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Research Article

Fuzzified Data Based Neural Network Modeling for Health Assessment of Multistorey Shear Buildings

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The present study intends to propose identification methodologies for multistorey shear buildings using the powerful technique of Artificial Neural Network (ANN) models which can handle fuzzified data. Identification with crisp data is known, and also neural network method has already been used by various researchers for this case. Here, the input and output data may be in fuzzified form. This is because in general we may not get the corresponding input and output values exactly (in crisp form), but we have only the uncertain information of the data. This uncertain data is assumed in terms of fuzzy number, and the corresponding problem of system identification is investigated.

1. Introduction

System identification methods in structural dynamics, in general, solve inverse vibration problems to identify properties of a structure from measured data. The rapid progress in the field of computer science and computational mathematics during recent decades has led to an increasing use of process computers and models to analyze, supervise, and control technical processes. The use of computers and efficient mathematical tools allows identification of the process dynamics by evaluating the input and output signals of the system. The result of such a process identification is usually a mathematical model by which the dynamic behaviour can be estimated or predicted. The system identification problem has been nicely explained in a recent paper [1]. The same statements from [1] are reproduced below for the benefit of the readers.

The study of structures dynamic behaviour may be categorized into two distinct activities: analytical and/or numerical modelling (e.g., finite element models) and vibration tests (e.g., experimental modal models). Due to different limitations and assumptions, each approach has its advantages and shortcomings. Therefore, in order to determine the dynamic properties of the structure, reconciliation processes including model correlation and/or model updating should be performed. Model updating can be defined as the adjustment of an existing analytical/numerical model in the light of measured vibration test. After adjustment, the updated model is expected to represent the dynamic behaviour of the structure more accurately as proposed by Friswell et al. [2]. With the recent advances in computing technology for data acquisition, signal processing, and analysis, the parameters of structural models may be updated from the measured responses under excitation of the structure. This procedure is achieved using system identification techniques as an inverse problem. The inverse problem may be defined as determination of the internal structure of a physical system from the system's measured behaviour, or estimation of an unknown input that gives rise to a measured output signal according to Tanaka and Bui [3].

Comprehensive literature surveys have been provided on the subject of model updating of the structural systems by Alvin et al. [4], and Time series methods for fault detection and identification in vibrating structures were presented by Fassois and Sakellariou [5]. Shear buildings are among the most widely studied structural systems. Previous works on model updating of shear buildings rely mostly on using modal parameter identification and physical or structural parameter

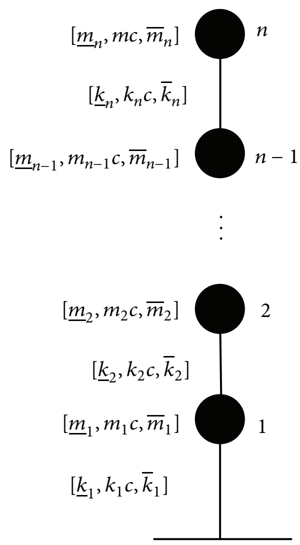

Figure 1: Multistorey shear structure with n-levels having fuzzy structural parameters.

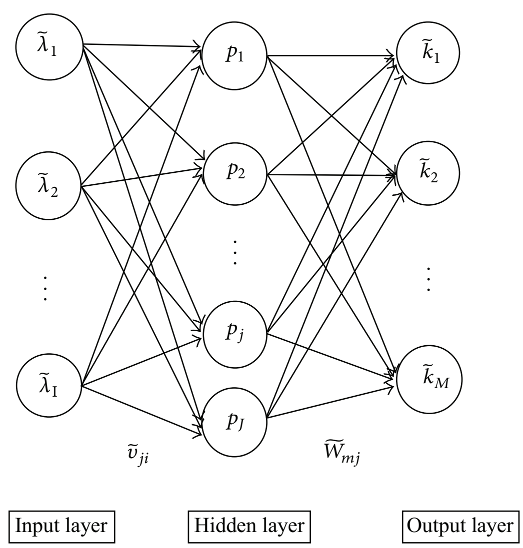

Figure 2: Layered feed-forward fuzzy neural network.

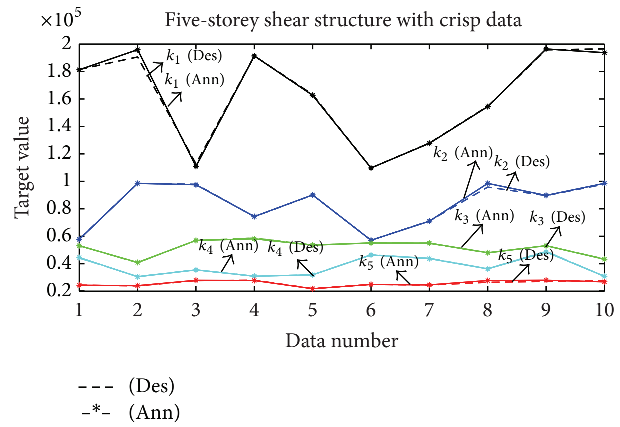

Figure 3: Comparison between the desired and the ANN values of $\tilde{K}$ for a single-storey shear structure.

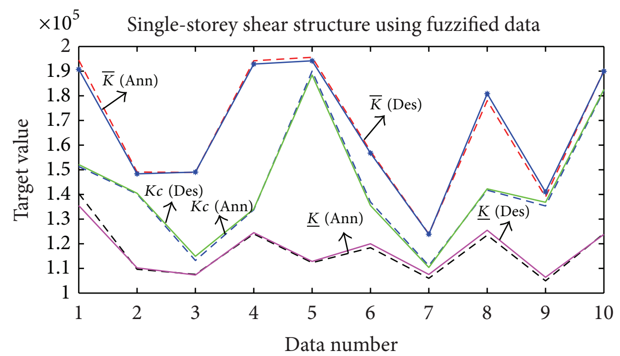

Figure 4: Comparison between the desired and the ANN values of $\tilde{K}$ for a single-storey shear structure.

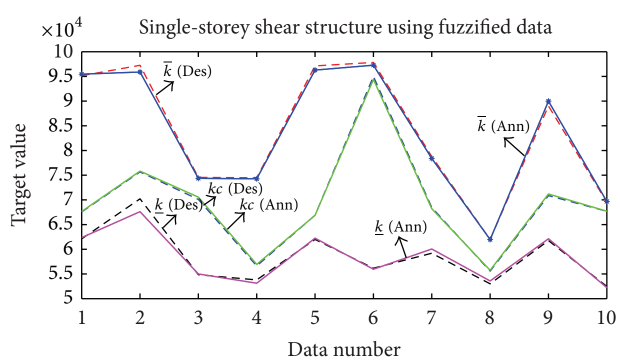

Figure 5: Comparison between the desired and the ANN values of $\tilde{K}$ for a single-storey shear.

identification to drive the corresponding update procedures. As regards the publications, Marsi et al. [6] gave various methodologies for different types of problems in system identification. Various techniques for improving structural dynamic models were reviewed in a review paper by Ibanez [7], and studies made by Datta et al. [8] related to system identification of buildings done until that date were also surveyed. Some of the related publications may be mentioned as those of Loh and Tou [9] and Yuan et al. [10].

It is known that, the systems which may be modeled as linear, the identification problem often turns in to a non-linear optimization problem. This requires an intelligent iterative scheme to have the required solution. There exists various online and offline methods, namely, the Gauss-Newton, Kalman filtering and probabilistic methods such as maximum likelihood estimation, and so forth. However, the identification problem for a large number of parameters, following two basic difficulties are faced often:

(i) objective function surface may have multiple maxima and minima, and the convergence to the correct parameters is possible only if the initial guess is considered as close to the parameters to be identified;

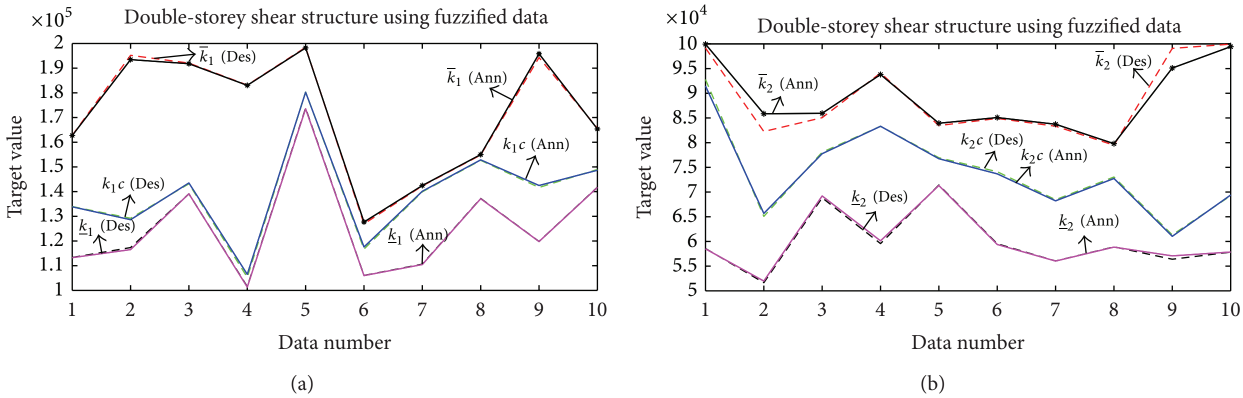

Figure 6: (a) Comparison between the desired and the ANN values of $\tilde{k}_1$ for a double-storey shear structure. (b) Comparison between the desired and the ANN values of $\tilde{k}_2$ for a double-storey shear structure.

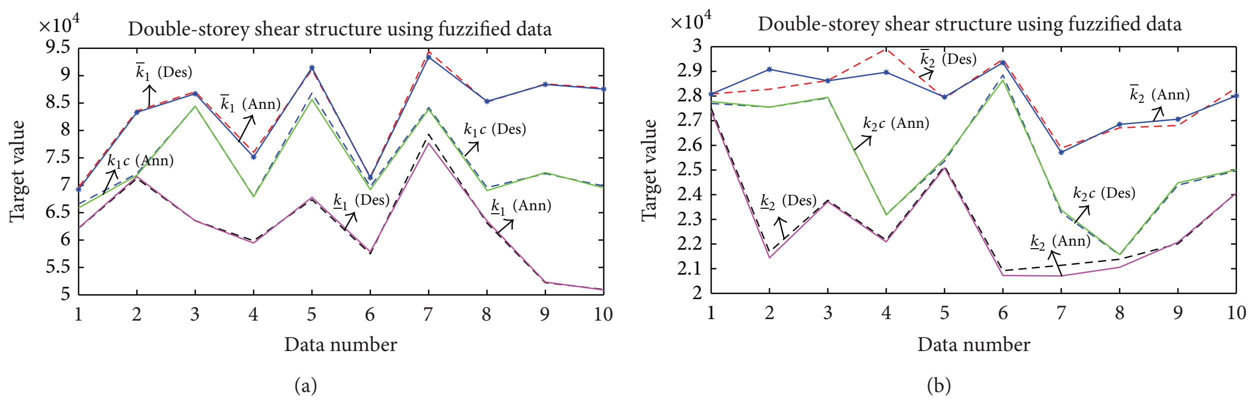

Figure 7: (a) Comparison between the desired and the ANN values of $\tilde{k}_1$ for a double-storey shear structure. (b) Comparison between the desired and the ANN values of $\tilde{k}_2$ for a double-storey shear structure.

(ii) inverse problem in general gives nonunique parameter estimates.

To overcome these difficulties, researchers have developed various identification methodologies for the said problem by using powerful technique of Artificial Neural Network (ANN). Chen [11] presented a neural network based method for determining the modal parameters of structures from field measurement. Using the observed dynamic responses, he trained the neural network based on back-propagation technique. He then directly identified the modal parameters of the structure using the weight matrices of the neural network. In particular, Huang et al. [12] presented a novel procedure for identifying the dynamic characteristics of a building using a back-propagation neural network technique. Another novel neural network based approach has been presented by Kao and Hung [13] for detecting structural damage. A decentralized stiffness identification method with neural networks for a multidegree of freedom structure has been developed by Wu et al. [14]. Localized damage detection and parametric identification method with direct use of earthquake responses for large-scale infrastructures has also been proposed by Xu et al. [15]. A neural network based strategy by Xu et al. [16] was developed for direct identification of structural parameters from the time domain dynamic responses of an object structure without anyeigen value analysis.

System identification on the other hand tries to identify structural matrices of mass, damping and stiffness directly. Among various methodologies in this regard Chakraverty [17], Perry et al. [18], Wang [19], Yoshitomi and Takewaki [20], and Lu and Tu [21] developed different techniques to handle the system identification problems. Yuan et al. [10] developed a methodology that identifies the mass and stiffness matrices of a shear building from the first two orders of structural mode measurement. Koh et al. [22] proposed several Ga-based substructural identification methods, which work by solving parts of the structure at a time to improve the convergence of mass and stiffness estimates particularly for large systems. Chakraverty [17] proposed procedures to refine the methods of Yuan et al. [10] to identify the structural mass and stiffness matrices of shear buildings from the modal test data. The refinement was obtained using Holzer criteria. Tang et al. [23] utilized a differential evolution (DE) strategy for parameter estimation of the structural systems with limited output data, noise polluted signals, and no prior

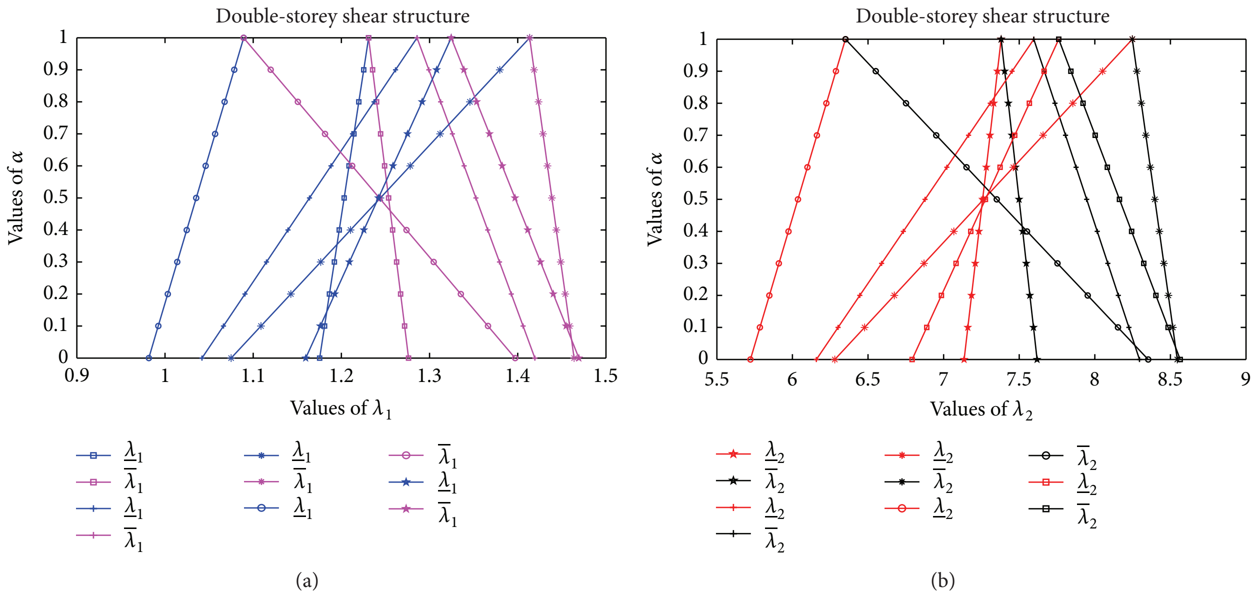

Figure 8: (a) Comparison of $\underline{\lambda_1}$ and $\overline{\lambda_1}$ with respect to α. (b) Comparison of $\underline{\lambda_2}$ and $\overline{\lambda_2}$ with respect to α.

knowledge of mass, damping, or stiffness matrices. Recent works on model updating of multistory shear buildings for simultaneous identification of mass, stiffness, and damping matrices using two different soft-computing methods have been developed by Khanmirza et al. [1]. It may be seen from above that Artificial Neural Networks (ANNs) provide a fundamentally different approach to system identification. They have been successfully applied for identification and control of dynamics systems in various fields of engineering because of excellent learning capacity and high tolerance to partially inaccurate data.

It is revealed from the above literature review that various authors developed different identification methodologies using ANN. They supposed that the data obtained are in exact or crisp form. But in actual practice the experimental data obtained from equipments are with errors that may be due to human or equipment error, thereby giving uncertain form of the data. Although one may also use probabilistic methods to handle such problems. Then, the probabilistic method requires huge quantity of data which may not be easy or feasible. Thus in this paper, a minimum number of data are taken in fuzzified form to have the essence of the uncertainty. Accordingly, in this paper, identification methodologies for multistorey shear buildings have been proposed using the powerful technique of Artificial Neural Network (ANN) models which can handle fuzzified data. It is already mentioned that identification with crisp data is known and also neural network method has already been used by various researchers for this case. Here, the input and output data may be in fuzzified form. This is because in general we may not get the corresponding input and output values exactly (in crisp form), but we have only the uncertain information of the data. This uncertain data has been assumed to be in terms of fuzzy numbers.

In this paper, the initial design parameters, namely, stiffness and mass and so the frequency of the said problem is known. But after a large span of time, the structure may be subjected to various manmade and natural calamities. Then, the engineers want to know the present health of the structure by system identification methods. It is assumed that only the stiffness is changed and the mass remains the same. As such equipments are available to get the present values of the frequencies and using these one may get the present parameter values by ANN. But while doing the experiment, one may not get the exact values of the parameters. But we may get those values as uncertain, namely, in fuzzy form. So if sensors are placed to capture the frequency of the floors in fuzzy (uncertain) form, then those may be fed into the proposed new ANN model to get the present stiffness parameters in fuzzified form. In order to train the new ANN model, set of data are generated numerically beforehand. As such, converged ANN model gives the present stiffness parameter values in interval form for each floor. Thus, one may predict the health of the uncertain structure. Corresponding example problems have been solved, and related results are reported to show the reliability and powerfulness of the model.

2. Analysis and Modelling

System identification refers to the branch of numerical analysis which uses the experimental input and output data to develop mathematical models of systems which finally identify the parameters. The floor masses for this methodology are assumed to be $[\underline{m_1}, m_1c, \overline{m_1}]$, $[\underline{m_2}, m_2c, \overline{m_2}], \ldots, [\underline{m_n}, m_nc, \overline{m_n}]$, and the stiffness $[\underline{k_1}, k_1c, \overline{k_1}]$, $[\underline{k_2}, k_2c, \overline{k_2}], \ldots, [\underline{k_n}, k_nc, \overline{k_n}]$ are the structural parameters which are to be identified. It may be seen that all the mass and stiffness parameters are taken in fuzzy form. As such here for each mass m_i, we have $\underline{m_i}$ as the left value, $m_i c$ as the centre value, and $\overline{m_i}$ as the right value. Similarly for the stiffness parameter for each mass k_i, we have $\underline{k_i}$ as the left value, $k_i c$ as the centre value, and $\overline{k_i}$ as the right value. The n-storey shear structure is shown in Figure 1. Corresponding dynamic equation of motion for n-storey (supposed as n degrees of freedom) shear structure without damping may be written as

$$\{\widetilde{M}\}\{\ddot{\widetilde{X}}\}+\{\widetilde{K}\}\{\widetilde{X}\}=\{\widetilde{0}\}, \tag{1}$$

where $\{\ddot{\widetilde{x}}\}=\{\underline{\ddot{x}},\ddot{x}c,\overline{\ddot{x}}\}$, $\{\widetilde{x}\}=[\underline{x},xc,\overline{x}]$.

$\{\widetilde{M}\}=[\underline{M},Mc,\overline{M}]$ is $n\times n$ mass matrix of the structure and is given by

$$\{\widetilde{M}\}=\begin{bmatrix}[\underline{m_1},m_1c,\overline{m_1}] & 0 & \cdots & \cdots & 0\\ 0 & [\underline{m_2},m_2c,\overline{m_2}] & 0 & \cdots & 0\\ \cdots & \cdots & \cdots & \cdots & \cdots\\ \cdots & \cdots & 0 & [\underline{m_{n-1}},m_{n-1}c,\overline{m_{n-1}}] & [\underline{m_n},m_nc,\overline{m_n}]\\ 0 & \cdots & \cdots & 0 & 0\end{bmatrix}. \tag{2}$$

$\{\widetilde{K}\}=[\underline{K},Kc,\overline{K}]$ is $n\times n$ stiffness matrix of the structure and may be written as

$$\{\widetilde{K}\}=\begin{bmatrix}\widetilde{k}_1+\widetilde{k}_2 & \widetilde{k}_2 & 0 & \cdots & 0\\ -\widetilde{k}_2 & \widetilde{k}_2+\widetilde{k}_3 & -\widetilde{k}_3 & \cdots & 0\\ \cdots & \cdots & & & \cdots\\ 0 & \cdots & -\widetilde{k}_{n-1} & \widetilde{k}_{n-1}+\widetilde{k}_n & \widetilde{k}_n\\ 0 & & \cdots & -\widetilde{k}_n & \widetilde{k}_n\end{bmatrix}, \tag{3}$$

and $\{\widetilde{X}\}=\{\widetilde{x}_1,\widetilde{x}_2,\ldots,\widetilde{x}_n\}^T$ are the vectors of displacement.

We will first solve the above free vibration equation for vibration characteristics, namely, for frequency and mode shapes of the said structural system in order to get the stiffness parameters in fuzzified form. Accordingly putting $\{\widetilde{X}\}=\{\widetilde{\phi}\}e^{i(\widetilde{\omega})t}$ in free vibration equation (1), we get

$$\left(\{\widetilde{K}\}-\{\widetilde{M}\}[\widetilde{\omega}]^2\right)\{\widetilde{\phi}\}=\{\widetilde{0}\}, \tag{4}$$

where $\{\widetilde{\omega}\}^2=[\underline{\omega},\omega c,\overline{\omega}]^2=[\underline{\lambda},\lambda c,\overline{\lambda}]$ are eigenvalues or the natural frequency and $\{\widetilde{\phi}\}$ are mode shapes of the structure, respectively.

3. Basic Concept of Fuzzy Set Theory

Definition 1. Let X be a universal set. Then, the fuzzy subset A of X is defined by its membership function

$$\mu_A : X \longrightarrow [0,1], \tag{5}$$

which assigns a real number $\mu_A(x)$ in the interval $[0,1]$, to each element $x\in X$, where the value of $\mu_A(x)$ at x shows the grade of membership of x in A.

Definition 2. Given a fuzzy set A in X and any real number $\alpha\in[0,1]$, then, the α-cut or α-level or cut worthy set of A, denoted by A_α, is the crisp set

$$A_\alpha=\{x\in X \mid \mu_A(x)\geq\alpha\}. \tag{6}$$

The strong α-cut, denoted by $A_{\alpha+}$, is the crisp set

$$A_{\alpha+}=\{x\in X \mid \mu_A(x)\geq\alpha\}. \tag{7}$$

Definition 3. A fuzzy number is a convex normalized fuzzy set of the real line R whose membership function is piecewise continuous.

Definition 4. A triangular fuzzy number A can be defined as a triplet $[a_1,a_2,a_3]$. Its membership function is defined as

$$\mu_A(x)=\begin{cases}0, & x<a_1\\ \dfrac{x-a_1}{a_2-a_1}, & a_1\leq x\leq a_2\\ \dfrac{a_3-x}{a_3-a_2}, & a_2\leq x\leq a_3\\ 0, & x>a_3.\end{cases} \tag{8}$$

Above TFN may be transformed to an interval form A_α by α-cut as

$$A_\alpha=\left[a_1^{(\alpha)},a_3^{(\alpha)}\right]=\left[(a_2-a_1)\alpha+a_1,-(a_3-a_2)\alpha+a_3\right]. \tag{9}$$

4. Operation of Fuzzy Number

In this section, we consider arithmetic operation on fuzzy numbers and the result is expressed in membership function:

$$\forall x,y,z\in R. \tag{10}$$

(1) Addition: $A(+)B$

$$\mu_{A(+)B}(z)=\bigvee_{z=x+y}\left(\mu_A(x)\wedge\mu_B(y)\right). \tag{11}$$

(2) Subtraction: $A(-)B$

$$\mu_{A(-)B}(z)=\bigvee_{z=x-y}\left(\mu_A(x)\wedge\mu_B(y)\right). \tag{12}$$

(3) Multiplication: $A(\cdot)B$

$$\mu_{A(\cdot)B}(z)=\bigvee_{z=x\cdot y}\left(\mu_A(x)\wedge\mu_B(y)\right). \tag{13}$$

Table 1: Comparison between the desired and the ANN values of k_1, k_2, k_3, k_4, and k_5 for a five-storey shear structure.

Data number	k_1 (Ann)	k_1 (Des)	k_2 (Ann)	k_2 (Des)	k_3 (Ann)	k_3 (Des)	k_4 (Ann)	k_4 (Des)	k_5 (Ann)	k_5 (Des)
1	181277.7318	181472.3686	57722.68	57880.6541	53111.561	53114.814	44531.8138	44120.9218	24304.5301	24387.4436
2	195883.7223	190579.1937	98497.3362	98529.6391	40890.7789	40714.2336	30510.5884	30636.6569	24013.4116	23815.5846
3	110889.324	112698.6816	97540.2878	97858.3474	56939.1333	56982.5861	35467.0709	35538.4597	27905.0723	27655.1679
4	191334.6369	191337.5856	74367.0906	74268.7824	58151.3678	58679.865	30921.7444	30923.4278	27758.983	27951.999
5	162671.148	163235.9246	90080.9291	90014.0234	53507.0758	53574.7031	31851.263	31942.6356	21775.0509	21868.726
6	109757.8778	109754.0405	57034.3391	57094.3169	55073.904	55154.8026	46360.9403	46469.1566	24899.5619	24897.644
7	127671.411	127849.8219	71003.1282	71088.0641	54999.758	54862.6494	43688.9611	43896.5725	24554.2598	24455.862
8	154429.3614	154688.1519	98500.0073	95786.7763	48031.3148	47844.5404	36250.0047	36341.9896	27719.1389	26463.1301
9	196399.16	195750.6835	89751.9025	89610.3665	53100.0372	53109.5578	48498.0106	49004.441	27950.5364	27093.6483
10	193722.4668	196488.8535	98520.881	97974.6213	43228.929	43423.7338	30822.0268	30688.9216	26813.9637	27546.8668

(4) Division: $A(/)B$

$$\mu_{A(/)B}(z) = \bigvee_{z=x/y} \left(\mu_A(x) \wedge \mu_B(y)\right). \tag{14}$$

(5) Minimum: $A(\wedge)B$

$$\mu_{A(\wedge)B}(z) = \bigvee_{z=x\wedge y} \left(\mu_A(x) \wedge \mu_B(y)\right). \tag{15}$$

(6) Maximum: $A(\vee)B$

$$\mu_{A(\vee)B}(z) = \bigvee_{z=x\vee y} \left(\mu_A(x) \wedge \mu_B(y)\right). \tag{16}$$

5. Artificial Neural Network (ANN) and Error-Back Propagation Training Algorithm (EBPTA) for Fuzzified Data

Traditional ANN and EBPTA are well known, but here for the sake of completeness, those are developed for fuzzy case. In ANN, the first layer is considered to be input layer and the last layer is the output layer. Between the input and output layers, there may be more than one hidden layer. Each layer will contain number of neurons or nodes (processing elements) depending upon the problem. These processing elements operate in parallel and are arranged in patterns similar to the patterns found in biological neural nets. The processing elements are connected to each other by adjustable weights. The input/output behavior of the network changes if the weights are changed. So, the weights of the net may be chosen in such a way so as to achieve a desired output. To satisfy this goal, systematic ways of adjusting the weights have to be developed to handle the fuzzified data which are known as training or learning algorithm. Neural network basically depends upon the type of processing elements or nodes, the network topology, and the learning algorithm. Here, error back-propagation training algorithm and feedforward recall have been used but to handle the uncertain system. The typical network is given in Figure 2.

In this Figure, Z_i, P_j, and O_m are input, hidden, and output layers, respectively. The weights between input and hidden layers are denoted by v_{ji}, and the weights between hidden and output layers are denoted by W_{kj}. Here, $\widetilde{Z}_i = [\underline{\lambda_i}\ \ \lambda_i c\ \ \overline{\lambda_i}]$ and $\widetilde{O}_k = [\underline{k_m}\ \ k_m c\ \ \overline{k_m}]$.

Given R training pairs $\{\widetilde{Z}_1, \widetilde{d}_1; \widetilde{Z}_2, \widetilde{d}_2; \ldots, \widetilde{Z}_R, \widetilde{d}_R\}$ where $\widetilde{Z}_i(I \times 1)$ are input and $\widetilde{d}_i(M \times 1)$ are desired values for the given inputs, the error value is computed as

$$\widetilde{E} = \frac{1}{2}\left(\widetilde{d}_m - \widetilde{O}_m\right)^2, \quad m = 1, 2, \ldots M, \tag{17}$$

for the present neural network as shown in Figure 2. The error signal terms of the output ($\widetilde{\delta}_{Om}$) and hidden layers ($\widetilde{\delta}_{pj}$) are written, respectively, as

$$\widetilde{\delta}_{Om} = 0.5 * \left(\widetilde{d}_m - \widetilde{O}_m\right)\left(1 - \widetilde{O}_m^{\,2}\right), \quad m = 1, 2, \ldots M,$$
$$\widetilde{\delta}_{Pj} = 0.5 * \left(1 - \widetilde{P}_j^2\right) \sum_{m=1}^{M} \widetilde{\delta}_{Om} \widetilde{W}_{Pj}, \quad j = 1, 2, \ldots J. \tag{18}$$

Consequently, output layer weights ($\widetilde{W}_{mj}$) and hidden layer weights ($\widetilde{v}_{ji}$) are adjusted as

$$\widetilde{W}_{mj}^{(\text{New})} = \widetilde{W}_{mj}^{(\text{Old})} + \eta \widetilde{\delta}_{Om} P_j, \quad m = 1, 2, \ldots M, \ j = 1, 2, \ldots J,$$
$$\widetilde{v}_{ji}^{(\text{New})} = \widetilde{v}_{ji}^{(\text{Old})} + \eta \widetilde{\delta}_{Pj} Z_i, \quad j = 1, 2, \ldots J, \ i = 1, 2, \ldots I, \tag{19}$$

where η is the learning constant.

6. Results and Discussion

To investigate the present method here, examples of one- and two-storey shear structures are considered. So, for example, the floor masses for two-storey shear structure are $[\underline{m_1}, m_1 c, \overline{m_1}]$, $[\underline{m_2}, m_2 c, \overline{m_2}]$ and the stiffnesses $[\underline{k_1}, k_1 c, \overline{k_1}]$, $[\underline{k_2}, k_2 c, \overline{k_2}]$ are the structural parameters. Here,

Table 2: (a) Comparison between the desired and the ANN values of k_1, k_2, k_3, k_4, and k_5 for a ten-storey shear structure. (b) Comparison between the desired and the ANN values of k_6, k_7, k_8, k_9, and k_{10} for a ten-storey shear structure.

(a)

Data number	k_1 (Ann)	k_1 (Des)	k_2 (Ann)	k_2 (Des)	k_3 (Ann)	k_3 (Des)	k_4 (Ann)	k_4 (Des)	k_5 (Ann)	k_5 (Des)
1	116900.6563	114999.7254	23626.293	23947.0748	25255.905	24299.2141	29078.6982	29493.0391	27766.1413	28842.8102
2	137413.4659	135922.821	22400.1311	21970.538	22076.7651	22160.1892	28671.6078	29898.7215	23928.6799	23185.2425
3	174166.5579	171165.6706	26751.8243	27587.6627	28439.4836	28089.9027	28056.19	27636.7332	28909.5075	29349.7909
4	185745.6345	187147.6518	28203.5977	29952.1598	23288.5994	23565.0893	25414.2964	25588.2055	24175.8385	24794.8455
5	131376.8088	132868.9612	22531.4396	21865.7144	20887.9013	20732.4343	22490.5032	21838.4294	21747.4496	22317.9161
6	174687.251	165011.8025	25813.5863	27811.4527	25015.1015	25909.9146	25615.7328	24979.4882	24612.1573	23962.9025
7	185115.3655	197483.6148	24841.291	21957.9798	27352.9705	29101.8783	25184.1779	25178.456	27414.6225	27050.7748
8	107439.5782	107596.7361	28408.1614	29923.5897	22079.0745	21937.6594	29361.5732	29942.4301	25283.6014	25585.5903
9	164872.2954	158701.9167	25498.9862	28022.6157	26269.1879	24323.6779	28505.5766	28548.5168	27421.7863	27566.307
10	134496.3197	136428.6869	23984.6699	23091.3643	26528.5422	27288.6387	20735.4877	20391.8449	26590.0291	26789.4101

(b)

Data number	k_6 (Ann)	k_6 (Des)	k_7 (Ann)	k_7 (Des)	k_8 (Ann)	k_8 (Des)	k_9 (Ann)	k_9 (Des)	k_{10} (Ann)	k_{10} (Des)
1	21170.0974	20899.5068	25777.6655	25605.5953	28204.3487	29899.5021	27503.4171	25859.8704	27163.5463	25814.4649
2	22417.1364	20549.7415	27621.6492	28654.3859	27612.505	28451.7819	28303.9996	29823.0322	22093.3505	22094.0508
3	29672.9685	29638.7013	25998.8211	27124.1481	22438.2305	21982.2179	26315.5549	26153.251	27684.8546	29019.9081
4	19962.2582	19656.5635	21156.2588	20166.7471	22269.5196	21950.7153	23818.7821	23766.1108	27240.5745	27020.6645
5	20161.805	20514.4829	25387.6098	28009.2088	23922.4631	23268.3965	27519.8427	28771.8175	23219.6412	23774.551
6	22307.0935	23043.4895	21527.1166	21425.0932	27311.6444	28803.3786	27670.7454	27848.5243	27234.7985	27349.5593
7	27804.4452	25801.9183	24442.8169	24784.7447	25319.1653	24711.0187	25870.6554	24649.5428	27640.8021	29541.0279
8	25509.2344	25309.6445	22738.1369	22568.3535	23936.8813	24039.6937	28924.1116	28139.7693	25172.6749	25428.1311
9	28341.8519	29012.0809	25380.1928	23690.9169	23071.1828	21792.3148	28034.5751	28984.4414	26519.4395	25401.0583
10	27911.2912	29624.314	26475.8553	24319.8061	21306.3632	21696.0881	25327.5363	24074.5574	24485.2563	23343.2942

Table 3: Comparison between the desired and the ANN values of $\widetilde{K}$ for a single-storey shear structure.

Data number	$\underline{K}$ (Ann)	$\underline{K}$ (Des)	Kc (Ann)	Kc (Des)	$\overline{K}$ (Ann)	$\overline{K}$ (Des)
1	124932.9319	124189.1286	135932.8213	135095.2381	191905.7285	190281.611
2	135763.4956	140411.2146	152464.2896	151324.954	191726.9669	194488.719
3	110291.5736	109665.4525	141591.1084	140180.8034	148514.9196	149096.4092
4	107394.0584	107596.6692	115134.7117	113217.3293	149119.797	148935.2638
5	124430.5911	123991.6154	134455.7107	133781.941	192947.0787	194225.0591
6	112574.5401	112331.8935	188853.0283	190015.3846	194542.4439	195633.454
7	120988.7913	118390.7788	138166.8698	136934.6781	157619.3944	157540.8595
8	108960.7756	105997.9543	113526.3083	111130.2755	126504.2017	123995.2526
9	124700.9011	123497.9913	143556.5197	141726.7069	179985.5092	178035.2068
10	105227.009	104965.443	135988.057	135335.8571	140612.991	138983.8837

masses are assumed to be constant (as mentioned earlier). So, we will identify the stiffness parameter in fuzzy form using the fuzzy form of the frequency where frequency may be obtained from some experiments. In the following paragraphs, we have used the proposed method to identify the stiffness parameter for one-, two-, five-, and ten-storey frame structures. Here, we have considered the cases with crisp data for five- and ten-storeys and then fuzzified data for one- and two-storeys. The training data are also considered with the influence of noise, namely, in terms of triangular fuzzy number data. Accordingly we have considered the following four cases:

Table 4: Comparison between the desired and the ANN values of $\widetilde{K}$ for a single-storey shear structure.

Data number	$\underline{k}$ (Ann)	$\underline{k}$ (Des)	kc (Ann)	kc (Des)	$\overline{k}$ (Ann)	$\overline{k}$ (Des)
1	62365.0341	62104.5643	67644.4378	67547.619	95458.8463	95145.8055
2	67613.8959	70215.6073	75826.931	75662.477	95893.1612	97249.3595
3	55005.0087	54842.7263	70556.3936	70090.4017	74368.7997	74553.2046
4	53128.7186	53798.3346	56947.542	56618.6646	74261.1768	74472.6319
5	62246.1626	61995.8077	66881.2194	66895.9705	96278.4523	97122.5295
6	55957.2602	56165.9467	94391.1219	95012.6923	97271.6645	97826.727
7	60056.7259	59195.3894	68223.7328	68472.3391	78385.7211	78780.4298
8	53587.3374	53008.9771	55747.5298	55570.1378	61968.3882	61997.6263
9	62126.6388	61758.9957	71196.546	70863.3535	89991.9346	89022.6034
10	52238.7913	52482.7215	67702.5259	67677.9286	69679.1387	69496.9418

Table 5: (a) Comparison between the desired and the ANN values of $\widetilde{k}_1$ for a double-storey shear structure. (b) Comparison between the desired and the ANN values of $\widetilde{k}_2$ for a double-storey shear structure.

(a)

Data number	$\underline{k_1}$ (Ann)	$\underline{k_1}$ (Des)	k_1c (Ann)	k_1c (Des)	$\overline{k_1}$ (Ann)	$\overline{k_1}$ (Des)
1	113258.5422	113317.1008	133858.2555	133969.3413	162741.2326	162807.3359
2	116526.66	117338.8613	128622.4646	129208.408	193447.2534	195183.0465
3	139119.0131	139093.7802	143501.0894	143175.117	191801.5675	192053.204
4	101316.7594	101558.7126	106512.8803	105287.6998	183040.5812	183137.9743
5	173554.7972	173805.8096	180269.037	180336.4392	198199.4731	198416.3724
6	105985.8857	106047.1179	117592.2043	116726.841	127688.8972	126931.9426
7	110472.1362	110631.6345	140132.9188	139925.7771	142461.6007	142303.5615
8	137120.3743	137250.974	152856.9037	152687.5831	155005.6994	154807.0901
9	119783.849	119821.8403	142480.6438	141679.9468	195824.6624	194293.6984
10	141708.5217	141794.4104	148654.6797	148978.7638	165370.4902	165685.9891

(b)

Data number	$\underline{k_2}$ (Ann)	$\underline{k_2}$ (Des)	k_2c (Ann)	k_2c (Des)	$\overline{k_2}$ (Ann)	$\overline{k_2}$ (Des)
1	58488.0205	58566.0533	91472.5908	92796.1403	99954.016	99152.6233
2	51977.6459	51640.041	65679.199	65072.7474	85856.2114	82258.2268
3	69213.7504	68833.6105	77764.8854	78069.9896	85939.2478	85054.9378
4	60124.2902	59566.1848	83319.0924	83316.9426	93794.9834	94103.325
5	71317.3378	71432.6496	76748.5343	76956.3233	83930.3883	83468.7652
6	59384.591	59531.6634	73687.8221	74121.1031	85087.5853	84905.276
7	56031.7629	56050.5807	68215.603	68455.8273	83728.3652	83326.3957
8	58849.1438	58906.6227	72741.8224	73046.2969	79796.3231	79495.3742
9	57077.8681	56400.72	61035.9761	61329.384	95110.8992	99091.8975
10	57858.7023	57830.2476	69404.8867	69250.9562	99433.354	99954.0197

Case(i): Five-storey shear structure with crisp data,

Case(ii): Ten-storey shear structure with crisp data,

Case(iii): Single-storey shear structure with fuzzified data,

Case(iv): Double-storey shear structure with fuzzified data.

Computer programs have been written and tested for variety of experiments for the above cases. For the first two cases, namely, Case(i) and Case(ii), the inputs are taken as the crisp

Table 6: (a) Comparison between the desired and the ANN values of $\tilde{k}_1$ for a double-storey shear structure. (b) Comparison between the desired and the ANN values of $\tilde{k}_2$ for a double-storey shear structure.

(a)

Data number	$\underline{k_1}$ (Ann)	$\underline{k_1}$ (Des)	k_1c (Ann)	k_1c (Des)	$\overline{k_1}$ (Ann)	$\overline{k_1}$ (Des)
1	62193.4503	62149.2679	65871.2249	66562.894	69219.2648	69672.8181
2	71578.6175	71235.4748	71816.4848	72130.1157	83311.5254	83571.557
3	63514.5116	63533.5212	84447.6191	84399.8043	86708.0123	87062.8972
4	59459.7849	59872.6899	67907.0231	67971.4105	75148.6421	76002.6234
5	67809.323	67385.6336	85655.9802	86827.0037	91460.6917	91106.0592
6	57879.7498	57499.8627	69206.8111	69745.3738	71387.5577	71516.0705
7	77679.4222	79304.6034	83870.4195	84180.7933	93380.175	94408.5477
8	63484.2106	63107.2659	69028.8134	69579.1498	85313.0398	85212.3715
9	52329.6174	52222.7046	72316.9085	72125.2707	88399.7894	88475.7194
10	50895.5951	50988.8812	69532.938	69859.5759	87547.575	87746.6634

(b)

Data number	$\underline{k_2}$ (Ann)	$\underline{k_2}$ (Des)	k_2c (Ann)	k_2c (Des)	$\overline{k_2}$ (Ann)	$\overline{k_2}$ (Des)
1	27396.6322	27507.0572	27776.8241	27698.5425	28078.4211	28085.141
2	21439.7109	21682.5355	27548.5904	27550.771	29081.9724	28275.8382
3	23717.5546	23773.9554	27948.7301	27919.6303	28617.4807	28629.8048
4	22090.0439	22160.1892	23180.7111	23205.2425	28962.7934	29908.7215
5	25086.5697	25154.2346	25465.6455	25360.6413	27961.1253	27904.0722
6	20724.6386	20919.5068	28645.592	28852.8102	29353.9707	29493.0391
7	20706.4881	21137.0574	23381.0249	23275.6543	25716.8788	25890.2606
8	21056.3736	21382.9255	21574.7879	21557.5235	26851.9289	26712.6437
9	22075.9397	22008.6282	24479.3131	24386.4498	27062.0237	26806.523
10	24070.1411	24079.5484	25009.5776	24971.7702	28009.5803	28335.006

frequency values and the outputs are the stiffness parameters which are also in crisp form. On the other hand, for Cases(iii) and (iv), the inputs are taken as the fuzzified frequency values and the outputs are the stiffness parameters again in fuzzified form in the developed Fuzzy Neural Network (FNN) algorithm.

For the first case, an example of a storey shear structure is taken where the masses are $m_1 = m_2 = m_3 = m_4 = m_5 = 36000$ and the stiffness parameters are within the range $k_1 = [100000\ 200000]$, $k_2 = [50000\ 100000]$, $k_3 = [40000\ 60000]$, $k_4 = [30000\ 50000]$, and $k_5 = [20000\ \ 30000]$. A comparison between the desired and ANN values has been presented in Table 1. This table has been plotted in Figure 3.

In Case(ii), an example for a ten-storey shear structure has been considered with constant masses similar to Case(i) and the stiffness parameters are in the range $k_1 = [100000\ \ 200000]$, $k_2 = k_3 = k_4 = k_5 = k_6 = k_7 = k_8 = k_9 = k_{10} = [20000\ \ 30000]$. The desired and ANN values for k_1 to k_5 and k_6 to k_{10} are compared in Tables 2(a) and 2(b), respectively.

For Case(iii), the first example is that of a single-storey shear structure with masses $\widetilde{M} = 36000$ and the stiffness parameters lie within the range $\underline{K} = [100000\ \ 200000]$, $Kc = [100010\ \ 200010]$, and $\overline{K} = [100020\ \ 200020]$. A comparison between desired and the ANN values has been incorporated in Table 3. This table has been plotted in Figure 4. In the second example, a single-storey shear structure is considered with masses $\widetilde{M} = 36000$ and the stiffness parameter varying within the range $\underline{K} = [50000\ 100000]$, $Kc = [50010\ 100010]$, and $\overline{K} = [50020\ 100020]$. Comparison between the desired and the ANN values is tabulated in Table 4 and is plotted in Figure 5.

In Case(iv), the first example of a double-storey shear structure is considered where the masses are $\widetilde{m}_1 = \widetilde{m}_2 = 36000$ and the stiffness parameters varying within the range $\underline{k_1} = [100000\ \ 200000]$, $k_1c = [100010\ \ 200010]$, $\overline{k_1} = [100020\ \ 200020]$ and $\underline{k_2} = [20000\ \ 30000]$, $k_2c = [20010\ \ 30010]$, and $\overline{k_2} = [20020\ \ 30020]$. The desired and ANN values have been compared in Tables 5(a) and 5(b). This table has also been shown in Figures 6(a) and 6(b). In the second example, a double-storey shear structure is implemented with masses $\widetilde{m}_1 = \widetilde{m}_2 = 36000$ and the stiffness parameters having the range $\underline{k_1} = [50000\ \ 100000]$, $k_1c = [50010\ \ 100010]$, $\overline{k_1} = [50020\ \ 100020]$ and

Table 7: (a) Comparison between the desired and the ANN values of $\underline{k_1}$, $\overline{k_1}$ and $\underline{k_2}$, $\overline{k_2}$ for a double-storey shear structure for $\alpha = 0.3$. (b) Comparison between the desired and the ANN values of $\underline{k_1}$, $\overline{k_1}$ and $\underline{k_2}$, $\overline{k_2}$ for a double-storey shear structure for $\alpha = 0.5$. (c) Comparison between the desired and the ANN values of $\underline{k_1}$, $\overline{k_1}$ and $\underline{k_2}$, $\overline{k_2}$ for a double-storey shear structure for $\alpha = 0.8$.

(a)

Data number	$\underline{k_1}$ (Ann)	$\underline{k_1}$ (Des)	$\overline{k_1}$ (Ann)	$\overline{k_1}$ (Des)	$\underline{k_2}$ (Ann)	$\underline{k_1}$ (Des)	$\overline{k_2}$ (Ann)	$\overline{k_2}$ (Des)
1	109470	109250	124660	123870	63676	63908	81668	81670
2	119370	119420	141760	141590	59687	59772	79075	78865
3	141840	141880	154360	154170	63017	63149	77680	77561
4	126590	126380	179820	178510	58265	57879	84888	87763
5	143790	143950	160360	160670	61323	61256	90425	90743

(b)

Data number	$\underline{k_1}$ (Ann)	$\underline{k_1}$ (Des)	$\overline{k_1}$ (Ann)	$\overline{k_1}$ (Des)	$\underline{k_2}$ (Ann)	$\underline{k_1}$ (Des)	$\overline{k_2}$ (Ann)	$\overline{k_2}$ (Des)
1	111790	111390	122640	121830	66536	66826	79388	79513
2	125300	125280	141300	141110	62124	62253	75972	75891
3	144990	144970	153930	153750	65795	65976	76269	76271
4	131130	130750	169150	167990	59057	58865	78073	80211
5	145180	145390	157010	157330	63632	63541	84419	84602

(c)

Data number	$\underline{k_1}$ (Ann)	$\underline{k_1}$ (Des)	$\overline{k_1}$ (Ann)	$\overline{k_1}$ (Des)	$\underline{k_2}$ (Ann)	$\underline{k_1}$ (Des)	$\overline{k_2}$ (Ann)	$\overline{k_2}$ (Des)
1	115270	114590	119610	118770	70827	71203	75968	76278
2	134200	134070	140600	140400	65779	65975	71318	71430
3	149710	149600	153290	153110	69963	70218	74153	74336
4	137940	137310	153150	152200	60244	60344	67851	68882
5	147270	147540	152000	152320	67096	66967	75411	75392

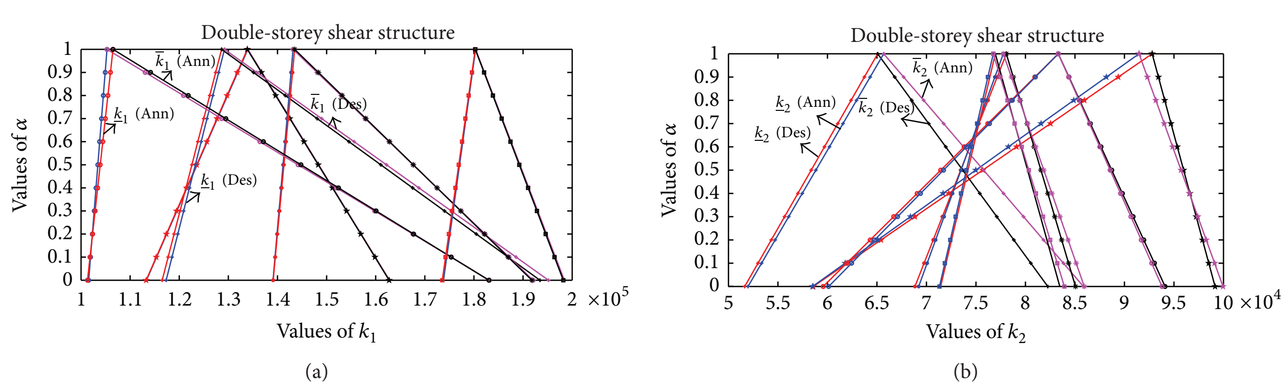

Figure 9: (a) Comparison of $\underline{k_1}$ and $\overline{k_1}$ with respect to α. (b) Comparison of $\underline{k_2}$ and $\overline{k_2}$ with respect to α.

$\underline{k_2}$ = [20000 30000], k_2c = [20010 30010], and $\overline{k_2}$ = [20020 30020]. Comparison between the desired and ANN values are again incorporated in Tables 6(a) and 6(b). This table is plotted in Figures 7(a) and 7(b).

The training data with the influence of noise for two-storey shear structure in TFN form for five sets of data have been presented here. Accordingly, Figures 8(a) and 8(b) refer the fuzzy plot of frequency. Moreover, the Triangular

Fuzzy Number (TFN) plots of identified stiffness are cited in Figures 9(a) and 9(b). Also for different alpha values such as $\alpha = 0.3$, $\alpha = 0.5$, and $\alpha = 0.8$, the comparison between the desired and ANN values with another five sets of data has been given in Tables 7(a), and 7(b), and 7(c).

7. Conclusion

Here, the procedure is demonstrated to identify stiffness parameters for multistorey shear structure using fuzzified data in ANN. The present study considers example problems of one-, two-, , and ten-storey shear structures. Identification study for and ten-storey shear structures has been done with crisp data. Then, fuzzified data has been considered for one- and two-storey shear structures for the present identification procedure. Initial design parameters, namely, stiffness and mass and so the frequency of the said problem is known in term of fuzzy numbers. The engineers want to know the present health of the structure by system identification methods. It is assumed that only the stiffness is changed and the mass remains the same. The present values of the frequencies may be obtained by available equipments, and using these, one may get the present parameter values by ANN. So, if sensors are placed to capture the frequency of the floors in fuzzy (uncertain) form, then, those may be fed into the proposed new ANN model to get the present stiffness parameters. The methods of one- and two-storey shear structures with fuzzified data may very well be extended for higher storey structures following the present procedure. As regards the influence of noise, it may be seen that the input and output data for two-storey shear structure are actually in terms of Triangular Fuzzy Number (TFN) which themselves dictate the noise in both monotonic increasing and decreasing senses. In order to train the new ANN model, set of data are generated numerically beforehand. As such, converged ANN model gives the present stiffness parameter values in fuzzified form for each floor. Thus, one may predict the health of the structure. Corresponding example problems (as mentioned) have been solved, and related results are reported to show the reliability and powerfulness of the model.

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