Scientia Iranica A (2018) 25(6), 2913–2925

SCIENTIA IRANICA

Sharif University of Technology

Scientia Iranica

Transactions A: Civil Engineering

http://scientiairanica.sharif.edu

Invited/Review Article

Wireless smart sensors for monitoring the health condition of civil infrastructure

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Received 2 November 2018; accepted 17 November 2018

KEYWORDS

Wireless smart sensor;
Structural health monitoring;
Sensors;
Signal conditioning;
Processors;
Wireless communication.

Abstract. A Wireless Smart Sensor (WSS) has an embedded processor, which is employed for signal processing, communication, and integration capabilities. A state-of-the-art review of recent articles on the WSS technologies employed in Structural Health Monitoring (SHM) is presented in this paper. Different types of WSS and communication technologies are reviewed, and their advantages and disadvantages are pointed out. WSS networks provide a number of advantages for SHM such as robust data management, higher flexibility, low cost, and high potential for providing data for a better understanding of structural response and behavior. Hybrid platforms, fusing different technological platforms, appear to be promising schemes as the strengths of each technology are exploited. Next-generation WSS must consume less power, integrate more with new sensors, have improved noise immunity, and be capable of working with a huge quantity of data without losses produced by wireless communication. Power harvesting based on wind, solar, and structural vibration energy needs to be explored further for a long-term period. Truly smart sensors should have an inherent pattern recognition and machine learning capabilities. Authors advance the research ideology of integrating the sensor technology with recent advances in machine learning technologies.

1. Introduction

According to a 2016 report by the American Society of Civil Engineers [1], the U.S. economy is estimated to lose about $4 trillion in GDP between 2016 and 2025 due to deteriorating civil infrastructure in the nation. This could increase to a whopping $14 trillion by 2040 if no investment is made to improve the decaying infrastructure. Civil structures are vulnerable to damage due to natural hazards such as tornadoes, earthquakes, wind, humidity, among others during their service life. Thence, it is crucial to assess their health condition and structural integrity continuously because any damage identified in its early stage can be repaired economically, thus avoiding or minimizing potentially significant subsequent economic and human losses.

Over the past two decades, Structural Health Monitoring (SHM) has become a key research area in a number of areas such as civil, aerospace, mechanical, and structural engineering with the aim of retrieving behavioral and damage information from the structure in order to estimate or asses its health condition [2-4]. An SHM system has three main components/stages:

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doi: 10.24200/sci.2018.21136

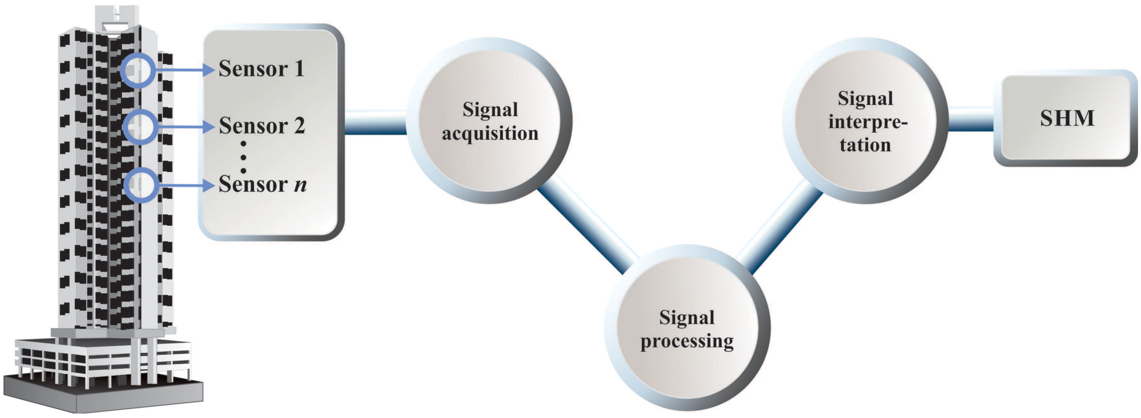


Figure 1. Components of an SHM system.

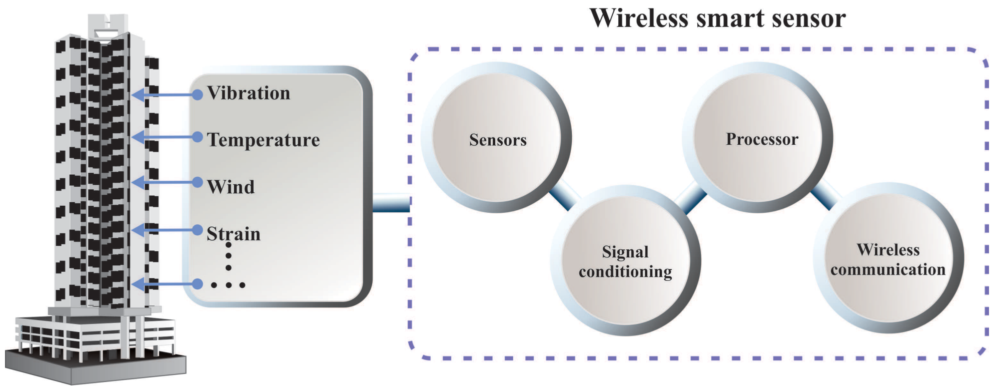


Figure 2. Components of a WSS system used in SHM.

(1) signal acquisition, (2) signal processing, and (3) signal interpretation (see Figure 1) [5]. In the first stage, different types of sensors [6,7] can be employed based on measured quantities of interest (e.g., deformation, displacement, drift, velocity, or acceleration). Further, the sensor signals are passed through a signal condition circuitry in order to store the data in a Data Acquisition System (DAS) for the subsequent stage of processing. In the second stage, the data are analyzed using different signal processing techniques in order to identify and classify features capable of assessing the health condition of the structure. In the last stage, features extracted in stage two are used to determine the health of the structure often employing pattern recognition and machine learning techniques [8-10]. The last two steps of SHM are performed on a personal computer. Sending data from DAS to the computer generates a delay in the evaluation of the structure, which depends mainly on the communication protocol (e.g., USB, RS-232, etc.). In addition, for large structures, a wired system is relatively costly. For these reasons, smart sensors with wireless communication have been investigated in recent years in various civil engineering applications [11] as well as an alternative for assessing the health of large civil structures with two advantages: eliminating the wires and reducing the delays in an SHM scheme. A Wireless Smart Sensor (WSS) has an embedded processor which can be employed for signal processing, communication, and integration capabilities for assessing the structural condition on the same board [12]. A WSS consists of four components: a primary sensor, signal conditioning, processor, and communication (Figure 2).

In recent years, vibration-based SHM has been the subject of numerous research articles [13-15]. Many articles have discussed different signal processing techniques, classifier techniques [16,17], and wireless network topologies employed in SHM [18,19]. Sirca and Adeli [20] presented a review of research on structural system identification [21,22]. Qarib and Adeli [23] presented a review of research on SHM. Amezquita-Sanchez and Adeli [24] reviewed feature extraction and classification techniques for SHM. Amezquita-Sanchez and Adeli [5] summarized recent advances in signal processing techniques for SHM. Perez-Ramirez et al. [25] reviewed time-frequency techniques for modal parameter identification of structures from acquired dynamic signals. This article presents a state-of-the-art review of journal articles on the WSS technologies employed for assessing the health condition of a structure with a focus on civil infrastructure including bridges and buildings.

2. Sensors

Many different types of sensors have been used in SHM for measuring mechanical properties (such as accelerometers, strain gauges, velocimeters, Global Positioning Systems or GPS) and environmental properties (such as temperature, humidity, wind) in civil structures such as bridges and buildings; however, only a few sensors such as accelerometers, piezoceramic-based sensors, strain sensors, and ambient sensors have been deployed into a WSS applied to SHM. The main characteristics of the aforementioned sensors as well as their advantages and disadvantages are reviewed in this section. In addition, some candidate sensors to be employed as smart sensors in SHM applications are also presented.

2.1. Accelerometers

Accelerometers are devices used for measuring the oscillatory movements caused by dynamic and ambient excitations in civil structures such as bridges [26,27] and buildings [10,28]. Three different types of accelerometers have been used in smart sensors applied in SHM: (a) capacitive sensor, which produces an electrical current according to the variation of distance between two fixed plates, (b) piezoelectric sensor, which produces an electrical current proportional to the pressure applied to the piezoelectric material, and (c) microelectromechanical sensor (MEMS), which produces an electrical current proportional to displacement of a small proof mass etched into the silicon surface of the integrated circuit and suspended by small beams. For example, Jindo Bridge, a cable-stayed bridge located in South Korea, was instrumented with smart wireless triaxial MEMS accelerometers with a range of ± 2 g in order to evaluate its health condition under dynamic excitations produced by ambient vibrations such as wind and traffic [29]. Continuing with the aforementioned work, Cho et al. [30] used the data measured by wireless accelerometers for updating the Finite Element Model (FEM) of the cable-stayed bridge. The authors concluded that the natural frequencies identified using the wireless sensors were similar to those obtained using existing wired sensors. Zou et al. [31] instrumented the Songpu Bridge located in Harbin, China with wireless accelerometers. They noted that the natural frequencies of the bridge were not influenced by the data loss in wireless communication.

In 2015, Kohler et al. [32] tested a WSS named ShakeNet, with a uniaxial MEMS accelerometer, in order to estimate the structural response of two buildings, the Millikan Library, a 9-story Reinforced Concrete (RC) building and a 15-story RC building, and the Vincent Thomas bridge located in Los Angeles, California, USA., subjected to ambient vibrations. The authors concluded that wireless accelerometers were effective in estimating the natural frequencies of the three civil structures in the range of 0.25 Hz to 100 Hz. Despite some promising results, most aforementioned wireless sensors have difficulty measuring low-level structural vibration responses, which is the case when a structure is subjected to ambient vibrations. An application of wireless accelerometers for measuring real-time dynamic displacements was reported by Ozdagli et al. [33].

To mitigate the problems found in the aforementioned wireless sensors, recently, a new generation of WSS, named Xnode, has been used for monitoring the health condition of civil structures based on a triaxial MEMS accelerometer from Seiko Epson Corporation model M-A351, which has a high resolution and low noise [34]. In order to validate these features, Zhu et al. [34] tested the Xnode by using a 6-DOF structural model on a shake table and measuring high-level excitations and low-level ambient vibrations.

Accelerometers are shown to be efficient in monitoring large civil structures; however, they present different features according to their operating principle. For example, the piezoelectric accelerometers are small and light, yet are not recommended for measuring low-frequency signals. On the other hand, accelerometers based on capacitive principles can measure a great range of frequencies, mainly low frequencies. Uniaxial accelerometers are often preferred for monitoring the health condition or extracting features of civil structures because structural engineers are often interested in responses in given directions.

2.2. Piezoceramic-based sensors

Piezoceramic-based sensors, made mainly of piezoelectric materials such as lead barium titanate or zirconium titanate (PZT), produce an electrical current when they are subjected to a stress or a strain field (this effect allows them to be used as a sensor); however, they can also act as an actuator if they are subjected to an electrical field [35]. This characteristic has allowed them to be used for health monitoring of beams [36-38] and a three-level steel frame model [39].

The PZT sensors are inexpensive, small and light. They have been shown to be a good alternative for monitoring the health condition of simple beams and small building structures in a controlled laboratory setting. However, their applicability or efficiency for large civil structures during ambient conditions or extreme dynamic natural events has yet to be verified.

2.3. Strain sensors

Strain Sensors (SSs), such as Strain Gauges (SGs) and fiber optic grating sensors (FBGs), are employed for measuring the deformations of structural elements such as beams, which in turn are used to estimate stresses and identify damage in structures [40]. SGs measure the strain of an object through variance in their resistance value when subjected to an external force that deforms the element or object under consideration. Their benefits include ease of installation, low cost, and high sensitivity to damage; however, their response is susceptible to environmental conditions [41,42]. On the other hand, FBGs work according to the quantity of light passing through the fiber optic, converting the mechanical strain variation into an optical wavelength shift. Their measurements are not affected by the environmental conditions; however, they require a temperature compensator, thus adding to the cost of this technology [43].

Wired SSs have been employed for monitoring the health of different civil structures such as buildings [44] and bridges [45-47]. The cost of wired SSs, however, increases substantially with the size of the structure. In addition, the life of a wired sensor is shorter than that of a comparable wireless sensor due to the environmental conditions, which affect the properties of the wire (e.g., its resistance) resulting in measurement error. As such, a wireless strain sensor allows creating a sensor network capable of monitoring large civil structures with low cost [48]. For example, Hu et el. [49] developed a WSS incorporating a strain sensor for estimating the modal properties of the Zhengdian prestressed concrete highway bridge located in Wuhan, China. The measurements allow updating the FEM for detecting and locating damage in the structure. Moreu et al. [50] installed a wireless strain sensor network for monitoring the responses of a double-track steel truss bridge located in Chicago, USA subjected to train loads. The measurements allow updating the FEM of the bridge. The authors noted that the wireless strain sensors represented a good alternative for monitoring the bridge continuously; however, they required additional investigation in order to observe their behavior under changing ambient conditions.

2.4. Ambiental sensors

An important aspect to consider in the design of an SHM scheme is the estimation of the temperature and wind speed since they can alter the physical properties of structures. For instance, the temperature can produce a change in the member length, thus generating a modification in the stiffnesses and modal properties of the structure [51]. On the other hand, the wind speed can generate an excessive excitation or force in the structure, creating an elevated concentration of stress in various zones of structure that, in certain cases, can produce damage [52,53]. Hence, these ambient variables need to be monitored continuously in order to estimate the mechanical properties of the structures accurately. Jang et al. [29] incorporated an ultrasonic anemometer in a WSS with a high resolution for measuring the velocity of wind applied to Jindo cable-stayed bridge in Haenam, South Korea, located in a zone with several typhoons each year. Hu et al. [49] integrated a temperature sensor in a WSS for compensating the effects of ambient temperature on the estimation of the natural frequencies of the Zhengdian prestressed concrete highway bridge in Wuhan, China. A historical building known as Foz Cŏa Church in Portugal was instrumented with wireless temperature and humidity sensors to remove the environmental influences during the displacement monitoring of the building [54]. Similar works for compensating the temperature effects in long-span and cable-stayed bridges were presented by Yarnold et al. [55]. It should be noted that the environmental conditions affect not only the properties of the structure but also the WSS, resulting in changes in the measurements due to variations in the temperature of the sensor board.

2.5. Vision-based sensors for WSS and SHM

The WSS technology in SHM has focused mostly on sensors that require to be in contact with the elements of a structure, e.g., beams, in order to measure its response; however, they are susceptible to measurement errors due to environmental conditions and a failure in the sensor mounting holder. In recent years, the applicability of vision-based sensors, e.g., cameras, has been investigated for structural system identification [56-58], damage detection [59], and traffic flow prediction [60]. Their advantage is not requiring a physical contact with the structure for measuring its response; however, their results can be affected by the quantity of light present. Their full potentials for WSS in SHM need to be explored further.

3. Signal conditioning

The second stage in a WSS is the signal conditioning which depends mainly on the output that the sensor provides: analog (e.g., current or voltage) or digital. If the sensor output is analog as is the case in many cases of sensors used in WSS (accelerometers, stains, and ambient sensors) for SHM [29,32], the following steps are required to obtain a correct signal for the analysis of the signal in the next stage (signal processing stage) (see Figure 3) [61-63]:

1. *Electrical sensor output:* The sensor output has to be preferably conditioned to a voltage signal in order to be interpreted adequately for the next stage of signal processing. For example, for sensors that provide a current output signal, it is recommended to use an operational amplifier to convert the current to voltage;
2. *Filter and amplification:* This stage has two functions: (1) to eliminate irrelevant signal frequencies (e.g., noise) and (2) to increase the signal amplitude

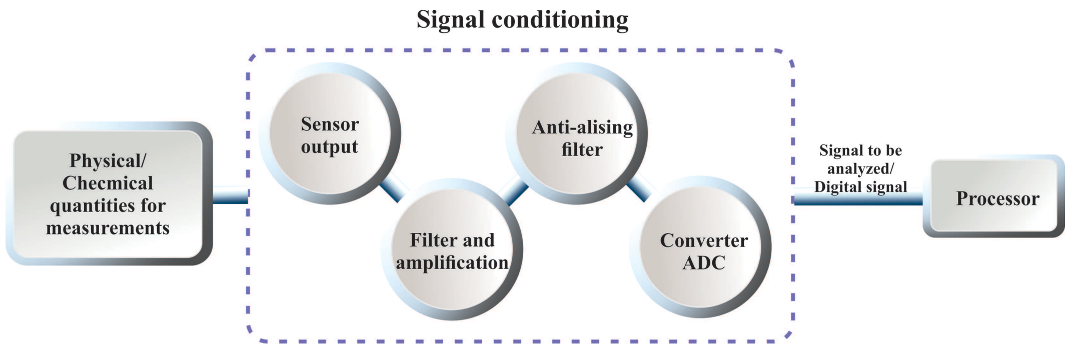


Figure 3. Steps for signal conditioning.

to the dynamic range of the Analog to Digital Converter (ADC) in order to avoid the loss of information of the sensor;

3. *Anti-aliasing filter:* After filtering and amplifying the signal, an anti-aliasing filter, a low pass filter, is used before application of the ADC in order to restrict the bandwidth of a signal and satisfy the Nyquist sampling theorem;
4. *Signal conversion:* Finally, the sensor output is transformed or converted to a digital signal through ADC in order to be processed by a digital system such as Digital Signal Processors (DSPs), Field-Programmable Gate Array (FPGAs), or microcontroller units (MCUs) [64] for assessing the health condition of the structure. This is the most important step in signal conditioning, since it is possible, depending on the ADC resolution, to measure signals of low amplitude, e.g., low-level ambient vibrations, which are frequently found in large bridges and buildings (16 and 24 bits).

All abovementioned steps are recommended for analog sensors; however, some of them can require special configurations to be employed. In contrast, a digital sensor does not require additional signal conditioning steps. It requires only a protocol communication for extracting the information. The most popular are the inter-integrated circuit (I^2C) and the Serial Peripheral Interface (SPI), which are available in modern digital signal processors and the previously mentioned WSS boards.

4. Processors

A main component of the smart sensor is the on-board processor (see Figure 2). It provides the intelligence to a standard sensor. That is, a processor can apply an embedded algorithm or different algorithms to extract information from raw data, make decisions according to the analysis of the measured data, store and send data to different time intervals (e.g., using different sampling frequencies or different reporting rates), manage power consumption, synchronize measurements and communications, and coordinate information with other sensors [65], converting the standard sensor into a smart one. For the implementation of these algorithms or tasks, different technologies can be used, e.g., an MCU, a DSP, an FPGA [64], an Application-Specific Integrated Circuit (ASIC), or a General Purpose Processor (GPP) such as a personal computer or a workstation [18].

Adams and Marketing [66] presented an analysis of benefits for such technologies in a real-time signal processing design context, highlighting that users want and need devices that are smarter, faster, smaller, and more interconnected than ever. In these devices, features such as power consumption, cost, ease of design, integrated functions, and others must be carefully selected in order to provide the best-suited processor for a specific SHM project. Lynch and Loh [18] presented a review of sensors used for SHM up to 2006, documenting various features such as data acquisition and embedded computing specifications for MCUs, DSPs, and FPGAs.

Chen and Liu [67,68] presented an ultra-compact embedded computer platform named Gumstix, along with the Atmega128 MCU for SHM of scaled steel bridges excited by a shaker. First, they presented a mobile agent-based framework [69] that looks for characteristics such as adaptability, distributed damage diagnosis, and sensor node collaboration [67]. Next, they presented a high computational wireless sensor network for distributed SHM where the sensor features high computational capability, multi-modality sensing, and the combined ability for both active and passive sensing [68].

Zhou et al. [70] used a TI MSP430 low-power MCU from Texas Instruments as an ultra-low-power active wireless sensor for SHM where the MCU can be operated in several modes and different levels of power consumption. The MSP430 MCU is also used by Zhou et al. [71] to develop a self-powered wireless autonomous SHM sensor, where the energy for powering up the sensor is generated from vibrations. Authors also present different strategies for saving energy. An ultra-low power TI MSP430F1611 MCU is used on the Tmode Sky sensor node by Meyer et al. [72] for long-term SHM, where ultra-low power hardware components, multi-hop communication, low duty-cycle operation, and significant data reduction are employed on the node in order to save energy consumption. The wireless sensing platform, named ISMO-2, is used by Bocca et al. [73] as a node of a synchronized wireless sensor network. This platform uses the TI MSP430F1611 MCU as a processor. Araujo et al. [74] used a PIC32 MCU for wireless SHM of three real bridges which presents high time-synchronization accuracy, obtaining a spatial jitter of 125 ns, far below the 120 μs required for high-precision acquisition systems. The spatial jitter is characterized by a lack of synchronization between different wireless sensors. Hu et al. [49] presented the S-Mode device as a node of a wireless sensor network for SHM of highway bridges. This device includes the MSP430F1611 MCU, where some aspects such as flash memory, normal-mode current, and sleep-mode current of ATmega128 and ATmega128L MCUs are compared. Dragos and Smarsly [75] presented a review of the sensor nodes used in the embedded computing approaches for SHM of bridges and steel towers, describing the platform for the wireless sensor node and the MCU specifications. For laboratory-scale experiments on SHM, Gürkan et al. [76] presented a multi-channel wireless data acquisition system for a two-story shear frame based on a low-power 8-bit microcontroller, PIC16LF877A. Girolami et al. [77] presented a low-cost distributed embedded system based on STM32F405 MCU for SHM using cost-effective MEMS accelerometers, instead of more expensive piezoelectric analog transducers. This system performs online filtering and fusion of the collected data [78]. Other works have used commercial devices such as Imote2 and CC1110. The former was used as a platform for SHM of bridges [79]. This platform is a high-performance wireless sensor network node based on an Intel PXA271 XScale Processor. Some features and applications of this platform were discussed by Harms et al. [79] and Nagayama et al. [80]. On the other hand, the commercial CC1110 System-on-a-Chip (SoC) wireless transceiver from Texas Instruments was employed by Casciati and Chen [81]. According to the aforementioned works, it is evident that MCUs represent a suitable solution to many SHM projects as processor platforms, where some advantages such as low cost, low-power consumption, and ease of programming are highlighted. However, as in any technology, features such as memory size, operating frequency, integrated functions, number of inputs and outputs, features of other integrated components such ADCs, Digital-to-Analog Converters (DACs), and communications ports, should be carefully selected in order to have a proper MCU for a specific SHM project.

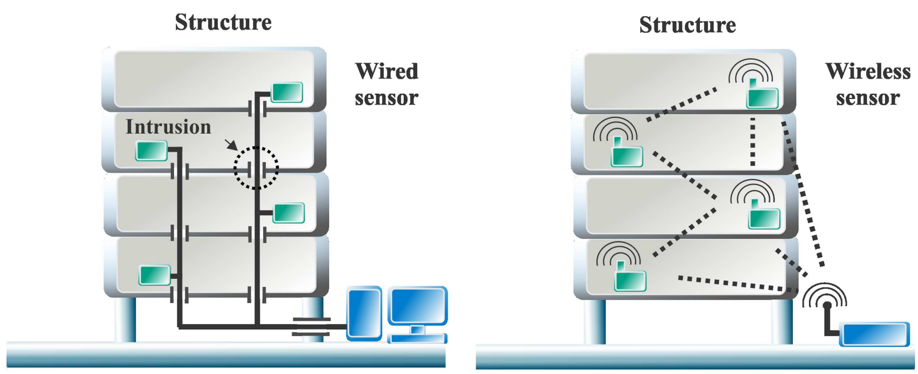
Despite the advantages of MCUs, the complexity and number of tasks of today's applications are constantly increasing, requiring the development and use of other technologies. In this regard, Field Programmable Gate Arrays (FPGAs) have been explored as they can carry out complex computations more efficiently than MCUs and DSPs while providing more flexibility for an iterative design process than ASICs [82]. Liu and Yuan [83] designed a wireless sensor using an FPGA chip with an integrated MCU, where the FPGA was used to control the data from an ADC to the Static Random Access Memory (SRAM) and the MCU was designed for simple signal filtering and wireless communication. Cigada et al. [84] presented a data acquisition strategy using the FPGA technology for SHM of the San Siro Meazza Stadium in Milan. Engel et al. [85] presented a low-power MCU with an FPGA device for distributed SHM and described an energy-efficient heterogeneous reconfigurable sensor. A phased array monitoring for enhanced life assessment (PAMELA)-SHM system using a Virtex 5 FPGA from Xilinx Inc. was presented by Aranguren et al. [86]. This system implements communication, data storage, excitation, acquisition, and processor modules, highlighting the flexibility and capabilities of the FPGA to perform several tasks in parallel. A cost-effective and flexible vibration data acquisition system (DAS) for long-term continuous SHM was presented by Nguyen et al. [87] using an optimized Ethernet-based peripheral system and FPGA technology.

A wireless transmission unit, a micro-processing unit, a GPS receiver unit, and the FPGA technology are used for SHM of the Harbin Songpu Bridge, a single-tower cable-stayed bridge with span lengths of 268 + 476 m, by Bao et al. [88] for compressive sensing-based lost data recovery, where the wireless base station is on board of a fast-moving vehicle. A Kintex-7 70T FPGA was used by Kypris and Markham [82] for measurement of 3D displacements in concrete using low-frequency magnetic fields, where the sensor can be either attached to the surface of the concrete structure or included in the concrete mix. A cyber-physical system embedded on an FPGA for 3D measurement in SHM tasks was presented by Miranda-Vega et al. [89], where an economic Altera development board with an ARM Cortex-A9 processor was used. From these works, it is clear that the FPGA technology has provided the solution to many SHM projects, offering both high application-specific performance and parallel computing [90-92]. However, this technology can be a more expensive and higher power alternative than MCUs. Besides, its programming based on Hardware Description Language (HDL) can be more complicated and time-consuming. Therefore, the requirements of each SHM project have to be carefully analyzed in order to select the best-suited on-board processor.

5. Wireless communication

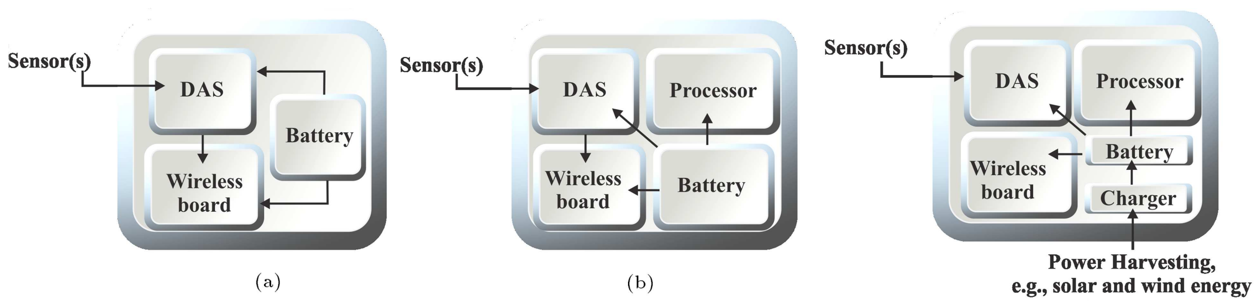
Over the past few years, technological advancements have increased the use of wireless technology in many fields. In SHM, wireless systems have been mainly focused on large structures such as buildings, bridges, and towers since the installation of wired systems can represent both high costs in material and modifications/intrusions to the structure due to the wiring throughout the structure. Figure 4 shows examples of a wired sensor network and a wireless sensor network in a structure. A WSN provides a set of advantages such as a reduction of installation and maintenance costs, ease of installation, applicability to both short-communication distances and long-communication distances, improvements in the processing as it can be distributed across the network, and improvement in the overall integrity as the system can continue working in case of a partial failure [65,74]. For wireless communication, different strategies can be used in the data aggregation process. For instance, in a centralized data collection strategy, a battery supplies power to the DAS and to the wireless board only (see Figure 5(a)); however, in an independent data processing strategy, the battery supplies power to the processor, as shown in Figure 5(b); the higher the computational load, the higher the power consumption. In recent years, the concept of self-powered WSS has been proposed where power is harvested from different natural sources of energy (see Figure 5(c)). Lynch and Loh [18] and Lynch [93] presented an overview of wireless sensor networks for SHM, where academic prototypes and commercial devices were discussed in terms of data acquisition specifications, embedded computing specifications, and wireless specifications.

Among the wireless communication protocols, the ZigBee protocol, an IEEE 802.15.4 standard for data communication, has been the option for many WSNs applied to SHM. This protocol provides a low-cost solution, allowing its widespread use in the scientific community, a low power consumption, allowing longer life with smaller batteries, and a mesh networking, providing a larger communication range. The ATAVRRZ502 ZigBee RF (radio frequency) telemetry module is used in capacitive-based and impedance-based sensors by Mascarenas et al. [94] for SHM applications. Chae et al. [95] presented the ubiquitous (u)-Node for wireless monitoring of suspension bridges. In the u-Node, two wireless communication protocols are presented: the ZigBee for short-distance communications and the Code Division Multiple Access (CDMA) for long-distance communications. The sensor nodes for the high computational power wireless sensor network presented by Chen et al. [68] also have



(a) (b)

Figure 4. (a) Wired sensor network. (b) Wireless sensor network.



(a) (b) (c)

Figure 5. (a) Wireless DAS, (b) WSS, and (c) self-powered WSS.

a ZigBee communication module. The CC2420 RF transceiver (in compliance with IEEE 802.15.4 and ZigBee) was used by Wu et al. [62] to test a multi-agent design method for a WSN-based SHM application. The Imote2 smart sensor, which includes a CC2420 RF transceiver, was used by Rice et al. [96] to develop a flexible WSS framework for full-scale and autonomous SHM. The analysis of data from the Jindo Bridge, a cable-stayed bridge in Korea, monitored by a WSN of 70 sensor node based on the Imote2 platform was presented by Cho et al. [30].

The Medium Access Control (MAC) protocol was implemented by Bocca et al. [73] to synchronize the samples collected from a wireless sensor network based on Imote2 nodes. Hackmann et al. [97] described a cyber-physical co-design approach for SHM using the Imote2 platform. Improvements in the power consumption using Imote2 platforms were presented by Lee et al. [98]. According to the aforementioned works, it is evident that the ZigBee protocol and the CC2420/Imote2 (or its family) RF transceiver have been used by a number of researchers; however, Bluetooth or Wi-Fi protocols can also be used for high-frequency vibration analysis since they offer a better data throughput, yet with a fraction of the power consumption [79]. In the wireless platform presented by Chen and Liu [68], the Gumstix embedded computer with the wifistix-CF expansion board had a Wi-Fi communication speed of 54 Mbps. Gürkan et al. [76] presented a low-cost multi-channel accelerometer system for SHM, where the communication protocol is the Bluetooth using a serial Bluetooth v2.0 + EDR module (HC-06). Similar to hybrid platforms, hybrid protocols which can be chosen according to the needs, e.g., short-communication distances or long-communication distances, is an attractive feature of WSS networks.

Although the aforementioned works have achieved good results due to both inherent benefits of using WSS network and the technological advancements, the limitations of WSS networks in battery power, synchronization, bandwidth, storage space, and data loss have motivated additional research on these topics. Bao et al. [88] and Zou et al. [31] proposed different strategies to prevent data loss. Regarding the power consumption, ultra-low-power wireless sensor schemes were presented by Zhou et al. [70] and Lee et al. [98], where the power consumption is on the order of nanowatts (nW). In addition, self-powered devices for SHM were presented by Hasni et al. [99]. Power harvesting is also considered, where energy sources such as wind energy, solar energy, or vibration energy are available and do not compromise the performance of the wireless sensor network [65,99]. For synchronization, Araujo et al. [74] presented different schemes to improve the time-synchronization accuracy of the wireless measurement for SHM. Other issues such as fault tolerance and optimal deployment of wireless sensors were studied by Bhuiyan et al. [100]. The capabilities of WSS networks and the integration of new functionalities in the next generation of WSS networks are expected to increase in the coming years.

6. Conclusions

A review of recent articles on the WSS technologies employed in SHM was presented in this paper. What makes a sensor *smart* is an embedded chip with processing capability. WSS networks provide a number of advantages for SHM such as robust data management, higher flexibility, low cost, and high potential for providing data for a better understanding of structural response and behavior. A WSS consists of four components: a primary sensor, signal conditioning, processor, and communication. Piezoelectric accelerometers have been the preferred sensor in WSS and SHM because of their ease of use, low cost, and good bandwidth. However, their measurement accuracy depends mainly on signal conditioning, where an ADC of 16 or 24 bits is recommended for measuring low amplitude vibrations. On the other hand, MCUs and FPGAs are shown to be effective platforms to implement different algorithms and tasks required in SHM projects. MCUs appear to represent a more attractive solution in terms of cost, energy consumption, and ease of programming; however, FPGAs can tackle more demanding computational tasks due to their parallelism. Hybrid platforms, i.e., the fusion of different technological platforms, have demonstrated to be promising schemes as the strengths of each technology are exploited. For instance, the FPGA may be used to perform only highly complex tasks which may not always be required and the MCUs can perform all other long-term operations.

Regarding wireless technologies and communication protocols, ZigBee and CC2420 transceivers appear to be the most widely-used devices due to their low-power consumption. Wi-Fi and Bluetooth have also been explored, but not to the fullest extent. These protocols may provide better data communication performance, yet consume more power. Therefore, they could not be a potential solution for long-term SHM in a WSS network. Similar to the hardware platforms, the integration of two or more communication protocols can be suitable for some SHM projects; for instance, when both short- and long-distance communications are required.

Notwithstanding the diversities of works presented in WSS applied to SHM, there is still a lot of room for improvement. The next-generation WSS must consume less power, integrate more with new sensors, have improved noise immunity, and be capable of working with a huge quantity of data without losses produced by wireless communication. In addition, power harvesting based on wind, solar, and structural vibration energy needs to be explored further for long-term SHM. Integration of functionalities such as self-configuration, self-healing, and self-calibration of WSSs also requires further research for creating the next generation of WSSs.

Finally, a processing chip embedded in a WSS provides only the potential for smartness. Truly smart sensors should have inherent pattern recognition and machine learning [101,102] capabilities. Authors advance the research ideology of integrating the sensor technology with recent advances in machine learning technologies such as Bayesian learning [103-106], deep machine learning [107-111], enhanced probabilistic neural network [112], competitive probabilistic neural network [113], and the recently-developed neural dynamics classification algorithm [114].

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