Journal of Cleaner Production 60 (2013) 152–162

Contents lists available at SciVerse ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

A rule-based decision support system for sensor deployment in small drinking water networks☆

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ARTICLE INFO

Article history:
Received 2 May 2011
Received in revised form
12 December 2011
Accepted 8 February 2012
Available online 1 November 2012

Keywords:
Decision support system
Drinking water
EPANET
Graph theory
Rule-based sensor deployment
Systems analysis

ABSTRACT

The physical layout of drinking water utilities makes them inherently vulnerable to contamination incidents caused by routine operations. These contaminations present environmental health concerns including but not limited to total trihalomethanes, lead, and chlorine residual issues. To achieve the goal of cleaner production, sensor placement in municipal drinking water networks in response to possible public health threats has become one of the most significant challenges currently facing drinking water utilities, especially in small-scale communities. Long-term monitoring is needed to develop modern concepts and approaches to risk management for these utilities. We developed a Rule-based Decision Support System (RBDSS), a methodology to generate near-optimal sensor deployment strategies with low computational burden, such as those we often encountered in large-scale optimization analyses. Three rules were derived to address the efficacy and efficiency characteristics of such a sensor deployment process: (1) intensity, (2) accessibility, and (3) complexity rules. Implementation potential of this RBDSS was assessed for a small-scale drinking water network in rural Kentucky, United States. Our case study showed that RBDSS is able to generate the near-optimal sensor deployment strategies for small-scale drinking water distribution networks relatively quickly. The RBDSS is transformative and transferable to drinking water distribution networks elsewhere with any scale.

1. Introduction

Drinking water distribution systems are inherently vulnerable to accidental or intentional water contamination incidents. Because those networks are large, spatially distributed, and complicated infrastructures, the possibility of human-related influences is significantly high (Buckle, 2000; Haestad et al., 2003; Karamouz et al., 2010). For example, in developing countries like Guatemala, inadequate clean water and waterborne bacterial infection among young children are the cause of disease and productivity losses equivalent to 2% of gross domestic product (Norstrom, 2007; Tune and Elmore, 2009); therefore, the numerous studies being conducted for vulnerability assessment, risk reduction, monitoring sensor network, and contamination warning system are rigorous. A recent case study of vulnerability assessment of water supply system components in a major city included five criteria: distribution, spread, visibility, exposure, and recovery. It found that the failure of water distribution networks and water treatment plants generated the highest human losses among other water supply failures (Karamouz et al., 2010). Because these incidents often have severe immediate and long-term human health consequences, drinking water distribution networks require intensive monitoring and security considerations using real-time early warning systems (EWS) (Clark and Deininger, 2001; National Research Council, 2002).

To build a functional EWS, a sensor location system should be designed to satisfy multiple criteria with or without optimization schemes (Berry et al., 2003), yet the optimization of sensor deployment locations is often necessary because of the high cost of monitoring devices and to achieve the highest degree of protection for a finite number of sensors (Thompson et al., 2007, 2009). Therefore, various methodologies for layout design of monitoring stations have been proposed in the past decade in water distribution systems to detect the migration of any contaminations that can cause adverse effects on consumer health (Kessler et al., 1998; Al-Zahrani and

☆ DOI of original article: http://dx.doi.org/10.1016/j.jclepro.2012.02.010.
Publishers' error resulted in this article appearing in the wrong issue. The article is reprinted here for the reader's convenience and for the continuity of the special issue. For citation purposes, please use the original details: N.-B. Chang et al., A rule-based decision support system for sensor deployment in small drinking water networks Journal of Cleaner Production 29-30 (2012) 28–37. doi of the original item: http://dx.doi.org/10.1016/j.jclepro.2012.02.010

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http://dx.doi.org/10.1016/j.jclepro.2012.10.036

Moied, 2001; Woo et al., 2001; Haught et al., 2003; Ostfeld and Salomons, 2004; Berry et al., 2003, 2005, 2006; Propato, 2006; Ghimire and Barkdoll, 2006; Preis et al., 2007; Aral et al., 2010; Hart and Murray, 2010; Weickgenannt et al., 2010). Numerous technical approaches were developed for optimizing sensor placement, including mixed-integer programming (MIP) models (Lee et al., 1991; Lee and Deininger, 1992; Watson et al., 2004; Berry et al., 2004, 2005; Propato et al., 2003), combinatorial heuristics (Kessler et al., 1998; Kumar et al., 1999; Ostfeld and Salomons, 2004), general-purpose metaheuristics (e.g., Ostfeld and Salomons, 2004), and lagrangian heuristics (Berry et al., 2008). Ideally a large number of sensors would increase the monitoring coverage of a network, but it would also increase cost accordingly; however, these methodologies are usually not applicable to small communities and developing countries due to the complication of methodologies and the lack of resources such as funding and technical computing software. More important, the lower capital cost of the projects will more likely be granted if performance is comparable to the higher-cost project, especially in small communities or developing countries. The remaining scientific question is how to generate sensor deployment strategies with low computational burden, such as we often encountered in large-scale optimization analyses.

This study developed a Rule-based Decision Support System (RBDSS), a new method for sensor deployment, to generate near-optimal sensor deployment strategies with low computational burden to improve consumers' health and safety by preventing civilians from consuming contaminated water. Three rules were derived to address the efficacy and efficiency characteristics: (1) intensity, (2) accessibility, and (3) complexity rules. Such an RBDSS is thus designed to minimize the total number of costly sensors and maximize the monitoring coverage to promote the cost-effectiveness of an EWS in small communities. Because a real-world case study is the most adequate research strategy for theoretical research to the real-world implementation, RBDSS was applied to the water distribution network in Hardin No. 1 County in Kentucky to validate the methodology. In this work we provide the formulation of the three rules for RBDSS, present a real-world application and results of an RBDSS, and apply these results to a rural community in Kentucky.

2. Methodology of rule-based decision support system

The RBDSS developed in this study is a decision support system to optimize sensor deployment location based on three rules, the intensity, accessibility, and complexity rules, for applications in small communities and developing countries to maximize the protection of contaminant exposure to the population and minimize the cost for sensor deployment. Because the Maximum Contaminant Levels (MCLs) are regulated by the US Environmental Protection Agency (EPA), the intensity rule, which has primary focus on concentration of contaminants, was analyzed prior to the accessibility and complexity rules in this RBDSS. To retrieve the information of population exposure in the context of the intensity rule, the EPA's water quality network (EPANET) model was applied for the vulnerability assessment (Rossman et al., 1994). EPANET is software developed by EPA's Water Supply and Water Resources Division (EPA, 2011) that models water distribution piping systems and performs extended-period simulation of the hydraulic and water quality behavior within pressurized pipe networks. In principle, the accessibility rule addresses the flow fraction downstream at a node driven by the downstream water demand within the prescribed spatiotemporal pattern of a drinking water distribution network. Thus, the fraction of water flow can be assumed as a surrogate index to indicate the percentage of population that could be affected when an unexpected contaminant intrusion occurs. The complexity rule aims to deconstruct the configuration of the node structure and translate the configuration to account for a larger population that might possibly be affected by an event within a network, eliminating the need to deal with temporal variability. Each of these three rules can be analyzed independently based on the same set of the collected data, and all three rules may also be grouped together, with flexibly contributing to the final decision of sensor deployment by differing collective methods. To illustrate the robustness of these three rules, the rules were applied in three scenarios for residual chlorine, total trihalomethanes (TTHM), and lead simulated by EPANET.

The analytical process of RBDSS consists of four phases, including data collection, dynamic simulation, development, and evaluation (Fig. 1). The collected data consist of Geographic Information System (GIS), water quality, and water flow data. The RBDSS is designed to ease the burden of large-scale sensor location optimization to minimize cost and maximize coverage of protection in drinking water networks with the aid of a predetermined number of sensors. Within this context, EPANET, EXCEL®, and LINGO 10.0 were selected to support essential dynamic simulations, data analysis, and bubble sorting of data and selection of sensor locations, respectively, in which EXCEL® was used to handle data streams in support of EPANET simulation and LINGO 10.0 optimization modules.

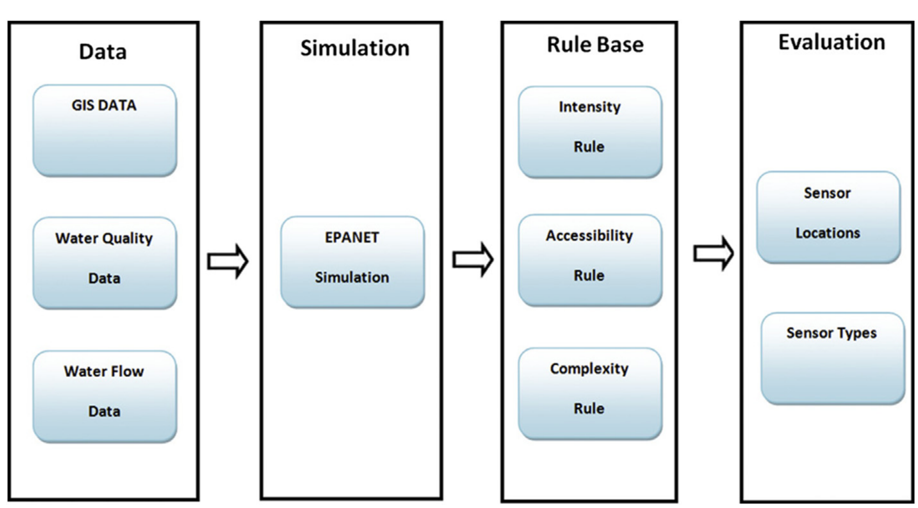

Fig. 1. Schematic of the RBDSS process.