remote sensing

Review

Research Progress of SHM System for Super High-Rise Buildings Based on Wireless Sensor Network and Cloud Platform

Yang Yang [1,*], Wenming Xu [1], Zhihao Gao [1], Zhou Yu [2] and Yao Zhang [3]

[1] School of Civil Engineering, Chongqing University, Chongqing 400044, China
[2] MCC Saidi Engineering Technology Co., Ltd., Chongqing 400013, China
[3] School of Architecture and Civil Engineering, Xiamen University, Xiamen 361005, China
* Correspondence: yangyangcqu@cqu.edu.cn

Abstract: In recent years, the number of super high-rise buildings is increasing due to the rapid development of economy and construction technology. It is important to evaluate the health condition of super high-rise buildings to make them operate safely. However, conventional structural health monitoring (SHM) system requires a great number of wires to connect the sensors, power sources, and the data acquisition equipment, which is an extremely difficult process to plan the layout of all wires. Hence, one of the usually used compromising approaches is to limit the number of sensors to reduce the usage of wires. Recently, wireless sensor networks and cloud platform have been widely used in SHM system for super high-rise buildings because of their convenient installation, low maintenance cost, and flexible deployment. This paper presents a comprehensive review of the existing SHM system for super high-rise buildings based on wireless sensor network and cloud platform, which usually consists of sensing network subsystem, data acquisition subsystem, data transmission subsystem, and condition evaluation subsystem. This paper also reviews the crucial techniques and typical examples of SHM system used for famous super high-rise buildings. In addition, the existing difficulties in wireless sensor network and cloud platform based SHM system for super high-rise buildings and the future research directions are discussed and summarized.

Keywords: SHM; super high-rise building; wireless sensor network; cloud platform

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1. Introduction

Super high-rise buildings are buildings with more than 40 floors or buildings higher than 100 m [1–3]. In the past few decades, with the rapid development of construction techniques, more and more super high-rise buildings have been constructed. As the height of super high-rise buildings increases, its operation safety becomes more important since loss of life and property caused by structural collapse of super high-rise buildings are much greater than that of ordinary buildings, which sets an even higher demand on SHM system. It refers to applying on-site nondestructive test approaches to identify structural damage and ensure the structural integrity by analyzing the dynamic and static characteristics of structure. The traditional SHM technology of high-rise buildings uses wired sensors because it requires a small number of sensors. However, with the increasingly complex structure of high-rise buildings and the increasingly high structural requirements, the demand for sensors gradually increases [4–6]. Wireless sensors have entered people's vision and has obvious advantages. First of all, the increase in the number of sensors makes the traditional wired sensors need to lay a large number of data lines and power lines, which makes the deployment more difficult, while wireless sensors do not need data lines and power lines, which makes the deployment more simple, flexible, and able to quickly complete the deployment, reducing the construction difficulty and cost. Secondly, the traditional wired sensors of high-rise buildings need to be connected through data lines and the transmission distance is limited, while the wireless sensors can be transmitted through wireless signals and the transmission distance is longer, which can cover a wider area, improving the comprehensiveness and accuracy of monitoring. Additionally, the structural health monitoring of super high-rise buildings needs to acquire data in real time, but the traditional wired sensors need to be connected to the data acquisition terminal through the data line, and the data acquisition terminal needs a certain time to transmit to the central server. There is a certain delay in the transmission and processing of the monitoring data, while the wireless sensor can directly transmit the data to the central server, which is more real-time. Finally, wireless sensors can be added, deleted, or moved at any time, which is more flexible. In the case of building reinforcement or structural reconstruction, the position and number of sensors can be changed at any time, which improves the reliability and stability of the system [7–14].

In the face of the increase of the number of wireless sensors in high-rise buildings—and the complex and changeable external environment and load to evaluate and predict the structural state—the structural monitoring of super high-rise buildings will generate massive data and need to occupy a large amount of computing resources, storage space, and involve many parameters [1–3,15]. How to process and analyze these data efficiently, quickly, and extract valuable information to realize the real-time accuracy of high-rise damage monitoring is an urgent problem to be solved. Compared with the SHM background data processing technology of traditional high-rise buildings, cloud platform technology has certain advantages [16–18]. First of all, the cloud platform can provide powerful computing power and storage resources and can easily cope with the big data processing needs of super high-rise buildings. Secondly, the cloud platform adopts a distributed computing architecture, which can divide large-scale computing tasks into multiple small tasks and allocate them to multiple computing nodes for parallel computing, thus improving the computing efficiency and data processing speed to solve the real-time problem of structural health monitoring of super high-rise buildings. Furthermore, using the cloud platform to process data in the background can dynamically increase or reduce computing resources according to actual needs, avoiding the problem that traditional data processing systems need to be upgraded or transformed on a large scale. Thirdly, the cloud platform provides advanced security measures and data backup mechanisms, which can effectively protect the security of monitoring data and avoid the risk of data loss or leakage. Finally, the cloud platform can monitor and manage the structural health monitoring system remotely through the network and can monitor and manage the structural health monitoring system anytime and anywhere, which is more convenient and efficient; it solves the convenience of structural health monitoring of super high-rise buildings.

In general, the wireless sensor network and cloud platform technology are more efficient, economical, and flexible, and can overcome the difficulties encountered by the traditional SHM system in the modern application of super high-rise buildings. Through efficient processing and analysis of real-time data collected by various sensors, it is possible to understand the working status in time and provide guarantees for the safe operation of super high-rise buildings in real time.

2. Wireless Sensor Network

Wireless sensor network [19–21] is an advanced type of sensor network that consists of a great number of sensor nodes with sensing ability, computing ability, and communication ability. It can collaboratively collect and process the information of the target object in the area cover by the network and send it to the observer. A typical wireless sensor network structure is shown in Figure 1, which mainly includes wireless sensor nodes, sink nodes, and transmission media (internet or satellite communication). Nodes are deployed in the monitoring area by means of aircraft seeding, rocket ejection, and manual placement, etc.; they communicate with each other in an ad-hoc manner. After preliminary processing, the useful information detected by the sensor node arrives at the sink node in the form of multi-hop forwarding, and then it is transmitted to the end user by the sink node through wireless network or satellite channel. The sensor node consists of four modules: sensor module, processor module, wireless communication module, and energy supply module. The schematic diagram of sensor node components is shown in Figure 2. However, its processing capacity, storage capacity, and communication capacity are relatively weak and the battery energy is limited. For the network function, each sensor node has the dual functions of traditional network nodes and routers. In addition to local information collection and data processing, it may also store, fuse, forward, and perform other processing data forwarded by other nodes. Sink node is a node with strong processing capacity, storage capacity, and communication capacity. It is responsible for connecting the sensor network with the external network in order to transmit the collected data to the user terminal through the external network. Users process and analyze the collected information, and finally, make decisions according to specific rules. Wireless sensor networks are widely used in national defense and military, environmental monitoring, facility agriculture, medical and health care, smart home, traffic management, anti-terrorism and disaster relief, and other fields.

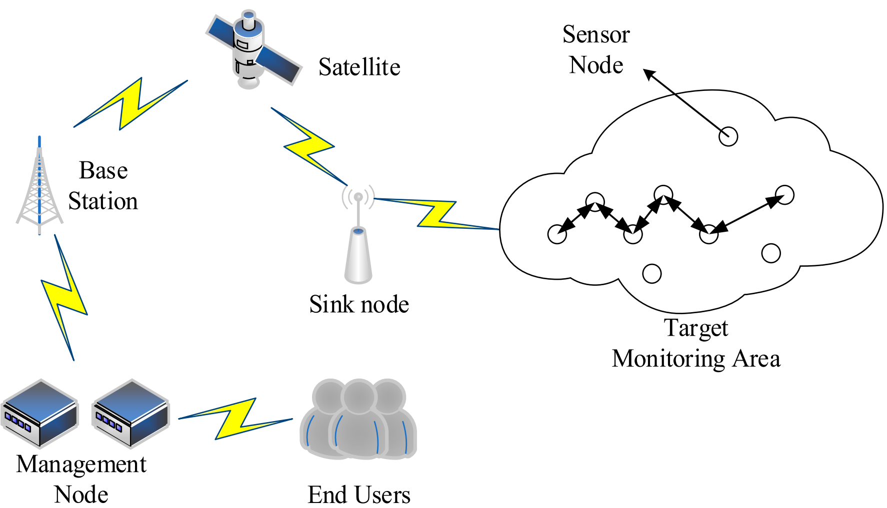

Figure 1. Framework of wireless sensor network.

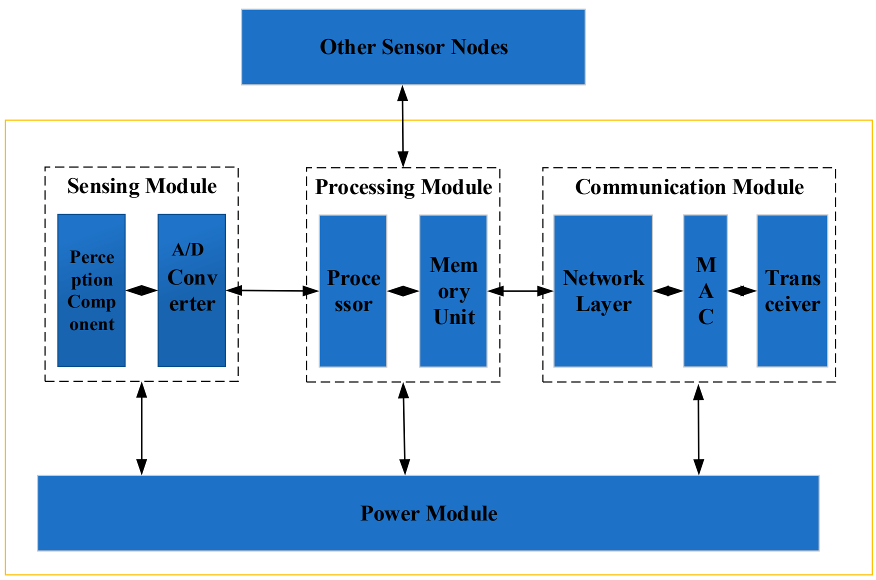

Figure 2. The schematic diagram of sensor node components.

SHM system based on wireless sensor network [22–25] includes three subsystems: sensing subsystem, data acquisition subsystem, and information transmission subsystem.

Each subsystem involves different software and hardware to achieve different functions; they cooperate with each other to complete tasks together. The sensing subsystem uses sensors to sense environmental data; the data collection subsystem collects and organizes these data; the data transmission subsystem wirelessly transmits these data to the following network cloud platform; and finally, the network cloud platform performs background computing to diagnose and predict the health of the structure.

2.1. Sensing Subsystem

There are some differences in the control load between high-rise buildings and bridges, tunnels, and other buildings. Because of the relatively high height of high-rise buildings, they are prone to wind load, earthquake load, etc., which can cause great deformation and easily cause transverse shear damage to the structure. Due to the structural characteristics of super high-rise buildings, lateral deformation monitoring becomes particularly important. Considering the cost and convenience brought by the increase in the number of sensors, the combination of acceleration sensor and other sensor instruments (such as inclination sensor, laser interferometer, resistance strain gauge, and other different types of sensors) will be considered for the structural deformation monitoring in super high-rise buildings to ensure the accuracy of structural deformation monitoring [26–40]. When the acceleration sensor is used for deformation monitoring, some correction methods (such as baseline calibration, empirical mode decomposition, and variational mode decomposition) are used to reduce the error caused by data drift and obtain good results. For example, Li et al. [3] used ultrasonic anemometers and acceleration sensors to jointly monitor the deformation of building structures. Brownjohn et al. [41] conducted long-term monitoring of dynamic response and extracted structural dynamic characteristics of a 65-story, 280 m high office building using accelerometer. Tomtorfs [42] adopted specially designed strain sensor nodes and acceleration sensor nodes to evaluate the damage severity of a super high-rise building under seismic loading.

In recent years, the development of intelligent materials have provided new ideas for SHM of high-rise buildings. Fiber Bragg grating (FBG) is considered an ideal sensing element to generate intelligent composite materials because of its small size, high precision, strong anti-electromagnetic interference ability, and good compatibility with the main material. FBG sensors have the advantages of high accuracy, high stability, high reliability, high security, and wireless transmission in the structural health monitoring of super high-rise buildings, which can provide important support and help for the operation and maintenance of buildings [43–45]. Through ultraviolet (UV) exposure method, phase mask method, online grating method, direct writing method, and other methods, the probability of refraction of its internal fiber core increases, so as to form a passive filter element of periodic modulation. When a beam of light enters the optical fiber and passes through FBG, only the light waves whose wavelength meets the central wavelength of FBG can be reflected, which is called center wavelength of FBG. Its schematic diagram is shown in Figure 3 [46–53].

According to the principle, many types of FBG sensors can be prepared, such as temperature, strain, inclination, settlement, displacement, etc. FBG sensors and flexible material can be made into a high-density distributed sensing flexible sensor through special preparation process. Compared with a single FBG, the signal processing algorithm of fiber-optic flexible sensor is more complex. With the development of pattern recognition and artificial intelligence, machine learning algorithm is used to reconstruct the surface shape [54]. Gaussian process regression method combined with machine learning can be used to analyze the temperature signal of FBG sensors [55]. Using Adam optimization algorithm, the convolutional neural network can be trained to recognize weak FBG signals [56]. Therefore, combining multi-channel FBG sensors and artificial neural networks to form a condition monitoring system [57,58] will be a new direction for the future development of artificial intelligence algorithms and flexible sensors.

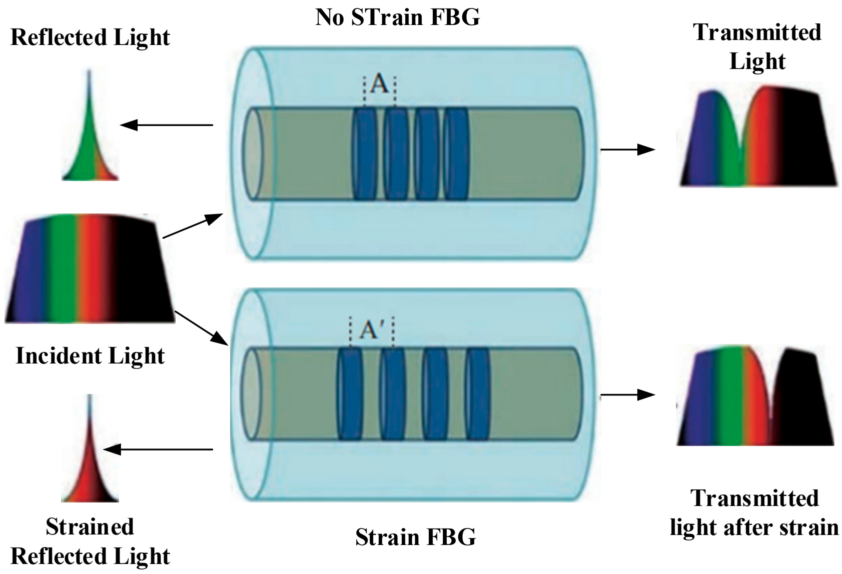

Figure 3. Schematic diagram of working principle of fiber Bragg grating sensor and its strain response.

2.2. Data Acquisition Subsystem

Due to the characteristics of many floors and complex structural forms of high-rise buildings—compared with other structural forms of bridges—more sensors are needed. At the same time, bridges are more incentive mechanisms for pedestrians and vehicles, while high-rise buildings are more incentive mechanisms for wind load, residents, and seismic load. In particular, signal sampling frequency, signal prepossessing, and data storage or transmission strategy should be considered in the data acquisition subsystem. The selection of sampling frequency is a key problem in the process of data acquisition. If the sampling frequency is too high, even a single node will quickly produce a large number of measured data and increase the storage and communication overhead. At the same time, the system requires greater synchronization between different nodes. If the sampling frequency is too low, the collected data cannot effectively reflect the structural characteristics of the super high-rise building structure. In practice, the sampling frequency is usually determined according to the focused frequency components of the monitored super high-rise building.

The SHM system also requires the collected data to be accurate [59,60]. On one hand, hardware devices like sensors, amplifiers, analog/digital (AD) converters, etc., need to be calibrated. On the other hand, the analog signal obtained by the sensor usually needs to be amplified, filtered, and denoised. The intelligent infrastructure and Transportation Technology Laboratory of Clarkson University in the United States has designed a wireless sensor solution (WSS) for SHM [61,62]. The single analog signals like displacement and acceleration collected by sensor nodes underwent signal conditioning including automatic offset zeroing, programmable gain amplification, and anti-aliasing low-pass filtering before AD conversion. Differential analog signals such as pressure, displacement, etc., were processed by ZMD31050 signal regulator, including offset correction programmable gain amplification, and AD conversion. In the SHM system of the Golden Gate Bridge [57], the analog signal obtained by the acceleration sensor was first processed by a 25 Hz anti-aliasing low-pass filter and then converted by a 16-bit AD conversion. The amount of data produced by a single node in the sampling process are dependent on the sampling frequency, the resolution of analog-to-digital converter, and the number of data channels. Due to the limited transmission bandwidth of wireless networks, unreliable wireless links, and other factors, the transmission of a large number of data in real time will inevitably lead to a sharp rise in packet loss rate. Therefore, the data storage and transmission strategies are very important. As shown in Table 1, data storage and transmission strategies are mainly divided into three categories: (1) real-time transmission, which can be used when the sampling frequency is not high or the number of nodes is limited [63]; (2) transmission after sampling raw data, which means that the node stores data locally and transmits it after a period of sampling [57]; and (3) transmission after pre-processing, which means that the nodes conduct local analysis and pre-processing of the data and transmit the processed results [58–63]. Lynch et al. [64] used the embedded damage detection algorithm in the wireless SHM system due to its operational power efficiency. Bhuiyan et al. [65] also used the decentralized decision-making method in the fault-tolerant health monitoring system.

Table 1. Comparison of storage and transmission schemes.

Transmission Strategy	Applicability	Advantage	Shortcoming	Example System
Real-time transmission	The sampling frequency is not high; not many nodes	Get real-time effective data	Limited application scenarios; limited real-time transmission bandwidth	Whelan [61]
Transmission after sampling raw data	Large local storage of nodes	Eliminate transmission bandwidth restrictions	Continuous monitoring is not possible; transmission time and energy consumption after sampling	Kim [63]
Transmission after pre-processing	Strong node processing capacity	Eliminate transmission bandwidth limitation; reduce data transmission energy consumption	Continuous monitoring is not possible; unable to perform global data analysis	Lynch [64] Bhuiyan [65]

2.3. Data Transmission Subsystem

Wireless-sensor-network-based SHM system usually adopts Bluetooth technology and Zigbee technology to transmit data, where small high-power radio station, Global System for Mobile Communications (GSM) technology, Code Division Multiple Access (CDMA) technology, General Packet Radio Service (GPRS) technology, and satellite transmission technology are frequently used. Bluetooth technology is a universal near-range wireless interface established for the communication of fixed or mobile devices. It works in the ISM 2.4 GHz band which is common in practice. Zigbee technology is a wireless transmission technology with low rate, low power consumption, low cost, and large network capacity. Although it works on the same band as Bluetooth, it has many advantages that make it more practical than Bluetooth. In addition to the advantages of low power consumption and high network capacity, Zigbee technology has the advantages of small delay, self-organization and self-healing of the sensor network, and safe and reliable data transmission. GPRS is a mature data carrying service developed from GSM system. It provides packet switching based data services for traditional telecommute users and supports mobile users to access the internet or other packet data networks with packet data mobile terminals. GPRS network is stable and reliable; it has wide coverage and fast data transmission speed. Therefore, it can provide 40–100 kbt/s bandwidth so that the wireless-network-based SHM system for super high-rise buildings can also be realized.

With the increasing demand for global information interaction, it is necessary to establish a high-speed global communication network. Compared with the ground communication system, the satellite-to-ground data transmission system has become an important part of the global high-speed communication network because it has large coverage area and long communication distance, and furthermore, it is not affected by airspace and region. At the same time, in terms of scientific exploration, remote sensing satellites are developing toward wider observation range, higher resolution, and more diverse observation tasks. With the continuous development of hardware and software of global navigation satellite system [66–75], especially the emergence of high sampling rate Global Navigation Satellite System (GNSS) receiver [76], it shows unique advantages in SHM system for super high-rise building: (1) the sampling frequency is high, which can be up to 100 Hz; (2) the data acquisition of GNSS receiver can be carried out automatically; (3) GNSS can not only carry out high-precision three-dimensional displacement measurement, but also obtain time information with an accuracy of 30 ns; and (4) the GNSS receiver can receive the working satellite signal at any time, and it can also work normally in the severe weather of wind, snow, rain, and fog, which is convenient for long-term continuous monitoring. In fact, the measurement accuracy of static response by GNSS can reach the millimeter level or even higher. The measurement accuracy of dynamic response by GNSS has also been significantly improved, with the nominal accuracy of plane and elevation reaching 10 mm and 20 mm, respectively. GNSS-based SHM has some successful application cases on bridges, buildings, and so on. Previous GNSS-based SHM system for bridge generally used the U.S. Global Positioning System (GPS) [77]. In the late-twentieth century, China began to explore its own satellite navigation system and established the BeiDou system. Compared with other GNSS, BeiDou system has the following characteristics: first, the space segment of BeiDou system adopts a mixed constellation of three orbiting satellite combinations, with more high-orbiting satellites and strong anti-obstruction capability, especially in low-latitude regions where performance characteristics are more obvious; second, BeiDou system is the world's first navigation system with complete service capability in three frequencies, which provides the possibility of realizing centimeter-level, high-precision real-time positioning; thirdly, BeiDou system innovatively integrates navigation and communication capabilities, with five major functions, including real-time navigation, fast positioning, accurate timing, position reporting, and short message communication services; and finally, BeiDou system adopts bi-directional time synchronization technology for the first time, which effectively reduces satellite clock errors and improves positioning accuracy and stability. However, due to the influence of satellite ephemeris error, ionosphere delay error, tropospheric delay error, multipath error, receiver measurement noise, and other factors, the measurement accuracy of GNSS dynamic monitoring technology is limited to the range of 10~20 mm.

2.4. Node Deployment Control and Perception Optimization

Due to the constraints of cost, the number of sensors that the system can use is always limited. How to choose suitable measuring points and deploy a limited number of sensors to achieve the optimal collection of structural response is one of the key technologies in building SHM system [78]. Therefore, when deploying wireless sensor networks, the characteristics of the monitored building should be considered, not just the characteristics of the network. In addition, according to relevant theories in civil engineering, Fisher information matrix (FIM) is an index used to measure the quality of deployment location [79,80] and effective independence method (EFI) [81] is a commonly used node deployment method [61,82–84]. Li et al. [82] proposed the problem of node deployment in the application of structural health monitoring in 2010; they developed a node deployment method combining the requirements of civil engineering and the characteristics of wireless sensor networks. As shown in Figure 4, the sensor placement using EFI method (SPEM) module and the computer science (CS) optimization module are added to the SHM framework [85]. The two modules are between the finite element model module and the node deployment module, which are used to select a reasonable location of measuring points. The SPEM module selects the optimal measuring point location and FIM value of each location according to the model information of the structure, the location set of the measuring points to be selected, and the actual number of nodes (from the CS optimization module).

The CS optimization module reconsiders the location set of points to be selected and the number of nodes required according to the output of SPEM module, combined with the characteristics of wireless sensor networks, and specific application requirements. After many iterations between the two modules, the final set of measuring points is obtained.

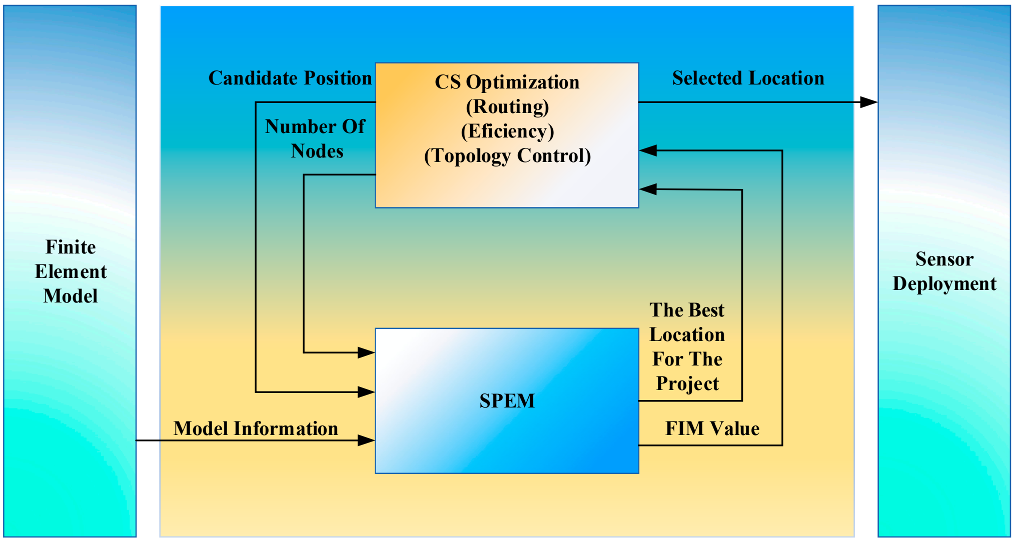

Figure 4. Sensor placement using EFI method.

The node deployment methods described above have certain limitations, as SPEM is only applicable to the finite element analysis method—but most existing building structures often do not have accurate finite element models. On the other hand, methods consider the node deployment from the general direction of SHM. They verify their effects by experiments on tower building structures, and there are certain differences between super high-rise buildings and these structures. Therefore, designing a sensor node deployment method suitable for super high-rise buildings is worth studying in the future, so that the network can not only meet the requirements of building monitoring in civil engineering, but also make full use of the characteristics of wireless sensor networks.

2.5. Energy Management Technology

When wireless sensor networks are used for building SHM system, they often require a long period of operation. However, the energy of the battery is usually very limited; the manual replacement of the battery is time-consuming, labor-intensive, and even impossible. Therefore, in the process of designing the whole network, the efficiency of node energy should be fully considered to maximize the life cycle of the network [86–88]. The energy consumption modules of sensor nodes include sensor module, processor module and wireless communication module. With the development of integrated circuit technology, the power consumption of sensor modules and processor modules has become very low, and nearly 80% of the node energy is consumed in wireless communication modules [89–91]. Therefore, in order to effectively reduce the data transmission by nodes, duty cycling mechanism and intra network information processing methods are widely used in wireless sensor networks. The duty cycling mechanism saves energy by scheduling the sleep/wake-up state of sensor nodes, while the information processing in the network is mainly realized by data compression and data fusion technology.

Xu et al. [92] adopted the method of data compression, the main process of which is shown in Figure 5. Firstly, the sensor node sets the threshold value of the collected vibration signal, stores the data that reaches the certain threshold, uses orthogonal CDF for wavelet decomposition, and stores the results (lossless data) in flash. The node only sends the date if the data collector at the base station needs to review the original data or other details. According to the experimental analysis, this method requires less computing time and storage capacity. In addition, when 4 bits are used for quantization, a compression ratio of 20 times and a root mean square error of 3.1 can be achieved.

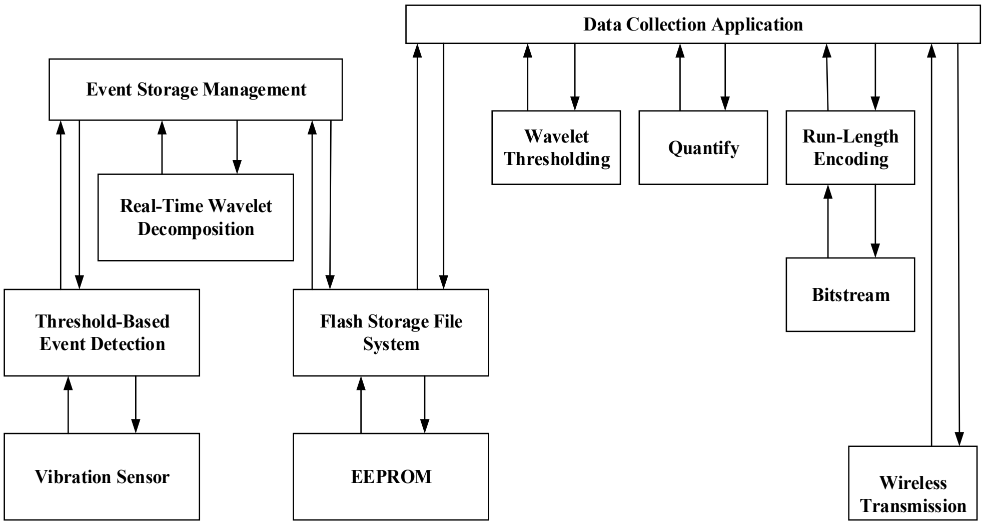

Figure 5. Data compression of Wisden.

Kundu et al. [93] designed power-aware, wireless-sensor-network-based SHM system for bridges, using both duty-cycling and data-fusion mechanisms. The sensor nodes formed a linear topology along the direction of the bridge, and two base stations, B1 and B2, were set at both ends. In order to save energy effectively, each node had two states: active and sleep. When the node was in active state, all functions were turned on; while the node was in sleep state, a wake-up antenna was used to monitor the channel. When the antenna received the wake-up signal, an interrupt was generated to wake up the node. The data transmission process started from a base station (B1), a wake-up signal was sent to wake up the first node, and then the S-MAC mechanism (rts/cts/data/ack four handshakes) was used [94] for data transmission. After receiving the data packet from the previous node, each node fused its own data, and then sent it to the next node in the same way. Finally, all the data reached the base station (B2) at the other end. In order to effectively balance the energy of nodes, data transmission was carried out in different directions each time.

Xiao et al. [95] proposed a distributed data aggregation active monitoring system (dams) for building structure diagnosis, which used router nodes with strong functions in the network for data fusion. The sensor node sent the data to the router and the latter waited for a certain time to collect the data of the child nodes, and then fused all the received data with its own data before sending. In this way, the number of data transmission can be effectively reduced to achieve the purpose of reducing energy consumption.

The methods used in the above systems to reduce node energy consumption have certain limitations: when the wavelet compression method is used, a great delay in data transmission can be observed; when the power-aware wireless sensor network is used, continuous building structure monitoring cannot be realized due to the duty cycling mechanism; and the data fusion method is only suitable for linear topology networks, but there is usually a large data transmission delay at the same time. Therefore, how to effectively reduce node energy consumption and prolong the working life of the whole network without affecting the normal work of the SHM system is a problem worthy of research and exploration. On the other hand, the application of energy collection technology [17,95,96] and wireless charging technology to building SHM system will also become an important issue in the future.

3. Damage Processing and Cloud Platform Technology

With the rapid development of modern sensing technology, computer and communication technology, signal analysis and processing technology, and structural vibration analysis theory, the high-rise buildings' natural vibration monitoring system based on wireless sensor network has become a research hotspot. It obtains the environmental excitation and structural response information of the structure through real-time monitoring of various sensors. It uses signal processing and modal analysis technology to extract the state index of the structure. Finally, combined with structural damage identification technology, the health status of the structure is evaluated to ensure the safe operation of the structure and provide scientific basis for its maintenance. Damage treatment and network cloud platform technology are particularly important. The damage processing technology can be divided into damage identification technology and damage prediction technology.

3.1. Damage Identification and Prediction Technology

The ultimate purpose of SHM system for super high-rise buildings is to detect the possible damage inside the structure, further evaluate the health status, and give an early warning of potential hazards. Therefore, the damage identification subsystem of SHM system for super high-rise buildings includes damage identification and damage prediction. In general buildings, damage is defined as intentional or unintentional changes in materials or geometric properties, including boundary conditions and connections, which adversely affect the current and future performance of the structure. The damage has obvious space-time multi-scale characteristics, including time and size scales. At present, the SHM system of super high-rise buildings based on wireless network has made great progress in smart sensors, system integration, wireless transmission, massive data storage, and analysis. It can realize the accumulation of long-term monitoring data, the tracking of historical data, and the safety assessment after abnormal events [97–104]. However, damage identification and damage prediction are usually at the laboratory level. It is difficult to identify the early damage of real super high-rise buildings and issue warnings, which is still a huge challenge [105–107]. The structural state assessment and safety prediction system diagram is shown in Figure 6.

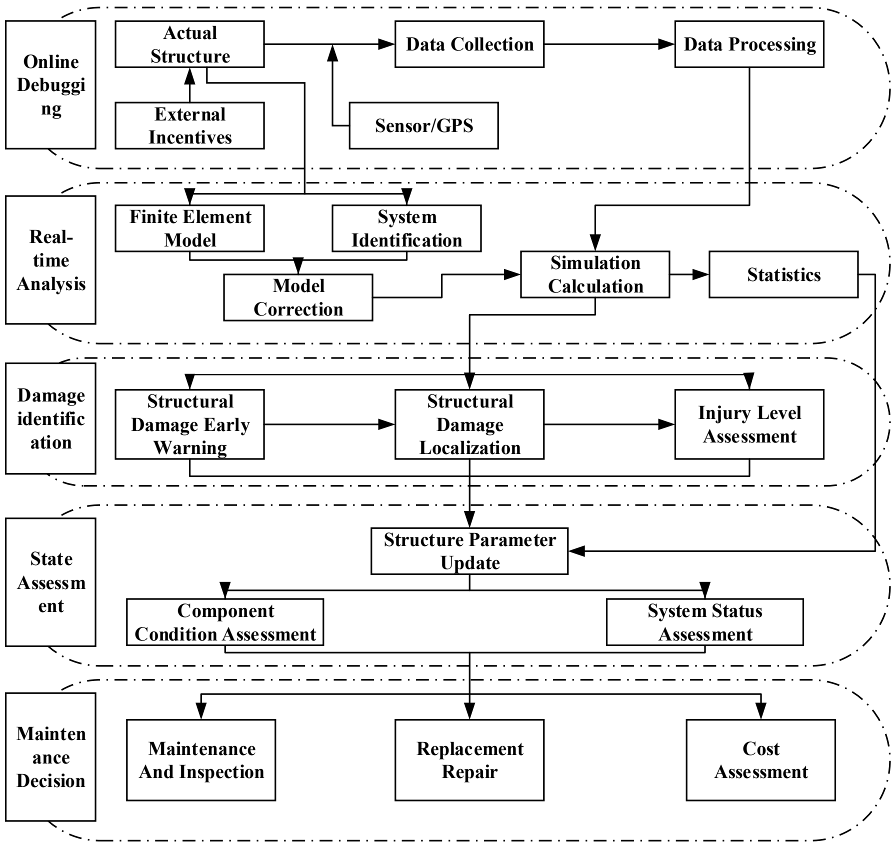

Figure 6. Schematic diagram of structural state assessment and safety prognosis system.

3.1.1. Damage Identification Method

At present, the research direction of damage detection of super high-rise structures is mainly to select appropriate dynamic damage indicators and detect the damage state of high-rise structures by analyzing the dynamic response signals of high-rise structures, according to the relationship between the dynamic characteristics of high-rise structures and their physical parameters. In recent years, damage detection based on dynamic test has become a research hotspot of civil engineering scholars. According to whether the damage factors are determined, they can be divided into two categories: damage detection methods under deterministic and uncertain conditions [108–117].

The deterministic damage diagnosis [113–115] method treats the damage characteristic parameter as a deterministic quantity, and its research focus is the deterministic mapping relationship between the damage characteristic parameter and the damage. Based on this mapping relationship, the damage can be identified by deterministic calculation and reasoning. Damage determination and diagnosis methods based on damage parameters mainly include damage detection methods based on frequency, damage detection methods based on structural modal shape, damage detection methods based on modal strain energy, damage detection methods based on frequency response function, damage detection methods based on flexibility matrix, and damage detection methods based on statistical moments. In 2017, Guo SX et al. [112] proposed the use of short-time Fourier transform for damage detection of high-rise frame structures. Through Matlab model analysis and shaking table test of 12-story frame structure model, it was found that the slope of frequency and time was positively correlated with the degree of damage, and the numerical simulation and experimental analysis could reach consistent conclusions, which verified the reliability of this method for damage detection of high-rise frame structures. In 2017, Ghasemi M R et al. [113] used strain energy to conduct damage detection, identified the elements that may be damaged, and verified that the method can be used to identify structural damage through several examples. In 2013, Gao et al. [114] proposed a quantitative index of structural damage based on the frequency response function, which is used to quantify the damage of frame structures under earthquake action. The research shows that this method can carry out effective quantitative analysis on recycled concrete frame structures. In 2013, Pandey et al. [115] proposed a generalized flexibility perturbation method for structural damage identification under environmental excitation, and furthermore, verified the feasibility of this method through numerical simulation of a two-story frame structure. In 2013, Zhang J et al. [116] further studied the damage detection method based on statistical moments and extended the statistical moment theory to the scope of time domain and applied it to any external excitation. In 2017, Yang et al. [117] proposed the two-dimensional Fourier spectral curvature mode method, which solved the instability problem of the classical curvature mode method. However, the methods mentioned above are basically obtained under the ideal conditions of the laboratory. At the same time, each damage determination and diagnosis method based on damage parameters has certain limitations. For example, the natural frequency is easy to measure and has high accuracy, but it is not sensitive to the local damage of the structure; the mode shape, especially the higher order mode shape, is sensitive to the change of local stiffness, but it is difficult to measure accurately; and the frequency response function contains more structural information than the modal data, but it is more complex in theoretical derivation and practical application. There are many uncertainties in the actual structural damage diagnosis process, including noise interference, test error, model error, environmental or load uncertainty, and other unknown uncertainties. The existence of uncertain factors leads to the ineffective deterministic damage diagnosis methods in theory, simulation or simple model test when applied to actual structures. How to deal with uncertain factors has gradually become a research hotspot in the field of damage diagnosis in recent years. In this paper, it is believed that on the basis of deterministic methods, various methods to deal with uncertainty problems will be integrated and the uncertainty method of damage diagnosis will be developed, which is expected to better solve practical engineering problems. In summary, the research of uncertain damage diagnosis methods will be an inevitable trend.

Considering the influence of various uncertain factors, the damage diagnosis uncertainty method [118–120] considers the damage characteristic quantity and the damage degree of the component as the uncertainty, and its research focus is the uncertainty mapping relationship between the damage characteristic quantity and the damage degree of the component. The research of damage diagnosis uncertainty method is divided into probabilistic and statistical damage diagnosis uncertainty method and data-fusion-algorithm-based damage diagnosis uncertainty method. The uncertainty method of damage diagnosis based on probability and statistics analysis method is to determine the probability and statistical distribution of the output of the model according to the probability distribution of the input parameters of the model. The uncertainty is expressed in the form of probability distribution. Under a certain degree of confidence, the damage diagnosis is carried out using statistical methods. According to the different principles of statistical inference, the uncertainty methods of damage diagnosis based on probabilistic statistical analysis are mainly divided into four categories: model correction method based on Bayesian statistical inference; model correction method based on stochastic finite element back analysis; damage diagnosis method based on statistical pattern recognition; and damage diagnosis method based on probabilistic neural network. The uncertainty method of damage diagnosis based on data fusion algorithm is to diagnose structural damage based on data complementarity, mutual coordination, mutual verification, and fusion of multiple or multiple sensors. The uncertainty method of damage diagnosis based on data fusion algorithm is divided into three levels: data level fusion, feature level fusion, and decision level fusion. In 2008, Jiang et al. [118] proposed the Bayesian wavelet probability method considering the nonlinear and noise effects of the structure and carried out numerical simulation on the 5-story rigid frame and the 38-story concrete building model. The results show that the method is effective for damage detection. In 2017, Enrique Sevilano et al. [119] proposed the modal interval analysis method to update the damage detection method considering uncertain but bounded parameters. In 2000, Sohn H et al. [120] proposed a statistical pattern recognition method based on process control technology, and the results of experiments on concrete columns show that this method can identify structural damage. However, the above uncertainty methods still have many problems to be solved. Although probabilistic method is a classical method for describing uncertainty, it is only suitable for describing random uncertainty and only suitable for the analysis of simple structures. For complex structures, both theoretical analysis and numerical simulation are quite difficult. Most of the research on data fusion in structural damage diagnosis focuses on "calculation" and strives to complete the data fusion process through numerical calculation; however, the thinking process of experts is not "calculation process", but more "reasoning diagnosis process".

In view of the current challenges and urgent problems in structural damage diagnosis. The following three aspects are worthy of in-depth study:

(1) Data fusion is an effective technical means to reduce the uncertainty of injury diagnosis results. The key to using data fusion is to determine the inference rule of data fusion, and moreover, studying the uncertainty interference law of structural damage-feature mapping relationship is the premise and basis for establishing the reasoning rule of data fusion. Therefore, this study has important value and significance;

(2) Non-probabilistic methods, such as likelihood theory and interval theory, are based on an axiom system that is weaker than probabilistic methods and can describe non-random uncertainty. Therefore, studying the diagnostic uncertainty method based on non-probabilistic methods is expected to better solve the uncertainty interference problem of structural damage in the process of structural damage diagnosis;

(3) The essence of artificial intelligence data deep fusion reasoning is to simulate the thinking of damage diagnosis of experts in the field. Its core is to establish targeted deep data fusion rules based on field knowledge and experts, and to make structural damage diagnosis combined with the uncertainty reasoning algorithm in the field of artificial

intelligence. The structural damage diagnosis system established based on the above methods will have stronger response, uncertainty interference ability and robustness, and can effectively integrate field knowledge and expert experience into the damage diagnosis system, so as to give more stable and reasonable diagnosis results.

3.1.2. Damage Prediction Method

At present, there is still a certain gap between the SHM system aimed at ensuring the safe operation of the bridge and the expectations of the bridge owner. The main reason is that the current health monitoring is mostly post-event damage detection (DD) rather than pre-event damage prediction (DP). We believe that DP is the future theme of SHM. Its basic definition is based on the SHM system: on the premise of understanding the damage evolution mechanism, combined with the structural service history and current situation; to evaluate the current damage state of the structure (level 1); predict the future load environment and structural performance of the structure (level 2); and predict the remaining service life of the structure through numerical simulation technology and historical experience (level 3). At present, the research on the methods of damage prediction and safety prediction mainly focuses on model-based methods, data-driven methods, and related integration methods. The prognosis method based on physical model is to modify and confirm the finite element model based on the monitoring information with the help of the finite element model, and then use the modified and confirmed model to predict the behavior of the structure. The data-driven method uses historical data to automatically train and learn a system behavior model, such as machine learning, neural network, decision tree, and support vector machine, so as to predict the future based on the results of training and learning.

The model-based method is probably the most effective and intuitive, which mainly focuses on material deformation, fracture, fatigue, and damage, as well as the connection between materials. The model-based structural damage prognosis inevitably faces two core scientific problems: namely, the multi-scale simulation and simulation methods of complex engineering structures from micro to macro and the numerical simulation analysis results under the specified accuracy and reliability. One of the key problems of structural damage prediction is the uncertainty in the prediction of damage prognosis. The uncertainty problem must be considered in the numerical simulation analysis under the specified accuracy and reliability. Only when the variability of structural calculation parameters is small can the deterministic analysis of the model give more practical results. In order to ensure that the model has certain reliability, the uncertainty of each parameter in the model must be incorporated into the simulation analysis, which involves model modification and model validation. Tang et al. [121] pointed out that effectively reducing the uncertainty of the model is the key to the damage prognosis; they proposed a dynamic model method to solve the uncertainty factors in the simulation structure of the model, and applied it to the damage prognosis process of mechanical gears. Engel et al. [122] carried out the damage prognosis for the SH60 helicopter gearbox, proposed that the uncertainty of the future environment and system components should be considered, and pointed out that the two keys to the damage prognosis were the selection of characteristic parameters and the reasonable and sufficient explanation of the expected phenomenon. Luchinsky et al. [123] proposed a model-based mixed probability method in the process of injury prognosis for solid rocket boosters and verified the effectiveness of this injury prognosis method through the experiments of sudden and slow opening on the boosters. Besson et al. [124] pointed out when analyzing the SHM system of a suspension bridge in Iceland that the dead weight of the bridge deck pavement, the elastic modulus of the cable, the main cable, and the bridge deck alignment will become the uncertainty factors in the finite element analysis, which has an uncertain impact on the accurate simulation of the response characteristics of the bridge.

The data-driven damage prediction method can build a learning model based on the measured data and can achieve real-time prediction [125–133]. At present, the most commonly used method in damage prediction research is artificial neural network (ANN). The ANNs learning ability, multi-input parallel processing ability, nonlinear mapping, and fault-tolerance ability—and the ability to obtain adaptively through new learning—ensure its good prediction ability. In terms of the fusion of neural network method and other methods, Ding et al. [126] explored the support vector machine genetic algorithm (GASVM), which combines neural network genetic algorithm (GA) with support vector machine (SVM), and applied it to the damage prognosis of aerospace electronic components. Catbas et al. [127] analyzed the uncertainty factors in the finite element analysis of the structure, constructed the ANN based on the L algorithm, and finally, applied the verified neural network model to the reliability prediction of the structure. Guan et al. [128] applied the maximum entropy method to the prediction of structural fatigue damage, obtained the corresponding relationship between the number of loading cycles and the size of cracks of aluminum alloy and verified the effectiveness of the algorithm with experimental data. The data-driven damage prognosis method is more efficient than the model-based damage prognosis method and can achieve real-time prognosis. It is more prominent in early warning; it is expected to be applied to online health monitoring, safety early warning, and condition assessment of bridge structures. However, when it is difficult to measure the data of a certain point in the structure, it is impossible to predict the point, resulting in incomplete basic prediction data.

At present, the concepts of damage prediction and safety prediction have just been introduced into the high-rise structure health monitoring system. Substantial prediction tests, theoretical research, and engineering practice have not yet been carried out. There are still a lot of key issues and technical challenges to be studied, mainly including:

(1) Large-scale, self-sensing, and embedded wireless intelligent sensing systems are now being developed, mainly including distributed sensing systems, local sensing systems, and sensing systems that can collect environmental energy [134–136];

(2) Using linear dynamic model to simulate super high-rise building is difficult to meet the requirements of conducting damage prognosis and safety prognosis. Therefore, efficient modeling methods like multi-scale simulation and effective model verification and validation have become urgent. Uncertainty description and quantitative transmission of nonlinear and strong coupling mathematical models are the key technologies of model verification and validation, which is also one of the greatest challenges;

(3) The damage identification methods or indicators are only applicable to numerical examples or simple laboratory scale models. Many indicators in actual engineering structures are insensitive to early damage. Hence, it is necessary to develop a damage identification method sensitive to slight damage in early stage. In addition, the statistical inference of damage prognosis and safety prognosis often assumes that the parameter uncertainty distribution obeys the Gaussian distribution, and the points at the tail of the Gaussian distribution often show structural nonlinearity. It leads to the change of the original design parameters of the damaged components, making damage identification and prognosis very difficult;

(4) At present, the research on prognosis mainly focuses on the fields of aerospace and industrial manufacturing and the methods of damage prognosis and safety prognosis suitable for civil engineering structures, especially for super high-rise building, are rarely involved. The prediction of loading condition needs to use data-driven time series prediction models, such as multivariable adaptive smooth regression (AR-MR) model [137], wavelet neural network model [138,139], etc. The prediction of structural response under future load is inseparable from the accurate finite element model, so the model-based prognosis method and the multivariate mixed prognosis method are also indispensable;

(5) The goal of probabilistic reliability analysis is to answer how many times the structure will reach the critical damage state after experiencing fatigue cyclic load [140,141]. In addition to estimating the probability of reaching the limit state, it also needs to assume the uncertainty of the model to predict the functional relationship between the frequency and the future load, the current health condition and the expected load. Because the closed

form expression of the failure region is usually difficult to obtain, the Monte Carlo sampling method or approximate expansion method must be used for integral approximation to obtain the simplified calculation model of the structure, and then based on the reliability theory to estimate the remaining service life of the structure under uncertain conditions.

3.2. Data Interaction, Monitoring, and Early Warning of Cloud Platform

In the SHM system for super high-rise buildings, the cloud platform, as the back end, undertakes the data interaction, monitoring, and early warning tasks of remote sensor devices, so as to realize the real-time monitoring of a relatively scattered large number of monitoring points [142–144].

Before the emergence of the cloud platform monitoring system, many self-designed traditional monitoring platforms have been produced [145–149]. They at least cover the model, including the implementation of specific algorithm logic and the creation and use of databases, the development of the controller responsible for forwarding the interactive data of the remote sensor device and processing the request, and the user interface. The development of traditional monitoring platforms involves a lot of components; hence, the development process is usually slow, and the portability and expansibility are poor. The data transmission methods and protocols between different traditional monitoring platforms vary significantly, which is not in line with the concept of cloud. The cloud platform monitoring system is purely an internet of things (IOT) platform, which is not particular to a specific function or project. As long as any type of sensor device carries out remote data transmission according to its transmission protocol, it can quickly build IOT. It completely encapsulates the underlying public drivers and protocol stack programs, leaving a friendly development environment for developers. The functional definitions, parameter definitions, early warning definitions, data storage definitions, and other related settings are left to developers to select.

Compared with traditional monitoring platforms, cloud platform monitoring system has many advantages. The cloud platform monitoring system is not specific to a particular application, so it can easily construct IOT applications with the support of the platform. The same platform can support different applications simultaneously. The cloud platform monitoring system has high scalability; its application scale can be adjusted and dynamically scaled at any time according to the needs of the application. It can easily allocate the resources required for IOT construction of thousands or even millions of sensor devices without considering any changes in hardware information. The cloud platform monitoring system has a perfect operation and maintenance mechanism [150–152]. It has a more professional team to complete information management and data storage, making the reliability of the connection and the security of the data better. The automatic centralized management of the cloud platform monitoring system improves the utilization of hardware, centralizes various traditional monitoring platforms designed by different enterprises in a decentralized manner, and manages and operates in a common way, reducing the overall operating cost and hardware idle rate.

In the cloud layer monitoring and early warning stage, for the parameter information transmitted by a large number of sensor devices, the current self-built monitoring platform adopts the working mode of setting threshold rules for parameters to give alarm notification. When the parameter is a continuous variable, the threshold is determined by construction engineering professionals based on experiences. However, in the future, with the increase of the types of parameters, the health status of building structures cannot be evaluated only by the threshold. In addition, with the explosive increase of collected parameter data, an intelligent evaluation system can be built in the cloud by means of big data fusion, machine learning, and deep learning. According to the comprehensive data and historical data of building parameters, its health status can be systematically evaluated, so as to give more accurate evaluation results and alarm information. This is also an important direction in the future of SHM system for super high-rise buildings.

Kijewski-Correa et al. [153] installed a unique SHM system on the Burj Khalifa Tower, the world's tallest building, using an existing internet cloud platform backbone as a virtual instrumentation cable system, allowing for modular and major plug-and-play deployment. The system supports a scalable approach to monitor high and complex structures that can be easily connected to a variety of sensors and data formats (analog and digital). It is also a great example to demonstrate the ability of a software-supported trigger framework to effectively monitor seismic and wind events from different main modules. Thus, it provides a truly multi-hazard platform for monitoring other built-up buildings. The deployment of a single-tier SmartSync during the construction phase of the Burj Khalifa Tower is shown in Figure 7.

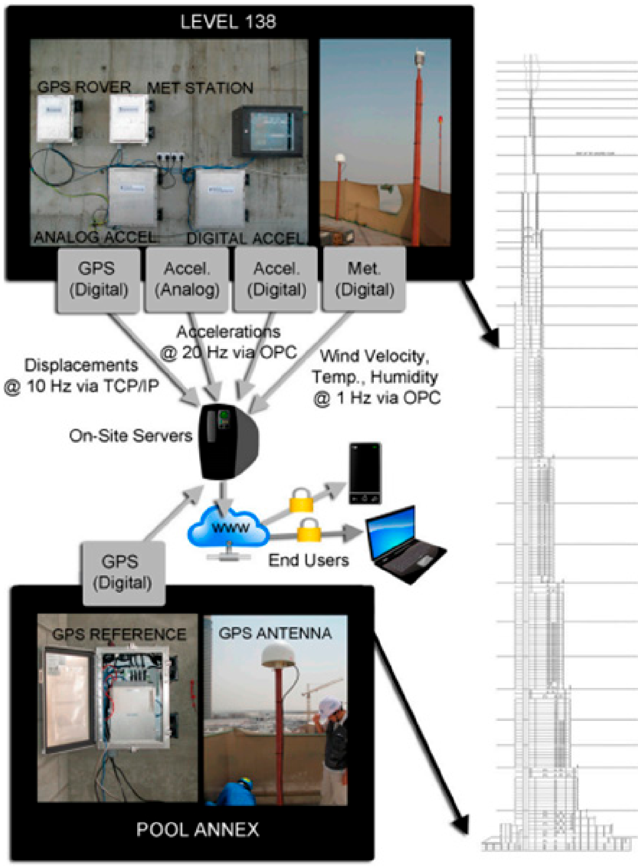

Figure 7. Single-layer deployment of SmartSync in Burj Khalifa Tower during construction.

Bazant and Wittmannl [154] proposed the stepwise method (SSM), which divides the entire construction process of a super high-rise building into multiple segmental time steps. The SSM method is a practical tool, but for complex high-rise structures, it takes a lot of computational time and occupies a lot of computational memory. Choi et al. [155] used a wireless sensor system based on cloud platform to monitor the structural condition of two super high-rise buildings with 66 and 72 floors. At the same time, a wireless sensor network based SHM system was proposed for the construction process. Wireless sensor network system for measurement of column shortenings in a high-rise building is shown in Figure 8. The system includes wireless sensing systems and network cloud platforms, where sensors and energy-efficient wireless sensing units (sensor nodes, master nodes, and repeater nodes) can accurately collect data. At the same time the use of cloud platforms enables real-time monitoring using web-based hypervisor. The locations of sensor nodes and master nodes for field measurement of columns in tower 1 and tower 2 are shown in Figure 9. The process of measuring the strain of vertical components and transmitting the measurement data to a remote server is automatic in order for the system to measure the shortening of vertical components automatically in real time.

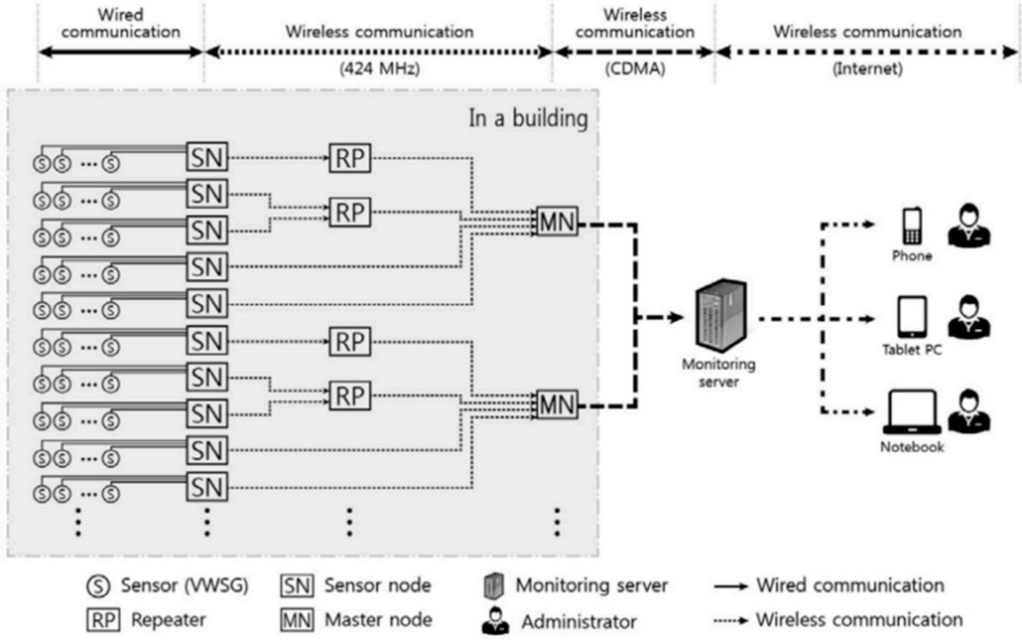

Figure 8. Wireless sensor network system for measurement of column shortenings in a high-rise building.

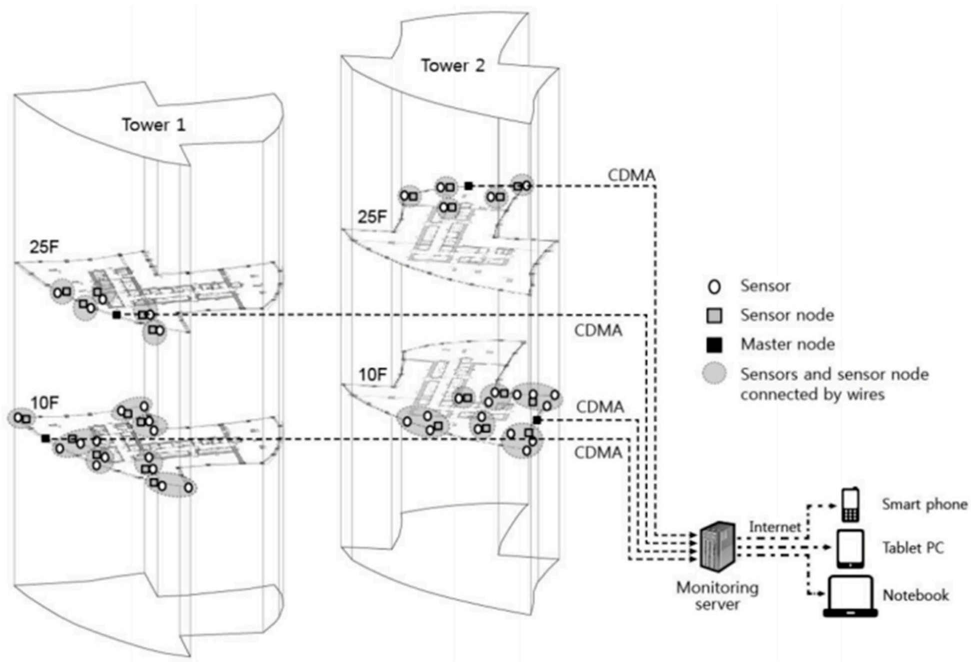

Figure 9. Location of sensor nodes and master nodes for field measurement of column shortenings in tower 1 and tower 2.

Yuan et al. [156] adopted the wireless sensor system of network cloud platform based on Sigma-Point Kalman Filter (SPKF) neural network to monitor the structural condition of super high-rise buildings. The system can be divided into four parts: the layout of sensor nodes in high-rise buildings; the wireless sensor network part; the serial communication middleware part of coordinator; and the monitoring software part of host computer based on Javaweb. The flow chart of high-rise building deformation monitoring based on remote wireless sensors is shown in Figure 10. Real-time deformation monitoring cloud platform is an automatic working mode of automatic control of various hardware acquisition devices. The platform consists of the bottom layer, middle layer, high layer, and top layer. Under the control of the data acquisition software, the collected raw observation data are standardized and transmitted to the real-time monitoring platform through the bottom data transmission subsystem. The platform is combined with the visualization subsystem to dynamically display the monitoring data, perform the initial and comprehensive analysis of the monitoring data in real time, and dynamically draw graphs such as process lines. This method can better solve the defects of back pagination (BP) neural network, such as long training time, large dependence on the initial value, and easiness by which to fall into the limitation of local extreme value. At the same time, it also realizes the advantages of neural network because it has the ability to approximate any continuous function and nonlinear mapping by SPKF. The feasibility and effectiveness of the proposed method is proved by the results of an example.

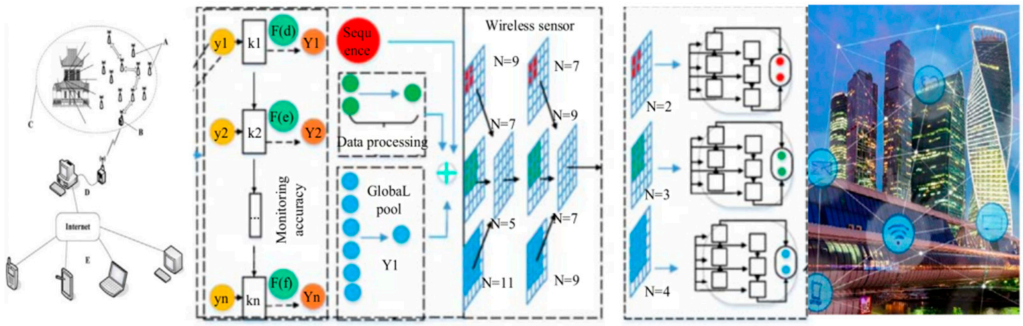

Figure 10. The flow chart of high-rise building deformation monitoring based on remote wireless sensors.

In order to reduce the computational cost and computational memory requirements in network cloud platform, Kim and Shin [157] combined several building structure floors into one structural group and assumed that the structural group was built at one time, so that the whole construction process of a high-rise building structure could be regarded as consisting of several structural groups from bottom to top. The high-rise building deformation monitoring model analysis diagram is shown in Figure 11. They also investigated the effect of group size and suggested that a group size of 1/15 of the total height of the structure could achieve an optimal balance between accuracy and computational efficiency.

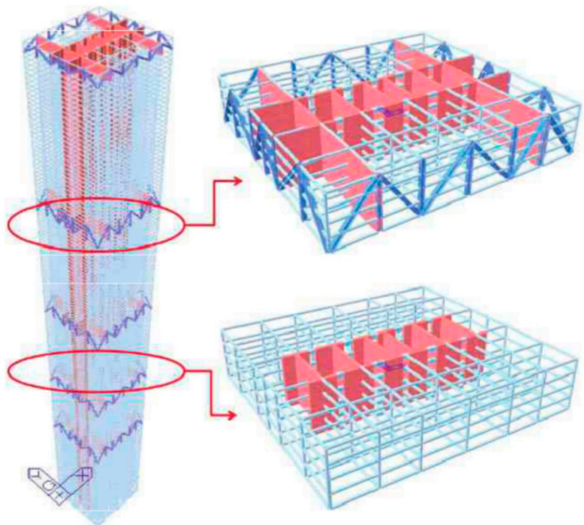

Figure 11. The high-rise building deformation monitoring model analysis diagram.

4. Conclusions

Compared with the traditional manual inspection method and wired network monitoring method, wireless sensor network has certain advantages in SHM system for super high-rise buildings because of its convenient installation, low maintenance cost, and flexible deployment. Therefore, it has recently become a hot spot. This paper summarizes the application of wireless-sensor-network-based SHM system for super high-rise buildings and analyzes the crucial technologies with some specific examples. It can be observed that in the actual engineering application, there are still some problems to be studied further:

(1) Selection and deployment of sensors.

When selecting sensors, it is necessary to determine the specific types and corresponding quantities according to the actual measurement requirements and the budget. Specifically, in addition to the technical indicators of measurement accuracy and measurement range, the reliability, durability, and cost of the sensor also need to be considered. Most of the existing SHM systems do not consider the rationality of node deployment, resulting in a waste of investment or the lack of key data, which affects the performance of the whole system. Therefore, the deployment method of sensor nodes is worthy of further study;

(2) Life of health monitoring system.

The life of health monitoring system depends on the residual energy of each node. Therefore, the effectiveness of node energy should be fully considered in the process of system design. Although the existing systems adopt the methods of duty cycling, data compression, data fusion, and so on to reduce the energy consumption of nodes, they all have certain limitations. Therefore, how to reasonably use the energy of each node without affecting the normal work of the SHM system—and how to use energy collection and wireless charging technologies to supplement the node energy in time—is a direction of future research and exploration.

(3) Data storage and processing.

The SHM system for super high-rise buildings will produce a lot of data every day. If it cannot be processed in time, it will cause data disaster. Therefore, on the one hand, it is necessary to select appropriate algorithms for timely analysis and processing of the data collected by sensors in real time; on the other hand, it is important to formulate a reasonable data storage strategy to regularly clear the redundant data in the database;

(4) Effect of structural damage identification.

The incompleteness and inaccuracy of the measured data and the limitations of the existing damage identification methods restrict the effect of structural damage identification, and then affect the accuracy of the system evaluation results. Therefore, how to improve the integrity and accuracy of measurement data is a direction that needs further research. On the other hand, we need to actively study new high sensitivity indicators to improve the effect of damage identification;

(5) Intelligence of network cloud platform.

With the gradual complexity of the structure form, the diversification of monitoring data and the efficiency of monitoring, the future development direction of wireless sensor network cloud platform in the structural health monitoring of super high-rise buildings should be intelligent. The network cloud platform should take data processing and analysis as the core, and comprehensively optimize the real-time monitoring and early warning, network reliability and security, and openness and sharing in order to achieve a more intelligent, efficient, and reliable building structure health monitoring system.

In general, there are still many problems in the application of wireless sensor networks in building SHM system for super high-rise building. These problems are interrelated and restrict each other, which constitute rich content for future research. However, we can predict that in the future the structural health monitoring system will play an increasingly important role in the management of building structures and that the era of digitalization of building structures is coming.

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