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Contaminations in water distribution systems: a critical review of detection and response methods

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ABSTRACT

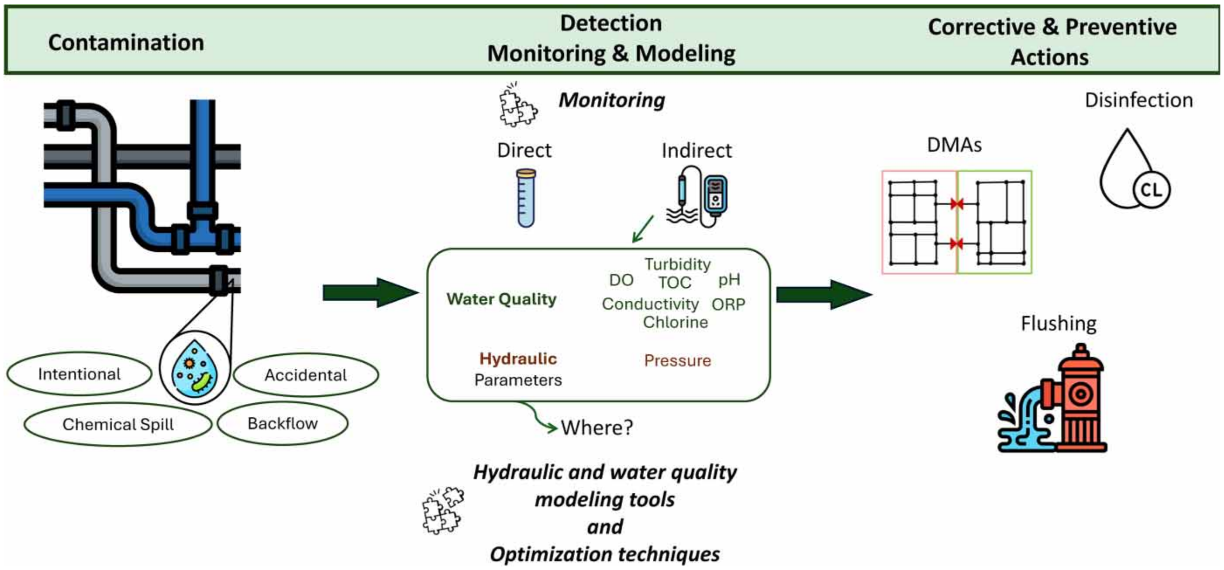
Water distribution networks play a crucial role in delivering safe water to communities. However, their extensive reach and complex structure make them susceptible to contamination. The development of efficient contamination warning systems (CWSs) can enable the monitoring and control of abnormal events. In an efficient CWS, several key aspects must be addressed: identifying potential contaminations that can occur, determining the most effective water parameters to monitor, and defining where these parameters can be strategically monitored. In the present study, literature articles will be analyzed to explore different parameters for detecting anomalies, assess the information they provide, and highlight the benefits of combining various parameters. Moreover, attention will be given to the definition of sensor placement, emphasizing the lack of attention in the literature for defining sensors' detection thresholds. Finally, the study underscores that ensuring human safety requires not only prompt intrusion detection but also the implementation of corrective and preventive actions capable of mitigating contaminant spread through WDNs.

Key words: contamination warning system, drinking water, sensor, water distribution network

HIGHLIGHTS

- Creating contamination warning systems involves assessing intrusion impacts on water parameters.
- Sensor placement studies must consider sensors' capabilities to detect contaminants.
- Ensuring public health demands prompt remedial actions upon contamination detection.

GRAPHICAL ABSTRACT



1. INTRODUCTION

Water distribution networks (WDNs) are critical infrastructure for public health since they are responsible for delivering safe water to the population. Despite their importance, these systems are vulnerable to intrusion due to their large spatial distribution, aging pipes and branched structure. This feature leads to the existence of several nodes accessible for contaminants and, as a result, to great difficulties for water utilities in developing a monitoring strategy that ensures water quality (WQ) monitoring and swift contaminant detection.

An efficient contamination warning system (CWS) serves as a tool designed to monitor hydraulic and/or WQ parameters throughout the entire WDN. To achieve this, sensors must be strategically placed at key nodes. The system aims to distinguish between normal variations and abnormal changes in these parameters, which may indicate the presence of contaminants. By analyzing how potential contaminants affect monitored parameters in strategic nodes, timely identification of contamination events while minimizing false alarms becomes feasible.

CWSs not only provide continuous monitoring of WQ but also play a crucial role in promptly alerting water utilities to anomalies, empowering them to take immediate actions to mitigate the impact of contamination events on public health and ensuring a steady supply of safe water to the population. To design an efficient CWS, the following key considerations must be addressed:

Identification of effective parameters: Determining which parameters are most effective in detecting contaminations is crucial. Not all parameters respond uniformly to different contaminants. Water utilities need to assess the contaminants posing the greatest threat and evaluate their impact on various parameters. This can be achieved through literature reviews or direct testing via simulations or experimental studies. By understanding how contaminants affect different parameters, water utilities can define the most suitable parameters to monitor and establish criteria for distinguishing between normal and abnormal variations. This ensures accurate control of water parameters, enables timely alarm triggering, and minimizes false alarms, which are essential for maintaining public trust in the water supply.

Optimal sensor placement: The distribution of sensors throughout the network plays a vital role in the effectiveness of a CWS. Not all nodes in the WDN are equally representative, and an efficient CWS must provide representative coverage of the entire distribution system. Therefore, it is essential to develop a strategic approach to determine the optimal locations for sensors. This ensures comprehensive monitoring of the network and enhances the system's ability to detect the highest number of contaminations.

Ingress of contaminants in WDN: Various forms of contamination can manifest within a WDN. These may arise from accidental incidents, such as those stemming from backflow (Cristo & Leopardi 2008; Laine *et al.* 2011; Viñas *et al.* 2022) or chemical spills (Troeschel *et al.* 2022). Copeland & Cody's (2010) report outlined the susceptibility of water infrastructure to deliberate contamination, raising concerns about potential acts of terrorism. The repercussions of such contaminations can be severe, impacting both human health and the economics of the affected WDN (Corso *et al.* 2003).

Challenges in the creation of CWSs: The creation of a CWS provides a way to recognize intrusion events promptly and allows a reduction of public health and economic impacts (Hart *et al.* 2008). The implementation of CWSs poses multiple challenges, primarily characterized by the need to define which WQ and hydraulic parameters to monitor and where monitoring should be conducted. Numerous critical reviews outlined various options for sensor placement optimization strategies (Hart & Murray 2010; Rathi & Gupta 2014; Adedoja *et al.* 2019). However, most studies proposed sensor placement optimization without specifying which parameters should be monitored and the information they yield.

In this paper, key WQ parameters that can be monitored within the network will be summarized, outlining the information they provide as single indicators or in combination. In fact, a combination of water parameters can enhance the understanding of the network's dynamics and improve the number of contaminations detected.

Corrective and preventive actions: To ensure safe water reaches customers, it is crucial not only to monitor WQ to detect intrusions promptly but also to implement corrective and preventive actions capable of mitigating contaminant spread in the WDN (Kroll & King 2010). In this review, common procedures for the mitigation of intrusion events are reviewed: disinfection, flushing, and the creation of district-metered areas (DMAs).

In this review paper, the intricacies of contaminant detection within WDNs are explored. The analysis spans the entire spectrum of contamination concerns, from identifying potential contaminants to outlining actionable steps upon detection.

A comprehensive understanding of contaminant detection and response methods in WDNs is provided, offering valuable insights for both researchers and practitioners in the field.

2. CONTAMINATION WARNING SYSTEMS

2.1. Contamination types

Different types of intrusion can affect WDNs. Intentional contaminations consist of the malicious introduction of hazardous substances into WDN to affect a significant part of the population. Since September 2001, the awareness of terrorist attacks has increased and guidelines for WQ monitoring have been developed (Robinson 2004). Although the likelihood of these events occurring seems very remote, history teaches us that we should know how to prevent and respond to catastrophic situations. In 1985, New York City faced a crisis due to a letter sent by an ex-con, who threatened to inject plutonium into water supplies. After this, traces of plutonium were found in water, but fortunately at concentrations not sufficient to affect people's health (Bogen *et al.* 1988). These types of events can cause terrible consequences for human health and are very challenging due to the uncertainty about the contaminant type and the higher unpredictability of their time and location. Intentional contaminations can be a serious threat to human health that can happen also by backflow attacks (Cristo & Leopardi 2008; Di Nardo *et al.* 2014). With the use of a pump, the contaminant can be injected into the network, and thanks to the Bernoulli effect, it can flow through the whole system.

Accidental contamination occurs during deficient network operations and three simultaneous conditions must be present: an exterior source of contamination around the pipes, an access point for the contaminant, and pressure deficient conditions (PDCs) (Lindley & Buchberger 2002; Besner *et al.* 2011). The outbreak event of Walkerton (Ontario) in 2000 shows the grave consequences of accidental contamination, with 7 people dead, 2,300 people ill, and an estimated cost impact of over $64.5 million (Vicente & Christoffersen 2006). The contamination was caused by heavy rainfall that allowed pathogenic *Escherichia coli* O157:H7 ingress in wells supplying drinking water (Salvadori *et al.* 2009), worsened by the absence of an adequate response plan.

From a modeling perspective, both intentional and accidental contaminations pose challenges. In the case of intentional contamination, the primary difficulty lies in the high unpredictability of the contaminant type and quantity, and the site of contamination for a given incident. To mitigate this, several studies have adopted a conservative approach by simulating the injection of a fixed contaminant amount at several points of the WDN (e.g., Ostfeld & Salomons 2004; Nilsson *et al.* 2005; Di Nardo *et al.* 2015). On the other hand, accidental contamination presents a different challenge, related to estimating the volume of intrusion, which can be defined through the orifice equation as a function of the pressure difference between the external and internal pipe environments. Furthermore, Hatam *et al.* (2019) underscored the criticality of selecting an optimal contaminant concentration for simulating accidental contamination. Indeed, variations in this parameter resulted in a substantial 235-fold difference in the number of infected people. This complexity has limited the number of studies addressing the modeling of contaminant ingress resulting from accidental events (Teunis *et al.* 2010; Hatam *et al.* 2020).

Backflow might also be the cause of accidental contamination. Lee *et al.* (2003), in their survey, reported that among over 700 North American water utilities, 38% of them experienced backflow incidents. Casteloes *et al.* (2015) analyzed previous instances of premise plumbing contaminations in both the United States (USA) and Canada and identified that one of the primary causes was backflow. In 2007 450,000 L of treated wastewater ran through Nokia's distribution system (Viñas *et al.* 2022) causing thousands of cases of diarrhea and vomiting among the population (Laine *et al.* 2011).

2.2. Challenges in the direct detection of microbial contamination

Dealing with extremely complex and often large systems, such as WDNs, makes it almost unfeasible to develop a CWS with the capability to detect all possible intrusions. WDN managers need to identify priority events and contaminant pathways and establish a CWS able to provide actionable and reliable solutions.

Intrusions can be detected by direct and indirect monitoring methods. In the direct approach, regulations typically require the periodical detection of pathogen indicators, mainly *E. coli* by culture-based methods, throughout the network. The limitation of this approach lies in its limited ability (1) to timely detect any microbiological contamination because of the detection response time, (2) the frequency of sampling, typically weekly, and (3) the limited number of sampling sites. In fact, the procedure to obtain the final measurement can be time-consuming, typically more than 24 h and up to 3 days (Smeets *et al.* 2009; Hammes & Egli 2010). The type of detection plays an important role not only in terms of obtaining the measurement as quickly as possible but also in terms of when and where the sampling is conducted. In the event of an intrusion, if *E. coli* sampling is not conducted at the right time and the right location, the detection of intrusion events is not possible (Hatam *et al.* 2020).

When using direct culture-based measurements, the number of compliance samples collected is typically low. Nonetheless, as demonstrated by Berg *et al.* (2015), even a substantial increase in sample quantity yields a very low likelihood of detecting contamination events. van Lieverloo *et al.* (2007) showed that, in the case of specific simulated contaminations, even when the number of samples taken exceeds the minimum requirement by fivefold, the average probability of *E. coli* detection remains as low as 5%.

Online detection systems would provide timely results (1 h) to trigger an alert and provide a time series of *E. coli* presence independent of sampling schedules. An example of online detection systems is the BACTcontrol systems, which detect the microbiological activity in water by measurements done with an interval of 180 min (Stadler *et al.* 2016). Although in-situ rapid response detection of *E. coli* is considered an alternative to standard monitoring for wastewater, bathing, and surface water (Burnet *et al.* 2021), applications to low *E. coli* levels found in WDNs still remain a challenge.

Moreover, *E. coli* is not always an effective indicator of intrusions: even if it is not detected it does not imply an absence of pathogens (Ashbolt *et al.* 2001). *E. coli*, compared to other pathogens, such as *Giardia* and *Cryptosporidium*, is easily inactivated by chlorine. Resistant pathogens can persist in the network without being detected by *E. coli* measurements (World Health Organization (WHO) 2022).

Regardless of the type of sampling, grab or near-real-time sampling, the high number of sites that should be covered raises serious challenges in terms of deployment and costs. Hatam *et al.* (2020) demonstrated that *E. coli* detection after major contamination by wastewater intrusion in the presence of chlorine is highly challenging. A more reliable sampling strategy based on numeral methods and online sensor pressure data could define effective sampling plans. Improved probability of detection can be achieved by selecting the affected location at the right time and by using larger sample volumes. Such an approach would reduce unnecessary resource allocation for sampling, avoid false negatives, prevent unjustified advisories, and allow data-based clearance.

Considering the challenges and limitations of direct detection of microbial contamination, indirect approaches based on online monitoring may provide a more robust assessment of contamination risk.

2.3. Indirect detection of contamination using online WQ monitoring

Continuous monitoring of WQ parameters is essential for the rapid detection of contaminants, thereby ensuring public health (USEPA 2005). However, a major challenge in establishing an online monitoring strategy is identifying the parameters that are most sensitive to intrusion events. The analysis of pilot and experimental studies within this critical review provides valuable insights into how tested contaminants affect monitored parameters. This facilitates well-informed decision-making, aiding water utilities in selecting the most suitable combination of parameters for monitoring in specific WDNs based on the contaminants they aim to detect.

Indeed, to detect the presence of contaminants, water utilities should establish a monitoring strategy that can continuously track changes in water parameters. However, even with real-time sensors, detecting contamination events remains challenging and characterized by uncertainties without effective control and data integration. Variations in a parameter time series registered by sensors can be the result of an intrusion, but also of various other factors, such as sensor failure or changes in demand. Nevertheless, the probability of an intrusion event increases if the change is captured by different sensors and associated with different parameters (USEPA 2005; Ghazali *et al.* 2010).

For water security, the parameters most sensitive to contaminants are total organic carbon (TOC), pH, free or total chlorine, and conductivity (Hall & Szabo 2005). Hall *et al.* (2007) demonstrated that conductivity, TOC, free chlorine, chloride, and oxidation-reduction potential (ORP) exhibited significant reactivity to a high number of simulated contaminants.

Combination of WQ parameters: Wang *et al.* (2018) emphasized how the alteration of a specific set of parameters is strictly related to the type of contaminant, and so for each contaminant, a specific set of parameters to monitor should be defined. Yang *et al.* (2009) developed a pilot scale WDN and simulated 11 different contamination events (both chemical and biological) while monitoring free and total chlorine, ORP, pH, dissolved oxygen (DO), turbidity, conductivity, and chloride. Results demonstrated that no one of these parameters (alone) can detect all types of contaminants but a combination of these can be exhaustive for all contaminants tested. Indeed, Saab *et al.* (2020) showed how monitoring multiple parameters (turbidity and chlorine) allows a more accurate estimation of the risk level for a contamination event. Jha *et al.* (2018) proposed a model that monitors and defines an acceptable range for pH, turbidity, temperature, and conductivity. These parameters are monitored for households in real-time and when a value is not acceptable, utility and consumers are advertised via SMS. Tinelli & Juran (2019) developed an artificial intelligence-based algorithm able to detect bio-contaminant intrusions by identifying deviations from the standard conditions of different WQ parameters. Lambrou *et al.* (2014) developed a multiparameter low-cost sensor, which measures turbidity, conductivity, pH, ORP, and temperature. They tested the effect of *E. coli* and arsenic injections on the developed sensor system. Results showed that under their experimental trial conditions, contamination by *E. coli* was detected by turbidity and conductivity, while it required more time for the ORP, and pH spikes with a delay. For the arsenic, none of the sensors considered was able to detect the event for low concentrations (lower than 25 μg/L).

Combination of hydraulic and WQ parameters: A combination of hydraulic and WQ parameters can be helpful to gain a comprehensive understanding of networks and increase cost-effectiveness. Preis *et al.* (2011) emphasized the need to develop sensor networks measuring both parameters at shared nodes, thereby creating a cost-efficient monitoring system. They proposed a method for determining the optimal placement of pressure and WQ sensors. However, the specifics regarding the WQ parameters to be measured were not provided. Oliker & Ostfeld (2015) highlighted the susceptibility of single-sensor systems to generate false alarms. To address this issue, they proposed an innovative event detection model that combines pipe flow data from the hydraulic model with real-time measurements of various WQ parameters. However, the approach can be further refined by incorporating optimal sensor placement within the event detection model and addressing the influence of distinct contaminant types on the monitored parameters. In general, a combination of WQ and hydraulic parameters to detect the presence of contaminants has received limited attention in the literature.

Table 1 summarizes the strengths and weaknesses of various online parameters focusing on their ability to detect different contaminants. Here, commonly used parameters for which water utilities typically have sensors or measurements are discussed.

Water pressure can be considered a useful indicator of accidental contamination events since these can occur only with PDCs. Maintaining constant control of pressure is essential for assessing the hydraulic performance of the network and ensuring sufficient water supply to consumers. However, the use of pressure sensors in WDNs to detect accidental contamination may be characterized by two challenges. Firstly, while pressure monitoring can detect abnormal events resulting from low-pressure occurrences, it cannot offer insights into the area of contaminant dispersion. When a contaminant enters the WDN, it may not significantly impact the system's pressure depending on local flow and pressure conditions; however, PDCs can drive the entry of external contaminants. Secondly, determining the pressure threshold that identifies a PDC poses difficulties. Several authors assumed PDCs when the value drops under 20 psi (Gullick *et al.* 2005; Besner *et al.* 2007; LeChevallier *et al.* 2011). Moreover, the risk associated with PDCs depends on the duration of the event (LeChevallier *et al.* 2011) and on the hydraulic characteristics of the network (presence of elevated storage, multiple reservoirs, etc.).

Table 1 | WQ and hydraulic parameters

Parameter	Strengths	Challenges	Contaminant detected
Pressure	Reliable indicator of potential accidental contamination	Difficult to define a pressure threshold; no info on contaminant dispersion area	–
pH	Stable parameter	Can also be a sign of nitrification; Influenced by source mixing	*E. coli*, glyphosate, mercuric chloride, nicotine, terrific broth, arsenic, dicamba, cadmium nitrate, lead nitrate, nickel nitrate, trivalent chromium (Panguluri *et al.* 2009; Yang *et al.* 2009; Lambrou *et al.* 2014)
Turbidity	Can be representative of changes in the flow regime	Significative changes over time/ noisy signal	Aldicarb, arsenic trioxide, *E. coli*, malathion, terrific broth, lead nitrate, atrazine, cadmium nitrate, glyphosate, lead nitrate, nickel nitrate, trivalent chromium (Hall & Szabo 2005; Panguluri *et al.* 2009; Lambrou *et al.* 2014)
Conductivity	High responsiveness to several contaminants	Affected by source mixing and temperature (need of compensation by probes)	*E. coli*, arsenic (with concentration above 500 μg/L) ammonium citrate, atrazine, cadmium nitrate, dicamba, mercuric chloride, potassium ferricyanide (Lambrou *et al.* 2014; Wang *et al.* 2018)
Chlorine	Inactivate microbial pathogens	High cost	Residual chlorine: aldicarb, arsenic trioxide, *E. coli*, glyphosate, malathion, nicotine, terrific broth, colchicine, mercuric chloride, nutrient broth, tryptic soy broth, cupric sulfate, potassium ferricyanide (Hall *et al.* 2007; Yang *et al.* 2009; Wang *et al.* 2018) Total chlorine: aldicarb, arsenic trioxide, *E. coli*, nicotine, terrific broth, colchine, glyphosate, nutrient broth, tryptic soy broth, potassium ferricyanide, dimethyl sulfoxide, anhydrous (Hall *et al.* 2007; Panguluri *et al.* 2009; Yang *et al.* 2009)
ORP	Sensitive to several contaminants	High background noise susceptibility	Aldicarb, arsenic trioxide, glyphosate, malathion, nicotine, Terrific broth, colchicine, dicamba, *E. coli*, nutrient broth, tryptic soy broth, potassium ferricyanide, mercuric chloride, atrazine, cadmium nitrate, lead nitrate, nickel nitrate, trivalent chromium (Hall *et al.* 2007; Yang *et al.* 2009; Lambrou *et al.* 2014)
TOC	Stable parameter	High cost and complexity of instruments	Aldicarb, *E. coli*, glyphosate, malathion, nicotine, terrific broth, cupric sulfate, potassium biphthalate, potassium ferricyanide, sodium nitrite, urea, mercuric chloride, anhydrous (Hall *et al.* 2007; Panguluri *et al.* 2009; Wang *et al.* 2018; Tinelli & Juran 2019)

Furthermore, pressure values can serve as parameters for estimating pipe break rates through robust artificial intelligence models, as demonstrated by Amiri-Ardakani & Najafzadeh (2021).

pH is a relatively stable parameter, so abnormal variations of typical range values can be related to an event and should be investigated (WHO 2003). The Canadian guidelines establish a pH range between 7.0 and 10.5 for drinking water (Health Canada 2015). Changes in pH can occur during an intrusion (Hall & Szabo 2005) or result from source mixing. However, this change can also be a sign of nitrification (Wilczak *et al.* 1996) or caused by acid or basic products yielded by microorganisms (Prescott *et al.* 1999). Although pH has no direct effect on consumers' health, continuous monitoring of this parameter in all the steps of water treatment is pivotal to certifying water clarification and disinfection (WHO 2022).

A commonly used parameter, typically measured online, is turbidity. This parameter can be representative of changes in the flow regime leading to the resuspension of loose deposits in water (Seth *et al.* 2004). In a review by De Roos *et al.* (2017), a link between water turbidity and acute gastrointestinal infections was demonstrated. However, the authors also highlighted the presence of other contributing factors (such as seasonality and treatment methods) that play a role in this association. In the Ikonen *et al.* (2017) study, variations in turbidity were observed during simulated *E. coli* intrusions, and similar changes were noted in the event of lake water intrusion. Furthermore, an unexplained peak in the time series was linked to a suspected biofilm detachment. Indeed, turbidity may undergo significant changes over time during normal operation, so it may not be ideal to infer the presence of contaminants and the signal that characterized this parameter can be too noisy (Hall & Szabo 2005; Panguluri *et al.* 2009).

Conductivity is a commonly measured WQ parameter that can be used to trace the mixing of multiple sources feeding a WDN. Hall & Szabo (2005) identified conductivity as one of the most sensitive parameters for detecting various water contaminations. This is mainly due to its stability and low variability under normal conditions, making it effective even when changes in the presence of contaminants are subtle. Indeed, as shown in Table 1, its responsiveness to the injection of various contaminants is well established. However, conductivity measurements are influenced by temperature, leading to the necessity of simultaneously monitoring temperature to compensate for this dependence (Banna *et al.* 2014).

Maintaining chlorine residuals in WDNs is common due to its potential to inactivate microorganisms. Secondary disinfection will reduce bacteria and viruses present in water, providing an additional barrier during distribution (USEPA 2011). External contamination, such as backflows or cross connections, can suppress chlorine as contaminated water can exert chlorine demand. Atypical changes in residual chlorine can be used to detect events across the WDS. Chlorine can finally be considered as a parameter responsive to contaminations, as in most of the pilot/experimental studies discussed in this review, it demonstrated excellent results in detecting the tested contaminants (Table 1). Due to the high cost associated with online free chlorine measurements, Lambrou *et al.* (2014) proposed to approximate these measurements with the ORP, pH, and temperature ones. Nevertheless, the authors did not test whether employing chlorine sensors would have yielded different results in the specific study.

Panguluri *et al.* (2009) identified free chlorine and TOC as the most valuable parameters for detecting water contaminations. Indeed, monitoring TOC can be effective in detecting organic contaminants and biological media, and this parameter is characterized by good stability over time. The challenge is the high cost and complexity that characterize these instrument types (Byer 2005; Hall & Szabo 2005; Panguluri *et al.* 2009). Tinelli & Juran (2019) simulated *E. coli* contaminations and proposed to estimate TOC variations by chlorine data.

ORP measures the water's tendency to oxidize or reduce another chemical element. Yang *et al.* (2009) demonstrated the ability of ORP to detect the presence of most of the tested contaminants (Table 1). Conversely, in a study by Lambrou *et al.* (2014), ORP sensors exhibited a delay in responding to *E. coli* contamination and only responded to a high concentration of arsenic. However, Panguluri *et al.* (2009) demonstrated that although sensors registered only small variations in ORP measurements for simulated contaminations (including *E. coli* in terrific broth), normalizing and filtering the measurements from background noise revealed a significant change.

DO is another parameter that can be used to monitor WQ. Reduction in DO levels could suggest chemical and biochemical processes occurring in the water (Hall & Szabo 2005). A weak positive correlation between DO with opportunistic pathogens, including Enterococci and *Mycobacterium spp*., was reported by Isaac & Sherchan (2020). From the technology point of view, DO sensors were assessed to be less practical to implement compared to other sensor options because of the need for multiple compensations to correct measurements and because they require frequent replacement of membranes (Lambrou *et al.* 2014). More recently, Wei *et al.* (2019) presented a comprehensive examination of intelligent DO sensors from various manufacturers (such as HACH and YSI) capable of signal processing and executing real-time dynamic compensation and correction for both temperature and pressure. In rivers, Najafzadeh *et al.* (2019) demonstrated the permissible efficiency of an artificial intelligence model in predicting DO levels using eight independent variables, such as electrical conductivity, pH, and turbidity. Uncertainty, reliability and resilience analysis can be performed to assess the consistency of the developed prediction model (Saberi-Movahed *et al.* 2020). However, in a study by Panguluri *et al.* (2009), no significant changes in DO levels were detected following the initial contaminations, and this parameter was not subjected to further examination.

For all WQ parameters considered, timely detection may be challenging, as potential contaminants can take time to reach the sensor, resulting in a delay before parameter variation is recorded by the sensor.

Based on the analysis of the discussed studies, certain parameters emerge as particularly informative. Chlorine, conductivity, TOC, and ORP exhibit reliability in providing valuable insights. While conductivity and TOC demonstrate stability, deviations from their normal values warrant investigation. Chlorine, often monitored for maintaining residual levels, serves as a barrier against microbial intrusion, making its variations indicative of potential contaminants. ORP measurements exhibit high sensitivity across all tested contaminants. However, there is no single parameter universally effective in detecting all potential contaminants that can be introduced into WDNs.

To establish an efficient monitoring system, a systematic approach is necessary. Begin by identifying the contaminants most likely to be present in the specific area or those posing the greatest concern for the municipality. Next, investigate how these identified contaminants influence various parameters. This exploration can be facilitated through a comprehensive review of existing literature, hydraulic and WQ modeling, or laboratory experimentation. Subsequently, choose to monitor the parameters that consistently demonstrate substantial changes during probable intrusion events. By adhering to this methodology, a more tailored and effective strategy for contaminant detection can be created.

2.4. Optimization of sensors' location

Once the best parameters to monitor in the specific network are selected, the location of sensors should be defined. The ideal solution to allow the detection of intrusions in a network would be to deploy multiple sensors in each node and monitor continuously all the different sections of the network. For obvious reasons, this is not a feasible solution due to the limited funding available to water authorities, the constraints of access and the cost of maintenance, but also due to the enormous amount of data generated by these sensors.

One of the main challenges in determining optimal sensor placement is defining the objective functions that accurately reflect the goal of the optimization process. Over the years, various research groups have proposed several objective functions.

A commonly adopted objective is to minimize the potential impact on public health in the event of contamination. This can be expressed through functions such as network protection coverage, population at risk, contaminated population, and volume of contaminated water consumed (Lee *et al.* 1991; Kumar *et al.* 1997; Kessler *et al.* 1998; Uber *et al.* 2004; Carr *et al.* 2006). The number of sensors available for use in WDNs is limited for practical management and cost reasons. Consequently, several authors have suggested using the minimization of the total number of sensors as an objective function, which is also a surrogate for the overall cost of the sensor system (Shastri & Diwekar 2006; Rico-Ramirez *et al.* 2007; Weickgenannt *et al.* 2010a; Naserizade *et al.* 2018; Cardoso *et al.* 2021).

Effective sensor systems must not only detect events but also do so promptly. Therefore, authors have included detection time as an objective function (Dorini *et al.* 2006; Krause *et al.* 2008; Ostfeld *et al.* 2008; Cardoso *et al.* 2021). Others have proposed objective functions that consider the number of undetected events from the sensors (Propato 2006). Krause *et al.* (2008) suggested incorporating a penalty reduction into the optimization process, defined as the difference between the penalty for an event going undetected and the penalty once it is detected. Weickgenannt *et al.* (2010b) based their objective on minimizing the risk of contamination, defined as the product of the probability of not detecting the contaminant's presence and the corresponding consequences. Jafari *et al.* (2021) introduced a multi-objective optimization approach, with one of the objectives being the minimization of the likelihood of sensor failure. This objective can be considered as the complement of the detection likelihood, which is frequently employed in optimization problems (Ostfeld *et al.* 2008; Preis *et al.* 2011; Zhao *et al.* 2016; Winter *et al.* 2019; Hu *et al.* 2020; Cardoso *et al.* 2021). Khorshidi *et al.* (2018) considered the information provided by monitoring stations and proposed to maximize the value of information (VOI). VOI for a specific node is calculated based on the probability of receiving a warning message and the maximum utility derived from the action that can be taken by water managers.

Objective functions depend on variables characterized by uncertainties (Carr *et al.* 2004; Berry *et al.* 2005), which can be difficult to include in the problem formulation. Shastri & Diwekar (2006) proposed a stochastic approach to consider demand uncertainty and the effect of this on sensor placement; for the evaluation of the uncertainties related to all the possible attacks and population density, Rico-Ramirez *et al.* (2007) considered the optimization problem as a stochastic mixed-integer linear programming problem.

To avoid the extremely high computational effort associated with optimization problems, different approaches based on the topological structure of the network were proposed in the literature. Results provided by Giudicianni *et al.* (2020) demonstrate that the CWS defined through a topological approach can provide satisfactory contamination protection. In fact, even if the use of an optimization algorithm provides more accurate results, the topological approach can be a valuable alternative option, especially because of its simplicity (Santonastaso *et al.* 2021). Moreover, in the topological approach, sensor placement is defined solely based on network structures, so there is no need to have a calibrated model, which is needed by the optimization-based approach.

This section aims to delineate the advancements proposed in optimization approaches to locate sensors in WDNs and underscore the areas yet to be explored for future development. Table 2 presents a brief outline of significant contributions proposed in the literature for the definition of sensor placement. The different articles are outlined according to the objective functions adopted, the approach used, the type of contamination simulated (intentional, accidental, or both), and the information available for the sensors adopted (the threshold value allowing the identification of contaminants and whether it is considered a generic or a specific sensor).

Zeng *et al.* (2018) implemented a genetic algorithm (GA) for the definition of sensor placement and to consider the budget constraint, two types of sensors of different prices were used. Unfortunately, no information about the measurements done by these sensors is specified and moreover, a minimum concentration for the detection of the contaminant is not required by the sensors but a time threshold is fixed. Naserizade *et al.* (2018) considered having simultaneous contaminations in multiple nodes of the network and proposed an NSGA-II approach based on four objective functions, two of which were evaluated with a stochastic approach. Sensors were considered fully reliable over a concentration of contaminant equal to 0.01 mg/L. Winter *et al.* (2019) utilized a greedy algorithm to address the multi-objective problem of sensor placement. In this article, sensors were defined as imperfect and different ranges of sensor failure probability were tested; it was demonstrated that by changing this value the optimal solution will also change. However, in reality, it can be complex to estimate with reliability the probability of failure. A modified NSGA-III was proposed by Hu *et al.* (2020), who identified the dominant individuals as

Table 2 | Significant selected recent contributions for optimization of sensors placement

Reference	Objective function	Approach	Contamination		Threshold	Specification of sensors
Zhao *et al.* (2016)	Average consumption of contaminated water	Greedy heuristic; branch and bound	I	Generic	N	N
Khorshidi *et al.* (2018)	VOI, transinformation entropy; number of sensors	NSGA-II	I	Arsenic	Y: 0.01 mg/L	N
Naserizade *et al.* (2018)	Population affected; time of detection; probability of undetected events; number of sensors	NSGA-II	I	Arsenic	Y: 0.01 mg/L	N
Sankary & Ostfeld (2018)	Population affected; number of false positive detections	GA	I	Nicotine/ Parathion	Y: *del*	Y
Zeng *et al.* (2018)	Coverage ratio	GA	NA	NA	N	N
Ciaponi *et al.* (2019)	Number of sensors; contamination event	NSGA-II	NA	NA	N	N
Winter *et al.* (2019)	Probability of detection; probability of identification; time of detection; impact of an attack	Greedy	I	Generic	N	N
Hu *et al.* (2020)	Time of detection; population affected; volume consumed; detection likelihood	PD-NSGA-III	B	Generic	N	N
Cardoso *et al.* (2021)	Detection time; probability of detection; number of sensors	NSGA-II	I	Parathion	N	N
Khaksar Fasaee *et al.* (2021)	NA	Evolutionary-based k-means cluster model	NA	Arsenic	Y: 0.0125 mg/L	N
Jafari *et al.* (2021)	Time of detection; volume consumed; likelihood of failed detection; cost; contamination of important nodes	NSGA-III	I	Arsenic	N	N
Giudicianni *et al.* (2022)	Time of detection; detection likelihood; population exposed; extent of contamination	Greedy	B	Generic	N	N

I = intentional contamination, A = accidental contamination, B = both; Y = yes, N = no the most connected. In this approach, the authors considered having a conservative contaminant source and perfect sensors. Cardoso *et al.* (2021) implemented an NSGA-II approach based on three objective functions: detection time, number of sensors, and probability of detection. An intrusion of *parathion* was simulated, considering the reaction of this species with water components, as free chlorine. Giudicianni *et al.* (2022) highlighted that when addressing sensor placement in real WDNs, sensors are typically located within pipes rather than at nodes, even though most researchers focus on defining the optimal sensor location in terms of nodes. The authors proposed a multi-step approach for sensor placement, where a centrality metric was used in the first step to reduce the number of pipes considered in the subsequent optimization step, to decrease the computational effort.

Several literature reviews on the optimization process for the positioning of sensors have been produced. Adedoja *et al.* (2019) and Rathi & Gupta (2014) focused mainly on the different optimization functions used by authors in previous research. Hart & Murray (2010) pointed out that authors at that time did not consider heterogeneous sensor platforms that include different types of sensors; after more than 10 years it is still possible to say that little research has been done in this regard. In any case, none of these has focused on the lack of attention towards sensor detection threshold: by monitoring a parameter it can be challenging to determine when a change of this parameter allows inferring that a contamination is happening. On the other hand, it is difficult to evaluate the real effectiveness of a monitoring strategy when the aforesaid is not addressed.

Table 2 summarizes various recent articles, each characterized by different assumptions, computational costs, and WDN sizes ranging from small (81 demand nodes) to large (12,523 demand nodes). However, almost all studies refer to generic sensors without specific consideration of the threshold value. Naserizade *et al.* (2018) considered that if the concentration of arsenic in a specific node is higher than 0.01 mg/L it is assumed that the sensor will detect arsenic. The use of generic sensors does not reflect the ability of commercially available and field operational sensors. Robust drinking water sensors only monitor selected parameters and do not include trace metals. Sensor threshold should be related not only to the minimum variation that the sensor can detect but also to the minimum value that allows us to ensure that a contaminant has entered the network. Indeed, an important aspect in the development of optimal sensor placement is the evaluation of the information provided by the sensors. Sankary & Ostfeld (2018) actually considered the optimal sensor placement as the location where the WQ signals can be most effective in case of contamination. To do so, they considered an intrusion of nicotine and evaluated the variation of signal in the sensors employed in the network (chlorine, pH, and alkalinity). Moreover, for each type of sensor a threshold value, *del*, is defined, and if the sensor registers a value above this, it is considered as an atypical event. This improved approach should be extended to consider multiple contaminant types and the ability of available sensors to detect contaminations. Furthermore, if pinpointing sensor placement is intricately linked to detecting specific contaminants, exploring the feasibility of different sensor types for detecting diverse contaminants can be highly effective. Subsequently, determining optimal sensor locations based on this consideration is warranted.

3. CORRECTIVE AND PREVENTIVE ACTIONS

The issue of contamination in WDNs extends beyond detection to encompass the implementation of corrective and preventive measures. Water utilities must be equipped to handle contaminant intrusions effectively. Consider a scenario where a highly efficient CWS promptly detects a contamination event. However, if the utility lacks appropriate response protocols, the efficacy of the CWS is compromised, resulting in wasted time. Conversely, proactive development of corrective measures enables immediate response to detected contaminations, safeguarding a larger consumer base. Such measures may include flushing procedures to expel the detected contaminant or isolation of specific DMAs to contain the contamination. Furthermore, the establishment of DMAs acts as a preventive measure by reducing loop levels and limiting potential contamination pathways. Disinfection serves as another preventive measure; in fact it is commonly mandated to maintain consistent residual disinfectant levels throughout the network, effectively safeguarding against microbial intrusion.

The implementation of DMA, disinfection, and flushing are the major actions used as a tool to contrast the propagation of contaminants and expel them. These are analyzed in detail in the next sections.

3.1. DMAs

The propagation of contaminants throughout WDNs can be limited by the creation of DMAs, which reduce the loops and improve water security (Di Nardo *et al.* 2014; Ciaponi *et al.* 2019; Lifshitz & Ostfeld 2019).

A DMA is a portion of a WDN bordered by cut-off valves and control devices. DMAs may be useful to mitigate leakage within networks, but also to deal with external intrusions (Khoa Bui *et al.* 2020). By dividing the network into clusters and reducing the loop level, in case of a contamination event, the contaminant can be isolated by closing valves and the damage gets reduced to a limited number of districts. According to Ciaponi *et al.* (2019), partitioning has been shown to reduce the number of potential paths for contaminant spread, resulting in a 12.4% decrease in the number of affected users for the simulated contaminations. Di Nardo *et al.* (2013) demonstrated through simulation of a terrorist attack that DMA isolation may be more effective than sole partitioning. Furthermore, their findings indicate that increasing the number of districts leads to a reduction in the number of exposed users. Lifshitz & Ostfeld (2019) introduced a novel parameter, the infection delay time, which aids in defining optimal DMA layout to mitigate the spread of contaminants during intentional contaminations.

3.2. Disinfection

Another strategy for countering the spread of microbial contaminants is disinfection. This can be accomplished through a boosting procedure, which can also be combined with other operations such as valve opening/closing or flushing operations.

Disinfection plays a crucial role in preventing WQ degradation between the treatment plant and the end users. Chloramine and chlorine are commonly used secondary disinfectants in WDNs (Health Canada 2020). In some cases, residual level requirements are specified, as exemplified by the AWWA Partnership for Safe Water's Distribution System Optimization Program in the USA, where a minimum of 95% of monthly sampling sites are expected to maintain residual levels (Lauer 2010). Microbial contamination in WDN can be limited by the presence of a disinfectant residual that can inactivate bacteria and viruses (USEPA 2011). Haas (1999) reported that registered outbreaks of *Salmonella* (1993) and *E. coli* (1989) could be prevented by maintaining a chlorine residual throughout the WDN.

To ensure the recommended disinfectant residual in all the nodes of networks, an option can be to increase the amount of disinfectant added at the source. However, this can cause an excessive quantity of disinfectant, especially near the plant, which can induce bad odors and the formation of disinfectant by-products (DBPs) such as trihalomethanes (THMs) and haloacetic acids (HAAs) (Villanueva *et al.* 2015). Moreover, due to the wide extension of WDNs, this procedure might still not be able to ensure the minimum residuals in all nodes (Tryby *et al.* 2002; Munavalli & Kumar 2003). Booster disinfection may address this challenge by injecting disinfectant at specific locations (Tryby *et al.* 1999; Prasad *et al.* 2004).

The optimization of booster disinfection has been explored as a research topic by several researchers aiming to optimize the chlorine injection schedule (Boccelli *et al.* 1998; Tryby *et al.* 2002; Prasad *et al.* 2004; Goyal & Patel 2018; Li *et al.* 2022). However, even booster disinfection can still not be sufficient to ensure minimum disinfectant residuals in all nodes, especially in terminal ones where the pressure is usually low and the water age is high (Avvedimento *et al.* 2022). For this reason, approaches that consider booster chlorination combined with other operations were developed. Kang & Lansey (2010) proposed an optimization approach to define the optimal valve operations with booster chlorination. Results showed that this approach can be very efficient in reducing the chlorine injection mass and also allowing disinfectants to arrive in terminal nodes. Avvedimento *et al.* (2022) outlined the advantages coming from the use of flushing operations in conjunction with booster disinfection. In fact, flushing allows water to move at high velocity, reducing in that way water age and increasing flow velocity.

Chloramines are less efficient than free chlorine in killing or inactivating pathogens, but they are more stable thus providing increased coverage and longer disinfection in WDNs. Furthermore, they do not generate regulated DBPs such as THMs or HAAs (Health Canada 2020). Because of these properties, chloramines are mainly used as secondary disinfectants to maintain a disinfectant residual and present an enhanced ability to inhibit biofilm (Park & Kim 2008; Kadwa *et al.* 2018). However, chloraminated systems exhibited worse performance in deactivating microorganisms than chlorinated ones (Kouame & Haas 1991; Hatam *et al.* 2020).

3.3. Flushing

Flushing is a widely employed procedure for eliminating the presence of contaminants from the network and can itself be coupled with valve operations, as well as with manual faucet activation by end users.

Flushing can result in pressure drops, water loss, and potential WQ problems, including migration of contaminants from one main to another, and disruption (Friedman *et al.* 2002; Gullick *et al.* 2004). Furthermore, the increase in flow during flushing can dislodge microorganisms from the biofilm within the pipe (Nilsson *et al.* 2008; Pick *et al.* 2021).

Articles addressing flushing procedures are here classified based on their focus on either optimizing the flushing process directly or developing decision-making frameworks, such as decision trees, to guide flushing operations.

Optimization: The formulation of a flushing strategy can be approached as an optimization problem, which may consider various objective functions, including minimizing costs, mitigating public health impacts, or maintaining satisfactory service levels (Alfonso *et al.* 2010; Zechman 2013). Alfonso *et al.* (2010) proposed two different approaches, a single objective, and a multi-objective optimization, to determine optimal operations of valves and flushing based on a specific contamination event. However, with the developed procedure, water utilities do not have a strategy ready a priori to employ in case of other contamination events. Indeed, a wide variety of contamination events can take place. Duplex optimization strategies, which combine flushing/valve operations with optimization of sensor placement are also proposed in the literature. Guidorzi *et al.* (2009) developed two optimizations: first an NSGA-II for the detection of the contaminant, and then a GA approach to identify the hydrants to open and the valves to close. Khaksar Fasaee *et al.* (2021) proposed an approach that integrates flushing operations into the optimization of sensor placement. The developed method identifies a potential intrusion area rather than the specific intrusion node, which may lead to an overestimation of the number of hydrants opened. These approaches not only facilitated event detection but also ensured a response to intrusion incidents.

Decision tree: In this case, a decision tree is readily available for water utilities to employ in case of a contamination event. Shafiee & Berglund (2015) proposed a sensor hydrant decision tree. Their approach focuses on classifying contamination events rather than dealing with each specific event individually and it provides water utilities with a prepared procedure, based on the specific sensors' activation. Shafiee & Berglund (2017) proposed a decision tree that uses an agent-based model that considers the presence of three different actors within the WDN: consumers, water utilities, and the water distribution infrastructure, which interact with one another and influence the results of the scheduled corrective action. The approach was implemented for a fictitious network and, for a real one, might be challenging to establish the sociotechnical dynamics involved in contamination problems. Moreover, due to the high time required to run each hydraulic simulation, only a few contamination events were generated (300). To get through this challenge, Khaksar Fasaee *et al.* (2020) proposed a new approach based on the generation of thousands of contamination events which are first clustered based on the sensor activated and then grouped considering the sensor activation time. The authors considered that events that are in the same groups will lead to flushing strategies that impact the WDN in similar ways, so simulation results will be the same for all the events in the same group. A decision tree was developed by Bazargan-Lari (2018) who employed a M5P model (a modified version of M5, a decision tree with linear regression functions) to define the optimal duration of flushing. Downstream to the use of this tree, there is the knowledge of the contaminant source node, which is not always easy to establish. The optimization proposed required about 29 days for a network of 147 nodes, so it can become infeasible for a more complex network.

Another option formulated by Marlim & Kang (2022) is the involvement of users in flushing operations by faucet control. In this case, no optimization was performed, and the optimal operation was defined by trial-and-error attempts. Anyway, it is extremely difficult to establish how many customers will take part in this operation and produce reliable results.

4. CONCLUSIONS

A thorough critical examination of processes involved in developing a CWS shows their benefits and limitations, providing a basis for defining robust and reliable procedures for contaminant detection and clearance.

Detecting contaminants in WDNs involves both direct and indirect methods, each with its own set of challenges and opportunities. Direct detection of microbial contamination faces difficulties due to the complexity and scale of these systems. Methods such as periodic sampling and culture-based techniques often struggle to provide timely detection and are characterized by a high risk of false negatives in determining the presence or absence of contaminants. Online detection systems offer potential solutions by enabling real-time monitoring, although their effectiveness varies based on monitored parameters and contaminant types. By continuously monitoring parameters such as conductivity, pH, turbidity, and chlorine residuals, an early indication of contamination can be achieved. However, challenges persist in identifying the most sensitive parameters and establishing effective monitoring strategies for the specific WDN. Developing effective contamination detection strategies requires a systematic approach. This involves considering the most pertinent specific contaminants, understanding parameter sensitivities, and integrating real-time monitoring technologies. By addressing these challenges, water utilities can better protect public health and respond efficiently to contamination incidents.

Optimizing sensor placement in WDNs is crucial for safeguarding public health and managing costs effectively. Various objective functions have been proposed to address this challenge, balancing priorities such as risk mitigation, cost reduction, and timely detection of events. While optimization algorithms offer precise solutions, simpler topological approaches also provide valuable insights, especially in resource-constrained settings. Future research should address two notable critical observations: (1) insufficient attention to sensor specificity, with many studies assuming generic sensors without actionable thresholds, potentially overestimating system effectiveness, and (2) limited exploration of integrating WQ and hydraulic sensors, which could offer cost-effective monitoring solutions. Addressing these gaps will enhance the accuracy and efficiency of contamination detection strategies in WDNs.

Finally, ensuring public health necessitates not only the real-time monitoring of water parameters but also the implementation of an effective response once a contaminant is detected in the network. The establishment of DMAs offers a swift means of isolating contaminants within WDNs. While disinfection serves as a vital strategy against microbial contaminants, maintaining optimal residual levels throughout the network remains challenging. Flushing procedures can be used to expel contaminants, yet effective management is imperative to address challenges such as pressure drops and WQ concerns. Optimization approaches and decision tree models show promise in enhancing flushing efficiency, but further refinement and validation are essential to effectively navigate real-world complexities.

The advancement of sensor technologies, coupled with the increased affordability of monitoring systems and the widespread adoption of machine learning techniques for data processing, heralds improvements in the creation of CWSs. These developments not only signify progress but also pave the way for innovative approaches, bringing water utilities closer to the realization of smart distribution systems.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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