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Data mining based damage identification using imperialist competitive algorithm and artificial neural network

Abstract

Currently, visual inspections for damage identification of structures are broadly used. However, they have two main drawbacks; time limitation and qualified manpower accessibility. Therefore, more precise and quicker technique is required to monitor the condition of structures. To aid the aim, a data mining based damage identification approach can be utilized to solve these drawbacks. In this study, to predict the damage severity of single-point damage scenarios of I-beam structures a data mining based damage identification framework and a hybrid algorithm combining Artificial Neural Network (ANN) and Imperial Competitive Algorithm (ICA), called ICA-ANN method, is proposed. ICA is employed to determine the initial weights of ANN. The efficiency coefficient and mean square error (MSE) are used to evaluate the performance of the ICA-ANN model. Moreover, the proposed model is compared with a pre-developed ANN approach in order to verify the efficiency of the proposed methodology. Based on the obtained results, it is concluded that the ICA-ANN indicates a better performance in detection of damage severity over the ANN method used only.

Keywords

Structural health monitoring; damage detection; data mining; artificial neural network; imperial competitive algorithm; hybrid algorithm

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1 INTRODUCTION

To prevent structural damage under vibrational loadings, different techniques, approaches and systems have so far used (Ghaedi et al. 2017), because structural damage can disturb safety and serviceability of civil structures. To this end, damage detection techniques are used to avoid catastrophic structural failure (Hakim et al. 2015). One of the common non-destructive damage identification techniques is visual inspection methods, but they are time consuming and costly due to accessibility of qualified manpower. In addition, their efficiency is limited to availability of structural damage locations. As a result, more precise and quicker technique should be used to monitor the structural health condition of structures (Hoseini et al. 2012; Hakim and Razak 2014; Hanif et al. 2016). On the other hand, data mining is commonly considered as one of the newest computing technologies which is rapidly emerging; capable of data extraction to discover useful information using collected sensor data (Saitta et al. 2009; Hou et al. 2013). Important knowledge and relationship between sensor data can then be extracted from raw databases using data mining technique.

In recent years, data mining techniques have been used in structural health monitoring (SHM). However, there is no straightforward workflow for data mining based SHM problems. For purpose of data mining analysis, a systematic model and applicable data mining methods are required. Therefore, a data mining process scheme along with optimization- and prediction- based algorithms was proposed by the authors (Gordan et al. 2017) to identify the severity and location of damage. Then, in the present study, an attempt has been made to demonstrate the feasibly of the proposed data mining based procedure.

On the other hand, in recent years, Artificial Neural Network (ANN) has obtained extensive attentions for damage detection of structures due to its high pattern recognition capability (Saeed et al. 2011). Nowadays many meta-heuristic-based biological evolution algorithms exist, for instance, genetic algorithm (Mitchell 1998), particle swarm optimization (Xue et al. 2013), ant colony optimization (Zhou et al. 2013), artificial immune algorithm

(Poteralski et al. 2013), firefly algorithm (Zhou et al. 2014), artificial bee colony algorithm (Civicioglu and Besdok 2013) and grey wolf optimization (Noshadi et al. 2015). However, meta-heuristic evolutionary algorithms are not limited to biological evolution. Since another side of evolution can be employed as a meta-heuristic algorithm, humans' social political behavior has been used for this purpose. To this end, in recent years, an evolutionary strategy has been introduced, known as Imperialist Competitive Algorithm (ICA) (Atashpaz-Gargari and Lucas 2007). This evolutionary strategy has shown its high performance to achieve better global optima with fast convergence speed in compare to other evolutionary algorithms (Atashpaz Gargari et al. 2008; Taghavifar et al. 2013). Therefore, ICA has also been applied into ANN method to determine the parameters of network structure (Berneti and Shahbazian 2011; Ahmadi et al. 2013).

Based on the above descriptions, in the present study an attempt is made to investigate the applicability of data mining for improvement of damage identification of beam-like structures by means of the presented model (Gordan et al. 2017) to propose ANN-ICA approach combining ANN and ICA. Experimental modal analysis of I-beam structure was carried out to generate natural frequencies and mode shapes measurements as the input database for data mining process to predict the severity of damage scenarios in I-beam structures. Totally, four individual networks corresponding to the first four modes were modeled to identify the damage severity. The database was applied to train the ANN, when the ICA was employed as weight initialization algorithm to optimize the initial weights of the ANN in the training procedure. Then, the proposed ICA-ANN method was compared with a pre-developed ANN in order to verify the efficiency of the proposed methodology. To the best of our knowledge, current research is the first attempt to illustrate the feasibly of data mining based procedure in SHM.

2 Data Mining

Data mining is the analysis of datasets to find out the valued data in the form of patterns in order to extract the relationships, novel correlations and trends of data (Han et al. 2001; Hand et al. 2001; Cury and Cremona 2012; Alves et al. 2015b). Data mining can make a proactive decision based on the knowledge by means of forecasting future plan. In general, it has two classes which are descriptive mining and predictive mining using various techniques and functions (see Figure 1 and Table 1) (Obenshain 2004; Pang-Ning et al. 2006; Liao et al. 2012; Chen and Huang 2013). The techniques play important roles to obtain effective models from observations. Besides, data mining techniques have also three main groups which are statistical techniques, machine learning techniques, and artificial intelligence techniques. It is noted that each of these techniques has particular algorithms for running the models to get the best solution. For instance, ANN, Bayesian analysis, ant colony optimization, ICA, support vector machine, principal component analysis, particle swarm optimization, genetic algorithm, fuzzy logic, regression analysis, clustering, classification, and decision tree are classified under data mining techniques (Saitta et al. 2009). Furthermore, the functions of data mining are categorized into clustering, prediction, classification, exploration and association (Liao et al. 2012; Chen and Huang 2013; Tayyebi et al. 2014; Alves et al. 2015a). Prediction as one of the most widespread tasks in data mining was commonly employed by a number of algorithms such as ANN (Taha et al. 2004; Kabir et al. 2008), support vector machine (He and Yan 2007), fuzzy system (Aydin and Kisi 2014), principal component analysis (Hsu and Loh 2010), ant colony optimization (Cottone et al. 2014), decision tree (Kim et al. 2011), Bayesian analysis (Jiang and Mahadevan 2008), particle swarm optimization (Tabrizian et al. 2013), genetic algorithm (Rus et al. 2006) and regression analysis (Laory et al. 2013) in damage identification of structural systems. It is noted that, a systematic model is required for data mining analysis. For instance, Knowledge Discovery in Databases (KDD), SEMMA, Cross-Industry Standard Process for Data Mining (CRISP-DM) models are mainly used as the systematic model in data mining (Azevedo and Santos 2008).

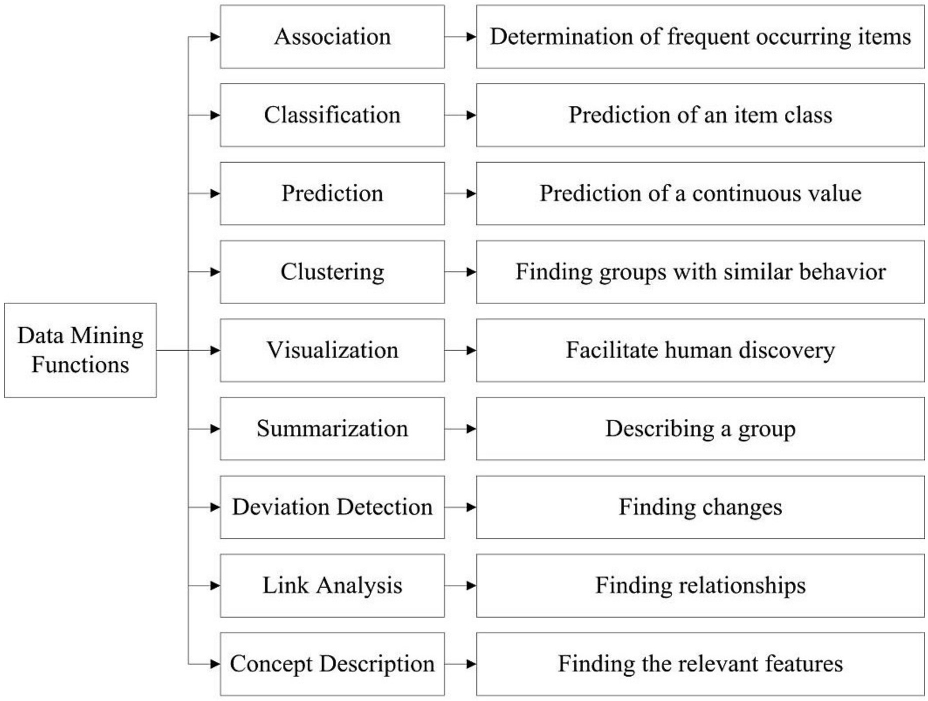


Figure 1: Data mining functions.

Table 1: Data mining techniques.

Data mining technique	Category	Learning type
Artificial neural network	Artificial intelligence	Supervised/Unsupervised
Support vector machine	Machine learning	Supervised
Decision tree	Statistical	Supervised
Clustering	Statistical	Unsupervised
Principal component analysis	Machine learning	Unsupervised
Regression	Statistical	Supervised
Fuzzy	Artificial intelligence	Supervised/Unsupervised
Meta-heuristics	Artificial intelligence	–
Classification	Statistical	Supervised
Bayesian	Machine learning	Supervised

For the present study a workflow is used based on the proposed damage identification method (Gordan et al. 2017) through data mining steps along with prediction and optimization-based algorithms, as shown in Figure 2. Based on this flow chart, measuring damage level is the first step of SHM assessment to collect data. In the next step (data preparation), all data are transformed as inputs for modeling. Then, in the modeling phase, appropriate algorithms are employed to train the database. The obtained results are used for damage identification. After pattern assessment, deployment of the procedure can be carried out introducing suitable activities to improve the health condition of structures.

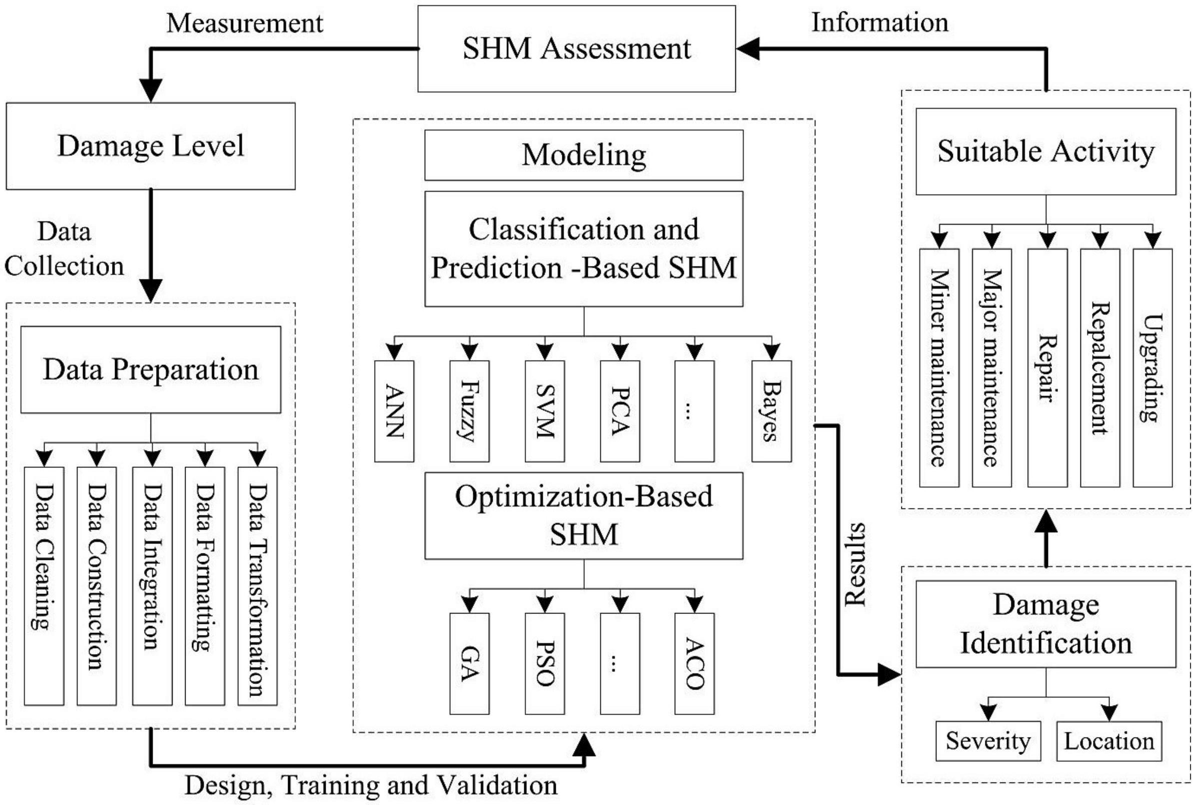


Figure 2: Diagram of the proposed data mining based damage identification procedure (Gordan et al. 2017).

3 Methodology

In this study, dynamic parameters of an I-beam structure through an experimental modal test were conducted as an input database for data mining procedure using the proposed model. The hybrid ICA-ANN technique was performed to predict the severity of damage including the first four flexural modes and all corresponding modes shape values at the points on the beam centerline (supports were excluded). Subsequent writings attempt to give a brief introduction to ANN and ICA in order to present how they are used in the study.

3.1 Artificial Neural Network (ANN)

ANN algorithm, introduced in 1980s, uses human brain simulation based on the development of biological neuron. Main components of a biological neuron are a cell body, axons, dendrites and synapses, which are the main concept to formulate artificial neurons. In the biological neuron, input signals are transferred by the dendrites into the cell body and axons carry the output signals from one neuron to others, while synapses are the point contacts between dendrites of one cell and axon of another cell. Principal parts of an artificial neuron are connection weights, bias and activation functions (Singh et al. 2010; Nascimento et al. 2011; Shahriar and Nehdi 2011; Karacý and Arýcý 2014; Ahmed et al. 2015).

Main components of a conventional ANN consist of three layers including the input layer, the hidden layer and the output layer (Ghaedi and Ibrahim 2017). Independent variables are represented by all neurons in the input layer. The neurons in the hidden layer are implemented for computing purposes and dependent variables are calculated using output neurons. The first layer receives the signals and signals go through the second layer and finally reaches to the third layer (Attarzadeh and Ow 2014; Palomares-Salas et al. 2014). Another method is multi-layer perceptron that is one of the most common approaches applied in structural identification problems (Wu et al. 2002). The most benefit of multi-layer algorithm is the feed-forward neural network with the back-propagation training algorithm owing to the mathematical design of the learning complex nonlinear relationships (Ahmadi et al. 2013). The performance index of the algorithm is the least mean square error (MSE) (see Equation (1)) (Talatahari and Mohajer 2015).

$$MSE = \frac{\sum_{i=1}^{n}(t_i - o_i)^2}{n} \quad (1)$$

where n is the number of the training, t_i is the target output and o_i is the network output.

3.2 Imperialist Competitive Algorithm (ICA)

ICA is one of the latest metaheuristic algorithms in the evolutionary computation domain based on human being's sociopolitical evolution. It was introduced by Atashpaz-Gargari and Lucas in 2007 (Ebrahimi et al. 2014). The goal of this optimization technique is to find a solution that represents the global maximum or minimum of a fitness function (Geetha Devasena et al. 2016). ICA is based on the imperialistic competition and it starts with initial populations called countries. Countries in ICA are corresponding to chromosomes in genetic algorithm. In ICA, countries categorize into two groups; colony and imperialist. These two groups create an empire. Figure 3 depicts ICA flowchart to show its procedure.

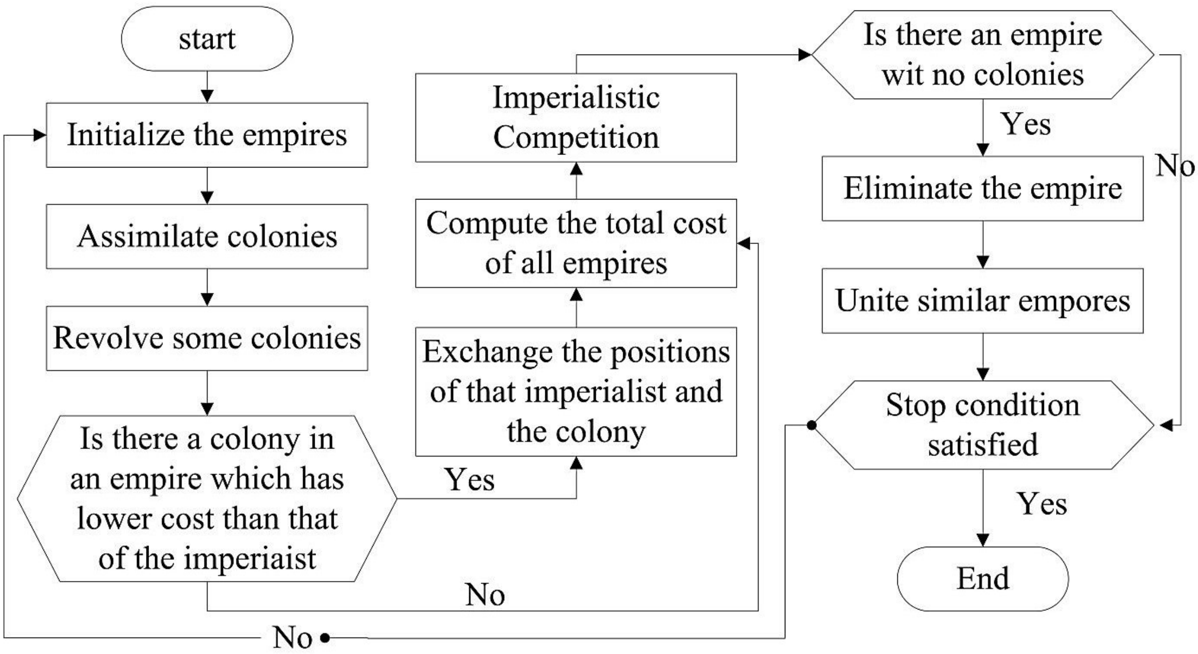


Figure 3: Flowchart of ICA.

According to Figure 3, in a N-dimensional optimization problem, a country (P_i) is shown by $1 \times N$ array which is as follows:

$$Country = [P_1, P_2, \ldots, P_{Nvariable}] \quad (2)$$

Corresponding cost function of the country is described as,

$$Cost = f(country) = f([P_1, P_2, \ldots, P_{Nvariable}]) \quad (3)$$

Based on the optimization terminology, the imperialists are countries with the least cost. The normalized cost of an imperialist (C_n) for colonization of the counties is determined as:

$$C_n = max_i\{c_i\} - c_n \quad (4)$$

where maxi$\{c_i\}$ is the imperialist with maximum cost (weakest imperialist) and C_n is the cost of n-th imperialist. The normalized power of each imperialist (P_n) is:

$$P_n = \left| \frac{C_n}{\sum_{i=1}^{N_{imperialist}} C_i} \right| \quad (5)$$

Therefore, each empire can occupy some colonies. The number of these colonies ($N.C_n$) occupied by the Nth empire is denoted by:

$$N.C_n = round\,\{P_n \,.\, N_{colony}\} \quad (6)$$

where *round* is a function represented the round numbers and N_{colony} is the total number of initial colonies.

Figure 4 illustrates the next step, which is the movement of colonies towards their proper imperialist. As shown in this figure, the colony moves to the imperialist by x units, which is obtained by:

$$x \approx U\,(0, \hat{a}\, x\, d) \quad (7)$$

where d is the initial distance between the colony and imperialist. $\hat{a}$ is a random number ($1 < \hat{a} \leq 2$).

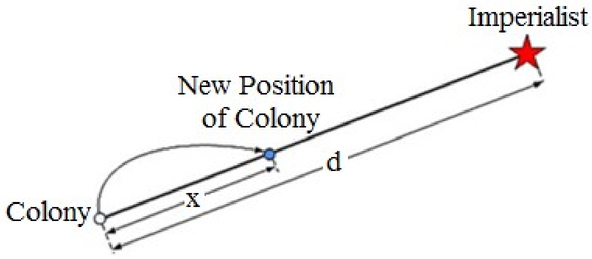


Figure 4: Movement of colonies toward their proper imperialist.

The total power of an imperialist is taken as:

$$T.C_n = Cost\,(Imperialsit_n) + \hat{\imath} mean\{Cost(colonies\ of\ impire_n)\} \quad (8)$$

where $T.C_n$ is the total cost of *Nth* empire, and $\hat{\imath}$ is a positive number ($0<\hat{\imath}<1$).

3.3 Modeling

Any ANN architecture has different features for training, such as, topology of the network, types of data, number of neurons in each layer, forms of activations, the weights and parameter settings of the network. Therefore, these criteria play important roles to construct the best network. In this study, amongst ANN functions, the back-propagation (BP) algorithm in feed-forward network with different topologies was assessed in order to obtain high quality patterns with the best forecasting capacity. However, the training process carries on updating and changing the connectivity weights up to the satisfactory level, the drawbacks of over-fitting and inefficient optimal topologies can reduce the accuracy of the network. Thus, ICA was employed in the training procedure of ANN to initialize the weights of the network. The variance of the predicted output and target output was considered as network error. In fact, reducing the network error was the main purpose in ANN training. Consequently, the Mean Square Error (MSE) was considered as a cost function in ICA. Hence, the most important goal of proposed algorithm was to minimize MSE cost function. As a result, ICA was obtained by means of the subsequent factors: the number of initial counties set to 100; imperialists set to 15 and coefficient â set to 2.

In this study, for identification of damage severity, four networks corresponding to mode 1 to mode 4 were modeled and a hybrid ICA-ANN technique was applied to build the pattern. The neural network was trained by means of ICA to perform optimization of weights for all nodes and bias terms. To build the patterns, the hybrid ICA-ANN technique was proposed using modeling step of data mining process and four networks corresponding to first four modes of vibration were modeled. The modeling phase of damage identification process started with the ICA-ANN design using the measured natural frequencies and all the mode shapes data (excluding the support positions) were obtained from mode 1. Consequently, a dataset comprising fifteen neurons in the input layer and one neuron in the output layer of the ICA-ANN was created. The first natural frequency (f_1) and fourteen mode shapes ($\phi_{1,2}$, $\phi_{1,3}$, $\phi_{1,4}$, …, $\phi_{1,14}$, $\phi_{1,15}$) of mode 1 were considered as inputs of the ICA-ANN.

In the output layer, one neuron was considered for damage severity (d_d/h ratio) of the structure. The dataset was divided randomly into training set and testing set. In the training process, numerous numbers of hidden neurons were picked and applied to the network to achieve the most appropriate architecture. Furthermore, different activation functions such as linear and sigmoid functions were tired. After all, the best network architecture trained with feedforward back propagation algorithm using hyperbolic tangent sigmoid transfer functions was 15-10-1 (15 input units, 10 hidden neurons and 1 output neuron).

3.4 Experimental test

An I-beam with length of 3200 mm with an overhang of 100 mm at both ends was studied. The flange width and section depth of the beam are 75 mm and 150 mm, respectively. Besides, the thickness of the flange and web are 5 mm and 7 mm, respectively. For material properties of the beam, the elasticity modulus of 2.1×10^{10} kg/m^2, mass density of 7867 kg/m^3 and Poisson's ratio of 0.2 were used. The experimental setup and a schematic diagram of experimental modal analysis of the beam are shown in Figures 5 and 6.

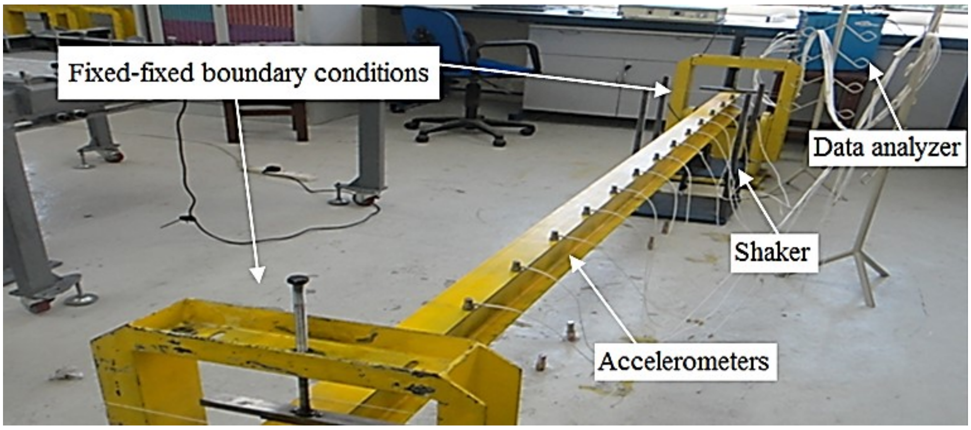


Figure 5: Experimental setup of the specimen.

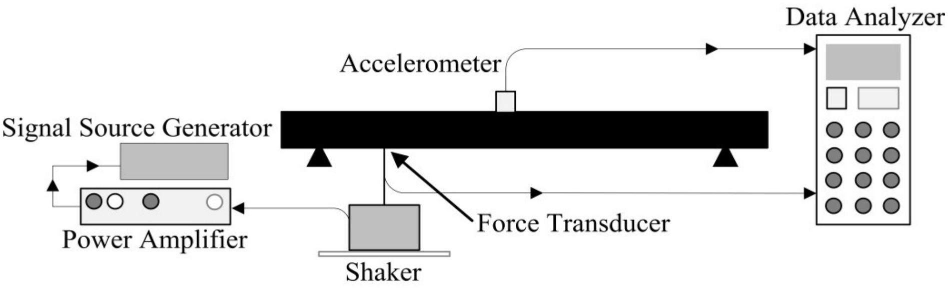


Figure 6: Schematic diagram of the experimental setup.

3.5 Data collection

The first step of the proposed model was measuring the damage levels to collect data. This step was started with collecting an initial data and then continued with activities in order to get familiar with the data. It was attempted to collect dynamic parameters of first four flexural modes obtained from the experimental modal analysis of the intact and damaged beam as input dataset for data mining. To aid the aim, the measured frequency response functions obtained from different damage scenarios were employed to identify natural frequencies and mode shapes of the structures.

3.6 Data preparation

In this step, the final dataset, which was used in the modeling step, must have been constructed from initial raw databases. Thus, a number of preparation tasks were considered in this step including data selection, data cleaning, data construction, data integration, data formatting and data transformation. For example, data cleaning aims to choice inapplicable and misplaced data in the dataset (Fernandez et al. 2002) and data integration transforms the raw data into various formats (Saltan et al. 2011).

4 Results and discussions

Experimental modal analysis was implemented using an intact I-beam as the reference structure. Afterwards, a number of damage cases were created with 5 mm width at mid-span of the structure considering 25 different damage depths from 3 mm to 75 mm with an increment of 3 mm were implemented, as indicated in Figures 7 and

8. Figure 9 displays the arrangement of the accelerometers considered for 48 points in three rows between supports. As it can be seen from this figure, the location of node No. 19 was chosen as the excitation point of the experiment due to the node points in other locations using first four modes. The outputs of the experimental modal analysis were then used as the input database for data mining procedure.

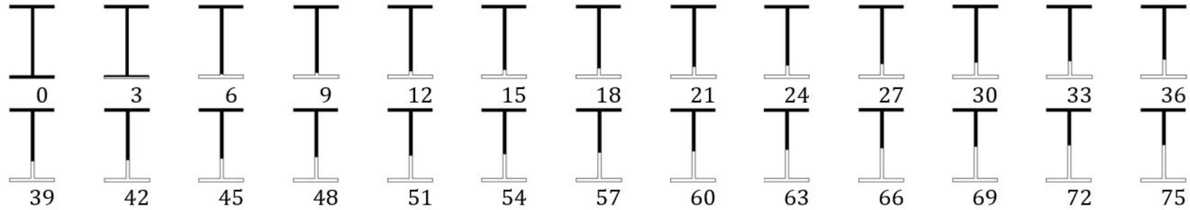


Figure 7: Induced damage levels on beam (mm)

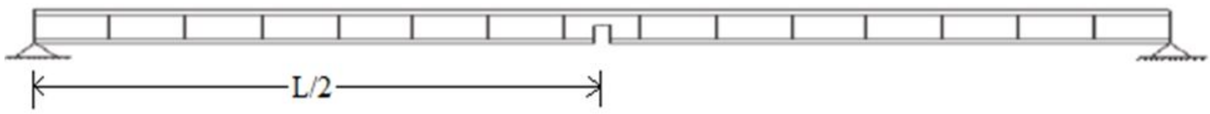


Figure 8: Damage location of the beam

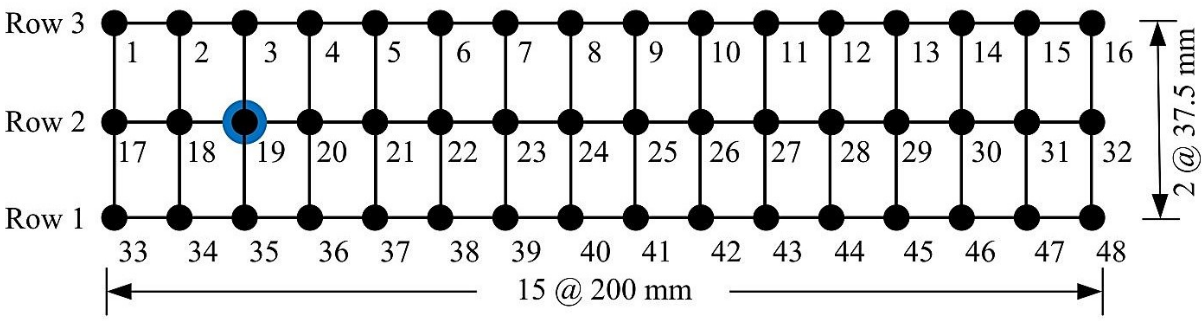


Figure 9: Potions of Accelerometers and shaker

Based on the damage identified from data collection and data preparation, first four modal parameters of the undamaged and damaged states were extracted, as tabulated in Table 2 and plotted in Figure 10. Accordingly, the natural frequencies of all the modes reduce with damage severity expansion. The most reduction of natural frequency was 21.3% for mode 1.

Table 2: Frequencies of intact beam.

Mode 1 f_1 (Hz)	Mode 2 f_2 (Hz)	Mode 3 f_3 (Hz)	Mode 4 f_4 (Hz)
55.01	209.24	443.2	733.15

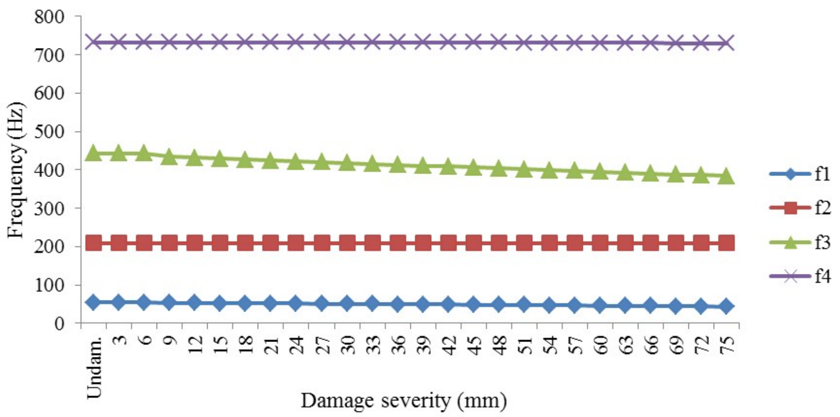


Figure 10: Frist four natural frequencies of damage states.

Table 3 indicates damage severities pertaining to the d_d/h ratio for various cut slots, in which d_d is the damage depth and h is the height of the beam. This table shows the 25 damage cases, from 2% to 50% created in the beam.

Table 3: Damage severity ratio.

Cut slot (mm)	d_d/h	Cut slot (mm)	d_d/h	Cut slot (mm)	d_d/h
3	0.02	30	0.20	57	0.38
6	0.04	33	0.22	60	0.40
9	0.06	36	0.24	63	0.42
12	0.008	39	0.26	66	0.44
15	0.10	42	0.28	69	0.46
18	0.12	45	0.30	72	0.48
21	0.14	48	0.32	75	0.50
24	0.16	51	0.34	-	-
27	0.18	54	0.36	-	-

Figure 11(a-d) illustrates the comparison between normalized predicted and real measured damage severities in the first four flexural modes at training and validation segments for the ICA-ANN model. In this figure, red circles represent the real measured data and blue squares represent the predicted results fitted to the real measured data. As it can be seen from the figures 11(a) to 11(d), the fitness of first model corresponding to mode 1 is greater than other models. Moreover, the results of damage identification in mode 4 indicate the lowest fitness between real and predicted data.

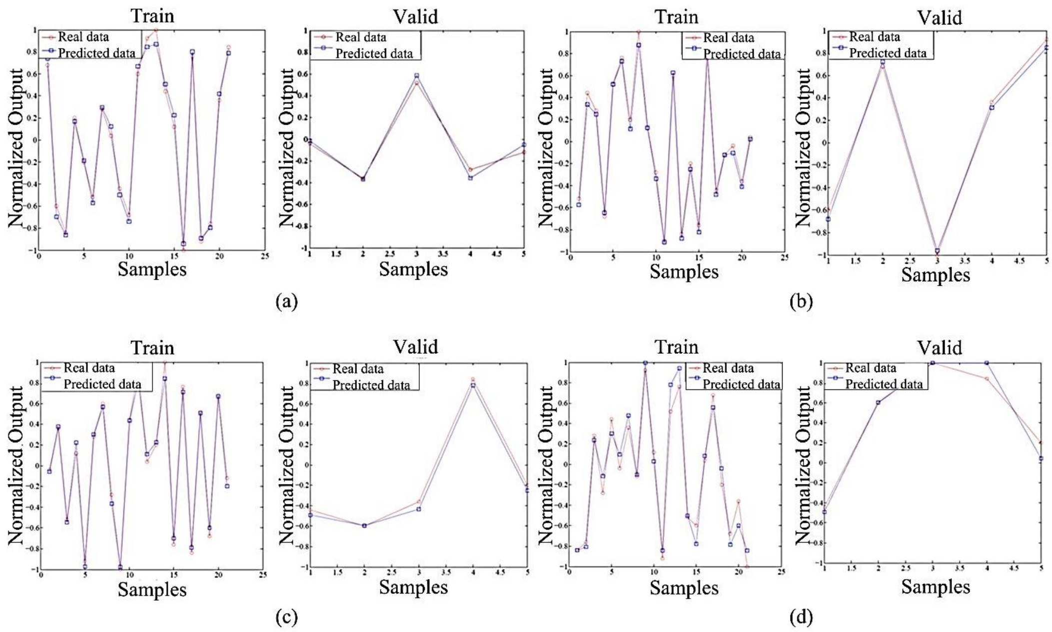


Figure 11: Comparison between results of damage identification in (a) mode 1, (b) mode 2, (c) mode 3, and (d) mode 4

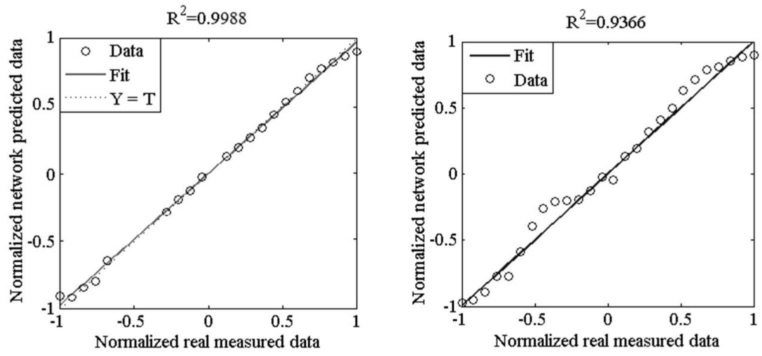
4.1 Pattern assessment

It is important to assess the proposed model built by ICA-ANN. Hence, the purpose of the pattern assessment is to validate the model in an appropriate manner. For this purpose, different tools can be utilized. In this study, the basis of efficiency coefficient (R^2) and *MSE* were used to evaluate the performance of the ICA-ANN model.

MSE was also considered as a cost function in ICA. The main goal of proposed algorithm was to minimize *MSE* cost function. The best costs of the four ICA-ANN models are listed in Table 4. It can be seen from the table that, the cost function of the network N_1 is less than others, which shows the higher accuracy of this model to predict the severity of damage. In this phase, a comparison of ICA-ANN and ANN was carried out to evaluate the performance of the ICA-ANN. Figure 12 presents the performance of the predicted values of the ICA-ANN and the ANN using efficiency coefficient. As shown in the figure, the measured and predicted values of damage severity obtained from the ICA-ANN with $R^2=0.9988$ is better than that obtained from the ANN with $R^2=0.9366$.

Table 4: Performance of different ICA-ANN networks.

Network	Best cost of the network
N_1 (Mode 1)	0.0029
N_2 (Mode 2)	0.0037
N_3 (Mode 3)	0.0042
N_4 (Mode 4)	0.0041



(a) (b)

Figure 12: The performance of predicted values of (a) ICA-ANN and (b) ANN

4.2 Deployment

The ICA-ANN model creation and prediction of the damage severity of single-type damage scenarios acquired from the experimental modal analysis of the I-beam structure is not the last step of the project. The achieved knowledge from data mining process should be employed for the future uses in decision making processes. In this regard, the outputs of the project were utilized as follows:

- Implementation of the real-time structural health monitoring of civil infrastructures;
- Prediction the remaining life of structures;
- Development a robust damage detection system.

5 Conclusion

In this research, a data mining approach was performed as data extraction method using a proposed hybrid ICA-ANN algorithm to predict the damage severity of single-point damage scenarios picked up from the experimental modal analysis of a beam-like structure. The ICA as a new optimization data mining algorithm and as a weight initialization algorithm was used to optimize the initial weights of the ANN in the training procedure. The ANN was implemented to examine the performance of the ICA-ANN using the efficiency coefficient and MSE. Based on the obtained results, the following conclusions are drawn.

- Capability of the proposed data mining-based damage identification model in SHM domain to predict damage severity of the steel I-beams was confirmed through data mining process.
- 6.23% improvement in the prediction error using the ICA-ANN showed the robustness of the proposed hybrid algorithm compared to the prediction using ANN. It is noted that, several deployment processes such as real-time data processing for vibration-based damage detection techniques, prediction of the remaining service life of structures and development a robust SHM system have so far been introduced to improve the identification of damage severity as knowledge discovery.
- The obtained results through ICA-ANN using the proposed procedure showed that, the proposed damage identification model can be considered as a precise and quick approach for monitoring the structural condition subjected to vibrational loads.
- Based on different damage rates, minor maintenance, major maintenance or their combination is required to maintain the structural performance of the members.

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