Contamination Detection in Drinking Water Distribution Systems Using Sensor Networks

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Abstract—Recent advances in low power networked embedded systems and electrochemical/optical water quality sensors have enabled the generation of low-cost, low-power water quality sensor nodes [1]. These sensor nodes leverage the idea of Wireless Sensor Networks (WSN) for water quality monitoring in Drinking Water Distribution Systems (DWDS), where large numbers of spatially distributed sensor nodes operate cooperatively to monitor and detect contaminations in DWDS in a timely manner. However, such approach it is expected to suffer from false alarm errors and missed detection errors due to low cost sensor inaccuracies and uncertainties.

The aim of this paper is to develop algorithms to process these inaccurate sensor data in order to minimize detection errors and improve contamination detection probability by correlating imperfect sensor decisions in space and time taking advantage of the large scale deployment and the drinking water distribution system topology. The objective is to develop a cyber-physical early warning system comprised of low-cost, inaccurate sensory devices (physical) and smart software (cyber) that are seamlessly integrated so that the software is able to compensate inaccuracies in hardware.

I. INTRODUCTION

Providing clean drinking water to the population has become an increasing challenge with depletion of water resources and the pollution of water bodies. The availability of clean drinking water is taken for granted in the developed world. However, even this highly treated water is subject to degradations in quality once it leaves the treatment plant and enters the distribution system. By the time water reaches the consumer, its quality might be very different from what it was when it left the plant.

A significant number of contamination events has been recorded in the last decades. Recent examples of accidental contaminations include: the “Nokia Water Crisis” in 2007, where a large-scale microbiological contamination occurred in DWDS of the town of Nokia, Finland and the “West Virginia Water Contamination Crisis” in 2014, where more than half a million people were advised not to use their tap water due to a chemical contamination. The importance of water infrastructure to human health and economy makes DWDS also a target for terrorism. A number of terrorist threats or attacks in DWDS has been recorded in the last decades. For instance in 2009, Moscow police warned about possible poisoning attack in Moscow’s water supply system.

There is a need for better water monitoring systems given that traditional methods (manual collection of water samples followed by laboratory analysis) are too slow to develop operational response, exhibit poor spatiotemporal coverage and do not provide a level of public health protection in real time. Rapid detection (and response) to instances of contamination is critical due to the potentially severe consequences to human health. Therefore, there is a clear need for continuous on-line water quality monitoring with efficient spatio-temporal resolution.

Recent advances in low power networked embedded systems and water quality sensors have enabled the generation of low-cost, low-power water quality sensor nodes [1], [2], [3]. These sensor nodes, which consist of sensing, data processing, and communicating components, leverage the idea of sensor networks for monitoring and detecting contaminations in DWDS in a timely manner. However, such approach is expected to suffer from false alarm and missed detection errors due to low cost sensor inaccuracies and uncertainties.

The motivation of this work is to develop a cyber-physical early warning system comprised of low-cost, inaccurate sensory devices (physical) [1] and smart software (cyber) that are seamlessly integrated so that the software is able to compensate sensor inaccuracies. Therefore, instead of having few, very expensive and accurate sensors to monitor the entire water distribution system, the key idea is to have multiple low cost and inaccurate sensors and develop smart software-algorithms that will enable these sensors to collaborate each other to account/compensate their inaccuracies. The algorithms developed improve contamination detection probability by correlating imperfect sensor decisions in space and time, taking advantage of the large scale sensor deployment and the drinking water distribution system topology and operating status in order to minimize detection faults.

The remaining of the paper is organized as follows: Section II briefly discusses the relevant literature for contamination detection in DWDS. Section III describes the problem formulation and the underlying assumptions. Section IV presents the distributed algorithms for network-wide fusion of imperfect sensor decisions in order to improve the contamination detection probability. Simulation results are presented in Section V to compare and evaluate the performance of the proposed algorithms and finally the paper concludes with Section VI.

II. RELATED WORK ON CONTAMINATION DETECTION

Much of the literature published on contamination detection has focused on the sensor placement problem. In
the last decade, there has been a substantial research in the area of sensor placement strategies for contamination warning systems in DWDS [4]. However, most of proposed work assumes a limited number of “perfect” sensors (that detect all contaminants with no detection limits) and focuses on sensor placement strategies to minimize a contamination impact (e.g. population exposed, contaminated water mass consumed, etc) instead of considering a sensor network approach where sensors are communicating/collaborating each other to process/fuse their decisions in order to improve the contamination detection probability as well as to localize contamination events. The problem of optimally placing water quality sensors in municipal water networks under the assumption that sensors may fail or exhibit false alarms has been studied in [5] using mixed-integer programming formulations. The need for using online water quality sensors to monitor physicochemical water parameters (e.g. chlorine residual, pH, temperature, oxidation-reduction potential, turbidity, conductivity, total organic carbon, pressure and flow) in order to detect events in DWDS has been demonstrated in [2], [6], [7]. In addition, various anomaly detection algorithms were developed for the analysis of multi-sensor on-line measurements to detect events in a single location of the DWDS. A thorough survey on recent advances in this area is provided in [8], [9]. Experimental and field validation of the proposed algorithms has been also illustrated in [1], [10], [11].

III. PROBLEM FORMULATION, MODELS AND ASSUMPTIONS

The envisioned smart water sensor network is illustrated in Fig 1. For the problem formulation we make the following definitions:

- The topology of a DWDS is modeled as a directed graph $G = (V, \mathcal{P})$, where $V = \{\nu_1, \nu_2, \ldots, \nu_M\}$, $\nu_i \in V \subseteq \mathbb{N}$, is the set of $M$ vertices (pipe junctions) and $\mathcal{P} = \{p_1, p_2, \ldots, p_L\}$, $p_i \in V \times V$ is the set of $L$ pipes (edges or links).

- Volumetric flow rate $Q_i(t)$ and flow velocity $v_i(t) = \frac{Q_i(t)}{\pi R_i^2}$ are assumed known with some bounded uncertainty $\delta_i$, $R_i$ is the radius and $\ell_i$ is the length of pipe $i \in \mathcal{P}$. This information can be acquired using flow sensors or using hydraulic network physical properties and operation characteristics (e.g. via hydraulic simulation of DWDS with nominal nodal water demands $O_i(t), i \in V$). In-pipe flow direction is also assumed known.

- A set $S$ of $N$ sensor nodes are randomly placed at the consumer sites, i.e. at the DWDS graph nodes, where $S \subseteq V$. It is assumed that all sensors know their location $\nu_i = (x_i, y_i), i = 1, \ldots, N$.

- Sensors are generally considered imperfect (inaccurate). Sensors take samples at discrete time intervals $t = k \Delta \tau, k = 1, 2, \ldots, T$, and $\Delta \tau$ is the sampling interval. $T \in \mathbb{Z}^+$ denotes the last simulation step. Sensors can only sense contamination events occurring in the backflow direction.

- Sensor nodes can communicate with their neighboring upstream and downstream sensors in the DWDS graph (i.e. each sensor can receive information from its neighboring sensors via Machine to Machine or Cloud based communication). $N^U_{\nu_i}(i)$ denotes the set of neighboring sensors of sensor $i \in S$ that are $h$-hops (i.e. pipes) away in the DWDS graph $G$ (i.e. sensors installed at upstream and downstream nodes in the DWDS graph that are $h$-hops away). The set $N^H_{\nu_i}(i) \subseteq N^U_{\nu_i}(i)$ denotes only the upstream sensors of sensor $i$.

- A contaminant is injected at time $t^{ON}_E$ at the DWDS node $i \in V$. The injection concentration remains constant till the time $t^{OFF}_E$.

- Contaminant transport in pipes is modeled based on advection-dispersion equation (see [12]). Assuming that flow velocity remains constant during the sampling interval $\Delta \tau$, the spatial and temporal variations of the contaminant concentration within pipe $i$ at any specified location $x$ (downstream) and time $t$ is given by solution of the following partial differential equation

$$\frac{\partial C_i(x,t)}{\partial t} + v_i \frac{\partial C_i(x,t)}{\partial x} = -a C_i(x,t),$$

where $C_i(x,t)$ is the unknown contaminant concentration, $v_i$ is the flow velocity and $a$ is the unknown concentration decay rate coefficient. The close form solution of the previous differential equation can be approximated by

$$C_i(x + v_i \Delta \tau, t + \Delta \tau) = C_i(x, t)e^{-a \Delta \tau}, \forall \Delta \tau \leq \tau.$$

To model the sensor nodes behavior, we assume that each sensor node $i \in S$ is equipped with a contamination sensor. The measurement of sensor $i \in S$ at time step $k$ is given by

$$z_i(k) = \min \{V_{sat}, \max \{0, f(C_i(k)) + w_i\}\}$$  \hspace{1cm} (1)

where $V_{sat}$ is the maximum measurement which can be recorded by the sensor, $f(C_i(k))$ is a function of contaminant concentration at sensor location and represents the measurement due to a contamination event\(^1\), $w_i$ is additive Gaussian noise.

\(^1\) A contamination event occurred somewhere in the DWDS causes a detectable contamination signal at a sensor location due to the flow of water.
noise with zero mean and variance $\sigma^2$ due to the low cost sensors inaccuracies.

If the sensor measurement is greater than a detection threshold $\tau_d$, the sensor node decides that a contamination event is present at time step $k$. This decision is indicated by a binary variable $u_i \in \{0,1\}$, $i \in S$ and is given by:

$$u_i(z_i(k)) = \begin{cases} 
1, & \text{if } z_i(k) \geq \tau_d \\
0, & \text{if } z_i(k) < \tau_d
\end{cases}$$  \hspace{1cm} (2)

This decision can either be a true positive (TP), if the sensor correctly detects contamination, a false positive (FP), if the sensor incorrectly detects contamination when there is none, a true negative (TN), if the sensor correctly detects that there is no contamination or a false negative (FN), if the sensor fails to detect the contamination when actually occurs. To model the above sensor inaccuracies, we utilize two parameters, the detection rate $p_d$ and the false alarm rate $p_f$ as follows:

$$P(u_i = 1|E) = p_{di}$$

$$P(u_i = 0|E) = 1 - P(u_i = 1|E) = 1 - p_{di}$$

$$P(u_i = 1|\bar{E}) = p_{fi}$$

$$P(u_i = 0|\bar{E}) = 1 - P(u_i = 1|\bar{E}) = 1 - p_{fi}$$ \hspace{1cm} (3)

where event $E$ is defined as $E : f(C_i(k)) > \epsilon$ and $\bar{E} : f(C_i(k)) \leq \epsilon$, where $\epsilon$ is a pre-defined threshold close to 0. In this model, $p_{di} = \frac{\sum_{i=1}^{N} TP_i(k)}{N}$ quantifies the probability that the sensor $i$ will correctly predict contamination when a contamination event $E$ is occurred (i.e. the fraction of event instances that were correctly detected) and $p_{fi} = \frac{\sum_{i=1}^{N} FP_i(k)}{N}$ represents the probability that the sensor will incorrectly predict contamination when no contamination event $\bar{E}$ is occurred. Both $p_{di}$ and $p_{fi}$ depend on the detection threshold $\tau_d$ and for a given $\tau_d$ they can be found from receiver operating characteristic (ROC) curves of the sensor node. If $p_{di} = 1$ and $p_{fi} = 0$, then the sensor is considered as perfect. If we assume white Gaussian noise, then $p_{fi}(\tau_d) = 1 - \Phi\left(\frac{\epsilon}{\sigma}\right)$, where $\Phi$ represents the standard normal cumulative distribution function.

A. Objectives and Performance Measures

The objective of the problem is to improve the contamination detection probability of the entire sensor network by fusing/correlating sensor decisions/measurements in a distributed manner to minimize false alarms and missed events. This objective can be expressed by

$$\max_{i \in S} P_d(k), \min_{i \in S} P_f(k), \quad k \in [1,T]$$ \hspace{1cm} (4)

Where $P_d$ denotes the probability of detection (true detection rate) of the sensor network which can be expressed as the total true positive rate of all sensor decisions till the simulation end time.

$$P_d = \frac{\sum_{k=1}^{T} \sum_{i=1}^{N} TP_i(k)}{\sum_{k=1}^{T} \sum_{i=1}^{N} TP_i(k) + \sum_{i=1}^{N} FN_i(k)}$$ \hspace{1cm} (5)

and $P_f$ denotes the probability of false alarms (false detection rate) of the sensor network which can be expressed as the total false positive rate of all sensor decisions till the simulation end time.

$$P_f = \frac{\sum_{k=1}^{T} \sum_{i=1}^{N} FP_i(k)}{\sum_{k=1}^{T} \sum_{i=1}^{N} TP_i(k) + \sum_{i=1}^{N} FN_i(k)}$$ \hspace{1cm} (6)

Therefore the objective of the problem is to develop algorithms to maximize $P_d$ and at the same time minimize $P_f$ (or at least do not increase the $P_f$).

This objective can be also expressed by maximizing the following objective function (i.e. the area under Receiver Operative Characteristic (ROC) curve)

$$\max \int_{0}^{1} P_d dP_f$$ \hspace{1cm} (7)

Maximizing eq.(7) is equivalent to maximizing the probability of detection $P_d$ for a fixed probability of false alarm $P_f$. In a typical (threshold based) DWDS sensor network, an increase in $P_d$ will be accompanied by an increase in $P_f$, therefore this objective ensures that improvements in $P_d$ will not be accompanied by increases in $P_f$ when appropriate fusion algorithms are applied.

An additional objective is to improve the accuracy of the sensor network, this can be expressed by maximizing the following accuracy function

$$A = \frac{\sum_{k=1}^{T} \sum_{i=1}^{N} TP_i(k) + \sum_{i=1}^{N} FN_i(k)}{\sum_{k=1}^{T} \sum_{i=1}^{N} TP_i(k) + \sum_{i=1}^{N} FN_i(k)}$$ \hspace{1cm} (8)

The accuracy denotes the total fraction of correct sensor decisions for all sensor till the simulation end time $k = T$.

IV. ALGORITHMS FOR NETWORK-WIDE FUSION OF IMPERFECT SENSOR DECISIONS

In this section, we present the development of algorithms to achieve the objectives of the problem. An effective algorithm should improve the contamination detection probability $P_d$ and minimize the probability of false alarms $P_f$. The idea is to employ the sensors’ topology in the DWDS (graph) to devise a clustering algorithm to network sensors and a fusion rule to filter sensors decisions in order to improve the overall sensor network fidelity in detecting contamination events. Using this methodology, each sensor node $i \in S$ forms a cluster to aggregate information from its topologically neighboring nodes $j \in N^2_i(i)$ (upstream and downstream nodes) and continuously execute the fusion rule to update
its decision in order to improve its fidelity in a distributed manner.

Several decision-level fusion methods exist, including voting, weighted voting decision, and Bayesian inference, Dempster-Shafer’s method, fuzzy logic method, etc. Our approach is to develop distributed fusion algorithms to fuse sensor decisions locally\(^3\) and regionally by using the minimum possible information in order to minimize false alarms and missed events. Next, we describe the details of the proposed fusion algorithms.

The first fusion algorithm is denoted as Voting Decision Fusion Algorithm (V DFA) and it employs a voting method (majority rule) to fuse topologically adjacent sensor nodes decisions. In this algorithm, at every step \(k\), temporal single sensor decisions are locally filtered\(^3\) by using a digital filter \(u_{ij}^F(k)\) (temporal averaging to filter outliers). Subsequently, sensor decisions are fused at regional level \(u_{ij}^F(k)\) by utilizing local decisions of adjacent upstream and downstream sensors. Adajcent upstream and downstream sensors are found by utilizing instantaneous flow direction information in the DWDS graph. Note that downstream sensors decisions are used only when upstream sensors do not exist.

For implementation of voting fusion rule, instantaneous filtered sensor decisions of adjacent sensors \(u_{ij}^F(k)\) are summed and the decision is positive if the majority of sensors have positive decisions.

\[
 u_{ij}^F(k) = \begin{cases} 
 1, & \text{if } \sum_{j \in N_2(i)}^{} u_{ij}^F(k) > \frac{|N_2(i)|}{2} \\
 0, & \text{otherwise}
\end{cases}
\]  

(9)

Where \(N_2(i)\) denotes the set of adjacent upstream or downstream sensors (if no upstream nodes exist) of sensor \(i\).

The previous algorithm ignores a very important known information in the fusion process, that is the sensor measurement signal (or anomaly signal) strength. The second fusion algorithm is denoted as Accumulative Signal Fusion Algorithm (ASFA) and it employs a fuzzy logic (based on signal strength) to fuse topologically neighboring sensor nodes decisions. In this algorithm, sensors utilized a “suspicion” threshold \(\tau_s < \tau_d\) and therefore have three decision outputs (ignore, suspect, detect).

If the measurement of the sensor \(i \in \mathcal{S}\), \(\tau_s < z_i(k) < \tau_d\), then sensor \(i \in \mathcal{S}\) acquires the measurements of its adjacent upstream and downstream sensors \(j \in N_2(i)\) (upstream node decisions only or downstream node decisions if no upstream nodes exist) and sums the measurements of sensors that their measurements are above the “suspicion” threshold \(\tau_s\). The decision is positive if the sum of measurements is above the detection threshold \(\tau_d\). This fusion rule is given by eq. (10).

\[
 u_i^F(k) = \begin{cases} 
 1, & \text{if } \sum_{j \in N_2(i), z_j(k) > \tau_s}^{} z_{ij}^F(k) \geq \tau_d \\
 0, & \text{otherwise}
\end{cases}
\]  

(10)

Where \(j \in N_2(i), z_j(k) > \tau_s\) denotes all adjacent sensors of sensor \(i\) (including \(i\)) with measurements greater that the suspicion threshold \(\tau_s\).

Finally, we describe a fusion algorithm that takes into account quantitative flow rate information in the pipes of the DWDS graph, this information can be provided by flow rate sensors. The algorithm is denoted as Spatial and Temporal Fusion Algorithm (STFA) and it employs quantitative pipe flow information which allows more advanced sensor correlation in time and space. Quantitative pipe flow information allows correlations not only with adjacent sensors but also with \(h\) hop away neighboring sensors is the DWDS graph. \(N_0^h(i)\) can include the first upstream sensors \((h=1, \text{one pipe away})\) or the \(1, 2, \ldots, h\)-hop upstream sensors (sensors that are maximum \(h\) links away topologically) as shown in Fig. 2.

![Fig. 2. Upstream nodes for node 1 are nodes 2 and 4. If all nodes are monitored by sensors, then \(N_0^2(1) = \{1, 2, 4\}\).](image)

In this algorithm, at every step \(k\), each sensor \(i \in \mathcal{S}\) acquires the past measurements of its topologically neighboring upstream sensors \(z_{ij}^F(k - \Delta \tau_i), j \in N_0^h(i)\) and fuses these measurements taking into account the travel time (delay) of water \(\tau_{ij}\) between sensor \(i\) and \(j\). The delay in time steps \(\Delta \tau_i\) (contamination time difference of arrival) is estimated based on the flow velocity information and inspired by the work described in [13], [14].

STFA recursively backtracks neighboring nodes and finds the travel time of the water packet to correlate the past measurements of \(h\) upstream sensors taking into account the travel time (delay) of water. STFA is comprised of two sub routines. When sensors \(i, j\) are connected with a single pipe (adjacent), Subroutine 1 finds for a given a node \(i\) at time step \(k\) all adjacent upstream nodes \(j\) and their respective past time steps \(k - \frac{\tau_{ij}}{\Delta \tau_i}\). In the case when sensors \(i, j\) are connected with multiple pipes (\(h\)-hop away neighboring sensors), Subroutine 2 finds for a node \(i\) at time step \(k\), all its \(h\)-hop upstream sensors \(j\) and their respective past time steps \(k - \frac{\tau_{ij}}{\Delta \tau_i}\) by searching all nodes in the set of \(h\)-hop neighboring nodes \(N_0^h(i)\). Subroutine 2 is based on a recursive call of the Subroutine 1 until all \(h\)-hop neighboring nodes in the graph are visited.

\(^3\)For all algorithms, temporal sensor decision filtering \(u_{ij}^F(k)\) at each individual sensor is not considered because it results in noise nullying (e.g. noise is removed if a digital filter is used to filter outliers in sensor decisions).
Finally, each sensor $i \in S$ updates its decision by utilizing the following fusion rule:

$$u_i^{RF}(k) = \begin{cases} 
1, & \text{if } \sum_{j \in \mathcal{N}_h^k(i, z_j(k) > \tau_s)} \Delta s_j^k(k - \tau_s) / \Delta t \geq \tau_d \\
0, & \text{otherwise}
\end{cases}$$  \hspace{1cm} (11)

Where $j \in \mathcal{N}_h^k(i, z_j(k) > \tau_s)$ denotes all $h$-hop upstream sensors of sensor $i$ (including $i$) with measurements greater than suspicion threshold $\tau_s$.

V. EVALUATION AND SIMULATION RESULTS

In this section, we investigate the performance of the proposed network-wide fusion algorithms using a case-study. All simulations performed in MATLAB using the EPANET programmer’s toolkit. The case study is demonstrated using the DWDS shown in Fig. 3. This network is composed of 13 pipes connected to 11 nodes (9 junctions, one tanks and one reservoir). Each junction node is assigned with a daily average consumption volume as well as a discrete signal describing the rate (profile) of water consumption within 24 hours, with a 30-minute time step. These are assumed to describe the normal operation.

The hydraulic dynamics are computed using the EPANET solver [15]. In all simulations, we consider a $\Delta \tau = 5$ min hydraulic and quality discretization step and total simulation time for each scenario is 24h. It is assumed that a contaminant is injected at a DWDS node and the contamination substance is decaying, $\alpha = 0.2/$day, according to the reactions occurring in the bulk water and at the pipe walls. The contaminant is injected at simulation time $t_{EN}^{ON}=2h$ (rectangular pulse function pattern) and the concentration at the injected DWDS node is $C = 3$ $\mu g/L$. The injection remains constant till the time $t_{EOFF}^{OFF}=10h$ (e.g. contamination event remains active within the time interval [2, 10] h).

For the illustrated case study of Fig. 3, we assume that 50% of the nodes of the DWDS are monitored by sensors and the contaminant is injected at a randomly selected DWDS node. The simulated scenario refers to detection threshold $\tau_d = 0.8$, suspicion threshold $\tau_s = 0.4$ and standard deviation of sensors’ additive Gaussian noise $\sigma = 0.2$.

For the simulated scenario, we acquire the total number of sensors’ true positives (TP), false positives (FP), true negatives (TN) and false negative (FN) decisions as well as the resulted true positive rate $P_d$, false positive rate $P_f$ and accuracy $A$ resulted from each distributed fusion algorithm. The results are presented in Table I where NoFA represents the case when no fusion algorithm is applied (simple threshold based decision). Fig. 4 presents the updated sensor decisions resulted from distributed fusion algorithms, where TRUE represents the ground truth decision.

Table I

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>$P_d$</th>
<th>$P_f$</th>
<th>$A$</th>
<th>TP</th>
<th>TN</th>
<th>FP</th>
<th>FN</th>
</tr>
</thead>
<tbody>
<tr>
<td>NoFA</td>
<td>0.9985</td>
<td>0.0397</td>
<td>0.9751</td>
<td>670</td>
<td>1015</td>
<td>42</td>
<td>1</td>
</tr>
<tr>
<td>VDFA</td>
<td>0.9493</td>
<td>0</td>
<td>0.9803</td>
<td>637</td>
<td>1057</td>
<td>0</td>
<td>34</td>
</tr>
<tr>
<td>ASFA</td>
<td>0.9851</td>
<td>0</td>
<td>0.9942</td>
<td>661</td>
<td>1057</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td>STFA</td>
<td>0.9911</td>
<td>0</td>
<td>0.9963</td>
<td>665</td>
<td>1057</td>
<td>0</td>
<td>6</td>
</tr>
</tbody>
</table>

Fig. 3. The simple drinking water distribution system used in the case study (big numbers represent the nodes’ indexes and small numbers represent the pipes’ indexes).

Fig. 4. Sensor decisions from each distributed fusion/correlation algorithm for the case study shown Fig. 3

It has significantly lower communication and computation cost. On the other hand, STFA achieves more precise results because it correlates sensor measurements more accurately in
time, this enables STFA to account the cases of reverse flows as well as the cases when the duration of a contamination event is very short.

VI. Conclusion

The objective of this work is to investigate the problem of monitoring contamination events in Drinking Water Distribution Systems using Wireless Sensor Networks or Internet of Things approaches with inaccurate, but inexpensive water quality sensors. We have developed and compared several algorithms that correlate and fuse imperfect sensor decisions or/and measurements in order to minimize detection errors and improve the contamination detection probability. Simulation results indicate that the proposed methodology and algorithms successfully fuse/filter inaccurate sensor decisions and improve the overall sensor network fidelity in detecting contamination events. In the future, we plan to investigate the performance of the algorithms in more complex DWDS and we also plan to perform more exhaustive (monte carlo) simulations to investigate the trade-offs in several important design parameters.

References