Structural Health Monitoring Using Wireless Sensor Networks: A Comprehensive Survey

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***Abstract*—Structural health monitoring (SHM) using wireless sensor networks (WSNs) has gained research interest due to its ability to reduce the costs associated with the installation and maintenance of SHM systems. SHM systems have been used to monitor critical infrastructure such as bridges, high-rise buildings, and stadiums and has the potential to improve structure lifespan and improve public safety. The high data collection rate of WSNs for SHM pose unique network design challenges. This paper presents a comprehensive survey of SHM using WSNs outlining the algorithms used in damage detection and localization, outlining network design challenges, and future research directions. Solutions to network design problems such as scalability, time synchronization, sensor placement, and data processing are compared and discussed. This survey also provides an overview of testbeds and real-world deployments of WSNs for SH.**

***Index Terms*—Wireless sensor networks, structural health monitoring, sensor placement, synchronization, clustering, scalability, energy harvesting, damage detection, mobile phone sensing.**

I. Introduction

Over the last decade Wireless Sensor Networks (WSNs) have emerged as a powerful low-cost platform for connecting large networks of sensors. These networks have found applications in commercial, health, military and industrial settings. Structural Health Monitoring (SHM) is one such application in which sensors distributed throughout a structure are used to assess the structure's health [1]–[3]. Historically, SHM systems were designed using wired sensor networks; however, the high reliability and low installation and maintenance costs of WSNs have made them a compelling alternate platform [4]–[7]. Due to their high installation costs, wired sensor networks are generally only feasible for long-term SHM applications where the structure's health is of critical importance. The significant cost reductions of using WSNs for SHM would enable their utilization in important public and private infrastructure and increase the use of applications such as short-term structural monitoring. Such systems could extend the lifespan of numerous structures by enabling earlier damage detection, eliminate the cost of routine inspections and, most critically of all, improve public safety. A summary of the key differences between wired sensor networks and WSNs for SHM is presented in Table I.

TABLE I
Comparison of Wired and Wireless Sensor Networks

Metric	Wired Sensor Networks	Wireless Sensor Networks
Cost	Very high, real world examples costing \$10,000 to \$25, 000 [8]	Low, each sensor node costing approximately \$500 [8]
Deployment Time	Very long, one real world example taking several days [9]	Short, same real world example taking a half hour [9]
Lifespan	Long, typically limited by hardware lifespan	Short, typically limited by node battery 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.

In WSNs for SHM sensors are deployed at various locations throughout a structure. These sensors collect information about their surrounding such as acceleration, ambient vibration, load and stress at sampling frequencies upwards of 100 Hz [5]. Hence, the sensing and sampling rates and amount of collected data are much higher than those in other applications in WSNs; and as a result, WSNs for SHM introduce challenges in network design. Sensor nodes transmit the sensed data to the sink either directly or by forwarding each other's packets. Data aggregation and processing is necessary for the detection and localization of structural damage and can occur in different locations (e.g., nodes, cluster-heads, and/or central server) depending on the network topology. Typically, damage detection requires the comparison of the structure's present modal features to those associated with the structure's undamaged state. Modal features of a structure are mainly represented by the mode shapes – the natural vibration pattern for a given structure. A diagram outlining the process of SHM using WSNs is displayed in Fig. 1.

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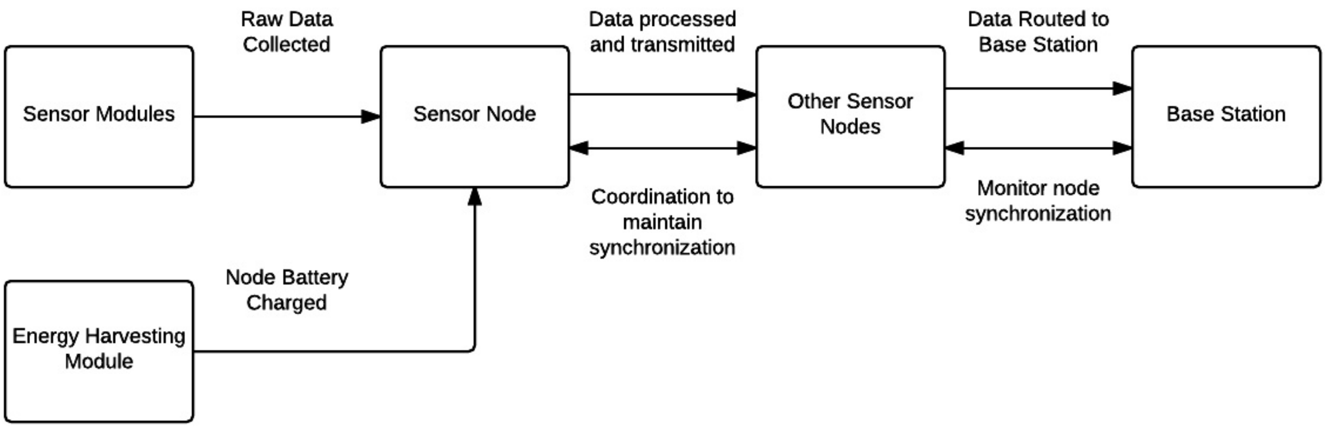

Fig. 1. SHM using WSNs.

SHM has been deployed in critical structures such as aerial vehicles, ships, high-rise buildings, dams, and bridges. Primarily, these installations have been wired; however, an increasing number are using WSNs. One of the first WSNs for SHM was installed on the Golden Gate Bridge in 2007 by a research team at the University of California in Berkeley [10]. Sensors in this network collect ambient vibrations which are then routed from the origin sensor node to a centralized base station. The base station then processes the data and makes a decision relating to the structure's overall health. This system is one of the largest WSN-based SHM systems to date – with a total of 64 sensor nodes deployed on the bridge. Another WSN-based SHM system has been recently deployed on the ZhengDian Bridge in China [3]. The sensors in this network collect ambient acceleration data and use the Fast Fourier Transform (FFT) and the resultant Power Spectral Density (PSD) to determine the structure's mode shape.

This paper presents a comprehensive survey of the state of the art research in the application of WSNs to the field of SHM. Existing surveys such as [4], [11], and [12] have primarily focused on topics such as sensor hardware, node hardware, network protocols, and software, and potential applications. Summaries such as [8] have provided a general overview of the challenges of WSNs for SHM but haven't highlighted future research directions. In addition, by presenting an overview of theoretical work, laboratory testbed-based experimental work, and real-structure experimental work, this paper provides a comprehensive description of existing challenges and future trends in the application of SHM to WSNs. Lastly, this paper focuses more on the telecommunications component of WSNs for SHM than existing surveys.

The organization of this paper is as follows: In Section II, background information about SHM using WSNs is provided. Section III provides an overview of existing research challenges: scalability, high synchronization requirements, sensor placement optimization and distributed processing. Section IV reviews experimental testbeds and current real-structure deployments of SHM based systems. Section V suggests future research directions. Finally, the paper is concluded in Section VI.

II. Structural Health Monitoring Using Wireless Sensor Networks

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

A. Sensors and Parameters

One of the most important considerations when designing an SHM system is the selection of sensors and sensed parameters. Factors such as 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. Typically, measured parameters are strain, crack and tension forces.
- 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.

To date, out of all of the above parameters, the most commonly measured are the structure's acceleration and velocity. One of the unique challenges posed by measuring global load response variables such as acceleration and velocity is that due to their global nature, it is difficult to detect the exact location of the damage [13].

In order to correctly capture the response of a given structure, sensors need to be installed at various locations and data should be collected at an appropriate sampling 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 [14]. Higher sampling rates allows 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.

2) Sensor Types: The sensing and acquisition of the above parameters requires the utilization of specific sensors. A summary of commonly used sensors in SHM systems are as follows [13], [14]:

- *Accelerometers:* Accelerometers used for SHM are either piezoelectric or spring-mass accelerometers. Piezoelectric accelerometers are light, small, and operate over wide acceleration and frequency ranges [15]. On the other hand, spring-mass accelerometers are relatively bulky and operate over a limited range of accelerations and frequencies. However, they are very sensitive to small accelerations and provide better resolution than the piezoelectric accelerometers. The piezoelectric accelerometer is made of a piezoelectric crystal element and an attached mass that is coupled to a supporting base. When the supporting base undergoes movement, the mass exerts an inertia force on the piezoelectric crystal element. The exerted force produces a proportional electric charge on the crystal. Accelerometers can have sampling rates upwards of 100 Hz [14].
- *Strain Sensors:* Strain sensors used for SHM can be classified as piezoresistive or embedment strain gauge based. Cement-based strain sensors are typically piezoresistive and are capable of measuring strain. These sensors generate signals with an incredibly low frequency (< 1 Hz) [16]. Embedment strain gauges can be used for measuring strains inside concrete structures [17]. An embedment gauge consists of a long foil gauge (about 100 mm) embedded in a polymer concrete block. Embedment strain gauges are sensitive to environmental conditions such as the weather and, consequently, must be protected with enclosures.
- *Corrosion Sensors:* Corrosion sensors typically measure the change in resistance introduced by the erosion of the sensor corrosion wafer. These sensors typically measure a structure's overall corrosion [18], [19].
- *Linear Voltage Differential Transducers (LVDT):* LVDTs are used for displacement measurement and consist of a hollow metallic casing in which a core or shaft, moves freely back and forth along the axis of measurement [20]. The core is made of a magnetically conductive material, and a coil assembly surrounds the metallic shaft. No voltage appears at the secondary windings when the core is equidistant between both secondary windings. However, when a displacement occurs, the core moves, a differential voltage is induced at the secondary output. The magnitude of the output voltage changes linearly with the magnitude of the core's displacement.
- *Optical Fiber Sensors:* The most common type of optical fiber sensor is the fiber Bragg grating sensor [21], [22]. These sensors can be used to measure parameters such as strain, temperature, pressure, and other quantities by modifying a fiber so that the quantity to be measured modulates the intensity, phase, polarization, and wavelength or transit time of light in the fiber. Fiber-optic sensors have been developed to measure temperature and strain simultaneously with very high accuracy using fiber Bragg gratings.

Out of the above sensor types, the most-commonly used are piezoelectric accelerometers due to their low cost and ease of use. 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. The remainder of this section discusses the commonly-used damage detection and localization techniques.

1) 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. A 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].

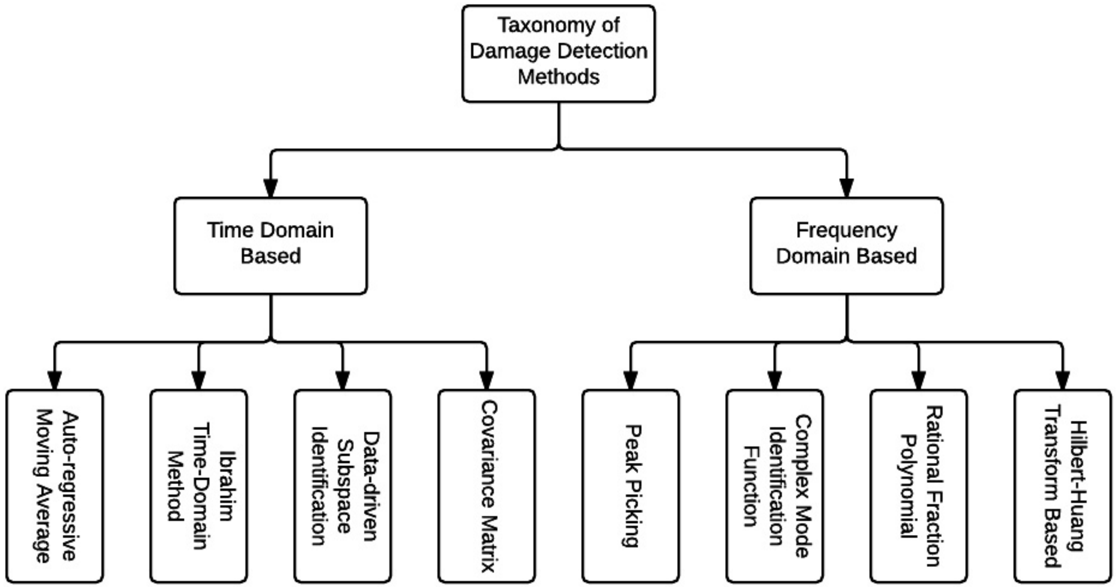

Fig. 2. Taxonomy of Damage Detection Methods.

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 Hankel 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 eigensystem realization algorithm (ERA) [31], which was proposed in 1985, however, a recent modification of ITD method was proposed in [32] 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], [33]. 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 [34].

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 Van Overschee and De Moor [35]. In this method, the covariance estimation process is replaced by a projection process between future and past outputs [36], [37]. 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 [38].

In **frequency domain analysis**, the collected time series data is transformed from the time domain to the frequency domain through transforms such as the Fast Fourier Transform (FFT) and the Wavelet Transform (WT). In the literature, frequency domain -based damage detection methods include the peak-picking (PP) method, the complex mode identification function method (CMIF), and 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 of which is leakage. Although the effect of leakage can be reduced by using windowing functions, its effect cannot be totally eliminated [25].

The PP method of modal parameter extraction is perhaps the simplest modal parameter extraction method. The FFT is applied to collected sensor data and the eigenfrequencies are identified at the peaks of the frequency response plot. The eigenfrequencies are used in the extraction of natural frequency, damping ratio and mode shape. This method, although simple, is difficult to apply in cases where the frequency response peaks are poorly defined and where the damping ratio is not low [28].

The CMIF method, also known as the frequency domain decomposition (FDD) method, is an alternate modal parameter estimation method based off the PP method [39]. This method uses singular value decomposition (SVD) to decompose the output power spectrum into all the mode shapes for the given structure. In addition to attaining all relevant mode shapes this method also extracts all modal parameters for each mode shape. The peaks generated through CMIF, which correspond to modal frequencies, are proportional to the amplitude of the frequency response, which can be thought of as an advantage since it provides the examiner to get a feeling for the strength and contribution of each mode. However, when a strong mode exists, it can dominate the output and consequently cause close by peaks to disappear [40].

The RFP method for modal parameter estimation which was first presented in [41], parameterizes the frequency response matrix as an RFP model [23]. Based on the RFP model, linear regression can be applied and the matrix coefficients estimated. Modal parameters can then be attained from the calculated coefficients. The main advantage of FRF damage detection method is its simplicity as well as its independency of acquiring modal analysis of mode shapes [42]. However, it has several drawbacks including deficiency in estimating severity of damage as well as inability to detect small damages [43].

Once modal parameters have been derived for a given structure, it becomes possible to assess the structure's overall health. Simple damage detection methods include time series analysis, mode frequency comparison and mode shape comparison. In time series analysis techniques, the ARMA model for the given structure is compared to the ARMA model for the undamaged structure. If the difference between the two models is greater than a specified tolerance the structure can be classified as damaged. Mode frequency and mode shape based damage detection methods compare the current mode and/or frequency shape to that of the undamaged structure. Once again, if the error becomes sufficiently large, the structure is considered damaged. These techniques, although simple, have found extensive use in SHM.

The **Hilbert-Huang transform** has found use in damage detection [44]–[46]. The proposed algorithm combines empirical modal decomposition (EMD), the random decrement technique and the Hilbert-Huang transform to identify the moment at which structural damage occurs. This technique can be applied in situations where structures experience significant noise and can detect both gradual and rapid changes in structural damage, however, it cannot separate very close frequencies [47], [48].

In [49], Lamb-wave-based damage identification approaches for composite structures is presented. The authors enhance the ability of the continuous wavelet transform in feature extraction from vibration signals. Composite damage monitoring rises as the top priority problem of SHM. Lamb wave method is very sensitive for small damages (crack or delamination). In addition Lamb wave is able to be propagated for a long distance without significant amplitude attenuation in plate structures. However, the phenomenon of dispersion and complicated transition, are hard to be analyzed and interpreted. Lamb wave is unavoidably affected by interferences and strong noise. It requires more precise and advanced signal processing and feature extraction techniques to identify damage information.

2) Damage Localization Methods: Once structural damage has been detected, it is then necessary to determine the damage's location. This process is called damage localization, which requires the installation of enough sensors such that sufficient sensor coverage is provided to locate damage anywhere in the structure. Insufficient sensor coverage can result in damage detection without localization. Commonly used damage localization techniques are frequency-based [50], mode shape–based [50], flexibility matrix based [51], [52], stiffness matrix based [53], and support vector machine based [54]. A taxonomy illustrating the different damage localization methods can be seen in Fig. 3.

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 [50] both frequency-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.

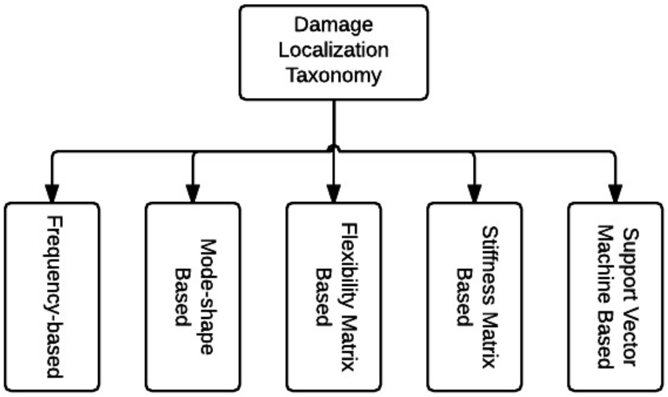

Fig. 3. Damage Localization Taxonomy.

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 [50], [55]. In addition, exploiting mode shapes for damage classification may be ineffective since damage is local and may not affect the shapes of lower modes [50], [56].

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 [51], the flexibility-difference method of damage detection is proposed. Damage is localized through computing the change in flexibility between the undamaged structure and 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 used in [52] 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 [57].

The stiffness approach to damage localization uses a structure's stiffness matrix. The stiffness matrix and flexibility matrix can be inverted from one another [58]. 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 [53], a stiffness matrix based damage localization method is used in which the detection of the current stiffness matrix is viewed as a local 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 [58], an approach for damage localization, using both a structure's flexibility and stiffness matrices, is proposed. First, the modal parameters are identified and used in the estimation of a flexibility matrix. The stiffness matrix is then achieved through the inversion of the flexibility 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 [54], SVMs are used to classify structural damage patterns for SHM systems with a minimal number of sensors. Through the use of a single sensor on the roof of a building and a single sensor on the 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 localization accuracy.

III. Challenges in WSN for SHM

In comparison to typical WSNs those designed for SHM face a number a unique challenges. In particular, WSNs for SHM nodes collect, process, and transmit large amounts of data, sensor node densities can be high, and the number of hops from node to base station can be large. In the reviewed literature, real-world deployments of SHM systems have had sensor sampling rates ranging from 100 to 1000 Hz, node densities up to 70 nodes, and the number of hops to traverse the network ranging from 1 to 46 [5], [59]–[61]. In existing SHM systems, delay requirements are low as very long delays can be acceptable for SHM systems monitoring a structure's long-term health. For example, a nine hour delay to collect, process and aggregate data at the base station can be acceptable as long as data transmission is reliable. However, SHM systems designed to monitor a structure's health in the event of an earthquake or other natural disaster could require a much smaller delay. Although delay is generally not a concern, synchronization of sensor nodes is particularly important in WSNs for SHM. Maximum node time synchronization error must be below 120 μs otherwise damage detection and localization becomes impossible due to significant mode shape errors [62]. Lastly, the algorithms used in WSNs for SHM are more complex than those used in other WSNs. SHM algorithms are computationally complex, may require the incorporation of data from other sensor nodes, and usually required centralized processing.

Although the above characteristics are relatively unique when compared to most WSNs, WSNs for SHM have similar reliability and quality of service requirements. Data transmission is expected to be reliable and lost packets must be recovered through retransmission. Packet loss rates can be high in monitored structures as transmission may require wireless propagation through materials such as concrete and steel [9]. Sensor nodes deployed on structures such as bridges and wind turbines must withstand harsh weather conditions such as rain and snow. WSNs for SHM have similar quality of service requirements to normal WSNs except, as discussed above, network time synchronization errors must be minimized.

The remainder of this section discusses the unique challenges associated with WSNs for SHM. Section III-A discusses the challenge of developing scalable WSNs for SHM and outlines several techniques that have been used to improve network scalability. Section III-B discusses how to minimize or mitigate time synchronization errors in WSNs for SHM such that damage detection and localization is possible. Section III-C introduces the sensor placement optimization problem and discusses numerous algorithms and the network parameters these algorithms optimize. Section III-D discusses energy efficiency in WSNs for SHM and discusses techniques. Section III-E discusses the usage of cluster-based and distributed processing in WSNs for SHM highlighting the advantages and disadvantages of the relevant techniques.

A. Network Scalability

Scalability is a network's ability to grow in size while continuing to provide a quality of service that meets application requirements with an acceptable complexity. Ensuring scalability is particularly challenging in WSNs for SHM due to the sheer quantity of data collection and transmission required for effective damage detection and localization. As SHM systems are applied to larger and larger structures the number of hops and nodes needed to monitor the structure successfully will continue to increase. Even in a SHM system for a fixed size structure increasing node density, to a point, will improve the system's ability to detect and localize damage. These factors makes the development of scalable WSNs for SHM a priority. Factors such as data transmission rate, data storage availability, power consumption, time-synchronization error, and processing algorithms all affect a network's overall scalability. In general, factors such as the chosen processing algorithm and data storage affects data transmission rate and vice-versa. As discussed above, a network can successfully scale as long as the maximum network node time-synchronization remains below 120 microseconds [62].

In [63], a WSN for SHM is proposed with one of the objectives being the design of a scalable architecture. The proposed architecture consists of a base station and several nodes controlled by the base-station through a master-slave relationship. This architecture improves scalability by ensuring a minimal time-synchronization error and limiting data transmission through the network. The time-synchronization error of network nodes is minimized through the use of a wireless synchronization module based on IEEE 802.15.4. In this module the server is responsible for ensuring that network nodes have a minimal time synchronization error. In the proposed system sensor data transmission is minimized by only transmitting log files containing information about the sensor data stored on a given network node. If the data is required, it can be requested from the sensor node by the base station using the information provided in the log file. As a consequence of only transmitting log files, damage detection and localization is not an ongoing process but one that is performed when the base station deems it necessary. In addition, network nodes require ample storage such that sensed data is not discarded prior to requests from the base station. A similar strategy to that used in [63] of delaying data transmission is investigated in [7]. The authors propose a distinction between WSNs for short-term (a few hours) SHM and WSNs for long-term SHM. In WSNs for short-term SHM it is proposed that the WSN should be focused on minimizing time-synchronization error between nodes and dedicate all available wireless resources to this task. Instead of transmitting sensed data, all collected sensor data is stored in the node's memory such that it can be retrieved later. Without having to transmit data, sensor sampling rates can be greatly increased improving damage detection and localization accuracy.

Network design decisions such as the distribution of processing between network nodes can improve overall network scalability by increasing communication efficiency. By performing most or all of the processing in network as opposed to at the base station, the amount of data transmitted through the network is reduced. In [64], an algorithm called ACF-CCF is proposed to detect and localize structural damage. The autocorrelation function (ACF) component of this algorithm computes the auto-correlation function locally and, if damage is detected, transmits the result to a paired sensor node which then calculates the cross-correlation function (CCF). This method minimizes data transmission and power consumption by performing most of the processing at the sensor nodes and then only transmitting data to its paired node if damage is detected. This technique is similar to cluster-based processing except two nodes are paired together instead of in a cluster-based processing system where one node is responsible for collecting data from a number of other sensor nodes. In [7] processing is distributed across multiple network nodes through transforming the ERA algorithm from a centralized processing technique to a cluster-based processing technique. It has been shown that local and cluster-based processing techniques improves network scalability by reducing data transmission [65], [66]. Additional details about the challenges of distributed processing and clustering is discussed in Section III-E below.

The use of hierarchical network architectures improves overall network scalability [67]. The proposed network improves scalability by using a multi-level time synchronization approach. By synchronizing the base station with cluster-heads and then ensuring cluster-heads handle synchronization of cluster sensor nodes, network scalability is improved. Additional details about how to mitigate the high time-synchronization error requirements are discussed in Section III-B below. Compressions algorithms can also improve overall scalability by reducing the amount of transmitted data [68], [69] and, consequently, reducing the amount of time consumed by data aggregation.

In conclusion, progress has been made in improving the scalability of WSNs for SHM. Increasingly, WSNs for SHM improve scalability by reducing data transmission. Data transmission can be reduced by storing data until it is needed or by reducing the amount of transmitted data through compression and alternate processing techniques. Finally, improvements in techniques that improve time synchronization of denser sensor node networks ensures larger WSNs can still detect and localize damage. Going forward, these techniques should be

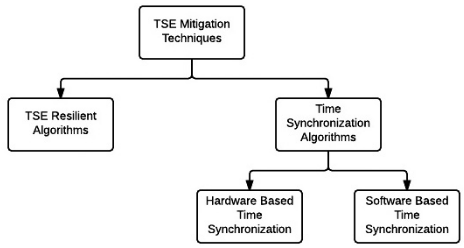

Fig. 4. Classification of TSE Correction Techniques.

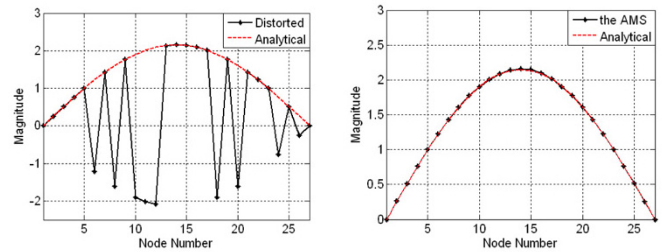

Fig. 5. Mode Shape Adjustment. a) before adjustment b) after sign adjustment [72].

applied to denser WSNs deployed over larger structures such that the limitations of existing techniques can be identified.

B. High Synchronization Requirements

In WSNs time synchronization has been considered an important research area over the past decade [70]. In SHM a lack of synchronization between sensor nodes introduces errors in modal parameter estimation, damage detection and damage localization. In particular, WSNs for SHM need precise time synchronization due to extensive sensor data sharing. In [71] factors affecting time synchronization error (TSE) were identified as clock synchronization errors, non-simultaneity in sensor start-up, differences in sampling frequency and non-uniform sampling intervals. Overall, the relationship between a sensor's clock and a reference clock can be mathematically described as [72]:

$$t_i = (1 + \alpha)t + \delta t_i \tag{1}$$

where t_i is the node clock, α is clock drift rate, δ is the initial clock offset and t is the reference clock time. It was found in [33] that the maximum measured clock drift was 50 μs and, for short packets, the clock drift can be neglected simplifying the above relationship to:

$$\mathrm{t_i} = t + \delta \mathrm{t_i} \tag{2}$$

The impact of TSE on modal parameter estimation using the frequency domain decomposition (FDD) method was investigated in [73]. For the FDD method it was shown that the introduced mode shape error is proportional to:

$$e^{\omega t_i} \tag{3}$$

where ω is the structure's modal frequency and $\mathrm{t_i}$ is the TSE. Conducted experiments showed that even for very small TSEs the mode shape error was significant [73]. Existing research into meeting the high synchronization requirements demanded by WSNs for SHM can be classified into two approaches: the development of TSE resilient algorithms [71], [72] and the development of synchronization algorithms [62], [63], [67], [74], [75]. Synchronization algorithms can be further classified as hardware or software based. The proposed classification taxonomy is presented in Fig. 4. The remainder of this section will discuss existing literature in relation to this taxonomy.

A TSE resilient algorithm is an algorithm that does not attempt to synchronize all sensor nodes and instead attempts modal parameter identification using non-synchronous data. Such algorithms reduce network energy consumption by eliminating or minimizing the use of time synchronization protocols [72]. In [71], an algorithm for computing the PSD using non-synchronous sensor data was proposed. By recognizing that the TSE is a combination of constant time shifts (due to sensor start-up differences) and linear time shifts (due to clock synchronization errors) an algorithm is developed for correcting the Fourier Transform (FT) for each collected segment of sensor data. The corrected FT can then be used in the calculation of the cross-spectral density (CSD) which then allows the application of normal damage detection algorithms. A shear structural model under white noise excitation was simulated and the developed algorithm detected the structure's mode shape with minimal error. A damage detection algorithm using TSE distorted mode shapes (DMS) and absolute mode shapes (AMS) is proposed in [72]. The AMS, as shown in Fig. 5, was defined as the absolute value of the DMS. Damage detection using DMSs is performed through the application of the classical flexibility difference method of damage detection. This damage detection method can be applied because the parameters of the flexibility matrix are the same regardless of the TSE. The classical flexibility difference method is inapplicable for AMS and instead the use of the angle-between-string-and-horizon (ASH) flexibility-based method is used. Using numerical simulations, it is shown that the maximum sampling delay for a simple supported beam was 43.4 ms and for a truss 173 ms. Real-world validation of the results showed a maximum tolerable delay of 107 ms in comparison to 14 ms for standard non-TSE resilient damage detection techniques.

Synchronization algorithms aim to minimize the TSE for all nodes in the sensor network. In [67], the Untethered Time Transmission Mapping (UTTM) synchronization algorithm is proposed for the usage in a football stadium based SHM system. The network architecture uses clustering with a coordinator mote (CM) governing each cluster-head (CH). Synchronization of collected data requires the collection of three time stamps: the timestamp for the first sample of a packet, the timestamp when the packet was sent, and the timestamp when the packet was received. These time stamps are used to estimate the relationship between the CM clock and the sensor node clock. Analysis of data collected from a football game showed 95% percent of collected data for one of the clusters had less than a 216 μs delay indicating the algorithm's suitability in modal analysis. A similar hierarchy-based time synchronization protocol was used in [75]. In this implementation each sensor node would attempt to synchronize with the above node in the hierarchy through the collection of four different timestamps.

Two other time-synchronization algorithms for SHM using WSNs were proposed in [74]. The first algorithm – applicable if a structure's excitation pattern is known - uses an ARX model to relate the input signal and measured output signal. Based on the relationship between input and output signal the time delay is attained and this delay used to synchronize the given node. The second algorithm uses two output signals and an ARMAV (autoregressive moving average vector) model to find the time delay between the two signals. The offset can be deduced from the time delay improving node synchronization. The UTTM synchronization algorithm, ARX model-based algorithm and ARMAV model-based algorithm can be used in environments without GPS making them applicable for many SHM based WSNs.

Some SHM-based WSNs have considered the use of advanced hardware to improve node synchronization [62], [63]. GPS modules cannot be used at each sensor node as the power consumption would greatly reduce the overall network lifetime. In [62], a hierarchical network architecture for synchronizing sensor nodes is proposed. As shown in Fig. 6, the goal of the design is to develop a tightly coupled system in which all CHs (alternatively called coordinator modes) are synchronized with other CHs and each of the CHs ensures synchronization with each node in the cluster. GPS modules are used to ensure synchronization between each of the CHs while the CHs ensure synchronization with each of the network nodes through the use of a compare-and-capture module in the microcontroller. Experimental results showed that the overall time synchronization error of each node was within 23 μs. The developed architecture is scalable and could be used in large networks due to its distributed hierarchical nature. An alternate hardware based approach is considered in [63]. The proposed system uses an IEEE 802.15.4 -based synchronization module in which a master node in a server controls synchronization of all slave sensor nodes. Synchronization overhead is reduced by calling the physical layer directly from the application layer. Each of the slave sensor nodes are equipped with a feature that detects transmission in the 2.4 GHz band which is used whenever the master node transmits a message. The slave sensor node stores the time at which the message is pulsed. When the slave nodes send information to the master node, these times are included and can be used by the master node to adjust the synchronization of the slave nodes in the future message transmissions.

In conclusion, significant progress has been made in addressing the particularly high time synchronization requirements in WSNs for SHM. The effect of TSE on damage detection have been investigated and, based on the investigations, maximum TSEs have been identified. Research into responding to the challenge of high time synchronization requirements can be classified into TSE resilient detection algorithms and synchronization algorithms. Synchronization algorithms have either been purely implemented in software

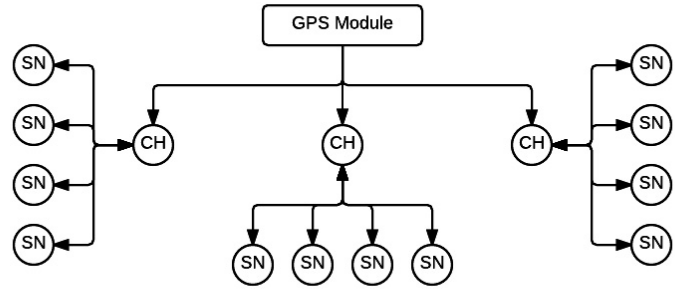

Fig. 6. Hierarchical Sensor Synchronization.

(e.g., UTTM) or have used a combination of software and hardware to improve synchronization between sensor nodes.

C. Sensor Placement Optimization

In structural health monitoring, sensor placement is an important consideration in wireless sensor network design. From a civil engineering (CE) perspective sensor placement determines how effectively the sensors collect structural information. If the chosen sensor locations are poor, the collected information will limit the system's ability to detect and localize damage. From a network design perspective sensor placement affects the network's lifespan, overall connectivity, robustness and routing protocol decisions. The primary challenge in sensor placement in WSNs for SHM is balancing civil engineering requirements and network design considerations.

The sensor placement optimization problem can be formulated as having a set of N potential locations for sensor placement and having a total of M sensors to be placed in those locations (where M<N). Sensor placement should then be selected such that a given set of criteria are optimized. Existing systems have optimized parameters such as the sensed information quality measured by the determinant of the Fisher Information Matrix (FIM), energy consumption, maximum sensing coverage, fault tolerance and network connectivity [76]–[83]. A summary of the algorithms developed for sensor placement optimization in WSNs for SHM is presented in Table II. The sensor placement optimization problem given the constraints of data routing, energy efficiency, and topology control has been shown to be NP-hard [76] and has motivated researchers to apply search heuristics when finding optimal sensor placements. Generally, brute force is not an option as large structures can have hundreds or even thousands degrees of freedom [83]. In [77], genetic algorithms were applied to the sensor placement optimization problem with the objective of optimizing energy consumption and network coverage. The algorithm was applied for a limited number of generations and results indicate reduced energy consumption and increased network coverage. Similarly, in [83] a search heuristic in the form a hybrid discrete firefly algorithm is used. The proposed algorithm was used to effectively optimize sensor placement along a bridge.

Optimization of the determinant of FIM is an excellent indicator of a designed network's ability to meet CE requirements. In general, the FIM can be viewed as the amount of structural information that a given sensor location contributes to the total

TABLE II
SENSOR PLACEMENT ALGORITHMS IN WSNS FOR SHM

Sensor Placement Algorithm	Optimization Metrics
Genetic Algorithm Based [77]	Network Lifespan, Network Coverage
SPEM [78]	Fisher Information Matrix, can select other network parameters
p-SPEM [76]	Network Lifespan, Fisher Information Matrix
TPSP [79]	Network Lifespan, Fisher Information Matrix
FTSHM [80]	Network Robustness, Fisher Information Matrix
Optimal Sensor Placement in Linear Network Topologies [81]	Network Lifespan, Connectivity

amount of structural information available for a given structure. If for M sensors and N locations the determinant of the Fisher Information Matrix is said to be 100% if M is equal to N.

This maximum value can then be used to normalize the value of FIM determinants for cases where M is less than N.

A number of researchers have used the FIM in the optimization of sensor node placement [76], [78]–[80]. Sensor placement using EFI model (SPEM) was one of the first sensor placement algorithms proposed specifically for SHM and implemented two sensor placement methods: Effective Independence (EFI) and Effective Independence Driving Point Residue (EFI-DPR) [78]. This algorithm is capable of optimizing both civil engineering requirements (through the optimization of the determinant of the FIM) and network requirements such as connectivity and power consumption. A modified version of SPEM called Power-aware SPEM (p-SPEM) was introduced in [76]. p-SPEM optimizes first the placement of sensors from a civil engineering perspective and subsequently optimizes the energy consumption for efficient communication. Simulated results showed more than a doubling the lifetime of traditional SPEM placements with additional location quality. This formulation neglected to consider the energy consumption of routing decisions due to such a consideration's added complexity. An iterative sub-optimal algorithm is used that decouples the structural health monitoring requirements from the network requirements. By using this technique, the overall complexity was reduced from $O(N^M)$ to $O(N^4M)$.

The sensor placement optimization problem using FIM was also investigated in [79]. A two-tier hierarchy was proposed with low-end nodes that are resource-poor and high-end nodes that are resource rich. Redundant low-end nodes were also added to the network to improve the network's reliability. Sensor placement was optimized with respect to the FIM determinant and network lifespan. The proposed sensor placement algorithm was called Three-Phase Sensor Placement (TPSP) and placed sensors in three phases with the first phase optimally placing high-end nodes, the second phase optimally placing low-end nodes and the last phase optimally placing redundant low-end nodes. Simulations using data collected from a real building and an implementation in a local tower confirmed that the TPSP matched p-SPEM in overall information quality while achieving a longer lifespan.

In [80], a sensor placement optimization technique called Fault Tolerance in Structural Health Monitoring (FTSHM) was proposed. The objective of FTSHM is to optimize the network's robustness while meeting civil engineering requirements. This is accomplished by identifying repairing points - a point where it is predicted the network will fail in the future – and adding nodes near those points that meet civil engineering requirements. Three different types of repairing points were identified: separable points (a sensor which is the only connecting node for a number of nodes in a cluster), critical middle points (given two nodes A and B, the critical middle point is the node located at the middle of the longest path between these two points in the cluster) and isolated points (a point connected to only one other point in the cluster). Conducted simulations and experiments showed that this method is resilient against node failures while others such as SPEM are not.

The use of network coding in data packet routing and its relationship with sensor placement has been explored in [81] and [82]. In [81], a methodology for optimal placing sensor nodes along linear network topologies such as bridges was considered. This methodology aimed to maximize link connectivity and network lifetime. Both simple packet relay and network coding were considered for the routing of the collected data packets. Through mathematical analysis it was shown that the proposed methodology leads to significant reductions in energy consumption. Likewise, in [82] network coding lead to a significant reduction in power consumption; however, the coding gain varied with sensor placement. A number of different sensor placements were considered demonstrating that sensor placement directly affects network coding gain however, at this time, formal algorithms for optimizing sensor placement in relation to network coding and civil engineering requirements have not been developed.

D. Energy Efficiency

A common constraint faced by all WSNs is a maximum network lifespan due to the limited energy storage available for each sensor node. Complicating the above, in WSNs for SHM it is often not feasible to replace depleted batteries as sensor nodes are often placed in difficult to access locations throughout a structure. In addition, SHM applications require high sampling rates and, consequently, an increase in on-node data processing and transmission. Lastly, in comparison to typical WSN algorithms, SHM algorithms are complex, can require incorporation of data from other sensor nodes, and are generally designed to be processed at a centralized location. These three factors make energy efficiency an essential consideration in WSNs for SHM.

Generally, energy efficiency can be improved in several ways. Radio optimization, data reduction, sleep/wakeup schemes, energy-efficient routing and battery repletion have all been identified as techniques that can be used to extend the lifespan of WSNs [84]. Out of the identified techniques, data reduction is particularly important in WSNs for SHM due to the high volume of data collected and transmitted. Consequently, most research in improving energy efficiency has been focused in this area. Although less researched, sleep/wakeup schemes and the usage of battery repletion techniques have also been investigated in the literature.

In WSNs for SHM significant data reduction can be achieved by distributing processing throughout the network as opposed to centralizing processing at the base station. Although this increases node processor utilization as more cycles must be dedicated to complex computations, significant reductions in the amount of data transmitted makes distributed processing schemes very energy efficient. A comparison between a centralized processing scheme and two distributed processing schemes demonstrated a significant reduction in the amount of data transmitted [61]. In the centralized processing scheme 667 bytes of traffic per second of network operation was transmitted while in the two distributed processing schemes 300 and 28 bytes of traffic per second of network operation were transmitted. These significant reductions are achieved despite increases in the sampling rate of the two cluster-based processing techniques. In the centralized scheme the sampling rate was only in 100 Hz while in the two cluster-based schemes sampling was 560 and 1000 Hz respectively. Additional details about how distributed processing techniques improve energy efficiency and how they affect network layout can be found in Section III-E below.

In [85] an event-based wakeup scheme for monitoring a railway bridge is proposed and implemented. The choice of an event-based wakeup scheme was selected as trains infrequently crossed the bridge and, as a result, the sensor nodes would waste power collecting data from an unexcited structure. In the proposed system there would exist two master nodes and a number of child nodes. These master nodes would be equipped with accelerometers and would wake-up in the event that the measured vibration signal exceeds a specified threshold. These nodes then wake-up the child nodes in the network such that the bridge's structural health could be assessed. In the proposed scheme one challenge is that the time between event detection and child node wakeup must be less than the time it takes for the train to arrive after detection – otherwise data will be missed and the system's efficacy limited. The proposed system is also resilient against false alarms such as humans or cattle crossing the bridge. This is accomplished by having the sensor node only wake-up when the moving average of the vibration signal exceeded the wake-up threshold – preventing a small number of measurements from waking up the network. This resiliency is further increased by spacing the master nodes apart from one another and requiring both master nodes to detect vibrations prior to waking up the rest of the network. One of the challenges of purely event-based wakeup schemes is ensuring synchronicity between sensor nodes [8].

A wakeup scheme combing elements of schedule and event-based wakeup schemes was used in a SHM system for the Jindo Bridge in South Korea [59]. In this wakeup scheme one sensor node is configured as the gateway node, a number are configured as sentry nodes, and the rest are configured as normal sensor nodes. The gateway node has a dedicated power supply while the other nodes are battery powered. In the network, sentry nodes wake up on a preconfigured schedule and measure wind or accelerometer data for a period of time. If the measured data exceeds a specified threshold then the sentry node communicates with the gateway node which proceed to wake up other network nodes. Once all the network nodes are awake they are synchronized and data may be collected. An advantage of this approach is that synchronicity can be more easily maintained as sentry nodes remain synchronized between sleep cycles. This ensures that the overall time-synchronization error in the network meets application requirements. A disadvantage of this scheme over a pure wakeup scheme is the increased energy consumption of the sentry nodes.

The use of coverage-preserving scheduling has been shown to be an effective technique to improve node energy efficiency and, consequently, the network lifespan in WSNs. In coverage-preserving scheduling each node is said to have a coverage area and, at any given time, the combined coverage area of all active nodes must span the network. With this criteria fulfilled, it becomes possible to turn network nodes on and off maximizing their lifespan as the entire network's coverage is maintained. Guo *et al.* [86] discuss how such an approach is not suitable in WSNs for SHM and propose a modified coverage-preserving scheduling scheme. Damage localization requires the cooperation of all of the sensor nodes in the damaged part of the structure and consequently it becomes impossible to define coverage areas for sensor nodes as it is the cooperation of sensor nodes that makes damage localization possible. To rectify this problem, the authors use a two-step strategy for damage detection and localization. Prior to beginning damage detection and localization, the sensor nodes are divided into SHM cover sets and these cover sets are activated and deactivated one after the other. These cover sets are chosen such that it is possible to detect damage in the structure however these cover sets are insufficient to localize damage. The process of detecting damage using these cover sets is the first step of the proposed two-step strategy. The second step of the strategy is that once damage has been detected all sensor network nodes are woke up and data is collected such that damage can be localized. One of the challenges in using this technique is the process of selecting the SHM cover sets. The authors show that the problem of selecting SHM cover sets such that network lifespan is maximized is NP hard. The effectiveness of two methods for selecting SHM cover sets is evaluated: the bounded multi-dimensional knapsack (BMKP) method and a genetic algorithm based solution. The genetic algorithm based solution is shown to be capable of producing results similar to the BMKP solution while taking significantly less time. This technique, although improving the energy efficiency of the network, would still suffer from the problems that typically occur in schedule-based wakeup schemes in WSNs for SHM in that processor cycles are wasted when the structure is unexcited.

Overall, event-based wakeup schemes are well suited to improve the energy efficiency of WSNs for SHM. This suitability stems from the fact that WSNs for SHM only need to collect data during structural excitation. Event-based wakeup schemes perfectly meet these requirements as they the wakeup event can be structural excitation. It is possible for particularly large structures that pure event-based wakeup schemes are unsuitable as the time to wake-up the entire network and time required to synchronize network nodes would be too high such that data can be collected in response to structural excitation. In such a case a wakeup scheme combining elements of schedule and event-based wakeup schemes will be ideal.

Lastly, the usage of battery repletion techniques has recently become a popular research area in WSNs for SHM. Energy harvesting techniques have the potential to greatly improve network lifespan and could allow the lifespan of WSNs for SHM to approach the lifespan of wired sensor networks. The usage of energy harvesting has been identified as an open research issue in WSNs for SHM and is discussed further in Section V-B.

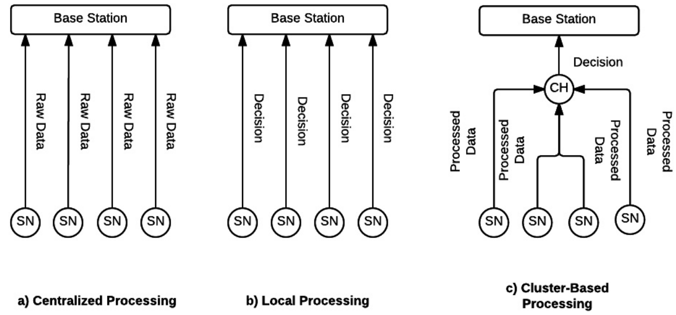

Fig. 7. Network Data Flow for a) Centralized b) Local c) Cluster-based Processing.

E. Clustering and Distributed Processing

A commonly used technique in WSN design is clustering. In clustering, sensors nodes are grouped into clusters and each cluster has a node designated as the cluster-head (CH). In a given cluster, all nodes, except for the CH, can only communicate with the CH. The CH can communicate with all nodes in its cluster and nearby CHs. Clustering improves scalability, simplifies routing, extends the network lifespan and conserves bandwidth [87].

An important consideration in WSNs for SHM is where in the network data processing is performed. In centralized data processing data is transmitted from the sensor nodes to a specified base station (BS) [10], [69]. The BS processes the data and, based on the results, can assess the structure's overall health. In local processing the data is processed locally, a decision about the structure's health is made locally, and the decision is transmitted from the SN to the BS [65]. In clustered WSNs, cluster-based processing can be used. In clustered WSNs, cluster-based processing can be used. In cluster-based processing, some of the processing is done locally, further processing at the CH, and the decision made at CH or at the BS [66], [80], [88]–[92]. The overall network data flow for centralized, localized and cluster-based processing is illustrated in Fig. 7.

1) Centralized Processing: Centralized processing is the data processing technique typically used in WSNs for SHM. This technique is simple to implement and minimizes the processing done at each of the sensor nodes. This technique was used in the design of a WSN based SHM system for the main span and south tower of the Golden Gate Bridge [10]. The system uses a total of 64 sensor nodes, had a total lifetime of 10 weeks and takes a total of 9 hours to complete a single round of data collection transmitting a total of 20 MB of data. The high latency, large amount of transmitted data and short lifespan demonstrates the problems with centralized processing in WSNs for SHM.

The use of centralized processing in SHM was also investigated in [69]. Sensor data was stored in flash memory until all memory was occupied after which data was transmitted from the sensing node to the base station where processing is completed. This system was deployed on a model test structure and results indicated that even with a small number of sensor nodes the data aggregation time was infeasible. The use of data compression to reduce the data aggregation time and the use of local processing to reduce the amount of data transmitted were two methods proposed to reduce overall data aggregation time.

Overall, centralized processing is the least complex processing technique and the easiest to implement. By only collecting data at each network node and routing it through the network on-node processing can be reduced potentially extending the lifespan of each individual node and, consequently, the network. For larger networks and for networks with poor link quality the energy reduction of on-node processing is reduced as nodes must spend a large number of cycles collecting and routing data which could be avoided by performing some of the end-processing prior to transmission. Centralized processing permits the use of all damage detection and localization algorithms and, consequently, can avail of those that are most accurate for a given SHM application. The major disadvantage of centralized processing is an incredibly high delay associated with an incredibly long data-aggregation time. If delay is an issue, such as in application that monitors a structure's health in response to earthquakes, centralized processing should be avoided. If delay isn't an issue centralized processing can be used however the scalability of systems and structures larger than the Golden Gate Bridge needs to be evaluated.

2) Local Processing: One of the challenging characteristics of SHM based WSNs is the large amount of data generated by network sensor nodes. This challenge motivated research into local processing techniques to reduce overall network traffic while maintaining a simple design. Due to a lack of a reference output signal, local processing renders common damage detection methods such as the Natural Excitation Technique - Eigen-System Realization Algorithm (NExT-ERA) method inapplicable [65].

One damage detection algorithm that has been investigated in the literature is the autoregressive-autoregressive exogenous (AR-ARX) method [65]. This method uses pattern recognition to match the structure's current data with the data collected at the beginning of the structure's lifetime. Through this comparison, each sensor calculates a damage sensitivity coefficient which is then used to detect, localize and quantify structural damage. The viability of this algorithm was tested in the simulation of a steel frame structure and it was found that the damage detection and localization method was effective. An advantage of this method over cluster-based processing is that it improves network robustness. By completely localizing processing, the network is made resilient against cases where an important node, such as a CH, fails and results in the loss of connectivity for that entire cluster.

Overall, local processing moves the complexity of damage detection and localization from the base station to the node itself. This improves network resiliency and greatly reduces the amount of transmitted data. An increase in on-node processing that can possibly lead to a reduction in node lifespan. The major disadvantage of local processing is that the damage detection and localization techniques that can be used without input from other nodes is limited and these techniques, such as AR-ARX, tend to be less accurate then techniques such as NExT-ERA [8].

3) Cluster-Based Processing: Cluster-based processing combines elements of centralized and local processing to improve overall network performance. By distributing the processing between each sensor node and the CH, the amount of data transmitted through the network is reduced in comparison to centralized processing and the amount of processing done at each of the SNs reduced in comparison to distributed processing. In general, the primary goal of using cluster-based processing is to reduce the overall energy network energy consumption and improve the scalability. Cluster-based processing permits the usage of damage detection methods that cannot be used in local processing.

The AR-ARX method has been applied in cluster-based processing systems, in addition to the distributed processing systems as discussed above. In [66], a WSN-based SHM system was proposed. This system supplements the AR-ARX method with the random decrement (RD) method [93] and the principle component analysis method [94] to reduce overall energy consumption. The random decrement method compresses the data received at the sensor node by averaging a large number of time segments together into a small average time segment. The compressed data is then transferred from each of the sensor node to the CH. Prior to AR-ARX processing, principal component analysis (PCA) is applied to the combined data set from each of the cluster nodes [94]. PCA extracts only the principle components from the input data set by sorting the eigenvalues of the covariance matrix and then selecting the largest eigenvalues until a specified threshold is reached. At this threshold, it is assumed that the included eigenvalues sufficiently describe the overall dataset. The AR-ARX method is then applied to the post-processed dataset and a decision about the structure's overall health is made. Fig. 8 displays the full algorithm and where in the network the different processing loads are completed. One of the drawbacks of using the PCA method is that it can increase overall energy consumption if the sensor placements within the network and cluster are not properly optimized. Consequently, genetic algorithms were used to converge on a near-optimal solution such that total energy consumption was minimized using this technique. The modified AR-ARX method was then applied in the monitoring of a plate structure and results attained showing an overall reduction in energy consumption.

Another algorithm that has found use in cluster-based processing systems is the Eigen-System Realization

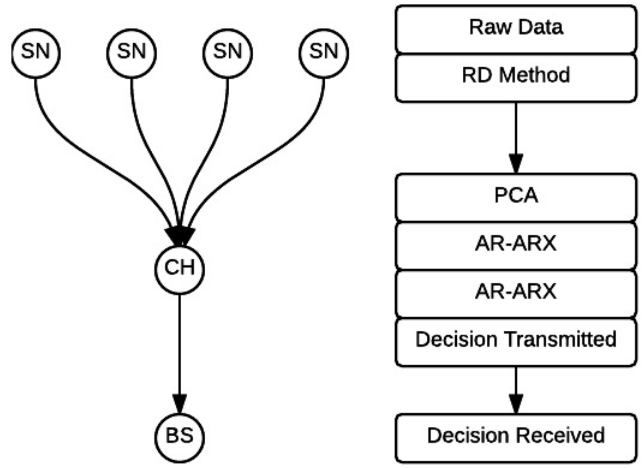

Fig. 8. AR-ARX Method for Cluster-based Data Processing.

Algorithm (ERA). Typically, a centralized processing algorithm, a distributed version of the algorithm with a comparable accuracy to the centralized version has been proposed in [88] and [89]. Instead of aggregating data at the BS, sensor nodes using this algorithm broadcast their data only along the path of the minimum connect dominating set. In the resultant system sensor nodes in a given cluster distribute data to a CH where the CH calculates the power-spectral density (PSD) and cross-spectral density (CSD). The inverse Fourier transform (IFT) is then used to determine the cross-correlation functions and auto-correlation function. ERA then uses these results to determine the overall mode shape. Experimental results for this system were conducted by deploying the sensors nodes in a building. The results showed a 40% reduction in energy consumption and a reduction in system delay in comparison to the centralized processing systems.

Out of all of the techniques used in cluster-based processing systems, the most common is the Fast Fourier Transform (FFT) [80], [90]–[92]. The FFT is used in conjunction with other post-processing algorithms such as the peak-picking (PP) method [80], [90] or power-spectral density (PSD) combined with cross-spectral density (CSD) and SVD [91], [92] to determine the cluster's mode shape and, consequently, whether damage has been detected. The peak-picking method allows extraction of the mode shape at the sensor itself while the use of the PSD combined with the CSD and SVD requires processing to occur at the cluster-head. As seen in Fig. 9, FFT-based systems combine overlapping mode shapes at the CH and then forward these results to the BS. The results from mode shape combination are displayed in Fig. 10. Cluster-based processing can reduce energy consumption through the use of algorithms that turn cluster nodes on and off based on whether damage was detected in the CH [91]. In addition to improving energy consumption, such algorithms can also improve the network's ability to localize structural damage.

One of the typical drawbacks of using cluster-based processing techniques is the degradation of network robustness. In [80] and [90], a technique called Fault-Tolerance in

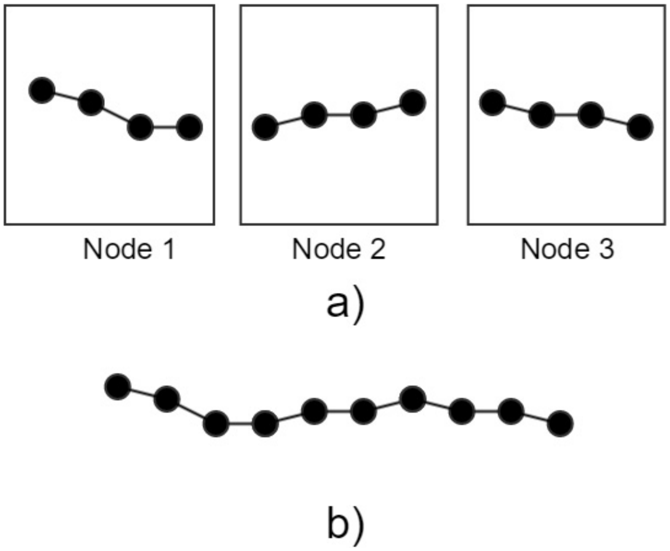

Fig. 9. CH Mode Shape Combination a) Uncombined b) Combined.

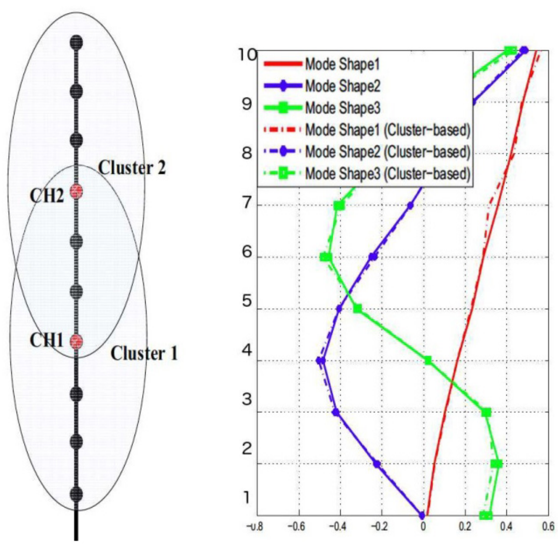

Fig. 10. Computation of Mode Shapes from Clusters [88].

SHM (FTSHM) is proposed. This algorithm detects fault-prone and weakly connected clusters during sensor placement optimization and places backup sensors such that a certain level of fault tolerance is guaranteed. This level of fault tolerance allows the failure of up to a specified number of sensors after which the cluster will fail. FTSHM improves the robustness of the network and, consequently, the network lifetime.

To date, most damage detection and localization algorithms have been developed for wired sensor networks and, consequently, assume that the algorithm will require sensor data to be processed in a centralized location. In [7] the challenge of transforming a centralized processing algorithm to one that can be used in WSNs for SHM is discussed. Unlike most algorithms employed in WSNs, those used in SHM require low level data fusion and, thus, data must be collected from all network nodes before a decision can be made. The authors propose that the development of efficient WSN based SHM algorithms must minimize the amount of raw data transmitted, be implementable on a sensor node, and must match the accuracy of fully centralized SHM algorithms. Based on this, two methods that can be used to try and convert a centralized SHM algorithm to a decentralized SHM algorithm are suggested. The first of these methods, called the divide and conquer approach, generally requires the use of clustering and uses different data aggregation functions depending on the type of sensor node. For example, a sensor node in a cluster would transmit raw data to the cluster-head which would then process the raw data to derive mode shapes. The cluster-heads then combine the derived mode shapes to assess a structure's health. The second method suggests that a given centralized SHM algorithm be modified such that the processing can be done incrementally. In such an algorithm data is collected incrementally and the result updated as new data is collected. The authors suggest that it is easier to develop SHM algorithms for WSNs using the divide and conquer approach however these algorithms are typically less accurate than incremental SHM algorithms. The main drawback of incremental SHM algorithms for WSNs is that they are difficult to develop. These proposed methods should be applied to existing damage detection and localization algorithms such that new SHM algorithms for WSNs can be developed.

Overall, significant progress has been made in the development of cluster-based processing techniques that reduce energy consumption in comparison to both centralized and distributed processing techniques and reduce data transmission in comparison to centralized processing techniques. Cluster-based processing techniques, through data incorporation from multiple sensors, can more reliably detect and localize structural damage then local processing and are similar to centralized processing techniques in their reliability [8]. These benefits come at the expense of overall network robustness since a failure of a CH means a loss of the ability to assess structural damage in an entire region of the network. In addition, cluster-based networks are significantly more complex than both centralized and localized processing networks.

IV. Testbeds and Experimental Work

This section surveys the experimental work conducted by some research teams on WSN for SHM. The surveyed work is divided into laboratory testbed results and experimental results from real structures. The first subsection surveys laboratory testbeds used in WSN-based SHM system. The second section surveys real-world deployment of WSN-based SHM systems and summarizes the overall results.

A. Laboratory Testbeds

Although cheaper and easier to deploy compared to typical wired sensor networks, WSN-based SHM systems are typically tested in a laboratory setting prior to deployment. Consequently, to maximize the efficacy of in-lab testing, testbeds for evaluating proposed WSN-based SHM systems have been developed.

The development of emulation frameworks permits design validation before real-world deployment. In [95], an emulation framework called WiSeREmulator is proposed. This framework allows emulation of both the testing environment and proposed WSN protocols. The emulation framework uses the COMSOL multi-physics software package in the emulation of piezo-electric transducers and wave propagation in concrete structures such that the testing environment can be as closely emulated as possible. Users can configure digital-to-analog converters, set-up networks of up to 25 nodes, and a base station. This framework permits users to synthesize their own data using a data synthesis module and permits signal processing through a signal processing module. A graphical-user-interface (GUI) has been developed to simplify simulation setup. Experiments conducted on a simple beam structure matched the results produced from this framework.

An alternative to emulation is installation of sensor networks on laboratory test structures such as trusses [60], beams [60], and model buildings [69]. Typically, excitation is applied to these structures through the use of shaking tables or similar equipment such that the structure's natural frequency can be measured [69], [96]. The use of laboratory test structures allows verification of the SHM system prior to real-world deployment however they cannot be used to model real-world deployment as they cannot emulate real-world electromagnetic interference and are typically quite small in size.

An alternate method for testing WSN-based SHM would be the development of a real-world environment for the test deployment of designed systems. In [97], the shortcomings of brief real-world deployments are discussed. The short deployment time, although providing valuable data, is generally insufficient in evaluating in the long-term performance of a network design. The idea of an over-provisioned testbed is proposed in which sensing nodes are provided a direct power supply (while emulating SHM behavior) and wired communication channels are available for application debugging.

B. Experimental Work With Real Structures

To date, most real-world systems have been designed and implemented on bridges around the world. These systems have had varying designs and objectives but have shown the efficacy of SHM using WSNs [10], [59], [98]. Aside from bridges, a number of other structures including football stadiums, buildings, and wind turbines have had WSN-based SHM systems designed and deployed on them [9], [67], [75], [99].

1) Structural Health Monitoring of Bridges: A large number of WSNs for the structural health monitoring of bridges have been designed and experimentally deployed. Bridge-based SHM systems have been deployed in locations such as Golden Gate Bridge [10], the Jindo Bridge [59], Caihong Bridge [98], and Jinzhou Bridge [98].

In [98], a system for SHM using WSNs called Wireless Multi-Radio-Frequency Channels Inspection (WMCIS) is proposed. The network architecture consists of eight wireless modules each equipped with eight wireless channels. The wireless modules have a modular design and they are equipped with piezo-electric sensors for acceleration measurement, a sensor interface in the form of an analog-to-digital converter (ADC), a microprocessor and a ZigBee based transmission unit. Each wireless module can be programmed and configured over the air and handles tasks such as local data collection. Each of these wireless modules communicates with a wireless controller using the ZigBee protocol. The wireless controller is responsible for coordinating communication wireless modules and managing data collection, storage and analysis. The wireless controller sends structural damage decisions to a PC over a serial connection. This system was deployed on both the Caihong and Jinzhou Bridge in China. The number of nodes in a given deployment can be scaled up or down based on the application requirements. Based on the experimental results it was concluded that the existing system is not suitable for long-term SHM but could be used for temporary SHM deployments.

In [10], a WSN for SHM is deployed on part of the Golden Gate Bridge in California. The overall network architecture consists of sensor nodes and a base station. Each sensor node is composed of a mote and sensor board. The sensor nodes use TinyOS as the operating system for running all processes relating to information dissemination, routing, synchronization, and information collection. A total of 64 sensor nodes were deployed on the bridge and a laptop was used for the central processing unit. The deployment of this system, although effective, demonstrated a number of challenges that must be met by SHM based WSNs. The proposed routing and time synchronization protocols performed as expected in a laboratory setting; however, it experienced difficulties during the real-world deployment. When first deployed, heavy network traffic initially caused interference with the software's routing protocol. The exact cause of this breakdown was unknown at the time but was resolved by freezing the routing tree during data collection. The system's lifespan was 10 weeks and data collection experienced a 9 hour delay. Despite difficulties, this deployment was particularly important due to the long length of the Golden Gate Bridge (2.7 km).

In [59] a SHM system using WSNs was deployed on the Jindo Bridge in South Korea. This bridge also hosts a wired SHM system that was used for verification. A total of 70 sensor nodes were deployed and solar panel based energy-harvesting systems installed on a small subset of them. The bridge length was 484 meters making single hop communication between nodes and the base station possible. The WSN based system's results were in agreement with those from the wired system validating the proposed design. The system lifespan when using three D-cell batteries was estimated to be about two months and the energy-harvesting system found to extend the sensor lifespan for most of the sensors in which the system was installed.

2) Structural Health Monitoring of a Football Stadium: A WSN-based SHM system for usage in a football stadium was designed in [67]. The proposed network architecture is a single-hop two-level WSN with each cluster containing 8 to 10 sensor nodes. Each sensor node transmits data packets to the cluster heads which, as needed, communicate with the base station. The proposed system was installed in a football stadium and could estimate whether a structure was experiencing torsion. The proposed system was capable of maintaining high time synchronization and accuracy; however, details such as network lifespan were not provided.

3) Structural Health Monitoring of Buildings: In [9], a SHM system using WSNs was designed and tested on two real world structures: a seismic test structure and an abandoned office building in Los Angeles. The designed system, called Wisden, was designed with ease of deployment as the primary goal with each experimental deployment taking around 30 minutes. Deployment results showed that real-structures are heavily damped and, consequently, have a structural response lasting about 1 second. The short structural response duration suggests that high sampling rates are needed for SHM systems where excitation is sudden and infrequent. The first deployment, in the seismic test structure, encountered no difficulties however the deployment in the abandoned office building encountered high packet loss rates on some of the sensor node links. These results indicate the importance of real-world deployment of SHM systems in validating system performance.

WSNs for SHM have also been applied to the monitoring of heritage buildings [75]. Torre Aquila is a 31 meter tall medieval tower in Italy and the structure is of historical significance. The proposed system used a total of 17 sensor nodes (16 monitoring nodes and a sink node) with each node equipped with a 32 Kbyte FRAM chip and running TeenyLime, a WSN middleware, on top of TinyOS. FRAM chips were used instead of flash memory due to the chip's low latency and low energy consumption. Sensor nodes either measured the acceleration, environmental conditions such as temperature, or the structure's deformation. TeenyLime allowed code reuse between the three different sensor types and simplified application development. The system was deployed in Torre Aquila and results indicated that the system was reliable with a loss rate below 0.01% and had a lifespan of 3.2 months before the first node failed.

4) Structural Health Monitoring of Wind Turbines: The application of WSNs for the SHM of wind turbines is discussed in [99]. Three different SHM systems using WSNs were installed: two on Vestas wind turbines and one on a Micon wind turbine. The sensor network nodes were distributed vertically along the structure and data was communicated to a server at the turbine's base. The deployments verified the applicability of WSNs for the SHM of wind turbines demonstrating that the electromagnetic interference of the turbine's electrical equipment was minimal and that the structure's modal frequencies could be identified at the base station.

V. Open Research Issues

Through confronting the previously identified challenges WSN-based SHM have demonstrated their potential as an alternate platform for SHM systems. Existing solutions have begun to meet application requirements and further real-world deployments should provide valuable information such that existing systems can be improved. A number of research opportunities have the potential to radically change

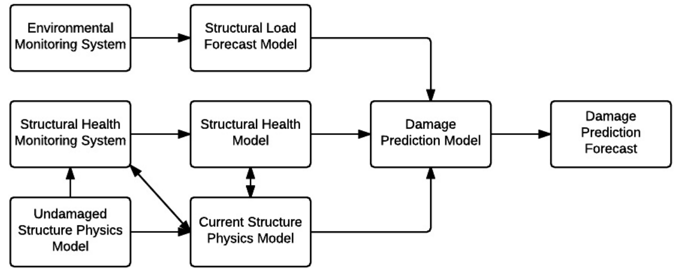

Fig. 11. Structural Damage Prediction Process.

WSN-based SHM. The main open research issues are discussed below.

A. Damage Prediction

Existing WSNs for SHM can assess a structure's current health such that once damage is detected corrective actions can be undertaken to prevent structural failure. Damage prediction, alternatively known as damage prognosis, is a concept that describes SHM systems in which the time of a structure's failure is forecasted such that corrective action can be planned ahead of time [100].

In [100] the damage prognosis problem and the requirements for an SHM monitoring system are discussed in detail. A successful damage prediction model, illustrated in Fig. 11, would require the assessment of the structure's current health, a forecast of the structure's load, and a physics model for the given structure. The structure's health and associated physics model would be developed through systems similar to the structural health monitoring systems that exist today. The development of a load forecast would require the collection of environmental information such as the types of wear experienced by the system and the frequency of such events.

Such an SHM system would pose additional challenges when deployed over WSNs. The assessment of a structure's environment and, consequently, the development of a predictive loading model for that structure would likely require the sensing of additional data and consequently additional data collection, aggregation and processing. The predictive model itself would further increase networking and data processing requirements.

B. Energy Harvesting (EH)

WSNs have been historically powered by batteries and, as a result, the limiting factor in their overall lifespan has always been the battery lifetime. It was shown in [4] and [76] that the battery lifetime in WSNs for SHM can be extended up to 6 - 18 months depending on the energy management techniques and the battery types, while the hardware can last for several years. Therefore, energy harvesting techniques are needed to extend the WSN lifetime to several years. Consequently, research has been concentrated on maximizing battery lifetime through optimizing routing, sensor placement and scheduling. Cost reductions in EH systems has motivated research into the use of such systems in WSNs [101].

Therefore, EH enabled WSNs for SHM could greatly improve network lifespan [102].

Wireless sensor networks can be classified according to their power sources into three categories: fully battery powered WSNs (FBP-WSNs), partial energy harvesting WSNs (PEH-WSNs), and full energy harvesting WSNs (FEH-WSNs). FBP-WSNs have lifespans limited by their battery lives and, as a result, the primary method to extend network lifespan is through minimization of power consumed during node tasks such as scheduling, processing and routing. PEH-WSNs have lifetimes that are still limited by their battery lives; however the EH system can extend network lifespan. Finally, FEH-WSNs have sufficient energy storage such that the network lifespan is no longer limited by battery life but instead by hardware lifespan. In all of the identified categories of WSNs, the key challenge is the development of network architectures that maximize resource utilization. The remainder of this section will discuss maximization of resources for each of the proposed categories and then discuss the application of EH systems to existing WSNs for SHM.

1) FBP-WSNs: Most existing WSN-based SHM systems fall in the category of FBP-WSNs. FBP-WSNs maximize the network lifespan through the minimization of energy consumption. This is accomplished through energy efficient routing protocols, minimization of data transmission, minimization of data processing and sleep cycling. The minimization of energy consumption can conflict with other network objectives such as low TSE, robustness and scalability.

2) PEH-WSNs: The use of energy-harvesting in WSNs can extend overall network lifespan. Such networks introduce the energy recharge rate as an additional parameter that should be considered in network design. Network architectures could choose to neglect energy recharge rate and just use existing network designs with the energy-harvesting solely extending network lifetime. Alternatively, network architectures could choose to consider energy-harvesting as an additional parameter in the development of routing protocols, data transmission and scheduling.

3) FEH-WSNs: Once the energy harvesting rate is sufficiently high and the energy storage capacity is large enough that nodes can be powered solely from the EH system, a network can be considered a FEH-WSNs. These networks open up the possibility of using routing techniques that attempt to optimize for other Quality of Service parameters than energy consumption. In addition, due to variable network of EH systems, it is possible for sensor nodes to be dynamically added and removed from the network once they have sufficient energy for communication.

4) SHM Using EH-WSNs: To date only a small number of WSNs for SHM have employed EH systems to extend network lifespan and optimize network design. Most WSNs for SHM are FBP-WSNs. In [98], a WSN for SHM was deployed on two bridges and experimental results suggested that the overall network architecture was suitable for short-term monitoring but not for long-term monitoring. The network's short lifespan was primarily due to the short battery life. Similarly, in [59], an SHM system using WSNs was deployed on Jindo Bridge, South Korea with the overall bridge lifespan estimated to be only two months. A small number of sensor nodes were equipped with solar-panel based EH systems and rechargeable batteries and it was estimated that the usage of such EH systems could expand the network lifespan to one year. These results indicate the potential for EH systems in WSNs for SHM.

In [103] an EH system for the SHM of highway bridges is proposed. The proposed system uses traffic vibrations as an energy source and the system aims to be a FEH-WSN, at least in the short term. A week long deployment was completed showing that the energy source is sufficient to power SHM based WSNs. The performance of the system in regards to damage detection and localization is not discussed. In [104] self-powered sensors for SHM bridge monitoring were developed and tested. The developed sensors converted ambient vibrations into electromagnetic energy. A field test was completed in which the self-powered sensors on a rural highway. The sensors were shown to be self-powering even during periods of low traffic.

The introduction of EH in WSNs for SHM will require re-addressing many of the design considerations discussed in Section III. Many important factors in EH WSNs for SHM such as optimal sensor placement, optimal routing protocols, and data processing location have not been investigated in experimental work.

C. Mobile Phone Sensing (MPS) for SHM

MPS is a new sensing paradigm for information collection through mobile devices and smart phones. Most mobile devices and smart phones are equipped with several sensors such as accelerometers, global positioning system (GPS), cameras, microphones, and proximity sensors. While mobile devices move around, they can sense and detect different physical parameters and phenomena, which can have many applications such as vehicular traffic monitoring, environmental monitoring, wireless signal coverage, and event/incident coverage. In SHM, while people cross a bridge or exist inside a building, mobile apps downloaded in their mobile devices and smart phones report the sensed data (mainly about structure vibration and acceleration) to a central processing unit. The central unit performs further processing to evaluate the structure conditions.

Although MPS has high potential and brings many opportunities as mentioned above, MPS comes with several challenges [105], [106]. The first challenge facing MPS is the large-scale of MPS resulting in a huge amount of data traffic, which may overwhelm the network resources. Therefore, some techniques must be employed to reduce the amount of traffic. This can be achieved by local data aggregation and processing at mobile devices and smart phones. The second challenge is the data accuracy. Mobile devices and smart phones are equipped with different types of sensors from different manufacturers; hence, sensors vary significantly in their sensitivity and noise. Thus, there is a need to improve the data accuracy by identifying devices that are likely to produce accurate sensed data, performing global centralized data aggregation, and taking into consideration the spatio-temporal mobility patterns of the users of the mobile devices and smart phones. The third challenge is the availability of adequate number of participants for the required application. Hence, incentive strategies, such as monetary or credit rewards, can be employed to increase the user penetration in [106].

MPS can utilize the large number of mobile devices and smart phones equipped with different types of sensors (e.g., accelerometers) and existing/moving in/on almost all buildings and structures. The advantage of using MPS for SHM is the low cost and minimum effort needed to collect information about hundreds of thousands of structures and buildings.

Experimental work has been conducted and reported in [107]–[109] for using mobile phones as sensors for SHM. The accelerometers in these phones are used to monitor the bridge vibrations. Mobile apps are used to sense and record the vibration signals. Then, the vibration signals are analyzed using damage detection techniques described earlier. However, these studies used a fixed mobile phone (by attaching the phones to the bridge). Thus, many important factors such as phone mobility, spatial and temporal correlation of the vibration signal, and undesired vibration sources have not been investigated in these experimental works.

D. Large-Scale WSNs for SHM

As mentioned above, WSNs for SHM can generate huge amount of data, especially when they are used to monitor large structures. This creates challenges in collecting, analyzing and storing data from thousands of sensors deployed on the large structure [110]. It becomes even more challenging when WSNs and MPS are used for SHM across a city, which might be needed for instance, after natural disasters such as earthquakes, floods, and Tsunamis.

Conventional data gathering, aggregation, fusion, compression, storage, and feature extraction are shown to be inefficient and too expensive to handle huge amounts of data from large-scale WSNs [110], [111]. Therefore, new technologies such as Big Data and Cloud Computing are good candidates for large scale WSNs and MPS for SHM. Big Data techniques such as Big Tables, Hadoop and MapReduce [112] can be used to facilitate the data processing and storage of large-scale WSNs for SHM.

Cloud computing is a good candidate for data collection, processing and storage in large-scale WSNs and MPS for SHM. On the other hand, mobile sinks and unmanned aeronautical vehicles (UAV) represent good candidates for collecting data from large-scale WSNs [113] as in large structures or large number of structures across a city.

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.

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