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DIPARTIMENTO DI INGEGNERIA INFORMATICA, MODELLISTICA, ELETTRONICA E SISTEMISTICA

Master Degree in Telecommunication Engineering:
Smart Sensing, Computing and Networking

Design and Realization of a Wireless Crack Detection System Based on IoT and Acoustic Emission

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INTRODUCTION

This thesis presents the design and implementation of a Wireless Crack Detection System that utilizes Acoustic Emission (AE) technology. The system is designed to detect cracks in real time and transmit the acquired data wirelessly to a central server for analysis.

The AE sensor is used to capture the crack signals, which are then processed through an analog signal processing circuit to enhance the signals and attenuate the noise. The processed signals are then thresholded and if the experimental threshold value is exceeded, the system acquires the signal, generates a timestamp using a Global Positioning System (GPS) module, and sends the data to the server (Raspberry Pi) using the Message Queuing Telemetry Transport (MQTT) protocol. The timestamp is generated with microsecond resolution to ensure precise timing information of the crack event.

The Raspberry Pi acts as a smart gateway between the sensor nodes and the cloud, where the data is sent to the cloud for long-term storage and real-time monitoring. The system is designed to be highly efficient, taking into account power consumption, and has the ability to accommodate multiple sensor nodes.

Node-RED is used to visualize the sensor nodes and the data, making it easy for users to monitor the system and analyze the crack signals. In conclusion, this project demonstrates the feasibility of using AE technology for crack detection and the potential of utilizing Internet Of Things (IoT) technologies for the real-time monitoring of critical infrastructure.

The thesis is organized into seven chapters, each contributing to the overall project:

- *Chapter 1* introduces the topic of the thesis, providing an overview of IoT and its applications, as well as discussing the challenges and future of IoT.
- *Chapter 2* focuses on the acoustic emission (AE) signal and system characteristics, explaining why AE is a suitable method for crack detection.
- *Chapter 3* provides background and existing knowledge about the system that has already been developed for crack detection using IoT.
- *Chapter 4* describes the sensor design and system integration process, detailing the selection of materials and components for the sensors and the integration of the sensors with the IoT system.
- *Chapter 5* covers the algorithm's design and firmware development, explaining how the crack detection algorithms were developed and implemented in the firmware of the IoT system.
- *Chapter 6* discusses the testing and data collection process, explaining how the system was tested and the data collected for analysis.
- *Chapter 7* concludes the thesis by summarizing the purpose and significance of the project and previewing future work that could be done to improve the crack detection system.

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This thesis is dedicated to my beloved country, Syria, and its people who have suffered through so much but have never lost their spirit of resilience and strength.
To my parents, Abdul Ghani and Samah, my brother Mayar and my sister Dalia.
To my dearest friend Bayan.

Chapter 1

Crack Detection and IoT

1.1 Introduction

The traditional methods of crack detection in critical infrastructure such as bridges and buildings have relied on manual inspections performed by trained operators. These manual inspections are time-consuming, costly, and may not provide real-time information about the condition of the infrastructure, leading to a limited number of buildings under monitoring and high costs. The accuracy and reliability of the inspection results also depend on the expertise of the human operator, which can impact the overall effectiveness of the inspection. The need for an efficient, cost-effective, and real-time crack detection system is evident in the aftermath of several disasters that have occurred due to unnoticed cracks in structures.[1]

There have been several disasters in the past that have occurred due to undetected cracks in structures. The Silver Bridge disaster in 1967 is a prime example of this. The collapse of the Silver Bridge in West Virginia was caused by a fracture in a single eye-bar of the suspension bridge. Despite regular inspections, the fracture was not detected through traditional inspection methods, leading to the collapse of the bridge and the loss of 46 lives. The cause of the disaster was the failure to detect the fracture, which would have been possible if a real-time monitoring system was in place.[2]

The I-35W Mississippi River Bridge collapse in 2007 is another example of a disaster that could have been prevented if a real-time monitoring system was in place. The collapse of the I-35W Mississippi River Bridge in Minneapolis, Minnesota was due to a design flaw and the failure of a gusset plate. Despite regular inspections, the problem was not detected, leading to the collapse of the bridge and 13 deaths and 145 injuries. The cause of the disaster was the failure to detect the design flaw and the failure of the gusset plate, which would have been possible if a real-time monitoring system was in place.[3]

The Genoa Bridge collapse in 2018 is another example of a disaster that could have been prevented if a real-time monitoring system was in place. The collapse of the Genoa Bridge in Italy was due to the corrosion of steel cables and the failure of a concrete pillar. Despite regular inspections, the problem was not detected, leading to the collapse of the bridge and 43 deaths. The cause of the disaster was the failure to detect the corrosion of steel cables and the failure of a concrete pillar, which would have been possible if a real-time monitoring system was in place.[4]

These examples highlight the importance of timely and accurate crack detection to ensure the safety of critical infrastructure. A wireless crack detection system using Acoustic Emission technology can provide real-time monitoring and help to identify potential problems more quickly, reducing the risk of a disaster. By providing real-time information, the system can help to detect problems before they become major issues, preventing the need for costly repairs and reducing the risk of a disaster.

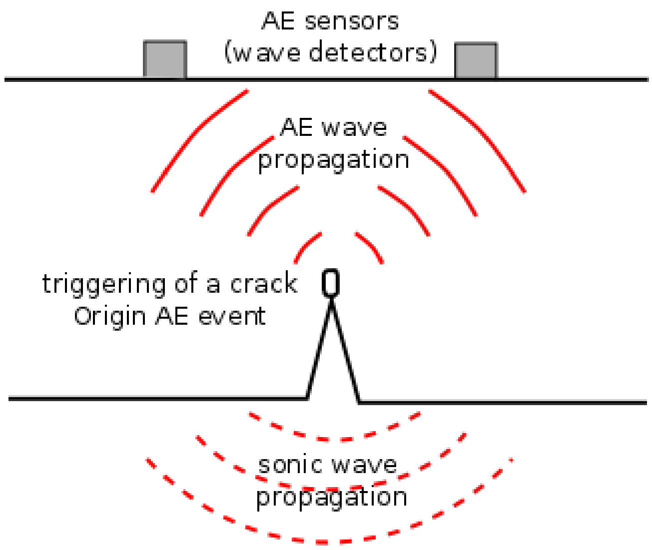

FIGURE 1.1: Principle of the acoustic emission wave detection [5].

Additionally, the system can be integrated into existing infrastructure, reducing the need for manual inspections and providing cost savings.

1.2 Crack Detection

Cracks are defects that can cause significant damage to structures, leading to the failure of the entire system. Crack detection is essential for ensuring the safety and longevity of structures. The early detection of cracks can help prevent catastrophic failure, thereby saving lives and minimizing the cost of repair or replacement. Crack detection is also critical for reducing maintenance costs and increasing the lifespan of structures.

The development of new techniques for crack detection has brought significant improvements over traditional methods. The traditional methods, such as visual inspection and dye penetrant testing, rely heavily on human expertise and are time-consuming. In contrast, the new techniques, such as Acoustic Emission (AE), Radio-Frequency Identification (RFID), and Image Processing, provide more accurate and reliable results and are more efficient. These techniques can detect small cracks that are not visible to the naked eye.[1]

1.2.1 Acoustic Emission AE

AE technology uses sound waves to detect cracks in structures and provide real-time monitoring of the condition of the infrastructure. When a crack occurs, it generates a unique sound wave pattern that can be picked up by an AE sensor (see Figure 1.1). These sensors can then transmit the data wirelessly to a central monitoring system for analysis and interpretation [5].

The benefits of using AE technology for crack detection include:

- Real-time monitoring: With AE technology, it is possible to monitor the condition of infrastructure in real-time, providing early warning of potential problems.
- Cost-effectiveness: The use of AE technology eliminates the need for manual inspections, reducing the cost of crack detection.

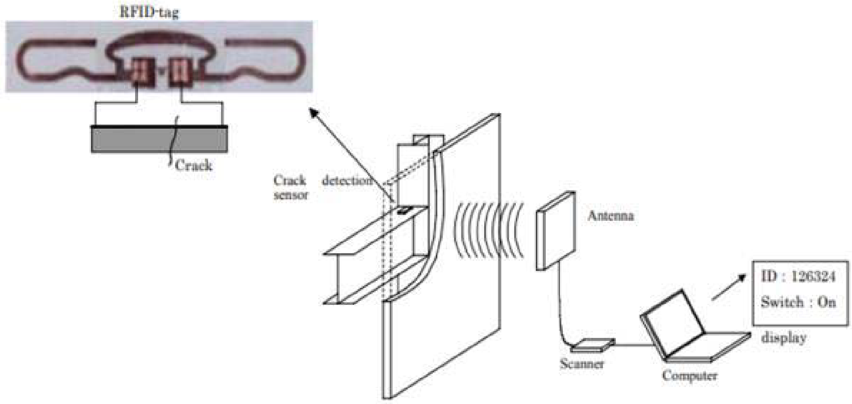

FIGURE 1.2: RFID crack detection system [6].

- Increased accuracy: Unlike manual inspections, AE technology is not dependent on human expertise, providing a more accurate and reliable assessment of the infrastructure.
- Non-invasive: Unlike other inspection methods, AE technology is non-invasive and does not require any physical contact with the structure, reducing the risk of further damage.

In conclusion, the use of AE technology for crack detection is an important step forward in maintaining the safety and longevity of critical infrastructure. By providing real-time monitoring, cost-effectiveness, increased accuracy, and a non-invasive inspection method, AE technology offers a superior solution for crack detection compared to traditional methods. AE method is suitable for real-time monitoring of critical structures, such as bridges and pipelines.

1.2.2 Radio Frequency Identification (RFID)

Radio Frequency Identification (RFID) is a modern technology that is used in crack detection methods. RFID systems use radio waves to communicate between a reader and a tag attached to the structure (see Figure 1.2). When a crack occurs, the tag will emit a signal that is received by the reader, which can be used to monitor the crack in real time. RFID systems can also be used to store information about the crack and its location, making it possible to track the progression of the crack over time.[6]

The advantage of using RFID in crack detection is that it provides real-time monitoring and can help to identify potential problems more quickly. This can reduce the risk of a disaster, as problems can be addressed before they become critical. Additionally, RFID systems are typically more cost-effective than manual inspection methods, as they require fewer personnel and can be monitored from a central location. However, there are some limitations to using RFID in crack detection. For example, the range of the radio waves is limited, meaning that the reader must be close to the tag in order to receive the signal. This can be a problem in large structures, where multiple readers may be needed to cover the entire surface. Additionally, RFID systems may not be able to detect all types of cracks, especially those that are not visible on the surface. Another limitation is Interference, RFID systems are vulnerable to interference from other RFID systems or electronic devices, which can

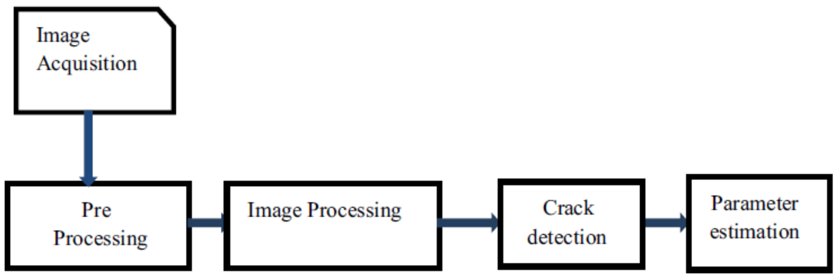

FIGURE 1.3: The architecture of image processing based crack detection [7].

affect their performance. Also Data Security, RFID systems rely on wireless transmission of data, which can be vulnerable to hacking or data breaches [6].

In conclusion, the use of RFID in crack detection is a promising technology that offers real-time monitoring and cost-effectiveness, but it has its limitations and may not be suitable for all types of structures. Nevertheless, it can be a valuable tool for ensuring the safety of critical infrastructure and reducing the risk of disasters caused by unnoticed cracks.

1.2.3 Image processing

Image processing techniques are a crucial aspect of many modern crack detection systems, particularly in the pre-processing stage. The goal of pre-processing is to prepare the data collected by cameras or other imaging devices for further analysis. This can involve removing noise and enhancing the images to make cracks more visible, such as by increasing the contrast or sharpness [7].

In the case of crack detection, image processing techniques can be used to locate cracks and measure their size, length, and orientation. For example, image segmentation can be used to separate cracks from the background, while edge detection techniques can be used to find the boundaries of cracks. Additionally, morphological operations such as dilation and erosion can be applied to further enhance the visibility of cracks (see Figure 1.3).

In real-time crack detection systems, image processing techniques are often used to analyze data as it is being collected. This allows the system to provide real-time information about the condition of the infrastructure, including the detection of new cracks or changes in existing cracks. This can be particularly useful for monitoring critical infrastructure in real time and taking prompt action if necessary. The main disadvantage of this technique is [7]:

- Complexity: Image processing algorithms for crack detection can be complex and require significant computational resources. This can be challenging when implementing real-time crack detection systems.
- Limited accuracy: Image processing techniques may not be able to detect all types of cracks or may produce false positive results. This can impact the reliability of the crack detection system.
- Lighting conditions: Image processing algorithms can be impacted by the lighting conditions at the time of the inspection. This can result in inaccurate or inconsistent results, especially in challenging lighting conditions such as low light or direct sunlight.

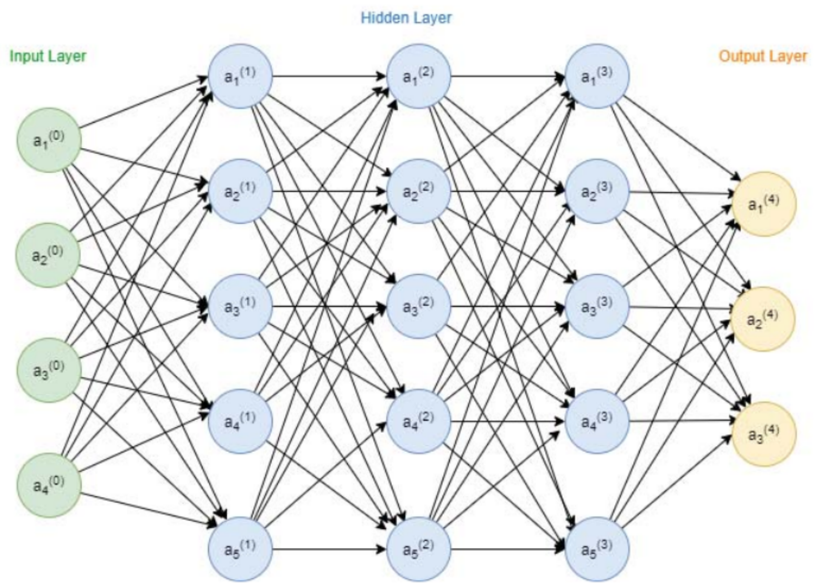

FIGURE 1.4: The architecture of the neural network [1].

- Cost: Image processing techniques can be expensive, both in terms of hardware costs and software development. This can make it challenging to implement image processing systems in resource-constrained environments.
- Maintenance: Image processing systems require ongoing maintenance and monitoring to ensure that they continue to perform accurately over time. This can be time-consuming and costly.

It's important to carefully consider the limitations of image processing techniques when designing a crack detection system and to select the best approach for a particular application based on the requirements and constraints of the project. There are a variety of image processing techniques available for use in crack detection, including machine learning algorithms, feature extraction methods, and computer vision techniques. However, it is important to select the most appropriate technique for the specific application, as the effectiveness of these techniques can vary depending on the type of data being analyzed and the desired outcome [7].

1.2.4 Machine Learning

In recent years, Machine Learning (ML) and Deep Learning (DL) techniques (see Figure 1.4) have been applied to crack detection in civil engineering structures, with the aim of improving accuracy, efficiency, and real-time capabilities. ML algorithms such as Support Vector Machines (SVM) and Neural Networks (NNs) can be trained on large datasets to automatically detect and classify cracks from images and signals acquired by sensors. On the other hand, DL techniques, specifically Convolutional Neural Networks (CNNs), have shown remarkable performance in image recognition tasks, and they have been successfully applied to crack detection in concrete and steel structures [1], [8]. The benefits of using ML and DL techniques in crack detection can be summarized as follows [9]:

- Improved Accuracy: ML and DL algorithms can be trained on large datasets, which increases the robustness of the crack detection system. Additionally, the use of DL techniques can reduce the need for feature extraction, which is a critical step in traditional image processing methods.

- Increased Efficiency: ML and DL algorithms can perform crack detection in real-time, which can reduce inspection time and costs. Furthermore, ML and DL algorithms can automate the process of detecting and classifying cracks, which reduces the dependence on human expertise.

- Real-Time Monitoring: ML and DL algorithms can be integrated into a wireless monitoring system, which allows for real-time monitoring of structures. This capability can be particularly useful in early warning systems, where prompt action can prevent catastrophic failures.

However, there are also some challenges associated with using ML and DL techniques in crack detection, Disadvantages of using Machine Learning algorithms for crack detection [9]:

- Need for large amounts of data: Machine learning algorithms require large amounts of data to be trained, which can be challenging to obtain in some cases.

- Computationally intensive: Machine learning algorithms can be computationally intensive, requiring significant processing power to run.

- Overfitting: Overfitting occurs when a model is too closely fit to the training data and doesn't generalize well to new data. This can lead to poor performance on real-world data.

- High false positive rate: The high false positive rate of some machine learning algorithms can lead to the detection of non-existent cracks, which can be costly and time-consuming to correct.

Despite these challenges, ML and DL techniques have the potential to revolutionize crack detection in civil engineering structures, and they will continue to be an active area of research in the coming years [9].

1.3 Internet Of Things

The number of IoT devices has been growing rapidly in recent years and is expected to continue to increase in the future. According to a report by Statista, the number of connected IoT devices worldwide is expected to reach 29.42 billion by 2030 (see Figure 1.5 [10]). This growth can be attributed to the increasing demand for automation, remote monitoring, and data analytics across various industries. With the increasing use of IoT in industries such as healthcare, transportation, and manufacturing, the number of IoT devices is expected to increase rapidly. In terms of crack detection, the future of IoT is promising. The development of advanced sensors and communication technologies is enabling the creation of new and innovative crack detection methods. IoT-enabled crack detection systems can provide real-time monitoring and alert notifications, allowing for timely intervention and prevention of catastrophic failures. Furthermore, the use of machine learning and AI algorithms can enhance the accuracy and reliability of crack detection systems. As the number of IoT devices continues to grow, the potential applications for IoT in crack detection are endless.

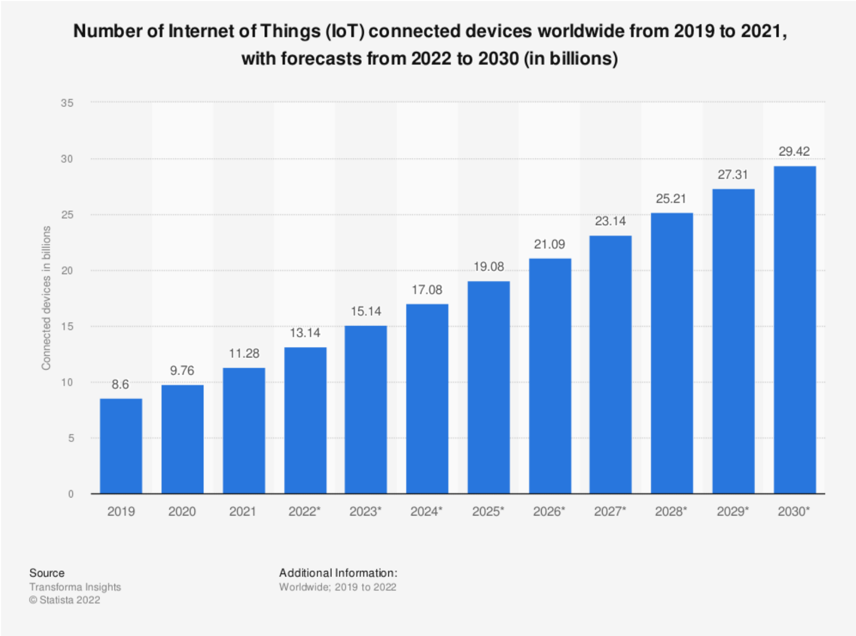

FIGURE 1.5: Number of Internet of Things (IoT) connected devices worldwide [10].

1.3.1 What is IoT?

IoT refers to the interconnection of physical devices, machines, and objects with the internet, enabling them to communicate and share data with each other. These devices, also known as "smart devices," can be anything from household appliances to industrial equipment, vehicles, and even wearable technology. They are equipped with sensors, actuators, and communication modules that enable them to connect to the internet and communicate with each other [11].

1.3.2 IoT Architecture

IoT architecture is composed of four layers: the Sensing Layer, the Network Layer, the Middleware Layer, and the Application Layer (see Figure 1.6 [11]).

1. Sensing Layer: This is the bottom-most layer and consists of all the sensors and actuators that are responsible for collecting data and controlling the physical environment. These devices can include temperature sensors, humidity sensors, pressure sensors, light sensors, motion sensors, and more. Actuators can be used to control devices such as motors, valves, and switches. This layer is also responsible for processing and aggregating the data collected from the sensors and sending it to the network layer.

2. Network Layer: This layer is responsible for transmitting the data between the devices and the cloud. This layer includes different communication protocols, such as Wi-Fi, Bluetooth, Zigbee, LoRaWAN, and cellular networks, that allow devices to connect with each other and with the cloud. The network layer is responsible for managing the data flow, ensuring data security, and optimizing the network performance.

3. Middleware Layer: The middleware layer is responsible for managing the communication and data exchange between the different components of the

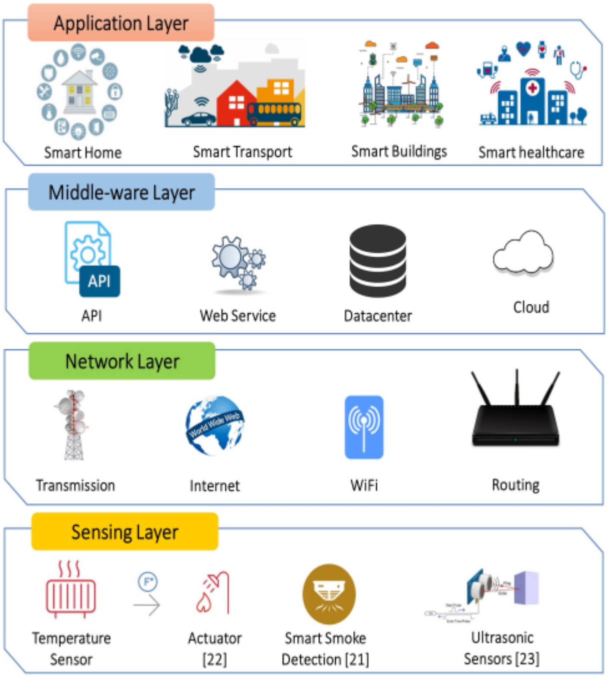

FIGURE 1.6: Layers in IoT System [11].

IoT system. It acts as an interface between the network layer and the application layer, providing functions such as data filtering, aggregation, and analysis.

4. Application Layer: This layer is responsible for processing and analyzing the data collected from the devices. The application layer includes software applications that are responsible for data processing, visualization, and analytics. This layer also includes machine learning and artificial intelligence algorithms that can help in predicting future events and optimize the system's performance.

In summary, the sensing layer collects data from various sources, the network layer transmits the data, the middleware layer processes the data, and the application layer provides end-user services. This four-layer architecture provides a structured approach to designing and implementing IoT systems [11].

1.3.3 IoT Application

Moreover, IoT can be applied in crack detection using different methods such as acoustic emission (AE), radio frequency identification (RFID), and image processing. By integrating IoT devices into these crack detection methods, the accuracy and efficiency of the crack detection process can be greatly improved. For example, IoT-enabled AE sensors can be placed in different locations to detect the occurrence and propagation of cracks in real time. The data collected from these sensors can be transmitted to the cloud for further analysis and processing.

Similarly, RFID technology can be used in crack detection by embedding RFID tags in the material that is being monitored. When a crack appears, it disrupts the electromagnetic field generated by the RFID tag, which can be detected and recorded by an RFID reader. This information can be transmitted to the cloud for further analysis and processing.

IoT-enabled image processing techniques can also be used for crack detection by analyzing images captured by cameras. The images can be processed to detect the presence of cracks and their severity. This information can be transmitted to the cloud for further analysis and processing.

By using IoT in crack detection, the effectiveness of crack detection methods can be enhanced through real-time monitoring, improved accuracy, and faster data processing. Furthermore, IoT enables the data collected from different devices to be aggregated and analyzed, leading to more informed decision-making and proactive maintenance strategies [11].

Chapter 2

AE Signal and System Characteristics for Crack Detection

2.1 Introduction

Techniques based on Acoustic Emission (AE) is a non-destructive testing technique that has gained popularity in recent years due to its ability to detect early-stage damage in materials. The phenomenon of AE involves the release of energy in the form of elastic waves generated by the deformation and damage of materials. AE monitoring can be used for various purposes such as structural health monitoring, quality control of materials, and characterization of damage. In this chapter, we will provide a comprehensive overview of AE, including its principles, types of signals, system characteristics, and advantages and limitations. We will also compare AE with other non-destructive testing methods and discuss its importance in crack detection. Additionally, we will present case studies of AE applications in crack detection, highlighting successful examples and discussing the methodology and results.

2.2 AE Signal Characteristics

Acoustic emission (AE) refers to the generation of stress waves in the frequency range of ultrasound, typically between 20 kHz and 1 MHz, within materials as a result of deformation, crack initiation and propagation, crack opening and closure, dislocation movement, twinning and phase transformation, fiber breakage, and delamination. The sources of AE are primarily damage-related, and monitoring AE can aid in predicting material failure [12].

Acoustic Emission (AE) is a non-destructive testing technique that operates on the principle of energy release from localized sources within a material. The energy release generates elastic waves that can be detected and analyzed to provide information about the damage mechanisms within the material. As a crack propagates, it generates elastic waves that can be detected by AE sensors placed on the surface of the material. The waveform of the AE signal contains information about the location, magnitude, and type of damage. This information is used for early detection and diagnosis of cracks, and to predict the remaining useful life of the material.

Acoustic emission (AE) signals can be classified into two categories: burst and continuous emissions. burst emissions are typically observed in the form of damped or sine detected by (resonant AE sensors), or as short pulses(see Figure 2.1) [13] detected by (broadband AE sensors).

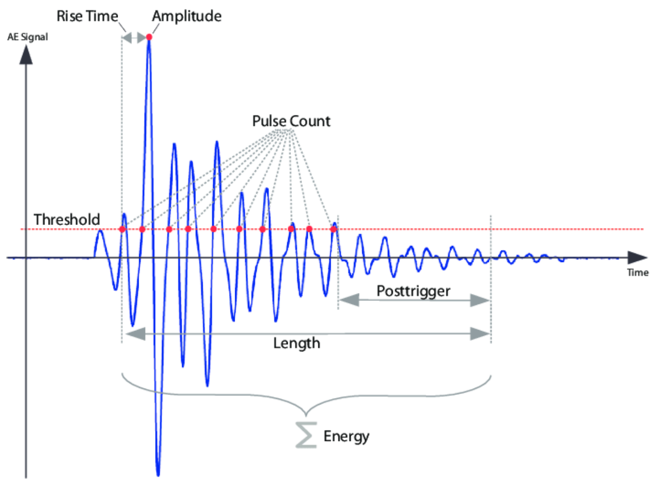

FIGURE 2.1: AE impulse parameters [13].

These emissions are often associated with damage phenomena such as crack initiation and propagation, stress corrosion, and fiber ruptures. On the other hand, continuous emissions occur when signals are frequent and overlap in a way that they cannot be separated into bursts. These emissions are mainly observed in metallic materials and are associated with dislocation movement due to plastic deformation [14].

AE has different properties depending on the damage mechanism that caused it. These mechanisms can be divided into two main types: chemical sources, such as corrosion, and mechanical sources. The present thesis focuses on the study of AE signals generated by mechanical sources, which can result from mechanical tests or low-frequency vibrations.

The burst Acoustic Emission (AE) signals can have various features that are useful for analyzing and interpreting the signals Here are some of the most common features of AE signals along with their corresponding equations [15]:

1. **Peak amplitude:** Peak amplitude is often used as a measure of the strength of the AE signal as shown in eq.2.1 and can provide information about the size and severity of the damage in the material being monitored. It can also be used to compare the amplitudes of different AE signals and to track changes in the signal over time.

$$A_{peak} = \max(A(t)) \tag{2.1}$$

where A_{peak} is the peak amplitude and max(A(t)) is the maximum value of the amplitude function over the duration of the burst.

2. **Rise time:** The rise time of an AE signal is the time it takes for the signal to reach its maximum amplitude from the start of the burst as shown in eq.2.2. The rise time is a measure of the speed at which the acoustic energy is released.

$$t_{rise} = t_{max} - t_{start} \tag{2.2}$$

where t_{rise} is the rise time, t_{max} is the time at which the signal reaches its maximum amplitude, and t_{start} is the time at which the burst starts.

3. **Decay time:** The decay time of an AE signal is the time it takes for the amplitude of the signal to decrease from its peak value to a certain percentage of the peak value as shown in eq.2.3. The decay time is a measure of the damping

properties of the material.

$$t_{decay} = t_{end} - t_{peak} \tag{2.3}$$

where t_{decay} is the decay time, t_{end} is the time at which the signal decays to a certain percentage of its peak amplitude, and t_{peak} is the time at which the signal reaches its peak amplitude.

4. **Duration:** The duration of an AE signal is the time it takes for the signal to decay to a certain percentage of its maximum amplitude as shown in eq.2.4. The duration is a measure of the length of time over which the acoustic energy is released.

$$t_{duration} = t_{end} - t_{start} \tag{2.4}$$

where $t_{duration}$ is the duration, t_{end} is the time at which the signal decays to a certain percentage of its maximum amplitude, and t_{start} is the time at which the burst starts.

5. **Energy:** The energy of an AE signal represents the total amount of acoustic energy released by the material as shown in eq.2.5. The energy can be calculated by integrating the area under the signal curve.

$$Energy = \int A(t)dt \tag{2.5}$$

where E is the energy, A(t) is the amplitude function, and the integration is taken over the duration of the burst.

6. **RMS:** The RMS (root mean square) of an AE signal is a measure of the root-mean-square value of the signal over a certain time interval as shown in eq.2.6. The RMS is a measure of the average power contained in the signal.

$$RMS = \sqrt{\frac{1}{T}\int A^2(t)dt} \tag{2.6}$$

where RMS is the root-mean-square value, T is the time interval over which the RMS is calculated, A(t) is the amplitude function, and the integration is taken over the time interval T.

7. **Signal-to-noise ratio (SNR):** A high SNR can indicate a strong AE signal that is likely to be a real event, while a low SNR may indicate a weak signal that is more likely to be background noise or a false positive as shown in eq.2.7. This information can be useful for distinguishing between real AE events and noise.

$$SNR = \frac{A_{peak}}{\sigma_{noise}} \tag{2.7}$$

where A_{peak} is the peak amplitude of the signal and σ_{noise} is the standard deviation of the background noise.

8. **Crest factor:** The crest factor of an AE signal is the ratio of the peak amplitude to the root mean square (RMS) amplitude of the signal. The crest factor can be expressed in eq.2.8.

$$CF = \frac{A_{peak}}{RMS} \tag{2.8}$$

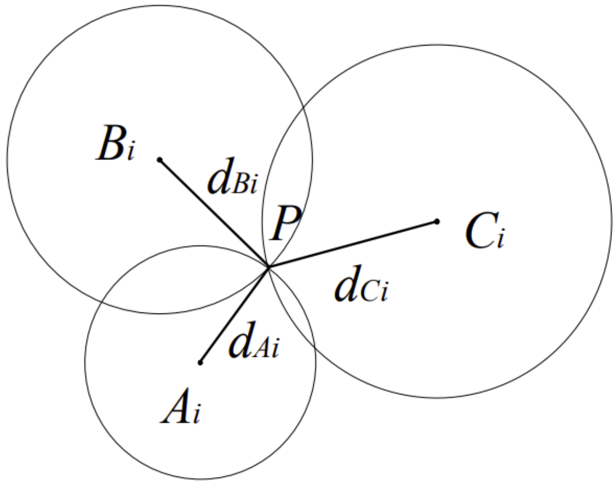

FIGURE 2.2: The diagram of trilateration positioning calculation [16].

where CF is the crest factor, A_{peak} is the peak amplitude of the signal, and RMS is the RMS amplitude of the signal.

9. **Frequency:** The frequency content of an AE signal can be analyzed using Fourier analysis, which decomposes the signal into its component frequencies. The dominant frequency, or center frequency, of the signal can be calculated using the eq.2.9:

$$f_c = \frac{\sum_{i=1}^{n}(f_i * A_i)}{\sum_{i=1}^{n} A_i} \tag{2.9}$$

where f_c is the center frequency, f_i is the frequency of the i^{th} component, and A_i is the amplitude of the i^{th} component.

10. **The arrival time:** arrival time in the context of acoustic emission (AE) refers to the time at which the AE signal arrives at a particular sensor after being generated by the source. This time delay is used to determine the location of the source of the AE signal.

To calculate the location of a crack using arrival time measurements from multiple sensors, we can use a mathematical approach known as trilateration. Trilateration involves calculating the intersection of three or more circles, each centered at a sensor and with a radius equal to the distance between the sensor and the crack. The point of intersection of the circles represents the location of the crack [16].

Let's consider the case of three sensors located at points A, B, and C with known positions relative to each other. Let (x,y) be the coordinates of the crack location. Let d_A , d_B , and d_C be the distances between the crack and each sensor, respectively. These distances can be calculated using the arrival times of the stress wave and the velocity of stress waves in the material, as mentioned earlier. Then, the distance between the crack and sensor can be calculated using eq.2.10

$$d_A = \sqrt{(x - x_A)^2 + (y - y_A)^2} \tag{2.10}$$

where (x_A,y_A) are the coordinates of sensor A. Similarly, we can write equations for d_B and d_C using the coordinates of sensors B and C. We can then rewrite these equations as shown in eq.2.11, 2.12, 2.13

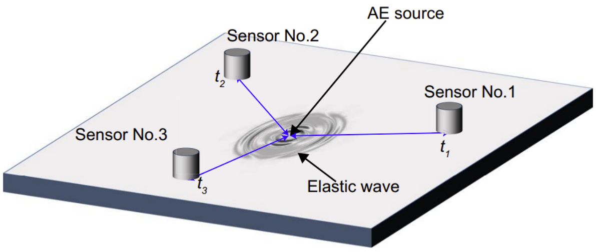

FIGURE 2.3: Schematic representation of two-dimensional localization method with three sensors [17].

$$(x - x_A)^2 + (y - y_A)^2 - d_A^2 = 0 \tag{2.11}$$

$$(x - x_B)^2 + (y - y_B)^2 - d_B^2 = 0 \tag{2.12}$$

$$(x - x_C)^2 + (y - y_C)^2 - d_C^2 = 0 \tag{2.13}$$

These equations represent three circles with centers at (x_A, y_A), (x_B, y_B), and (x_C, y_C) and radius d_A, d_B, and d_C, respectively. The intersection of these circles represents the location of the crack (see Figure.2.2)

To solve for (x,y), we can use a system of nonlinear equations solver such as the Levenberg-Marquardt algorithm. This algorithm iteratively updates the estimate of (x,y) until the sum of the squared errors between the measured and predicted distances is minimized[16]. In summary, the location of a crack can be calculated using trilateration and arrival time measurements from multiple sensors (see Figure 2.3). The method involves calculating the intersection of circles centered at each sensor and using a nonlinear equations solver to find the location of the crack[17].

2.3 AE System Characteristics

The acoustic Emission (AE) System is widely used in non-destructive testing (NDT) for the detection and monitoring of defects such as cracks, delaminations, and corrosion in structures. AE technology relies on the detection of acoustic signals that are generated when a material undergoes deformation or failure. The AE system consists of five main parts (see Figure 2.4) sensing, amplification, filtering, Analog to Digital Converter (ADC), then Processing Unit.

2.3.1 Sensing Part

AE sensors are the sensing component of an Acoustic Emission (AE) system that detect and convert mechanical stress waves generated by the deformation or failure of a material into electrical signals. These signals are then processed by the other components of the AE system to extract useful information about the material being tested.

There are various kinds of AE sensors, including:

1. **Piezoelectric sensors:** Piezoelectric sensors are the most common type of AE sensor used in non-destructive testing (NDT) applications. They work on the principle of the piezoelectric effect, which is the ability of certain materials to produce an electrical charge when subjected to mechanical stress.

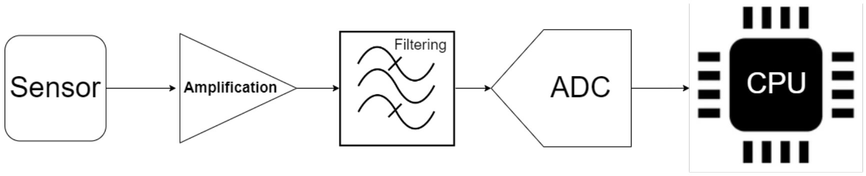

FIGURE 2.4: The main parts of AE system

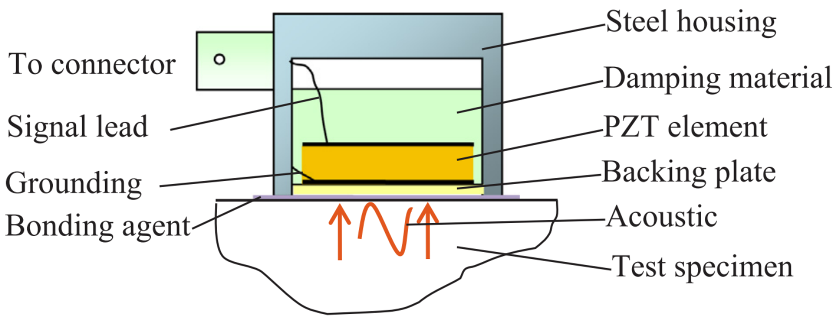

FIGURE 2.5: Cross-section of a typical commercial AE sensor [18].

The architecture of piezoelectric sensors consists of a piezoelectric element, a backing material, and a protective coating (see Figure 2.5). The piezoelectric element is usually made of a ceramic material such as lead zirconate titanate (PZT) or quartz, which is sandwiched between two electrodes. When subjected to mechanical stress or deformation, the piezoelectric element produces an electrical charge across its electrodes. This electrical signal is proportional to the magnitude of the mechanical stress, and can be measured and recorded by the AE system [18].

The backing material is used to provide mechanical support to the piezoelectric element and to reduce the sensitivity of the sensor to off-axis vibrations. It is typically made of a material with low acoustic impedance, such as epoxy or rubber.

The protective coating is used to protect the piezoelectric element from environmental factors such as moisture, dust, and temperature changes. It is usually made of a thin layer of material such as polyurethane or silicone.

Piezoelectric sensors can be designed in various shapes and sizes depending on the application. They can be cylindrical or flat, with the shape and size of the sensor being optimized for the specific application. In general, cylindrical sensors are used for detecting AE signals in large structures such as bridges or pipelines, while flat sensors are used for detecting AE signals in thin plates or sheets.

Overall, piezoelectric sensors are highly sensitive and can detect very low-level AE signals. They are also rugged and reliable, with a long service life. However, they are susceptible to electrical noise and require careful handling and maintenance to ensure accurate and reliable measurements [18], [19].

2. **MEMS sensor:** MEMS (Micro-Electro-Mechanical Systems) sensors can be used as AE (Acoustic Emission) sensors for detecting and measuring mechanical stress waves generated by the deformation or failure of a material. AE is

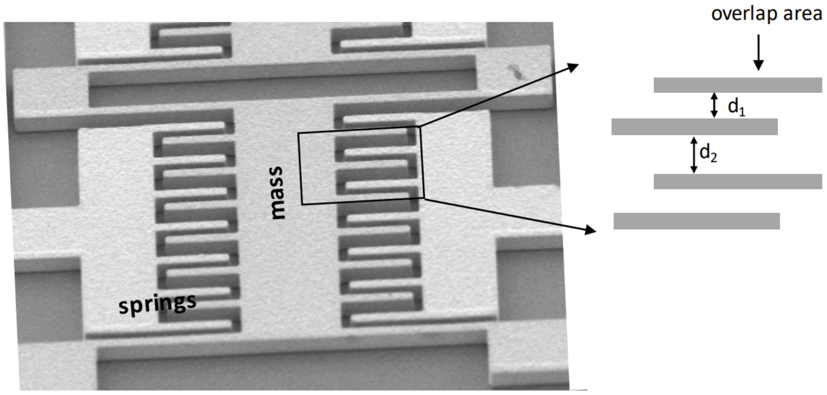

FIGURE 2.6: Capacitive MEMS AE sensor [20].

a non-destructive testing technique that is widely used for structural health monitoring of materials and structures [20].

MEMS-based AE sensors typically consist of a MEMS microphone or a piezoresistive sensor that can detect and convert the acoustic waves generated by the material under stress into electrical signals. These signals are then processed by signal conditioning and interface circuits to extract useful information about the material being tested.

The MEMS microphone is a type of condenser microphone that uses a diaphragm to detect sound waves. When an acoustic wave impinges on the diaphragm, it vibrates, causing a change in capacitance (see Figure 2.6). This change in capacitance is then converted into an electrical signal that can be processed to obtain information about the material being tested [20].

Piezoresistive sensors, on the other hand, work on the principle of piezoresistance, where the electrical resistance of material changes in response to mechanical stress. When an acoustic wave impinges on the piezoresistive sensor, it generates a stress wave that changes the electrical resistance of the sensor (see Figure 2.7). This change in resistance is then converted into an electrical signal that can be processed to obtain information about the material being tested.

MEMS-based AE sensors have several advantages over traditional AE sensors, including their small size, low cost, and high sensitivity. They can be integrated into other systems, such as wireless sensor networks, for remote monitoring and data acquisition. Additionally, MEMS-based AE sensors can be used for a wide range of applications, including aerospace, automotive, civil engineering, and medical diagnostics.

In conclusion, MEMS-based AE sensors are micro-scale devices that can detect and measure acoustic waves generated by the deformation or failure of a material. They work on the principle of microfabrication and are used for non-destructive testing and structural health monitoring of materials and structures. The architecture of MEMS-based AE sensors typically consists of a sensing element, signal conditioning, and interface circuits.

3. **Fiber optic sensors:** Fiber optic sensors are a type of sensor that uses optical fibers to detect and measure physical, chemical, or biological parameters. In the context of Acoustic Emission (AE), fiber optic sensors can be used to detect

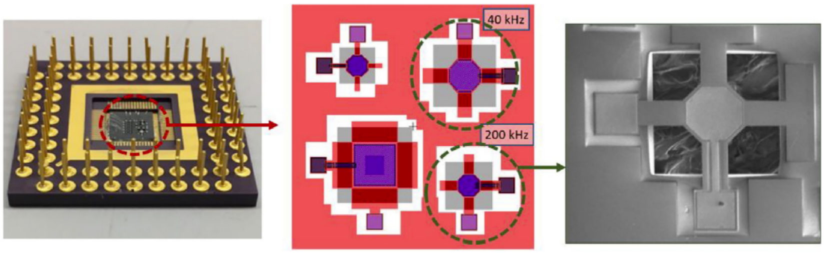

FIGURE 2.7: Piezo-MEMS device [20].

and measure the mechanical stress waves generated by the deformation or failure of a material [21].

The architecture of a fiber optic AE sensor typically consists of a fiber-optic cable that is attached to the surface of the material being tested. The cable contains one or more optical fibers that are sensitive to changes in strain or temperature. The fibers are typically coated with a material that enhances their sensitivity to strain, such as a polymer or metal.

The basic principle of operation of a fiber optic AE sensor is based on the phenomenon of interferometry. When an acoustic wave propagates through the material being tested, it causes a strain in the fiber-optic cable. This strain changes the optical path length of the fiber, which in turn causes a phase shift in the light that is transmitted through the fiber (see Figure 2.8). This phase shift can be measured using interferometry techniques to determine the amplitude, frequency, and location of the AE event [21].

There are two main types of fiber optic AE sensors: extrinsic and intrinsic sensors. Extrinsic sensors use a fiber-optic cable that is attached to the surface of the material being tested, while intrinsic sensors are embedded within the material itself.

Extrinsic fiber optic AE sensors are easier to install and can be used for a wide range of applications. They are typically more sensitive than intrinsic sensors, but they are also more susceptible to noise and interference.

Intrinsic fiber optic AE sensors, on the other hand, are embedded within the material being tested and are less susceptible to noise and interference. They can be used for monitoring the structural health of materials and structures in real time, but they are more difficult to install and require more specialized equipment.

Overall, fiber optic AE sensors offer several advantages over other types of AE sensors, including high sensitivity, low noise, and the ability to measure AE signals over long distances. They are also immune to electromagnetic interference and can be used in harsh environments. However, they can be more expensive and require specialized equipment for installation and operation.

In summary, the choice of AE sensor depends on the specific application and the level of sensitivity and accuracy required.

2.3.2 Amplification Part

A pre-amplifier, also known as a pre-amp, is an electronic device that amplifies weak signals from a sensor before they are processed by a signal conditioning circuit

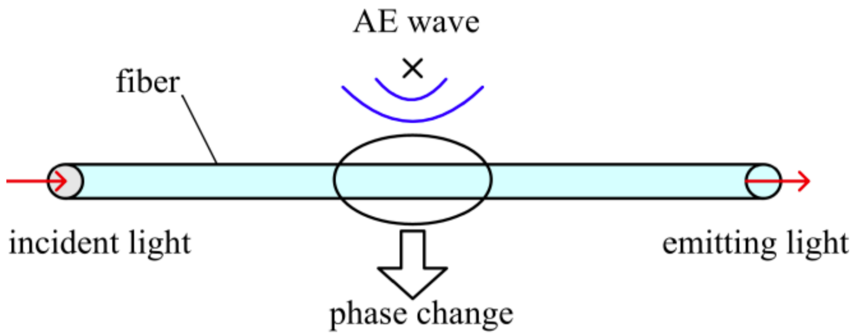

FIGURE 2.8: Optical fiber sensing principle [21].

or other electronic components. Pre-amplifiers are commonly used in various applications, including audio systems, instrumentation, and non-destructive testing[22]. The characteristics of a pre-amplifier are important for obtaining high-quality amplified signals. Here are some important characteristics of pre-amplifiers [22]:

- Gain: The gain of a pre-amplifier is the ratio of the output signal amplitude to the input signal amplitude. It is typically expressed in decibels (dB). A high-gain pre-amplifier amplifies weak signals to a higher level, allowing them to be processed and analyzed by other electronic components.
- Noise: Noise is any unwanted signal that interferes with the desired signal. The noise level of a pre-amplifier is usually measured in terms of the noise figure or noise floor, which indicates the minimum input signal level that can be detected above the noise. A low-noise pre-amplifier reduces the effects of noise and improves the signal-to-noise ratio of the amplified signal.
- Bandwidth: The bandwidth of a pre-amplifier refers to the range of frequencies that it can amplify effectively. The bandwidth of a pre-amplifier should match the frequency range of the signal being amplified to prevent loss or distortion of the signal.
- Input impedance: The input impedance of a pre-amplifier is the resistance that the amplifier presents to the sensor or source of the signal being amplified. A high input impedance pre-amplifier minimizes loading on the sensor or source, reducing the risk of signal distortion.
- Output impedance: The output impedance of a pre-amplifier is the resistance that the amplifier presents to the next stage in the electronic circuit. A low-output impedance pre-amplifier provides a stable, high-quality output signal that is less susceptible to noise and other forms of interference.
- Linearity: The linearity of a pre-amplifier is its ability to amplify signals accurately over a wide range of input amplitudes. A highly linear pre-amplifier ensures that the amplified signal accurately represents the original input signal.
- Power consumption: Pre-amplifiers consume power, and the amount of power consumed can be an important consideration in applications where power consumption is critical, such as battery-powered devices.

In summary, a pre-amplifier is an essential component in electronic circuits, and its characteristics play an important role in the quality and reliability of the amplified

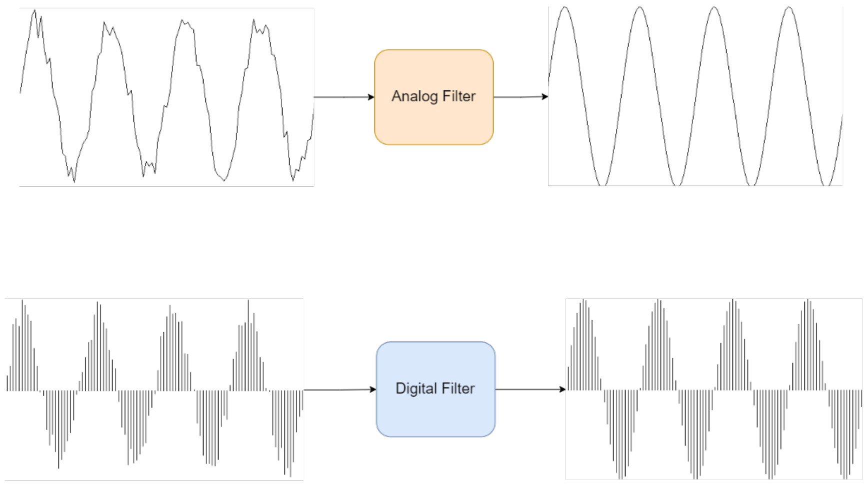

FIGURE 2.9: Filter system.

signal. The gain, noise level, bandwidth, input and output impedance, linearity, and power consumption are some of the key characteristics to consider when selecting a pre-amplifier for a particular application.

2.3.3 Filtering Part

Filtering is a process of removing or attenuating unwanted components from a signal while preserving the desired components. Filters are used in a variety of applications, including signal processing, communication systems, and audio equipment. The characteristics of a filter describe how it modifies the signal, and these characteristics depend on the type of filter[22]

There are two main types of filters: analog filters and digital filters. Analog filters operate on continuous-time signals, while digital filters operate on discrete-time signals (see Figure 2.9). The characteristics of analog filters include [22]:

- Frequency response: This describes how the filter modifies the amplitude and phase of the signal as a function of frequency. The frequency response is usually plotted as a graph, with frequency on the horizontal axis and gain (or attenuation) on the vertical axis.

- Order: This describes the complexity of the filter, which is determined by the number of poles and zeros in the transfer function. Higher-order filters have a steeper roll-off (i.e., they attenuate unwanted frequencies more quickly).

- Cut-off frequency: This is the frequency at which the filter begins to attenuate the signal. For low-pass filters, the cut-off frequency is the highest frequency that passes through the filter; for high-pass filters, it is the lowest frequency that passes through.

- Q-factor: This is a measure of the filter's selectivity, or how well it separates desired frequencies from undesired frequencies. A high-Q filter has a narrow passband and a sharp roll-off, while a low-Q filter has a wide passband and a gradual roll-off.

The characteristics of digital filters include [22]:

- Frequency response: This describes how the filter modifies the amplitude and phase of the signal as a function of frequency in the digital domain. The frequency response is usually plotted as a graph, with frequency on the horizontal axis and gain (or attenuation) on the vertical axis.
- Order: This describes the complexity of the filter, which is determined by the number of taps in the filter kernel. Higher-order filters have a steeper roll-off (i.e., they attenuate unwanted frequencies more quickly), but they also have more taps in the filter kernel, which can increase the computational load.
- Cut-off frequency: This is the frequency at which the filter begins to attenuate the signal. For low-pass filters, the cut-off frequency is the highest frequency that passes through the filter; for high-pass filters, it is the lowest frequency that passes through.
- Sampling rate: This is the rate at which the digital filter operates. The sampling rate should be at least twice the highest frequency in the signal to avoid aliasing.
- Filter design method: Digital filters can be designed using a variety of methods, including windowing, frequency sampling, and least squares. Each method has its own advantages and disadvantages, and the choice of method depends on the application requirements.

In summary, the characteristics of a filter describe how it modifies the signal, and these characteristics depend on the type of filter. Analog filters operate on continuous-time signals, while digital filters operate on discrete-time signals. The most important characteristics of a filter include the frequency response, order, cut-off frequency, Q-factor, and sampling rate. The choice of filter depends on the application requirements, and proper design and implementation of filters are critical for achieving the desired results.

2.3.4 Analog to Digital Converter:

ADC stands for Analog to Digital Converter, which is an electronic device that converts continuous analog signals to digital signals that can be processed by a computer or digital system. An ADC is commonly used in data acquisition systems, measurement instruments, and communication systems [22].

ADC Architectures

ADC (Analog-to-Digital Converter) architectures refer to the different ways in which the analog signal is converted to a digital format. There are several ADC architectures, including [22]:

1. **Successive Approximation ADC:** Successive Approximation ADC is a type of analog-to-digital converter that is commonly used in applications where high resolution and speed are required.

   The Successive Approximation ADC works by comparing the input analog voltage with a reference voltage and producing a digital output that represents the input voltage. The process starts with the most significant bit (MSB) being set to the reference voltage, and the least significant bit (LSB) being set to zero. The ADC then compares the input voltage with the voltage midway between

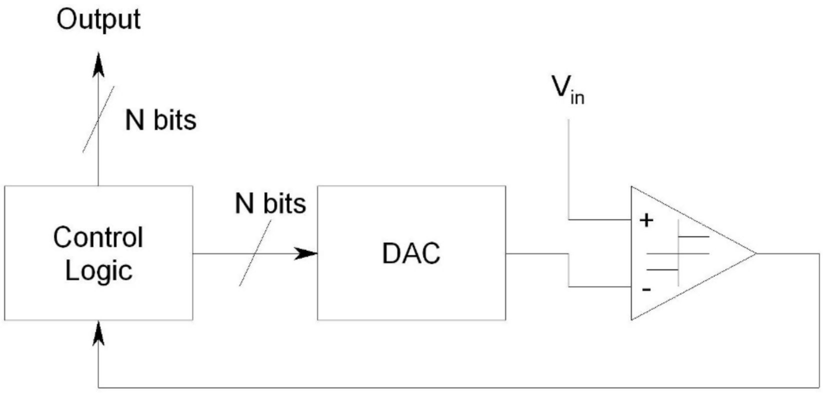

FIGURE 2.10: A schematic representation of a successive approximation ADC [23].

the MSB and the LSB. If the input voltage is greater than the midpoint voltage, the MSB is set to 1, and if it is less than the midpoint voltage, the MSB is set to 0. The process then continues with the next bit, and the comparison is made between the input voltage and the voltage midway between the previously determined voltage and the next bit [22] [23]. This process continues until all the bits have been compared, and the digital output is produced (see Figure 2.10).

Characteristics:

- High resolution: Successive Approximation ADCs are capable of high resolution with 12-16 bits of accuracy.
- Fast conversion time: These ADCs have a fast conversion time of a few microseconds to a few milliseconds, depending on the resolution.
- Low power consumption: The power consumption of a Successive Approximation ADC is low compared to other ADC architectures, making it suitable for battery-powered applications.
- Good linearity: The ADC has good linearity, which means that the digital output is proportional to the input voltage.

Advantages:

- High accuracy and resolution.
- Fast conversion time.
- Low power consumption.
- Simple design.

Disadvantages:

- Limited sampling rate: The sampling rate of a Successive Approximation ADC is limited compared to other ADC architectures.
- Complex control logic: The control logic required for the Successive Approximation ADC is more complex than that of other ADC architectures, making it more challenging to design and debug.
- Limited bandwidth: The ADC has limited bandwidth, which makes it unsuitable for high-speed applications.

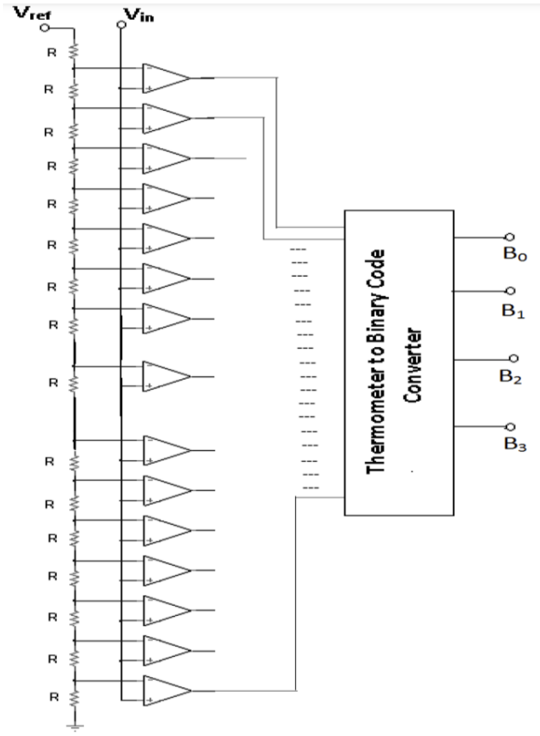

FIGURE 2.11: Architecture of 4-bit Flash ADC [24].

Applications: Successive Approximation ADCs are commonly used in applications where high resolution, fast conversion time, and low power consumption are required. Some of the common applications include:

- Medical equipment: Used in blood pressure monitors, ECG machines, and other medical equipment where high accuracy and resolution are required.
- Audio equipment: Used in digital audio recorders, mixers, and amplifiers.
- Industrial automation: Used in control systems, measurement equipment, and sensors.
- Communication systems: Used in modems, satellite receivers, and other communication systems.

2. **Flash ADC:** The Flash ADC (also known as parallel ADC) is a type of analog-to-digital converter that is commonly used for high-speed applications. It is called a "flash" ADC because it provides a digital output in a single clock cycle, as opposed to other types of ADCs that require multiple clock cycles.

   A flash ADC uses a ladder network of comparators to convert an analog input signal into a digital output signal. The input signal is compared with a set of reference voltages (equal in number to the number of bits of the output digital word) simultaneously. Each comparator produces a binary output (1 or 0) depending on whether the input voltage is greater or less than the reference voltage (see Figure 2.11). These binary outputs are then combined to form the digital output [24].
   Characteristics:

- Speed: Flash ADCs are very fast, typically operating at speeds of up to several gigahertz.
- High resolution: Flash ADCs can achieve high resolution with large numbers of comparators.
- Linearity: Flash ADCs have excellent linearity due to the use of comparators.
- No conversion time: Flash ADCs can convert an analog signal to a digital output in a single clock cycle, making them useful in applications that require high-speed conversion.
- High power consumption: Flash ADCs use a large number of comparators and consume a significant amount of power, making them unsuitable for low-power applications.
- Limited resolution: The number of comparators required for high resolution results in a large number of input pins, making the design of flash ADCs impractical beyond a certain resolution.

Advantages:

- Very fast conversion speed.
- Excellent linearity.
- Simplicity of operation.

Disadvantages:

- High power consumption.
- Limited resolution due to the large number of comparators required.
- High cost due to a large number of comparators and other components required.
- Complex layout due to a large number of input pins.

Applications:

- High-speed data acquisition systems
- High-speed instrumentation
- Video signal processing
- Telecommunications
- Radar systems
- High-speed image processing

In conclusion, flash ADCs are a popular choice for high-speed applications that require high resolution and linearity. While they have some drawbacks, such as high power consumption and limited resolution, their speed, and simplicity make them valuable tools in certain applications.

3. **Delta-Sigma ADC :** Delta-Sigma ADC (also known as Delta-Modulation ADC) is a type of analog-to-digital converter that uses a delta-sigma modulation technique for high-resolution digital conversion. It is a one-bit oversampling ADC, meaning that it oversamples the input signal with a high sampling rate to improve the resolution of the output.

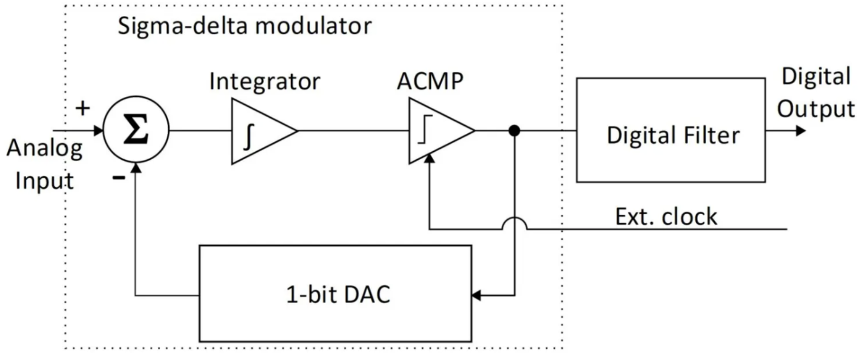

FIGURE 2.12: The schematic shows the basic building blocks of delta-sigma ADC [25].

A delta-sigma ADC consists of a delta-sigma modulator, a digital filter, and a decimation filter. The input analog signal is first oversampled by a high sampling rate, typically several hundred times higher than the Nyquist rate. The delta-sigma modulator then converts the analog signal into a high-frequency one-bit digital signal, where the output is either a '1' or a '0' depending on whether the input signal is higher or lower than the threshold [25].

The high-frequency one-bit digital signal is then passed through a digital filter, which removes the high-frequency noise and shapes the signal into a low-pass filtered version. Finally, the signal is decimated by a factor of several hundred, reducing the sampling rate and providing a high-resolution digital output (see Figure 2.12).
Advantages:

- High resolution: Delta-sigma ADCs can achieve resolutions of up to 24 bits, making them suitable for applications that require high accuracy and precision.
- Low noise: The oversampling and noise-shaping techniques used in delta-sigma ADCs reduce the noise level, resulting in a high signal-to-noise ratio.
- Simple implementation: Delta-sigma ADCs are relatively simple to implement, requiring only a few analog components and a digital filter.

Disadvantages:

- Slow speed: The oversampling and filtering process can result in a slow conversion rate, making delta-sigma ADCs unsuitable for high-speed applications.
- Complexity of the digital filter: The digital filter used in delta-sigma ADCs can be complex and may require significant computational power to implement.

Applications:

- Audio applications: Delta-sigma ADCs are commonly used in audio applications, such as digital audio recorders and high-end sound systems, where high resolution and low noise are critical.

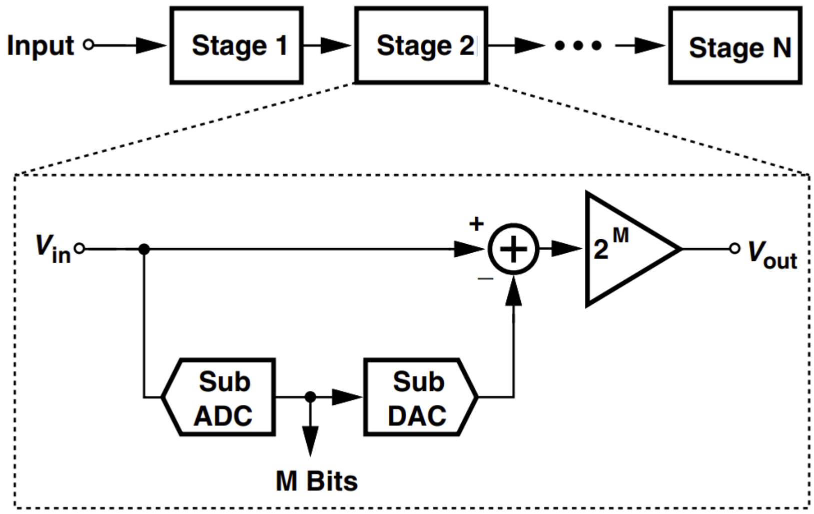

FIGURE 2.13: Pipelined ADC architecture [26].

- Instrumentation: Delta-sigma ADCs are used in precision measurement applications, such as strain gauges, pressure sensors, and temperature sensors.
- Communication systems: Delta-sigma ADCs are used in digital communication systems, such as wireless communication systems and data modems, where high accuracy and low noise are important.

4. **Pipeline ADC:** Pipeline ADC is a type of analog-to-digital converter (ADC) that uses a series of stages to convert an analog signal into a digital signal. Each stage performs a partial conversion of the analog signal, and the outputs of the stages are combined to obtain the final digital output.

   The architecture of a pipelined ADC is illustrated in (see Figure 2.13). In this design, each stage uses a sub-ADC to digitize the analog input signal, Vin, with a resolution of M bits, which may not be identical for all stages. The sub-ADC then converts the resulting "estimate" to digital using a sub-DAC. The analog estimate is then subtracted from Vin, producing a "residue." The residue is amplified by a power of two and passed on to the next stage for further digitization [26].
   Advantages:

   - High-speed operation: Pipeline ADCs are known for their high conversion rates, making them suitable for applications that require high-speed analog-to-digital conversion.
   - High resolution: Pipeline ADCs can achieve high resolution by using multiple stages, each with a low-resolution ADC, to achieve a high overall resolution.
   - Low power consumption: The pipeline ADC architecture allows for lower power consumption compared to other high-speed ADCs.

   Disadvantages:

   - Complexity: The pipeline ADC architecture is more complex than other ADC architectures, making it difficult to design and implement.

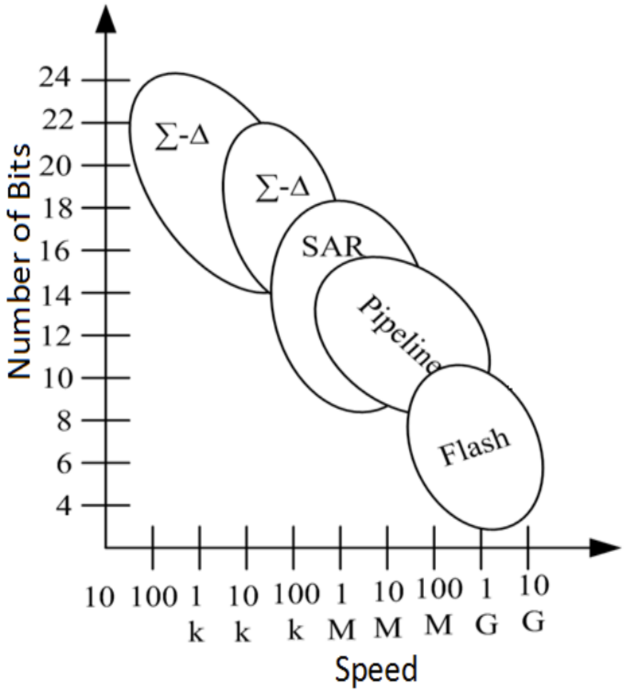

FIGURE 2.14: Comparison of various ADC architectures [24].

- Non-linear errors: Non-linear errors such as gain error, offset error, and non-linearity can occur due to component mismatches and DAC errors, which can affect the accuracy of the conversion.

Applications:

Pipeline ADCs are used in applications that require high-speed and high-resolution analog-to-digital conversion, such as digital signal processing, high-speed data acquisition, medical imaging, and communication systems. They are also used in industrial automation and control systems for process monitoring and control.

In the summary, Figure 2.14 compares four common ADC architectures: Successive Approximation (SAR), Delta-Sigma, Pipeline, and Flash. The Y-axis shows the resolution in bits, and the X-axis shows the conversion speed in samples per second (SPS). Flash ADC has the highest speed but the lowest resolution, while Delta-Sigma ADC has the highest resolution but the lowest speed. SAR and Pipeline ADCs fall in between, with SAR having higher speed but lower resolution than Pipeline. Overall, the choice of ADC architecture depends on the specific application's requirements for resolution and speed [24].

ADC Characteristics

ADC characteristics include resolution, sampling rate, input voltage range, and accuracy.

- **Resolution:** Resolution refers to the number of bits used to represent the digital output. Higher resolution results in a more accurate representation of the analog signal.

- **Sampling Rate:** Sampling rate refers to the number of times per second that the analog signal is sampled and converted to a digital format. A higher sampling rate results in a more accurate representation of the analog signal.

- **Input Voltage Range:** Input voltage range refers to the range of analog input voltages that the ADC can convert to a digital format. A larger input voltage range allows for a wider range of signals to be converted.

- **Accuracy:** Accuracy refers to how closely the digital output represents the analog input. Accuracy is affected by several factors, including linearity, offset error, and gain error.

ADC Error Sources

ADC (Analog-to-Digital Converter) errors refer to the inaccuracies that may arise during the conversion of an analog signal to a digital signal. Here are some of the most important ADC errors [22]:

- **Quantization Error:** ADCs convert analog signals into digital signals by sampling and then quantizing the signal into discrete values. Quantization error occurs when the signal falls between two quantization levels, resulting in an error in the digital output.

- **Non-Linearity Error:** ADCs should ideally have a linear transfer function, but in reality, they may have some non-linearity, resulting in errors in the conversion.

- **Offset Error:** This error occurs when there is a non-zero output when the input is zero. It may be caused by factors such as DC offset in the signal or errors in the ADC's reference voltage.

- **Gain Error:** Gain error occurs when the ADC's gain factor is not exactly as specified, resulting in a scaling error in the digital output.

- **Integral Non-Linearity Error:** This error occurs due to the non-linear relationship between the input and output of the ADC. It results in a deviation from the ideal straight-line transfer function.

- **Aperture Error:** Aperture error is caused by the time delay between the sampling of the input signal and the actual conversion of the sample. This delay can result in errors in the conversion.

- **Noise Error:** Noise can be introduced in the input signal, which can result in errors in the conversion. ADCs typically have a specified signal-to-noise ratio (SNR) that indicates their noise performance.

- **Temperature Drift Error:** This error occurs due to the variation of the ADC's performance with temperature. As the temperature changes, the ADC's transfer function may change, resulting in errors in the conversion.

It's important to understand these errors to properly evaluate the performance of an ADC and to take corrective measures.

2.3.5 Processor Part

ARM processors are a type of microprocessor that is widely used in various devices such as smartphones, tablets, wearables, and Internet of Things (IoT) devices. They are designed to be energy-efficient, highly scalable, and adaptable to a wide range of applications.

The ARM architecture is based on Reduced Instruction Set Computing (RISC) principles, which means that it uses a simplified instruction set that can be executed more quickly and efficiently. This allows ARM processors to provide high performance while consuming minimal power, making them ideal for mobile and IoT applications where battery life is critical [27].

One of the most significant advantages of ARM processors is their low power consumption. This is achieved through a combination of efficient instruction execution, power management features, and the ability to dynamically adjust processor frequency and voltage. As a result, ARM processors offer a significant advantage over other processors in terms of energy efficiency. This advantage makes them an ideal choice for battery-powered devices such as wearables, medical devices, and IoT sensors that need to operate for an extended period without recharging.

Another critical advantage of ARM processors is their adaptability. The ARM architecture is highly modular, with a range of processor cores and peripheral components available that can be combined to create customized solutions. This adaptability allows ARM processors to be used in a wide range of applications, from small embedded systems to large-scale servers. Moreover, ARM-based systems are easy to develop and debug and offer a high degree of compatibility, interoperability, and standardization, which are essential in complex systems [27].

ARM processors are also highly reliable and secure. The ARM architecture includes built-in security features, such as secure boot and TrustZone technology, which help to protect against cyber attacks and ensure the integrity of the device's software and data. ARM processors also support encryption, decryption, and authentication mechanisms, making them ideal for security applications.

In conclusion, ARM processors are a versatile, energy-efficient, and adaptable choice for a wide range of applications. Their low power consumption, adaptability, reliability, and security features make them ideal for mobile and IoT devices. ARM-based systems offer high performance, scalability, and compatibility, and have become the preferred choice for many developers and designers. The ARM ecosystem includes a wide range of hardware and software components, development tools, and community support, making it easy for developers to create custom solutions for specific applications [27].

2.4 Advantages of AE Method

Acoustic Emission (AE) technology offers several advantages over other non-destructive testing methods for crack detection. Some of these advantages include:

1. Non-invasive: AE does not require physical access to the material or structure being monitored, making it a non-invasive technique. This means that it can be used to monitor materials or structures that are difficult to access, such as those located in hazardous or hard-to-reach areas.

2. Early detection: AE can detect damage that is not visible to the naked eye or detect early-stage damage before it becomes a major problem. This allows

for early detection and preventative maintenance, potentially saving time and money in the long run.

3. Real-time monitoring: AE can be incorporated into wireless sensor networks, enabling real-time monitoring and analysis of critical infrastructure. This can provide valuable data to help make informed decisions about maintenance and repair schedules.

4. Wide range of materials: AE can be used to monitor a wide range of materials, including metals, composites, and ceramics. This makes it a versatile technique that can be applied to many different types of structures.

5. Cost-effective: Compared to other non-destructive testing techniques, such as x-ray or ultrasonic testing, AE is generally more cost-effective. This is because it does not require expensive equipment or highly skilled technicians to perform the testing.

6. Minimal surface preparation: AE can detect cracks without the need for extensive surface preparation, such as cleaning or coating removal. This makes it a quick and efficient technique that can be used in many different settings.

7. Sensitivity: AE is highly sensitive and can detect damage that is not visible to the naked eye or detect early-stage damage before it becomes a major problem. This makes it a valuable technique for monitoring critical infrastructure, such as bridges and pipelines, where even small cracks can have significant consequences.

8. Localization of damage: AE technology is capable of localizing the source of damage within a material or structure. This allows for more targeted and efficient repairs, reducing downtime and costs associated with repairing larger areas.

9. Continuous monitoring: AE can be used to continuously monitor structures and materials, providing a wealth of data over time. This can help identify trends and patterns in damage and inform predictive maintenance strategies.

10. Versatility: AE can be used in a variety of applications, from detecting cracks in metallic structures to monitoring the structural integrity of concrete bridges. This versatility makes it a valuable tool for a wide range of industries, including aerospace, automotive, and civil engineering.

11. Environmental considerations: AE is a non-invasive technique that does not produce waste or require the use of hazardous chemicals. This makes it an environmentally friendly option for crack detection and monitoring.

Overall, the advantages of AE technology make it a valuable tool for detecting and monitoring cracks in structures and materials. Its sensitivity, ability to localize damage and versatility make it an attractive option for many different industries and applications. Its cost-effectiveness, safety, and environmental considerations also make it a sustainable and responsible choice for crack detection and monitoring.

2.5 Limitations of AE Method

While Acoustic Emission (AE) technology has numerous advantages, it also has several limitations that must be considered:

1. Limited penetration depth: AE is limited in its ability to detect damage below the surface of a material or structure. This can be a problem when attempting to detect cracks in thicker materials or those with complex geometries.

2. Limited sensitivity to certain types of damage: AE technology may not be sensitive enough to detect certain types of damage, such as those caused by slow-developing cracks or chemical degradation. In these cases, other non-destructive testing techniques may be more appropriate.

3. Difficult to distinguish different types of damage: AE signals can be difficult to interpret, and it may be challenging to distinguish between different types of damage, such as corrosion or cracking. This can lead to false positives or false negatives in the data.

4. Environmental factors can affect data quality: Environmental factors, such as temperature and humidity, can affect the quality of AE data. Careful consideration must be given to the environmental conditions in which the sensors are placed to ensure accurate and reliable data.

5. Data analysis can be complex: The data generated by AE sensors can be complex and require specialized analysis techniques.

In conclusion, while AE technology has many advantages for detecting and monitoring cracks in structures and materials, it also has several limitations that must be carefully considered when selecting a crack detection method.

2.6 Applications of AE Method

The acoustic emission (AE) method has a wide range of applications in various industries, including aerospace, civil engineering, transportation, power generation, and more. Some of the key applications of AE technology include:

1. Structural health monitoring: AE sensors can be used to monitor the structural health of buildings, bridges, dams, and other infrastructure. The technology can detect cracks and other defects that can compromise the structural integrity of these assets.

2. Non-destructive testing: AE technology can be used to perform non-destructive testing on a wide range of materials, including metals, composites, and plastics. The technology can detect cracks, delamination, and other defects that may not be visible to the naked eye.

3. Quality control: AE technology can be used to monitor the manufacturing process of various products, including pressure vessels, pipelines, and other components. The technology can detect defects early on, ensuring that products meet quality standards and are safe for use.

4. Condition-based maintenance: AE sensors can be used to monitor the condition of various assets, including rotating machinery, pipelines, and other components. The technology can detect early signs of damage or wear, enabling maintenance personnel to schedule repairs before the asset fails.

5. Environmental monitoring: AE technology can be used to monitor environmental conditions, including seismic activity, landslides, and glacier movements. The technology can detect changes in the acoustic emissions of these phenomena, providing early warning of potential hazards.

6. Medical imaging: AE technology can be used in medical imaging to detect cracks and other defects in bones and other tissues. The technology can help diagnose various conditions and guide medical interventions.

In summary, the AE method has numerous applications across various industries, enabling the detection of defects and damage in a wide range of materials and structures. The technology can improve safety, quality, and efficiency in various applications, and is a valuable tool for many professionals.

Chapter 3

Background and Existing Knowledge

3.1 Introduction

Cracks are a common problem in various industrial and engineering applications, such as pipelines, bridges, and aircraft structures. The detection of cracks at an early stage is crucial to prevent catastrophic failures and ensure the safety and reliability of these structures. Traditional crack detection methods, such as visual inspection and non-destructive testing, are time-consuming, expensive, and may require shutdowns or disassemblies.

With the advancement of the Internet of Things (IoT) and sensor technologies, there has been a growing interest in developing automated and real-time crack detection systems. One promising approach is to use Acoustic Emission (AE) sensors, which can detect and analyze the high-frequency signals generated by the crack growth process. The AE-based crack detection systems have shown high accuracy and sensitivity, and they can be integrated with IoT platforms for continuous monitoring and data analysis.

This chapter provides a state-of-the-art review of crack detection methods using IoT and AE sensors. We will discuss the basic principles of AE-based crack detection and the advantages and limitations of different types of AE sensors. We will also review the recent developments in IoT-based crack detection systems, including hardware design, data acquisition and analysis, and application scenarios. Finally, we will identify the challenges and opportunities in the field and provide some future research directions. This chapter aims to provide a comprehensive overview of the IoT and AE-based crack detection systems and to inspire further research in this field.

3.2 Wireless Structural Health Monitoring

Wireless Structural Health Monitoring (SHM) is a rapidly evolving field that has the potential to revolutionize the way we monitor the health and safety of our critical infrastructure. Wireless sensors are becoming increasingly popular in SHM applications due to their ease of installation, low maintenance requirements, and ability to transmit data wirelessly to monitoring systems. One type of wireless sensor that is commonly used in SHM applications is the Wireless Sensor Network (WSN). WSNs consist of a group of wirelessly connected sensors that are placed throughout a structure and can be used to monitor a wide range of parameters, such as temperature, strain, and vibration. These sensors can provide real-time data on the health and performance of a structure, allowing maintenance teams to identify potential problems before they become critical [28]. In the next sections, we will discuss the latest research on wireless Acoustic Emission (AE) sensors in more depth. This type of sensor can detect and localize the source of acoustic emissions, which are often a precursor to failure in structures. The ability to detect and locate these emissions can help maintenance teams identify potential problems and take appropriate action to prevent structural failure. Wireless SHM systems are rapidly gaining popularity due to their many benefits, such as remote accessibility, real-time monitoring, and the ability to perform automated analysis. These systems have been successfully deployed in various types of structures, including bridges, buildings, and wind turbines. One of the key advantages of wireless SHM systems is that they can provide continuous, real-time monitoring of a structure's health and performance. This allows maintenance teams to detect potential problems early on before they become critical, and take appropriate action to prevent downtime and structural failure. Another advantage of wireless SHM systems is their ease of installation and low maintenance requirements. Wireless sensors can be easily installed on a structure without the need for extensive wiring or structural modifications and can be easily replaced if necessary. Wireless SHM systems can also be used to optimize the performance of a structure, by providing real-time feedback on the loads and stresses experienced by the structure. This can help engineers and maintenance teams to identify potential design improvements and optimize maintenance schedules to ensure the long-term health and performance of the structure. In conclusion, wireless SHM systems and wireless sensors, such as wireless AE sensors, have the potential to greatly improve the safety, reliability, and performance of our critical infrastructure. In the next sections, we will delve deeper into the latest research on wireless AE sensors, and how they are being used to detect and prevent structural failures.

3.3 Literature Review of Wireless Sensor AE-Based Crack Detection Systems

Cracks in structures can significantly impact their safety, functionality, and lifespan. As a result, it is essential to detect and monitor cracks in structures. Various crack detection techniques have been developed over the years, including visual inspection, ultrasonic testing, and acoustic emission (AE) testing. While each technique has its advantages and disadvantages, AE testing is particularly useful for monitoring the initiation and propagation of cracks in real-time. Furthermore, the integration of wireless sensor networks with AE technology has enabled remote monitoring and data collection, reducing the need for physical access to the structures. In this section, we will review the literature on wireless sensor AE-based crack detection systems, including their development, implementation, and effectiveness.

Chilibon et al [29] introduced a wireless acoustic emission sensor that relies on the R15 α sensor (see table 3.1) characteristics to detect and convert mechanical signals produced by a crack into electrical signals. The signal is then amplified and processed by an 8-bit microcontroller, which converts it into digital form using ADC before transmitting the message via a 433 MHz transmitter. The system design is visually represented in Figure 3.1.

However, the study by Chilibon et al did not provide details regarding the frequency sampling or the number of samples acquired by the ADC. Furthermore, the researchers did not apply any IoT protocols to the system, which may have limited the device's capability to connect and interact with other devices in the network. The

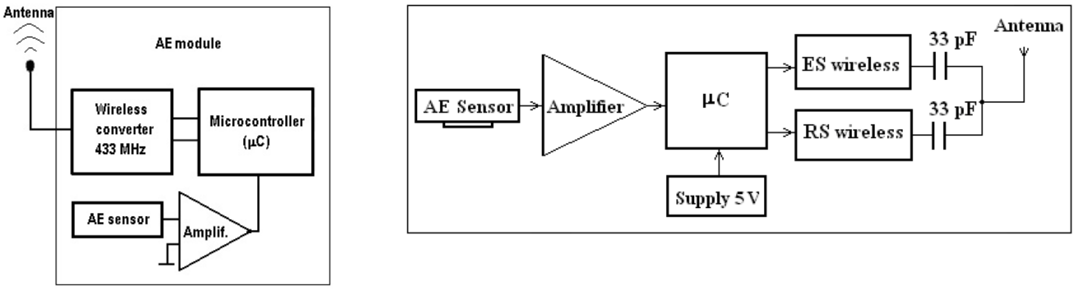

FIGURE 3.1: Block Diagram of experimental wireless module acoustic emission sensor [29].

TABLE 3.1: Characteristic Sensor Acoustic Emission R15 α

Properties	AE sensor
Frequency range	100 kHz - 450 KHz
Sensitivity	-40 $dB_V to 100 dB_V$
Dynamic range	140 dB
Temperature range	-20°C to 85°C
Outer dimension	Diameter: 20.5 mm x 14 mm
Effective sensing area	Around 230 mm^2
Total mass (g)	12

study also did not consider the issue of power consumption, which could be critical in wireless sensor devices that need to operate autonomously for an extended period. Another significant concern is the distortion resulting from the ADC's low-frequency sampling in this type of microcontroller, which may impact the accuracy of the system's data. While Chilibon et al's proposed system appear to be a promising solution for acoustic emission sensing, these gaps in the research should be addressed to fully understand the device's capabilities and limitations.

The paper by Yin Wu et al. [30] presents a wireless acoustic emission (AE) sensor node that has the capability of detecting and localizing fracture cracks in structures. This system combines three critical technologies: Wi-Fi communication, a different encoding algorithm, and two-branch dataflow management. The hardware design of the system involves a dual-core architecture (see Figure 3.2), where the CC3200 on the radio board performs wireless communication and time synchronization tasks, while the STM32F407 on the base board carries out the computation-intensive data processing task. The radio board uses a DS3232M RTC to synchronize time, and the STM32F407 collects data about the sensing signal by the AE sensor. They have addressed the sampling rate and have chosen a 5 MSPS rate for data acquisition.

The software design of the system features a process diagram that demonstrates the primary stages of the wireless AE node's operation. The system begins with data acquisition of the AE signal, and then the diagnosis algorithm is executed to calculate the AE event features. If the activity and intensity are normal, the node enters the "normal checking" workflow, where the data is compressed to save transmission payload, and then wireless communication to the control center begins. On the other hand, if the node is in an abnormal state, it enters the "closely monitoring" stage, where raw data is transferred directly to the control center without any data compression (see Figure 3.3). Finally, feature extraction and damage localization are carried out to compute the health status of the entire structure. However,

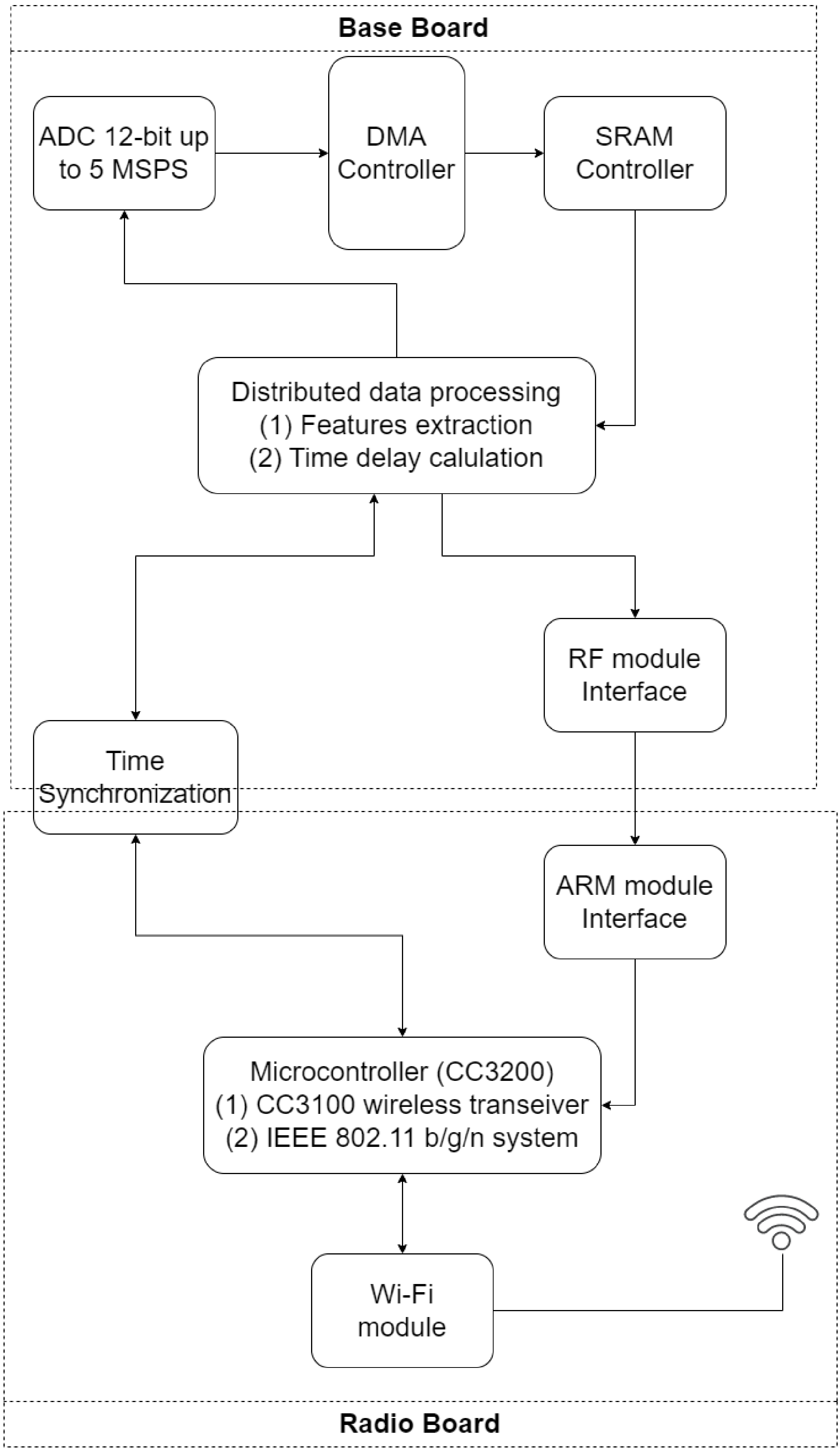

FIGURE 3.2: Block diagram of the sensor node [30].

it is important to note that the authors have used an RTC unit to provide synchronization between the nodes, but this method does not guarantee synchronization. Additionally, the energy consumption of the node has not been thoroughly studied, and further research is required to explore energy harvesting methods. It is also worth mentioning that the analog processing aspect of the system, such as amplification and filtering, has not been addressed in this paper. In addition to the aforementioned gaps, it is worth noting that the paper does not explicitly address the Internet of Things (IoT) paradigm, which has become increasingly important in recent years. IoT involves connecting physical devices to the internet, allowing them to communicate with each other and exchange data. While the proposed wireless AE sensor node does utilize Wi-Fi communication and can transmit data to a control center, there is no discussion of how this device could be integrated into a larger IoT system or how it could be used to collect and share data with other devices or platforms. Given the potential for IoT to revolutionize structural health monitoring and other related fields, it would be beneficial for future work to consider how this device could be adapted and integrated into larger IoT systems to enable more sophisticated data collection, analysis, and sharing. Overall, while this wireless AE sensor system presents a promising solution for fracture detection and localization, there are still some gaps and areas for improvement that need to be addressed in future research. The paper by Shi Yan et al [31]. presents a wireless smart aggregate structural health monitoring (SHM) system setup and its signal flow. The system includes a detected reinforced concrete (RC) structure, signal excitation module, signal data acquisition module, wireless communication module, and power module. Smart aggregates are pre-embedded in the RC structure.

The signal excitation module uses a NI9074 and a power amplifier to generate the excitation signal on the smart aggregates. The signal data acquisition module converts monitoring signals from stress waves received by the sensor smart aggregates into an electrical signal. The amplifier amplify the signal because the sensor's signal is a weak signal, and its amplitude is just a few millivolts then the amplified signals are transmitted to the sampling module. The wireless communication module uses an analog-to-digital (A/D) converter and Zigbee wireless network to transmit the received voltage signals as digital binaries to a gateway, which then sends them to a personal computer (PC) for signal processing (see Figure 3.4).

The signal transceiver module of the wireless radio module consists of four submodules: the wireless radio module, the power supply module, the data acquisition module, and the amplifier module. The RF chip MC13193 from Freescale is used as the Zigbee implementation solution. The power module uses the MSP430F2 chip as a microcontroller for battery monitoring and control, with a lithium battery of 1000 mAh capacity. The sampling module uses STM32F103 series chips with a sampling rate of 1 MSPS for the ADC.

Overall, the methods used in the paper provide a detailed overview of the wireless smart aggregate SHM system setup and its signal flow, which can be useful for researchers and practitioners interested in structural health monitoring of RC structures using smart aggregates. However, the Authors did not address the issues about the ADC and sampling rate despite its a vital issue in these kinds of systems and they did not take into their account the accuracy of the system, the uncertainty, and power consumption.

F Zahedi and H Huang [32] describe a light-powered wireless Acoustic Emission (AE) sensing system consisting of a battery-free wireless AE sensor node and a sensor interrogation unit (SIU). The wireless sensor node is installed on a structure and is powered by a solar cell-based energy harvester that converts light emitted

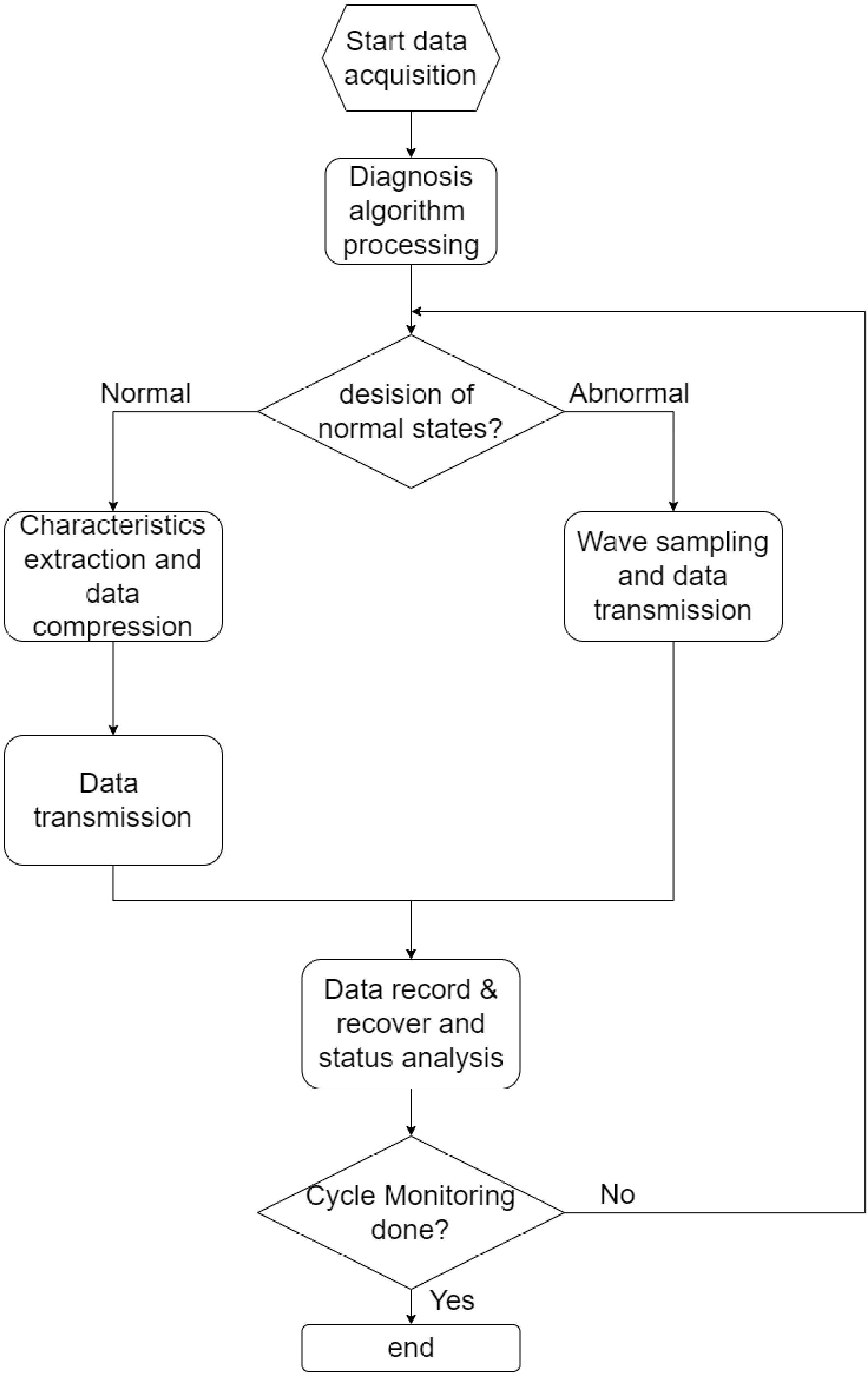

FIGURE 3.3: Operating cycle carried out by the node [30].

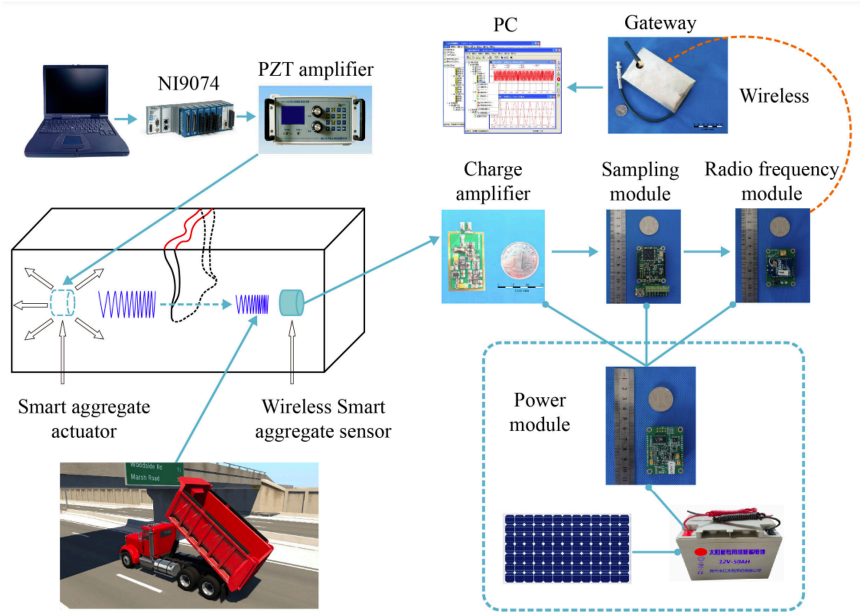

FIGURE 3.4: The architecture of proposed system by Shi Yan and et al [31].

by the SIU into electric energy. The system uses a PWAS (Piezoelectric Wafer Active Sensor) to acquire the AE signal, which is then supplied to a voltage follower. The wireless transponder in the sensor node uses antennas and a frequency mixer to transmit the AE-modulated microwave signal without the need for an analog-to-digital converter (ADC). The SIU generates an interrogation signal and receives the AE-modulated microwave signal using antennas, and a homodyne receiver is used to recover the AE signal from the received wireless signal (see Figure 3.5).

Advantages:

- Battery-free operation: The wireless sensor node is powered by a solar cell-based energy harvester, eliminating the need for batteries and reducing maintenance requirements.
- Wireless communication: The AE signal is transmitted wirelessly without the need for physical connections, enabling remote sensing and reducing installation complexity.
- Continuous or on-demand operation: The system can be operated continuously or on-demand, depending on the availability of light, providing flexibility in monitoring options.

Disadvantages:

- Dependence on the light source: The system relies on a sufficient light source for energy harvesting, which may not be available in all environments or during certain times of the day or year.
- Limited transmission range: The wireless communication range may be limited by the power of the interrogation signal and the sensitivity of the homodyne receiver, which may restrict the system's applicability to certain monitoring scenarios.

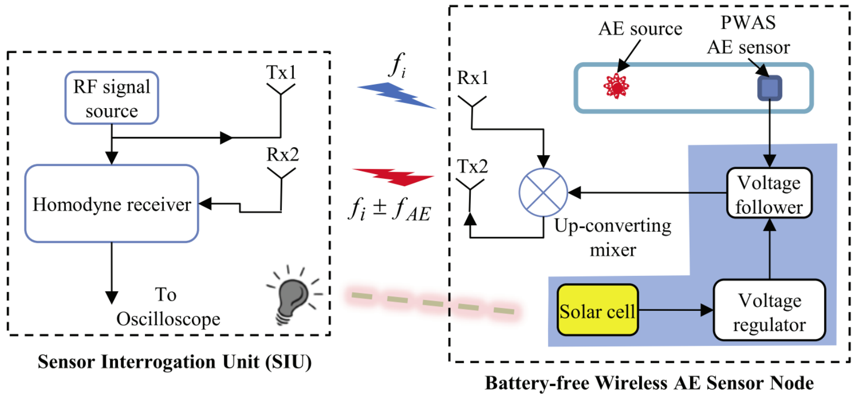

FIGURE 3.5: Wireless AE sensing system powered by solar energy harvester [32].

- Complex system setup: The system requires multiple components, including antennas, mixers, and a homodyne receiver, which may require skilled installation and setup, increasing the complexity and cost of implementation.

The paper describes a wireless analog method for transmitting AE signals, but this approach introduces challenges related to bandwidth and potential interference with other systems. However, the paper does not provide details on how the received signal is processed, and no protocols for signal transmission are addressed by the authors. Additionally, the paper does not discuss any measures or techniques for mitigating potential interference or bandwidth issues associated with the wireless analog transmission method. Overall, these aspects could be considered limitations of the presented approach.

Zhibo Zhang and et al [33], discuss the wireless acoustic emission sensing system, which is composed of a transmitter node and a receiver node. The transmitter node is placed on the surface of the structure being monitored, while the receiver node is positioned remotely to receive and interrogate the RF signal. The selection of the carrier wave frequency is based on several factors. To meet the requirements of common industrial applications, the wireless transmission distance should exceed 100 m. The propagation power loss of the transmitting electromagnetic wave in the air can be modeled as a function of the transmission distance and operating frequency. Therefore, the transmission distance greatly decreases as the carrier wave frequency increases. Furthermore, since many IoT devices in the industrial environment use the 2.4 GHz carrier wave frequency, it may cause undesired interference to the wireless acoustic emission sensing system. The carrier wave frequency should also provide adequate frequency bandwidth for the AE modulation signal. Hence, a 170 MHz carrier wave frequency was chosen for the proposed method. The paper includes a schematic diagram of the wireless acoustic emission sensing system (see Figure 3.6). At the transmitter node, the acoustic emission signal is first converted to an electrical signal using an acoustic emission sensor. The voltage-controlled oscillator then provides a high-frequency carrier at 170 MHz, which is output to the multiplier circuit and amplitude modulated with the acoustic emission signal to generate an amplitude modulated signal. After amplification by the power amplifier, the amplitude-modulated signal is transmitted through an antenna. At the receiver node, the amplitude-modulated signal is received by the antenna of the same operating frequency and recovered by the envelope detection circuit. The acoustic signal is then amplified by a low noise amplifier (LNA) and a band-pass filter to suppress

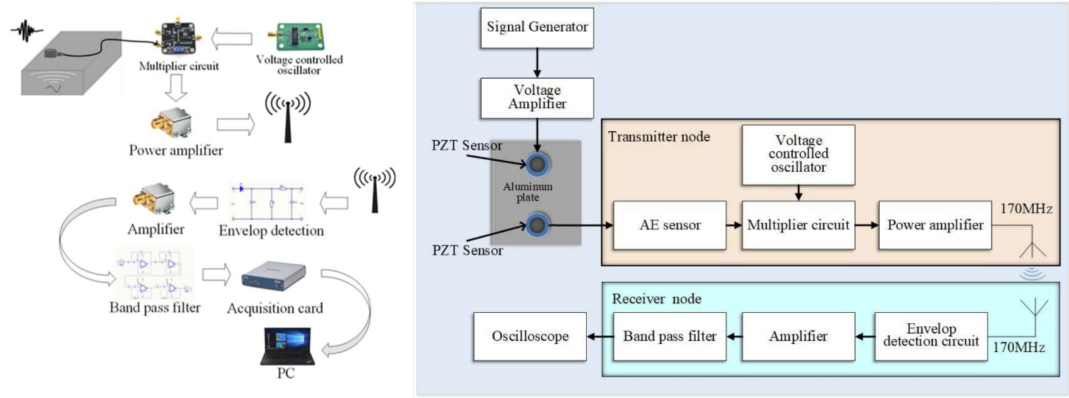

FIGURE 3.6: The schematic diagram for the proposed method [33].

noise. Finally, the acoustic signal is converted to digital format using a data acquisition card and can be further analyzed on a computer. The authors did not address the issue of multiple sensors connected to the base station and the multiple access. The carrier wave frequency of 170 MHz is not free, and there may be potential interference from other devices operating on the same frequency. The system consumes a lot of power due to the use of the amplitude modulation (AM) technique, which is not effective against noise. There are no mechanisms to control or correct potential noise interference in the system, which may impact the accuracy of the data collected. In summary, the paper provides a detailed description of the structure and operation of a wireless acoustic emission sensing system that can be used for structural health monitoring. The system can operate over a long distance (more than 100 meters) due to the use of a carrier wave frequency of 170 MHz. The system has a high-frequency bandwidth for the AE modulation signal, allowing for the acquisition of accurate data.

Shang Gao paper's [34] investigates the fatigue behavior of Ultra High Strength Steel Specimens (UHSSS) subjected to High Cycle Fatigue (HCF) tests. The study focuses on using Acoustic Emission (AE) technology to monitor the fatigue characteristics of UHSSS and proposes the use of AE information entropy to overcome the limitations of traditional AE parameters that depend on the threshold. The results show that AE entropy can better reflect the fatigue characteristics of UHSSSs and provides a promising approach to predict fatigue limit and recognize the fatigue status of steel structures based on the AE signal.

The study uses a wireless AE system to acquire the AE signals during HCF testing. The system consists of an acquisition module, a power module, a storage module, a control module, and a communication module. The system hardware architecture uses a 32-bit Cortex-M3 core microcontroller unit (MCU) STM32F103ZET6 and a low-power RF chip silicon SX1278 as the processor and communication module. The data acquisition unit uses the AD9226 chip with 12-bit resolution and a conversion rate of up to 65 MSPS. The high-speed operational amplifier chip NE5532 is selected to amplify the acoustic signal, and the acquisition data is temporarily stored in a secure digital card (SD) card and transmitted to the upper computer wirelessly (see Figure 3.7). The AE sensor SR150m produced by Physical Acoustic Corporation is connected to the transmitter, fixed at the positions of the clamp during HCF testing, and records the entire HCF of the specimens continuously. A high-pass filter with a cutoff frequency of 100 kHz is used to remove the noise. The paper provides a detailed process of real-time extraction of AE signals during HCF testing, including filtering, finding the initial value of the AE signal, and determining the peak and

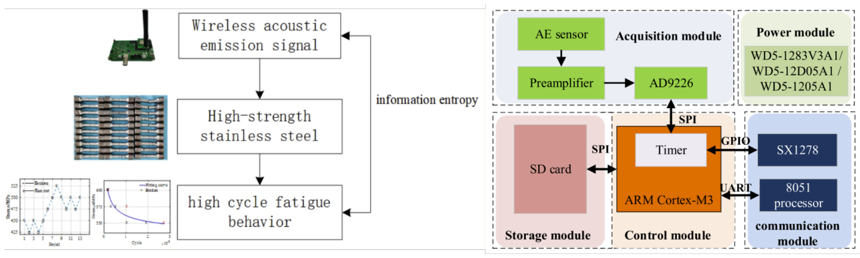

FIGURE 3.7: Hardware and implementation of the system [34].

continuous AE signal within specific time parameters.

Overall, the paper presents a comprehensive study of the fatigue behavior of UHSSSs using AE technology and proposes a promising approach to predict fatigue limits and recognize the fatigue status of steel structures based on the AE signal. The wireless AE system architecture used in the study provides a reliable and efficient method to acquire and process the AE signals during HCF testing. The authors of the paper did not provide a thorough explanation of the wireless system. They did not specify the type of protocols or wireless technology employed in the system, which is a significant gap in their analysis. Additionally, they did not give sufficient consideration to power consumption and IoT issues, which are critical aspects of wireless systems.

Mayur Kadlag et al [35], describe the design and implementation of an Acoustic Emission (AE) monitoring system using a preamplifier with a variable gain and a self-power supply. The system is designed to acquire AE signals from a sensor node, amplify them with a selectable gain of 40dB or 60dB, decouple them from the DC supply, digitalize them using an inbuilt ADC of the controller STM32F303, and transmit the digital values via ZigBee wireless communication module. The collected data is then received by a PC running LabVIEW software, where it is displayed on the front panel, and the AE factor is calculated. The focus of the paper is on the architecture of the AE monitoring system (see Figure 3.8), which includes the preamplifier with a variable gain, the decoupling circuit, the digitalization process, the ZigBee wireless communication, and the LabVIEW software interface. The preamplifier is designed using negative feedback resistors and includes a small switch button to change the gain of the preamplifier. The decoupling circuit is designed to decouple both the AE signal and DC supply, which is connected after the preamplifier circuit. The digitalization process involves using the inbuilt ADC of the controller to convert the amplified AE signal into digital values. The digital values are then transmitted via ZigBee wireless communication to the LabVIEW software, where the AE factor is calculated and the data is displayed on the front panel.

Overall, the architecture of the AE monitoring system described in the paper is well-designed and implemented to provide accurate and reliable monitoring of AE signals. The use of a preamplifier with a variable gain, a self-power supply, and a decoupling circuit ensures that the AE signals are accurately acquired and amplified without any interference from the DC supply. The use of ZigBee wireless communication and LabVIEW software provides a user-friendly interface for the data acquisition and analysis process.

However, the paper lacks a discussion of the accuracy and uncertainty of the system, and the authors do not present any results to support their claims. Additionally, while the authors have decoupled the DC component to separate the AE signal, they fail to address the issue of negative values, which the stm32f303 ADC cannot read. The high frequency and short duration of the AE signal also present a

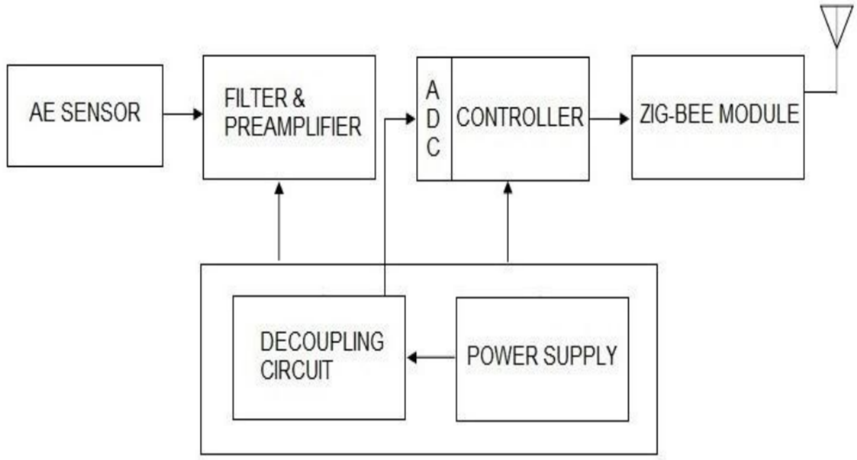

FIGURE 3.8: Block Diagram of Sensor Node [35].

challenge, as the system must acquire a large number of samples, which cannot be sent at a sufficient speed of 9600 bps via Zigbee. Furthermore, the authors do not address the problem of power consumption.

3.4 Analyze the Literature Review

Wireless crack sensor detection using Acoustic Emission (AE) has been a topic of interest in the field of structural health monitoring. However, despite its potential significance, there are only a few research studies that have addressed this kind of wireless sensor. One significant observation is that no study has yet explored the use of the Internet of Things (IoT) paradigm and edge computing in this kind of application. This is important because the use of IoT and edge computing can enhance the efficiency and effectiveness of wireless sensor networks, particularly in terms of data processing, storage, and transmission. Additionally, some studies have overlooked the importance of frequency sampling, which can significantly affect the accuracy of the detection system. Furthermore, energy consumption has been identified as another critical issue that requires attention in the design and development of wireless AE detection systems. Some studies have attempted to design wireless sensor systems using analog communication paradigms, which can create problems such as interference and multiple access, as well as issues related to the licensing of these frequency bands. These problems can limit the usefulness of these systems in real-world applications. Hence, the use of digital communication paradigms, such as Zigbee or LoRa, can provide a more efficient and reliable means of wireless communication, particularly in terms of reducing the likelihood of interference and the power consumption of the system. As we know, synchronization between wireless sensors is crucial for the accurate detection of cracks in structures. However, this aspect has not been addressed in the current research. In addition, the application of TinyML, or tiny machine learning, in detecting cracks using AE-based wireless sensors is a promising area for future research. TinyML involves deploying machine learning algorithms on small, low-power devices, enabling on-device analysis of sensor data. This would potentially reduce the energy consumption of the wireless sensors, making them more efficient and cost-effective. Moreover, the implementation of TinyML would allow for real-time analysis of the AE signals, providing rapid and accurate detection of cracks in structures. Therefore, future research in wireless structural health monitoring using AE-based sensors should explore the synchronization of wireless sensors and the application of TinyML for more efficient and effective detection of cracks. In summary, despite the importance of wireless crack sensor detection using AE, there are still gaps in the current research literature. These gaps relate to the use of IoT and edge computing, the importance of frequency sampling, the issue of energy consumption, and the use of appropriate digital communication paradigms. Addressing these gaps will contribute to the development of more efficient, effective, and reliable wireless crack sensor detection systems.

Through this thesis, our aim is to address the gaps identified in the literature review and advance the state-of-the-art in wireless structural health monitoring using acoustic emission-based crack detection systems. Specifically, we will focus on the following objectives:

1. Design and develop a wireless sensor network using IoT paradigm and edge computing to enable real-time monitoring of structural health.

2. Develop a novel synchronization method to ensure accurate and reliable data acquisition from the wireless sensors.

3. Investigate and optimize frequency sampling techniques to capture high-frequency AE signals and improve the accuracy of crack detection.

4. Implement an efficient algorithm used to detect cracks with high accuracy and low power consumption.

5. Evaluate the performance of the proposed system through experimental testing using statistical tools and comparison with existing methods.

By achieving these objectives, we aim to contribute to the advancement of wireless structural health monitoring and enable the early detection of cracks in structures, which can lead to improved safety and reduced maintenance costs.

Chapter 4

Sensor Design and System Integration

4.1 Introduction

Integration is a crucial stage in developing complex systems, like wireless sensors for health-structural monitoring applications. This process involves designing the system architecture, selecting hardware components, designing the hardware, developing software, testing the system, and debugging. The process must be structured and rigorous to ensure that the system meets the functional requirements and specifications defined in the system architecture. The thesis discusses these aspects in detail in this chapter and subsequent chapters.

4.2 System Overview

The proposed system is designed for health-structural monitoring applications and involves integrating various technologies, including sensors, wireless sensor networks, embedded systems, and IoT. The system architecture is composed of different components, as shown in Figure 4.1. The platform is purposefully designed to meet the requirements of health-structural monitoring applications.

4.3 Design Objectives and Requirements

Designing this system poses significant challenges due to the critical requirement of amplifying the signal, as discussed in the previous chapter, where the signal level is only a few millivolts. Moreover, the sensor generates a signal with a frequency of approximately 350 KHz, necessitating the use of an ADC with a high-frequency sampling rate, along with Analog components such as op-Amp with high-bandwidth responses. In addition, power consumption is a crucial factor that must be carefully considered in this type of application. Another significant challenge is achieving synchronization between all nodes. To address these challenges, a meticulous selection of hardware components is necessary.

4.4 Components Selection Methodology

Selecting the appropriate components for a system is a complex process that requires careful consideration of various factors such as the component's characteristics, cost, and size. It is crucial to have a deep understanding of the system's design requirements to make informed decisions.

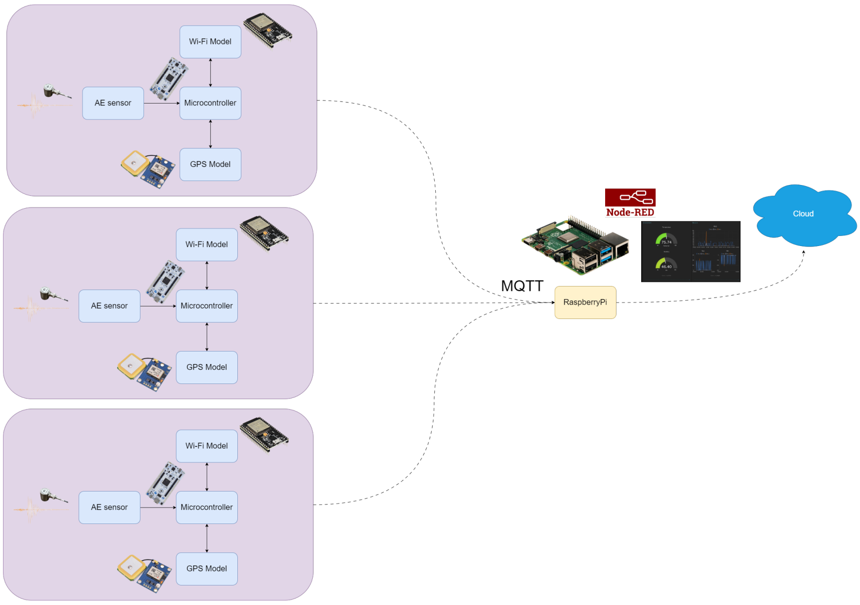

FIGURE 4.1: Conceptual diagram of the proposed system.

For the proposed health structure monitoring system, several stages are involved, including sensing, amplification, filtering, digitization, processing, and wireless transmission to the central server. In the processing stage, the system identifies the features of the acquired signal before sending the information to the server wirelessly. The server acts as an edge device and processes the data before storing it in both the edge and cloud, enabling remote monitoring of the system. Given the complexity of the system, selecting the right components is critical. Therefore, a comprehensive methodology must be used to identify the most suitable components that meet the system's requirements. The methodology should involve analyzing the component's characteristics, including the frequency response, power consumption, and signal-to-noise ratio. Additionally, the cost and size of the components should be considered to ensure they fit within the system's budget and space constraints. By following a well-thought-out component selection methodology, the health structure monitoring system can be designed to achieve optimal performance and functionality.

4.4.1 Sensing Stage

In a health structure monitoring system, the sensing stage is critical as it involves selecting the appropriate sensor to detect and measure the structural responses of the monitored structure. Choosing the right sensor requires careful consideration of various factors such as the expected types of defects or damage, the material being monitored, the required sensitivity, and the environmental conditions of the monitoring site. In general, acoustic emission (AE) sensors are a suitable choice for structural health monitoring as they can detect high-frequency signals generated by damage or defects in the material. AE sensors work on the principle of detecting the release of energy from the material in the form of elastic waves, and these waves are detected and measured by the sensor. There are different types of AE sensors available in the market, each with its own advantages and limitations. For example, piezoelectric sensors are commonly used as they are sensitive to high-frequency signals and have a wide frequency range. Fiber optic sensors, on the other hand, offer high accuracy and can detect low-frequency signals [36]. In the case of the health structure monitoring system proposed in this thesis, the R15 α sensor was selected as the sensing component. The R15 α sensor is a piezoelectric sensor with a frequency range of 100 kHz - 450 KHz and a sensitivity of -40 dB_V to 100 dB_V (see table3.1). These specifications make it suitable for detecting high-frequency signals that may be indicative of structural damage or defects. Additionally, the R15 α sensor is compact and lightweight, making it suitable for use in applications with limited space or where portability is a requirement. However, it is worth noting that the selection of the AR15 α sensor was based on the specific requirements and constraints of the proposed health structure monitoring system. The selection of a sensor for a particular application should always be based on a thorough evaluation of the system requirements and a careful consideration of the available sensor options.

4.4.2 Amplification Stage

In the proposed health structure monitoring system, an amplifier is used to amplify the low-level signals received from the R15 α sensor before processing by other electronic components. The selection of the amplifier is critical as it directly affects the quality of the amplified signal and ultimately impacts the accuracy of the monitoring system. When selecting an amplifier, various characteristics such as gain, noise level, bandwidth, input/output impedance, linearity, and power consumption must be considered. The gain of the amplifier should be high enough to amplify weak signals from the sensor, while the noise level should be low to minimize interference and maintain signal integrity. The amplifier's bandwidth should match the signal's frequency range to ensure accurate signal amplification, and the input impedance should be high to minimize loading effects on the sensor. In addition to these characteristics, the amplifier's linearity and power consumption are also important factors to consider. The amplifier's linearity ensures that the amplified signal is an accurate representation of the original signal, while power consumption is a crucial consideration in battery-powered devices [22]. Based on these considerations, the amplifier chosen for the proposed health structure monitoring system is specifically designed to be compact and compatible with the microcontroller STM32F303ze, which features four operational amplifiers with external or internal follower routing and (Programmable Gain Amplifier) PGA capability. The operational amplifier has a bandwidth of 8.2 MHz and a 0.5 mA output capability, with rail-to-rail input/output [37]. The PGA mode of the operational amplifier allows for gain programming of 2, 4, 8, or 16. This flexibility in gain programming enables the system to adapt to different monitoring scenarios and adjust the gain accordingly (see Figure 4.2). In summary, the selection of the amplifier for the health structure monitoring system is a critical step in ensuring accurate signal amplification and high-quality monitoring data. By considering various characteristics such as gain, noise level, bandwidth, input/output impedance, linearity, and power consumption, a suitable amplifier can be selected to meet the specific requirements and constraints of the monitoring system.

4.4.3 Filtering Stage

The filter used in the proposed architecture is an analog filter that is designed to prevent aliasing and remove high-frequency noise from the signal. Aliasing occurs when the signal frequency is higher than the sampling frequency, which can lead to

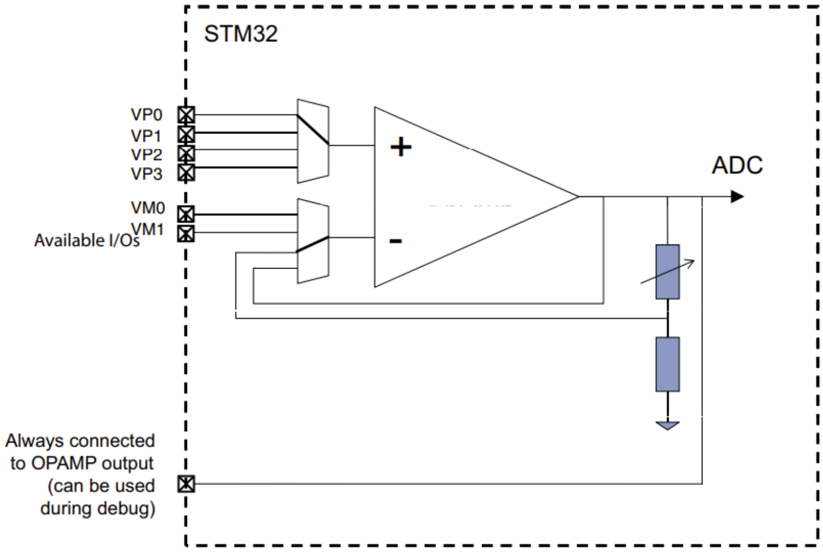

FIGURE 4.2: The schematic of an amplifier that compacts in STM32F303ze [37].

inaccurate readings and distortions in the output signal. To avoid this, the filter is designed to limit the signal bandwidth and prevent any unwanted high-frequency components from passing through. The filter is integrated with the amplifier to ensure optimal signal processing, and the two components work together to produce accurate and reliable crack detection in concrete structures. The filter is designed to have a frequency response that matches the signal's frequency range, with a cut-off frequency that is set to remove any high-frequency noise that may be present in the signal. To achieve this, another amplifier with a gain is used in STM32F303ze, which features four operational amplifiers with external or internal follower routing and PGA capability (see Figure 4.3). By integrating this amplifier with the filter, the proposed design ensures that the amplified signal is of high quality and free from any unwanted noise or distortions [37].

4.4.4 Analog to Digital Converter and Processor Stage

The choice of processor and ADC are critical components in the design of a wireless sensor system for detecting cracks in concrete structures. The processor must have the capability to process the data efficiently and with low power consumption. The ARM Cortex processor architecture is a popular choice for wireless sensor applications due to its low power consumption, high processing power, and versatility. In particular, the Cortex-M series is designed for microcontroller and low-power applications and comes in different configurations with various memory options and interfaces. The Cortex-M processors are supported by a range of development tools, making it easier to develop and debug software for wireless sensor systems. This architecture is suitable for wireless sensor systems that operate in harsh environments where power and space are limited, such as the case of concrete structures [27].

The STM32F303ze microcontroller was specifically chosen for its low power consumption, high processing power, and ability to operate in harsh environments. It is a member of the ARM Cortex-M4 processor family, which is designed for microcontroller applications and offers a balance between power efficiency and processing power(see Figure 4.4). One of the key advantages of the STM32F303ze is its low

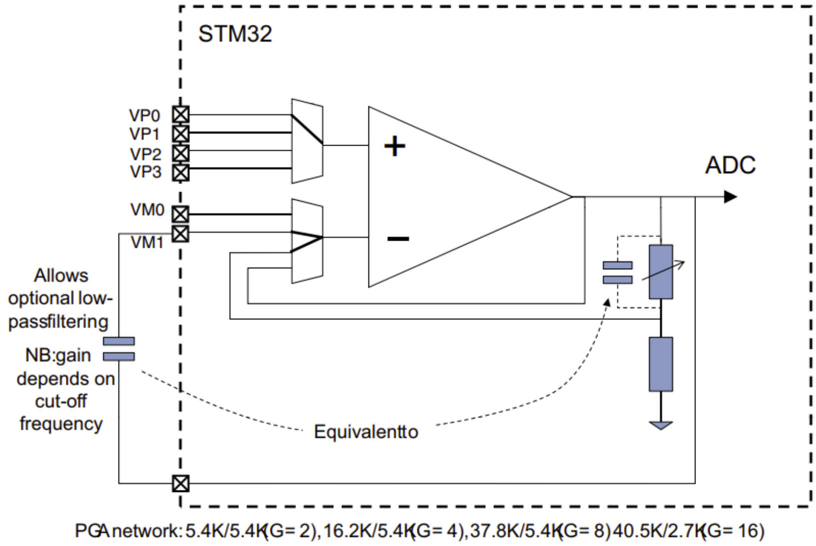

FIGURE 4.3: The schematic of a filter that compacts in STM32F303ze [37].

power consumption, which is critical in wireless sensor applications where battery life is a primary concern. The microcontroller features a power management unit (PMU) that allows for the efficient use of power, with multiple low-power modes to optimize energy consumption. This makes the STM32F303ze ideal for use in wireless sensor systems, where power consumption must be carefully managed to extend battery life and minimize maintenance requirements. Another advantage of the STM32F303ze is its high processing power. It features a 32-bit ARM Cortex-M4 processor with a clock speed of up to 72 MHz, which provides the necessary performance to handle the real-time processing requirements of the system. The microcontroller also includes 256 KB of flash memory and 40 KB of RAM, providing ample storage for the firmware and data. In addition to its low power consumption and high processing power, the STM32F303ze is designed to operate in harsh environments, making it suitable for use in the proposed crack detection system for concrete structures. The microcontroller features a wide operating temperature range of -40°C to 85°C, which allows it to operate in extreme temperature conditions. It also includes features such as a watchdog timer and a hardware CRC calculation unit, which improve the reliability of the system and protect against errors [37]. Overall, the STM32F303ze is a suitable choice for the proposed crack detection system due to its low power consumption, high processing power, and ability to operate in harsh environments. Its features and capabilities enable the system to capture and process AE signals efficiently and accurately, making it an ideal microcontroller for wireless sensor applications in concrete structures.

In concrete structure monitoring, the detection of cracks requires a high-speed and high-resolution ADC to capture the acoustic emission (AE) signals. The ADC used in the design is compact and embedded inside the STM32F303ze microcontroller, providing a sampling rate of 5 MSPS and a selectable resolution between 12 and 6 bits (see Figure 4.5). The ADC's low noise floor ensures that the signals are captured with minimal interference, improving the accuracy of crack detection. The use of a high-speed ADC is critical to capture the fast AE signals. The sampling rate of the ADC is determined by the Nyquist frequency, which is twice the highest frequency component in the signal, but for the practical aspects choose the frequency

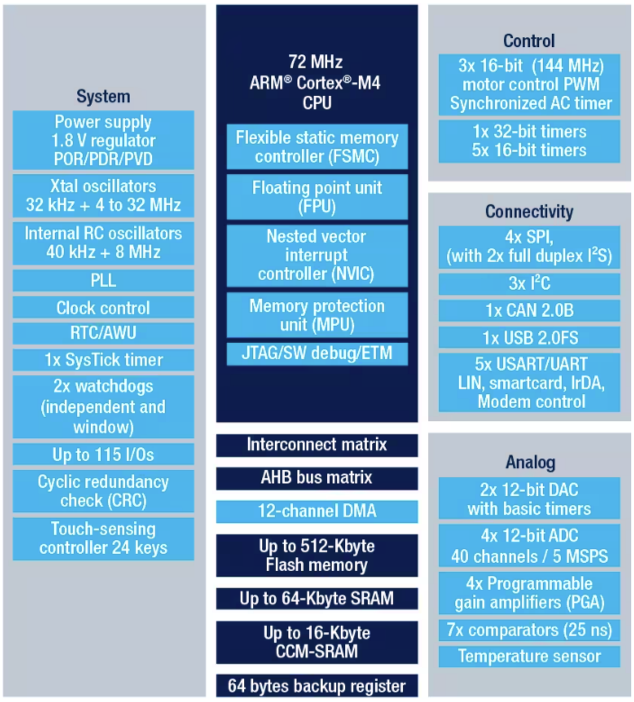

FIGURE 4.4: Circuit Diagram of STM32F303ze [37].

sampling 10 times the frequency's signal. For AE signals, which have frequencies in the range of a few hundred kHz, a high sampling rate is required to avoid aliasing. Aliasing occurs when the signal frequency is higher than the sampling frequency, which causes distortion in the output signal. The ADC used in this design also has a selectable resolution, allowing for flexibility in optimizing the trade-off between resolution and power consumption. Higher resolution results in better accuracy in capturing the AE signals but at the cost of increased power consumption. The selectable resolution allows for a balance between the two. The analog watchdog feature in the ADC allows for precise monitoring of the converted voltage and generates an interrupt when the voltage is outside programmed thresholds, effectively filtering out unwanted noise and improving the efficiency of the system. This feature is useful in reducing the amount of noise in the captured signals, thereby improving the accuracy of crack detection. Overall, the choice of processor and ADC are critical in the design of a wireless sensor system for detecting cracks in concrete structures. The ARM Cortex processor architecture and the high-speed, high-resolution ADC used in this design provide an efficient and reliable method for acquiring and processing AE signals.

4.4.5 Synchronization Stage

The Global Positioning System (GPS) is a satellite-based navigation system that allows accurate and dependable positioning and timing information to be obtained from anywhere on the Earth's surface. The utilization of GPS technology for synchronization in the proposed system has several advantages, such as accuracy, reliability, and compatibility with existing infrastructure. To ensure synchronization among all nodes in the proposed system, each node is outfitted with a GPS module, such as the GPS NEO-8M. This GPS module is capable of receiving signals from various GPS satellites and calculating precise location and time information. The GPS

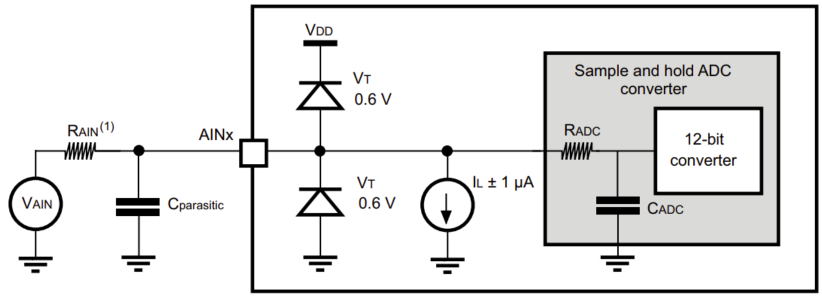

FIGURE 4.5: The schematic of ADC that compacts in STM32F303ze [37].

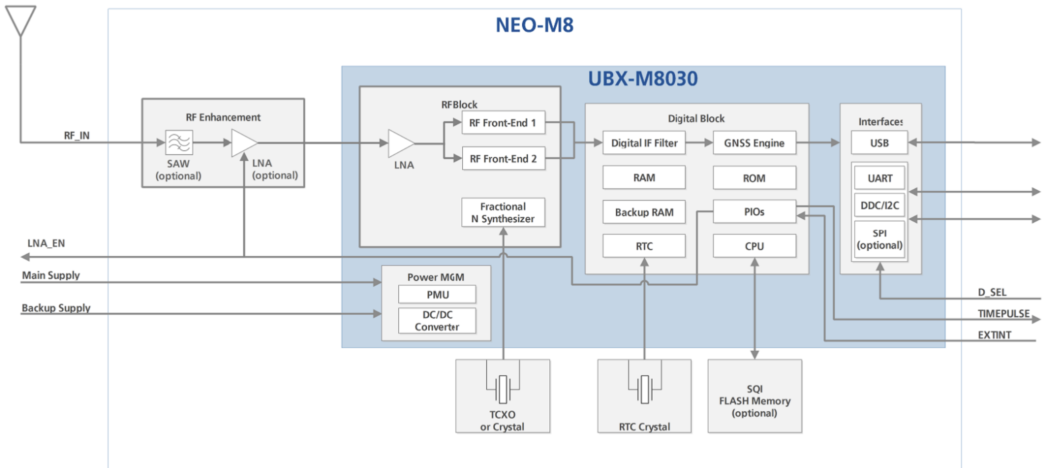

FIGURE 4.6: NEO-M8 Block Diagram [38].

module transmits this information, including the nanosecond-resolution timestamp and PPS (pulse per second), which can be utilized to synchronize all the nodes. The algorithm for synchronizing the data will be discussed in detail with the microcontroller in each node in the next chapter, as depicted in Figure 4.6, which illustrates the GPS module's architecture [38]. The use of GPS for synchronization guarantees that all nodes in the system are operating with the same time reference, which is critical for accurately analyzing the acoustic emission signals generated by the crack. This approach eliminates the need for a centralized timing system, which can be costly and challenging to implement. Moreover, GPS technology provides a high degree of accuracy in time-stamping the crack event. This level of accuracy is critical for precisely synchronizing the data from different nodes, especially in large-scale concrete structures, where various factors such as distance, angle, and material properties can affect the propagation of acoustic emission signals. With precise synchronization, the signal from different nodes can be aligned and analyzed to determine the location, severity, and type of crack, allowing informed decisions to be made regarding maintenance and repair. To summarize, the use of GPS technology for synchronization in the proposed system provides an accurate and reliable method to timestamp the crack event and synchronize the data collected by different nodes. The use of GPS eliminates the need for a centralized timing system and offers several advantages, including accuracy, reliability, and compatibility with existing infrastructure.

The GPS NEO-8M is an appropriate choice for the proposed system due to its compatibility with the ARM Cortex-M processor architecture, high performance, and reliability.

4.4.6 Wireless Transmission Technology and Protocols

Wi-Fi, short for wireless fidelity, is a wireless networking technology that uses radio waves to provide high-speed wireless Internet and network connections. It is widely used in many applications due to its high speed, range, and reliability. Wi-Fi operates on frequencies of 2.4 GHz or 5 GHz, and devices using Wi-Fi are typically connected to a router or access point that provides Internet or network connectivity. One of the main advantages of Wi-Fi is its ability to provide wireless connectivity over a large area, commonly referred to as its range. Wi-Fi can provide connectivity over distances ranging from a few meters to hundreds of meters, depending on the specific hardware and environmental conditions. This range can be extended even further through the use of Wi-Fi range extenders or mesh networking systems. Another advantage of Wi-Fi is its high speed, which allows for the transfer of large amounts of data quickly and efficiently. Wi-Fi speeds can range from a few megabits per second (Mbps) to several gigabits per second (Gbps), depending on the specific hardware and protocol being used. In addition to its range and speed, Wi-Fi is also known for its reliability. Wi-Fi networks are designed to be resilient and can automatically adjust to changes in the environment or network conditions. Wi-Fi devices can also connect to multiple networks, allowing for seamless switching between networks as needed. However, Wi-Fi does have some limitations and challenges. One of the main challenges is interference from other devices or networks operating on the same frequency band. This can cause slow or unreliable connections, especially in densely populated or congested areas. Wi-Fi signals can also be affected by physical obstacles such as walls or metal structures. Overall, Wi-Fi is a versatile and reliable wireless technology that has revolutionized the way we connect and communicate. Its high speed, range, and reliability have made it a popular choice for a wide range of applications, including IoT, smart homes, and wireless audio and video streaming [39].

The Message Queuing Telemetry Transport (MQTT) protocol is a lightweight, publish-subscribe-based messaging protocol that is designed to be simple and efficient, making it ideal for IoT applications. It has several features that make it suitable for the proposed design First, MQTT allows for efficient and reliable communication between the nodes and the central Raspberry Pi server. The publish-subscribe model used by MQTT ensures that messages are delivered to only the appropriate subscribers, reducing network traffic and increasing efficiency. This is important in the proposed design, as it involves real-time analysis and monitoring of acoustic emission signals from multiple nodes. MQTT ensures that the data is delivered to the appropriate subscribers in a timely and efficient manner. Second, MQTT supports Quality of Service (QoS) levels, which allow for reliable and efficient communication between the nodes and the server. QoS levels ensure that messages are delivered in a timely and efficient manner, even in the presence of network disruptions or failures. This is crucial in the proposed project, as it involves the real-time monitoring of structural health, and any delay or loss of data could have serious consequences. Third, MQTT is designed to be lightweight and efficient, making it ideal for IoT applications with limited resources such as memory, processing power, and bandwidth. The use of MQTT in the proposed design ensures that the data transmission is efficient and does not put unnecessary strain on the limited resources of the nodes

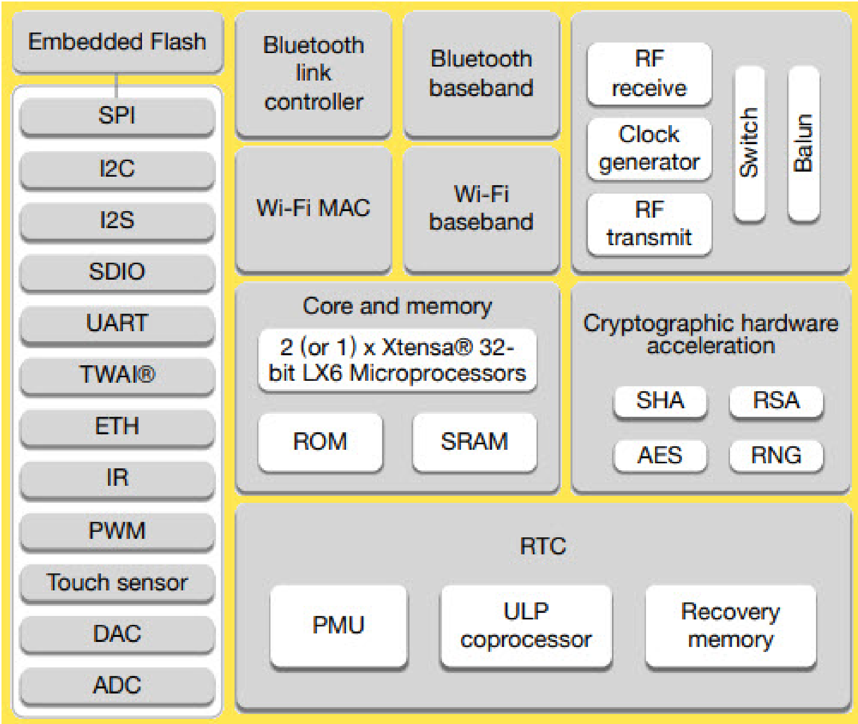

FIGURE 4.7: ESP32-Block-Diagram [40].

and the Raspberry Pi server. Overall, MQTT is a suitable protocol for the proposed project due to its efficiency, reliability, and support for QoS levels. It enables real-time monitoring and analysis of acoustic emission signals from multiple nodes and ensures that the data is delivered to the appropriate subscribers in a timely and efficient manner [39].

The ESP32 is a versatile microcontroller and system-on-a-chip that is widely used in IoT applications due to its low power consumption, dual-core processor, and built-in Wi-Fi and Bluetooth capabilities (see Figure 4.7). It is an ideal choice for the proposed project, which requires a low-cost and low-power node to monitor acoustic emission signals in concrete structures [40]. One advantage of using the ESP32 is its integrated Wi-Fi module, which allows for easy and reliable wireless communication between the nodes and the central Raspberry Pi server. The Wi-Fi module supports both 2.4 GHz and 5 GHz frequency bands and can be configured to connect to access points or act as an access point itself. The ESP32's Wi-Fi module is also compatible with the MQTT protocol, making it easy to implement the publish-subscribe model for communication between nodes and the server. Another advantage of using the ESP32 is its low power consumption. The ESP32 has multiple power modes, including deep sleep mode, which can reduce power consumption to as low as a few microamps. This is important for the proposed project as it will allow the nodes to operate for long periods of time without the need for frequent battery replacements or recharging. The ESP32's dual-core processor is another advantage that makes it suitable for the proposed project. The dual-core processor allows for the efficient processing of acoustic emission signals while leaving one core free for other tasks, such as communication with the server. Overall, the ESP32 is an ideal choice for the proposed project due to its low power consumption, built-in Wi-Fi and Bluetooth capabilities, and dual-core processor. It can be easily configured to communicate using the MQTT protocol, which allows for efficient and reliable communication between the nodes and the central Raspberry Pi server. The combination of the ESP32, Wi-Fi, and MQTT provides a flexible and reliable solution for monitoring acoustic emission signals in concrete structures.

4.4.7 Edge device and smart Gateway

In the context of IoT, an edge device refers to a device that collects data from sensors or other devices and performs some initial processing or analysis of the data locally, before transmitting it to a central server or cloud-based platform for further analysis and storage. Edge devices are important for IoT applications as they can reduce the amount of data that needs to be transmitted over the network, and can also provide real-time processing and analysis of data. A smart gateway, on the other hand, is a device that acts as an intermediary between the edge devices and the central server or cloud-based platform. Smart gateways can perform additional processing and analysis of the data before transmitting it to the central server, and can also provide additional features such as security, protocol translation, and data filtering. In the proposed design, the Raspberry Pi serves as the smart gateway for the edge devices, which are the nodes that collect data from the AE sensors. The Raspberry Pi is a popular choice for IoT applications as it is a low-cost, compact, and powerful device that can run various operating systems and programming languages. It also has built-in Wi-Fi and Ethernet connectivity, which makes it easy to connect to a local network or the Internet. The MQTT protocol is used to transmit data between the edge devices and the smart gateway. The nodes publish data to specific topics on the MQTT broker, which is hosted on the Raspberry Pi. The Raspberry Pi, acting as a subscriber, receives the data from the MQTT broker and processes it before storing it in a database or transmitting it to a cloud-based platform for further analysis. The use of Raspberry Pi as a smart gateway provides several advantages for the proposed design. It allows for additional processing and analysis of the data before it is transmitted to the central server or cloud-based platform, which can reduce the amount of data that needs to be transmitted and improve the overall efficiency of the system. It also provides additional security features, such as the ability to encrypt data and restrict access to certain users or devices. Overall, the use of edge devices and smart gateways, such as the nodes and Raspberry Pi in this design, can greatly improve the performance and efficiency of IoT systems. By performing initial processing and analysis of data locally, edge devices can reduce the amount of data that needs to be transmitted over the network, while smart gateways can provide additional features such as security and protocol translation. The use of MQTT as the communication protocol also ensures reliable and efficient transmission of data between the devices and the central server [41].

4.5 Architecture of the purpose system

The architecture of the proposed health-structural monitoring system is designed to enable the detection and analysis of acoustic emission signals in concrete structures. It consists of various components that work together to capture, process, and transmit the data for real-time monitoring and analysis. The discussion to choose each component was shown in the previous sections. Figure 4.8 illustrates the hardware architecture of the proposed system.

The proposed architecture enables the collection, processing, and analysis of acoustic emission signals in real-time following the algorithm shown in Figure 4.9, allowing for the timely detection and evaluation of cracks or defects in concrete

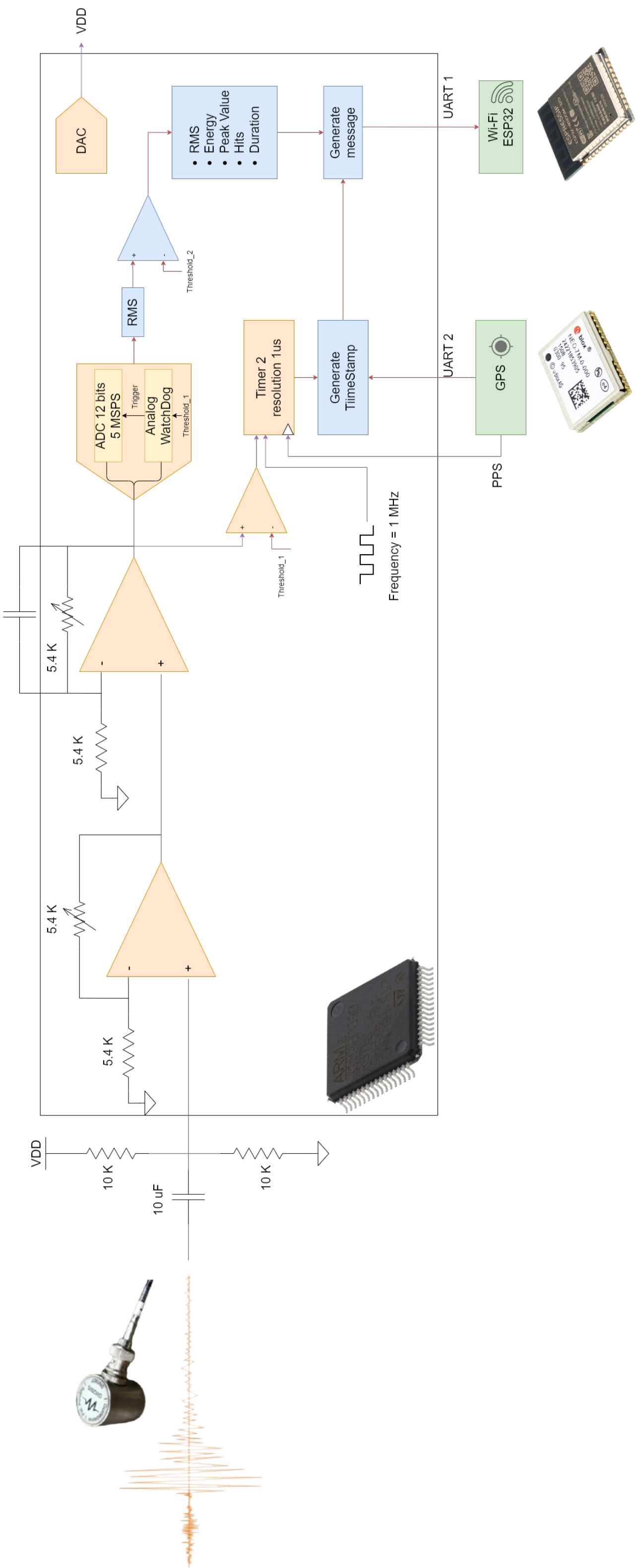

FIGURE 4.8: Hardware architecture of the proposed health-structural monitoring system.

structures. The integration of various hardware components ensures accurate signal amplification, precise digitization, and reliable wireless communication, enabling efficient monitoring and maintenance of the structures.

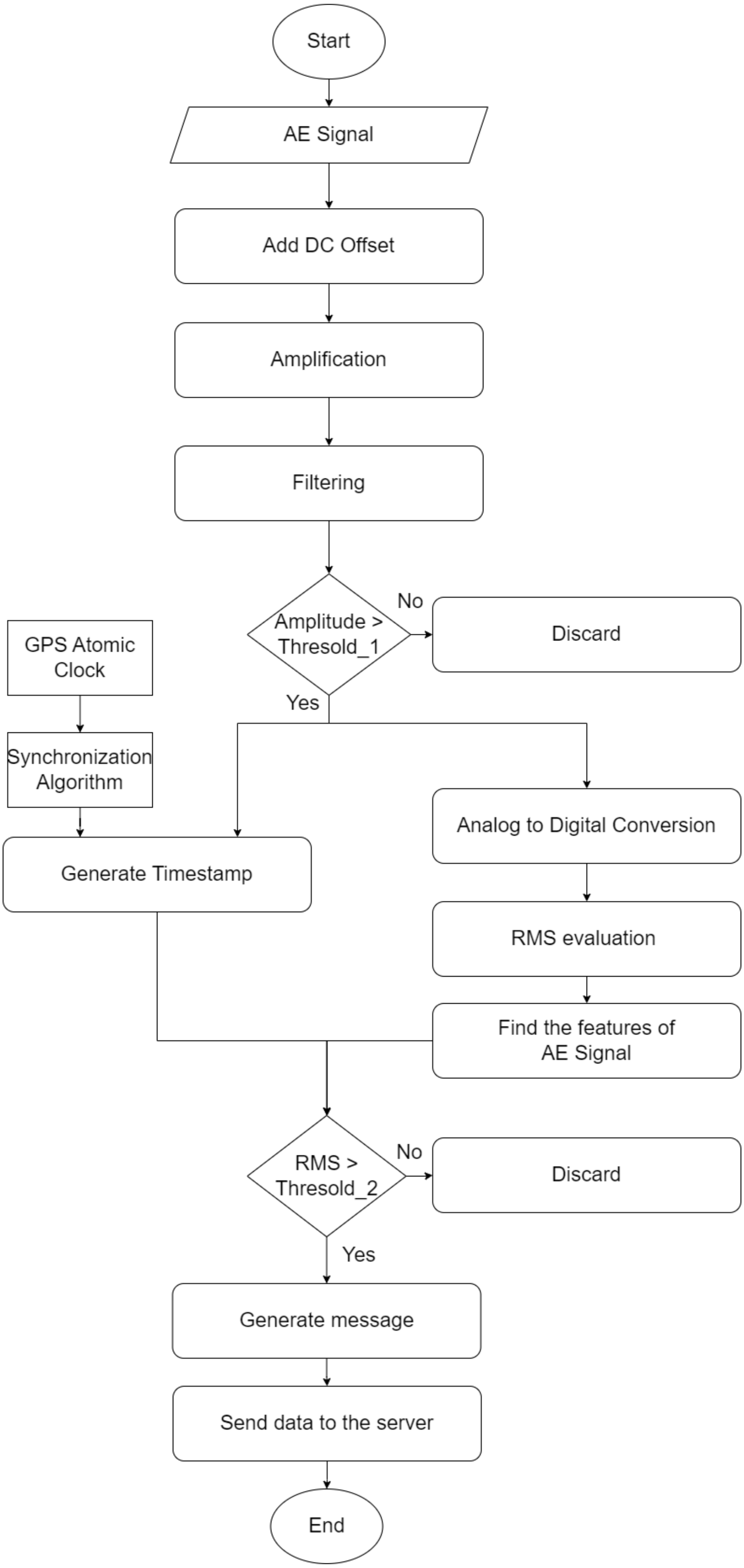

FIGURE 4.9: Flowchart of the proposed architecture.

Chapter 5

Algorithm Design and Firmware Development

5.1 Introduction

To ensure the detection of cracks, it is essential to utilize precise AE sensors. Consistent sampling rates are critical for accurate detection. Assessing the safety of a structure and the potential hazard posed by a crack depends on evaluating crack characteristics, such as RMS, Energy, Amplitude, Hits, and Duration. The precision of crack assessment relies on the effectiveness of algorithms used to identify these features. Accurate crack localization depends on the exact time-stamping of crack arrival, which hinges on the efficiency of the time-synchronization (T-Sync) algorithm.

In this chapter, we discuss the development and implementation of various unique algorithms for monitoring buildings to safeguard them against cracks. These include algorithms for crack detection and identifying crack features. Additionally, algorithms for synchronizing all nodes within microseconds are covered. Lastly, we explore communication algorithms with edge devices and processing data at the edge, in preparation for transmitting this information to the AWS cloud for storage.

5.2 Detection & Evaluation Crack Algorithm

The main goal of this thesis develops a standalone system that has the capability to detect a crack in an efficient way. At the same time take into account the energy consumption and constraints on resources. In order to achieve this goal the detection algorithm starts after the filtering stage as shown in Fig 4.9 The ADC uses an analog watchdog to monitor the signals coming from the AE sensor at all times. When the signal exceeds the threshold. The watchdog triggers an interrupt that works to stop the watchdog temporarily and triggers the ADC with active DMA (direct access memory) to transfer the data from ADC to the Signal buffer. Upon collecting 10,000 samples, the ADC triggers another interrupt called to notify the processor the transfer data process is completed as illustrated in Figure 5.1.

Then the processor starts executing the software routine of the interrupt to detect and evaluate the crack. At this point, the controller starts a new phase and executes a software routine to find the features of signals (RMS, Energy, Amplitude, Hits, and Duration). Choosing these characteristics of the signals was based on the studies presented in a paper [42]. These characteristics of the signal play a vital role in evaluating the level of danger of the crack.

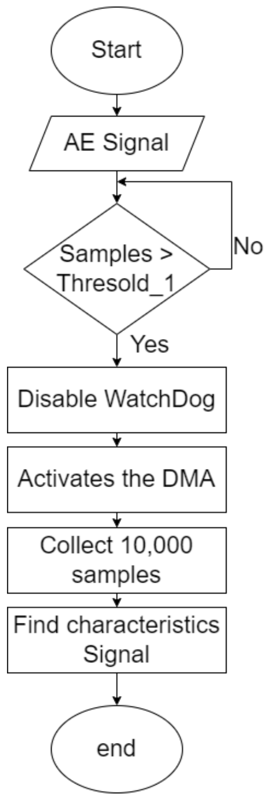

FIGURE 5.1: Flowchart of the detection AE crack algorithm.

5.3 Synchronization Algorithm

Global Positioning System (GPS) satellite signals are not only used for positioning and determining the speed of an object but also for providing an accurate timing system. The GPS enables highly accurate synchronization of distributed measurement systems, with precision reaching the nanosecond order in NEO-M8N [43]. The GPS receiver supplies the system with Coordinated Universal Time (UTC) messages, achieving an accuracy of 30 ns in NEO-M8, and Pulse Per Second (PPS) with an accuracy of 60 ns [38]. The synchronization algorithm takes advantage of these GPS features to establish a synchronized system between nodes distributed throughout a building. Each node operates a 32-bit resolution timer, counting 1 µs with each clock pulse. The timer is reset every second using the 1PPS signal from the GPS, and at the same time, the microcontroller updates the UTC time, as illustrated in the flowchart in Figure 5.2 Using this method, all nodes reset the timer and begin counting simultaneously. To achieve all of the crucial steps the microcontroller used the hardware capability to do some tasks that provide the microcontroller with some parallelism in work and execute interrupt service routines that provide the microcontroller with the speed of work. When the AE crack occurs, the timer's capture mode is used to read the value in the timer's register. The counter value represents the time in µs. Subsequently, the synchronization algorithm sends this information to the communication algorithm.

5.4 Communication Algorithm

One of the most crucial components in any distributed measurement system employing the Internet of Things (IoT) paradigm is the communication unit, coupled

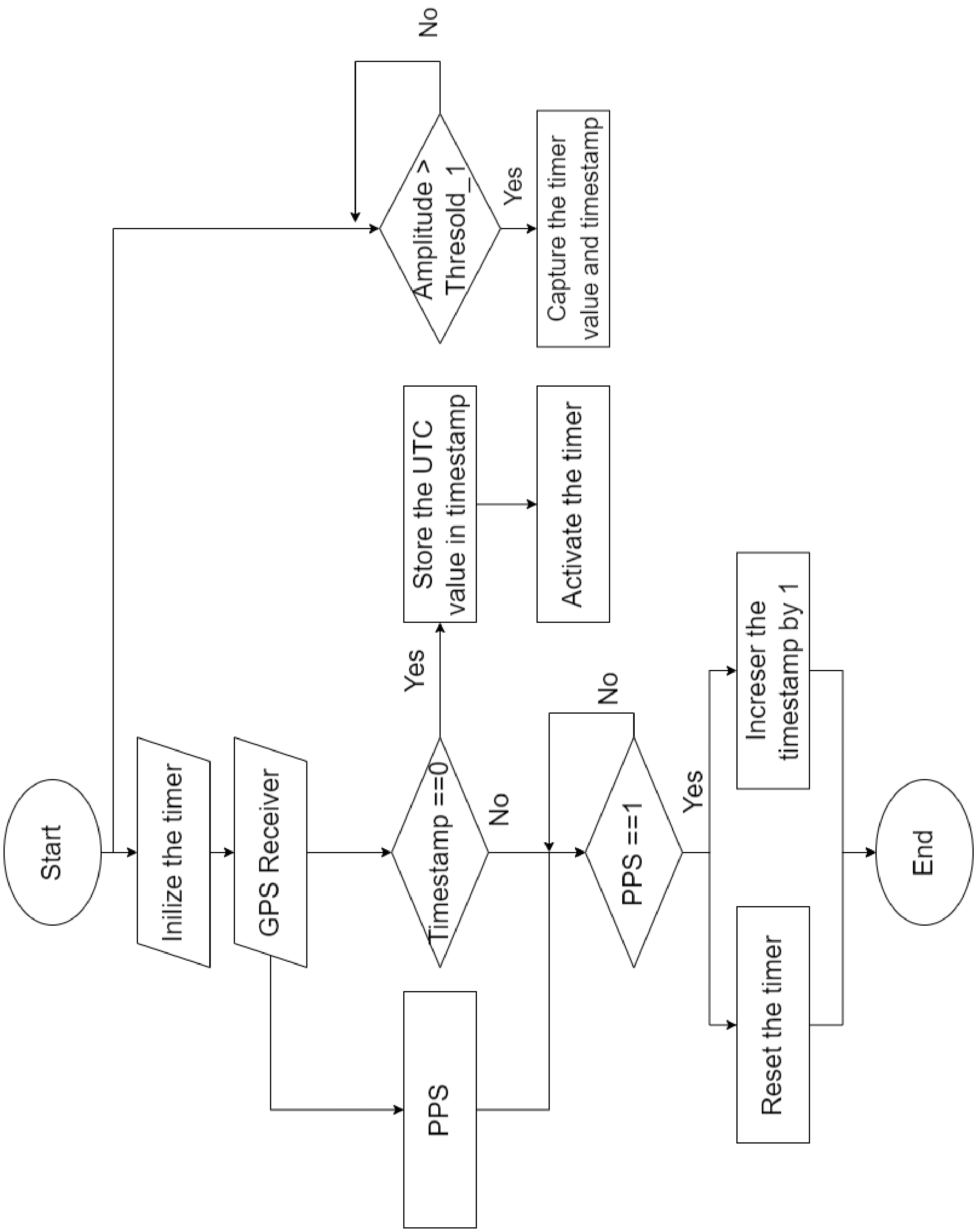

FIGURE 5.2: Flowchart of Synchronization Algorithm.

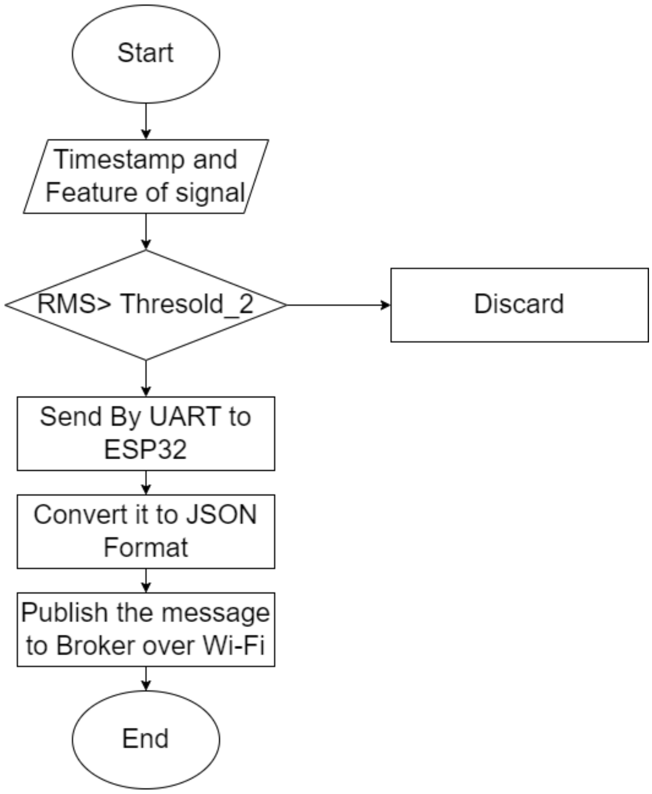

FIGURE 5.3: Flowchart of Communication Algorithm.

with an efficient algorithm. In the system we propose, the moment a crack is detected, the crack evaluation and synchronization algorithms gather and transmit all relevant information to the communication algorithm. This algorithm then determines whether to transmit or discard the data based on the RMS value. The decision to send the data relies on the RMS value. If the algorithm identifies an RMS value exceeding the predetermined threshold, the data is sent via a Universal Asynchronous Receiver-Transmitter (UART) interface to the ESP32 microcontroller (see Figure 5.3). The ESP32, in its assigned role, receives the packet from the UART and undergoes a series of processing steps to ensure the data is formatted appropriately for transmission. Subsequently, the data is sent using the MQTT protocol over Wi-Fi to a smart gateway, such as a Raspberry Pi.

Chapter 6

Test and Analyse the System

6.1 Introduction

This chapter provides detailed information about the digital twin of the system. Moreover presents comprehensive various statistical data analyses for all features of the system (RMS, Energy, Peak Amplitude, Hits, Duration). These studies allow us to evaluate the system and find the error and uncertainty for these features. It also shows the server implementation to detect the crack.

6.2 Simulation Using Digital Twin

A crucial component in creating a Wireless Crack Detection System (WCDS) Node involves devising a reliable and effective algorithm to process the AE signals collected by the sensor. Consequently, a WCDS node digital twin was established within the LabView environment. The considerations and procedures involved in designing and implementing the WCDS node digital twin are as follows:

1. Data Acquisition: The suggested algorithm relies on real data obtained from a prior experiment referenced in [44]. The signals were gathered using the NI DAQ 6110, equipped with a 12-bit ADC and 5 MSPS, and employing R15α sensors.

2. Signal Pre-processing: The signals from the previous step are scaled to simulate acquisition from an ADC with a range of [0.0, 3.3] V. Subsequently, noise filtering and amplification are simulated.

3. Algorithm: The processed signals are compared to an experimentally established threshold (refer to Figure 6.1). If the signal exceeds the threshold, two actions are taken:

   - The algorithm gathers samples of the signal above the threshold and calculates the root mean square (RMS), and all the features of these samples. Simultaneously, the algorithm activates a time unit synchronized with the GPS system's atomic clock to capture the timestamp of the signal occurrence.
   - This information is then sent to the central unit, implemented on a Raspberry Pi, which functions as a server for the MQTT protocol to make a decision. If the RMS surpasses the threshold, the algorithm identifies a crack as having occurred. The threshold is determined by analyzing the previously acquired experimental signals.

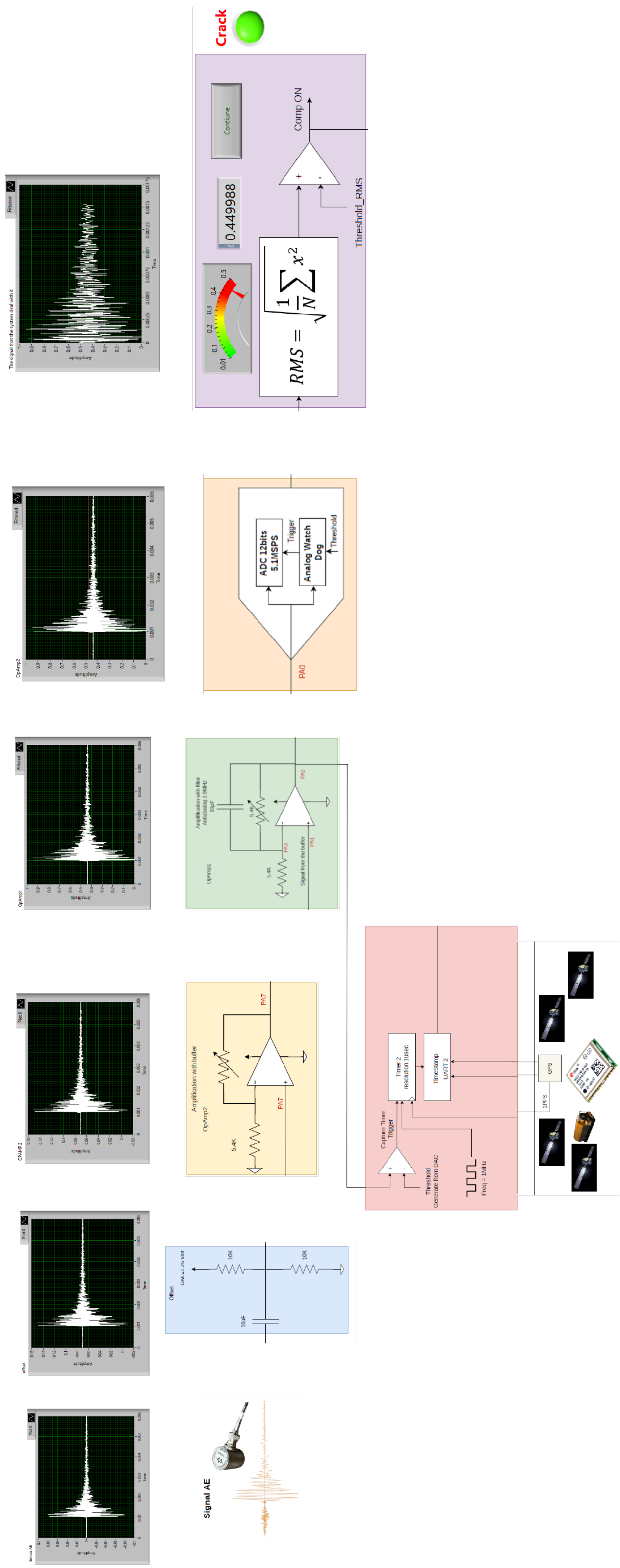

FIGURE 6.1: Digital twin of the proposed architecture for the AE acquisition and processing.

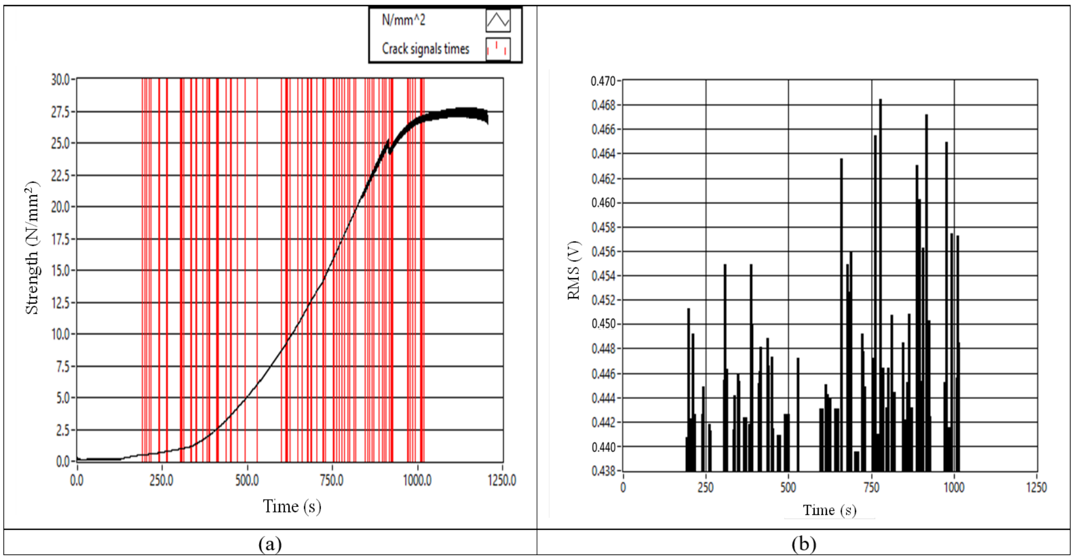

FIGURE 6.2: (a) Occurrence of the AE signals with respect to the load curve during specimen compression. (b) The AE RMS values correspond with the stress curve.

To determine the best RMS threshold for the detection of the crack signals, AE signals were studied on the proposed system, and the RMS of these signals that corresponded with the stress curve was evaluated as shown in Figure 6.2. Based on the results, the optimal threshold value for detecting crack signals was found to be 0.47 V for the amplitude and 0.4 V for RMS, as it produced the highest detection rate.

6.3 Test bed Validation

To evaluate the system and estimate the accuracy and uncertainty of its features, a proposed testbed is presented. This testbed consists of the AE signal recorded by Prof. Lamonaca through the experiments described in detail in [42]. The testbed system uses the same signals to regenerate them using the NI DAQ 6110, 12 bits, and 5 MSPS with the assistance of LabVIEW software. The generated signal is then applied to the proposed system to evaluate the hardware components and the firmware. The system is monitored by various measurement instruments, such as oscilloscopes and multimeters. Additionally, data extracted from the system (RMS, Energy, Peak amplitude, Hits, Duration) are stored in CSV format. Finally, the features of the generated signal by LabVIEW, along with all data collected from the CSV files and measurement instruments, will be analyzed using MATLAB. The testbed diagram is shown in Figure 6.3.

6.4 Hardware Validation

In order to thoroughly assess the hardware components used in the proposed WCDS, a series of tests were conducted. The first step involved measuring the system's generated offset, which is crucial in preventing negative AE signal values. This process can be visualized in Figure 6.4, where the offset value is also provided as 65mV.

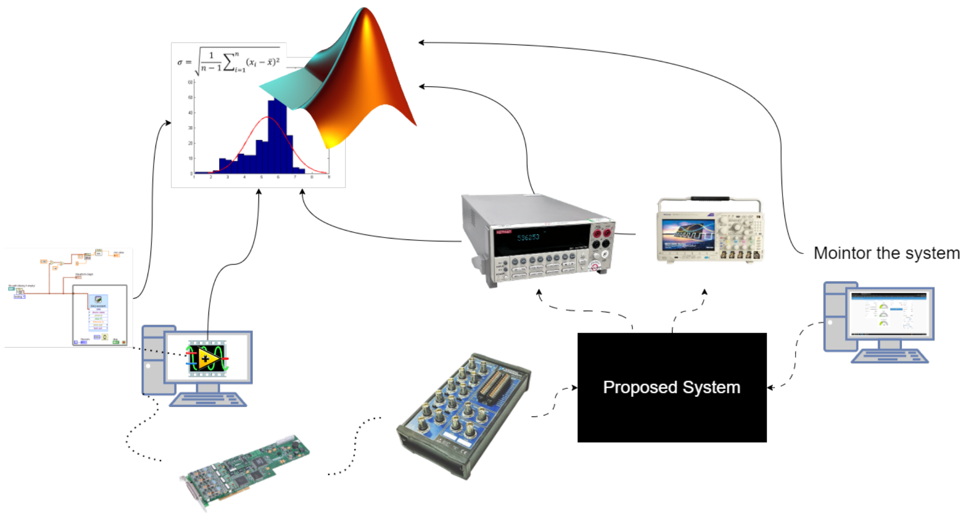

FIGURE 6.3: The testbed diagram.

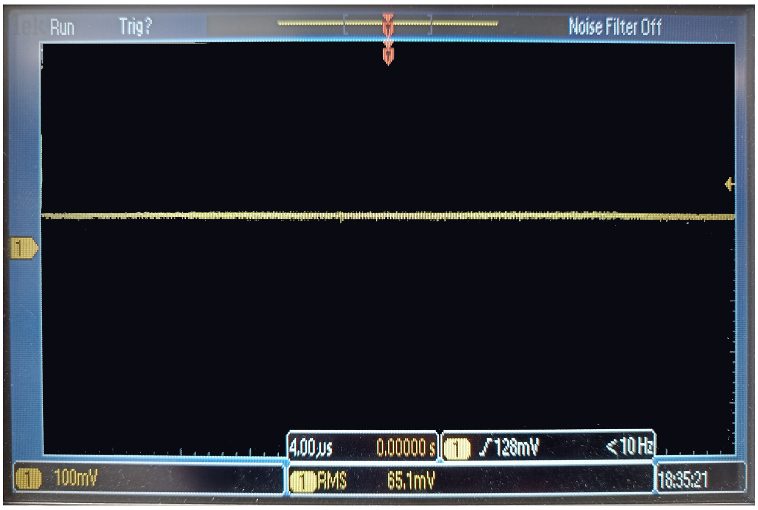

FIGURE 6.4: The offset DC signal.

Following this, the focus shifted to the AE signal generated by the NI DAQ 6110. This signal was examined at the input port, as depicted in Figure 6.5. This step was essential in ensuring the proper functioning and compatibility of the hardware components in relation to the AE signal generation. The WCDS system features two amplification stages, one of which is responsible for filtering the signal. The signal in the output of these stages can be seen in Figure 6.6. This stage is crucial for refining the signal quality and eliminating any potential noise or interference that could affect the system's performance. Upon completion of these tests, it was determined that the hardware components functioned as intended, demonstrating their reliability and compatibility with the overall WCDS system. This thorough evaluation serves as a strong foundation for future system optimization and potential improvements, ensuring the WCDS's ability to deliver accurate and reliable results in its intended applications.

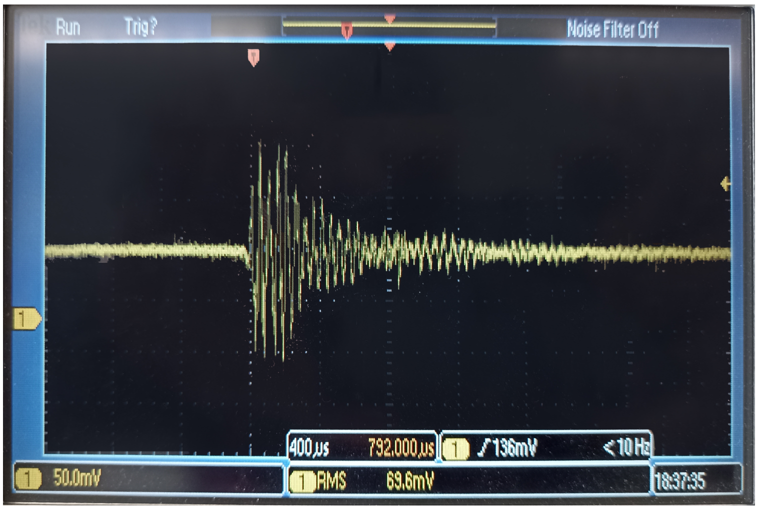

FIGURE 6.5: The AE signal with the DC offset on the input port.

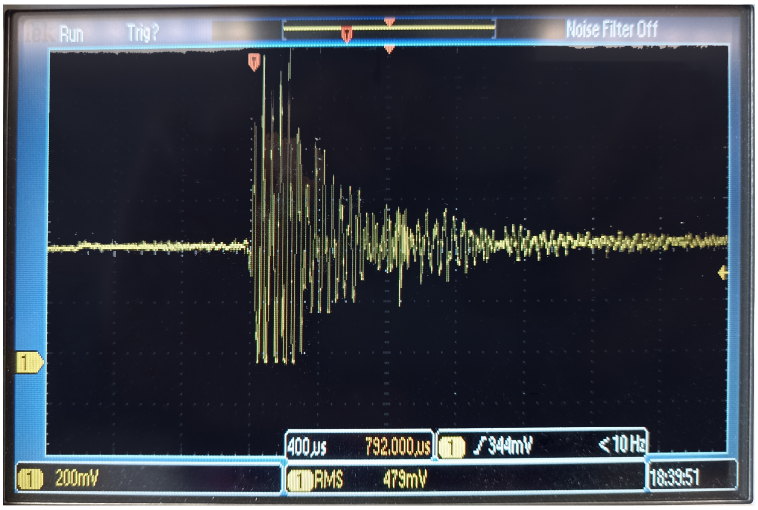

FIGURE 6.6: The AE signal with the DC offset on the input port.

6.5 Measurements Validation

In order to comprehensively analyze and evaluate the response of the WCDS system, a testbed was established to facilitate extensive data collection. Over 200 samples of the same signal were gathered in order to conduct a detailed analysis and apply statistical methods for a more in-depth understanding of the system's performance.

The statistical evaluation encompassed all parameters that can be monitored by the server, as illustrated in Figure 6.7. This thorough examination allowed for a better understanding of the system's behavior under various conditions and provided valuable insights into potential areas for improvement.

In addition to monitoring the system's performance parameters, the server also offers the capability to estimate and record environmental conditions. This feature is particularly useful in understanding the impact of external factors on the system's performance, and in identifying any possible correlations between the system's behavior and the surrounding environment.

The statistical studies carried out in the evaluation process were focused on estimating the main characteristics of the output features of the WCDS, which include

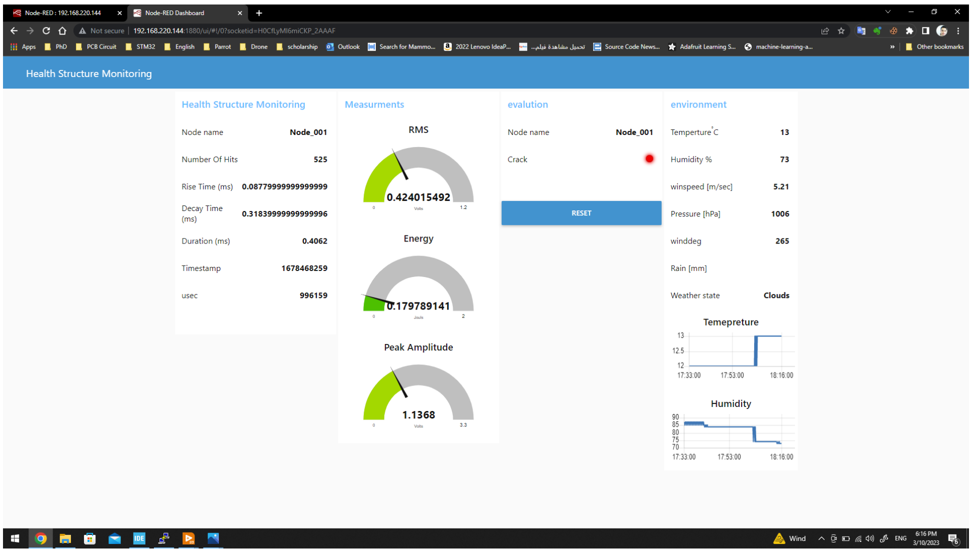

FIGURE 6.7: User interface of the server.

RMS (Root Mean Square), Energy, Peak, Hits, and Duration. These estimations can be found in Table 6.1 and in Figure 6.8, providing valuable insights into the system's performance.

TABLE 6.1: Statistical Analysis of WCDS Output Features

Parameters	**RMS (V)**	**Energy (J)**	**Peak Amplitude (V)**	**Hits**	**Duration (µs)**
Mean	0.455626	0.207636	1.217918	1679.6	1457.8939
Median	0.455097	0.207118	1.219200	1686.0	1477.0600
Standard deviation	0.006003	0.005501	0.042541	85.870	133.0643
Uncertainty	0.000296	0.000271	0.002096	4.230745	6.555609
True Value	0.464169	0.215453	1.2	1672	1500.6
The Mean Error	2.09%	4.13%	1.97%	1.81%	4.46%

Upon examining the table 6.1, we can see a detailed statistical analysis of the WCDS system's output features, such as RMS, Energy, Peak Amplitude, Hits, and Duration. Assessing these features allows us to better comprehend the system's performance and pinpoint areas that may require improvements. The table presents the mean, median, standard deviation, uncertainty, true value, and mean error for each output feature, providing insights into the data's central tendency, dispersion, and measurement accuracy. Mean and Median: By comparing the mean and median values for each feature, we can evaluate the data's symmetry or skewness. In this case, the mean and median values are quite similar, indicating a symmetric distribution for each feature. Standard Deviation: The standard deviation serves as a measure of the data's spread. When the standard deviation is higher, it indicates greater variability in the measurements. For this analysis, the standard deviations are relatively low, suggesting that the data points are tightly clustered around the mean. Uncertainty: The uncertainty values denote the degree of confidence in the measurements. Smaller uncertainty values signal a higher confidence level in the data. In this table, the uncertainty values are fairly low, reflecting a high degree of confidence in the measurements. True Value and Mean Error: The true value refers

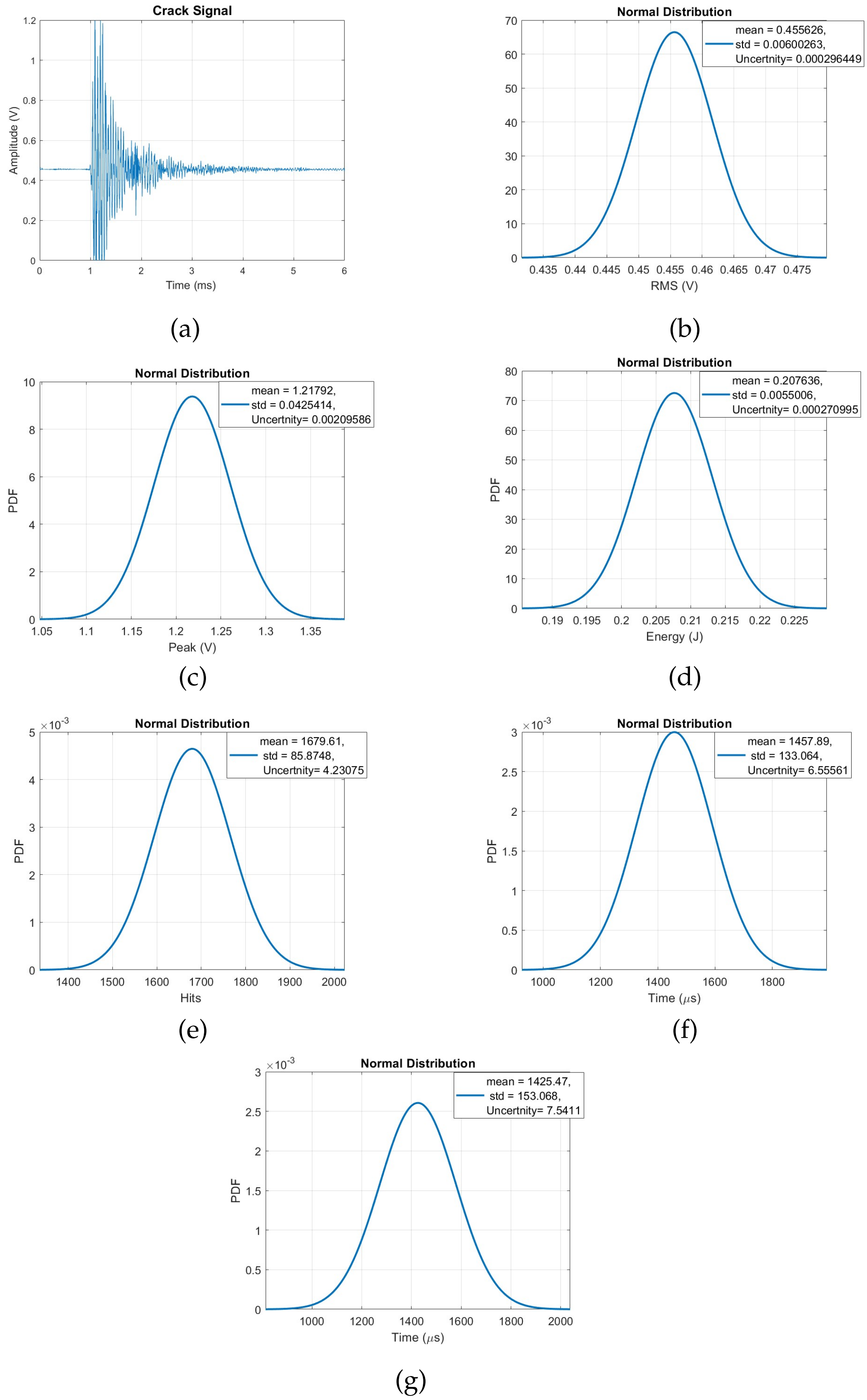

FIGURE 6.8: (a) The crack signal under study, (b) The RMS distribution, (c) The Peak distribution, (d) The Energy distribution, (e) The Hits distribution, (f) The Duration of signal distribution, (g) The Decay of signal distribution .

to the actual or expected value for each parameter. By comparing the mean to the true value, we can determine the mean error, which indicates the accuracy of the measurements. The mean errors for each feature are displayed as percentages and are fairly low, suggesting a high level of accuracy in the measurements.

The results of the statistical analysis demonstrate that the WCDS system performs reliably across all its output features, with a low degree of variability and a high level of accuracy. These insights can inform future optimizations and enhancements to the system, ensuring its effectiveness across a range of applications.

Chapter 7

Conclusion

In conclusion, this thesis has successfully demonstrated the design and implementation of a Wireless Crack Detection System (WCDS) using Acoustic Emission (AE) technology. The system has been developed to effectively detect cracks in real-time and wirelessly transmit the acquired data to a central server for comprehensive analysis. The utilization of AE sensors and an analog signal processing circuit ensures that the crack signals are captured, enhanced, and filtered from noise. The thorough experimental analysis of the system provided essential insights into its performance. Over 200 samples of the same signal were collected and analyzed to determine the statistical characteristics of the output features of the WCDS, including RMS, Energy, Peak Amplitude, Hits, and Duration. The results indicated that the components of the system functioned as intended, demonstrating the system's reliability and consistency. The WCDS processes signals through thresholding, and once the threshold is surpassed, the system acquires the signal, generates a timestamp with microsecond resolution via a GPS module, and transmits the data to the Raspberry Pi server using the MQTT protocol. This precise timing information guarantees accurate event tracking. Acting as a smart gateway between the sensor nodes and the cloud, the Raspberry Pi further forwards the data to Amazon Web Services (AWS) for long-term storage and real-time monitoring. The system's design emphasizes efficiency, particularly in terms of power consumption, and accommodates multiple sensor nodes. The use of Node-RED for data visualization simplifies the monitoring process and allows users to effectively analyze crack signals. Moreover, the statistical evaluation of the system's output parameters, as well as the ability to estimate and store environmental conditions, facilitates a more in-depth understanding of the system's performance. Ultimately, this project showcases the potential of AE technology for crack detection and highlights the benefits of leveraging IoT technologies to monitor critical infrastructure in real time. The successful integration of these technologies within the WCDS lays the foundation for further improvements and potential applications in various industries that rely on the monitoring and maintenance of critical structures.

In the future, the Wireless Crack Detection System (WCDS) could be further improved and expanded in several ways, including:

- Enhanced Sensitivity and Precision: By refining the design and implementation of the AE sensor and signal processing components, the system's sensitivity and precision in detecting cracks can be improved. This could involve researching more advanced sensors or developing algorithms for better noise reduction and signal enhancement.

- Integration of Machine Learning and AI: Machine learning techniques and artificial intelligence could be incorporated into the system to enable more accurate and automated identification of crack signatures. This could lead to a more robust and efficient crack detection system capable of identifying different types of cracks and predicting the potential risk they pose to the structure.

- Scalability and Multi-Sensor Support: The system's design could be modified to support a larger number of sensor nodes, making it more scalable for monitoring larger structures or multiple locations simultaneously. This may involve the development of more efficient data transmission and management protocols, as well as optimizing the system's power consumption for extended battery life.

- Expansion to Other Structural Monitoring Applications: The WCDS could be adapted for other structural monitoring applications beyond crack detection, such as monitoring corrosion, vibration, or temperature changes in critical infrastructure. This would increase the system's versatility and expand its potential use cases.

- Robustness and Reliability in Harsh Environments: The WCDS could be made more robust and reliable for use in harsh environments, such as extreme temperatures, humidity, or exposure to corrosive substances. This would involve researching materials and designs that are more resistant to these conditions and implementing them into the system.

By pursuing these future developments, the Wireless Crack Detection System has the potential to become an even more powerful and versatile tool for monitoring the integrity and safety of critical infrastructure across a wide range of industries.

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