$$P_{CM} = \frac{\text{The position of CM - }\frac{b}{2}}{b} \times 100 \qquad (4)$$

$$P_{CR} = \frac{\text{The position of CR - }\frac{b}{2}}{b} \times 100 \qquad (5)$$

Than develop a finite element model for the training phase which has the same position ratios of the mass and stiffness centres. In such conditions, the predicted eccentricity is more accurate.
Table 1 summarises the simulation results by ANN of 11 models where we varied different parameters like: the eccentricity, the excitation, the model dimensions, the stiffness centre position and the number of levels.

The real eccentricities of numerical models used for training and validation, with the error on the eccentricity and the ratio e_e calculated by the formula (6) are also presented in the table1.

$$e_e = \frac{\text{Absolute error}}{b} \qquad (6)$$

Table 1. Eccentricities calculated by ANN

models	real eccentricity (cm)	Eccentricity calculated by ANN (cm)	The absolute error about the eccentricity (cm)	The relative error on the eccentricity (%)	b (m)	e_e (%)
1	24.35	19.62	4.73	19.42	4	1.18
2	75.19	66.53	8.66	11.52	5	1.73
3	19.42	24.82	5.4	27.81	4	1.35
4	0	0	0	0	4	0
5	79.73	79.72	0.01	0.01	6	1.67x10-3
6	83.21	92.88	9.67	11.62	7	1.38
7	16.91	19.35	2.44	14.43	5	0.49
8	16.26	18.97	2.71	16.66	4	0.68
9 level 1	43.23	34.56	8.67	20.05	7	1.24
9level 2	43.23	35.38	7.85	18.16	7	1.12
9level 3	83.21	92.28	9.07	10.9	7	1.29
10 level 1	16.42	17.61	1.19	7.25	4	0.30
10 level 2	59.98	60.63	0.65	1.08	4	0.16
11	112.8	100.2	12.6	11.17	4	3.15

According to this table we note that the NN model is able to predict any eccentricity with an error of 1.5% b.
If more precision is sought, the database from the finite element model for the training phase should have the same position ratios of the mass and stiffness centres (P_{CM}, P_{CR}) calculated by the formulas (4) and (5).

PREDICTION OF THE ECCENTRICITY VARIATION CAUSED BY AN UNEVEN YIELDING

The nonlinearity is among the different sources of accidental eccentricity, for this reason, the variation of the eccentricity is evaluated from only output data in the time domain, when the structure undergoes large nonlinear deformation. The equivalent structural eccentricity depends on the amount of the difference in the strength level between the lateral resisting elements in the flexible and the rigid side of the structure. It depends also on the stress distribution in the elements of the structure and their sequence of yielding. Hence, the equivalent structural eccentricity varies with time in accordance with the intensity variation of the ground acceleration time history. For these reasons, the determination of the eccentricity variation due to non-uniform structural yielding is very difficult; there are no means of quantifying explicitly this variation of the eccentricity.

The advantage of the neural network models used in this study is that the prediction is based on the differences between the displacements at the edges regardless of the origin that causes it. Therefore the training based on a database from a linear finite element model will remains valid for nonlinear case.

In order to test the performance of the model for a nonlinear case, a numerical finite element model initially symmetric with non-uniform strength distribution is elaborated (Fig.9.). Four Links elements with Wen hysteresis model have been placed between the columns and the floor with two different Yields. The model is subjected to an acceleration ground motion that causes yielding on the elements of one side of the model leading to a temporary unbalanced stiffness during the strongest part of the excitation which provokes the rotational component of the floor displacement that can be detected by the ANN model (Figs.3 and 4).

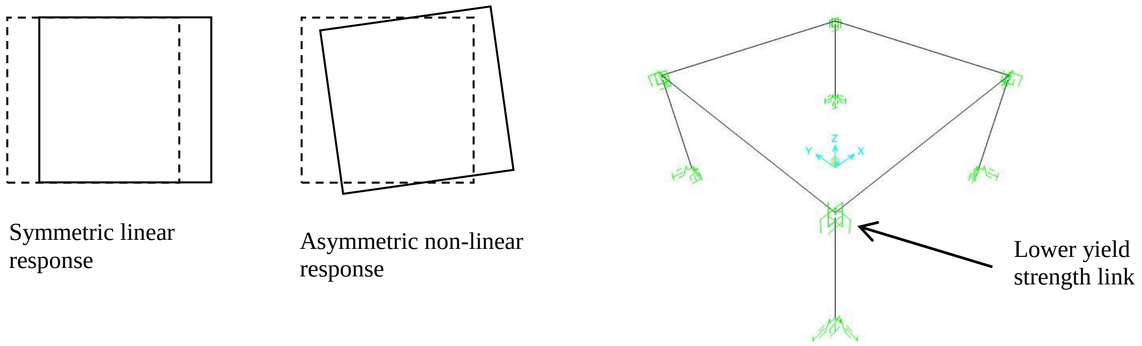

Figure 9. Nonlinear finite element model

The displacements of two points at the edges of the floor are used as input into the two neural networks to predict the responses of the mass and stiffness centres. Before the determination of the eccentricity, the effectiveness of the proposed neural network model is evaluated on the basis of the capability of the networks in simulating accurately the correlation between input and target signals. As an illustration, a segment of the displacement time history predicted by the neural network is plotted simultaneously with the target signal in Fig.10. The neural network performs very well and simulates closely the target signal even during the nonlinear response.

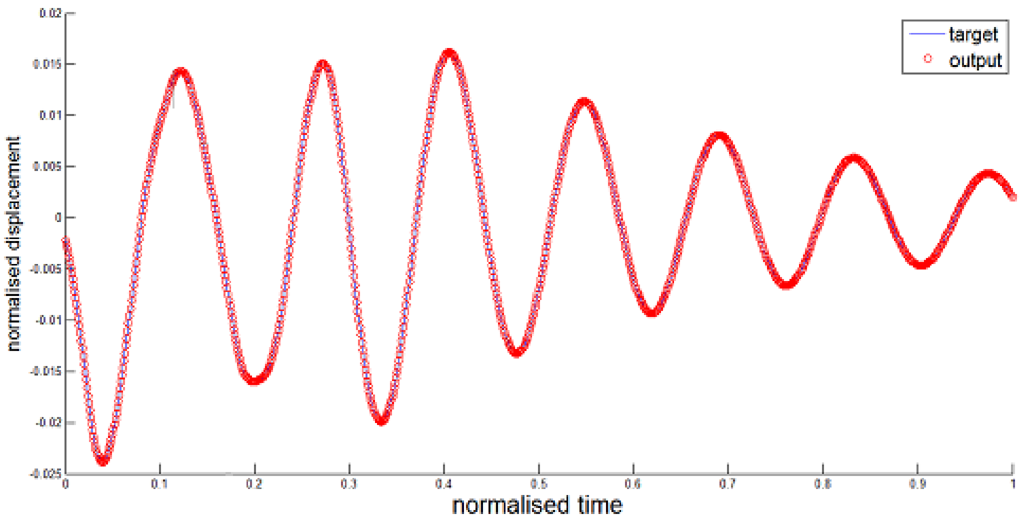

Figure 10. Neural network output and target signals

The predicted instantaneous apparent eccentricity computed from nonlinear dynamic response is shown on Fig.11.

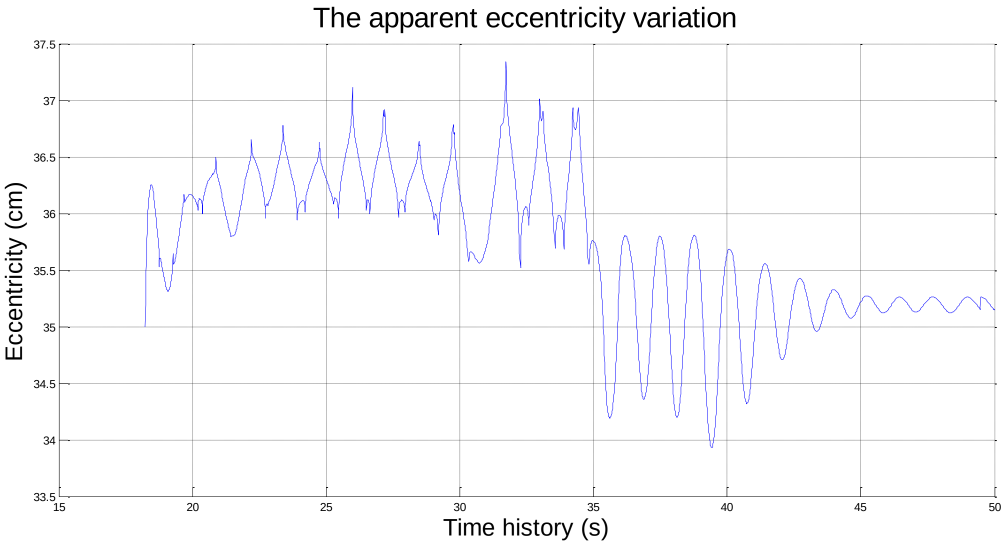

Figure 11. The apparent eccentricity variation

During the elastic response the predicted eccentricity is equal to zero. When the model undergoes nonlinear excursion a rotational component is initiated because of yielding that occurs in weaker elements. In this case the apparent eccentricity reaches 36 cm as shown in Fig. 11. which represents 5.14% of b. As long as the displacements are coupled the NN detects an apparent eccentricity which will remain until the rotational component is dissipated.

CONCLUSIONS

Torsional coupling is a major issue in the design of new buildings or strengthening of existing structures. The evaluation of the eccentricity in the design phase is relatively easy. However, in ancient existing buildings where, in many cases structural information are lacking or incomplete, the evaluation of the eccentricity is a difficult task. In this paper, a procedure for quantifying the eccentricity including the accidental from a dynamic response of a multi-storey structure has been proposed. This procedure uses the technique of neural networks to predict the actual eccentricity of the building and subsequently the accidental eccentricity. It requires only two displacements records on two extreme sides of the building. The latter are used as an input vector to the neural network in order to predict the displacements of mass and stiffness centres. Knowing these displacements, it became possible to calculate the actual eccentricity of the building and subsequently the accidental eccentricity. A sensitivity study showed that the accuracy of the neural network model is better when the position of mass or stiffness centre during training is close to the position of mass or stiffness centre in the simulation, and that the accuracy of ANN model does not decrease for multi-storey buildings.
Symmetric buildings with uneven strength distribution may undergo significant torsional coupling during nonlinear response. This issue has been addressed and the NN model has been used to detect the apparent eccentricity during the nonlinear response.
In practice this technique can be used to investigate the behaviour of instrumented buildings subjected to real earthquakes in order to assess the effect of the eccentricity during severe ground motion or the ambient vibration tests for both symmetrical and unsymmetrical structures. This will serve as a tool in seismic vulnerability studies of existing buildings. This procedure can also be applied to improve the empirical formula of the accidental eccentricity recommended by the codes.

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