Recent advances in wireless sensor networks for structural health monitoring of civil infrastructure

Xiao Yu[1], Yuguang Fu[2*], Jian Li[3], Jianxiao Mao[4], Tu Hoang[5], Hao Wang[6].

[1] School of Civil and Environmental Engineering, Nanyang Technological University, Singapore

[2] School of Civil and Environmental Engineering, Nanyang Technological University, Singapore

[3] Department of Civil, Environmental and Architectural Engineering, The University of Kansas, USA

[4] School of Civil Engineering, Southeast University, China

[5] Palo Alto Research Center, USA

[6] School of Civil Engineering, Southeast University, China

Abstract

Wireless Smart Sensor Networks (WSSN) have seen significant advancements in recent years. They act as a core part of structural health monitoring (SHM) systems by facilitating efficient measurement, assessment, and hence maintenance of civil infrastructure. This paper presents the latest technology developments of WSSN in the last ten years, including ones for a single sensor node and those for a network of nodes. Focus is placed on critical aspects of such advancements, including event-triggered sensing, multimeric sensing, edge/cloud computing, time synchronization, real-time data acquisition, decentralized data processing, and long-term reliability. In addition, full-scale applications and demonstrations of WSSN in SHM are also summarized. Finally, the remaining challenges and future research directions of WSSN are discussed to promote the further development and applications.

Keywords: Structure health monitoring, Wireless sensor networks, Edge and cloud computing, Time synchronization, Full-scale application

1. Introduction

Deterioration and damage of civil infrastructure such as high-rise buildings and bridges pose potentially significant risk to public safety as they can lead to catastrophic hazard such as collapses. Through continuous monitoring, the purpose of SHM is to keep track of structural integrity by assessing structural performance under different loads and identifying any damage or deterioration for a better understanding of its overall conditions. Eventually, SHM helps to prevent catastrophic failures. It can potentially extend the service life of existing structures, significantly reduce maintenance costs and enhance public safety. Wireless smart sensors (WSS) are one of the cornerstones for building efficient SHM systems. Over the past decades, WSS has undergone significant development, and wireless smart sensor networks (WSSN) have been widely deployed for SHM (Lynch et al., 2006). Compared with its wired counterparts, WSSN has several advantages, such as ease of installation and low cost (Sofi et al., 2022). There is no need to deploy complex cables, no cable protection work, and on-board data conditioners can eliminate expensive stand-alone demodulators, not only simple and time-saving but significantly reducing costs. The sensors in the WSSN-based SHM system are untethered and communicate wirelessly, which makes it easy to update, add, move, and replace sensors. The network can be quickly reassembled without interfering with the original data acquisition operation. Accordingly, there is a growing trend to replace the wired sensors with WSSN (Zhou & Yi, 2013). Several state-of-the-art wireless sensors include Martlet (Kane et al., 2014), Xnode (Spencer et al., 2017), Waspmote (Libelium, 2016), G-Link-200 (Microstrain, 2017), and so on.

This article introduces the recent advances of WSSN in SHM in the last ten years (i.e., 2012-2022). In details, the development of several key functionalities in both a single node and a network of nodes are introduced in Section 2. Section 3 summarizes the full-scale applications and performance evaluations of wireless sensors in real structures. Section 4 discusses several critical challenges and future studies. Section 5 is a summary of this paper including recent advances of WSS and WSSN and existing limitations and future expectations.

2. Wireless Smart Sensors in Structure Health Monitoring

This section presents the summary of advancements for wireless smart sensors, with respect to a single sensor node in Section 2.1 and a network of sensor nodes in Section 2.2.

2.1 Advances of key functionalities in wireless smart sensors

Wireless smart sensors typically have three or four functional subsystems: sensing interface, computing core, wireless radio, and actuation interface (for some smart sensor platforms). Deploying a single wireless smart sensor comes with its own set of challenges. The most critical one is the constraints in resources in such edge devices. For example, one major obstacle is the limited battery power. To address the challenge, event-triggered sensing is one of the promising solutions. Meanwhile, some advances have been made to expand the functionalities of traditional WSS, such as multimeric sensing and edge computing. We will discuss the advances of these functionalities in the following subsections, as shown in Fig.1.

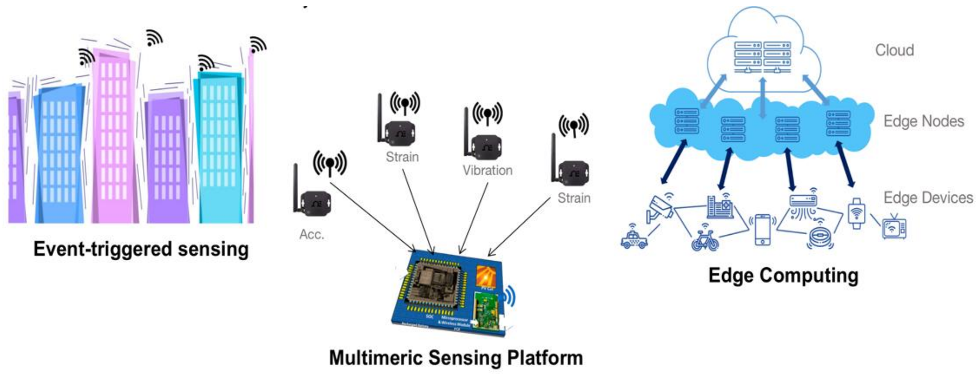

Fig.1 Advances of key functionalities in wireless smart sensors

2.1.1 Event-triggered sensing

Event-triggered sensing is a promising solution for long-term large-scale monitoring systems needed in civil infrastructure, which often face the challenge of power constraints for the deployment of WSS operating on battery power. To address this issue, strategies encompass the optimization of sensor dormancy periods and the schemes focused on duty cycling utilization. Event-triggered sensing and schedule-based sensing are two main mechanisms for wireless data acquisition aimed at enhancing energy efficiency in long-term deployment.

Popovic et al. (2017) proposed an event-driven wireless sensor network for monitoring railroad infrastructure. Sentinel nodes and monitoring nodes were positioned on the tracks to detect train events and sense strain and then went back to sleeping mode, which extended the monitoring nodes' battery life to several months. Sarwar et al. (2020) introduced a design for an event-based sensing system that employs an ultra-low-power microcontroller with a customizable event-detection mechanism, enabling uninterrupted monitoring during a long-term operation. However, both methods face the challenge of missing data due to sensing response latency, particularly for transient structural responses. Fu et al. (2018) created a demand-based wireless smart sensor that serves as a universal solution, built upon Xnodes. This sensor is equipped with a programmable event-based switch that automatically activates and deactivates the high-fidelity sensor platform to prevent data loss. Lin et al. (2021) developed a technique that enables speedy reconstruction of missing data in structural condition monitoring when caused by transmission errors and sensor malfunctions. Fu et al. (2022) developed an intelligent wireless monitoring system that uses ultra-low-power, event-triggered wireless sensor prototypes to enable on-demand, high-fidelity sensing without missing unpredictable impacting events.

2.1.2 Multimeric sensing

In SHM systems, single-metric sensing provides limited information, which limits its ability to address complex problems, e.g., estimating nonlinear residual structural deformation from purely acceleration records. Therefore, multimeric sensing plays a crucial role in providing accurate and comprehensive information regarding complex structural behaviors. Multimeric sensing involves measuring various factors to gather multimeric data, e.g., acceleration, strain, temperature, etc. (2011). It enables comprehensive monitoring of a structure and reduces the number of sensors needed. Sarwar (2020) introduced a device that is activated by vibration, strain, or a timer and has a designated threshold that leads to the minimal power consumption of the sensor node. They expanded on this sensing prototype to make it multimeric event-driven, allowing it to be triggered by both vibration and strain. In order to gather more detailed structural information, it's important to have a wider range of sensing capabilities available for WSSN. This can be achieved through a flexible sensing platform that can integrate different types of sensors. Interface boards may be necessary to convert physical responses into voltage signals, which can then be acquired by the WSSN. Dong et al. (2014) developed the Martlet wireless sensing system with an extensible design that allows the incorporation of multiple sensor boards, collecting structural response data simultaneously from a set of heterogeneous sensors. Additionally, the Xnode sensing platform allows for five external sensing channels, allowing for a broader range of capabilities such as capacitance-based sensing skin for crack monitoring (Taher et al., 2022) and anemometers for wind hazard monitoring (Shaheen et al., 2022).

2.1.3 Edge Computing

One of the most important parts in WSSs is the onboard central processing unit (Lynch et al., 2006). This component provides intelligent capabilities like edge computing, which is an emerging computing paradigm where computation is conducted at the edge of the network to increase efficiency and scalability for rapid data analytics and decision making (Cao et al., 2020). Edge computing has the potential to convert raw data into valuable information by enabling data processing and analysis at the network edge, reducing the workload for WSS, and addressing data inundation (Park et al., 2013). Various studies have been conducted to advance edge computing, including signal filtering and system identification. By processing data onboard, edge computing can improve the performance of wireless sensor nodes. Wireless smart sensors with edge computing face a major challenge due to limited resources including memory space, power supply, and microprocessor speed. These limitations restrict the complexity of applications, particularly real-time ones, as the sensor node can slow down the application process or drain batteries quickly. To overcome these obstacles, various hardware, software, and algorithmic co-design efforts have been made. For instance, Spencer et al. (2017) made significant improvements in Xnodes' computation and concurrent execution capabilities on the hardware side. On the software side, Fu et al. (2016) implemented preemptive multitasking to enhance the efficiency of managing and consuming limited resources in real time. Additionally, Hoang and Spencer (2022) developed a lightweight on-board reference-free displacement estimation algorithm that transforms raw acceleration measurement data, which is 100,000 times faster than the conventional methods.

2.2 Advances of key functionalities in wireless smart sensor networks

After sensing and processing the data within each sensor node, they deliver the data back to the gateway node and further to the end users, which have several challenges for follow-up structural health monitoring applications, such as time synchronization, transmission delay, and data loss. To address them, various improvements have been introduced to enhance the performance of WSSN. Among these studies, significant advancements have been made in the techniques of time synchronization, real-time data acquisition, decentralized data processing, cloud computing, and long-term reliability of WSSN. We will discuss the advances of these functionalities in the following subsections, as shown in Fig.2.

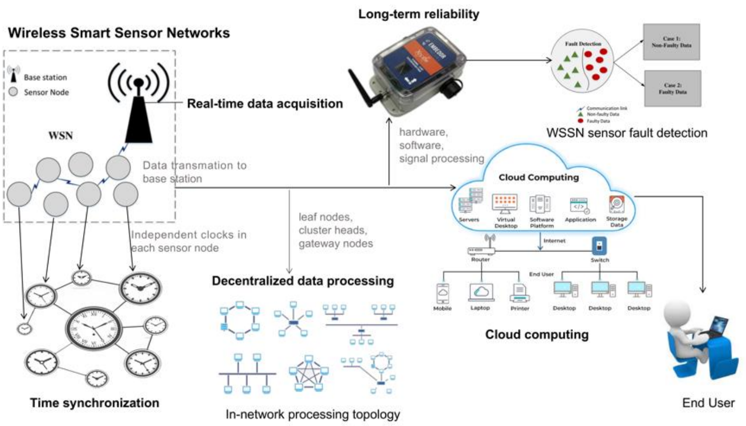

Fig.2 Advances of key functionalities in wireless smart sensor networks

2.2.1 Time synchronization

For data collection from wireless sensor nodes with independent clocks, time synchronization is crucial. Several protocols such as Time-sync Protocol for Sensor Networks (TPSN), Reference Broadcast Synchronization (RBS), and Flooding Time Synchronization Protocol (FTSP) have been developed to address this challenge. Although these protocols can help to ensure synchronized clocks among WSS, uncertainties in software processing time and lowquality crystals can still lead to variations in sensing start time and fluctuations in sampling rates. Additional challenges are also found due to extended sensing duration and temperature variation. These factors can cause synchronization errors in the measurement data, which can potentially lead to inaccurate application results, such as system identification and damage detection (Krishnamurthy, et al., 2008). Nagayama and Spencer (2007) developed a two-stage approach involving linear clock drift compensation and resampling techniques, to achieve data synchronization with an impressive accuracy of 30 microseconds (30 μs). Built upon this strategy, Li et al. (2016) introduced nonlinear clock drift compensation with two implementations to accommodate different radio communication environments. Kim et al. (2016) further implemented a low-cost GPS-based strategy in conjunction with the two-stage method to realize accurate synchronized sensing for spatially large infrastructure monitoring. More recently, by incorporating pre-emptive multitasking and the state-of-the-art real-time operation system, Fu et al. (2021) further improved the protocols to achieve sudden synchronized event monitoring and real-time synchronized sensing through offline and online beacon exchange, respectively. It also presents the comparison between most state-of-the-art time synchronization strategies.

2.2.2 Real-time data acquisition

Wireless data transmission is generally conducted after sensing is completed, which can be time consuming due to potential radio interference and limited bandwidth. It can cause delays in subsequent applications, such as real-time data visualizations and structural control (Linderman et al., 2013). Accordingly, some efforts are made to acquire data in real-time and eliminate transmission delays. Real-time wireless data acquisition faces two primary challenges. Firstly, the sensor node needs to sense and transmit data within a sampling interval, which can cause scheduling conflicts in event-driven operating systems like TinyOS, commonly used in wireless sensors. Secondly, a network of sensor nodes must be able to transmit data lossless to the base station concurrently in a given bandwidth, despite the potential radio interference. Traditional strategies, however, do not fully address both issues; hence they have limited network throughput and are not practical for large-scale sensor networks. To resolve the limitations, Linderman et al. (2013) conducted a comprehensive timing analysis of TinyOS executions and set reasonable sampling intervals to avoid scheduling conflicts and implemented staggered time division multiple access (TDMA) to enable high-throughput real-time data acquisition with a throughput of up to 46kbps. Xiao et al. (2017) proposed a Master-Slave scheme to separate the sensing and transmission in two processors and improved TDMA to achieve the maximum throughput of 86.4 kbps. Fu et al. (2021) implemented pre-emptive multitasking using FreeRTOS on Xnodes to resolve scheduling conflicts and developed adaptive TDMA with real-time time synchronization to increase the network throughput to 115.2 kbps.

2.2.3 Decentralized data processing

Decentralized data processing (aka, distributed computing strategy) is an important aspect for WSSNs. The associated network is organized as three levels, including leaf nodes, cluster heads, and gateway nodes. In each cluster, neighboring sensor nodes work together to process raw data, which reduces data transmission and improves the scalability of sensor networks (Sim, 2011). This concept has been studied for system identification (Sim et al., 2010) and damage detection (Jang et al., 2012). Decentralized data processing faces several challenges, especially related to network topologies. For example, the resource distribution (e.g., power and memory) in the sensor network is possibly nonuniform, and sensor failures may also disturb the functionalities of multi-layer networks. In addition, reliable multi-hop communication should also be considered, especially for large-scale sensor networks. Therefore, to maintain the high performance of decentralized data processing, one should carefully design and reconfigure network topology. Long & Büyüköztürk (2020) proposed a power-optimized and reprogrammable system. This system can remotely allocate sensor nodes' computational operations in a MapReduce-style syntax, ensuring optimal performance of WSSNs. Additionally, sensor network topology reconfiguration has been discussed in the context of sensor failures (Younis et al., 2014). For multi-hop networks, Gao et al. (2019) have created a multi-hop slot segmenting scheduling and multichannel data communication algorithm, which ensures high accuracy of synchronous acquisition. Tronci et al. (2022) proposed a low-power multi-hop wireless sensor network, incorporating synchronized communication and transmission time. In addition, the network utilizes time-division communication, allowing wireless devices to enter sleep mode when not actively required to further save power resources.

2.2.4 Cloud computing

With the increase of WSSN scale and application complexity, it is highly desired to have cloud servers with sufficient resources for large-volume data storage, analytics and management. In the field of SHM, researchers have been exploring the use of software-based database management systems (DBMS) since the early 2000s (Li et al., 2006) and further towards cloud infrastructure for data analytics and visualization (Fraser et al., 2010). However, big data analytics enabled by ubiquitous sensing and cloud computing has several challenges, such as the lack of a systematic framework and practical computation techniques for long-term and/or near-real-time monitoring goals. To address the challenges, Jeong et al (2016) introduced a cyberinfrastructure platform for SHM, that incorporates bridge information modelling (BrIM) and utilizes a NoSQL database. Chang et al. (2018) built a real-time cloud-based system that can receive heterogeneous IoT data, allow users to create a three-dimensional model online as the real-world structure, and visualized the monitoring results in that model. Hoang et al (2020) implemented time-series and relational databases to manage sensor data of a railroad bridge network. Martín et al. (2022) present an Edge/Fog/Cloud architecture for SHM in civil infrastructures, enabling high availability and easy distribution of the components over the architecture. Furthermore, to improve big data analytics efficiency in SHM, parallel computing and machine learning techniques have been increasingly explored recently. For example, deployed on the amazon web server, Khazaeli et al (2016) demonstrated the efficiency of machine learning algorithms for near-real-time damage detection of a ten-story shear building. Dang et al. (2021) present a Digital Twin framework based on cloud computing and deep learning that can perform real-time monitoring and proactive maintenance efficiently. The feasibility is demonstrated via real bridge structures with accuracy of 92%.

2.2.5 Long-term reliability

Long-term reliability in WSSNs refers to the network's ability to maintain consistent and precise operation throughout an extended duration, typically in demanding or adverse environmental conditions. In some SHM applications, wireless sensor networks are deployed in the long term and/or under harsh environments, and the reliability of WSSN is critical. WSSN are often susceptible to issues that can affect their reliability and hence compromise their functionality in coverage and connectivity (Spencer et al., 2016). Such issues mainly include power failures, hardware failures, software failures, and harsh environmental conditions (Mao et al., 2021). The reliability of a WSSN can be assessed on node-to-node communication performance through link characterization (Robin et al., 2011). To enhance network reliability and minimize the occurrence of malfunctions (i.e., sensor failures and sensor faults), advances in hardware, software, or signal processing are highly desired. The hardware improvements include the optimal design of sensor enclosure layouts (Fu, et al., 2019); the software improvements include network power management, self-reconfiguration and self-diagnosis (Liang et al., 2015); for signal processing, data anomaly (aka, faulty data) detection and diagnosis have attracted a lot of attention in recent years (Peng et al., 2017). Zhang et al. (2020) proposed an approach to detect anomalies in time-series status data (e.g., operating voltage and panel temperature), named median filter (MF)-stacked long short-term memory-exponentially weighted moving average (LSTM-EWMA). Poornima et al. (2020) present an Online Locally Weighted Projection Regression (OLWPR) for anomaly detection in WSN. It's a non-parametric method and only uses subset data to perform predictions, reducing computation complexity. Srivastava et al. (2023) proposed a Hybrid Model of One-class SVM and Isolation Forest (HMOI) to flag the anomalous data and its source. The model adopts a 'Classification + Classification' framework, enabling the identification of anomalous data instances and the subsequent tagging of the associated mote-ids belonging to the sensors exhibiting anomalies within the network.

3. Recent Full-scale applications in SHM

The SHM using WSSN plays a vital role in monitoring critical infrastructure such as bridges, high-rise buildings, and stadiums, which holds the significant potential for enhancing public safety and extending the lifespan of these structures (Noel et al., 2017). To ensure that WSS and WSSN prototypes work effectively in real-world scenarios, they must be demonstrated or evaluated on full-scale structures. Even though these devices have been tested in the lab, several practical challenges that are different from the lab setting must be carefully addressed, such as noise levels, data transmission distance, network topology, and signal interference (Zhou & Yi, 2013). This section will summarize the full-scale applications of WSSN in recent years and list them in Table 1.

Phanish et al. (2015) developed a WSSN-based SHM platform, which was deployed at Bobby Dodd Stadium at Georgia Tech. This platform utilized a testbed to gather real-time data during football games and other significant events. By employing this power-efficient, scalable and clustered WSN testbed, the system captured real-time data during sports and major gatherings, allowing for the evaluation of the stadium's structural behavior and its correlation with spectator activities. The sensing devices in the test bench achieved synchronization without relying on GPS or beacons, while still ensuring sufficient accuracy for modal analysis. A cognitive radio backhaul link was developed to establish the communication between WSSN in the stadium and the lab's servers.

Potenza et al. (2015) conducted permanent seismic monitoring of the historic building Basilica S. Maria di Collemaggio using WSSN. This masonry church suffered damage and partial collapse during the L'Aquila earthquake. They deployed 16 accelerometer sensors, 8 extensometers, 3 wall inclinations, and 1 node gateway on the structure. The design, deployment, and performance of sensor networks are specifically for the long-term monitoring of huge masonry structures in earthquake zones. From the perspective of information technology, the paper analyzed the key issues in wireless data acquisition and communication; from the perspective of experimental signal analysis, the acceleration data collected during the three-year seismic monitoring period were analyzed in the frequency domain and time domain. The results revealed the complex interaction between the masonry structure and some temporary protective devices.

Häckell et al. (2016) propose a three-layer algorithmic framework for SHM systems and apply it to an operating 3 kW wind turbine, collecting acceleration and environmental and operational conditions (EOC) data to explore the modularity of the three-layer framework. The wind turbine is installed with six three-axis accelerometers, and six Martlet wireless sensor nodes. In total, 354 datasets were collected from turbines, including lateral acceleration of the tower in two orthogonal directions of six heights, wind speeds, and wind directions; 317 datasets correspond to wind turbines in a healthy state and 37 datasets correspond to wind turbines in a damaged state.

Liu et al. (2016) deployed Martlet nodes on an in-service prestressed concrete highway bridge on dry creek SR113 in Bartow County, Georgia. During the test, a total of 29 Martlet units are deployed and integrated with four types of sensors: accelerometers, strain gauges, strain sensors, and magneto strictive displacement sensors, measuring the bridge's response due to traffic and environmental excitations. The hammer tests were also carried out and acceleration data was collected and analyzed to obtain the modal properties of the bridge. Field test results demonstrate the reliability of Martlet's wireless sensing system.

Using a cable-stayed bridge in Pietratagliata (Italy) as a case study, Baden et al. (2018) conducted a comprehensive experimental verification of the developed wireless MEMS accelerometer. The study was carried out using ten sensors and was designed to acquire and monitor the deformation of the bridge slab. Based on the available MEMS sensors and collected measurements, the dynamic parameters of the bridge were estimated by the Structural Modal Identification Toolsuite software. MEMS accelerometers in the prototype stage offer a reliable way to assess the dynamic characteristics of bridges, demonstrating their potential use in low-cost and practical applications.

Fu et al. (2019) conducted the field test of a pedestrian bridge located in Lake Woods in Mohammed, Illinois to verify the fidelity of data acquisition using Xnode wireless smart sensors. Eight Xnodes were deployed on the bridge, with one serving as a gateway node near the dock and connected to a PC. The remaining seven nodes acted as leaf nodes, positioned on the bridge to measure dynamics bridge responses. Each test is configured with a measurement time of 1 minute, resulting in a collection of 6,000 data points in the longitudinal, horizontal, and vertical directions. Modal analysis using wireless sensor data is performed and compared with that using wired sensor data. The good match of the results demonstrates the Xnode's performance in terms of high-fidelity data acquisition.

Hoang et al. (2020) deployed a Xnode-based wireless monitoring system on a on nine timber trestle and two steel truss railroad bridges in Marion, Illinois, USA, from December 2018 to January 2019. The wireless system recorded 944 datasets that include 419 train crossing events. The system was able to maintain the battery power level readings of above 3.5 V leveraging solar panels, indicating excellent operating conditions in field tests. The research recorded an average reading of 90% battery charge (3.82 V average, 4.0 V when fully charged), which demonstrated efficient use of energy. Records of pier cap accelerations and subsequently estimated displacements were obtained from the WSS. For an initial assessment of the structural condition, control chart analysis using Statistical Process Control (SPC) was applied to peak dynamic displacement measurements.

Luo et al. (2021) applied WSSN to the Hangzhou East Railroad Station. The customized academic WSN system incorporates four distinct sensor types as its measuring components including a vibrating wire sensor node for monitoring strains, acceleration, temperature, and wind load. Each individual multitype sensing module facilitates the seamless operation of these diverse sensors within the network deployed at Hangzhou East Railway Station. The system includes 323 sensors that communicate with each other through a flexible tree-type network. It is used to measure various aspects of the structure during both the construction process and the in-service stage. Data is collected throughout the entire life cycle of the structure to better understand its complex states and internal force redistribution.

Table 1. Full-scale applications of wireless sensor networks for structural health monitoring

Study	Structure	Purpose	Sensors	Measurements	No. of sensor nodes
Phanish et al. 2015	Bobby Dodd Stadium	Verify the accuracy of the new synchronization algorithm	LIS344ALH by STMicroelectronics	Acceleration	40–50 nodes and 5–10 cluster heads
Potenza et al. 2015	Basilica S. Maria di Collemaggio building	Assess a building's response to a real-world seismic event	Accelerometer without specific names	Acceleration	16 sensors
Häckell et al. 2016	Wind turbine	Validate and in-situ test the Martlet wireless sensor nodes	Martlet	Acceleration	6 three-axis accelerometers and 6 Martlet wireless sensor nodes
Liu et al. 2016	Concrete highway bridge	Verify the reliability of Martlet's wireless sensing system	Martlet	Acceleration, strain, and displacement.	29 Martlet units

Baden et al. 2018	Pietratagliata bridge	Verify the original MEMS accelerometer	Accelerometer (Kionix KXR94-2050)	Acceleration	10 sensors
Fu et al. 2019	Suspension Bridge	Verify the fidelity of data acquisition	Xnodes	Acceleration	8 Xnode wireless smart sensors
Tu et al. 2020	Nine timber trestle and two steel truss railroad bridges	Assess the displacement-based condition	Xnodes	Acceleration	2-3 sensors on each trestle bridge 6–8 sensors on each steel truss railroad bridge
Luo et al. 2021	Hangzhou East Metro Station	Monitor station state and internal force redistribution	Various sensor nodes without specific names	Stress, acceleration, wind load, and temperature	323 sensors (49 accelerometers, 100 wind sensors, 174 vibrating wire sensors and temperature sensors in total)

4. Challenges and future studies

Based on the investigations and literature review, several remaining challenges are revealed. In particular, some critical challenges include missing data due to event-triggered sensing, more complexity of the SHM algorithms, limited resources constraining the speed of data processing, needs of high sampling frequency and resolution, etc. Among the challenges, several critical ones are selected and elaborated in the following subsections, including limited power resources, insufficient computing capabilities, and environment vulnerabilities. For each one, future studies are also discussed accordingly.

4.1 Limited power resources

Wireless sensors are usually powered by batteries, which have limited capacity. (Lynch et al., 2006) Once a battery has drained all of its charges, the node becomes inactive or requires manual replacement. Remote replacement of the component can be a costly, labor-intensive, or even impractical endeavor. Although extensive research efforts have focused on power saving and optimization, in many cases, wireless sensor lifetimes are still below the levels needed for intensive sensing applications. Power supply and reservation issue is still considered one of the most important challenges to prevent the adoption of WSSN to replace the wired counterparts in structural health monitoring. This motivates the optimization of the cluster size, utilization of lower-power mode sensor nodes and application of energy harvesting techniques. The most early and widely used energy sources are solar and wind power. (Cao & Li, 2017) However, its discontinuity for energy obtained from nature varies throughout the day and year and is absent sometimes when sensors are deployed in sheltered locations. (Grossi, 2021) Vibration energy harvesting is an alternative effective solution but its applicability is constrained by limitations such as the power generated by traffic-induced vibrations, particularly in the context of low data rate applications for WSN. (Gaglione et al., 2018) Future studies should focus on the development of innovative strategies to harvest energies more efficiently and reliably. On the other hand, adaptively putting WSS into low-power or even deep sleep modes using either rule-based methods or data-driven algorithms are promising to make the power consumption more effective.

4.2 Insufficient computing capabilities

WSSNs are expected to generate large amounts of data in the future, which require sufficient resources to handle big data challenges. Recently, edge computing and cloud computing are being explored by researchers and engineers to transform raw data into information for subsequent informed decisions. However, limited resources in WSSN, such as memory storage space and microprocessor speed, limit the application complexity. It becomes more challenging, if complex algorithms or models, like machine learning, are about to be deployed in the WSSN, in recent years. On the other hand, the limited resources will also compromise the real-time execution performance, e.g., real-time data visualization of massively collected data. In addition, practical computing techniques are also desired to address long-term monitoring goals in full-scale applications. Future studies should be dedicated to the development of prevision and high-efficiency algorithms, strategies, or models suitable for computing in WSSN, with great potential for large-scale data processing and real-time execution. On the other hand, enhancing structural health monitoring capabilities using powerful edge/fog/cloud data architecture, including advanced hardware and flexible software, towards data-driven high-rate computing is another promising direction.

4.3 Environment vulnerabilities

Ensuring reliability in WSSN is a challenging problem due to the harsh environment and sensor vulnerability. Deployed in outdoor conditions, WSSN is susceptible to various natural phenomena, such as rain, snow, wind, thunder, and extreme temperature variation, resulting in frequent and unpredictable errors and accelerating the deterioration of sensor durability. (Mohapatra & Rath, 2020) For example, the strain gauge exhibits readings drift with temperature changes, necessitating the implementation of suitable compensation methods. (Dutta et al., 2021) In addition, WSSN is usually deployed in large-scale civil infrastructures, all sensors transmit measured data to the central location, and signal transmission interruptions make WSSN unreliable. Long-distance transmission as well as dramatically drains sensor batteries, reducing the reliability of the WSSN. Meanwhile, while traditional signal processing techniques can detect and isolate sensor faults, they often require significant human interventions to diagnose and recover them. When anomalous data is detected, differentiating between actual events, and measurement errors poses another challenge. It still lacks an automatic fault detection and localization mechanism, practicable for large-scale long-term deployment. In sum, more efforts should be contributed to the use of advanced signal processing and efficient algorithms/strategies for reliable data collection, sensor fault detection and diagnosis, as well as network topology management and adaptation.

5 Conclusions

WSSN present a promising solution for long-term SHM by offering ease installation and lower costs than traditional wired counterparts. Various recent advances, including event-triggered sensing, multimeric sensing, and edge computing, have extended the functionalities of each sensor node for more complex applications. Likewise, series of technology improvements, such as time synchronization, real-time data acquisition, decentralized data processing, cloud computing, and long-term reliability, make WSSN work smoothly with each other in a timely and efficient manner. Despite of the advancements, there are still some limitations and challenges in wireless sensing technology, such as limited power resources, insufficient computing capabilities, and environment vulnerabilities. Much remains to be done to make this promising technology meet the requirements for monitoring and evaluating complex structures. Interdisciplinary efforts by civil, mechanical, electrical, and computer science engineering researchers are highly encouraged to further improve and facilitate the full-scale deployment of WSSNs.

Acknowledgments

This research is supported by the Ministry of Education Tier 1 Grants, Singapore (No. RG121/21), and the start-up grant at Nanyang Technological University, Singapore (03INS001210C120).

References

Bedon, C., Bergamo, E., Izzi, M., & Noè, S. (2018). Prototyping and validation of MEMS accelerometers for structural health monitoring—The case study of the Pietratagliata cable-stayed bridge. *Journal of Sensor and Actuator Networks*, *7*(3), 30.

Cao, K., Liu, Y., Meng, G., & Sun, Q. (2020). An overview on edge computing research. IEEE access, 8, 85714-85728.

Cao, S., & Li, J. (2017). A survey on ambient energy sources and harvesting methods for structural health monitoring applications. Advances in Mechanical Engineering, 9(4), 1687814017696210.

Dutta, C., Kumar, J., Das, T. K., & Sagar, S. P. (2021). Recent advancements in the development of sensors for the structural health monitoring (SHM) at high-temperature environment: A review. IEEE Sensors Journal, 21(14), 15904-15916.

Chang, H. F., & Lin, T. K. (2019). Real-time structural health monitoring system using internet of things and cloud computing. arXiv preprint arXiv:1901.00670.

Dang, H. V., Tatipamula, M., & Nguyen, H. X. (2021). Cloud-based digital twinning for structural health monitoring using deep learning. IEEE Transactions on Industrial Informatics, 18(6), 3820-3830.

Fraser, M., Elgamal, A., He, X., & Conte, J. P. (2010). Sensor network for structural health monitoring of a highway bridge. *Journal of Computing in Civil Engineering*, *24*(1), 11-24.

Fu, Y., Hoang, T., Mechitov, K., Kim, J. R., Zhang, D., & Spencer Jr, B. F. (2021). xShake: Intelligent wireless system for cost-effective real-time seismic monitoring of civil infrastructure. *Smart Struct. Syst*, *28*, 483-497.

Fu, Y., Mechitov, K., Hoang, T., Kim, J. R., Lee, D. H., & Spencer Jr, B. F. (2019). Development and full-scale validation of high-fidelity data acquisition on a next-generation wireless smart sensor platform. *Advances in Structural Engineering*, *22*(16), 3512-3533.

Fu, Y., Mechitov, K., Hoang, T., Kim, J. R., Memon, S. A., & Spencer Jr, B. F. (2021). Efficient and high- precision time synchronization for wireless monitoring of civil infrastructure subjected to sudden events. *Structural Control and Health Monitoring*, *28*(1), e2643.

Fu, Y., Mechitov, K., Hoskere, V., & Spencer, J., BF. (2016). Development of RTOS-based wireless SHM system: Benefits in applications. Transforming the Future of Infrastructure through Smarter Information: Proceedings of the International Conference on Smart Infrastructure and ConstructionConstruction, 27–29 June 2016,

Fu, Y., Zhu, L., Hoang, T., Mechitov, K., & Spencer Jr, B. (2018). Demand-based wireless smart sensors for earthquake monitoring of civil infrastructure. Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2018,

Fu, Y., Zhu, Y., Hoang, T., Mechitov, K., & Spencer Jr, B. F. (2022). xImpact: Intelligent Wireless System for Cost-Effective Rapid Condition Assessment of Bridges under Impacts. *Sensors*, *22*(15), 5701.

Gaglione, A., Rodenas-Herraiz, D., Jia, Y., Nawaz, S., Arroyo, E., Mascolo, C., Soga, K., & Seshia, A. A. (2018). Energy neutral operation of vibration energy-harvesting sensor networks for bridge applications.

Gao, S., Shang, F., & Du, C. (2019). Design of multichannel and multihop low-power wide-area network for aircraft vibration monitoring. *IEEE Transactions on Instrumentation and Measurement*, *68*(12), 4887-4895.

Grossi, M. (2021). Energy harvesting strategies for wireless sensor networks and mobile devices: A review. Electronics, 10(6), 661.

Häckell, M. W., Rolfes, R., Kane, M. B., & Lynch, J. P. (2016). Three-tier modular structural health monitoring framework using environmental and operational condition clustering for data normalization: Validation on an operational wind turbine system. *Proceedings of the IEEE*, *104*(8), 1632-1646.

Hoang, T., Fu, Y., Mechitov, K., Sánchez, F. G., Kim, J. R., Zhang, D., & Spencer, B. F. (2020). Autonomous end-to-end wireless monitoring system for railroad bridges. *Advances in Bridge Engineering*, *1*, 1-27.

Hoang, T., & Spencer Jr, B. F. (2022). Autonomous wireless smart sensor for monitoring of railroad bridges. *Report# 54*.

Jang, S., Spencer Jr, B. F., & Sim, S.-H. (2012). A decentralized receptance-based damage detection strategy for wireless smart sensors. *Smart Materials and Structures*, *21*(5), 055017.

Jeong, S., Zhang, Y., Hou, R., Lynch, J. P., Sohn, H., & Law, K. H. (2016). A cloud-based information repository for bridge monitoring applications. Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2016.

Khazaeli, S., Ravandi, A., Banerji, S., & Bagchi, A. (2016). The application of data mining and cloud computing techniques in data-driven models for structural health monitoring. Health Monitoring of Structural and Biological Systems 2016.

Kane M, Zhu D, Hirose M, et al. (2014) Development of an extensible dual-core wireless sensing node for cyber-physical systems. In: 2014 sensors and smart structures technologies for civil, mechanical, and aerospace systems, vol. 9061, San Diego, CA, 9-13 March, p. 90611U. Bellingham, WA: International Society for Optics and Photonics.

Kim, R. E., Li, J., Spencer, B. F., Nagayama, T., & Mechitov, K. A. (2016). Synchronized sensing for wireless monitoring of large structures. *Smart Struct. Syst*, *18*(5), 885-909.

Lawal, O., V. Shajihan, S. A., Mechitov, K., & Spencer Jr, B. F. (2023). An event-classification neural network approach for rapid railroad bridge impact detection. *Sensors*, *23*(6), 3330.

Li, H., Ou, J., Zhao, X., Zhou, W., Li, H., Zhou, Z., & Yang, Y. (2006). Structural health monitoring system for the Shandong Binzhou Yellow River highway bridge. *Computer‐ Aided Civil and Infrastructure Engineering*, *21*(4), 306-317.

Li, J., Mechitov, K. A., Kim, R. E., & Spencer Jr, B. F. (2016). Efficient time synchronization for structural health monitoring using wireless smart sensor networks. *Structural Control and Health Monitoring*, *23*(3), 470-486.

Libelium (2016) Waspmote datasheet. Available at: http:// www.libelium.com/downloads/documentation/waspmote_ datasheet.pdf (accessed 31 December 2018).

Lin, J.-F., Li, X.-Y., Wang, J., Wang, L.-X., Hu, X.-X., & Liu, J.-X. (2021). Study of building safety monitoring by using cost-effective MEMS accelerometers for rapid after-earthquake assessment with missing data. *Sensors*, *21*(21), 7327.

Linderman, L. E., Mechitov, K. A., & Spencer Jr, B. F. (2013). TinyOS‐ based real‐ time wireless data acquisition framework for structural health monitoring and control. *Structural Control and Health Monitoring*, *20*(6), 1007-1020.

Liu, X., Dong, X., & Wang, Y. (2016). Field testing of Martlet wireless sensing system on an in-service pre-stressed concrete highway bridge. Health Monitoring of Structural and Biological Systems 2016,

Long, J., & Büyüköztürk, O. (2020). A power optimised and reprogrammable system for smart wireless vibration monitoring. *Structural Control and Health Monitoring*, *27*(2), e2468.

Luo, Y.-Z., Shen, Y.-B., Fu, W., Yun, C. B., Liu, D., Yang, P., Yang, G., & Zhou, G. (2021). Implementation of SHM system for Hangzhou East Railway Station using a wireless sensor network. *Smart Structures and Systems, An International Journal*, *27*(1), 19-33.

Lynch, J. P., & Loh, K. J. (2006). A summary review of wireless sensors and sensor networks for structural health monitoring. Shock and vibration digest, 38(2), 91-130.

Lynch, J. P., Wang, Y., Loh, K. J., Yi, J.-H., & Yun, C.-B. (2006). Performance monitoring of the Geumdang Bridge using a dense network of high-resolution wireless sensors. *Smart Materials and Structures*, *15*(6), 1561.

Krishnamurthy, V., Fowler, K., & Sazonov, E. (2008). The effect of time synchronization of wireless sensors on the modal analysis of structures. *Smart Mater Struct*. 17:1-13.

Mao, J., Wang, H., & Spencer Jr, B. F. (2021). Toward data anomaly detection for automated structural health monitoring: Exploiting generative adversarial nets and autoencoders. *Structural Health Monitoring*, *20*(4), 1609-1626.

Martín, C., Garrido, D., Llopis, L., Rubio, B., & Díaz, M. (2022). Facilitating the monitoring and management of structural health in civil infrastructures with an Edge/Fog/Cloud architecture. *Computer Standards & Interfaces*, *81*, 103600.

Microstrain (2017) G-link-200 wireless accelerometer node. Available at: http://www.microstrain.com/sites/default/files/g-link-200_datasheet_8400-0102_2_0.pdf (accessed 31 December 2018).

Nagayama, T., Sim, S.-H., Miyamori, Y., & Spencer Jr, B. (2007). Issues in structural health monitoring employing smart sensors. *Smart Structures and Systems*, *3*(3), 299-320.

Nagayama, T., & Spencer Jr, B. F. (2007). Structural health monitoring using smart sensors. *Newmark Structural Engineering Laboratory Report Series 001*.

Noel, A. B., Abdaoui, A., Elfouly, T., Ahmed, M. H., Badawy, A., & Shehata, M. S. (2017). Structural health monitoring using wireless sensor networks: A comprehensive survey. *IEEE Communications Surveys & Tutorials*, *19*(3), 1403-1423.

Peng, C., Fu, Y., & Spencer, B. F. (2017). Sensor fault detection, identification, and recovery techniques for wireless sensor networks: a full-scale study. Proceedings of the 13th international workshop on advanced smart materials and smart structures technology,

Phanish, D., Garver, P., Matalkah, G., Landes, T., Shen, F., Dumond, J., Abler, R., Zhu, D., Dong, X., & Wang, Y. (2015). A wireless sensor network for monitoring the structural health of a football stadium. 2015 IEEE 2nd World Forum on Internet of Things (WF-IoT)

Poornima, I. G. A., & Paramasivan, B. (2020). Anomaly detection in wireless sensor network using machine learning algorithm. Computer communications, 151, 331-337.

Popovic, N., Feltrin, G., Jalsan, K.-E., & Wojtera, M. (2017). Event-driven strain cycle monitoring of railway bridges using a wireless sensor network with sentinel nodes. Structural Control and Health Monitoring, 24(7), e1934.

Potenza, F., Federici, F., Lepidi, M., Gattulli, V., Graziosi, F., & Colarieti, A. (2015). Long-term structural monitoring of the damaged Basilica S. Maria di Collemaggio through a low-cost wireless sensor network. *Journal of Civil Structural Health Monitoring*, *5*, 655-676.

Kim, R., Song, J., & Spencer Jr, B. F. (2011, July). Reliability analysis of wireless sensor networks. In *Proceedings of the 6th international workshop on advanced smart materials and smart structures technology ANCRiSST2011* (pp. 1-12).

Mohapatra, H., & Rath, A. K. (2020). Fault-tolerant mechanism for wireless sensor network. IET wireless sensor systems, 10(1), 23-30.

Sarwar, M. Z., Saleem, M. R., Park, J.-W., Moon, D.-S., & Kim, D. J. (2020). Multimetric event-driven system for long-term wireless sensor operation for SHM applications. *IEEE Sensors Journal*, *20*(10), 5350-5359.

Shaheen, M., Li, J., Taher, S., Bennett, C., & Collins, W. (2022). Wind-induced vibration monitoring of high mast illumination poles. Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2022,

Sim, S.-H., Spencer Jr, B., & Nagayama, T. (2011). Multimetric sensing for structural damage detection. *Journal of engineering mechanics*, *137*(1), 22-30.

Sim, S.-H., Spencer Jr, B., Zhang, M., & Xie, H. (2010). Automated decentralized modal analysis using smart sensors. *Structural Control and Health Monitoring*, *17*(8), 872-894.

Sim, S. H. (2011). *Decentralized identification and multimetric monitoring of civil infrastructure using smart sensors*. University of Illinois at Urbana-Champaign.

Sofi, A., Regita, J. J., Rane, B., & Lau, H. H. (2022). Structural health monitoring using wireless smart sensor network–An overview. *Mechanical Systems and Signal Processing*, *163*, 108113.

Spencer, B. F., Jo, H., Mechitov, K. A., Li, J., Sim, S.-H., Kim, R. E., Cho, S., Linderman, L. E., Moinzadeh, P., & Giles, R. K. (2016). Recent advances in wireless smart sensors for multi-scale monitoring and control of civil infrastructure. *Journal of Civil Structural Health Monitoring*, *6*, 17-41.

Spencer Jr, B., Park, J.-W., Mechitov, K., Jo, H., & Agha, G. (2017). Next generation wireless smart sensors toward sustainable civil infrastructure. *Procedia engineering*, *171*, 5-13.

Srivastava, A., & Bharti, M. R. (2023). Hybrid Machine Learning Model for Anomaly Detection in Unlabelled Data of Wireless Sensor Networks. Wireless Personal Communications, 129(4), 2693-2710.

Taher, S., Li, J., Jeong, J.H., Laflamme, S., Jo, H., Bennett, C., Collins, W.N., and Downey, A. R.J. (2022). "Structural Health Monitoring of Fatigue Cracks for Steel Bridges with Wireless Large-Area Strain Sensors. " Sensors, 22(14).

Tronci, E. M., Nagabuko, S., Hieda, H., & Feng, M. Q. (2022). Long-Range Low-Power Multi-Hop Wireless Sensor Network for Monitoring the Vibration Response of Long-Span Bridges. *Sensors*, *22*(10), 3916.

Xiao, H., Lu, C., & Ogai, H. (2017). A new low-power wireless sensor network for real-time bridge health diagnosis system. 2017 56th Annual Conference of the Society of Instrument and Control Engineers of Japan (SICE),

Younis, M., Senturk, I. F., Akkaya, K., Lee, S., & Senel, F. (2014). Topology management techniques for tolerating node failures in wireless sensor networks: A survey. *Computer networks*, *58*, 254-283.

Zhang, M., Guo, J., Li, X., & Jin, R. (2020). Data-driven anomaly detection approach for time-series streaming data. Sensors, 20(19), 5646.

Zhou, G.-D., & Yi, T.-H. (2013). Recent developments on wireless sensor networks technology for bridge health monitoring. *Mathematical Problems in Engineering*, *2013*.