The Battle of the Water Sensor Networks (BWSN): A Design Challenge for Engineers and Algorithms

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Abstract: Following the events of September 11, 2001, in the United States, world public awareness for possible terrorist attacks on water supply systems has increased dramatically. Among the different threats for a water distribution system, the most difficult to address is a deliberate chemical or biological contaminant injection, due to both the uncertainty of the type of injected contaminant and its consequences, and the uncertainty of the time and location of the injection. An online contaminant monitoring system is considered as a major opportunity to protect against the impacts of a deliberate contaminant intrusion. However, although optimization models and solution algorithms have been developed for locating sensors, little is known about how these design algorithms compare to the efforts of

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human designers, and thus, the advantages they propose for practical design of sensor networks. To explore these issues, the Battle of the Water Sensor Networks (BWSN) was undertaken as part of the 8th Annual Water Distribution Systems Analysis Symposium, Cincinnati, Ohio, August 27–29, 2006. This paper summarizes the outcome of the BWSN effort and suggests future directions for water sensor networks research and implementation.

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Introduction

Since the early days of King Hezekiah (late eighth to early seventh centuries BCE), who constructed a 533-m underground tunnel to channel the Gihon Spring outside Jerusalem into the city as part of his war against Sennacherib, water resources systems were the subject of threats and conflicts throughout history with diverse intensities (Gleick 1998).

Related water terrorist activities were reported in ancient Rome, in the United States during its Civil War, in Europe and Asia during World War II, and in 1999 in Kosovo. Hickman (1999) and Deininger and Meier (2000) discussed the topic of deliberate contamination of water supply systems.

For the last decade there has been increasing interest in the development of sensor networks to cope with both deliberate and accidental hazard's intrusions into water distribution systems. Optimization models and solution algorithms have been developed for identifying the most efficient sensor locations. These optimization models and solution algorithms have involved simplifying assumptions about design objectives, network contaminant transport, sensor response, event detection, emergency response, installation and maintenance costs, etc. Little is known about how these design algorithms compare from one design methodology to another, and thus, what advantages they provide for practical design of sensor networks. To explore these issues, the Battle of the Water Sensor Networks (BWSN) was held (Ostfeld et al. 2006) as part of the Eigth Annual Water Distribution Systems Analysis Symposium, in Cincinnati, on August 27–29, 2006.

The BWSN was aimed at objectively comparing the performance of contributed sensor network designs, as applied to two water distribution systems examples. Fifteen independent research groups and practicing engineers contributed their designs. All the teams were asked to develop designs according to a set of rules, which defined the design performance metrics and the characteristics of the contamination events. Teams were free to develop their designs and methodologies, yet, for comparison, all outcome designs were evaluated using identical procedures.

The objective of this paper is to summarize the outcome of the BWSN effort and to highlight future directions for water sensor networks research. The following describes: (1) the BWSN design objectives; (2) design assumptions and cases; (3) a synopsis of the teams' design approaches; (4) a comparison of the design results; and (5) conclusions and future research directions.

Design Objectives

Contributed sensor network designs were evaluated using the following four quantitative design objectives:

Expected Time of Detection (Z_1)

For a particular contamination scenario, the time of detection by a sensor is the elapsed time from the start of the contamination event, to the first identified presence of a nonzero contaminant concentration. The time of first detection, t_j, refers to the jth sensor location. The time of detection for the sensor network for a particular contamination event, t_d, is the minimum among all sensors present in the design

$$t_d = \min_j t_j \tag{1}$$

The objective function to be minimized is the expected value computed over the assumed probability distribution of contamination events

$$Z_1 = E(t_d) \tag{2}$$

where $E(t_d)$ denotes the mathematical expectation of the minimum detection time t_d. Since undetected events had no detection times, they were not included in the analysis. This acknowledged limitation pertains to all of the design objectives and is discussed later in the paper.

Expected Population Affected prior to Detection (Z_2)

For a specific contamination scenario, the population affected is a function of the ingested contaminant mass. The ingested contaminant mass, in turn, depends on the time of detection for the sensor network, as described above; two key assumptions are that no mass is ingested after detection and that all mass ingested during undetected events is not counted. For a particular contamination scenario, the mass ingested—prior to detection—by any individual at network node i is

$$M_i = \varphi \Delta t \sum_{k=1}^{N} c_{ik}\rho_{ik} \tag{3}$$

where φ=mean amount of water consumed by an individual (L/day/person); Δt=evaluation time step (days); c_{ik}=contaminant concentration for node i and time step k (mg/L); ρ_{ik} = "dose rate multiplier" (Murray et al. 2006) for node i and time step k (unitless); and N=number of evaluation time steps prior to detection, i.e., the largest integer such that $N\Delta t \leqslant t_d$. The series ρ_{ik}, $k=1,\ldots,N$ has a mean of 1 (so, φ is truly the mean volumetric ingestion rate) and is intended to model the variation in ingestion rate throughout the day. It is assumed that the ingestion rate varies with the water demand rate at the respective node, thus

$$\rho_{ik} = q_{ik}/\bar{q}_i \quad \forall\, k \in N \tag{4}$$

where q_{ik}=water demand for time step k and node i; and $\bar{q}_i$=average water demand at node i.

A dose–response model (Chick et al. 2001, 2003) is used to express the probability that any person ingesting mass M_i will be affected (i.e., becomes infected or symptomatic)

$$R_i = \Phi\{\beta \log_{10}[(M_i/W)/D_{50}]\} \tag{5}$$

where R_i=probability [0, 1] that a person who ingests contaminant mass M_i will become infected or symptomatic; β

$=$so-called Probit slope parameter (unitless); W=assumed (average) body mass (kg/person); D_{50}=dose that would result in a 0.5 probability of becoming infected or symptomatic (mg/kg); and Φ=standard normal cumulative distribution function.

The population affected, P_a, for a particular contamination scenario is calculated as

$$P_a = \sum_{i=1}^{V} R_i P_i \tag{6}$$

where P_i=population assigned to node i; and V=total number of nodes. The objective function to be minimized is the expected value of P_a computed over the assumed probability distribution of contamination events

$$Z_2 = E(P_a) \tag{7}$$

where $E(P_a)$ denotes the mathematical expectation of the affected population P_a.

Expected Consumption of Contaminated Water prior to Detection (Z_3)

Z_3=expected volume of contaminated water consumed prior to detection

$$Z_3 = E(V_d) \tag{8}$$

where V_d denotes the total volumetric water demand that exceeds a predefined hazard concentration threshold C; and $E(V_d)$ =mathematical expectation of V_d. As for the expected population affected, key assumptions are that no water is delivered after detection and undetected events are not counted. Z_3 (as Z_2 and Z_1) is to be minimized.

Detection likelihood (Z_4)

Given a sensor network design (i.e., number and locations) the detection likelihood (i.e., the probability of detection) is estimated by

$$Z_4 = \frac{1}{S}\sum_{r=1}^{S} d_r \tag{9}$$

where $d_r=1$ if contamination scenario r is detected, and zero otherwise; and S denotes the total number of the contamination scenarios considered. Z_4 is to be maximized.

The variables that constitute the design objectives are subject to right censoring as a result of the finite-simulation durations used to compute their values (96 h for the small network; 48 h for the large network). The variable that is directly censored is the time to detection, t_d, which cannot exceed the difference between the end of the simulation period and the start of the contamination event (that is, there are varying censoring times for t_d, depending on when the event begins). The other variables: population affected prior to detection (P_a); the demand of contaminated water prior to detection (V_d); and the detection indicator variable (d_r); are all co-censored along with t_d, although not by an amount that can be determined a priori by knowing the start time of the contamination event and the duration of the simulation period. In addition, as noted below, the expectations for these variables (Z_1–Z_4) were computed in this study using only the events that were detected. As such, the random variables were in fact truncated (rather than censored), introducing an even greater downward bias in the computed values of their expectations. While this truncation was viewed as the only feasible approach for implementing this evaluation, approaches that explicitly recognize the censoring caused by finite-simulation durations are considered in the concluding section, which addresses future research needs.

Design Assumptions and Cases

Participants were asked to provide designs for locating five sensors and 20 sensors for a base case (A) and three derivative cases (B, C, and D) using EPANET Version 2.00.10 (http://www.epa.gov/ORD/NRML/wswrd/epanet.html). The four cases are described below.

Base Case A

1. All quantities affecting network model water quality predictions were assumed to be known and deterministic. Sensor network designs were challenged by an ensemble of contamination scenarios sampled from a statistical distribution; the probability distribution of contamination events is described herein. Contaminant intrusions occurred at network nodes, with an injection flow rate of 125 L/h, contaminant concentration of 230,000 mg/L, and injection duration of 2 h. The contaminant was assumed conservative after injection. Each contamination scenario involved a single injection location, which may occur at any network node and begin at any time with equal probability. For purposes of design evaluation, contaminant concentrations were evaluated using a 5-min time step.
2. For purposes of calculating the expected population affected prior to detection (Z_2): φ=2 L/day, β=0.34 (-), D_{50} =41 mg/kg, and W=70 kg. For purposes of estimating node population, the total per capita water demand rate was assumed to be 300 L/day.
3. For purposes of calculating the expected demand of contaminated water prior to detection (Z_3), the hazard concentration threshold was C=0.3 mg/L.
4. Sensors instantly detected any nonzero contaminant concentration and action was taken to eliminate further exposure without delay.

Derivative Case B

Identical to Base Case A except that the injection duration was increased to 10 h.

Derivative Case C

Identical to Base Case A except that the response delay was 3 h, i.e., it took 3 h after detection for emergency response to limit contaminant exposure.

Derivative Case D

Identical to Base Case A except that all contamination scenarios involved two injection locations, which may occur at any two distinct nodes with equal probability. The contamination scenario may begin at any time with equal probability, but both injections were synchronized to begin at the same time.

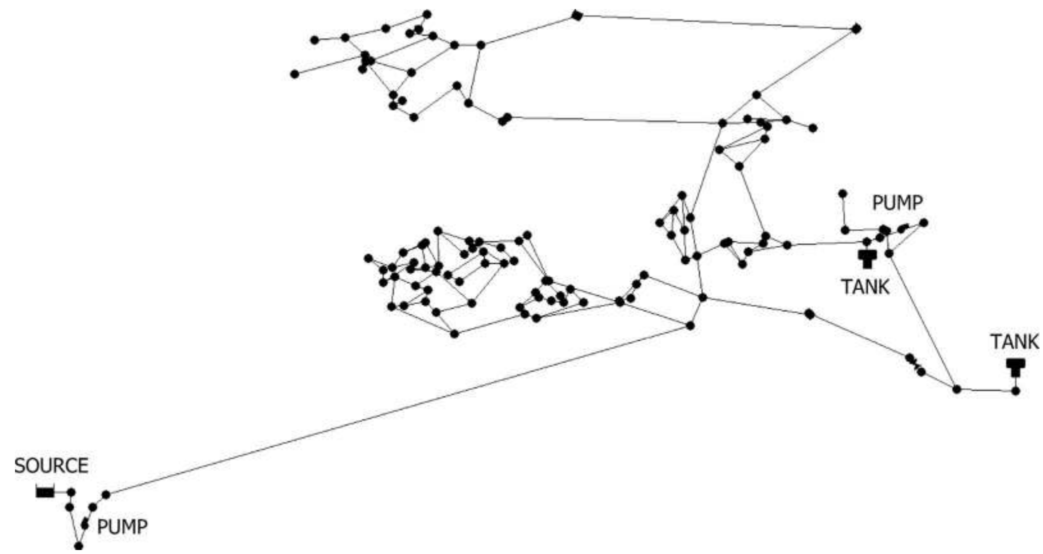

Fig. 1. Layout of Network 1 (126 nodes, 1 source, 2 tanks, 168 pipes, 2 pumps, 8 valves)

Design Approaches

Fifteen sensor designs were submitted to the BWSN. This section gives a brief description of each contribution.

Alzamora and Ayala (2006) suggested a general framework for sensor locations using topological algorithms. Berry et al. (2006) proposed a *p*-median formulation adapted from discrete location theory to define the sensors location problem, which was further solved using a heuristic method. Dorini et al. (2006) suggested a constrained multiobjective optimization framework entitled the noisy cross-entropy sensor locator (nCESL) algorithm, which is based on the cross-entropy methodology proposed by Rubinstein (1999). Eliades and Polycarpou (2006) proposed a multiobjective solution, using an "iterative deepening of Pareto solutions" algorithm. Ghimire and Barkdoll (2006a,b) suggested a heuristic demand-based approach in which sensors were located at the junctions with the highest demands (Ghimire and Barkdoll 2006a), or the highest mass released (Ghimire and Barkdoll 2006b). Guan et al. (2006) proposed a genetic algorithm simulation–optimization methodology based on a single objective function approach in which the four quantitative design objectives were embedded. Gueli (2006) suggested a predator–prey model applied to multiobjective optimization, based on an evolution process. Huang et al. (2006) proposed a multiobjective genetic algorithm framework coupled with data mining. Krause et al. (2006) applied a greedy algorithm for the sensors locations, noting that a limitation in the BWSN formulation was that the Z_i $(i=1,2,3)$ objectives were being evaluated against only the scenarios that were detected, thus not considering the effects of the undetected scenarios, which might be critical. Ostfeld and Salomons (2006) and Preis and Ostfeld (2006) used the multiobjective nondominated sorted genetic algorithm-II (NSGA-II) (Deb et al. 2000) scheme. Propato and Piller (2006) used a mixed-integer linear program to solve the sensors' locations. Trachtman (2006) suggested an engineering "strawman" approach for locating the sensors taking into consideration factors such as population distribution, system pressure and flow patterns, critical customer locations, etc. Wu and Walski (2006) used a multiobjective optimization formulation, which was solved using a genetic algorithm, with the contamination events randomly generated using a Monte Carlo scheme.

Case Studies

Two water distribution systems of increasing complexity were used for the designs.

Network 1 (Fig. 1) was comprised of 126 nodes, one constant head source, two tanks, 168 pipes, two pumps, eight valves, and was subject to four variable demand patterns. The system was simulated for a total extended period duration of 96 h.

Network 2 (Fig. 2) had 12,523 nodes, two constant head sources, two tanks, 14,822 pipes, four pumps, five valves, and was subject to five variable demand patterns. The system was simulated for a total extended period duration of 48 h.

Both networks were real water distribution systems that were "twisted" to preserve their anonymity. Space limitation prohibits the description of all of their details (e.g., pipe lengths, base de-

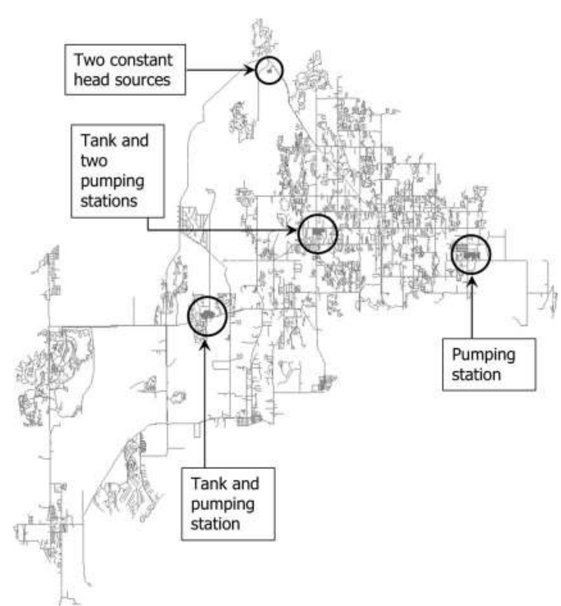

Fig. 2. Layout of Network 2 (12,523 nodes, 2 sources, 2 tanks, 14,822 pipes, 4 pumps, 5 valves)

Table 1. Network 1, Case A: Five Sensor (N1A5) Solutions

Reference	Sensor location (nodes)	Z_1 (min)	Z_1 (people)	Z_1 (gal)	Z_1 (detection likelihood)
Berry et al. (2006)	17, 21, 68, 79, 122	542	140	2,459	0.609
Dorini et al. (2006)	10, 31, 45, 83, 118	1,068	258	7,983	0.801
Eliades and Polycarpou (2006)	17, 31, 45, 83, 126	912	221	7,862	0.763
Ghimire and Barkdoll (2006a)	126, 30, 118, 102, 34	432	357	4,287	0.367
Ghimire and Barkdoll (2006b)	126, 30, 102, 118, 58	424	331	3,995	0.402
Guan et al. (2006)	17, 31, 81, 98, 102	642	159	2,811	0.663
Gueli (2006)	112, 118, 109, 100, 84	794	403	10,309	0.699
Huang et al. (2006)	68, 81, 82, 97, 118	541	280	4,465	0.676
Krause et al. (2006)	17, 83, 122, 31, 45	842	181	3,992	0.756
Ostfeld and Salomons (2006)	117, 71, 98, 68, 82	461	250	4,499	0.622
Preis and Ostfeld (2006)	68, 101, 116, 22, 46	439	151	7,109	0.477
Propato and Piller (2006)	17, 22, 68, 83, 123	711	164	3,148	0.725
Trachtman (2006)	1, 29, 102, 30, 20	391	142	2,504	0.237
Wu and Walski (2006)	45, 68, 83, 100, 118	704	303	8,406	0.787

mands, diameters, and elevations). The network's EPANET input files can be downloaded from the Exeter Centre for Water Systems (ECWS) (http://www.exeter.ac.uk/cws/bwsn).

Design Results

A methodology for evaluating a given sensor design should comply with two basic requirements: (1) it should be objective, and (2) it should assess a design regardless of the method used to receive it; thus, solutions from academia, practitioners, utilities, etc., all would be assessed on the same basis. To accomplish this task, a utility was developed by Salomons (2006).

The utility was comprised of two stages: (1) generation of a matrix of contamination injection events in either of two mechanisms: random, using Monte Carlo-type simulations selected by the user; or deterministic, injection at each node each 5 min, and (2) evaluation of Z_i $(i=1,\dots,4)$ according to the matrix of contamination injection events constructed in Stage 1.

The utility was distributed to all participants prior to the

Table 2. Network 1, Case A: 20 Sensors (N1A20) Solutions

Reference	Sensor locations (nodes)	Z_1 (min)	Z_1 (people)	Z_1 (gal)	Z_1 (detection likelihood)
Berry et al. (2006)	3, 4, 17, 21, 25, 31, 34, 37, 46, 64, 68, 81, 82, 90, 98, 102, 116, 118, 122, 126	287	68	408	0.770
Dorini et al. (2006)	0, 10, 14, 17, 31, 34, 39, 45, 49, 68, 74, 82, 83, 90, 100, 102, 114, 122, 124, 128	408	72	642	0.855
Eliades and Polycarpou (2006)	10, 11, 14, 17, 19, 21, 31, 35, 45, 68, 74, 83, 90, 100, 102, 114, 118, 123, 124, 126	368	96	969	0.893
Ghimire and Barkdoll (2006a)	126, 30, 118, 102, 34, 17, 58, 68, 93, 27, 42, 82, 45, 35, 83, 89, 99, 70, 18, 32	377	104	750	0.792
Ghimire and Barkdoll (2006b)	126, 30, 102, 118, 58, 68, 17, 93, 82, 34, 99, 98, 89, 83, 100, 96, 70, 27, 32, 35	370	106	787	0.769
Guan et al. (2006)	4, 11, 17, 21, 27, 31, 34, 35, 46, 68, 75, 79, 82, 83, 98, 100, 102, 118, 122, 126	337	78	503	0.854
Gueli (2006)	112, 1, 103, 24, 21, 102, 35, 19, 116, 85, 61, 73, 114, 31, 7, 8, 64, 28, 93, 124	226	88	1,181	0.577
Huang et al. (2006)	8, 11, 42, 46, 52, 68, 70, 75, 76, 82, 83, 95, 97, 99, 100, 109, 111, 117, 123, 126	375	148	1,799	0.849
Krause et al. (2006)	17, 83, 122, 31, 45, 100, 11, 126, 68, 90, 21, 35, 34, 118, 123, 114, 124, 76, 10, 19	401	93	865	0.900
Ostfeld and Salomons (2006)	68, 5, 40, 65, 51, 69, 88, 89, 22, 72, 34, 71, 53, 112, 63, 78, 122, 28, 118, 97	198	115	1,039	0.647
Propato and Piller (2006)	11, 17, 34, 37, 38, 45, 49, 68, 76, 83, 90, 100, 102, 106, 114, 118, 123, 124, 125, 126	433	106	934	0.879
Trachtman (2006)	1, 29, 102, 30, 20, 18, 58, 5, 3, 76, 98, 17, 126, 68, 93, 27, 42, 82, 46, 35	325	99	862	0.739
Wu and Walski (2006)	10, 12, 19, 21, 34, 35, 40, 45, 68, 75, 80, 83, 98, 100, 102, 114, 118, 123, 124, 126	370	142	1,158	0.901

BWSN for testing Case A of Networks 1 and 2, and is used herein to compare the results of the contributed designs.

Although not defined explicitly in the BWSN rules (Ostfeld et al. 2006), it became evident during the groups' design preparations and during the BWSN that the expected time of detection (Z_1), the expected population affected prior to detection (Z_2), and the expected demand of contaminated water prior to detection (Z_3), competed against the detection likelihood (Z_4); thus, the BWSN was inherently a multiobjective problem.

In a multiobjective context the goal is to find, from all the possible feasible solutions, the set of nondominated solutions, where a nondominated solution is optimal in the sense that there is no other solution that dominates it (i.e., there is no other solution that is better than that solution with respect to all objectives).

This leads to two observations: (1) comparisons can be made on the Z_i $(i=1,2,3)$ versus Z_4 domains, and (2) a unique single optimal solution cannot be identified, thus a "winner" cannot be declared. It should also be emphasized in this context that alternate comparison methods could have been employed, thus there is no claim that the adopted comparison approach is better in an absolute sense than an alternative methodology.

Network 1

Tables 1 and 2 and Figs. 3–9 provide the results for Network 1 for Cases A–D. To evaluate Network 1, Base Case A (N1A), Network 1, Base Case B (N1B), and Network 1, Base Case C (N1C) the full matrices of 37,152 injection events were generated (each node, every 5 min, for an extended period simulation time of 24 h), and for Network 1, Base Case D (N1D), 30,000 random events. Each injection event simulation took about 10 s on an IBM PC 3.2 GHz, 1 GB RAM. All matrices used for Networks 1 and 2 can be downloaded from ECWS (http://www.exeter.ac.uk/cws/bwsn).

Krause et al. (2006) published Node identification (ID) numbers for all their solutions to the BWSN networks and scenarios. In the present work, the evaluation was based on junction ID. Thus, Krause et al. (2006) solutions were converted from node ID to junction ID. For Network 2, this is a simple offset of −1 to all node numbers. For Network 1 there are no junction numbers 107 and 108; therefore, junctions were offset −1 from nodes for those below 107 and +1 for those above 109.

Tables 1 and 2 show the participants' detailed sensor designs for N1A5 Network 1, Base Case A, five sensors (N1A5), and for Network 1, Base Case A, 20 sensors (N1A20), respectively; Fig. 3 describes the layout of the suggested designs for N1A5; Fig. 4 presents tradeoff curves for Z_i $(i=1,2,3)$ versus Z_4 for N1A5; Fig. 5 shows tradeoff curves for Z_i $(i=1,2,3)$ versus Z_4 for N1A20.

It can be seen from Fig. 3 that most of the participant groups' solutions chose Node 83 as a sensor location, which is a downstream node of the system, and Nodes 68 and 118, at the southern and northern parts of the system, respectively. At those locations, most of the nondominated solutions (Fig. 4) were present.

Observing Fig. 4, it can be seen that the relative locations on the Z_i $(i=1,2,3)-Z_4$ plane of the different parties' solutions are alike and that the Z_i objective functions are correlated (i.e., a nondominated solution obtained by a specific method would likely remain regardless of the objective function used). This is also evident in Fig. 5. An improvement of the results can be

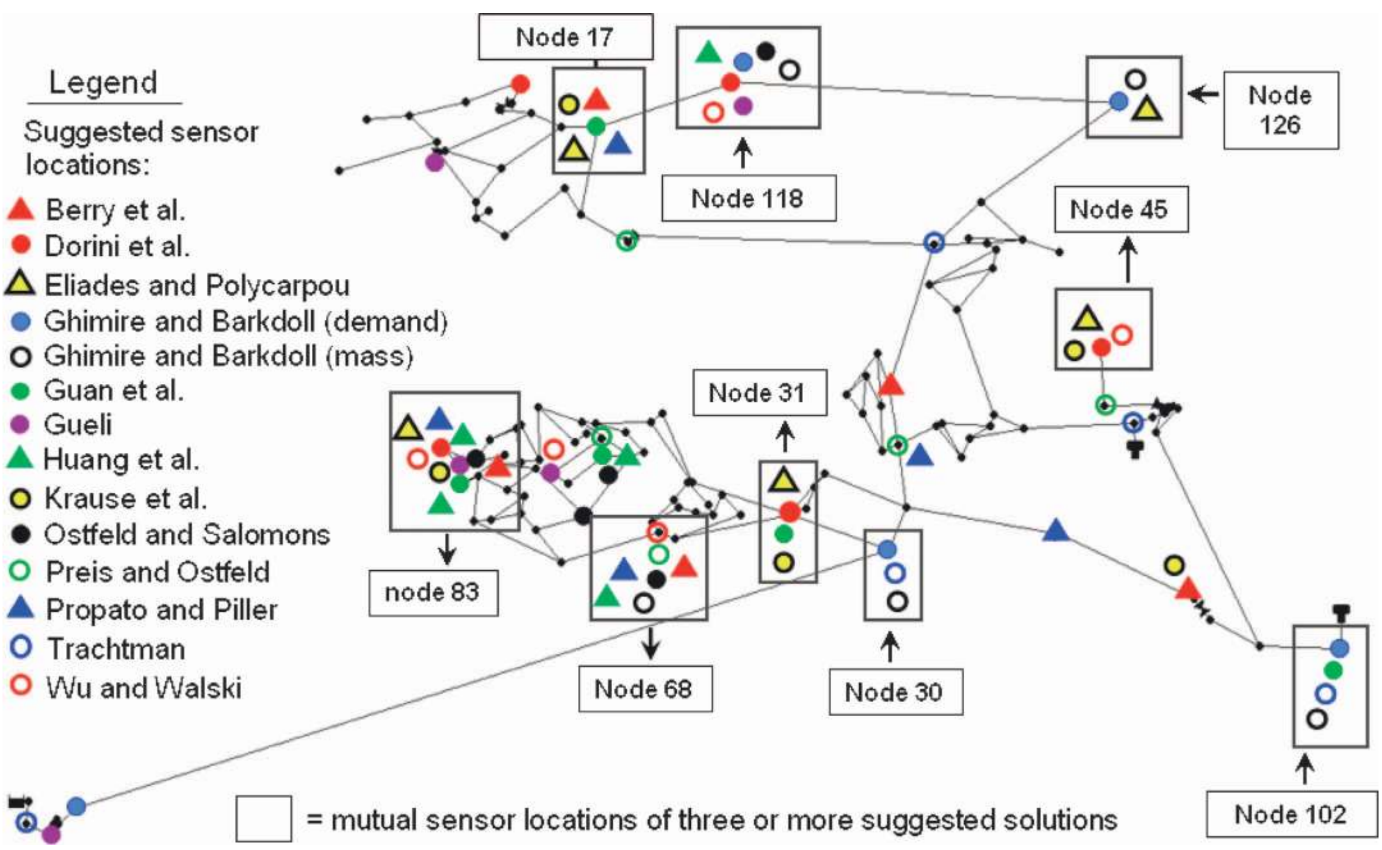

Fig. 3. (Color) Network 1, Case A: 5 sensors (N1A5) solutions layout

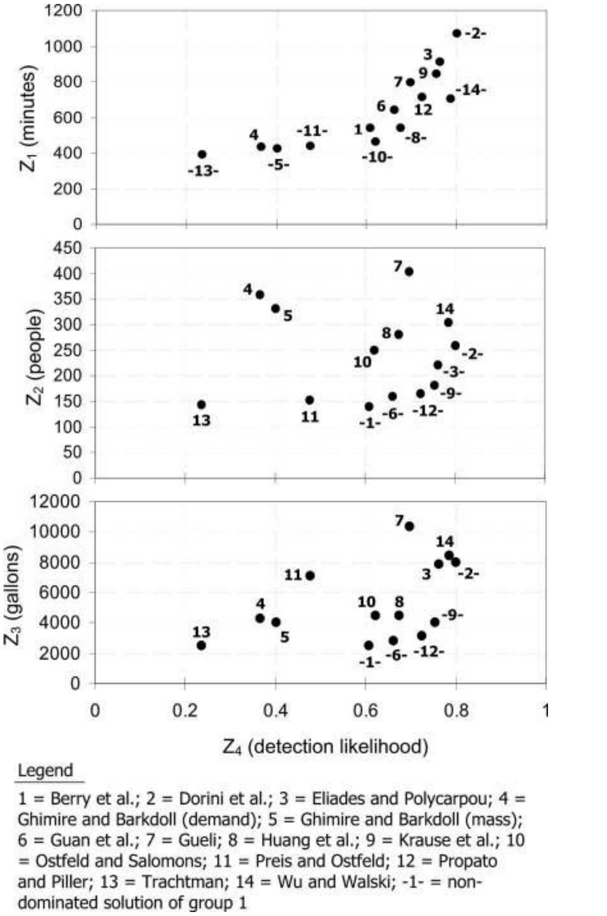

Fig. 4. Network 1, Case A: 5 sensors (N1A5) trade-off solution curves

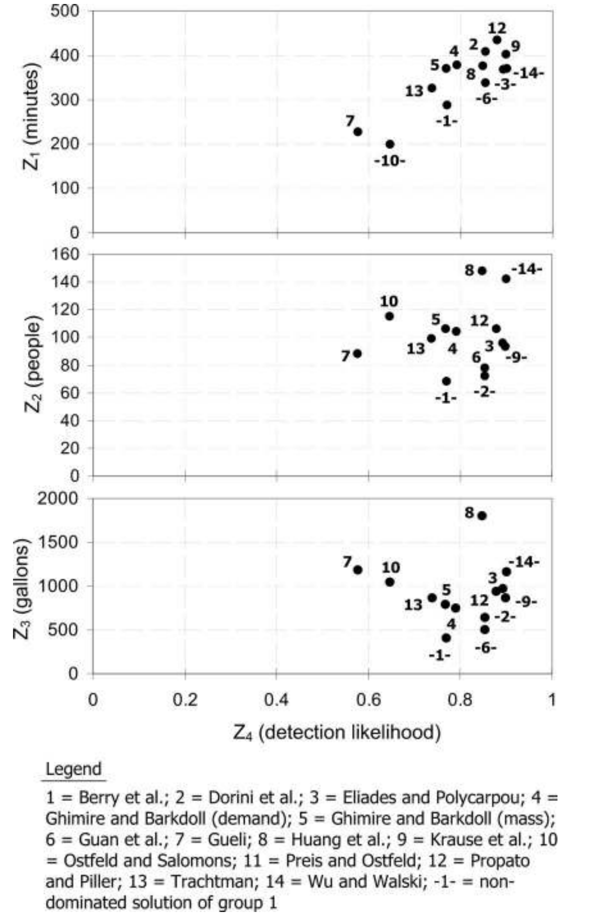

Fig. 5. Network 1, Case A: 20 sensors (N1A20) trade-off solution curves

inspected when matching Figs. 4 and 5 (i.e., results for systems of five versus 20 sensors, respectively).

Fig. 6 outlines tradeoff curve results for Derivative Cases B, C, and D for Z_1 versus Z_4; Fig. 7 for Derivative Cases B, C, and D for Z_2 versus Z_4; and Fig. 8 for Derivative Cases B, C, and D for Z_3 versus Z_4.

It can be seen from Figs. 6–8 that similar patterns of solutions were received for Cases B and C, but significantly different for Case D. As Case D considers two simultaneous injections beginning at the same time, but at different random locations, the detection likelihood increased considerably, with all solutions having a detection likelihood of above 0.8 for 20 sensors. In most solutions the Z_i $(i=1,2,3)$ values were reduced for Case D, compared to Cases B and C.

In Fig. 9, Z_2 versus Z_4 for N1A5 and for N1C5 are plotted for each of the group's solutions. It can be seen from Fig. 9, as expected, that as the detection delay increased (Derivative Case C), the expected population affected prior to detection (Z_2) increased, for all the solutions.

Network 2

Tables 3 and 4 and Figs. 10 and 11 provide results for Network 2 for Base Case A. To evaluate Network 2, Base Case A (N2A), a randomized matrix of 25,054 events (two injections at each node of the system, at two random times) was generated. Each injection event simulation took about 2.1 min on an IBM PC 3.2 GHz, 1 GB RAM. Krause et al. (2006) noted that the full matrix of simulated results for Network 2 can be computed using parallel processing and optimized storage algorithms.

Tables 3 and 4 provide the participants detailed sensor designs for Network 2, Base Case A, five sensors (N2A5) and for Network 2, Base Case A, 20 sensors (N2A20), respectively; Fig. 10 presents tradeoff curves for Z_i $(i=1,2,3)$ versus Z_4 for N2A5, and Fig. 11 shows tradeoff curves for Z_i $(i=1,2,3)$ versus Z_4 for N2A20. Note that for N2A5 both Berry et al. (2006) and Krause et al. (2006) found the same solution (see Table 3 and Fig. 10), which is nondominated, using different approaches.

It can be seen from Figs. 10 and 11 (and for Network 1 with Figs. 4 and 5), that the relative locations on the Z_i $(i=1,2,3)-Z_4$ plane of the different solutions are similar; thus, the Z_i objective functions are correlated. Compared to Network 1, the number of nondominated solutions was reduced considerably in Network 2.

There are an infinite number of intrusion scenarios possible on a water distribution system, due to varying durations, locations, etc. The BWSN utilized Cases B, C, and D as variations on Case A, but they were different.

Table 5 provides a summary of the nondominated solutions received by the participant groups for all the explored cases as presented in Figs. 4–11 [e.g., Berry et al. (2004) obtained two nondominated solutions for N1A5, as shown in Fig. 4]. Krause et al. (2006) received the highest total number of 26 nondominated solutions for all the explored cases.

The BWSN results do not support the assumption that Case A

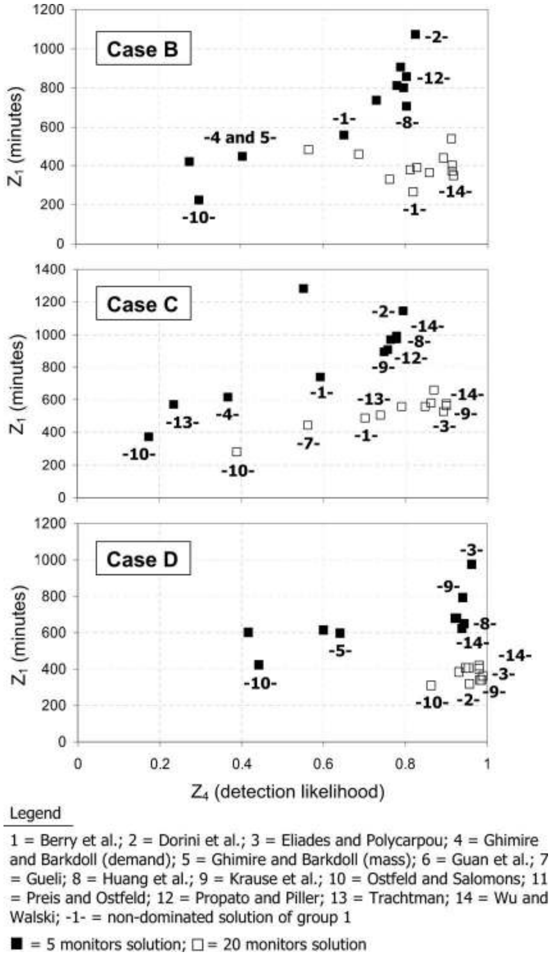

Fig. 6. Network 1: Z_1 versus Z_4 for Cases B, C, and D

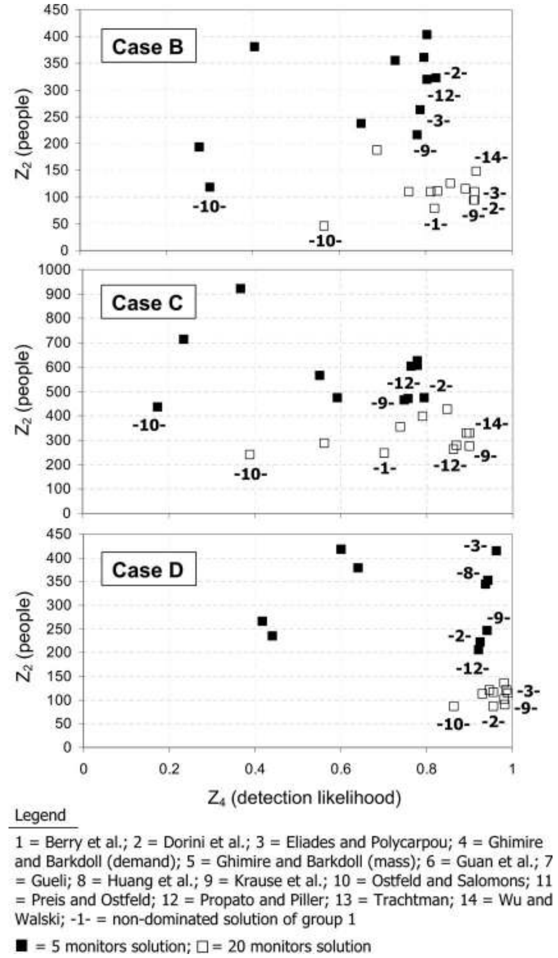

Fig. 7. Network 1: Z_2 versus Z_4 for Cases B, C, and D

is the most critical and a design that performs well in Case A would also do reasonably well in other cases. However, the BWSN results did prompt additional research, which indicated that for the two water distribution systems used in the BWSN, sensor networks based on Cases A, B, and C, were spatially similar. Due to this attribute, a sensor network design that performs well in Case A will also do reasonably well in Cases B and C (Isovitsch and VanBriesen 2008).

Observations

Nondetect Events

The evaluation of sensor design was made in the presence of a varied ensemble of contamination incidents. In real life, each of these incidents would play out over many days. Therefore, it was important that the hydraulic models be sufficiently calibrated to support extended period simulations, and that these should be used in the evaluation of any sensor design.

Consider one such simulation. Regardless of the objective being evaluated, the contamination plume will propagate through the network until the simulation has run its course. If, at the end of the simulation, no sensor has experienced contamination, this condition is referred to as a "nondetection." In a large ensemble of potential incidents in a sizable network protected by a small number of sensors, occasions of nondetections are inevitable. A decision should be made whether or not to include the impact of these nondetections in the calculation of the mean impact over all incidents. This decision is heavily influenced by the objective(s) in question, as demonstrated below.

First, consider Z_1—the time to detection. If an incident is detected by a sensor, this detection will often occur within a few hours of the injection. However, there are many injection points on the periphery of a network that lead to small plumes that do not permeate the network and are never detected. When the impact of these nondetections are included in the calculation of the Z_1 objective, nonintuitive behavior ensues. Specifically, recalling that the analysis depends on extended period simulations, note that the impact of nondetections is very severe and dwarfs that of detections. Optimizing for minimum time to detection in the presence of nondetections means avoiding nondetections at all costs, and results in sensor placements that are directly correlated with those optimizing the number of failed detections (Z_4). In real terms, this means placing sensors far from the center of a network in order to maximize detections. This is exactly opposed to an intuitive approach for minimizing the time to detection. In order to avoid this nonintuitive behavior, it was decided to not include nondetections in the evaluation of objective Z_1.

The situation was different for Z_2, the population exposed. In the discussion above, it was shown that nondetections in the periphery of the system with very small real impact, were penalized severely in terms of the time to detection Z_1, and could trick optimizers into selecting nonsensical solutions. With Z_2, however,

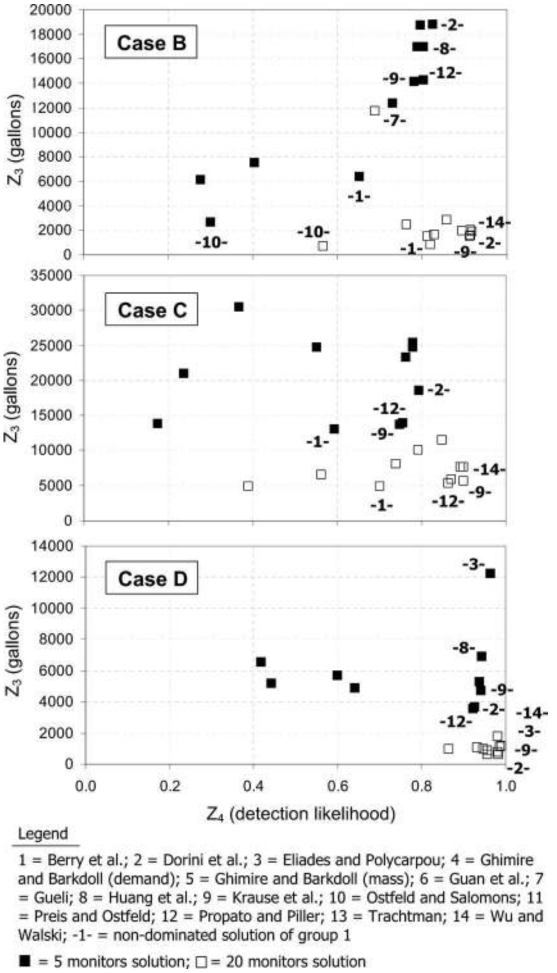

Fig. 8. Network 1: Z_3 versus Z_4 for Cases B, C, and D

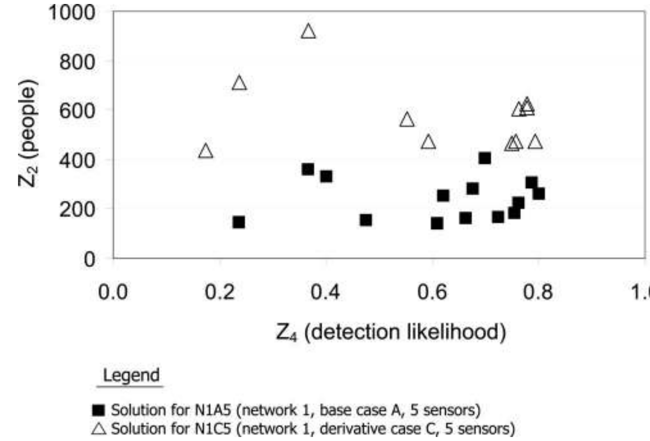

Fig. 9. Network 1: Z_2 versus Z_4 for N1A5 and N1C5

this pathology does not exist. A small incident that does not spread has small impact, no matter how long the simulation is run. Therefore, it does not disproportionately affect the solution. It is noted that including nondetections in this case would be desirable. In effect, doing so would improve Z_4 without requiring an explicit multiobjective solution. However, in the interest of a "clean" design of experiments, and noting that Z_1 does not make sense in the context of nondetections, it was chosen to evaluate Z_1, Z_2, and Z_3 without considering nondetections, and to challenge multiple objective solvers with the addition of Z_4 as a separate objective.

System's Properties

The experimental design in the BWSN was constrained by limitations on available datasets. Despite the size of Network 2, which is considered in this study as a complicated system, it is a fairly simple network that has properties unlike those of more complex networks. Some research teams on this proposal (e.g., Berry et al., 2006) have experience with the latter, and point out that these can be more challenging for sensor placement algorithms.

One example of a property that both Networks 1 and 2 share, but more complex networks might not, is that the average plume size over the possible set of injections was very small. This is due to the relatively simple structure of these network models, which have few pumps and a largely homogeneous flow pattern over a 24-h period. A simple analysis of the plume extent showed that the average injection in Network 2 contaminated roughly 2% of the network, and in fact, many injections contaminated closer to 0.2% of the network. Furthermore, these injections of small extent ware usually independent of the injection time since flow patterns did not change drastically from one time to the next. In a

Table 3. Network 2, Case A: Five Sensor (N2A5) Solutions

Reference	Sensor locations (nodes)	Z_1 (min)	Z_1 (people)	Z_1 (gal)	Z_1 (detection likelihood)
Berry et al. (2006)	3,357; 4,684; 10,874; 11,184; 11,304	789	1,515	95,403	0.259
Dorini et al. (2006)	636; 3,585; 4,684; 9,364; 10,387	1,285	2,393	221,461	0.303
Eliades and Polycarpou (2006)	532; 1,486; 3,357; 4,359; 4,609	1,249	2,560	251,856	0.299
Ghimire and Barkdoll (2006a,b)	9,271; 1,486; 4,482; 5,585; 4,609	1,243	2,757	310,672	0.103
Guan et al. (2006)	321; 3,770; 4,084; 4,939; 7,762	795	1,731	119,219	0.227
Huang et al. (2006)	3,355; 5,088; 5,430; 9,005; 9,550	940	2,372	203,215	0.227
Krause et al. (2006)	10,874; 4,684; 11,304; 3,357; 11,184	789	1,515	95,403	0.259
Ostfeld and Salomons (2006)	5,039; 4,646; 1,515; 3,234; 5,541	1,443	2,605	270,496	0.285
Preis and Ostfeld (2006)	871; 1,917; 2,024; 4,115; 4,247	825	1,739	123,344	0.173
Trachtman (2006)	5,420; 542; 12,505; 12,514; 12,509	1,759	4,968	650,176	0.126
Wu and Walski (2006)	3,709; 4,957; 6,583; 8,357; 9,364	1,189	2,590	249,710	0.310

Table 4. Network 2, Case A: 20 Sensors (N2A20) Solutions

Reference	Sensor locations (nodes)	Z_1 (min)	Z_1 (people)	Z_1 (gal)	Z_1 (detection likelihood)
Berry et al. (2006)	636; 1,917; 3,357; 3,573; 3,770; 4,132; 4,240; 4,594; 5,114; 6,583; 6,700; 7,652; 8,999; 9,142; 9,722; 10,614; 10,874; 11,177; 11,271; 12,258	540	548	17,456	0.366
Dorini et al. (2006)	647; 928; 1,478; 1,872; 2,223; 2,848; 3,573; 4,650; 5,076; 5,366; 6,835; 7,422; 8,336; 8,402; 9,204; 9,364; 10,874; 11,271; 11,528; 12,377	915	1,325	90,255	0.401
Eliades and Polycarpou (2006)	532; 1,426; 1,486; 1,976; 3,231; 3,679; 3,836; 4,234; 4,359; 4,609; 5,087; 5,585; 6,922; 7,670; 7,858; 8,629; 9,360; 9,787; 10,885; 12,167	1,108	1,600	121,574	0.409
Ghimire and Barkdoll (2006a,b)	9,271; 1,486; 4,482; 5,585; 4,609; 4,359; 9,787; 532; 5,953; 12,341; 4,808; 4,662; 4,638; 3,864; 1,667; 3,806; 1,590; 7,858; 9,303; 12,220	1,090	1,924	189,281	0.300
Guan et al. (2006)	174; 311; 1,486; 1,905; 2,589; 2,991; 3,548; 3,757; 3,864; 4,184; 4,238; 5,091; 6,995; 7,145; 7,689; 8,826; 9,308; 9,787; 10,614; 12,086	645	966	43,585	0.308
Huang et al. (2006)	73; 108; 1,028; 1,112; 1,437; 2,526; 3,180; 4,036; 4,648; 5,363; 5,826; 5,879; 6,581; 8,439; 8,580; 8,841; 9,363; 9,616; 10,216; 10,385	829	1,264	78,533	0.342
Krause et al. (2006)	10,874; 4,684; 11,304; 3,357; 11,184; 1,478; 9,142; 1,904; 4,032; 9,364; 4,240; 4,132; 3,635; 2,579; 3,836; 6,700; 8,999; 3,747; 8,834; 3,229	665	699	27,458	0.397
Ostfeld and Salomons (2006)	2,872; 4,319; 4,782; 3,281; 8,766; 3,712; 11,184; 4,433; 22; 11,623; 8,560; 3,129; 9,785; 8,098; 10,734; 6,738; 7,428; 611; 7,669; 7,500	1,093	1,554	109,931	0.384
Trachtman (2006)	5,420; 542; 12,505; 12,514; 12,509; 7,962, 7,469; 8,617; 3,070; 3,180; 11,314; 12,237; 6,390; 12,135; 1,795; 5,089; 4,892; 10,917; 3,817; 10,211	913	1,555	116,922	0.217
Wu and Walski (2006)	871; 1,334; 2,589; 3,115; 3,640; 3,719; 4,247; 4,990; 5,630; 6,733; 7,442; 7,714; 8,387; 8,394; 9,778; 10,290; 10,522; 10,680; 11,151; 11,519	850	1,353	77,312	0.420

complex network with many pressure zones, both the expected plume size and the behavior of injections beginning at different times can be quite unlike those of Network 2.

Conclusions

This paper provides a summary of the BWSN (Ostfeld et al. 2006), the goal of which was to objectively compare the solutions obtained using different approaches to the problem of sensor placement in water distribution systems.

Participants were requested to place five and 20 sensors for two real water distribution systems of increasing complexity and for four derivative cases, taking into account four design objectives: (1) minimization of the expected time of detection (Z_1); (2) minimization of the expected population affected prior to detection (Z_2); (3) minimization of the expected demand of contaminated water prior to detection (Z_3), and (4) maximization of the detection likelihood (Z_4). Fifteen contributions were received from academia and practitioners, spanning a range of approaches and computational methods ranging from pure heuristic engineering judgment to sophisticated mathematical optimization algorithms.

As the BWSN evolved, it became clear that the problem of sensor placements is multiobjective. As only compromised nondominated solutions can be defined in a multiobjective space, determination of the "best" received solution was not possible, but this assessment provided indications of breadth and similarity of findings, as desired using different mathematical algorithms.

From a practical perspective, the most practical conclusion that can be drawn is that general guidelines cannot be set. Engineering judgment and intuition alone are not sufficient for effectively placing sensors. Both engineering judgment and intuitive processes need to be supported by quantitative analysis. The analysis on both examples has shown that sensors do not need to be clustered and that placing sensors at vertical assets (sources, tanks, and pumps) is not a necessity. In fact, most of the designs have not placed sensors at vertical assets. In some cases (e.g., see Fig. 3), there were considerable similarities where the same nodes (or nodes at a immediate vicinity) were selected by many of the methodologies.

Future Research Directions

The BWSN highlighted the following issues that need further consideration and research efforts:

Contamination Warning Systems Evaluation

For Network 1 the full event matrix (i.e., all possible injection times and locations) was utilized for one possible injection (Derivative Cases A, B, and C). For Network 2, the 25,054 random events matrix generated for Testing Case A was only a small portion of the entire space of possible injection events. Hence, generation of different event matrices will likely produce

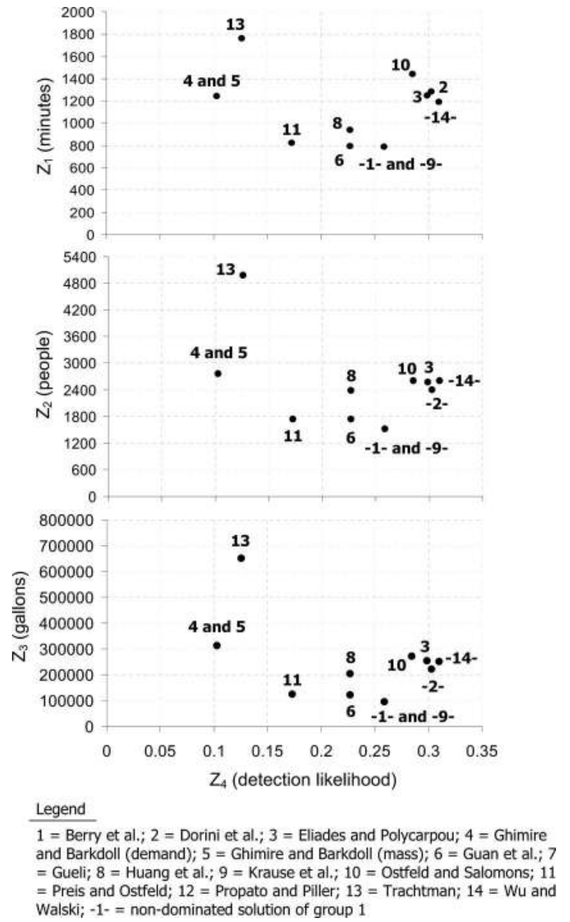

Fig. 10. Network 2, Case A: 5 sensors (N2A5) tradeoff solution curves

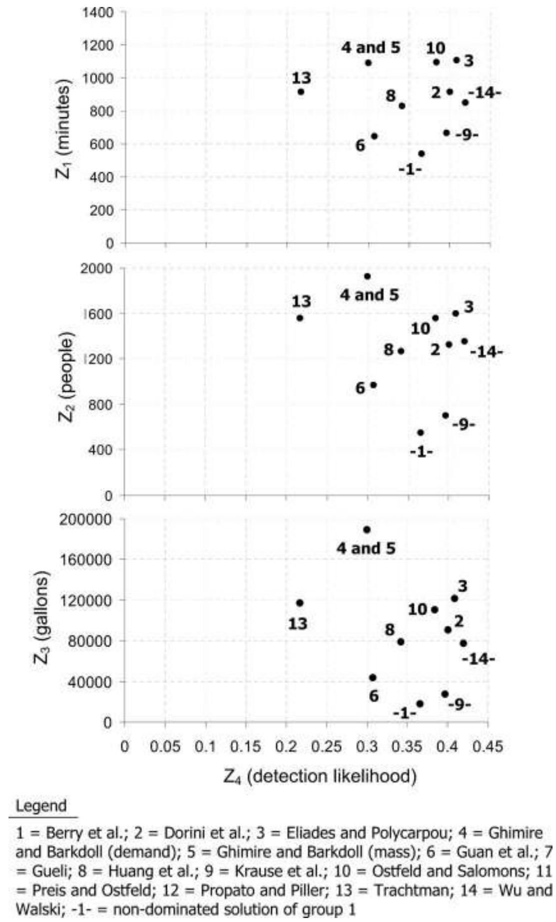

Fig. 11. Network 2, Case A: 20 sensors (N2A20) tradeoff solution curves

different solutions. For Network 2 the research challenge is to identify procedures by which efficient sampling from the entire set of contamination events can be computed for a rare subset (i.e., a subset of events with a small probability to occur, but with an extreme impact), which will provide an "upper bound" (i.e., worst-case estimation) for contamination warning system evaluations.

Aggregation

Because the sensor placement problem rapidly becomes too complex to explore thoroughly, there would be great merit in developing a water-quality aggregation algorithm that can construct an "equivalent" but reduced network of a water distribution system, containing fewer nodes and links but matching both the hydraulics and the water quality of the original system.

Multiobjective Optimization

The study identified some correlations between objectives, and these correlations should inform future studies. In particular, the objectives Z_1, Z_2, and Z_3 are positively correlated with one another, and are negatively correlated with Z_4. Stopping the damage from the average injection more quickly tends to decrease the population infected and the volume of contaminated water consumed, while maximizing the detection probability tends to generate more conservative sensor placements that tolerate slow detections. A greater multiobjective challenge for the future would be to select only one of Z_1, Z_2, and Z_3, and then to compare the selection of representative "quick detection" to Z_4, and possibly with objectives not closely related to either.

Selection of Number of Sensors

Since sensors involve significant capital and operational expenditures, research is needed to identify the marginal returns for additional sensors as guidance in establishing the number of sensors appropriate, for different water distribution networks.

Dual Use of Sensors

Sensors should comply with dual use benefits. Sensor locations and types should be integrated not only for achieving water security goals but also for accomplishing other water utility objectives, such as satisfying regulatory monitoring requirements or collecting information to solve water quality problems. Such an objective would be particularly interesting and likely to be highly correlated with security objectives.

Criteria for Identifying Areas of Higher Risk of Threat and Protection

In assessments to date, equal likelihoods of threat and need for protection have been employed. The reality is that particular em-

Table 5. Summary of Number of Nondominated Solutions

Reference	Network 1								Network 2		
	N1A5	N1A20	N1B5	N1B20	N1C5	N1C20	N1D5	N1D20	N2A5	N2A20	Total
Berry et al. (2006)	2	3	2	3	2	3			3	3	21
Dorini et al. (2006)	3	2	3	2	3		2	3	2		20
Eliades and Polycarpou (2006)	1	1	1	1		1	3	3			11
Ghimire and Barkdoll (2006a)			1		1						2
Ghimire and Barkdoll (2006)	1		1				1				3
Guan et al. (2006)	2	2									4
Gueli (2006)			1			1					2
Huang et al. (2006)	1		2		1		3				7
Krause et al. (2006)	2	2	2	2	3	3	3	3	3	3	26
Ostfeld and Salomons (2006)	1	1	3	2	2	2	1	2			14
Preis and Ostfeld (2006)	1										1
Propato and Piller (2006)	2		3		3	2	2				12
Trachtman (2006)	1				1	1					3
Wu and Walski (2006)	1	3		3	1	3	1	2	3	3	20
Total	18	14	19	13	17	16	16	13	11	9	146

Note: N1=Network 1; N2=Network 2; A, B, C, and D=base case; and 5 and 20=number of sensors.

phasis should be given to areas of greater threat and, equally likely, areas of likely greater need for protection, and methods to improve prioritization are definitely warranted.

Inclusion of Risk

In the BWSN, the assessments for the four design objectives were completed on the basis of expected values. There is substantial merit in considering risk inclusion as opposed to expected value. A sensor design should comply with its associated risk.

Sensor Reliability

In reality, the correct functioning of sensors is not guaranteed; both false positive and false negative rates need to be considered. The challenge is to develop methodologies for incorporating the uncertainty of sensor detections as part of the design process for sensor layouts and the extent to which action can be taken before there is confirmation that there is, indeed, a contaminant event.

Incorporation of Operational Conditions

Once sensors are placed they should address different operational conditions and account for problems such as providing data for identifying the location of the contaminant intrusion, and for implementing a containment procedure. Methodologies should be developed for incorporating in one framework both design and operational objectives.

Acknowledgments

The contributions of Alzamora and Ayala (2006) and Guan et al. (2006), and the verification of solution accuracy by Dr. Zheng Wu, are gratefully acknowledged.

Notation

The following symbols are used in the paper:

C = hazard concentration threshold (mg/L);
c_{ik} = contaminant concentration for node i and time step k (mg/L);
D_{50} = dose that would result in a 0.5 probability of becoming infected or symptomatic (mg/kg);
d_r = detection flag for the rth contamination scenario, receiving 1 if the rth contamination scenario is detected, and zero otherwise;
$E(P_a)$ = mathematical expectation of the affected population P_a;
$E(t_d)$ = mathematical expectation of the minimum detection time t_d;
$E(V_d)$ = mathematical expectation of V_d;
M_i = mass ingested—prior to detection—by any individual at network node i (mg);
N = number of evaluation time steps prior to detection;
P_a = population affected for a particular contamination scenario;
P_i = population assigned to node i;
$\bar{q}_i$ = average water demand at node i;
q_{ik} = water demand for time step k and node i;
R_i = probability $[0, 1]$ that a person who ingests contaminant mass M_i will become infected or symptomatic;
S = total number of contamination scenarios considered for computing Z_4;
t_d = minimum sensors detection time;
t_j = time of first detection at the jth sensor location;
V = total number of nodes (for calculating Z_2);
V_d = total volumetric water demand that exceeds a predefined hazard concentration;
W = assumed (average) body mass (kg/person);
Z_1 = expected time of detection;
Z_2 = expected population affected prior to detection;

Z_3 = expected volume of consumed contaminated water prior to detection;
Z_4 = detection likelihood;
β = probit slope parameter (unitless);
Δt = evaluation time step (days);
Φ = standard normal cumulative distribution function;
φ = mean amount of water consumed by an individual (L/day/person); and
ρ_{ik} = dose rate multiplier for node i and time step k (unitless).

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