Available online at www.CivileJournal.org

Civil Engineering Journal

Vol. 3, No. 10, October, 2017

Experimental Investigation of Damage Detection in Beam Using Dynamic Excitation System

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Received 9 August 2017; Accepted 17 October 2017

Abstract

Most structural failures are due to break in consisting materials. These breaks begin with a crack, the extension of which is a serious threat to the behaviour of structure. Thus the methods of distinguishing and showing cracks are the most important subjects being investigated. In this article, a new smart portable mechanical system to detect damage in beam structures via using fuzzy-genetic algorithm is introduced. Acceleration-time history of the three points of beam is obtained. The signals are then decomposed into smaller components using new EMD (Empirical Mode Decomposition) method with every IMF containing a specific range of frequency. The dominant frequencies of the structure are obtained from these IMFs using Short-term Fourier transform. Subsequently, a new method of damage detection in simply supported beams is introduced based on fuzzy-genetic algorithm. The new method is capable of identifying the location and intensity of the damage. This algorithm is developed to detect the location and intensity of the damage along the beam, which can detect the damage location and intensity based on the pattern of beam frequency variations between undamaged and damaged states.

Keywords: Damage Detection; Dynamic System; EMD Method; Fuzzy-Genetic Algorithm.

1. Introduction

Since the defect and failure in structures can lead to wasting human and financial resources. Detection of failures in structures has been considered by many researchers. However, modal analysis methods have been popular in recent years due to their practicality. The methods based on modal analysis are based on the fact that the modal parameters (natural frequencies, mode shapes and damping of the modal) are functions of the physical parameters (mass, damping, stiffness) and, therefore, assuming that a fault resulted in a change in the profile of modal constructions are reasonable [1-2]. Normally, initial data for comparison can be extracted from the data measured from damaged structures or finite element models without fault. Modal parameters used for detection of structural defects include frequency functions, natural frequencies, mode shape curvature, bending modal, etc. [3-5]. The task of any damage detector system is divided into several sections, which consist of damage detection, damage location identification, damage rate detection, and prediction of the life of damage. In order to obtain good performance, there needs to be a mathematically rigorous modeled system. Yet, modeling errors could affect the performance of damage detector systems, especially when the monitored systems are non-linear. The use of computational intelligence methods may compensate for modeling errors, so that these methods provide a good approximation of nonlinear systems. Lina Ding et al. conducted a research on assessment of dynamic axial forces of the chariots with different road surface conditions [6]. Innovation of this research is in the use of "evolutionary spectral method" for assessing dynamic loads of the chariots on beams, which moves at a constant speed on a rough surface. Jean-Charles et al. proposed a method for prediction of the local responses of the

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http://dx.doi.org/10.28991/cej-030925

stimulating beam by a chariot [7]. Wu and Law conducted a study to identify axial load of a chariot on a beam with a rough surface road. Axial loads on beams used in this study were estimated by considering roughness of the road surface [8].

Neves et al. used a direct method to analyze the vertical interaction of structure - chariot. Their proposed method was more suitable for systems with high structural volume than the ways that are being constantly updated [9]. Law et al. conducted a study in the field of statistical prediction of dynamic response of the beam structure with unknown intrinsic properties on the effect of moving loads [10]. Unknown properties in structural beam assumed to be Gaussian were modeled with the help of finite element method and the unknown properties of the chariot were offered with Gaussian distribution model with the help of Karhunen-Loeve expansion. Na et al. used genetic algorithm to detect stiffness changes in shear in a twenty-story frame floor [11]. Marano et al. used genetic algorithm to detect damages in a shear frame with incomplete measurements [12]. Mosquera et al. used genetic algorithm for damage detection in a shear frame with incomplete measurements [13]. The tablet has modeled a 3D crack in the structure and by the use of wavelet transforms and Fourier detected the damage on an RC frame placed on a trembling table [14]. Ganguli showed the damage as a decrease in hardness in modulus of elasticity and by the use of fuzzy logic determined the place of damage in the helicopter blades [15]. Njafabadi et al. began monitoring damage of cracked aluminum sheets and, introduced a method to analyze the frequency of the waves and tried to identify the frequency range of different damages, where in this state the frequency ranges represent a property of the sheet [16]. Hasannezhad et al. defined the issue of identification of crack parameters, wherein the purpose was to minimize the difference between natural frequencies calculated and measured by this model. In doing so, they used the Binary Cat Swarm Algorithm [17]. From among the modal parameters, the natural frequency is used more often since it can be calculated more easily and more accurately. One of the advantages of the present study as compared to the previous works is the way it extracts the natural frequency, where EMD and short-term Fourier transform are used.

In the present article, the moving load including the concentrated mass and linear elastic springs, with constant speed is used for dynamic stimulating of the simply supported beam. Then the acceleration-time history in three points of the beam is extracted by accelerometer. For conversion of the acceleration-time history into usable information for damage detection, the method of signal decomposition into the main modes is used via EMD method. In this paper, firstly, the empirical method of signal decomposition is introduced into major modes and then its capabilities for damage detection are reviewed. The IMFs obtained via EMD are then converted from time range to frequency range by the use of short-term Fourier transform. Then, dominant frequencies of each IMFs are used as properties for fuzzy-genetic algorithm, by which the location and intensity of damage in the structures will be detected.

2. EMD Method

EMD method is based upon this very simple hypothesis that every signal is constituted of some fundamental components. Based on this method, each signal can be decomposed to some signals that must meet the following criteria [18].

A. The difference in the number of zeros and extremes of the signal must be equal to 1 at most.

B. Average value of local maximum and minimum ranges of the signal is zero.

These decomposed signals are called IMFs. In order to decompose the time-domain signal and to obtain the IMFs, the following steps must be taken in order: 1. Determination of local maximum and minimum of a signal. 2. Connection of maximum points to each other with 3rd grade spline, application of the same thing for the minimum curve. 3. Calculating the average value of the maximum and minimum m_1 and its difference from the value of main entering signal related to the vibration, which is h_1 [18].

$$x(t) - m_1 = h_1 \tag{1}$$

h_1 value is the first part to be monitored to see whether it meets the terms of IMFs. To do so, the two conditions of IMFs should be checked. In the case of being IMF, h_1 is separated as the first IMF, from the original signal and is called c_1. The remainder is called r_1. r_1 then behaves like a basic signal and the above process is repeated [18].

$$r_1 = x(t) - c_1 \tag{2}$$

$$r_{n-1} - c_n = r_n \tag{3}$$

If h_1 was not a component of the IMFs, yet, it would operate as a reference signal and the steps 1, 2 and 3 are repeated. We would repeat these steps until the k step so as to reach a position where it becomes part of the IMFs [18].

$$h_1 - m_{11} = h_{11} \tag{4}$$

$$c_1 = h_{1k} \tag{5}$$

The decomposition process is complete when the r_n function is steady. For this case, the condition displayed in the above equation must be checked [18].

$$sd = \sum_f [\frac{|h_{n-1}(t) - h_n(t)|^2}{h_{n-1}^2(t)}] < \varepsilon \tag{6}$$

n is the stages of this process and ε is considered between 0.2 to 0.3. If the r function had the above condition, the algorithm is finished; otherwise the previous processes would be repeated. Upon completion of the decomposition, the original signal can be represented as the following equation [19-21].

3. Modeling Moving Beams and Loads

For this purpose, an aluminum($E = 69\ Mpa, v = 0.32$) beam with cross-sectional dimension of $10 \times 20\ mm$ with a length of $2\ m$ was tested where the beginning and the end of the beam were modeled by two columns of half a meter with two connected supports. The aluminum beam enters these two supports and the connected ball bearings will precisely have the joint support behavior. For modeling the dynamic excitation system, a reverse chariot has been used, which is shown in Figure 1. in laboratory and in Figure 2 physically. Figure 2. shows that this chariot contains two Teflon wheels that due to the weight move along the beam and there is no possibility of separation from the beam and two masses $m_1$andm_2, weighing $0.5\ kg$ that are connected to another mass, weighing $2\ kg$, by two stretching springs. This chariot is pulled on the beam with a constant speed of $1\ m/s$ by an electric motor, which is equipped with a gearbox and causes a vibration in the beam. Moreover, the shapes of the cracks and their locations are shown in Figure 3.

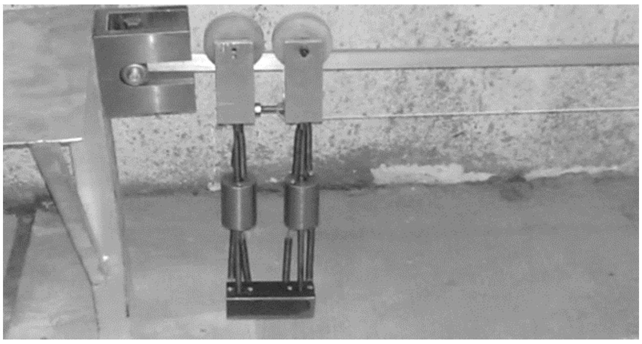

Figure 1. Simple support

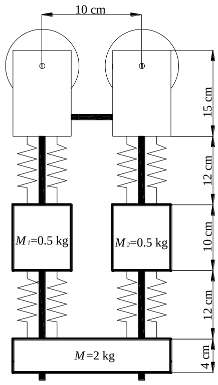

Figure 2. Physical model of moving load

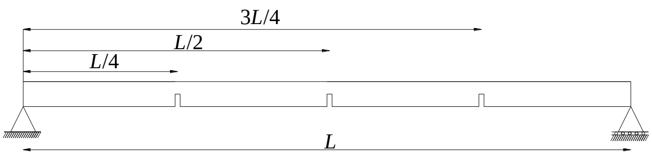

Figure 3. Location of crack in beam

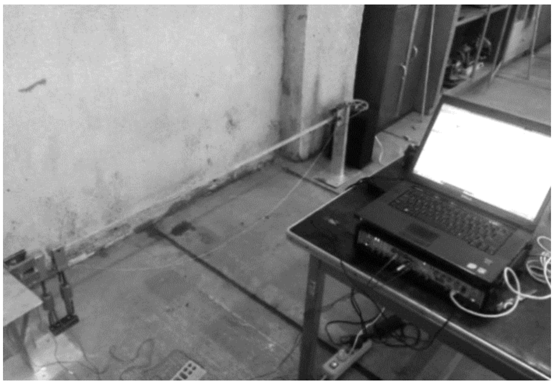

Figure 4. Beam in laboratory

4. Extraction of Vibration Signals

To extract the vibrating signals from the beams, B&K model 4507 accelerometer sensors with sampling frequency 6.4 kHz are installed in three parts of the beam by distances of $168, 94, 54\ cm$ from the beginning of the beam. These sensors have the ability to record the slightest vibration on the beam, and then the mentioned chariot is moved by the electronic motor with a speed of one meter per second and passes the whole length of the beam, which produces vibration along the beam.

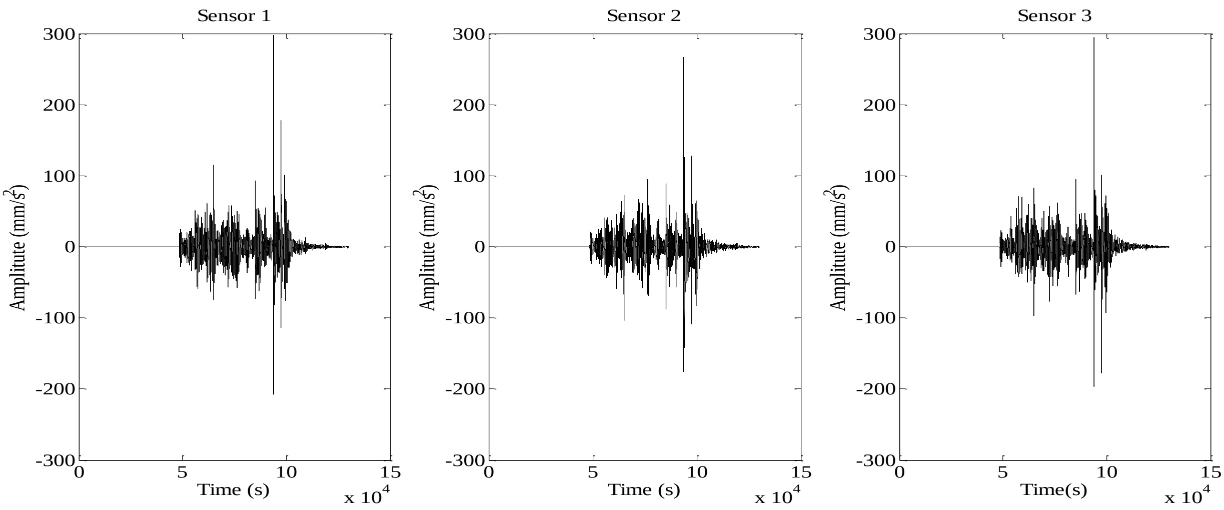

Figure 5. Acceleration time history for a damage beam in the first test

The accelerometers then store these vibrations and in order to make higher reliability, this action is repeated for 20 times. In the general case for a damage scenario, 60 signals are achieved. This is demonstrated in the laboratory in Fig. 4. Three cracks are placed on the beam on locations of 1.4, 1.2 and 3.4 of the beam with intensities of 50% and 80% (d/h). In order to create cracks in the mentioned places saws with thin thickness have been used and the test was repeated for twenty times on each of them. In the first case, the intact beam is placed on two simple supports and the chariot is moved at a constant speed of one meter per second for twenty times on the beam and the obtained results of the acceleration in each test are stored separately. The result of passing of the chariot is shown in Figures 5

As shown in Figure 5, as the chariot moves, the beam vibrates. These vibrations decrease by complete passing of the chariot and become inactive and by evaluating the given signals of the twenty-time tests, it can be concluded that the system has reproducibility. In the second case, the crack in 1.2, is put to intensities of 50 and 80 percent and the mentioned stages are repeated in the intact condition. The results of the twenty-time tests are stored separately. The results of the first two tests are shown in Fig. 6. In the third and fourth states, the crack in 1.4 and 3.4 parts are put firstly by intensities of 50 and 80 and the chariot again is passed over the beam for twenty times and the results are stored separately, but due to the repetition of the operation, the shapes of these status are not shown.

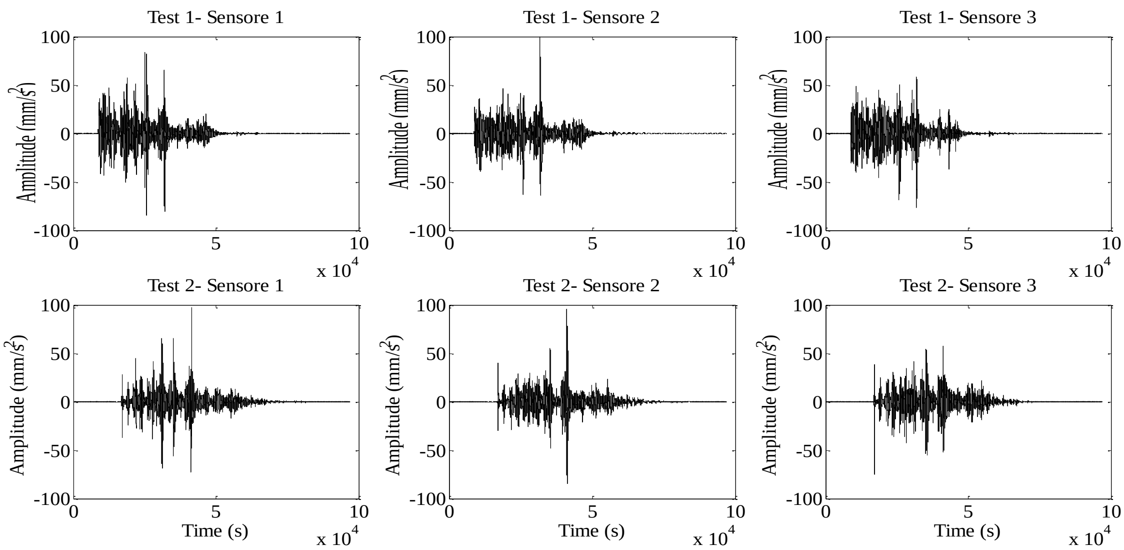

Figure 6. Acceleration time history for damage beam in first and second test

The obtained signals from each state are divided into 31 parts separately via EMD method and as it was mentioned earlier the frequency value that has the highest range (the dominant frequency) is chosen as a feature for fuzzy-genetic algorithm. The obtained results from the EMD method are converted from the time domain to frequency domain via short-term Fourier transform and then the dominant frequencies of each IMFs is obtained. These frequencies are then used as a feature for genetic-fuzzy algorithms. It should be noted that at this stage 31 IMFs are obtained from each signal. Then, using Fourier transform the dominant frequency of each part is acquired. In other words, in each experiment three signals can be obtained and from each signal 31 dominant frequencies are achieved that in total, out of twenty times of testing, 1860 frequencies are obtained. As this number of features for the genetic-fuzzy algorithm is very much and there is no necessity for this issue, therefore 3 frequencies are extracted out of each signal and with this calculation in each test there has been obtained $3 \times 3 = 9$. Furthermore, as mentioned earlier, fuzzy-genetic algorithm should be trained initially and then after the completion of the testing process it must be validated and the percentage of correct answers must be explained. So, the first 10 tests are for the training algorithm and the next 10 are for verification. Fig. 7 shows the frequencies of intact beam for the first test and the first sensor using a short-term Fourier transform. It should be noted that these 3D figures are time-frequency-value that are shown in this article as the two dimensions of frequency-value.

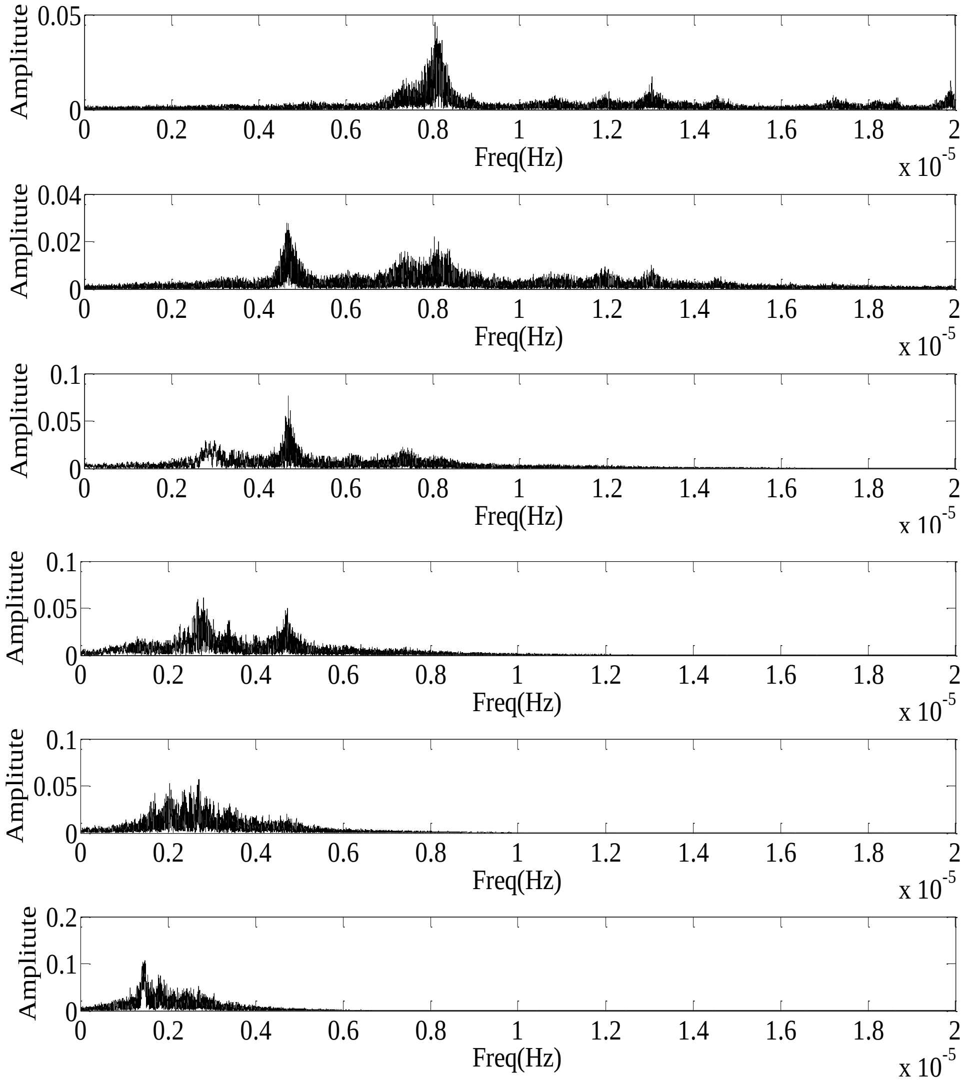

Figure 7. STFT diagram of time-frequency-value no-damage beam for all IMF in first test in sensor 1 (for 6 IMFs of 31 IMFs)

5. Fuzzy-Genetic Algorithm

The fuzzy logic based on function form memberships have a high potential to classify data. Since it would be needed to determine the mean and variance in the data, these variables are optimized using genetic algorithms. Therefore, combination of these two would result in an efficient algorithm.

5.1. Modeling Damage Indicator

Damage indicator in the beam of the node achieved dominant natural frequencies from the extract of the short-term Fourier transform of the beam, which are considered in the –damage and damage modes, where in a dimensionless mode is as follows:

$$\Delta\omega = \frac{\omega^{(u)} - \omega^{(d)}}{\omega^{(u)}} \tag{7}$$

$\Delta\omega$ is equal to the difference frequency in the dimensionless mode. $\omega^{(u)}$ determines the dominant natural frequency in no-damage mode and $\omega^{(d)}$ determines the dominant natural frequency in damage mode.

5.2. Designing the Damage Detector System

In this system the natural frequencies of each scenario of the no-damage beam decrease and is divided into the number of the obtained frequencies from the no-damage beam and these numbers are normalized between zero and one. The obtained numbers are given in Table 1. Out of this operation, there are produced one no-damage mode and six damage scenarios. Fuzzy system inputs, the difference of the normalized frequency and its output location and intensity of damage are the concerned issues. The aim is to find a relationship between them. The first step in the definition of fuzzy systems is the fuzzing of the available data, which means to convert them to linguistic phrases. For this purpose, any normalized difference frequency is divided into five parts, which are shown in Table 2.

Table 1. Normalized frequency difference between 0 and 1

Damage Location	Intensity	Δω1	Δω2	...	Δω90
50 cm	%50	0.49	0.15	...	0.05
	%80	0.53	0.29	...	0.56
100 cm	%50	0.45	0.34	...	0.67
	%80	0.65	0.56	...	0.56
150 cm	%50	0.98	0.87	...	0.09
	%80	0.34	0.56	...	0.34

Table 2. Fuzzy-Gaussian functions to fuzzify numerical values

Numerical frequency difference	0-0.125	0.125-0.375	0.375-0.625	0.625-0.875	0.875-1
Linguistic terms	Very Low (VL)	Low(L)	Medium(M)	High(H)	Very High(VH)

Table 3. Fuzzy system rules

Damage Location	Intensity	Δω1	Δω2	…	Δω90
Un Damage	Un Damage	N	N		N
50 cm	%50	M	L	…	VL
	%80	M	L	…	M
100 cm	%50	M	L	…	H
	%80	H	M	…	M
150 cm	%50	VH	H	…	VL
	%80	L	M	…	L

In the next step, the membership functions should be defined. The membership function is a function that, according to the data input to that output, is a number between zero and one. In this paper, the Gaussian membership functions are used for the input variables. This function can be defined by the following equation:

$$\mu(x) = e^{-0.5(\frac{x-m}{\delta})^2} \tag{8}$$

In this equation, m is the center point of the fuzzy function, and δ is its range (standard deviation) related to the variables. Gaussian fuzzy membership functions have been popular in fuzzy systems in recent years. The middle points for these functions should be selected in such a way that they cover the difference-frequency range. The choice of standard deviation for the fuzzy functions is very important since it greatly affects the fuzzy system performance. To obtain fuzzy rules by converting numerical difference frequency to linguistic phrases to any location and intensity of the damage, a rule is dedicated. According to the defined member function in the previous step the membership degree related to each difference frequency is obtained. Any difference frequency is dedicated to the membership function with the maximum value. Following the above process and with regard to linguistic phrases defined in Table 2, seven rules are produced, which are shown in Table 3. These rules can be defined for special mode as follows:

If the first difference frequency is M and the second difference frequency is L and the node difference frequency is VL, then the damage at a distance of 50 cm is, with 50% intensity, related to other damages and are interpreted similarly. A closer look at Table 3 indicates that each rule has a unique effect and is different from other rules. Therefore, the defined fuzzy system is a good classifier. These rules make a base knowledge and show how an expert use the interpretation of the frequency changes to determine the damage. After defining the rules to optimize the membership functions the genetic algorithm was used. Genetic algorithms are very different from the old methods. In these algorithms the design space should be converted into genetic space. Therefore, genetic algorithms work with a number of coded variables. The purpose of using this method in this paper is to find centeral points and range for the Gaussian functions considered in the fuzzy section. Hence the cost function must be firstly defined for finding the minimum. For defining the purpose function, the following is done:

$$\mathrm{FF} = \frac{\sum_{i=1}^{27}\sum_{j=1}^{9}(\alpha_{ij}-\beta_{ij})^2}{27\times 9} \tag{9}$$

In the above equation,α is the desired output value of the fuzzy system design and β is the actual output of the fuzzy system. The desired output is such assumed that if for example the data relating to a damage to be applied to a fuzzy system, the rule relating to that damage gives an output of one and the output of other rules will be zero. Next-generation, based on the obtained values of the purpose function, the best persons in the present generation are copied at the rate of one. For producing other people, the acts of genetic parts must be used. The intersection agent is a hybrid agent that includes three actions: First, a pair of strands is chosen randomly; second, a place for the intersection action along the length of the strand is randomly selected and, finally, in the third step with respect to the intersection the two strands are replaced. This rate is intended to produce 8 pieces of offspring. The Other agent in genetic algorithm is the mutation agent, which is the application of random changes in a person of a population for producing children, the rate of which is considered 2. By doing above process the optimum points for the centers and the fuzzy functions were achieved after 100 replications and the function value of the purpose was obtained equal to 0.69.

Table 4. Output of fuzzy rules with different frequency data

Damage Detection	Intensity	Output1	Output2	Output3	Output4	Output5	Output6	Output7
Un Damage	Un damage	1	0.34	0.76	0.63	0.08	0.97	0.32
Damage in 50 cm	%50	0.34	1	0.54	0.13	0.76	0.21	0.16
	%80	0.34	0.32	1	0.11	0.21	0.28	0.26
Damage in 100 cm	%50	0.25	0.41	0.42	1	0.11	0.06	0.43
	%80	0.31	0.42	0.27	0.42	1	0.08	0.32
Damage in 150 cm	%50	0.13	0.54	0.44	0.59	0.31	1	0.14
	%80	0.12	0.68	0.54	0.60	0.23	0.19	1

For testing the designed fuzzy system, the values of difference frequencies were applied to the system as inputs; in addition, to obtain the output fuzzy system, the average of outputs of the fuzzy functions related to the frequency difference node were intended as outputs of the fuzzy system. Table 4. shows these outputs. As it is specified in this table, in any case, the damage to the fuzzy system had produced the greatest output, which is 1, and could predict the intensity of all the damages correctly.

After the training phase (fuzzy classification), which was done by the use of the first 10 tests, the proposed method is evaluated. For this purpose, 10 other tests that have not been used during the training phase are used for verification. In this case, similar to the training mode, the features are extracted and are entered into the fuzzy system as inputs and the class number is received as output. Comparing this number with the correct class number in each simulation, the success rate is calculated as follows:

$$S_R = \left(\frac{N_C}{N}\right)\times 100 \tag{10}$$

Where N is the number of the total simulated samples and Nc is the number of cases that are diagnosed correctly. The corresponding class is shown in Table 5. In this table, the percentage of any successful damage is listed and finally the percentage of average success rate has also been announced. Moreover, in order to study the effect of the measured noise, the noise with different percentages is applied on the extracted features and then the success rate is shown for each class. The noise also causes errors in the measured data.

Although the use of modern equipment has diminished this type of trouble, it can never be eliminated. The damage detector system therefore must not work with ideal values, but it must also have the ability to work with data that are with noise. In this article, uncertainty in the modeling and measuring noise is added to the difference frequency values. For this purpose, the following equation is used. In the Equation 11, the random number u is selected in the range of {-1, 1} and α shows the noise level [19]:

$$\Delta\omega_{\mathrm{noisy}} = \Delta\omega + \alpha u \Delta\omega \tag{11}$$

The parameter α specifies the maximum variance of $\Delta\omega$ and the value of the simulated $\Delta\omega_{\mathrm{noisy}}$. For example, if α = 0.1, the value of $\Delta\omega_{\mathrm{noisy}}$ can to the value of ten percent can vary from the amount of $\Delta\omega$. So α is used for controlling the amount of noise in the logging data in the fuzzy system.

To evaluate the performance of the damage detector system, for each noise level, the frequency data of the beams are infected with noise by the Equation 11 and then they are applied to the fuzzy systems, where the detection of the correct results is calculated from the Equation 11. Table 5 shows the results at various levels of noise. According to this table, firstly, in the noise mode 0:05, damage detection has been done perfectly in all damage classes, and been successful with very high percentages. Secondly, by the increase of noise, as it is expected, the capability of the proposed method in successful detection of damage classes will reduce; however, there is the possibility of detection, which shows the superiority of this method.

Table 5. Amount of Success Rate

	$\alpha = 0.05$	$\alpha = 0.1$	$\alpha = 0.2$	$\alpha = 0.3$
Low 1	98.3	91.2	88.3	81.9
Low 2	99.3	89.4	81.3	76.4
Low 3	97.4	81.3	74.3	70.3
Low 4	98.5	85.5	76.6	69.9
Low 5	96.8	90.4	86.6	71.1
Low 6	92.5	88.4	71.2	61.2

Table 5 shows the results of 10 other tests that had not been used in the training phase. At this stage they are infected with different levels of noise and then were used in the algorithm and the results of the top of the table indicate the accuracy and power of the proposed method.

6. Conclusion

In the present study, a new portable and smart mechanical system is introduced for damage detection in beam structures by the use of fuzzy-genetic algorithm. This system has the ability to detect the location and intensity of damage. For obtaining the properties, the moving load including the concentrated mass and linear elastic springs, with constant speed is used for dynamic stimulating of the simply supported beam. Then the acceleration-time history in three points of the beam is extracted by accelerometer. For conversion of the acceleration-time history into usable information for damage detection, the method of signal decomposition into the main modes is used via EMD method. The IMFs obtained via EMD are then converted from time range to frequency range by the use of short-term Fourier transform. Then, dominant frequencies of each IMFs are used as properties for fuzzy-genetic algorithm. The damage detector system has the ability to detect the location and the intensity of the damage in all different conditions, which is one of the advantages of this study as compared to previous works.

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