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Review

Wireless Sensor Placement Optimization for Bridge Health Monitoring: A Critical Review

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Abstract: In recent years, wireless sensors have progressively supplanted conventional limited sensors owing to their attributes of small size, low cost, and high accuracy. Consequently, there has been a growing interest in leveraging wireless sensor networks for bridge structural health monitoring applications. By employing wireless sensor nodes to gather data from various segments of the bridge, information is relayed to a signal-receiving base station. Subsequently, the health status of the bridge is inferred through specific data processing and analysis, aiding monitoring personnel in making informed decisions. Nonetheless, there are limitations in this research, particularly pertaining to power consumption and efficiency issues in data acquisition and transmission, as well as in determining the appropriate wireless sensor types and deployment locations for different bridge configurations. This study aims to comprehensively examine research on the utilization of wireless sensor networks in the realm of bridge structural health monitoring. Employing a systematic evaluation methodology, more than one hundred relevant papers were assessed, leading to the identification of prevalent sensing techniques, data methodologies, and modal evaluation protocols in current use within the field. The findings indicate a heightened focus among contemporary scholars on challenges arising during the data acquisition and transmission processes, along with the development of optimal deployment strategies for wireless sensor networks. In continuing, the corresponding technical challenges are provided to address these concerns.

Keywords: bridge; data technology; optimal sensor placement; sensing technology; structural health monitoring; wireless sensor networks

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1. Introduction

With the advancement of computer technology and the progress in wireless sensor manufacturing, wireless sensor networks (WSNs) are increasingly utilized for monitoring the structural health of various infrastructures, particularly large structures like bridges, which are vulnerable to minor vibrations. WSNs consist of spatially distributed autonomous sensors that communicate wirelessly to monitor physical or environmental conditions. These sensors are typically equipped with sensing, computation, and communication capabilities which enable them to collect data from their surroundings and transmit it to a central location for further processing and analysis. By employing wireless sensor nodes to monitor modal parameters such as natural frequency, damping, and vibration patterns, the condition of bridges can be assessed [1,2]. Furthermore, these networks can discern passing vehicle characteristics to provide early warnings regarding traffic flow [3], thereby offering comprehensive monitoring of bridge health from multiple perspectives.

This study focuses on recent developments and applications of WSNs in the structural health monitoring of bridges.

Selecting the appropriate wireless sensors serves as a fundamental step in constructing a wireless sensor network. Across various bridge typologies, researchers have deployed diverse wireless sensors in distinct sections of the bridge to monitor varying indicators corresponding to the monitoring objectives. Given that acceleration represents the second-order derivative of displacement, acceleration sensors can significantly amplify subtle vibrations within the bridge structure, thus enhancing the accuracy of monitoring outcomes [1,4]. Consequently, acceleration sensors have emerged as one of the most prevalent sensor types in the realm of structural health monitoring for bridges, finding application in simply supported girder bridges [5], arch bridges [6], cable-stayed bridges [7], and suspension bridges [8]. In addition to acceleration sensors, strain sensors, magnetic sensors, ultrasonic sensors, piezoelectric sensors, and specialized WSNs integrated with GPS are employed in bridge projects owing to their respective advantages [3,9,10]. Regarding wireless sensor hardware, current research endeavors focus on enhancing measurement accuracy [7,11], reducing node energy consumption [12], lowering sensor costs [1,10], and minimizing sensor dimensions [13].

Data technology encompasses various components such as data acquisition, data transmission, data processing, and data analysis, as depicted in Figure 1. In recent years, scholars have focused on enhancing five key aspects in data collection and transmission: efficiency, storage capacity, low power consumption, data quality, and long-distance transmission. Researchers have sought to improve the efficiency of wireless sensors through the adoption of suitable transmission protocols and algorithms, which operate at the software level [14,15]. Strategies to enhance efficiency include employing wireless sensor nodes with a high sampling rate or configuring nodes within a topological network, thereby augmenting both data collection speed and coverage area [7,16]. Moreover, enhancing data storage primarily involves hardware improvements, such as increasing the memory capacity of nodes to extend storage capabilities and monitoring durations [1,12], and streamlining transmission post-acquisition to alleviate data congestion [7]. Mitigating power consumption relies on employing low power, low-duty cycle transmission protocols like ZigBee [11,12], or implementing specific acquisition and transmission schedules to keep nodes in a low-current dormant state when not in operation [8]. Furthermore, digital filtering and secure copy protocols significantly enhance data security and quality, facilitating robust node-to-node communication [13,15]. Topological network architectures and multi-hop communication protocols enable long distance data transmission across extensive bridge spans through the extensive deployment of wireless sensor nodes [12,14]. This approach is further augmented by utilizing specialized radio communication bands [8]. For data analysis, modal analysis through finite element software modeling [6,17], the frequency-domain decomposition method [8,18], and the Stochastic Subspace Identification method are commonly employed to extract bridge modal characteristics for subsequent analysis [13]. Currently, artificial intelligence techniques are tightly integrated with data processing and analysis methodologies [15], wherein data analysis involves setting thresholds [5] or employing machine learning algorithms [19] for race selection and eliminating data outliers.

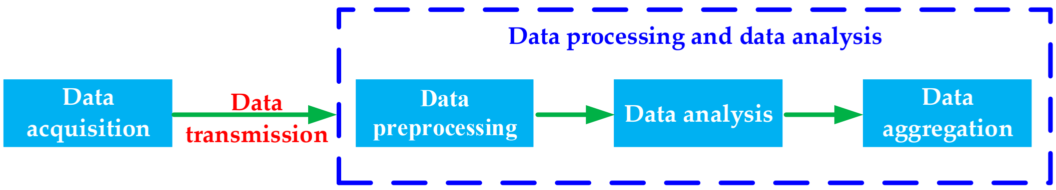


Figure 1. Data technology flow chart.

As advancements in wireless sensor technologies continue to evolve, scholars are increasingly turning their attention to investigating strategies for deploying wireless sensors [20–27]. The deployment scheme of wireless sensors involves strategically placing sensors throughout the monitoring area to ensure effective coverage and reliable data collection [27]. Various scholars have utilized diverse modal evaluation criteria and performance metrics for wireless sensor networks to model their deployment in accordance with the requirements of bridge projects. They have employed different intelligent algorithms to derive near-optimal deployment schemes for wireless sensors, considering factors such as sensor quantity, placement, and energy consumption, based on the solution of mathematical models. Current research in this domain primarily focuses on the singular objective of an integrated index [20,25,26,28], aiming to provide guidance for technicians in deploying sensors in a more rational manner.

The utilization of wireless sensor technology for data acquisition, transmission, and deployment in bridge projects has experienced significant growth over the past decade. However, there exists a dearth of research literature elucidating the outcomes of wireless sensor applications in bridge projects. A thorough review of these studies is imperative to discern the most suitable applications of wireless sensors, thereby facilitating informed decision-making concerning bridge type selection, location determination, data collection modalities, and deployment strategies. Furthermore, such a review will enable the identification of deficiencies in current methodologies pertaining to the application of wireless sensors in bridge projects. This knowledge is invaluable for practitioners seeking to integrate wireless sensor technology into their bridge projects. Additionally, developers of wireless sensor technologies can leverage this information to refine next-generation solutions, thereby addressing the limitations inherent in existing methodologies. Hence, the aim of this study is to evaluate the applications and potential capabilities of wireless sensor technologies across various facets of bridge projects, and to ascertain the significance and impact of these technologies on decision-making processes and project management. The overarching goal of wireless sensor applications in bridge projects is to foster the development and optimization of innovative deployment solutions aimed at reducing project deployment costs, enhancing data collection and transmission quality, as well as prolonging the lifespan of wireless networks. Realizing these objectives necessitates the implementation of diverse strategies such as data transmission via different frequency channels, multi-hop communication protocols or topology network structures, and the utilization of multi-objective deployment optimization models. Section 2 delineates the research methodology employed in this review, Section 3 elaborates on the various types of wireless sensors, and Section 4 provides an overview of wireless sensor applications across different bridge types and locations, accompanied by an analysis of sensor technologies based on five key aspects: (1) Efficiency, (2) data storage, (3) low power consumption, (4) data quality, and (5) long-distance transmission capabilities. Section 5 deliberates on the deployment methodologies of wireless sensors on bridges, while Section 6 examines the challenges associated with sensor technology and suggests potential avenues for future research.

This research examines and synthesizes the present state of wireless sensor networks (WSNs) in structural health monitoring (SHM) applications for bridges. It provides an overview of current advancements in sensing and data technologies, and proposes solutions to existing challenges in data collection, transmission technologies, and wireless sensor deployment. These proposed solutions are intended to inform the trajectory of future research endeavors within the realm of WSNs for bridge projects. Furthermore, the present review aims to aid professionals in the bridge sector by providing insights into the selection of suitable wireless sensors, including their types, quantities, and deployment locations, as well as the corresponding data analytics technologies, for SHM applications in bridges.

2. Research Methods

This research undertook a systematic review in accordance with the PRISMA framework. The primary literature sources for this study were primarily drawn from Elsevier, Scopus, and Google Scholar, chosen for their robust search capabilities, comprehensive coverage, and high academic authority. The principal keywords utilized in this search encompass "bridge structures", "structural health monitoring (SHM)", "wireless sensor networks", while secondary keywords include "sensor technology", "data technology", and "wireless sensor deployment". The search formula employed for Elsevier comprised the criteria: title, abstract, or author-specified keywords = "bridge structures" and ("structural health monitoring" or "SHM") and ("wireless sensor network" or "wireless sensor deployment") and ("sensing technology" or "data technology"). Similar search criteria were adapted for Scopus and Google Scholar with necessary syntactic adjustments. The Boolean operator "OR" was employed to broaden the search scope, facilitating the retrieval of a diverse array of relevant literature, while the "AND" operator was utilized to refine relevance, ensuring the inclusion of pertinent literature. Given the relatively nascent nature of wireless sensor networks applied to bridge structure health monitoring, the majority of retrieved literature spans the last decade (2014–2024). Eighty-seven, one hundred-two, and ninety-eight documents were retrieved from Else-vier, Scopus, and Google Scholar, respectively. The number of records retained for screening, following the elimination of duplicates, amounted to 164 journal articles. Subsequently, after screening titles and abstracts, 142 records were selected for full-text review, as depicted in Figure 2.

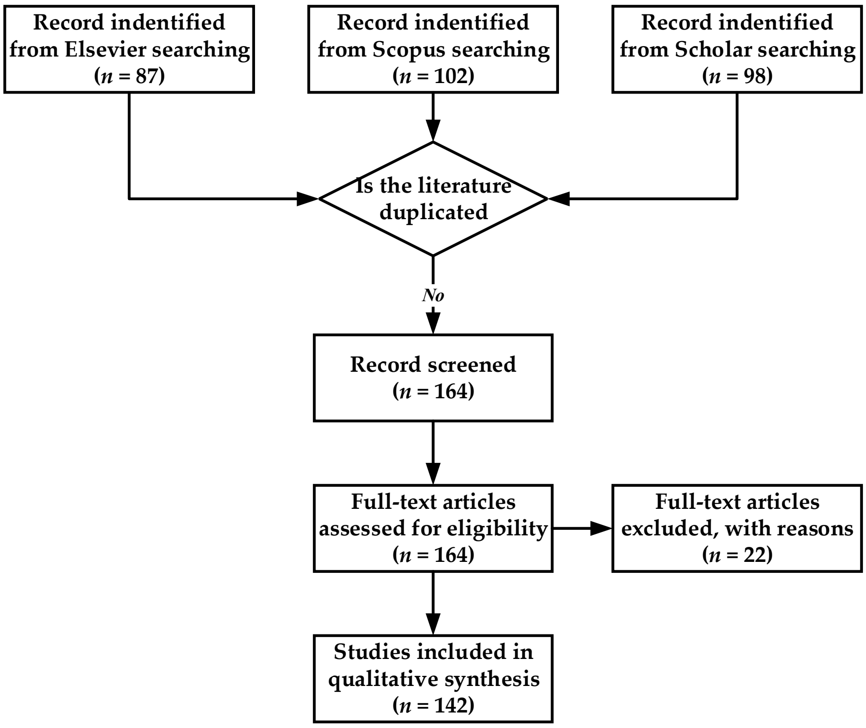


Figure 2. PRISMA flow diagram.

3. Sensing Technologies for Bridge Health Monitoring

In recent decades, wireless sensor networks have garnered increasing popularity for the health monitoring of large structures characterized by high design life and stringent safety requirements [29]. Their primary benefits include low cost, ease of installation, and the capability to facilitate effective data management through onboard computation [12]. This section offers an overview of the latest advancements and applications of wireless sensing technologies currently employed in bridge structures. These technologies encompass acceleration sensors, Global Navigation Satellite System (GNSS), magnetic sensors, strain sensors, piezoelectric sensors, and ultrasonic sensors, among others. Table 1 presents a comprehensive summary detailing the primary functions, specifications, advantages, disadvantages, and limitations of various types of wireless sensors.

Table 1. Data summary of different wireless sensors.

Types	Function	Specification	Advantages	Disadvantages	Limitations	Reference
Accelerometer sensor	Monitoring bridge acceleration to ascertain modal vibration patterns.	• Full-scale range: ±2 g. • Flash memory: 256 kB. • RAM memory: 8 kB. • Noise density: 30 µg Hz. • CPU speed: 16 MHz.	• Low power consumption: less than 0.6 mW. • Low cost and low noise. • High monitoring efficiency: monitoring data can be obtained within one hour. • Compact size: easy to install directly, can obtain better vibration transmission.	Sensitivity and resolution are limited, making it difficult to precisely measure minute changes in acceleration.	Due to the influence of temperature and vibration, significant errors are present in the measurements.	[1,4–6,8,11–13]
GNSS	Collaborate with various wireless sensors to acquire satellite data and transmit wireless sensor data packets to the server.	• Support: GPS, GLONASS, Galileo, Compass frequency. • Sampling rates: 20 Hz. • Working current: 400 mA.	• Low power consumption: node life ranging from 20–200 days. • High measurement accuracy: can reach 1–5 mm level of precise positioning. • GSM base station can receive information from multiple sensors.	Signal exhibits poor resistance to interference.	Signal coverage is not comprehensive.	[7,9]
Magnetic sensor	Detecting vehicle length passing through the bridge and classifying it.	• Working voltage: 1–25 V. • Flash memory: 256 kB. • RAM memory: 8 kB. • CPU speed: 16 MHz.	• Non-destructive inspection without contacting the object to be inspected.	Sensitivity and response frequency are relatively low.	High power consumption.	[3,30]
Strain sensor	Measurement of member stress state; monitoring of bridge strain state.	• Range: ±5000 microstrain. • Accuracy: ±0.1 microstrain. • Output voltage: 2.5 mV/V. • Power requirement: 2.5–5 V. • Resistance: 120 Ω.	• Can use additional jigs to accurately measure surface stress. • Strong durability and long measurement time.	-	Direction of force application may be constrained.	[3,5,11]
Piezoelectric sensor	Monitoring bridge cracks.	• Supply voltage: 1.8–3.8 V. • Piezo-sensor: 8. • Data rate: 50 kps. • Clock speed: 48 MHz. • Cache memory: 8 kB. • SRAM memory: 20 kB. • Working current: 2.5 mA.	• Low cost. • Cracks sufficient to threaten the health of the structure can be detected.	-	Under low pressure conditions, issues related to linearity and stability may arise.	[10]
Ultrasonic sensor	Detecting and classifying vehicle height passing through bridges.	• Flash memory: 256 kB. • RAM memory: 8 kB. • CPU speed: 16 MHz.	• High recognition accuracy.	Ultrasound may generate multipath propagation interference.	Smoothness level of the reflective surface receiving ultrasonic waves requires a high degree of precision.	[3]

3.1. Acceleration Sensors

The functionality of acceleration sensors hinges upon the principle of structural vibration, whereby the health condition of bridges is ascertained through the monitoring of structural vibration acceleration. This data is then converted into modal parameters such as damping, thereby emphasizing the criticality of accurate modal damping estimation for the assessment of the health of expansive and flexible civil infrastructures [19]. Accelerometers exhibit signal characteristics such as a wide frequency range, low noise, high linearity, and minimal temperature drift [8]. Figure 3 illustrates an example of its signal. Among the most prevalent types of acceleration sensors employed for structural health monitoring of bridges are Micro-Electro-Mechanical Systems (MEMS) sensors [4,5,8,13], force-balanced (FB) sensors [11], and piezoelectric sensors [11]. Acceleration sensors offer notable advantages, including high accuracy, cost-effectiveness, and low power consumption [4,5,13], with MEMS sensors capable of identifying two additional structural modes compared to FB accelerometers [8]. Moreover, due to their compact size, MEMS accelerometers can be directly mounted onto bridge structures to facilitate efficient vibration data transfer [13]. Although FB accelerometers are relatively larger, they demonstrate superior performance in measuring low-frequency vibrations and are commonly deployed for vibrations in bridge stiffening trusses [11]. On the other hand, piezoelectric sensors are available across various measurement ranges and exhibit excellent durability and stability, albeit necessitating higher voltage requirements [11]. Figure 4 illustrates a hardware setup for a MEMS accelerometer and a FB accelerometer, respectively. Refer to Figure 5 for a schematic representation of the piezoelectric sensor model.

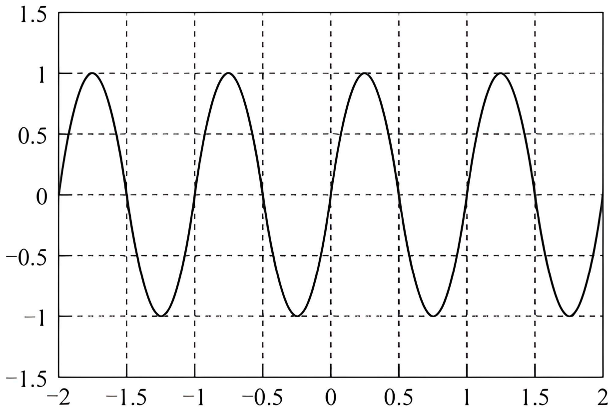


Figure 3. Schematic diagram of an accelerometer signal ([8]).

Manufacturer	NewConsTech. Inc (Korea)
Sensitivity (±5%)	2000 mV/g
Measurement range	±2 g pk
Frequency range	0–300 Hz
Overload limit	±2000 g pk
Temperature range	−40–80°C (Operating)
Excitation voltage	9–20VDC
Current consumption	10 mA
Output impedance	1 Ω
Spectral noise	13 μg
Size	26×27.5×10 mm
Non linearity	0.5–1% of span

(**a**)

Figure 4. *Cont.*

Manufacturer	Kinemetrics Inc. (U.K.)
Dynamic range	140 dB+
Bandwidth	DC~200 Hz
Linearity	1000 μg/g^2
Hysteresis	<0.1% of full scale
Power consumption	9 mA of +/−12 V
Operation temperature	−20–70 °C
Current consumption	10 mA
Weight	0.35 kg
Full scale range	±0.25 g, ±0.5 g, ±1 g, ±2 g ±4 g
Calibration coil	Standard
Cross axis sensitivity	<0.1%

(**b**)

Figure 4. Partial acceleration sensor hardware device [11]. (**a**) MEMS acceleration sensor (**b**) FB acceleration sensor.

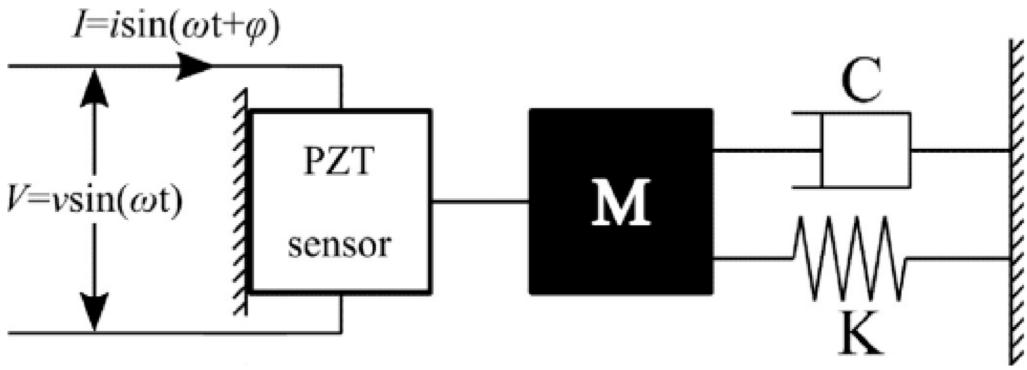
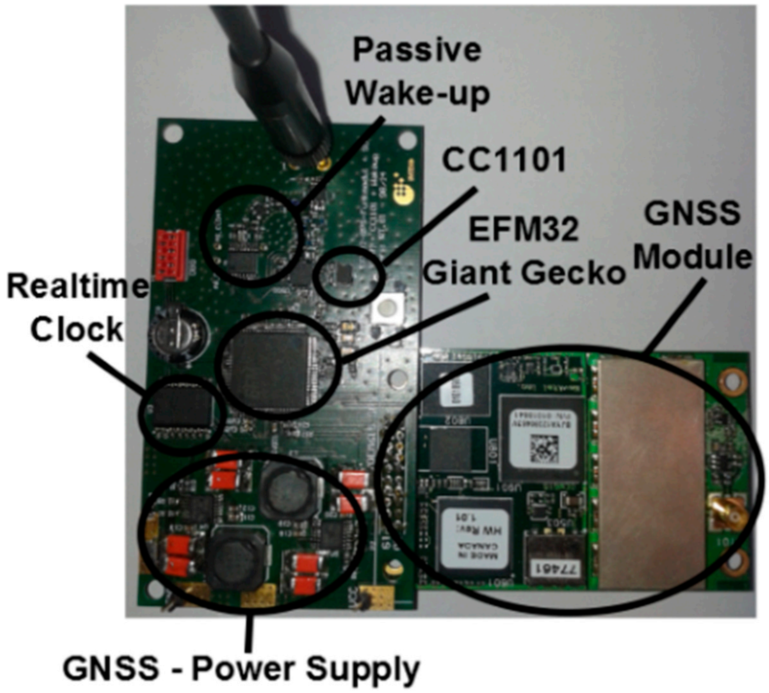


Figure 5. Sensor model [10].

3.2. Global Navigation Satellite System (GNSS)

Global Navigation Satellite Systems (GNSS) have the capability to furnish users with 3D coordinates, velocity, and temporal information across all weather conditions on the Earth's surface. They can be effectively employed in the domain of bridge structural health monitoring by integrating with various wireless sensors such as accelerometers, strain gauges, and gas sensors [9]. The GNSS sensor functions to receive satellite data, while the GSM Base Station serves as a gateway linking the wireless sensor network with the remote server, facilitating the transmission of data packets to the server. One of the primary advantages of GNSS lies in its high measurement accuracy. By following differential post-processing, it can achieve precise positioning of static and dynamic displacements within the range of 1–5 mm [7], as depicted in Figure 6. However, despite its merits, GNSS still faces challenges in effectively monitoring the displacement of bridge piers resulting from settlement or collisions with ships beneath the bridge deck [31].



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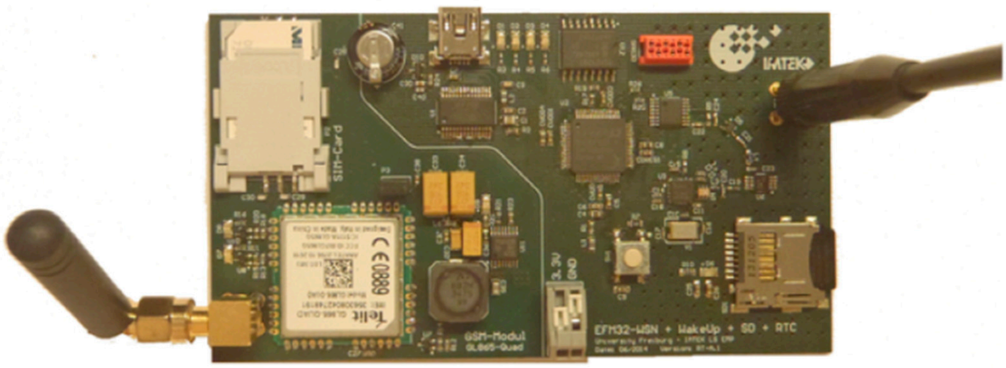

(**b**)

Figure 6. Photo of the GNSS sensor node and the GSM base station node [7]. (**a**) Photo of the GNSS sensor node (**b**) Photo of the GSM (global system for mobile communications) base station node.

3.3. Magnetic Sensors

The primary principle underlying magnetic sensors involves the detection of disturbances caused by the presence of ferromagnetic materials and the mechanical deformation thereof when subjected to a magnetic field. These sensors operate by converting the resultant change in magnetic energy into an electrical signal, thereby enabling the detection of parameters such as stress and strain in steel bridges. Figure 7 displays an example of magnetic sensor signals. Among magnetic sensors, magnetostrictive sensors stand out, as they have the capability to generate and monitor guided waves within ferromagnetic materials. Remarkably, these sensors do not necessitate direct contact with the object under observation, rendering them nearly non-destructive [30]. Figure 8 illustrates a schematic representation of magnetostrictive sensors. Moreover, magnetic sensors can be utilized to monitor and classify the length of vehicles traversing a bridge, offering timely alerts in instances of excessive heavy vehicle presence within the traffic flow [3].

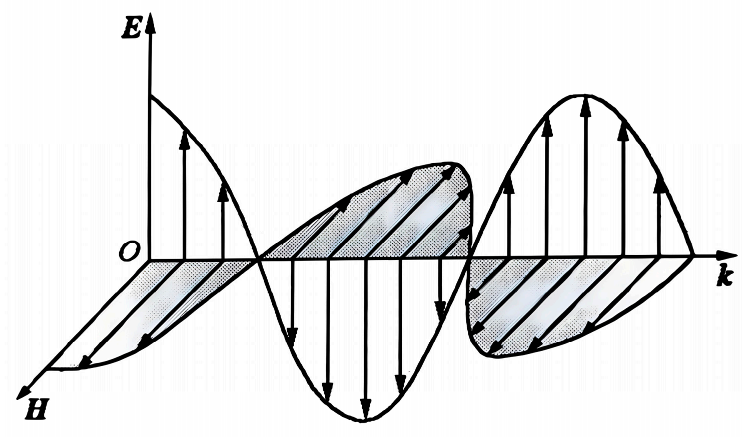

Figure 7. Schematic diagram of a magnetic signal [30].

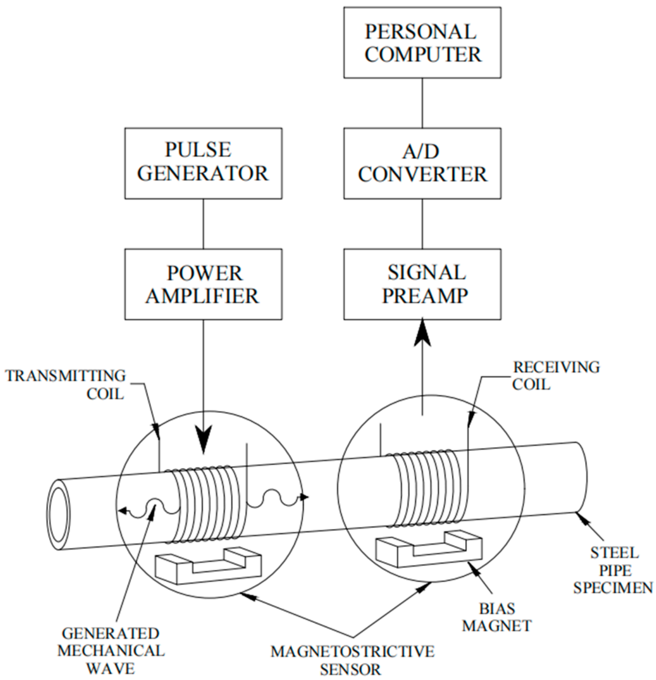

Figure 8. Sensor configuration for passive detection of transient stresses [30].

3.4. Strain Sensors

Strain sensors represent wireless sensing devices predicated on the assessment of strain induced by the deformation of a structure subjected to external forces. They constitute one of the most extensively employed sensors for gauging the stresses exerted on structural elements, owing to the capacity to derive stresses through the multiplication of measured strain by the elasticity coefficient [11]. Notably, strain sensors offer notable advantages, including high sensitivity, minimal error, and a broad measurement range, rendering them adaptable to diverse and challenging environmental conditions. Figure 9 displays an example of magnetic sensor signals. Furthermore, these sensors have been utilized for monitoring strains induced by vibrations resulting from train passage over bridges and for issuing prompt alerts in emergency scenarios where strains surpass predefined thresholds [3,5].

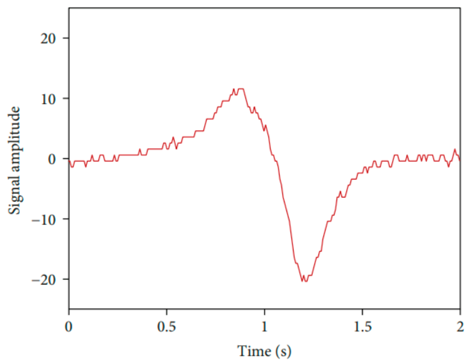

Figure 9. Schematic diagram of a magnetic signal [3].

4. Wireless Sensors for Bridge Health Monitoring

This section will delineate the particular applications of wireless sensor networks (WSNs) in the domain of bridge structural health monitoring in recent years. It will also consolidate the prevalent techniques for data collection and transmission, as well as data processing and analysis methods utilized within WSNs.

4.1. Current Applications

Due to the lack of specific regulations or guidelines requiring the precise placement of sensors on different types of bridges, scholars utilize various factors, such as engineering standards, project specifications, and personal experience, to apply different types and quantities of wireless sensors at different locations on different bridge types to monitor various structural health indicators. Specifically, simply supported beam bridges are primarily used in highway or railway bridges [5,13]. Wireless sensors need to be uniformly distributed on the bridge deck, web, or beams, while more dense array measurements can be performed on the central main beam [13]. Figures 10–12 illustrate the layouts for positioning acceleration sensors on cable-stayed bridges, simple girder bridges, suspension bridges, and arch bridges, respectively [5,12]. Table 2 provides a synthesis of the aforementioned pertinent details.

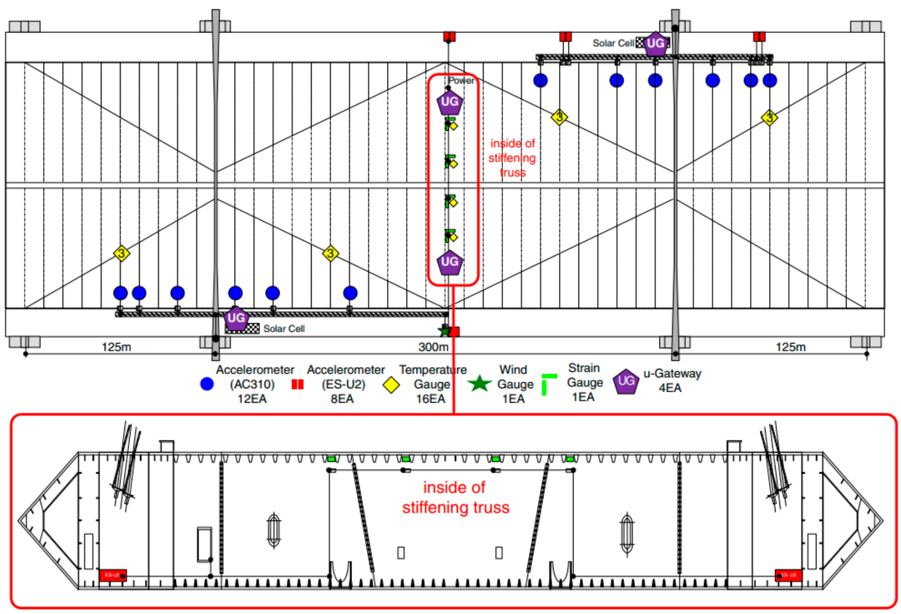

Figure 10. Sensor location for Yongjong Grand bridge [11].

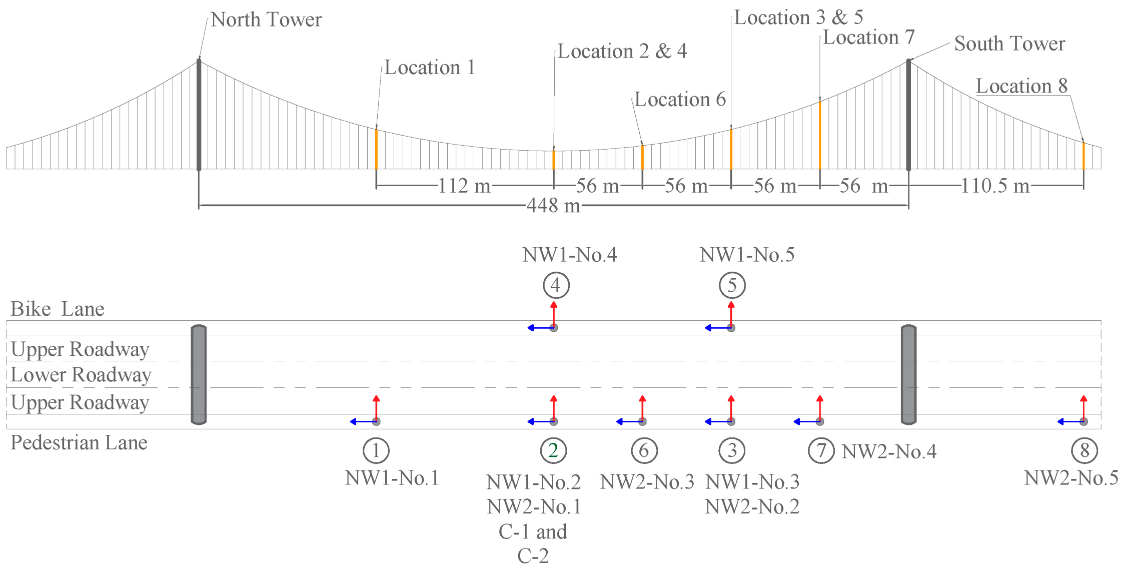

Figure 11. Sensors' location along the bridge [8].

(**a**)

(**b**)

Figure 12. Sensor node with sonar mounted on a light pole [3]. (**a**) The monitored road bridge (**b**) Sensor node with sonar mounted on a light pole.

Table 2. Sensor placement on bridges.

Wireless Sensor Types	Bridge Types	Object to be Monitored	Quantity	Monitoring Indicators	Reference
Accelerometer sensor	Simply supported girder bridge	Deck	4	Bridge vibration.	[5]
		Web	20	Structural damping, vibration pattern, natural frequency.	[13]
	Suspension bridge	Deck	10	Vibration type, torsional vibration type.	[8]
		Stiffening truss	4	Stiffening truss vibration	[11]
		Hanger cable	12	Hanger tension.	
	Cable-stayed bridges	Deck	113	Structural damping, vibration pattern, natural frequency.	[1]
		Deck	1	Bridge resonance frequency.	[7]
		Deck	19	Bridge vibration.	[12]
		Cable	19		
		Pylon	2		
		Bearing	2		
	Arch bridge	Deck	48	Bridge vibration.	[6]
GNSS	Cable-stayed bridges	Deck	3	Bridge resonance frequency.	[7]
Magnetic sensor	Simply supported girder bridge	Deck	6	Vehicle length.	[3]
Strain sensor	Simply supported girder bridge	Deck	3	Small amplitude strain cycle.	[3]
		Web	11	Damping, vibration pattern, natural frequency.	[13]
		Crossbeam	6	Bridge strain.	[5]
	Suspension bridge	Stiffening truss	4	Stiffening truss stress.	[11]
Ultrasonic sensor	Simply supported girder bridge	Deck	1	Vehicle height.	[3]

The table above illustrates that acceleration sensors are the most extensively utilized in the realm of structural health monitoring for bridges, being applied across a wide array of bridge types. Acceleration sensors primarily monitored are the modal characteristics of the bridge [7,13]. In addition to acceleration sensors, several other wireless sensors find application primarily in simple girder bridges, typically deployed on the bridge deck. Magnetic and ultrasonic sensors, among others, possess a restricted range of applications and are primarily employed for the purpose of monitoring and classifying the length and height of vehicles traversing straightforward girder bridges. They function as an early warning system, particularly tailored for heavy vehicles.

4.2. Data Collection and Transmission

In the realm of wireless sensor networks, the technology employed for data collection and transmission plays a pivotal role. Data collection technology must satisfy the imperatives of *efficiency* and *data storage*, while data transmission technology predominantly seeks *low power*, *data quality*, and *long-distance transmission*.

4.2.1. Efficiency

For an individual wireless sensor node, employing a receiver with a high sampling rate of 20 Hz is advocated to ensure rapid data acquisition [7]. Conversely, for the entire wireless sensor network, spanning a vast area, the achievement of data collection is facilitated through the utilization of a topological network structure [14,16,18]. The link-by-link data transfer protocol facilitates the concurrent transmission of data by multiple adjacent nodes equipped with distinct frequency channels, thereby attaining a data collection rate of 7 kB/s [14]. In low power multi-hop networks, cycle management slot allocation allows for the adjustment of transmission timing in accordance with the type of data being gathered and the sampling requisites, thus facilitating efficient data collection tailored to the application's demands [8]. Moreover, the pick peaking algorithm automates the transmission of data collected on a per-minute basis, mitigating data congestion and enhancing data collection efficacy [15].

4.2.2. Data Storage

Data storage predominantly depends on advancements in hardware devices. For instance, the smart sensor platform Imote2 boasts 32 MB more memory than its predecessor, thereby enhancing the capacity for storing data and prolonging monitoring durations [1,12]. Wireless sensor nodes equipped with wake-up receivers collect data and consolidate them into significant packages, transmitting them uniformly upon completion of collection [7].

4.2.3. Low Power

Controlling wireless sensor nodes to transmit data selectively while maintaining dormancy during inactive periods has been demonstrated to effectively reduce energy consumption for data transmission. This assertion is supported by empirical evidence showing significantly lower current intensity during dormancy compared to active operation [8], as well as by studies highlighting the extended lifespan of wireless sensor nodes [7]. The utilization of the Zigbee communication protocol plays a crucial role in achieving low power consumption. For instance, Kumalasari et al. employed the ZigBee communication protocol based on the IEEE 802.15.4 standard for large-scale wireless sensor networks [12]. Additionally, Chae et al. [11] proposed a low power multi-hop communication network, termed u-node, by integrating the ZigBee protocol with CDMA technology. This innovative approach enables low power transmission and a reduced duty cycle, contributing to enhanced energy efficiency.

4.2.4. Data Quality

Data quality stands as a pivotal indicator of the efficacy of data transmission technology within wireless sensor networks, highlighted by the imperative to safeguard data security during transmission and strive for minimal loss. The implementation of a secure copy protocol facilitates data transmission between hosts while ensuring data security through authentication and encryption during transmission [15]. Employing digital filtering represents a method to enhance data quality, with the resultant average data transmission rate post-processing reaching 99.91%, thereby approaching near-lossless data transmission [13]. Furthermore, Whelan et al. employ a proprietary network communication protocol developed by Ref. [32], which enables data transmission between nodes through packet acknowledgment and retransmission [6], thereby fostering robust communication between nodes and preserving the integrity of time histories utilized in subsequent system identification processes.

4.2.5. Long-Distance Transmission

Multi-hop communication protocols represent the prevailing method for achieving long-range communication [11,14]. Additionally, multi-tier probabilistic polling protocol MTTP [16] and topological network structures [12] serve the same purpose. These approaches facilitate long-distance data transmission through the strategic deployment of wireless sensor nodes. For instance, a maximum communication distance of 1 km in a line-of-sight environment has been achieved using sub-GHz radio communication bands in LPMN [8].

4.3. Data Processing and Analysis

4.3.1. Data Processing

Wireless sensor data processing refers to the analysis, filtering, and extraction of meaningful information from raw sensor measurements. Common methods for wireless sensor data processing include filtering, feature extraction, statistical analysis, pattern recognition, data fusion, and signal reconstruction. The functions and techniques of these methods are listed in Table 3.

Table 3. Data processing methods.

Method	Function	Technique	Reference
Filtering	Remove noise or unwanted components from the data.	Utilizing filters such as low-pass, high-pass, band-pass, or median filters.	[33–35]
Feature extraction	Identifying and extracting relevant features or characteristics from the data.	Using a feature extraction algorithm, such as short-time Fourier transform (STFT) or wavelet transform (WT).	[36–38]
Statistical analysis	Summarize and analyze data distributions and relationships.	Applying statistical methods such as mean, median, standard deviation, correlation analysis, or regression analysis.	[39,40]
Pattern recognition	Recognize and classify patterns or anomalies in the data, facilitating automated decision making and fault detection.	Employing machine learning algorithms, deep learning methods or pattern classification techniques.	[40–46]
Data fusion	Enhance the accuracy, reliability, and completeness of the resulting data, improving situational awareness and decision-making capabilities.	Integrating information from multiple wireless sensors or sources.	[34,47,48]
Signal reconstruction	Reconstruct missing or incomplete data.	Employing techniques such as interpolation, extrapolation, or resampling.	[49,50]

These methods can be applied individually or in combination, depending on the specific requirements of the application and the characteristics of the wireless sensor data.

4.3.2. Data Analysis

Data analysis methods can be divided into two main categories: modal analysis and artificial intelligence.

Modal analysis methods (MAM) are highly useful for obtaining the dynamic responses of structures in analytical closed form. In order to utilize MAM, it is imperative to acquire accurate information on natural frequencies, mode shapes, and orthogonality of mode shapes a priori [51]. Software analysis pertains to a modal analysis technique, wherein the modal characteristics of a bridge structure are identified through the utilization of software tools, predominantly employing finite element analysis. Finite element analysis proves effective in examining quantifiable alterations in bridge modal parameters attributable to variations in material properties and boundary conditions, among other factors [6]. By constructing a 3D finite element model of the bridge, fundamental data such as load moment diagrams [15], mass and stiffness matrices [6], and the analysis of modal parameters such as natural frequency and vibration patterns can be derived [1,13,52]. The LUSAS Bridge Plus v13.0 finite element software facilitates the determination of optimal sensor locations and types, thereby effectively minimizing the number of sensors required and the volume of data collected [17].

Frequency domain decomposition and Stochastic Subspace Identification methods are viable approaches for modal analysis. The frequency domain decomposition method discerns the inherent frequencies and modal shapes of a bridge. Meanwhile, the semi-automated data-driven stochastic subspace identification procedure extracts modal characteristics from the system response, yielding modal shapes, inherent frequencies, and damping ratios of the bridge [8]. In contrast, the frequency domain decomposition method necessitates complete excitation of the eigenfrequencies to generate smooth mode shapes compatible with finite element analysis, whereas stochastic subspace identification requires less time and relatively simple extraction of modal parameters [13]. Additionally, the frequency domain decomposition method can be integrated with NExT and ERA methodologies to analyze modal parameters concerning temperature and excitation level [1], as well as modal parameters in relation to damage severity [18].

Artificial intelligence (AI) represents an analytical methodology stemming from the convergence of civil engineering and computer science disciplines. It finds predominant application in various domains such as damage detection, data diagnosis, data interrogation, anomalies in data sensing, and data storage facilitated through cloud computing [29]. For instance, Concepcion demonstrated the utilization of a machine-trained artificial neural network for the classification of structural health in bridges [15]. This involved employing principal component analysis to mitigate the influence of temperature variations on vibration data, thereby enhancing the reliability of processed data. The trained machine exhibited a high level of accuracy in assessing the health condition of the bridge structures.

4.3.3. Data Aggregation

Wireless sensor data aggregation involves combining or summarizing data collected from multiple sensors to comprehensively represent the cohesion of the monitored object [53]. Common methods of sensor data aggregation currently include spatial aggregation, temporal aggregation, hierarchical aggregation, event-based aggregation, data fusion, and quality-aware aggregation, with the functionalities and techniques of these methods listed in Table 4.

Table 4. Data aggregation methods.

Method	Function	Technique	Reference
Spatial aggregation	Generate spatially representative measurements.	Averaging, interpolation, or weighted aggregation, et al.	[54–56]
Temporal aggregation	Generate aggregated summaries or statistics.	Averaging, summing, or calculating the maximum or minimum values over specific time periods.	[54,57,58]
Hierarchical aggregation	Aggregating data from sensors organized in a hierarchical structure, such as sensor nodes grouped into clusters or tiers.	Data summarized and passed up the hierarchy to higher-level nodes for further processing.	[59–61]
Event-based aggregation	Only when certain thresholds are exceeded or when specific patterns or anomalies are detected.	Aggregating data triggered by specific events or conditions detected by sensors.	[62–64]
Data fusion	Integrate data from multiple sensors of different types or modalities.	Sensor fusion methods such as sensor selection, sensor calibration, feature fusion, and decision-level fusion.	[34,47,48]
Quality-aware aggregation	Reliability and quality of data collected from different sensors when performing aggregation.	Weighting data based on the accuracy, precision, or trustworthiness of individual sensors.	[65–67]

These methods can be customized and combined to accommodate the specific requirements and constraints of the application, including the characteristics of the involved sensors, communication infrastructure, as well as the accuracy and efficiency required in data aggregation.

5. Wireless Sensor Placement Optimization

Wireless sensor networks (WSNs) are anticipated to enhance the ability to capture dynamic structural behaviors through dense instrumentation and a multihop communication protocol, while also facilitating the evaluation of structural conditions [14,68–70]. However, the complexity of bridges introduces numerous monitoring parameters and structural degrees of freedom, rendering it impractical and unreasonable to deploy sensors for each one [71–74]. The aim of a sensor optimization layout is to achieve comprehensive structural information for bridges using the minimum number of sensors possible [75–78]. Consequently, scholars engage in detailed research on criteria for structural modal evaluation and network performance assessment. Presently, WSN-based structural health monitoring (SHM) systems have been successfully deployed on various full-scale bridges, including the Golden Gate Bridge in the United States [79], the second Jindo Bridge in Korea [80], and the New Carquinez Bridge in the United States.

5.1. Modal Evaluation Criteria

In practical structural health monitoring (SHM) systems, there may be challenges in accurately distinguishing identified mode shapes from one another, thereby potentially compromising the precision of vibration analysis [81–84]. Hence, it is advisable to utilize measures of information effectiveness, such as the modal assurance criterion (MAC) [22,25,27,85–89], modal strain energy (MSE) [21,23,24,90,91], singular value decomposition ratio (SVDR) [26,92–94], least square method (LSM) [95–97], and Fisher information matrix (FIM) [98–104], to assess the linear independence of identified mode shapes. The various modal evaluation criterias are detailed in Table 5 and Figures 13–17 as shown.

Table 5. Different modal evaluation criteria.

Category	Uses	Features	References
Modal assurance criterion (MAC)	Measure the linear independence among the identified mode shapes.	Off-diagonal elements in the MAC matrix offer a direct measure of the information effectiveness that is collected by the wireless sensor configurations.	[22,25,27,85–89,105]
Modal strain energy (MSE)	Measure the dynamic contribution of each candidate sensor to the target mode shapes.	MSE helps to select sensor positions with possible large amplitudes and to increase the signal-to-noise ratio.	[21,23,24,90,91]
Singular value decomposition ratio (SVDR)	Measure of the mode orthogonality.	Offer a desirable metric of the condition for mode expansion and the observability of the modes.	[26,92–94,106]
Least square method (LSM)	Minimize the sum of squares of deviations.	The sum of the squares of distance from the fitting point to straight line on the coordinate system should be the smallest.	[95–97,107]
Fisher information matrix (FIM)	Useful information among the unknown parameters available in the measured values.	FIM helps to select the neighboring node around the target node, while a large number of nodes are available around the target node.	[98–104]

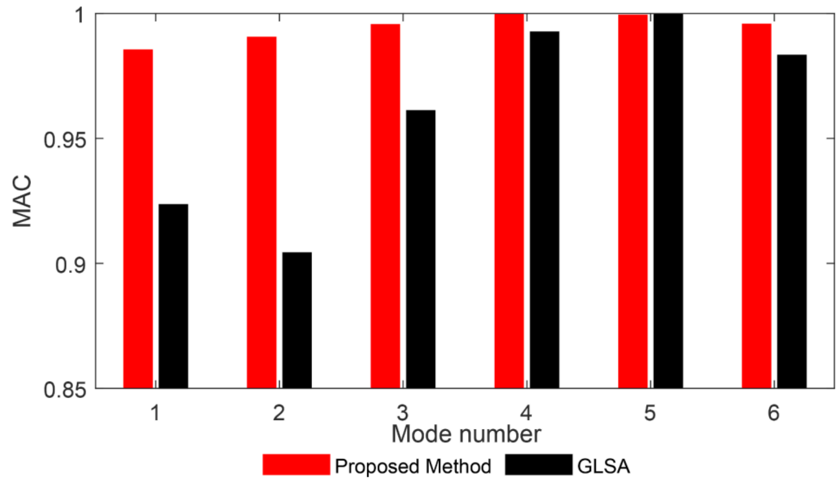

Figure 13. MAC values obtained from the optimal sensor configuration [105].

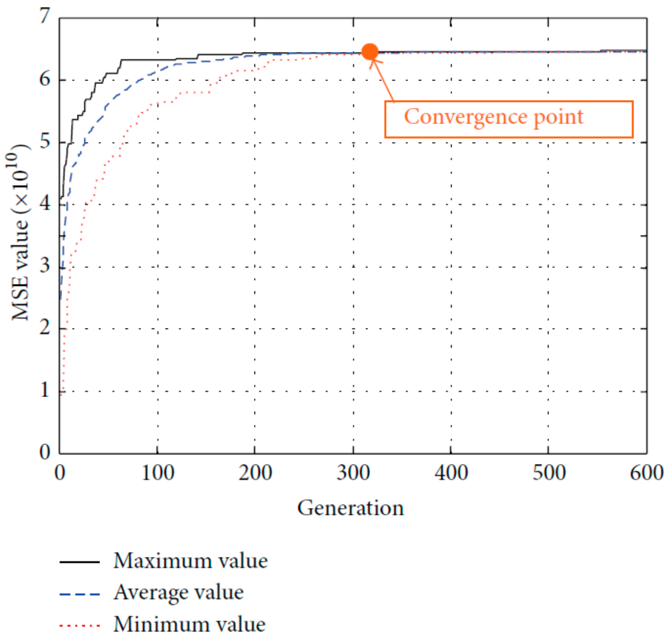

Figure 14. Iteration progress of the objective function [24].

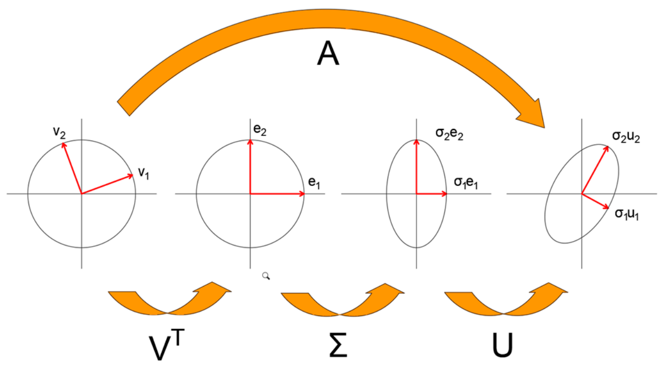

Figure 15. Algorithmic process of the singular value decomposition ratio [106].

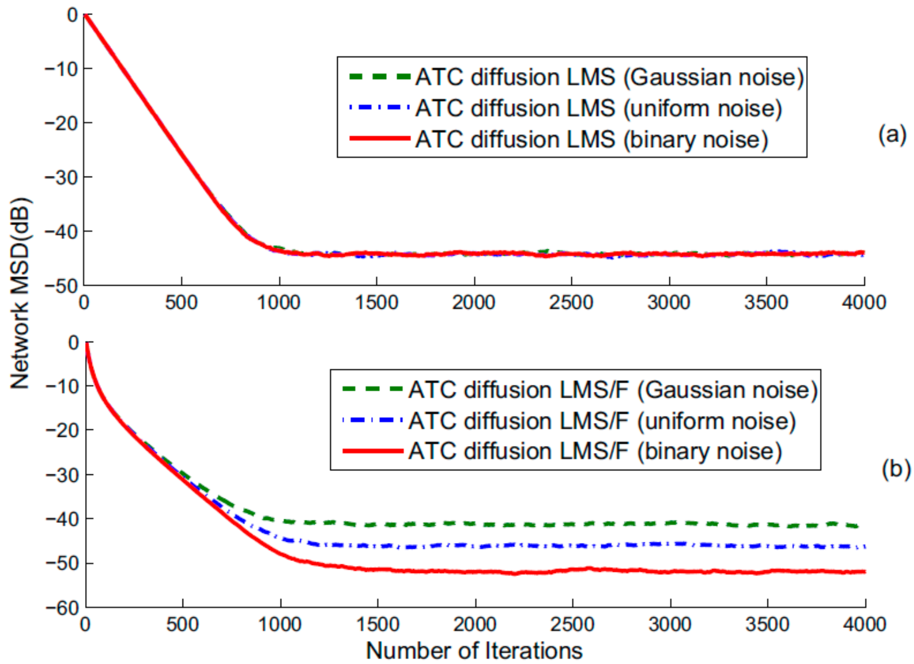

Figure 16. (**a**,**b**) Least mean square error [107].

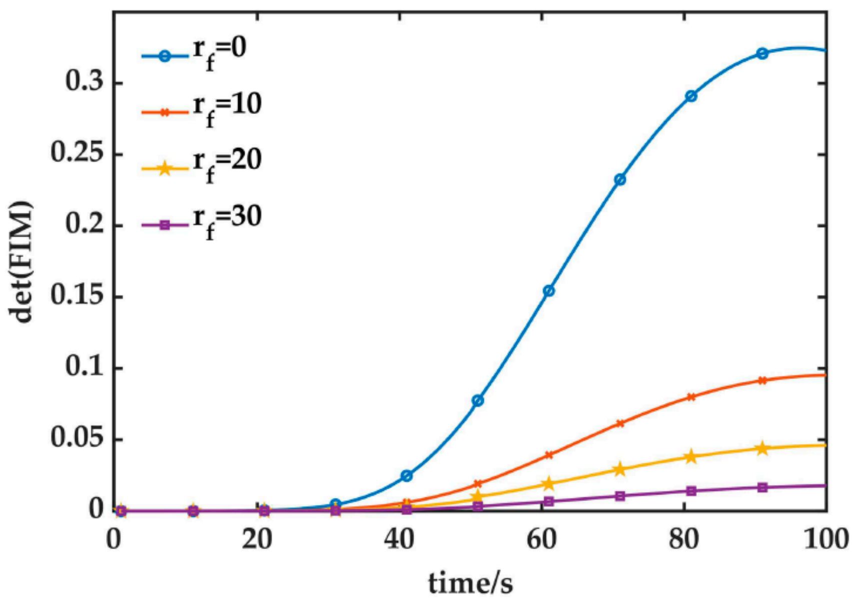

Figure 17. Relationship between FIM and floating noise [104].

A significant numerical advantage arises when computing off-diagonal modal assurance criterion (MAC) elements, particularly when the MAC matrix for vectors is already available. This approach facilitates the evaluation of a vast array of degrees of freedom (DOF) from a large finite element method (FEM) without encountering computational challenges, thereby enabling the direct acquisition of a sensor set capable of reducing off-diagonal MAC elements [85]. The quality of placement for strain gauges and accelerometers is quantified by the ratio of the modal clarity index and mode shape expansion values derived from a finite element model of the monitored bridge [23]. Compared to the conventional method of gathering raw vibration data and performing singular value decomposition (SVD) at a central location, conducting SVD within the network can lead to significantly lower energy consumption and reduced latency [92,93]. A novel framework is proposed for least-squares localization based on estimated ranges, encompassing cases such as time-difference-of-arrival (TDoA), time-of-arrival (ToA), and received signal strength (RSS) [95]. This approach substantially reduces the computational workload in each iteration compared to classical nonlinear least-squares (NLS) methods, resulting in a 67% reduction in computation for a 3-D positioning system. A higher trace of the Fisher information matrix (FIM) indicates more information in the measurement, leading to more accurate estimation results [102].

5.2. Wireless Sensor Network Performance Evaluation

Wireless sensors deployed within expansive civil structures spanning several miles typically face challenges due to their distance from central systems, compounded by the limited radio range and energy resources inherent in these sensors. This scenario underscores the complexities involved in data collection. Achieving robust connectivity, facilitating reliable communication between the wireless sensors and central systems (sinks), emerges as a critical prerequisite for a wireless sensor network (WSN)-based structural health monitoring (SHM) system [25,86]. Furthermore, ensuring a prolonged operational lifespan spanning several decades remains paramount for any SHM system [25]. Presently, the performance evaluation of wireless sensor networks predominantly centers on aspects such as network connectivity and network longevity [25,26]. The detailed information is presented in Table 6 as shown below.

Table 6. Performance evaluation of different wireless sensing networks.

Category	Meaning	Methods	References
Network connectivity	Deliver data packets to a destination that is beyond the radio range.	Adjacency matrix, Judgment matrix.	[25,26,108–115]
Network lifetime	Life cycle of a WSN-based SHM system.	Inversely proportional to the highest energy consumption rate of the nodes.	[25,26,86,87,89,91,109,110,116–121]

In conjunction with sensor placement, we facilitate the development of "connectivity trees" among sensor nodes, ensuring the maintenance of both structural health state and network connectivity. This approach allows for decentralized management, which is particularly useful in scenarios such as sensor faults [109]. Energy consumption in wireless sensors encompass data sensing, processing, transmission, and reception [89].

5.3. Multi-Objective Optimization Models and Algorithms

The reliability and serviceability of evaluation results in a wireless sensor network (WSN)-based structural health monitoring (SHM) system heavily depend on the placement of wireless sensors [87,122,123]. Moreover, within WSNs, the energy stored in batteries is limited, and the transmission range of wireless sensors is constrained. Considering these factors, the objective of optimal wireless sensor placement (OWSP) is to identify configurations that not only facilitate accurate structural parameter identification, but also prolong network lifetimes [25]. Several researchers have made significant contributions to the exploration of optimal wireless sensor configurations for WSN-based SHM systems. The detailed information is presented in Table 7 as shown below.

The table illustrates that research on sensor layout optimization in bridges predominantly revolves around single and double objectives. Key decision objectives include the adoption of the modal assurance criterion (MAC) [22,25,27], modal strain energy (MSE) [21,23,24,90], and singular value decomposition ratio (SVDR) as a modal evaluation criterion [26]. Notably, these studies commonly employ the firefly algorithm (FA) [21,24–28], genetic algorithm (GA) [22,25,27], and particle swarm algorithm (PSA) [20] as primary solving algorithms.

Table 7. Evaluation of different optimization model applications.

Target Number	Decision Objectives	Important Parameters	Algorithm	Effect	Not Enough	References
1	Optimal performance for the bridge modal and the energy consumption of wireless networks.	• Strain modal vector. • Strain modal coordinate. • Length and width of the bridge.	Improved particle swarm algorithm (IPSA)	• The actual modal data of the bridge must have some deflection with the simulation data.	• Number of sensors is not taken as a decision variable.	[20]
1	Optimal performance for MSE.	• Mode shape matrix of a structure. • Stiffness coefficient.	Cluster-in-cluster firefly algorithm (CiCFA)	• Random selection of indexes and number of elements avoid the iteration falling into local optimization. • CiCFA is at least 2% more accurate than GA.	• The application scope of CiCFA is not verified.	[21,24]
1	Optimal performance for MAC.	• Identified modal matrix.	Modified variance (MV) method	• A nonlinear relationship between the numbers of target modes and the number of sensors was observed.	• This study fails to reflect the influence of dynamic changes in the number of sensors on MAC.	[22]
1	Optimal performance for MAC, network connectivity, and network lifetime.	• Identified modal matrix. • Adjacency matrix. • Data packet size. • Transmission distance. • Number and position of sensor.	Information-fusing firefly algorithm (IFFA)	• Solved the OWSP single target problem. • Directly estimate the connectivity of the self-organizing multi-hop networks. • IFFA is at least 11% more accurate than SDFA.	• Number of sensors is not taken as a decision variable. • Multi-objective problem between MAC and network performance is not studied.	[25]
1	Optimal performance for SVDR, network connectivity, and network lifetime.	• Mode shape matrix. • Adjacency matrix. • Energy consumption.	Automatic-learning firefly algorithm (ALFA)	• ALFA is at least 12% more accurate than SDFA.	• Load and the congestion of wireless sensors are left out of consideration in this study.	[26]
1	Optimal performance for identified mode shapes, network connectivity, and network lifetime.	• Structural mass matrix. • Stiffness matrix. • Damping matrix. • Position, energy, load of the wireless sensors. • Routing protocol. • Cost.	Hybrid discrete firefly algorithm (HDFA)	• Proposed evaluation criterion can restrict the search to a space that is a trade-off between the effectiveness of the information and the performance of the WSNs. • HDFA outperforms the SDFA and the SGA in terms of the computational efficiency (>20%) and the capability of searching the global optimization.	• Number of sensors is not taken as a decision variable.	[28]

Table 7. *Cont.*

Target Number	Decision Objectives	Important Parameters	Algorithm	Effect	Not Enough	References
1	Optimal performance for MSE.	• Mode shape matrix of a structure. • Stiffness coefficient.	Generalized genetic algorithm (GGA)	• The elite conservation strategy and worst elimination policy improve the convergence speed dramatically. • The gradual change and sudden change effectively prevent solutions from falling into local optimal spaces.	• This work is only a preliminary attempt for the OWSP. • The real applications of WSNs are more complex and the performance of WSNs is affected by many factors.	[90]
2	• Optimal performance for MSE/MCI (Modal Clarity Index). • Network energy consumption.	• Modal identification using vibration. • Modal clarity index. • Power consumption. • Spent time. • Residual energy consumption.	Genetic algorithm (GA)	• Multi-objective layout optimization of wireless SHM systems is feasible with the application of GA and discrete discrete-event simulation. • Optimization yields 12 Pareto Pareto-optimal solutions with different network lifetime and information quality values that can be used for deciding on the final deployment layout.	• Further analysis is required to evaluate the optimization performance such as the population diversity.	[23]
2	• Optimal performance for MAC. • Optimal performance for network connectivity, and network lifetime.	• Identified modal matrix. • Adjacency matrix. • Data packet size. • Transmission distance. • Energy consumption. • Number and position of sensor.	Multiobjective discrete firefly algorithm based on neighboring searching (MDFA/NS)	• Solved the OWSP multiobjective optimization problem. • Neighboring searching instead of the global exploration quickens the speed of finding the Pareto optimal solution set. • MDFA/NS has a strong ability in finding the Pareto optimal wireless sensor configurations and outperforms the widely used NSGA-II.	• Number of sensors is not taken as a decision variable.	[27]

5.4. Adverse Environmental Effects

Although wireless sensors have been developed and deployed in bridge applications, lightweight sensors are susceptible to damage in harsh environments and may not continue to function as planned [124–126]. Harsh environments include attacks such as high pressure or vibration, like typhoons; sudden accidents such as fires; and the influence of corrosive environments, such as acid rain [124,126]. Harsh environments may cause sensors to malfunction, leading to sensor failures. When the number of failed sensors exceeds an acceptable level, the structural health monitoring (SHM) system may provide unreliable monitoring or predictions of structural performance. To avoid this situation, the current practice is to use high-cost sensors designed to withstand harsh environments in SHM systems [127–129], with a large amount of redundant sensor placements, resulting in a widespread application of costly and burdensome systems.

6. Challenges and Future Work

In the context of large-scale environmental wireless sensor networks (EWSN), sensor nodes typically comprise a data processing and storage unit, a communication interface, and a power source characterized by limited capacity, often deployed in remote environments [94]. Nevertheless, several challenges persist alongside potential avenues for enhancement, including issues related to efficiency, energy consumption, long-distance transmission, and optimal layout solutions.

6.1. Efficiency

In practical engineering applications, it is customary to account for sensors operating at varying sampling rates and communication bandwidths within a network [91]. Concurrent transmission of data from multiple neighboring nodes utilizing distinct frequency channels holds the potential to augment data collection and transmission rates close to the maximum laboratory transmission rate, thereby substantially enhancing the efficacy of wireless sensors. Nevertheless, managing the transmission timing of numerous independent sensors and achieving synchronized frequency switching can pose challenges [14]. Future research endeavors will expand the scope of dynamic channel and channel mode optimization (DCCMO) to encompass heterogeneous wireless sensor networks, while also considering the presence of multiple sinks and accommodating mobile sinks [91].

6.2. Energy Consumption

The majority of wireless sensors operate on batteries with limited energy resources. Consequently, minimizing energy consumption and extending network lifetime present significant challenges in the implementation of wireless sensor network (WSN)-based structural health monitoring (SHM) systems [25,26]. However, the pursuit of low power solutions introduces additional complexities. The imperative for reduced power consumption dictates a corresponding decrease in data transmission rates for wireless sensor nodes [12], complicating the delivery of large packets [8,11]. Optimal selection of routes characterized by low load and congestion could potentially extend network lifetime and alleviate data transmission delays, representing a focal point for our forthcoming research efforts [26].

6.3. Long-Distance Transmission

Long-distance data transmission relies on various techniques such as multi-hop communication protocols [11,14], the multi-tier probabilistic polling protocol MTTP [16], topological network structures [12], other configurations of wireless sensor network nodes, or specialized radio communication bands [8]. However, with an increase in the number of multi-hop layers, there is a corresponding escalation in conflicts among polled packets, resulting in heightened transmission delays [16]. This packet collision issue can be addressed through frequency slot division, involving the utilization of multiple RF channels [14]. Similarly, U-node multi-hop communication networks encounter a comparable challenge: the CDMA mode struggles to transmit large volumes of data simultaneously, leading to packet loss. This issue can be mitigated by expanding the memory of the modulation mediator, optimizing packets, and transitioning from CDMA to CMDA2 or 3G+ [11].

6.4. An Integrated Layout Solution

The discrete-event simulation, incorporating random input, lacks the capacity to provide a singular representation of a layout's average performance [23]. Advanced structural health monitoring (SHM) necessitates a more adaptable sensor configuration to comprehensively assess a structure's performance [28]. Future endeavors will entail the integration of additional factors such as quality of service, energy efficiency routes, and network topology within the Optimal Wireless Sensor Placement (OWSP) framework [21]. Furthermore, the exploration of a multi-objective optimization algorithm that incorporates the effects of adverse environmental conditions presents a promising avenue for future research endeavors. [24,124]. A Monte Carlo method, involving the simulation of multiple replications to derive the empirical distribution function for the layout, can be employed [23,130].

7. Conclusions

Wireless sensor networks (WSNs), which are characterized by their ease of deployment, wireless communication capabilities, onboard computation, battery-powered operation, low cost, and compact size, have emerged as novel paradigms for structural health monitoring (SHM) [25,131]. They represent a promising technology for SHM applications [132–136]. The inherent limitations of wireless sensors and their constrained power resources underscore the importance of optimal wireless sensor placement (OWSP) in the designing of SHM systems. OWSP facilitates the capture of the most relevant information while maximizing the network's operational lifetime.

The present study summarizes and compares recent developments in wireless sensor networks for bridge structural health monitoring, encompassing wireless sensing technologies, practical applications, data collection and transmission technologies, data processing and analysis methods, and addresses common issues in data technologies such as efficiency, power consumption, long-range transmission, and deployment schemes. Additionally, it proposes future research directions and technical challenges:

1. Utilizing wireless sensor networks across different frequency channels to enable multiple adjacent nodes to simultaneously transmit data, enhancing data collection and transmission efficiency while considering potential collisions during data packet transmission.
2. Striking a balance between energy consumption and data transmission efficiency of wireless sensors, while mitigating data blockage issues stemming from low power consumption.
3. Implementing multi-hop communication protocols or topological network structures to facilitate long-distance data transmission of wireless sensors, thereby reducing data packet loss due to extended distances through increased memory and allocation of frequency slots.
4. Develop multi-objective optimization algorithms that comprehensively consider factors related to harsh environments and the deployment of wireless sensor networks.
5. Exploring the integration of these technologies with building information modeling (BIM) and geographic information system (GIS) technologies to expand sensor capabilities toward digital twin applications [137–142].
6. Furthermore, sensor deployment can be combined with bridge selection and site selection to mitigate the aging of sensor equipment.

These strategies offer practical insights for practitioners in the field of bridge structural health monitoring and aid in advancing the application of wireless sensor networks in this domain.

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