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An effective deep feedforward neural networks (DFNN) method for damage identification of truss structures using noisy incomplete modal data

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ABSTRACT

Structural damage assessment is a challenging problem of study due to lack of information in data measurement and the difficulty of extracting noisy features from the structural responses. Therefore, this paper proposes an effective deep feedforward neural networks (DFNN) method for damage identification of truss structures based on noisy incomplete modal data. In the proposed approach, incomplete datasets are randomly generated by a reducing finite element (FE) model. Based on the collected data, the DFNN model is constructed to predict damage position and severity of structures. To obtain a better performance of the network, the new ReLu activation function and Adadelta algorithm are employed in this work. In addition, the state-of-the-art mini-batch and dropout techniques are adopted to speed up the training process and avoid the over-fitting issue in training networks. Various hyperparameters such as number of hidden units, layers and epoches are surveyed to built a good training model. In order to demonstrate the efficiency and stability of the proposed method, a 31-bar planar truss structure and a 52-bar dome-like space truss structure are investigated with various damage scenarios. Moreover, the performance of the DFNN method is not only illustrated with the noise free input data but also with noisy input data. Different noise levels of the input data are taken into account in this study. To accurately predict the damage location and severity of the structures, 10000 and 20000 data samples corresponding to the 31-bar planar truss and the 52-bar dome-like space truss are randomly created in term of quantity of damage members, damage locations and damage severity of the structures for training the DFNN models. The results predicted by the DFNN using incomplete modal data are compared with those of the complete and actual models. The obtained results indicate that the DFNN is a promising method in damage localization and quantification of civil engineering structures.

1. Introduction

During the operational life of engineering structures, it is difficult to avoid damages that occur under the effect of environmental, human factors and aging of materials. If damages are not detected timely to deploy the maintenance for stopping deterioration propagation, structures will be early collapsed and lead to catastrophic failures. Therefore, providing promptly high-precision information of damage locations and severity is very important to guarantee lifetime safety of structures. For this reason, an approach using various visual inspection methods was used to detect damages in structures. However, this approach is suitable only for surfaces and large defects which can be observed by human eyes. For small scale or unseen damages, the method may not work. Additionally, it requires heavy human efforts and cost. To overcome these limitations of the visual inspection, another approach using various structural health monitoring (SHM) techniques [1] has been developed to monitor the status of structures and evaluate the structural integrity and safety. Among them, the finite element (FE) model updating has attracted considerable attention of the scientific community in the last decade. Many studies concerning the application of the FE model updating in structural damage detection have been published. For instance, Jaishi and Ren [2] combined FE model updating with the

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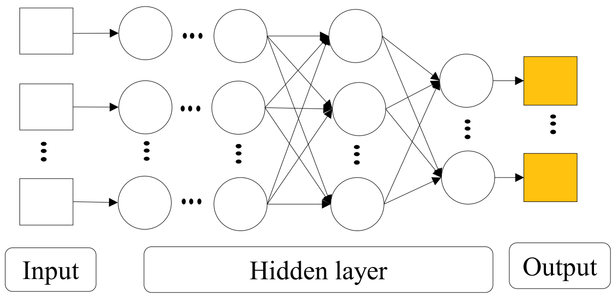


Fig. 1. A typical architecture of deep feedforward neural networks.

trust region newton algorithm for damage detection of the simply supported beam. Sun and Liu [3] used a multi-objective genetic algorithm (GA) and the FE model updating to recognize damages in a steel suspension bridge. Jafarkhani and Masri [4] investigated the efficiency and reliability of an evolutionary strategy in the FE model updating by detecting defects in a quarter-scale two-span reinforced concrete bridge system. Zheng et al. [5] employed the FE model updating to identify damages in a plane frame and a 12-story shear building. Vo-Duy et al. [6] adopted an improved differential evolution (DE) and the FE model updating to identify damages in laminated composite plates. Nanthakumar et al. [7] combined an extended finite element method (XFEM) with the level set method in determining the number, approximate location and shape of defects in a damaged piezoelectric structures. Dinh-Cong et al. [8] applied the teaching-learning-based optimization (TLBO) algorithm and the FE model updating for damage detection of the 2D frame structure. A combination of the FE model updating and the Jaya algorithm for damage assessment of truss structures, concrete and laminated composite plates has been examined by Dinh-Cong et al. [9,10]. In another work, Dinh-Cong et al. [11] utilized the lightning attachment procedure optimization (LAPO) algorithm and the FE model updating for damage identification of three kinds of structures including a two-span continuous beam, a 2D frame and a cantilever plate. Other related outstanding studies on damage detection using the FE model updating could be found in Refs. [12–19]. In general, although the FE model updating has provided satisfactory results in structural damage detection, the computational cost of such approaches is still high due to the finite element procedures and complex integral calculations.

Recently, a new approach using artificial neural networks (ANN), a branch of the artificial intelligent (AI), has been used as one of useful mathematical tools for many different applications [20]. In particular, there are increasing interests in using the ANN to predict the damage level and evaluate the safety of engineering structures in recent years. Specifically, the ANN has been successfully applied in detecting the damage location and severity of many distinct structures such as trusses [21,22], steel frames [23], beams [24–26] and laminated composite plates [27]. Additionally, various ANN architectures have been also developed for structural damage identification. For instance, the convolution neural network (CNN) has been employed to identify the damages of steel and concrete structures [28–30], or an adaptive neuron fuzzy inference system (ANFIS) was utilized to identify defects in a model steel girder bridge [31], or for detecting damage location and severity of truss structures, we can list various artificial intelligent methods such as back-propagation neural networks (BPNN), least square support vector machines (LS-SVMs), radial basis function neural network (RBFN), large margin nearest neighbor (LMNN), extreme learning machine (ELM), gaussian process (GP), multivariate adaptive regression Spline (MARS), random forests, or Kriging [21]. These results showed that the conventional ANN architectures can provide expected solutions in identifying the structural defection. However, as shown in the reference [32], the performance of these methods are significantly effected by the input features. When the noise factor is considered in the

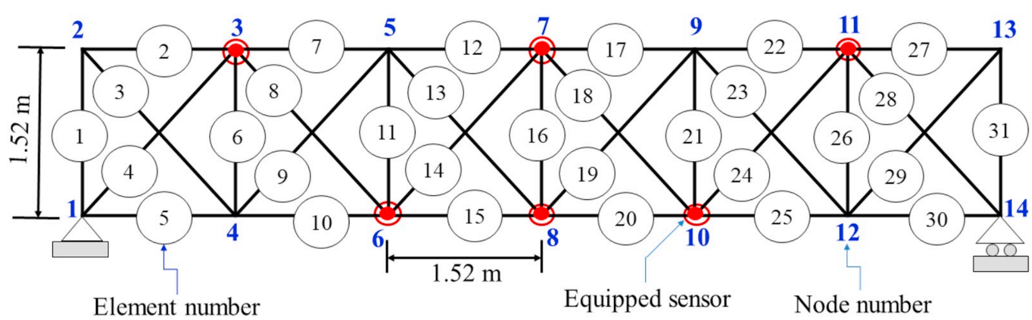


Fig. 2. The finite element model of the 31-bar planar truss.

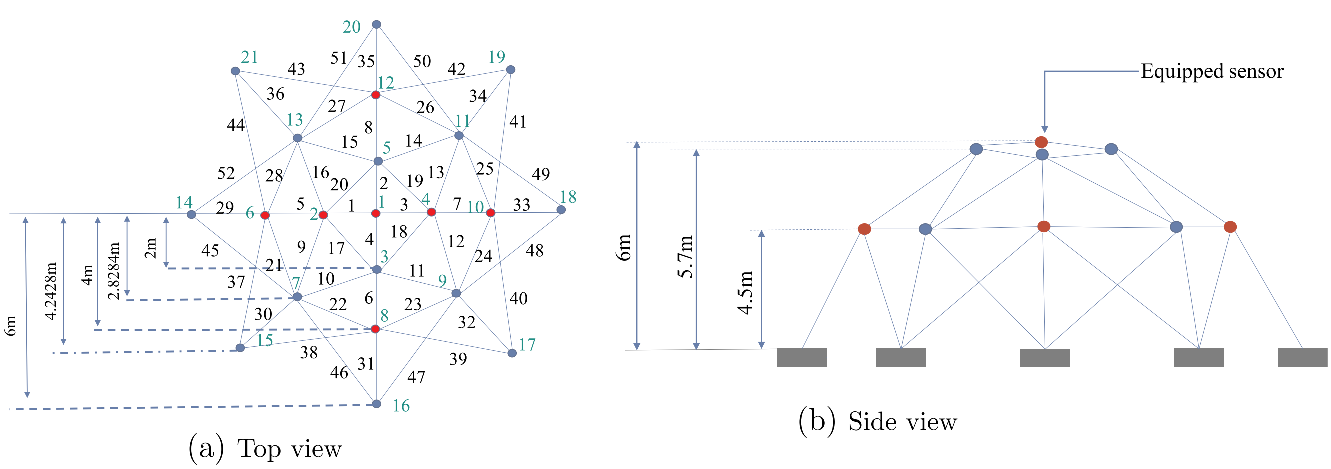


Fig. 3. The finite element model of the 52-bar dome-like space truss.

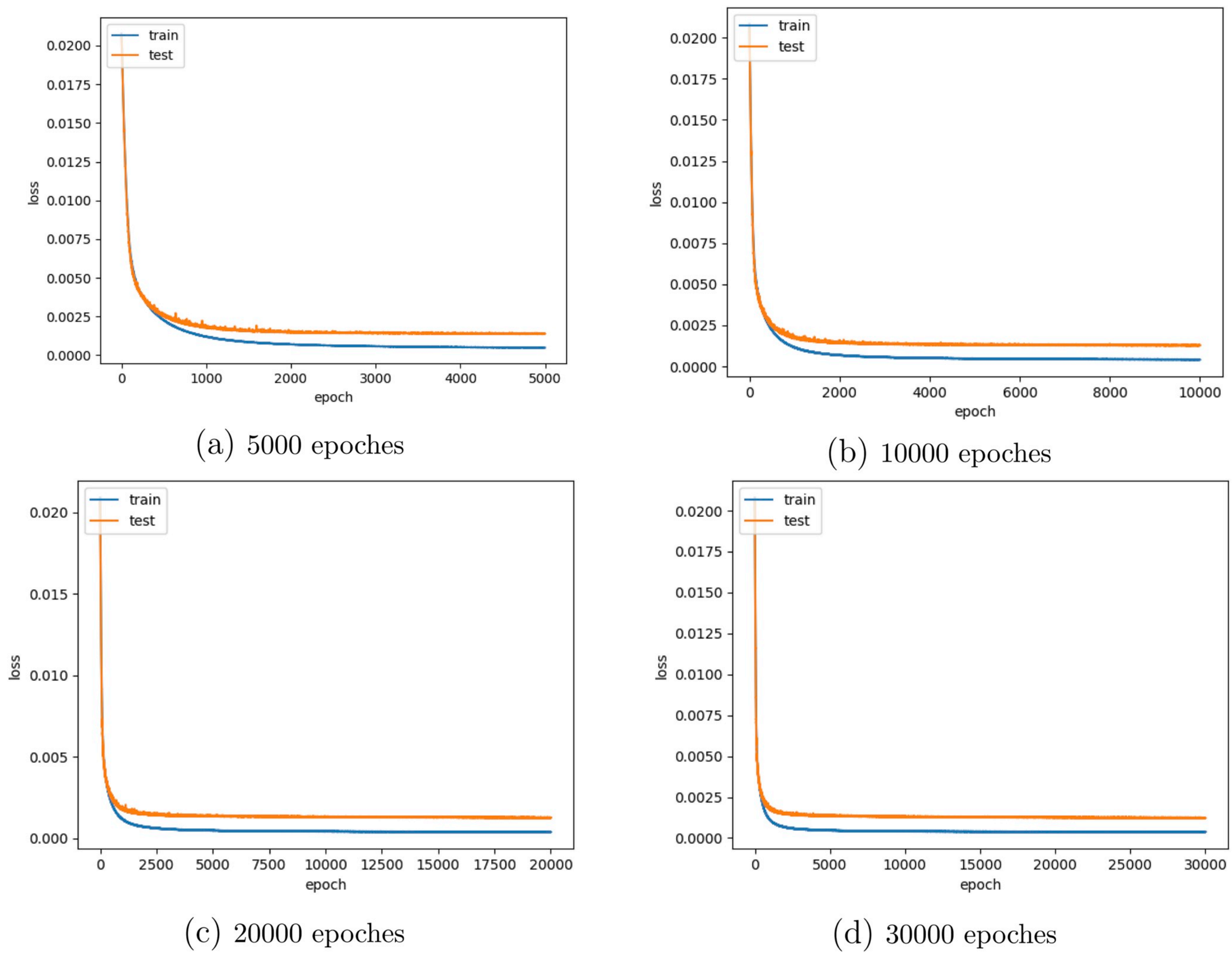


Fig. 4. The convergence history of the loss function for the training and test with the (65-500-500-500-500-500-31) architecture obtained by the Adadelta optimizer and the ReLU activation function.

input data, these approaches may not work well. Moreover, they are also time consuming when problems become more complicated with multiple hidden layers.

Accordingly, deep neural network (DNN) or deep learning (DL) architectures with multiple levels of representation have been developed to solve complex and high non-linear problems. The DNN can learn to transform from one-level description into a multi-level one, which is more abstract level. Thanks to the distribution of such adequate transformations, the DNN can learn very complicated functions. One of main advantages of the DNN is that feature layers are learned from data via a general purpose learning process without being designed by human engineers. Moreover, the DNN was discovered to be very efficient in dealing with complicated structures in high dimensional data. Consequently, it has been applied in various areas such as business [33–35], medicine [36–38], image recognition [39,40], speech recognition [41–43], topic classification [44], sentiment analysis [45], question answering [46], and language translation [47]. Recently, the DNN architectures have been widely applied to solve different engineering problems. For example, Guo et al. [48] employed a deep collocation method to predict the bending behavior of the Kirchhoff plate with various shapes, loads and boundary conditions. Fan et al. [49] used the DNN model to predict the building energy. Do et al. [50] combined the DNN with modified symbiotic organisms search algorithm to solve a material optimization problem of functionally graded plates. Noraas et al. [51] successfully applied the deep convolutional neural network to predict processing structural property relations from materials microstructures images, surpassing current best practices and modeling efforts. More recently, the application of DNN architectures in structural health monitoring field has been intensively concerned. For instance, Liu and Zhang [52] adopted the deep convolution neural network (DCNN) model for detecting damages in steel fuse members. In that study, a large number of images created by the FE simulation was employed for the data training. The efficiency and reliability of the DCNN method have been validated through two different case studies of perforated steel shear link beams and dogbone steel plates. Pathirage et al. [53] proposed a deep sparse autoencoder framework for identifying damages in a steel frame structure and a concrete bridge. In this study, the effect of noise in the measurement data and uncertainties in the finite element modeling was taken into account to show the performance and stability of the proposed framework. Xu et al. [54] introduced a modified faster region based convolution neural network (faster R–CNN) for the seismic damage identification and localization of defected reinforced concrete columns from images. Obtained results indicate that the faster R–CNN is capable of automatically identifying and localizing the aforementioned multi-type seismic damages. More recently, Wang et al. [55] also employed faster R–CNN model based on ResNet101 framework to automatically detect defects in historic masonry buildings. The results showed that the DNN models can also provide expected solutions in identifying the structural defection. However, as shown in the above literature review, the DNN models

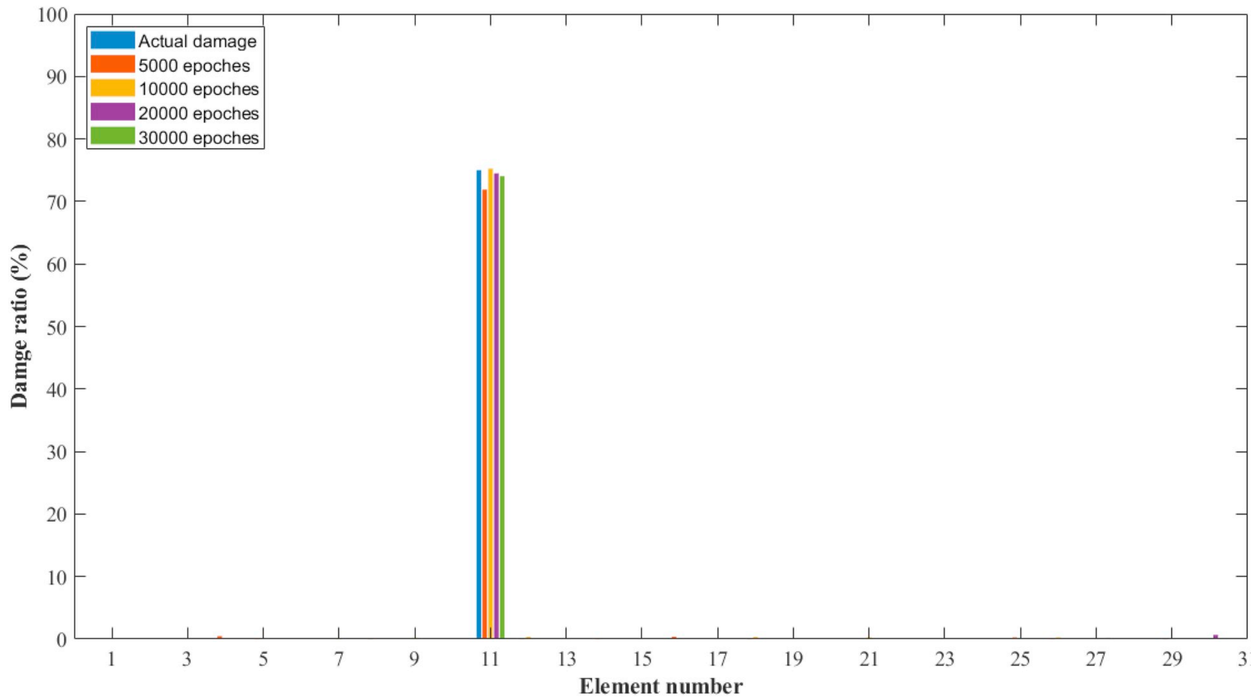


Fig. 5. Prediction results of the (65-500-500-500-500-500-31) architecture after several number of training epoches.

almost only work with complete modal data. The application of DNN models in identifying defects of engineering structures with noisy incomplete modal data has not been studied yet.

In order to fill in the above research gap, an effective deep feedforward neural network (DFNN) method is proposed for damage detection of truss structures using noisy incomplete modal data. In this study, different incomplete datasets are randomly generated in term of quantity of damage members, damage locations and damage severity of structures using a reducing FE model. Relied on the given datasets, the DFNN models are established for the data training process. The new ReLu activation function and Adadelta algorithm are adopted in the DFNN model to achieve the better performance of the network. Additionally, the dropout and minibatch techniques are also applied in the network to avoid the over-fitting problem and speed up the training procedure. Several hyperparameters of the DFNN model such as, number of hidden units, layers, epoches are surveyed to seek a suitable DFNN training model. The accuracy and reliability of the proposed method are investigated through two different numerical examples including a 31-bar planar truss and a 52-bar dome-like space truss. In addition, the performance and stability of the DFNN method are further examined with the effect of different noise levels in the input data. The results predicted by the DFNN using noisy and noise-free incomplete modal data are compared with those of the complete and the actual ones.

The paper is outlined as follows, the detailed description of the deep neural networks model is given in Section 2. Section 3 provides the extension of DFNN in structural damage detection and several test results of numerical examples. Finally, some conclusions are presented in Section 4.

2. Deep feedforward neural networks

Deep feedforward neural network (DFNN) is the quintessential deep learning (DL) model [56]. The goal of the DFNN is to learn a complicated and abstract representation of the data in a hierarchical manner by passing the data through multiple transformation layers [57]. The architecture of the DFNN is commonly included three parts, namely, input layer, hidden layer and output layer, in which each layer has a number of interconnected processing units. A typical architecture of the DFNN is shown in Fig. 1. In the DFNN, each layer utilizes a nonlinear transformation on its input and provides a representation in its output. We assume that the neural network consists N layers. The output signal of $(l)^{th}$ layer is expressed as follows

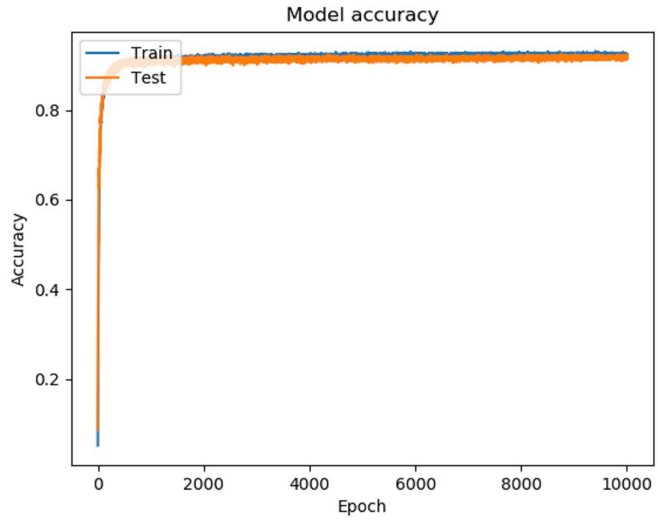
$$z_j^l = f\left(w_j^T a_j^{l-1} + b_j\right), \quad l = 1,\ 2,\ 3,\ \ldots, N, \tag{1}$$

where f is the activation function; w_j^T is the weight vector which indicates the effect of all units in a same hidden layer; a_j^{l-1} defines the output signal of the $(l-1)^{th}$ layer; b_j is the bias parameter of j^{th} unit in the $(l)^{th}$ layer.

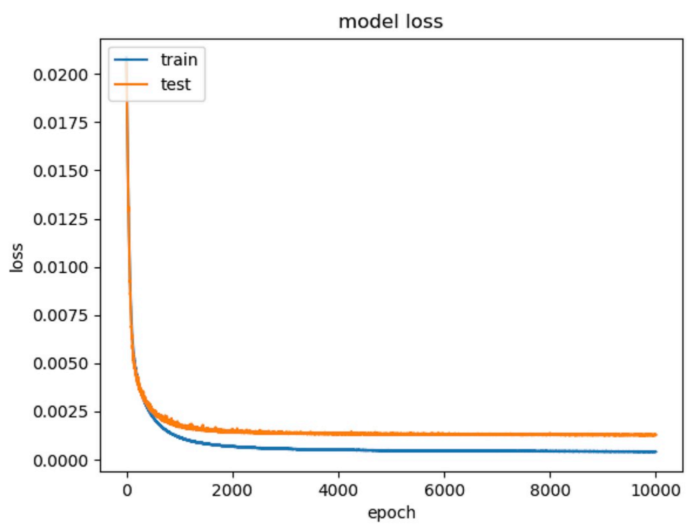
For a regression problem, choosing an activation function to transfer input signals to output ones for a certain neural network architecture is crucial for the accuracy of output data. In traditional neural network, the sigmoid and hyperbolic tangent activation functions are widely employed to define a specific output value of the network. Nevertheless, when the layer of the network becomes deeper, using these smooth nonlinear activation functions fails to receive useful gradient information of the loss function. The gradient of the loss function is back propagated through the network and adopted to modify the internal parameters. When each hidden layer using these activation functions is added in the network, the gradient of loss approaches to zero. This is called the vanishing gradient issue. Vanishing gradients make it hard to know which direction the parameters should move to improve the cost function [56]. In order to overcome this problem, the rectified linear unit (ReLU) is proposed to give the better performance of the DFNN. Because the ReLU is nearly linear, it owns many properties that make linear models easy to optimize with gradient-based methods. Moreover, the ReLU can learn faster with the networks consist of many layers and allow to train deep supervised network without unsupervised pre-training [58]. Hence, the ReLU activation function is employed to denote the expected output value of networks in this work. The mathematical formulation of the ReLU can be denoted as

$$f(x) = \begin{cases} 0 & \text{for} \quad x < 0 \\ x & \text{for} \quad x \geq 0 \end{cases}. \tag{2}$$

In order to evaluate the accuracy of the output model's prediction,



(a) The convergence history of the model accuracy for the training and test.



(b) The convergence history of the loss function for the training and test.

Fig. 6. The convergence history of the model accuracy and the loss function of the 65-500-500-500-500-500-31 architecture for damage detection of the 31-bar planar truss.

the DFNN should be trained to minimize the loss function. Mean square error (MSE) which is most popularly utilized as a loss function in the regression problem is employed in this study to judge the precision of the prediction results. The formulation of the MSE can be expressed as follows

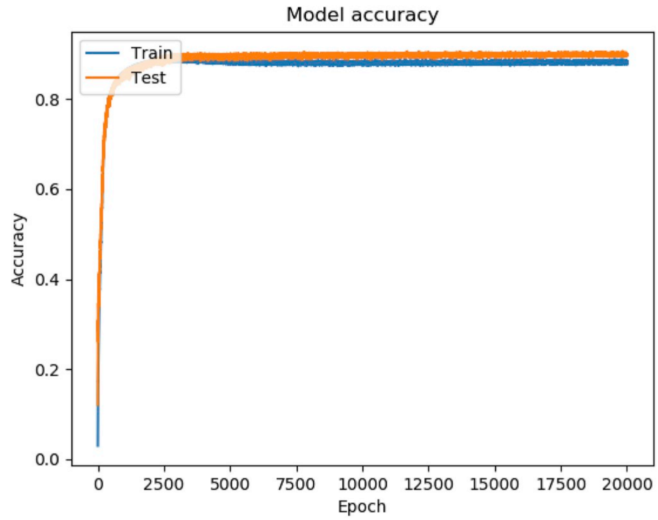
$$E_{\text{mse}} = \frac{1}{n}\sum_{k=1}^{n}(y_k - \bar{y}_k)^2, \tag{3}$$

in which n is the number of samples in a training set; y_k is the actual desired output and $\bar{y}_k$ is the output of model prediction.

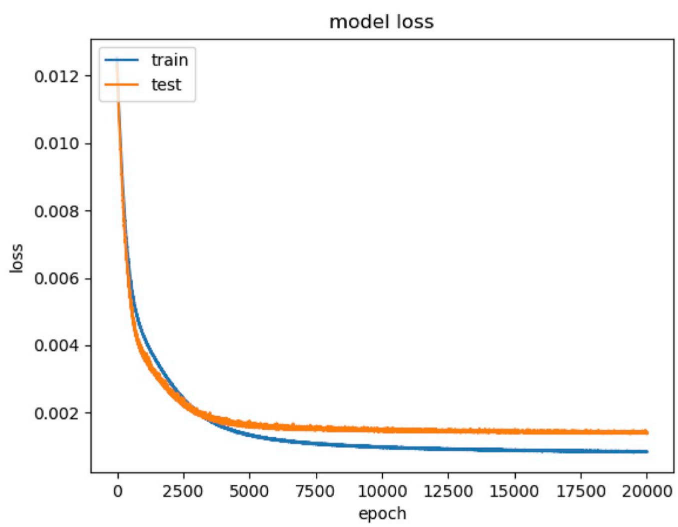
During the training process of the network, the MSE loss function is minimized using a specific gradient decent algorithm. Recently, many algorithms have been developed to search optimal parameters of the network so that its loss function becomes minimum, such as, stochastic gradient descent (SGD) [59]; adaptive gradient algorithm (Adagrad) [60]; adaptive moment estimation (Adam) [61]; RMSprop [62] and Adadelta [63]. Among these methods, the RMSprop, Adam and Adadelta are very similar methods that work well in the same circumstances [64]. However, there is not the most efficient algorithm among these methods. Because they depend on the specific problems and different conditions. As the result shown in Table 4, it can be seen that the combination of ReLU and Adadelta attains the lowest training MSE after 10000 epoches while the ReLU combined with the Adam gains the highest value of MSE. Therefore, the Adadelta is used as an optimizer for the MSE loss minimization in this work.

When optimizing weights in a network, batch gradient descent calculates the error for each sample in the training set, however, this model is only updated after all training samples have been evaluated. This process can make the model updates and training speed become very slow for large datasets. To handle this problem, mini batch technique introduced by Hinton [65] is adopted in this work. Mini-batch gradient descent helps split the training dataset into small batches that are used to compute model error and update model parameters.

In training networks, the overfitting problem may occur in DFNN networks. To deal with this issue, the dropout method which is proposed by Srivastava et al. [66] is applied in this study.



(a) The convergence history of the model accuracy for the training and test.



(b) The convergence history of the loss function for the training and test.

Fig. 7. The convergence history of the model accuracy and the loss function of the 110-900-900-900-900-900-52 architecture for damage detection of the 52-bar dome-like space truss.

Table 1
Material properties of the 31-planar bar truss.

Property	Value
Young modulus $E(\mathrm{N}/\mathrm{m}^2)$	7×10^{10}
Density ρ $(\mathrm{Kg}/\mathrm{m}^3)$	2770
Sectional area A (m^2)	0.0025

3. Damage identification using deep feedforward neural network

In order to demonstrate the accuracy and reliability of the proposed method. Two different numerical examples using incomplete modal data collected by a limited number of measurement equipments are investigated. The first five natural frequencies and mode shapes of the damaged structure are assumed to be measurable for the stiffness parameters estimation. The damage in structures is simulated by considering a reduction in the elastic modulus of individual elements as

Table 2
Five different damage scenarios in the 31-bar planar truss.

Scenario	1	2		3		4			5		
Element number	2	10	11	7	20	10	14	24	2	16	27
Severity of damage (%)	30	5	10	35	45	40	30	30	30	30	40

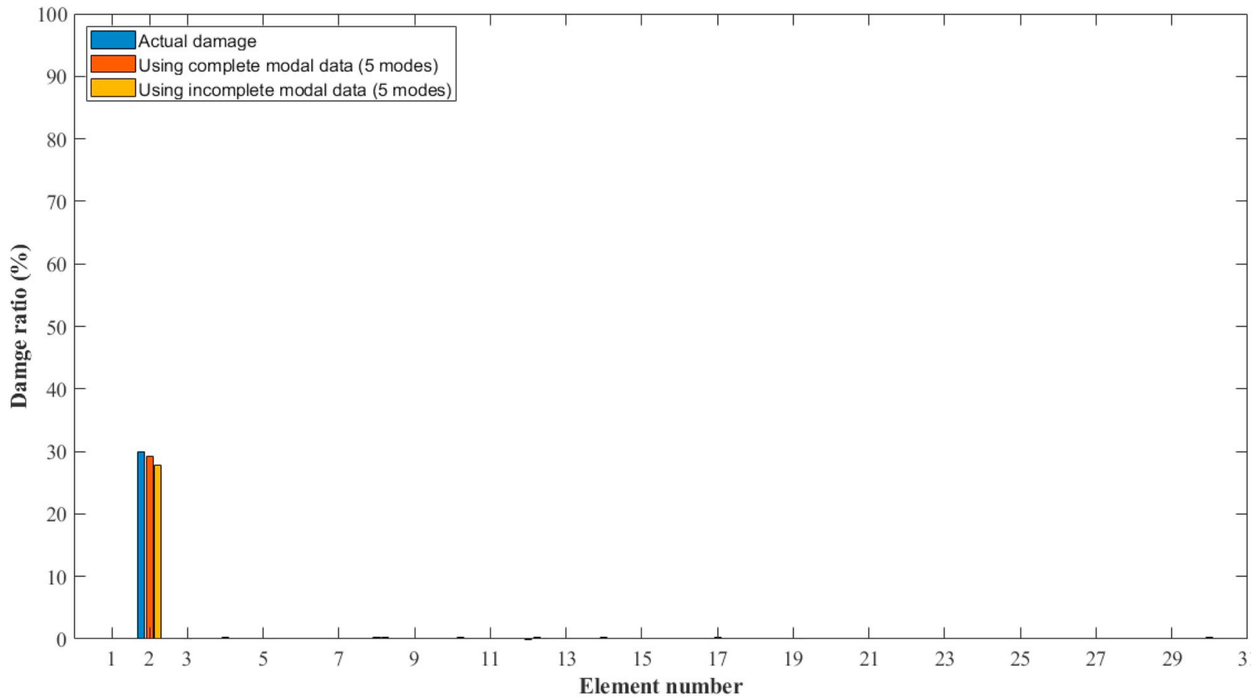


Fig. 8. Prediction results of the 31-bar planar truss for the case of single damage on noise free data.

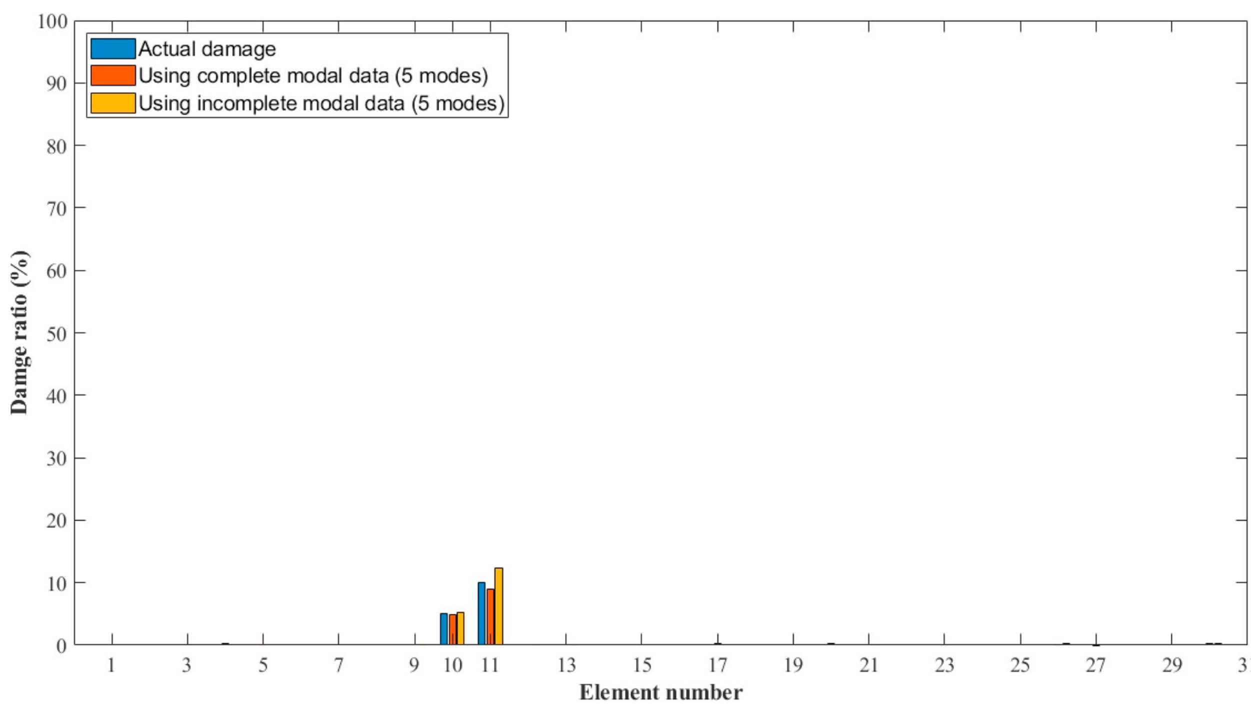


Fig. 9. Prediction results of the 31-bar planar truss for the case of two damages on noise free data.

$$x_i = \frac{E_o - E_{d,i}}{E_o}, \quad i = 1, n, \tag{4}$$

in which E_o is the original modulus of elasticity; $E_{d,i}$ is the elasticity modulus of the damaged i^{th} element; n is the number of elements. Various damage patterns are considered to show the effectiveness and stability of the proposed method. Additionally, the performance of the DFNN is not only inspected with noise free input data but also with noisy input data. Distinct noise levels in frequencies and mode shapes are examined. Test results with incomplete modal data are compared with those of complete ones and actual damages as well. For the above purposes, a 31-planar bar truss and a 52-bar dome-like space truss with various damage scenarios are studied. The detailed implementation and simulation results are presented in the subsequent sections.

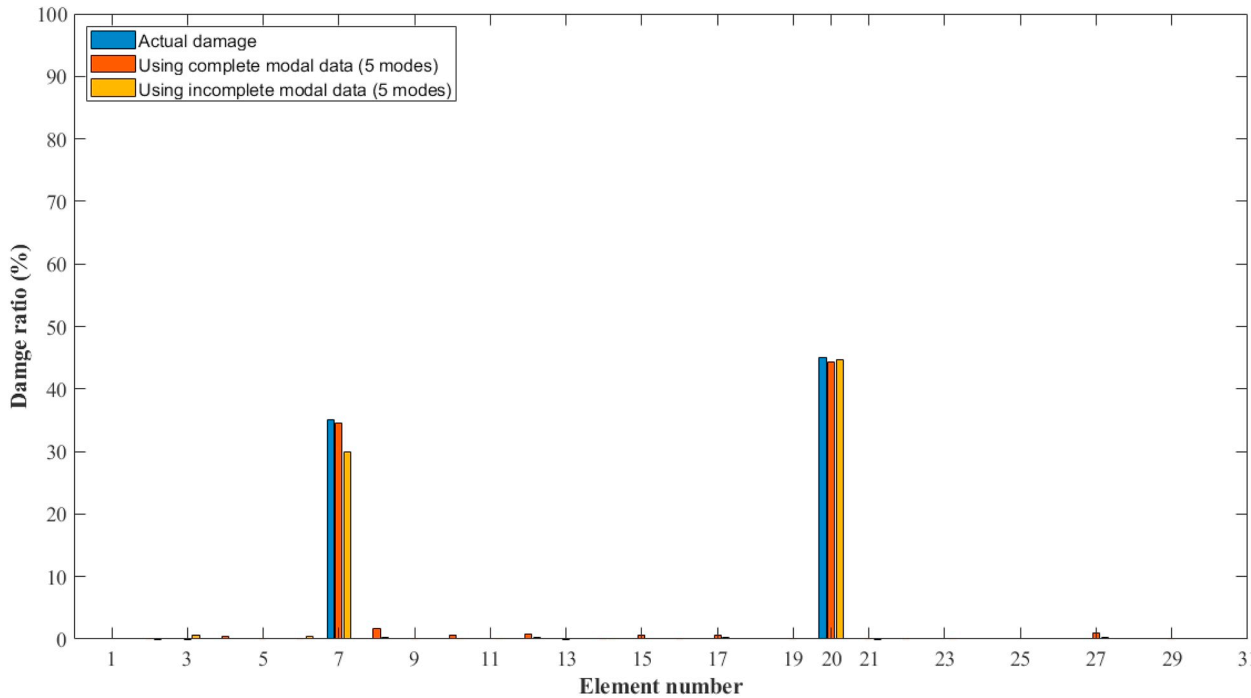


Fig. 10. Prediction results of the 31-bar planar truss for the case of two damages on noise free data.

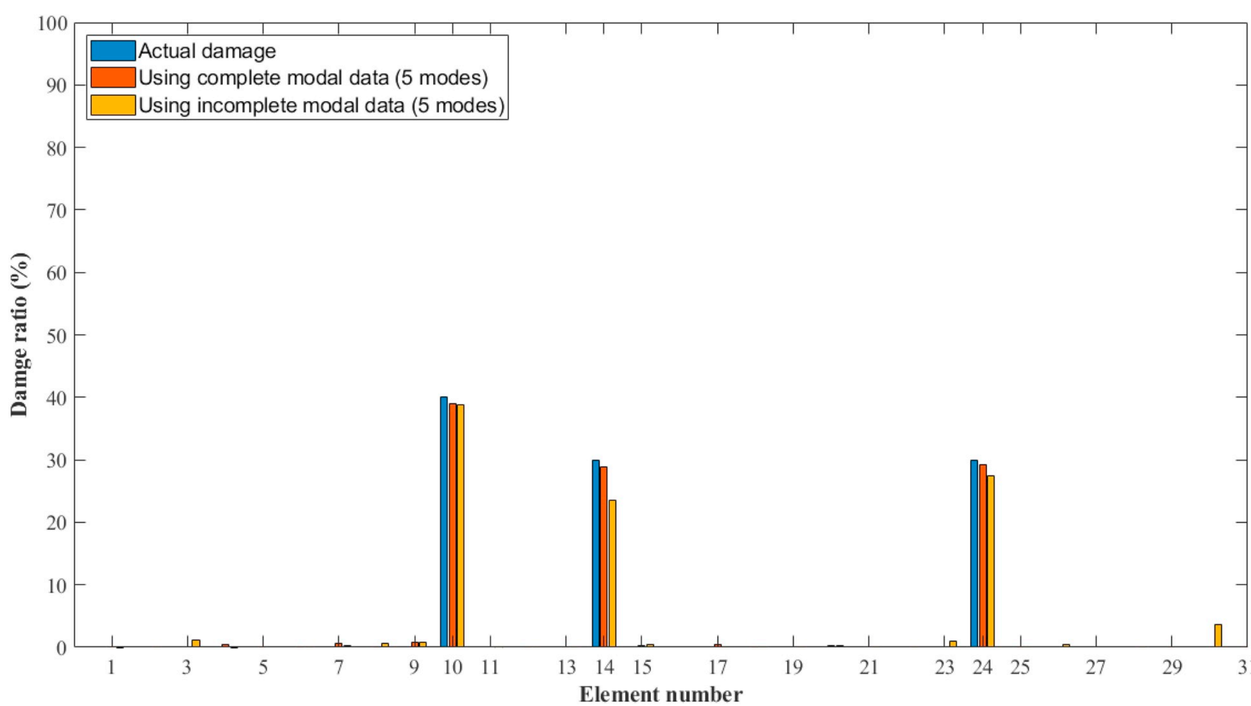


Fig. 11. Prediction results of the 31-bar planar truss for the case of three damages on noise free data.

3.1. Implementation

3.1.1. Data collection

In this study, the FE model of the 31-bar planar truss as shown in Fig. 2 and the 52-bar dome-like space truss as given in Fig. 3 are considered as a representation of practical structures. The first five frequencies and mode shapes of the structures are considered as the input data of the DFNN to predict the damage location and severity. Since there exists no publicly available data concerning the free vibration behavior of the damaged 31-bar planar truss and 52-bar dome-like space truss, a FE model is constructed to create datasets for the training and test purpose of the DFNN. The mathematical formulation of the FE model can be expressed as,

$$\left(\mathbf{K} - \lambda^2\mathbf{M}\right)\Delta = 0, \tag{5}$$

where **K** and **M** are the stiffness matrix and mass matrix, respectively; λ^2 is the eigenvalue; Δ defines the eigenvector corresponding to an eigenvalue.

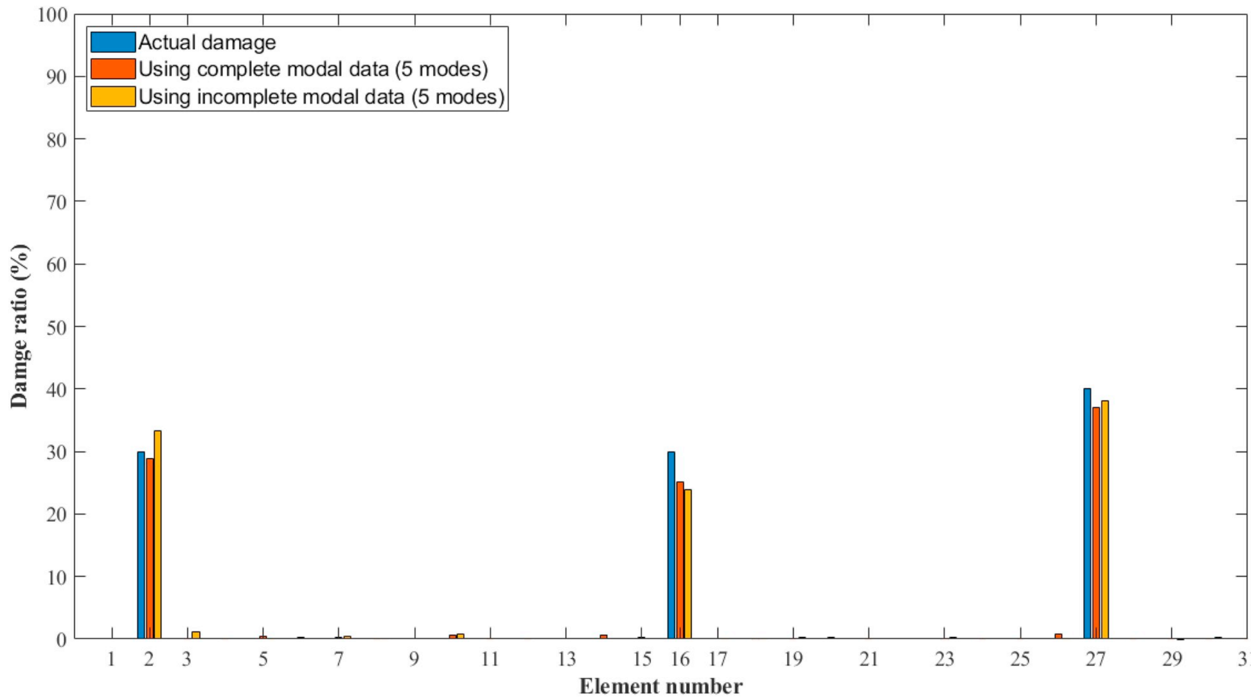


Fig. 12. Prediction results of the 31-bar planar truss for the case of three damages on noise free data.

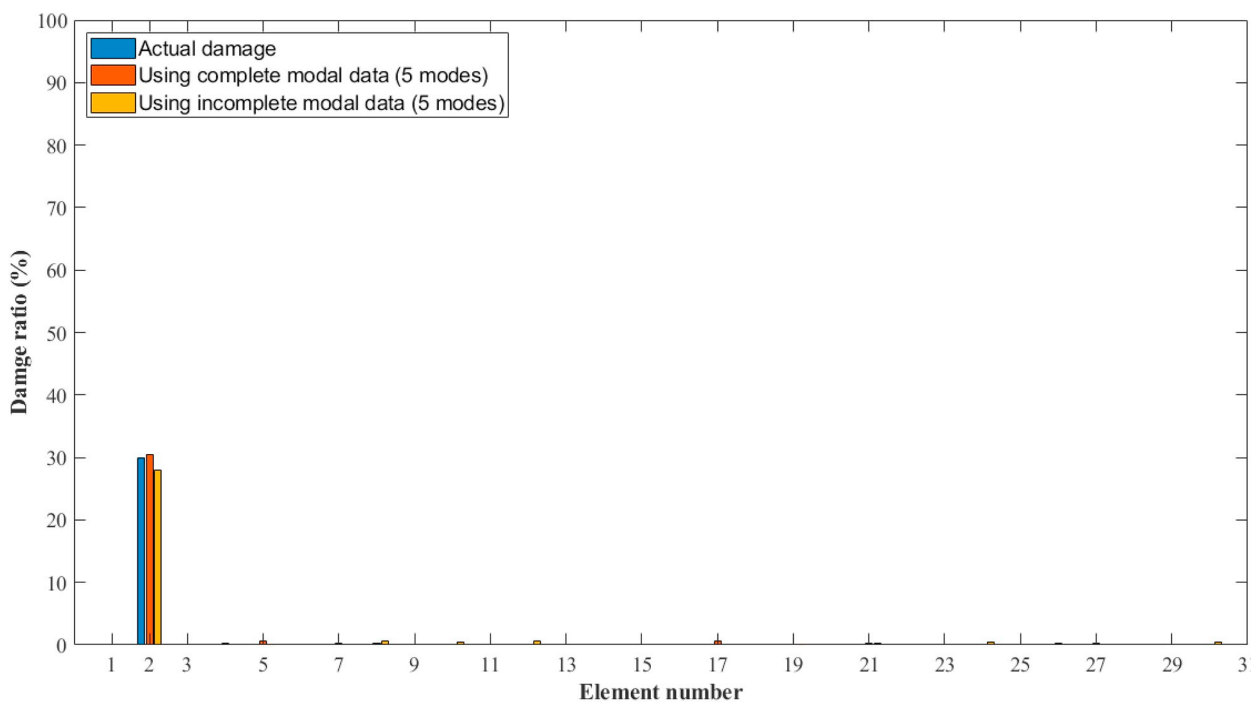


Fig. 13. Prediction results of the 31-bar planar truss for the case of single damage on noisy data (±1% noise in frequencies and ±5% noise in mode shape).

By solving the above FE problem, various damaged scenarios on the monitored structures are randomly created for training the DFNN model. To predict damages in the 31-bar planar truss, one dataset including 10000 samples is used to train the model. Meanwhile, another dataset containing 20000 samples is adopted to train the DFNN for damage detection of the 52-bar dome-like space truss. Each data sample including an input-output data pair is randomly generated in term of quantity of damage members, damage locations and damage severity of structures. The severity of each defected element is randomly created in range of [0,1]. To train the DFNN, only 80% collected dataset is used. This means that only 8000 and 16000 data samples are used to train the DFNN for predicting the damages in the 31-bar planar truss and 52-bar dome-like space truss, respectively. The performance of the network is then evaluated by the 20% remaining dataset. All the generated data are assumed to be collected from the limited sensor set at specific nodes of the structures. This means that only the information at the limited nodes in the FE model of the studied structures is given corresponding to each scenario. Additionally, the effect of noise factor is taken into account in

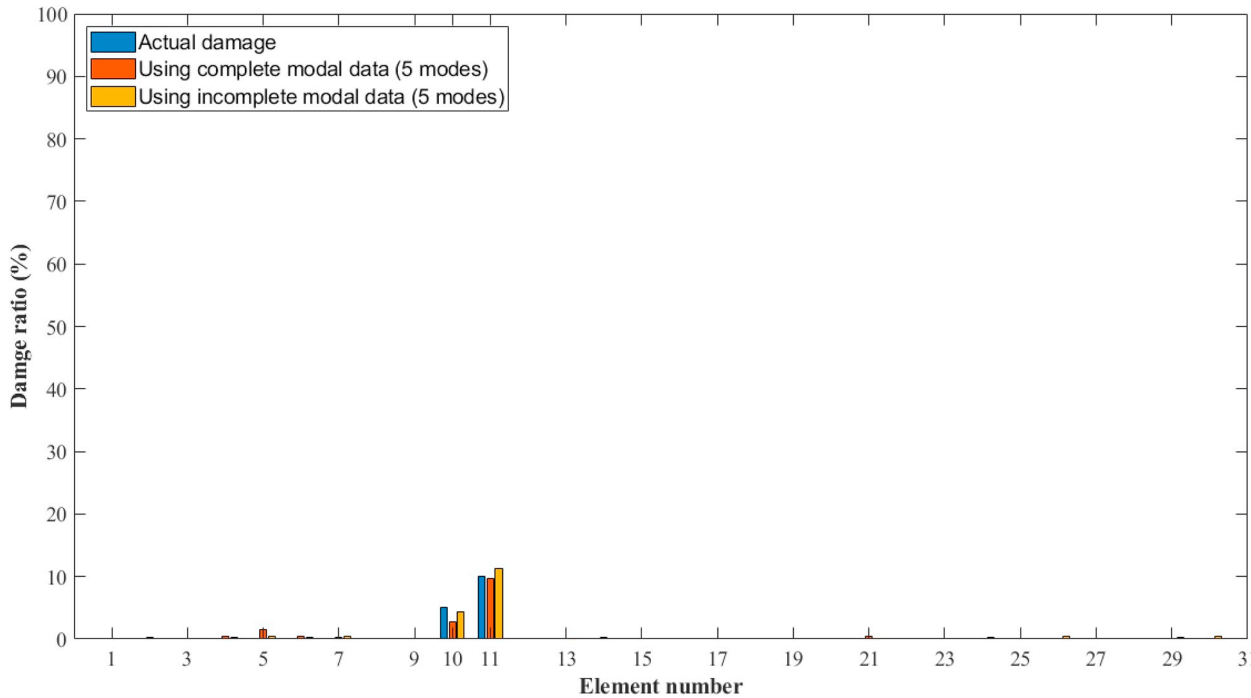


Fig. 14. Prediction results of the 31-bar planar truss for the case of two damages on noisy data (±1% noise in frequencies and ±5% noise in mode shape).

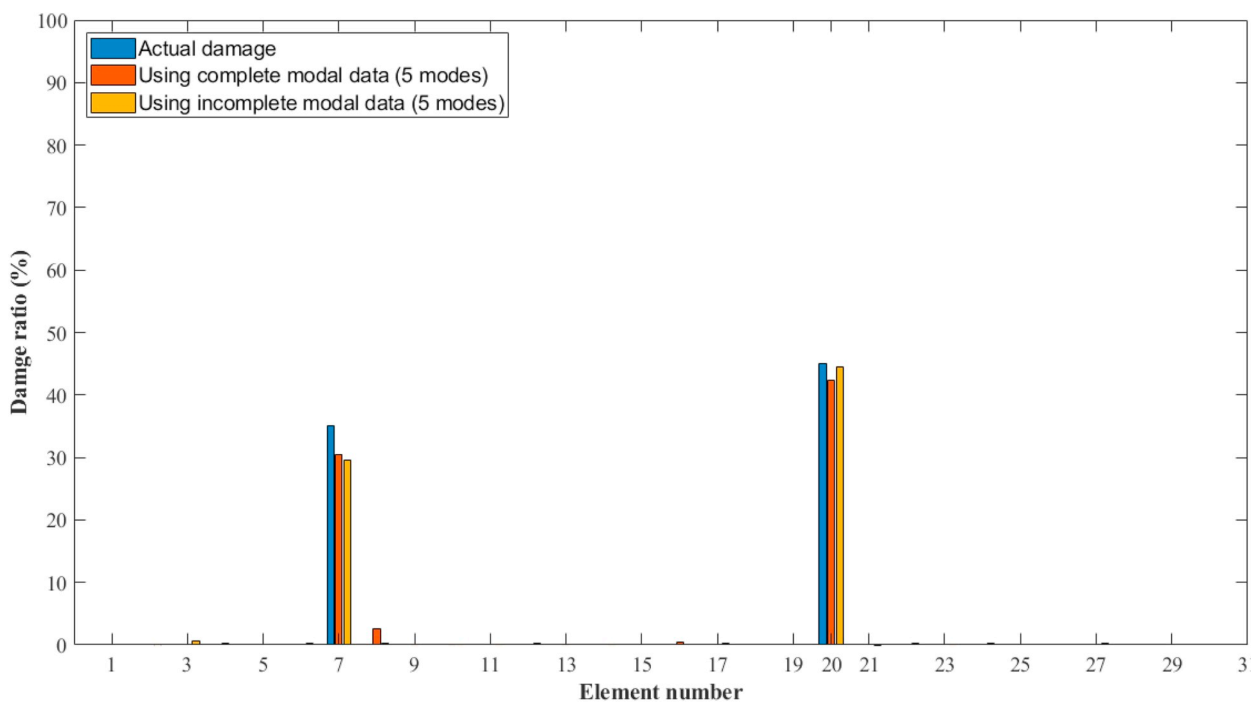


Fig. 15. Prediction results of the 31-bar planar truss for the case of two damages on noisy data (±1% noise in frequencies and ±5% noise in mode shape).

the input data. To simulate the influence of noise factors in the generated input data, the following formulation is applied to compute the natural frequency and mode shape of structures effected by noise factors [11].

$$\theta_{\text{noise}} = \theta + \alpha(2\text{rand}() - 1)\theta, \tag{6}$$

where θ_{noise} defines the natural frequency or mode shape of the structure influenced by the noise; θ is the ideal natural frequency or mode shape; α is the noise level; rand() is the random number in the range of [0,1].

3.1.2. Hyperparameters settings

Hyperparameters are variables that can be divided into two categories including model specific hyperparameters and optimizer hyperparameters. In which, the model specific hyperparameters are utilized to construct the network structure. Meanwhile, the optimizer hyperparameters are used to determine how the network to be trained. For each specific model and learning algorithm, setting values to these parameters is very important for constructing a training model with high precision. In order to choose an appropriate number of hidden units,

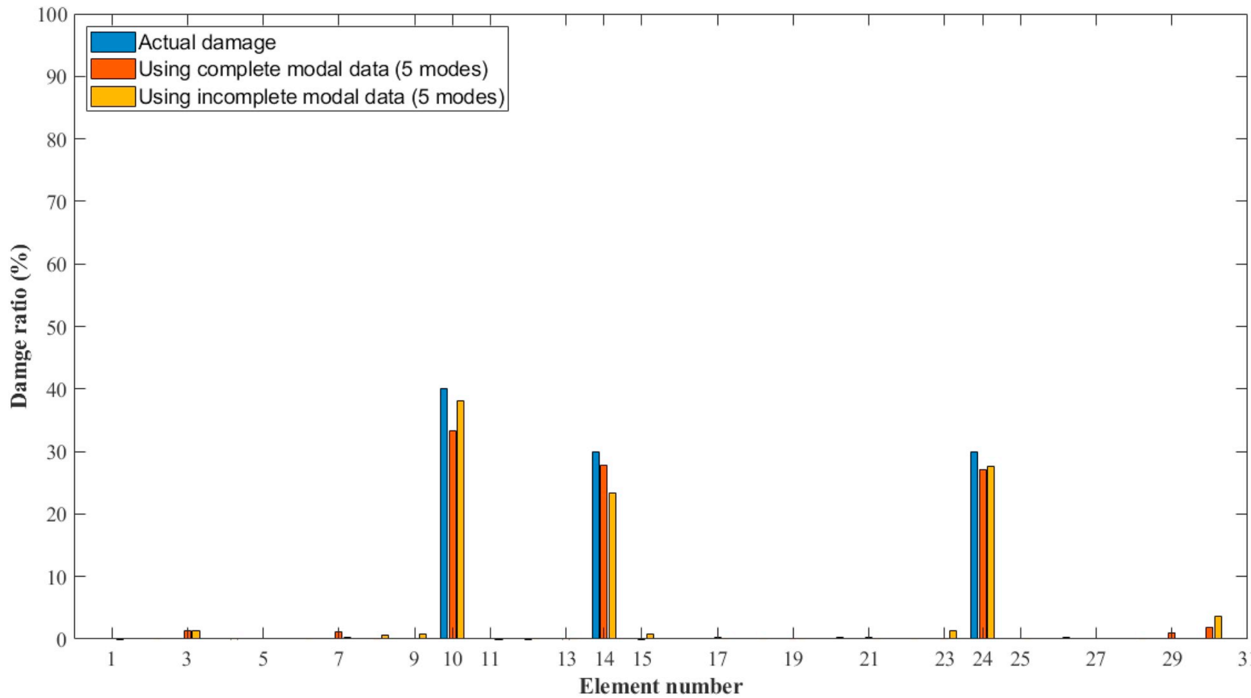


Fig. 16. Prediction results of the 31-bar planar truss for the case of three damages on noisy data (±1% noise in frequencies and ±5% noise in mode shape).

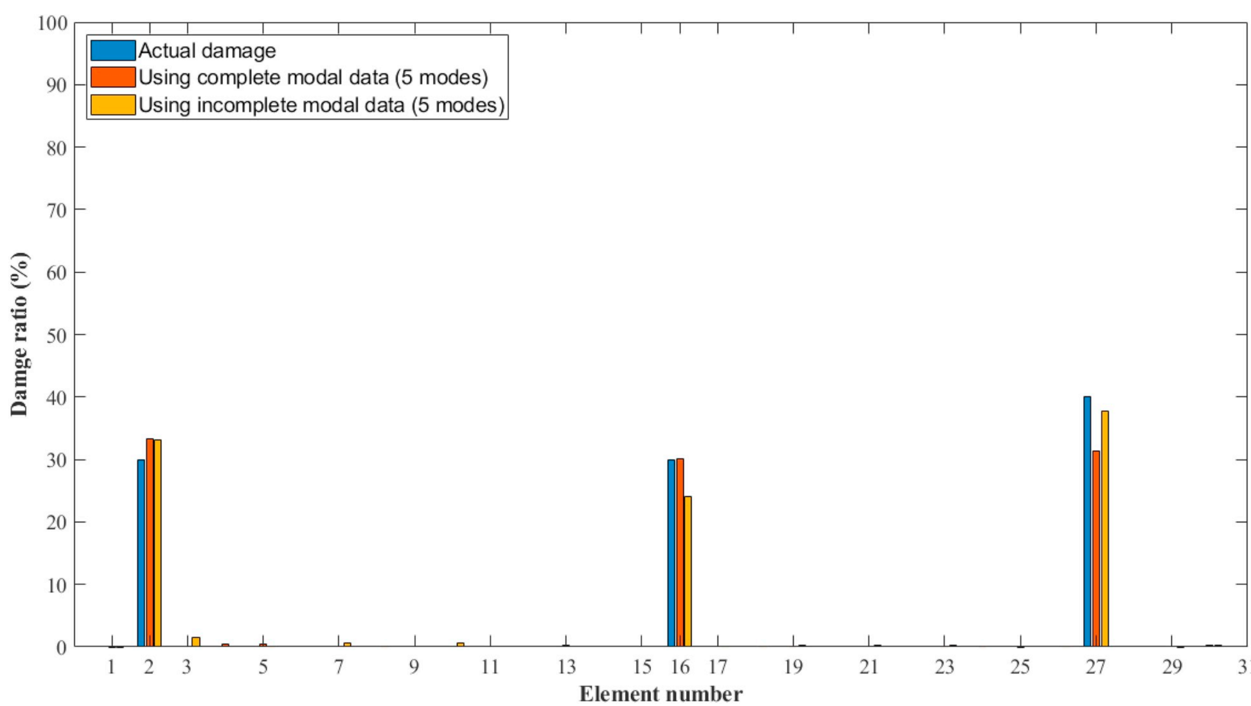


Fig. 17. Prediction results of the 31-bar planar truss for the case of three damages on noisy data (±1% noise in frequencies and ±5% noise in mode shape).

layers and epoches for training process, various number of hidden units, layers and epoches of the DFNN architecture are investigated in this work.

For the 31-bar planar truss, the DFNN trains with 65 input data points including the first five frequencies and mode shapes measured at nodes 3, 6, 7, 8, 10 and 11 of the structure and 31 output signals containing the random quantity of damage elements, location and severity of the 31 bar elements. Tables 5 and 6 show the effect of different numbers of hidden units and layers on the MSE of the model. It can be found that the more number of hidden layers and units in each layer of the neural network is, the more accurate the training model is. In addition, it can be also seen from both two tables that the architecture consisting of 5 hidden layers with 500 units in each layer (i.e. the 65-500-500-500-500-500-31 architecture) has the lowest MSE value in comparison with other architectures. Therefore, the 65-500-500-500-500-500-31 architecture is adopted to train the data of the 31-bar planar truss in this study. Moreover, a dropout layer is added in the architecture, where 20% random units is selected to temporarily remove

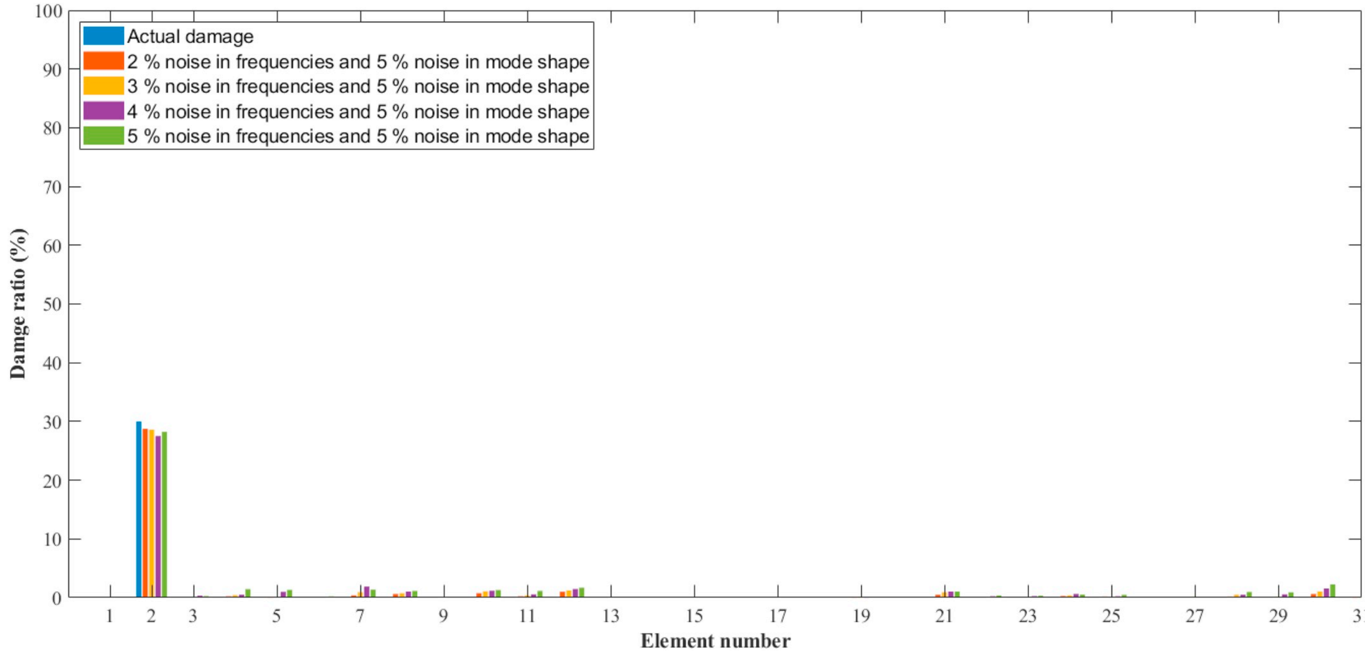


Fig. 18. Prediction result for the case of single damage (scenario 1) in the 31-bar planar truss with different noise levels.

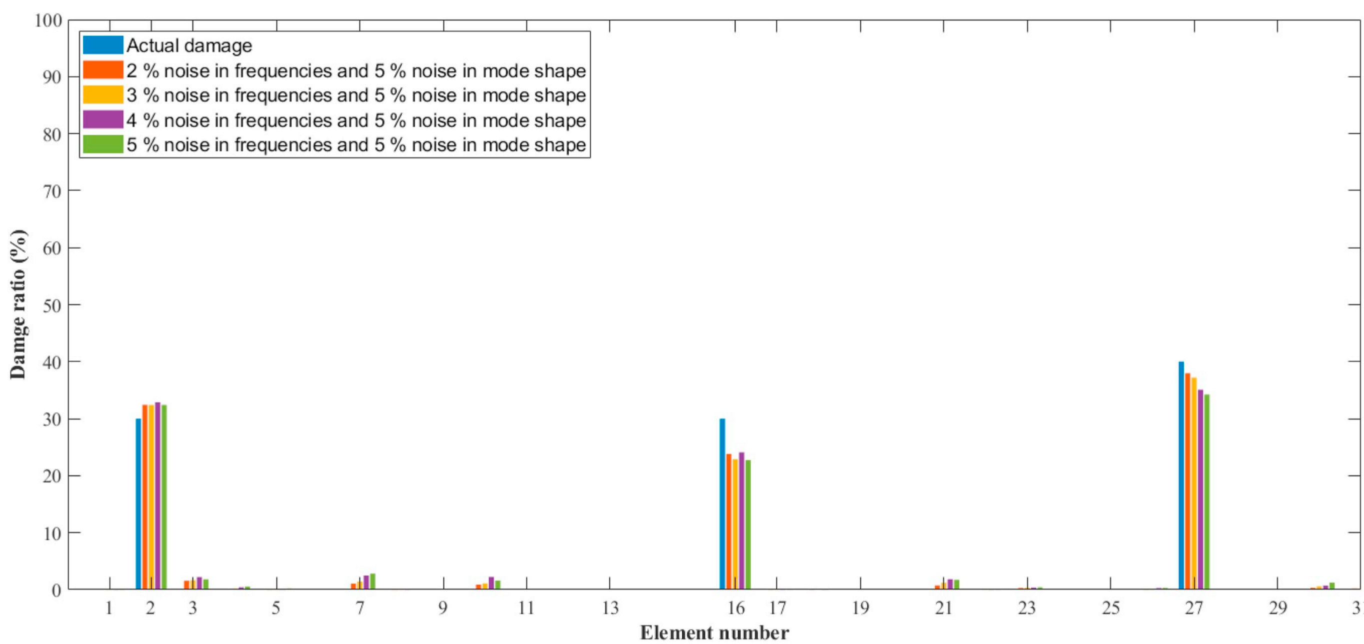


Fig. 19. Prediction result for the case of three damages (scenarios 5) in the 31-bar planar truss with different noise levels.

Table 3
Four different damage scenarios in the 52-bar dome-like space truss.

Scenario	1	2		3		4		
Element number	13	45	47	9	40	37	40	45
Severity of damage (%)	20.53	34.96	97.02	36.28	14.86	8.63	13.52	71.51

in the network to avoid the over-fitting phenomenon. Furthermore, because the number of training epoches influences the precision of the model, the training time is saved if the number of epoches is small. However in this case, the obtained model is less accurate and stable. On the contrary, for a large number of epoches, the model will be more precise and stable. However, the large training time is required. Hence, in order to avoid the waiting time for training the network, a search for suitable number of epoches is necessary. For this reason, a survey with four numbers of disparate epoches such as 5000, 10000, 20000 and 30000 is inspected. Table 7 presents the MSE of the training and test sets of the network corresponding to four different numbers of epoches. The results show that when the number of epoches becomes larger, the

Table 4
Comparisons of the mean square error for training and test sets of the 65-100-100-100-31 architecture with various gradient descent optimization algorithms combined with the ReLU activation function after 10000 epoches.

Algorithm	Adam	RMSprop	AdaGrad	Adadelta	SGD
	(lr = 0.001)	(lr = 0.001)	(lr = 0.01)	(lr = 1.0)	(lr = 0.01)
Training	0.02151	0.01179	0.01324	0.00044	0.00111
Test	0.02153	0.01230	0.01397	0.00228	0.00230
Time (Second)	5574	5158	5220	5317	4858

Table 5
Effect of hidden layer number on the loss function (MSE) of the training model after 10000 epoches.

Architecture	MSE ($x10^{-5}$)		Time (Second)
	Training	Test	
65-500-31	102.99	231.39	6786
65-500-500-31	18.13	169.39	19587
65-500-500-500-31	6,99	137.99	25711
65-500-500-500-500-31	5.22	130.15	46775
65-500-500-500-500-500-31	4.33	126.90	63693

Table 6
Effect of hidden neuron number on the loss function (MSE) of the training model after 10000 epoches.

Architecture	MSE ($x10^{-5}$)		Time (Second)
	Training	Test	
65-100-100-100-31	43.71	228.12	5317
65-200-200-200-31	19.49	180.46	7643
65-300-300-300-31	13.72	162,45	11949
65-400-400-400-31	7.76	140.72	19424
65-500-500-500-31	5.74	141.62	30662

Table 7
Effect of epoch number on the loss function (MSE) of the training model.

Epoch number	MSE ($x10^{-5}$)		Time (second)
	Training	Test	
5000	9.39	138.69	13022
10000	4.33	126.90	63693
20000	3.57	125.92	84711
30000	1.76	122.39	94331

smaller value of MSE is achieved and the larger number of training time is also required. Additionally, Fig. 4 illustrates the convergence history of the loss function for the training and test with the 65-500-500-500-500-500-31 architecture corresponding to distinct epoches. It can be observed that the loss value of the trained network is almost converged and stable after 10000 epoches. Moreover, Fig. 5 illustrates a test result obtained from the architecture after four different number of training epoches. It can be seen that the model trained with 10000 epoches can provide a good prediction result in comparison with those of 20000 and 30000, while the training time entails less than those of both the 20000 and 30000 epoches. Therefore, the 65-500-500-500-500-500-31 architecture in this study is trained with the epoch of 10000. Similarly, for the case of the 52-bar dome-like space truss, an architecture included 5 hidden layers with 900 units in each unseen layer (i.e. the 110-900-900-900-900-900-52 architecture) is utilized to train the DFNN model. In this case, the model is trained with 20000 epoches.

All the DFNN architectures trained at Adadelta learning rate of 1.0, decay factor of 0.95 and fuzz factor of 10^{-8}. Additionally, in order to have a fast converging learning process while the accuracy of the model is attained, the batch size is set to the value of 32.

3.1.3. Training process

To begin training process, each dataset is split into two subsets. In which, 80% data samples are adopted for the training set and the 20% remaining data is for the test set. The training set is then fed into the network for training model. During the implementation procedure, the DFNN produces an output corresponding to each sample. The MSE function is employed to compute the average error between the predicted output and the target one of all training data samples. The network then adjusts the internal weights of the model to decrease the error. This process is repeated until the average of the loss function stops reducing and a good set of weights is obtained. After training, the accuracy and stability of the model are inspected on the different set of samples of the test set. The information of trained model for damage detection in the 31-bar planar truss and the 52-bar dome-like space truss is provided in Table 8. Additionally, the convergence history of the model accuracy and loss function obtained by training the 65-500-500-500-500-500-31 and the 110-900-900-900-900-900-52 architectures are shown in Fig. 6 and Fig. 7.

3.2. Test results

3.2.1. 31-Bar planar truss

In the first investigation, a simply supported 31-bar planar truss consisting of 31 elements and 14 nodes with the finite element model as shown in Fig. 2 is considered. The structure has material properties as shown in Table 1. To detect damage location and severity in the structure, the DFNN method is employed. The accuracy and reliability of the proposed methodology are verified though five different damage scenarios with noise free and noisy incomplete modal data. In this case, only six equipped sensors are used and set at nodes 3, 6, 7, 8, 10 and 11 to measure the input data [8]. Additionally, the performance of the method is also inspected with the effect of noise factors in the input data. The results obtained by the DFNN using noise free and noisy incomplete modal data are compared with those using noise free and noisy complete modal data. Table 2 presents the detailed information of five considered damage scenarios.

The final damage prediction results of five different damage scenarios using complete and incomplete modal data in comparison with the actual damage model are shown in Figs. 8–12, respectively. It can be observed that for all scenarios, the DFNN method can exactly locate all damaged elements in the 31 planar bar truss despite using the incomplete modal data from limited sensors. In addition, the damage severity of elements in the structure is predicted with high accuracy. Especially, an excellent prognosis of two tiny damages for levels 5% and 10% is illustrated on both the complete and incomplete modal data as shown in

Table 8
Information of training model for structural damage detection.

Structure	Architecture	Epoch	MSE ($x10^{-5}$)		Accuracy (%)	Adjust R^2		Predicted R^2	
			Training	Test		Train	Test	Train	Test
31-bar truss	65-500-500-500-500-500-31	10000	4.33	126.9	92.30	0.9667	0.9141	0.9974	0.9268
52-bar truss	110-900-900-900-900-900-52	20000	10.8	139.3	89.95	0.9973	0.8964	0.9934	0.8703

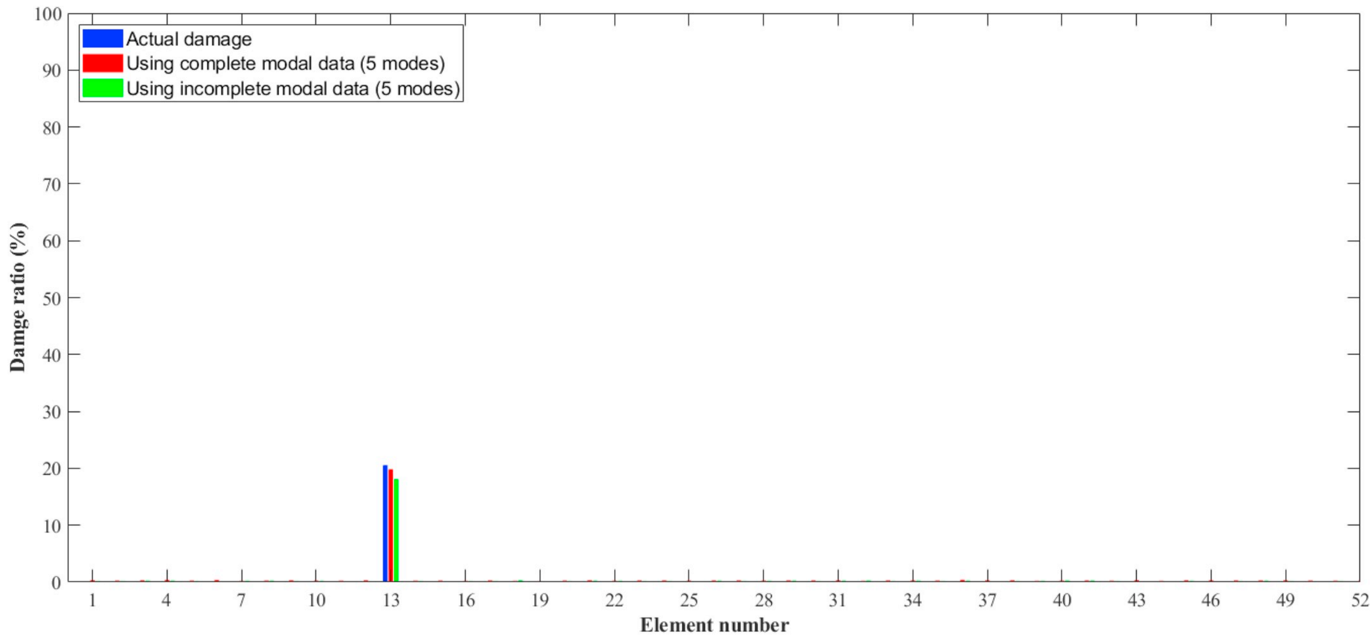


Fig. 20. Prediction results of the 52-bar dome-like space truss for the case of single damage on noise free data.

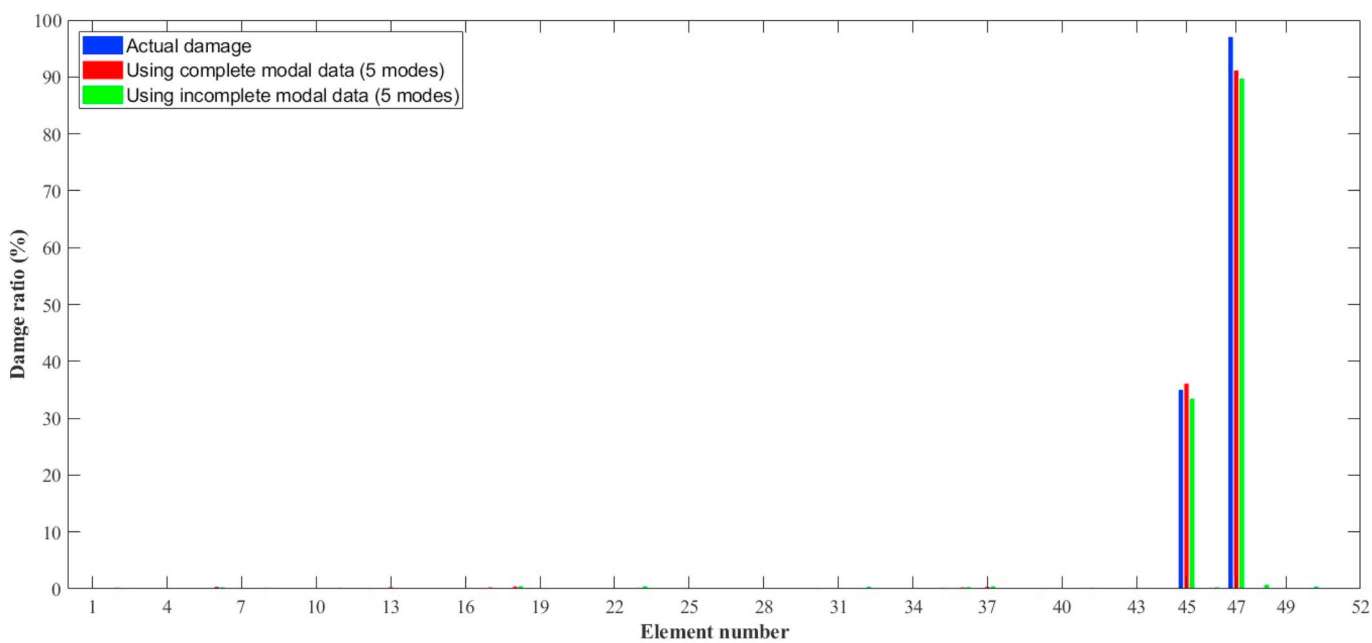


Fig. 21. Prediction results of the 52-bar dome-like space truss for the case of two damages on noise free data.

Fig. 9. For the case of three damages as shown in Fig. 11, the correct localization is still recognized by the DFNN using the incomplete modal data and a relative small error with 3.5% damage at the element 30 is attained. These results show the capability and efficiency of the proposed method in identifying and quantifying the damaged structure (see Fig. 10).

For further examination, the effect of noise factors on the complete and incomplete modal data is considered. Specifically, the level of $\pm$ 1% noise in frequencies and $\pm$5% noise in mode shapes are investigated. Figs. 13–17 depict the average results of damage ratio of all elements obtained by running 100 independent times for both single and multiple damage cases. The results show that the DFNN can provide accurately the location of damages in the structure with a small false identification under the effect of noise. Typically, as the predicting results illustrated in Fig. 16, all damaged elements are successfully identified even under the effect of noise factor and a little error with 3.7% damage at the element 30 is achieved. Additionally, the damage degree of all elements is also determined with a relative small error. Moreover, the influence of four higher noise levels containing $\pm$2%, $\pm$3%, $\pm$4% and $\pm$5% noise in frequencies combined with $\pm$5% noise in mode shapes on the scenario 1 and 5 is inspected in Fig. 18 and Fig. 19, respectively. It can be seen that the location of damages in the structure is still exactly identified for both cases even under the influence of different higher noise levels and incomplete modal data. Particularly, the damage percentage in the scenario 1 is almost unaffected by the noise factor as shown in Fig. 18. For the scenario 5 with three damages, the damage severity of all elements is also estimated with an acceptable error percentage. These results again show the good performance and applicability as well as

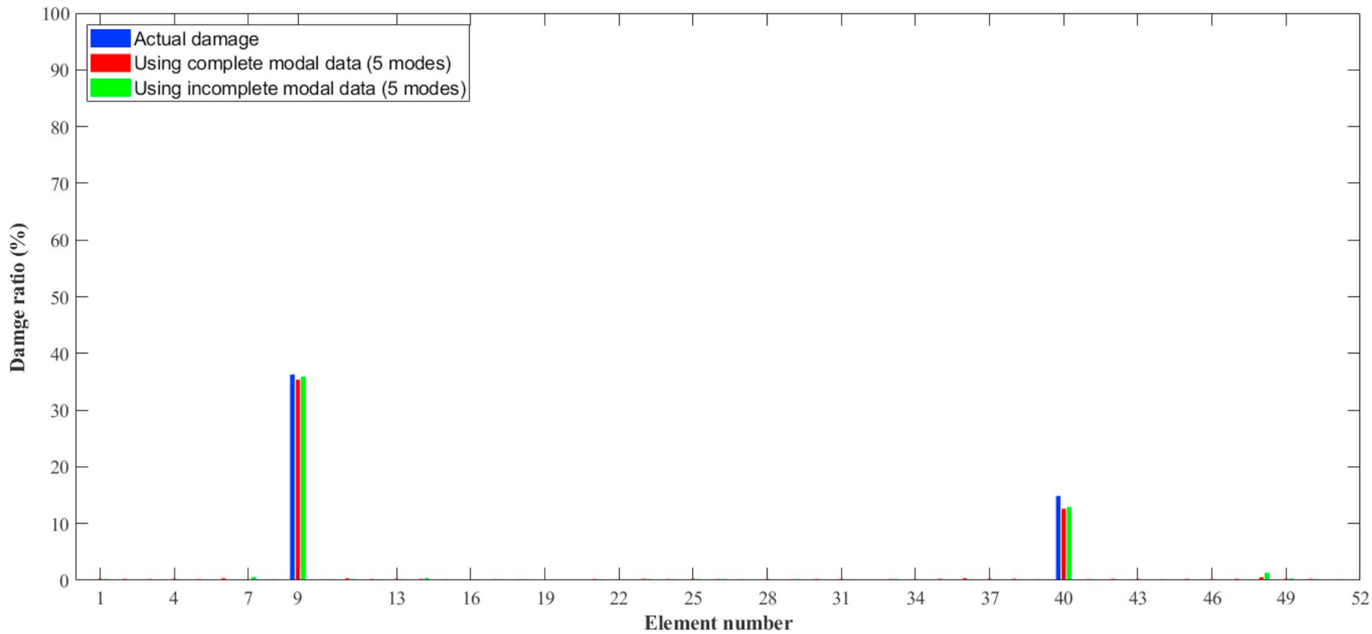


Fig. 22. Prediction results of the 52-bar dome-like space truss for the case of two damages on noise free data.

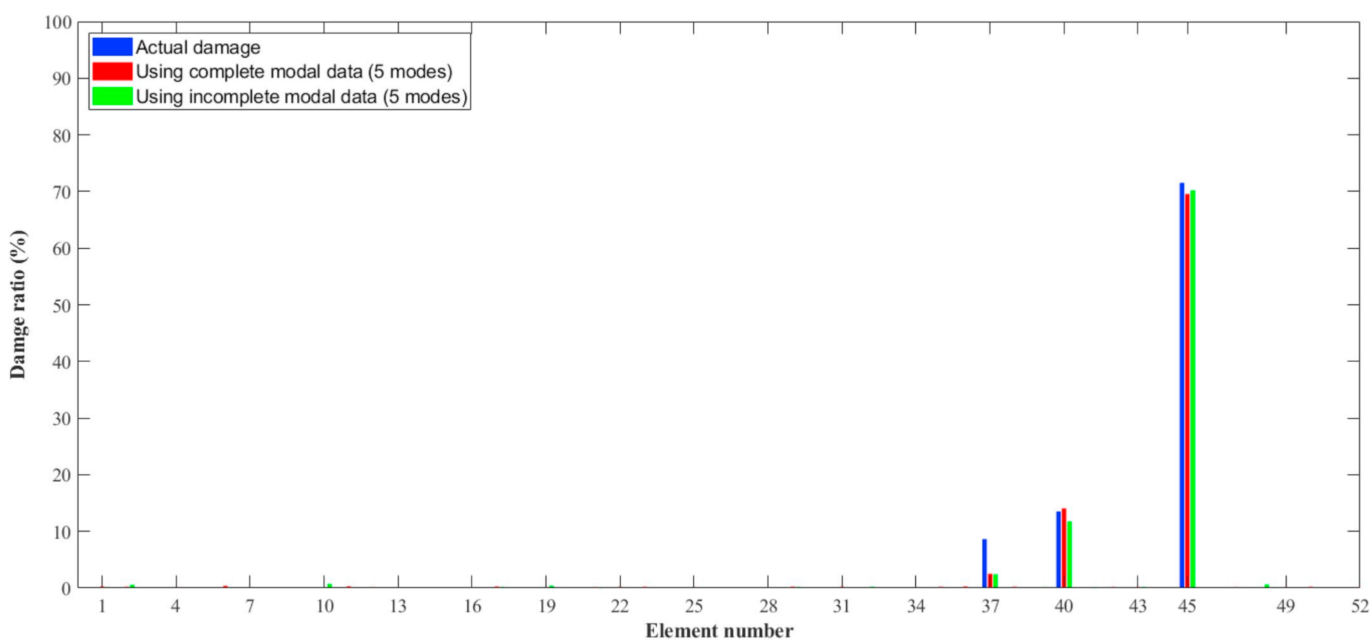


Fig. 23. Prediction results of the 52-bar dome-like space truss for the case of three damages on noise free data.

stability of the proposed method in structural damage detection via noisy incomplete modal data.

3.2.2. 52-Bar dome-like space truss

This example examines a more complicated structure which is the 52-bar dome-like space truss. Fig. 3 shows the finite element model of the structure consisting of 52 elements, 21 nodes and 63 degree of freedoms (DOFs). The Young's modulus of each bar element is $E =$ 210 GPa and the mass density is $\rho = 7800\ \mathrm{kg/m^3}$. Similar to the previous example, only seven sensors are assumed to be placed at nodes 1, 2, 4, 6, 8, 10 and 12 of the structure to collect data [8]. By using the DFNN method, the damage location and severity in the 52-bar dome-like space truss are detected. The applicability and stability of the proposed methodology are demonstrated with both the noise free and noisy input data. The results predicted by using the complete and incomplete data are compared with those of the real one to show the accuracy of the DFNN method. For these above purposes, four damage scenarios presented in Table 3 are inspected.

Figs. 20–23 illustrate the prediction solutions of all induced damage scenarios in the 52-bar dome-like space truss using complete and incomplete modal data. It can be seen that the DFNN method can exactly identify the location of damages in the structure in spite of using the limited data. Especially, the damage severity of all elements is determined with high precision and there is no confusion in localization. These results indicate the capacity and effectiveness of the DFNN method in detecting the damage location and estimating the severity of defects in a more complicated space truss. Furthermore, the performance and stability of the DFNN are also demonstrated by considering

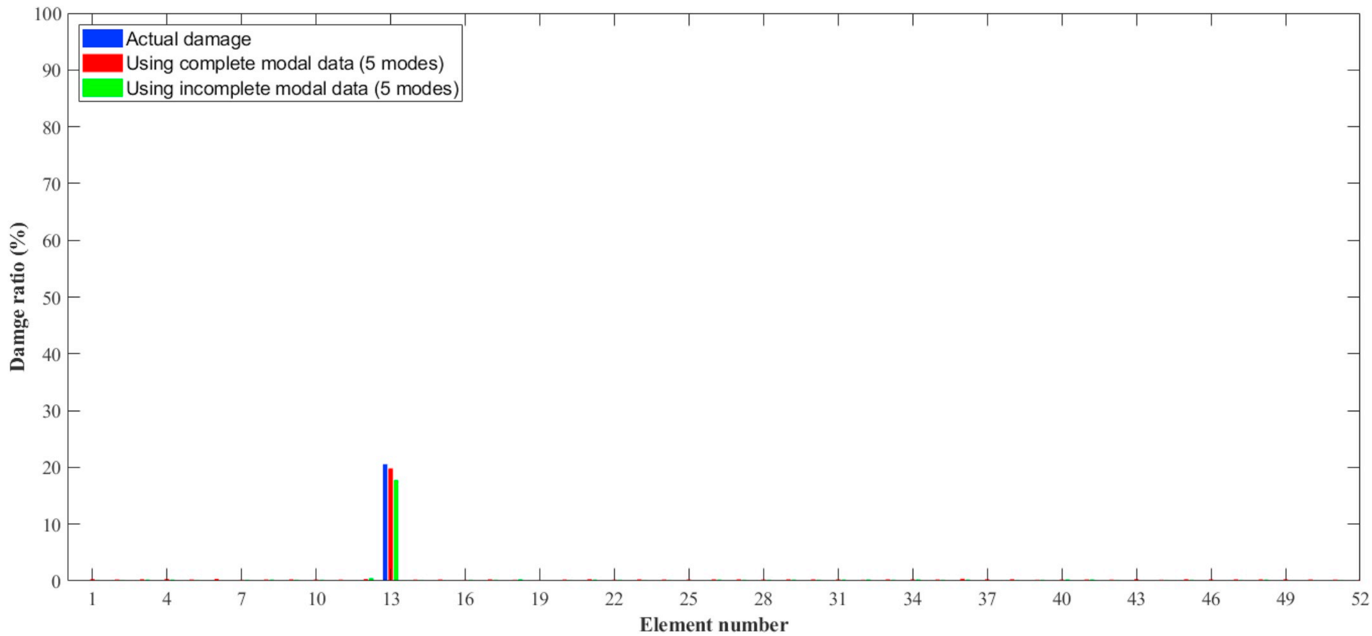


Fig. 24. Prediction results of the 52-bar dome-like space truss for the case of single damage on noisy data (±1% noise in frequencies and ± 5% noise in mode shape).

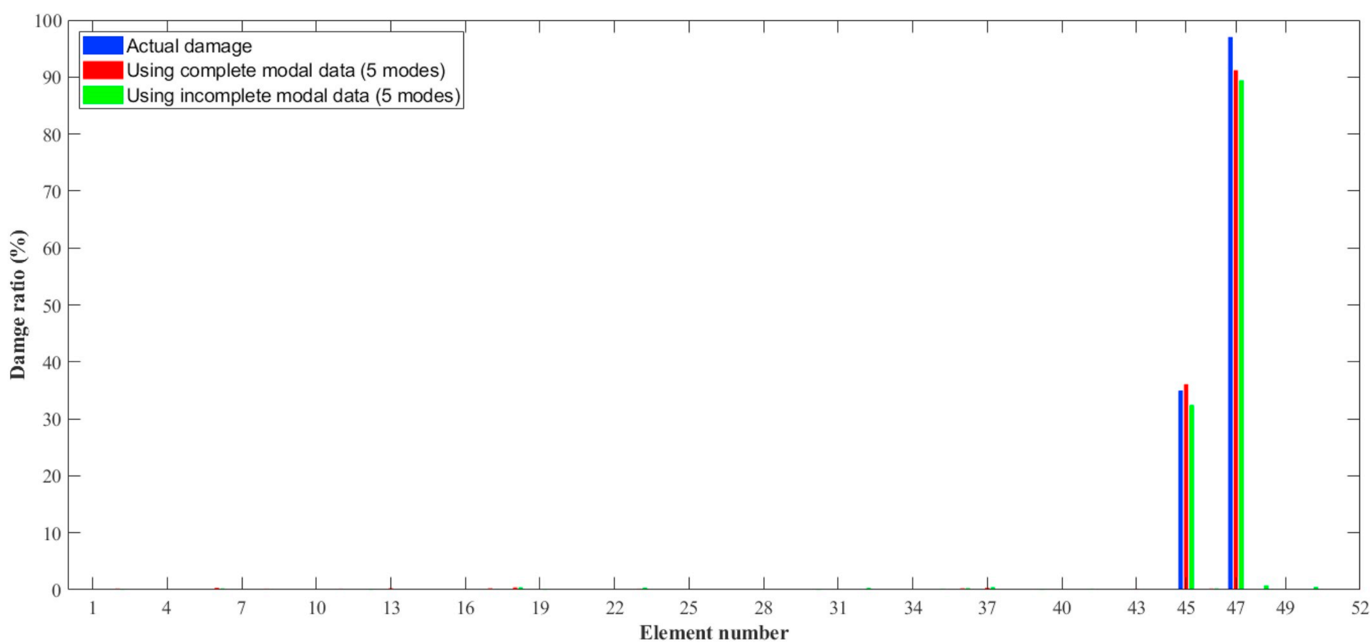


Fig. 25. Prediction results of the 52-bar dome-like space truss for the case of two damages on noisy data (±1% noise in frequencies and ±5% noise in mode shape).

the effect of different noise levels in the measurement input data. In the first investigation, the influence of ±1% noise in frequencies and ± 5% noise in mode shape is examined for all damage scenarios. Figs. 24–27 plot the average results of damage severity for all elements after running 100 independent times. As expected, the DFNN can accurately localize damages in the structure without any confusing prediction in spite of considering the effect of the noise factor. Next, four higher noise levels including ±2%, ±3%, ±4% and ±5% noise in frequencies combined with ±5% noise in mode shape are further investigated for the scenario 1 and 3 to show the robustness of the proposed method. The average results of damage ratio of all elements of the structure are depicted in Fig. 28 and Fig. 29, respectively. It is seen that even though different higher noise levels are added into the input data, the DFNN accurately recognizes the position of damaged elements in the structure. Especially, there is no confusing detection despite under the effect of higher different noise levels. The damage percentage of all elements is also predicted with an acceptable accuracy. The obtained results again show that the proposed method is not only robust in identifying damages using the noise free incomplete input data but also efficient in detecting damages using the noisy incomplete input data of the complicated structure.

4. Conclusions

An effective DFNN method was successfully applied to detect the location and severity of damaged elements in the 31-bar planar truss and the 52-bar dome-like space truss using the noisy incomplete modal data. The state-of-the-art ReLu activation function, Adadelta optimizer, mini-

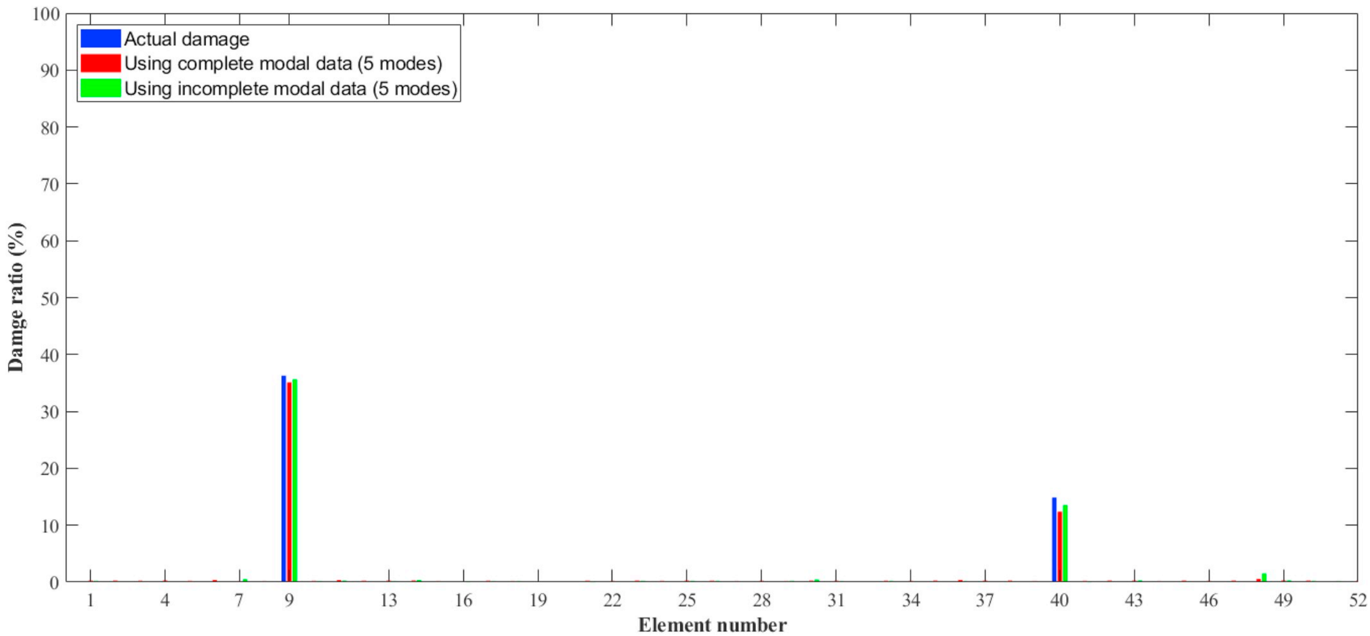


Fig. 26. Prediction results of the 52-bar dome-like space truss for the case of two damages on noisy data (±1% noise in frequencies and ±5% noise in mode shape).

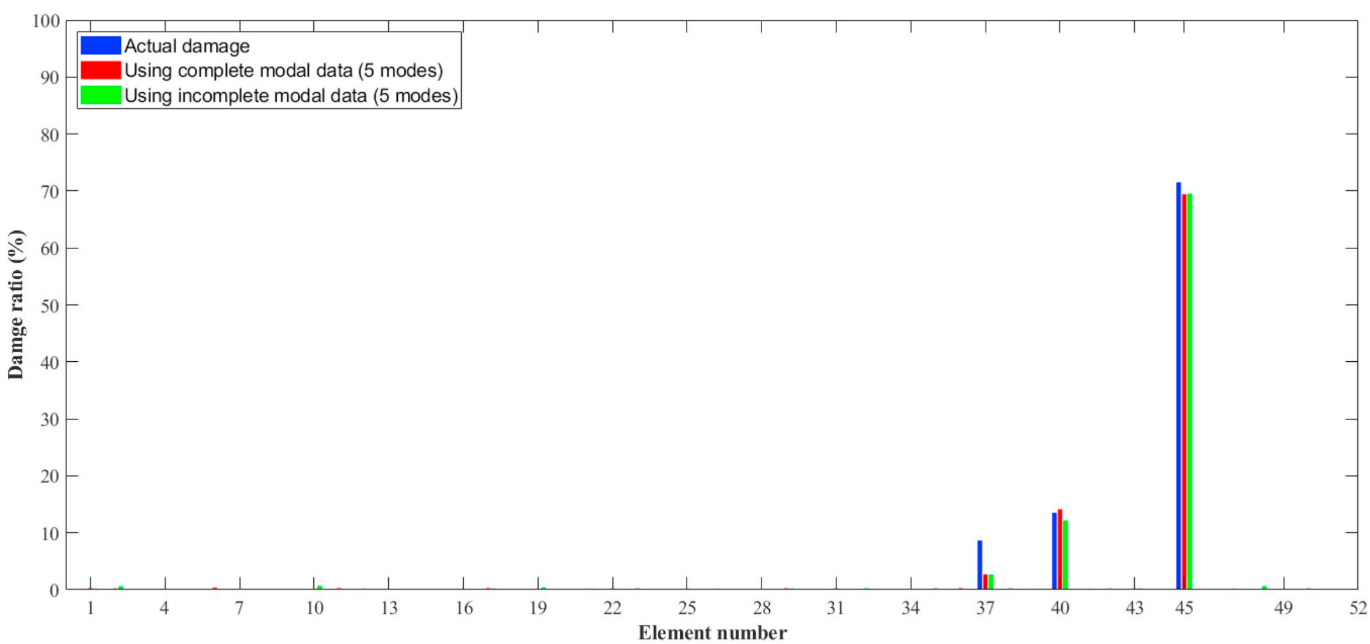


Fig. 27. Prediction results of the 52-bar dome-like space truss for the case of three damages on noisy data (±1% noise in frequencies and ± 5% noise in mode shape).

batch and dropout techniques were adopted to enhance the performance of the DFNN. In order to search a suitable DFNN model for data training, various hyperparameters such as number of hidden units, layers and epoches were examined. Two different incomplete datasets including 10000 and 20000 samples corresponding to the 31-bar planar truss and the 52-bar dome-like space truss were randomly generated by a reducing FE model for training. The accuracy and reliability of the proposed method were demonstrated through various damaged scenarios. Different noise levels were considered in the measurement input data to investigate the capability and stability of the proposed method. Results achieved by the DFNN method using the noise free and noisy incomplete modal data were compared with those of the complete and actual ones. The simulation results illustrated the effectiveness and stability of the DFNN method in damage detection of the 2D and 3D truss structures despite of using the incomplete data. Especially, the results demonstrated the good performance of the DFNN in predicting damages with both the noise free and noisy input data. In addition, the results also indicated that the increment of noise level in the input data has a little effect on the accuracy of the proposed method. This shows that structural damage detection with a high noise level including in the incomplete modal data is still a challenging. In the future works, this kind of problem will be continuously studied.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

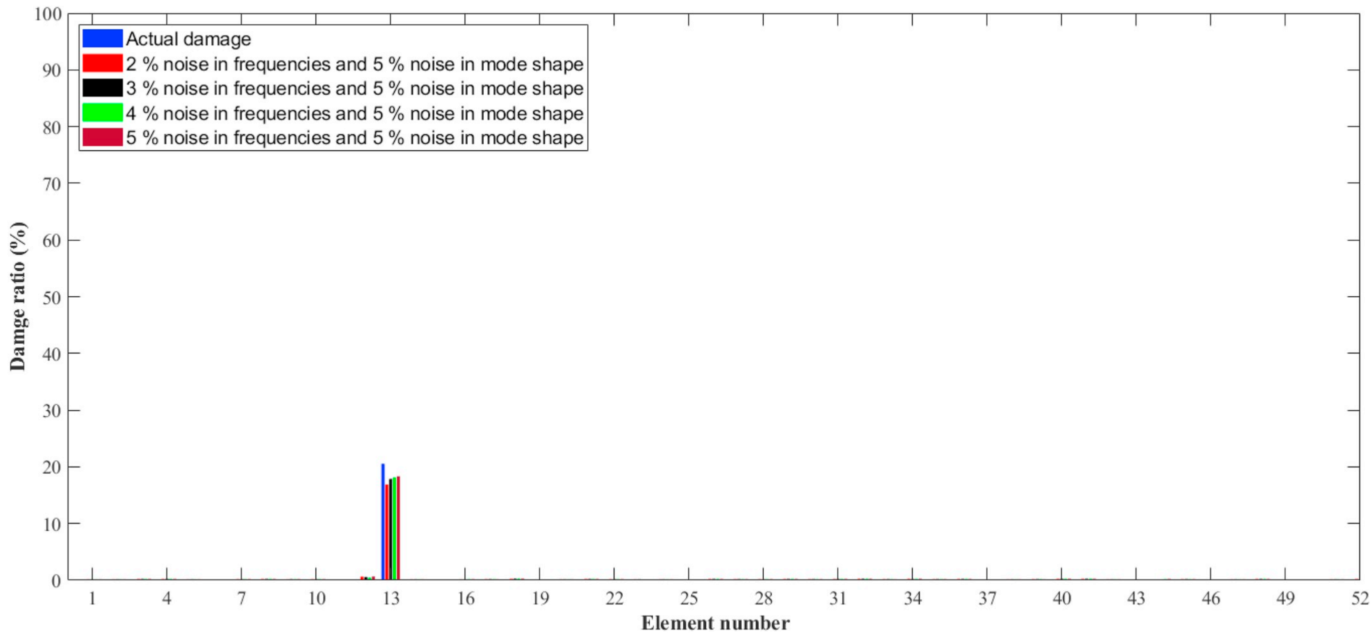


Fig. 28. Prediction results for the case of single damage in the 52-bar dome-like space truss with different noise levels.

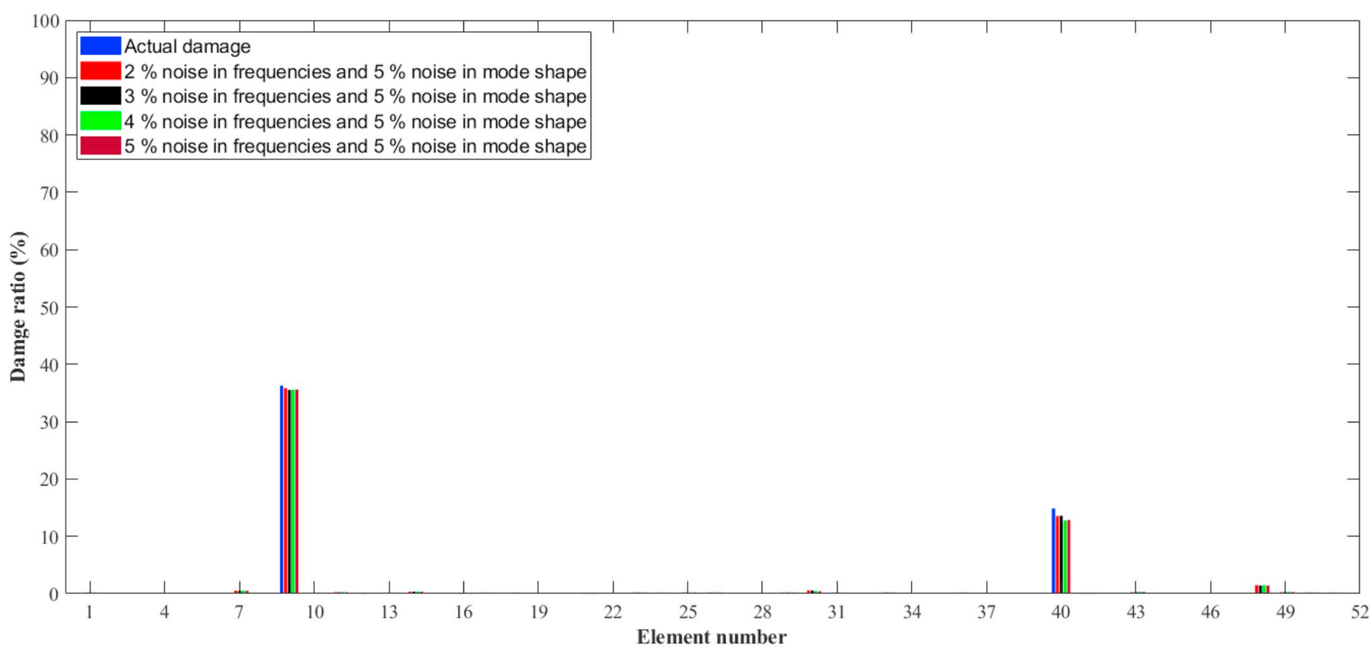


Fig. 29. Prediction results for the case of two damages in the 52-bar dome-like space truss with different noise levels.

CRediT authorship contribution statement

Tam T. Truong: Conceptualization, Methodology, Data curation, Validation, Visualization, Writing - original draft, Formal analysis, Software. **D. Dinh-Cong:** Conceptualization, Methodology, Data curation, Validation, Visualization, Writing - original draft, Formal analysis. **Jaehong Lee:** Investigation, Supervision, Writing - review & editing. **T. Nguyen-Thoi:** Conceptualization, Methodology, Funding acquisition, Project administration, Resources, Investigation, Supervision, Writing - review & editing.

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