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THE INTERNET OF THINGS IN WATER DISTRIBUTION NETWORKS: A LITERATURE REVIEW ON THE IN-DEPTH ANALYSIS OF ITS IMPACT ON MONITORING AND CONTROL SYSTEMS

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Résumé

L'incorporation de la technologie IoT dans les réseaux d'approvisionnement en eau offre la possibilité d'améliorer la surveillance, le contrôle et l'efficacité opérationnelle, représentant ainsi une révolution dans la gestion des infrastructures urbaines. Cette revue synthétise l'avancement actuel de la recherche dans les systèmes de distribution d'eau stimulés par l'IoT, et scrute les fondements scientifiques, les applications notables ainsi que les défis en cours qui définissent ce domaine en perpétuelle progression. Après un examen approfondi des précédentes études, nous arrivons à la conclusion que l'IoT contribue majoritairement à la régulation des systèmes de distribution d'eau en permettant de surveiller en direct la qualité et la pression de l'eau, de détecter et situer les fuites, et d'anticiper la demande. Toutefois, de nombreux obstacles demeurent tels que le besoin de directives d'application constantes, les limites de capacité de mise à l'échelle, les vulnérabilités en cybersécurité et les enjeux d'interopérabilité. Cet article présente une classification organisée des applications IoT dans les réseaux d'approvisionnement en eau et souligne des axes de recherche pertinents, tels que l'intégration des doubles jumeaux numériques, l'apprentissage fédéré et l'intelligence artificielle explicable dans la gestion des décisions des systèmes d'eau.

Mots-clés: Internet des Objets, Réseaux de distribution d'eau, Systèmes d'eau intelligents, LPWAN, Détection de fuites, Informatique en périphérie

Abstract

The integration of Internet of Things (IoT) technology into Water Distribution Networks (WDNs) enables previously unheard-of levels of monitoring, control, and operational efficiency, signifying a paradigm shift in urban infrastructure management. This review summarizes the current state of research on IoT-enabled water distribution systems and examines the scientific foundations, significant applications, and ongoing challenges that characterize this rapidly evolving field. Based on a comprehensive analysis of previous research, we conclude that IoT primarily aids WDN management through real-time water quality monitoring, leak detection and location, pressure management, and demand forecasting. The convergence of edge computing architectures, machine learning techniques, and Low-Power Wide-Area Network (LPWAN) technologies has accelerated the transition from traditional reactive maintenance to proactive, data-driven management paradigms. However, there are still significant challenges, including the need for consistent implementation guidelines, scalability constraints, cybersecurity flaws, and interoperability issues. This analysis offers a structured taxonomy of IoT applications in WDNs and highlights interesting research directions such as digital twin integration, federated learning, and explainable artificial intelligence in water system decision-making. The findings highlight the need for additional research to address implementation challenges and provide dependable, sustainable water distribution systems while also showcasing the transformative potential of IoT technologies.

Keywords: Internet of Things, Water Distribution Networks, Smart Water Systems, LPWAN, Leakage Detection, Edge Computing

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1. Introduction

With aging infrastructure, growing urbanization demands, and water shortages brought on by climate change, the world's water demand is still rising [1]. Maintaining service quality, reducing losses, and guaranteeing public health protection present previously unheard-of challenges for Water Distribution Networks (WDNs), which are intricate networks of pipelines, storage facilities, pumps, valves, and meters that transport water from treatment plants to consumers [1, 2].

The scope and complexity of today's water system problems are becoming too much for traditional methods of WDN management, which are typified by sporadic manual inspections and reactive maintenance [1].

The administration of water distribution systems could be completely transformed by the Internet of Things (IoT), a revolutionary technological paradigm. IoT provides automated control, data-driven decision-making, and continuous real-time monitoring by integrating sensing, communication, and computational capabilities throughout the network architecture [3]. What the literature refers to as "Smart Water Distribution Systems" (SWDS) or "Smart Water Grids" (SWG) is based on this incorporation of information and communication technology (ICT) into water infrastructure.

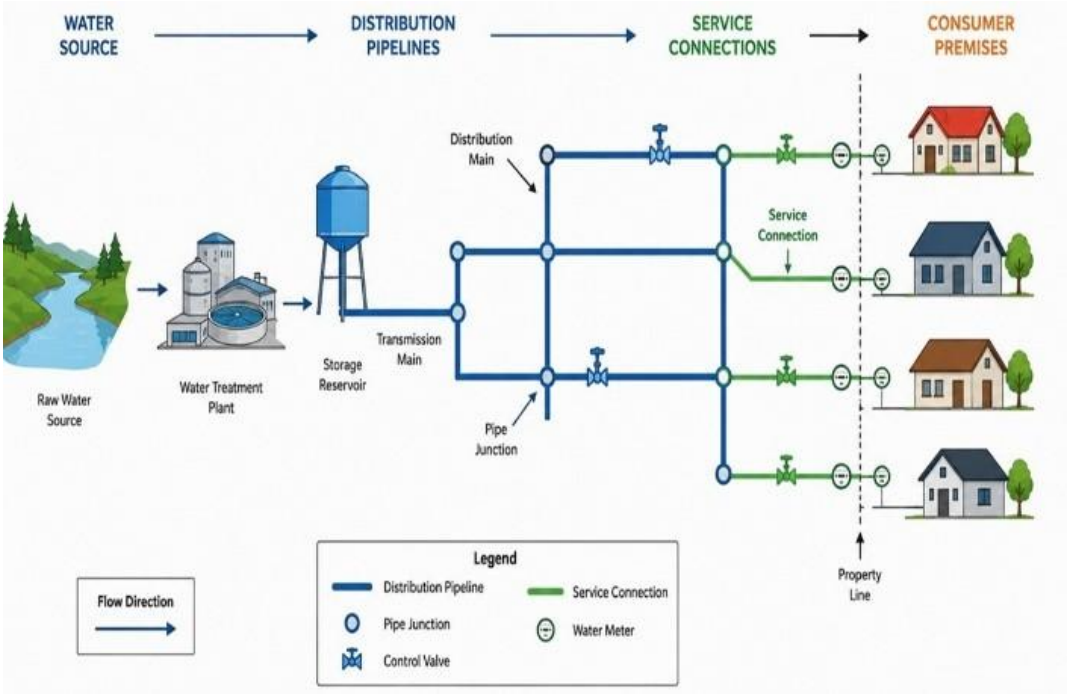


Figure 1: *Diagram of water distribution network*



Figure 2: *IoT-enabled Smart Water Network architecture*

The IoT-enabled water distribution system uses a layered architecture: the communication layer sends data to processing nodes via wireless networks; the application layer handles data analytics, visualization, and control tasks; and the sensing layer includes a variety of sensors that measure parameters like pressure, flow rate, water quality indicators, and acoustic signatures [4]. Applications including water quality monitoring, demand forecasting, pressure optimization, and leak detection and localization are made possible by this architecture [5, 6]. The scope of the problem IoT tackles highlights its importance in WDN administration. Water utilities throughout the world bear a significant financial and environmental burden from non-revenue water (NRW), which is water that is generated but lost before it reaches consumers. Through early detection and quick reaction to leaks and bursts, IoT-based monitoring systems have the potential to significantly cut water losses. Additionally, IoT makes it possible to comply with increasingly strict water quality rules by continuously monitoring factors including turbidity, pH, chlorine residual, and the presence of contaminants [3]. The goal of this review is to present a thorough summary of the state of the art regarding IoT contributions to water distribution network control and monitoring systems. We specifically target the following research questions [4]:

- Which technology elements and architectures are essential to IoT-enabled water distribution systems?
- In WDN monitoring and control, what are the main uses of IoT technologies?
- What are the main obstacles and difficulties that water distribution networks face when using IoT on a wide scale?
- What are the latest developments and potential avenues for further research in this field?

This paper's remaining sections are structured as follows: IoT integration in water distribution systems is reviewed in Section 2 together with its context. Sensor technologies, communication protocols, and computational architectures are among the technological underpinnings that are examined in Section 3. In Section 4, important applications are examined in accordance with a suggested taxonomy. In Section 5, the main obstacles and unanswered research problems are identified. Future directions and new trends are discussed in Section 6, and the results and consequences are summarized in Section 7.

2. Background and Context

2.1 Water Distribution Systems: Structure and Operational Challenges

The water distribution system (WDS), which delivers water from transmission mains to individual consumers via smaller-diameter pipelines, valves, meters, and service connections, and the water transmission system (WTS), which moves massive volumes of water from sources to distribution areas through large-diameter pipelines and pumping stations, make up a water supply system [6].

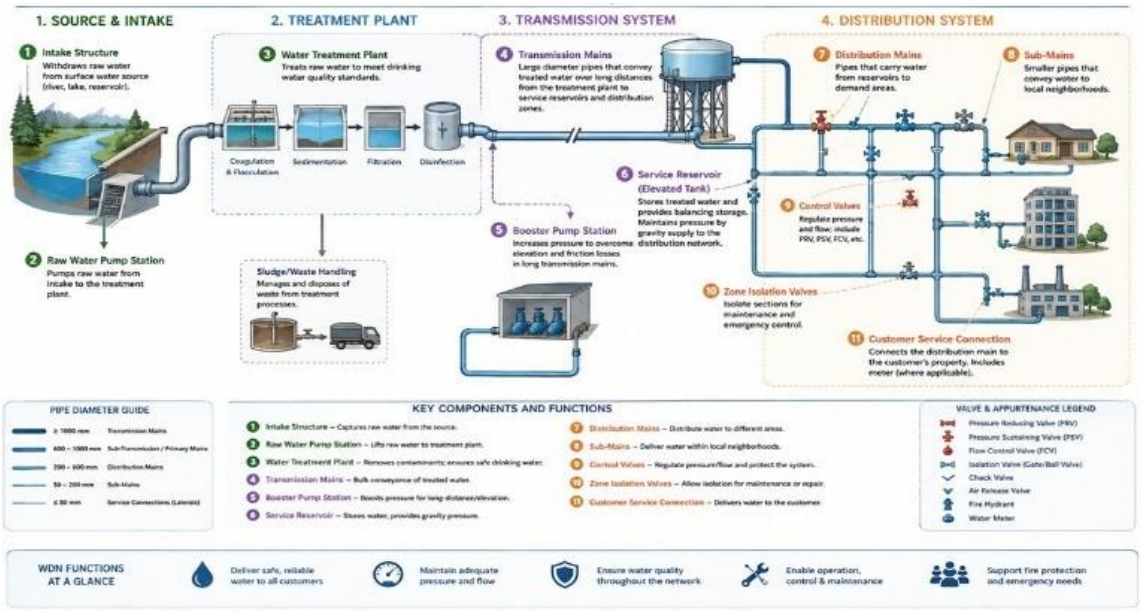


Figure 3: *Components and functions of the WDN architecture from source to customer.*

WDN operational management poses a number of noteworthy difficulties. Frequent leaks and pipe bursts caused by aging infrastructure, especially in industrialized countries, lead to significant water losses and service interruptions [6]. Biofilm formation, pollutant entry, and corrosion of pipe materials can all lead to a decline in water quality [7, 8]. In order to maintain sufficient service while reducing losses and energy consumption, demand oscillations brought on by diurnal patterns and seasonal variations necessitate sophisticated pressure control. Furthermore, climate change-related extreme weather events are becoming more frequent and intense, which presents significant difficulties for system resilience [7, 9].

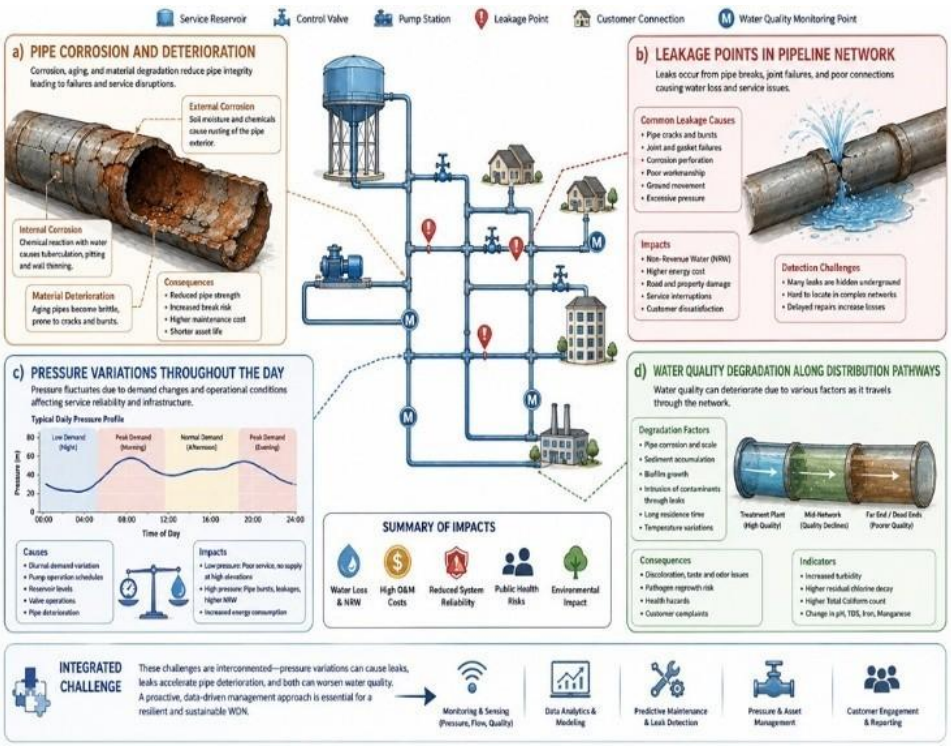


Figure 4: *The key operational challenges in WDNs.*

2.2 The Emergence of Smart Water Distribution Systems

The idea of "smart" water distribution systems refers to the use of ICT, IoT sensors, digital controls, and analytics tools to monitor, automate, and regulate water distribution, guaranteeing effective customer water delivery [8].

The Fourth Industrial Revolution (4IR), which is defined by the convergence of technologies like IoT, cloud computing, cyber-physical systems (CPS), and artificial intelligence (AI), is the larger framework in which this digital revolution is taking place [9, 25]. From the early adoption of software platforms and sensors to the creation of creative, digitally conscious companies that use integrated systems for automated decision making, the Digital Water Adoption Roadmap (DWAR) envisions the development of water utilities along a digitization journey [10].

Many utility companies are still in an opportunistic or early stage, indicating tremendous development potential, even though some have made significant progress down this curve [11].

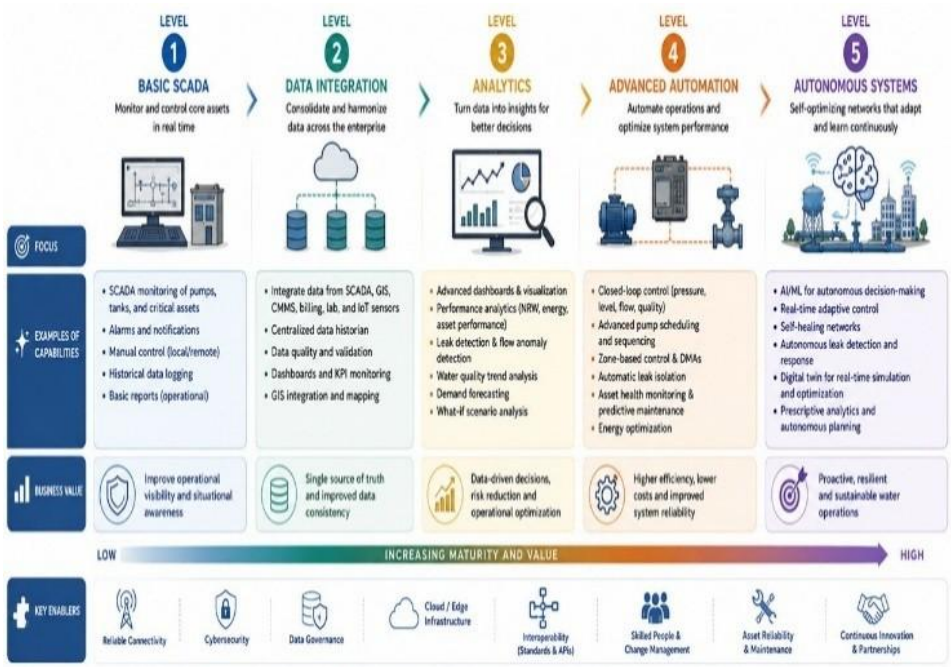


Figure 5: *The DWA Roadmap progression to an intelligent, resilient and autonomous water utility*

2.3 Prior Review Studies

Numerous review and survey studies, each focusing on a distinct facet of the field, have accompanied the expanding corpus of literature on IoT in water distribution systems. A comparative overview of the major review contributions is given in Table 1:

Table 1: Comparative analysis of review studies on IoT in water distribution systems.

References	WDS background	IoT overview	Challenges	Edge computing	Massive IoT
Lalle et al. [4]	*X*	✓	✓	*X*	*X*
Oberascher et al. [5]	*X*	✓	✓	*X*	*X*
Ismail et al. [6]	*X*	✓	*X*	✓	*X*
Yuan et al. [7]	*X*	*X*	✓	✓	*X*
Li et al. [8]	*X*	✓	✓	*X*	*X*
Velayudhan et al. [10]	✓	✓	✓	✓	✓
This review	✓	✓	✓	✓	✓

Sources: Adapted from [1, 7, 9].

Leak detection techniques, IoT technology and applications, and data-driven strategies for smart water management have all been covered in earlier reviews of IoT in WDNs. However, few studies have offered an integrated study that concurrently tackles the technologies, implementation guidelines, and constraints for huge IoT scenarios in water distribution systems [9]. The current review, which attempts to offer a thorough and integrated viewpoint on IoT contributions to WDN control and monitoring, is motivated by this gap [11].

3. The Technological Foundations of IoT-Enabled WDS

3.1 Sensing Technologies

The network-wide sensing infrastructure is the cornerstone of IoT-enabled WDNs. Among the important sensing technologies are [13]:

- Among the most extensively used sensors in WDN monitoring, **pressure sensors** offer vital information for leak detection, hydraulic model calibration, and pressure control. Transient analysis for burst detection and localization is made possible by high-frequency pressure sensors that can sample at hundreds of Hertz. The literature does point out that there are still few known uses of high frequency pressure sensors in actual, large-scale WDNs [14].

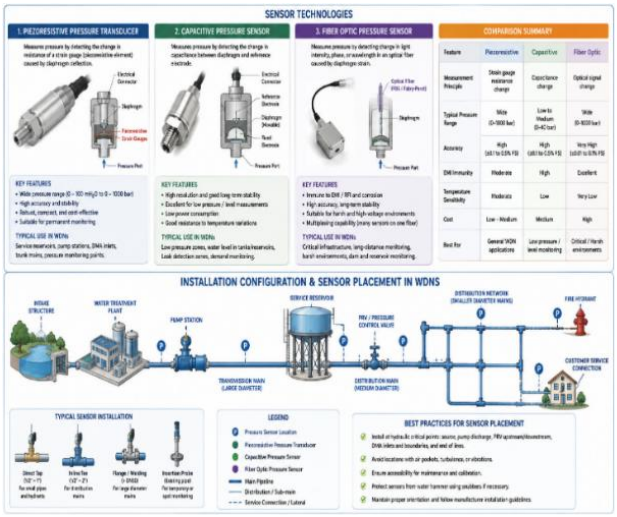


Figure 6: *should show different types of pressure sensors used in WDNs.*

- **Flow meters** provide vital information for demand analysis, water balance computations, and leak identification by measuring the rate of water flow through pipes. By examining flow patterns, sophisticated flow meters can differentiate between genuine usage and leakage.
  One important supporting technology for demand-side management is smart meters at customer locations, which allow for the collection of detailed consumption data [12, 14].
- **Water quality sensors** track variables like conductivity, turbidity, dissolved oxygen, pH, and residual chlorine [14, 15]. These sensors are essential for maintaining legal compliance and safeguarding public health. The integration of water quality sensors into Internet of Things systems facilitates optimal water treatment operations and early detection of contamination incidents.

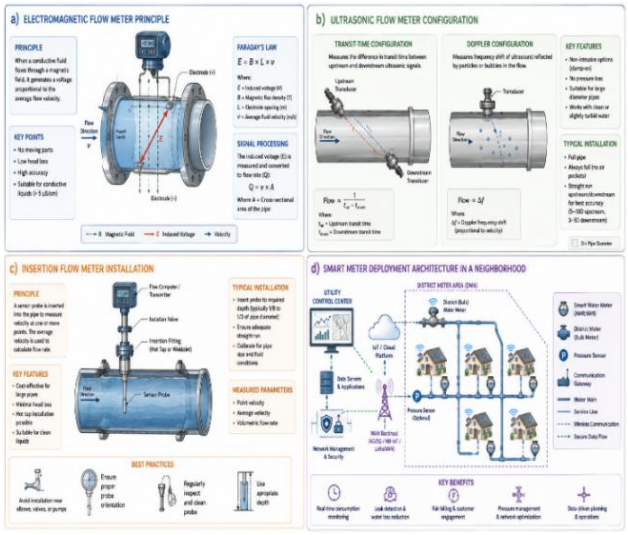


Figure 7: *Flow measurement technologies and smart meter deployment in WDNs.*

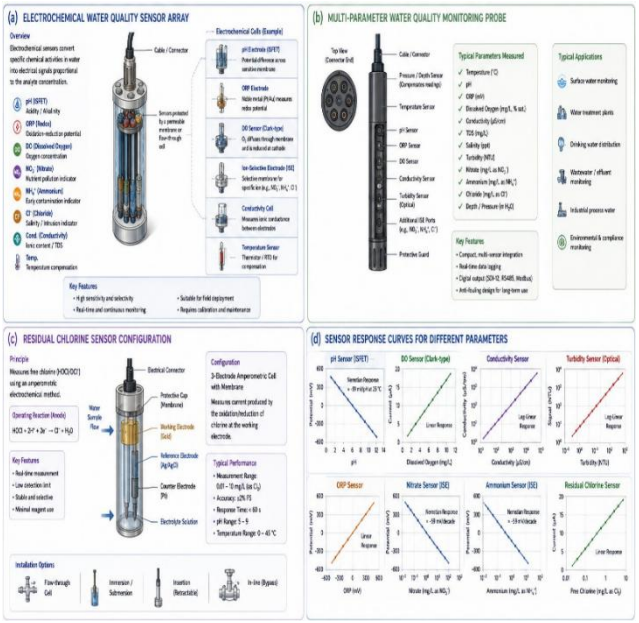


Figure 8: *Water quality sensors (Technologies, configurations and performance).*

- In metallic pipelines, where leaks produce distinctive acoustic signatures that travel through the pipe wall and water column, acoustic sensors are utilized for leak detection [15]. Although applications are still mostly restricted to particular site conditions in developed nations, **acoustic sensing** has been recognized as a promising method for accurate leak detection and localization.

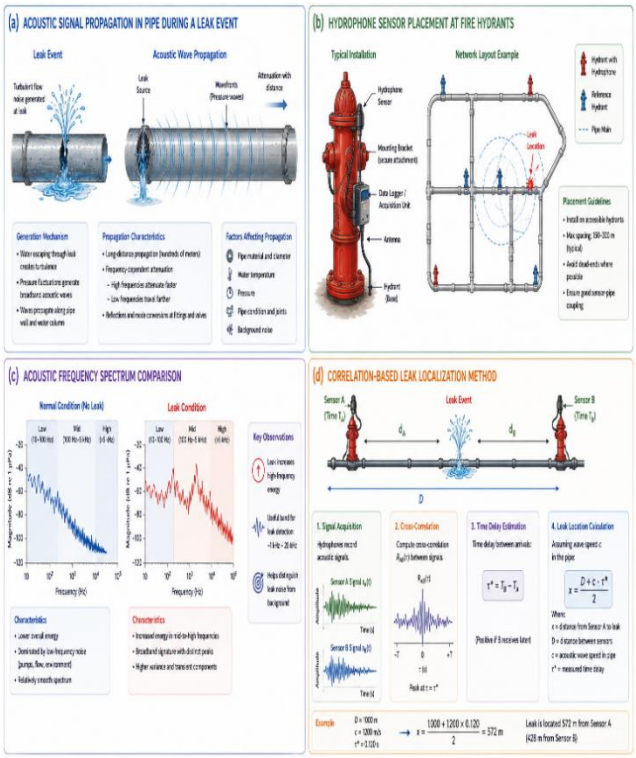


Figure 9: *Acoustic leak detection and localization in WDN*

3.2 Communication Technologies

Technologies that balance range, data rate, power consumption, and cost are needed for the communication layer, which links sensors and actuators to data processing infrastructure. Due of its applicability for large-scale IoT deployments, Low-Power-Wide Area Network (LPWAN) technologies have drawn special interest for WDN monitoring [14, 19].

- Battery-powered sensors can run for extended periods of time thanks to **LoRaWAN** (Long Range Wide Area Network), which operates in unlicensed spectrum and provides long-range communication (several kilometers in urban settings) with minimal power consumption [19]. Because LoRaWAN can penetrate subterranean infrastructure and supports a high number of end devices, it has been widely deployed in water monitoring applications [22].
- With ultra-low-power sleep modes that allow battery-operated nodes to function for months or years on a single cell, **the LoRa SX1278 Ra-02 (433 MHz)** module facilitates long-range communication with a practical connectivity range of 2–5 km in semi-urban environments and up to 15–20 km under ideal rural line-of-sight conditions. IoT devices are connected to several gateways in LoRaWAN's cell-free architecture [15, 19, 26].

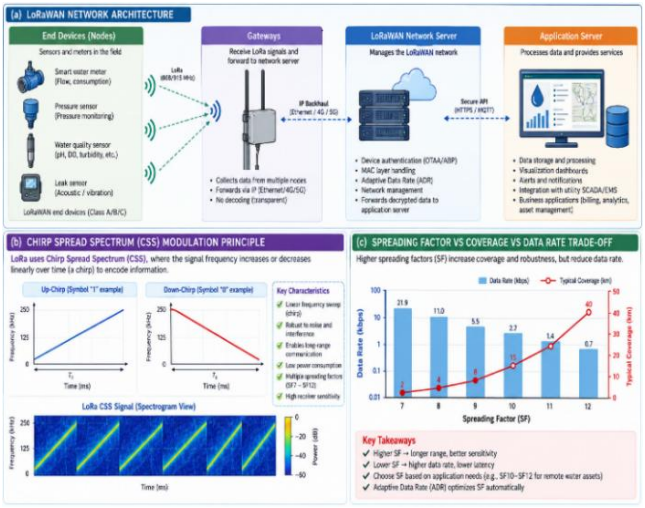


Figure 10: *LoRaWAN Technology for IoT in Smart water Networks.*



Figure 11: *LoRa communication modules (Signal propagation and gateway placement.*

- Although it has higher device and subscription costs than unlicensed alternatives, **NB-IoT** (Narrowband Internet of Things) works on licensed cellular spectrum and provides better coverage and dependability. Applications needing larger data volumes or where network dependability is crucial are especially well-suited for NB-IoT [22].
- With extremely low power consumption and constrained uplink data speeds, **SigFox** provides an alternative LPWAN technology that operates in unlicensed spectrum. SigFox's simplicity and low device cost make it appealing for low-data applications like pressure monitoring, even though it offers lower data speeds than LoRaWAN or NB-IoT.

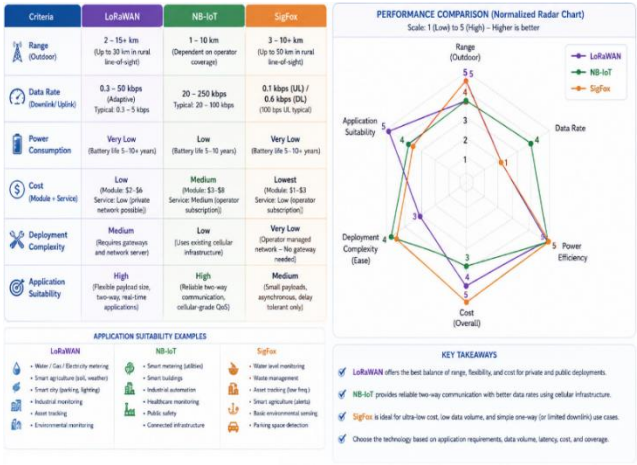


Figure 12: *Comparison of LPWAN technologies (LoRaWAN vs NB-IoT vs SigFox)*

Wi-Fi for local area connection, ZigBee for short-range sensor networks, and cellular networks (4G/5G) for higher-bandwidth applications are **other communication technologies** pertinent to WDN monitoring [15]. The deployment-specific criteria, such as network coverage, data speeds, power limitations, and cost, determine which communication technology is best [22].

TECHNOLOGY OVERVIEW

Technology	Range	Data Rate (Typical)	Power Consumption	Relative Cost (Device / Service)	Best Suited Use Cases	Environmental Suitability
Bluetooth Low Energy (BLE)	< 100 m	125 kbps – 2 Mbps	Very Low	Low	Asset tracking, wearable tools, local device configuration	Indoor / Protected
Zigbee (IEEE 802.15.4)	10 – 100 m	20 – 250 kbps	Very Low	Low	Smart meters (networked), sensor networks	Indoor / Normal
Wi-Fi (IEEE 802.11)	30 – 100 m	Up to >100 Mbps	High	Low (No license) (Infra cost)	High data logging, video surveillance, SCADA backhaul	Indoor / Normal
Wi-Fi Mesh	100 m – 2 km (hop-by-hop)	Up to >50 Mbps	Medium	Medium	Distributed monitoring, pipe network connectivity	Outdoor / Normal
Private LTE / 4G (Small Cell)	1 – 10 km	Up to 100 Mbps	Medium – High	High (Spectrum + Infra)	SCADA, real-time control, high reliability systems	Outdoor / Harsh
LTE-M (Cat-M1)	Up to 15 km	Up to 1 Mbps	Low	Medium (Subscription)	Metering, telemetry, alarms, mobile assets	Outdoor / Normal
LoRaWAN (Private)	2 – 15+ km	0.3 – 50 kbps	Very Low	Low (Gateway + No license)	Water quality sensors, pressure monitoring, leak detection	Outdoor / Harsh
Satellite IoT	Global	0.1 – 100 kbps	Low – Medium	High (Subscription)	Remote reservoirs, remote sites, disaster recovery areas	Extreme / Remote

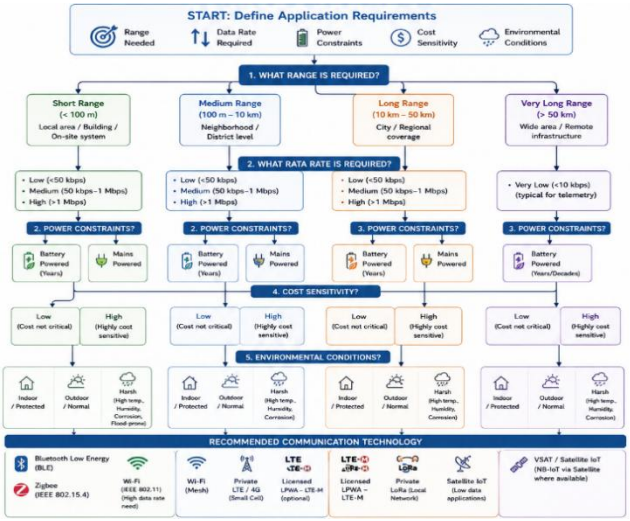


Figure 13: *Selecting the right IoT communication Technology for WDs*

3.3 Computing Architectures

Water distribution systems have historically processed IoT data using a cloud-centric design, sending sensor data to cloud platforms for analysis and storage [16]. However, the development of edge computing architectures has been

fueled by the enormous size of IoT deployments in WDNs and the requirement for real-time responses to events like pipe bursts.

- By bringing compute and data storage closer to the data sources, **edge computing** enables real-time data processing, lowers latency, and uses less network capacity [1]. Without needing to communicate with central cloud platforms, edge nodes at pumping stations or district metered areas in WDN applications can carry out preliminary data processing, anomaly detection, and even localized control decisions.
- Through a distributed computing infrastructure that enables processing and storage between edge devices and cloud data centers, **fog computing** expands cloud computing to the network edge [12]. With long-term data storage and sophisticated analytics carried out in the cloud and time-sensitive analysis carried out at edge nodes, this architecture facilitates hierarchical data processing.
- According to [1], **cloud computing** is still crucial for applications that need long-term trend monitoring over vast geographic areas, model training for machine learning techniques, and intensive data analytics. Edge, fog, and cloud computing together offer a range of computing resources that can serve various WDN applications [14].

3.4 Simulation and Modeling Tools

A variety of simulation and modeling tools facilitate the design, assessment, and operation of IoT-enabled WDNs [16]:

- **Water network simulation tools** that provide hydraulic and water quality modeling elements required for system design, calibration, and operational analysis include EPANET, WaterGEMS, WaterCAD, and WDNetXL. The integration of these technologies with IoT data streams enables digital twin applications, which continuously update virtual representations of the physical network with sensor data.
- Communication network performance can be assessed under different deployment situations using **Wireless Sensor Network Simulation Tools** like ns-3, OMNeT++, and LoRaSim. Before a network is physically deployed, these technologies are crucial for evaluating its scalability, coverage, and energy usage.
- A new approach to WDN management is represented by **digital twin** frameworks, which combine real-time IoT data with simulation models to offer scenario analysis, predictive analytics, and continuous monitoring. One promising technology for assisting sustainable urban infrastructure management is digital twins [17].

4. Methodology

This review was conducted as a systematic literature review (SLR) following the general guidelines of Kitchenham and the PRISMA-style reporting adapted to engineering reviews [12, 18]. The methodology is summarized below.

4.1 Review Protocol

A review protocol was defined prior to the search to reduce selection bias. The protocol specified the research questions (already stated in Section 1), the search strings, the inclusion and exclusion criteria, the quality-assessment checklist, and the data-extraction template.

4.2 Search Strategy

Four bibliographic databases were queried: Scopus, Web of Science, IEEE Xplore, and ScienceDirect. The search string combined three concept blocks with Boolean operators:

- ‘’Internet of Things’’ OR IoT OR LPWAN OR LoRaWAN OR ‘’wireless sensor network’’;
- ‘’Water distribution network’’ OR ‘’water supply system’’ OR "smart water grid’’ OR ‘’water distribution system’’;
- ‘’monitoring OR control’’ OR "leak detection" OR "demand forecasting" OR "water quality" OR ‘’architecture’’ OR ‘’algorithm’’.

The search was restricted to 2020–2025 to capture the post-LPWAN era, and to peer-reviewed journal articles, conference papers, and authoritative technical reports. A backward snowballing pass on the reference lists of the retained reviews [4, 5, 6, 7, 8, 10, 18, 21] complemented the database search.

4.3 Inclusion and Exclusion Criteria

Table 2: Criteria of inclusion and exclusion

Inclusion	Exclusion
Studies on IoT sensing, communication, computing, or analytics applied to WDNs	Studies on water treatment or wastewater only
Studies reporting algorithms, architectures, or deployment results	Purely theoretical papers with no water-domain relevance
English or French language	Non-retrievable full text
2020–2025	Duplicate or predatory publications

4.4 Screening and Selection

The search returned an initial pool of records. After removal of duplicates, titles and abstracts were screened against the criteria, followed by full-text assessment. Disagreements between reviewers were resolved by consensus.

4.5 Data Extraction and Synthesis

For each retained study, the following data were extracted:

- WDN application domain (infrastructure, demand, quality);
- Sensing and communication technologies;

- computing architecture (cloud, fog, edge);
- Algorithm family and reported computational complexity, where available;
- Deployment scale (pilot, district, city);
- Reported challenges. Findings were synthesized thematically in this paper.

4.6 Quality Assessment

Each study was scored on a five-item checklist adapted from [12]: clarity of objectives, reproducibility of the method, scale of validation, reporting of complexity or resource usage, and discussion of limitations. This score informs the weighting given to studies in the next sections.

5. Key Applications of IoT in WDN Monitoring and Control

We suggest a taxonomy of IoT applications in water distribution systems based on the synthesis of the reviewed literature, arranged around three key domains: infrastructure analysis, demand analysis, and water quality monitoring [1].

5.1 Infrastructure Analysis

Infrastructure analysis includes applications that concentrate on the water distribution infrastructure's operational effectiveness and structural integrity.

a) One of the most important IoT applications in WDNs is leak detection and localization. Leaks can be found via pressure monitoring, flow analysis, acoustic detection, and combinations of these methods by IoT-enabled systems. The following major categories apply to leak detection techniques [18]:

- **Pressure-based techniques**, such as pressure-flow deviation methods, pressure residual vector methods, negative pressure wave methods, and transient analysis techniques, identify leaks by examining departures from anticipated pressure-flow relationships. These techniques profit from pressure sensors' quick response time and comparatively low cost [17, 19].
- By analyzing the acoustic signals produced by water escaping from pressured pipes, **acoustic technologies** find leaks. Leak detection in metallic pipes has been found to be especially successful with acoustic reflectometry.
- **Data-driven approaches** use machine learning algorithms to identify trends in sensor data that are abnormal and suggest leaks. Burst and leakage detection has been done using statistical, prediction-classification, and classification techniques [19].

According to the literature, hybrid systems that combine several detection strategies outperform single-method approaches in terms of accuracy and false alarms. However, it is still difficult to apply these methods practically for large-scale WDNs [17, 27].

b) Utilities can maximize network pressures through pressure management to avoid leaks, prolong the life of infrastructure, and use less energy. IoT-enabled pressure monitoring offers early detection of pressure anomalies suggestive of operational issues and real-time visibility into network pressure conditions, allowing proactive pressure adjustments based on demand patterns [16].

c) By evaluating the state of WDN assets using IoT sensors, Asset Condition Monitoring enables risk-based asset replacement and predictive maintenance. In order to support data-driven infrastructure management decisions, this involves tracking pipe corrosion, valve condition, and pump performance [6].

5.2 Demand Analysis

Applications for demand analysis concentrate on comprehending and improving service delivery and water use trends.

A. IoT-enabled water meters are installed at customer locations as part of smart metering, which provides comprehensive usage data with precise temporal precision [18] enables:

- Demand forecasting uses machine learning algorithms to anticipate future demand by analyzing past consumption trends.
- Segmenting customers to find usage trends and customize conservation initiatives.
- Models that adjust to shifting consumption patterns without retraining have been made possible by incremental learning techniques.
- State Estimation uses sensor data to infer unobserved network states (pressures, flows at unmonitored sites) through hydraulic model calibration and data assimilation techniques. This enables complete network awareness with minimal sensor deployments.

B. In order to enable focused conservation initiatives and customer feedback, Water End-Use Analysis examines high-resolution consumption data to determine the water end-uses (such as showers, toilets, and irrigation) that contribute to overall consumption [21].

5.3 Water Quality Monitoring

Applications for water quality monitoring help regulatory compliance and guaranty that consumers receive safe water.

a) Chlorine residual, pH, turbidity, temperature, and conductivity are among the important water quality characteristics that Real-Time Water Quality Monitoring uses IoT sensors to continually monitor [22] This makes:

- Early detection of contaminated events.
- Enhanced disinfection via feedback regulation of chlorine dosage.
- Tracking adherence to legal obligations.
- To identify variations in the quality of raw water, source water monitoring is used.

b) To find variations from baseline conditions suggestive of contamination events, pipe corrosion, or other water quality problems, Event Detection applies data analytics to water quality sensor data.

5.4 Taxonomy Overview

The taxonomy of IoT applications in WDNs is represented graphically in Figure 15, which shows the connection between application domains and the underlying technology enablers.

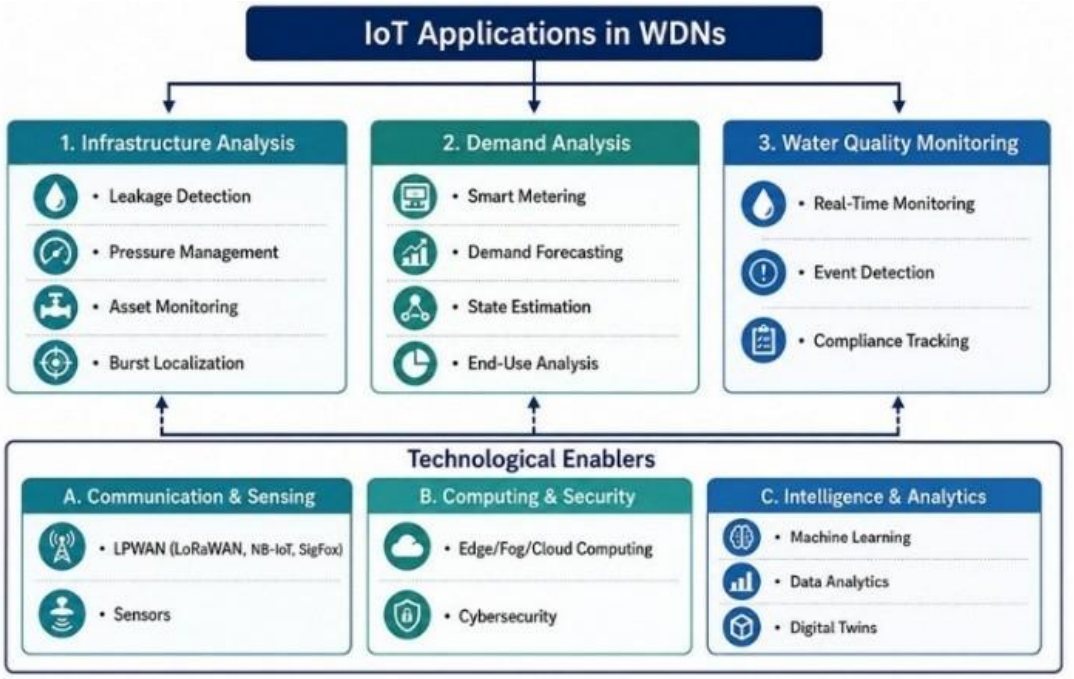


Figure 15: *Taxonomy of IoT Applications in Water Distribution Networks.*

6. Challenges and Barriers to IoT Deployment in WDNs

IoT technologies have a lot of potential, but there are a lot of obstacles in the way of their widespread, sustainable implementation in water distribution systems.

6.1 Technical Challenges

- In IoT-enabled WDNs, **interoperability and heterogeneity** are key issues. Significant integration challenges arise from the variety of sensor types, communication protocols, and data formats in typical deployments. The development of open, interoperable systems is hampered by the proprietary nature of many solutions, and legacy infrastructure components might not be compatible with contemporary IoT systems [23].
- As WDN IoT implementations expand from tiny pilots to city-scale systems, **scalability** becomes a crucial issue. While data processing infrastructure must manage enormous data volumes demanding real-time analysis, communication networks must accommodate thousands of devices. Additional scalability issues arise when IoT is integrated with traditional SCADA systems [18].
- **Power consumption and energy efficiency** are significant constraints for Internet of Things (IoT) deployments in wireless networks (WDN), particularly for underground sensors, where battery replacement is costly and disruptive. While LPWAN technologies offer improved energy efficiency compared to cellular alternatives, power remains a limiting factor for high-frequency monitoring applications [23].
- The **coverage and reliability network** pose challenges for the monitoring of wireless sensor networks (WSN), due to the underground location of many sensors. The attenuation of wireless signals through soil, concrete, and water limits the range and reliability of communications. Optimizing network topology and using LPWAN technologies can partially address these challenges, but coverage gaps remain a common problem during deployment [19].
- **Measurement** and sensing difficulties include sensor calibration and drift issues, particularly for water quality sensors requiring frequent maintenance, limited sensor lifetimes in harsh environmental conditions, and difficulties in sensor placement optimization. The limited application of high-frequency pressure and acoustic sensors in real, large-scale WDNs has been identified as a particular gap.

6.2 Economic and Organizational Challenges

- **Cost and return on investment** are major barriers to IoT deployment, especially for utilities in the small networks with limited budgets. While IoT solutions offer significant potential benefits through reduced water loss and improved

operational efficiency, the initial investment in sensors, communication infrastructure, and analytics platforms can be prohibitive [17].

- The challenges associated with **data integration** and management stem from the need to combine IoT data with existing operational data from SCADA systems, billing systems, and geographic information systems. The volume of data generated by IoT deployments also requires significant data management and analysis capabilities, which many utilities lack [31].

- **Skills and Capacity** constraints limit IoT adoption in many utilities. The operation and maintenance of IoT systems necessitates expertise in sensor technology, communications, data analytics, and cybersecurity, which are sometimes lacking in traditional water utility workforces [20].

6.3 Cybersecurity

Cybersecurity has emerged as a critical concern for IoT-enabled WDNs, with the interconnected nature of IoT systems creating multiple potential attack vectors that could compromise operational safety and public health.

Water utilities have been highlighted as appealing targets for cyber-attacks. The merging of operational technology (OT) with information technology (IT) in IoT installations widens the attack surface. Among the main cybersecurity challenges identified in the literature are the following [22]:

- The weaknesses of Internet of Things devices with constrained security features and processing power;
- Safeguarding communication networks against denial-of-service, jamming, and eavesdropping assaults;
- The necessity for safe authentication and authorization procedures for system access; the security of cloud platforms holding sensitive water system data.

Blockchain technology has been offered as a potential solution to cybersecurity issues in IoT-based water management systems.

6.4 Privacy and Data Governance

- Data privacy concerns come from the acquisition of comprehensive consumption data at the individual customer level via smart meters. This data can disclose household occupancy patterns, lifestyle information, and even the use of certain appliances, posing privacy hazards that must be managed through suitable data governance structures [20].
- The restrictions of open data and data sharing impede field research and innovation. The availability of free datasets for WDN IoT applications is constrained by data sensitivity, privacy issues, and economic interests. This limits the development and benchmarking of machine learning algorithms for water-system applications.

7. Algorithms and Computational Complexity in IoT-Enabled WDNs

The algorithms reported in the reviewed literature can be grouped into five families according to the WDN function they serve. For each family we report the representative methods, the typical input size, and the computational complexity where stated or inferable. Table 3 summarizes the comparison; the discussion highlights the trade-offs between accuracy, latency, and deployability on resource-constrained IoT nodes.

7.1 Leak Detection and Localization

Three algorithmic sub-families dominate [18, 19, 27]:

- **Model-based / pressure-residual methods**. These compare measured pressures against a hydraulic model (EPANET, WaterGEMS) [16]. A residual vector is computed and thresholded, or an inverse problem is solved to locate the leak. The dominant cost is the hydraulic solve: for a network with n nodes and mm links, a full EPANET simulation is approximately $O(m.n)$ per time step, and the inverse localisation adds a least-squares or optimisation layer that scales as $O(n^2)$ to $O(n^3)$ in the worst case. These methods are accurate but require a well-calibrated model, which is itself an offline $O(n^2)$-class calibration problem.
- **Signal-based / acoustic methods**. Acoustic reflectometry and cross-correlation of two sensor signals operate on time series of length L. Cross-correlation is $O(L\ \log L)$ using FFT, and spectral peak detection is $O(L)$. This is near-linear in the window length and therefore attractive for edge deployment. However, accuracy degrades in plastic pipes and noisy environments [15, 19].
- **Data-driven / machine-learning methods.** These include statistical process control (SPC), one-class SVM, random forests, and deep networks (CNN, LSTM, autoencoders) [21, 25, 27]. Complexity depends on the model:

Table 3: Leak detection algorithm and their complexity

Model	Training complexity	Inference complexity
SPC/ Threshold	$O(N)$	$O(1)$
One-class SVM	$O(N^2)\ to\ O(N^3)$	$O(N_{SV})$
Random forest	$O(L\ \log N.T)$	$O(T.d)$
1-D CNN	$O(N.K.F^2)$ per epoch	$O(K.F^2)$
LSTM	$O(N.H^2)$ per epoch	$O(H^2)$

Where N is the number of training samples, T the number of trees, d the tree depth, K the kernel size, F the number of filters, and H the hidden-state dimension. SPC and random forests are the only families comfortably deployable on MCU-class edge nodes; deep models generally require fog or cloud execution [21, 27].

7.2 Demand Forecasting and State Estimation

Demand forecasting is dominated by time-series and regression models: ARIMA or SARIMA ($O(N)\ to\ O(N.p^2)$) for order p), gradient-boosted trees ($O(N.T.d)$), and recurrent/deep networks as above [21], [21]. State estimation (inferring unmonitored pressures and flows) is typically formulated as a weighted least-squares or Kalman problem. The classical WLS state estimator solves a normal-equation system of size equal to the number of state variables ss, at cost $O(s^3)$ per snapshot; the extended Kalman filter adds $O(s^3)$ per step for the covariance update. For a district metered area with a few hundred state variables this is tractable at the edge; for city-scale models it isn't [18].

7.3 Water Quality Event Detection

Water quality event detection uses multivariate anomaly detection: PCA-based residual monitoring, clustering, and autoencoders [22, 25]. PCA is dominated by the eigendecomposition of the covariance matrix, $O(d^3)$ offline and $O(d^2)$ online for dd monitored variables; since dd is small (typically 5 to 10 water quality parameters), this is negligible. Autoencoder inference is $O(\sum_l n_l n_{l-1})$, which for shallow encoders is small enough for edge nodes [21].

7.4 Optimisation and Control

Pressure management and pump scheduling are formulated as non-linear, mixed-integer, or model-predictive control (MPC) problems [16, 18]. The complexity of the underlying optimisation is the dominant cost:

Table 4: Optimization algorithm and their complexity

Formulation	Complexity
Linear programming (LP)	Polynomial (interior-point)
Mixed-integer LP	NP-hard in general
Non-linear programming (NLP)	Polynomial per iteration; non-convex
MPC over horizon NN	N x the per-step NLP cost
Genetic algorithm / PSO	$O(G.P.C)$

Where G is generations, P population size, and C the cost of one fitness evaluation (often one hydraulic simulation). Metaheuristics are frequently preferred in the WDN literature because the hydraulic model is non-convex and the fitness evaluation is expensive, but their cost grows quickly with network size and horizon length [18, 21].

7.5 Communication and Network-Level Algorithms

At the communication layer, LPWAN scheduling, gateway placement, and adaptive data-rate algorithms are the main computational tasks [15]. Gateway placement is a set-cover or facility-location problem, NP-hard in general, and is usually solved with greedy heuristics at $O(n^2)$ or with metaheuristics. LoRaWAN ADR is a per-node greedy loop with negligible cost. Data aggregation and compression at the edge are $O(L)$ in the payload length L.

7.6 Comparative Synthesis

Table 2 compares the algorithm families along four axes: application, representative methods, complexity class, and deployment tier (edge / fog / cloud). The key observation is that the most accurate methods (deep learning, full MPC, model-based localization) are also the most computationally expensive, while the cheapest methods (thresholds, SPC, cross-correlation) are the least accurate.

This accuracy cost trade-off, rather than any single algorithmic limitation, is the principal reason why large-scale WDN deployments still rely on hybrid and hierarchical pipelines in which cheap edge filters trigger expensive cloud analytics [11, 12, 27].

Table 5: Comparative analysis of algorithm families in IoT-enabled WDNs

Application	Representative algorithms	Complexity (typical)	Deployment tier
Leak detection (model-based)	Pressure residual, inverse transien	$O(n^2)\ to\ O(n^3)$	Fog / cloud
Leak detection (signal-based)	Cross-correlation, FFT, spectral peaks	$O(L\ \log L)$	Edge
Leak detection (data-driven)	SPC, one-class SVM, RF, CNN, LSTM	$O(1)\ to\ O(N^3)$	Edge (SPC/RF) to cloud (DL)
Demand forecasting	ARIMA, GBT, LSTM	$O(N.p^2)\ to$ $O(N.H^2)$	Fog / cloud
State estimation	WLS, EKF	$O(s^3)$	Fog
Water quality event detection	PCA, clustering, autoencoder	$O(d^3)$ or $O(\sum_l n_l n_{l-1})$	Edge or fog
Pressure or pump optimisation	LP, MINLP, MPC, GA, PSO	Polynomial to NP-hard	Cloud or fog
Gateway placement	Greedy set cover, metaheuristics	$O(n^2)$	Offline or cloud

8. Algorithmic and Computational Barriers

The complexity analysis of this section exposes four barriers that are not always separated in the literature from the more general technical challenges:

- First, the accuracy–complexity frontier. The most accurate algorithms in nearly every application family are the most expensive: deep networks for leak detection and forecasting, full MPC for pressure control, and model-based inverse methods for localization. Yet the WDN sensing layer is dominated by battery-powered, MCU-class nodes with kilobytes of RAM [15, 17, 19]. The literature therefore increasingly recommends tiered pipelines in which an $O(1)$ or $O(L)$ edge filter performs first-stage detection and only anomalies are escalated to $O(N^2)$ to $O(N^3)$ cloud analytics [1, 12, 27]. This pattern is echoed in the edge/fog/cloud architectures.

- Second, the scalability of model-based methods. Hydraulic-model-based localization and MPC both scale poorly with network size. A full EPANET solve on a city-scale model, repeated inside a metaheuristic loop with $G.P$ evaluations, can become prohibitive for real-time control [16, 18]. The literature mitigates this through network decomposition (district metered areas), surrogate models, and linearized MPC, but reports that these simplifications trade accuracy for tractability, and that the trade-off is rarely quantified [18, 21].
- Third, training-data and non-stationarity costs. Data-driven methods carry a hidden complexity: the cost of acquiring, labelling, and periodically retraining on data whose distribution drifts with season, demand growth, and infrastructure ageing. Federated learning has been proposed precisely to distribute this cost and preserve privacy [25, 27], but its communication complexity per round scales with the number of participating utilities, and convergence is not guaranteed under heterogeneous data a point acknowledged but not yet resolved in the WDN literature [21].
- Fourth, the absence of standard complexity reporting. A recurring finding of this review is that most WDN-IoT papers report accuracy but not runtime, memory, or energy cost [12, 21, 27]. This makes cross-study comparison of algorithms difficult and hampers the selection of methods for resource-constrained deployments. The quality-assessment checklist of Section 1.5.6 was therefore weighted towards studies that report at least one resource metric. We recommend that future work adopt standardized reporting of accuracy, latency, memory, and energy per inference, alongside the deployment tier, so that the accuracy–complexity frontier of Table 2 can be refined empirically rather than inferred.

Together with the interoperability, power, coverage, and cybersecurity barriers, these algorithmic and computational barriers explain why large-scale IoT adoption in WDNs remains, in the words of [1] and [23], a "pilot-rich, city-scale-poor" landscape.

8.1 Added Research Direction: Benchmarking Algorithms and Complexity

To the future directions, we add one item that follows directly: the creation of open, standardized benchmarks for WDN-IoT algorithms. Such benchmarks should include:

- Reference network models of increasing size (e.g., a small DMA, a medium city, and a large metropolis);
- Synthetic and real leak/quality event libraries;
- Fixed hardware targets spanning MCU, edge gateway, and cloud tiers;
- Mandatory reporting of accuracy, latency, memory, and energy. This would allow the complexity claims of Table 3 to be tested reproducibly and would accelerate the transition from pilot deployments to sustainable city-scale operations recommended by [1].

9. Emerging Trends and Future Research Directions

9.1 Integration with Artificial Intelligence

The integration of IoT with AI and ML is an important growing trend in WDN management. Data-driven approaches are increasingly acknowledged as crucial for obtaining useful insights from the huge volumes of IoT sensor data produced by SWDS [23].

- **Deep learning** has shown special potential for smart water applications, with deep neural networks capable of learning complicated patterns from water system data. Applications include leak detection, demand forecasting, and water quality prediction. The authors in [21] established a taxonomy that divides deep learning applications in smart water systems into three domains: infrastructure analysis, demand analysis, and water quality monitoring.
- **Federated learning** has been recognized as a viable solution to privacy-preserving model training in WDN applications. This paradigm allows model training across many decentralized data sources while keeping sensitive data localized, solving the privacy concerns associated with centralized data collecting.
- **Explainable AI (XAI)** is increasingly seen as crucial to building trust in AI-driven water system decisions by allowing operators to comprehend and confirm automated control decisions. Transparency and interpretability are especially important in crucial water infrastructure, where decisions have a direct impact on public health.

9.2 Digital Twins

Digital Twin technology, which generates virtual replicas of actual water distribution systems, has become a major trend in WDN administration. Digital twins combine IoT sensor data with hydraulic and water quality models to deliver real-time system status awareness, predictive capabilities, and what-if scenario analysis. Key uses of digital twins in WDNs include [18, 26]:

- Continuous monitoring and anomaly detection by comparing expected and observed system states.
- Simulation of component degradation enables predictive maintenance and operational optimization through control techniques.
- Using scenario analysis to plan emergency responses.

Smart city efforts have prioritized the creation of digital twin frameworks for water distribution systems [21]. The combination of IoT, AI, and digital twins is a confluence of technologies that could drastically improve WDN management.

9.3 5G and Beyond

The deployment of 5G networks provides new opportunities for WDN IoT applications, including [23]:

- Increased data rates for high-frequency sensors and video surveillance;
- Ultra-low latency allows for real-time control applications;
- Massive device connectivity enables dense sensor installations.
- Network slicing provides quality-of-service guaranties for key applications.

While LPWAN technologies now dominate WDN IoT applications, 5G and future 6G networks may broaden the available applications [23].

9.4 Blockchain and Decentralized Ledger Technologies

Blockchain technology has been proposed for various applications in WM, including safe data sharing, transaction verification for water trading, and cybersecurity enhancement. Blockchain could facilitate [22]:

- WQ and usage data have immutable audit trails;
- Secure data sharing between utilities and regulators;
- Decentralized water management through smart contracts.

However, the use of blockchain to WDN IoT systems remains in its early stages, with extensive research needed to address performance, scalability, and integration difficulties [20].

9.5 Sustainability and Resilience

a) Sustainability is becoming crucial to IoT implementation in WDNs, with emphasis to [20]:

- Energy independence using energy harvesting solutions for IoT devices;
- Lifecycle management to reduce the environmental effect of IoT device production, deployment, and disposal;
- Resource efficiency via optimizing water and energy consumption.

b) Resilience to climate change impacts, such as increased droughts and floods, extreme weather events, and sea-level rise, is an important issue for WDN IoT systems. IoT monitoring and digital twin skills can help with adaptive management, infrastructure planning, and operational solutions to climate-related concerns [21].

9.6 Guidelines for Sustainable Deployment

Based on their systematic research, Pagano et al. propose suggestions for sustained, large-scale IoT adoption in WDS, stressing:

- Creating holistic frameworks that take into account technological, economic, and organizational factors;
- Using edge data processing to reduce cloud dependency and boost scalability;
- The choice of suitable LPWAN technology depending on deployment criteria;
- Integration of simulation technologies for network design and evaluation.

These guidelines aim to help utilities transition from pilot deployments to sustainable city-scale operations.

10. Conclusion

The contribution of IoT technologies to water distribution network control and monitoring systems has been investigated in this review, which summarizes the state of the art and identifies important issues and potential future paths. WDN management is changing from a reactive to a proactive, data-driven paradigm due to the convergence of IoT with LPWAN technologies, edge computing, and machine learning.

Three main areas of IoT application in WDNs have been identified: demand analysis (including smart metering, demand forecasting, and state estimation), water quality monitoring (including real-time monitoring and event detection), and infrastructure analysis (including leak detection, pressure management, and asset monitoring). These applications make use of edge-to-cloud computing architectures, LPWAN communication technologies, and an integrated stack of sensors.

However, there are still significant obstacles to overcome in order to achieve long-term, widespread acceptance, such as problems with interoperability and scalability, cybersecurity, deployment costs, and skills gaps. Promising avenues for resolving these issues are provided by the identified research directions, which include AI integration, digital twins, upcoming communication technologies, and sustainability considerations.

With major advantages for water saving, operational effectiveness, and public health protection, IoT has the potential to significantly improve WDN performance. It will take ongoing research to overcome implementation obstacles, the creation of standards and best practices, and ongoing cooperation between researchers, utilities, and technology providers to realize this promise. IoT will surely

become more crucial in guaranteeing the effective, resilient, and sustainable management of water distribution infrastructure as the water industry continues its digital revolution.

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