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Article

Wireless Sensors for Measuring Drinking Water Quality in Building Plumbing: Deployments and Insights from Continuous and Intermittent Water Supply Systems

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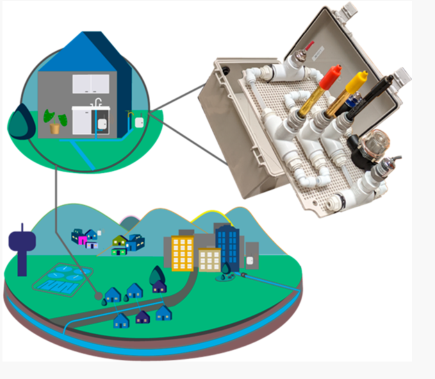
ABSTRACT: Despite continued calls to increase the monitoring of drinking water systems, few communities and utilities have adopted modern, distributed, and real-time monitoring systems. Measurements of drinking water quality are often only made at the treatment plant, with limited grab sampling taking place throughout the distribution system. At the building level, where most of the public's exposure to drinking water takes place, the capacity to make continuous measurements to characterize water quality dynamics has been almost impossible. Innovation in sensors, microcontrollers, and data services is underpinning a broader smart cities movement, but their value as a tool in the management of drinking water systems is still unclear. In this paper, we present a new open-source wireless sensor platform, which allows water quality to be measured at the tap. Our internet-connected devices transmit data back to cloud hosted services, where they can be analyzed in real-time. We provide examples of large-scale deployments within buildings in Ann Arbor, Michigan, USA and Mexico City, Mexico. In each of these studies, we demonstrate the detection of phenomena that would have been missed through existing, low-throughput monitoring approaches. The deployment in Ann Arbor emphasizes the importance of real-time measurements in a drinking water distribution system, highlighting shifts in neighborhood-scale electroconductivity (a proxy for total dissolved solids) that would have been missed as part of established sampling procedures. The Mexico City deployment demonstrates highly variable water quality and supply in intermittent systems and characterizes the variability of chlorine concentrations between continuous and intermittent portions of the city.



KEYWORDS: *smart water, ORP, residual disinfectant, monitoring, event detection*

1. INTRODUCTION

Despite continued calls to increase the monitoring of drinking water systems,[1−3] few communities and utilities have adopted comprehensive, distributed, and real-time monitoring systems.[4] Sensors have been lauded for their promise to revolutionize drinking water management, but the adoption of real-time data technologies lags behind other infrastructure sectors.[5] As we embark on unprecedented water challenges around the world, including natural and anthropogenic pressures on water resources,[6,7] real-time water quality monitoring systems should be considered as part of a new generation of information-driven infrastructure to support drinking water management and research.[4,5,8,9]

In most countries, federal regulations require public water managers to monitor treated drinking water to support safety and public health. Such monitoring typically includes quantifying the concentrations of disinfectant residuals, disinfection byproducts, lead, copper, total coliforms, and some waterborne pathogens at the entry points of and throughout the distribution system. In the United States, nearly 100 contaminants are required to be monitored periodically,[10] and regulations are regularly updated based on public health risk.[11] Because water quality characteristics change throughout distribution, most parameters are required to be monitored by collecting water from different locations in the distribution system (e.g., residual disinfectant, total coliforms), while a few contaminants are monitored at the tap due to the impact plumbing materials have on water quality (i.e., lead and copper).[10] The required residual disinfectant and total coliforms monitoring frequency for a public water system depends on the number of people served, ranging from 480 samples per month in the largest systems (>3.96 M people) to once per month for the smallest systems (<1000 people).[10]

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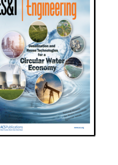

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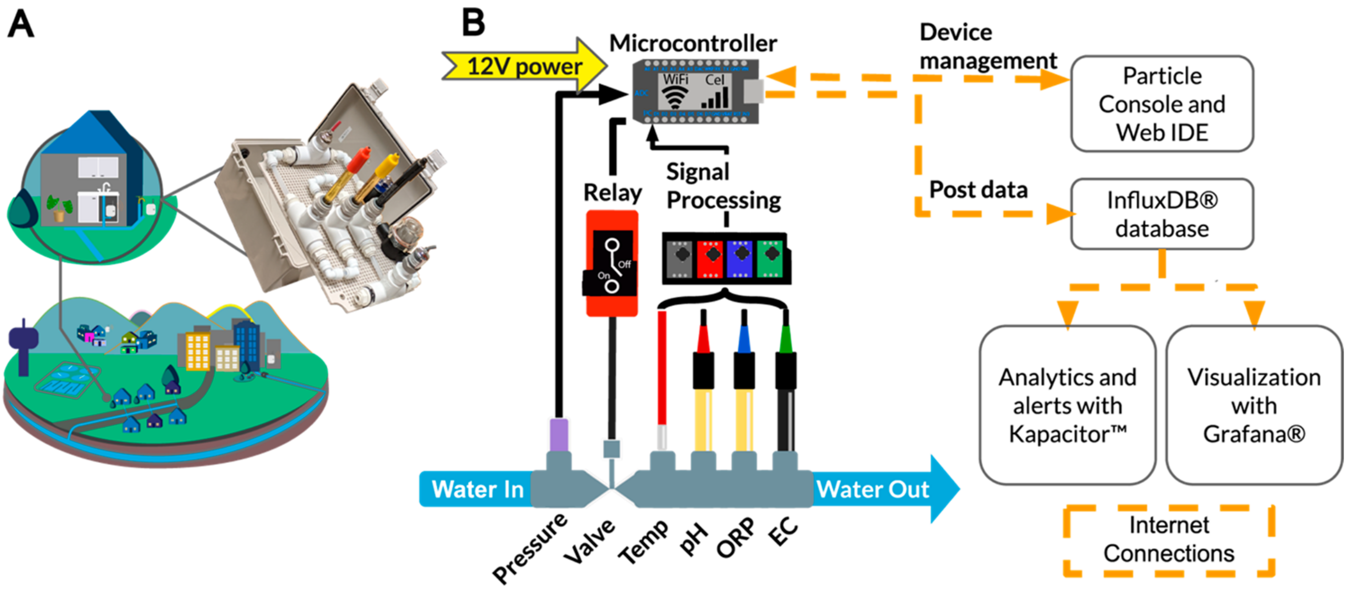

Figure 1. (A) Compact formfactor deployed on standard household pipes, such as kitchen sinks or outdoor spigots. The flow cell with the sensors and electronics is contained within the enclosure. (B) System architecture including data collection and conditioning within the enclosure and the cloud architecture for data management and visualization.

Manual sampling and analyses are labor and resource intensive, which limits the number of measurements that can be collected. Achieving a high spatiotemporal measurement resolution, therefore, is not possible with grab sampling, and important information can be missed if water quality varies across the distribution system or changes from day to day.[3]

Innovations in sensors, microcontrollers, data communications, and web services have allowed for the rapid expansion of wireless sensor networks, which are increasingly used to monitor, model, and control municipal services as part of a broader smart cities movement.[3,12] The fields of stormwater and wastewater management,[13,14] transportation,[15] and power distribution,[16] for example, have improved performance and lowered operational costs through the adoption of real-time analytics and control. There is an equally exciting opportunity to harness these technologies for a better understanding of drinking water systems.

A number of sensor platforms for drinking water have been evaluated over the past decade.[17−22] Most recently, a study used multiple sensors to study water quality in different stories of an institutional building to predict chlorine residuals at each floor based on floor occupancy.[23] Organic, inorganic, and biological contaminants have been detected in lab-scale experiments using high frequency sensor data from free and total chlorine, pH, oxidation−reduction potential (ORP), electroconductivity (EC), and chloride probes.[24−27] To our knowledge, no studies have measured water distribution at the scale of an entire city nor at the residential tap level. Despite the demonstrated benefits of real-time monitoring, cities and municipalities have not yet implemented sensors on a large scale.

To date, most examples of using wireless sensor networks to monitor drinking water rely on single-site demonstrations or short-term deployments. Challenges to large-scale deployments include the maintenance cost of the systems;[25] the management and storage of real-time, high-frequency data; and the uncertainty of sensor behavior.[4] PipeNet in Boston, Massachusetts, USA[18] and WaterWiSe in Singapore[19] are examples of large-scale deployments that demonstrated the reliability of node network data communications and detected leaks and pipe bursts with high-frequency pressure sampling. These two systems also included pH sensors as a proof of concept for water quality monitoring. In the PipeNet, WaterWiSe, and Skadsen et al.[25] deployments, sensors were placed into distribution system pipes or reservoirs. A reliable and compact formfactor to deploy water quality sensors in buildings would provide insights where drinking water is ultimately used.

Drinking water quality changes throughout the distribution system, as well as inside building plumbing. Variables like water age, temperature, pipe and fixture materials, and the pipe surface area to volume ratio have effects on the physicochemical and biological composition of water at the tap.[28,29] This is part of the reason why some contaminants, such as lead and copper, are required to be monitored at the tap.[30] Additionally, granular data at the building level could provide information about water quality across intermittent water supply systems. Intermittent water supply is often unreliable and inconsistent and has been shown to pose risks to public health.[31,32] An estimated 1 billion people worldwide depend on intermittent water supply, and that number is projected to increase significantly in the next decades.[32,33]

To advance the goal of adopting sensor networks for drinking water distribution systems, this paper introduces a novel open-source, end-to-end wireless platform for the real-time monitoring of drinking water systems capable of measuring pH, ORP, EC, temperature, and pressure. We provide results and observations of two large-scale wireless sensor network deployments, one within buildings in Ann Arbor, Michigan, USA and one within homes in Mexico City, Mexico. Our specific objective is to evaluate the performance of this platform in situ and to summarize practical deployment considerations for others interested in carrying out similar studies.

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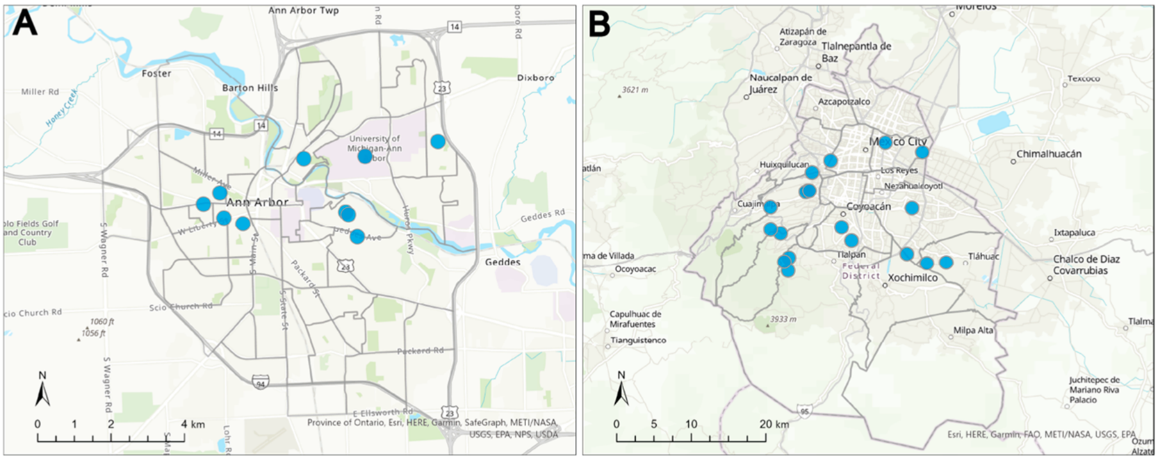

Figure 2. Locations of deployment of drinking water quality sensor nodes. (A) Map of Ann Arbor, Michigan, USA, deployments. Ten sensor nodes were deployed within the time period between August 2019 and June 2020. (B) Map of Mexico City, Mexico deployments. Nineteen deployment sites were part of the study, which took place between January 2019 and March 2020.

2. METHODS

An open-source wireless sensor node for monitoring drinking water quality was designed and constructed using low-cost commercial sensors and electronics, web services, cloud analytics, and real-time visualization. The design objective was to create a small, portable, and reproducible platform that can be connected to a wide range of complex piping setups used in drinking water distribution, including standard building taps (Figure 1A). With the use of existing in-home internet or cellular connectivity, sensor nodes report data in real-time and are deployable in most buildings and neighborhoods. The system's architecture includes (A) hardware and (B) cloud services and applications. The hardware includes wireless microcontrollers, analog conditioning circuits, and sensors. The cloud services include a central database, visualization capabilities, and remote management tools. An architecture diagram is provided in Figure 1B.

2.2. Hardware. *2.2.1. Embedded System and Hardware.* The communications core of the hardware platform was built upon the Particle series of microcontrollers (Photon and Boron 2G/3G), which can be programmed in C++ and updated over-the-air using a web interface.[34] The node connects to the internet using wi-fi or cellular—depending on the connection stability at each site. The core is powered by a DC 12 V power supply, allowing the node to be plugged directly into a nearby wall socket or powered via a 12 V battery. Although the system can operate across lower voltages (3−5 V), 12 V is necessary to open most commercial solenoid valves, which are used to trigger sampling. The remaining electronics, including the microcontroller, carrier boards, and the sensors, operate with 5 V delivered by an embedded voltage converter. A backup battery ensures that the nodes remain operational, even when household power goes out.

The sensors communicate with the microcontroller using the I^2C protocol.[35] The sensors are implemented with signal-conditioning circuits (Atlas Scientific EZO) that facilitate required and customizable sensor operations, such as calibrations, temperature corrections, and measurements. The EZO circuits are electrically isolated and mounted on a carrier board designed by Whitebox Laboratories.[36] A pressure transducer is connected to the microcontroller's analog to digital converter (ADC) via a voltage divider. The measurement timing and transmission frequency of all parameters can be easily modified remotely to suit a wide range of field conditions. The sensors are described in more technical detail in the SI.

The flow cell (housing that exposes the sensors to the water flow stream) was designed to have a low water consumption footprint, to include simple operational requirements using readily available parts, and to be modular. It was built using off-the-shelf plastic tubing and PVC fittings that hold the sensors in place. The arrangement of the flow cell, valve, and the sensors is presented in Figure 1B. The pressure transducer was placed first in line and outside of the flow cell so that pressure can always be measured without actuating the valve. The solenoid valve separates the sensors from the pressurized pipes and only opens to flush new water into the flow cell. The flow cell was designed to exhibit plug flow hydraulics to minimize mixing with previous samples and to prevent the probes from drying. At the time of writing (2021), the cost of materials to build the entire unit was approximately \$1200 U.S. The sensor nodes can be built entirely by a single person with limited electronics experience. The plans for building the entire unit are shared on our open-source Web site: https://github.com/kLabUM/DrinkingWaterNodes.

2.3. Cloud Services. The cloud services layer provides storage of sensor data in an online, secure, timeseries database (*InfluxDB*) and facilitates interactions between user-defined applications (*Kapacitor*) and visualization tools (*Grafana*). Node operations push conditioned sensor readings to the database in a custom *JSON* format after each measurement. The user-defined applications query the database for the latest reported readings, and the user can write commands to change the behavior of desired nodes. The cloud architecture also facilitates remote management of individual nodes through Particle's web-based development environment.[34]

3. DEPLOYMENTS

The sensor nodes (29 nodes in total) were deployed in two cities that differ in size, demographics, and drinking water distribution characteristics. One deployment took place in Ann Arbor, Michigan, USA and another in Mexico City, Mexico (Figure 2). Both deployments took place within residences, at the tap level or entry point into the home. This approach provided us with two distinct data sets to evaluate the sensor

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system. In each study, we detected phenomena that would have been missed by using existing, low-throughput monitoring approaches. The deployment in Ann Arbor illustrates the importance of collecting real-time measurements in a continuous supply drinking water system that is consistently in compliance with regulations by highlighting shifts in neighborhood-scale EC that would have been missed as part of established monitoring. The deployment in Mexico City results in the first dense and continuous water quality data set available for an intermittent water supply system. The Mexico City data demonstrate highly variable water quality and supply, and variable chlorine concentrations between continuous and intermittent portions of the city. The two cities use different secondary or residual disinfectants, which offered an opportunity to apply ORP sensors in systems with chloramine or combined chlorine (Ann Arbor) and free chlorine (Mexico City).

3.2. Ann Arbor. The sensor network in Ann Arbor, Michigan, USA was deployed to study spatiotemporal building plumbing water quality in a city with a relatively homogeneous system. Ann Arbor has a population of 120 000 people, covers 75 km^2, and contains 800 km of water distribution pipes. The drinking water is supplied by one drinking water treatment plant that blends surface water (Huron River) and groundwater. The source waters are blended with varying ratios, with higher proportions of surface water during the spring, summer, and fall and a higher proportion of groundwater during the winter months. The treatment plant provides 400 L per capita per day, and finished drinking water is distributed with monochloramine as the residual disinfectant at a concentration of approximately 3 mg/L as Cl_2. The distribution system is divided into five pressure districts, all of which are operated independently and have interconnections to regulate flow, pressure, and water quality. Previous studies have documented the drinking water infrastructure in Ann Arbor, including detailed descriptions of the water treatment train,[25,37] the distribution system, and water quality parameters.[37,38] The Ann Arbor drinking water system is part of the 1% of public water systems in the United States that serve more than 100,000 people; more than 50% of the population in the United States is provided drinking water through public water systems within this size range.[39]

A total of 10 sensor nodes were deployed in four of the five pressure districts at a range of distances between 1.7 and 8.5 km from the treatment plant (as measured from a street layout, not the distribution system). Sensor nodes were placed inside single family homes: two under a kitchen sink, one under a bathroom sink, and seven under a laundry/utility room sink. The deployments lasted from 29 days to 177 days starting in August 2019 and ending in July 2020 and thus included seasonal transitions. The deployment study was interrupted by the COVID-19 pandemic, and visits to households were not possible for maintenance or collection of grab samples.

Minor and reversible plumbing modifications were made to accommodate the sensor node water intake and to allow all effluent water to be discharged directly to the closest drain. The sampling protocol was identical for all nodes and throughout the deployment period. It consisted of pressure readings every 5 min and an open-valve flushing action of 5 s followed by water quality measurements every 60 min. The samples taken represented building plumbing water due to the short amount of time the valve remained open.

3.3. Mexico City. The sensor network in Mexico City was used to study spatial differences in household water quality and supply dynamics in neighborhoods across the city. Technical information on the operation and management of the drinking water system of Mexico City is not readily available through public channels. Regions of the city have continuous water supplies (70% of grid connections), while others have intermittent water supplies (30% of grid connections).[40] The city has a population of 9 million, covers 3773 km^2, and contains 12 500 km of water distribution pipes.[40] The city's drinking water sources consist of 42% surface water and 58% groundwater from 450 wells of various depths tapping into multiple aquifers.[41] There are 58 drinking water treatment plants that supply an average of 200 L per capita per day and distribute water with free chlorine as the residual disinfectant.

Of the 19 sensor nodes deployed across the city, 13 were placed at homes with a continuous drinking water supply, and six were in homes with intermittent supply. Of the six sites with intermittent supply, three were supplied water for 8 h per day (daily intermittency) and three were supplied water for a few hours at a time throughout the week (weekly intermittency). The duration of each sensor node deployment ranged from 4 days to nine months between January 2019 and April 2020. This period encompassed dry winter and spring as well as wet summer seasons.

The sensor nodes were connected to a tap next to the water meter to capture pressure data from the distribution system and to provide the water availability dynamics at locations with an intermittent water supply. The sampling protocol included a pressure reading every 5 min and an open-valve flush action of 10 s followed by a water quality reading every 60 min. When pressure readings were zero, the flushing and water quality readings were postponed until water was available again. In one intermittent home, water quality was measured continuously to evaluate any potential impacts of stagnation in the flow cell.

Grab samples were also collected from each deployment site, ranging from one to three times per location during household visits, and select water quality parameters were measured on-site, including free chlorine (Palintest 7100, DPD method) and pH and EC (Hanna hand-held pH-EC combo sensor).

4. RESULTS AND DISCUSSION

4.1. Ann Arbor. The 10 sensor nodes in Ann Arbor collected 437 157 pressure readings and 85 405 water quality measurements. The average readings obtained for each of the 10 sensor nodes fell in the following ranges: pH, 9.2−10.0; ORP, 356−669 mV; EC, 558−997 uS/cm; and pressure, 24−88 psi. A summary of water quality results is provided in Table 1.

The ORP sensors have a "warmup" time (Figure S1), requiring an average of 3 h to reach equilibrium once deployed. We therefore filtered the full data set to remove start-up data (Figure 3B and Figure S1). The resulting ORP data averaged 454 mV, with a range of 300−750 mV (Figure 3B). On the basis of average replicate data reported by Copeland and Lytle,[42] at pH 9 and 23 °C, the average ORP value (454 mV) corresponds to a monochloramine concentration of 2.7 mg/L as Cl_2 and the ORP range corresponds to monochloramine concentrations ranging from 0.4 to >4 (out of range) mg/L as Cl_2. Considering that the finished water distributed by the Ann Arbor treatment plant has a monochloramine concentration of approximately 3 mg/L as Cl_2, and monochloramine concentrations in the distribution system average 2.55 mg/L as Cl_2

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Table 1. Ann Arbor Water Quality Nodes Deployment Summary Statistics Per Pressure District in Ann Arbor

pH		EC (uS/cm)		ORP (mV)		pressure (psi)	
mean[a]	SD[a]	mean	SD	mean	SD	mean	SD
Northeast							
9.2	0.2	755	55	505	129	24	34
10.0	0.1	774	58	418	14	74	20
West							
9.7	0.0	744	133	409	22	88	2
Gravity							
9.4	0.2	740	59	489	132	55	20
9.5	0.2	832	63	555	94	60	1
9.3	0.2	737	30	493	66	60	2
9.3	0.2	997	352	669	147	59	7
Geddes							
9.5	0.3	717	55	541	100	69	7
9.8	0.0	732	48	424	40	73	5
9.5	0.2	588	272	356	76	50	5

[a]Due to common probe malfunction, pH statistics were calculated using only the first five days of data.

(data provided by the Ann Arbor treatment plant), our ORP results agree with expected monochloramine concentrations. Three nodes exhibited an increase in ORP starting in March 2020 (Figure 3B). All three of these devices were located in the same pressure district.

The deployment in Ann Arbor highlights the benefits of a sensor network for the purposes of event detection and system-scale monitoring. The network captured events that would have been missed as part of conventional sampling campaigns. For example, the entirety of the Ann Abor system experienced a rise in EC across a number of weeks (Figure 3A). This period would provide sufficient time to utility personnel to investigate the change in more detail, for example, by performing laboratory tests or by running a cross-reference data log to check operational status at the plant. Grab sampling was not possible as part of this study due to the COVID-19 pandemic and stay-at-home orders.

Given that all sensors measured the EC event, a strong case can be made for the occurrence of a system-scale event, compared to if just one sensor node or grab sample would have reported the change. In consultation with Ann Arbor drinking water treatment plant personnel, we believe the increase in EC was related to operational and maintenance changes at the treatment plant, which included changes in source water blend ratio and chemical dose adjustments. While these events did not pose a health risk to the public, our observations highlight the potential benefits of continuous and distributed monitoring for future events. It also emphasizes that water quality parameters do not only vary at the plant but variations can extend throughout the water system and can be measured at the tap. The sensor nodes continuously measured the event as it developed, capturing a baseline trend, a maximum, a return to baseline conditions, and an additional rise (Figure 3A, Figure S2). While EC is not a regulated parameter under the U.S. EPA's primary drinking water standards, it still provides aesthetic information about water quality since a typical conversion factor between EC and TDS is 0.5. TDS (total dissolved solids) is included in the U.S. EPA's list of secondary drinking water standards and is recommended to be below 500 mg/L.[43] This means that the observed peak in Figure 3A (933 uS/cm, 466 ppm TDS) did not reach the threshold of TDS that may negatively influence the taste, smell, or color of drinking water.

Using ORP signals to accurately measure residual disinfectant remains a challenge. Copeland and Lytle[42] reported an increasing variation between ORP duplicate (using two different sensors) measurements of the same solution, at increasing pH values. For a sample with chloramine at a pH of 9, they observed an average and maximum ORP variation of 47 mV and 71 mV. Ann Arbor maintains its chloraminated finished water at a pH slightly above 9, suggesting that ORP measurements across the system may exhibit high variation associated with the probes. The relative fluctuations of ORP signals correspond to changes in disinfection residual, which make the sensors a valuable tool to detect fluctuations in disinfectant residual and assist with flushing strategies during regular distribution system maintenance. For granular decision making, we recommend taking grab samples for ORP checks to complement the real-time sensor node signals.

As shown in Figure 3B, three sensor nodes located in buildings in the same pressure district showed gradually increasing ORP signals. In the context of drinking water, ORP is typically associated with disinfectant concentration because disinfectants are the strongest oxidants present in drinking water. Therefore, this increase in ORP may point to a higher concentration of disinfectant in this neighborhood. Following

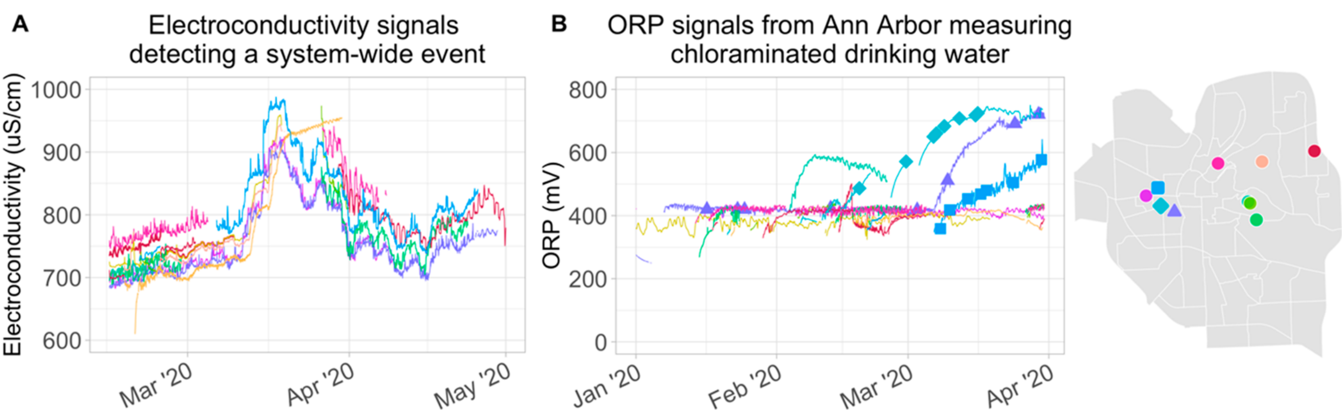

Figure 3. Signals from the sensor deployment in Ann Arbor, Michigan. The time series are color-coded by the site shown in the map. (A) EC signals from deployed sensor nodes are shown capturing a system-wide event. (B) ORP signals are used as an indicator to monochloramine concentrations. Three signals from the same pressure district exhibited a rise in ORP, shown by the triangular, square, and diamond markers.

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the event, the ORP sensors were inspected and tested; they did not show any damage nor biofilm growth, and they responded accurately during calibration. This absence of sensor problems suggests that a transient event indeed may have transpired in this neighborhood, but no clear cause could be identified (we verified that no disinfection booster stations are used in Ann Arbor's distribution system). This observation underscores why continuous and distributed sampling is important, as it could be used as a tool to detect water quality regime shifts as they occur.

4.2. Mexico City. The 19 sensor nodes deployed across Mexico City resulted in 358 761 pressure readings and 168 685 water quality data points. The average ranges measured by all sensor nodes were as follows: pH, 6.8−8.2; EC, 212−1064 uS/cm; ORP, 204−921 mV; and pressure, 2−50 psi. ORP values from each deployment site were compared to free chlorine from grab samples for continuous systems (Table 2) and intermittent systems (Table 3). EC signals from the sensor nodes are compared to grab samples at each deployment site in Table 4. The average pH signals are compared to the respective grab samples per site and shown in Table S1 in the Supporting Information.

Table 2. Continuous Systems ORP and Free Chlorine Summary Statistics of Deployment Signals and Grab Samples from Mexico City

ORP signal (mV)		free chlorine (mg/L as Cl_2)		
mean	SD	mean	SD	*n*
Chlorinated				
795[a]	18	1.06	0.18	3
806[a]	58	1.25	0.18	3
808[a]	25	0.88	0.41	3
688	169[b]	0.68	0.08	3
922	68	1.34	0.62	2
Not Chlorinated				
257	154	0.04	0.02	2
204	50	0.04	NA	1
Variable Chlorination				
542	159	0.78	0.74	3
493	144	0.17	0.14	2
533	94	0.89	0.56	3
644	156	0.37	0.30	2
736	281	0.00	NA	1

[a]Nodes deployed in the same neighborhood. [b]High variability likely attributed to probe lowered sensitivity during deployment period.

For the 13 sensor nodes placed in households with continuous supply, chlorine residuals from grab samples were used to bin the ORP signals into categories of chlorinated, not chlorinated, or having varying levels of chlorination. Measurement time series for these households are categorized and shown in Figure 4, with summaries provided in Table 2. The ORP averages for chlorinated systems ranged from 688 to 922 mV, with the corresponding average free chlorine concentrations ranging from 0.68 to 1.34 mg/L as Cl_2. The ORP averages in systems categorized as not chlorinated ranged from 204 to 257 mV, corresponding to grab samples that had free chlorine concentrations below the detection limit. The third category—varying levels of chlorination—exhibited average ORP readings ranging from 493 to 736 mV and free chlorine concentrations in the corresponding grab samples ranging from zero to 0.89 mg/L as Cl_2.

The ORP signals measured in the intermittent households are summarized in Table 3. Two of the three ORP signals obtained from the weekly intermittent households averaged 325 and 733 mV, with standard deviations 79 and 137 mV; these were normalized to the duration of intermittency. One of the three ORP signals with weekly intermittency—measuring water quality continuously—resulted in an average of 500 mV with a standard deviation of 219 mV. This means the data among these signals is not necessarily comparable, as the former explains the variability of supplied water only, while the latter explains the variability of supplied and stored water. The latter ORP signal is shown in Figure 4C. The variability was caused by free chlorine decay during periods of stagnation in between intermittency periods.[32,44,45]

Table 3. Intermittent Systems ORP and Free Chlorine Summary Statistics of Deployments Signals and Grab Samples from Mexico City

	ORP signal (mV)		free chlorine (mg/L as Cl_2)		
supply type	mean	SD	mean	SD	*n*
Weekly Intermittency[a]					
chlorinated	733[b]	137	0.17	0.13	3[c]
chlorinated	500[b]	219[d]	0.01	0.01	3[c]
chlorinated	325[b]	79	0.12	0.11	2[c]
Daily Intermittency[a]					
variable Cl_2	497	151	0.73	0.98	2
chlorinated	769	75	0.86	NA	1

[a]Determined from pressure data and from interviews with household members. [b]Nodes deployed in the same neighborhood. [c]Grab samples associated with these deployments are from household storage since field visits did not align with water supply hours. [d]Node with continuous measurements. High variability associated with water quality change during storage periods. Statistics not normalized to the intermittency time.

Of the three daily intermittent sites, one signal was determined to be associated with a variable chlorination system based on the high standard deviations from the grab samples and the ORP signal. The second site with daily intermittency shows the highest signal average as well as the lowest standard deviation of all intermittent sites. The third site with daily intermittent supply was removed from the data set because of technical issues.

Use of wireless sensor nodes in Mexico City captured previously unmeasured supply dynamics across a large intermittent system. Intermittency varies across the city and can be highly variable in terms of time and water quality. A grab-sample schedule that captures multiple intermittent events is complicated, may miss the first flush window, and is likely impractical in a city the size of Mexico City. ORP signals from intermittent systems with measurable free chlorine showed high variability throughout the study period. As confirmed by grab samples, the observed ORP variability corresponded with the variability of the disinfectant concentrations. Although our data sets are not sufficiently large to allow for a detailed comparative analysis that links ORP to free chlorine concentrations, we found that compared to weekly intermittency sites, one daily intermittent site resulted in a higher ORP average and lower standard deviation (Table 3); this may be related to less chlorine variability in supplied water when the intermittency periods are shorter. This suggests that the frequency of intermittency plays a role in delivering

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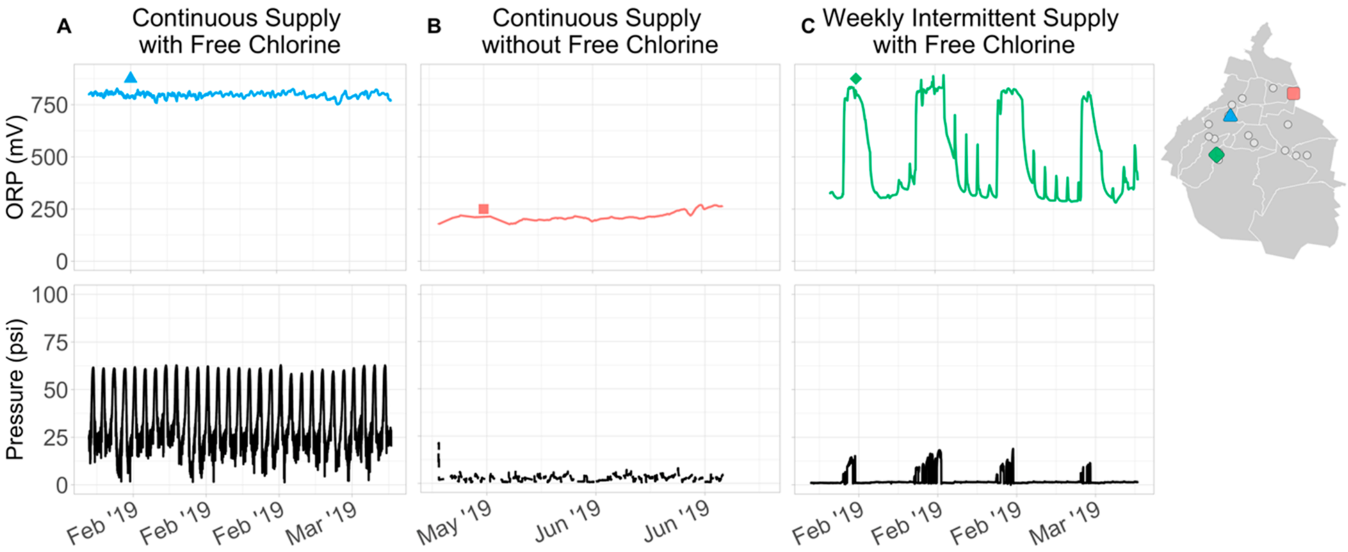

Figure 4. ORP and pressure signals from three different deployment sites in Mexico City show the difference in water quality and supply experienced in neighborhoods across the city: (A) signal from a continuous supply household in the west of the city with measurable free chlorine and high diurnal pressure variations, (B) signal from a continuous supply household located in the east of the city without measurable free chlorine and a consistently low supply pressure—gaps in data due to connectivity issues, and (C) signal from a weekly intermittent supply household in the southwest of the city with measurable free chlorine and chlorine decay during periods of intermittency; spikes in pressure correspond to periods of supply, while the flat line corresponds to periods of no supply.

consistent disinfectant residual concentrations. In other words, the longer the period between water delivery times, the higher the risk of not meeting a particular residual disinfectant concentration target. Generally, the risk of microbial contamination and transmission of illnesses increases as the duration of in-home storage increases.[44] Data from real-time sensor networks could be used to manage risk associated with poor water quality and inform flushing strategies in intermittent systems.

As water resources become more limited and rationed, intermittency may become the new norm for many cities. For example, the water utility of Mexico City expects that, if the amount of government investment into water supply systems does not increase, the proportion of intermittency systems within the city will increase from 30% to 72% over the next decade.[40] Real-time wireless sensor networks provide an opportunity to monitor and manage such systems more closely, which could become increasingly useful as more continuous systems around the world will face greater water demands and a decrease in water resources.[31−33]

The system in Mexico City is highly heterogeneous due to the multiple water sources and treatment plants that supply the city−surface water, 450 wells, and 58 drinking water treatment plants.[40] This heterogeneity was captured through our wireless sensor network, which provided an unprecedented spatiotemporal data set. As seen in Figure 4A, B, and C, water quality (ORP) varied significantly across the city, as compared to Ann Arbor. The pressure signals show different supply quality that may have impacts on water quality during distribution. Similarly, EC signals varied across the city (Table 4). For example, as measured by the grab samples, 11 sites show an average range of 178−243 uS/cm, two sites range from 404 to 615 uS/cm, and four sites range from 1030 to 1688 uS/cm. Similar ranges resulted from the EC signals in the sensor nodes.

Heterogeneity across the Mexico City water supply has been studied by Mazari-Hiriart et al., who provide results from a grab sample campaign.[41] Their findings report varying concentrations of metals, other inorganic contaminants, and biological contaminants. While our wireless sensor network focused on a limited set of physical parameters, our data are consistent with the assessment that the system is highly heterogeneous. This is particularly evident when comparing the variability of measurements in Mexico City to those made in Ann Arbor.

Public knowledge about drinking water quality stands at the core of public health around the world. Trends and projections

Table 4. Electroconductivity Summary Statistics of Deployment Signals and Grab Samples from Mexico City

EC signal (uS/cm)		grab sample (uS/cm)		
mean	SD	mean	SD	*n*
		Continuous		
9[a]	1	216	26	3
9[a]	1	218	41	3
9[a]	0	243	54	3
309	293	232	28	2
296	12	204	6	2
772	1695	1688	NA	1
1065	5194	1041	NA	1
8[a]	2	224	44	3
278	5442	1030	406	2
10[a]	1	212	11	2
573	72	615	170	2
26[a]	11	1031	NA	1
		Weekly Intermittent		
8[a]	5	199	19	3
224	6334	197	1	2
213	90	178	8	2
		Daily Intermittent		
475	35	404	9	2
301	89	181	NA	1

[a]Early calibration issue, which was subsequently resolved.

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show increasing per capita consumption of purchased water,[46] often reported to have worse water quality, and bottled products, including sugared drinks,[47,48] which have led to global obesity and diabetes type 2 epidemics.[49] Trust in water quality is a complex subject requiring cross disciplinary research. Our sensor network deployment in Mexico City is currently being cross-analyzed with qualitative and quantitative data sets studying public trust in drinking water.[50,51] Sensors may serve as an objective tool to help households and utility managers "turn on the lights" on an otherwise invisible infrastructure.

4.3. Platform Performance. As measured by data transmission reliability (expected vs delivered data packets), the sensor nodes and cloud architecture successfully collected and delivered data throughout the deployment study. By leveraging proven hardware and commercial cloud services, reliability and server uptime could be maintained without interruption. One of the novel elements of our sensor node and cloud architecture is its ability to be deployed at any location with wi-fi or cellular service. Some individual sensor nodes experienced outages, mainly due to the instability of residential wi-fi. The nodes have a built-in feature to automatically reconnect once wi-fi outages resolve. The easy upgrade to cellular connectivity provides added reliability with an extra cost per node and excess data transferred. In terms of cellular coverage, Particle Inc. provides a list of countries currently supported through their cellular data plans.[52] Regardless of preliminary connectivity, tests should be performed to scout the wireless reliability of each location prior to deployment. Some outages were also caused by residents moving the unit or disconnecting it manually, but not due to the architecture of the system.

The platform reliably time stamped system-wide events such as the EC event in Ann Arbor and distributed water quality and supply variations across Mexico City. By making technology more accessible and easier to use, these sensor nodes provide the potential to begin capturing building plumbing dynamics that have so far remained elusive. To our knowledge, our study is the first example of a large-scale deployment in distributed and intermittently supplied households made possible by a built-for-purpose technology.

4.4. Constrains, Limitations, and Practical Considerations. This paper presents a first step toward making water quality measurements more accessible through an open source, real-time water quality wireless sensor network. As with any new tool, several new venues remain to be studied before it can become a vetted method. For those interested in carrying out similar studies, a major time barrier should be reduced since the steps of our study are provided in detailed web guides, source code, and blueprints that accompany this paper. While the platform is an end-to-end solution, it cannot be bought as an off-the-shelf product and will require hands-on construction, calibration, and fine-tuning. We expect these practical barriers to be reduced as the community of adopters grows.

The ease of deployment ensured that our team could install each household with a sensor node in a single visit of one hour. This feature limited the need for professional installations and reduced the burden on residents. All things considered, we recommend that a team of at least two people construct and build a fleet of devices. Given the sporadic need to troubleshoot the nodes or expand their functionality, some basic knowledge of circuits, electronics, and coding is required. A basic undergraduate course in these topics should be sufficient to cover these. Installations require nonintrusive plumbing modifications (e.g., connecting and disconnecting threaded fittings), and system maintenance requires data monitoring and field visits. For reference, the 10 nodes used in the Ann Arbor deployment were built and tested by two students in 2 weeks and deployed over a period of 2 weeks. Recruiting household participants is perhaps the most practical constraint and may require approval by city authorities or an internal review board (IRB). This should be considered as early as possible, as it may take a long time to establish these relationships. For comparison, the nodes used in Mexico City were deployed over nine months. The limiting factor in Mexico City was coordination with residents and the sheer logistics deploying and maintaining a system in one of the largest cities in the world. This underscores even further the reliability of the network, as this limits long and unnecessary trips and coordination across large areas.

Our sampling protocol remained static throughout the study period (pressure every five minutes, water quality every hour); we recommend the use of more advanced operational scripts to automatically modify the sampling frequency as needed and to label data points within the script for a more streamlined analysis (e.g., first flush, bulk supply, building vs water main). Groups can do this by taking advantage of the microcontroller's internet features by simply writing new code and uploading it wirelessly to field deployed units.

The limitations of the water quality sensors should be characterized further. When signals show gradual or sudden changes, but grab samples are not available to validate such observations, it remains challenging to draw general conclusions about water quality. pH and ORP signals can drift or spike due to sensor malfunction, but unexpected results may also point to previously unrecognized water quality dynamics at the tap. Spatial redundancy of a deployment is a benefit of our cost-effective and distributed approach in such cases, since it is unlikely that multiple sensors will fail in the same neighborhood. Further research is needed to understand the sensor signal dynamics of water quality at the tap. In the meantime, we recommend the deployment of multiple sites within a single study region. Furthermore, the real-time dashboard accompanying the platform should be used daily for quality control (at least in the early weeks of a deployment) to ensure that no major sources of noise or outages are present. As the team becomes more familiar with the individual nuances of their deployment, the need to quality control the data daily will become less important.

ORP and EC sensors showed the most potential in our study, but more detailed process studies are needed to evaluate the strength of the correlation between measured ORP and disinfectant residual. While these specific parameters have been studied in a broad range of water applications, their use as part of real-time drinking water monitoring networks remains uncharted. The sensitivity of ORP sensors to new conditions needs to be further evaluated, since there are existing known relationships between the ionic strength of a solution and the time it takes an ORP sensor to stabilize. Currently, ORP sensors can take anywhere between 15 min and several hours to reach equilibrium when measuring low ionic strength waters, such as some drinking waters.[53] Because this is the case, real-time ORP measurements will need further operational tuning and technology development to achieve measurements that can be confidently linked to other parameters of interest.

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During regular operation, the time to reach ORP sensor stabilization was variable (one to three hours). The Mexico City deployment shows that the sensor stabilization is an initial phenomenon when sensors are first turned on, rather than caused by exposure to water (intermittent vs continuous). While it should be evaluated on a deployment-by-deployment basis, this stabilization period is likely caused by power supply state, which underscores the need for a stable power source and battery backup. Our platform supports this with using a built-in backup battery, which we recommend as a vital component of future deployments. When nodes are reset, the stabilization time period should be accounted for through visual inspection and an initial grab sample.

4.5. Research Opportunities. In addition to event detection and monitoring benefits, the EC signals from the Ann Arbor deployment (Figure 3A) show how a study may be conducted to quantify the water age and hydraulic patterns of a distribution system based on the delay and magnitude of the signals. A dedicated sensor node at the treatment plant could serve as the baseline for water quality characteristics, while a deployed sensor network within the distribution system could inform the time and possible flow paths of the water in the distribution system. We see future potential to use these sensor nodes in applications such as water age model calibration using approaches such as the ones published by Rubulis et al.,[54] where EC was proposed as a natural tracer to track the flow of various water sources within the distribution system. Woo et al.[55] implement dynamic time warping to computationally find the corresponding elements of various water quality signals that are offset by a time component and signal magnitude. Access and availability to sensors has been a major barrier to release these theoretical approaches but it is now entirely possible to accomplish this with our platform.

Even when relying on sensors that are lower cost and less maintained than those used at the plant, the option to generate long-term summary statistics and time series using real-time wireless sensor networks has the potential to provide substantial value. After the sensor network has been deployed and the water quality baseline has been established through summary statistics, specific signals can be queried for relative changes. For example, stable ORP signals can be taken as validation that chloramine concentrations throughout the day and across the city remain within a safe range. If the average and range continuously correspond to previously set values (e.g., 400 ± 100 mV in chloraminated waters), the wireless sensor network may have the potential to alleviate some of the efforts required in field grab sampling, assuming that the regulator would allow for a reduced number of regulatory samples. Furthermore, the real-time data could point to locations of the distribution system that require more attention. Although U.S. EPA regulations in the United States still require mandatory grab samples for compliance, more resources are becoming available for utilities to adopt real-time online water quality tools that can be used to monitor common water quality incidents such as nitrification and corrosion.[56] The sensor node architecture presented in this paper (Figure 1) can be modified to address and monitor the parameters that are most relevant to each system and study site.

5. CONCLUSION

Our wireless sensor network shows how a drinking water distribution system can be continuously monitored at the level of building plumbing using a cloud-based architecture. This may present a valuable tool for water quality monitoring, compliance, research, maintenance, warning system design, and operations. Potential allocation of resources for infrastructure projects may benefit from continuous monitoring to ensure that designs meet intended goals. For those wishing to implement and evaluate these technologies, our team has made available all the blueprints and guides as part of a broader effort to open source water technologies.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acsestengg.1c00259.

Details on the methods and deployments specific to each city are described; summary statistics tables of the signals and grab samples of Mexico City nodes (pH in Table S1, pressure in Table S2); Ann Arbor's deployment results from Figures S1 and S2 complementing Figure 3A and B (PDF)

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