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ORIGINAL PAPER

Health monitoring of ultra high fiber performance reinforced concrete communication tower using machine learning algorithms

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Abstract

Within the last decades, the needed for communication towers has accelerated with the requirements for effective communication, especially for radio, radar, and television. The complexity configuration of the tower and limit access to the structure body especially inner part of the tower with hollow section is led the health monitoring of tower as the main challenging issue to maintenance during its function. The change of natural frequencies can be considered as one of the prevalent damage detection methods in structural assessment procedures. Therefore, the main aim of present research is to develop health monitoring system for Ultra High Fiber Performance Reinforced Concrete (UHPFRC) communication tower based on frequency domain response. Since the frequency data of tower is mostly noisy and interpreting of frequency in different modes in variant case of tower damage. The hybrid algorithm based on the Adaboost, Bagging and RUSBoost algorithms are implemented to identify the damage in the UHPFRC communication tower using frequency domain data. The training samples for the algorithm are obtained from a finite element simulation and full-scale experiment testing is also performed to generate the testing samples. The finite element simulation dynamic frequency results are verified through conducting a full-scale experimental test on 30 m height UHPFRC communication tower. For this propose, frequency Response Functions (FRF's), for healthy and damaged structures were obtained by exciting of tower by an impact hammer and the acceleration response recorded by three accelerometers sensors attached in suitable positions. The developed hybrid algorithm to identifying the damage is tested and verified by considering the part of tower segments 2–3 and conducting experimental testing on the healthy structure as well as a damaged structure which caused using dynamic actuator. The testing results proved the accuracy of the developed optimized hybrid algorithm to identify damage in the tower structure in variant condition.

Keywords Health monitoring · Communication tower · Vibration · Ultra high performance fiber concrete · Dynamic load

1 Introduction

Structural Health Monitoring (SHM) has great importance in many engineering applications, such as enhancing the structure safety, forecasting structure failure, reducing the cost of structure maintenance and improving productive efficiency. Structural health monitoring (SHM) was evolved in the last 50 years when engineers had some difficulties by complicated structures geometry and measurement technologies. In the last 10 years, the development gets progressed with utilizing of electronic data processing and storage technologies and the field broadened to data analysis algorithms [1]. Evaluation of foundation aging is one of the main challenges in the Structural Health Monitoring (SHM) process [2]. Brownjohn [3] covered several case studies based on the vibration technique from the practical perspective and presented the application issues of SHM on various forms of civil infrastructure, such as dams, tall buildings, bridges, towers, offshore and nuclear installations Erazo et al. [4] also worked on vibration technique on beam bridges. Many various techniques of signal processing have been investigated for health monitoring of structures through vibration frequencies [5]. Klikowicz et al. [6]. Presented a review of the importance of using an SHM system to minimize the possibility of damage and increase structural safety using a bridge structure as an example. A different method has been implemented for damage detection in SHM. In the last

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three decades, SHM methods based on changes in dynamic properties have been studied. When damage is significant, these methods successfully determine the damage [7]. In the structural heath monitoring process, the state of a structure is examined using modal parameters, like the natural frequency, mode shape, and damping ratio, in which usually determine by vibration measurements, to calculate the structural safety [8]. 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. Many environmental disasters are occurring as strong winds and severe ground motions which could affect to structural performance in their lifespan. These forces are unstable in magnitude and frequency [9]. The structural response control systems under these types of loadings have developed noticeably in the last 30 years [10, 11].

When damage happens in a structure, the stiffness reduces and leads to reduce in the natural frequencies of the system, which can be observed. The frequency measurements can be quickly and easily conducted and have a low-cost experimental procedure. Moreover, the frequency measurements can be extracted with relatively high accuracy, and doubts in the measured frequencies can be easily measured if the experimental measurements are conducted under perfectly controlled experimental conditions [12]. Moreover, fatigue damage can arise when the structure is excited by the load impact and the load frequency is near the structural frequency of structure. Therefore, natural frequencies are the most common dynamic parameters used in damage detection. According to the Euro code Standard, 2005 [13], the first natural frequency is undoubtedly a key parameter in estimating the response of the structure [14].

The Frequency Response Functions (FRF) is often implemented in frequency domain methods through Fast Fourier Transform (FFT) analysis [15]. There are several studies have been discussed the structural health monitoring and damage detection using shifts in frequencies method with different structures type. Doebling et al.[16]. Reported an early work that used the change in frequency and mode shape of the structures for health monitoring to detect damage. A review based on the structural damage detection through shifts in frequencies has been discussed by Zou et al. [17] and Salawu [18] which suggested that the frequency changes can be used for predicting the fatigue life of a structure by correlating the rate of decrease the first natural frequency of the fatigue life. Yang et al. [19] detected a sawfish cut in an aluminum beam using the 3D plot depth and location of a crack against the frequency change. They found that the location and depth of the crack are indeed identified from the contour lines obtained from each frequency change. Kim and Adeli [20] presented as a breakthrough in development of structural control with the introduction of wavelets in vibration control in a developed innovative wavelet- based algorithms for dynamic vibration control of smart structures. The natural frequencies and mode shapes are controlled in real time and damage detection algorithms based on the modal properties can check the performance of the structure in the real time [20]. Mao et al. in 2019 [21] studies a bridge case study in both finite element modeling and experimental test. A nonlinear structural control using integrated DDA/ISMP on tuned mass damper in FRF also investigated by Karami et al. in 2019 [22].

Dixit [23] 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. Patjawit and Chinnarasri [24] found that using natural frequency shifts to identify damage in embankment dams subjected to ground vibration is useful to a health monitoring system. Cantieni [25] (discussed the health monitoring of two dams, one is between Switzerland and France and the other is in northern Sweden) as case studies using dynamic testing (natural frequency and mode shape) analysis. Ashwear and Eriksson [26] studied the vibration health monitoring for tensegrity structures based on frequency analysis and presented several solutions for the application of vibration health monitoring methods for tensegrity structures. Chen et al. [27] studied about numerical damage localisation for building system including dynamic soil-structure interaction.

Recently, there has been a growing awareness of structural health monitoring (SHM) of large infrastructures, including the structure of aircraft, towers, long-span bridges and high-rise buildings. Since the damage of the structure resulting from the load, failures in the joints, etc., it can cause a tremendous disaster. The towers are one of the important infrastructures of physical supports for the installation of radio equipment that allow various services, such as radio, television and / or mobile communications. 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 [28] and led to health monitoring the structure. Aktan et al. [29] discussed the challenges in health monitoring systems using the modal analysis test for bridge and tower structures and highlighted that dynamic testing is often required for an effective and feasible solution to vibration problems. Antunes et al. [14]. Presented the dynamic monitoring system of two tall slender steel telecommunication towers, which are 50 m high, in Portugal using the frequency domain. Their findings indicated that stiffness loss can occur due to the connections and degradation of existing materials. Saisi et al. [30]. 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. [31]. Proposed an algorithm for reconstructing the wind load based on the algorithm proposed by [32]. 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, and then the modal properties of the Canton tower were identified by operational modal analysis (OMA). The response of a structure during dynamic loading due to strong ground motions is measured using sensors and actuators are used to apply internal forces to compensate for the effects of the external forces [10].

Many techniques have been used before to generate the frequency response [33–35]. The impact hammer test has been used in many engineering areas to analyze frequency response functions (FRF) of the structures, due to suitability and simplicity of the experiments, as well as the validity of the analysis procedures [36, 37]. Schwarz and Richardson [38] presented a review of all the main topics associated with experimental modal analysis test using impact hammer test; the results indicated that the impact testing has a low-cost, fast, and appropriate way to find modes. FAIZAL [39] studied the structural evaluation using low-frequency technique and impact hammer test through experimental modal analysis and computational analysis software for beam members. 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. Da Silva et al.[40]. 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. According to Lam and Wong [41] 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 were identified through the impact hammer test [42]. As per the findings, the proposed method has the possibility to detect the damage.

As a result of the mentioned studied SHM is essential to access the structural integrity and ensure the performance of structures. The changes in natural frequencies is affected by the degradation of the structure and this parameter is a suitable indicator of the structure health condition and allows taking preventive action if needed to save money and, sometimes, lives. However, the recorded data for dynamic frequencies for special structure such as communication tower is noisy, randomness, unstable and skewed data, due to some uncontrolled environmental condition such as vibration sources include of an automobile engine, reciprocating motion in a machine, or broadband noise from wind or environment which cause many challenges in interpret of frequency data and recognize the damage. Therefore, this study aims to develop a hybrid algorithm as health monitoring system for communication tower based on machine learning method which can function with noisy, randomness, instable and skewed data.

2 Health monitoring for UHPFRC communication tower

Damage is the main cause of structural failure and often occurs on structures due to loading, joint failure and, etc. Interest in the ability to monitor structures and detect damage at the earliest possible stage is widespread in all civil, mechanical and aerospace engineering communities. The existence of structural damage in an engineering system leads to variation in natural frequency and vibration modes. These variations manifest themselves as changes in modal parameters such as natural frequencies that can be obtained from the results of dynamic (vibration) tests. Knowing about nature of damage and vibration response of target structure can implement suitable approaches to detect location and size of the damage. Structural health monitoring very efficient tools to detect the damage based on the vibration of structures. Within the last decades, the need for tall structures to install the communication equipment for radio, television and mobile communication has been increased. Due to the rapid growth of the telecommunication technology, many challenges are related with tall and slender structures such as communication towers. The difficulty in capturing low-frequency responses and the complexity configuration of the tower and limit access to the structure especially the inner part of the tower with hollow section are leaded the health monitoring of tower as the main challenging issue to maintenance the tower structure during its function.

Moreover, the recorded data for dynamic frequencies for special structure such as communication tower is noisy, randomness, instable and skewed data, due to some uncontrolled noise such as vibration sources include of an automobile engine, reciprocating motion in a machine, or broadband noise from wind or environment which cause many challenges in interpret of frequency data and recognize the damage.

Therefore, this study aims to develop a computation procedure based on AdaBoost, Bagging and RUSBoost algorithms as health monitoring system for communication tower which can work with noisy, randomness, instable and skewed data to identify the location and type of damage for UHPFRC communication tower in frequency domain with high convergence, quality solutions and lower iterations. At the first stage of this research, few attempts have been made to implement the Artificial Neural Network (ANN) method for identify the damages in UHPFRC tower, however due to the low accuracy in prediction, the hybrid ensemble methods with AdaBoost, Bagging and RUSBoost algorithms have been considered.

3 Damage detection for UHFPRC communication tower using machine learning algorithms

The purpose of machine learning algorithms in SHM, is to enhance the damage detection in structures subjected to different operational and environmental conditions. The suitable algorithm to use depends on the capacity to function supervised or unsupervised learning. The supervised studying refers to the case where data from the undamaged and broken cases are available. Unsupervised learning refers to the case the place records are only accessible from the undamaged situation of the structure. For excessive capital expenditure structures, such as most civil engineering infrastructure, the unsupervised studying algorithms are frequently required since only information of the undamaged situation is available [43]. Recently, researchers are focused on implementing machine learning methods for damage detection in the structures [44]. Freund and Schapire [45–47] proposed the adaptive boosting (AdaBoost) algorithm. The aim of this algorithm is to make an arbitrarily robust classifier via combining a set of weak classifiers. It can be used in conjunction with many other mastering algorithms to enhance their performance. It is adaptive in the sense that the weights of records misclassified data through previous classifiers increase for subsequent classifiers. The key concept at the back of Adaboost is to use weighted versions of the same training facts as a substitute of randomly subsamples thereof.

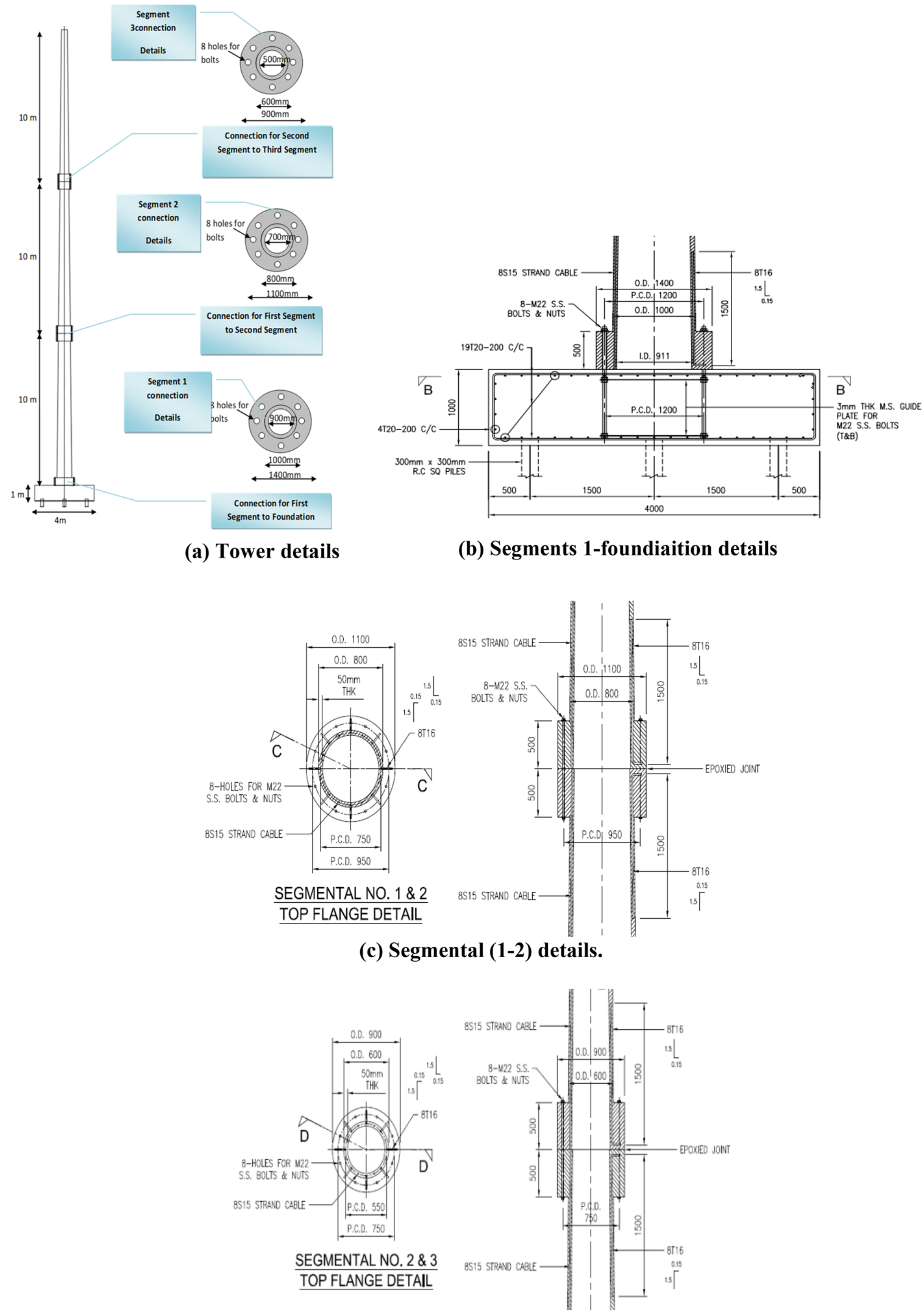
In investigating corrosion and crack cases, AdaBoost and time frequency have been used to classify damage [48]. Cord and Chambon [49] studied the identification of cracks on roads by considering the compositional description and statistical learning procedure, with the AdaBoost-dependent image processing. The use of the bagging technique improves the classification results whenever the base classifiers are unstable; this is why the bagging method works effectively for classification [43]. The main effect of boosting is to reduce variance [50] 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.

Moreover, RUSBoost is a new technique for learning from skewed datasets. Kesikoglu et al. [51] 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.

Different ensemble algorithms have been proposed and developed for classification methods to achieve robust generalization ability. This study focused on the Adaptive, Bagging, and RUSBoost algorithm. With the present knowledge for using these algorithms to deal with noisy, randomness, instable and skewed data with high convergence, quality solutions and lower iterations. The recorded data for dynamic frequencies for a special structure such as communication tower is noisy, randomness, instable and skewed data, due to some uncontrolled noise such as vibration sources include of an automobile engine. Therefore, this study aims to develop computation algorithm based on Adaptive Boosting, Bagging and RUSBoost algorithms as damage identification procedure for UHPFRC communication tower.

4 Considered UHFPRC tower

The communication tower that used in this study is 30 m height located in Malaysia and contains three segments, each segment with 10 m height fixed to a reinforcement concrete foundation block with Sect. 4.00 m in plan and 1 m in deep as shown in Fig. 1. The tower system is considered as a rigid hollow column (cantilever) which is able to stand against horizontal load through its lateral stiffness which is provided through tower component such as the prestress tendons inside the segmental can help to increase the resistance against the lateral load. Bolts and nuts will be used to connect the segments. Eight holes are made to connect the segments. The length of bolts and diameter is about 1000 mm and 25 mm, respectively. Meanwhile, the length and diameter of first segment connection are about 1000 mm and 32 mm, respectively. An epoxy layer is also used in the interface between concrete segmental connections. Each segment is arranged with eight tendons and each connection is arranged with eight holes for bolts. The total mass density for (UHPFRC) material is 2500 kg per cubic meter with grade 150Mpa, young modulus of elasticity (55GPa), 0.18 Poisson's. The reinforcement diameter is (15.2 mm) with density (7.85*10^-7), the young modulus (200GPa). Table 1 listed the details of UHFPRC communication tower.



(a) Tower details
(b) Segments 1-foundiaition details
(c) Segmental (1-2) details.
(d) Segmental (2-3) details

Fig. 1 Locally detailed of UHP-FRC tower details

5 Numerical modeling of UHPFRC tower

Finite element method was used to develop the UHFPRC communication tower similar to the geometry and properties of the considered structure as shown in Fig. 2a. A convergence study was conducted to verify the material properties and meshing size of the suggested FE models of the UHPFRC communication tower. The 3D model was carried out using ABAQUS 6.14 software. All tower parts meshed with a mesh size of 150 mm as shown in Fig. 2b. A fixed boundary condition is applied to the UHPFC tower foundation as shown in Fig. 2c.

The details of the fix boundary conditions in terms of displacements (U) and rotations (UR) have been defined as below.

$$U1 = U2 = U3 = UR1 = UR2 = UR3 = 0 \quad (1)$$

The Lanczos eigensolver analysis is implemented to generate the frequency.

5.1 Considered damages

The most frequent damage for the towers which reported in previous studies is crack in the concrete sections. The cracks appear in body of tower segment in vertical or horizontal direction during loading and functioning of communication tower and mostly start narrow and sharp in one direction than take place in the other directions. The cracks can be formed due to many situations, such as over stress, vibration, applied excessive load, creep, fatigue, impact, manufacturing and molding issues. Although in the segmental structures, the bolts losing in the segment joints is a common damage issue due to applied vibrations, bolts corrosion and construction matters.

Therefore, in this study, different damage scenarios (damage index) for cracks and losing bolts are considered and created using the FE method as listed in Table 2.

These 78 damages consist of removing one to six bolts from each connection separately from the UHPFRC tower which will be used later to develop the hybrid algorithm for damage detection of UHPFRC communication tower.

In this study, the crack width and length for the communication tower segments have been considered as 2 mm and 200 mm respectively. Based on many trial attempts for modeling and analysis, it is revealed that the crack width

Table 1 The UHPFRC communication tower details

Type	Height	External diameter at bottom (mm)	Internal diameter at bottom (mm)	External diameter at top (mm)	Internal diameter at top (mm)	Thickness (mm)
Seg. 3	10 m	1000	900	800	700	50
Seg. 2	10 m	800	700	600	500	50
Seg. 1	10 m	600	600	400	300	50
Connection for segmental 1 to foundation	0.5	–	–	1400	900	500
Connection for segment 1 to 2(upper and lower)	0.5	1100	700	1100	700	400
Connection for segment 2 to 3(upper and lower)	0.5	900	500	900	500	400

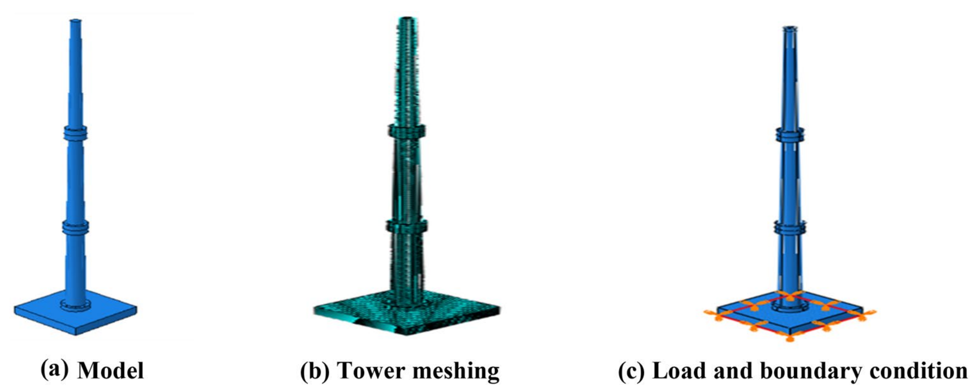


Fig. 2 Finite element modeling for UHPFRC tower

Table 2 Damage class type and damage case number for UHPFRC communication tower

Damage type and location	Segment	Case No	Class no
Healthy	All	0	0
Losing 1 to 6 bolt	Connection of seg1- foundation	1 to 6	1
Horizontal crack at 1 m to 10 m	Seg 1 with 10 m height	7 to 16	2
Vertical crack at 1 m to 10 m	Seg 1 with 10 m height	17 to 26	3
Losing 1 to 6 bolt	Connection of seg 1–2	27 To 32	4
Horizontal crack at 1 m to 10 m	Seg 2 with 10 m height	33 to 42	5
Vertical crack at 1 m to 10 m	Seg 2 with 10 m height	43 to 52	6
Losing 1 to 6 bolt	Connection of 2–3	53 to 58	7
Horizontal crack at 1 m to 10 m	Seg 3 with 10 m height	59 to 68	8
Vertical crack at 1 m to 10 m	Seg 3 with 10 m height	69 to 78	9

less than 2 mm and crack length less than 200 mm has no considerable effect on dynamic and frequency response of structure as well as strength of the segment. During conducting experimental test also, it was observed that small cracks (about 0.1 mm width and less than 200 mm) has no effect on dynamic frequency response of the considered structures. Besides, in some references also [52] these range are discussed as the most common width and length for concrete cracks.

Then, 60 cracks are simulated with 200-mm cracks width which consists of 30 vertical cracks and 30 horizontal cracks (Fig. 3) at 1 m intervals.

5.2 FE results for UHFPRC communication tower in frequency domain

Numerical analysis is conducted to estimate the frequency response of UHPFRC communication tower in healthy condition (no damage) through free vibrating analysis of tower. Besides, Different damages scenarios have been created using finite element method as mentioned in above.

The finite element results of frequency response for UHFPRC communication tower in healthy and different damage cases were determined. These dynamic frequencies for all 78 cases of tower structure in healthy condition as well as damaged conditions are used for training of hybrid algorithm for damage detection.

6 Experimental modal analysis using impact hammer

Experimental modal analysis portrays the dynamic properties when the structure excites artificially to determine the vibration modes [53]. When damage occurs in the structure, then the dynamic characteristics of the structure in the form of natural frequencies also are changed.

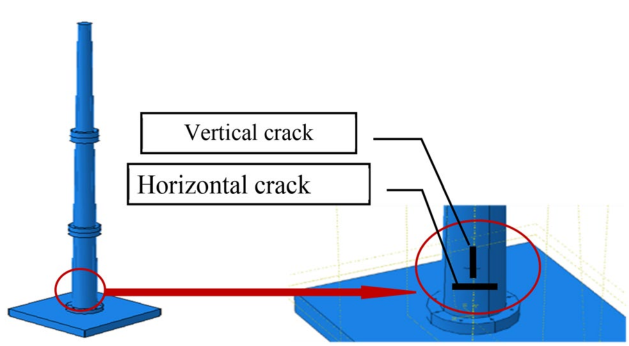


Fig. 3 Vertical and horizontal crack for UHPFRC communication tower

Also, it should be mentioned that, based on observation during experimental test, frequency response of the considered components is not affected by micro cracks since small cracks are not changing overall stiffness of structure. Hence, by increasing of the crack width, its effect on frequency content of structure appears.

Modal analysis relies on the vibration response of a linear time-invariant dynamic system, which can be described as the linear combination of a set of harmonic motions called natural modes of vibration. The modal testing is theoretically based on establishing the relationship between the vibration response in one location and excitation in the same or another location. This connection, which is often a complex mathematical function, is known as the FRF. Experimental tests on the UHPFRC communication tower have been conducted by excitation using impact hammer test to verify the frequency results of the numerical analysis and the structural responses are measured by three accelerometers. The excitation types and sources, data acquisition, signal processing, and modal parameters extraction are explained in the following sections.

6.1 Excitation

Impact hammer type KISTLER model 9728A20000 was used to excite the UHFPRC communication tower as shown in Fig. 4a. The hammer is used to excite the samples at each selected point.

6.2 Accelerometers

Three accelerometers type KISTLER model 8702B50M1 as shown in Fig. 4b were used to record the acceleration response. Each accelerometer is placed in a specific position.

6.3 Data acquisition and signal processing system

Noise and vibration analyzer, OROS36 (Fig. 4c) is used to convert the analog input signal from the transducer into a digital form. A computer with NVGATE software was used to raw and saved the measured data. Then, the MODAL software was used to model the communication tower and to calculate FRFs response.

Then, the FRF values are obtained through fast Fourier transform (FFT) by dividing the accelerometer signals by the corresponding signals from the hammer. Then, the experimental modal parameter (frequency) is obtained from a set of FRF measurements which recorded through data acquisition and signal processing system.

The test procedure is presented as follows:

- The three accelerometers are installed.

Fig. 4 Impact hummer and Accelerometer (KISTLER type 8702B50M1)

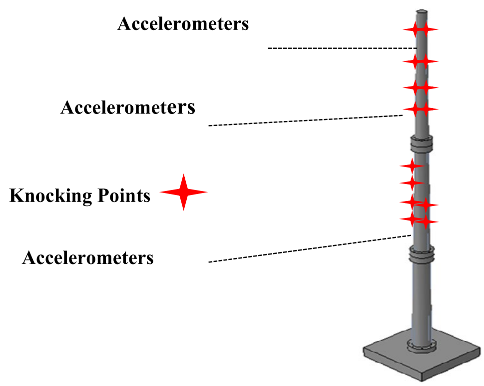


Fig. 5 Marking the knocking point for UHPFRC tower

- The knocking point is determined and marked as shown in Fig. 5. The excitation points are placed at 22 points at each 1.5 m (11 points in front of the tower and 11 points at the tower side) for better excitation since it is cylinder and symmetric. Besides, to ensure adequate adhesion, epoxy resin is applied between the accelerometer and tower surface.
- Develop geometry model of tower using MODAL software and determine the knocking points and the accelerometers position.
- The data logger is set up, the hammer and accelerometers are connected to the data logger, to start the knocking as shown in Fig. 6.
- Recorded the acceleration data using NVGATE software which used to raw and save the data.
- Transfer acceleration data from NVGATE to MODAL software.
- Convert acceleration to FRF and filter the noise by FFT and generate of Modal frequency.

6.4 Experimental results of UHPFRC tower test in healthy condition

In this study for modal testing, the communication tower is excited by the impact hammer in various points of tower body, and the response of the tower is recorded using three DC accelerometers. In the experimental modal analysis, the transformed signal from the hammer and the accelerometers were analyzed, and the modal parameters of the structure were obtained.

From the time history of the acceleration response, the frequencies of the structures can be obtained using FFT response. The accelerometers were set, and the response signals were recorded with a signal analyzer of OROS (8-channel). The equipment was used to convert input analog signals of the transducers to digital data. These data were recorded in the analyzer, and NVGATE software converted the data into FFT response. The NVGATE software exports the FFT results in the UFF format. The MODAL utility program read the UFF files and exported them to FRF. FRFs were determined by dividing the Fourier transform signal of the accelerometers by that of the impact hammer.

The acceleration data corresponded to a frequency bandwidth of 0–400 Hz to measure the natural frequencies with improved accuracy. FRF data were generated by knocking with an impact hammer at 22 points of tower body as well as connections at each 1.5 m of the full-scale tower. The tower has a cylindrical and symmetrical shape. Therefore, knocking of tower by impact hammer conducted in one direction only and effect extend to the other direction due to symmetrical configuration of the tower. Three accelerometers were used to measure the acceleration response of the structure after excitation by the hammer located at top, middle and bottom of tower. The communication tower was tested in healthy condition (undamaged) to determine the natural frequencies.

In the following sections, the results for the undamaged condition are discussed. Figure 7 shows the knocking at the selected points of the UHPFRC communication tower.

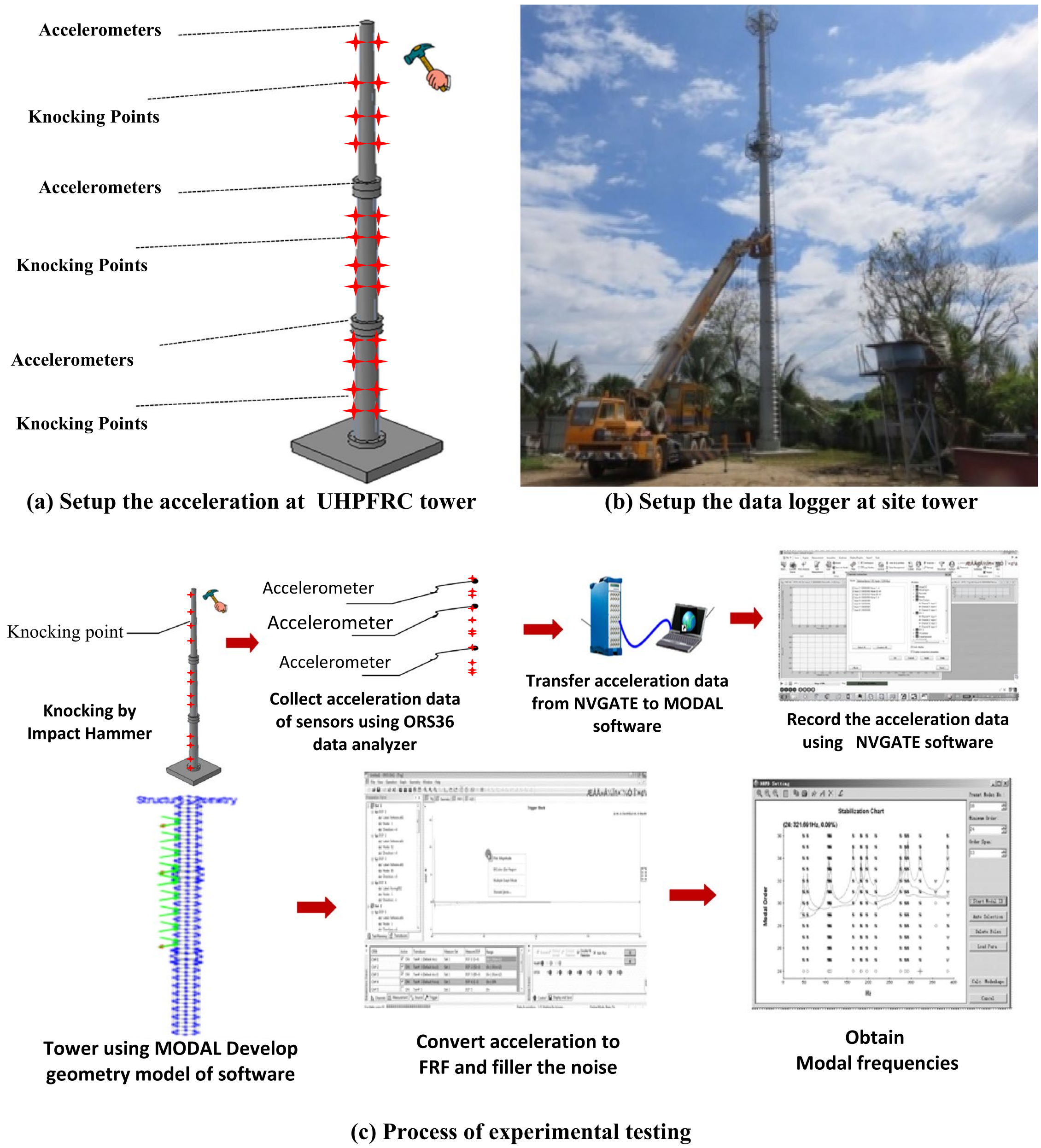


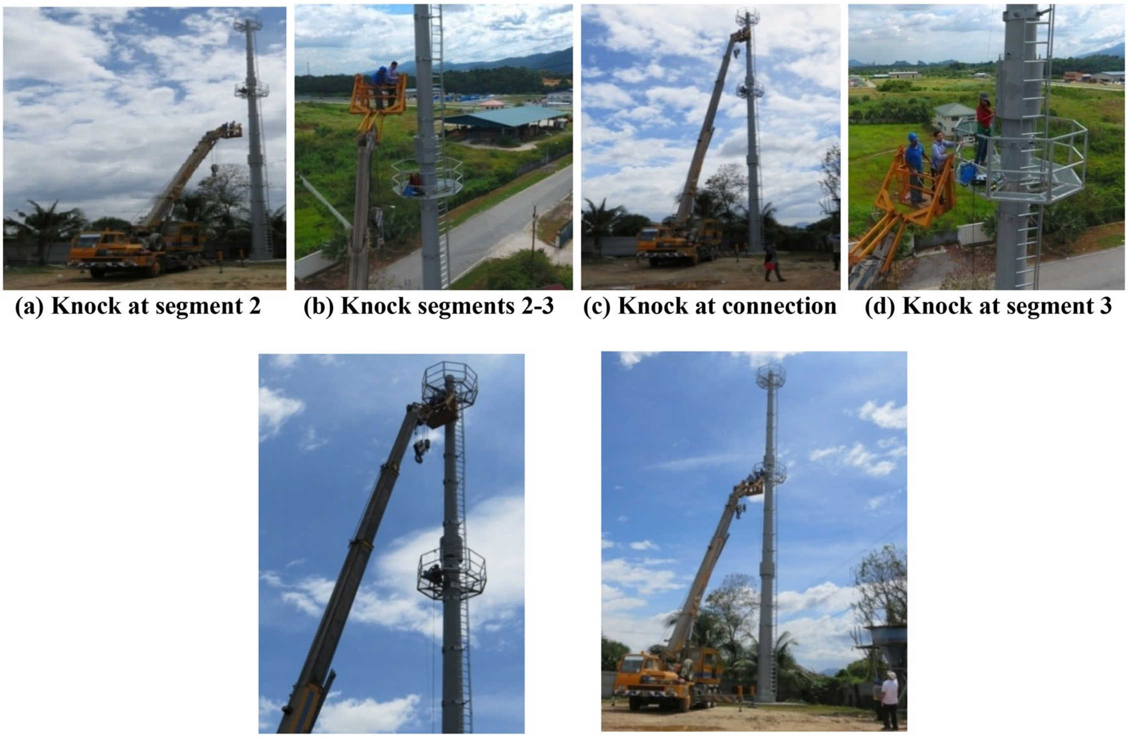
Fig. 6 Setup the data logger at UHPFRC tower

The dynamic properties of the tower, including FRFs and natural frequencies, were determined at the undamaged condition from the experimental modal analysis through MODAL software. Different peaks of frequency recorded which depicted the first 11 modes through frequency bandwidth in the range of 0 Hz to 400 Hz as generated by MODAL software.

These are the maximum number of modes that could be captured with high precision through the selected setup.

As mentioned before the frequency range of 0–400 Hz is considered for the communication tower as depicted in stabilization chart for modal frequency variations, as it can be seen the peaks of modal frequency for the tower in healthy case is appeared in 0.9 Hz as the second peak modal frequency damage is follow the first mode and appeared on 1.13 Hz and the last mode (mode number 11) appeared in 138.49 Hz because the frequency of the pole does not change in the range after 138.49 Hz.

Table 3 shows the average frequencies, which were determined through the dynamic tests for the UHPFRC tower on the site. These values were used to verify the numerical results and test the hybrid learning algorithm for damage detection. The peak frequency of the



(a) Knock at segment 2 (b) Knock segments 2-3 (c) Knock at connection (d) Knock at segment 3

(e) Knock at top of segment 2 (f) knock at top of segment 3

Fig. 7 Impact hammer test for UHPFRC communication tower

Table 3 Verification of experimental and numerical frequency results for the UHPFRC communication tower

Mode No	M.1	M.2	M.3	M.4	M.5	M.6
f. EXP	0.9	1.13	3.45	8.63	15.36	18.1
f. FE	0.93	0.94	3.80	8.87	17.79	20.1

Mode No	M.7	M.8	M.9	M.10	M.11
f. EXP	42.83	79.21	101.56	119.46	138.49
f. FE	41.35	74.15	104.14	113.86	137.44

UHPFRC tower was approximately 0.9 Hz for low mode and 138.49 Hz for high mode.

6.5 Validation of finite element frequency results for UHPFRC communication tower

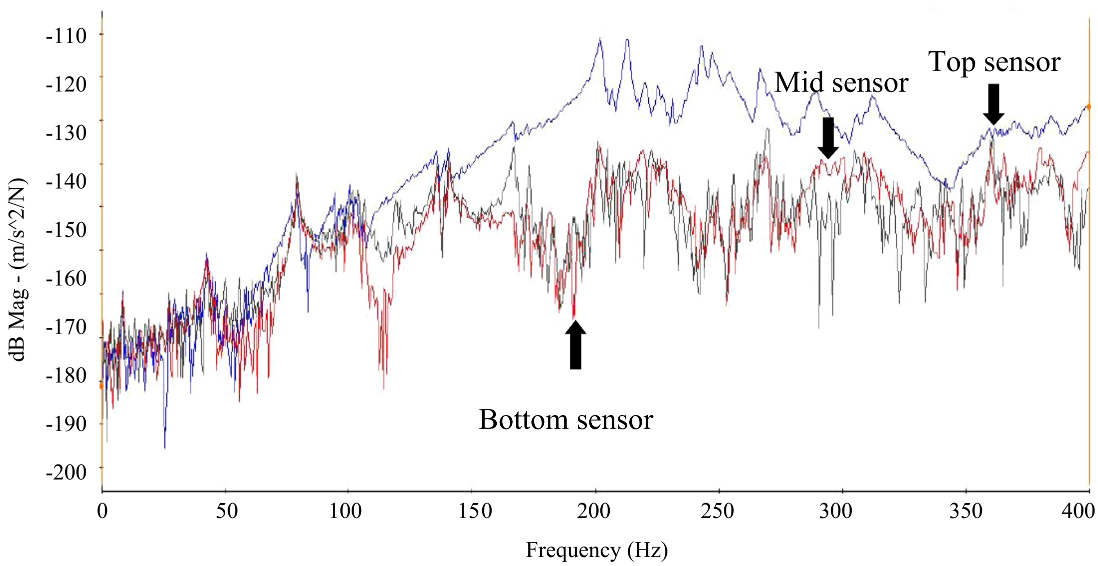
Experimental analysis was conducted to evaluate and verify the numerical frequency response of the 30-m high communication tower in healthy condition, as shown in Table 3. The vibration modal frequencies of the UHPFRC communication tower before damage, which were obtained from the modal experimental test, were compared with the vibration modes resulted via FE modal analysis. The difference in variation is less than 20% for all modal frequency results for the full-scaled tower. The maximum variation in the frequencies of the finite element and experimental results was 16.81% for the UHPFRC communication tower. This difference proves that FEM is an appropriate method to predict the modal frequency properties of the UHPFRC communication tower.

Both experimental tests for the 30 m communication tower in the site and also the tower segments in the lab were conducted by having very noisy environment due to vehicle traffics in very nearby highway, operation of equipment in the site factory or lab buildings.

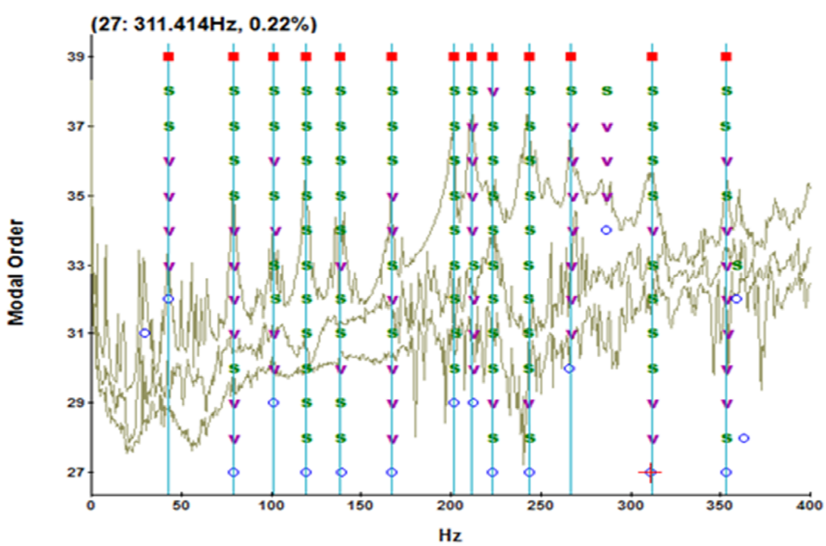
Specially for the tests which have been conducted in the lab, there were many noises due to operating hydraulic pump for dynamic actuator, water cooling, water pumping, fans, forklift, drills, cutting machine, air pump and traffic in the side street which all of these machines were continuously performed during test. Although the results of prediction by developed hybrid ensemble method were highly match with FEM results which obtained without considering any environment noise. Therefore, the comparison revealed that the proposed method is capable to predict accurately even using noisy data.

The Frequency Response Functions (FRFs) recorded at different accelerometer points after knocking of the UHPFRC communication tower by impact hamper are showed in Fig. 8 along with stabilization chart to calculate the frequency of structure. Therefore, Fig. 8a shows the FRF graphs which recorded by three acceleration sensors after knocking of tower body by impact hammer. Different frequency peaks have been obtained through analysis by MODAL software, which the first 11 modes appeared in the frequency bandwidth in the range of 0 Hz to 400 Hz. These are the maximum number of modes that could be captured with high precision through the selected setup.

The frequency range of 0–400 Hz is considered for the communication tower as depicted in stabilization chart for



(a) Envelope of FRFs recorded at different accelerometer points for UHPFRC communication tower



(b) Stabilization chart to calculate the frequency of UHPFRC tower

Fig. 8 Recorded FRFs and modal frequencies during experimental test of UHPFRC communication modal frequency variations (Fig. 8b). As it can be seen in this figure, the first peak modal frequency for the tower is appeared in 0.9 Hz while the second peak modal frequency damage is appeared on 1.13 Hz and then the last mode (mode number 11) occurred in 138.49 Hz.

6.6 Development of hybrid algorithm for damage detection of UHPFRC communication tower as SHM system

The damage detection algorithm adopted in this study for the UHPFRC communication tower is based on the Adaboost, Bagging, and RUSBoost algorithms since these algorithms gives better accuracy and can treat a larger set of data.

A total of 78 damage scenarios are simulated using the FE software and input as training samples for the hybrid algorithm. The 79 cases include the healthy case utilized to train 9 classifiers for the UHPFRC communication tower. The training data consist of 869 frequency values. The experimental frequency (f_1 to f_{11}) results are used as a testing sample to validate the accuracy of the hybrid algorithm and examine if the correctness of the prediction. Moreover, the developed hybrid algorithm for identifying the damage is tested and verified by considering two tower segments (1–2 and 2–3) and conducting experimental testing on the healthy and damaged structures using a dynamic actuator.

The 79 including of healthy case with damages cases training samples were utilized to train a 10-classes (0–9) classifiers which set as an output for the Hybrid algorithm. The experimental frequency result of the healthy tower was setting as case 0 to check the cross-validation accuracy of the hybrid algorithm.

The hybrid algorithm for detecting damage in the communication tower is developed through the following steps:

Step 1: The numerical frequency data for the healthy and different types of damage for the UHPFRC communication tower are set as input data for training the hybrid algorithm.

Step 2: The output data are set as the type and location of damage (Damage Index, DI). DI is given as follows:

Step 3: Develop hybrid algorithm using input and output data.

Step 4: The frequency results of the experimental test of the UHPFRC communication tower are set as data for testing.

Step 5: The developed hybrid algorithm is tested using frequency result of experimental testing.

Step 6: Finally, the hybrid algorithm is tested and compared with the goal to make the decision with all the structural states (damaged or not).

In this study, three methods are used to develop hybrid algorithm for damage detection as describe in following:

6.6.1 Bagging

The main reason for error in learning is noise, bias, and variance. Noise leads to error by the target function. Bias is where the algorithm cannot learn the target. Variance comes from the sampling, and how it affects the learning algorithm. The bagging algorithm helps to reduce these errors. It enhances the classification results when the base classifiers are unstable. Variety in bagging is determined by the bootstrapped replicas of the original training set: different training datasets are randomly pulled with replacement. Then, a single decision tree is constructed with each training data replica using the standard approach (Breimanet al., 1984). Finally, bagging predictions are combined by a majority vote but takes the average during testing.

The bagging algorithm implemented in this study is defined as follows:

Input: Dataset $\Psi = \{_{\psi 1}, _{\psi 2}, \ldots, _{\psi N}\}$, with $\Psi_i = (F, DI)$, where $F \in f_1$ to f_{11}, and $DI \in \{0, 9\}$.

Where F is frequency and DI is the damage index.

Number of bootstrap samples: B

Output: A classifier H: f1 to f11 → {0, 9}.

1: For b = 1 to B do.

2: Draw, with replacement, N samples from Ψ to obtain the b-th bootstrap sample Ψ_b^*.

3: From each bootstrap sample Ψ_b^*, learn classifier H.

5: The final classifier by a majority vote of H1, …, HB is $H(x) = \text{argmax}\,(\sum_{b=1}^{B} H_b(x))$.

Figure 9 depicts the bagging approach for the classification.

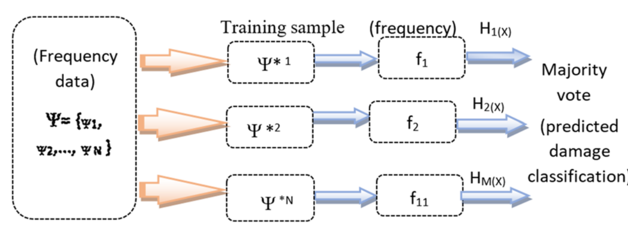


Fig. 9 Depicts the bagging approach for the classification

6.6.2 Adaptive boost learning approach

Adaboost is an ensemble method that produces robust classifiers by combining multiple weak classifiers. It uses only one classification algorithm to construct diverse weak base classifiers, which are trained on datasets that are selectively sampled from an initial training dataset. Each sample is given a weight that represents the possibility of selection as a training sample, and all examples share an equal weight in the first iteration. In subsequent iterations, the samples that are correctly classified by the base classifier of the last iteration get lower weights, and the samples that are misclassified get higher weights. Thus, the base classifiers focus on the "difficult" data points that may be near the classification margin and finally improve the classification accuracy. After a certain number of iterations, the base weak classifiers are gathered to become a strong classifier, and the final classification result is the output (Sunet al., 2017). The Adaboost algorithm that is implemented in this study is defined as follows:

Input: Dataset $\Psi = \{\Psi1, \Psi2,\ldots, \Psi N\}$, with $\Psi i = (F, DI)$, where $F \in f1$ to f11,and $DI \in \{0, 9\}$.

Where F is frequency data, DI is damage index.

The maximum number of classifiers: M

Output: A classifier H: f1 to $f11 \rightarrow \{0, 9\}$.

1: Initialize the weights.$w_i^{(1)}$ = 1/N, $i \in \{1, \ldots, N\}$, and set $m = 1$

2: While $m \leq M$ do.

3: Run the weak learner on F using weights $w_i^{(1)}$ to yield classifier DIm: f1 to $f11 \rightarrow \{0, 9\}$.

4: Calculate $errm = N \sum i = 1\ w_i^{(1)}\ h\ (-DI\ Hm\ (F))$, the weighted error of Hm.

5: Calculate $\alpha m = 1/\ 2\ \ln\ (\frac{1-err_m}{err_m})$ {/* Weight of the weak learner. */}.

6: Update the weight $v\ i\ (m) = w_i^{(1)} \exp(-\alpha m\ DI\ Hm\ (F))$. For each sample $i = 1, \ldots, N$.

7: Renormalize the weights: calculate $Sm = \sum_j^N = 1\ v\ j$ and, for $i = 1,\ldots, N$, $w_i^{(m+1)} = vi(m)\ /Sm$.

8: Increment the iteration counter: $m \leftarrow m + 1$.

9: Finally, the strong classifier: $H(x) = \text{argmax} \sum_{j=1}^{M} (\alpha jHj(x))$

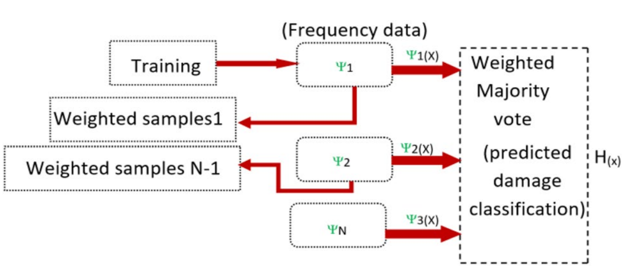


Fig. 10 Adaptive boosting classification or Scheme for Adaptive boosting algorithm

The Adaboost algorithm produces a set of suppositions, which are combined and weighted with the majority voting method of the class prediction using each hypothesis. To produce the preceding hypotheses by training a weak classifier, instances that are drawn from an iteratively updated distribution of training instances are utilized. This distribution is updated in such a manner for the misclassified instances from the previous hypothesis to be similar and included in the training data of the coming classifier. Figure 10 depicts the structure of Adaboost.

6.6.3 RUSBoost

RUSBoost combines data sampling and boosting to produce a simple and efficient technique for enhancing classification performance when training data are imbalanced. It was designed to increase the performance of trained models when data are skewed.

In the first step of this algorithm, the weights of each example are initialized to 1/m, where m is the number of frequencies in the training dataset. Then, the weak hypotheses are trained. Random under sampling is applied to remove majority classes and the weight to update parameters. Finally, hypothesis H(x) is generated as the weighted vote of the weak hypotheses.

The RUSBoost algorithm implemented in this study is defined as follows:

Input: Set Ψ of examples (F1, DI1), …, (Fm, DIm).

Where F is frequency data, DI is damage index.

T is the number of iterations.

The required percentage of total instance to represent the minority class is N.

1: Initialize w1(i)= 1/m, for all i.

2: Do for $t = 1, 2, \ldots$, Ta

a: Create a temporary training dataset Ψt with distribution ẁt using random under sampling.

b: Call the weak learner provided, with examples Ψt and their weighted ẁt.

c: Get back hypotheses ht $F \times DI$ {0, 9}d: Estimate the pseudo loss for (Ψ and Wt):

$t = \sum wt(i)(1 - ht(Fi, DIi) + ht(Fi, DI))$e: Calculate the weight update parameter: $\alpha t = \frac{\varepsilon t}{1 - \varepsilon t}$f: Update W t

$Wt + 1(i) = Wt\ (i)\ \alpha t^{(1 + ht(Fi,DIi) - ht(Fi,DI:DI \neq DIi)}$

g: Normalize $Wt + 1(i)$: let $Zt = \sum_i Wt + 1(i)$

$wt + 1(i) = \frac{Wt+1(i)}{Zt}$

3: The final hypotheses is $H(x) = \text{argmax} \sum_{t=1}^{T} ht(F, DI) \log \frac{1}{\alpha t}$

Iter	Eval result	Objective	Objective runtime	BestSoFar (observed)	BestSoFar (estim.)	Method	NumLearningC-ycles
1	Best	0.097222	7.9289	0.097222	0.097222	Bag	319
2	Accept	0.125	4.6628	0.097222	0.099804	AdaBoostM2	163
3	Accept	0.97222	12.972	0.097222	0.12077	RUSBoost	427
4	Accept	0.097222	0.31694	0.097222	0.097239	Bag	10
5	Best	0.027778	0.46107	0.027778	0.027953	AdaBoostM2	14
6	Accept	0.097222	0.28803	0.027778	0.028156	AdaBoostM2	357
7	Accept	0.86111	1.0617	0.027778	0.027854	AdaBoostM2	40
8	Accept	0.041667	1.8606	0.027778	0.027976	AdaBoostM2	147
9	Accept	0.027778	11.955	0.027778	0.027812	Bag	483
10	Accept	0.90278	0.39792	0.027778	0.027816	Bag	14
11	Accept	0.027778	12.307	0.027778	0.027769	Bag	498
12	Accept	0.069444	12.048	0.027778	0.02778	Bag	498
13	Accept	0.55556	0.45524	0.027778	0.027779	RUSBoost	12
14	Accept	0.041667	11.13	0.027778	0.027778	AdaBoostM2	401
15	Accept	0.027778	13.493	0.027778	0.02778	AdaBoostM2	490
16	Accept	0.027778	12.059	0.027778	0.027691	Bag	496
17	Accept	0.13889	11.591	0.027778	0.027684	AdaBoostM2	418
18	Accept	0.027778	11.706	0.027778	0.027474	AdaBoostM2	423
19	Accept	0.055556	0.35086	0.027778	0.025142	AdaBoostM2	10
20	Accept	0.083333	0.3238	0.027778	0.025348	Bag	10
Iter	Eval result	Objective	Objective runtime	BestSoFar (observed)	BestSoFar (estim.)	Method	NumLearningC-ycles
21	Accept	0.041667	9.3781	0.027778	0.029207	AdaBoostM2	329
22	Accept	0.055556	0.34991	0.027778	0.028709	AdaBoostM2	12
23	Best	0.013889	12.32	0.013889	0.020338	Bag	497
24	Accept	0.013889	12.275	0.013889	0.018241	Bag	499
25	Accept	0.027778	12.261	0.013889	0.020571	Bag	492
26	Accept	0.5	15.226	0.013889	0.020577	RUSBoost	486
27	Accept	0.93056	0.4334	0.013889	0.020607	RUSBoost	12
28	Accept	0.97222	0.37382	0.013889	0.020583	RUSBoost	10
29	Accept	0.61111	12.191	0.013889	0.020577	AdaBoostM2	463
30	Accept	0.55556	0.38595	0.013889	0.02055	RUSBoost	10

Fig. 11 The optimization process of hybrid algorithm for damage detection of UHPFRC communication tower

6.6.4 Development of hybrid algorithm for damage detection of UHPFRC communication tower

The frequency data of tower are mostly can be random, unstable, and with skewed data. There for, this study aims to develop the optimized hybrid prediction method as health monitoring system based on the AdaBoost, Bagging, and RUSBoost algorithms for damage detection of UHPFRC communication tower using frequency domain.

The classification learner toolbox of MATLAB was used to develop the hybrid algorithm to detect the condition (healthy, with cracks, and with lost bolts) of the UHPFRC communication tower.

In this study, the Hybrid Ensembles Optimization method has been adopted by combining Ensembles and Sampling Based Ensembles methods [54]. Where Random Balance Ensemble Method is used for preprocessing stage while processing is conducted using Different Contribution Sampling (DCS) and Bagging method. The implemented trained classification ensemble model object contains the results of boosting 100 classification trees and the predictor and response data in the AdaBoost, Bagging, and RUSBoost algorithms [55]. The purpose of Hybrid Ensembles optimization is to reduce the size of required training data to obtain desirable prediction accuracy since due to difficulty of access to the communication tower structure, limited number of knocking by impact hammer (or shaker) and acceleration sensors for collecting data could be arranged.

A large number of training data generated using the finite element analysis for the UHPFRC tower in the healthy and damage conditions were utilized as input data for the hybrid algorithm. The experimental results were used as testing data to verify the accuracy of the proposed hybrid learning algorithm for damage detection.

The optimization process of the hybrid learning algorithm that predicts damage using frequency is depicted in Fig. 11. The figure shows that through the optimization process, three different learning techniques such as Bagging, AdaBoost, and RUSBoost are implemented. The results of estimated damage using input frequency are evaluated based on objective function, which indicates the minimum error in estimating damage classification. The best learning technique is considered the best damage identifier. Then, the learning coefficients of all three methods are changed and the result of estimation is evaluated and sorted based on the minimum objective function to achieve higher accuracy. The process is repeated until the best technique is achieved and the coefficient with minimum objective function in estimating damage classification is identified.

The operating time for each learning process is presented in the fourth column. The number of cycles, which was obtained to minimize the objective function (difference between damage estimation and actual damage classification) to achieve an acceptable algorithm for damage prediction, is presented in the last column.

The figure shows the verification of the objective function during the optimization process using various types of learning methods with different learning coefficients. The objective function, which represents the percentage error between the actual and damage cases and the predicted damage, is evidently reduced after the 5th, 22nd, and 23rd cycles of optimization, thereby indicating an increase in accuracy. In addition, during the optimization process, the graph of the estimated damage classification shows excellent agreement with the minimum objective function, thereby confirming the accuracy of the hybrid algorithm to estimate and predict the damage classification based on dynamic frequency.

The objective function (difference of predicted and real damage for UHPFRC communication tower) is shown in Fig. 12 which indicated close agreement between predicted and real damage scenario in the optimized and trained algorithm.

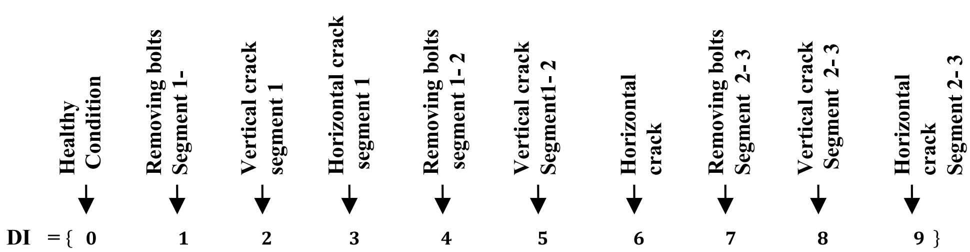
6.6.5 Testing of optimization hybrid learning algorithm

After completing the optimization process, few actual damage cases for the tower are considered to test the trained algorithm.

The frequency of the damaged tower is used to test the trained algorithm. Due to limitation of obtained frequency data because of difficulties to access various parts of tower structure to generate excitation by knocking using impact hammer (or shaker) and record data by sensors (using long cables to connect impact hammer and also all 3 sensors to the data logger which located at the middle height of the tower are caused more noise on data), it is tried to use the maximum number of data to have a better training. Therefore, 90% of data were selected for train of hybrid algorithm and 10% of data were randomly selected to test the trained prediction method.

However, few attempts have been made to use various proportion of data in range of 50% to 98% for training of hybrid algorithm, and it was revealed that as expected using more data set for training is resulted more accurate prediction. Hence, for the considered communication tower, accuracy of training using almost above 80% of data led to acceptable accuracy, therefore, it is decided to use 90% of frequency results for training of hybrid algorithm and remained 10% for accuracy testing of trained system. Therefore, data for frequency response were divided to two parts as 90% for training and 10% for testing. Therefore, the 10% of frequency data which considered for testing, were not used in the training process.

The 79 cases, which were divided into 9 classes from FEM, were used to train the hybrid algorithm. A total of 90% of the finite element results used for training and 10% of the data were used for testing the algorithm to verify the hybrid algorithm. The comparison between the prediction damage classification and the finite element damage classification. The prediction accuracy of actual cases, confirming the accuracy of the hybrid algorithm to predict the damage scenarios.



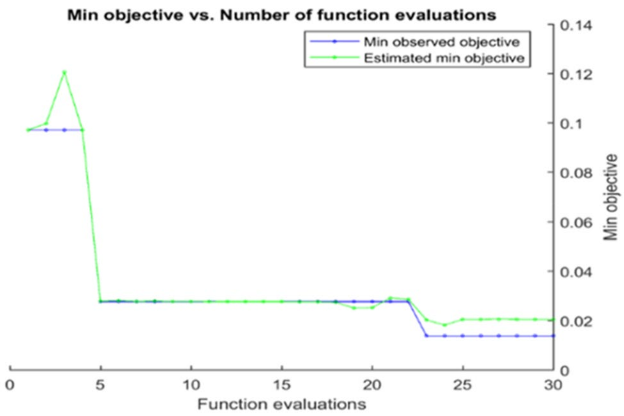


Fig. 12 Measured vs. predicted damage classification of UHPFRC communication tower using

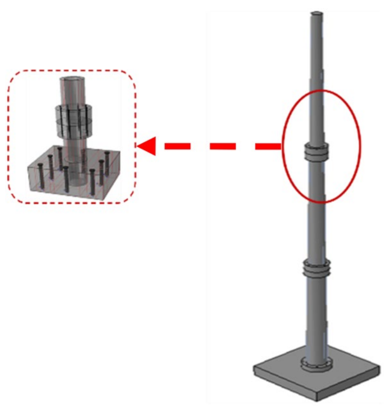


Fig. 13 Communication tower segments 2–3 details

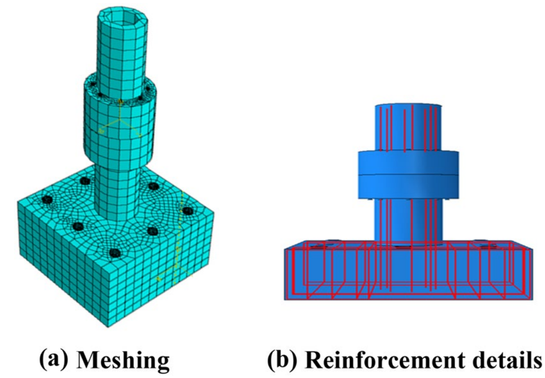
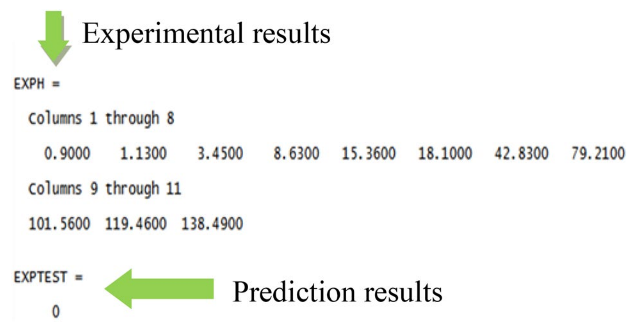
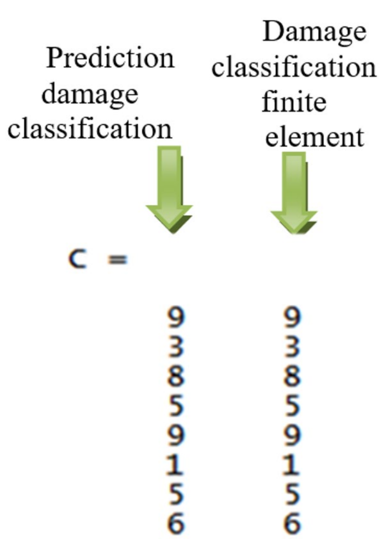


Fig. 14 Details for segments 2–3





Also, the frequency result of the tower in the healthy condition is implemented to test the hybrid algorithm, as shown in. The predicted classification was compared with the actual case that resulted from the experimental test. The predicted results (0) were accurately classified and confirmed the high accuracy of the hybrid algorithm in predicting the healthy case of the UHPFRC communication tower. Therefore, the developed hybrid algorithm can accurately predict the damage classification for the UHPFRC communication tower. The testing samples were accurately classified, and the estimated time to operate the hybrid algorithm was approximately 12.3085 s. The minimum estimated objective function value was0.02055 (the agreement between predicted and real damage scenario in the optimized and trained algorithm).

7 Verification of hybrid algorithm with case study of Segments 2–3

Due to limitation and feasibility of making damage in the 30 m tower, another part is considered to create damage and test them to validate the accuracy of develop optimized

Table 4 Damage class type and damage case number for segments 2–3

Damage type and location	Segment	Case No	Class No
Healthy	No. damage	0	0
Losing 1 bolt	Connection of seg 2–3	1	1
Losing 2 bolt		2	
Losing 3 bolt		3	
Losing 4 bolt		4	
Losing 5 bolt		5	
Losing 6 bolt		6	
Without epoxy		7	
Horizontal crack at 0.25 m	Segment 2	8	2
Horizontal crack at 0.5 m		9	
Horizontal crack at 0.75 m		10	
Horizontal crack at 1 m		11	
Horizontal crack at1.25		12	
Horizontal crack at 1.5 m		13	
Vertical crack at 0.25 m	Segment 2	14	3
Vertical crack at 0.5 m		15	
Vertical crack at 0.75 m		16	
Vertical crack at 1 m		17	
Vertical crack at1.25		18	
Vertical crack at 1.5 m		19	
Horizontal crack at 0.25 m	Segment 3	20	4
Horizontal crack at 0.5 m		21	
Horizontal crack at 0.75 m		22	
Horizontal crack at 1 m		23	
Horizontal crack at1.25		24	
Horizontal crack at 1.5 m		25	
Vertical crack at 0.25 m	Segment 3	26	5
Vertical crack at 0.5 m		27	
Vertical crack at 0.75 m		28	
Vertical crack at 1 m		29	
Vertical crack at1.25		30	
Vertical crack at 1.5 m		31	
Horizontal and vertical crack at mid of seg 2 and 3	Seg3-2	33	6

hybrid algorithm to predict damage condition. For this purpose, tower segments and their connection (2–3), are considered and tested experimentally before and after making damage to validate the proposed hybrid algorithm model. As showed in Fig. 13, a part of segment 2–3 and its connection is cut with 5 m high to conduct testing before and after creating damage and verify the computation procedure for damage detection.

A dynamic actuator is used to apply load and make damages in the tower segments. Same procedure that used for test the UHPFRC tower was considered to test tower segments 2–3 as explained in the following.

Implementing various structural frequency response in different conditions such as healthy, slight damage (small cracks), damage (medium cracks) and large damage (large cracks) for training of hybrid system indicated that the prediction was not effective for very slight damages. As mentioned before, it is because of very small cracks (0.1 mm width and less than 200 mm) have no effect on frequency response of structure therefore, training of prediction method which is based on learning data (frequency response in this study) cannot be done properly. In the other side, similar issue has been occurred for the major cracks which happened due to widening of the medium cracks by applying higher loads. Since the stiffness of structural member has already changed through experiencing medium cracks which led to losing the integrity of material, then by widening of cracks and also increasing of length of crack, there were only slight change on the frequency response of structure which effected on the training of the hybrid system. Therefore, the best effective results which obtained was for medium cracks which as civil engineer aspect, it is the main important damage condition to be considered for the structural stability. For this reason, in this study, medium damages have been considered and corresponding results have reported.

7.1 Numerical modeling of UHPFRC tower segments 2–3

Is used to develop segments 2–3 as same as the considered segment. A fixed boundary condition is applied to the foundation of segments 2–3.

The Lanczos eigensolver analysis is implemented to generate the frequency. A 150-mm mesh size is used to mesh segments 2–3 as shown in Fig. 14.

Similar damage scenarios for UHPFRC communication tower are created for segments 2–3 using the FE method. The 33 damage scenarios (damage index) consist of removing one to six bolts from the connection separately of segments 2–3, vertical crack, horizontal crack, and the combination of vertical and horizontal cracks. The 200-mm cracks are located at 500-mm intervals. Table 4 listed the conditions class type and number for segments 2–3.

7.2 Finite Element frequency analysis results for UHPFRC communication tower segments 2–3

A total of 33 damage scenarios, including the separate removal of 1 to 6 bolts from the connection of segments 2–3, vertical cracks, horizontal cracks, and a combination of vertical and horizontal cracks, were used to assess the frequency after damage to UHPFRC communication tower segments 2–3.

(a) Cut of segments 2-3

(b) Attached seg2 to foundation

(c) Lab Segments 2-3section after cutting

Fig. 15 Construct of UHPFRC communication tower segment 2–3

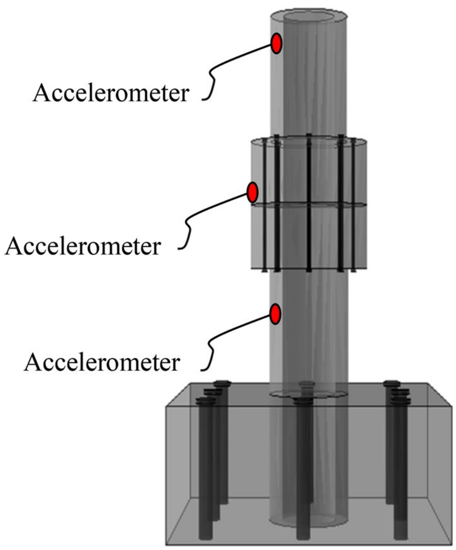


Fig. 16 Install the accelerometers for segment 2–3 in vertical position

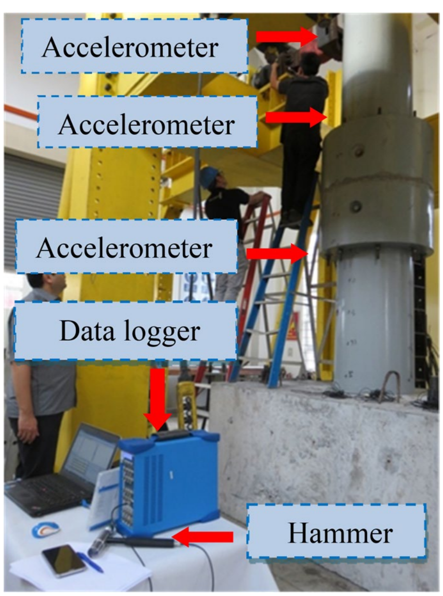


Fig. 17 Setup the Data logger for segment 2–3

7.3 Experimental test procedure for Segments 2–3

A part of segment 2–3 and its connection cut to conduct the test in healthy condition and after damage and verify the computation procedure for damage detection. For this purpose, 1.5 m of segment two and 1.5 m of segment three was cut after constructed the tower as shown in Fig. 15. Then these two parts are connected to each other from the joints using epoxy and bolts and embedded in the foundation with 1 m height for hold end of segment 2–3 which bolted to the strong floor. The cyclic load is applied to the top of segment laterally to make damage in the body of segments 2–3.

Figure 16 shows the details of UHPFRC communication tower segments 2–3 and their conection in the vertical position with a fixed boundary condition by bolting the segments foundation to the ground.

The same procedure for testing the UHPFRC communication tower is implemented for testing of segments 2–3. An impact hammer Type 9726A5000 is utilized to excite segments 2- 3 in healthy and damage conditions, and the response is recorded using three accelerometers.

The setup of the test is explained in following:

1. The tower specimen is located to the ground.
2. The tower foundation is tied to the floor using bolts to create a fixed support as a boundary condition for segments 2–3 in the vertical position.
3. Connecting of dynamic actuator to the top of segment 3 to apply the vibration and damage the considered segments.

The test procedure is presented as follows:

1. The accelerometers are installed. To ensure adequate adhesion, epoxy resin is applied between the accelerometer and the surface of tower segments 2–3.
2. The knocking point is marked as shown. The excitation points are placed at 16 points (8 points in front of

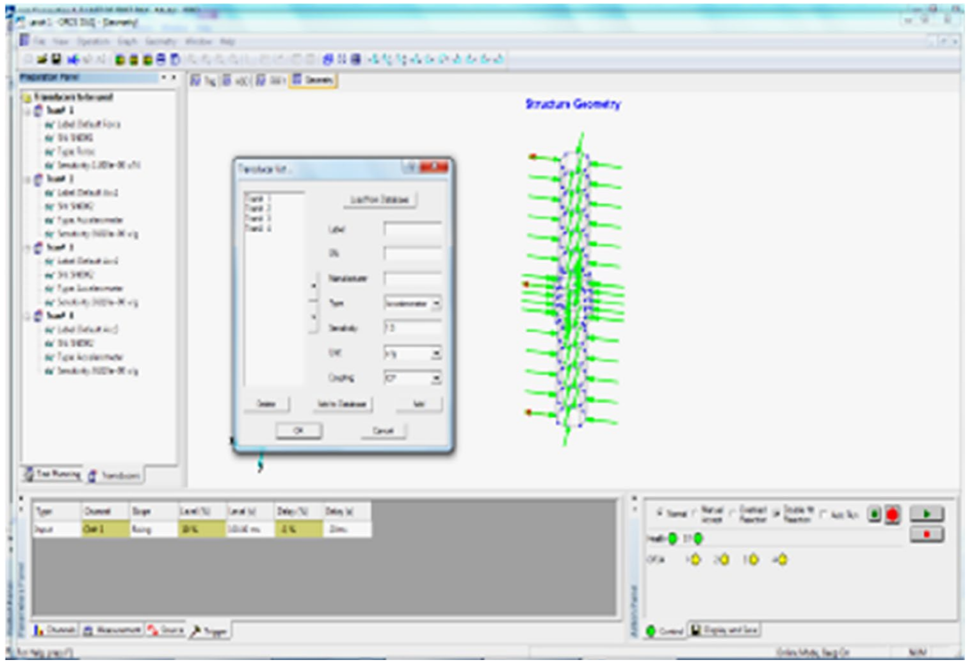


Fig. 18 UHPFRC segments 2–3 using MODAL software

the segments and 8 points at the side) to provide better excitation.

3. Setup the data logger. The hammer and accelerometers are connected to the data logger for segments 2–3 as shown in Fig. 17.

The acquired response time history signals are converted into the frequency spectra domains using the Fourier transform by dividing the Fourier transform signals of the accelerometers (output signals) by the Fourier transform signal of the impact hammer (input signals). After the raw data are measured and saved using the NVGATE software, the MODAL analysis software is used to model segments 2–3, as shown in Fig. 18, and to calculate the FRFs results.

The acquired response time history signals are converted into the frequency spectra domains using the Fourier transform by dividing the Fourier transform signals of the accelerometers (output signals) by the Fourier transform signal of the impact hammer (in- put signals). After the raw data are measured and saved using the NVGATE software, the MODAL analysis software is used to model segments 2–3, and to calculate the FRFs results. The modal parameter that contains the natural frequencies are extracted from the FRFs by a curve fitting technique. In other words, from the experimental modal analysis, the dynamic properties of segments 2–3, including the FRFs and natural frequencies, are determined at each undamaged and damaged state.

To evaluate the frequency response of tower for various types of cracks, the cyclic displacement is applied using dynamic actuator up to 75 mm and then test stopped and frequency response is measures. Then by applying more displacement it is tried to cause more crack in vertical and horizontal direction and evaluate the response frequency again to test the developed algorithm to predict the damage.

The MTS dynamic actuator with 1000kN capacity was used to apply dynamic cyclic load make damages in the segments 2–3. The extension plate was needed to design and fabricate to fit to the tower segments and connect it to the actuator for applying the cyclic load with maximum 150-mm displacement as presented in Fig. 19.

Figure 20 shows the installation of the extension plate for the dynamic actuator and prepares it for applying cyclic load to the top side of segment 3. The damage levels considered in step of 75 and 150 mm displacement.

In the initial stage of initiating damage during experimental testing, some slight cracks appeared with width of 0.1 mm and length of less 50 mm to 200 mm, which only could be able to observe them using magnifier. However, these slight cracks had no effect on the dynamic response of considered structure and once cracks width increase more than 0.2 mm width and 200 mm length, then frequency response of structures showed some changes.

7.3.1 Experimental results of undamaged case segments 2–3

In this section, segments 2–3 and their connection were tested to obtain the dynamic characteristics of the structure in the frequency domain. The segments were excited, and the same procedure as explained for communication tower was conducted to extract the modal parameters of

Fig. 19 Displacement Vs time

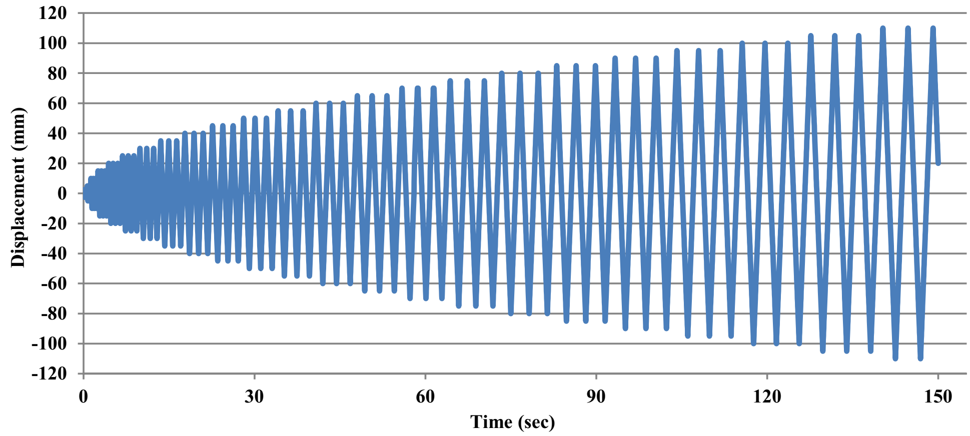
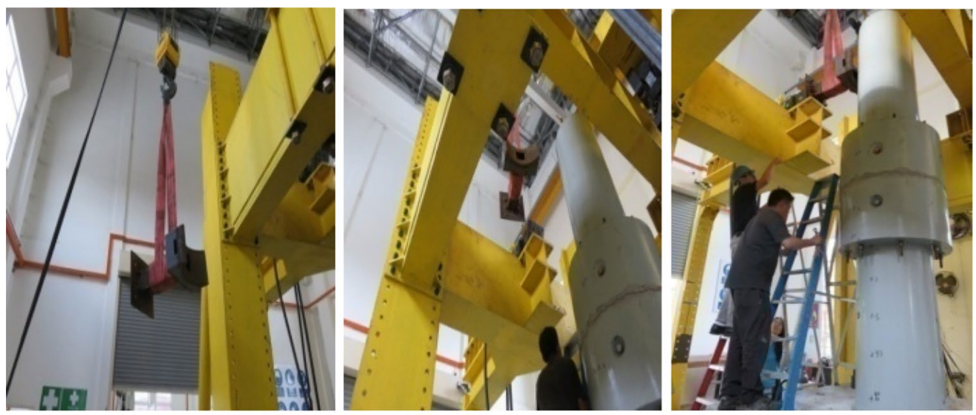


Fig. 20 Installation of the extension plate for dynamic actuator



segments 2–3 in a healthy condition (bolted foundation segment after adding epoxy), as shown in Fig. 21.

The maximum number of modes that could be captured using the selected setup with the presented bandwidth from 0 to 400 Hz was illustrated from the FRF measurements.

FRFs results were determined at the undamaged condition for segments 2–3 from the experimental modal analysis through MODAL software. The peaks of modal frequency for segments 2–3 before damage is appeared in 17.56 Hz while the last mode (mode number 10) is appeared at 339.05 Hz as presented in the Stabilization chart to calculate the frequency of segments 2–3 before damage in frequency bandwidth 0-400 Hz.The frequencies values for the undamaged segments 2–3 are presented in Table.5.

7.4 Experimental results of damaged segments 2–3

In this experimental test, various damage scenarios were examined. These scenarios consisted of the following cases:(1) bolted foundation to the ground without using epoxy in connection, (2) bolted foundation to the ground with epoxy in connection, (3) bolted foundation to the ground with four loose bolts from connection, and (4) applied cyclic forces to carry segments to make crack damage using a dynamic actuator with 75 and 150 mm displacement amplitude. The modal testing was conducted for each damage scenario as mentioned.

The specimen (segments 2–3) was excited in a frequency bandwidth of 0 Hz to 400 Hz using the impact hammer. Then, using three accelerometers, the response of the structure was recorded. The measured data in the analyzer were transferred, and NVGate software was used to convert them in terms of fast Fourier transform. The NVGate software exported the FFT results in a UUF format. Modal utility read the UFF format files and exported them to FRF; then, the frequency and damping were generated through MODAL software.

The outcomes of the experimental modal analysis of the damaged and undamaged seg- ments (2–3) were obtained and explained in this section.

Figure 22 shows the knocking of segments (2–3) after segment damage by applying lateral force on the tower segment connection. Incremental load was applied for displacement of75 and 150 mm through the dynamic actuator. The FRF response was measured at two-step damage with 75

Fig. 21 Knocking bolted foundation segment after adding epoxy

Table 5 Experimental frequency values for undamaged segmental 2–3

Mode No	f Healthy(Hz)	Mode No	f Healthy(Hz)
Mode 1	17.56	Mode 6	231.95
Mode 2	51.91	Mode 7	236.75
Mode 3	137.2	Mode 8	259.5
Mode 4	149.43	Mode 9	330.42
Mode 5	168.01	Mode 10	339.05

and 150 mm from the applied displacement due to different damage scenario of crack. The dynamic frequency was evaluating in different crack level.

Horizontal and vertical cracks appeared in the middle of segments 2–3 after applying 75 and 150 mm displacement through the dynamic actuator. This type of damage (vertical and horizontal cracks in both segments) was classified as damage class number (6).

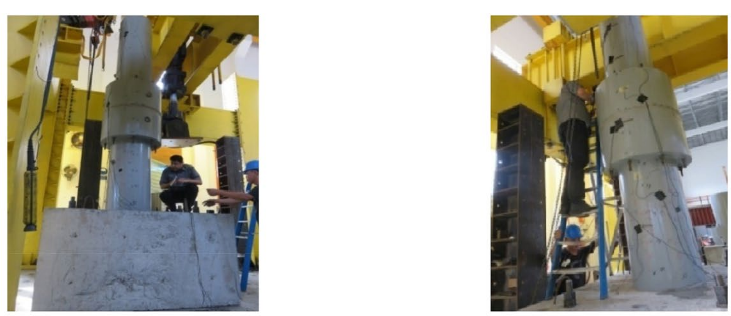
The modal parameter (natural frequencies) of the intact segments 2–3 were extracted from the FRFs using the post-processing module in MODAL software. For each case of experimental test, the envelopes of recorded FRFs were obtained to observe a shift in natural frequencies. The stabilization chart to calculate the peaks of modal frequency for the first 11 modes of segments 2–3 with different damage cases in frequency bandwidth 0–400 Hz was evaluated.

The frequency values and their variation with respect to undamaged condition at different damage degrees were determined. The analysis results of the recorded frequency show that the frequency decreased with the increase in damage severity. Therefore, frequency related to tower segment with the removal of bolts from the foundation is approximately 13.35 Hz and that due to the reduction of the stiffness in comparison of the frequency of healthy segments 2–3 is approximately 17.56 Hz. In addition, the result indicates that the increase in stiffness with the use of epoxy between the segment connections 2–3 was up to approximately 16.06 and that without using epoxy was approximately 17.56 Hz.

The damage generated a localized reduction in the stiffness of the structure; thus, the natural frequencies decreased as compared to those corresponding to the healthy segments. The result of 4 loose bolts at the connection or with damage (75 and 150 mm) using the dynamic actuator decreased due to the reduced stiffness in comparison to the healthy segment.

The maximum reductions of the natural frequency were 23.97%, 8.71%, 8.54%, 6.83%, and 4.48% for mode 1, f2, f4, f5, and f6, respectively, with respect to the frequency of the healthy segment case. Moreover, when the crack increased, the modal natural frequency decreased.

Fig. 22 Knocking segments (2–3) with 150 mm damage in a different position



(a) Knocking segment 2-3 with 75mm damage **(b) Knocking segments 2-3 with 150 mm damage**

Table 6 Verification of experimental and numerical frequency results for UHPFRC tower segment 2–3

Mode No	f EXP Healthy	f FE Healthy	Variation % (f EXP-f FE)/f EXP
Mode 1	17.56	17.5292	0.175399
Mode 2	51.91	57.3287	− 10.4386
Mode 3	137.2	145.581	− 6.1086
Mode 4	149.43	146.773	1.77809
Mode 5	168.01	169.468	− 0.86781
Mode 6	231.95	248.749	− 7.24251
Mode 7	236.75	275.388	− 16.3202
Mode 8	259.5	284.191	− 9.51484

7.5 Verification of FE results of Segments (2–3)

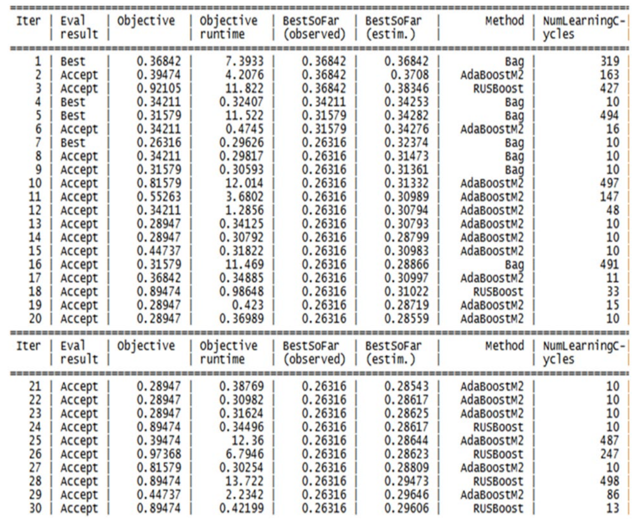
To validate the FEM, the FE analysis frequency values were compared with recorded ex- perimental frequency values for segments 2–3 healthy condition as listed in Table.6. Moreover, the variation of finite element frequency results and experimental frequency results was in- troduced, and the variation was less than 20% for all modes, which proved the capability of FEM to generate the frequency results for segments 2–3 after damage.

7.6 Verification of hybrid algorithm using case study 2

Same procedure for UHPFRC communication tower was considered for segments 2–3 in verify the Hybrid learning algorithm. A large number of frequencies data consist of 33 damage cases were used as input to the Hybrid algorithm which it is about 380 for segments 2–3 and its connections. The output data were divided into 8 classifiers (0–7) including of healthy case (0) and set as output (damage index). Training and testing of Hybrid algorithm with segments 2–3.

A large number of data consisting of 34 cases generated from FEM, including healthy and damaged cases, were considered to train the hybrid algorithm as input data. The 34 cases were divided into seven classifiers (0–6). The experimental data were used as testing data for the hybrid algorithm to validate the developed hybrid algorithm and were divided into five cases. The healthy case was numbered (0) and the damaged cases were numbered (5) and (6) based on the damage type that was generated through the experimental test.

The optimization process through the AdaBoost, Bagging, and RUSBoost algorithms for the damage detection of UHPFRC communication tower segments 2–3 is shown in Fig. 23. The number of cycles is presented in column 8, which considered the learning process to minimize the objective function and obtain an acceptable algorithm for damage prediction.



Iter	Eval result	Objective	Objective runtime	BestSoFar (observed)	BestSoFar (estim.)	Method	NumLearningC-ycles
1	Best	0.36842	7.3933	0.36842	0.36842	Bag	319
2	Accept	0.39474	4.2076	0.36842	0.3708	AdaBoostM2	163
3	Accept	0.92105	11.822	0.36842	0.38346	RUSBoost	427
4	Best	0.34211	0.32407	0.34211	0.34253	Bag	10
5	Best	0.31579	11.522	0.31579	0.34282	Bag	494
6	Accept	0.34211	0.4745	0.31579	0.34276	AdaBoostM2	16
7	Best	0.26316	0.29626	0.26316	0.32374	Bag	10
8	Accept	0.34211	0.29817	0.26316	0.31473	Bag	10
9	Accept	0.31579	0.30593	0.26316	0.31361	Bag	10
10	Accept	0.81579	12.014	0.26316	0.31332	AdaBoostM2	497
11	Accept	0.55263	3.6802	0.26316	0.30989	AdaBoostM2	147
12	Accept	0.34211	1.2856	0.26316	0.30794	AdaBoostM2	48
13	Accept	0.28947	0.34125	0.26316	0.30793	AdaBoostM2	10
14	Accept	0.28947	0.30792	0.26316	0.28799	AdaBoostM2	10
15	Accept	0.44737	0.31822	0.26316	0.30983	AdaBoostM2	10
16	Accept	0.31579	11.469	0.26316	0.28866	Bag	491
17	Accept	0.36842	0.34885	0.26316	0.30997	AdaBoostM2	11
18	Accept	0.89474	0.98648	0.26316	0.31022	RUSBoost	33
19	Accept	0.28947	0.423	0.26316	0.28719	AdaBoostM2	15
20	Accept	0.28947	0.36989	0.26316	0.28559	AdaBoostM2	10
Iter	Eval result	Objective	Objective runtime	BestSoFar (observed)	BestSoFar (estim.)	Method	NumLearningC-ycles
21	Accept	0.28947	0.38769	0.26316	0.28543	AdaBoostM2	10
22	Accept	0.28947	0.30982	0.26316	0.28617	AdaBoostM2	10
23	Accept	0.28947	0.31624	0.26316	0.28625	AdaBoostM2	10
24	Accept	0.89474	0.34496	0.26316	0.28617	RUSBoost	10
25	Accept	0.39474	12.36	0.26316	0.28644	AdaBoostM2	487
26	Accept	0.97368	6.7946	0.26316	0.28623	RUSBoost	247
27	Accept	0.81579	0.30254	0.26316	0.28809	AdaBoostM2	10
28	Accept	0.89474	13.722	0.26316	0.29473	RUSBoost	498
29	Accept	0.44737	2.2342	0.26316	0.29646	AdaBoostM2	86
30	Accept	0.89474	0.42199	0.26316	0.29606	RUSBoost	13

Fig. 23 Running of hybrid algorithm for segments 1–2

Figure 24 shows the objective function for the estimated minimum objective function with minimum observed objective function for the frequency of damaged and healthy segments 2–3. As shown in the presented graph, the objective function gradually decreases between the 3rdand 9th cycles to reach the minimum objective function. This decreasing trend proved the accuracy of the hybrid algorithm in estimating and predicting the damage classification based on dynamic frequency.

The 34 training samples were used to train the hybrid algorithm. After completing the training, the developed hybrid algorithm was tested by an experimental test, which was conducted in healthy condition as well as damage condition using a dynamic actuator. As mentioned previously, the five experimental test cases were conducted as follows:

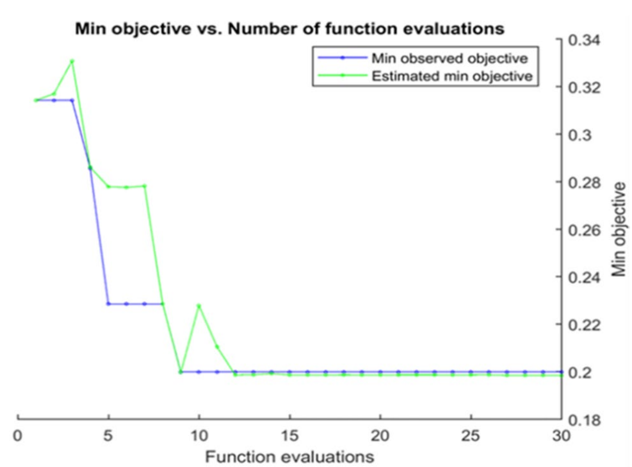


Fig. 24 Measured vs. predicted for frequency

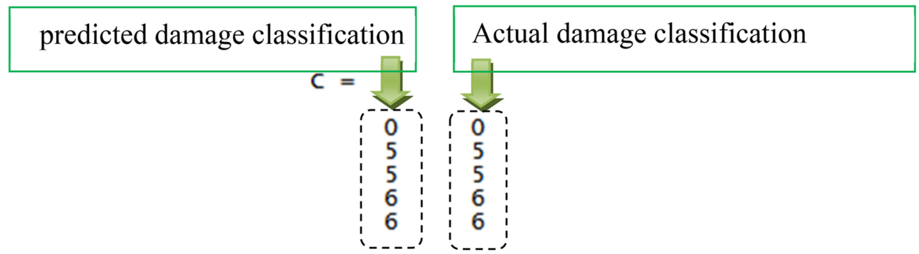


Fig. 25 Damage detection using a hybrid algorithm for segments 2–3

1) f_1: frequency of bolted foundation with epoxy at connection segments,
2) f_2: frequency of bolted foundation without epoxy at connection,
3) f_3: frequency with four loose bolts at segment connection,
4) f_4: frequency of segments with 75 mm damage pushed using an actuator, and
5) f_5: frequency of segments with 150 mm damage pushed using an actuator.

After inputting the dynamic frequency testing results for the aforementioned experimental test, the damage classifications were predicted by trained hybrid algorithm as shown in Fig. 25. The comparison of the predicted damage classification with the actual damaged case resulting from the experimental test shows that the first classification was related to the healthy condition, which was in accordance with the frequency test result made before any damage in segments 2–3 and their connection. However, the second and third frequency inputs led to the prediction of damage classification no. 5, which was for loose bolts and connection without epoxy as a result of the same experimentally tested damaged cases.

The last two cases were related to the prediction of damage class no. 6, which had vertical and horizontal cracks in segments 2–3. The same cracks and damage classification appeared after experimental test of segments 2–3 by applying 75and 150 mm cyclic displacement using the dynamic actuator. Although the crack numbers and sizes were different for applied displacement in experimental test, robust hybrid algorithm successfully predicted real damage classification, which proved the accuracy of the developed hybrid algorithm in identifying damage classification using frequency data with noticeable variation. Therefore, the developed hybrid algorithm can accurately predict the damage classification of the UHPFC communication tower with desire accuracy. The testing samples were correctly classified in 1.2604 s predicted time and 0.29606 objective function value.

The finite element analysis results are compared with the recorded frequency values of the experimental test before damage to validate FEM analysis. Furthermore, the variation of finite element frequency results and experimental frequency results was presented in Table.5. The variation is less than and equal to 20%. Although, the verification of experimental and numerical frequency results for UHPFRC tower segment 2–3 showed up to 20% variation, but the robust algorithm successfully predicted the actual damaged case with 100% accuracy.

This issue proved the reliability and performance of the developed hybrid algorithm with numerical simulation results by having unavoidable variations and differences with the actual result.

As demonstrated before, since the small cracks with less than 0.1 mm width and 200 mm length have no effect on overall strength and stiffness of considered tower segments, therefore the developed hybrid ensemble method was not performed to predict small cracks through obtained dynamic frequency response. However, as reported, the output of trained hybrid system to identify medium cracks was highly satisfied. Therefore, it is concluded that if the considered parameters have no effect on training data, then, the hybrid system also will not be capable to perform proper prediction.

8 Overall procedures for development and verification of hybrid algorithm for damage detection

To simplify presenting and demonstrating the developed procedure, the overall flowchart for train the hybrid algorithm for damage detection in communication tower using dynamic frequency response and it is verification is depicted in Fig. 26. Although the developed procedure is developed for communication tower but same process can be implemented to any type of structure such as high-rise building, dams, tower and etc.

9 Conclusion

This study aims to develop a hybrid optimized prediction method based on AdaBoost, Bagging and RUSBoost algorithms as health monitoring system for communication tower which can work with noisy, randomness, instability

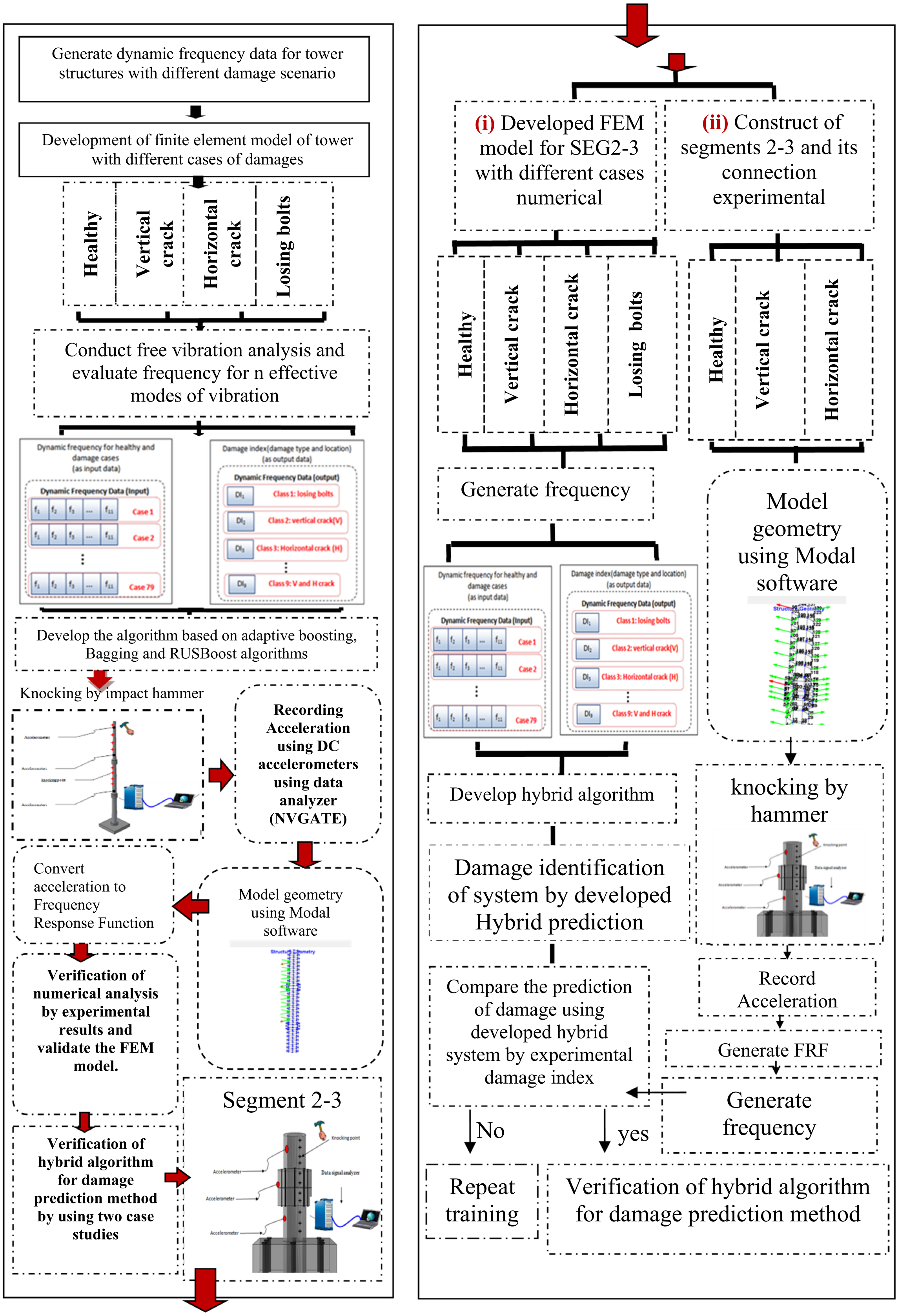


Fig. 26 Methodology procedure for development of hybrid algorithm

and skewed data to identify the location and type of damage for UHPFRC communication tower using frequency domain response with high convergence, quality solutions and lower iterations.

For this purpose, UHFPRC communication tower with 30 m height located in Malaysia was considered in this study. Damage classification algorithm is adopted based on Adaptive Boosting, Bagging, and RUSBoost algorithms. The FEM was used to generate the frequency of the healthy and different type of damage for UHFPRC communication tower as input data for training the hybrid algorithm. The type and location of damage set as output (Damage Index).

The frequency response functions (FRF's), for healthy UHFPRC communication tower, was obtained using the excitation caused by an impact hammer and the signal gathered by three accelerometers sensors attached in suitable positions. Then the frequency results were generated using the MODAL simulation tools.

The frequency results of the experimental test of UHFPRC communication tower was used as data for testing the algorithm. The results of the testing for hybrid algorithm indicated the high accuracy prediction damage classification and finite element damage classification. Moreover, the comparison of predicted damage classification with the actual case resulting from the experimental test shows that the testing samples were correctly classified with a minimum estimated objective function and running time for the hybrid algorithm.

In addition, another case study consists of tower segments 2–3were considered to verify and validate the proposed hybrid algorithm in damage detection. The results showed that, the testing samples were correctly classified for healthy and damage cases. Therefore, it is concluded that the developed hybrid algorithm can be used for damage detection for special structure such as communication tower.

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Data availability All generated data in this research are presented in the manuscript.

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