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

By

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Abstract

Following the events of 9/11 2001 in the US, 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 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, U.S.A., August 27-29, 2006. This manuscript summarizes the outcome of the BWSN effort and suggests future directions for water sensor networks research and implementation.

Introduction

Since the early days of King Hezekiah (late 8th - early 7th century 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 along history with diverse intensities (Gleick, 1998).

Related water terrorist activities were reported in ancient Rome, in the US during the 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 the other, 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 8th Annual Water Distribution Systems Analysis Symposium, Cincinnati, Ohio, U.S.A., 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 manuscript 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 non-zero contaminant concentration. The time of first detection, t_j, refers to the j-th 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:

$$M_i = \varphi \, \Delta t \sum_{k=1}^{N} c_{ik} \, \rho_{ik} \qquad (3)$$

where φ is the mean amount of water consumed by an individual (Liters/day/person), Δt is the evaluation time step (days), c_{ik} is the contaminant concentration for node i and time step k (mg/Liter), ρ_{ik} is a "dose rate multiplier" (Murray et al., 2006) for node i and time step k (unitless), and N is the number of evaluation time steps prior to detection, i.e., the largest integer such that $N\Delta t \leq t_d$. The series ρ_{ik}, k = 1,…,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:

$$\rho_{ik} = q_{ik} \, / \, \overline{q}_i \qquad \forall \, k \in N \qquad (4)$$

where q_{ik} is the water demand for time step k and node i, and $\overline{q}_i$ is the 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):

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

where R_i is the probability [0, 1] that a person who ingests contaminant mass M_i will become infected or symptomatic, β is the so-called Probit slope parameter (unitless), W is the assumed (average) body mass (kg/person), D_{50} is the dose that would result in a 0.5 probability of becoming infected or symptomatic (mg/kg), and Φ is the Standard Normal Cumulative Distribution Function.

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

$$P_a = \sum_{i=1}^{V} R_i\ P_i \qquad (6)$$

where P_i is the population assigned to node i, and V is the 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:

$$Z_2 = E\ (P_a) \qquad (7)$$

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 is the expected volume of contaminated water consumed prior to detection:

$$Z_3 = E\ (V_d) \qquad (8)$$

where V_d denotes the total volumetric water demand that exceeds a predefined hazard concentration threshold C, and $E\ (V_d)$ is the 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 equals 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 hours for the small network, 48 hours 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, though 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 that addresses future research needs.

Design assumptions and cases

Participants were asked to provide designs for locating five sensors and twenty sensors for a base case (A) and three derivative cases (B, C, and D) using EPANET version 2.00.10 (USEPA, 2002). The four cases are described below.

Base Case (A)

1. All quantities affecting network model water quality predictions are assumed to be known and deterministic. Sensor network designs will be challenged by an ensemble of contamination scenarios sampled from a statistical distribution; the probability distribution of contamination events is described herein. Contaminant intrusions occur at network nodes, with an injection flow rate of 125 (Liter/hr), contaminant concentration of 230,000 (mg/L), and injection duration of 2 (hrs). The contaminant is assumed conservative after injection. Each contamination scenario involves 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 are evaluated using a five minute time step.

2. For purposes of calculating the expected population affected prior to detection (Z_2): $\varphi = 2$ (Liters/day), $\beta = 0.34$ (-), D50 = 41 (mg/kg), W = 70 (kg). For purposes of estimating node population, the total per capita water demand rate is assumed to be 300 (Liters/day).

3. For purposes of calculating the expected demand of contaminated water prior to detection (Z_3), the hazard concentration threshold is C = 0.3 (mg/Liter).

4. Sensors instantly detect any non-zero contaminant concentration and action is taken to eliminate further exposure without delay.

Derivative Case (B)

Identical to base case (A) except that the injection duration is increased to 10 (hrs).

Derivative Case (C)

Identical to base case (A) except that the response delay is 3 (hrs), i.e., it takes 3 (hrs) after detection for emergency response to limit contaminant exposure.

Derivative Case (D)

Identical to base case (A) except that all contamination scenarios involve 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 are synchronized to begin at the same time.

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 adopted 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, 2006b) suggested a heuristic demand-based approach in which sensors are 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 is that the Z_i (i = 1, 2, 3) objectives are being evaluated against only the scenarios that are 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 Non-Dominated 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) is comprised of 126 nodes, one constant head source, two tanks, 168 pipes, two pumps, eight valves, and is subject to four variable demand patterns. The system was simulated for a total extended period duration of 96 hours.

Network 2 (Fig. 2) has 12523 nodes, two constant head sources, two tanks, 14822 pipes, four pumps, five valves, and is subject to five variable demand patterns. The system was simulated for a total extended period duration of 48 hours.

Both networks are 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 demands, diameters, and elevations). The network's EPANET input files can be downloaded from the Centre for Water Systems at the University of Exeter (ECWS, 2007).

Design results

A methodology for evaluating a given sensors 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., will all be assessed on the same basis. To accomplish this task, a utility was developed by Salomons (2006).

The utility is 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 five minutes, and (2) evaluation of Z_i (i = 1, ..,4) according to the matrix of contamination injection events constructed in stage 1.

The utility was distributed to all participants prior to the 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), compete against the detection likelihood (Z_4), thus the BWSN is inherently a multiobjective problem.

In a multiobjective context the goal is to find, from all the possible feasible solutions, the set of non-dominated solutions, where a non-dominated solution is optimal in the sense that there is no other solution which 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 N1A (Network 1, base case A), N1B, and N1C, the full matrices of 37152 injection events were generated (each node, every five minutes, for an extended period simulation time of 24 hrs), and for N1D - 30000 random events. Each injection event simulation took about 10 sec on an IBM PC 3.2 GHz, 1GB RAM. All matrices used for Networks 1 and 2 can be downloaded from ECWS (2007).

Krause et al. (2006) published node ID numbers for all their solutions to the BWSN networks and scenarios. In the present work, the evaluation is based on junction ID. Thus, Krause et al. (2006) solutions are 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 are 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, 5 sensors), and for 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 non-dominated solutions (Fig. 4) are 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 non-dominated solution obtained by a specific method will likely remain regardless of the objective function used). This is also evident in Fig. 5. An improvement of the results can be inspected when matching Figs. 4 and 5 (i.e., results for systems of five versus twenty 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 twenty 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 increases (derivative case C), the expected population affected prior to detection (Z_2) increases, 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 N2A (Network 2, base case A) a randomized matrix of 25054 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, 1GB 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 N2A5 (Network 2, base case A, five sensors), and for 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 non-dominated, 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 non-dominated 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 are different.

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

The BWSN results do not support the assumption that case A 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, are 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

Non-detect events

The evaluation of sensor design is 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 is 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 "non-detection." In a large ensemble of potential incidents in a sizable network protected by a small number of sensors, occasions of non-detections are inevitable. A decision should be made whether or not to include the impact of these non-detections 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 which do not permeate the network and are never detected. When the impact of these non-detections are included in the calculation of the Z_1 objective, non-intuitive behavior ensues. Specifically, recalling that the analysis depends on extended period simulations, note that the impact of non-detections is very severe and dwarfs that of detections. Optimizing for minimum time to detection in the presence of non-detections means avoiding non-detections 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 non-intuitive behavior, it was decided to not include non-detections in the evaluation of objective Z_1.

The situation is different for Z_2, the population exposed. In the discussion above, it is shown that non-detections in the periphery of the system with very small real impact, are penalized severely in terms of the time to detection Z_1, and can trick optimizers

into selecting nonsensical solutions. With Z_2, however, 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 non-detections 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 non detections, it was chosen to evaluate Z_1, Z_2, and Z_3 without considering non-detections, 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 Network 1 and Network 2 share, but more complex networks might not, is that the average plume size over the possible set of injections is 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 hour period. A simple analysis of the plume extent shows that the average injection in Network 2 contaminates roughly 2% of the network, and in fact, many injections contaminate closer to 0.2% of the network. Furthermore, these injections of small

extent are usually independent of the injection time since flow patterns do not change drastically from one time to the next. In a 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 manuscript provides a summary of the Battle of the Water Sensors (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 twenty 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 non-dominated solutions can be defined in a multiobjective space, determination of the "best" received solution is not possible, but this assessment provides 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 immediate vicinity) were selected by many of the methodologies.

Future research directions

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

(1) *Contamination warning systems (CWS) 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 25054 random events matrix generated for testing case A is only a small portion of the entire space of possible injection events. Hence, generation of different event matrices will likely produce 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 sub-set (i.e., a sub-set 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.

(2) *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.

(3) *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.

(4) *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.

(5) *Dual use of sensors.* Sensors should comply with dual use benefits. Sensors location and type 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.

(6) *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 emphasis 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.

(7) *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.

(8) *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 sensors layout and the extent to which action can be taken before there is confirmation that there is indeed a contaminant event.

(9) *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.

Acknowledgements

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Appendix I: References

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Appendix II: Notation

The following symbols are used in this paper:

C = hazard concentration threshold (mg/L),

c_{ik} = contaminant concentration for node i and time step k (mg/Liter),

D_{50} = the dose that would result in a 0.5 probability of becoming infected or symptomatic (mg/kg),

d_r = a detection flag for the r-th contamination scenario, receiving 1 if the r-th contamination scenario is detected, and zero otherwise,

$E(P_a)$ = the mathematical expectation of the affected population P_a,

$E(t_d)$ = the mathematical expectation of the minimum detection time t_d,

$E(V_d)$ = the 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 = the population assigned to node i,

$\overline{q}_i$ = the average water demand at node i,

q_{ik} = the water demand for time step k and node i,

R_i = the 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 j-th 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 = the Standard Normal Cumulative Distribution Function,

φ = mean amount of water consumed by an individual (Liters/day/person), and

ρ_{ik} = a "dose rate multiplier" for node i and time step k (unitless).

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Authors	Sensor locations (nodes)	Z_1 (minutes)	Z_2 (people)	Z_3 (gallons)	Z_4 (detection likelihood)
Berry et al.	17, 21, 68, 79, 122	542	140	2459	0.609
Dorini et al.	10, 31, 45, 83, 118	1068	258	7983	0.801
Eliades and Polycarpou	17, 31, 45, 83, 126	912	221	7862	0.763
Ghimire and Barkdoll (demand)	126, 30, 118, 102, 34	432	357	4287	0.367
Ghimire and Barkdoll (mass)	126, 30, 102, 118, 58	424	331	3995	0.402
Guan et al.	17, 31, 81, 98, 102	642	159	2811	0.663
Gueli	112, 118, 109, 100, 84	794	403	10309	0.699
Huang et al.	68, 81, 82, 97, 118	541	280	4465	0.676
Krause et al.	17, 83, 122, 31, 45	842	181	3992	0.756
Ostfeld and Salomons	117, 71, 98, 68, 82	461	250	4499	0.622
Preis and Ostfeld	68, 101, 116, 22, 46	439	151	7109	0.477
Propato and Piller	17, 22, 68, 83, 123	711	164	3148	0.725
Trachtman	1, 29, 102, 30, 20	391	142	2504	0.237
Wu and Walski	45, 68, 83, 100, 118	704	303	8406	0.787

Table 1

Authors	Sensor locations (nodes)	Z_1 (minutes)	Z_2 (people)	Z_3 (gallons)	Z_4 (detection likelihood)
Berry et al.	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.	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	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 (demand)	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 (mass)	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.	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	112, 1, 103, 24, 21, 102, 35, 19, 116, 85, 61, 73, 114, 31, 7, 8, 64, 28, 93, 124	226	88	1181	0.577
Huang et al.	8, 11, 42, 46, 52, 68, 70, 75, 76, 82, 83, 95, 97, 99, 100, 109, 111, 117, 123, 126	375	148	1799	0.849
Krause et al.	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	68, 5, 40, 65, 51, 69, 88, 89, 22, 72, 34, 71, 53, 112, 63, 78, 122, 28, 118, 97	198	115	1039	0.647
Propato and Piller	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	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	10, 12, 19, 21, 34, 35, 40, 45, 68, 75, 80, 83, 98, 100, 102, 114, 118, 123, 124, 126	370	142	1158	0.901

Table 2

Authors	Sensor locations (nodes)	Z_1 (minutes)	Z_2 (people)	Z_3 (gallons)	Z_4 (detection likelihood)
Berry et al.	3357, 4684, 10874, 11184, 11304	789	1515	95403	0.259
Dorini et al.	636, 3585, 4684, 9364, 10387	1285	2393	221461	0.303
Eliades and Polycarpou	532, 1486, 3357, 4359, 4609	1249	2560	251856	0.299
Ghimire and Barkdoll (demand, and mass)	9271, 1486, 4482, 5585, 4609	1243	2757	310672	0.103
Guan et al.	321, 3770, 4084, 4939, 7762	795	1731	119219	0.227
Huang et al.	3355, 5088, 5430, 9005, 9550	940	2372	203215	0.227
Krause et al.	10874, 4684, 11304, 3357, 11184	789	1515	95403	0.259
Ostfeld and Salomons	5039, 4646, 1515, 3234, 5541	1443	2605	270496	0.285
Preis and Ostfeld	871, 1917, 2024, 4115, 4247	825	1739	123344	0.173
Trachtman	5420, 542, 12505, 12514, 12509	1759	4968	650176	0.126
Wu and Walski	3709, 4957, 6583, 8357, 9364	1189	2590	249710	0.310

Table 3

Authors	Sensor locations (nodes)	Z_1 (minutes)	Z_2 (people)	Z_3 (gallons)	Z_4 (detection likelihood)
Berry et al.	636, 1917, 3357, 3573, 3770, 4132, 4240, 4594, 5114, 6583, 6700, 7652, 8999, 9142, 9722, 10614, 10874, 11177, 11271, 12258	540	548	17456	0.366
Dorini et al.	647, 928, 1478, 1872, 2223, 2848, 3573, 4650, 5076, 5366, 6835, 7422, 8336, 8402, 9204, 9364, 10874, 11271, 11528, 12377	915	1325	90255	0.401
Eliades and Polycarpou	532, 1426, 1486, 1976, 3231, 3679, 3836, 4234, 4359, 4609, 5087, 5585, 6922, 7670, 7858, 8629, 9360, 9787, 10885, 12167	1108	1600	121574	0.409
Ghimire and Barkdoll (demand, and mass)	9271, 1486, 4482, 5585, 4609, 4359, 9787, 532, 5953, 12341, 4808, 4662, 4638, 3864, 1667, 3806, 1590, 7858, 9303, 12220	1090	1924	189281	0.300
Guan et al.	174, 311, 1486, 1905, 2589, 2991, 3548, 3757, 3864, 4184, 4238, 5091, 6995, 7145, 7689, 8826, 9308, 9787, 10614, 12086	645	966	43585	0.308
Huang et al.	73, 108, 1028, 1112, 1437, 2526, 3180, 4036, 4648, 5363, 5826, 5879, 6581, 8439, 8580, 8841, 9363, 9616, 10216, 10385	829	1264	78533	0.342
Krause et al.	10874, 4684, 11304, 3357, 11184, 1478, 9142, 1904, 4032, 9364, 4240, 4132, 3635, 2579, 3836, 6700, 8999, 3747, 8834, 3229	665	699	27458	0.397
Ostfeld and Salomons	2872, 4319, 4782, 3281, 8766, 3712, 11184, 4433, 22, 11623, 8560, 3129, 9785, 8098, 10734, 6738, 7428, 611, 7669, 7500	1093	1554	109931	0.384
Trachtman	5420, 542, 12505, 12514, 12509, 7962, 7469, 8617, 3070, 3180, 11314, 12237, 6390, 12135, 1795, 5089, 4892, 10917, 3817, 10211	913	1555	116922	0.217
Wu and Walski	871, 1334, 2589, 3115, 3640, 3719, 4247, 4990, 5630, 6733, 7442, 7714, 8387, 8394, 9778, 10290, 10522, 10680, 11151, 11519	850	1353	77312	0.420

Table 4

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

Legend: N1A5 = Network 1, base case A, 5 sensors

Table 5

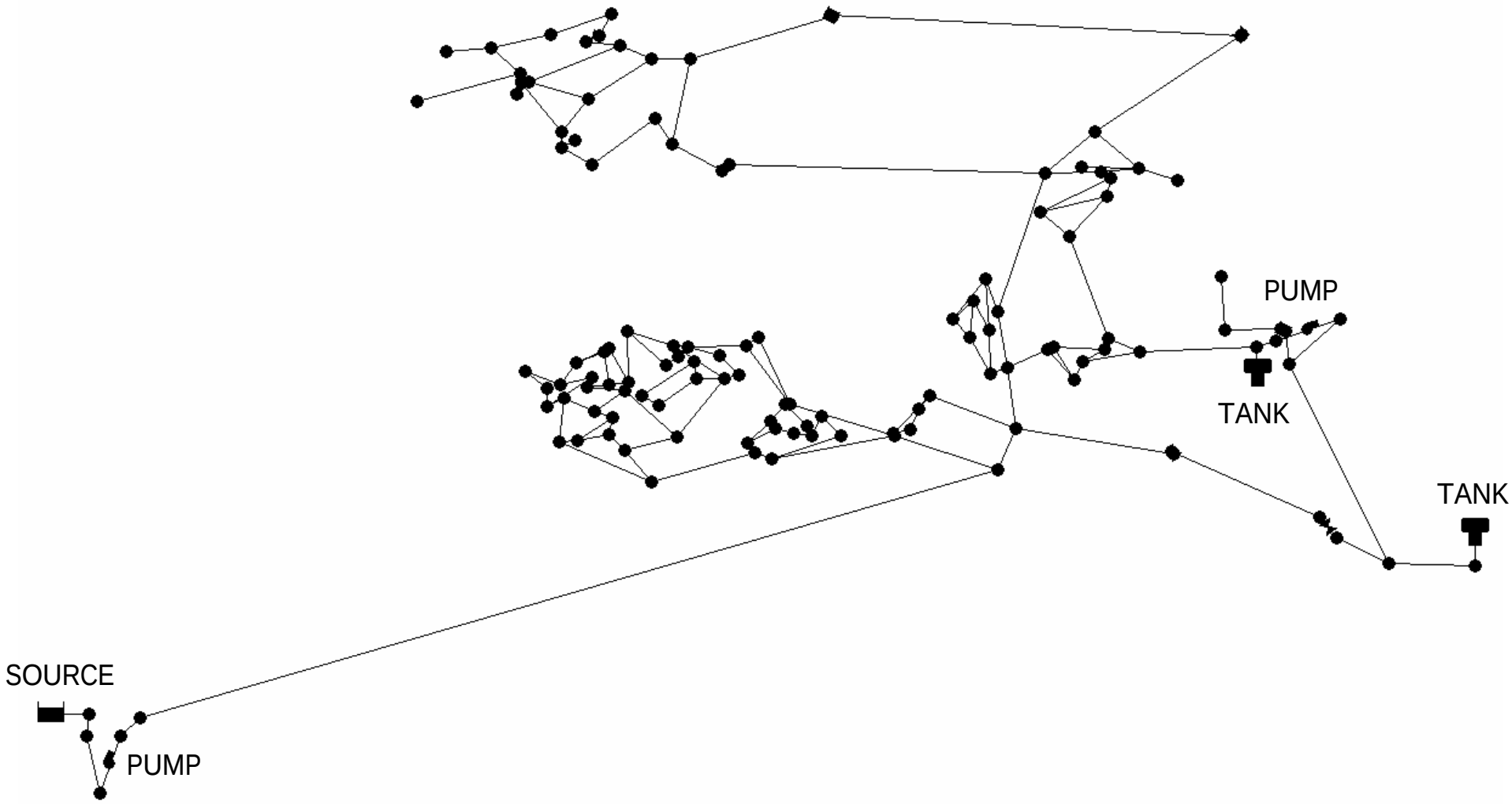


Fig. 1

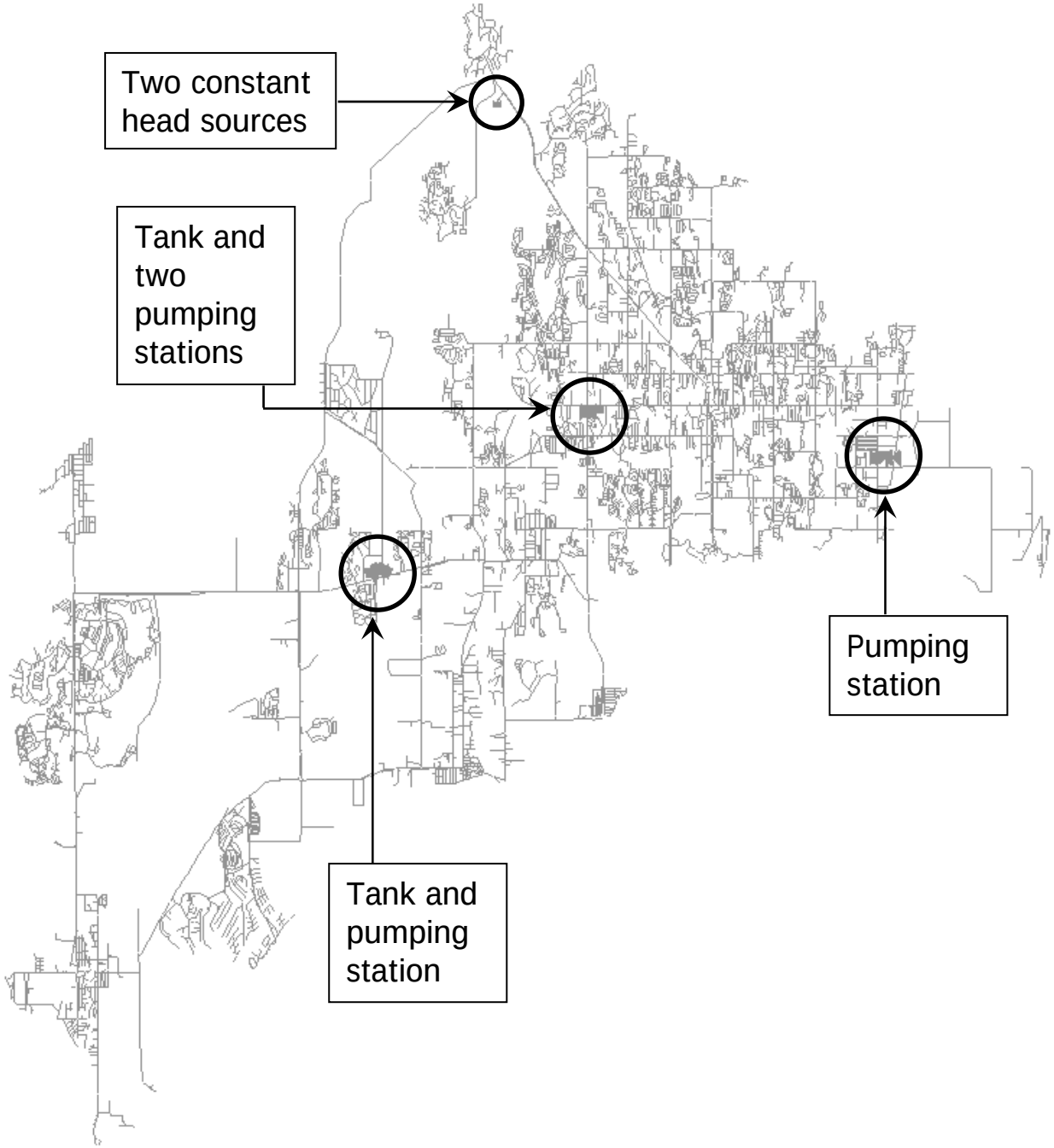

Two constant head sources
Tank and two pumping stations
Pumping station
Tank and pumping station

Fig. 2

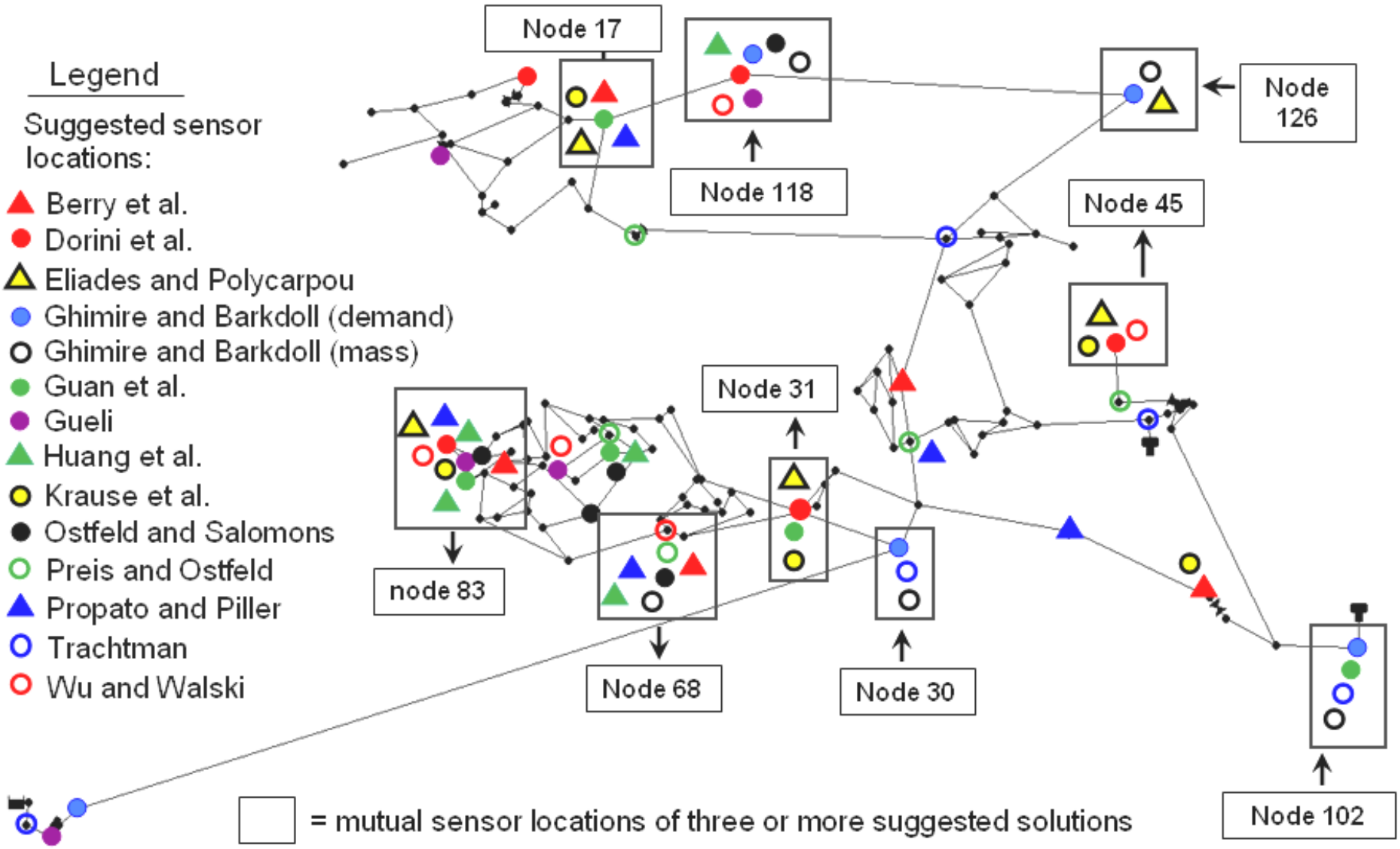
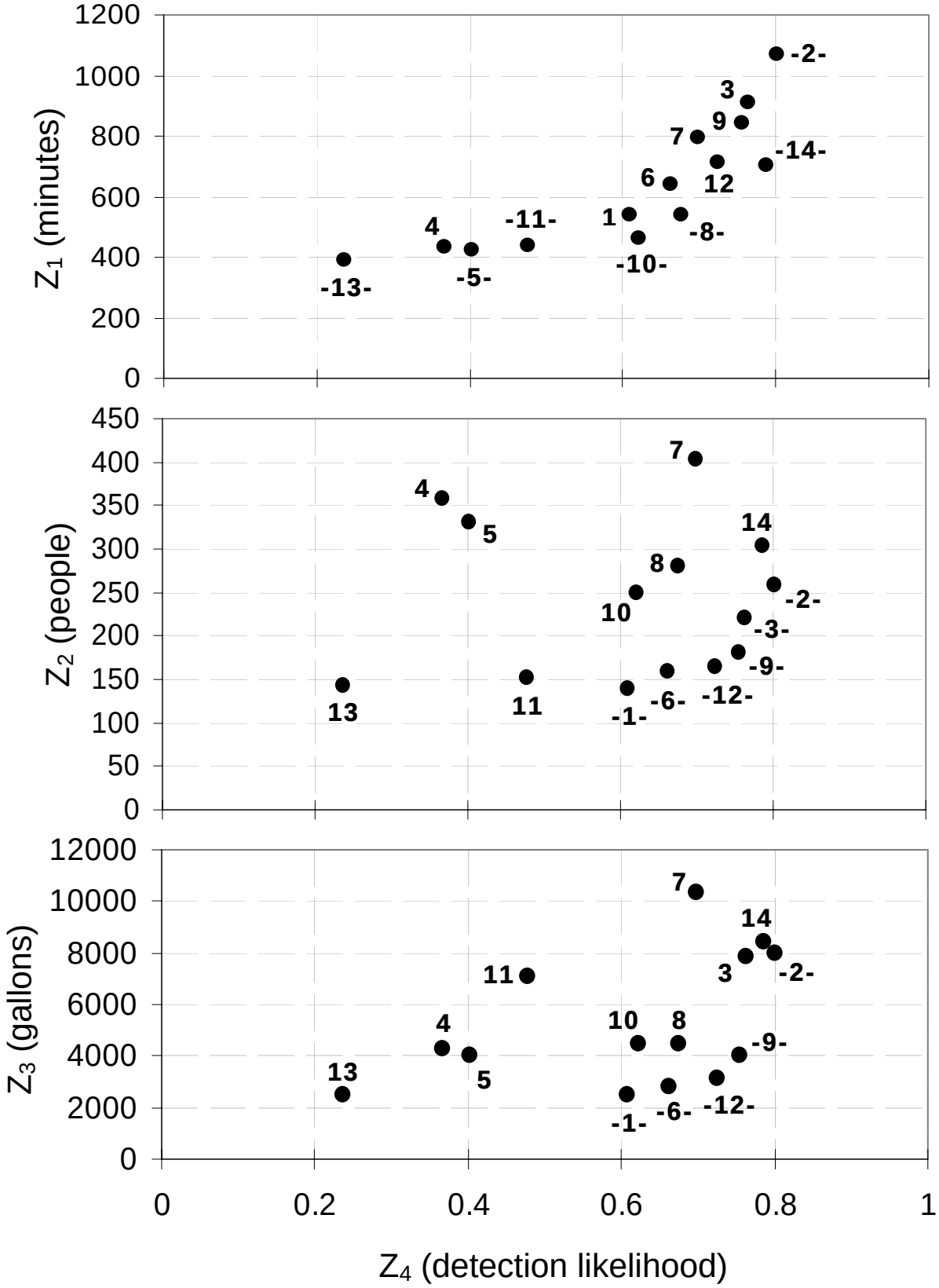

Legend
Suggested sensor locations:
Berry et al.
Dorini et al.
Eliades and Polycarpou
Ghimire and Barkdoll (demand)
Ghimire and Barkdoll (mass)
Guan et al.
Gueli
Huang et al.
Krause et al.
Ostfeld and Salomons
Preis and Ostfeld
Propato and Piller
Trachtman
Wu and Walski
Node 17
Node 118
Node 126
Node 45
Node 31
node 83
Node 68
Node 30
Node 102
= mutual sensor locations of three or more suggested solutions

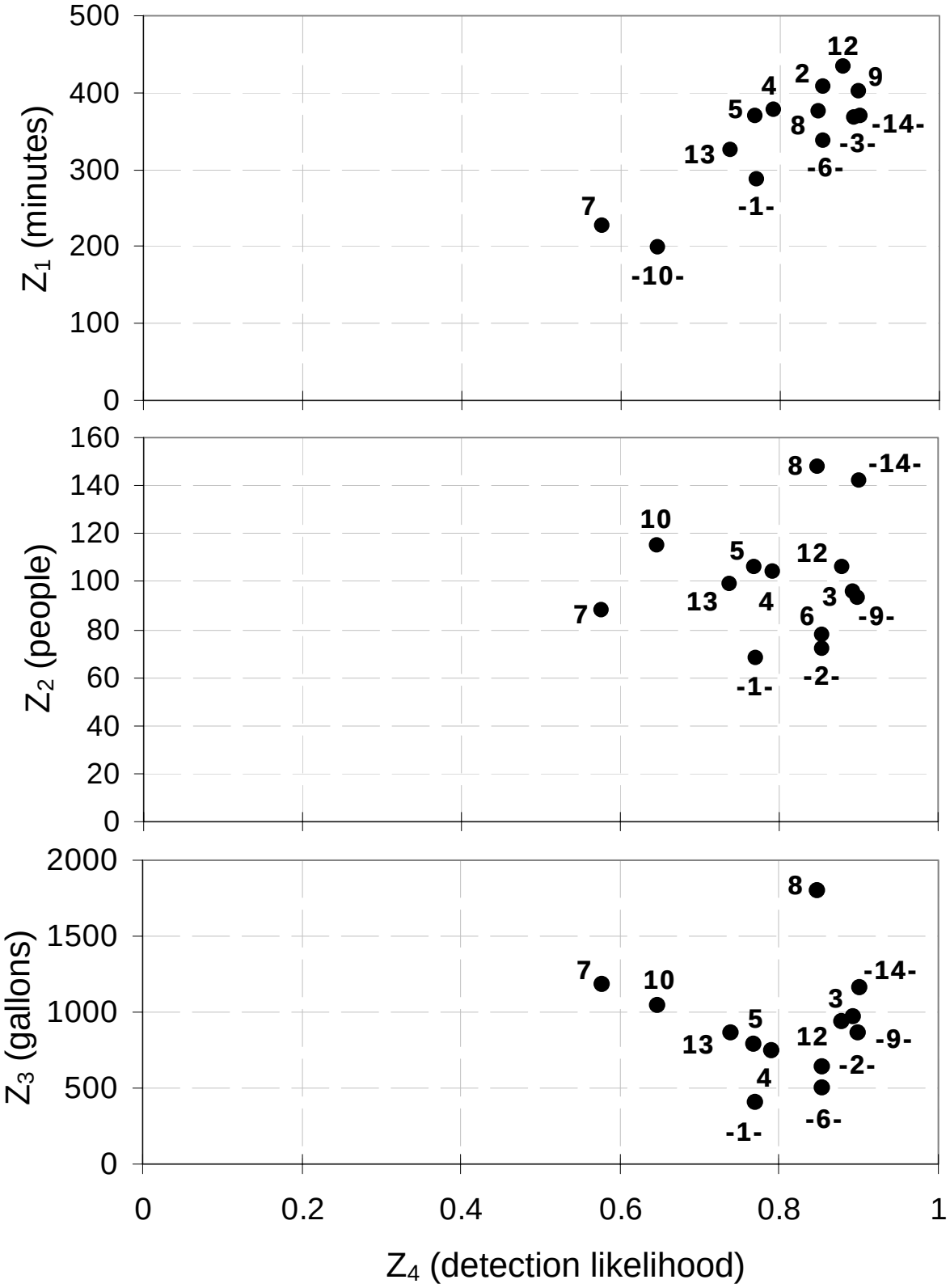
Fig. 3



Legend

1 = Berry et al.; 2 = Dorini et al.; 3 = Eliades and Polycarpou; 4 = Ghimire and Barkdoll (demand); 5 = Ghimire and Barkdoll (mass); 6 = Guan et al.; 7 = Gueli; 8 = Huang et al.; 9 = Krause et al.; 10 = Ostfeld and Salomons; 11 = Preis and Ostfeld; 12 = Propato and Piller; 13 = Trachtman; 14 = Wu and Walski; -1- = non-dominated solution of group 1

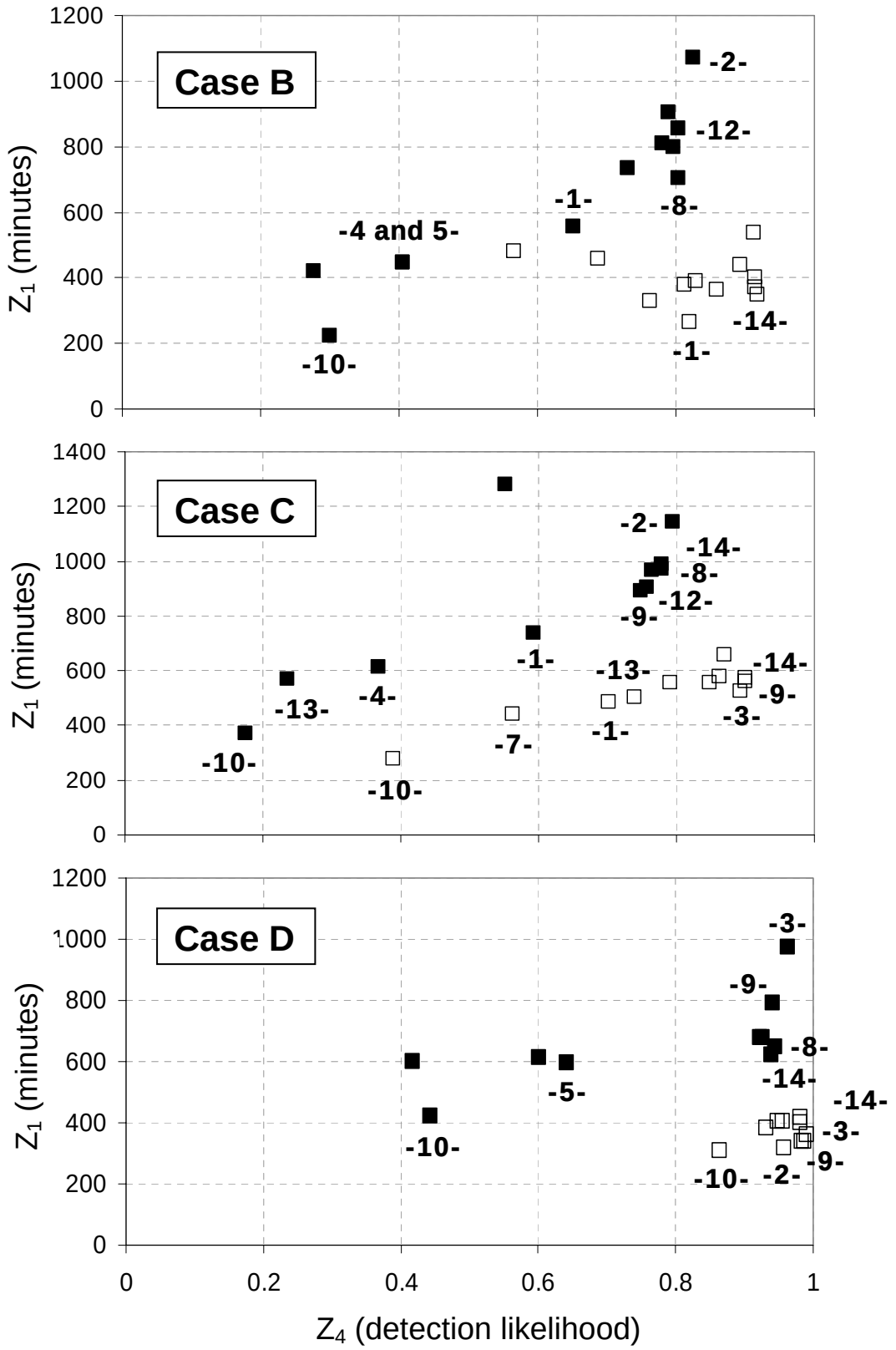
Fig. 4



Legend

1 = Berry et al.; 2 = Dorini et al.; 3 = Eliades and Polycarpou; 4 = Ghimire and Barkdoll (demand); 5 = Ghimire and Barkdoll (mass); 6 = Guan et al.; 7 = Gueli; 8 = Huang et al.; 9 = Krause et al.; 10 = Ostfeld and Salomons; 11 = Preis and Ostfeld; 12 = Propato and Piller; 13 = Trachtman; 14 = Wu and Walski; -1- = non-dominated solution of group 1

Fig. 5

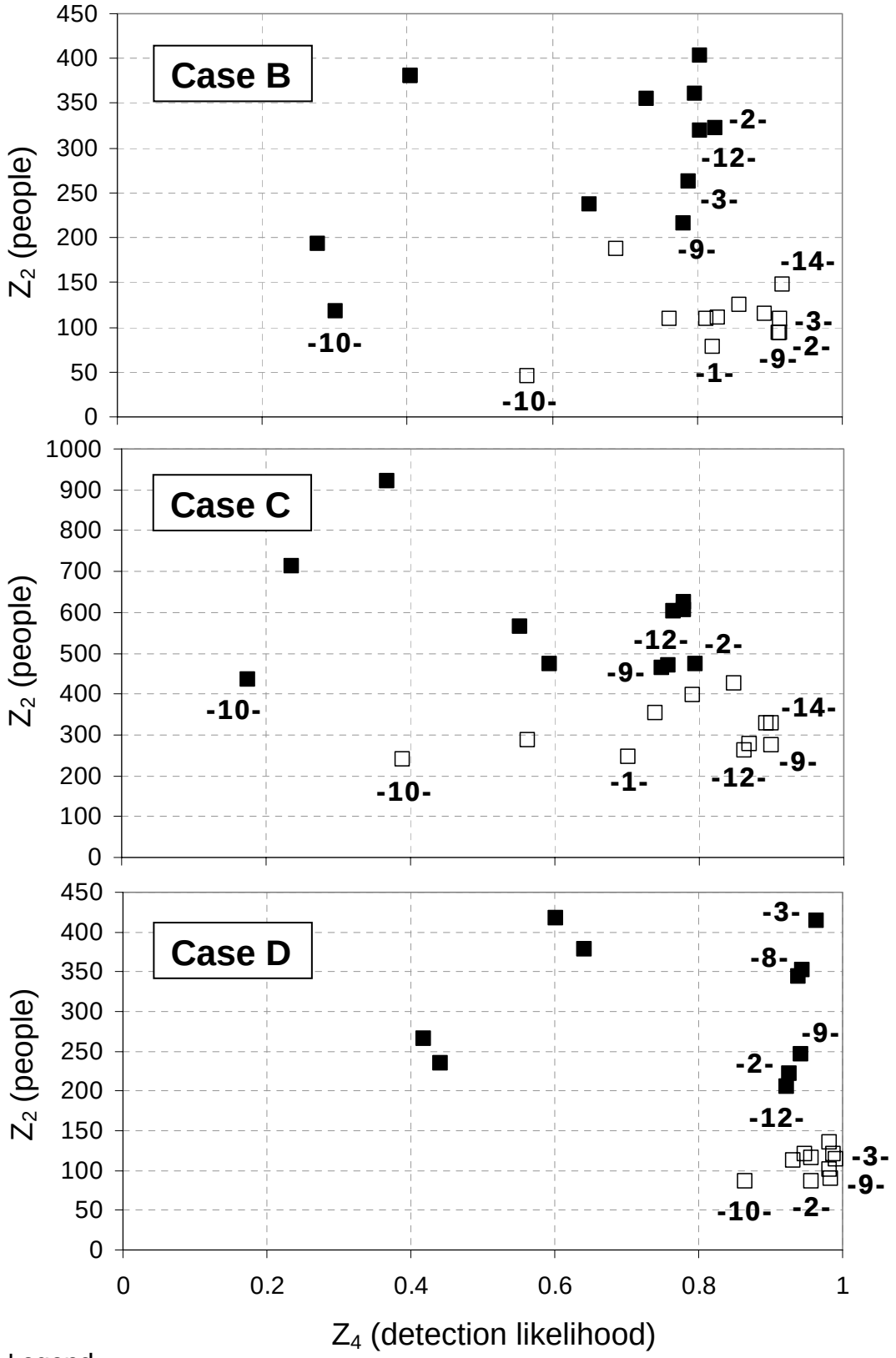


Legend

1 = Berry et al.; 2 = Dorini et al.; 3 = Eliades and Polycarpou; 4 = Ghimire and Barkdoll (demand); 5 = Ghimire and Barkdoll (mass); 6 = Guan et al.; 7 = Gueli; 8 = Huang et al.; 9 = Krause et al.; 10 = Ostfeld and Salomons; 11 = Preis and Ostfeld; 12 = Propato and Piller; 13 = Trachtman; 14 = Wu and Walski; -1- = non-dominated solution of group 1

■ = 5 monitors solution; □ = 20 monitors solution

Fig. 6

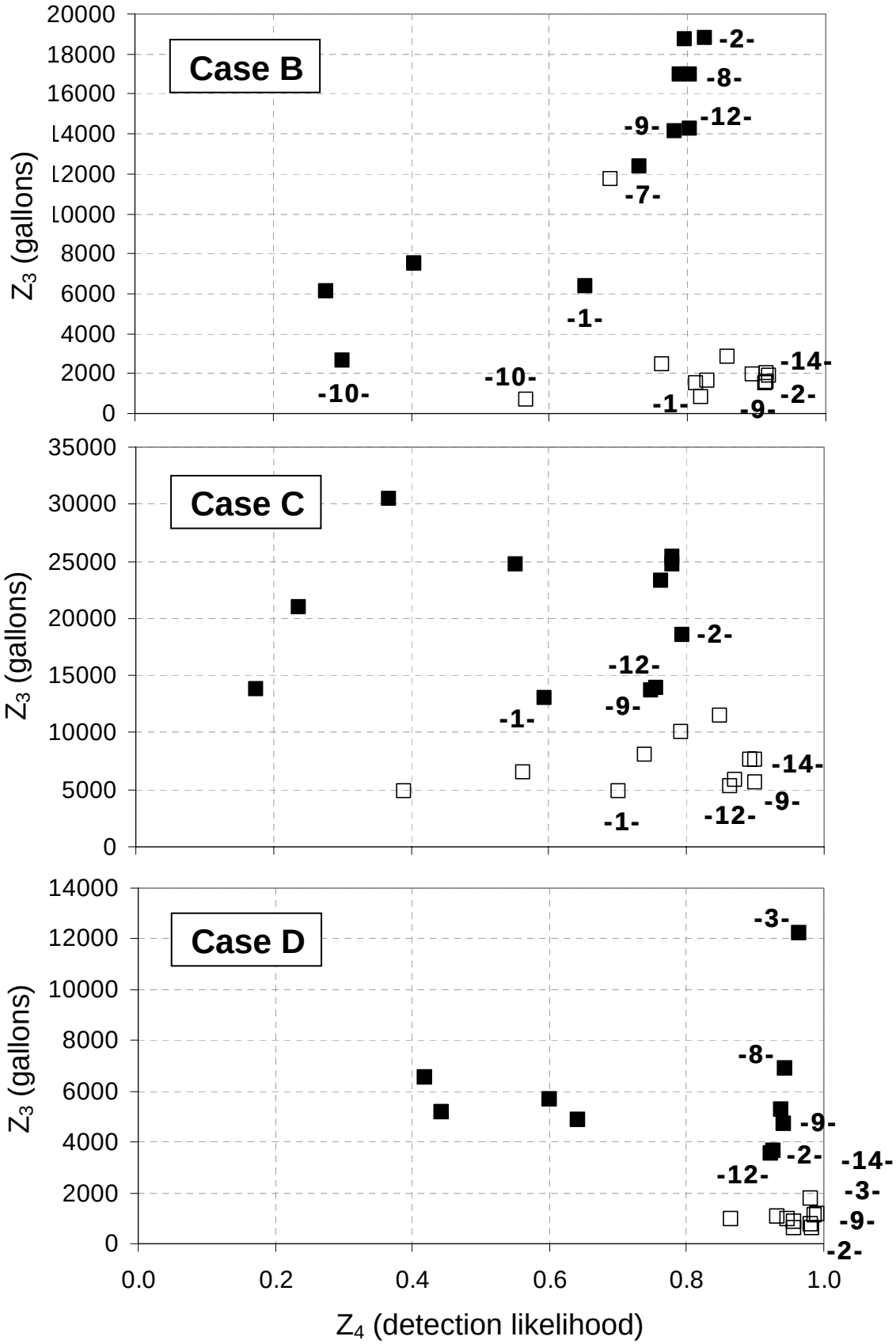


Legend

1 = Berry et al.; 2 = Dorini et al.; 3 = Eliades and Polycarpou; 4 = Ghimire and Barkdoll (demand); 5 = Ghimire and Barkdoll (mass); 6 = Guan et al.; 7 = Gueli; 8 = Huang et al.; 9 = Krause et al.; 10 = Ostfeld and Salomons; 11 = Preis and Ostfeld; 12 = Propato and Piller; 13 = Trachtman; 14 = Wu and Walski; -1- = non-dominated solution of group 1

■ = 5 monitors solution; □ = 20 monitors solution

Fig. 7

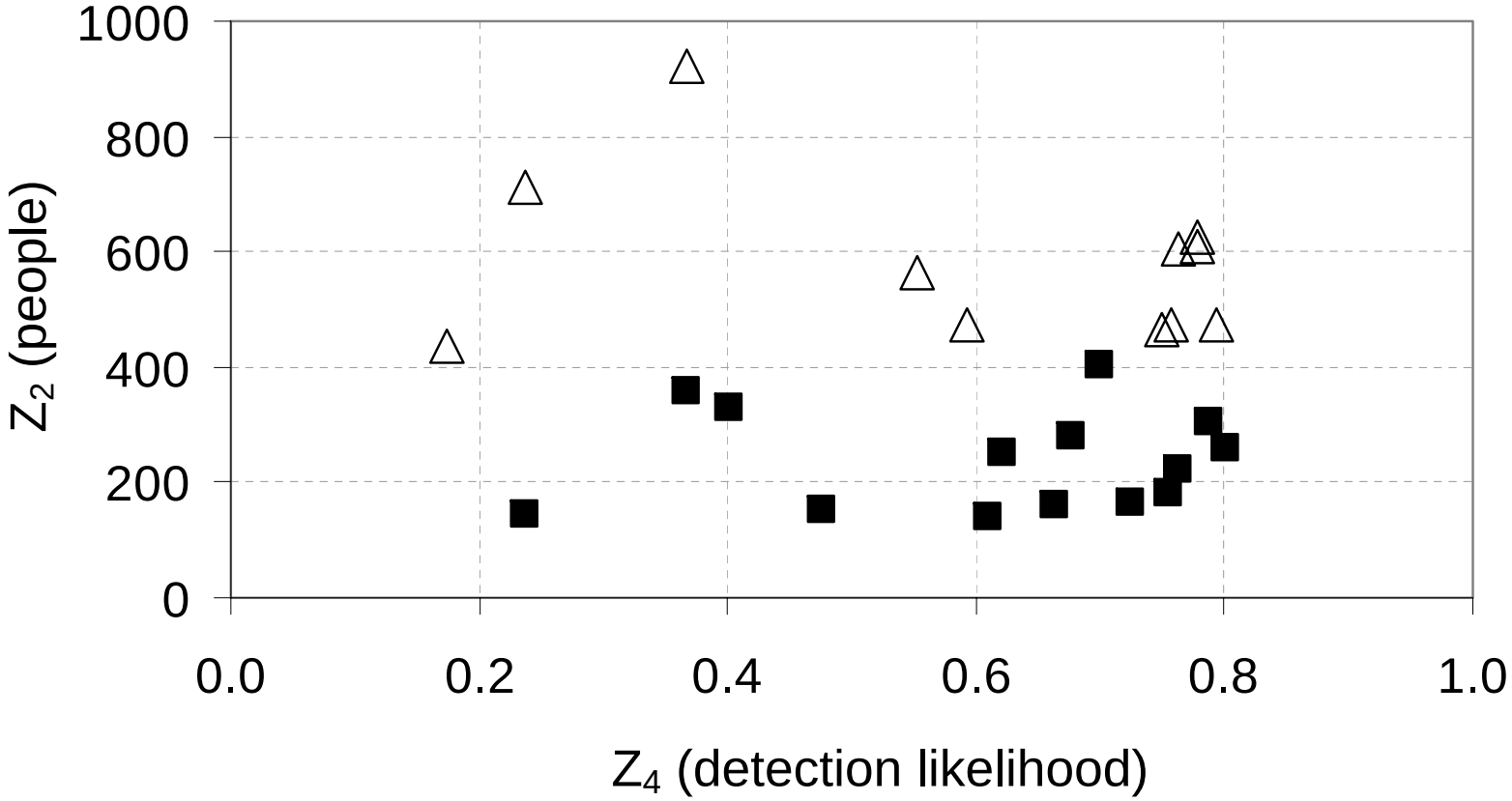


Legend

1 = Berry et al.; 2 = Dorini et al.; 3 = Eliades and Polycarpou; 4 = Ghimire and Barkdoll (demand); 5 = Ghimire and Barkdoll (mass); 6 = Guan et al.; 7 = Gueli; 8 = Huang et al.; 9 = Krause et al.; 10 = Ostfeld and Salomons; 11 = Preis and Ostfeld; 12 = Propato and Piller; 13 = Trachtman; 14 = Wu and Walski; -1- = non-dominated solution of group 1

■ = 5 monitors solution; □ = 20 monitors solution

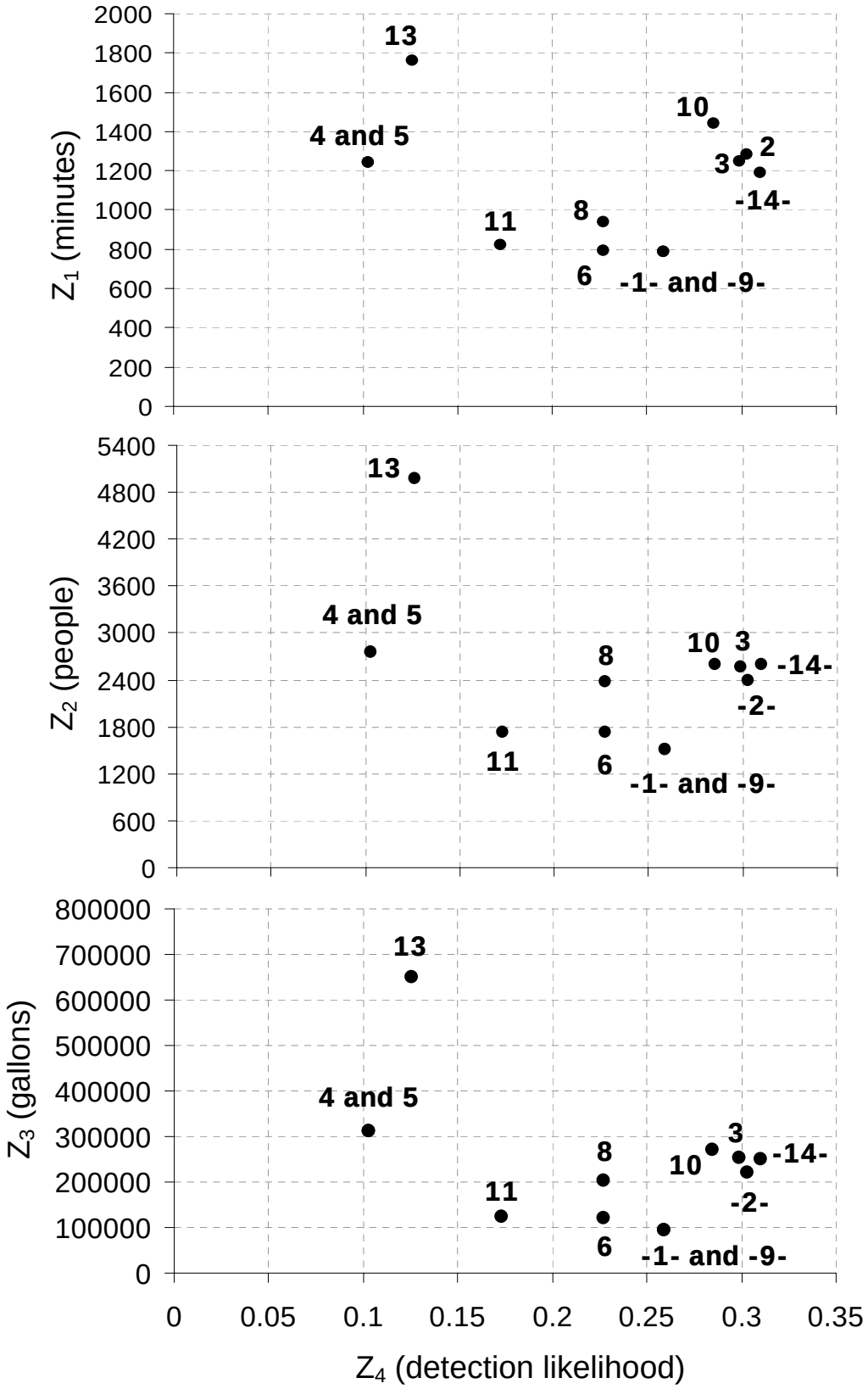
Fig. 8



Legend

■ Solution for N1A5 (network 1, base case A, 5 sensors)
△ Solution for N1C5 (network 1, derivative case C, 5 sensors)

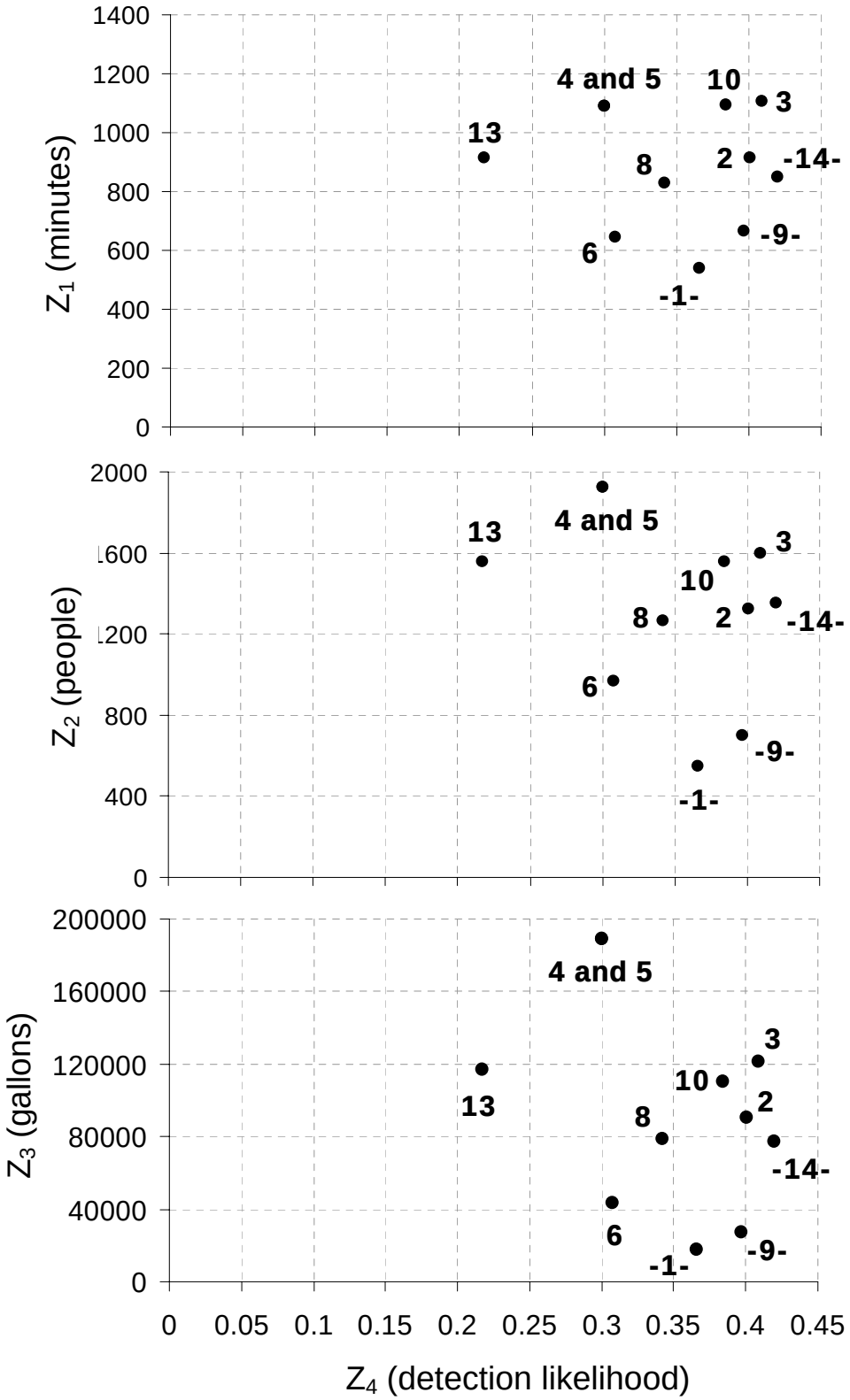
Fig. 9



Legend

1 = Berry et al.; 2 = Dorini et al.; 3 = Eliades and Polycarpou; 4 = Ghimire and Barkdoll (demand); 5 = Ghimire and Barkdoll (mass); 6 = Guan et al.; 7 = Gueli; 8 = Huang et al.; 9 = Krause et al.; 10 = Ostfeld and Salomons; 11 = Preis and Ostfeld; 12 = Propato and Piller; 13 = Trachtman; 14 = Wu and Walski; -1- = non-dominated solution of group 1

Fig. 10



Legend

1 = Berry et al.; 2 = Dorini et al.; 3 = Eliades and Polycarpou; 4 = Ghimire and Barkdoll (demand); 5 = Ghimire and Barkdoll (mass); 6 = Guan et al.; 7 = Gueli; 8 = Huang et al.; 9 = Krause et al.; 10 = Ostfeld and Salomons; 11 = Preis and Ostfeld; 12 = Propato and Piller; 13 = Trachtman; 14 = Wu and Walski; -1- = non-dominated solution of group 1

Fig. 11