A Review of Dynamic Analysis in Frequency Domain for Structural Health Monitoring

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Abstract Recently, many different techniques for health monitoring of structure are developed with aim of monitoring the stability of structure with high accuracy and low cost. Nowadays, by advancing technology in the civil engineering field many infrastructures and megastructure are constructed such as towers, dams, bridges and etc. Evaluation of the building stability is complicated in the structure with a complex configuration which led the structural health monitoring process as a challenging issue to ensure the function of the structure during the operation period. To evaluate the serviceability and strength of the building, the subject experts have made a number of attempts to develop damage detection techniques for special building, for example, high-rise building, towers, bridges and dams besides exhibiting economical and practical techniques about structural health monitoring systems. In structural assessment procedures, one of the well-known damage detection techniques is referred to as the change of natural frequencies. In addition, many researchers are frequently using the machine learning methods in SHM for identification of damage. Hence, by using these methods, a summary regarding monitoring of special building through frequency domain response of the structure is presented by this study.

1. Introduction

The need for tall structures has increased due to the requirements for efficacious communication, especially with the advent of television, radar, and radio. In addition, the increasing use of cellular phones has led to a new era of masts and towers, which are smaller in height but larger in number. Several challenges are associated with these slender and tall structures, such as the complexity of the structural system itself. These challenges have attracted the interest of many civil engineering researchers focusing on design, construction, modifications, and maintenance areas to enhance structural safety.

In recent years, the development of vibration-based SHM has increased due to its high potential in enhancing the serviceability and functionality of structures and its significant economic contributions. Non-destructive inspection (NDI) has demonstrated its major role in the service of structures, particularly since the introduction of the damage tolerance philosophy of maintenance. This approach involves embedding a non-destructive evaluation (NDE) system into a structure for continuous damage monitoring with minimal human intervention. Conventional NDI techniques are not easily implemented on-line for the following reasons:

Most conventional NDI techniques, such as radiography, require large pieces of equipment.
Traditional NDI techniques are dependent on skilled mechanical labor and human intervention for the application of the technique and the interpretation of the indications. Conventional techniques are not easily adaptable to modern methods of data acquisition and storage and interpretation through intelligent information systems because they were developed before the advent of modern electronics.

For the aforementioned reasons, researchers have looked elsewhere for SHM systems that can be employed on-line, require minimal human intervention, and can be monitored remotely in real time using intelligent data interpretation systems. Various methods are used to detect damage to structures. The basic principle is any damage in the structure system changes certain characteristics, affecting the structure response. Various techniques have been proposed by researchers based on different types of structural characteristics or responses. Techniques that are based on global dynamic response are an example of this method for detecting damage in structures.

The main principle of these methods is that the modal parameter, such as natural frequency, is a function of the structure of the physical properties of stiffness and mass. Thus, any change in the physical properties from damage will lead to a change in the modal parameter. Depending on the modal parameter employed, this technique can be classified into four types:

- based on frequency changes,
- based on mode shape change,
- based on modal damping change, and
- based on updating the structural model parameter.

Frequency-based methods have the advantage of needing to estimate only at a single location compared to mode shape-based methods (Kannappan, 2009). Meanwhile, a damping ratio has been rarely used for detecting damage because it is difficult to evaluate, and model updating is not a very reliable method for health monitoring and requires long mathematical calculations (Shankar, 2009). Therefore, this chapter reviews and presents the technical literature on structural damage detection and health monitoring using vibration-based methods of the past few decades. Vibration-based methods rely on the fact that damage causes a local change in the stiffness and material properties of the structure, which changes its dynamic characteristics, such as natural frequency. The structure’s natural frequencies are among the best response candidates for damage detection (Kaveh and Zolghadr, 2015). Moreover, this technique can be quickly and easily employed. In this study, damage detection is identified as an inverse problem using the AdaBoost, Bagging, and RUSBoost algorithms from the measured frequency responses of excitation on the structure. In addition, the PSO method is implemented in this study to optimize the optimum correlation factor for the damaged system.

2. Structural Health Monitoring Based Change in Natural Frequencies

Health monitoring of and damage detection in structures are not only important for safe operations but also for retaining the structural performance. When a structure suffers from damage, one or more of its dynamic properties change (Zhong et al., 2017). A review based on the importance of SHM in damage detection has been provided by many researchers. Brownjohn (2007) presented the application issues of SHM on various forms of civil infrastructure, such as dams, tall buildings, bridges, towers, and offshore and nuclear installations. They covered several case studies based on the vibration technique from the practical perspective. Klikowicz et al. (2016) presented a review of the importance of using an SHM system to minimize the possibility of damage and increase structural safety by using a bridge structure as an example. (Verma and Mishra) presented a review of SHM in different countries with various case studies. Carden and Fanning (2004) presented a review of damage identification methods on papers published from 1996 to 2003. Dixit (2012) discussed the challenges in the SHM area by estimating and predicting the sensitivity of structural vibration properties, such as natural frequencies to the existence of damage. With a unique focus on composite materials, a review of a vibration-based SHM was presented by Montalvao et al. (2006).

In addition, Yan et al. (2007) presented a review of vibration-based methods for damage detection.
Fan and Qiao (2011) reported a review of the damage identification algorithms in a health monitoring system for detecting damage in beams or plates.

A different method has been implemented for damage detection in SHM. In the last three decades, SHM methods based on changes in dynamic properties have been studied. When damage is significant, these methods successfully determine the damage (Chang and Chen, 2003). The frequency of the structure is a key factoring examining the dynamic performance of the structure because its effect on the stability and strength of the structure is significant for health monitoring. When a structure is indicative of the damage, there is an evident decrease in the stiffness, which leads to a reduce in the natural frequencies. The frequency measurements have a low-cost experimental procedure and we can easily and quickly perform them. Additionally, the relatively high accuracy can extract the frequency measurements. Moreover, if the experimental measurements are conducted under perfectly controlled conditions, we can easily determine the doubts in the measured frequencies (Sinou, 2009).

Early research on detecting damage focused on using the information of natural frequency changes, which detected the damage in a composite material through the frequency shift method (Adams et al., 1979). The researchers considered a parameter based on the ratio of frequency shifts of two different modes. Stubbs and Osegueda (1990) extended their work by developing a technique to detect the damage using the sensitivity of the modal frequency change. Doebling et al. (1998) reported an early work that used the change in frequency and mode shape of the structures for health monitoring to detect damage. Nikolakopoulos et al. (1997) used the change in the first three natural frequencies to determine a single crack in an experimental single-story frame. The depth and location of the crack from the crossing of the contour plots were determined for all depth and location variations versus the change in natural frequencies. Salawu (1997) presented a review of the structural damage detection by using frequency changes. The author mentioned that modal frequency is a global parameter and depends on the sum of properties at each point of the structure, although many previous works used a simple structure and its element. Williams and Messina (1999) proposed a method for identifying multiple damage locations by using natural frequency shifts. Their algorithm was applied to a three-beam experimental test with two damage locations, and the proposed method successfully detected the damage. Vestroni et al. (1996) used measured frequencies to identify the damage that affects one zone of a beam. Their findings indicated that the stiffness is less than the healthy value of the beam model.

In regard to the damage-induced changes in a pair of natural frequencies, an identification method was presented by Morassi (2001) for a single crack in a vibrating rod.

Chen et al. (1995) discovered the damage in a steel channel by using the shifts in natural frequencies and found that the shift in natural frequencies is not greater than 5% for the first four modes. Banks et al. (1996) demonstrated that natural frequency is affected by the geometry of the damage and not solely by the location and severity. Yang et al. (2001) detected a sawfish cut in an aluminum beam by using the 3D plot depth and location of a crack against the frequency change. They found that the depth and location of the crack are indeed identified from the contour lines obtained from each frequency change. Kessler et al. (2002) investigated the influence of different types of damage (delamination, drilled through holes, impact damage, fatigue damage, and bending-motivated cracks) on frequency response by using clamped composite plates. The authors concluded that fatigue damage is the only kind of damage distinguishable from others at the low-frequency range.

According to (Ren and De Roeck, 2002), a technique was recommended to envisage the gravity and location of damage by using the variations in mode shapes, frequencies, and FE modeling.

To discover the severities and the locations of damage in structures, a new algorithm was developed by (Kim and Stubbs, 2002) using low modes of vibration. A two-span continuous beam was considered to verify the algorithm. Best accuracy was demonstrated by the algorithm with respect to specifying the location and severity of damage.

Smith et al. (2004) studied the bounding natural frequencies in structures. They found that the general effects of each parameter on the natural frequency are the coefficient for given boundary conditions, the coefficient for given beam cross-section, material function sensitivity, and size
function sensitivity. Farrar and Jauregui (1998) reported that frequencies, which are possibly the most modal parameters, are sensitive to change due to the loss of stiffness, which immediately affects the frequency values.

An FE test of a cantilever beam under cracking was carried out by Sutar (2012) and the link between modal natural frequencies with location and crack depth was examined. In addition, it was noticed that the modal natural frequency is decreased with the increase in the depth of crack, and it is increased with the crack location from the fixed end. Sutar (2012) conducted an FE analysis of a cantilever beam under cracking and examined the relationship between modal natural frequencies with crack depth and location; they observed that when the depth of crack increases, the modal natural frequency decreases and increases with the crack location from the fixed end.

The essential parameters used to determine the natural frequency of the structure are stiffness and mass (Wu et al., 2013). Regarding damage detection, a method utilizing the frequency change curve with an auxiliary mass on a structure was proposed by (Zhang et al., 2013). Habtour et al. (2016) tested cantilever beam at variable rotational base motions by exciting it experimentally. The result demonstrated that studying the change in the dynamic response results of fatigue damage accumulation with wary monitoring of the nonlinearities in the structural dynamic response can be an effective parameter for detection of damage.

By using the frequency shift method, the damage detection in numerical and experimental steel beams was examined by (Wang et al., 2016). Besides recommending a damage index called FRESH curvature to identify local stiffness reduction, a new method called Frequency Shift (FRESH) path was introduced by the authors to explain the dynamic behavior of structures blended with auxiliary mass. According to the outcomes of the test, the method is found to be rational and computationally operational in identifying the loss.

Wang et al. (2017) applied the proposed method based on auxiliary mass induced frequency shift in supports under railway tracks to detect the damage through numerical and experimental analysis applied on a steel beam. The result indicated that the when the auxiliary mass moved over the damaged support the natural frequencies are clearly dropped.

To estimate the damaged frequency, an analytical technique was presented by (Ursos et al., 2017) for calculating the natural frequencies of locally damaged inhomogeneous beams. This was done through statistical data generated from FE analysis and a multiplier function was used for reduction in length, extent area and damage location. According to the findings, we can confidently use this method in place of FE analysis and this can be used for SHM to forecast the damage state of beams.

The need for safety and reliability is increasing in civil structures because of aging structures and growth in the number of new ones. Early warnings of damage are provided. Thus, much effort has been exerted to develop the fields of SHM and non-destructive testing (NDT) (Fröjd and Ulriksen, 2016). Identification and detection of damage in civil structures have high importance for the safety and maintenance of these structures. Therefore, damage detection techniques by monitoring the changes of structural dynamic properties have attracted much interest over the past two decades. Different methods have been successfully applied, and most of them use simulated data or simple laboratory specimens such as plates or beams or idealized small-scale structures with artificially presented damage because tests on real structures are seldom possible and mostly do not show satisfactory results due to environmental and other uncontrollable effects (Paultre et al., 2016). Paultre et al. (2016) investigated seismic damage response of a moment resisting high-strength concrete frame by subjecting it to a repeated pseudo-dynamic vibration to obtained modal damping, resonant frequencies, and mode shapes. The author developed a methodology with regularization that showed that it is an effective approach to be used in predicting localization and level of damage in structures subjected to earthquake excitation. On the basis of frequency analysis, the vibration health monitoring for tensegrity structures was examined by (Ashwear and Eriksson, 2017) and a number of solutions were offered for the application of vibration health monitoring for tensegrity structures.

To prevent the resonance that can lead to structural failure, the system natural frequencies should be far from the dominant components of the harmonic excitation force (Belotti et al., 2018). Many
techniques have been used to generate the frequency response. The impact hammer test has been used in many engineering areas to analyze frequency response functions (FRF) of the structures because of the validity of the analysis procedures and simplicity and convenience of the experiments. Schwarz and Richardson (1999) presented a review of all the main topics associated with experimental modal analysis test by using impact hammer test; the results indicated that the impact testing has a low-cost, fast, and appropriate way to find modes. Faizal (2007) studied the structural evaluation by using low-frequency technique and impact hammer test through experimental modal analysis and computational analysis software for beam members as shown in Figure 1. The study found that using the impact hammer test to detect the damage provides a close approximation between 3D modeling in computational analysis and experimental modal analysis.

![Impact Hammer Test](image1.jpg)  
**Figure 1.** Hammer test by using the beam (Faizal, 2007)

Da Silva et al. (2009) presented the vibration analysis based on the impact hammer test for multilayer damage detection in the pipeline and found that this method is simple to conduct in measuring and determining the dynamic response parameters. Tirelli (2010) compared the use of the fast impact hammer testing method (FIHT) with the results obtained by other existing methods and confirmed that FIHT is accurate and highly effective in saving time for the tests and signal processing. According to (Lam and Wong, 2011), the likelihood of identifying the damage in railway ballast under a sleeper was examined. For this purpose, they continued by monitoring the vibration of the parallel sleeper and the simple impact hammer test was used in this regard. As per the findings, the suggested method can be used to identify the ballast damage and the natural frequencies of the sleeper are changed as a result of the damage-induced changes.

With the help of frequency response function (FRF)-based statistical method, the characteristic frequencies of railway tracks as shown in Figure 2 were identified through the impact hammer test (Oregui et al., 2015). As per the findings, the proposed method has the possibility to detect the damage.
The damage detection for a cantilever beam based on damage location assurance criterion (DLAC) correlation method was explored by (Mohan et al., 2014), which is believed to be a relationship between vectors of experimental natural frequency change ratios and vectors of analytical natural frequency change ratios. According to the authors, high performance was shown by the DLAC correlation in the continuous system.

In recent years, an increasing awareness of the SHM of major structures, such as high-rise buildings, long-span bridges, dams, and towers, has been observed. In complex bolted structures, damage should be detected and classified for SHM (Chakraborty, 2005). Since the damage in the structure is resulting from joint failure and loading etc. may cause the massive disaster. Therefore, many studies have discussed the importance of using an SHM system for various types of structures. SHM is extremely important in many engineering applications, such as predicting the failure of the structure, increasing structural safety, and reducing the maintenance cost of the structure. The development of an SHM system aims to examine the structural integrity and provide warnings on disaster damage in real time. Many types of structures have been explored with the new SHM system, including civil infrastructure such as high-rise buildings, towers, bridges, dams and laboratory specimens, such as beams and composite plates, which are explained as follows.

2.1. Health monitoring of bridges

The new SHM system is being used to examine a number of structures, such as, civil infrastructure including bridges, towers, high-rise buildings and dams, and laboratory specimens, for example, composite plates and beams, which are described in this way:

Hence, a widely used technology to identify and assess the safety and condition of a bridge is recognized as the SHM. One of the key attributes of the SHM is natural frequencies of bridges (Nagayama et al., 2017). Salawu and Williams (1993) and Green (1995) presented a review of the experimental modal analysis testing method (ambient vibration, shaker, and impact hammer) for bridges with a frequency domain. They reported that the impact method produces the best result for exciting a bridge with a length of less than 30 m. Soh et al. (2000) studied the SHM and damage detection for an RC bridge structure using dynamic analysis in the frequency domain. According to (Aktan et al., 2005), the challenges in health monitoring systems were reviewed through the modal analysis test for tower and bridge structures. Moreover, the authors mentioned that for an effective and feasible solution to vibration problems, we would need the dynamic testing. Lynch et al. (2006) investigated the dynamic response in the frequency domain of the 273 m-long Geumdang Bridge (Figure 3) in Korea as a health monitoring tool for the bridge.
Comanducci et al. (2015) studied the SHM system of suspension bridges through the natural frequency method. Their findings indicated that variations in frequency can appear even with small variations in incoming wind speed, which is more significant than those that occur from a minor damage. Yarnold and Moon (2015) developed and evaluated a novel 3D numerical and graphical temperature-driven method by using the natural frequencies and mode shapes for long-span bridge SHM systems. Zong et al. (2015) proposed a procedure for SHM as illustrated on a full-size prestressed continuous bridge; they used the FE model updating method and frequency variation. Rolek et al. (2016) presented a method for the SHM of railway axles to detect the presence of a crack in the axle by estimating the axle bending with low-frequency vibration.

2.2. Health monitoring of high-rise buildings

Recently, numerous tall buildings have been built in many modern cities worldwide, and many others are still under construction. Different environmental conditions, such as wind, earthquake, and temperature, which result in lateral motions, affect these slender and flexible super-tall structures. Therefore, monitoring the deformation of tall structures under various environmental conditions by detecting the fault before it reaches a critical state is important in rating the safety and serviceability of structures. Many researchers have worked on the SHM for tall buildings using various methods with frequency analysis.

The damping ratios and normal frequencies of a high-rise building were evaluated by (Arakawa and Yamamoto, 2004). Moreover, the dynamic attributes of natural frequencies and damping ratios were tested by them for 60 months. A gradual decrease in the natural frequencies over time was reported as per their findings. There is a bigger fluctuation of damping ratios in the first mode and reduced in a higher mode.

Saemundsson (2007) studied the first natural frequency of high-rise buildings in Sweden to investigate the effects of wind on such buildings and observed better norms for tall slender buildings when the first natural frequency has low values. Grünbaum (2008) calculated the frequencies of tall building structures and displacements by using the 3D FE method with three different structures and compared their behavior due to wind load. The result showed that frequency increases as buildings become stiffer and decreases when buildings are heavier.

An algorithm to identify the vibrational frequencies and corresponding mode shape of elevated buildings was presented by (Malekinejad and Rahgozar, 2012). By defining the mode shapes and natural frequencies of the structure, (Kaynardağ and Soyöz) analyzed the SHM for a 26-story building in Istanbul using an FE updating procedure. The impact of the identified damping ratio was investigated on seismic performance.

The frequency and the damping ratio of six high-rise buildings (three in Beirut, Lebanon, and the other three (Grenoble, France) were investigated by (Nasser et al., 2016). In this regard, they used an automatic model-based approach by which the damping ratios and natural frequencies of all modes can be automatically identified. An experimental and computational methodology of SHM was
developed by (Belostotsky and Akimov, 2016), which handles the load-bearing structures of unique buildings and this is done with the calculation of the mode shapes and natural frequencies of a dynamic system.

2.3. Health monitoring of dams
Concrete dams hold greater importance for countries, since water for hydroelectricity generation, irrigation and flood control is provided by them. As a result of age-related impairment in the structure itself, floods, and other factors, the performance of these structures may decrease with time under operational and environmental loads. There might be a disaster and it would result in human and financial losses if we fail to maintain the concrete dams (Bukenya et al., 2014). By means of health monitoring system, dam safety is ensured through their evaluation and the optimum safety for the affected population in case of dam failure will be provided by this assessment (Bianchi and Bremen, 2001). On the basis of static and dynamic tests, a review of the SHM of concrete dams was presented by Bukenya et al. (2014). According to them, dams are affected by many factors, for example, fluid-structure interaction foundation deformability, water level and nonlinear behavior of cracks, by which the dynamic properties (natural frequencies) of structures can be affected.

Patjawit and Chinnarasri (2014) found that using natural frequency shifts to identify damage in embankment dams subjected to ground vibration is useful to a health monitoring system. (Cantieni) discussed the health monitoring of two dams (one is between Switzerland and France, and the other is in northern Sweden) as case studies, as shown in Figure 4, by using dynamic testing (natural frequency and mode shape) analysis.

![Figure 4 (a, b). Dams case study (Cantieni)](image)

2.4. Health monitoring of towers
Unluckily, the changes in geometric/material properties are experienced by the structural system, including system connectivity and changes in the boundary conditions, by which the system performance is affected (Guidorzi et al., 2014). Based on the frequency-dependent feature of both the load and structure properties, the frequency domain usually performs the dynamic analysis of tall slender towers.

The dynamic analysis of tall slender towers is usually performed in the frequency domain based on the frequency-dependent feature of both the load and structure properties. Therefore, dynamic analysis is required to estimate the resonance response of the structure because this resonant response is
important when the first natural frequency of these structures is below 1 Hz. Guidorzi et al. (2014) discussed the new and advanced SHM system (autoregressive AR + noise models) installed at the 45 m-high tower of the Engineering School of Bologna University in Italy by using the frequency domain as measurement data and found that the proposed method is useful for implementing modal-based SHM analyses. By means of the frequency domain, the dynamic monitoring system of two tall slender steel telecommunication towers was presented by (Antunes et al., 2012), which are 50 m high, in Portugal (see Figure 5). As per their findings, the connections and degradation of existing materials can result in the stiffness loss.

![Figure 5. Tall slender monopoles with 50 m high installed in Portugal (Antunes et al. (2012)](image)

Saisi et al. (2015) conducted a study on the dynamic monitoring system of the 54-m high Gabbia Tower in Mantua, Italy using fault detection methods based on shifts in natural frequencies. The effect of earthquake and temperature on tower frequency was also investigated. Their findings indicated that an increase in temperature leads to an increase in the modal frequencies. They found that when a far-field seismic event occurs, the natural frequency decreases slightly. Niu et al. (2015) proposed an algorithm for reconstructing the wind load based on the algorithm proposed by (Hwang et al., 2009). Their study was applied to Canton Tower, which is 600 m tall, in an active typhoon-prone area. The method (FEM) used in this first study of the Canton Tower was modified, then the modal properties of the Canton tower were identified by operational modal analysis (OMA). In addition, the SHM technology has a potential application in wind turbines. Therefore, numerous studies have been conducted for the SHM of wind turbine towers by using the dynamic properties (frequency, mode shape) analysis to check their stability ((Robinson and Hamilton, 1992), (Swartz et al., 2007), (Ghaemmaghami et al., 2013), (Nicholson, 2011); (Hu et al., 2015), (Rolfes et al., 2007), (Negm and Maalawi, 2000).

According to Table 1, various research scholars have reported the natural frequencies of masonry towers with variations in height and geometrical attributes.
| Reference               | Tower height (m) | Frequency (Hz) | 1st mode |
|-------------------------|------------------|----------------|----------|
| (Preciado, 2015)        | 32               | 1.064          |          |
| (Ramos et al., 2010)    | 20.4             | 2.15           |          |
| (Ivorra et al., 2008)   | 33               | 2.15           |          |
| (Kim, 2013)             | 169              | 0.23           |          |
| (Antunes et al., 2012)  | 145              | 0.31           |          |
| (Saisi et al., 2015)    | 138              | 0.24           |          |
| (Guidorzi et al., 2014) | 50               | 0.429x         |          |
| (Antunes et al., 2012)  | 54.0             | 0.661y         |          |
| (Guidorzi et al., 2014) | 45               | 0.989          |          |
| (Aktan et al., 2005)    | 83               | 1.6x           |          |
| (Nasser et al., 2016)   | 21story          | 2.2y           |          |
| (Tsogka et al., 2017)   | 18story          | 0.84           |          |
| (Niu et al., 2015)      | 610              | 0.1129         |          |

3. Damage Detection Based on Machine Learning Method

A neural network, rule learning, ensemble methods, and statistical models are several machine learning methods for detection. Machine learning methods are used extensively because they exhibit good performance in the learning process and effective intrusion detection systems (Gaikwad and Thool, 2015).

3.1. Damage detection by using the artificial neural network (ANN) and frequency shift

The change in dynamic parameters such as natural frequencies can be triggered due to any change in structure stiffness. A fault in the structure might be generated because of a change in this parameter from the reference data. Hence, to determine the health condition of the structure, the researchers should determine the relationship between the damage in a structure and its dynamic parameter. In the recent past, the damage assessment has been performed and reported by the several researchers. By using a dynamic parameter, a summary of the ANNs based application is presented by this section to develop the damage identification algorithms.

An ANN was developed by (Leath and Zimmerman, 1993) for damage identification using a cantilever beam. In their study, Young’s modulus was reduced up to 95% and used to model the damage in the beam.

As far as the first two bending frequencies up to the level of fault in each member are concerned, the subject experts applied the ANN to detect the fault. In this research, the ANN was used to detect up to 35% of the damage. Ferregut et al., (1995) performed an evaluation of damage in a numerically simulated cantilever beam using natural frequencies.

There are three layers in the neural network together with six neurons in the input layer, which represents the first six natural frequencies containing 11 and 17 neurons in the output and hidden layers. The first neuron was assigned for damage severity in the output layer, whereas, the other 10 neurons were for damage location. Foregoing in view, we made a damage simulation by minimizing the depth and width of the corresponding element from 1% to 30%, and 240 datasets were used to train the network. The findings revealed the critical defects because the low levels of damage are not
taken care of by the natural frequencies.

Suh et al. (2000) detected the depth and location of cracks in a beam and a plane frame through natural frequencies and ANNs with a genetic algorithm (GA). The depth and location of a crack were used as inputs to the ANN, and the structural eigenfrequencies were the outputs. After training the ANN, GA was employed to detect the depth and location of cracks from natural frequencies. This study was expanded by (Sahoo and Maity, 2007) to consider the problems in selecting suitable values of ANN, such as learning rate, momentum, type of activation function, convergence criteria, and training algorithm. A neuron GA based on modal parameters and strain values was applied to detect the severity and location of the defect.

The analysis of the relative sensitivities of structural dynamic parameters using ANN based on combined parameters in cantilever beam and truss structures was reported by (He-Sheng et al., 2005). The combined parameters that were calculated with the three different parameters are as follows:

i) Adjustment in the percentage of the frequencies
ii) Change in rates of the natural frequencies, and
iii) Declaration criteria of flexibilities.

Basically, these are the input parameters for the ANN. As far as the results are concerned, the combined parameters and the input samples of ANNs have strong compatibility with each other.

To discover the location, extent, and magnitude of damage, (Kim and Stubbs, 2002) applied the ANNs. The inputs to ANNs were the natural frequencies of a damaged beam, and the extent, location and damage magnitude were among the output. The damage was identified by employing the differences in the natural frequencies of the healthy and damaged beams. For improving the sensitivity of the natural frequencies, high-frequency modes may be used. Nevertheless, low-frequency modes as compared to high-frequency modes have the least concern with the environmental conditions, which is one of the key shortcomings of ANNs.

To discover the height and location of cracks in cantilever beams, a modular ANN was used by Suresh et al. (2004). The inputs in this study are the first three natural frequencies, while, the outputs were the depth and location of the cracks. The authors were of the view that the damage in structures with high accuracy can be detected by applying the natural frequencies. In addition, the performance of the radial basis function (RBF) network is preferable than the multilayer perceptron (MLP) network and this was revealed by the findings of a comparative study.

Jeyasehar and Sumangala (2006) assessed the damage in PSC beams through an ANN with natural frequencies. Based on their findings, a strong relationship exists between natural frequency, ultimate load, crack load, crack width, and deflection on the damage identification of PSC beams. ANNs do not require a mathematical model. In this study, ANNs were utilized to evaluate the damage in PSC beams. The parameters mentioned were used as inputs to train and test the neural network for both damaged and undamaged beams. Two hidden layers with 7 and 5 neurons were considered in this study. The output of the network was the predicted damage extent. The results for the healthy and damaged beams were obtained experimentally. After the ANN was trained with natural frequencies, the damage level can be obtained with an error less than 10%.

Lin and Jianjun (2010) presented a damage detection technique for detecting defects at different severities and locations for simply supported beams using an ANN based on frequency changes. The detected accuracy was not influenced by the insufficient estimation information.

To determine the depth and location of cracks in cantilever beams, Kazemi et al. (2011) applied the particle swarm optimization (PSO) and the ANN-based procedure. The FEA delivered the first three natural frequencies of the beam and then they were applied as inputs to the ANN. To envisage the depths and location of cracks, the researchers applied the PSO approach so that the ANNs could be trained.

The actual data and the findings were in line with one another. It demonstrated the feasibility of the ANN application, which was directed with the help of the natural frequency data.

Sumangala and Jeyasehar (2011) have made their input to devise a technique. In this regard, they used the lab-based study findings. Besides introducing corrosion in the prestressed wires, the
engineers cast the PSC beams and they were consequently snapped using an accelerated corrosion process. The natural frequencies, as well as the stiffness of healthy and damaged beams, were used to train the network. By using the natural frequencies of a PSC beam at different loads, the desirable outcomes were acquired by the trained network.

To identify the gravity of damage, an innovative neural network was presented by Min et al. (2012), and via the optimal frequency analysis, it is operated on a simply-supported aluminum beam. To select the quantitatively detecting damage and the damage-sensitive frequency ranges, the induced type of damage and the neural network-based intelligent method is likely to affect the sensing capability of the frequency range. By employing a vibration measurement test through GA and ANN, the detection of crack location and depth in a cantilever beam was explored by Mhaske and Shelke. As per the findings, the desired results can be effectively obtained via the GA search technique for vibrating beams or structures. In order to have an acceptable resemblance, the engineers observed the validation of experimental results with ANN.

Furthermore, the damage was detected in a steel bridge element using ANN by (Spillman et al., 1993). In this study, the damage was simulated by cutting the element and bolting plate on top of the defect. Thus, by removing the plate and loosening and tightening its bolts, the full, partial, and undamaged states of the elements could be considered. According to this study, when the plate was attached, the element was considered undamaged. Three sensors that consist of two accelerometers and a fiber optic modal sensor were installed on the element. The amplitudes and frequencies of the first two modes, the impact location, and the intensity were supplied as inputs to the neural network, while the possible damage states were designated as outputs. These findings demonstrated that accurate diagnosis was achieved in 58% of the cases considered.

The location of damage and its rigorousness in bridges have been discovered through ANNs using natural frequencies. For uncovering the damage, Chan et al., (1999) have applied the first 12 natural frequencies (measured from the Tsing Ma suspension cable tension bridge in Hong Kong) as the inputs to and outputs of the auto-associative neural network. Since the output layer exhibited the reproduction of the input samples, this network is therefore known as auto-associative. The index is referred to as the difference between the outputs and the target from the network, by which the aberration caused by a 5% reduction in cable tension could be acknowledged. As per their results, the changes because of natural system variations and the changes caused by the damage can be differentiated by the auto-associative network.

To calculate the size and location of damage in a cantilever beam, the impact of natural frequencies as inputs to ANNs was presented by Islam and Craig (1994). The input parameters to the ANN were basically the first five frequencies. Both numerical and experimental examples were used to corroborate this study. Moreover, the location and size of damage in a cantilever beam can be identified by the ANN as per the outcomes.

Furthermore, good results were determined by using the natural frequencies of the damaged composite beams generated from the FE simulations by (Okafor et al., 1996) using ANNs. In this study, the existence and location of damage were identified by comparing the experimental and numerical results. The size of damage was estimated by ANN and indicated that the third and fourth natural frequencies were better indicators of damage detection.

Composite materials, because of their strength and high stiffness, are being used by a number of structural engineering applications. The widespread on in composite structures is delamination, which increases the modal damping and decreases the structure stiffness. By through the shifts in natural frequencies, the location and size of delamination have been discovered using ANNs. To develop the damage classification method in composite plates, the ANNs and the FE analysis method was used by Dua et al. (2001). An ANN model was recommended by Chakraborty (2005) so that the size, shape, and location of delamination in laminated samples could be predicted with an elliptical embedded delamination. In this analysis, the input variables to the ANN contained the 10 natural frequencies of the specimen, while the shape, size, and location of delamination were included among the outputs. The FE and ANN based results were compared by the author and good harmony and conformity were
obtained.

By employing the first and second natural frequencies together with an ultrasonic lamb wave, a damage detection method for detecting transverse cracks in the composite beam was suggested by Ramadas et al. (2008). The inputs to the ANN were first and second natural frequencies, amplitude ratio and time of flight, while, the outputs entailed the depth area and the crack location. The FEA was used to generate the training data sets for the ANN. According to the authors, if we individually apply the vibration technique and lamb wave method for calculating the gravity of damage, the latter one fails when the damage location is near the fixed boundary. In addition, the former one remains unsuccessful, when the damage location is near the free edge. Accordingly, when we integrate the damage features of more than one technique, we can more accurately recognize the damage as compared to their usage on an individual basis. The ANN was found efficient and the depth and damage location with an accuracy of 89% and 95.8% respectively was also predicted by the ANN.

Several researchers have used natural frequencies with ANN for structure damage detection. A structural damage detection system that uses natural frequencies was proposed by (Tsuchimoto et al., 2004). In this system, the damage sites were first detected globally using the ANN method, and then the fault was identified locally by determining the changes in the eccentricity of the structure between the centers of rigidity and the weight due to the damage. This strategy was applied to a scaled five-story structure. This structure was modeled as a five-mass shear system. In this study, the neural network used in the global damage detection strategy included five input and five output neurons. The first five natural frequencies were the inputs, and the reduction rate of the stiffness of each element or story was selected as the output. According to the results, the ANN showed good accuracy in detecting the extent of damage, and then by detecting a change in eccentricity, the damage locations could be narrowed down. With the help of an RBF neural network, an algorithm for the harshness and location prediction of crack damages in beam-like structures was applied by (Li et al., 2005). As far as the first three natural modes are concerned, the dynamic attributes of healthy and damaged cantilever steel beams were found by performing the FEA. The engineers have taken the experimental validation into account and modal parameters, for example, strain mode shapes and resonant frequencies were acquired. Afterward, the localization and strictness of crack damage can be successfully calculated by the ANN, which was trained by the data produced from the numerical damage case.

Moreover, the damage in a steel lattice mast that was subjected to wind excitation was detected by (Kirkegaard and Rytter, 1994) using ANNs. An ANN was trained using the patterns of the relative changes of the first five natural frequencies. Training sets were provided from the FE method and using data with 0% to 100% reduction in selected diagonals. Four outputs that correspond to four diagonals were selected. The ANN could generate the training data, but it had less operation on the test data. The authors indicated that at 100% damage, the ANN could quantify and locate the damage, whereas, at 50%, it could only predict the damage existence. In this study, a damage of less than 50% could not be detected.

Ceravolo and De Stefano (1995) employed natural frequencies as input parameters to the ANN to predict the two-dimensional coordinates that represent the damage location in a truss structure. In this study, the damage was modeled by removing the truss elements. A back-propagation neural network (BPNN) model, with 10 input neurons representing the 10 natural frequencies and two output neurons corresponding to the y and x directions, was applied. One hidden layer that consists of 10 hidden neurons was selected based on trial and error. In this work, the only single damage was considered and the truss structure was modeled by FEA. Eighteen patterns consisting of various single damage cases were considered for neural network training. Their results indicated a good agreement between the natural frequencies and the locations of damage. In addition, the damage detection of a cracked column using ANN was studied by (Yau, 2005). In this study, the first natural frequency of the cracked column under different loads was applied as inputs, while the compression load, the crack location, and the crack size were chosen as outputs to the ANN. The authors concluded that ANN can predict the compression force and cracks on a cracked column with good accuracy.
3.1. Limitations of neural network. Shanker (2009) introduced several limitations of ANN, which are described as follows:

1. ANN always produces approximate results. They cannot be used where exact results are required. The accuracy depends on the training process. If the network is not properly trained, inaccurate results are produced.
2. Big data are required to train the network. A significant amount of time and resources might be required to generate the data.
3. A trained ANN can be used only on the same type of problem for which the data are trained.
4. Several trials are required to train the network with different numbers of hidden layers and neurons until the appropriate configuration of the network is achieved.
5. For data not in the training set and where no explicit relation exists between the input and the output, the correctness of the results produced by ANN cannot be determined.

3.2. Damage detection by using learning technique

The supervised and unsupervised learning are the two types of the learning methods. The target figure on invisible examples is discovered by the supervised learning. Some ingrained allocation datum is forecasted by the unsupervised learning and label datum is not required in this regard. The learning method contains two types of classifiers, namely: multiple and single classifiers. The ensemble of classifiers is the other name of the doubled classifiers. A weak classifier is the one who cannot accurately classify the objects. The detection of the weak classifier is almost a random guess. Meanwhile, a strong classifier, which is also known as a multiple classifier, consists of a set of weak classifiers that can detect with high accuracy (Schölkopf and Smola, 2002).

Many learning algorithms have been presented for classifying the cases or samples in a dataset. These learning algorithms consist of decision trees, linear discriminate analysis, naïve Bayes classifier, neural networks, support vector machine, and k-nearest neighbor (Buntine andNiblett, 1992). This part focuses on the ensemble method.

3.2.1. Ensemble method. The learners become vulnerable to generate a strong learner because of the ensemble method or ensemble learning combines. Generally, the ensemble term is put up for techniques by which double suppositions are developed through the identical base learner. We can term an ensemble classification method as a supervised learning algorithm because it has self-training abilities besides forecasting accurate outputs. For a desirable prediction, it can identify improved suppositions. To generate multiple suppositions, utilizing the same base learner is the key objective of the ensemble method (Freund et al., 1997). The common ensemble architecture is illustrated in Figure 6.

![Figure 6. Simple Ensemble procedure introduced by (Prusti, 2015)](image)

Ensemble methods have many advantages:
- Simple and fast
- Can handle large data well (with automatic feature selection)
- Performs excellently
Ensemble learning provides the best prediction method from several and often weaker models to produce a strong model or an estimator that provides better results than the individual models.

Many researchers have applied the machine learning technique for damage detection in the structure of SHM.

The method learns a set of classifiers using weak learners to provide a strong classifier (Ferreira and Figueiredo, 2012). The other name of base learners is the weak learners, which are generally delivered from base learning algorithms. In addition, these can be a decision tree, a neural network, or any type of learning algorithm. Combining the prediction of different models constructed with a learning algorithm is the key objective of the ensemble technique so that the improved robustness or generalize ability could be derived from the single model.

Ensemble methods are divided into two types that consist of boosting and averaging methods (De Souza and Matwin, 2011).

- Many models are developed by the averaging technique and subsequently, the average prediction is obtained to choose the best one. An example is the bagging algorithm.

In simple averaging, the outputs of individual learners are averaged to determine the combined output. Given below is the simple averaging output, $H(x)$:

$$H(x) = \frac{1}{T} \sum_{i=1}^{T} h_i(x) \quad (2-1)$$

- The second model is dependent on the first one in the boosting method. Models have developed automatically in a logical sequence. Besides minimizing the bias of the combined models, the goal is to merge the weak models to generate a strong one. An example is “AdaBoost”.

Concerning weighted averaging, the output of individual learners with different weights is first averaged to produce the combined output. Given below is the representation of the weighted average, $H(x)$:

$$H(x) = \sum_{i=1}^{T} w_i \times h_i(x) \quad (2-2)$$

Different studies have applied the machine learning techniques for damage detection. Khoa et al. (2014) applied machine learning techniques in detecting damage in SHM for the Sydney Harbour Bridge. The authors found that the proposed method helps minimize the computational time and safeguard the accuracy of detection. Vitola Oyaga et al. (2016) presented a damage detection and classification method for aluminum plates based on machine learning algorithms. Their results showed a proper classification and detection of damage for different simulated and real defects by using the proposed method. In addition, several machine learning algorithms with different working principles have been proposed by (Long and Buyukozturt, 2014) for damage detection. Santos et al. (2016) proposed algorithms that showed better classification for damage detection.

Different ensemble algorithms have been proposed and developed by many researchers for classification methods to achieve robust generalization ability. This study focused on the Adaptive, Bagging, and RUSBoost algorithms, which are discussed in the following sections.

### 3.2.2. Bagging

One of the simplest ensemble learning techniques developed by (Breiman, 1996) was bagging (bootstrap aggregation). Aggregation with bootstrap sampling is used in this technique. At the outset, the training set is swapped to randomly sample the data cases, from which, the bootstrap replicates are determined. Subsequently, different bootstrap replicates are to determine each base model.

In addition, the bagging method takes less time to build the model (Gaikwad and Thool, 2015). The bagging method provides better classification results, especially when the base classifiers are unstable, which occurs when slight changes in the training data can result in high changes in the resulting classifier, that is, when the learning method is unstable (Breiman, 1996). This is why the bagging method works effectively for classification (Ferreira and Figueiredo, 2012). Figure 7 depicts the bagging approach for the classification.
The major reasons for errors in learning are referred to as the variance, noise, and bias. The target function is likely to trigger the noise, i.e., an error. When the target cannot be learned by the algorithm, it is said to be the bias. The sampling generally yields variance and the learning algorithm is affected as a result. These errors can be reduced due to bagging because minimizing variance is the major effect of boosting.

The situations taking place when data sets have incorrect class labels in their training sets or/and test data sets are referred to as the noise in classification. As far as machine learning techniques are concerned, it is significant to observe the desirable performance of classifiers on data sets containing classification noise.

The problems associated with the performance of ensembles of decision trees with noisy data domains have been emphasized by a number of researchers ((Freund and Schapire, 1996);(Dietterich, 2000); (Melville and Mooney, 2004)). As per their findings, the boosting performance is extremely deteriorated, while bagging ensembles are sound in nature and goes above than ensembles in these circumstances.

Training data with noise mostly increases the variance in the prediction of classifiers. Therefore, bagging ensembles are used to reduce the difference. Bagging has two main advantages:

- Increases the classifier accuracy and stability (Ferreira & Figueiredo, 2012).
- Minimizes the variance of classifiers (Friedman et al., 2001).

Therefore, different researchers have applied the bagging algorithm for damage detection. Simidjievski et al. (2015) showed that bagging process-based models can improve the predictive performance based on experimental tests. Camacho-Navarro et al. (2017) used ensemble learning based on the bagging algorithm to detect the damage in carbon steel pipes. Their results showed the potential of ensemble learning in detecting damage.

3.2.3. Adaptive Boosting. The term “boosting” generally refers to a method of determining certain predictions with precision by combining a group of these predictions with minimal accuracy that were studied from various sets of training data. Freund et al. (1997) proposed an implementation of the AdaBoost algorithm that uses the boosting approach to ease the classification routine. The iterative nature of the AdaBoost algorithm implies that at each iteration, AdaBoost uses numerous sequences of training data to study the base models. The correct classification (increase) or incorrect classification (decrease) is dependent on previous iterations at every instance. Thus, a change in the sequence of iterations is conducted subsequently on the training models. This in turn goes a long way to concentrate on individual weak forecasts at different instances with an all-round combination.

The popularity of the AdaBoost algorithm has led to numerous studies, especially on the
construction of a high-performing ensemble of classifiers (Friedman et al., 2001).

The AdaBoost algorithm works toward producing the final classifier by using a weak learner to study a given set of classifiers. To obtain weak classifiers continuously usually involves the use of re-weighted variations from the iterative process that uses the training data, with each data weight linked to the precision of previous classifiers. In each iterative process, the same training set is utilized, which in turn is subsequently weighted by the previous classifiers in terms of its classification or misclassification. The utilization of the weak learner at each iteration prioritizes the patterns previously classified by precursory weak classifiers. The value obtained from allowing weak learners to learn without a significant decrease can only be achieved by obtaining base classifiers directly from the weak learners from previously weighted and corrected classified cases. Figure 8 depicts the structure of Adaboost.

The strength of the base learner may lead to higher levels of accuracy with only outliers and noisy cases remaining with a considerable amount of weight left in the next rounds to be learned. The utilization of the AdaBoost algorithm includes performing regression analysis tasks. Avnimelech and Intrator (1999) compared the threshold and prediction errors to distinguish errors and then proceeded further by using the AdaBoost version for classification. Drucker (1997) maintained probabilities from the AdaBoost algorithm based on the degree of error. In cases where large errors occur on the previously used learners, the chances of the learners being chosen to train the next base learner are further increased. The predictions of various base learners are then determined by taking the average weight of each prediction.

The underlying concept behind the use of the adaptive boosting algorithm lies in the fact that the training of weak learners is based on the various weighted versions of the training data available. The performance of previous learners is a direct function of the weighted versions in each case without sampling the training data for the following round. This means that the final output of the boosted classifiers is a combination of the measured outputs of the weaker learning algorithms. The convergence toward a strong learner can be established regardless of the performance of individual weak learners with some level of precision (Mahajan, 2015).

The AdaBoost algorithm can be used as a machine learning algorithm alongside different well-known learning algorithms with a considerable increase in learning performance. With the massive success of using the AdaBoost algorithm, numerous studies have been conducted to understand better what makes the AdaBoost algorithm function effectively. In an attempt to explain the circumstances behind the success of the AdaBoost algorithm, Schapire and Singer (1999) tried to shed more light by making use of training examples. Simply put, the boundary of an example with regard to a classifier boils down to the classification result. They proved that the ability of an upper boundary to rationalize the error of a voting classifier is not dependent on the number of combined classifiers, but rather on the boundary distribution over the given training set, number of training sets, and size of the base classifiers, such as the VC dimension. They also showed the potential of the AdaBoost algorithm in
providing a good margin. To explain the success of the AdaBoost algorithm in the experimental set-ups, this hypothesis postulated that the success could be attributed to the production of good margins of distribution and further explains the surprising phenomena observed in the experiments conducted. Meir and Rätsch (2003) presented an overview of general ensemble methods and the boosting and leveraging algorithms.

A summary of the current studies on boosting, particularly, the AdaBoost algorithm was presented by (Schapire, 2001). The author was of the view that the accuracy of any learning algorithm would be enhanced as a result of boosting. According to Worden et al., (2007), seven principles were set up for SHM so that its general aspects could be captured, which includes decades of experiences. As per the Principle III, the unsupervised learning can identify the location and presence of damage, while the supervised learning can discover the severity and nature of damage.

In investigating corrosion and crack cases, AdaBoost and time frequency have been used to classify damage (Kim and Philen, 2011). The method successfully classified the two different damages of crack and corrosion with some level of accuracy. Cord and Chambon (2012) studied the identification of cracks on roads by considering the compositional description and statistical learning procedure, with the AdaBoost-dependent image processing. Herfeh et al. (2013) presented a method for classifying and ascertaining damage on buildings using images from satellites and digital mapping. In comparing the results of detecting damage via AdaBoost and neural networks, the AdaBoost results were more precise in detecting and classifying collapsed buildings when compared to the results obtained from neural networks.

3.2.4. RUS Boost algorithm. According to Seiffert et al. (2010) the random under sampling algorithm or RUSBoosting algorithm specifically groups a specific class from other classes by design, especially when making comparisons between classes that have more observations and good reference results.

Simply put, the RUSBoost algorithm is designed to properly categorize a class with more observations than another class with good reference results (Seiffert et al., 2010). With the inherent problems associated with class imbalance and skewed sets of data, especially in data acquisition, the RUSBoost algorithm works by combining random undersampling with boosting, which results in better classification from a set of skewed data. The construction of new models becomes quite challenging, especially when working with a highly skewed data with class imbalance. The RUSBoosting algorithm is a technique that removes imbalances in data distribution (from skewed data sets) to improve the performance of weak classifiers and is highly recommended for use from a group of other techniques used in data sampling, such as random resampling. The RUSBoosting algorithm randomly deletes data from skewed training data (i.e., random data extraction) until a balanced classification of data sets is finally achieved (Seiffert et al., 2010). Compared to other hybrid boosting algorithms, the RUSBoosting algorithm displays improved performance and faster results within short periods of training time for models and is an advanced data sampling technique. In the comparison of the precision of results from the classification of imbalanced datasets of the ANN and RUSBoost classifications, Blackard and Dean (1999) reported a 70.6% accuracy for the ANN and an accuracy of more than 76% for the RUSBoost. In addition, Kesikoglu et al. (2016) reported that using the RUSBoost classification algorithm increases the classification accuracy of the remote sensing techniques employed to ascertain impenetrable surface areas in Kayseri, Turkey.

4. Discussion and Conclusion

Structural health monitoring (SHM) is essential to ensure the structural safety and stability during its lifetime. Several flexible and long-span buildings such as slender structures have been excited by wind or any other source of dynamic loads. The structural damage can result from joint failure, member crack, section crush and so on and may cause building collapse. Therefore, the detection of damage in the structural system is the key point of SHM to give a good understanding of the imposed excitation and dynamic responses of the structure. Recently, an increasing consciousness of SHM for large structures, like long-span bridges, high-rise buildings, dams, and towers, has been observed.
For testing of the full-scale large structure finding the suitable and feasible method with high accuracy is one of the main concern of researchers. However, results from the review of literature indicated that the vibration testing is a useful tool to determine the structural condition. Besides, many of the existed reports were focusing on the dynamic behavior of the tested structures with analytical models and other reports dealt with detection of damage in the structural system.

This study provides a review to summarize the progress that has been made by researchers regarding the critical issues of SHM system and focus on structural health monitoring with dynamic frequency analysis for different types of structures. A different method has been implemented in damage detection for SHM. The change in natural frequencies can be utilized as a damage detection method for assessing structural procedures. Several studies have discussed the SHM and damage detection using changes in frequencies. However, the partially recorded data for dynamic frequencies for special structures, such as communication tower, are noisy, random, unstable, and skewed, due to uncontrolled noise, such as vibration sources that include an automobile engine, reciprocating motion in a machine, or broadband noise from wind or environment, which cause many challenges in interpreting frequency data and recognizing damage. Besides, there are many challenging issues to use the frequency method for SHM as difficulty in capturing low-frequency responses of the structure.

Also, Many SHM systems for identifying damages in the structures using frequency domain response are based on an unsupervised learning method which is challenging to precisely detect and track damages in long-term monitoring which is needed to more investigation. In addition to an SHM system, the sensor network should be fail-safe during online monitoring. That is, the sensor should not be damaged after being installed in a structure. Otherwise, a redundancy algorithm should be used to acclimatize to the new sensor network when one or more sensors are damaged.

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