Distributed Sensing for Monitoring Water Distribution Systems

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Abstract

The primary goal of sensing technologies for water systems is to monitor the quantity and quality of water and to collect information pertaining to the physical state of system components. Combined with advanced modeling and computational tools, data collected from various sensing devices distributed throughout the water network allows for a real-time decision support system for analyzing, modeling, and controlling water supply systems. Since only a limited number of sensors and monitoring devices can be deployed due to physical constraints and limited budget, a crucial design aspect is to determine the best possible locations for these devices within a network. Optimal sensor placement problems in turn depend on several factors including, performance objectives under consideration, type of data and measurements being collected from sensors, sensing and detection models used, water distribution system dynamics, and other deployment challenges. In this chapter, we provide an overview of these important aspects of sensors deployment in water distribution networks, and discuss applications and usefulness of continuously monitoring parameters associated with water system hydraulics and water quality. We also highlight major challenges and future directions of research in this area.

Keywords: Water distribution systems; Sensor placement; Hydraulic and water quality; Event detection.

1 Introduction

Water distribution systems (WDSs) are complex infrastructure systems that span large geographical distances and are responsible for providing water from few points of source (PoS) to numerous points of use (PoU) through thousands to tens of thousands of hydraulic components of the WDS. Intelligent water systems aided by sensing technologies have been identified as a primary mechanism enabling resilient urban systems [24, 23]. Continuous monitoring of the state of the WDS, PoS, and PoU can support network operation in terms of real-time flow distribution, pressure management, water quality, and water loss control. Traditionally, the most common hydraulic sensors in water infrastructure systems measure the water level in storage tanks, flow and pressure in pipelines, whereas chlorine, total organic carbon, and pH levels are the focus of the most common water quality sensors [33]. Management of modern infrastructures needs advanced sensing technologies, automated data transfer, processing, and computing to provide useful information to water managers to support decision making. Among many technological components of a modern WDS, this chapter focuses on technologies for sensing the performance of hydraulic components and water quality.

Traditionally, the Supervisory Control and Data Acquisition (SCADA) system provides hydraulic and water quality (H&WQ) measurements at remote PoS such as pumping stations, storage tanks, and water treatment facilities. SCADA system keeps operators informed of the states of the water system's key components. Using this information, operators can then react to the conditions and perform control actions, such as emergency shutdowns of processes, starting or stopping pumps, and opening or closing valves. However, due to a limited spatial coverage of the traditional SCADA systems, whose measurements include information only at the few PoS, the collected information prevents monitoring network-wide state of the WDS. It follows that unlike the PoS, the WDSs are highly unmonitored given the small amount of sensing compared to its large scale and huge number of components. On the consumer side, that is, at the PoU, advanced metering infrastructure (AMI) automatically collects and transmits water consumption information at fine temporal-spatial scales. This information has a potential to improve demand management including characterizing end-users and end-uses, modeling demand, identifying opportunities for technology implementation, and for guiding infrastructure management and investment decisions. Today, however, AMIs in water infrastructure are primarily used for improved billing and for limited sharing of information with end-users.

Rapid developments in wireless/wired sensor networks (WSN) for various applications in the built environment have motivated the application of WSN for monitoring WDS, employing different sensors capable of continuously collecting and transmitting H&WQ measurements. In urban WDS, motivating examples of intelligent systems include the PipeNet@Boston [29], WaterWise@Singapore [4], SWND@Bristol [35], and WATSUP@Austin [36]. Such deployments extend the capabilities of traditional SCADA systems by providing real-time information at a fine spatial-temporal resolution that was previously unavailable, and improve water management by monitoring pressure and water quality [3, 23]. The application of WSN in water supply systems for securing H&WQ principally focuses on: (1) selecting measurable H&WQ parameters that are good indicators of system state and the corresponding sensing technology, (2) deciding on the number and locations of sensors in a WDS, and (3) performing continuous analysis of the data combined with other available information and models for state estimation, event detection, and forecasting. We discuss these important aspects in this article with a focus on the sensor placement problem in WDS.

In the next section, we discuss some of the common challenges in managing modern WDS that can greatly benefit from advances in sensing technology. We then briefly review common event detection and sensor placement models for monitoring WDS, and also provide an overview of challenges faced in sensors deployment. Finally, we present some future directions in this area.

2 Managing WDS with Sensors

We begin by highlighting some examples of the usefulness of information collected from online H&WQ sensors in routine and emergency operation of water systems. Although traditionally, problems of managing the hydraulic and water quality integrity of WDSs are treated separately, water quality practices heavily rely on hydraulic applications.

Model calibration – is a process of adjusting model parameters to make model prediction consistent with measured data [14]. The most common WDS parameters for calibration are roughness of pipes, consumer demands, and pump characteristics. While more information can reduce the uncertainty about demands and pump characteristics, the roughness of pipes is not directly observable. By assuming that some partial information pertaining to flows, pressures, and demands in the WDS is available, various calibration approaches have been proposed including: (1) trial-and-error, (2) explicit inverse methods for fully determined systems, and (3) implicit inverse optimization methods for over-determined systems. Due to the limited data availability calibration of water quality in WDS has been primarily restricted to simulated case-studies [15]. Many WDS problems rely on calibrated models for their management, and advanced sensing and monitoring can greatly contribute to model calibration.

State estimation – typically refers to near real-time estimation of state variables, for instance, flows, pressures, and concentrations, given some limited observations. In WDS, the state estimation problem typically tries to overcome the limitations of conventional forward hydraulic solvers that allow solving fully determined problems for the set of unknown flows and pressures in the system given known end-user demands, pump and valve settings, and water level in tanks. With increasing availability of sensing technologies in WDS and PoU, system observability can be improved thus alleviating some modeling assumptions and the need for pseudo-measurements [20, 34].

Real-time control – involves optimizing pumping schedules to minimize associated energy costs, valve control for pressure management, and operation of booster disinfectant stations for water quality purposes, while satisfying changing demands and operational constraints. Ultimately, real-time control depends on the ability to perform network H&WQ simulations efficiently, the ability of the optimization problem to find good solutions in near real-time, the effectiveness of state estimation, and making good forecasts of future water demands [20]. The latter heavily relies on network observability and the available information from distributed sensors.

Event detection – has notably received the most attention by the water systems research community in terms of utilizing the information collected by distributed H&WQ sensors. For water quality, events include intentional and unintentional contaminant intrusion into the WDS. For hydraulics, events include the detection and localization of water leaks and pipe bursts [1, 24]. Sensors are part of a warning system, which integrates data from different sources, performs analysis of the given information, and raises alarms when an event is detected. Subsequent localization of the event can then inform response and recovery actions. The sensor placement problems for detecting contamination events as well as leaks and bursts in WDSs have been well-studied in the literature [9, 24].

Condition assessment – and hydraulic integrity of pipelines can be indirectly inferred from pressure readings and used to assess the condition and develop risk indicators [28, 39]. WDS unsteady response to rapid changes is manifested as transient pressure waves traveling through the system. By monitoring pressure and analyzing the pressure signal, the physical condition of the system can be estimated through inverse transient analysis. Raw pressure readings can be converted using various time-frequency domain techniques into distress indicators of pipe aging and deterioration process, blockages, and presence of leaks, thus providing additional benefits to managing WDSs [37].

3 Event Detection and Sensor Placement Models

A variety of sensors deployed in WDSs that collect data and information regarding the overall state of the system can be further used to make inferences about potential H&WQ events as follows:

Water quality – contamination event detection methods rely on identifying abnormal behavior of the measured parameters. Online instrumentation capable of continuously measuring and detecting all possible contaminants is impractical to deploy, but the presence of some contaminants can be inferred through measuring surrogate water quality parameters suitable for online monitoring. The main assumption behind monitoring surrogate parameters is that a contaminant transported with the flow will react with some of the routinely monitored water quality parameters; then, detecting irregularities in monitored water quality parameters can give early indication of a potential contamination event in the WDS. The United States Environmental Protection Agency (EPA), academic institutions, and private companies have been conducting research exploring the range of the water quality parameters that are responsive to a variety of contaminants (e.g. pesticides, insecticides, metals, bacteria) and have provided results from experiments that tested the response of commercial water quality sensors of different designs and technologies to chemical and biological loads [32]. These tests suggested that free chlorine, total organic carbon (TOC), oxidation reduction potential (ORP), conductivity, and chloride were the most reactive parameters to the majority of contaminants. Hence, information from online water quality sensors deployed in WDS, which are reactive to many contaminants, can provide an early indication of possible pollution, as opposed to intermittent grab sampling targeting specic contaminants [17].

Hydraulics – WDS hydraulics is governed by the flow continuity and energy conservation principles. Thus, disturbances in flows (e.g. leaks and excessive demands) and structure (e.g. valve closure and pipe isolation) cause changes in flows and pressures in the system. The basic premise of model- and data-based detection models is that flow and pressure sensors that continuously collect and transmit information can be utilized for detecting the above mentioned events [19, 21]. Since the effect of medium and small events is relatively local, many flow and pressure sensors need to be deployed in the WDS to achieve good coverage and localization of the events. More precise and accurate surface and inline direct inspection techniques include acoustic, umbilical, and autonomous robots; however, these tools are mostly suitable for local inspections and their operation is typically time consuming and expensive, making them not suitable for continuous operation [38].

Once the sensing model is established, the detection model, for both water quality and hydraulics, relies on model-based and/or data-driven detection schemes. Data-driven detection ranges from threshold-based models in time-frequency domain [27, 38] to k-nearest neighbor, logit models, and genetic algorithms [10]. Aside from the specific approach, data-driven models process either single- or multi-parameter signals collected from single- or multiple-sensor locations. Model-based approaches range from simple [8] to complex hydraulic and water quality models including single- and multi-species using EPANET and EPANET-MSX [26].

As discussed next, in practice, several challenges limit the number of sensors that can be deployed within a system. Consequently, it becomes crucial to place sensors at strategic locations such that they provide the most useful information regarding water quality and hydraulics of the WDS. Before formulating and solving the optimal sensor placement problem, the scope of the problem and its components need to be defined, including determining the WDS dynamics, event and sensing characteristics, as well as the impact and performance models. The common design objectives that can be found in the literature include maximizing detection likelihood, minimizing the time to detection, minimizing the volume of delivered contaminated water, and maximize event localization. The main steps involved in framing the sensor placement problem are summarized in Table 1.

To obtain a sensor placement that optimizes one or multiple performance objectives, a number of solution approaches have been proposed in the literature [22]. *Mixed integer programming (MIP)*, in which the problem is often formulated similar to facility location, was used to accommodate a wide range of design objectives in the formulation and taking advantage of efficient solution schemes for solving large-scale problems [6, 23]. *Greedy approximation* is another useful solution approach, in which sensor locations are typically selected in an iterative manner. In each iteration, a sensor location that optimizes a single or multiple performance objectives under consideration is selected. In many cases, it is also possible to provide performance guarantees of greedy approximations, for instance, if the objective function is submodular [12]. *Evolutionary algorithms* have also been successfully employed to obtain sensor placements in water networks [5]. These solution approaches primarily rely on heuristic search techniques and the integration of hydraulic simulations to optimize various performance objectives. *Graph-theoretic* methods have also been proposed, in which the underlying network topology is explored and various network-based centrality measures are suggested to find the optimal sensor locations [18].

Table 1: Main steps involved in the sensor placement framework

Design steps	*Hydraulic features*	*Water quality features*
Process dynamics	• Steady-state hydraulics • Unsteady hydraulics	• Transport and reaction model • Single/multi-species
Event characteristics	• Excess loads, reduced connectivity • Duration, intensity, location • Random, strategic	• Contaminant intrusion • Duration, magnitude, location • Random, strategic
Sensor characteristic	• Continuous, intermittent • Measurements uncertainty, sensor robustness	• Continuous, intermittent • Measurements uncertainty, sensor robustness
Detection model	• Deterministic, stochastic • Distance, threshold, model-based	• Deterministic, stochastic • Distance, threshold, model-based
Impact measure	• Detection likelihoood, water loss, energy loss	• Detection likelihood, contaminated volume, population at risk
Performance measure	• Mean, worst case, value at risk	• Mean, worst case, value at risk
Solution approach	• Engineering principles • Network connectivity • Model-driven optimization	• Engineering principles • Network connectivity • Model-driven optimization
Testing & validation	• Test-bed • Simulation	• Test-bed • Simulations
Routine management activities	• Pressure management • Leak detection • State estimation	• Water quality management • Residual disinfectant • State estimation
Emergency management activities	• Network recovery to emergency event • Fire-fighting conditions	• Contaminant intrusion • Changes in source water quality

4 Challenges in Sensors Deployment

Despite the extensive literature, the application of continuous monitoring within water WDS has been limited in practice for several reasons, some of which include:

Cost – high initial investment, operations and management costs limit the widespread deployment of sensors by budget-constrained water utilities.

Accuracy and reliability – although better and cheaper water quality sensors suitable for continuous deployment in the field are continuously being developed and improved, the low level of reliability of the generated data, frequent calibration requirements, and demanding power needs introduce additional challenges in field-implementation [3].

Physical constraints – since most of the hydraulic components are buried underground, physical access to locations of interest, while minimizing interference and disruptions to routine operations, additionally hinders the deployment of sensing apparatus within the WDS.

Data management – integration of distributed sensing increases the amount and variety of data generated. For example, sampling water consumption at the PoU at one minute resolution implies replacing the typical twelve annual meter readings with 525,600 readings [25]. Unavoidably, several related challenges in collecting and managing the data are introduced including: data heterogeneity necessitates advanced warehousing, cloud dependency requires constant accessibility to the data, and errors can arise from various sources including hardware, firmware, and communication.

Security and privacy – sabotaging and disrupting WDS, physically or through cyber means, could result in catastrophic consequences on population health and dependent infrastructure. Moreover, the access to vast amounts of data generated from various sensing devices across the system must be controlled and regulated to prevent any misuse and to safeguard users' privacy.

Advanced sensing and metering promises benefits to water utilities by enabling intelligent operation and planning decisions. Nevertheless, it is crucial to understand the trade-offs between the information gained from distributed sensors and the associated challenges in deployment and operation. In summary, currently the benefits of smart sensing technologies for WDS have not been realized to their full potential and there is a need for proven methods for incorporating these cyber-systems in current decision making processes.

5 Summary and Future Directions

Information and data collected through an assortment of sensing devices enable water system operators to continuously monitor, control and effectively deal with any disruptive events in real time. Despite the many opportunities that advanced sensing and metering technologies create, in the context of WDS, the sensor deployment for contamination events has indisputably received the most attention, while there are still several future research direction in the area of sensor placement in WDS, as we briefly outline next.

Resilience to cyber-physical attacks – in smart water networks, sensing devices are a part of closed, real-time control loops, and hence observed data from them can directly impact the operation of physical infrastructure assets (pumps, valves, tanks). By exploiting vulnerabilities, a malicious attacker can compromise a subset of these devices, and attain a certain level of control to manipulate physical processes. Thus, a resilient sensor network that maintains the task of transmitting correct sensor data with minimal and tolerable disruption despite adversarial attack is crucial for a safe water infrastructure. There has been increased focus in recent years towards security and resilience of water distribution systems to malicious disruption [16, 30, 2]. There is a need to develop analytical tools to assess vulnerabilities and risks associated with malicious attacks on WDS.

Heterogeneous sensors – in WDSs, heterogeneity of sensors can be interpreted and exploited in many different ways for a better performance. Sensors can be heterogeneous in terms of parameters they measure and information they collect about the system's state, such as water flow, pressure, and quality. Another aspect of heterogeneity is that sensors measuring the same network parameter can be of different types and have multiple variants. For instance, they might have distinct operating systems, software packages, and hardware platforms. Diverse implementations of sensing devices can be conducive towards improving the overall security of the sensor network against cyber-attacks [13]. Sensors can also be heterogeneous in terms of the level of information they provide [1]. For instance, sensors deployed to detect the disturbance in the form of a pressure wave caused by a pipe burst can be single-level in which case they only report the existence of some disturbance without much detail, or they can be multi-level in which case they also report the physical features of the disturbance, such as the intensity, duration, and frequency of the detected disturbance. This information can be helpful in distinguishing between different events. Sensors with better accuracy and more information are typically expensive. Thus, to better exploit cost versus performance trade-off, employing a combination of more expensive and low-priced sensors could yield better results as compared to using only one type of sensors. Interesting problems would then be to determine the right distribution and locations of expensive but highly accurate and low-priced but relatively less accurate sensors within the network. Incorporating these factors in the design of sensor networks for WDS can lead to more effective and applicable solutions in practice.

Modeling framework and benchmarking – optimal sensor locations with respect to any performance criteria highly depend on the selection of network flow, event (disturbance), and sensing models considered during the problem formulation. Several variants of these models have been developed over the years and are used by researchers and practitioners [9]. However, there has been little effort in establishing standardized conditions for such formulations, for instance, what hydraulic dynamics should be used? What is the right level of abstraction regarding the network structure? Which event propagation dynamics should be considered? To have sensor placement solutions that work well in practice, it is crucial to clearly understand, outline, and compare the scope of various modeling frameworks. Moreover, although a myriad of optimization tools have been developed for optimal sensor placement, little effort has been made to make these advances accessible to the practitioners, and these tools typically remain limited to the domain of their developers. Some noteworthy freely available software for water quality event detection are CANARY and PECOS [31, 11], and TEVA-SPOT [7] for sensor placement.

6 Cross References

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