Optimal mobile self-powered sensor operation for water distribution systems water quality enhancements

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Abstract

In recent years there have been fast developments in mobile sensor networks for various applications such as environmental monitoring, infrastructure security, and traffic control. Mobile micro sensors monitoring for various parameters for security and reliability of municipal water distribution networks are ongoing with prototypes expected to be released in the very near future. Ideally, these mobile sensors will act as mobile agents capable of conducting continuous multivariate measurements and reporting them as they are distributed with flow. The goal of this study is to explore the inclusion of mobile sensors in water distribution systems for enhancing the deployment of sensor networks through increasing coverage and reducing fault detection time. This study is aimed at enhancing water quality management in water distribution systems by developing a mathematical framework for processing the sensing data transmitted by mobile sensors and integrate them with the existing knowledge provided by fix-placed monitoring stations. The methodology suggests a near optimal operation of the mobile sensors and their release into the distribution system. The method is demonstrated on a small water distribution system providing operational guidance for a higher level of water quality control in water distribution systems.

1. Introduction

In recent years there have been fast developments in Wireless/Wired Sensor Networks (WSN) for various applications such as environmental monitoring, infrastructure security, and water distribution systems monitoring. Securing water distribution systems is inherently crucial to protect public health as supply systems infrastructure is comprised of numerous exposed elements which can be exploited for malicious actions (Kroll 2006). Physically securing each of these apparatuses is not feasible, thus other methods ensuring the delivery of sufficient and adequate drinking water need to be developed. Application of WSN for water distribution is being extensively studied employing multi-parameter sensors capable of continuously collecting and transmitting hydraulic and water quality measurements at fine temporal resolution facilitating in an accurate constantly updating representation of the conditions in the distribution system. This allows for an improved on-line decision support system for analyzing, modeling, and controlling water supply systems. The application of WSN in water supply systems principally focuses on locating the sensors in the distribution...
system and performing temporary data analyses for different purposes such as estimation and prediction of the hydraulic state of the system and identification of possible hydraulic or/and quality faults.

The problem of an accidental or a deliberate contamination of water supply system has been widely studied in recent years, starting with placement of sensors to optimize certain objectives and moving on to source identification and response modeling. Models for optimal sensor network include deterministic and stochastic optimization techniques and graph-theory algorithms optimizing one or more objectives as detection likelihood, expected contaminated water volume and affected population, and design cost. Kessler et al. (1998) presented a design methodology capable of allocating an optimal set of monitoring stations for detecting contamination intrusion events in distribution networks for a given level of contamination exposure. Ostfeld and Salomons (2004) presented a methodology for finding the optimal layout of an early warning detection system. The methodology integrates EPANET (USEPA, 2002) as a model for extended period hydraulics and water quality simulation with a genetic algorithm for the optimization process. Berry et al. (2006) formulated the sensor placement optimization problem as a mixed-integer programming model. The problem was formulated as a p-median facility problem of locating a given number of sensors such that the total contamination impact on all consumers is minimized. Xu et al. (2008) introduced an alternate heuristic methodology for sensor placement based on graph theory techniques for cases when hydraulic and water quality models are not available and/or when simulation-based techniques are computationally infeasible. Preis and Ostfeld (2008) employed a multiobjective genetic algorithm scheme for sensor placement, trading off the sensor detection likelihood, the sensor detection redundancy, and the sensor expected detection time. Krause et al. (2008) developed sensor placement algorithms for large water distribution networks showing a diminishing return effect when objective functions such as reduction of detection time or the population protected from consuming contaminated water are used. Isovitsch and VanBriesen (2008) used a geographic information system and a chi-square analysis for sensor placement showing that different optimization criteria and attack scenarios are expected to propose similar protection to water distribution systems. The optimal sensor placement problem was also challenged at the battle of the water sensor networks (BWSN) (Ostfeld et al., 2008). The problem presented at the BWSN was defined as a multiobjective optimization problem taking into consideration minimization of the expected time of detection, the expected population affected prior to detection, the expected demand of contaminated water prior to detection, and the maximization of the detection likelihood.

An important subset of WSNs is represented by Mobile Wireless Sensor Networks (MWSNs), where the sensing unit is not deployed in fixed, permanent positions, but it is able to move within the selected environment. An emerging field of interest in the lasts years is the application of MWSNs to the monitoring of conduits used to distribute fluids: water, gas or oil, for different purposes such as the identification of possible faults or leakages. Lai T. et al (2010) presented a mobile sensor PipeProbe pilot test bed for determining the spatial topology of hidden water pipelines behind walls. A tiny wireless capsule, equipped with pressure and gyroscope sensors, is dropped into the water source and traverses the pipelines. The spatial topology of the system is mapped through analysis of the pressure and angular velocity from sensor readings, after the sensor flows out of the system. The mobile sensor was tested on a
small network constructed in lab with paths lengths up to 10 m. Trinchelro and Stefanelli (2010) explored the implementation of mobile wireless sensor networks within conduits used for fluids and liquids transportation. Two solutions were shown for possible data transmission through inside antenna, depending on the electromagnetic characteristics of the pipe (plastic, concrete, metallic), its location under the ground, and the electromagnetic characteristics of the fluid. A suitable microwave design methodology was proposed and validated from theoretical analyses and laboratory experiments. An ongoing project is being conducted at the Purdue University supported by the Environmental Protection Agency, Advancing Public Health Protection through Water Infrastructure Sustainability (2009), to design, fabricate and test a self-powered mobile microsensor network for monitoring critical parameters in the security and reliability of municipal finished water distribution networks. The desired outcome of this project is multiple numbers of individual multifunctional sensors released into a water distribution system capable of conducting continuous measurements and reporting measurement data as they move in the flow stream. Sensor analytic targets will be organized into suites to cover water quality (temperature, O2, pH), disinfection (chlorine) and trace contaminants (lead, copper, cadmium, arsenic, nitrate).

Although MWSN has not been deployed yet to real water distribution system, it appears that they will be released in the very near future. Ideally, these mobile sensors will act as mobile agents capable of conducting continuous multivariate measurements and reporting them as they are distributed with flow. Figure 1 shows the schematic architecture of mobile sensor deployment in a water pipeline. The sensor travels along the pipe, transported by the water itself, acquires and stores physical information. It transmits the gathered data out of the conduit to fixed receiving ground units when reaches the proximity of their location. Once the obtained data is available at the fixed units, it can be manually collected or retransmitted for real time analyses. The objective of this study is to explore the inclusion of MWSN and suggest a near optimal operation for enhancing the deployment of sensor networks through increasing coverage and reducing fault detection time.

2. Methodology

2.1. Problem formulation and assumptions

2.1.1. Objective functions

The proposed methodology suggests optimizing mobile sensors operation by controlling release time and location to attain maximum performance gain given existing fixed-sensors network design (i.e., monitoring stations locations). The performance of the MWSN is measured as the expected Time of Detection (TD) and Detection Likelihood (DL) (Ostfeld et al. 2008), which are calculated as:

$$TD = E(t_d)$$  \hspace{1cm} (1)

where $E(t_d)$ is the expectation of minimum detection times $t_d$ for all detected events, undetected events are not included in the analysis.
\[ DL = \frac{\sum_{i=1}^{N_c} I_d}{N_c} \]  

where \( N_c \) is the number of contamination events and \( I_d \) is an indicator function receiving the values of 1 or 0, if the event was detected or not, respectively.

Figure 1. Mobile Wireless Sensor Node (MWSN) applied to pipelines. A. Mobile sensor schematic architecture in a pipeline. B. Sensor node scheme – hardware units.

2.1.2. Sensor transport model

Assuming that the sensor is carried by water flow, in each junction connecting more than two pipes, the sensor may turn to any one of the outgoing pipes. Thus there are a number of possible paths that may be taken by the sensor released at the same time and same location. The sensor transport model needs to account for the uncertainty in sensor's route in junction nodes. The initial assumption in this work is that the sensor flows down the pipe with the highest velocity. Since the hydraulic model is deterministic, the outcome of the selected path is deterministic as well. In such a case, the transport model results in a unique solution and the objective function is evaluated for each operation of mobile sensor.

2.2. Sampling contamination events

One of the main obstacles facing optimal sensor operation is the significant computational effort imposed by the water quality simulations required for modeling transport of a constituent in a distribution system due to uncertainty in release time, location, duration, and concentration. Some of the preceding studies addressed the importance of the contamination sampling stage and its influence on sensor network design (e.g., Berry et al., 2006; Krause et al., 2008; Ostfeld et al., 2008; Preis and Ostfeld, 2008). Complete enumeration of all contamination events is impracticable as the number of possible intrusion events and simulation run times grow substantially.

\[ \text{On-site analysis} \]
\[ \text{Ground receiver} \]
\[ \text{Remote analysis} \]
with system size. As systems grow sampling techniques are used to generate a (representative) set of contamination events. Several approaches can be applied:

1. **Monte Carlo (CM) simulation.** The direct MC simulation technique (Kroese and Rubinstein, 2004a) can be used to generate a subset of random contamination events using predefined discrete or continuous probability distributions of events parameters, such as time and location of the intrusion.

2. **Rare events simulation.** Importance sampling can be utilized for sampling extreme contamination events, which most likely will not be sampling using MC simulation. A heuristic scheme was previously suggested (Perelman and Ostfeld 2010, 2011) for establishing a representative sampling of critical contamination events which reduces the problem’s complexity for simulation-based optimization techniques. The method proposes an importance sampling approach (Rubinstein, 1997) combined with a Cross Entropy (CE) (Rubinstein and Kroese, 2004b) optimization algorithm for rare events simulations.

### 2.3. Optimization method

A methodology extending the Cross Entropy combinatorial optimization method, originated from the adoptive algorithm for rare events simulation, to multiobjective optimization was previously successfully applied to water distribution system design (Perelman et al, 2008) and is briefly presented next.

The Cross Entropy method (Rubinstein and Kroese, 2004b) for optimization seeks to find the optimal sampling probability \( p^*(\theta) \) by minimizing the Kullback-Leibler distance (Kullback and Leibler, 1951) between \( p^*(\theta) \) and the theoretical zero-variance probability. The CE algorithm is a two-stage iterative procedure involving generating random samples and updating the sampling probability. Starting with some initial probability density, the sampling probability is updated each iteration, until convergence. The main CE algorithm:

1. Choose an initial probability \( \hat{p}_0 \). Set an iteration counter \( t = 1 \).

2. Generate a random sample \( \theta_1, \theta_2, ..., \theta_N \) from the density \( \hat{p}_{t-1} \) and evaluate each sample using some measure function (e.g. detection time \( S(\theta) \)). Sort their performances in a descending order and select \( \rho \) percentage of samples with the best performance, i.e., the elite samples and set \( \hat{\omega}_t = \{ \{1-\rho\}N \} \).

3. Update \( \hat{p}_t \) using the same elite samples by:
   \[
   \hat{p}_{t,i} = \frac{\sum_{i} I_{\theta_i} \cdot \hat{I}_{\theta_i}}{N} I_{\theta_i}
   \]
   where \( I_{\theta_i} \) is an indicator function. Set \( \hat{p}_t (\theta) \leftarrow \alpha \cdot \hat{p}_t (\theta) + (1-\alpha) \cdot \hat{p}_{t-1} (\theta) \), where \( \alpha \) is a smoothing parameter between 0 and 1.

4. If stopping criteria are met then STOP; otherwise set \( t = t + 1 \) and return to step 2.
The development of the CE algorithm for multiobjective optimization can be found in Perelman et al (2008).

3. Application to Network 1

Initial stages of the proposed method are demonstrated on Example 1. The system consists of twelve pipes, eight demand nodes (2 to 9), a source, a pumping station, and an elevated storage tank. It is subjected to a 24 hr demand pattern, and is simulated for an extended period of 48 hrs. The full system data can be found in the EPANET User's manual (USEPA, 2002) and thus is not repeated herein.

The WSN design for Network 1 (Ostfeld and Salomons, 2004) suggests locating sensors at nodes 21 and 32. Next, the WSN design was tested on sampled contamination events. The contamination events were generated assuming equal injection likelihood for each of the 9 nodes of the system every hour during the first 24 hours. The mass injection rate and duration are 100 [gr/min] and one hour, respectively. The quality model is established using EPANET extended period simulation. The configuration of the distribution was adapted to attain chemical concentrations along pipelines, which are not available in the software output results. The simulation results of the original and the modified systems were compared and verified to give similar results with high accuracy. The decision variables for the mobile sensor operation are the release time and location of the mobile sensor. A single mobile sensor is assumed to be released into the system at any one of system nodes every hour during the day.

Figure 2 shows detection likelihood versus expected time of detection of the fixed-sensor network, fixed and a mobile sensor, and the non-dominated solutions (i.e. Pareto front). Table 1 lists the detection likelihood and expected time of detection of the different designs. From the results it can be seen that the majority of non-dominated solutions suggest releasing the mobile sensor at node 13 of the network. This is reasonable since it enables the mobile sensor to detect events which fixed-sensors fail to detect. This agrees with the optimal sensors location suggested by Kessler et al (1998) placing sensors at nodes 22, 23, and 32.
4. Conclusions and future research

The deployment of mobile sensors to water supply systems is an emerging field which is starting to attract more attention and realize its various possibilities. Some of current undergoing projects include development of mobile sensors which will travel in system pipes collecting information. The intent of this work is to assess the performance of mobile sensors in addition to fixed sensors in terms of spatial and temporal data collected. Initial results demonstrate the gain of using mobile sensors to increase detection likelihood and reduce expected time of detection. The operation of mobile sensors in water distribution systems needs to be tested on larger systems and further explored including: a) operation of several mobile sensors released in different time and locations. b) Relaxing mobility constraint by allowing non-deterministic and
stochastic traverse of system pipelines thus introducing uncertainty to the outcome of the trajectory model. c) Apply appropriate simulation-based stochastic optimization to account for the uncertainty of the sensor trajectory. d) Exploit collected data for inverse and response modeling for identifying the source of contamination and suggesting response actions to contain the contaminant.

The main issues arise with the development of the sensors directly affect the assumptions made in the mathematical algorithms, in other words, hardware constraints directly influence software constraints and need to be accounted for, such as: a) The type of data collected by the mobile sensors. b) Sufficient power for the duration of pipeline inspection. c) Sensor mobility – carried by the flow or controlled transport. d) Sensor extraction from the system. e) Collected data transmission – data is retrieved from the sensor with its extraction and the analysis is performed off-line; or mobile sensor transmits information to fixed ground units which can be placed at junction nodes, i.e., nearly on-line analysis. f) Location finding system – most of sensing tasks require knowledge of location with high accuracy, especially, since water pipelines are mostly berried underground.

5. References

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