IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 5 July 2023, accepted 19 August 2023, date of publication 28 August 2023, date of current version 7 September 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3308905

SURVEY

Wireless Sensor Networks for Water Quality Monitoring: A Comprehensive Review

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This work was supported in part by the National Council of Humanities, Sciences and Technologies (CONAHCyT) under Grant 1112709. The work of Gustavo Adulfo López-Ramírez was supported by the U.S. Department of Commerce under Grant BS123456.

ABSTRACT This comprehensive review examines the use of Wireless Sensor Networks as a solution for addressing water quality monitoring and data scarcity. It compares Wireless Sensor Networks with traditional laboratory-based and in-situ monitoring methods, highlighting their superior response speed, cost-effectiveness, ease of deployment, and reliable measurements. The paper provides an overview of wireless sensor node architecture, discussing subsystems, Quality of Service requirements, and the significance of low power consumption in microcontroller units. Network solutions for short, medium, and long-range applications are explored, highlighting that Low-Power Wide Area Network is the most effective option for water quality monitoring. Furthermore, the review acknowledges the potential of machine learning techniques within Wireless Sensor Networks for Water Quality Monitoring, highlighting their versatility. A case study analysis of three LPWAN applications is presented, discussing their key characteristics, potential benefits, and important considerations for future implementations. By consolidating current knowledge, this review emphasizes the capacity of Wireless Sensor Networks to overcome data scarcity challenges in water quality monitoring. Valuable insights are provided for researchers, practitioners, and decision-makers seeking to leverage Wireless Sensor Networks, LPWAN technologies, and machine learning techniques for efficient and cost-effective global water quality monitoring.

INDEX TERMS Wireless sensor networks, water quality monitoring, IoT, wireless sensor node, microcontroller unit, energy management, IEEE 802.11ah, Zigbee, bluetooth, Sigfox, LoRa, NB-IoT, machine learning.

I. INTRODUCTION

Water is one of the most valuable and essential natural resource for the development of life on Earth. It is a finite resource that is recurrently directly threatened by overexploitation, pollution, and climate change. Therefore, sustainable water management is a global concern and a key point to ensure food security, human health, biodiversity, and socio-economic development [1].

According to the United Nations [2], only 60% of bodies of water in 89 evaluated countries have good environmental water quality, largely because 80% of wastewater generated by human activity is discharged into bodies of water without any prior treatment. If we add to the above the fact that water quality data is not routinely collected in most of these countries, we face a problem that puts the health of more than 3 billion people at risk.

The limited amount of water quality (WQ) data is mainly attributed to a constrained monitoring and reporting capacity, especially in underdeveloped countries [3]. The 20 poorest countries reported only on 1,000 water bodies, while the 24 richest reported on almost 60,000, as revealed by the gap highlighted in [2]. This discrepancy is noteworthy, as it makes it challenging to make a generalized statement about the global status and trends of WQ. However, new Internet of Things (IoT) developments and projects aim to narrow this gap [4]; particularly those focused on Wireless Sensor Networks (WSNs) for Water Quality Monitoring

The associate editor coordinating the review of this manuscript and approving it for publication was Yuan Gao.

(WQM) through the deployment of WSNs with increasingly accessible and economically viable infrastructures capable of acquiring data from hard-to-reach areas over large distances and extended periods of time.

The advent of IoT, which in simple terms refers to the point in time when the number of devices connected to the internet surpasses the number of people connected [4], offers researchers a wide range of possibilities to access data that previously required in-situ measurements or manual sampling for analysis in specialized laboratories.

WSN technologies are a central part of IoT due to machine-to-machine (M2M) communication, which allows two or more devices to communicate without human intervention. The fields of application for WSNs are varied and not limited to WQM [5], [6], [7], [8], [9], [10], including agriculture, detecting mechanical failures in industrial environments, and smart homes. However, prior research data indicates a growing use of WSNs for monitoring water bodies [11], [12], [13], [14], [15], [16], and it is expected to keep increasing with the advent of new computational strategies involving Artificial Intelligence (AI) and Machine Learning (ML), as well as Energy Harvesting (EH) methods that extend the network's lifespan.

Despite being a specific application within WSNs, there is no unique solution that satisfies the full spectrum of characteristics that distinguish WQM [11]. That is to say, different variables must be considered depending on the problem to be solved with the network, such as the type of sensors to be used, the sampling rate of water quality parameters, the requirements to be met by the network nodes and their deployment location, energy sources, and the technologies and standards to be adopted to define a network architecture. These characteristics depend largely on the particular WSN for WQM application that is being implemented.

In order to standardize the implementation of WSNs, there are requirements aimed at evaluating the Quality of Service (QoS) of the network. In general, the QoS requirements considered for a water monitoring network are as follows: a) energy efficiency, b) efficient data transmission rate, c) broad communication coverage, d) real-time communication, e) deployment cost, f) reliable data communication, and g) flexibility [11], [13]. These metrics allow us to observe the obstacles encountered when developing a WSN for WQM, among which the following stand out: limited available energy, low computational capacity of the nodes, data unavailability and insufficient storage, and coverage issues.

This review paper undertakes a comprehensive analysis of the latest works carried out in the area of WSNs for WQM, particularly exploring the hardware architectures and network standards used in order to evaluate them based on QoS metrics.

The methodology employed in this review encompasses a meticulous selection process aimed at encapsulating a representative array of relevant research contributions. The inclusion of papers was guided by the goal of comprehensively exploring the landscape of WSNs for WQM, while acknowledging the inherent limitations in the scope of a single paper. To ensure the integrity of the review, a multi-faceted approach was adopted, involving keyword-based searches across reputable academic databases. The criteria for selecting papers centered on their alignment with the core themes of energy efficiency, hardware range, and communication protocols pertinent to WSNs for water quality monitoring. While every effort was made to encompass a diverse range of research, the vastness of the field necessitates a discerning selection process. As acknowledged, the review may not encompass every paper; however, each chosen contribution was meticulously assessed based on its relevance, scientific rigor, and potential to contribute to the overarching discourse. The geographic consideration in paper selection was indeed factored in, aiming to capture global perspectives and ensure a well-rounded representation. To the author's best knowledge, this work provides one of the first investigations that fuse prior knowledge about WSNs for WQM with current energy management technologies, low-power microcontroller units (MCUs), ML, and functions as a guide to choose the most suitable technologies for the application being developed.

The study delves into the comparison between WSNs and traditional monitoring methods, such as laboratory-based and in-situ approaches, revealing WSNs exceptional advantages in terms of response speed, cost-effectiveness, deployment simplicity, and reliable measurements.

The paper offers a comprehensive overview of wireless sensor node architecture, detailing crucial subsystems, Quality of Service (QoS) requisites, and the paramount significance of low power consumption in microcontroller units. By exploring network solutions for short, medium, and long-range applications, the review underscores that Low-Power Wide Area Network (LPWAN) stands as the most efficient choice for water quality monitoring, ensuring long battery life and wide coverage.

Crucially, the study addresses the untapped potential of integrating machine learning techniques into WSN for WQM. The versatility and adaptability of these techniques within WSNs open up new dimensions for enhancing monitoring accuracy and predictive capabilities.

In support of these findings, the review showcases a detailed case study analysis of three LPWAN applications, showcasing their distinctive features, potential benefits, and critical considerations for future implementations. By consolidating existing knowledge, this review underscores how WSNs offer a pivotal means to overcome data scarcity challenges in the field of WQM.

Overall, this paper provides valuable insights for researchers, practitioners, and decision-makers looking to harness the synergy of Wireless Sensor Networks, LPWAN technologies, and machine learning techniques for establishing efficient, cost-effective, and globally impactful water quality monitoring systems.

However, it is important to acknowledge certain limitations inherent in this study. Firstly, the review primarily focuses on the technical aspects of WSNs for WQM, potentially omitting a comprehensive exploration of the socio-economic and policy-related challenges that can arise during real-world implementation. Secondly, while the case study analysis provides valuable insights, the scope is limited to a select number of LPWAN applications, which may not fully encompass the wide array of scenarios and challenges that can emerge in diverse geographical and environmental contexts. Additionally, the study may not delve extensively into sensor calibration methodologies, which are crucial for ensuring accurate and reliable data collection. Future research efforts should strive to address these limitations to provide a more well-rounded understanding of the practical implications and potential constraints associated with deploying WSNs for water quality monitoring.

The rest of this paper is organized as follows. Section II conducts a comparison between traditional water monitoring methods and WSN-based approaches, followed by a description of observable quality parameters. Section III outlines the general architecture of the WSN hardware, including the characteristics of different types of sensors, transceivers, with a particular focus on low-power MCU's. Additionally, the power sources are discussed, and energy management is further elaborated upon. In Section IV, the main network standards utilized in WSN applications for WQM are described and classified according to their scope, followed by a comparison of their main features. Novel applications are mentioned in Section V. Finally, Section VI concludes this research work.

II. WATER QUALITY MONITORING

Monitoring the quality of water is a crucial aspect for its conservation as well as for the preservation of aquatic ecosystems and protection of human health. This monitoring is defined by the International Organization for Standardization (ISO) as a continuous process of sampling, measurement, signal acquisition, and assessment of various characteristics of water in order to evaluate it according to specific objectives [1]. It is through this monitoring process that it can be ensured that water resources are free of contaminants, in addition to enabling the timely detection of any alterations in their quality.

In this section, we outline both the traditional monitoring methods that are typically performed in laboratories or on-site, as well as the wireless sensor network (WSN) approach. Furthermore, we provide an overview of the parameters that are commonly observed during the water quality monitoring process.

A. TRADITIONAL MANUAL LAB-BASED AND IN-SITU APPROACHES

The traditional manual laboratory-based method (TMLB) was the most commonly utilized approach from the 1960s up until the 2000s [12]. In this approach, trained personnel directly visit the site of interest for water sampling, as shown in Figure 1, for subsequent transportation to a laboratory for analysis to detect contaminants, followed by post-processing of the data for visualization.

FIGURE 1. TMLB approach for WQM.

This procedure follows a linear workflow and provides decent monitoring; however, it presents important limitations that must be considered. As highly specialized laboratory equipment and trained personnel for both sampling and analysis are required, it often proves to be expensive and time-consuming to carry out the entire process, which directly affects the sampling frequency and results in the loss of valuable information between sampling events. Additionally, there is a risk of losing important quality control measurements of the samples [13]. These difficulties may hinder the strategies proposed by the UN Environment Programme in its Evaluation Manual [17].

To address some of these limitations, specialized equipment and techniques are used to analyze samples on-site using portable sensors in the traditional manual in-situ (TMIS) approach. The equipment may include sampling bottles, multiparameter meters, portable sensors, and other specialized devices [13]. The working process is both less costly and faster than the TMLB approach, while also avoiding the loss of sample quality due to long transportation times. However, this method entails the mobilization of human personnel to the areas of interest for evaluation, which can result in prolonged periods without sampling.

Advancements have been made in the TMIS approach, introducing novel ways to perform sampling. In [18], a smart boat is employed to enable the collection of samples over long distances using LoRa wireless technology, albeit still requiring direct interaction between the human operator and the sampling tool.

B. WIRELESS SENSOR NETWORK BASED APPROACH

The aforementioned drawbacks of TMLB and TMIS approaches render them inefficient methods for accurate WQM that requires fast response times, low costs, ease of deployment, and reliable measurements [11]. The WSN approach extends the capability of the TMIS method for obtaining vital parameters of a water body [13]. By enabling automatic data transmission, the possibility of detecting anomalies in real-time and the ability to obtain information on the water body through distributed sensing are achieved. Figure 2 illustrates the general workflow of this approach: a) sensor nodes are distributed at defined points of the water body to collect the desired information, b) the data is transmitted to a base station via defined wireless communication protocols, and c) subsequently analyzed and visualized by end-users.

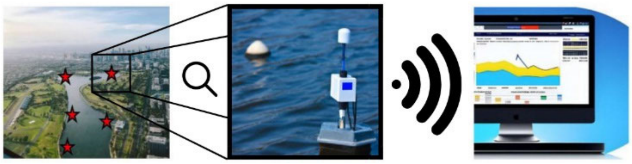

FIGURE 2. WSN-based approach for WQM: (a) Multiple sensor nodes located around the water body in question. (b) Sensor node. (c) Data processing and visualization.

In order to achieve an effective WSN solution for WQM, it is necessary to address the QoS requirements [11]. These metrics allow an objective evaluation of the quality of the sensor network, ensuring that the collected data is reliable, accurate, and timely, enabling informed decision-making once analyzed. The compliance with these metrics is greatly facilitated by the establishment of a standardized scheme that defines the network's structure, with specifications on its operation, network standards used, and how energy and information flow are managed.

A smart water quality monitoring system (SWQMS) refers to a standardized scheme for implementing a wireless sensor network (WSN) tasked with measuring the physicochemical parameters of bodies of water, transmitting them through the network, and analyzing them for decision-making purposes [14]. This standardization, as depicted in the block diagram in Figure 3, facilitates the operation and communication between the different sections of the monitoring process, promotes better practices for the development and maintenance of each subsystem, and enhances information management across each block.

The **data collection subsystem** constitutes the first stage of the entire monitoring process, upon which the success of the rest of the system depends. As its name implies, this phase involves establishing the sensor network design, the parameters of WQM to be collected [13], [14], the node locations [19], [20], and the sampling frequency. It is noteworthy that the acquisition of real-time data is heavily contingent on both the sampling frequency and the specific application in question. For instance, in the case of WQM applications intended for deployment over extended periods of time, sampling frequencies of 10 minutes or an hour may be regarded as being indicative of real-time data acquisition. However, for critical applications where it is imperative to constantly verify water quality, such frequent sampling intervals of 10 minutes may impede the monitoring process.

Novel research has emerged in this stage of the process, such as simple methods based on the optimization of objectives for selecting sensor locations in small water supply networks [21] providing a list of critical locations for placement with the aim of reducing the amount of people affected by a contaminant, or multi-objective probabilistic approaches like the one developed in [22] which uses the k-means method. Methods for optimizing energy efficiency such as that described in [23] for cluster-head selection, and ML techniques like k-nearest neighbors (k-NN) or Reinforcement Learning (RL) also for determining node locations [24]. Section III.c delves deeper into recent studies in the area of energy management for the collection subsystem.

The **transmission channel** is responsible for wireless communication between wireless nodes (WNs), sink nodes (SNs), and base stations (BSs) according to the communication standard defined for the application. It is also responsible for connectivity with the data management subsystem. In this subsystem, the network topology and routing algorithms are established [14]. Selecting the correct topology largely solves the coverage, scalability and flexibility of the network, and the routing algorithm allows data to reliably reach its destination with the lowest possible energy consumption. Section IV discusses the communication standards used in WSN for WQM and the encompassing topologies.

Recent research has contributed to the field of transmission channels by applying machine learning techniques such as decision trees, artificial neural networks (ANN), and evolutionary computation for classifying connected and disconnected nodes in the network and identifying nodes based on their level of connectivity [25]. Random forest techniques have also been used to predict optimal routes [26] for a dynamic selection of high energy nodes for routing in a static WSN, proposing an algorithm with good performance in terms of energy management, packet delivery ratio, and delivery delay, thus extending the network operational lifetime. Additionally, supervised learning techniques such as Support Vector Machine (SVM) have been suggested in [24] for channel assignment issues in the MAC layer discussed in [27].

The **data management subsystem**, on the other hand, is responsible for the storage of data, its analysis for evaluation, and aiding in decision-making for interested parties. It is also responsible for the platform on which these results will be visualized in real-time for the end-user, ensuring they are always readily available [28].

Previous works such as those developed in [29], [30], [31], and [32] depict this subsystem through platforms like ThingSpeak, Blynk, and Blue Water for visualizing historical and real- time water quality data. The Blue Water platform was exclusively developed for the project described in [29], while applications such as Blynk and ThingSpeak are third-party platforms designed for visualizing and analyzing data streams.

Given the level of data analysis required, a wide variety of ML techniques have been applied in different novel investigations. In [33], techniques such as random forest, Cubist, and SVR were used for the estimation of water quality on the west coast of South Korea, showing best results with the SVM method, whilst RF and Cubist agreed with previous non-linear regression analysis. In [34], gradient boosting was used to solve regression and classification problems for the identification of parameters in water quality, with a focus on disease detection in fish, providing a high-accuracy model that produces decision-making against the proliferation of diseases in the habitat. The K-means clustering algorithm employed in [35] was utilized for the training datasets, and

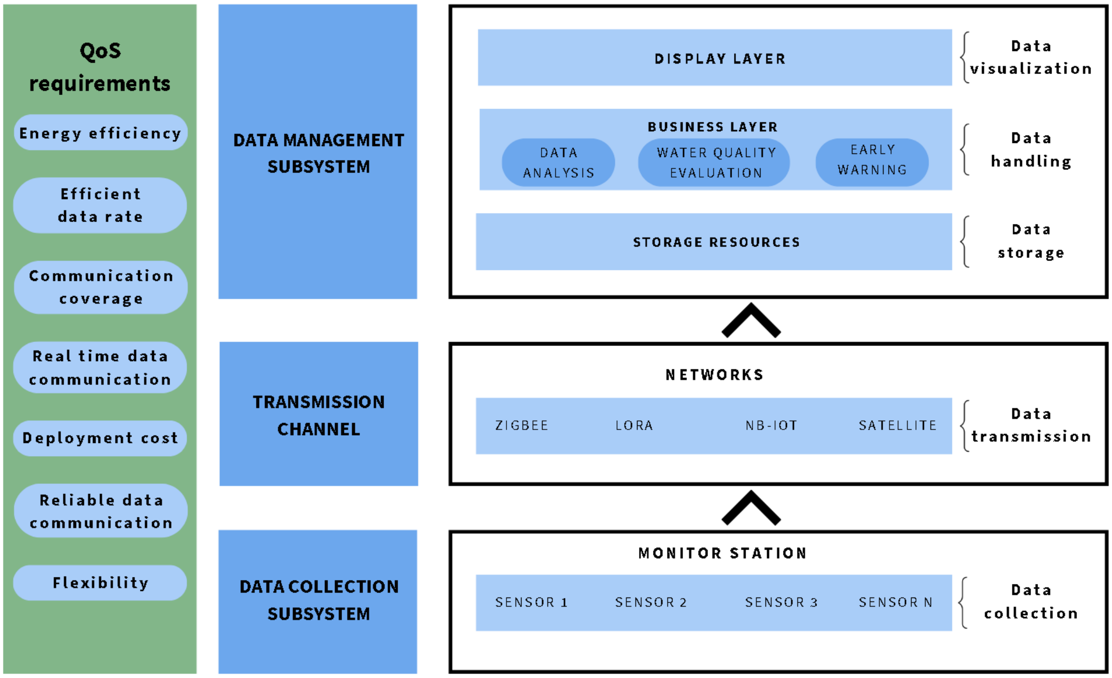

FIGURE 3. Block diagram for a QoS-compliant SWQMS.

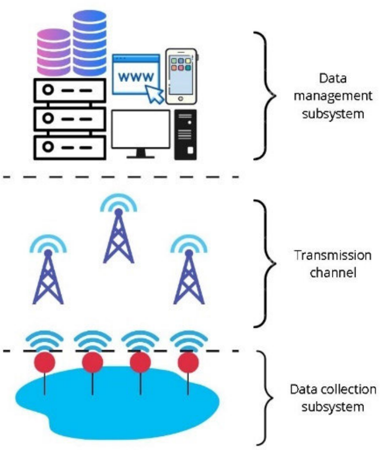

FIGURE 4. SWQMS schematic diagram.

along with the predicted data, it was stored in the Cloud for mobile phone access. Generally, techniques such as PCA, deep learning, evolutionary computing, and Bayesian learning are used for event monitoring, tracking, and object detection [24], [36]. The work carried out in [37] delves deeply into a variety of ML applications for water quality assessment.

Figure 4 illustrates a schematic diagram of a SWQMS in a general and straightforward manner. It can be observed that the transmission channel originates from the sensor nodes; however, the parameter acquisition process belongs to the data collection subsystem. The complexity of the SWQMS may vary depending on the required application, and the following sections delve into the main elements of this structure.

Despite the innovative application of Wireless Sensor Networks (WSN) for Water Quality Monitoring (WQM), one of the main reasons why these solutions have not been fully adopted is that, initially, these systems tended to have a significantly high cost, enough to continue favoring TMLB and TMIS approaches. However, with the introduction of Internet of Things (IoT) for Smart Cities, the cost has significantly decreased, providing an opportunity for this approach to gain more acceptance [38].

The WSN approach for WQM stands out from TMLB and TMIS approaches due to its versatility, flexibility, low cost, and the ability to enable faster decision-making through access to data. However, it is important to focus network resources on real-time detection of contaminants, evaluation of collected parameters according to established safety ranges, development of predictive models that best describe data behavior, proper selection of network standards to upgrade communications, and improvement in terms of results visualization.

C. *WATER QUALITY PARAMETERS*

WQ can be classified into four types [39]:

1) [1] Potable water. Safe for human consumption, pleasant to taste, and suitable for domestic uses.
2) [2] Palatable water. Pleasing to the eye, may contain chemicals that are not harmful to health.
3) [3] Contaminated water. Contains physical, chemical, and biological elements, and is not suitable for human consumption or domestic use.
4) [4] Infected water. Contains pathogenic organisms.

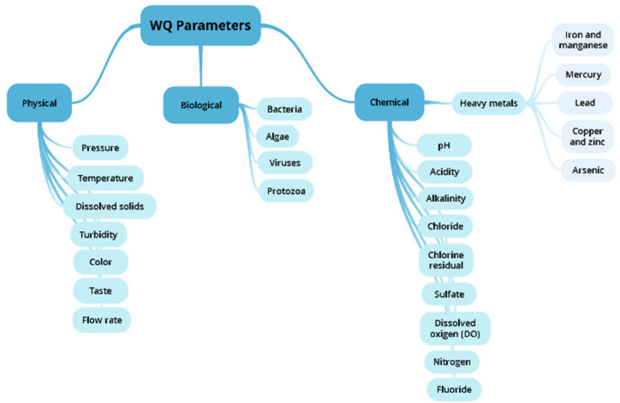

FIGURE 5. Water quality parameters.

To classify water into one of these categories, the sample must be evaluated to determine which parameters are present and in what quantity. These parameters are classified into three types [39]: physical, chemical, and biological. Figure 5 summarizes the parameters considered for evaluating WQ according to this classification.

Although these parameters allow us to evaluate water quality, the requirements that must be met for each of them, or even which ones should be considered for evaluation, largely depend on the intended use of the water. For instance, the requirements for drinking water differ significantly from those for irrigation water. Government agencies are responsible for standardizing these requirements, which are typically categorized as in-stream, potable water, and wastewater effluent [39]. The World Health Organization (WHO) outlines in [40] the minimum requirements that countries should implement for drinking water.

III. WIRELESS SENSOR NETWORK NODE HARDWARE ARCHITECTURE

A WSN for WQM is composed of numerous wireless nodes (WNs) that allow monitoring of the water body in question, and at the same time, are responsible for transmitting the collected data, enabling an autonomous functioning network. Technological advancements have allowed these elements to become increasingly smaller and consume less energy.

Commonly, the architecture of a WN is composed of four main elements: a sensing unit, a processing unit, a transceiver system, and a power unit that is responsible for powering all the previous elements [11]. Figure 6 graphically illustrates the basic architecture of a WN.

This section aims to describe these main components and current trends in detail.

A. SENSING UNIT

The sensing unit is a fundamental part of the hardware architecture of the wireless node, as it allows the acquisition of water quality parameters. The current generation of sensors has evolved from using laboratory-based sensors

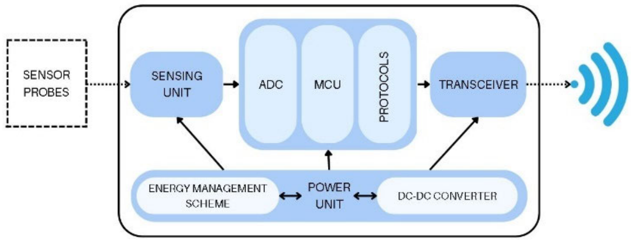

FIGURE 6. Generic architecture of a WSN node.

that employed potentiometric, conductometric, mass spectrometry, ion-sensitive electrodes, and amperometric sensors to sensors that allow parameter acquisition on-site, such as biosensors [41], microfluidic sensors [42], optical fiber sensors [43], electromagnetic wave sensors, ultrasound sensors [38], and fluorescent detection. The miniaturization of these techniques has given rise to multiparameter lab-on-chip sensors, which incorporate the capability of acquiring different parameters in a single device.

The most commonly found sensors in the literature typically measure temperature, pH, turbidity, ammonium, dissolved solids, and dissolved oxygen, as applied in [44], [45], [46], [47], [48], [49], and [50]; but there are works considering quality parameters such as color, chlorine, dissolved oxygen, fluoride, heavy metals, nitrogen, phosphorus, oxidation-reduction potential, algae detection, and total coliforms, recent technologies and significant advances in nanotechnology have allowed the development of these devices [51].

The selection of which sensors to use largely depends on the objective pursued in each specific application. Figure 7 describes the general process for making this selection.

- **Parameter identification**: Prior to selecting a sensor, it is essential to define the parameters that must be collected. As previously mentioned, there are standard parameters that are used to monitor the vital signs of a body of water (pH, DS, DO, turbidity, etc.). Applications such as those described in [52] and [53] usually make this standard parameter selection. However, for specific applications such as the one developed in [54], a study of the problem to be addressed is required, such as the identification of specific contaminants such as oil pollution or volatile phenols.
- **Accuracy and sensitivity evaluation**: Once the parameters have been selected, there is a wide range of sensing units available commercially. At this stage, it is important to select the appropriate unit that can detect changes in the parameter being measured.
- **Consideration of environmental conditions**: It must be considered that the sensor must be able to work normally in difficult environmental conditions, such as high or low temperatures, or situations with high humidity.
- **Cost analysis**: More than just referring to the acquisition costs of the sensor, it is necessary to evaluate the maintenance costs that depend intimately on the environmental

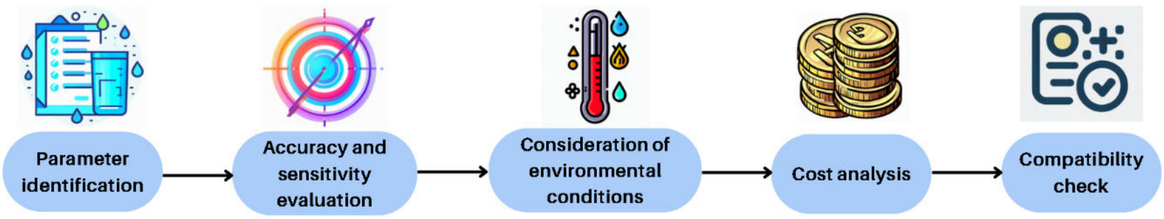

FIGURE 7. **Sensor selection process.**

conditions in which it operates. It should be considered that the most expensive sensors are not always the most suitable for certain applications.

- **Compatibility check**: If an SWQMS has already been established, an appropriate sensor must be found that is compatible and can be integrated correctly. In the case of a new implementation system, it is recommended to search for a sensor that provides flexibility and scalability, thus facilitating compliance with future QoS evaluations.

Integrating commercial water quality sensors into wireless sensor networks has revolutionized the way we monitor and gather data on water quality parameters. These sensors, purpose-built for seamless integration with wireless sensor nodes, offer a robust solution for real-time data collection, remote monitoring, and informed decision-making in diverse environmental settings. In the following paragraphs, we delve into a selection of prominent commercial water quality sensors that are designed to be effortlessly connected to wireless sensor nodes. By exploring the capabilities of these sensors and their compatibility with wireless communication protocols, we aim to provide insights into the array of options available for constructing efficient and effective wireless water quality monitoring systems. Whether deployed in freshwater bodies, industrial facilities, or research projects, these sensors and their integration into wireless networks mark a significant advancement in the field of water quality assessment.

- **Sensorex Smart Sensors**: crafted with IoT applications in mind, Sensorex introduces a line of smart water quality sensors. These advanced sensors adeptly measure vital parameters including pH, ORP (oxidation-reduction potential), conductivity, and dissolved oxygen. Remarkably, these sensors seamlessly synchronize with wireless sensor nodes, enabling real-time data acquisition that empowers comprehensive water quality monitoring across diverse environments.
- **Libelium Waspmote Plug & Sense! Smart Water**: propelling the frontier of smart water solutions, Libelium introduces their Smart Water ecosystem. Within this domain, a diverse array of sensors thrives, encompassing pH, turbidity, dissolved oxygen, and more. An inherent feature of these sensors is their innate compatibility with the Waspmote Plug & Sense! wireless sensor nodes. Such harmony ensures fluid deployment within wireless sensor networks, driving agile and adaptable water quality monitoring initiatives. The node comprises a sturdy waterproof enclosure, featuring designated external sockets for sensor connections, solar panel integration, antenna placement, and even USB cable utilization for node reprogramming. Its design places a premium on scalability, streamlined deployment, and straightforward maintenance. It supports radio technologies such as 802.15.4, ZigBee, WiFi, Sigfox, and LoRaWAN.
- **YSI EXO-series**: YSI presents the EXO series sensors, the successor of the popular 6-series from YSI. A symphony of measurements is conducted, spanning turbidity, dissolved oxygen, pH, and beyond. These sensors harmonize seamlessly with the EXO sondes, a platform tailored for telemetry systems, which facilitates wireless data transmission with eloquence and precision.
- **Xylem ProDSS (Digital Sampling System)**: the ProDSS ecosystem, a creation of Xylem, sets the stage for comprehensive water quality analysis. A diverse ensemble of sensors graces this system, proficient in gauging parameters such as pH, turbidity, dissolved oxygen, and beyond. The ProDSS handheld unit, facilitating wireless data transfer and seamless integration with sensor nodes for an immersive monitoring experience. However, this option is more geared towards in-situ measurements due to the handheld unit. Furthermore, it offers enhanced portability and ease of use for field applications, allowing for quick data collection and analysis on-site. The handheld design facilitates real-time monitoring and immediate decision-making, making it a suitable choice for scenarios where on-the-spot measurements are crucial.
- **Aanderaa SeaGuard RCM Blue**: the RCM Blue serves as a self-recording Current Meter, proficient in measuring water temperature in both salt and fresh water. It comes equipped with a battery container that accommodates a battery capacity of up to 70Ah. The Doppler Current Sensor, an upgraded version of the well-established SeaGuard ZPulse sensor, complements this system. Simplifying instrument configuration and data retrieval, Bluetooth technology eliminates the need to open the pressure case for repetitive deployments.

These purpose-built sensors have paved the way for a robust solution encompassing real-time data collection, remote monitoring, and informed decision-making across diverse environmental contexts. The selection of prominent sensors showcased here underscores the versatility and advancement in this domain. From Sensorex's smart sensors adept at measuring critical parameters to Libelium's Smart Water ecosystem driving agile monitoring initiatives, the YSI EXO-series facilitating wireless data transmission with precision, Xylem's ProDSS ecosystem enabling comprehensive water quality analysis, to the Aanderaa SeaGuard RCM Blue's proficiency in self-recording measurements, each sensor contributes uniquely to the evolving landscape of wireless water quality assessment.

B. MICROCONTROLLER UNIT

The microcontroller unit (MCU) lies at the heart of the data collection subsystem and can be thought of as the brain of each wireless node. Its primary task is to process signals acquired by the sensing unit, which are subsequently sent to the next subsystem via the transceiver [55]. In order to accomplish this work, the MCU must meet a series of important requirements, considering the WSN application for WQM:

- **Low power consumption**: given that nodes are battery-powered, an MCU that consumes few resources is preferable. This extends the lifetime of each node [56].
- **Processing and memory capacity**: the MCU must possess the necessary tools to process all data collected by the sensing unit and store it prior to transmission. Capacities of around 2 kB of RAM, 32 kB of FLASH memory, and 1 kB of EEPROM memory are typically found in the literature [55] for monitoring applications; however, the choice depends largely on each specific application.
- **Connectivity to the sensing unit**: the chosen MCU must have the necessary interface to connect to different sensing devices.
- **Control**: the MCU must be able to activate and deactivate measurement according to its programming, among other control tasks assigned in the network.
- **Compatibility**: the MCU must be compatible with wireless communication standards.
- **Security**: depending on the level of security required for data in the WQM application, the MCU must possess the capability to incorporate mechanisms to protect it.

To date, platforms such as Arduino or Raspberry Pi have become popular for project development, including WSN implementations for WQM; their implementation in works such as [32], [45], [46], [48], and [57] demonstrates their flexibility, scalability, and tools for user interface development [58]. The use of these platforms has expanded due to their extensive documentation, community, and online support, which facilitates their application. However, they present some limitations compared to dedicated MCUs for specific WSN applications for WQM, such as:

- Arduino and Raspberry Pi boards have higher costs, which can significantly increase the budget required for the project, especially if the deployment of many nodes is required.
- The energy required by these boards is significantly higher than dedicated MCUs, putting the network lifetime at risk.
- The size of the boards is usually larger than those developed with dedicated MCUs, increasing the dimensions of the nodes.
- Being designed for general purposes, Arduino and Raspberry Pi can be less reliable, less stable, and have difficulties in hostile environments compared to dedicated MCUs.

Considering the above points is important for choosing the central processing unit of the node. For prototyping applications, boards such as Arduino and Raspberry Pi are often suitable options [59]; however, for more complex implementations, it is recommended to design using dedicated MCUs. Table 1 lists a series of dedicated MCUs for IoT applications, their memory, and active and sleep power consumption characteristics.

Important applications have been developed using dedicated MCUs. In [60], the deployment of a WSN for air monitoring and WQM using sensors integrated into the RENESAS RX64M MCU is documented. Furthermore, the sensor implementation is modular, allowing for rapid deployment and low maintenance costs. As a result, the solution is energy-efficient.

In [52], the PIC16F877A is used as an MCU, reporting flexibility and low economic cost. However, the work does not delve into important aspects such as compatibility with standards beyond the one used (Bluetooth), or energy consumption. Although it can be said, from the data gathered and shown in Table 1, that the MCU's consumption is low, it is not the best option among those described.

In [61], the results of the ICARUS mote are presented, the first sensor node capable of maintaining an extremely low current of 22nA during sleep state by implementing a real-time-clock (RTC) circuit outside the MCU, being the only section that remains on while in sleep state. The STM32L476RG is used in this work, which already achieves very low current consumption by itself.

In [62], an ATmega324PA MCU is used for the development of MEGAN, a low-cost and energy-efficient sensor node. Studies indicate that after deployment, it has an average lifetime of 3.77 years using Bluetooth with sampling twice per hour, generating a total consumption of 16.44mA. It also indicates a total price of approximately $20 per node. The implementation of the ATmega324PA for this solution is a key factor for its energy performance, allowing it to consume very little energy in each of its states.

An LPC2148 MCU and a CC2430 are used in [63] and [64] respectively. Both works highlight their reliability, performance, and compatibility with recognized wireless standards.

In terms of energy consumption, good memory capacity, and compatibility with wireless standards, the STM32L0 series stands out among all the listed MCU options in Table 1, as it was mainly designed to offer excellent energy efficiency.

TABLE 1. MCUs memory and current consumption characteristics.

MCU	RAM	FLASH	EEPROM	Clock Frequency (MHz)	Current Consumption	
					Active	Sleep
ATmega328P	2 kB (SRAM)	32 kB	1 kB	16	14 mA	66μA
STM32L152	16 kB (SRAM)	128 kB	4 kB	32	6.24mA	4.6μA
JN5139	96 kB	Supports external FLASH memory	192 kB ROM	32	37mA	2.6μA
ATmega324PA	2kB SRAM	32 kB	1 kB	20	0.4mA @ 1 MHz, 1.8V	0.6μA (RTC on)
ATmega88	1 kB SRAM	128 kB	4 kB	20	0.3mA	0.8μA (RTC on)
MSP430FR5969	64 kB non-volatile FRAM	-	-	16	103μA/MHz	0.25μA (LPM3.5)
STM32L476RG	128 kB	1 MB	-	80	100μA/MHz	420nA RTC
CC430F5137	4 kB	32 kB	-	20	160μA/MHz	2μA
SAMD21	32 kB (SRAM)	256 kB	-	48	7mA	12.8μA
CC3200	256 kB	-	-	80	229mA	250μA (LPDS)
ATmega1281	8 kB (SRAM)	128 kB	4 kB	16	500μA @ 1MHz	0.1μA @ 1.8V
ATmega32U4	2.5 kB (SRAM)	32 kB	1 kB	8	15mA	12μA
STM32L0	8 kB	64 kB	2 kB	32	88μA	0.27μA
PIC16F877A	4 x 128 kB	8 kB	256 kB	20	2mA @ 4MHz	40μA
RENESAS RX64M	512 kB (SRAM)	2 MB	4 MB ROM	120	0.3mA/MHz	-
CC2430	8 kB	32-128 kB	-	32	27mA	0.5μA
LPC2148	8-40 kB(SRAM)	512 kB	32	100mA	-	

It has an ARM Cortex-M0+ processor architecture, and its CMOS technology manufacturing allows for this low power characteristic.

C. TRANSCEIVER

The transceiver is the unit responsible for achieving proper wireless communication between WNs and external elements, which can include base stations, gateways, or other nodes (depending on the adopted network topology) [11]. Often referred to as the communication unit, the transceiver is the component that consumes the most energy within the node [65]. Therefore, an appropriate choice will enable efficient use of energy resources.

For WSN applications in WQM, radio frequencies are used for communication, which are defined from 3 kHz to 300 GHz [11], and the use of the ISM bands of the electromagnetic spectrum is recommended due to their cost-effectiveness.

This unit serves as a platform for accessing the MAC layer and initiating the data transmission process. The transceiver converts data into radio waves using specific modulation schemes and ensures, through the protocols described in Section IV, how communication will take place with other network devices.

The transceiver has four operating modes: transmit, receive, idle, and sleep. While the device is waiting, sending, or receiving data, it is considered active, and it is inactive when in sleep mode. Each operating mode consumes different amounts of energy, so defining how much time is spent in each mode is crucial to preserving node resources through duty cycling [11].

D. POWER SOURCES AND ENERGY MANAGEMENT

Wireless network devices for WQM are often located in remote or hard-to-reach areas, without power sources available. Therefore, to address this difficulty, they are equipped with batteries that allow them to extend their lifetime to the maximum [66]. Applications such as those described in [60], [63], [64], and [67], use this approach. To maximize the lifetime of each node, duty cycling techniques are used [68] so that they are active only for the time necessary for parameter acquisition, data processing, and transmission [69], the latter being the most energy-consuming process [66].

However, issues such as the use of more complex sensors, greater amount of data, more demanding computational requirements, the transmission technology to be used, or the very nature of the node's location, make energy consumption higher, therefore, alternative approaches that increase device energy efficiency are sought. These energy harvesting (EH) techniques are employed at the software and/or hardware level, but it is important to emphasize that, regardless of the technique used, the entire device must be energy-efficient, i.e., capable of fulfilling its entire function with the minimum amount of energy so that its service time is as extended as possible.

One of the EH techniques that has become popular in recent years for WSN is energy harvesting through solar panels, consisting of a DC-DC conversion, a rechargeable battery, and PWM or MPPT energy management circuits [70] in order to increase panel efficiency [71], and then transfer this energy to the WN. The works described in [60], [71], and [72] show the potential that this technique provides to WSN solutions for different wireless standards, extending their lifespan. However, due to changes that may exist in terms of solar availability, the collection rate must be evaluated. The novel work directed in [73] presents an ML approach using neural networks; the proposal is a MAC protocol that allows adapting the duty cycle by predicting future energy incomes, optimizing network performance through efficient use of what is collected.

Another existing technique is radio frequency (RF) EH, also known as a wireless information and power transfer (WIPT) system, which allows energy to be transferred wirelessly to increase battery life. This electromagnetic energy can be harvested without limit, as well as being a clean source, with the disadvantage of its low power density and its efficiency being inversely proportional to the distance between the generator and the receiving antenna [74]. RF energy sources can be of two types [75]: ambient or dedicated.

An ambient RF energy source (ARFES) is not specifically dedicated to power transmission and has a low density, while a dedicated RF energy source (DRFES) is an on-demand source that provides higher power density thanks to its highly directional transmission and is used to power nodes that require it. DRFESs use the ISM band [75].

Although the concept of WIPT systems for powering WNs looks quite promising, there is still a significant gap that must be reduced with implementations. The work done in [76] and [77] is dedicated to developing algorithms to optimize both the collected energy and the system throughput using a time-division multiple-access (TDMA) model, prolonging the lifespan of the WIPT system.

As previously stated, in addition to hardware implementations, software-based approaches exist for energy management in a WSN. In the works developed in [78], [79], [80], and [81] various techniques are used to reduce energy consumption. [78] presents a genetic algorithm and an artificial bee colony algorithm, demonstrating an increase in the lifetime of the WSN. [79] and [80], on the other hand, present energy-efficient transmission schemes, while [81] develops a data aggregation scheme that reduces communication costs thus improving the network life. Although these latter mentioned works do not directly address energy sources, it is important to note how they do affect the energy. Therefore, their significance for future efficiency improvements should not be overlooked.

IV. NETWORK SOLUTIONS

Given the nature of the water monitoring application presented in this research, and as repeatedly emphasized, the solution to be adopted must meet the QoS requirements. With regard to network solutions, standards that enable adequate coverage for the application, efficient data transmission, low power consumption, flexibility, low costs, and reliable and secure communication should be utilized.

This section discusses existing network solutions, the communication standards they use, and their main features according to three transmission distance ranges: short, medium, and long. A proper comparison will be made to evaluate the solutions.

A. SHORT RANGE

The solutions presented in this range fall within what is referred to as Low-rate Wireless Personal Area Network (LR-WPAN), which are short-range networks, typically ranging from 10 to 100 meters. The main objectives of these networks are to facilitate installation, provide reliable data transfer, achieve low costs, and have a relatively extended lifespan, while maintaining a flexible protocol [82].

1) IEEE 802.15.4

Developed by the IEEE Working Group, the IEEE 802.15.4 technology is defined as a standard for low-rate, low-cost, and low-power consumption transmission. For this reason, it has been adopted by other technologies that are analyzed later, such as Zigbee, which are developed on this standard. Its range does not exceed 100 meters and operates in the PHY and MAC protocol layers [82]. It is designed to operate in the unlicensed ISM bands of 2.4 GHz, 915 MHz, and 868 MHz. For 2.4 GHz, transmission rates of up to 250 kbps can be achieved using QPSK modulation, while for the 915 MHz and 868 MHz bands, transmission rates of up to 40 kbps and 20 kbps, respectively, can be obtained using BPSK modulation in the PHY layer [11]. These speeds, as well as the high-performance characteristics, make this standard acceptable for many IoT applications, including WQM.

The modulation scheme used in the MAC protocol is carrier sense multiple access based collision avoidance (CSMA-CA) for handling access to the wireless channel [82].

IEEE 802.15.4 allows for star, tree, cluster tree, or mesh topologies. The advantage of a mesh topology implementation is reduced energy consumption, as nodes can communicate with any neighboring nodes to reach the base station thanks to the multi-hop technique, which also allows communication to continue in case a node fails.

2) ZIGBEE

Zigbee is a solution created by the Zigbee Alliance based on the IEEE 802.15.4 standard, which is capable of creating networks in star, cluster tree, and mesh topologies [15], but in turn depends on the standard for transport services in the PHY and MAC layers [11]. However, Zigbee adds an extra layer of software for more complex communication and device management services. Zigbee allows for the definition of profiles for specific applications with a set of established rules that allow compatibility and interoperability with other Zigbee devices [83]. The IEEE 802.15.4 standard allows for transfer rates of 250, 40, and 20 kbps in the ISM bands of 2.4 GHz, 915 MHz, and 868 MHz, respectively. The latest addition to Zigbee was the possibility of internet connectivity to enable the creation of IP-based networks through 6LoWPAN technology.

Applications that use the Zigbee solution are reported in [30], [47], [48], [63], [84], and demonstrate feasibility of deployment, low cost, and low energy consumption, as well as the possibility of adapting energy harvesting techniques for network nodes. However, little has been reported on the network performance in terms of propagation in different environments, especially for WQM applications. In [85], the performance of a Zigbee network is evaluated, suggesting the mesh topology over the others if better results are desired in terms of PDR and delay, while the tree topology provides better results in terms of load and throughput.

Although Zigbee provides a solid infrastructure for the network, the characteristics mentioned previously must be considered, especially the coverage of the network, which can be a problem if deploying a network that covers long distances is desired.

3) 6LOWPAN

6LoWPAN stands for IPv6 Low Power Wireless Personal Area Network. It is a technology for encapsulating data packets through a compression mechanism of the IPv6 protocol headers, which reduces the overhead represented by IPv6 packets [86]. This compression is what makes it particularly applicable for communication between low power and resource-limited devices such as IoT devices, especially WSN applications for WQM. This technology provides the ability to add IPv6 internet capability to the existing IEEE 802.15.4 standard [11], and therefore, the transmission rates are identical to those of that standard for the 2.4 GHz, 915 MHz, and 868 MHz bands.

The IP protocol is open, which is an advantage of 6LoWPAN. It can easily connect with established IP networks, which adds the factor of flexibility. This technology is recommended for high-density networks given this advantage [87].

Research conducted in [87], [88], and [89] presents applications of 6LoWPAN technology for WQM that demonstrate successful implementations. In [87], IPv6 sensor nodes, a 6LoWPAN gateway that functions as the link between the network and the internet, and a web application server deployed on a remote IP network are used. [88] presents the design of a WQM system that uses TelosB motes for communication between the transmitter and the receiver for subsequent internet connection that allows generating an early warning based on water pollution levels. In [89], the Texas Instruments CC2538 MCU is used for nodes that use pH and ORP sensors. This implementation is compared to a Zigbee stack that consumes 800 mA with a power of 176 mW. As a result, the 6LoWPAN stack demonstrates better energy performance, consuming 450 mA with a power of 99 mW.

4) BLUETOOTH AND BLUETOOTH LOW ENERGY

Bluetooth (BT) technology supports the IEEE 802.15.1 standard, providing connectivity up to 100 meters with transmission rates up to 1 Mbps in the 2.4 GHz ISM band, and in the PHY layer uses Gaussian frequency shift keying (GFSK) or frequency-hopping spread-spectrum (FHSS) modulation schemes [11]. BT uses star and peer-to-peer (P2P) topologies. The limitation it presents is that communication is typically limited to two devices connected at the same time, the primary and the secondary.

Due to the high transfer rate, the energy consumption of BT is high, putting this technology at a disadvantage compared to others used in IoT devices, such as Zigbee. As a measure to reduce this consumption, there is a variant that also reduces cost: Bluetooth Low Energy (BLE) [15]. In addition to supporting the same modulation schemes and using the same frequency band, it allows massive connectivity of up to 5917 secondarys per primary device [11].

The widespread implementation of Bluetooth (BT) and Bluetooth Low Energy (BLE) is mainly due to their low cost, and research analyzing their performance has been developed in [52], [90], [91], [92], and [93]. BLE is implemented in [90] through mobile gateways, achieving energy consumption in nodes of 12.7 mA on wake-up and 7.8 mA during data transmission, while demonstrating autonomy when powered by solar cells, performing measurements every minute, and scalability as an open system; however, it lacks security systems. In [91], BT communication is used to handle an Unmanned Surface Vehicle (USV) for real-time WQM; however, this application resembles more of a TMIS approach, with the advantage that measurements can be taken outside the water body thanks to the USV. In [92] and [93], a sensor node deployment with BT communication is used to monitor water quality using Arduino and BT HC-5 and BT04-A modules, respectively. The implementations are low-cost; however, in contrast to [90], they are simpler and, by using the Arduino platform, it can be assumed that energy consumption is much higher.

BLE technology is emerging as one with great potential in short-range IoT applications, but a more thorough and in-depth analysis is still required, especially in advanced network deployments. Existing studies demonstrate its low cost and good energy performance; however, issues such as low security or the need for more devices that allow the BT network to connect to the internet must be evaluated.

Table 2 summarizes the short range network solutions covered in this subsection and highlights their main characteristics.

B. MEDIUM RANGE

The network solutions shown in this section fall within the WLAN category. A Wireless Local Area Networks (WLANs) have become an essential part of modern communications. WLANs are widely used in various environments such as homes, offices, schools, airports,

and public spaces. They offer more mobility and convenience compared to short range solutions, as devices can connect to the network anywhere within a wider range of the wireless signal. WLANs are not without limitations; however, security breaches and signal interference from other devices

TABLE 2. Short range network solutions summary.

Solution	Standard	Data rate	Coverage	Topology	Carrier freq	Energy cost	Deployment cost	Applications
IEEE 802.15.4	IEEE 802.15.4	250 kbps	Less than 100 m	Star, tree, cluster tree, mesh	868 MHz, 915 MHz, 2.4 GHz	Low	Low	-
Zigbee	IEEE 802.15.4	250, 40, and 20 kbps	Above 100 m	Mesh, star, tree	868 MHz, 915 MHz, 2.4 GHz	Low	Low	[30], [47], [48], [63], [84]
6LoWPAN	IEEE 802.15.4	250 kbps	Less than 100 m	Mesh, star	868 MHz, 915 MHz, 2.4 GHz	Low	Low	[87]–[89]
Bluetooth	IEEE 802.15.1	1 Mbps	Up to 100 m	Star, P2P	2.4 GHz	Low	Low	[52], [91]–[93]
BLE	IEEE 802.15.1	1 Mbps	Up to 200 m	Star, P2P	2.4 GHz	Very low	Low	[90]

operating on the same frequency bands can pose a threat to the network. Proper configuration and management are required to ensure the secure and efficient operation of WLANs.

1) WI-FI

The Wi-Fi technology, designed by Wi-Fi Alliance and based on the IEEE 802.11 standard, enables high wireless data transfer rates of up to 54 Mbps in the 2.4 and 5 GHz frequency bands, with a coverage range of up to 200 meters. In the PHY layer, modulation schemes such as offset QPSK, BPSK, and multi-code DSSS are utilized [94].

The infrastructure topology represents the most frequently employed configuration in Wi-Fi networks. In this setup, Wi-Fi devices link up to a wireless access point (WAP) that is tied into a wired network. Acting as a hub, the WAP enables multiple devices to join the network through it. On the other hand, mesh topology is less commonly seen in Wi-Fi networks. With this arrangement, Wi-Fi devices engage in direct communication with one another to generate broader and more resilient network coverage. Every device in the mesh network acts as a repeater, extending the signal throughout the network. Mesh topology is more commonly deployed in wide-area networks and in scenarios where more extensive or robust network coverage is required [94].

The works developed in [32], [46], [57], [63], [90], [95], and [96], utilize Wi-Fi technology and reveal a high energy consumption, especially for the transmission stage. Therefore, it is mainly used as an internet access point in base stations to provide connectivity to remote networks. Despite being a widely used solution, these drawbacks must be carefully evaluated, as it is very energy inefficient for a deployment of WNs that rely on batteries or even energy harvesting.

2) LOW-POWER WI-FI

Unlike Wi-Fi technology, which is designed to provide high data transfer rates between devices at the expense of high energy consumption, Wi-Fi HaLow or Low-Power Wi-Fi is a modification that extends the capabilities of the IEEE 802.11 standard to provide Wi-Fi connectivity to low-power IoT devices [97]. This technology follows the IEEE 802.11ah standard, which offers a simple, robust, and energy-efficient solution in the sub-GHz ISM band [98], [99].

With the 802.11ah standard, two data transfer rates can be obtained, ranging from 0.15 to 4 Mbps using a 1 MHz bandwidth, and from 0.65 to 7.8 Mbps using a 2 MHz bandwidth, although it allows for the use of channel bandwidths of 4, 8, and 16 MHz [100], allowing for packet transmissions of up to 100 bytes [98]. This technology allows for transmission distances of up to 1000 m outdoors, using BPSK, QPSK, 16, 64, and 256-QAM modulations in the PHY layer with Orthogonal Frequency Division Multiplexing (OFDM) transmission [98]. In terms of the MAC layer, Wi-Fi HaLow uses Restricted Access Window (RAW) to allow devices to transmit data only in specific pre-negotiated time slots, thanks to the combination of medium access by TDMA and CSMA-CA [100]. Thanks to these characteristics, devices significantly reduce energy consumption and collisions.

Wi-Fi HaLow uses a star topology; however, nodes can only communicate with a dedicated gateway [100], which can be an advantage in terms of security, as data remains within the network.

To the best of the author's knowledge, unfortunately, there are no applications that study this technology in the field of WSN for WQM to review its performance, only simulations like the one developed in [101]; however, this provides an opportunity to develop novel proposals to be taken to the field, as its characteristics of energy consumption, range, and transmission rate are suitable for this application.

Table 3 summarizes the medium range network solutions covered in this subsection and highlights their main characteristics.

C. LONG RANGE

This section reviews wireless technologies that fall within the category of Low-Power Wide Area Network (LPWAN).

TABLE 3. Medium range network solutions summary.

Solution	Standard	Data rate	Coverage	Topology	Carrier freq	Energy cost	Deployment cost	Applications
Wi-Fi	IEEE 802.11	Up to 54 Mbps	200 m	Infrastructure, mesh	2.4 GHz, 5 GHz	High	Low	[32], [46], [57], [63], [90], [95], [96]
Wi-Fi HaLow	IEEE 802.11ah	0.15 to 4 Mbps @ 1 MHz bandwidth, and 0.65 to 7.8 Mbps @ 2 MHz bandwidth	1000 m	Star	ISM Sub-GHz	Low	Low	[100]

However, before delving into this topic, it is necessary to clarify why WAN technologies of cellular networks and high-power WAN solutions are not being considered. While 2G, 3G, and 4G cellular networks can provide coverage ranges of up to 30 kilometers and internet connectivity [11], these features make them seem suitable for a Wireless Sensor Network (WSN). However, they are too energy demanding for a Water Quality Monitoring (WQM) application and do not represent an optimized solution for WSN. Similarly, satellite technology and WiMAX offer ranges of up to 6,000 km and 50 km, respectively, but come at high costs and consume a significant amount of energy, making them unsuitable for WSN in WQM. Additionally, sensors are not designed to handle the high transfer rate required by these technologies [11].

Although a solid 5G proposal for communication between IoT devices is still under development, it is expected that 5G technology will solve the energy consumption issues of previous cellular networks and enable the incorporation of water resource management into a smart city framework [102]. These drawbacks are widely recognized by researchers. For instance, in [103], an algorithm is developed to reduce energy consumption in a simulated 5G network by limiting massive device access without negatively affecting Quality of Service (QoS). Furthermore, by using the network slicing technique, which involves dividing a physical network into virtual end-to-end networks separated into logical sections [104], greater efficiency, security, flexibility, and performance can be achieved in managing IoT device connectivity on the 5G network, while separating it from other services that may be offered, such as ultra-HD video or telephony.

Next, the LPWAN solutions used for WSN in WQM applications are described.

1) LORAWAN

LoRaWAN is an open standard technology maintained by LoRa Alliance for low power, long-range communication between IoT devices. The LoRaWAN protocol establishes a communication scheme in the MAC layer of pure ALOHA [105], meaning that devices can transmit at any time without needing to request permission. This allows devices to transmit information on the designated channel when ready, and if there is no interference, the communication is successfully completed, and the receiver sends an acknowledgment message to the transmitter. However, if two or more devices transmit simultaneously, a collision occurs, and the message is lost. The transmitter must then wait for a random time before sending the message again.

LoRaWAN uses the ISM Sub-GHz bands of 868 and 915 MHz. The LoRa modulation scheme is proprietary and owned by Semtech Corporation. It uses a chirp spread spectrum (CSS) modulation in the PHY layer, but it can also support QFSK modulation. However, QFSK is more sensitive to noise and interference than CSS, and it allows for shorter transmission ranges [11]. QFSK is used in LoRa for short-range transmissions and higher speeds, while CSS is used for longer range and lower power transmissions, making it more suitable for IoT applications like WQM, with a range of up to 5 km in urban areas and 15 km in rural areas.

The network architecture using this technology involves a LoRa gateway that provides IPv6 connectivity. In this way, the LoRa devices in the network can support star-to-star topologies using single-hop communication. Each device communicates with the gateway, which has the role of providing internet connectivity [106].

Novel and important implementations that use this technology have been documented in [18], [31], [60], [107], and [108]. In [107], the deployment of three LoRa sensor nodes at different distances from the LoRa gateway for the acquisition of parameters such as pH, turbidity, temperature, conductivity, and dissolved oxygen is reported, using the ESP32-LoRa32 transmitter to emit the signal in the 920-923 MHz band. This application does not require long-distance transmissions, so FSK modulation is used, allowing for a transfer rate of 1.2 kbps to 300 kbps, with no data packet loss reported. However, a comprehensive study of LoRa's full capabilities is not clear. In [108], the deployment of six sensor nodes and two LoRa gateways on a fish farm in Latvia for the monitoring of dissolved oxygen, pH, conductivity, temperature, and ORP over an eight-month period is reported. The sensor nodes use an STM32L4 MCU that ensures ultra-low power consumption, an RN2483 LoRa module, and Atlas Scientific ADCs placed behind load switches for power cut-off during the sleep cycle. Energy is managed by two rechargeable Li-ion batteries and a solar panel. This paper, unlike the others, provides information on the construction of the buoys on which the sensors are mounted, which is important to consider in the planning of the WSN. This design uses JSON Web Token to increase network security. In [18], LoRa is used for monitoring water quality using a Smart Boat. It also uses an ESP32 MCU with a LoRa module for 868/915 MHz and supports GPS connectivity. The results show a transmission range of up to 2 km, maintaining a transmission efficiency of 95% and up to 3 km with an efficiency of 85.5%. However, it mentions the opportunity to create another antenna for LoRa technology, hoping to improve the transmission signal.

2) SIGFOX

Sigfox is a proprietary LPWAN protocol technology based on ultra-narrow band (UNB) at the PHY layer that enables long-distance coverage with very low energy consumption. The modulation used at this layer is differential binary phase shift keying (DBPSK) with a low rate of 100 bps, using a bandwidth of approximately 100 Hz. At the MAC layer, Sigfox uses the random frequency time division multiple access (RFTDMA) method, which gives it some resemblance to the ALOHA scheme in that nodes access the medium randomly. However, this access occurs by choosing the carrier frequency within a continuous bandwidth interval, rather than a discrete set [109]. This protects the message from external interference and limits energy use, but at the same time, this uncontrolled medium access can generate interference between active nodes.

Like LoRa, Sigfox uses the ISM bands of 868 and 915 MHz and supports the 3GPP specifications for providing IPv6 connectivity. Its architecture requires a gateway that offers the service of a network provider. This technology allows distances of up to 10 km and 50 km for urban and rural areas, respectively [11], although propagation up to 100 km is reported in [109], and the ability to handle up to one million devices per base station as long as bandwidth is not shared with another IoT technology, which can be a disadvantage in terms of flexibility and compatibility with other communication technologies such as LoRa.

Several studies have analyzed the performance of a network with Sigfox, including [110], [111], [112], [113]. In [110], the influence of the number of devices in the network and the bandwidth on collisions, packet error rate (PER), and spectrum is observed. Simulations evaluate the effect of up to 1000 devices in the network, and it is observed that the more devices there are, the more collisions and lost packets there are, indicating approximately 100 collisions and 2.5% PER for 1000 devices. This should be considered in network design.

The work described in [111] shows the performance of a very small Sigfox compliant sensor node for monitoring temperature, humidity, and luminosity in a vineyard. The node uses an ATmega328P MCU, a Microchip ATA8520E radio module and antenna that reports a consumption of 10.4 mA and 31.8 mA during reception and transmission and 5 nA during sleep, and a solar energy harvesting unit. The node can also be powered by a 90 mAh battery, reporting up to a thousand transmissions. The results demonstrate an autonomous node with the ability to operate for up to 8 hours in complete darkness, performing transmissions every half hour, while with low light it can transmit data every 5 minutes. In this application, only two nodes were deployed, but the capacity of communication using Sigfox, and, above all, its high energy efficiency is demonstrated.

The WaterS prototype, on the other hand, is the work developed in [112], which focuses on WQM. The WN monitors pH, turbidity, and temperature. It is also equipped with the Microchip ATA8520E module, an Arduino MKRFOX1200 board, which is Arduino's bet for Sigfox, a 720 mAh LiPo battery, and a solar panel that provides autonomy to the prototype. The overall consumption of the node is 126.4 mA with a duty cycle of 0.4\%, meaning it performs its actions for 15 seconds every hour. This last point is important to consider because more frequent sampling may be required for other WQM applications. In [114], this work is complemented using the deep learning neural network technique, demonstrating the applicability of data analysis using ML.

Sigfox can provide reliable and low-power data transmission. However, its limited bandwidth may not be suitable for applications that require real-time monitoring or high-frequency data transmission. In scenarios where water quality parameters change rapidly, Sigfox may not be able to provide real-time data, reducing the effectiveness of the monitoring system. Nonetheless, Sigfox remains a viable option for water quality monitoring applications that require infrequent data measurements or are located in areas with adequate network coverage. Careful evaluation of the specific application requirements and limitations of Sigfox is necessary before selecting it as a communications technology for WQM.

3) INGENU RPMA

Ingenu RPMA (Random Phase Multiple Access) is a proprietary long-range protocol technology that utilizes the 2.4 GHz ISM band and is specifically designed for IoT applications. It employs a RPMA direct sequence spread spectrum (DSSS) scheme in uplink (UL) [115] and code division multiple access (CDMA) in downlink (DL) at the PHY layer, which is necessary to mitigate the interference encountered at 2.4 GHz, and is based on TDMA at the MAC layer [116]. One of the advantages of this technology is that it utilizes a random access scheme for data transmission, significantly reducing power consumption in comparison to other communication protocols.

Ingenu RPMA technology allows for star and tree topologies, and the establishment of private networks. The estimated range provided is up to 15 km for urban areas and up to 48 km in rural areas [116].

According to Ingenu's technical documentation, RPMA has been designed to be highly energy efficient. In fact, the technology has been specifically optimized for low-power devices, enabling devices to operate for several years on a single battery. Unlike other LPWAN solutions, to the best of the author's knowledge, Ingenu RPMA technology has not been studied for WQM solutions, which hinders evaluation in real-life situations; however, this provides an opportunity for future research development.

4) NB-IOT

Narrow Band IoT (NB-IoT) is a cellular network technology designed by 3GPP as part of its Release 13, which coexists as part of the LTE or GSM standard, utilizing QPSK modulation in the PHY layer [117], and MAC schemes such as Single-Carrier Frequency Division Multiple-Access (SC-FDMA) in uplink [118] and Orthogonal FDMA (OFDMA) in downlink [119], but is considered a new air interface. It uses a very narrow bandwidth, hence its name, of 180 and 200 kHz, which corresponds to a physical resource block (PRB) in LTE or GSM transmissions, respectively, in DL and UL [120], and thanks to this, it can operate in four different modes: stand-alone operation, guard-band operation, and in-band operation. Figure 8 illustrates this PRB allocation.

This technology is specifically designed to meet the needs of IoT devices operating in remote locations or in deep indoor situations, which implies improvements of up to +20 dB of gain compared to GPRS [121]. NB-IoT has the ability to provide connectivity to over 100,000 devices per cell, delivering a transfer rate of up to 200 kbps in DL and 20 kbps in UL, with a payload of 1600 bytes in each message [119] within a range of up to 25 km [11], although the latter depends on the environment.

Additionally, it provides Access Stratum (AS) and Non-Access Stratum (NAS) security levels inherited from LTE [121]. The AS security layer is in charge of securing the wireless connection between the IoT device and the base station. It supplies authentication, integrity, and confidentiality tools for the data sent between the device and the cellular network. Specifically, an encryption algorithm safeguards the transmitted data, and an authentication protocol verifies that only authorized devices can access the network. On the other hand, the NAS layer of security is responsible for ensuring security between the IoT device and the core of the cellular network. It provides authentication and confidentiality tools for data transferred between the device and the network's core. Encryption techniques are also utilized to protect user information, such as identity, billing details, and transaction history. Security systems in both the AS and NAS of NB-IoT are crucial to guarantee the privacy and integrity of the data transferred between IoT devices and the cellular network while preventing unauthorized access to the network and user data.

Papers that develop NB-IoT technology are described in [123], [124], [125], [126], [127], [128], [129], [130], and [131]. In [123], this technology is integrated with blockchain to increase the load on the DL channel, demonstrating better performance compared to the use of NB-IoT alone, as well as increasing security capabilities. This application is shown to be viable for environmental monitoring applications, specifically those that rely on sensitive information such as air pollution. Other applications that focus on air quality monitoring are [125] and [126]; WNs have very low energy consumption and high measurement accuracy. Data is sent using an NB-IoT module on the LTE network, using Arduino Mega 2560 and Raspberry Pi 3, and Linkit Smart 7688 control board, respectively. In [124], the capabilities of NB-IoT are demonstrated to extend indoor communication, as well as showing flexibility with other technologies such as Zigbee to transmit PM2.5, temperature, humidity, and light parameters in the environment to the NB-IoT module, which then sends the data to the server database and is displayed on a mobile phone.

Regarding WQM, [127] presents the design of a very low-cost, low-power remote transfer unit (RTU) that functions as a gateway for the collection of hydrographic data. This RTU was experimentally tested and successfully used to visualize data on Android devices. The architecture features an STM32L151 MCU, an NB-IoT module BC28, and a monolithic synchronous buck regulator MP2303 for power management. This paper provides schematics for circuit development. Applications using this technology for aquaculture are documented in [128] and [130]. In the first, pH, temperature, and dissolved oxygen are monitored at three sensor nodes using an STM32L151C8 MCU, an NB-IoT module BC95-B5, and a 3000 mAh rechargeable battery. This work indicates machine learning techniques such as gradient boosting decision tree (GBDT) and long short-term memory network (LSTM) for WQ model prediction. The second work presents an NB-IoT-based WQMS that uses a photovoltaic battery for energy storage (PV/BES). Parameters such as dissolved oxygen, pH, electrical conductivity, temperature, and turbidity are monitored, processed on an Arduino MEGA 2560 R3, and sent to a cloud server using an NB-IoT module AIS DEVIO NB-DEVKIT I via HTTP requests. The implementation of the EH unit allows for the continuous operation of the monitoring system. The system is capable of providing an accurate solution for WQM, as well as demonstrating a very low packet loss of 0.89%. This application is reviewed in detail in the following section.

The excellent adaptability of the NB-IoT-based system with respect to LTE and GSM is evaluated in the City Open Water project developed in [129], where a multi-parameter sensor network is deployed in Bolong Lake. However, it is indicated that the deployment is carried out with few WNs, which can be improved for future evaluations of the network's performance. Finally, in [131] it is compared with LoRaWAN technology, indicating its ability to surpass it in terms of throughput, latency, and especially security.

NB-IoT operates coexistently with LTE and GSM in a proprietary portion of the radio spectrum in a friendly manner, giving it an advantage over technologies that use ISM bands, which are subject to interference. However, adapting to a cellular network can increase network complexity [122] Another advantage of using this technology is network reliability, as NB-IoT ensures the delivery of data packets, unlike its competitors. The low energy consumption it offers comes at the expense of variability in terms of packet delivery, which must be considered when choosing this option. Additionally, since the infrastructure is operator-owned, a set price is charged for each transmitted byte, which can be a cost limitation.

For the success of a network using NB-IoT for WSN in WQM, it is important to consider several factors:

- **Network coverage**: good network coverage is essential for effective WSN. NB-IoT has better penetration in buildings and remote areas compared to other mobile network technologies, making it suitable for WSN applications in WQM.
- **Power consumption**: power consumption is critical for WSN applications, especially since sensors are often deployed in remote locations without access to the power grid. NB-IoT consumes less power than traditional cellular networks, extending the battery life of the sensors.
- **Bandwidth**: the available bandwidth in a NB-IoT network is lower than in 3G and 4G networks, but sufficient for most WSN applications in WQM.
- **Security**: security is critical in WSN applications, especially in WQM where data tampering can have a direct impact on public health. NB-IoT provides a high level of security to ensure data integrity.
- **Cost**: the cost of implementing a NB-IoT network should be considered, as it can be higher than other WSN technologies. However, the energy efficiency and high network coverage can provide a better cost-benefit ratio in the long run.
- **Reliability**: network reliability is critical in WSN applications, as a lack of data can have a significant impact on system responsiveness. NB-IoT is a highly reliable network technology and can effectively guarantee data transmission.

Table 4 summarizes the long range network solutions covered in this subsection and highlights their main characteristics, whereas Table 5 summarizes features of the network technologies discussed in this section.

LPWAN solutions represent a highly effective alternative for wireless sensor network applications in water quality monitoring. Thanks to their low energy consumption, high data transmission capacity, and wide range, LPWAN solutions are more efficient and cost-effective than other available network options.

Furthermore, their easy implementation and low infrastructure make them highly attractive for WSN applications in WQM, allowing users to obtain real-time accurate information, optimize their processes, and improve decision-making. In summary, LPWAN solutions are a promising alternative for water quality monitoring and can significantly contribute to the management and conservation of water resources globally.

V. CASE STUDIES

The LPWAN solutions stand out among the technologies discussed in the previous section due to their high energy efficiency and long transmission range. In recent years, WSN applications for WQM have been developed using these technologies for network design. This section analyzes three studies developed with LoRaWAN, Sigfox, and NB-IoT in that order, with the aim of dissecting and evaluating their characteristics.

A. ON CONSTRUCTION OF A CAMPUS OUTDOOR AIR AND WATER QUALITY MONITORING SYSTEM USING LORAWAN [60]

This paper presents the experimental results of an air and water quality monitoring system on the Tunghai University campus using a low-power LoRa network. The article describes the system's design architecture and presents the services of aeronautical data collection, real-time processing, and data analysis. It also showcases historical data visualization using the ELK platform and evaluates the system's performance.

The study includes data visualization through IDW map calculation and real-time presentation of information such as PM2.5, temperature, and humidity. A comparison of energy consumption between data transmission via LoRa modules and Wi-Fi is conducted, demonstrating the advantage of LoRa's long-range transmission. Additionally, gateway reception sensitivity, maximum transfer performance of a single device, and communication channel capacity are evaluated and discussed.

The article concludes by highlighting the advantages of LoRa network, such as its low energy consumption and long-distance transmission capability. The possibility of expanding the monitoring system to other areas and incorporating deep learning for improved water quality prediction is mentioned. The utility of the collected data in enhancing water quality is emphasized, and the application of the system in different areas is suggested.

The key factors for the success of the LoRa network application project in air and water quality monitoring on the Tunghai University campus are as follows:

- **Low energy consumption**: LoRa's ability to operate at low power ensures an extended battery life for monitoring devices. This is particularly important for long-term monitoring systems where frequent battery replacements would be costly and impractical.

TABLE 4. Long range network solutions summary.

Solution	Standard	Data rate	Coverage	Topology	Carrier freq	Energy cost	Deployment cost	Applications
LoRa	LoRaWAN	50 kbps	5 km for urban areas and 15 km for rural areas	Star	868 MHz, 915 MHz	Very low	Low	[18], [31], [60], [107], [108]
Sigfox	Proprietary protocol	100 bps	10 km for urban areas and 50 km for rural areas	Star	868 MHz, 915 MHz	Very low	Low	[110]–[113]
Ingenu RPMA	Proprietary protocol	20 kbps	15 km for urban areas and 48 km for rural areas	Star, tree	2.4 GHz	Very low	Low	-
NB-IoT	LTE, GSM	DL: 200 kbps, UL: 20 kbps	25 km depending on the environment	Star	LTE and GSM licenced cellular network spectrum	Very low	High. Requires SIM card	[123]–[131]

TABLE 5. Network solutions features summary.

Network solution	Energy efficiency	Reliability	Internet connectivity support	Operational cost
IEEE 802.15.4	Yes	Low	No	Low
Zigbee	Yes	Low	No	Low
6LoWPAN	No	Low	Yes	Low
Bluetooth	No	Low	No	Low
BLE	Yes	Low	No	Low
Wi-Fi	No	Low	Yes	Low
Wi-Fi HaLow	Yes	Low	Yes	Low
LoRa	Yes	Low	No	Low
Sigfox	Yes	High	No	Low
Ingenu RPMA	Yes	Low	No	Low
NB-IoT	Yes	High	Yes	High

- **Long-distance transmission**: LoRa's long-range transmission capability enables efficient communication between monitoring devices and the base station or gateway. This is especially useful in university campuses or extensive areas requiring coverage over large geographical areas.
- **Modularization and ease of deployment**: The ability to modularize sensors and utilize a printed circuit board (PCB) facilitates rapid deployment and configuration of the monitoring system. This reduces maintenance costs and allows for agile implementation in different locations within the campus.
- **Data visualization**: The use of tools like Grafana and ELK allows for clear visualization of data collected from various sources. The ability to present data in an understandable and accessible manner is essential for comprehending and analyzing air and water quality on campus.
- **Integration of multiple sensors**: The capability to integrate different sensors, such as temperature, humidity, PM2.5, and potentially dissolved oxygen and pH sensors in the future, provides a more comprehensive and accurate picture of air and water quality. This enables a more thorough assessment and effective monitoring.
- **Collaboration with external entities**: The project mentions comparing the collected data with information provided by the Taiwan government's environmental protection department. Collaborating with external entities

for data validation and analysis reinforces the project's reliability and relevance.

However, as mentioned throughout this review paper, it is important to consider the potential drawbacks when implementing the LoRa network application for air and water quality monitoring. Evaluating whether they align with the project's specific requirements and the limitations of the intended environment is crucial. The potential downsides include:

- **Limited bandwidth**: LoRa network has limited bandwidth compared to other communication technologies like WiFi or cellular networks. This can restrict the amount of data that can be transmitted simultaneously and the data transfer speed. Therefore, determining the expected data volume beforehand is necessary when choosing this technology.
- **Reduced transmission speed**: Due to bandwidth limitations, data transmission speed in a LoRa network can be slower compared to other communication technologies. This can impact the ability to obtain real-time data or transmit large data volumes quickly.
- **Payload limitations**: While LoRa is suitable for low-power and low-speed data applications such as WQM, it may not be the best choice for applications requiring high payload capacity, such as video transmission or large datasets.
- **Interference and Obstacles**: The LoRa network signal can be susceptible to interference and physical obstacles, such as buildings, trees, or other structures. These obstacles can affect the signal quality and reduce the effective transmission distance.
- **Coverage Limitations**: Although the LoRa network can provide long-distance coverage, its range can be affected by environmental and geographical factors. In densely populated areas or areas with complex topography, the coverage of the LoRa network may be limited.

The paper suggests possible future directions for the project, such as expanding the system to cover other areas and incorporating deep learning to improve water quality prediction. The usefulness of the collected data in improving water quality is emphasized, and the application of the system in different areas is suggested.

In conclusion, the paper presents the experimental results of an air and water quality monitoring system on the campus of Tunghai University using a LoRa low-power network. The study highlights the advantages of LoRa in terms of its low power consumption and long-distance transmission capability. The key factors for the success of the project are also discussed, including low power consumption, long-distance transmission, modularization and ease of deployment, data visualization, integration of multiple sensors, and collaboration with external entities. It is also important to consider the potential downsides of implementing LoRa in air and water quality monitoring, such as limited bandwidth, reduced transmission speed, and limitations on payload capacity. Overall, this paper contributes to the advancement of knowledge in the field of environmental monitoring and demonstrates the potential of LoRa technology for such applications.

B. WATERS: A SIGFOX-COMPLIANT PROTOTYPE FOR WATER MONITORING [112]

The article describes the application of a Sigfox-compliant WQMS, called WaterS, which uses a WSN and IoT technology to remotely collect information on water quality parameters. The system was designed using a phased approach that includes application characterization, detailed specification study, analysis of commercial solutions for detection of specified values, preliminary design, assembly, preliminary testing and validation, and experimental campaign.

The system consists of five key components: a mobile device (also called a sensor node), a Sigfox gateway, the Sigfox cloud, an application server, and an Android-based mobile application. The mobile device is composed of a mainboard, detection units, and a GPS module. The mainboard is an Arduino MKRFOX12001, based on the Microchip SAMD21 microcontroller unit (MCU) with a clock speed of 48 MHz and a Sigfox ATA8520 module. Sensors include a pH probe, a turbidity sensor, and a thermal probe to measure water temperature. Additionally, the device has a GPS to provide georeferenced information.

To ensure the autonomy of the system, it has been equipped with a main power source, a 3.7V 720mAh LiPo battery, and a Seedstudio V2.2 solar shield. The 6V - 2W solar panel connected through the solar shield is capable of fully charging the battery in two hours and thirty minutes under favorable sunlight conditions. Duty cycling policies have been implemented to reduce power consumption. The use of the LowPower software library allows for a drastic reduction in power consumption during periods of inactivity.

WaterS allows for remote and real-time detection of water quality parameters, which is a major advantage compared to traditional sampling systems. Additionally, the possibility of georeferencing the collected information helps identify possible sources of contamination and evaluate water quality at different locations and times. However, it also presents some disadvantages, such as the need for a power source for the sensor nodes and the possibility of measured values being affected by environmental conditions and signal interference.

The application goes a step further in [114], where the collected data is used for predicting water quality using Machine Learning (ML) approaches. WSN have the potential to greatly benefit from the application of ML techniques in predicting water quality, whether in monitoring bodies of water or tracking treated water in wastewater treatment systems. Some advantages of this technique include increased accuracy in real-time predictions of water quality through the detection of patterns that would otherwise be difficult to identify with conventional methods, resource efficiency resulting from more accurate predictions that can reduce costs for sampling and chemical analyses, and automation of the monitoring and prediction process for faster and more accurate decision-making in response to possible contaminations or problems.

However, there are also some challenges that need to be addressed when using ML for WQM. These include data scarcity, which may limit the ability of Machine Learning algorithms to make accurate predictions if there is not enough accurate data to train them, lack of transparency as more complex techniques are used, making it difficult to understand decisions and interpret results without specialized knowledge, and sensitivity to changes in sensor conditions, weather, and other external factors that may require measures to ensure the algorithms remain robust and adaptable to change.

In general, the application of WSN for WQM is a promising tool for improving water management and environmental protection. WaterS represents an interesting example of this technology and presents a novel approach for ensuring sensor node autonomy and optimizing energy consumption. The described work solely focuses on the deployment of a single node; however, given the capabilities of Sigfox, this paves the way for future applications involving the deployment of multiple nodes to create a more complex network. This would enable a more comprehensive evaluation of the role played by Sigfox.

C. A STANDALONE PHOTOVOLTAIC/BATTERY ENERGY-POWERED WATER QUALITY MONITORING SYSTEM BASED ON NARROWBAND INTERNET OF THINGS FOR AQUACULTURE: DESIGN AND IMPLEMENTATION [130]

This work develops an autonomous NB-IoT based SWQMS. The system uses a solar charge controller to power a load or charge the battery energy storage (BES) with the photovoltaic (PV) module as the primary energy source. The monitoring system consists of two layers, the data acquisition layer, and the communication layer. The data acquisition layer collects water quality data from a series of sensors to measure dissolved oxygen, pH, electric conductivity, salinity, temperature, and turbidity, while the electrical data from the PV/BES system is also measured. The main microcontroller sends the data to the gateway via an Arduino Mega 2560 board, and the gateway uses NB -IoT wireless technology to send the relevant data to a cloud database. The cloud server layer provides a graphical user interface for remote monitoring and makes the data available to other applications.

The objective of this research was to determine the optimal size of a photovoltaic/battery energy storage (PV/BES) system for powering a sensor network efficiently. The study involved a technical-economic optimization to determine the optimal size of the PV/BES system. Sensitivity analyses were performed to evaluate the effect of changes in energy generation and load consumption on the Robustness Index (RI). A dynamic energy analysis was also conducted using the optimal size derived from the first analysis to determine the dynamic behavior of the energy system. Finally, the proposed system implementation was validated.

The use of a PV/BES system ensures a reliable and sustainable power supply, making it ideal for remote and off-grid applications. NB-IoT communications ensure low power consumption and reduced packet loss, demonstrating an excellent communication reliability with a packet loss rate of 0.89%, while a range of water quality parameters are collected for comprehensive monitoring. For the cloud server layer, an open source database management system (MySQL) is used to ensure reliable database operation.

However, the use of PV modules may not be possible in all locations, and NB-IoT communications may be limited in areas with poor network coverage. The complexity of the monitoring system may also make it difficult for non-experts to use or maintain, while the cost of PV modules may be prohibitive in some cases.

The optimal size of the PV/BES system was determined to be a PV capacity of 50 W and a BES capacity of 480 Wh to achieve an RI of 100%. The proposed PV/BES system was implemented and validated in a WQMS in Thailand. The system consisted of a PV panel, a battery bank, a charge controller, a DC-DC converter, and the data acquisition system. The PV/BES system was capable of providing power to the monitoring station for up to 30 days, even during periods of low solar radiation. The data acquisition system was also capable of sending real-time water quality data to a central server using a cellular network.

According to the results of the field validation, the PV/BES system proposed in this study successfully met the power requirements of the water quality monitoring system, with a 100% reliability index indicating continuous power supply without interruption. Additionally, the system's levelized cost of energy (LCOE) was relatively low, suggesting that it was economically feasible for this application.

Overall, this study demonstrates the potential of using a PV/BES system to power NB-IoT SWQMS to achieve efficient data transmission. It offers valuable insights into the optimal sizing of the system and how it responds to changes in PV generation and load consumption. Furthermore, the study provides evidence of the system's feasibility and effectiveness through a successful field implementation, which shows a continuous operation without losing power supply allowing WQM continuously in the NB-IoT network.

VI. CONCLUSION

This review paper describes the advantages of implementing a WSN for WQM, compared to existing traditional methods for evaluating the vital parameters of bodies of water. It presents a standardization that allows the SWQMS to be divided into data collection, transmission, and data management subsystems, so that each one meets QoS requirements. This standardization facilitates the understanding of the network, as well as the implementation, operation, and maintenance, and promotes best practices for the development of each subsystem.

A general guide is provided for selecting the appropriate sensor or sensors for the node, emphasizing that this choice is closely linked to the quality parameters that need to be evaluated. Given the specific application of WQM, it is of utmost importance that sensor nodes are as energy-efficient as possible, which is why special emphasis is placed on the development of hardware architecture with low power consumption. The choice of a low-power MCU, together with an adequate power source and proper energy management, is crucial for extending the life of the node.

The review of existing network solutions indicates a strong preference for LPWAN technologies for WQM, primarily due to their low power characteristics and wide coverage. However, there is the possibility of combining long-range technologies for communication between nodes located in a remote area and a base station, with technologies such as Wi-Fi HaLow, in order to provide internet connectivity. Of the applications reviewed, few consider the development of complex networks involving the deployment of many sensor nodes. Additionally, no applications have been reported that use technologies such as Wi-Fi HaLow or Ingenu RPMA, which provides an opportunity for future developments.

The three dissected case studies serve to provide a deep insight into relevant applications in the LPWAN area. These applications clearly demonstrate the very low energy consumption and the possibility of integration with energy harvesting techniques, in order to further expand the life of the SWQMS. It is also demonstrated that the success of implementations requires multidisciplinary knowledge, meaning that applications should incorporate knowledge of aquaculture, wireless networks, data management, electrical circuits and microcontroller programming, database management, and skills in using platforms for visualizing monitored parameters.

Machine Learning techniques are also present in different areas of SWQMS; in this review, the importance they are taking for locating sensor nodes, selecting optimal routes for data transmission, and undoubtedly for predicting water quality is highlighted. Implementing ML in WSN for WQM is expected to be of fundamental importance for improving the applications developed in the future, both for more efficient energy management and for better data interpretation.

The identification and implementation of the concepts, techniques, and solutions developed in this review paper seek to improve the contextualization of WSN for WQM, so that future work is structured according to the QoS-compliant standard of subsystems described, and select the best components and protocols so that the specific needs of the application are met.

REFERENCES

[1] J. Bartram and R. Ballance, *Water Quality Monitoring: A Practical Guide to the Design and Implementation of Freshwater Quality Studies and Monitoring Programmes*. World Health Org., United Nations Environ. Programme, E & FN Spon, 1996. [Online]. Available: https://apps.who.int/iris/handle/10665/41851

[2] *Summary Progress Update 2021: SDG 6-Water and Sanitation for All*, UN Water, Geneva Switzerland, 2021.

[3] *The United Nations World Water Development Report 2023*, UN Water, Geneva Switzerland, 2023.

[4] D. Evans, "The internet of things. How the next evolution of the internet is changing everything," Cisco Internet Business Solutions Group (IBSG), Whitepaper, 2011. [Online]. Available: https://www.cisco.com/c/dam/en_us/about/ac79/docs/innov/IoT_IBSG_0411FINAL.pdf

[5] H.-C. Lee, Y.-C. Chang, and Y.-S. Huang, "A reliable wireless sensor system for monitoring mechanical wear-out of parts," *IEEE Trans. Instrum. Meas.*, vol. 63, no. 10, pp. 2488–2497, Oct. 2014, doi: 10.1109/TIM.2014.2312498.

[6] J. Gutiérrez, J. F. Villa-Medina, A. Nieto-Garibay, and M. Á. Porta-Gándara, "Automated irrigation system using a wireless sensor network and GPRS module," *IEEE Trans. Instrum. Meas.*, vol. 63, no. 1, pp. 166–176, Jan. 2014, doi: 10.1109/TIM.2013.2276487.

[7] J. P. Amaro, R. Cortesão, J. Landeck, and F. J. T. E. Ferreira, "Harvested power wireless sensor network solution for disaggregated current estimation in large buildings," *IEEE Trans. Instrum. Meas.*, vol. 64, no. 7, pp. 1847–1857, Jul. 2015, doi: 10.1109/TIM.2014.2383052.

[8] S. Yoon, W. Ye, J. Heidemann, B. Littlefield, and C. Shahabi, "SWATS: Wireless sensor networks for steamflood and waterflood pipeline monitoring," *IEEE Netw.*, vol. 25, no. 1, pp. 50–56, Jan. 2011.

[9] M. Hulea, G. Mois, S. Folea, L. Miclea, and V. Biscu, "Wi-sensors: A low power Wi-Fi solution for temperature and humidity measurement," in *Proc. 39th Annu. Conf. IEEE Ind. Electron. Soc.*, Nov. 2013, pp. 4011–4015.

[10] M. Collotta and G. Pau, "A novel energy management approach for smart homes using Bluetooth low energy," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 12, pp. 2988–2996, Dec. 2015, doi: 10.1109/JSAC.2015.2481203.

[11] S. O. Olatinwo and T.-H. Joubert, "Enabling communication networks for water quality monitoring applications: A survey," *IEEE Access*, vol. 7, pp. 100332–100362, 2019, doi: 10.1109/ACCESS.2019.2904945.

[12] D. Dhayal and M. K. Choudhary, "Water quality monitoring using wireless sensor network technology," *Pharma Innov. J.*, vol. 11, no. 11, pp. 17–21, 2022. [Online]. Available: www.thepharmajournal.com

[13] K. S. Adu-Manu, C. Tapparello, W. Heinzelman, F. A. Katsriku, and J.-D. Abdulai, "Water quality monitoring using wireless sensor networks: Current trends and future research directions," *ACM Trans. Sensor Netw.*, vol. 13, no. 1, pp. 1–41, Jan. 2017, doi: 10.1145/3005719.

[14] J. Dong, G. Wang, H. Yan, J. Xu, and X. Zhang, "A survey of smart water quality monitoring system," *Environ. Sci. Pollut. Res.*, vol. 22, no. 7, pp. 4893–4906, Apr. 2015, doi: 10.1007/s11356-014-4026-x.

[15] M. Pule, A. Yahya, and J. Chuma, "Wireless sensor networks: A survey on monitoring water quality," *J. Appl. Res. Technol.*, vol. 15, no. 6, pp. 562–570, Dec. 2017, doi: 10.1016/j.jart.2017.07.004.

[16] M. Miller, A. Kisiel, D. Cembrowska-Lech, I. Durlik, and T. Miller, "IoT in water quality monitoring—Are we really here?" *Sensors*, vol. 23, no. 2, p. 960, Jan. 2023, doi: 10.3390/s23020960.

[17] *UNEP Evaluation Manual*, United Nations Environment Programme Evaluation Office, Nairobi Kenya, 2022. [Online]. Available: https://wedocs.unep.org/bitstream/handle/20.500.11822/42025/2023%200903%20Evaluation%20Manual.pdf?sequence=1&isAllowed=y

[18] S. Promput, S. Maithomklang, and C. Panya-isara, "Design and analysis performance of IoT-based water quality monitoring system using LoRa technology," *TEM J.*, vol. 12, pp. 29–35, Feb. 2023, doi: 10.18421/TEM121-04.

[19] O. S. Adedoja, Y. Hamam, B. Khalaf, and R. Sadiku, "A state-of-the-art review of an optimal sensor placement for contaminant warning system in a water distribution network," *Urban Water J.*, vol. 15, no. 10, pp. 985–1000, Nov. 2018, doi: 10.1080/1573062X.2019.1597378.

[20] S. Rathi and R. Gupta, "Sensor placement methods for contamination detection in water distribution networks: A review," *Proc. Eng.*, vol. 89, pp. 181–188, Jan. 2014, doi: 10.1016/j.proeng.2014.11.175.

[21] S. Tsitsifli and V. Kanakoudis, "Identification of suitable locations in a small water supply network for the placement of water quality sensors based on different criteria under demand-driven conditions," *Water*, vol. 14, no. 16, p. 2504, Aug. 2022, doi: 10.3390/w14162504.

[22] S. M. Cardoso, D. B. Barros, E. Oliveira, B. Brentan, and L. Ribeiro, "Optimal sensor placement for contamination detection: A multi-objective and probabilistic approach," *Environ. Model. Softw.*, vol. 135, Jan. 2021, Art. no. 104896, doi: 10.1016/j.envsoft.2020.104896.

[23] J.-G. Lee, S. Chim, and H.-H. Park, "Energy-efficient cluster-head selection for wireless sensor networks using sampling-based spider monkey optimization," *Sensors*, vol. 19, no. 23, p. 5281, Nov. 2019, doi: 10.3390/s19235281.

[24] H. Sharma, A. Haque, and F. Blaabjerg, "Machine learning in wireless sensor networks for smart cities: A survey," *Electronics*, vol. 10, no. 9, p. 1012, Apr. 2021, doi: 10.3390/electronics10091012.

[25] M. Kwon, J. Lee, and H. Park, "Intelligent IoT connectivity: Deep reinforcement learning approach," *IEEE Sensors J.*, vol. 20, no. 5, pp. 2782–2791, Mar. 2020, doi: 10.1109/JSEN.2019.2949997.
[26] C. Xu, Z. Xiong, G. Zhao, and S. Yu, "An energy-efficient region source routing protocol for lifetime maximization in WSN," *IEEE Access*, vol. 7, pp. 135277–135289, 2019, doi: 10.1109/ACCESS.2019.2942321.
[27] A. Kumar, M. Zhao, K.-J. Wong, Y. L. Guan, and P. H. J. Chong, "A comprehensive study of IoT and WSN MAC protocols: Research issues, challenges and opportunities," *IEEE Access*, vol. 6, pp. 76228–76262, 2018, doi: 10.1109/ACCESS.2018.2883391.
[28] S. Geetha and S. Gouthami, "Internet of Things enabled real time water quality monitoring system," *Smart Water*, vol. 2, no. 1, pp. 1–19, Dec. 2016, doi: 10.1186/s40713-017-0005-y.
[29] S. Sandha, S. Randhawa, B. Srivastava, and S. S. Sandha. (2015). *Blue Water: A Common Platform to Put Water Quality Data in India to Productive Use by Integrating Historical and Real-time Sensing Data*. [Online]. Available: http://domino.watson.ibm.com/library/CyberDig.nsf/home
[30] O. Nathan, S. Esomu, J. D. Cruz, and C. Rica, "Implementation of an IoT-based water quality monitoring system in water battery electricity generation plants," National Open Univ. Nigeria, Abuja, Nigeria, Tech. Rep., 2022.
[31] W. M. Sanya, M. A. Alawi, and I. Eugenio, "Design and development of smart water quality monitoring system using IoT," *Int. J. Adv. Sci. Res. Eng.*, vol. 8, no. 3, pp. 1–13, 2022, doi: 10.31695/ijasre.2022.8.3.1.
[32] N. Vijayakumar and R. Ramya, "The real time monitoring of water quality in IoT environment," in *Proc. Int. Conf. Innov. Inf., Embedded Commun. Syst.*, 2015, pp. 1–5.
[33] Y. H. Kim, J. Im, H. K. Ha, J.-K. Choi, and S. Ha, "Machine learning approaches to coastal water quality monitoring using GOCI satellite data," *GISci. Remote Sens.*, vol. 51, no. 2, pp. 158–174, Mar. 2014, doi: 10.1080/15481603.2014.900983.
[34] A.-A. Nayan, J. Saha, A. N. Mozumder, K. R. Mahmud, A. K. Al Azad, and M. G. Kibria, "A machine learning approach for early detection of fish diseases by analyzing water quality," *Trends Sci.*, vol. 18, no. 21, p. 351, Oct. 2021, doi: 10.48048/tis.2021.351.
[35] S. Pappu, P. Vudatha, and S. Sankaranarayanan. (2017). *Intelligent IoT Based Water Quality Monitoring System*. [Online]. Available: http://www.ripublication.com
[36] L. Gutiérrez-Madroñal, L. La Blunda, M. F. Wagner, and I. Medina-Bulo, "Test event generation for a fall-detection IoT system," *IEEE Internet Things J.*, vol. 6, no. 4, pp. 6642–6651, Aug. 2019, doi: 10.1109/JIOT.2019.2909434.
[37] M. Zhu, J. Wang, X. Yang, Y. Zhang, L. Zhang, H. Ren, B. Wu, and L. Ye, "A review of the application of machine learning in water quality evaluation," *Eco-Environ. Health*, vol. 1, no. 2, pp. 107–116, Jun. 2022, doi: 10.1016/j.eehl.2022.06.001.
[38] M. Singh and S. Ahmed, "IoT based smart water management systems: A systematic review," *Mater. Today, Proc.*, vol. 46, pp. 5211–5218, Jan. 2020, doi: 10.1016/j.matpr.2020.08.588.
[39] N. H. Omer, "Water quality parameters," in *Water Quality-Science, Assessments and Policy*. U.K.: IntechOpen, 2019, pp. 1–34.
[40] *Guidelines for Drinking-water Quality*, World Health Organization, Geneva, Switzerland, 2017.
[41] I. Yaroshenko, D. Kirsanov, M. Marjanovic, P. A. Lieberzeit, O. Korostynska, A. Mason, I. Frau, and A. Legin, "Real-time water quality monitoring with chemical sensors," *Sensors*, vol. 20, p. 3432, Jun. 2020, doi: 10.3390/s20123432.
[42] S. A. Jaywant and K. M. Arif, "A comprehensive review of microfluidic water quality monitoring sensors," *Sensors*, vol. 19, no. 21, p. 4781, Nov. 2019, doi: 10.3390/s19214781.
[43] J. Bhardwaj, K. Gupta, and R. Gupta, "A review of emerging trends on water quality measurement sensors," in *Proc. Int. Conf. Technol. Sustain. Develop.*, 2015, pp. 1–6.
[44] M. Manoj, V. Dhilip Kumar, M. Arif, E.-R. Bulai, P. Bulai, and O. Geman, "State of the art techniques for water quality monitoring systems for fish ponds using IoT and underwater sensors: A review," *Sensors*, vol. 22, no. 6, p. 2088, Mar. 2022, doi: 10.3390/s22062088.
[45] W. J. Hong, N. Shamsuddin, E. Abas, R. A. Apong, Z. Masri, H. Suhaimi, S. H. Gödeke, and M. N. A. Noh, "Water quality monitoring with Arduino based sensors," *Environments*, vol. 8, no. 1, pp. 1–15, Mar. 2021, doi: 10.3390/environments8010006.
[46] R. de Fátima, B. Ali, and A. Shemshad, "River water quality monitoring through IoT enabled technologies," *Computational Algorithms Numer. Dimensions*, vol. 1, no. 1, pp. 35–39, 2021.
[47] B. O'Flynn, R. Martinez-Catala, S. Harte, C. O'Mathuna, J. Cleary, C. Slater, F. Regan, D. Diamond, and H. Murphy, "SmartCoast: A wireless sensor network for water quality monitoring," in *Proc. 32nd IEEE Conf. Local Comput. Netw. (LCN)*, Oct. 2007, pp. 919–926, doi: 10.1109/LCN.2007.34.
[48] C. Hernández, V. Benítez, and J. Pacheco, "Wireless sensor networks for water quality monitoring: Prototype design," *Int. J. Environ. Ecol. Eng.*, vol. 10, no. 2, pp. 162–167, 2016.
[49] B. Sun, F. Ahmed, F. Retiz, and Q. Qian, "Development and implementation of wireless sensor networks (WSNs) for measuring water quality," in *Proc. World Environ. Water Resour. Congr.*, 2014, pp. 836–845.
[50] B. O'Flynn, F. Regan, A. Lawlor, J. Wallace, J. Torres, and C. O'Mathuna, "Experiences and recommendations in deploying a real-time, water quality monitoring system," *Meas. Sci. Technol.*, vol. 21, no. 12, Dec. 2010, Art. no. 124004, doi: 10.1088/0957-0233/21/12/124004.
[51] G. M. E. Silva, D. F. Campos, J. A. T. Brasil, M. Tremblay, E. M. Mendiondo, and F. Ghiglieno, "Advances in technological research for online and in situ water quality monitoring—A review," *Sustainability*, vol. 14, no. 9, p. 5059, Apr. 2022, doi: 10.3390/su14095059.
[52] V. Angadi, A. Karadge, N. Sanadi, A. P. Shingade and D. Ghate. (2022). *Water Quality Monitoring System*. [Online]. Available: www.ijrpr.com
[53] N. M. Ansari, T. Tariq, M. S. Alam, R. Iqbal, R. Azeem, A. Nasir, and S. Rana, "Design and performance evaluation of low-cost IoT-based water quality monitoring device using WSN," *J. Hunan Univ. Natural Sci.*, vol. 59, pp. 29–35, Nov. 2022, doi: 10.17605/OSF.IO/C6PYU.
[54] S.-C. Yang and Y. Pan, "The application of the wireless sensor network (WSN) in the monitoring of Fushun reach river in China," in *Proc. 2nd Int. Conf. Comput. Netw. Technol.*, Apr. 2010, pp. 331–333, doi: 10.1109/ICCNT.2010.70.
[55] A. Khalifeh, F. Mazunga, A. Nechibvute, and B. M. Nyambo, "Microcontroller unit-based wireless sensor network nodes: A review," *Sensors*, vol. 22, no. 22, p. 8937, Nov. 2022, doi: 10.3390/s22228937.
[56] T. Shu, "Power management in a sensor network for automated water quality monitoring," Univ. British Columbia, Tech. Rep., 2016, doi: 10.14288/1.0300325.
[57] Z. Hao, "Water quality monitoring through IoT enabled technology," *Comput. Algorithms Numer. Dimensions*, vol. 1, no. 3, pp. 116–121, 2022, doi: 10.22105/cand.2022.161802.
[58] M. Maksimovic, V. Vujovic, N. Davidović, V. Milosevic, and B. Perisic. (2015). *Raspberry PI as Internet of Things Hardware: Performances and Constraints*. [Online]. Available: https://www.researchgate.net/publication/280344140
[59] V. Vujovic and M. Maksimovic, "Raspberry PI as a wireless sensor node: Performances and constraints," in *Proc. 37th Int. Conv. Inf. Commun. Technol., Electron. Microelectroon. (MIPRO)*, May 2014, pp. 1013–1018, doi: 10.1109/MIPRO.2014.6859717.
[60] H.-Y. Miao, C.-T. Yang, E. Kristiani, H. Fathoni, Y.-S. Lin, and C.-Y. Chen, "On construction of a campus outdoor air and water quality monitoring system using LoRaWAN," *Appl. Sci.*, vol. 12, no. 10, p. 5018, May 2022, doi: 10.3390/app12105018.
[61] G. Kazdaridis, N. Sidiropoulos, I. Zografopoulos, P. Symeonidis, and T. Korakis, "The ICARUS mote: Employing off-chip RTC to attain 22 nA sleep current in duty-cycled IoT devices," in *Proc. 10th Int. Conf. Internet Things Companion*, Oct. 2020, pp. 1–4, doi: 10.1145/3423423.3423469.
[62] S. Misra, S. K. Roy, A. Roy, M. S. Obaidat, and A. Jha, "MEGAN: Multipurpose energy-efficient, adaptable, and low-cost wireless sensor node for the Internet of Things," *IEEE Syst. J.*, vol. 14, no. 1, pp. 144–151, Mar. 2020, doi: 10.1109/JSYST.2019.2920099.
[63] G. Mois, T. Sanislav, and S. C. Folea, "A cyber-physical system for environmental monitoring," *IEEE Trans. Instrum. Meas.*, vol. 65, no. 6, pp. 1463–1471, Jun. 2016, doi: 10.1109/TIM.2016.2526669.
[64] Z. Wang, Q. Wang, and X. Hao, "The design of the remote water quality monitoring system based on WSN," in *Proc. 5th Int. Conf. Wireless Commun., Netw. Mobile Comput.*, 2009, pp. 1–4.
[65] F. Karray, M. W. Jmal, A. Garcia-Ortiz, M. Abid, and A. M. Obeid, "A comprehensive survey on wireless sensor node hardware platforms," *Comput. Netw.*, vol. 144, pp. 89–110, Oct. 2018, doi: 10.1016/j.comnet.2018.05.010.
[66] S. García, D. F. Larios, J. Barbancho, E. Personal, J. M. Mora-Merchán, and C. León, "Heterogeneous LoRa-based wireless multimedia sensor network multiprocessor platform for environmental monitoring," *Sensors*, vol. 19, no. 16, p. 3446, Aug. 2019, doi: 10.3390/s19163446.

[67] S. C. Folea and G. Mois, "A low-power wireless sensor for online ambient monitoring," *IEEE Sensors J.*, vol. 15, no. 2, pp. 742–749, Feb. 2015, doi: 10.1109/JSEN.2014.2351420.

[68] T. Bhowmik, R. Mojumder, D. Ghosh, and I. Banerjee, "Efficient scheduling algorithm based on duty-cycle for e-Health monitoring system," in *Proc. Int. Conf. Comput. Intell. Pattern Recognit.*, Jun. 2022, pp. 211–220, doi: 10.1007/978-981-19-3089-8_21.

[69] Y. Tripathi, A. Prakash, and R. Tripathi, "A novel slot scheduling technique for duty-cycle based data transmission for wireless sensor network," *Digit. Commun. Netw.*, vol. 8, no. 3, pp. 351–358, Jun. 2022, doi: 10.1016/j.dcan.2022.01.006.

[70] P. Singh and M. Lata, "Enhancement of the solar energy harvesting system for WSN nodes through INC-MPPT: A review," Dogo Rangsang Res. J., UGC Care Group I J., Tech. Rep., Sep. 2019, vol. 12, no. 9.

[71] H. Sharma, A. Haque, and Z. A. Jaffery, "Maximization of wireless sensor network lifetime using solar energy harvesting for smart agriculture monitoring," *Ad Hoc Netw.*, vol. 94, Nov. 2019, Art. no. 101966, doi: 10.1016/j.adhoc.2019.101966.

[72] F. M. E. Haroun, S. N. M. Deros, A. A. Alkahtani, and N. M. Din, "Towards self-powered WSN: The design of ultra-low-power wireless sensor transmission unit based on indoor solar energy harvester," *Electronics*, vol. 11, no. 13, p. 2077, Jul. 2022, doi: 10.3390/electronics11132077.

[73] S. Sarang, G. M. Stojanovic, M. Drieberg, S. Stankovski, K. Bingi, and V. Jeoti, "Machine learning prediction based adaptive duty cycle MAC protocol for solar energy harvesting wireless sensor networks," *IEEE Access*, vol. 11, pp. 17536–17554, 2023, doi: 10.1109/ACCESS.2023.3246108.

[74] L. G. Tran, H. K. Cha, and W. T. Park, "RF power harvesting: A review on designing methodologies and applications," *Micro Nano Syst. Lett.*, vol. 5, no. 1, pp. 1–16, 2017, doi: 10.1186/s40486-017-0051-0.

[75] D. Mishra, S. De, S. Jana, S. Basagni, K. Chowdhury, and W. Heinzelman, "Smart RF energy harvesting communications: Challenges and opportunities," *IEEE Commun. Mag.*, vol. 53, no. 4, pp. 70–78, Apr. 2015.

[76] J. C. Kwan and A. O. Fapojuwo, "Radio frequency energy harvesting and data rate optimization in wireless information and power transfer sensor networks," *IEEE Sensors J.*, vol. 17, no. 15, pp. 4862–4874, Aug. 2017, doi: 10.1109/JSEN.2017.2714130.

[77] S. Olatinwo and T.-H. Joubert, "Optimizing the energy and throughput of a water-quality monitoring system," *Sensors*, vol. 18, no. 4, p. 1198, Apr. 2018, doi: 10.3390/s18041198.

[78] S. Alshattnawi, L. Afifi, A. M. Shatnawi, and M. M. Barhoush, "Utilizing genetic algorithm and artificial bee colony algorithm to extend the WSN lifetime," *Int. J. Comput.*, vol. 21, pp. 25–31, Mar. 2022, doi: 10.47839/ijc.21.1.2514.

[79] H. Alwazani and A. Chaaban, "IRS-enabled ultra-low-power wireless sensor networks: Scheduling and transmission schemes," *Sensors*, vol. 22, no. 23, p. 9229, Nov. 2022, doi: 10.3390/s22239229.

[80] H.-C. Lee and H.-H. Lin, "Design and evaluation of an open-source wireless mesh networking module for environmental monitoring," *IEEE Sensors J.*, vol. 16, no. 7, pp. 2162–2171, Apr. 2016, doi: 10.1109/JSEN.2015.2507596.

[81] D. Wang, R. Xu, X. Hu, and W. Su, "Energy-efficient distributed compressed sensing data aggregation for cluster-based underwater acoustic sensor networks," *Int. J. Distrib. Sensor Netw.*, vol. 12, no. 3, Mar. 2016, Art. no. 8197606, doi: 10.1155/2016/8197606.

[82] *IEEE Standard for Low-Rate Wireless Networks*, IEEE, Standard 802.15.4, 2020.

[83] J. M. Moreno and D. Ruiz. *Informe Técnico: Protocolo ZigBee*, IEEE Standard 802.15.4, 2007.

[84] S. Sharma and A. Sarkar, "Solar powered water quality monitoring system using Zig-Bee," *J. Intell. Comput. Math.*, vol. 1, pp. 36–41, Apr. 2022, doi: 10.55571/jicm.2022.04015.

[85] A. A. Allahham and M. A. Rahman, "A smart monitoring system for campus using ZigBee wireless sensor networks," *Int. J. Softw. Eng. Comput. Syst.*, vol. 4, no. 1, pp. 1–14, Feb. 2018, doi: 10.15282/ijsecs.4.1.2018.1.0034.

[86] D. Jenzeri and A. Chehri, "Data analysis for IoT system using 6LoWPAN and constrained application protocol for environmental monitoring," *Proc. Comput. Sci.*, vol. 207, pp. 1472–1481, Jan. 2022, doi: 10.1016/j.procs.2022.09.204.

[87] X. Wang, Y. Feng, J. Sun, D. Li, and H. Yang, "Research on Fishery water quality monitoring system based on 6LoWPAN," *J. Phys., Conf.*, vol. 1624, no. 4, Oct. 2020, Art. no. 042057, doi: 10.1088/1742-6596/1624/4/042057.

[88] B. U. Adarsh, D. B. Divya, K. R. Shobba, K. Natarajan, A. Paventhan, S. K. Allu, and N. Pahuja, "Design of 6LoWPAN enabled real time water quality monitoring system using CoAP," in *Proc. Asia–Pacific Adv. Netw.*, vol. 38, Dec. 2014, pp. 42–54, doi: 10.7125/apan.38.7.

[89] S. Anjana, M. N. Sahana, S. Ankith, K. Natarajan, K. R. Shobha, and A. Paventhan, "An IoT based 6lowpan enabled experiment for water management," in *Proc. IEEE Int. Conf. Adv. Netw. Telecommuncations Syst.*, Dec. 2015, pp. 1–6.

[90] G. Mois, S. Folea, and T. Sanislav, "Analysis of three IoT-based wireless sensors for environmental monitoring," *IEEE Trans. Instrum. Meas.*, vol. 66, no. 8, pp. 2056–2064, Aug. 2017, doi: 10.1109/TIM.2017.2677619.

[91] W. Jo, Y. Hoashi, L. L. P. Aguilar, M. Postigo-Malaga, J. M. Garcia-Bravo, and B.-C. Min, "A low-cost and small USV platform for water quality monitoring," *HardwareX*, vol. 6, Oct. 2019, Art. no. e00076, doi: 10.1016/j.ohx.2019.e00076.

[92] N. Abdul, J. Salih, I. J. Hasan, and N. I. Abdulkhaleq, "Design and implementation of a smart monitoring system for water quality of fish farms," *Indonesian J. Electr. Eng. Comput. Sci.*, vol. 14, no. 1, pp. 45–52, 2019, doi: 10.11591/ijeecs.v14.i1.pp45-52.

[93] R. Bogdan, C. Paliuc, M. Crisan-Vida, S. Nimara, and D. Barmayoun, "Low-cost Internet-of-Things water-quality monitoring system for rural areas," *Sensors*, vol. 23, no. 8, p. 3919, Apr. 2023, doi: 10.3390/s23083919.

[94] *IEEE Standard for Information Technology–Telecommunications and Information Exchange between Systems—Local and Metropolitan Area Networks–Specific Requirements—Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications—Corrigendum 1—Correct IEEE 802.11ay Assignment of Protected Announce Support Bit*, IEEE Standard 802.11-2020/Cor, 2022.

[95] Y. Chen and D. Han, "Water quality monitoring in smart city: A pilot project," *Autom. Construction*, vol. 89, pp. 307–316, May 2018, doi: 10.1016/j.autcon.2018.02.008.

[96] H. Khaleeq, A. Abou-ElNour, and M. Tarique, "A reliable wireless system for water quality monitoring and level control," *Netw. Protocols Algorithms*, vol. 8, no. 3, p. 1, Dec. 2016, doi: 10.5296/npa.v8i3.9719.

[97] E. Khorov, A. Lyakhov, A. Krotov, and A. Guschin, "A survey on IEEE 802.11ah: An enabling networking technology for smart cities," *Comput. Commun.*, vol. 58, pp. 53–69, Mar. 2015, doi: 10.1016/j.comcom.2014.08.008.

[98] T. Adame, A. Bel, B. Bellalta, J. Barcelo, and M. Oliver, "IEEE 802.11AH: The WiFi approach for M2M communications," *IEEE Wireless Commun.*, vol. 21, no. 6, pp. 144–152, Dec. 2014.

[99] B. K. Prasad and B. Sinha, "Empowering IoT through improving technology," in *Proc. MDPI AG*, Feb. 2023, p. 12633, doi: 10.3390/mol2net-08-12633.

[100] R. Verhoeven, S. Kempinski, and N. Meratnia, "Performance evaluation of Wi-Fi HaLow, NB-IoT and LoRa for smart city applications," in *Proc. 19th ACM Int. Symp. Perform. Eval. Wireless Ad Hoc, Sensor, Ubiquitous Netw., 19th ACM Int. Symp. Perform. Eval. Wireless Ad Hoc, Sensor, Ubiquitous Netw.*, Oct. 2022, pp. 17–24, doi: 10.1145/3551663.3558596.

[101] L. Tian, S. Deronne, S. Latré, and J. Famaey, "Implementation and validation of an IEEE 802.11ah module for ns-3," in *Proc. Workshop Ns-WNS*, 2016, pp. 49–56, doi: 10.1145/2915371.2915372.

[102] R. Dangi, P. Lalwani, G. Choudhary, I. You, and G. Pau, "Study and investigation on 5G technology: A systematic review," *Sensors*, vol. 22, no. 1, p. 26, Dec. 2021, doi: 10.3390/s22010026.

[103] A. Slalmi, H. Chaibi, R. Saadane, A. Chehri, and G. Jeon, "5G NB-IoT: Efficient network call admission control in cellular networks," *Concurrency Comput., Pract. Exper.*, vol. 33, no. 22, p. e6047, Nov. 2021, doi: 10.1002/cpe.6047.

[104] S.-J. Hsiao, "Employing a wireless sensing network for AIoT based on a 5G approach," *Electronics*, vol. 11, no. 5, p. 827, Mar. 2022, doi: 10.3390/electronics11050827.

[105] H. Wang and A. O. Fapojuwo, "A survey of enabling technologies of low power and long range machine-to-machine communications," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 4, pp. 2621–2639, 4th Quart., 2017, doi: 10.1109/COMST.2017.2721379.

[106] *LoRa and LoRaWAN: A Technical Overview LoRa and LoRaWAN: A Technical Overview*, Semtech Corporation, Camarillo, CA, USA, 2020.
[107] S. N. S. Taha. (2022). *Implementation of LoRa in River Water Quality Monitoring*. [Online]. Available: www.um.edu.my
[108] D. Pikulins, R. Gotlaufs, T. Solovjova, A. Aboltins, J. Grizāns, and S. Migla, "On the development of long-range water quality monitoring system for outdoor aquaculture objects," *Electr., Control Commun. Eng.*, vol. 18, no. 1, pp. 37–42, Jun. 2022, doi: 10.2478/ecce-2022-0005.
[109] G. Ferré and E. P. Simon, "An introduction to Sigfox and LoRa PHY and MAC layers," Tech. Rep., 2018. [Online]. Available: https://hal.science/hal-01774080
[110] N. Izzeldin, M. Osman, and E. B. Abbas, "Performance evaluation of LoRa and Sigfox LPWAN technologies for IoT," *Academic J. Res. Sci. Publishing*, vol. 4, pp. 5–6, May 2022. [Online]. Available: www.ajrsp.comwww.ajrsp.com
[111] L. Joris, F. Dupont, P. Laurent, P. Bellier, S. Stoukatch, and J.-M. Redouté, "An autonomous Sigfox wireless sensor node for environmental monitoring," *IEEE Sensors Lett.*, vol. 3, no. 7, pp. 1–4, Jul. 2019, doi: 10.1109/LSENS.2019.2924058.
[112] P. Di Gennaro, D. Lofu, D. Vitanio, P. Tedeschi, and P. Boccadoro, "WaterS: A Sigfox-compliant prototype for water monitoring," *Internet Technol. Lett.*, vol. 2, no. 1, p. e74, Jan. 2019, doi: 10.1002/itl2.74.
[113] F. Pitu and N. C. Gaitan, "Surveillance of Sigfox technology integrated with environmental monitoring," in *Proc. Int. Conf. Develop. Appl. Syst. (DAS)*, May 2020, pp. 69–72.
[114] P. Boccadoro, V. Daniele, P. Di Gennaro, D. Lofù, and P. Tedeschi, "Water quality prediction on a Sigfox-compliant IoT device: The road ahead of WaterS," *Ad Hoc Netw.*, vol. 126, Mar. 2022, Art. no. 102749, doi: 10.1016/j.adhoc.2021.102749.
[115] S. Jung, G. Im, D. Jung, P. Kim, J. G. Ryu, and J. Kang, "Performance analysis of DSSS- and CSS-based physical layer for IoT transmission over LEO satellites," *ETRI J.*, vol. 44, no. 4, pp. 543–559, Aug. 2022, doi: 10.4218/etrij.2021-0038.
[116] M. A. M. Almuhaya, W. A. Jabbar, N. Sulaiman, and S. Abdulmalek, "A survey on LoRaWAN technology: Recent trends, opportunities, simulation tools and future directions," *Electronics*, vol. 11, no. 1, p. 164, Jan. 2022, doi: 10.3390/electronics11010164.
[117] R. S. Sinha, Y. Wei, and S.-H. Hwang, "A survey on LPWA technology: LoRa and NB-IoT," *ICT Exp.*, vol. 3, no. 1, pp. 14–21, Mar. 2017, doi: 10.1016/j.icte.2017.03.004.
[118] A. Khalifeh, K. Aldahdouh, K. Darabkh, and W. Al-Sit, "A survey of 5G emerging wireless technologies featuring LoRaWAN, Sigfox, NB-IoT and LTE-M," in *Proc. Int. Conf. Wireless Commun. Signal Process. Netw.*, 2019, pp. 561–566.
[119] K. Mekki, E. Bajic, F. Chaxel, and F. Meyer, "Overview of cellular LPWAN technologies for IoT deployment: Sigfox, LoRaWAN, and NB-IoT," in *Proc. IEEE Int. Conf. Pervasive Comput. Commun. Workshops (PerCom Workshops)*, Mar. 2018, pp. 197–202.
[120] C. B. Mwakwata, H. Malik, M. Mahtab Alam, Y. Le Moullec, S. Parand, and S. Mumtaz, "Narrowband Internet of Things (NB-IoT): From physical (PHY) and media access control (MAC) layers perspectives," *Sensors*, vol. 19, no. 11, p. 2613, Jun. 2019, doi: 10.3390/s19112613.
[121] C. Yu, L. Yu, Y. Wu, Y. He, and Q. Lu, "Uplink scheduling and link adaptation for narrowband Internet of Things systems," *IEEE Access*, vol. 5, pp. 1724–1734, 2017, doi: 10.1109/ACCESS.2017.2664418.
[122] B. Martinez, F. Adelantado, A. Bartoli, and X. Vilajosana, "Exploring the performance boundaries of NB-IoT," *IEEE Internet Things J.*, vol. 6, no. 3, pp. 5702–5712, Jun. 2019, doi: 10.1109/JIOT.2019.2904799.
[123] L. D. Nguyen, A. E. Kalor, I. Leyva-Mayorga, and P. Popovski, "Trusted wireless monitoring based on distributed ledgers over NB-IoT connectivity," *IEEE Commun. Mag.*, vol. 58, no. 6, pp. 77–83, Jun. 2020.
[124] H. Ji, L. Miao, and J. Dong, "Indoor environment remote monitoring system based on NB-IoT," *IOP Conf. Ser., Mater. Sci. Eng.*, vol. 452, Dec. 2018, Art. no. 022162, doi: 10.1088/1757-899X/452/2/022162.
[125] S. Duangsuwan, A. Takarn, and P. Jamjareegulgarn, "A development on air pollution detection sensors based on NB-IoT network for smart cities," in *Proc. 18th Int. Symp. Commun. Inf. Technol. (ISCIT)*, Sep. 2018, pp. 313–317, doi: 10.1109/ISCIT.2018.8587978.
[126] S. Duangsuwan, A. Takarn, R. Nujankaew, and P. Jamjareegulgarn, "A study of air pollution smart sensors LPWAN via NB-IoT for Thailand smart cities 4.0," in *Proc. 10th Int. Conf. Knowl. Smart Technol. (KST)*, Jan. 2018, pp. 206–209, doi: 10.1109/KST.2018.8426195.
[127] I. Ganchev, Z. Ji, and M. O'droma, "Designing an ultra-low-power RTU for use in NB-IoT water applications," in *Proc. MATEC Web Conf.*, 2019, p. 02004, doi: 10.1051/matecconf/201929202004.
[128] J. Huan, H. Li, F. Wu, and W. Cao, "Design of water quality monitoring system for aquaculture ponds based on NB-IoT," *Aquacultural Eng.*, vol. 90, Aug. 2020, Art. no. 102088, doi: 10.1016/j.aquaeng.2020.102088.
[129] H. Sui, G. Zheng, J. Zhou, H. Li, and Z. Gu, "Application of NB-IoT technology in city open water monitoring," in *Proc. 6th Int. Symp. Syst. Softw. Rel.*, Oct. 2020, pp. 95–98, doi: 10.1109/ISSSR51244.2020.00023.
[130] C. Jamroen, N. Yonsiri, T. Odthon, N. Wisitthiwong, and S. Janreung, "A standalone photovoltaic/battery energy-powered water quality monitoring system based on narrowband Internet of Things for aquaculture: Design and implementation," *Smart Agricult. Technol.*, vol. 3, Feb. 2023, Art. no. 100072, doi: 10.1016/j.atech.2022.100072.
[131] S. Ugwuanyi, G. Paul, and J. Irvine, "Survey of IoT for developing countries: Performance analysis of LoRaWAN and cellular NB-IoT networks," *Electronics*, vol. 10, no. 18, p. 2224, Sep. 2021, doi: 10.3390/electronics10182224.

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