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Survey paper

A survey on massive IoT for water distribution systems: Challenges, simulation tools, and guidelines for large-scale deployment

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ABSTRACT

This survey explores the convergence of Internet of Things (IoT) technologies with Water Distribution Systems (WDSs), focusing on large-scale deployments and the role of edge computing (EC). Effective water management increasingly relies on IoT monitoring, resulting in massive deployments and the generation of Big Data. While previous research has examined these topics individually, this work integrates them into a comprehensive analysis. We systematically reviewed 255 studies on IoT in WDS, identifying key challenges such as interoperability, scalability, energy efficiency, network coverage, and reliability. We also examined technologies like LPWAN and the growing use of EC for real-time data processing. In large-scale WDS scenarios, where vast amounts of data are generated, we highlighted the importance of technologies like NB-IoT, SigFox, and LoRaWAN due to their low power consumption and wide coverage. Based on our findings, we provide guidelines for sustainable, large-scale IoT deployment in WDS, emphasizing the need for edge data processing to reduce cloud dependency, improve scalability, and enable smarter cities and digital twins.

1. Introduction

Water Distribution Systems (WDSs) optimization and digitalization are becoming key objectives in our modern society. Global water consumption is constantly increasing, having a huge demand increment each year while on the other side the world is facing a global water deficit, foreseen to be about 40% by 2030 [1]. Climate change is going to make the situation worse. Current changes in temperatures, storms and rain behaviors urgently require better management of water distribution between different regions.

At the same time, massive amounts of water are lost because of leakages mainly due to dated water distribution infrastructures. According to recent statistics of the European Federation of National Associations of Water Services (EurEau), the average value of water lost is about 26% in Europe [2], although this value can even be higher than 50% in some regions. In this context, it is of paramount importance to invest in Information and Communication Technologies (ICTs) solutions that will help improve the monitoring and the management of WDSs. Internet of Things (IoT) technologies, and especially those equipped with Low Power Wide Area Network (LPWAN), have become a consolidated way to deploy applications to monitor and control smart systems at a large scale [3]. Indeed, the advantages of LPWAN architectures include a wide coverage, in the order of kilometers, and a low power consumption, with batteries lasting up to 10 years. Additionally, a majority of existing Smart Water Distribution Systems (SWDSs) operate primarily by gathering data from terminal points and transmitting this information to cloud servers for centralized analysis. This process can be visualized in Fig. 1. The sequence begins with data generation at the meter level, followed by collection via the concentrator. The IoT operator then processes this information before it is ultimately relayed to the water operator through dedicated Application server.

Implementing a Smart Water Grid (SWG) in massive scenarios poses its own set of challenges. For instance, the coexistence of multiple IoT technologies could lead to interference phenomena, causing packet or data loss. Ensuring the reliability of these massive IoT systems is crucial, as loss of information could result in serious consequences, such as the waste of thousands of liters of water. With water resources

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Table 1
Graphical outline of the survey: Structure and main points.

Section	Name	Content
1	Introduction	Introduction to SWDS in Massive Scenarios.
2	Related Surveys	Comparison with related Surveys, Overviews, and Reviews in the context of SWDSs
3	Research Method	Research Questions, Inclusion and Exclusion Criteria, Search and Selection Procedure, Data Extraction
4	Bibliometrics Results	Distribution by Type of Venue, Distribution by Location, Distribution by Affiliation
5	Challenges in IoT for WDS (RQ1)	Selection of IoT technologies for WDSs, Interoperability and Heterogeneity, Scalability, Power Consumption and Energy Efficiency, Network Coverage and Reliability, Edge Computing, Measurement and Sensing, WDS Applications, Summary and Main Findings
6	IoT Technologies for Water Systems Monitoring (RQ2)	LoRaWAN, SigFox, Fog vs. Edge in IoT for WDS, Summary and Main Findings
7	Edge Computing in Massive IoT for WDS (RQ3)	Description, Summary and Main Findings
8	WDS in Large Scale Scenarios (RQ4)	Description, Summary and Main Findings
9	Simulation Tools for Massive IoT in WDSs (RQ5)	Water Network Simulation Tools (WNTR, WaterGEMS, WaterCAD, WDNetXL, MATLAB), Wireless Sensor Network Simulation Tools (ns-3, OMNeT++, LoRaSim, SEAMCAT), Summary and Main Findings
10	Lessons Learned and Guidelines for Sustainable Large-Scale Deployment	Introduction and description of the framework as a holistic approach
11	Discussion and Future Directions	Discussion of challenges and future research topics
12	Conclusions	

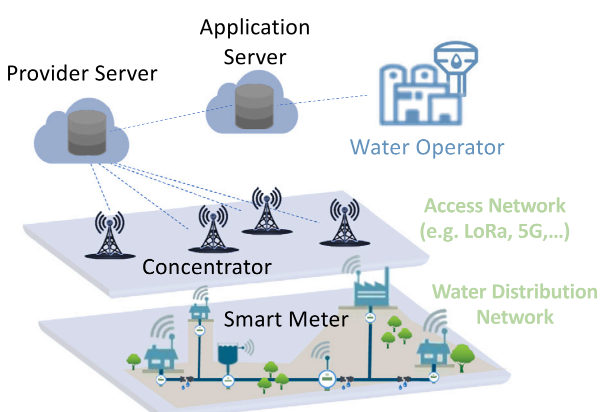

Fig. 1. IoT architecture in SWDSs.

increasingly limited, it is essential to find new and innovative ways to manage and distribute this vital resource.

Most of relevant literature focus on the study of WDS, concentrating solely on either wireless networks or only water-related aspects, leaving just a few that address a holistic analysis of massive IoT scenarios in WDSs.

On this context, the primary goal of the present article is to conduct an in-depth study of WDS in massive scenarios, listing the challenges to be faced in integrating IoT technology into these scenarios. Another goal is to create a complete comparison of the current literature on this topic and, based on the latter, design and provide the scientific community with guidelines for sustainable and large scale deployment for the future. Consequently, we introduce a new framework that represents our vision for studying WDS in massive scenarios and provides guidelines to the scientific community, based on the identified challenges on this field. We apply the proposed guideline to a use case focused on energy consumption in a massive LPWAN network and optimal concentrators placement.

Finally, this comprehensive study of these massive IoT scenarios can further enhance the planning of Wireless Sensor Networks (WSN) in SWGs, making our water systems more efficient, sustainable and resilient for the future.

The remainder of this article is organized as follows: Section 2 discusses the relevant literature, while Sections 3 and 4 outline our research methodology. The results are presented in the following sections. Section 5 delves into the challenges associated with massive IoT deployment for WDS, Section 6 details the IoT technologies applicable for water system monitoring, Section 7 introduces the role of edge computing in the WDS domain, and Section 8 discusses WDS in massive IoT scenarios. Section 9 provides context for the simulation tools used for massive IoT in WDSs. Additionally, Section 10 presents and elaborates on the guidelines for sustainable and large-scale deployment. Section 11 presents the discussion of challenges and future research direction for massive SWDSs. The article concludes with Section 12, where we summarize our findings. Furthermore, Table 1 provides a graphical outline of the survey to provide a clear overview of the structure.

2. Related surveys

The convergence of IoT and WDSs represents a crucial advancement in infrastructure management. With global water demand escalating and climate change amplifying water scarcity, efficient WDSs are paramount, and understanding this dynamic landscape is essential for tackling pressing water management issues. In this context, few survey studies have been conducted approaching the IoT in WDS and Table 2 summarizes these contributions as explained below.

Despite lacking a background analysis of WDS, Lalle et al. [4] and Oberascher et al. [5] provide a detailed view of IoT technologies, offering a solid foundation for understanding the potential integration of IoT in WDSs. However, this lack of contextualization could hinder the practical application of the results. In contrast, Ismail et al. [6] comprehensively analyze the role of IoT in WDS applications but does not delve into the recommended architecture for IoT-based systems. This provides detailed insight into the potential of IoT in improving water distribution processes, although the absence of a recommended architecture may limit practical implementation in massive scenarios.

Islam et al. [11], while providing a comprehensive overview of current technologies and trends in water leakage detection and identifying the most common sensors and communication technologies, do not adequately address issues related to interoperability and scalability necessary for massive IoT applications and do not discuss edge computing-based leakage detection.

Table 2
Comparative analysis of survey or overview studies in IoT-based water distribution systems.

Secondary study	Background of WDS	Overview of IoT	Challenges in IoT based WDS	Overview of IoT for leakage detection	Focus on edge computing for WDS	Massive IoT scenario in WDS	Guidelines for massive IoT based WDS
Lalle et al. [4]	x	✓	✓	✓	x	x	x
Oberascher et al. [5]	x	✓	✓	x	x	x	x
Ismail et al. [6]	x	x	✓	x	x	x	x
Yuan et al. [7]	x	x	x	✓	x	x	x
Li et al. [8]	x	x	✓	x	x	x	x
Abu-Bakar et al. [9]	x	x	x	x	x	x	x
Velayudhan et al. [10]	✓	✓	✓	✓	✓	x	x
Islam et al. [11]	x	✓	x	✓	x	x	x
This survey	✓	✓	✓	✓	✓	✓	✓

Yuan et al. [7] and Li et al. [8] examine both the role of IoT in WDS applications and the challenges associated with IoT-based water distribution. Nonetheless, they do not provide a comprehensive overview of IoT technologies, which may limit their completeness. Finally, Abu-Bakar et al. [9] and Velayudhan et al. [10] address the role of IoT in WDS applications and provide a recommendation for an IoT architecture in WDS. However, it does not specifically address the challenges related to water distribution based on massive IoT scenarios, potentially limiting the understanding of potential obstacles.

In addition, various literature works discuss the application of advanced technology for security purposes within the field of WDS. Adu-Manu et al. [12] focus on Water Quality Monitoring (WQM) applications using WSNs, highlighting the shortcomings of traditional laboratory-based manual monitoring (TMLB) and in situ monitoring (TMIS) approaches for WQM via WSNs. Likewise, Laspidou [13] addresses the importance of ICT in urban water management, highlighting the need for solutions to address security challenges and threats in IoT-enabled water distribution networks, introducing blockchain technology as a solution, and providing a conceptual framework for implementing a smart water supply system. Later on, Dogo et al. [14] explore the importance of blockchain technology in various applications within IoT-based water management systems, focusing on a scenario in Africa.

Vidács & Vida [15] and Geetha & Gouthami [16] cover real-time water quality monitoring, presenting applications, communication technologies, controllers, sensors, and energy consumption issues with IoT-based hardware and software architecture, as well as WSN systems and use cases, illustrating water quality monitoring in domestic and industrial settings and critical activities in WDSs, such as potential leakage and efficiency.

As reported in Table 2, we can conclude that most of the relevant literature concentrates on the study of WDS or wireless networks individually, with only a few addressing the holistic analysis of massive IoT scenarios in WDS. Indeed, the last three columns of the table represents the novelty contribution of this work that includes Edge Computing (EC), massive IoT and guideline in the WDS context. Thus, our work aims to dive deeper into WDSs in large-scale scenarios, outlining the challenges of integrating IoT technology into such environments.

3. Research method

To identify relevant papers, we employed an adaptation of PRISMA guidelines [17]. In the following subsections, we define the scope of the literature review through the set of research questions, providing details of the exclusion and inclusion criteria, the search and selection procedure, and the extraction of data.

3.1. Research questions

The scope of this survey is an in-depth study of WDS in massive scenarios, and it is defined by the following Research Questions (RQs):

1. **RQ1**: *What are the challenges in IoT for WDS?*
2. **RQ2**: *What are the IoT technologies for WDS?*
3. **RQ3**: *How is Edge Computing applied in large-scale IoT deployment for WDS?*
4. **RQ4**: *What are the problems of massive IoT for WDS?*
5. **RQ5**: *What are the simulation tools for massive IoT deployment for WDS?*

RQ1 aims to identify the challenges associated with gathering data from large-scale IoT scenarios where water meters are deployed, drawing insights from existing literature and categorizing them accordingly. RQ2 gathers the available technologies solutions to address the collection of measurement in WDS as well as to report the analysis of the best IoT solutions for WDS. Later on, RQ3 delves into the utilization of EC within massive IoT deployments for WDS, highlighting its advantages and applications. Furthermore, RQ4 explores the issues surrounding massive IoT, considering various scales of WDS within large scenarios. Finally, RQ5 examines the feasibility of employing simulation tools to assess massive IoT scenarios, providing a means to replicate complex environments for research purposes.

3.2. Inclusion and exclusion criteria

This subsection outlines the criteria used for evaluating the relevance of the studies. We excluded all publications that met any of the following criteria: (E1) studies unrelated to WDSs, and (E2) non-English publications.[1]

On the other hand, we incorporated publications that satisfied at least one of the following criteria: (I1) research studies that underwent a stringent peer-review process, focusing on WDSs and IoT, and (I2) pertinent gray literature sources like arXiv studies, project reports, and manuals/books that met the first criterion.

3.3. Search and selection procedure

The database search was mainly conducted on Google Scholar, and we reviewed known repositories (IEEE Xplore, ACM Digital Library, SpringerLink, and Elsevier) to ensure comprehensive coverage. A set of searches were carried out from June 2022 until April 2024.

In order to refine the process, we searched using the 10 strings listed in Table 3 between 1970 and 2024.

We evaluated the study's research output by reviewing the titles, abstracts, and keywords. When a decision could not be made, the article's structure, introduction, methodology, results and conclusions of the article were also reviewed. Initial screening was conducted by the first and second authors, with any discrepancies resolved through discussion among all six authors to reach a consensus.

To identify pertinent studies, we initially analyzed document titles and metadata. Following the database search, duplicate entries were eliminated. Next, during the screening phase, inclusion and exclusion criteria were applied. Finally, an eligibility assessment was performed on 255 publications, ultimately leaving 107 publications included.

[1] An exception was made to include a document in Portuguese, specifically a thesis closely related to our goals, topics, and domain. See study P95.

Table 3
Query and search strings used.

Query number	Search query
1	*“Water distribution networks”* **OR** *“Water distribution systems”* **OR** *“Water supply systems”*
2	*“Water distribution networks”* **AND** *“Internet of Things”*
3	*“Water distribution systems”* **AND** *“Internet of Things”*
4	*“Water supply system”* **AND** *“Internet of Things”*
5	*“Water distribution networks”* **OR** *“Water distribution systems”* **OR** *“Water supply system”* **AND** *“Internet of Things”*
6	*“Water distribution networks”* **OR** *“Water distribution systems”* **OR** *“Water supply system”* **AND** *“Internet of Things”* **AND** *“Edge computing”*
7	*“Water distribution networks”* **OR** *“Water distribution systems”* **OR** *“Water supply system”* **AND** *“LPWAN”* **AND** *“Edge computing”*
8	*“Water monitoring”* **AND** *“Massive IoT”*
9	*“Water monitoring”* **AND** *“IoT”*
10	*“Water Measurement”* **OR** *“Water sensor”* **OR** *“Water sensing”*

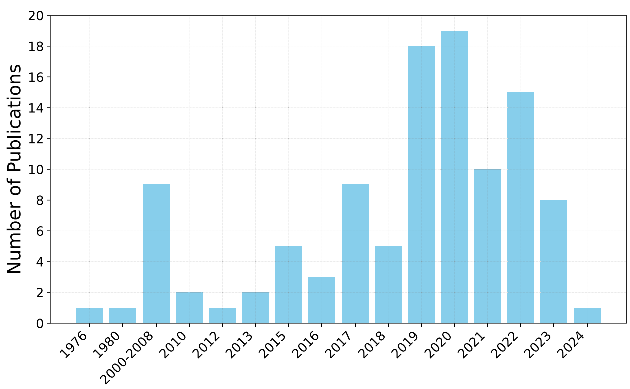

Fig. 2. Number of publications per year (1976–2024).

3.4. Data extraction

The data items that were collected from each publication are title, author name(s), publication year, affiliation, type of affiliation (academy, industry, shared affiliation), country, type of venue (conference, forum, journal, symposium, workshop), name of venue, and publisher, which provided contextual information.

For RQ1, we extracted the following challenges: interoperability and heterogeneity, scalability, power consumption and energy efficiency, network coverage and reliability, EC, measurement and sensing, and WDS applications.

For RQ2 and RQ3, we extracted the wireless technology (LoRaWAN, ZigBee, Bluetooth, SigFox, Wi-Fi, GSM, 4G, NB-IoT), study type (experimental, real-world application, simulation), WDS (yes, no), massive IoT scenario (yes, no), EC (yes, no).

For RQ4, we identified the focus of study, the amount of nodes/pipes, number of sensors, software of tools, IoT study (yes, no), leakage detection (yes, no), water quality (yes, no).

Finally, for RQ5, we extracted water network simulation tools (EPANET, WNTR, WaterGEMS, WaterCAD, WDNetXL, MATLAB, R, Python) and wireless sensor network simulation tools (ns-3, OMNet++, LoRaSim, SEAMCAT, Python).

4. Bibliometrics results

After the eligibility assessment, we selected a set of publications from which we were able to extract relevant data to answer the research questions. The full list of studies is composed of 107 publications, labeled as P01 to P107. The complete list of publications can be found here [18].

The demographic analysis examines the 107 selected publications in terms of venue type, geographic distribution, and author affiliation. These publications span from 1976 to 2024, showing a consistent upward trend in the number of articles published each year. In particular, the output of the research paper per year is shown in Fig. 2, and it can be noted that there was 1 study in 1976, 1 in 1980, 1 from 2000 to 2008, 1 in 2012; 2 in 2010 and 2013; 5 in 2015, 3 in 2016, 9 in 2017, 5 in 2018, 18 in 2019, 19 in 2020, 10 in 2021, 15 in 2022, 8 in 2023, and 1 in 2024, with the highest peaks between 2019 and 2022.

4.1. Distribution by type of venue

The majority of the articles were published in journals, with 67 studies. This is followed by conferences, which accounted for 26 studies. Additionally, we identified 3 articles from symposiums and workshops, and 1 from a congress. It is interesting to note that out of the 26 conference articles, there were 25 different conferences represented, with only one conference (the ACM International Conference on Information & Knowledge Management) having 2 articles.

Regarding the journals, we identified 46 different ones. The top 4 journals are: *Sensors* with 6 articles, *Water* with 5, and *Environmental Modelling & Software*, *IEEE Access*, and *Journal of Physics: Conference Series* each with 3 articles. Following these, *Computers & Chemical Engineering*, *IEEE Internet of Things Journal*, *Internet of Things*, *Journal of Water Resources Planning and Management*, *Procedia Engineering*, *Water Research*, and *Water Supply* each have 2 articles.

4.2. Distribution by location

The analysis reveals a multifaceted picture of global research, with China as the leading country with 13 studies, closely followed by the USA, India and Italy with 10, 9 and 8 studies, respectively. Countries like the United Kingdom and Australia also make notable contributions, exemplifying the broader landscape of the community. Collaborations between countries such as Tunisia-Portugal (P56, P92, P93), Cuba-Mexico (P35, P103), Portugal-Brazil (P79, P80), UK-Italy-Greece (P86, P87), Italy-Qatar (P82), Nigeria-South Africa (P105), among others, highlight the importance of cross-border partnerships in advancing scientific knowledge and addressing complex challenges. Furthermore, we have identified a set of countries with only one contribution such as New Zealand (P28), Denmark (P53), Czech Republic (P19), Egypt (P99) and Malaysia (P77). These findings are illustrated in Fig. 3, which clearly depicts the distribution of research studies across continents. In particular, it can be noted that Asia leads significantly with 50% of the total contribution of studies, highlighting its prominent role in global research endeavors. In contrast, both America and Europe contribute equally, with 22.7% each, reflecting their ongoing engagement in scientific exploration. Meanwhile, Africa and Oceania exhibit notably lower contributions at just 2.3%, with only 1 study each.

4.3. Distribution by affiliation

Within the 107 publications, we have identified that authors are affiliated with 125 universities, 7 centers, 19 institutes, 24 companies, 1 consortium (*Consorzio Nazionale Interuniversitario per le Telecomunicazioni*, Bari, Italy), and 8 government agencies such as the *National Homeland Security Research Center*, USA and *Xiayuan Multipurpose Dam Water Diversion and Irrigation Project Construction and Management Bureau of Henan Province*, China, showing the dynamic and interconnected research landscape.

The most frequently mentioned university is the *Central China Normal University* (Wuhan, China) identified 3 times within the affiliations related to the *Key Laboratory for Geographical Process Analysis & Simulation of Hubei Province*, the Department of Computer Science, and the College of Urban and Environmental Sciences. Other frequently mentioned universities include the *University of Exeter*, England and

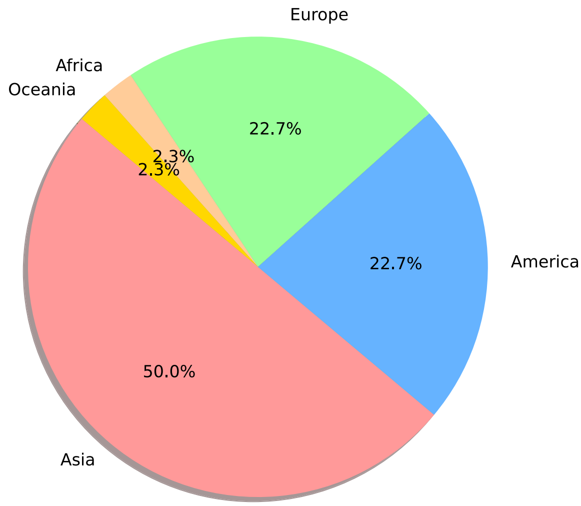

Fig. 3. Distribution of studies by continent.

the *Universitat Politècnica de Catalunya*, Spain, each appearing twice as affiliations.

Regarding the companies, the most frequent ones include *Tata Consultancy Services*, appearing twice with locations in Haryana and Noida, India, and water-related companies, such as the *Water Resources Information Center of Henan Province* and the *Jiangsu Provincial Planning and Design Group* both in China. European companies also show significant representation with AGBAR Barcelona Water Company and SingularLogic in Greece, highlighting a regional presence in technological and water management solutions. In addition, specialized firms and various engineering and technology companies in Australia (e.g., *ECS and Water Division at Energy Conservation Systems Pty Ltd.*) demonstrate a global spread in innovative research and development activities.

5. Challenges in IoT for WDS (RQ1)

In this section, we initiate our analysis related to the research questions provided. More specifically, we tackle here the challenges associated with technology selection, which encompass aspects of interoperability, heterogeneity, scalability, energy efficiency, network coverage, and reliability.

5.1. Selection of IoT technologies for WDSs

Regarding sensor technology, there is no universal technology for WDS monitoring. IoT chips with low power consumption and long-distance wireless communication capability are ideal for these purposes such as LPWAN networks. LPWAN devices are expected to dominate the industry [11], with different infrastructure requirements: (i) dependent on cellular infrastructure, such as NB-IoT; (ii) dependent on third-party infrastructure, such as SigFox [19]; and (iii) autonomous LPWANs, such as LoRa/LoRaWAN [20]. Cellular-based LPWANs offer broad coverage, capacity, battery life, quality of service, and security, but are not cost-effective due to subscription costs and reliance on commercial networks. SigFox, a patented network, has spurred rapid innovation by increasing competition among LPWAN technologies. LoRaWAN offers numerous advantages, including low power consumption, vast coverage, simplicity and easy management thanks to its features. However, it faces potential scalability issues in large-scale scenarios.

The implementation of smart sensor networks to monitor WDSs involves the generation of massive IoT scenarios. For example, studies on WDS in Refs. [21,22], and [23] had a number of pipes of 4494, 13 897, and 362,648, respectively. Assuming that we want to monitor each of these pipes with wireless sensors, with a transmission time between 5–15 min based on work [24], we would obtain a traffic load that can be considered in a massive IoT scenario. However, according to Jouhari et al. [25] massive IoT is a new category of IoT networks driven by scale and not by communication speed.

The number of connected devices in massive IoT can range from hundreds to billions, where the main goal is to efficiently transmit a small amount of sensing data from large numbers of connected devices [25]. Therefore, establishing efficient, adaptable and cost-effective systems within the massive IoT paradigm is becoming more difficult due to increasing IoT connectivity demands and different application requirements [26]. In this context, sensors in WDSs face challenges of interoperability, heterogeneity, scalability, energy efficiency, network coverage and reliability [27–31].

In the strategic selection of IoT technologies for WDS, it is crucial to address the multifaceted challenges posed by the evolving landscape of the IoT. This complexity underscores the need for reliable and secure communication among a growing number of devices, as well as efficient management of the vast amounts of data they generate. Moreover, the integration of various IoT technologies, including the need to mitigate potential interference issues arising from operating within the same unlicensed frequency bands [32].

Effective solutions must entail meticulous planning and resource management to ensure uninterrupted connectivity [33]. Additionally, managing widely distributed IoT devices, including sensors for water quality monitoring and actuators for network control, necessitates robust strategies for powering and maintaining these devices, particularly given their reliance on long-lasting battery solutions.

Furthermore, as IoT solutions become increasingly pervasive in water distribution networks, prioritizing data security and privacy becomes paramount. Robust measures must be implemented to safeguard sensitive data pertaining to water networks and consumer habits, mitigating the risk of unauthorized access and potential cyber threats. In navigating these challenges, the strategic selection of IoT technologies for WDSs demands a holistic approach that encompasses reliability, efficiency, scalability, and security considerations to drive sustainable and resilient water management practices.

In the following Section 6, we will examine the optimal selection of IoT technology for WDSs by comparing various existing solutions and providing a comprehensive overview.

5.2. Interoperability and heterogeneity

WDS are heterogeneous in terms of sensors, and, in some cases, there is a need to integrate various communication technologies [11]. For instance, when multiple platforms coexist, data may originate from different subsystems. Interoperability, defined by the ability to unify heterogeneous objects in a dynamic way, is therefore an important step for the development of massive IoT solutions. As outlined in [34], there is a proposal to integrate various technologies, such as cloud computing, massive IoT, and software-defined networking. The study also delves into the associated challenges, opportunities, and AI solutions for interoperability. Ensuring communication in heterogeneous water monitoring systems is a critical issue, as studied in [35], where a hybrid communication system is implemented using LoRa and ZigBee.

Specifically, two LoRa sensor clusters and two ZigBee sensor clusters are utilized and combined with two ZigBee-to-LoRa converters to communicate within a network managed by a LoRa GW. The ZigBee network employs the token ring protocol, while the LoRa network utilizes a polling mechanism. The system demonstrates effective operation with a packet loss rate of less than 0.5%. The article [28] proposes a new method to overcome interoperability challenges in WSNs for smart water networks. The syntactic interoperability approach addresses data format issues for applications, while semantic interoperability aligns the ontologies of IoT and applications.

By utilizing domain-specific standards such as WaterML2, DIIM makes IoT data interoperability, easing the connection between IoT platforms and various applications in smart water networks. Architectures such as BIG IoT [36], IoTexpert [37], and ISA-95 [38] can drive interoperability in WDS by connecting dozens of IoT platforms like FIWARE [39], Cayenne [40], ThingWorx [41], among others. These architectures aim to bridge the gap between different IoT platforms and build an IoT ecosystem by creating APIs for cross-platform communication.

5.3. Scalability

The main scalability concerns may include, for example, interference due to two or more wireless technologies sharing the same frequency band, as discussed in [32]. Additionally, a database can be the primary bottleneck in some circumstances. The authors in [29] found a scalability limit associated with MongoDB. Nevertheless, the platform is suitable for massive IoT scenarios, demonstrating the ability to handle 10 000 sensors without significant performance issues.

However, it is worth noting that scalability could be further improved by adopting more efficient databases other than MongoDB. Scalability is a fundamental feature of LPWAN technology, thanks to its long range and the capacity for a large number of devices to reach a given concentrator or gateway (GW). The network scales effectively with dynamic transmission parameters and multiple sinks. Additionally, Machine Learning (ML) can be applied to model and analyze technical issues, thereby enhancing the scalability of LPWAN networks and predicting network congestion [42]. Further developments could include improved adaptive data rate mechanisms, optimization of GW locations, and interference cancellation techniques [43].

5.4. Measurement and sensing

The selection of sensors plays a crucial role in monitoring the condition of water pipelines, which undergo progressive aging and face challenges associated with rapid intervention. Effective network monitoring relies on dedicated systems, with primary metrics including flow, pressure, temperature, and water quality. As a result, a key component in managing water supply networks is the implementation of devices for monitoring flow and pressure at various points within the network.

In general, there are three types of devices: mechanical, electromechanical, and electronic devices. Most countries prefer fully mechanical meters due to their low cost and high reliability. However, these meters require manual reading, leading to limitations in obtaining measurements with fast and accurate sampling intervals. Fully mechanical meters for water flow measurement can be categorized by their operating principle: velocity-based or displacement-based. Turbine meters fall into the former category, while meters with integrated oscillating pistons belong to the latter [44].

In the last two decades, there has been a gradual integration of electronic circuit components into mechanical meters to enable automatic functionalities, such as Automatic Meter Reading (AMR). These meters, referred to as electromechanical meters [45], maintain a mechanical measurement basis while possessing the capability to automate data collection procedures.

In recent times, fully electronic meters based on innovative measurement principles have been developed, including electromagnetic meters [46], fluidic meters [47], and ultrasonic meters [48]. The electromagnetic method relies on the principle that the induced electromotive force produced by the fluid in a magnetic field is proportional to the fluid's velocity. The fluidic method utilizes the Coanda Effect, resulting in a frequency oscillation proportional to the fluid's velocity [47]. Ultrasonic meters employ one or more ultrasonic transducers to send signals through the fluid, detecting its velocity using time-of-flight and the Doppler effect [49].

In contrast, fully mechanical devices often use magnetic coupling to hermetically separate the reading from the water flow chamber, known as dry dial devices [48]. Wet dial devices submerge the reading mechanism in the liquid, eliminating magnetic coupling. Dry dial devices, more common but vulnerable to interference, can be equipped with electronic systems that detect measurements through magnetic coupling.

Some manufacturers offer devices with a special housing for inserting a probe, transforming them into electromechanical devices [50]. Electronic or smart meters generally provide higher measurement accuracy than mechanical meters, showing promise for enhancing water supply management in smart cities. Smart meters require a power supply, commonly relying on replaceable batteries, although self-powered meters, as proposed in [51,52], are also available.

5.5. Power consumption and energy efficiency

Energy efficiency is not typically a principal concern for measurements taken at water supply system tanks or pumping stations, as these usually receive energy from the power grid. However, the situation changes when considering smart meters and flow monitoring sensors within the water supply system, as they are generally battery-powered [24]. In these scenarios, sensors with minimal power consumption need to be paired with high-energy-efficient communication technologies to enable the sensors to have energy autonomy for several years. In addition, minimizing the use of batteries is crucial to reduce disposal costs, maintenance, and pollution in WDSs.

Encouraging the deployment of battery-free wireless devices through energy harvesting from the environment is essential. Various established energy sources, including solar, piezoelectric, thermal, wind, water, and radio frequency, can be utilized [53]. However, achieving complete energy neutrality requires a detailed analysis of energy consumption in different operational states [54]. For example, integration of renewable energy sources based on water into monitoring devices has been facilitated, as seen in [55]. Energy source and supply analysis is influenced by numerous factors, and its case-by-case nature makes it challenging for systematic analysis.

On the other hand, ML algorithms can significantly contribute to this field. ML approaches have successfully been applied in various contexts, enabling efficient location-based renewable energy selection [56] and accurate energy forecasting [57]. Among the various technologies shown in Fig. 4, categorized by energy consumption and coverage range, LPWAN technologies (enclosed in a dashed box) provide the most suitable solution for meeting the needs of smart water systems. Indeed, by combining long-range wireless communication with low power consumption, LPWAN technology allows for extended battery life [58]. This is particularly crucial for flow monitoring, where sensor locations are often at the periphery of the WDS without the possibility of connecting their power supply to a power grid.

5.6. Network coverage and reliability

Coverage maximization in WDS is an IoT optimization and reliability problem. In short, within the context of coverage maximization, the goal is to ensure that every point in the area of interest is within the detection range of distributed sensors [59]. Consequently, it is essential to choose technology with high coverage and reliability, for example, to promptly identify any anomalies or leaks in WDSs.

Using long-range communication technologies, such as LPWANs, is crucial for extending coverage and improving connectivity in remote areas [60]. In addition, ad-hoc and mesh network implementations facilitate connectivity between devices, facilitating the efficient extension of coverage [61]. However, spectrum sharing poses an additional challenge, requiring advanced strategies to optimize frequency allocation [32]. Complying with specific standards and regulations is essential to ensure consistent and reliable management of massive IoT networks. One innovative approach to coverage and reliability challenges is the introduction of artificial intelligence-based solutions that

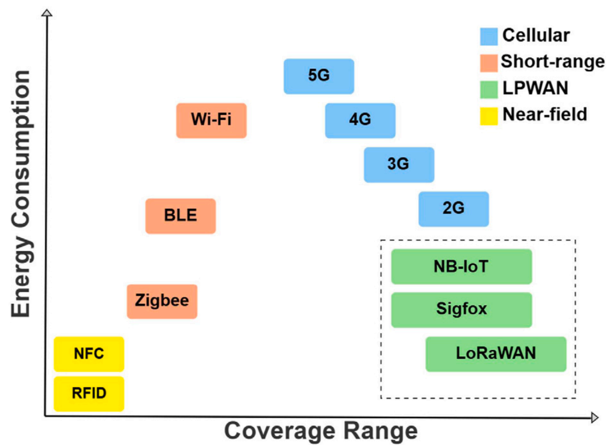

Fig. 4. Energy consumption versus communication range for various wireless technologies.

can dynamically optimize network performance and improve overall system resilience [42]. Successfully integrating these solutions is a crucial step toward creating more robust and reliable massive IoT networks in a constantly evolving technology landscape.

5.7. WDS applications

Applications in WDSs play a crucial role in ensuring safe and efficient water supply. Among these, leakage detection is essential to prevent wastage and infrastructure damage. Models like Random Walk Community Detection (RWCD) are used to divide WDS into different segments. Subsequently, a long-term leakage detection model (Extended Period Leakage Detection or EPLD) is employed to optimally position pressure sensors, which monitor pressure variations that could indicate leaks [62].

The goal is to maximize leak detection and reduce average detection time. To reduce leaks, proper monitoring and maintenance of the WDS are required. Moreover, the lack of historical scientific data on the distribution system can lead to improper management and maintenance of resources and consumer connections, such as supply deficiency, leaks, higher demand, and low pressure [10].

Another crucial concern within the context of WDS pertains to the continuous monitoring of water pressure and flow rate values. This is combined with an extensive control process for immediate prediction of pressure peaks, which could potentially cause leaks or other forms of damage [63].

In most cases, maintaining disinfectant levels is usually of interest to avoid bacteria regrowth and to protect against potential cross-contamination. However, disinfectants, such as chlorine, decay over time and produce potentially harmful disinfectant by-products when they react with organic material in the water. Therefore, maintaining a minimum chlorine residual requirement throughout the WDS is a complex but essential task. When online booster disinfection is combined with source disinfection, it has been shown that the total chlorine dosage can be reduced while maintaining minimum chlorine residuals across the system.

In this case, optimal valve operation can be combined with booster disinfection to improve the system's water quality [64]. A long-term water quality detection model is employed to position water quality sensors, which monitor parameters such as contaminant presence or the percentage of clean water. The objective is to maximize intrusion detection, clean water percentage, and reduce average detection time. Lastly, flow reconstruction helps understand water system behavior. Through hydraulic analysis friction factors and leak quantities are calibrated to identify leak presence and location. This aids in optimizing flow management and identifying anomalies [65].

5.8. Edge computing

To prevent overloading the cloud-based processing, existing literature underscores the importance of integrating processing at the edge layer. This approach involves processing data at the edge, where it originates from the sensor layer. Within the context of IoT, the authors in [66] propose an intelligent edge-cloud framework designed for water quality monitoring within WDS. The framework is evaluated under various scenarios, including cloud computing, EC, and a hybrid edge-cloud approach, to determine the most efficient platform.

In the first scenario, the analysis is conducted closer to the data generation point (at the edge), aiming to optimize performance. The second and third scenarios involve a combination of edge and cloud platforms. In the third scenario, sensor data are directly transmitted to the cloud for analysis. Rigorous testing of the proposed framework across these scenarios yields insightful results. The findings indicate that EC (scenario 1) outperforms cloud computing in terms of latency (20.33 ms), throughput (148 Kb/s), and packet delivery ratio (97.47%).

Notably, collaborative strategies between edge and cloud platforms enhance the accuracy of classification models, achieving up to 94.43%. This improvement in accuracy is achieved while maintaining the energy consumption rate at its lowest value. The design of an embedded edge-processing IoT-based water quality monitoring system tailored for monitoring irrigation and drinking water extracted from water wells is very challenging. In [67], the authors outline the design and implementation of this solution, with a specific focus on deployment in central Chile.

The system's design takes into account the region's challenging topographic conditions, which significantly impact power availability and communication resources. Captured data from the monitoring system are stored in a data lake, facilitating further processing based on water quality models. This comprehensive approach aims to enhance the understanding of underground water dynamics, enabling more informed and effective decision-making in the face of expanding drought areas and increasing demand for water resources in the region.

5.9. Summary and main findings (RQ1)

Selecting the appropriate architecture is crucial for IoT in WDS, with LPWAN technologies being widely adopted due to their cost-effectiveness, though they present scalability challenges. For WDS, integrating sensors and platforms demands addressing interoperability issues, leveraging cloud computing, software-defined networking (SDN), and AI for better coordination. Large-scale sensor networks face interference and database constraints, necessitating scalable solutions and ML to optimize network performance.

Energy efficiency is key, as smart sensors typically rely on battery power. Innovations such as energy harvesting and more efficient wireless communication are essential for prolonging sensor lifespan. In remote areas, ensuring broad coverage and reliable communication is vital, with LPWAN and AI improving performance. Processing data at the edge – closer to the source – helps minimize network load, reduces latency, and enhances real-time decision-making. Lastly, advanced electronic sensors and smart meters are progressively replacing traditional mechanical ones, offering improved accuracy and automated data collection.

6. IoT technologies for water systems monitoring (RQ2)

IoT promises to connect more than 30 billion devices by 2025 in smart city applications such as SWG, Smart Electrical Grid, Smart Home, machine-to-machine (M2M), among others [10]. The growth of the IoT can be identified from various statistical data. There are currently 21.7 billion active connected devices worldwide, with 11.7 billion (or 54%) being IoT device connections. Since IoT is a highly

Table 4
Comparative analysis of IoT for water monitoring systems.

Reference (year)	Wireless technology	Study type	Water distribution system	Massive IoT scenario	Edge computing
Verma et al. [68] (2015)	LoRa/LoRaWAN	Experimental	✓	x	x
Suciu et al. [69] (2017)	LoRa/LoRaWAN, ZigBee, Bluetooth, SigFox	Real-world application	✓	x	x
Predescu et al. [70] (2017)	Wi-Fi	Experimental	✓	x	x
Cattani et al. [71] (2017)	LoRa/LoRaWAN	Experimental	✓	x	x
Barbosa [72] (2017)	SigFox	Experimental	x	x	x
Wang et al. [73] (2018)	LoRa/LoRaWAN	Experimental	x	x	x
Niswar et al. [74] (2018)	LoRa/LoRaWAN	Experimental	x	x	x
Srihari [75] (2018)	Wi-Fi	Simulation and experimental	✓	x	x
Chinnusamy et al. [76] (2018)	LoRa/LoRaWAN, GSM, Wi-Fi	Experimental	✓	x	x
Wu and Khan [77] (2019)	LoRa/LoRaWAN	Experimental	x	x	x
Pal and Kant [78] (2019)	ZigBee, Wi-Fi	Simulation	✓	x	x
Liu et al. [79] (2019)	ZigBee, 4G	Simulation and experimental	✓	x	x
Amorsi et al. [80] (2019)	LoRa/LoRaWAN, Sigfox	Real-world application	✓	x	✓
Lalle et al. [27] (2019)	LoRa/LoRaWAN, Sigfox, NB-IoT	Simulation	✓	✓	x
Silva et al. [81] (2019)	LoRa/LoRaWAN	Real-world application	x	x	x
Babazadeh [82] (2019)	LoRa/LoRaWAN	Real-world application	x	x	✓
Amaxilatis et al. [83] (2019)	LoRa/LoRaWAN	Real-world application	✓	✓	✓
Di Gennaro et al. [84] (2019)	SigFox	Real-world application	x	x	x
Lalle et al. [85] (2020)	LoRa/LoRaWAN	Simulation	✓	✓	x
Bria et al. [86] (2020)	Wi-Fi	Real-world application	x	x	✓
Fuentes and Mauricio [87] (2020)	Wi-Fi	Experimental	x	x	x
Pérez-Padillo et al. [88] (2020)	Sigfox	Experimental	✓	x	x
Phua et al. [89] (2020)	Wi-Fi	Experimental	x	x	x
Gericke and Kuriakose [90] (2020)	Sigfox	Experimental	✓	x	x
Roy et al. [91] (2020)	ZigBee, GPRS	Real-world application	x	x	✓
Benedict [92] (2020)	LoRa/LoRaWAN, ZigBee, Wi-Fi	Real-world application	x	x	✓
Yeram et al. [93] (2020)	LoRa/LoRaWAN	Experimental	x	x	x
Alves Coelho et al. [94] (2020)	LoRa/LoRaWAN, NB-IoT	Experimental	✓	x	x
Lin et al. [95] (2020)	NB-IoT	Experimental	x	x	x
Gautam et al. [96] (2020)	Wi-Fi	Experimental	✓	x	x
Yang et al. [97] (2020)	LoRa/LoRaWAN, Wi-Fi, 4G, NB-IoT	Experimental	x	x	✓
Nkemeni et al. [98] (2020)	Wi-Fi, Bluetooth	Experimental	✓	x	✓
Amaxilatis et al. [99] (2020)	LoRa/LoRaWAN, Wi-Fi, 5G	Simulation	✓	x	✓
Slaný et al. [100] (2020)	LoRa/LoRaWAN	Experimental	x	x	x
Lalle et al. [101] (2021)	LoRa/LoRaWAN	Simulation	✓	✓	x
Che et al. [102] (2021)	GSM	Experimental	x	x	x
Garlisi et al. [3] (2022)	LoRa/LoRaWAN	Simulation	✓	✓	✓
Bao et al. [103] (2022)	Wi-Fi	Experimental	x	x	x
Ali et al. [104] (2022)	Wi-Fi	Experimental	✓	x	x
Boccadoro et al. [105] (2022)	SigFox	Experimental	x	x	✓
Castillo et al. [106] (2023)	LoRa/LoRaWAN	Experimental	✓	x	x
Restuccia et al. [107] (2023)	LoRa/LoRaWAN	Simulation and experimental	✓	✓	✓
Garlisi et al. [108] (2023)	LoRa/LoRaWAN	Simulation	✓	x	✓
Yauri et al. [109] (2023)	LoRa/LoRaWAN	Experimental	x	x	x

advanced technology, it can trigger the development of intelligent devices, smart sensors, actuators, and M2M devices, with the coexistence of different IoT technologies like, Bluetooth, ZigBee, Wi-Fi, LoRaWAN, Sigfox, and NB-IoT. The IoT communication technologies are intended to connect heterogeneous objects or devices within one framework to achieve smart applications and services, with low cost and low power even in adverse communication environments such as lossy and noisy communication links.

Table 4 provides a comparative analysis of IoT approaches applied to water monitoring systems. It is possible to observe the publication year as well as the wireless technology (LoRa/LoRaWAN, ZigBee, Bluetooth, SigFox, Wi-Fi, 4G, among others). The table also indicates whether the study directly involved a WDS with a holistic approach or not. Additionally, it shows the presence of massive IoT scenarios and EC data processing, as well as the type of study, specifying whether it is an experimental application, simulation-based study, or real-world application. An interesting fact that emerges from this table is that, out of the selected 44 articles, only 6 (about 13.6%) address the study of WDSs in massive IoT scenarios. Furthermore, the studies primarily approach the research from a simulation standpoint. This could be attributed both to the relative novelty and limited prevalence of such studies, as well as the difficulty of conducting studies in massive scenarios, considering factors such as data availability or the implementation of large-scale deployments in the real world.

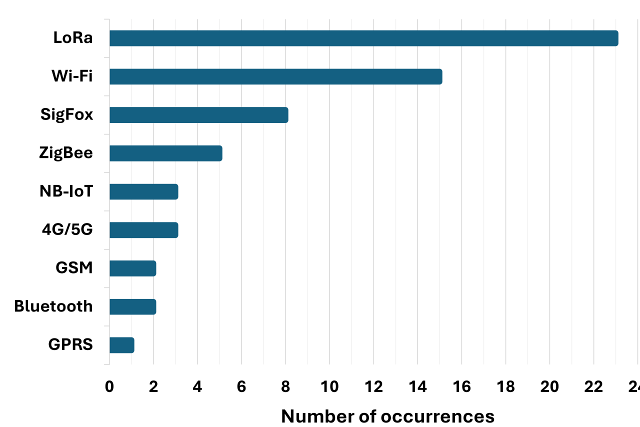

Fig. 5. Wireless technologies distribution in water monitoring systems.

Fig. 5 illustrates the distribution of adopted wireless technologies in terms of number of occurrences among the works listed in Table 4. From pie chart in Fig. 6 it is evident that the most used technologies are LoRa/LoRaWAN and Wi-Fi, representing respectively 37% and 24% of the works. This suggests that LoRa/LoRaWAN and Wi-Fi are widely

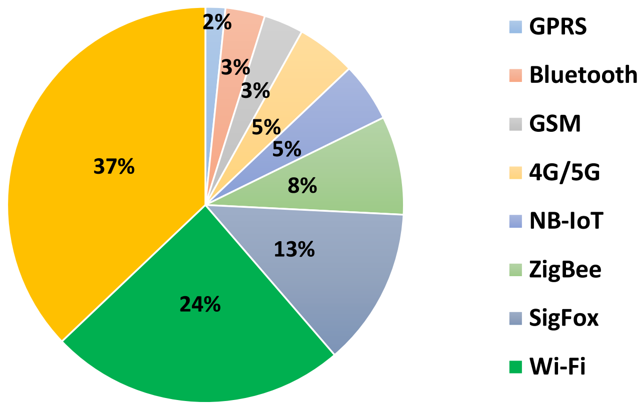

Fig. 6. A pie chart of the percentage of the wireless technologies used in water monitoring systems.

preferred for the implementation of IoT systems in water monitoring contexts. However, when considering LPWAN technologies as a whole, it emerges that these are widely adopted, representing 55% of the works (37% for LoRa, 13% for SigFox, and 5% for NB-IoT). This underscores the importance of technologies with efficient energy consumption and long-range communication capabilities in the field of water monitoring through the Internet of Things.

In this field, LPWAN technologies have emerged as a viable alternative to traditional wireless technologies to provide power-efficient and cost-effective wide area connectivity for the IoT. Indeed, the advantages of the LPWAN architectures include a wide coverage in the order of kilometers, and a low power consumption, with batteries lasting up to 10 years. According to IoT Analytics, NB-IoT, LoRaWAN, and Sigfox are today the most popular technologies for LPWAN, representing the 86% of the market, both in terms of end-user adoption as well as ecosystem support. The authors in [110] present various LPWAN technologies categorized based on the frequency spectrum used, whether licensed or unlicensed bandwidth.

The study [32] proposes the emphasis is on LPWAN technologies, with particular attention to the most prominent ones in the ISM band, such as LoRa/LoRaWAN and Sigfox. While NB-IoT utilizes licensed bands, both LoRaWAN and Sigfox operate in the sub-GHz ISM bands, potentially causing interference with each other, as illustrated in [32]. Therefore, in our opinion, LPWAN technologies such as LoRa/LoRaWAN and Sigfox, which use unlicensed bands and collectively represent the most widely adopted solutions in the market, are suitable for monitoring WDSs.

Both technologies are based on a simple star of stars topology, as shown in Fig. 7, End Devices (EDs), such as sensors or actuators deployed in the WDSs, transmit packets on the wireless medium to fixed devices called GWs which, in turn, forward the collected packets to a central Network Server (NS) interacting with several Application Servers (ASs). The cloud layer also include the Join Server to serve the authentication and security procedures.

The network infrastructure between GWs, NS, and ASs is typically based on Internet technology, while EDs are not associated to a specific GW, which greatly simplifies implementation (e.g., in case of mobility): in case a duplicate packet is simultaneously received by multiple GWs, the NS is responsible of filtering these packets and performs other simple decisions on network configuration.

In the following subsection we provide additional details on this two select technologies.

6.1. LoRaWAN

To minimize protocol complexity and energy consumption, LoRaWAN employs a simple Aloha MAC protocol and defines three classes of devices. Device classes represent different ways of managing reception operations performed by EDs. Class A devices, corresponding to the lowest energy profile, can receive downlink packets only in two-time windows following the transmission of their own packet to the GW. This means that devices can sleep all the time and the downlink transmission is triggered only after an uplink event. Class B devices add to this possibility a periodic scheduling of reception windows by keeping a time synchronization with the GW. Finally, class C devices are constantly listening to the channel for downlink packets.

LoRaWAN is a technology promoted by LoRa Alliance [111] that works on top of LoRa modulation, a proprietary physical layer technology patented by Semtech using a robust chirp-based modulation scheme, LoRa provides limited data rates from 0.3 to 27 kb/s. Moreover, LoRa transmissions are regulated by having a maximum transmission power of 25 mW (14 dBm) in the uplink, a configurable bandwidth of 125, 250, or 500 kHz, and a duty cycle of 0.1%, 1.0%, and 10%, which permit low energy consumption. Although LoRa technology is limited to the physical layer, different network solutions can be built on top of it, by exploiting its transmission interfaces.

Any time new packet is ready for transmission, devices attempt to transmit by randomly selecting one of the available channels in the ISM bands e.g., in the 868 MHz there are 16 channels in Europe, together with a modulation parameter called Spreading Factor (SF). In particular, six different SFs are used in LoRaWAN (from SF7 to SF12), which result in distinct symbol times and in almost orthogonal transmissions; when two signals modulated at different SFs overlap, the GW is able to decode both transmissions in a wide range of power ratios among the signals [112].

Unlike many other IoT technologies, the LoRaWAN specification offers dedicated end-to-end encryption to application providers, together with network-level security primitives, which allow sharing the same network among multitenant applications. Summarizing, the ease of deployment with excellent coverage, the availability of devices with very low energy demand, and intrinsic security mechanisms make these systems very suitable for innovative water metering applications. Indeed, several state-of-the-art IoT applications in smart water grid are based on LoRa/LoRaWAN networks. For example, LoRa/LoRaWAN is used to connect sensor nodes for measuring hydraulic parameters or controlling different kinds of actuators e.g., solenoid valves, and in applications such as leakage detection [3,100,109].

6.2. SigFox

SigFox adopts an innovative approach to address the IoT concept. This technology is designed for applications requiring minimal data transfer, utilizing Ultra Narrow Band (UNB) technology as its foundation. The communication bandwidth is approximately 100 bps (e.g., 100 Hz bandwidth) and 600 bps (e.g., 600 Hz bandwidth) for the ETSI and FCC regions, respectively [113]. Sigfox operates within unlicensed spectrum frequencies, adhering to spectrum access regulations. For instance, in Europe, the bands employed by Sigfox for uplink and downlink transmission are constrained by duty cycle limitations, set at 1% and 10%, respectively. Additionally, the maximum power for transmission is capped at 14 dBm within a 2-s timeframe, and a sensor can transmit up to 40 packets.

In regions where FCC regulations are observed, the highest power emitted by Base Stations is approximately 30 dBm [114]. The primary strength of this technology lies in its ability to resist interference, achieved through the implementation of a diversity mechanism in both time and frequency. Consequently, each sensor transmits each data packet across three communication channels at randomly selected time intervals. The communication operates asynchronously and is initiated by the device, allowing the device to default to a sleep state and minimize energy consumption [115].

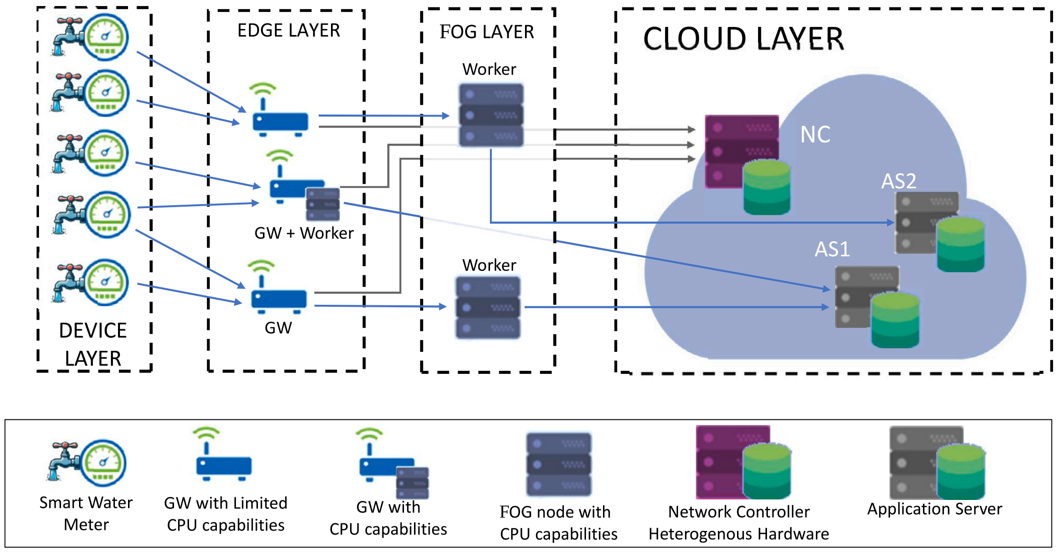

Fig. 7. LPWAN architecture and integration of edge computing into WDS.

Uplink message transmissions can be received by multiple base stations (typically around three base stations on average), facilitating cooperative reception and spatial diversity. While this mechanism introduces redundancy at the communication level, a significant drawback is the increased channel occupancy and, consequently, the potential for collisions. It employs a simple Aloha MAC protocol.

Differential Binary Phase-Shift Keying (DBPSK) is employed for uplink modulation, while Gaussian Frequency-Shift Keying (GFSK) is utilized for downlink modulation. DBPSK holds an advantage in bandwidth efficiency over GFSK, contributing to an extended uplink range, thereby compensating for the lower permissible transmit power in the uplink band. Furthermore, DBPSK provides robust protection against interference, such as jamming, as the received power concentrates within a narrow bandwidth, reaching a high power level. The achieved performance level opens up the possibility of further increasing the number of sensors theoretically by implementing load balancing. The study [116] delved into the performance analysis under conditions characterized by large-scale, high-density scenarios associated with SigFox networks. The use of Sigfox has recently been proposed for various applications and research fields, such as monitoring water quality, flow, and pressure in smart water grids, [27,72,84,88,105] to name a few.

6.3. Fog vs. edge in IoT for WDS

Fog computing and EC are two complementary paradigms used to improve efficiency in water monitoring systems [3,99]. Fog computing serves as an ideal complement by introducing an intermediate layer between the cloud and the edge. This architecture not only alleviates the load on the central network, but also enhances the overall scalability and resilience of the system, as demonstrated by real-world implementations in smart water networks [99,117]. However, EC is essential for processing data directly on devices close to the source, significantly reducing latency and allowing for quick and localized responses to anomalies such as leaks or pressure surges. The literature shows that Fog computing offers a promising solution for improving WDSs. For example by integrating Fog computing with LoRaWAN, water management systems can benefit from faster detection of abnormal consumption patterns and increased resilience [118]. The integration of Fog computing with IoT has shown significant potential to improve energy efficiency in drinking water facilities [119]. Fan et al. discuss a Cloud/Fog architecture for the water transfer project, emphasizing a hybrid model for effective resource management, but note the complexities of implementation in diverse geographical contexts [120]. Emami et al. explore the application of evolutionary game theory to enhance Quality of Service (QoS) in Fog environments, suggesting that further empirical validation is necessary to confirm its real-world effectiveness [121]. Mirzaie et al. focus on anomaly detection in urban water distribution grids using Fog Computing, showing that localized data processing can identify irregularities, although generalizability to different environments poses further research questions [122]. Lastly, the works [123,124] present an IoT system utilizing Fog Computing for constrained LoRa and LoRaWAN networks in smart irrigation and water quality monitoring which raises concerns about the long-term sustainability of such solutions in various climates [123].

Overall, although Fog computing and EC are often used interchangeably, they represent distinct paradigms in data processing. However, the adoption of EC in the field of WDS is not yet widespread and presents a challenge. For this reason, we have focused our research primarily on EC. In fact, EC could help address the future challenges of large-scale water distribution systems, for example, by enabling quick responses to anomalies close to data sources with cost-effective hardware such as Raspberry Pi [125].

6.4. Summary and main findings (RQ2)

By 2025, the IoT is projected to connect over 30 billion devices, playing a significant role in WDS field. However, a comprehensive analysis of 44 studies on IoT for water monitoring reveals that only 13.6% of these studies address large-scale IoT deployments, with the majority focusing on simulations rather than real-world implementations. In the realm of WDS applications, LPWAN technologies, particularly LoRaWAN, SigFox and Wi-Fi, dominate the landscape. Among the analyzed studies, 55% of them adopt LPWAN for its energy-efficient and long-range communication capabilities. LoRaWAN and Sigfox are commonly utilized in WDS applications due to their operation in unlicensed sub-GHz ISM bands. However, it should be noted that these two technologies can interfere with each other. LoRaWAN proves to be ideal for water monitoring applications, such as leak detection.

Finally, the literature has shown that EC can be implemented in LPWAN networks with low-cost hardware such as Raspberry Pi boards, reducing latency by processing data close to the sources and optimizing traffic and bandwidth [125].

7. Edge computing in massive IoT for WDS (RQ3)

The emergence of new services, not only those related to WDS, which are based on massive and complex deployment scenarios, requires a shift from classical monitoring models to low-latency, distributed, and collaborative data aggregation models. EC has been proposed as an evolution of the traditional high-end central cloud computing towards a continuum of collaborative distributed computing elements from the cloud to the network edge. For example, although LoRaWAN has been an excellent starting point for integrating WDS infrastructures with cloud services and big data analytics, the centralized architecture must address some bottlenecks when extending to large-scale deployment areas.

Indeed, when considering massive scenarios, the increase in the number of GWs forwarding large volumes of raw IoT data to the centralized infrastructure puts significant pressure on the backbone network in terms of energy, bandwidth, and security [126]. Such scenarios require a paradigm shift in IoT data processing towards low-latency distributed and collaborative aggregation, where the latter could be a relevant feature in WDS, for example, to promptly intercept a leak. At the same time, the growing demand for IoT services requires a transition from the classic two-level model to multi-level models involving EDs, GWs, Network Controller (NS), applications, and data sources, as shown in Fig. 7. EC represents a natural evolution in the provision of computing and storage by information technology, traditionally associated with centralized data centers, to include resources available at the network edges [127].

In the case of LoRaWAN, which adopts the design approach involving the use of simple protocols to create a centralized architecture, multiple implications arise when attempting to incorporate it into the EC. Recently, some researchers have explored various approaches to modifying the specified operation of the protocols, proposing alternative architectures to reduce the significant pressure imposed on central cloud services in the case of massive IoT data streams or limited-time IoT data consumption [128]. At the same time, introducing changes to the architecture and specific operation of the protocols while maintaining compatibility with previous versions is a challenging task. Therefore, it is necessary to find a compromise between the traditional functionality of GWs as simple bridges, which allows for rapid and cost-effective implementation of unlicensed LPWANs, and potentially serving as reliable intermediate processing and storage elements in the EC without increasing complexity and thus maintaining backward compatibility with the network [125].

For example, Fiware4Water [80] is a distributed system for water supply systems that leverages the FogFlow framework, an ICT infrastructure that is geo-distributed, hierarchical, and heterogeneous, encompassing IoT devices, cloud nodes, and edge nodes [129]. With FogFlow, it is possible to detect real-time anomalous water consumption in a WDS with a large number of distributed nodes. For instance, to monitor water consumption, a Raspberry Pi (edge node) can be installed on each water node. This device can recognize anomalous consumption at the edge and send an alert to both the user and the water network manager for information aggregation. Moreover, FogFlow enables serverless EC, a distributed processing paradigm where developers can write and deploy processing functions (or operators) without worrying about managing the underlying infrastructure.

Practical details of an edge implementation on the wireless sensor network for anomaly detection in WDS are also reported in [82]. Furthermore, benefits in terms of storage space, energy consumption, and communication uptime are evaluated using various edge data compression techniques. Indeed, performing data processing directly on the cloud requires a constant data flow communication channel between smart meters and remote cloud infrastructures, resulting in significant energy consumption and an increase in network traffic.

On the contrary, if the choice is made to perform data pre-processing on edge devices, a reduction in generated traffic is achieved. By employing EC, multiple packets can be combined over larger time intervals and transferred all together to the cloud, as proposed by Amaxilatis et al. [83]. In particular, they highlighted that even a small city with 50,000 water meters can generate up to 13 GB per day, creating a significant amount of traffic that may be excessive for an IoT network. However, the use of pre-processing in massive scenarios can reduce daily data production by up to 80%.

In the study [98], a distributed solution is presented where losses in a WDN are detected through local computations between a sensor node and its closest neighbors, without the need for long-distance transmissions and without the requirement of a centralized station for signal processing. It is demonstrated how distributed computation, implemented through a Kalman filter, improves the accuracy of loss detection and reduces energy consumption. The aim was to eliminate multi-hop communications, reduce latency, decrease sensor node energy consumption, and extend battery life. The study emphasizes the importance of distributed data fusion in improving the reliability of loss detection systems. Results showed that the bandwidth usage of the distributed Kalman filter was approximately 16 times lower than that of a centralized Kalman filter.

An intelligent implementation of water measurement based on the EC paradigm is also presented in [99], where the proposed solutions significantly reduce the overall load on wireless and cloud network resources. In fact, only about 5% of the total network traffic was transmitted to the cloud. In [3], the authors introduced LoRaSURFING, a tool that incorporates a data-driven approach to detect losses in a WDN using a LoRaWAN IoT network and EC. They trained various ML models to identify the best model for predicting losses at the edge. Furthermore, it was demonstrated that the proposed approach provides good performance even when only a subset of measurements is used to train the artificial intelligence model. In fact, the results indicated an average accuracy of 99% for the DecisionTree model when all leakage nodes are present during training, and an average accuracy of 85% when some leakage nodes are not present in the training dataset.

The WaterS architecture proposed in [105] is capable of performing edge prediction within the Sigfox network nodes using deep learning solutions. WaterS addresses the issue of water pollution while considering the specific constraints of IoT, such as energy efficiency and autonomy. Additionally, it is demonstrated that it is possible to predict water quality parameters such as pH, conductivity, oxygen, and temperature by integrating into WaterS an algorithm based on a Long Short-Term Memory recurrent neural network.

Finally, further benefits of EC for leakage detection in WDS are addressed in [107,108]. In particular, LeakStream [108] proposed a new approach to detect leaks through the combined use of clustering techniques and ML models, aiming to accurately and promptly identify anomalies within distribution networks. Data processing at the edge is carried out using NebulaStream [130] to reduce latency and traffic on the backhaul. NebulaStream is an example of a new data processing platform that addresses the challenges of heterogeneity, reliability, and scalability in IoT systems and includes an inference operator to support edge processing.

7.1. Summary and main findings (RQ3)

LoRaWAN is effective for integrating IoT in WDS but faces challenges in massive deployments, necessitating protocol adjustments for better compatibility with EC. EC reduces the need for continuous cloud communication, thereby minimizing energy consumption and network traffic. Fiware4Water utilizes EC to detect real-time anomalies in water usage, leveraging distributed nodes and edge devices such as Raspberry Pi to trigger alerts for abnormal patterns. LoRaSURFING integrates ML models at the edge to identify water losses in WDS with high accuracy, reaching up to 99% for certain models.

Other systems like WaterS and LeakStream combine ML and deep learning models at the edge to predict water quality parameters (e.g., pH, conductivity) and detect leaks, delivering real-time insights while optimizing key IoT constraints, such as energy efficiency. EC platforms like NebulaStream are designed to meet the growing demand for scalable, reliable, and low-latency data processing, making them well-suited for massive IoT deployments in WDS.

8. WDS in large scale scenarios (RQ4)

Massive-scale data extraction is crucial for realizing the potential of the smart city [131], especially in WDS deployed at large scales. In this section, we delve into the significance of WDS in extensive deployments. Understanding the operation and optimization of WDS is essential for ensuring efficient water supply, reducing losses, preserving water quality, and ultimately contributing to the sustainability and resilience of urban infrastructure. For example, in a massive scenario considering up to 2,700,000 water meters, up to 270 GB of daily data could be generated [83]. This extensive data volume could lead to scalability issues. Therefore, it becomes necessary to move data processing closer to the production site, eliminating the transfer of data to the cloud and reducing network traffic.

Table 5 presents a summary of research focused on WDS management, sorted on network size. The third and fourth columns detail the number of nodes, pipes, and sensors, respectively. Two categories, medium and large-scale scenarios, are separated by a horizontal line in the table. In the context of WDS, nodes and pipes are key components for defining the type of scenario. For example, a wide range of system sizes is observed, with the number of nodes and pipes varying from a minimum of 92 nodes and 117 pipes in medium-sized studies to a maximum of 257,362 nodes and 363,648 pipes in large-scale contexts.

In our classification, we consider scenarios as medium-sized when fewer than 1000 nodes/pipes are considered (top of the table), while publications considering 1000 or more pipes are classified as large-scale scenarios (bottom of the table). Additionally, we consider the employed software tools and techniques, such as EPANET, WNTR, MATLAB, and Python, to simulate, analyze, and optimize water system management in column fifth. Finally, the table highlights the presence of leakage detection and water quality application management in the last two columns. We address each of the selected studies mentioned below.

The importance of edge data processing is further highlighted in works [3,107], where ML models are studied to detect leaks in a WDS with 2099 sensor nodes. In particular, 84 next-generation LoRaWAN GWs are deployed in the study [3], which are capable of collecting data from sensor nodes and processing it to execute advanced software for the desired ML analysis. The procedure was able to identify the impact of the GWs' positions on the performance of the ML models for predicting leakage. In fact, the procedure only considered data from nodes that were within the coverage of the GW under consideration for training. Therefore, the prediction performance consistently showed very high accuracy (99%) for most GWs, with the exception of a small number of GWs where accuracy exceeded 90%.

The study [152] focuses on the implementation of efficient algorithms for hydraulic analysis of water distribution networks, leveraging sparse structure to reduce computations and enable rapid control of large-scale networks. For example, a network with a density of 15.5%, measured by the ratio of the average node connections to the number of pipes, is analyzed, indicating an intricate and interconnected network characterized by 12,527 nodes and 14,831 pipes.

The analysis of this network allows for evaluating the effectiveness of the proposed algorithms under conditions of high complexity and considerable size, providing valuable insights into the performance and applicability of hydraulic analysis methods for large-scale, high-density water distribution networks. Although the article focuses solely on hydraulic analysis, the results obtained could certainly be utilized in a broader study considering the installation of an IoT network. Similarly, a radio planning for massive IoT for water monitoring can be performed by taking into account the results of study [23]. Indeed, the work employed an approach based on Graph Neural Networks (GNNs) to integrate structural, geographical, and temporal information in order to study large-scale water networks. Specifically, the utilization of the Multi-hop Attention-based GNN (MAG) model to address challenges related to predicting losses in large-scale water distribution networks was discussed, considering the importance of the water network structure, the geographical effects of neighbors, and the temporal pattern of leaks.

Guidelines for conducting large-scale distribution system assessments are presented in [151]. Specifically, it contains information on hydraulic and water quality models, planning studies, equipment needs, monitoring methodologies, and the integration of geospatial technology for distribution system management and modeling. Additionally, the document offers guidance on equipment selection techniques and software required for modeling contaminant transport (or water quality changes) in complex piping systems. The guide also presents real-world case studies, such as a network with 1062 miles of pipes and approximately 12,000 nodes, with an average daily demand of about 20 million gallons and an estimated population of 130,000 people. In this case, a node selection process was applied to reduce computational intensity and identify sources of contamination, determining the optimal number and placement of monitors to detect potential contamination and mitigate the impacts of such events.

The study [22] describes an unsupervised clustering method for dividing a WDN into different district metering areas. The method is applied to a large WDS that supplies water to 400,000 people. It includes five water sources, 11,063 water demand nodes, and 13,896 pipelines. The approach uses a graph neural network to update node characteristics based on connections and another neural network to group nodes. The importance of boundary pipes is also calculated to determine the optimal location for the installation of sensors (flow meters) and valves.

Capacity analyses of LPWAN networks in massive WDS contexts are provided in the studies [27,85,101]. In [101], routing strategies for multi-hop LoRaWAN networks in the 1000-node smart water network are presented. The proposed methods reduced the packet error rate and total energy consumption compared to a standard single-hop network. The study [85] analyzed the capability of the LoRaWAN network and its application in smart water metering as a use case. The size of the network reached up to 7000 nodes, and simulations were performed with ns-3 to find the optimal strategy for assigning SFs based on the sensitivity of the GW. Using this strategy, a single GW was able to support approximately 1000 smart water meters with a packet delivery ratio of approximately 92%.

Finally, a scalability study comparing LoRaWAN, SigFox, and NB-IoT is reported in [27], with WDS scenarios involving up to 20,000 nodes. The study demonstrated that NB-IoT is a promising candidate for massive scenarios due to its good scalability compared to LoRaWAN and SigFox. However, the results obtained from LoRaWAN were unexpected, which may be attributed to the configuration of LoRa physical parameters within the ns-3 simulator. Conducting a more in-depth study of these parameters could improve the performance of LoRaWAN. Furthermore, the studies [27,85,101] could be improved in the WDS context by considering a more holistic approach. For example, studying the wireless network taking into account some water features such as the topology of the water network or the sampling period of the physical quantities to be measured, such as flowrate, pressure, among others.

Summarizing, from the above analysis, only 20% (6 out of 29 articles) of the selected studies addressed WDS study scenarios from an IoT perspective (sixth column in Table 5). Moreover, the percentage decreases to about 7% (2 out of 29 articles) when considering studies that address the study of WDS from both water and wireless perspectives. For this reason, we believe that it is necessary to provide a workflow that holistically integrates the behavior of a water system into a sustainable and massive IoT scenario.

Table 5
Comparison of water distribution system in medium and large scale scenarios.

Reference	Focus of study	Nodes/Pipes	Number of sensor	Software and tools	IoT study	Leakage detection	Water quality
Hu et al. [132]	Method for pipe burst location based on deep learning	92/117	6	EPANET	x	✓	x
Fan and Yu [133]	ML framework for leakage detection and localization	388/429	24	WNTR	x	✓	x
Li et al. [134]	Optimal sensor placement for leak localization	92/117	5	EPANET	x	✓	x
Hu et al. [135]	Optimization sensor placement for leak detection	407/443	400	EPANET	x	✓	x
Zhao et al. [136]	Sensor placement for pipe burst detection with cost–benefit analysis	92/117	25	EPANET	x	✓	x
Ge and Wang [137]	Energy efficient networks for monitoring water quality	200/–	200	–	x	x	✓
Garðarsson et al. [138]	Graph-based learning for leak detection and localization	782/–	–	–	x	✓	x
Li et al. [139]	Leakage localization using spatial clustering	491/509	20	EPANET	x	✓	x
Romero-Ben et al. [140]	Leak localization based on graph interpolation	782/909	–	EPANET and MATLAB	x	✓	x
Chen et al. [141]	Leak identification by clustering and ML interpolation	375/469	30	EPANET and Python	x	✓	x
Zanfei et al. [142]	Burst detection in WDS based on graph neural networks	267/317	14	Python	x	✓	x
Nejjari et al. [143]	Optimal pressure sensor placement in WDS	883/927	311	EPANET	x	✓	x
Quiñones-Grueiro et al. [144]	Leak location WDS with clustering and classification	268/317	25	EPANET and MATLAB	x	✓	x
Zhou et al. [145]	Deep learning identifies burst locations in WDS	480/567	4	EPANET	x	✓	x
Zhou et al. [146]	Contamination source identification by graph neural networks	1786/1985	6	EPANET	x	x	✓
Kim et al. [147]	Leak detection and localization using interval estimation	1154/–	6	–	x	✓	x
Capelo et al. [148]	Burst location and sizing in WDS by Multi–Layer Perceptron	4448/4494	24	EPANET and MATLAB	x	✓	x
Lalle et al. [101]	Routing strategies for LoRaWAN in WDS	–	1000	LoRaSim	✓	x	x
Klise et al. [149]	Simulate the effects of an earthquake on a WDS	3323/3829	–	WNTR	x	✓	✓
Difallah et al. [150]	Spatio-temporal anomaly detection in WDS	1891/2465	–	MATLAB and R	x	✓	x
Lalle et al. [85]	LoRaWAN network capacity for WDS	–	7000	ns-3	✓	x	x
Lalle et al. [27]	Scalability of LPWAN technologies in WDS	–	20 000	ns-3	✓	x	x
Rong et al. [22]	Clustering method based on a graph neural network	11 063/13 896	–	–	x	x	x
Panguluri et al. [151]	Reference guide for hydraulic and water quality models	12 000/–	–	EPANET	x	✓	✓
Liang et al. [23]	Failure prediction for large-scale WDS using GNN	257 362/363 648	–	–	x	✓	x
Abraham and Stoianov [152]	Algorithms for large-scale WDS	12 527/14 831	–	EPANET and MATLAB	x	x	x
Garlisi et al. [3]	Leakage detection in LoRaWAN-based WDS	2099/–	2099	WNTR and LoRaSIM	✓	✓	x
Amaxilatis et al. [83]	Edge processing oriented IoT for smart meter	–	2 700 000	–	✓	x	x
Restuccia et al. [107]	Distributed analysis for leakage detection in WDS	2099/–	2099	WNTR	✓	✓	x

As shown in Fig. 8, the Venn diagram represents the classification of articles related to massive scenarios and IoT. It was obtained by combining the works from Table 4 with the massive scenarios from Table 5, resulting in a total of 55 articles. Two main sets are highlighted: Massive and IoT. In the first set, there are 15 articles, 9 of which deal with contexts involving significant data volumes but without analyzing IoT, while the other 6 overlap with articles studying IoT systems in the water context. The IoT set, on the other hand, comprises forty four articles divided into various categories, including IoT in relation to WDS, together with EC and combinations of both, or in different contexts unrelated to WDS (14 studies). This diagram provides a clear view of the various intersections between massive scenarios and IoT in water applications, identifying specific areas of interest and research within this field.

8.1. Summary and main findings (RQ4)

In massive deployments, such as those involving up to 2.7 million water meters, enormous volumes of data—up to 270 GB daily—can lead to scalability challenges. WDS studies are categorized by system size, with medium systems having fewer than 1000 nodes/pipes, and large systems featuring 1000 or more pipes. The largest WDS deployments involve up to 257,362 nodes and 363,648 pipes.

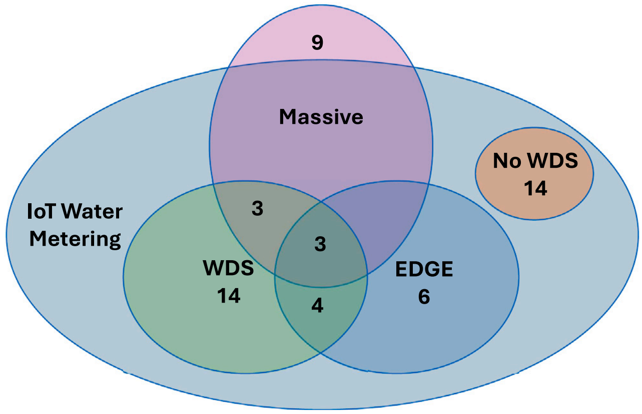

Fig. 8. Venn diagram of articles per topic area. The numbers inside each area indicate the quantity of papers identified in each of them.

Various software tools like EPANET, MATLAB, and Python are widely used for simulation and optimization, particularly focusing on leakage detection and water quality management. To address computational challenges in large-scale, high-density water networks, algorithms utilizing sparse structures have been proposed to enhance hydraulic analysis, improving both computation speed and network control.

When comparing LPWAN technologies for scalability in massive WDS, studies suggest that NB-IoT outperforms LoRaWAN and SigFox in large deployments. LoRaWAN's performance has been found sub-optimal in some simulations, necessitating further investigation into the configuration of physical parameters. Notably, only 20% of the reviewed studies approached WDS from an IoT perspective, with a mere 7% integrating both water and wireless perspectives. A more comprehensive approach that fully incorporates both IoT and water system behavior is essential for sustainable large-scale WDS implementations.

9. Simulation tools for massive IoT in WDSs (RQ5)

The development of intelligent WDSs within the framework of a massive IoT requires careful consideration of sophisticated computational systems for hydraulic modeling alongside specialized software for the analysis of wireless systems. The design of massive and complex smart WDS can require the support of large-scale testbeds. Often, these testbeds or their associated data are difficult to find in real-life scenarios, which is why the use of scalable simulation tools is preferred. In simulations, the number of nodes in the scenario and the level of detail required for the interactions between the nodes are key elements for the scalability of the simulator [153]. For this reason, the subsequent two subsections will present the predominant software tools employed in the WDS examination, approaching the subject from both hydraulic and wireless sensor network perspectives.

9.1. Water network simulation tools

A review of the principal software tools for investigating the hydraulic properties of networks was presented in [154]. Water distribution software encompasses public domain solutions including EPANET and commercial alternatives like WaterGEMS, WaterCAD, and others.

It is a modeling software for WDS that falls under the public domain. It was created by the Water Supply and Water Resources Division of the United States Environmental Protection Agency (EPA). The software conducts extended-period simulations to analyze the hydraulic and water-quality dynamics in pressurized pipe networks. Its primary purpose is to serve as a research tool, enhancing our comprehension of how drinking-water constituents move and behave within distribution systems [155].

Control rules, water consumption, and network architecture are represented by files in the ".inp" format [156]. There are many modeling packages that support this format; it is generally accepted, both free and commercial. As a result, it is frequently considered the industry standard. EPANET provides an extensive and long-term hydraulic study that can handle systems of different sizes. Additionally, the software facilitates the simulation of water demand that varies both spatially and temporally, along with the option to incorporate constant or variable speed pumps. It also considers minor head losses associated with bends and fittings in the system.

The modeling capabilities encompass the generation of data such as pipe flows, junction pressures, contaminant propagation, chlorine concentration, water age, and the exploration of alternative scenarios. This functionality not only aids in calculating pumping energy and costs, but also in modeling different valve types, including shutoffs, check pressure regulating, and flow control. Additionally, the software facilitates the simulation of water demand that varies both spatially and temporally, along with the option to incorporate constant or variable speed pumps. It also considers minor head losses associated with bends and fittings in the system. The modeling capabilities encompass the data generation such as pipe flows, junction pressures, contaminant propagation, chlorine concentration, water age, and the exploration of alternative scenarios. This functionality aids in calculating pumping energy and costs, as well as in modeling different valve types, including shutoffs, check pressure regulating, and flow control.

9.1.1. WNTR

Water Network Tool for Resilience (WNTR) is a Python package designed to simulate and analyze the resilience of water distribution networks based on EPANET, open-source software for modeling the hydraulic and quality dynamics of a WDN [157]. WNTR was developed to extend the capabilities of EPANET and simulate the dynamics of water flows across pipelines, taking into account bulk flows and pipe wall reactions, as well as the availability of water sources and reservoirs. WNTR has an Application Programming Interface (API) that is flexible and allows the configuration of the network topology and the scheduling of disruptive incidents and recovery actions. WNTR generates, for example, a complete trace, with the status of each node over time. This simulation tool streamlines the execution of experiments, enhancing sharing and integration into broader Python-based workflows.

9.1.2. WaterGEMS

This tool stands out as a versatile hydraulic modeling software package, showcasing advancements in interoperability and network optimization [158]. It offers robust model building capabilities supported by geospatial and asset management tools. This highly efficient and dynamic software provides a comprehensive range of analyses and solutions, including fire-flow analysis, water quality modeling, and energy and capital cost management. The software excels at presenting results, offering visually appealing displays through tools such as ArcMap visualization, thematic mapping, contouring, profiling with color coding, and symbology. As its user base continues to grow, *WaterGEMS V8i* has established itself as one of the most popular and user-friendly hydraulic modeling and optimization software packages. The software incorporates strong design algorithms to ensure accuracy in the design of water distribution networks. It effectively controls distribution network variables such as flow, pressure, and velocity, all while providing optimization capabilities [159].

9.1.3. WaterCAD

This is a comprehensive hydraulic modeling software package providing a broad range of functionalities, including graphical and profiling advancements, flexible data archiving and representations, and improvements in the Graphical User Interface (GUI) with customization options [154]. It offers enhanced capabilities for hydraulic and water quality analysis, steady state, and extended period simulations. There are a number of shared features and functions between WaterCAD and WaterGEMS, such as streamlined model building, integration with GIS and AutoCAD functionalities, and optimized model calibration, design, and operation. WaterCAD boasts several advantages over other software options. It simplifies model building through geospatial modules and tools such as LoadBuilder and TRex. Additionally, it excels at water quality modeling, fire flow analysis, optimization, and scenario management. The software's user-friendly nature and versatility make it widely accepted for various applications in water distribution and quality modeling [158].

9.1.4. WDNetXL

It is an integrated system for WDN analysis, planning, and management distributed as an MS-Excel add-in [160]. It integrates advanced and robust hydraulic simulation of water networks with topological analysis and optimization strategies to support engineers in the complex problems of water network analysis, planning and management. The WDNetXL system enables just-in-time technology transfer from technical research to WDN management through a holistic platform, ready for possible extensions to the latest innovations, thus providing upgradeable support to meet current and future needs. Additionally, it portrays a practical tool for training engineers from university courses to continuing education at water companies.

Its versatility also makes the system dynamic for implementing customized solutions through a virtuous cycle between users, researchers, and developers. The WDNetXL system is open source, which means that although the DLLs are binary files, it is possible to use them beyond the models provided in the original package and link them to GIS or other systems through standard programming languages that link MS-Excel to external applications [161]. A fundamental tool for advanced hydraulic simulation comparable to EPANET in terms of robustness, hydraulic consistency, and flexibility in analyzing many elements of the water network, such as water demand components, leaks, control devices, among others.

9.1.5. MATLAB

It is a widely used tool for the analysis and simulation of WDS [162,163]. It can be employed to create simulation models to assess the impact of various pump activation strategies on water distribution [164]. Another application of MATLAB when studying WDS is the evaluation of water quality. It can be used to create simulation models that allow the assessment of the influence of different factors on water quality, such as temperature, pH, and the presence of chemicals [165]. Some practical examples involve using SIMULINK, a software tightly integrated with MATLAB, to model pipeline systems or implement optimal water scheduling policies [166,167]. Finally, MATLAB has also been used to detect leaks in WDSs through clustering and sub-network classification [144].

9.2. Wireless sensor network simulation tools

Nowadays, various tools are available for researchers conducting advanced studies on WSNs, including both general-purpose simulators and those specifically designed for WSNs. In the context of WSN, these simulation tools are categorized into three distinct approaches: Monte Carlo Simulation, Trace-Driven Simulation, and Discrete-Event Simulation. Monte Carlo Simulation relies on statistical analysis by running multiple random scenarios [168].

Simulation tools that use historical data or real traces to guide the system's behavior are faced in [169]. It provides more detailed information, enabling users to get an in-depth understanding of the simulation model. However, side-by-side, trace-driven simulation has various drawbacks: sometimes, in-depth details increase the complexity of the simulation. Lastly, Discrete-Event Simulation models the system in terms of specific events occurring at discrete time instances [170]. Typically, this type is used in WSN due to its ease of simulating various tasks running on different sensor nodes. Each of these methods provides a unique approach to understanding and evaluating the performance of WSN. A selection of specific simulation tools for LPWAN technologies is outlined below. Our analysis primarily concentrates on these tools' ability to simulate LoRaWAN networks, which, according to our research, are the most appropriate for the context of WDS.

9.2.1. ns-3

This is an open-source discrete-event network simulator for educational and research purposes [171]. It is an extensible network simulation platform used under the GNU GPLv2 license. One of the fundamental design goals of ns-3 was to improve the realism of the models by allowing the model's implementation to be closer to the actual software or real-world implementations they modeled. The core and models of ns-3 are implemented in the C++ programming language, with an optional Python Scripting API interface. Users can use C++ or a Python program to write their simulation scripts. For example, to simulate LPWAN networks, there is a LoRaWAN module in ns-3. Each LoRa sensor and GW of the LoRaWAN module for ns-3 contain a single LoRaWAN MAC/PHY pair component, and the interaction/communication between each sensor's PHY layer and its respective gateway's PHY layer is through the spectrum channel module [172].

Furthermore, the ns-3 LoRaWAN module collision model is based on the capture effect. The stronger signal picks up the weaker signal when two simultaneous uplink transmissions with the same frequency and SF collide. As a result, the GW only receives the frame with the highest received signal power. Over time, numerous researchers have created various iterations of ns-3 modules to simulate LoRaWAN networks. The authors of [173] provide a thorough analysis of four distinct LoRaWAN module implementations in the ns-3 simulator for the first time. They were made publicly available and further compared them to highlight the most appropriate scenarios for each module. The four modules are open-source on GitHub, an internet repository for software development and version control. Many researchers have validated, extended or improved their work using either the different implementations of the ns-3-based LoRaWAN modules or their proposed LoRaWAN modules in the ns-3 simulation [174].

9.2.2. OMNeT++

It is an open-source, component-based discrete event network simulator [175]. The simulator primarily supports standard wired and wireless IP communication networks, with some extensions available for WSN (WSN). Similar to ns-3, OMNeT++ is popular, extensible, and actively maintained by its user community in academia, which has also developed extensions specifically for WSN simulation. OMNeT++ utilizes the C++ language for simulation models. Simulation models, or modules, are assembled using the high-level language Network Description Language (NED) to create larger components that represent entire systems.

The simulator provides graphical tools for building simulations and evaluating results in real-time. The simulator performs well when handling extensive network topologies, with its scalability constrained by the computer's memory capacity. However, OMNeT++ is unable to simulate delays in OS-application layer execution time [176]. It does allow for definable delays in lower layers, such as MAC and the wireless channel. In the absence of suitable simulation models or framework extensions, the simulator lacks adequate protocols and accurate energy modeling for sensor networks, as its primary support is designed for IP networks. For example, the FLoRa simulator was developed to evaluate the LoRa network's performance using the ADR mechanism [177].

The efficacy of the ADR in raising the PDR while enhancing energy efficiency was demonstrated. Utilizing both INET system components and the OMNeT++ network simulator, FLoRa is an end-to-end simulation framework for LoRa networks. The creation of LoRa networks that facilitate the integration of LoRa nodes, GWs, and network server modules is made possible by FLoRa code, which is produced using C++. In addition, each LoRaWAN MAC protocol module aims to emulate the physical layer [178]. Given that it is built on OMNeT++ and a graphical network description, this provides a far more robust GUI than the other simulation programs. For simulating a LoRa network, several parameters need to be selected, such as the simulation time, warm-up period, SF, the transmission power for each LoRa end device, backhaul network configuration, and links. Once the run is over, the OMNeT++ GUI can be used to view the simulation statistics and tracing files [179].

9.2.3. LoRaSim

This simulation tool has been created utilizing SimPy as a discrete event simulator with Python, aimed at simulating, exploring, and analyzing the scalability and collision functionality within LoRaWAN networks [179]. LoRaSim encompasses numerous Python scripts capable of simulating both single and multiple GW scenarios. Additionally, it can emulate devices equipped with directional antennas and function across multiple networks. LoRaSim implements a radio propagation model based on the well-known long-distance path loss model. The radio transceiver sensitivity at room temperature concerning various spreading factors and bandwidth settings is estimated. It also considers various related parameters, such as thermal noise power, receiver bandwidth, noise figure, and SNR [180]. Many improvements for LoRaSim have been proposed to make it multipurpose and to support the downlink, as the original version supported only the uplink. Therefore, it can test scalability, energy consumption, and other performance metrics [180].

9.2.4. SEAMCAT

It is a complex statistical simulator based on the Monte Carlo method, devised to assess the interference between different radio communication technologies [181]. It has been developed to deal with a complex range of spectrum engineering and radio compatibility problems. This simulation tool is developed by CEPT/ECC Working Group Spectrum Engineering (WGSE) within its sub-entity SEAMCAT Technical Group (STG). The exhaustive handbook for using SEAMCAT has been published by CEPT as ECC Report 252 [182]. The simulator is based on the definition of a victim link, characterized by a transmitter and a receiver of a given technology, as well as one or more interfering links (including different technologies).

For each technology, it is possible to specify several physical parameters of the device, including for example, the propagation model, location e.g. indoor/outdoor and height, antenna radiation diagram, transmission power - including emission mask, and receiver blocking mask. Any of these parameters can have a statistical distribution among end devices. The evaluation of the interference probability is performed by averaging the results of multiple simulated events.

Furthermore, following the statistical distributions of the physical parameters, for each event, the impact of interference is computed by comparing the signal strength of the victim link with the sum of the interfering signals, filtered by the transceiver power masks (including also adjacent channels). Thus, for each event, the power received by the victim is computed taking into account both the transmission power and the relative path-loss (PL), evaluated by considering the propagation model, and the environment parameters (e.g. position and height). Lastly, some studies in the literature have used SEAMCAT for interoperability, spectrum sharing, and interference studies in massive IoT scenarios [32,183,184].

In conclusion,

9.3. Summary and main findings (RQ5)

Regarding the Water Network Simulation Tools, our review identified several key tools, including EPANET, WNTR, WaterGEMS/WaterCAD, WDNetXL, and MATLAB which are widely used for modeling, analysis, simulation, and optimization of WDS. Beyond these, there are other numerous tools developed for similar purposes that were not covered in this review, such as WATSYS, Synergi Water, HYDROFLO3, InfoWorks, DisNet, Netis, Archimede, Cross, and Pipe Flow Expert.

EPANET and WNTR stand out as the most suitable tools for WDS simulation. WNTR, developed as an extension of EPANET, offers advanced capabilities that enhance experimentation, facilitate sharing, and integrate seamlessly into larger workflows. It enables two-way simulations between hydraulic systems and IoT elements, making it particularly useful for combining hydraulic modeling with IoT-based applications.

Later on, for WSN Simulation Tools, tools like ns-3, OMNeT++, LoRaSim, and SEAMCAT are frequently used. Based on our analysis, SEAMCAT and ns-3 are the most appropriate simulators for WDS needs. SEAMCAT is ideal for assessing physical layer aspects, such as LPWAN coexistence, while ns-3 excels in analyzing energy efficiency and protocol network performance.

In conclusion, for WDS hydraulic modeling, EPANET and WNTR are the top choices due to their robustness and ease of use. For WSN simulation, SEAMCAT and ns-3 are recommended for their capabilities in interference assessment and network protocol analysis, respectively.

10. Lessons learned and guidelines for sustainable large-scale deployment

Take into account the analysis above, in this section, we introduce the lessons learned and an innovative framework designed to investigate the utilization of massive IoT for monitoring and optimizing WDS in the future deployements. In fact, the main lesson learned is that many works in the literature on WDS focus exclusively on wireless networks or only on water-related aspects, while no studies address a multidisciplinary analysis in massive IoT scenarios for WDS that includes both aspects. For these reasons, we provide a holistic approach to overcome challenges and optimize the efficiency of massive IoT implementations in WDSs, with a specific emphasis on sustainable applications.

10.1. Framework description

The workflow, illustrated in Fig. 9, enables a comprehensive analysis of WDS by integrating short and long term decision making processes facilitated by continuous and extensive data collection via IoT, EC, graph signal processing, and AI analysis. The framework blocks, depicted in Fig. 9, are discussed in the following subsections.

10.1.1. Water distribution system

The initial step involves identifying the architectural model of a WDS and subsequently creating a dataset based on the network's topology. This task can be accomplished using WNTR and EPANET, as explained in Section 9. WNTR enables the automation of experiments, streamlining the integration into larger workflows, and facilitating the creation of datasets aligned with the WDS topology.

Our proposed methodology involves using WNTR to generate a dataset. This process will export the physical values of the WDN network into a file in comma-separated value (CSV) format, containing the features listed in the left block of the framework called *Water Network analysis*, as shown in Fig. 9. Finally, a subset of this dataset containing node location and sampling time information is provided as input to the IoT simulators to perform an analysis of various wireless network parameters, shown in the right-hand side of the framework. Upon completion of the process, two data structures are generated. The

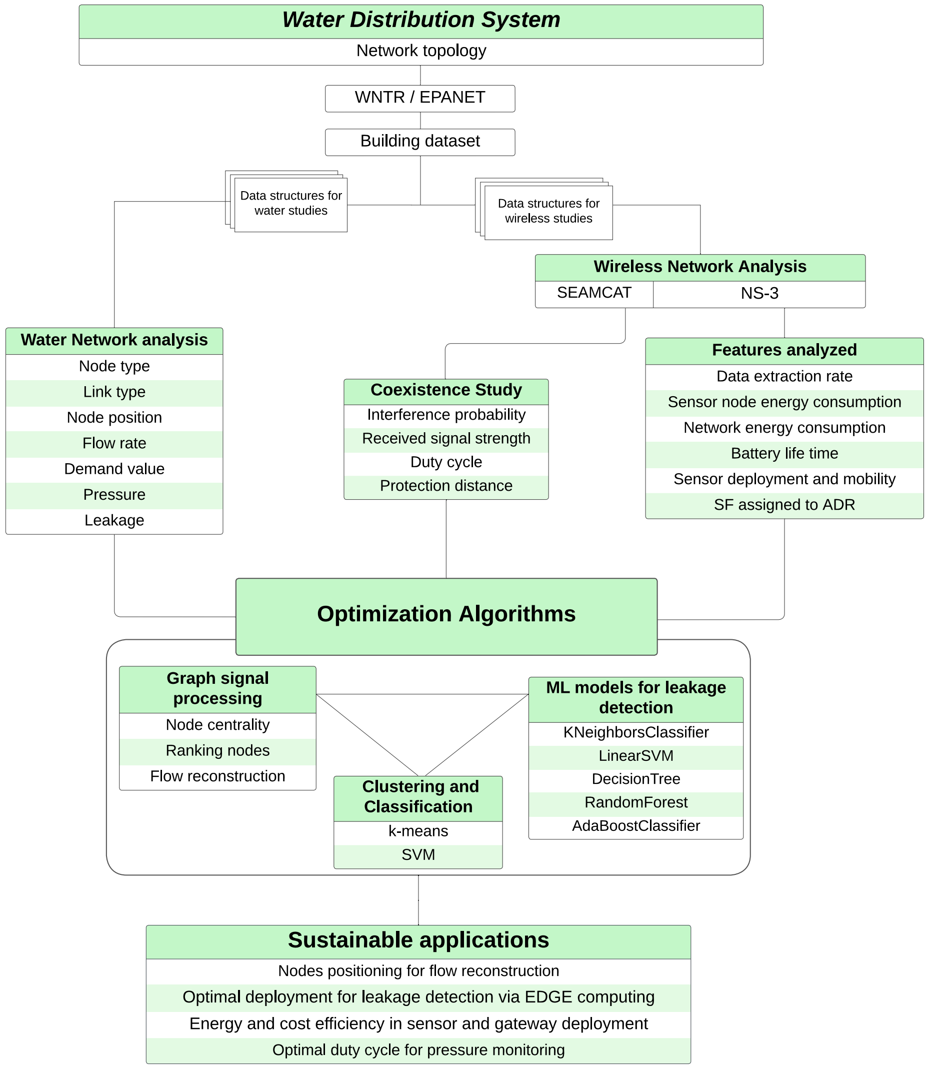

Fig. 9. Framework for green and large-scale IoT deployment in WDS.

first pertains to the file for water hydraulic analysis, while the second encompasses field parameters necessary for conducting network data analysis. Both, including relevant parameters, are shown in the middle of Fig. 9.

10.1.2. Water network analysis

This block provides a set of different features related to the selected scenario, including dynamically generated hydraulic values during the simulation and statically set values that represent the status of each node in the network at the observed time interval. Furthermore, the data is augmented to include information from ns-3 simulations. Hydraulic features include: (i) timestamp representing the time-interval, (ii) unique ID of a node inside the network, (iii) demand value, that is the rate of water withdrawal from the network, (iv) pressure in the node of the WDS, (v) node position: coordinates of the node, (vi) node type (i.e., "Junction", "Reservoir", "Tank"), (vii) presence of leakage (in terms of leak discharge, leak area and current leak demand), (x) the flow rate of the water inside the pipe at the current timestamp.

10.1.3. Wireless network analysis

The wireless network analysis block considers the SEAMCAT and ns-3 simulator tools, with SEAMCAT focusing on aspects related to the physical layer and ns-3 being instrumental for network and energy-related considerations. Wireless network parameters include: (i) data extraction rate, (ii) sensor node energy consumption, (iii) node battery lifetime, (iv) network energy consumption, (v) sensor and gateway position, (vi) spreading factor/data rate, (vii) received signal strength, (viii) duty cycle, (ix) packet numbers. By combining available features of both water and wireless, it is possible to address a WDS holistically. Therefore, the following subsection will provide some examples.

10.1.4. Optimization algorithms and sustainable applications

In the second phase of the framework, all water and wireless features are processed by various optimization algorithms, encompassing network classification and clustering, ML models focused on leakage prediction and graph signal processing techniques for water flow reconstruction within the network [185]. Together, these algorithms ensure sustainable network optimization, addressing both water management and wireless communication perspectives. Some illustrative use cases are listed in the following paragraphs. For example, ML algorithms have been employed in distributed analysis for leak detection in WDS with EC [3,107]. In this scenario, the system can identify leaks at the earliest opportunity. One of the primary objectives is to minimize the latency in leak detection by training the most effective ML model for each GW within the WDS [3]. In general, predicting the behavior of an entire network to detect leaks, especially in large scenarios, poses significant challenges. However, by clustering nodes based on shared features, it becomes feasible to develop models capable of predicting behavior within specific subnets or clusters [144]. The use of classification and clustering algorithms facilitates the deployment of ML models

Table 6
Future research challenges and possible solutions on massive IoT for WDSs.

Main research challenge	Motivation	Possible solution
Massive IoT	To provide interoperable, scalable, energy-efficient and reliable massive IoT for WDS	Employ LPWAN technologies
Suitable LPWAN	To enhance large-scale implementations and to mitigate interference	LoRaWAN
Edge computing in massive scenario	To reduce latency for real-time anomaly detection and high-accuracy localization of water losses	EC with graph signal processing and clustering-based ML
Simulators in large-scale scenario	To implement large-scale simulations including hydraulic and wireless aspects	IoT ecosystem simulators by creating APIs for cross-platform communication such as ns-3 and WNTR

tailored for leak prediction within clusters, thus improving prediction accuracy [141].

In addition, to demonstrate the framework methodology, we discuss a use case involving a massive IoT network supporting a WDS in paper [186]. This case shows the systematic approach for assessing and optimizing the performance of the SWDS, ensuring efficient water distribution and network operation. The specific focus of this use case is on evaluating strategies for LoRaWAN GW deployment in alignment with the WDS hydraulic flow. The proposed solution utilizes the hydraulic data of the WDS to determine the optimal GW deployment. For this purpose, graph signal processing on the network graph is employed. The goal of the proposed Degree Centrality Deployment is to utilize the data and metrics produced in the preceding stages of the methodology to discern the relationship between centrality and hydraulic flow. This analysis aids in determining the optimal locations for GWs. The use case focuses on a large network, which consists of 4419 nodes, 3 reservoirs, and 5066 pipes, represented as a topology and dataset in a public repository at this link.[2] The results show that the proposed method has lower energy consumption when a context-aware GW deployment is performed compared to a Regular Grid GW deployment [186]. This comparison sheds light on the potential energy efficiency benefits of using degree centrality for GW deployment strategies in SWDS.

11. Discussion and future directions

We identified several interesting challenges and technologies in IoT for WDS, which could also serve as directions for future research. Specifically, Table 6 summarizes the four main challenges highlighted in this analysis and outlines potential solutions that could guide future efforts to address them.

Within the challenges of IoT for WDS (**RQ1**), there is a significant focus on integrating IoT to improve monitoring and management, with ongoing innovations in sensor technologies and communication protocols that address deployment challenges [25].

Robust data collection, storage, and analysis mechanisms are crucial, but a lack of universal standards for sensor technologies and communication protocols, as well as difficulties in scaling IoT solutions and ensuring interoperability, remain significant issues that have not been solved yet [28,187]. With respect to Scalability, as WDSs expand to include thousands or even millions of sensors, scalability remains a significant challenge. Research should explore advanced data management techniques, efficient database systems, and optimized network architectures to handle the massive scale of IoT deployments in water management [29].

Despite advancements in low-power IoT devices, achieving sustainable energy autonomy remains critical. Future efforts could center on integrating renewable energy sources and improving energy harvesting technologies to prolong sensor lifespan and reduce maintenance costs in WDS.

Furthermore, ensuring reliable connectivity across large and often remote WDS areas is crucial. Future research might focus on enhancing network coverage through advanced mesh networking, spectrum management strategies, and AI-driven optimization techniques to improve reliability and responsiveness [66,67].

Approaching integration and interoperability, while various IoT technologies like LoRaWAN, NB-IoT, and SigFox offer solutions for WDS monitoring (**RQ2**), there is a need for standardized interoperability protocols to seamlessly integrate heterogeneous systems [28,59]. Future research could focus on developing robust interoperability frameworks that accommodate diverse sensor networks and communication technologies.

In terms of EC in large-scale IoT deployment for WDSs (**RQ3**), it is increasingly used to process data in real-time, reducing the need for constant data transmission to central servers and enhancing the responsiveness of IoT systems [66]. Distributed computing architectures improve system resilience and scalability, but managing distributed EC resources and integrating them with existing infrastructures are ongoing challenges, alongside the lack of standardized frameworks for implementation. In this line, studies to come could explore optimal edge-cloud architectures tailored for real-time monitoring, predictive analytics, and decision support in water distribution [97].

Also, regarding advanced sensing technologies, developing next-generation sensors capable of real-time monitoring for water quality, leak detection, and pressure management is essential. Future research could focus on enhancing sensor accuracy, reliability, and resilience against environmental conditions to improve overall system efficiency and water quality management [3,66].

For WDSs in large-scale scenarios (**RQ4**), addressing network congestion due to the high volume of data generated by IoT devices and developing automated maintenance solutions are major trends [23,27]. Ensuring the reliability and accuracy of the collected data, robust infrastructure support, and qualified professionals to manage and maintain complex IoT systems are critical needs [99]. Concerning Security and Privacy, with the increase in IoT devices, ensuring robust cybersecurity measures to protect sensitive data and infrastructure becomes paramount. Future research topics could include developing encryption standards, intrusion detection systems, and privacy-preserving techniques tailored for WDS IoT environments [188].

Leveraging advanced data analytics, AI, and ML for predictive maintenance, anomaly detection, and decision support systems could optimize WDS operations [94]. New research might explore AI-driven predictive models and adaptive control strategies for efficient water resource management [108].

Finally, regarding simulation tools for massive IoT deployment in WDSs (**RQ5**), advanced hydraulic modeling tools like EPANET [156] and WNTR [149] are used to simulate WDSs, alongside specialized tools for wireless sensor networks [173]. Integrated simulation environments combining hydraulic and wireless network simulations are being developed [186]. There is a need for more accurate and realistic simulation models, user-friendly interfaces for non-experts, and addressing the high complexity and computational requirements of existing tools.

[2] https://github.com/WITS-Restart/WDN-IoT-Dataset-Workbench.

12. Conclusion

This survey provides a holistic analysis of the integration of IoT technologies with WDS, focusing on the challenges and opportunities that arise in massive IoT scenarios. In fact, optimizing and digitalizing WDSs are becoming key objectives in modern society as global water consumption increases. The integration of IoT technologies offers a viable solution with their extensive coverage and low power consumption. However, implementing SWGs on a large scale presents challenges, including potential interference among multiple IoT technologies and ensuring system reliability to prevent significant water wastage. As water resources become increasingly limited, innovative management and distribution strategies are essential.

Based on the analysis of selected studies, we introduced a framework designed to provide a holistic approach to overcoming future challenges and optimizing the efficiency of massive IoT implementations in WDSs. This includes the increasing application of EC, ML, and AI for predictive maintenance and anomaly detection. The study highlights future challenges such as the need for more energy-efficient IoT devices to prolong battery life and reduce maintenance costs, while ensuring data security and privacy remains a critical concern.

Moreover, addressing challenges like interoperability, scalability, network coverage is critical for the successful deployment of massive IoT in WDSs. As well as employing data mining for promoting the potential of smart cities and digital twins.

LPWAN networks offer appropriate sensor technologies to overcome future challenges and to implement effective data management practices, which are vital for monitoring and managing water systems. Lastly, Utilizing EC enhances data processing efficiency, reduces network traffic, and improves system reliability, making it crucial for large-scale implementations. Implementing these technologies and methodologies will contribute to more efficient, sustainable, and resilient WDSs, addressing the pressing global need for better water management.

CRediT authorship contribution statement

Antonino Pagano: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Domenico Garlisi:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization. **Ilenia Tinnirello:** Visualization, Supervision, Methodology, Funding acquisition. **Fabrizio Giuliano:** Writing – original draft, Supervision, Investigation. **Giovanni Garbo:** Supervision, Funding acquisition. **Mariana Falco:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis. **Francesca Cuomo:** Writing – review & editing, Funding acquisition, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

References

[1] U. Wwap, World water assessment programme: The united nations world water development report 4: Managing water under uncertainty and risk, 2012, p. 39.
[2] EurEau, Europe's water in figures. 2021 edition, 2021, URL https://www.eureau.org/resources/publications/eureau-publications/5824-europe-s-waterin-figures-2021/file.
[3] D. Garlisi, G. Restuccia, I. Tinnirello, F. Cuomo, I. Chatzigiannakis, Leakage detection via edge processing in LoRawan-based smart water distribution networks, in: 2022 18th International Conference on Mobility, Sensing and Networking, MSN, 2022, pp. 223–230, http://dx.doi.org/10.1109/MSN57253.2022.00047.
[4] Yandja Lalle, Mohamed Fourati, Lamia Chaari Fourati, João Paulo Barraca, Communication technologies for smart water grid applications: Overview, opportunities, and research directions, Comput. Netw. 190 (2021) 107940.
[5] Martin Oberascher, Wolfgang Rauch, Robert Sitzenfrei, Towards a smart water city: A comprehensive review of applications, data requirements, and communication technologies for integrated management, Sustainable Cities Soc. 76 (2022) 103442.
[6] Shereen Ismail, Diana W Dawoud, Nadhem Ismail, Ronald Marsh, Ali S Alshami, IoT-based water management systems: Survey and future research direction, IEEE Access 10 (2022) 35942–35952.
[7] Zhiguo Yuan, Gustaf Olsson, Rachel Cardell-Oliver, Kim van Schagen, Angela Marchi, Ana Deletic, Christian Urich, Wolfgang Rauch, Yanchen Liu, Guangming Jiang, Sweating the assets–the role of instrumentation, control and automation in urban water systems, Water Res. 155 (2019) 381–402.
[8] Jiada Li, Xiafei Yang, Robert Sitzenfrei, Rethinking the framework of smart water system: A review, Water 12 (2) (2020) 412.
[9] Halidu Abu-Bakar, Leon Williams, Stephen Henry Hallett, A review of household water demand management and consumption measurement, J. Clean. Prod. 292 (2021) 125872.
[10] Nibi Kulangara Velayudhan, et al., IoT-enabled water distribution systems-a comparative technological review, IEEE Access (2022).
[11] Mohammed Rezwanul Islam, Sami Azam, Bharanidharan Shanmugam, Deepika Mathur, A review on current technologies and future direction of water leakage detection in water distribution network, IEEE Access (2022).
[12] Kofi Sarpong Adu-Manu, Cristiano Tapparello, Wendi Heinzelman, Ferdinand Apietu Katsriku, Jamal-Deen Abdulai, Water quality monitoring using wireless sensor networks: Current trends and future research directions, ACM Trans. Sensor Netw. 13 (1) (2017) 1–41.
[13] Chrysi Laspidou, ICT and stakeholder participation for improved urban water management in the cities of the future, Water Util. J. 8 (1) (2014) 79–85.
[14] Eustace M Dogo, Abdulazeez Femi Salami, Nnamdi I Nwulu, Clinton O Aigbavboa, Blockchain and internet of things-based technologies for intelligent water management system, Artif. Intell. IoT (2019) 129–150.
[15] Attila Vidács, Rolland Vida, Wireless sensor network based technologies for critical infrastructure systems, Intell. Monit. Control Secur. Crit. Infrastruct. Syst. (2015) 301–316.
[16] S. Geetha, SJSW Gouthami, Internet of things enabled real time water quality monitoring system. Smart water 2 (1): 1, 2016.
[17] Rafael Sarkis-Onofre, Ferrán Catalá-López, Edoardo Aromataris, Craig Lockwood, How to properly use the PRISMA statement, Syst. Rev. 10 (2021) 1–3.
[18] Complete list of publications, 2024, https://docs.google.com/spreadsheets/d/1C-IxAUvX_qVmxcP53LyCIy0vXWPgRNPOhSY9WAe4hpo/edit?usp=sharing. (Access 28 October 2024).
[19] SigFox, https://build.sigfox.com/sigfox-device-radio-specifications.
[20] Semtech, LoRa. EU patent EP2763321, US Patent no. 7, 791, 415.
[21] M. Capelo, B. Brentan, L. Monteiro, D. Covas, Near–real time burst location and sizing in water distribution systems using artificial neural networks, Water 13 (13) (2021) 1841, http://dx.doi.org/10.3390/w13131841.
[22] Kezhen Rong, Minglei Fu, Yangyang Huang, Ming Zhang, Lejin Zheng, Jianfeng Zheng, Miklas Scholz, Zaher Mundher Yaseen, Graph attention neural network for water network partitioning, Appl. Water Sci. 13 (1) (2023) 3.
[23] Shuming Liang, Zhidong Li, Bin Liang, Yu Ding, Yang Wang, Fang Chen, Failure prediction for large-scale water pipe networks using GNN and temporal failure series, in: Proceedings of the 30th ACM International Conference on Information & Knowledge Management, 2021, pp. 3955–3964.
[24] M. Pointl, D. Fuchs-Hanusch, Assessing the potential of LPWAN communication technologies for near real-time leak detection in water distribution systems, Sensors 21 (1) (2021) 293, http://dx.doi.org/10.3390/s21010293.
[25] M. Jouhari, N. Saeed, M.-S. Alouini, E.M. Amhoud, A survey on scalable LoRaWAN for massive IoT: Recent advances, potentials, and challenges, IEEE Commun. Surv. Tutorials 25 (3) (2023) 1841–1876.

[26] M. Alshaikhli, T. Elfouly, O. Elharrouss, A. Mohamed, N. Ottakath, Evolution of internet of things from blockchain to IOTA: A survey, IEEE Access 10 (2021) 844–866.
[27] Yandja Lalle, Lamia Chaari Fourati, Mohamed Fourati, João Paulo Barraca, A comparative study of LoRawan, sigfox, and nb-iot for smart water grid, in: 2019 Global Information Infrastructure and Networking Symposium, GIIS, IEEE, 2019, pp. 1–6.
[28] Mandeep Singh, Wenyan Wu, Stamatia Rizou, Edlira Vakaj, Data information interoperability model for IoT-enabled smart water networks, in: 2022 IEEE 16th International Conference on Semantic Computing, ICSC, IEEE, 2022, pp. 179–186.
[29] I. Zyrianoff, A. Heideker, D. Silva, C. Kamienski, Scalability of an internet of things platform for smart water management for agriculture, in: 2018 23rd Conference of Open Innovations Association, FRUCT, 2018.
[30] Juan Pablo García-Martín, et al., IoT solution for smart water distribution networks based on a low-power wireless network, combined at the device-level: A case study, Internet Things 22 (2023).
[31] P. Tian, C.A. Boano, X. Ma, J. Wei, LoRaHop: Multihop support for LoRaWAN uplink and downlink messaging, IEEE Internet Things J. 10 (17) (2023) 15376–15392.
[32] D. Garlisi, A. Pagano, F. Giuliano, D. Croce, I. Tinnirello, A coexistence study of low-power wide-area networks based on LoRaWAN and sigfox, in: 2023 IEEE Wireless Communications and Networking Conference, WCNC, IEEE, 2023, pp. 1–7.
[33] Y. Nagai, J. Guo, P. Orlik, T. Sumi, B.A. Rolfe, H. Mineno, Sub-1 GHz frequency band wireless coexistence for the internet of things, IEEE Access 9 (2021) 119648–119665.
[34] M.R. Belgaum, S. Musa, M. Alam, M.S. Mazliham, Integration challenges of artificial intelligence in cloud computing, internet of things and software-defined networking, in: 2019 13th International Conference on Mathematics, Actuarial Science, Computer Science and Statistics, MACS, 2019.
[35] Van-Truong Truong, Anand Nayyar, S. Ahmad Lone, System performance of wireless sensor network using LoRa–Zigbee hybrid communication, Comput. Mater. Contin. 68 (2) (2021) 1615–1635.
[36] A. Bröring, et al., Enabling IoT ecosystems through platform interoperability, IEEE Softw. 34 (1) (2017) 54–61.
[37] V. Geetanjali, I. Subramanian, G. Kannan, S. B. Prathiba, G. Raja, IoTexpert: Interconnection, interoperability and integration of IoT platforms, in: 2019 11th International Conference on Advanced Computing, ICoAC, 2019, pp. 212–219.
[38] Chen Li, et al., An ISA-95 based middle data layer for data standardization—enhancing systems interoperability for factory automation, in: Advances in Automotive Production Technology–Theory and Application: Stuttgart Conference on Automotive Production, SCAP2020.
[39] Victor Araujo, et al., Performance evaluation of FIWARE: A cloud-based IoT platform for smart cities, J. Parallel Distrib. Comput. 132 (2019) 250–261.
[40] Kirana Astari Pranoto, et al., Comparison analysis of data sending performance using the cayenne and ThingSpeak IoT platform, in: 2022 International Conference on Informatics, Multimedia, Cyber and Information System, ICIMCIS, IEEE, 2022.
[41] S. Doshi, P. Ghatage, R. Borole, IIoT for factory optimization and logistics management using PTC thingworx and kepware, in: 2023 11th International Conference on Emerging Trends in Engineering '&' Technology - Signal and Information Processing, ICETET - SIP, IEEE, 2023.
[42] F. Cuomo, D. Garlisi, A. Martino, A. Martino, Predicting LoRaWAN behavior: How machine learning can help, Computers 9 (3) (2020) 60.
[43] D. Garlisi, S. Mangione, F. Giuliano, D. Croce, G. Garbo, I. Tinnirello, Interference cancellation for LoRa gateways and impact on network capacity, IEEE Access 9 (2021) 128133–128146.
[44] G. Hauber-Davidson, E. Idris, Smart water metering, Water 33 (2006) 38–41.
[45] Y.W. Lee, S. Eun, S.-H. Oh, Wireless digital water meter with low power consumption for automatic meter reading, in: Proceedings of the 2008 International Conference on Convergence and Hybrid Information Technology, Daejeon, Korea, 2008.
[46] V. Cushing, Electromagnetic water current meter, in: Proceedings of the OCEANS '76, Washington, DC, USA, 1976.
[47] P.H. Wright, The coanda meter-a fluidic digital gas flowmeter, J. Phys. E Sci. Instrum. 13 (1980) 433.
[48] R.J. Paulsen, C.F. Smith, D. O'Rourke, T.-F. Wong, Development and evaluation of an ultrasonic ground water seepage meter, Groundwater 39 (2001) 904–911.
[49] Yicheng Yu, Ali Safari, Xudong Niu, Bruce Drinkwater, Kirill V Horoshenkov, Acoustic and ultrasonic techniques for defect detection and condition monitoring in water and sewerage pipes: A review, Appl. Acoust. 183 (2021) 108282.
[50] V. Elster, 100 (PSM-t) volumetric cold potable water meters: Product specification, 2017, https://prod-edam.honeywell.com/content/dam/honeywell-edam/pmt/hps/products/sme/water/residential-metering/volumetric-meters/v100/V100-PSM-T-SML001-SpecSheet-English.pdf. (Accessed 19 November 2024).
[51] V. Tasic, T. Staake, T. Stiefmeier, V. Tiefenbeck, E. Fleisch, G. Tröster, Self-powered water meter for direct feedback, in: Proceedings of the 2012 3rd IEEE International Conference on the Internet of Things, Wuxi, China, 2012.
[52] X.J. Li, P.H.J. Chong, Design and implementation of a self-powered smart water meter, Sensors 19 (2019) 4177, http://dx.doi.org/10.3390/s19194177.
[53] F.K. Shaikh, S. Zeadally, Energy harvesting in wireless sensor networks: A comprehensive review, Renew. Sustain. Energy Rev. 55 (2016) 1041–1054.
[54] H. Chao, Y. Chen, J. Wu, Power saving for machine to machine communications in cellular networks, in: Proc. IEEE GLOBECOM Workshops, GC Wkshps, 2011, pp. 389–393.
[55] W. Zhao, S. Lin, J. Han, R. Xu, L. Hou, Design and implementation of smart irrigation system based on LoRa, in: Proc. IEEE Globecom Workshops, 2017, pp. 1–6.
[56] P. Lissa, M. Schukat, E. Barrett, F. Seri, M. Keane, Machine learning methods applied to building energy production and consumption prediction, in: Proc. AICS, 2019, pp. 236–247.
[57] L.F.J. Alvarez, S.R. González, A.D. López, D.A.H. Delgado, R. Espinosa, S. Gutiérrez, Renewable energy prediction through machine learning algorithms, in: Proc. IEEE ANDESCON, 2020, pp. 1–6.
[58] Hafiz Husnain Raza Sherazi, et al., Energy-efficient LoRaWAN for industry 4.0 applications, IEEE Trans. Ind. Inform. 17 (2) (2020) 891–902.
[59] E.Q. Shahra, W. Wu, M. Romano, Considerations on the deployment of heterogeneous IoT devices for smart water networks, in: EEE SmartWorld, Ubiquitous Intelligence '&' Computing, Advanced '&' Trusted Computing, Scalable Computing '&' Communications, Cloud '&' Big Data Computing, Internet of People and Smart City Innovation, 2019.
[60] A.M. Yousuf, E.M. Rochester, B. Ousat, M. Ghaderi, Throughput, coverage and scalability of LoRa LPWAN for internet of things, in: 2018 IEEE/ACM 26th International Symposium on Quality of Service, IWQoS, 2018.
[61] J.R. Cotrim, J.H. Kleinschmidt, LoRaWAN mesh networks: A review and classification of multihop communication, Sensors 20 (15) (2020) 4273.
[62] Tianwei Mu, Manhong Huang, Shi Tang, Rui Zhang, Gang Chen, Baiyi Jiang, Sensor partitioning placements via random walk and water quality and leakage detection models within water distribution systems, Water Resour. Manage. 36 (13) (2022) 5297–5311.
[63] Maroua Abdelhafidh, Mohamed Fourati, Lamia Chaari Fourati, A genetic algorithm-based intelligent solution for water pipeline monitoring system in a transient state, Concurr. Comput.: Pract. Exper. 34 (7) (2022) e5959.
[64] Doosun Kang, Kevin Lansey, Real-time optimal valve operation and booster disinfection for water quality in water distribution systems, J. Water Resour. Plan. Manage. 136 (4) (2010) 463–473.
[65] Joseba Quevedo, V Puig, G Cembrano, J Blanch, J Aguilar, D Saporta, G Benito, M Hedo, A Molina, Validation and reconstruction of flow meter data in the Barcelona water distribution network, Control Eng. Pract. 18 (6) (2010) 640–651.
[66] Essa Q. Shahra, Wenyan Wu, Shadi Basurra, Adel Aneiba, Intelligent edge-cloud framework for water quality monitoring in water distribution system, Water (ISSN: 2073-4441) 16 (2) (2024) http://dx.doi.org/10.3390/w16020196, URL https://www.mdpi.com/2073-4441/16/2/196.
[67] Christian Correa, Diego Dujovne, Fernando Bolaño, Design and implementation of an embedded edge-processing water quality monitoring system for underground waters, IEEE Embedded Syst. Lett. 15 (2) (2023) 81–84, http://dx.doi.org/10.1109/LES.2022.3184925.
[68] Prachet Verma, Akshay Kumar, Nihesh Rathod, Pratik Jain, S. Mallikarjun, Renu Subramanian, Bharadwaj Amrutur, M. S. Mohan Kumar, Rajesh Sundaresan, Towards an IoT based water management system for a campus, in: 2015 IEEE First International Smart Cities Conference, ISC2, 2015, pp. 1–6, http://dx.doi.org/10.1109/ISC2.2015.7366152.
[69] George Suciu, Laurentiu Bezdedeanu, Andrei Vasilescu, Victor Suciu, Unified intelligent water management using cyberinfrastructures based on cloud computing and IoT, in: 2017 21st International Conference on Control Systems and Computer Science, CSCS, IEEE, 2017, pp. 606–611.
[70] Alexandru Predescu, Mariana Mocanu, Ciprian Lupu, Real time implementation of IoT structure for pumping stations in a water distribution system, in: 2017 21st International Conference on System Theory, Control and Computing, ICSTCC, IEEE, 2017, pp. 529–534.
[71] Marco Cattani, Carlo Alberto Boano, David Steffelbauer, Stefan Kaltenbacher, Markus Günther, Kay Römer, Daniela Fuchs-Hanusch, Martin Horn, Adige: an efficient smart water network based on long-range wireless technology, in: Proceedings of the 3rd International Workshop on Cyber-Physical Systems for Smart Water Networks, 2017, pp. 3–6.
[72] R.M.R. Barbosa, Sistema de monitorização de consumo de água utilizando tecnologia sigfox, 2017.
[73] Jian-xiong Wang, Yang Liu, Zhi-bin Lei, Kang-heng Wu, Xiao-yu Zhao, Chao Feng, Hong-wei Liu, Xue-hua Shuai, Zhong-min Tang, Li-yang Wu, et al., Smart water LoRa IoT system, in: Proceedings of the 2018 International Conference on Communication Engineering and Technology, 2018, pp. 48–51.
[74] Muhammad Niswar, Sonny Wainalang, Amil A Ilham, Zahir Zainuddin, Yushinta Fujaya, Zaenab Muslimin, Ady Wahyudi Paundu, Shigeru Kashihara, Doudou Fall, IoT-based water quality monitoring system for soft-shell crab farming, in: 2018 IEEE International Conference on Internet of Things and Intelligence System, IOTAIS, IEEE, 2018, pp. 6–9.

[75] M.M. Srihari, Intelligent water distribution and management system using internet of things, in: 2018 International Conference on Inventive Research in Computing Applications, ICIRCA, IEEE, 2018, pp. 785–789.

[76] Saravanan Chinnusamy, Prasanna Mohandoss, Partha Paul, IoT enabled monitoring and control of water distribution network, in: WDSA/CCWI Joint Conference Proceedings, Vol. 1, 2018.

[77] Nansong Wu, Muhammad Khan, Lora-based internet-of-things: a water quality monitoring system, in: 2019 SoutheastCon, IEEE, 2019, pp. 1–4.

[78] Amitangshu Pal, Krishna Kant, Water flow driven sensor networks for leakage and contamination monitoring in distribution pipelines, ACM Trans. Sensor Netw. 15 (4) (2019) 1–43.

[79] Yang Liu, Xuehui Ma, Yuting Li, Yong Tie, Yinghui Zhang, Jing Gao, Water pipeline leakage detection based on machine learning and wireless sensor networks, Sensors 19 (23) (2019) 5086.

[80] Natacha Amorsi, S Deveughele, L Echeverria, R Elelman, V Kuzmickaite, C Nanu, et al., D6. 1 communication and dissemination strategy towards a smart water society, 2019.

[81] Diego RC Silva, Marcelo B Nogueira, Marconi C Rodrigues, Judson S Costa, Daniel VA Silveira, Guilherme MB Oliveira, A concrete architecture for smart solutions based on IoT technologies, IEEE Instrum. Meas. Mag. 22 (2) (2019) 52–59.

[82] Mehrdad Babazadeh, Edge analytics for anomaly detection in water networks by an Arduino101-LoRa based WSN, ISA Trans. 92 (2019) 273–285.

[83] Dimitrios Amaxilatis, Ioannis Chatzigiannakis, Christos Tselios, Nikolaos Tsironis, Sparks-edge: Analytics for intelligent city water metering, 2019.

[84] P. Di Gennaro, D. Lofú, D. Vitanio, P. Tedeschi, P. Boccadoro, WaterS: A sigfox-compliant prototype for water monitoring, Internet Technol. Lett. 2 (1) (2019) e74.

[85] Yandja Lalle, Lamia Chaari Fourati, Mohamed Fourati, João Paulo Barraca, LoRaWAN network capacity analysis for smart water grid, in: 2020 12th International Symposium on Communication Systems, Networks and Digital Signal Processing, CSNDSP, 2020, pp. 1–6, http://dx.doi.org/10.1109/CSNDSP49049.2020.9249623.

[86] Alessandro Bria, Gianni Cerro, Marco Ferdinandi, Claudio Marrocco, Mario Molinara, An IoT-ready solution for automated recognition of water contaminants, Pattern Recognit. Lett. 135 (2020) 188–195.

[87] Henry Fuentes, David Mauricio, Smart water consumption measurement system for houses using IoT and cloud computing, Environ. Monit. Assess. 192 (2020) 1–16.

[88] José Pérez-Padillo, Jorge García Morillo, José Ramirez-Faz, Manuel Torres Roldán, Pilar Montesinos, Design and implementation of a pressure monitoring system based on iot for water supply networks, Sensors 20 (15) (2020) 4247.

[89] Wee Kee Phua, Sarbudeen Mohamed Rabeek, Beibei Han, Edwin Njihof, Tyler Tianlu Huang, Kevin Tshun Chuan Chai, Jason Hock Huat Yeo, Soon Thor Lim, AIN-based MEMS (micro-electro-mechanical system) hydrophone sensors for IoT water leakage detection system, Water 12 (11) (2020) 2966.

[90] G.A. Gericke, R.B. Kuriakose, IoT water monitor implementation strategy, in: Journal of Physics: Conference Series, Vol. 1577, IOP Publishing, 2020, 012045.

[91] Sanku Kumar Roy, Sudip Misra, Narendra Singh Raghuwanshi, Sajal K Das, AgriSens: Iot-based dynamic irrigation scheduling system for water management of irrigated crops, IEEE Internet Things J. 8 (6) (2020) 5023–5030.

[92] Shajulin Benedict, Serverless blockchain-enabled architecture for iot societal applications, IEEE Trans. Comput. Soc. Syst. 7 (5) (2020) 1146–1158.

[93] Prachi Yeram, Nobin Gonsalvez, Clinton D'Souza, Elizabeth Abraham, Vinay Patil, Smart water management system in urban areas using LoRa technology, in: Proceedings of the 3rd International Conference on Advances in Science & Technology, ICAST, 2020.

[94] João Alves Coelho, André Glória, Pedro Sebastião, Precise water leak detection using machine learning and real-time sensor data, IoT 1 (2) (2020) 474–493.

[95] Huiwen Lin, Hezhi Lin, Xiaoxuan Fang, Mingkang Wang, Lianfen Huang, Intelligent pipeline leak detection and analysis system, in: 2020 15th International Conference on Computer Science & Education, ICCSE, IEEE, 2020, pp. 206–210.

[96] Jyoti Gautam, Amlan Chakrabarti, Shruti Agarwal, Anushka Singh, Shweta Gupta, Jatin Singh, Monitoring and forecasting water consumption and detecting leakage using an IoT system, Water Supply 20 (3) (2020) 1103–1113.

[97] Tsun-Hua Yang, Chia-Wei Wang, Sheng-Jhe Lin, ECOMSNet–An edge computing-based sensory network for real-time water level prediction and correction, Environ. Model. Softw. 131 (2020) 104771.

[98] Valery Nkemeni, Fabien Mieyeville, Pierre Tsafack, A distributed computing solution based on distributed kalman filter for leak detection in WSN-based water pipeline monitoring, Sensors 20 (18) (2020) 5204.

[99] Dimitrios Amaxilatis, Ioannis Chatzigiannakis, Christos Tselios, Nikolaos Tsironis, Nikos Niakas, Simos Papadogeorgos, A smart water metering deployment based on the fog computing paradigm, Appl. Sci. 10 (6) (2020) 1965.

[100] V. Slaný, A. Lučanský, P. Koudelka, J. Mareček, E. Krčálová, R. Martínek, An integrated IoT architecture for smart metering using next generation sensor for water management based on LoRaWAN technology: A pilot study, Sensors 20 (17) (2020) 4712.

[101] Yandja Lalle, Mohamed Fourati, Lamia Chaari Fourati, João Paulo Barraca, Routing strategies for LoRaWAN multi-hop networks: A survey and an SDN-based solution for smart water grid, IEEE Access 9 (2021) 168624–168647, http://dx.doi.org/10.1109/ACCESS.2021.3135080.

[102] N.N. Che, K.N.F. Omar, Ku Azir, M.F. Kamarudzaman, Water pipeline leakage monitoring system based on internet of things, in: Journal of Physics: Conference Series, Vol. 1962, IOP Publishing, 2021, 012025.

[103] Nengsheng Bao, Yuchen Fan, Zihao Ye, Alessandro Simeone, A machine vision—Based pipe leakage detection system for automated power plant maintenance, Sensors 22 (4) (2022) 1588.

[104] Ahmed S Ali, Mahmoud N Abdelmoez, Mahmoud Heshmat, Khalil Ibrahim, A solution for water management and leakage detection problems using IoTs based approach, Internet Things 18 (2022) 100504.

[105] P. Boccadoro, V. Daniele, P. Di Gennaro, D. Lofù, P. Tedeschi, Water quality prediction on a Sigfox-compliant IoT device: The road ahead of WaterS, Ad Hoc Netw. 126 (2022) 102749.

[106] D.A. Carnevale Castillo, D.M. Crafa, C. Riboldi, M. Carminati, Water leak monitoring by means of a wireless network of impedance sensing nodes, in: 2023 IEEE Conference on AgriFood Electronics, CAFE, 2023, pp. 187–191, http://dx.doi.org/10.1109/CAFE58535.2023.10291290.

[107] Gabriele Restuccia, Ilenia Tinnirello, F Lo Valvo, Giacomo Baiamonte, Domenico Garlisi, Costantino Giaconia, A distributed analysis of vibration signals for leakage detection in water distribution networks, Mater. Res. Proc. 26 (2023).

[108] Domenico Garlisi, Gabriele Restuccia, Ilenia Tinnirello, Francesca Cuomo, Ioannis Chatzigiannakis, Real-time leakage zone detection in water distribution networks: A machine learning-based stream processing algorithm, in: International Symposium on Algorithmic Aspects of Cloud Computing, Springer, 2023, pp. 86–99.

[109] R. Yauri, M. Gonzales, V. Gamero, Remote monitoring and control system of a water distribution network using LoRaWAN technology, Network (2023) 13–14.

[110] Juan Pablo García-Martín, Antonio Torralba, Model of a device-level combined wireless network based on NB-IoT and IEEE 802.15. 4 standards for low-power applications in a diverse IoT framework, Sensors 21 (11) (2021) 3718.

[111] K. Mekki, E. Bajic, F. Chaxel, 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, 2018, pp. 197–202.

[112] D. Croce, M. Gucciardo, S. Mangione, G. Santaromita, I. Tinnirello, Lora technology demystified: From link behavior to cell-level performance, IEEE Trans. Wireless Commun. 19 (2) (2020) 822–834.

[113] SigFox specifications, 2019, URL https://build.sigfox.com/sigfox-device-radio-specifications. Ref.: EP-SPECS Rev., Feb. 2019. [online].

[114] A. Lavric, A.I. Petrariu, V. Popa, Sigfox communication protocol: The new era of IoT? in: 2019 International Conference on Sensing and Instrumentation in IoT Era, ISSI, 2019, pp. 1–4.

[115] C. Gomez, J.C. Veras, R. Vidal, L. Casals, J. Paradells, A sigfox energy consumption model, Sensors 19 (3) (2019) 681.

[116] A. Lavric, A.I. Petrariu, V. Popa, Long range SigFox communication protocol scalability analysis under large-scale high-density conditions, IEEE Access (2019).

[117] Elarbi Badidi, Zineb Mahrez, Essaid Sabir, Fog computing for smart cities' big data management and analytics: A review, Future Internet 12 (11) (2020) 190.

[118] Hamidreza Arkian, Dimitrios Giouroukis, Paulo Souza Junior, Guillaume Pierre, Potable water management with integrated fog computing and LoRawan technologies, IEEE IoT Newslett. (2020) 1–3.

[119] Adrian Korodi, Ruben Crisan, Andrei Nicolae, Ioan Silea, Industrial internet of things and fog computing to reduce energy consumption in drinking water facilities, Processes 8 (3) (2020) 282.

[120] Yaoling Fan, Qiliang Zhu, Yang Liu, Cloud/fog computing system architecture and key technologies for south-north water transfer project safety, Wirel. Commun. Mob. Comput. 2018 (1) (2018) 7172045.

[121] Mina Emami Khansari, Saeed Sharifian, A modified water cycle evolutionary game theory algorithm to utilize QoS for IoT services in cloud-assisted fog computing environments, J. Supercomput. 76 (7) (2020) 5578–5608.

[122] Sara Mirzaie, MohammadReza AvazAghaei, Omid Bushehrian, Anomaly detection in urban water distribution grids using fog computing architecture, in: 2021 29th Iranian Conference on Electrical Engineering, ICEE, IEEE, 2021, pp. 591–595.

[123] Iván Froiz-Míguez, Peio Lopez-Iturri, Paula Fraga-Lamas, Mikel Celaya-Echarri, Óscar Blanco-Novoa, Leyre Azpilicueta, Francisco Falcone, Tiago M Fernández-Caramés, Design, implementation, and empirical validation of an IoT smart irrigation system for fog computing applications based on LoRa and LoRawan sensor nodes, Sensors 20 (23) (2020) 6865.

[124] Laura García, José Miguel Jiménez, Sandra Sendra, Jaime Lloret, Pascal Lorenz, Multi-layer fog computing framework for constrained LoRa networks intended for water quality monitoring and precision agriculture systems, in: WINSYS, 2021, pp. 46–55.

[125] Stefano Milani, Domenico Garlisi, Carlo Carugno, Christian Tedesco, Ioannis Chatzigiannakis, Edge2LoRa: Enabling edge computing on long-range wide-area internet of things, Internet Things (ISSN: 2542-6605) (2024) 101266, http://dx.doi.org/10.1016/j.iot.2024.101266, URL https://www.sciencedirect.com/science/article/pii/S2542660524002075.

[126] Wajid Rafique, Lianyong Qi, Ibrar Yaqoob, Muhammad Imran, Raihan Ur Rasool, Wanchun Dou, Complementing IoT services through software defined networking and edge computing: A comprehensive survey, IEEE Commun. Surv. Tutor. 22 (3) (2020) 1761–1804.

[127] Carla Mouradian, Diala Naboulsi, Sami Yangui, Roch H Glitho, Monique J Morrow, Paul A Polakos, A comprehensive survey on fog computing: State-of-the-art and research challenges, IEEE Commun. Surv. Tutorials 20 (1) (2017) 416–464.

[128] Lu Hou, Kan Zheng, Zhiming Liu, Xiaojun Xu, Tao Wu, Design and prototype implementation of a blockchain-enabled LoRa system with edge computing, IEEE Internet Things J. 8 (4) (2020) 2419–2430.

[129] FIWARE, FIWARE edge computing tutorial, 2024, https://github.com/FIWARE/tutorials.Edge-Computing. (Accessed 19 November 2024).

[130] Steffen Zeuch, Ankit Chaudhary, Bonaventura Del Monte, Haralampos Gavriilidis, Dimitrios Giouroukis, Philipp M Grulich, Sebastian Breß, Jonas Traub, Volker Markl, The nebulastream platform: Data and application management for the internet of things, 2019, arXiv preprint arXiv:1910.07867.

[131] Shikhar Verma, Yuichi Kawamoto, Zubair Md. Fadlullah, Hiroki Nishiyama, Nei Kato, A survey on network methodologies for real-time analytics of massive IoT data and open research issues, IEEE Commun. Surv. Tutorials 19 (3) (2017) 1457–1477, http://dx.doi.org/10.1109/COMST.2017.2694469.

[132] Zukang Hu, Dingtao Shen, Wenlong Chen, Deep learning-based burst location with domain adaptation across different sensors in water distribution networks, Comput. Chem. Eng. 176 (2023) 108313.

[133] Xudong Fan, Xiong Yu, An innovative machine learning based framework for water distribution network leakage detection and localization, Struct. Health Monit. 21 (4) (2022) 1626–1644.

[134] Juan Li, Cong Wang, Zhihong Qian, Changgang Lu, Optimal sensor placement for leak localization in water distribution networks based on a novel semi-supervised strategy, J. Process Control 82 (2019) 13–21.

[135] Zukang Hu, Wenlong Chen, Debao Tan, Beiqing Chen, Dingtao Shen, Multi-objective and risk-based optimal sensor placement for leak detection in a water distribution system, Environ. Technol. Innov. 28 (2022) 102565.

[136] Mengke Zhao, Chi Zhang, Haixing Liu, Guangtao Fu, Yuntao Wang, Optimal sensor placement for pipe burst detection in water distribution systems using cost–benefit analysis, J. Hydroinform. 22 (3) (2020) 606–618.

[137] Fei Ge, Yuanni Wang, Energy efficient networks for monitoring water quality in subterranean rivers, Sustainability 8 (6) (2016) 526.

[138] Garðar Örn Garðarsson, Francesca Boem, Laura Toni, Graph-based learning for leak detection and localisation in water distribution networks, IFAC-PapersOnLine 55 (6) (2022) 661–666.

[139] Xin Li, Shipeng Chu, Tuqiao Zhang, Tingchao Yu, Yu Shao, Leakage localization using pressure sensors and spatial clustering in water distribution systems, Water Supply 22 (1) (2022) 1020–1034.

[140] Luis Romero-Ben, Débora Alves, Joaquim Blesa, Gabriela Cembrano, Vicenç Puig, Eric Duviella, Leak localization in water distribution networks using data-driven and model-based approaches, J. Water Resour. Plan. Manage. 148 (5) (2022) 04022016.

[141] Jingyu Chen, Xin Feng, Shiyun Xiao, An iterative method for leakage zone identification in water distribution networks based on machine learning, Struct. Health Monit. 20 (4) (2021) 1938–1956.

[142] Ariele Zanfei, Andrea Menapace, Bruno M Brentan, Maurizio Righetti, Manuel Herrera, Novel approach for burst detection in water distribution systems based on graph neural networks, Sustainable Cities Soc. 86 (2022) 104090.

[143] Fatiha Nejjari, Ramon Sarrate, Joaquim Blesa, Optimal pressure sensor placement in water distribution networks minimizing leak location uncertainty, Procedia Eng. 119 (2015) 953–962.

[144] Marcos Quiñones-Grueiro, Cristina Verde, Orestes Llanes-Santiago, Novel leak location approach in water distribution networks with zone clustering and classification, in: Pattern Recognition: 11th Mexican Conference, MCPR 2019, Querétaro, Mexico, June 26–29, 2019, Proceedings 11, Springer, 2019, pp. 37–46.

[145] Xiao Zhou, Zhenheng Tang, Weirong Xu, Fanlin Meng, Xiaowen Chu, Kunlun Xin, Guangtao Fu, Deep learning identifies accurate burst locations in water distribution networks, Water Res. 166 (2019) 115058.

[146] Yujue Zhou, Jie Jiang, Kai Qian, Yulong Ding, Shuang-Hua Yang, Ligang He, Graph convolutional networks based contamination source identification across water distribution networks, Process Saf. Environ. Protect. 155 (2021) 317–324.

[147] Yeonsoo Kim, Shin Je Lee, Taekyoon Park, Gibaek Lee, Jung Chul Suh, Jong Min Lee, Robust leak detection and its localization using interval estimation for water distribution network, Comput. Chem. Eng. 92 (2016) 1–17.

[148] Miguel Capelo, Bruno Brentan, Laura Monteiro, Dídia Covas, Near–real time burst location and sizing in water distribution systems using artificial neural networks, Water 13 (13) (2021) 1841.

[149] Katherine A Klise, Michael Bynum, Dylan Moriarty, Regan Murray, A software framework for assessing the resilience of drinking water systems to disasters with an example earthquake case study, Environ. Model. Softw. 95 (2017) 420–431.

[150] Djellel Eddine Difallah, Philippe Cudre-Mauroux, Sean A McKenna, Scalable anomaly detection for smart city infrastructure networks, IEEE Internet Comput. 17 (6) (2013) 39–47.

[151] S. Panguluri, W.M. Grayman, R.M. Clark, L.M. Garner, R. Haught, Water Distribution System Analysis: Field Studies, Modeling and Management, Technical Report EPA/600/R-06/028, U.S. Environmental Protection Agency, Washington, DC, 2005.

[152] Edo Abraham, Ivan Stoianov, Sparse null space algorithms for hydraulic analysis of large-scale water supply networks, J. Hydraul. Eng. 142 (3) (2016) 04015058.

[153] Gabriele D'Angelo, Stefano Ferretti, Vittorio Ghini, Simulation of the internet of things, in: 2016 International Conference on High Performance Computing & Simulation, HPCS, 2016, pp. 1–8, http://dx.doi.org/10.1109/HPCSim.2016.7568309.

[154] Nitin P. Sonaje, Mandar G. Joshi, A review of modeling and application of water distribution networks (WDN) softwares, Int. J. Tech. Res. Appl. 3 (5) (2015) 174–178.

[155] L.A. Rossman, Computer models/EPANET, in: Water Distribution Systems Handbook, McGraw-Hill companies, Inc., New York, NY, 1999, (Chapter 12).

[156] L.A. Rossman, EPANET 2 users manual, 2000.

[157] Katherine A. Klise, et al., A software framework for assessing the resilience of drinking water systems to disasters with an example earthquake case study, Environ. Model. Softw. 95 (2017) 420–431.

[158] Oloche Ekwule, Joseph Utsev, Evaluation of a municipal water distribution network using waterCAD and waterGEMS, Kastamonu Univ. J. Eng. Sci. 5 (2) (2019) 147–156.

[159] Darshan J. Mehta, et al., Design of optimal water distribution systems using WaterGEMS: a case study of surat city, in: E-Proceedings 37th IAHR World Congr, 2017, pp. 1–8.

[160] Daniele Laucelli, Luigi Berardi, Orazio Giustolisi, WDNetXL: hydraulic and topology analysis integration and features, Procedia Eng. 119 (2015) 669–679.

[161] Francesco Gino Ciliberti, et al., Digital transformation paradigm for asset management in water distribution networks, in: 2021 10th International Conference on ENERGY and ENVIRONMENT, CIEM, IEEE, 2021.

[162] Shahab Araghinejad, Data-Driven Modeling: Using MATLAB® in Water Resources and Environmental Engineering, vol. 67, Springer Science & Business Media, 2013.

[163] AD Bello, Waheed A Alayande, Johnson A Otun, Abubakar Ismail, Umar F Lawan, Optimization of the designed water distribution system using MATLAB, Int. J. Hydraul. Eng. 4 (2) (2015) 37–44.

[164] MathWorks, Water supply system. URL https://www.mathworks.com/help/hydro/ug/water-supply-system.html.

[165] Ying Zhao, Jun Nan, Fu-yi Cui, Liang Guo, Water quality forecast through application of BP neural network at Yuqiao reservoir, J. Zhejiang Univ. Sci. A 8 (2007) 1482–1487.

[166] MathWorks, Water distribution system scheduling using ... - MATLAB & simulink. URL https://it.mathworks.com/help/reinforcement-learning/ug/water-distribution-scheduling-system.html.

[167] MathWorks, Model a thermal liquid pipeline - MATLAB & simulink - MathWorks. URL https://www.mathworks.com/help/hydro/ug/model-a-thermal-liquid-pipeline.html.

[168] C.P. Robert, G. Casella, Monte Carlo Statistical Methods, second ed., Springer-Verlag, New York, ISBN: 0-387-21239-6, 2004.

[169] Giao T. Nguyen, et al., A trace-based approach for modeling wireless channel behavior, in: Proceedings of the 28th Conference on Winter Simulation, 1996.

[170] M. Dyk, A. Najgebauer, D. Pierzchala, SenseSim: An agent-based and discrete event simulator for wireless sensor networks and the internet of things, in: 2015 IEEE 2nd World Forum on Internet of Things, WF-IoT, Milan, Italy, 2015.

[171] ns-3 manual, 2023, URL https://www.nsnam.org/docs/release/3.35/manual/ns-3-manual.pdf. (Accessed November 2023).

[172] F. Van den Abeele, J. Haxhibeqiri, I. Moerman, J. Hoebeke, Scalability analysis of large-scale LoRaWAN networks in ns-3, IEEE Internet Things J. 4 (2017) 2186–2198.

[173] J. Silva, D. Flor, V.A. de Junior, N. Bezerra, A. Medeiros, A survey of LoRaWAN simulation tools in ns-3, J. Commun. Inf. Syst. 36 (2021) 17–30.

[174] S. Idris, T. Karunathilake, A. Förster, Survey and comparative study of LoRa-enabled simulators for internet of things and wireless sensor networks, Sensors 22 (2022) 5546.

[175] C. Mallanda, A. Suri, V. Kunchakarra, et al., Simulating wireless sensor networks with OMNeT++.

[176] Marko Korkalainen, et al., Survey of wireless sensor networks simulation tools for demanding applications, in: 2009 Fifth International Conference on Networking and Services, IEEE, 2009.

[177] Mariusz Slabicki, G.P. Di Francesco, FLoRa—Framework for LoRa, 2023, https://omnetpp.org/download-items/FLoRA.html. (Accessed November 2024).

[178] Mariusz Slabicki, Gopika Premsankar, Mario Di Francesco, Adaptive configuration of LoRa networks for dense IoT deployments, in: NOMS 2018 - 2018 IEEE/IFIP Network Operations and Management Symposium, 2018, pp. 1–9, http://dx.doi.org/10.1109/NOMS.2018.8406255.

[179] Mukarram AM Almuhaya, Waheb A Jabbar, Noorazliza Sulaiman, Suliman Abdulmalek, A survey on LoRawan technology: Recent trends, opportunities, simulation tools and future directions, Electronics 11 (1) (2022) 164.

[180] Mukarram A.M. Almuhaya, et al., An overview on LoRaWAN technology simulation tools, in: International Conference of Reliable Information and Communication Technology, Springer International Publishing, Cham, 2021.

[181] SEAMCAT - spectrum engineering advanced Monte Carlo analysis tool. URL https://cept.org/eco/eco-tools-and-services/seamcat-spectrum-engineering-advanced-monte-carlo-analysis-tool.

[182] ECC report 252: SEAMCAT handbook, 2016.

[183] A. Marinčić, A. Kerner, D. Šimunić, Interoperability of IoT wireless technologies in ambient assisted living environments, in: 2016 Wireless Telecommunications Symposium, WTS, 2016, pp. 1–6.

[184] R. Dionísio, T. Lolić, P. Torres, Electromagnetic interference analysis of industrial IoT networks: From legacy systems to 5G, in: 2020 IEEE Microwave Theory and Techniques in Wireless Communications, MTTW, Riga, Latvia, 2020, pp. 41–46.

[185] Tiziana Cattai, Stefania Colonnese, Domenico Garlisi, Antonino Pagano, Francesca Cuomo, GraphSmart: a method for green and accurate IoT water monitoring, ACM Trans. Sensor Netw. (2024).

[186] Antonino Pagano, Domenico Garlisi, Fabrizio Giuliano, Tiziana Cattai, Francesca Cuomo, SWI-FEED: Smart water IoT framework for evaluation of energy and data in massive scenarios, 2024, arXiv preprint arXiv:2404.07692.

[187] Nibi Kulangara Velayudhan, Preeja Pradeep, Sethuraman N Rao, Aryadevi Remanidevi Devidas, Maneesha Vinodini Ramesh, IoT-enabled water distribution systems—A comparative technological review, IEEE Access 10 (2022) 101042–101070.

[188] Fatai Adeshina Adelani, Enyinaya Stefano Okafor, Boma Sonimiteim Jacks, Olakunle Abayomi Ajala, Theoretical frameworks for the role of ai and machine learning in water cybersecurity: insights from african and US applications, Comput. Sci. IT Res. J. 5 (3) (2024) 681–692.

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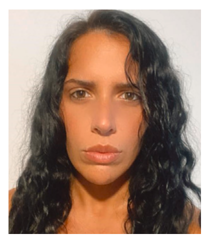

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