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Damage detection of truss bridge joints using Artificial Neural Networks

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Abstract

Recent developments in Artificial Neural Networks (ANNs) have opened up new possibilities in the domain of inverse problems. For inverse problems like structural identification of large structures (such as bridges) where in situ measured data are expected to be imprecise and often incomplete, ANNs may hold greater promise. This study presents a method for estimating the damage intensities of joints for truss bridge structures using a back-propagation based neural network. The technique that was employed to overcome the issues associated with many unknown parameters in a large structural system is the substructural identification. The natural frequencies and mode shapes were used as input parameters to the neural network for damage identification, particularly for the case with incomplete measurements of the mode shapes. Numerical example analyses on truss bridges are presented to demonstrate the accuracy and efficiency of the proposed method.
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Keywords: Neural networks; Damage detection; Finite element method; Modal data; Truss bridges

1. Introduction

One of the most important aspects of evaluation of structural systems and ensuring their lifetime safety is structural damage detection. This theme is related to the fact that the number of damaged or deteriorated structures grows rapidly in many countries. The majority of the identification techniques involve the use of the measured structural responses under dynamic excitation. Damage causes changes in structural parameters (e.g., the stiffness of a structural member), which in turn, modify dynamic properties (such as natural frequencies and mode shapes) (Doebling, Farrar, Prime, & Shevitz, 1996).

With the recent developments in computing technology for data acquisition, signal processing and analysis, the parameters of structures can be identified from the measured responses under excitation of the structure, using system identification techniques as an inverse problem. What is an inverse problem? The inverse problem may be defined as determination of the internal structure of a physical system from the system's measured behavior or identification of the unknown input that gives rise to a measured output signal (Tanaka & Bui, 1994). Inverse problems usually involve ill-posedness. A problem is defined as ill-posed if the solution is not unique or if it is not continuous function of the data. This means an arbitrary small perturbation/error of the data can cause an arbitrarily large perturbation of the solution.

The conventional mathematically-based engineering methodologies (i.e., hard-computing methods) are not very efficient in solving inverse problems (Ghaboussi & Wu, 1998). Soft-computing methods are biologically inspired and are based on nature's problem solving strategies. Soft-computing methods have capabilities which are suitable for solving inverse problems in engineering. Currently, these methods include a variety of neural networks, evolutionary computational models (such as genetic algorithms), and linguistic-based methods (such as fuzzy logic) (Koh et al., 2003a). Comprehensive literature surveys have been

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provided for the subject of structural damage detection (e.g., Dimarogonas, 1996; Doebling, Farrar, & Prime, 1998; Farrar & Lieven, 2007; Salawu, 1997; Sohn et al., 2004; Zou, Tong, & Steven, 2000) in which Artificial Neural Networks (ANNs) are among the most widely used soft-computing methods. ANNs have recently drawn considerable attention in civil engineering community due mainly to their ability to approximate an arbitrary continuous function and mapping (e.g., Mehrotra, 1997; Patterson, 1996). ANNs are capable of learning and predicting the functional mapping between inputs and outputs of a set of training data. Among various neural networks, Multi-Layer Perceptron (MLP) is the most commonly used in structural identification problems (Chen & Wang, 2002; Garg, Roy Mahapatra, Suresh, Gopalakrishnan, & Omkar, 2004; Ko, Sun, & Ni, 2002).

Several researchers used ANNs to detect, localize, and quantify damage in bridge structures. Faravelli and Pisano (1997) used MLP neural networks to detect and locate damage in a numerical simulation of a two-dimensional, nine-bay truss structure assuming that damage occurs in only one element at a time. Only the three lowest modes of the truss where considered to train the neural networks. Liu and Sun (1997) applied neural networks to identify damage in a simply supported three-span bridge. The neural networks were trained using simulated data from a finite element model of the bridge. The bridge model was discretized into thirty uniform beam elements. Damage was simulated by reducing element stiffness. Barai and Pandey (1997) adopted MLP neural networks for damage detection of a simulated railway bridge. Vibration signals from the bottom chord of the truss bridge model were used as inputs for the neural networks. The vibration signals where simulated by traveling a moving load on the truss bridge at a constant speed. The performance of the trained neural networks was examined for both complete and incomplete measurements available during the testing phase. Damage was simply introduced by reducing stiffness in one element at a time. Chan, Ni, and Ko (1999) utilized MLP neural networks to detect changes of cable on the Tsing Ma suspension bridge in Hong Kong. In their study, the first 12 natural frequencies where used as the inputs to networks. Lee, Lee, Yi, Yun, and Jung (2005) presented a neural networks-based damage detection method using the modal properties, which considers the modeling errors in the baseline finite element model from which the training patterns were generated. The differences or the ratios of the mode shape components between before and after damage were used as the input to the neural networks for damage assessment of multiple-girders simply supported bridges. Yeung and Smith (2005) assessed a damage detection procedure using pattern recognition of the vibration signature, using a finite element model of a suspension bridge. Realistic damage scenarios were simulated and the response under moving traffic was evaluated. Feature vectors generated from the response spectra were presented to neural networks for examination.

In the present work, an MLP neural network-based strategy is proposed for the estimation of structural damages in the joints of truss bridges, from the modal specification of the structure. Substructural identification is employed to overcome the issues associated with many unknowns. To demonstrate the effectiveness of neural network approach, two numerical example analyses on truss bridge structures are presented. First a suppositional simple truss was employed and after the success on simple truss, the same method was employed on a real bridge truss.

2. Multi-layered feed-forward neural networks

Multi-layered feed-forward neural networks are currently the most commonly used neural networks in engineering applications. These neural networks are used to establish relations (mappings) between a vector of input variables $\mathbf{x}$, and a vector of output variable $\mathbf{y}$, within the domain of the training data set $\mathbf{D} = \{(\mathbf{x}_j, \mathbf{y}_j); j = 1, \ldots, k\}$ in which k indicates the number of the training data set points. The mathematical expression of the problem is a function relating $\mathbf{x}$ to $\mathbf{y}$ and coinciding with the k points in the $(\mathbf{x}, \mathbf{y})$ space (Ghaboussi & Wu, 1998).

Network architecture is an arrangement of the artificial neurons and their relationships. A multi-layered perceptron consists of an array of input neurons known as the input layer, an array of output neurons called the output layer, and a number of hidden layers. Each neuron receives a weighted sum from each neuron in the preceding layer and provides an input to every neuron of the next layer. The activation of each neuron is governed by a threshold function such as sigmoid function. In order to train the network, the back-propagation algorithm where the error calculated at the output of the network is propagated back through the layers of neurons to update the weights, may be used (Mehrotra, 1997). Therefore, a multi-layered feed-forward neural network is trained with the training set, such that within the domain of the training data it approximately represents the training data set. The approximation in neural networks is represented by the error vectors $\mathbf{e}_j$ within the domain of the training data. Training of the multi-layered feed-forward neural network is the process of reducing the norm of the error vector to below a tolerance ε, which is shown by

$$\|\mathbf{e}_j\| = \|\mathbf{y}_j - \mathbf{y}(\mathbf{x}_j)\| \leqslant \varepsilon; \quad (\mathbf{x}_j, \mathbf{y}_j) \in \mathbf{D} \tag{1}$$

in which, $\mathbf{y}(\mathbf{x}_j)$ is the vector of output functions at the jth vector of input variables $\mathbf{x}$. A multi-layered feed-forward neural network learns to satisfy its training data set approximately. It differs fundamentally from a mathematical interpolation function, which matches the training data set exactly. Multi-layered feed-forward neural networks are also different from regression analysis, which requires a specified function whose parameters are determined (Rumelhart & McClelland, 1986). In general, the output errors for the training data depend on a number of factors such as the complexity of the underlying process represented in the training data set, the network architecture and the training process. It is important to note that it is not desirable to reduce the error too much. In the limit, if the network errors are reduced to zero, then the neural network would be functioning similar to an interpolation function and it may lose its generalization capacity (Ghaboussi & Wu, 1998).

3. Structural damage detection

3.1. Type of damage studied in this investigation

Various types of damages including main members (Barai & Pandey, 1997; Faravelli & Pisano, 1997; Liu & Sun, 1997), suspension cables (Chan et al., 1999), girders (Lee et al., 2005; Yeung & Smith, 2005), and joints (Yeung & Smith, 2005) which are suspicious to damage in bridge structures have recently drawn remarkable attention. One of the damages that are prevalent in truss bridges is fatigue damage that often occurs at joints location. Mechanism of fatigue damage is as follows: In truss bridges which are assembled by bolts or rivets, while punching gusset plates or members, some micro-cracks are developed around the holes. Micro-cracks may also be created while welding, if the welded type of joints is used. When bridges are exploited and are subjected to iterative loading and unloading, these micro-cracks may begin to grow larger and as a result, cross-sectional area of members may decrease in joints location. Such type of damages is unavoidable and occurs in many cases, and may not be recognizable by visual inspection. In Fig. 1 a schematic view of such damage is displayed. Up to 40% of truss bridge structures experience such damage occurs during their lifetime (Chan, Li, & Ko, 2001). Therefore, the type of damage that is considered in this paper is fatigue in joints location. It is assumed for simplification that when a truss joint is damaged, the cross-sectional area of all elements linked to that joint, is reduced proportional to the damage intensity percentage at the joint. A tiny element is then defined at the end of all elements common in a joint, and for modeling damage at joints in finite element model, cross-sectional area of all tiny elements joined to that joint, is proportionally reduced.

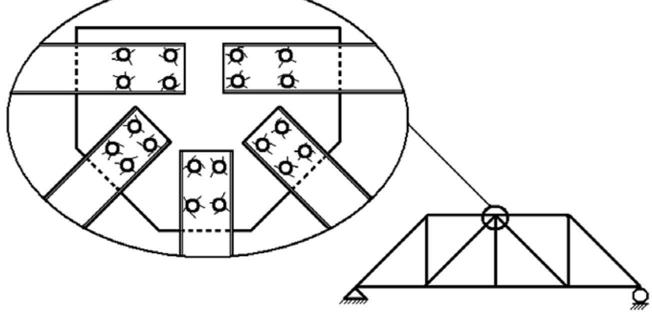

Fig. 1. A schematic picture of fatigue damage in a truss joint.

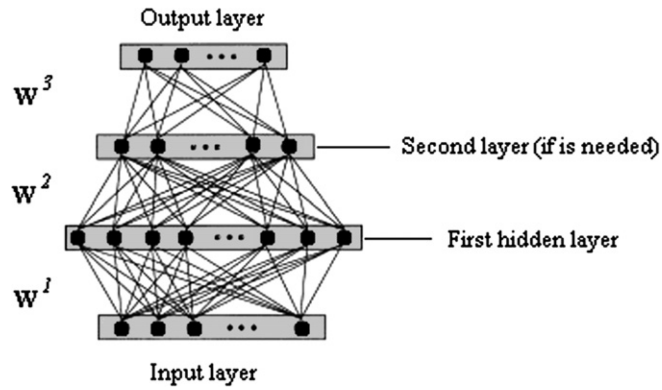

Fig. 2. A typical architecture of multi-layered feed-forward neural network.

3.2. Neural network

In this study as discussed in Section 2, multi-layered feed-forward neural network architecture is implemented for structural damage detection. Such network consists of an input layer, one or more hidden layers, and an output layer (Fig. 2). The input and output relationship of a neural network are determined by the weights assigned to the connections between nodes in two neighboring layers. Weight coefficient matrices are denoted by $\mathbf{W}^n$ in which n indicates number of layers associated with weight coefficient matrices (Fig. 2). Systematic adjustment of determining the weights of the network to achieve a desired input/output relationship are referred to as training or learning algorithm. In this study, the standard back-propagation (BP) algorithm is used (Rumelhart & McClelland, 1986).

In the present study, the fundamental strategy for developing a neural network-based approach is to train the BP algorithm to recognize the joint damage intensities from the measured data of the dynamic behavior of the structure (such as, natural frequencies and mode shapes). The network is first trained using initial training data sets consisting of assumed joints damage percentage as target outputs and their corresponding dynamic characteristics as inputs. Thus the number of the input neurons is limited to the number of the measured degree of freedoms (DOFs) multiplied by the number of used modes, plus the number of used modes. The number of output neurons is equal to the number of joints included in the structure. The value in each neuron indicates damage percentage (DP) of related joint. The number of hidden layers and of neurons in hidden layers is determined with trial and error method. After the completion of training, the structural parameters that have been identified from the measured vibration signals are used to asses the location and intensity of damages.

4. Substructural identification technique

For the identification of a structure with many unknowns, it is not practical to identify all of the parameters in the structure at a same time, because most of the

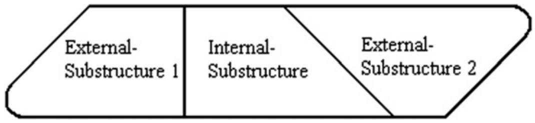

Fig. 3. Substructuring for localized identification.

identification techniques require expensive computation that would be even prohibitive, as the number of unknown parameters increases. Several researches (Koh et al., 1991, Koh, Hong, & Liaw, 2003b; Oreta & Tanabe, 1994; Yun & Lee, 1997) reported on identification of a part of a structure so as to reduce the size of the system under consideration. Those works were based on the fact that the expected damages of a structure occur at several critical locations. Furthermore, there may be many cases where we can estimate which region shall be investigated through visual inspection or knowledge of experts. Hence, it is more reasonable to focus the identification at critical regions of the structure.

The local-identification method is based on substructuring technique, in which the structure is subdivided into several substructures and the identification is achieved on a substructure at a time (Fig. 3). In the present study, the truss bridge structures with many joints are subdivided into some substructures including internal and external substructures, and then damage identification procedure could be employed to each substructure. To show various aspects of this approach, internal substructure with more joints than the external ones is selected in numerical validations. Since the parameters to be estimated are limited to an internal substructure, it is expected that the numerical problems such as divergence or falling into local minima may be avoided. Another advantage of this approach is that it requires limited data measurement only on the substructure under investigation instead of data collection on the whole structure (Yun & Lee, 1997).

5. Neural networks training patterns

Choosing the patterns that represent the characteristics of the structure, which are to be used as the input and output of neural networks, is one of the most important subjects in the present methodology. As discussed in Section 1, several researchers have used various input/output patterns (or input/output vectors) appropriate for their problems (Barai & Pandey, 1997; Chan et al., 1999; Faravelli & Pisano, 1997; Lee et al., 2005; Liu & Sun, 1997; Yeung & Smith, 2005).

In the present study, the natural frequencies and modes of a structure are used as the input patterns. By this choice, the following advantages are obtained:

- The length of the input patterns is limited to the number of the measured DOFs multiplied by the number of modes (concerning to the natural mode shapes), plus the number of modes (corresponding to the natural frequencies).
- The natural frequencies represent global behaviors, while the natural mode shape vectors represent local characteristics.
- The input patterns may be obtained from the measurements of the structural behavior, numerically or experimentally.

Therefore, the input pattern can be defined as:

$$\text{Input pattern vector} = \{(f_i, \phi_{ji}); i = 1, \ldots, m; j = 1, \ldots, n\} \tag{2}$$

in which, f_i is the ith natural frequency, ϕ_{ji} represents the jth component of ϕ_i, n denotes the number of DOFs measured for structure or substructure, and m is the number of modes to be considered in the identification.

The Number of outputs of neural network is equal to the number of joints included in the structure or substructure under identification. In the output layer, the value of each neuron represents damage percentage (DP) of the related joint.

6. Numerical examples

In the present study, damage identification strategy is applied on two planar truss bridges to illustrate the applicability of the proposed approach.

The first example is a simple warren truss which contains 7 truss elements, 5 nodes and 7 nodal DOFs as shown in Fig. 4 in which, the tiny elements defined at the end of all elements common in a joint, have been indicated by light lines compared to the sound main members shown by heavy lines. The assumed dead loads presented in joints location have also been shown. Values for the material and geometric properties are as follows: the elastic modulus = 200 GPa; the cross-sectional area of all elements = 0.0143 m^2; the length of horizontal members = 12 m; the length of inclined members = 8.5 m; and the mass density = 8000 kg/m^3. After solving the eigenvalue problem of this example, the natural frequencies and mode shapes of the reference structure, in which all the joints are sound, are shown in Fig. 5.

In the second example, the strategy was employed on a real truss bridge that is the two-span planar truss shown in Fig. 6. This is the structure of Louisville Bridge in the United States. Fig. 6 also shows the prime bridge structure with the assumed dead load defined in joint locations. Table 1 shows the specifications of different elements for this bridge. The natural frequencies and mode shapes of the reference structure, in which all the joints are sound, are shown in Fig. 7. The aim was to identify 16 unknown joint damage percentage (DP), DP_i $i = 1, \ldots, 16$, based on the measured modal data. Instead of identifying the whole DPs simultaneously, substructuring technique was used in which, the structure was divided into three substructures as shown in Fig. 8. Identification was then employed on the internal substructure which involves more unknown

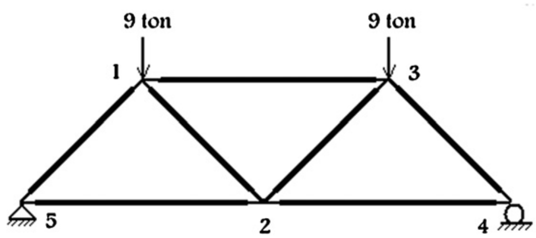

Fig. 4. The first example, a simple warren truss.

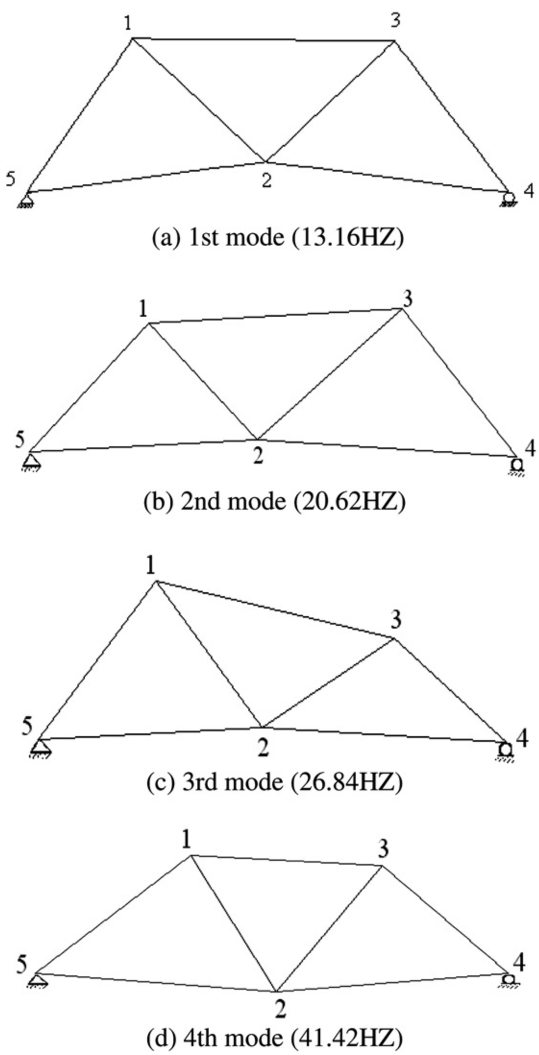

Fig. 5. First four mode shapes of simple truss structure. The numbers in parentheses are the natural frequencies.

Table 1
The specifications of different elements in truss structure of Louisville Bridge

Elements	Elements length (m)	Cross-sectional area (cm^2)	Section
B1B3	16.0	181.0	IPB360
B3B5	16.0	373.0	IPBV300 + 2PL350 * 10
B1T1	11.3	463.0	IPBV300 + 2PL400 * 20
B2T1	8.0	72.7	IPE360
B3T1	11.3	181.0	IPB360
B3T2	8.0	143.0	IPBL360
B3T3	11.3	373.0	IPBV300 + 2PL350 * 10
B4T3	8.0	72.7	IPE360
B5T3	11.3	143.0	IPBL360
B5T4	8.0	143.0	IPBL360
T1T3	16.0	373.0	IPBV300 + 2PL350 * 10
T3T4	16.0	463.0	IPBV300 + 2PL400 * 20

than two other substructures. It was assumed that the unknown DPs for the joints are between 0% and 40% as illustrated in Section 3. The mode shapes were assumed to be measured only at 12 DOFs, which include the displacements in horizontal- and vertical-directions at six nodes in the internal substructure.

7. Generation of training and testing patterns

The results of neural network-based system identification are dependent on the training patterns used for network training. Therefore, it is critically important to prepare training patterns or data sets of proper size. In general, the number of training patterns must be large enough to represent the relationship between the inputs and its corresponding outputs. On the other hand, for computation efficiency, the number of training patterns ought to be reasonably small, because preparing the training patterns and training the network takes most of the computational time required in the system identification of structures. The training patterns for the proposed neural network-based method consist of the modal data as input and the corresponding DPs as output. To generate training patterns, a series of eigenanalyses were performed. Because the input information to the neural network is limited to the components of the mode vectors for the internal substructure, the information regarding the damage parameters of the internal substructure was included in the components of the mode vectors of the internal substructure, rather than those of the external substructures. Thus, those damage parameters may be estimated with a reasonable accuracy from the

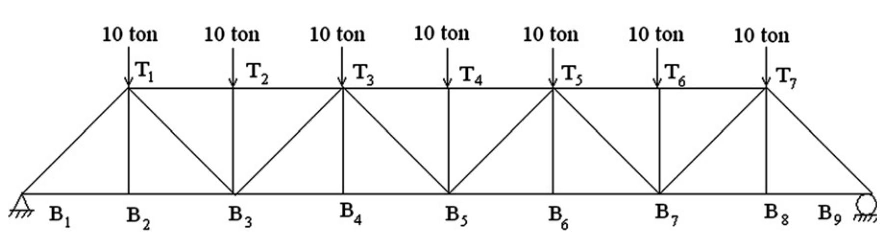

Fig. 6. Truss structure of Louisville Bridge.

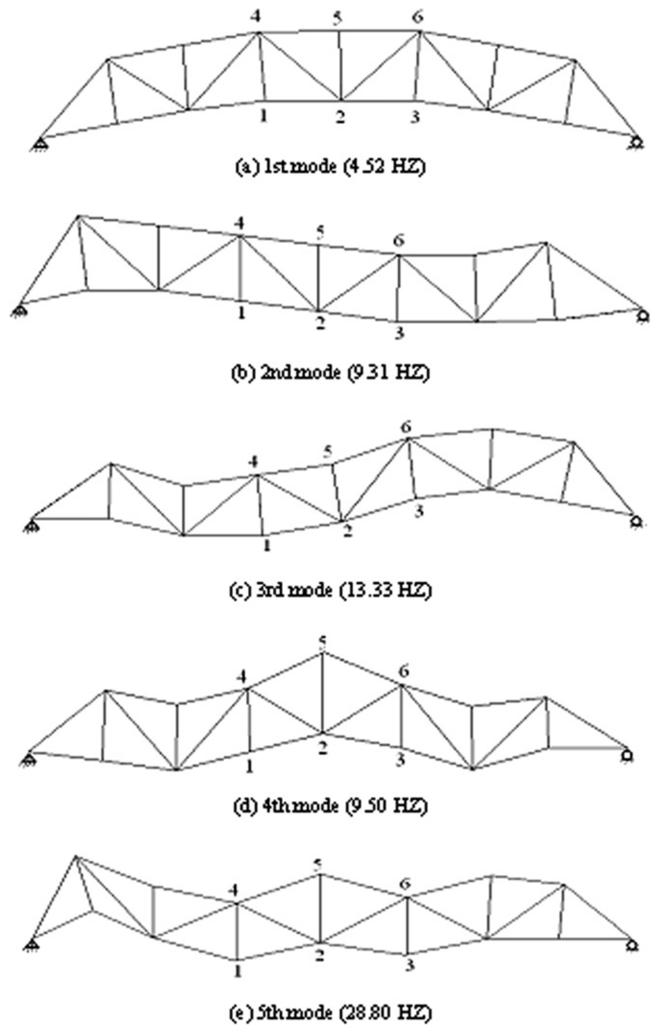

Fig. 7. First five mode shapes of Louisville Bridge truss structure. The numbers in parentheses are the natural frequencies.

components of mode vectors of the internal substructure as the input to the neural network. Hence, to generate training patterns, a significant number of associated structures with different modal properties, using DP values equal to 0%, 20% and 40% for every joint in the structure or substructure were considered, and their responses to the dynamic excitation were computed using numerical analyses. The total combination of the assigned DPs was 273 for the simple truss and 729 for Louisville Bridge truss. Consequently, 273 associated structures for the simple truss and 729 associated structures for Louisville Bridge truss were designed and investigated for natural frequencies. The results were used for training patterns. After training, the root-mean-square (RMS) difference vector of DP between each associated structure and the reference structure was then determined. Also 30 patterns for the simple truss and 50 test patterns for Louisville Bridge truss were held aside for testing the trained networks and the evaluation of its performance.

8. Training and testing of the damage detection neural networks

The training patterns, consisting of structural parameters and their corresponding DPs constructed above, are used to train the parametric evaluation neural network. The 273 training patterns for the simple truss and 729 training patterns for Louisville truss are arranged randomly before training. Each of the training patterns is used once for training at an epoch. The first four and five natural modes were used for the training process of the simple truss and Louisville truss, respectively. The complete training process of networks took approximately 75,000 epochs using the standard BP algorithm. The learning curve in the case of using five modes in input patterns is shown in Fig. 9. This curve shows the variations of RMS difference

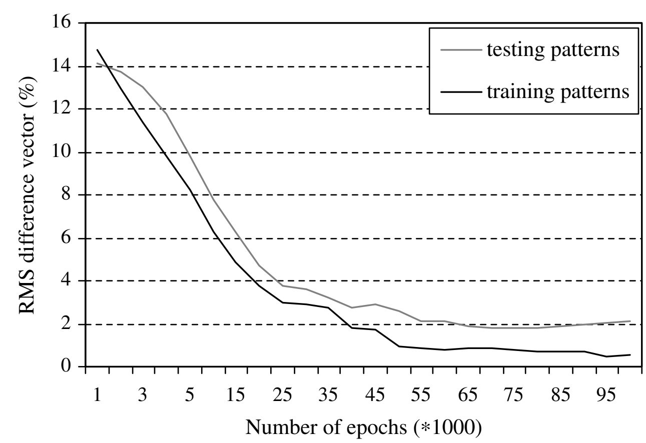

Fig. 9. The variations of RMS difference vector of outputs for learning and testing patterns with different number of epochs.

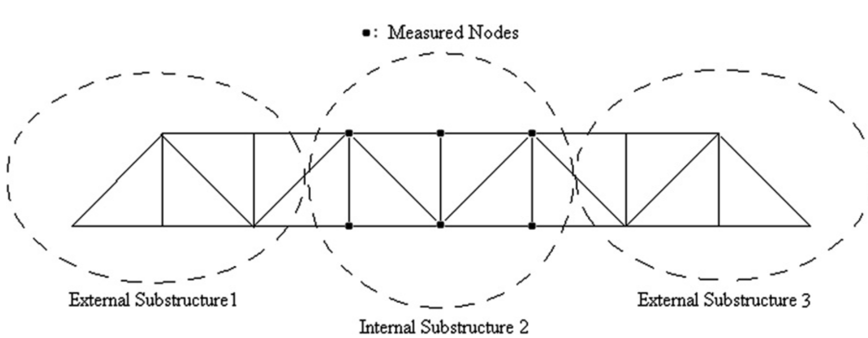

Fig. 8. Substructuring for localized identification of the second example.

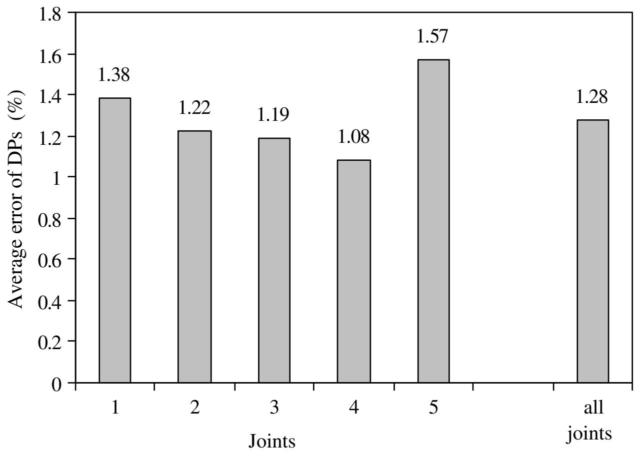

Fig. 10. The average error values of estimated damages for testing data set of the simple truss bridge (Error = |Estimated DP − Exact DP|).

vector of outputs for learning and testing patterns versus different number of epochs. As shown in Fig. 9, the RMS difference vector for training and testing patterns decreases with increase in number of epochs. When the number of epochs increases, the RMS difference vector for training patterns decreases but the RMS difference vector for testing patterns starts to increase. This is because, when the number of epochs exceeds a limit, network is slightly overtrained and it slightly loses its generality. Thus, optimal epochs for training ought to be considered and network should not be trained for more than optimal epochs. In this problem as seen in Fig. 9, the number of optimal epochs is around 75,000. After training the neural network, it can be employed to identify the DP of joints directly, when frequencies and mode shapes of internal substructure is available.

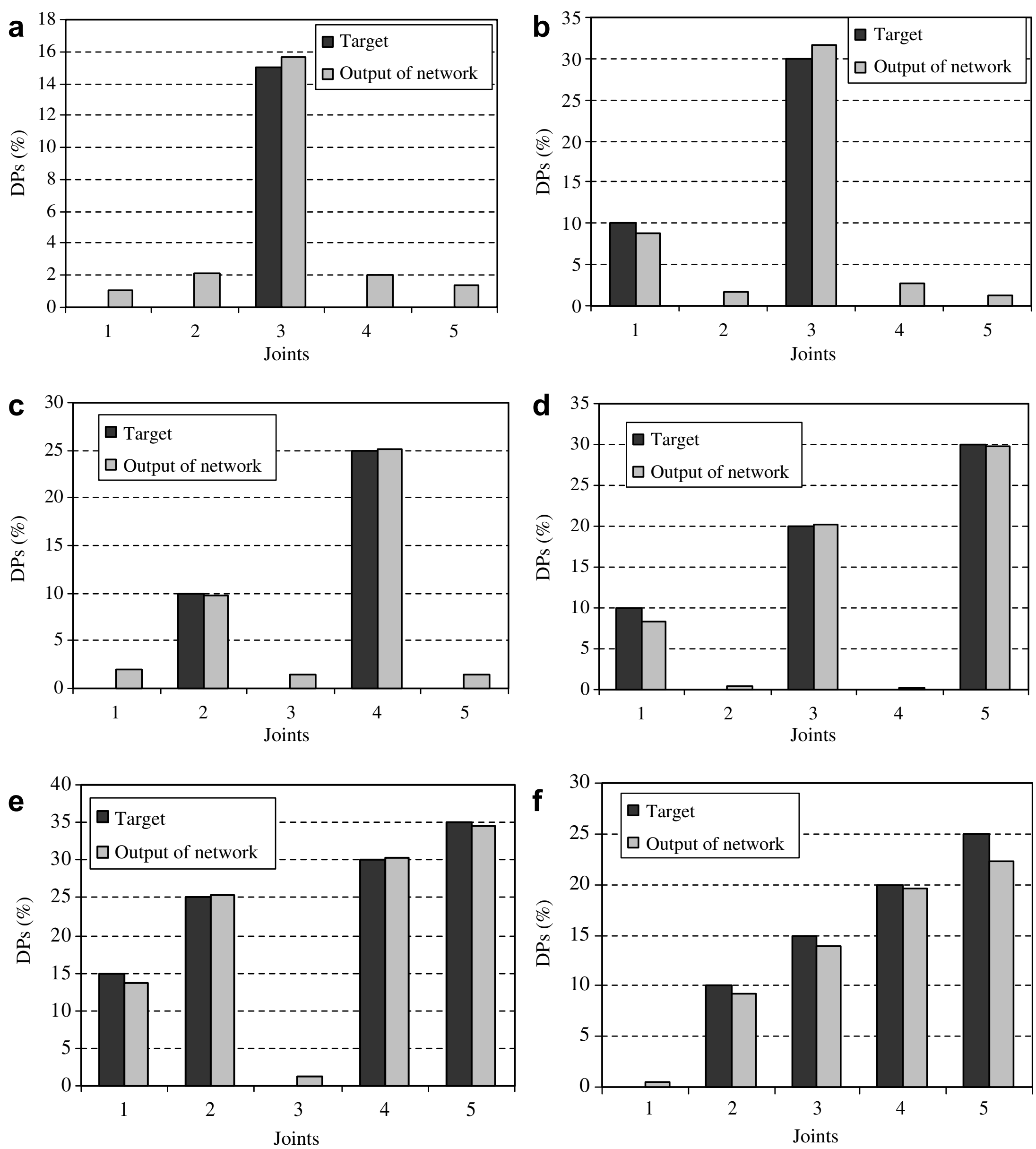

Fig. 11. Identification results of some testing patterns for the simple truss.

9. Neural networks damage identification results

The proposed methodology in this study is used to identify the joints damage of the two aforementioned examples.

9.1. The simple truss

In the case of simple truss in which first four modes specifications were used for training and testing the network, the best configuration for the network is obtained by trial and error, as follows: the number of input layer neurons = 32; the number of output layer neurons = 5; the number of hidden layer neurons = 50; learning coefficient = 0.95; learning coefficient rate = 0.5; momentum rate = 0.3.

The results of precision evaluation of trained network for training and testing patterns were obtained as follows: the RMS difference vector of training patterns = 0.66%; the RMS difference vector of testing patterns = 1.65%; the average error of testing patterns = 1.25%.

The identified damage of the joints for test patterns was compared with the exact values. The average error values for every joint and for all joints are shown separately in Fig. 10. It can be observed that the average of error for all joints is 1.28%.

For some of test patterns, the comparison of identified damage of the simple truss with the exact values is depicted in Fig. 11. In this figure, six testing patterns with quite randomly distributed joint DPs were controlled. For example, Fig. 11(a) represents a pattern in which joints 1, 2, 3, 4, and 5, involve 0%, 0%, 15%, 0%, and 0% of DPs, respectively. It is clearly seen that the proposed neural network strategy performs with good precision for the simple truss.

9.2. Louisville Bridge truss

Training network associated with Louisville Bridge truss was implemented using various numbers of first modes. The best architecture of networks for various cases was obtained by trial and error. Configuration of networks depending on the number of modes included in input data is shown in Table 2.

Precision evaluation of the results of trained network that depends on the number of modes included in input data for training and testing patterns is represented in Table 3.

The identified damages of the structure for test patterns are compared with exact values, and then average error values for every joint and for all joints are calculated. Fig. 12 shows the average of error values in the estimated DPs for various states with different number of modes included in the input patterns. It can be found that the accuracy of the results generally improves with increasing the number of modes included until the fifth mode. However, adding the sixth mode did not improve the estimates. Hence, the first five modes were included in the input values to the neural networks. Considering the case in which all joints are involved for average estimation of error values shows that in the state of using the first three modes, accuracy

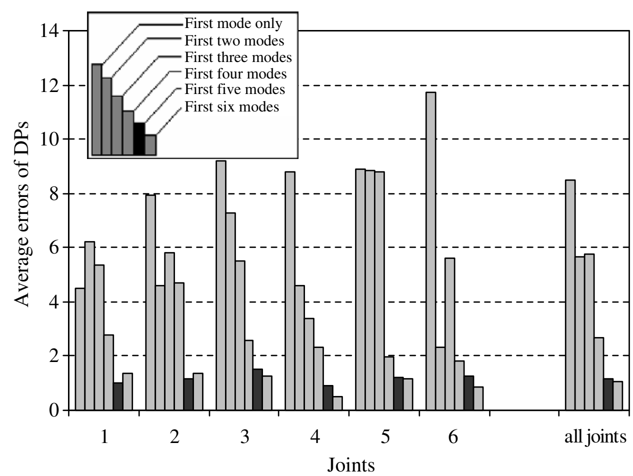

Fig. 12. Average estimation of DPs errors for different modes used in input patterns (testing data set) for Louisville Bridge truss.

Table 2
Configuration of networks depending on the number of modes included in input training data

Configuration of networks	First mode only	First two modes	First three modes	First four modes	First five modes	First six modes
Input layer	13	26	39	52	65	78
Output layer	6	6	6	6	6	6
Hidden layer	35	35	50	52	57	78
Learning coefficient	0.95	0.95	0.95	0.95	0.95	0.95
Momentum rate	0.2	0.5	0.4	0.4	0.3	0.3
Learning coefficient rate	0.5	0.5	0.5	0.5	0.5	0.5

Table 3
Evaluation of trained network precision depending on the number of modes included in input data

Precision criteria	First mode only	First two modes	First three modes	First four modes	First five modes	First six modes
RMS difference vector of training patterns	7.96	5.27	5.21	1.86	0.79	0.64
RMS difference vector of testing patterns	10.81	7.55	7.47	3.66	1.77	1.65
Average error[a] of testing patterns	8.51	5.74	5.65	2.68	1.18	1.08

[a] Error = $|\text{Estimated DP} - \text{Exact DP}|$.

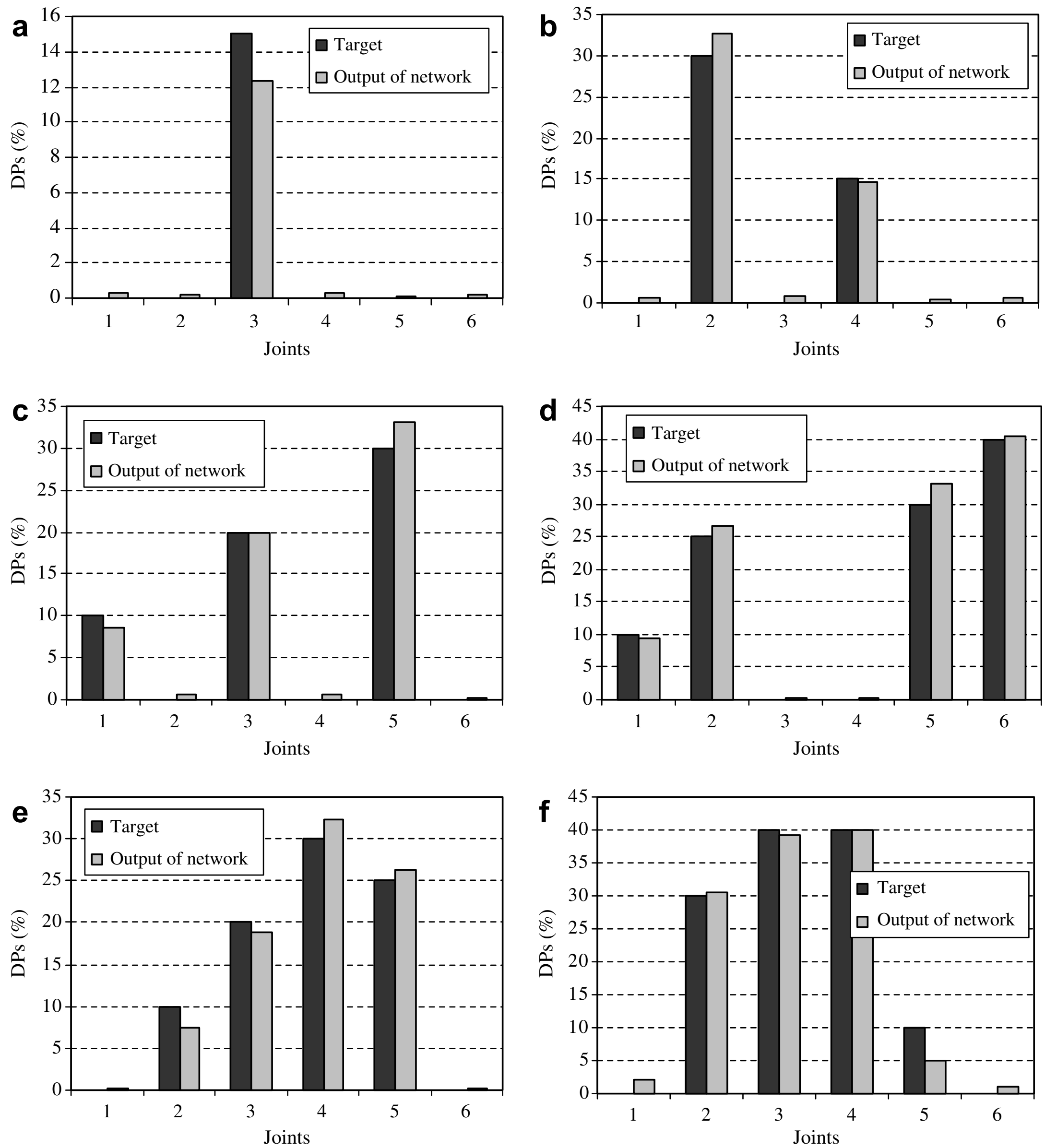

Fig. 13. Identification results of some testing patterns for Louisville Bridge truss structure.

does not change in comparison with the state of using the first two modes. Therefore, the third mode may be eliminated from training data.

For some of test patterns, comparison of identified damage of the Louisville Bridge truss structure with the exact values is shown in Fig. 13. It is clearly seen that in the case of a real bridge, there are good agreements between the results of the neural network strategy proposed in this study and the exact values.

10. Conclusions

A neural network-based system identification approach is presented for the estimation of the damage percentage of joints for truss bridge structures. The numerical example analyses were carried out on a simple truss and a real truss bridge. In the case of a real truss structure with many unknowns, substructural technique was used to reduce the number of unknown parameters. The obtained results were summarized as follows:

(1) In the proposed approach, the location and severity of damages in joints location of truss bridges can be found with good precision.
(2) The substructuring technique was found to be very efficient to reduce the number of unknown damage parameters to be estimated.
(3) Using an MLP network architecture is sufficient for the identification of damage location and severity in truss bridges.
(4) The average errors for testing data set in case of using five modes were found to be approximately 1%, which shows the applicability of the present method for the identification of large structural systems.

(5) In damage detection of truss bridges using this approach, five mode specifications is sufficient.
(6) This approach is very attractive for on-line or real-time damage diagnosis of structures in the framework of structural health monitoring.

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