"Structural Health Monitoring System using Wireless Sensor".

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Abstract — **The long life and health monitoring of structure are most important for their lifespan optimization and preservation. WSN technology has proved to be a back boon for structural health monitoring in 21st century due to its easy of installation, minimal structural damage and low cost. This paper provides a review on the recent developments in the area of SHM using WSs.**

Keywords: wireless sensor network; structural health monitoring; scheduling approach; energy efficiency

I. Introduction

Structural Health observance (SHM) is outlined because the method of implementing harm or broken detection and characterization strategy for applied science structures. This changes to the fabric, resistivity and/or geometric properties of a structural system, as well as changes to the boundary conditions and system property that badly have an effect on the system's performance, is outlined as harm. In SHM method we tend to observe system mistreatment sporadically sampled dynamic (time varying) response measurements from associate degree array of sensors. Then the extraction of injury, damage-sensitive options from these measurements are taken out. To work out the present state of system health, the applied mathematics (mathematical) analysis of the options is performed. There'll be inevitable aging and degradation and weakening within the structure ensuing from operational atmosphere. Long run SHM is outlined as output of this method that's sporadically updated relating to the power of the structure to perform its calculated performs. Relating to the integrity of the structure, SHM is employed for speedy condition screening and it gives real time info, as an example just in case of maximum events like earthquakes or blast loading [1]. To estimate the state of structure health, SHM detects the changes in structure that affects its performance. Time-scale of amendment and severity of amendment are 2 major factors. However quickly the amendment happens is time- scale of amendment, and degree of amendment is severity of amendment. SHM has 2 major categories: disaster response (earthquake, explosion, etc.) and continuous health observance (ambient vibration, etc.). SHM has 2 approaches: direct harm detection (visual scrutiny, and X- ray, etc.) and indirect harm detection (change in structural properties/behavior). A typical SHM system, in general, includes 3 major categories: a detector system, information /knowledge/information} process system (including data acquisition, transmission, and storage), and health analysis system (including diagnostic algorithms and knowledge managements).

Why SHM?

WSN with SHM gives an effective technology for sensing and telecommunication. Due to feature, the reliability and availability are guaranteed. WSN with SHM provides an early prediction of risks. WSNs serve as a best to provide a stable structure for SHM systems [2]. The limitation in WSN includes usage of the sensor nodes, high amount of data and connectivity. The Existing system uses the centralized mechanism to determine the health status of the sensor nodes. But it is inappropriate to changing environment and enabling wireless technology. The proposed system provides a decentralized mechanism and an adoption of wireless technology. The backup sensors are used to avoid the failures that occur during the transmission. The objective of energy consumption and prolonged lifetime are achieved.

Parameter	Wired Sensor Networks	Wireless Sensor Networks
Cost	Very high, real world examples costing \$10,000 to \$25,000 [3]	Low, each sensor node costing approximately \$200[3]
Deployment Time	Very long, one real world example taking several days [4]	Short, same real world example taking a half hour [4]
Lifespan	Long, typically limited by hardware	Short, typically limited by node battery

	lifespan	lifespan
Number of Sensors	Typically low due to sensor installation difficulty.	Typically higher due to ease of sensor installation
Connection Bandwidth	High bandwidth due to wired connection	Limited bandwidth and unreliable connection
Data Rate	High sensor data rates	Lower sensor data rates but higher than conventional WSNs
Sensor Synchronicity	Very high due to wired connections.	Concern due to wireless connection.

TABLE I COMPARISON OF WIRED AND WIRELESS SENSOR NETWORKS

II. LITERATURE SURVEY:

In WSNs for SHM sensors are bring into effective action at varied locations throughout a structure. These sensors collect data regarding their close like acceleration, close vibration, load and stress at sampling frequencies upwards of one hundred rates [3]. Hence, the sensing and sampling rates and quantity of collected knowledge are abundant on top of those in different applications in WSNs; and as a result, WSNs for SHM introduce challenges in network style. Detector nodes transmit the perceived knowledge to the sink either directly or by forwarding every other's packets. Knowledge aggregation and process is very important for the detection and precise localization of structural injury and might occur in different-different locations (e.g., nodes, cluster-heads, and/or central server) reckoning on the configuration. Typically, injury detection needs the comparison of the structure's gift modal options to those related to the structure's uninjured state. Modal options of structures are chiefly depicted by the mode shapes the natural vibration pattern for a given structure.

SHM has been transportation into effective action in crucial structures like aerial vehicles, ships, high-rise buildings, dams, and bridges. Primarily, these installations are wired; but, associate increasing variety are mistreatment WSNs. one in every of the primary WSNs for SHM was put in on the sound Bridge in 2007 by a quest team at the University of Calif. in Berkeley [8]. Sensors during this network collect close vibrations that are then routed from the origin detector node to a centralized base station. The bottom station then processes the information and makes a call regarding the structure's overall health. This method is one in every of the biggest WSN-based SHM systems to this point – with a complete of sixty-four detector nodes deployed on the bridge. Another WSN based SHM system has been recently deployed on the Zheng Dian Bridge in China [3]. The sensors during this network collect close acceleration knowledge and use the quick Fourier remodel (FFT) and also the resultant Power Spectral Density (PSD) to see the structure's mode form. This paper presents a comprehensive survey of the state of the art analysis within the application of WSNs to the sphere of SHM. Existing surveys like [4], [10], and [8] have primarily centered on topics like detector hardware, node hardware, network protocols, and software system, and potential applications.

Summaries like [8] have provided a general summary of the challenges of WSNs for SHM however haven't highlighted future analysis directions. Additionally, by presenting an outline of theoretical work, laboratory test bed-based experimental work, and real-structure experimental work, this paper provides a comprehensive description of existing challenges and future trends within the application of SHM to WSNs. Lastly; this paper focuses additional on the telecommunications part of WSNs for SHM than existing surveys.

III. BLOCK DIG. SHM USING WSNS

In general, SHM requires the installation of an outsized number of sensors throughout a structure capable of collecting sensed data. The collected data is processed such decisions about the structure's overall health are often made. This section provides a comprehensive overview of the components and processes involved in SHM using WSN. This section begins with a summary of commonly sensed structural health parameters then an summary of the sort of sensors used. Next common damage detection algorithms used in damage detection systems are presented and discussed. The section concludes with summary of injury localization techniques.

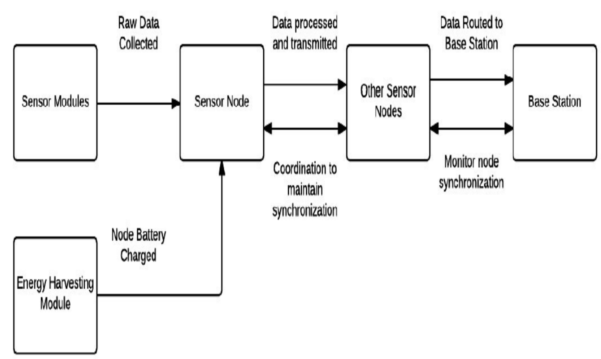

Figure 1: SHM using WSNs

A. Sensors and Parameters

One of the most important considerations when designing SHM system is the selection of sensors and sensed parameters. Factors like sensor power consumption and sensed parameters influence overall network design by influencing routing

protocol selection, damage detection algorithm selection, damage localization algorithm selection, and network lifespan.
1) Sensor Parameters:
Parameters commonly detected, recorded and monitored in SHM systems can be broadly classified as the following types [13]

• Load - Loads are the forces applied to the structure. Possible loads are environmental loads such as wind speeds, and loads due to passing vehicles. Loads can be static or dynamic. Typically, the response of the structure to these loads can be measured by the SHM system.
• Global Load Response – Global loads responses are the structure's response to a given load that can be measured throughout the entire structure. Typically, measured parameters are a structure's acceleration and velocity.
• Local Load Response – Local load responses are the structure's response to a given load that can only be measured in a specific part of the structure
• Environmental Factors – Environmental factors are external to the structure itself and relate to the structure's environment. Measured parameters include temperature, salinity, humidity, and atmospheric acidity. These parameters can be used in the estimation of environmental loads such as winds.

In order to properly capture the response of a given structure, sensors got to be installed at various locations and data should be collected at an appropriate rate for a sufficient period of time. The frequencies of dominant modes are typically around 10 Hz; however, sampling frequencies can be chosen at values that are upwards of 100 Hz [24]. Higher sampling rates allow the inclusion of higher-frequency modes which can be used in damage detection and localization. The high sampling rate required for successful SHM significantly increases the amount of collected data and, consequently, the amount of data aggregated, processed and transmitted in the overall network.

SENSORS FOR SHM

The sensing system in the SHM is formed by smart materials/sensors; Fiber optic sensors (FOS), piezoelectric sensors, magneto resistive sensors, and self - diagnosing fiber reinforced structural composites. The sensors are characterized with very important capabilities of sensing various physical and chemical parameters related to the health of the structures such as vibrations and all other important factors

FIBRE OPTIC SENSORS (FOSS)

FOS may be classified by many ways. FOS may be classified supported the modulation of sunshine characteristics (intensity, wavelength, phase, or polarization etc.) by the parameters to be detected. It also can be classified by the tactic through that the sunshine within the sensing segments is changed within or outside the fiber (intrinsic or extrinsic). FOS also can be classified supported the sensing range; native (Fabry-Perot FOS or long-gauge FOS etc.), similar distributed (fiber full general grating) and distributed sensors (Brillouin-scattering-based distributed FOS). FOS square measure embedded in recently made civil structures, together with bridges, buildings, and dams to yield data concerning strain (static and dynamic), temperature, defects (delamination, cracks, and corrosion) and concentration of chloride ions. On existing structures, FOSs are typically surface mounted. The info collected by FOSs is employed to judge the protection of each the new-built structures and repaired structures, and diagnose.

PIEZOELECTRIC SENSORS:

Piezoelectric materials exhibit synchronous actuator/sensor behavior supported electrical-mechanical deformation. There are many varieties of electricity materials: electricity ceramics, electricity polymers, and electricity composites. Supported the measure of electrical electrical resistance and elastic wave's electricity sensors were fresh introduced into SHM of engineering science structures as a vigorous sensing technology.

C. MAGNETOSTRICTIVE SENSORS

Ferromagnetic materials are the materials that are automatically ill-shapen once placed in robust field [7]. This development is thought because the magnetostrictive result. Within the inverse magnetostrictive result, the magnetic induction of the fabric changes once the fabric is automatically ill-shapen. supported the higher than phenomena, Kwun and Bartels made-up a kind of magnetostrictive device (MsS) while not direct physical contact to the fabric surface that might generate and notice target-hunting waves within the magnetic force materials beneath testing. Khazem et al. additionally utilised MsS to examine clothing ropes on the President Bridge in big apple. A pulse of ten kilocycles per second longitudinal target-hunting wave on the length of the clothing detected the mirrored signals from geometric options and defects within the clothing, a cement and degree of hurt [11].
Out of the above sensor types, the most-commonly used are piezoelectric accelerometers due to their low cost and ease of use [30]. As a result, most damage detection and localization methods have been developed for these sensors.
B. Damage Detection and Localization in WSNs for SHM, sensor nodes collect parameter data such as acceleration, strain, velocity, and displacement. This raw data must be processed such that features such as the structure's modal parameters can be extracted. These features are used by SHM based WSNs in both damage detection and localization [23]. The remainder of this section discusses the commonly-used damage detection and localization techniques.
Damage Detection Methods one of the primary goals in SHM is the detection of structural damage. Typically, damage detection requires the collection of sensor data that can be used to extract parameters related to the structure's overall health. The most common parameters used in damage detection are modal parameters like the natural frequency and mode shape. Modal parameter estimation can be performed in both the time and frequency Domain [23]. Once modal parameters are extracted, damage detection algorithms are used to determine whether damage has occurred. Taxonomy of damage-detection methods is Illustrated in Fig. 2. In time domain analysis, the time series data collected from a sensor node is directly

processed to extract modal parameters. Common techniques used are the two-stage least
Squares method (alternatively known as the auto-regressive moving average (ARMA) model method), the Ibrahim time domain (ITD) method, the impulse response function (IRF) -driven method [23], and the covariance matrix method [24]. One common advantage of time domain techniques is that they provide stable results, however they work for slightly damped systems since they require a significant number of time domain samples to efficiently operate on highly damped systems [25].

IV Taxonomy of Damage Detection Methods

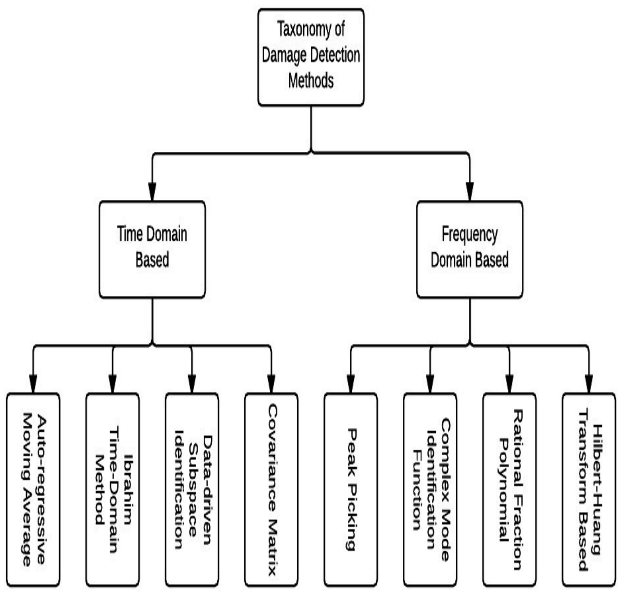

Fig. 2 Taxonomy of Damage Detection Methods

The ARMA model method uses statistical modelling to represent the relationship between the excitation pattern and the structural response under undamaged and damaged states. The response of the structure at any instant of time is presented in terms a number of stored observations and a number of residual error terms [26]. There exist several variations of ARMA model based damage detection, one of which is based on the sum of the squares of the residuals [27]. In a different technique [28], [29] ARMA models are fitted to an excitation pattern through a two stage method. First, the AR model is produced and the residuals from the AR model used as an input for the second stage. Next, depending on the excitation pattern, an AR or ARX model is fitted to the residuals. The two-stage method, unlike other ARMA methods, guarantees convergence. The resultant model can be used in the extraction of modal parameters such as the damping ratio, natural frequency, mode shape and damped natural frequency [28]. Typically, ARMA models are only applicable in systems with white noise excitation patterns. If alternate excitation patterns are applied, the resultant model is an autoregressive exogenous (ARX) model. The same modal parameter extraction method can be used for ARX models. One drawback of the technique presented in [27] is that the data used to build the model was collected through forced excitation experiments. Hence, this technique may not be valid for structures subjected to other sources of excitation. Although ARMA model techniques can detect damage effectively, they fail to detect minor damages and they require installation of a large number of sensors [30]. The ITD method uses the Inverse Fourier Transform (IFT) to attain the IRF from the given sensor data [23]. The IRF can then be used to estimate modal frequencies and then, using those frequencies, the remaining modal parameters such as mode shape and natural frequency. The IRF are first stacked to form the Henkel matrix, which is then decomposed into modal observability matrix and modal controllability matrix, from which the modal parameters are obtained. Once the modal parameters are obtained, they are compared to those of undamaged structure to decide on the current state of the structure. One common IRF-driven algorithm is the Eigen system realization algorithm (ERA) [21], which was proposed in 1985, however, a recent modification of ITD method was proposed in [22] to address the main drawback of ITD related to deficiency in identifying closely spaced structure modal shapes and hence their modal parameters. The covariance-driven subspace damage detection techniques are based on the fact that a state-space model can be used to represent a vibrating structure [10], [23]. The state space model representation of a vibrating structure comprises the definitions of state transition matrix, input matrix and output matrix. In the first step of covariance-driven method is to estimate the covariance matrix of the collected time domain measurements as well as the next state-output covariance matrix. Using these two covariance matrices, the state transition matrix is estimated. In the second step, an eigenvalue decomposition operation is applied on the estimated state transition matrix. Using the resultant eigenvector matrix as well as the input and output matrices, the modal participation and mode shape matrices are estimated. In [24], the covariance matrix method of damage detection is used on the acceleration response covariance matrix. This method was shown to be more effective than traditional damage detection techniques such as the mode shape comparison method. On the other hand, one drawback of subspace based damage detection techniques is that they are affected by variations in unknown ambient excitations, which leads to a false alarm of damage detection [24]. Data-driven subspace identification techniques operate directly on the collected time-domain measurements rather than the estimated covariance matrix as in the covariance based method presented above. This method was first presented by the pioneering work of Overschee and De Moor in [15]. In this method, the covariance estimation process is replaced by a projection process between future and past outputs [16], [27]. In particular, the row space of the future outputs is projected into the row space of the past outputs. To perform this, a QR decomposition operation is applied. One main advantage of data-driven subspace method is that by avoiding estimation of covariance matrix, squaring both error and noises is also avoided. However, the drawback of this method is that no information is available regarding the accuracy of the estimated modal parameters [28].

In frequency domain analysis, the collected statistic data is transformed from the time domain to the frequency domain through transforms like the Fast Fourier Transform (FFT) and therefore the Wavelet Transform (WT). Within the literature, frequency domain -based damage detection methods include the peak-picking (PP) method, the complex mode identification function method (CMIF), and therefore the rational fraction polynomial method (RFP) [23]. The advantage of frequency domain methods over the time domain methods is that less noise modes are obtained. However, the FFT operation has its own drawbacks, one among which is leakage. Although the effect of leakage is often reduced by using windowing functions, its effect can't be totally eliminated [25]. The PP method of modal parameter extraction is probably the only modal parameter extraction method. The FFT is applied to collected sensor data and therefore the Eigen frequencies are identified at the peaks of the frequency response plot. The Eigen frequencies are utilized in the extraction of natural frequency, damping ratio and mode shape. This method, although simple, is difficult to use in cases where the frequency response peaks are poorly defined and where the damping ratio isn't low [28]. The CMIF method, also referred to as the frequency domain decomposition (FDD) method, is an alternate modal parameter estimation method based off the PP method [29]. This method uses singular value decomposition (SVD) to decompose the output power spectrum into all the mode shapes for the given structure. Additionally, to attaining all relevant mode shapes this method also extracts all modal parameters for every mode shape. The peaks generated through CMIF, which correspond to modal frequencies, are proportional to the amplitude of the frequency response, which may be thought of as a plus since it provides the examiner to urge a sense for the strength and contribution of every mode. However, when a robust mode exists, it can dominate the output and consequently cause accessible peaks to disappear [27].The RFP method for modal parameter estimation which was first presented in [20], parameterizes the frequency response matrix as an RFP model [23]. Supported the RFP model, rectilinear regression is often applied and therefore the matrix coefficients estimated. Modal parameters can then be attained from the calculated coefficients. The most advantage of FRF damage detection method is its simplicity also as its independency of acquiring modal analysis of mode shapes [20]. However, it's several drawbacks including deficiency in estimating severity of injury also as inability to detect small damages [20]. Once modal parameters are derived for a given structure, it becomes possible to assess the structure's overall health. Simple damage detection methods include statistical analysis, mode frequency comparison and mode shape comparison. In statistical analysis techniques, the ARMA model for the given structure is compared to the ARMA model for the undamaged structure. If the difference between the 2 models is bigger than a specified tolerance the structure are often classified as damaged. Mode frequency and mode shape based damage detection methods compare the present mode and/or frequency shape thereto of the undamaged structure. Once more, if the error becomes sufficiently large, the structure is taken into account damaged. These techniques, although simple, have found extensive use in SHM. The Hilbert-Huang transform has found use in damage detection [24], [25], [25]. The proposed algorithm combines empirical modal decomposition (EMD), the random decrement technique and therefore the Hilbert-Huang transform to spot the instant at which structural damage occurs. this system are often applied in situations where structures experience significant noise and may detect both gradual and rapid changes in structural damage, however, it cannot separate very close frequencies [25], [25]. In [20], Lamb-wave-based damage identification approaches for composite structures is presented. The authors enhance the power of the continual wavelet transform in feature extraction from vibration signals. Composite damage monitoring rises because the top priority problem of SHM. Lamb wave method is extremely sensitive for little damages (crack or delamination). Additionally, Lamb wave is in a position to be propagated for an extended distance without significant amplitude attenuation in plate structures. However, the phenomenon of dispersion and sophisticated transition, are hard to be analyzed and interpreted. Lamb wave is unavoidably suffering from interferences and powerful noise. It requires more precise and advanced signal processing and has extraction techniques to spot damage information once structural damage has been detected, it's then necessary to work out the damage's location. This process is named damage localization, which needs the installation of enough sensors such sufficient sensor coverage is provided to locate damage anywhere within the structure. Insufficient sensor coverage may result in damage detection without localization. Commonly used damage localization techniques are frequency based [20], mode shape–based [20], flexibility matrix based [21], [22], stiffness matrix based [22], and support vector machine based [24]. A taxonomy illustrating the various damage localization methods are often seen in Fig. 3.

V. Damage Localization Taxonomy

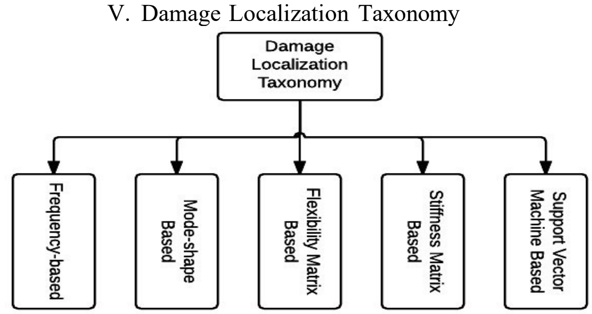

Fig. 3 Damage Localization Taxonomy

The usage of modal parameters such as frequency and mode shape in damage localization is desirable due to the simplicity in determining these modal parameters. In [20] both frequencies based damage localization and mode-shape based damage localization algorithms are proposed. The proposed frequency based damage detection algorithm uses changes in measured mode shapes to localize damage and changes in measured natural frequencies to estimate damage severity. Similarly, a mode-shape based damage detection algorithm, that uses changes in modal strain energy to localize damage, was proposed. Experiments showed that the frequency-based method localized damage with a small error while the mode based method localized damage with almost no errors. Both algorithms could also estimate the severity of the damage. On the other hand, the drawbacks of frequency based damage localization include that variations such as in mass structure or measurement temperature can lead to uncertainty in the estimated frequency [20], [15]. In addition, exploiting mode shapes for damage classification may be ineffective since damage is local and may not affect the shapes of lower modes [20], [26]. The flexibility approach for damage localization uses a structure's flexibility matrix to localize structural damage. Damage localization typically requires the flexibility matrix from the undamaged structure and an estimate of the structure's current flexibility matrix. In [21], the flexibility-difference method of injury detection is proposed. Damage is localized through computing the change in flexibility between the undamaged structure and therefore the current structure. This method reliably localizes a structure's damage and, in cases of poor sensor coverage, will find the sensor node closest to the structural damage. A similar damage localization strategy is employed in [22] with the difference matrix computed from the estimated flexibility matrix and undamaged flexibility matrix of the structure. The main disadvantage of this technique is the necessity of construct an accurate model for the undamaged structure [17]. The stiffness approach to damage localization uses a structure's stiffness matrix. The stiffness matrix and adaptability matrix are often inverted from each other [17]. It is difficult to directly estimate the stiffness matrix and, consequently, most efforts have been in using statistical techniques to estimate the stiffness matrix. In [22], a stiffness matrix based damage localization method is employed during which the detection of the present stiffness matrix is viewed as an area optimization problem. Evolutionary algorithms are used to produce the stiffness matrix and the estimated stiffness matrix compared to that of the undamaged structure to localize damage. This method was shown to be effective in scenarios where damage slowly spreads throughout the structure but would be ineffective in localizing damage in an already damaged structure. In [18], an approach for damage localization, using both a structure's flexibility and stiffness matrices, is proposed. First, the modal parameters are identified and utilized in the estimation of a flexibility matrix. The stiffness matrix is then achieved through the inversion of the pliability matrix. Both of estimated matrices, the undamaged flexibility, and the undamaged stiffness matrix are used to localize structural damage. This method is more reliable due to the usage of both flexibility and stiffness matrices. This approach was shown to work well except in scenarios where sensor coverage is sparse. The application of support vector machines (SVM) is a relatively new phenomenon in SHM. In [14], SVMs are wont to classify structural damage patterns for SHM systems with a minimal number of sensors. Through the utilization of one sensor on the roof of a building and one sensor on rock bottom floor, damage was shown to be localizable to a specific floor in the building. Damage localization was shown in simulations to scale to buildings up to 21 stories height. These results show the promise of applying SVMs to damage localization as they minimize the number of installed sensors while having comparable damage.

VI. Conclusion

This paper presented a comprehensive review of WSN based SHM systems. Background information relating to structural health monitoring such as common sensors, commonly measured parameters and damage detection and localization algorithms were discussed. The main challenges of scalability, time synchronization, sensor placement optimization and data processing were presented and solutions to these problems discussed and compared. Experimental work performed in the lab and on real-world structures was presented and discussed. Finally, future research directions for SHM systems using WSNs were presented.

VII . ACKNOWLEDGMENT

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VIII. Reference

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