Rule-based Decision Support System For Sensor Deployment In Drinking Water Networks

Natthaphon Prapinpongsanone
University of Central Florida

RULE-BASED DECISION SUPPORT SYSTEM FOR SENSOR DEPLOYMENT IN DRINKING WATER NETWORKS

by

NATTHAPHON PRAPINPONGSANONE

B.S. Florida Institute of Technology, 2009.

A thesis submitted in partial fulfillment of the requirements

for the degree of Master of Science of Environmental Engineering

in the Department of Civil, Environmental and Construction Engineering

in the College of Engineering and Computer Science

at the University of Central Florida

Orlando, Florida

Spring Term
2011

ABSTRACT

Drinking water distribution systems are inherently vulnerable to malicious contaminant events with environmental health concerns such as total trihalomethanes (TTHMs), lead, and chlorine residual. In response to the needs for long-term monitoring, one of the most significant challenges currently facing the water industry is to investigate the sensor placement strategies with modern concepts of and approaches to risk management. This study develops a Rule-based Decision Support System (RBDSS) to generate sensor deployment strategies with no computational burden as we oftentimes encountered via large-scale optimization analyses. Three rules were derived to address the efficacy and efficiency characteristics and they include: 1) intensity, 2) accessibility, and 3) complexity rules. To retrieve the information of population exposure, the well-calibrated EPANET model was applied for the purpose of demonstration of vulnerability assessment. Graph theory was applied to retrieve the implication of complexity rule eliminating the need to deal with temporal variability. In case study 1, implementation potential was assessed by using a small-scale drinking water network in rural Kentucky, the United States with the sensitivity analysis. The RBDSS was also applied to two networks, a small-scale and large-scale network, in "The Battle of the Water Sensor Network" (BWSN) in order to compare its performances with the other models. In case study 2, the RBDSS has been modified by implementing four objective indexes, the expected time of detection (Z1), the expected population affected prior to detection (Z2), the expected consumption of contaminant water prior to detection, and the detection likelihood (Z4), are being used to evaluate RBDSS's performance and compare to other models in Network 1 analysis in BWSN. Lastly, the implementation of

weighted optimization is applied to the large water distribution analysis in case study 3, Network 2 in BWSN.

ACKNOWLEDGMENTS

First and foremost, I would like to show my deepest gratitude to my advisor, Dr. Ni-Bin Chang, who has consistently provided me with guidance and knowledge, which enlightens me in many ways. His enthusiasm and dedication to academic research helped me develop creative problem solving. Without his Supports, the thesis and researches could not be completed.

My gratitude is also devoted to Dr. Scott Hagen, Dr. Martin Wanielista, and Dr. Avelino Gonzalez, the committee members during my defense, who spares their valuable time to review this thesis. I also wish to express my gratitude to all of my course instructors for enlightening my knowledge. My sincere appreciation also goes to Dr. Ammarin Daranpob who served as my mentor and provided much knowledge on the research, Dr. Andrew Ernest who provided funding and knowledge in the research project in Hardin No. 1 County, Yuming Fang who helped me in the research project, and Elad salomons who helped me with the coding in Utilities Software in BWSN.

I would like to thank my parents for their unconditional love and care. Lastly, I am grateful for my wife, Kaewfah, who is always being Supportive during the research and study and my son, Zane, who brings me joy every time I see you. This thesis is also dedicated to my grandmother who passed away on January 30, 2011.

TABLE OF CONTENTS

LIST OF FIGURES viii

LIST OF TABLES xi

CHAPTER ONE: INTRODUCTION 1

1.1 Overview 1

1.2 Objectives 3

CHAPTER TWO: METHODOLOGY OF RULE-BASED DECISION SUPPORT SYSTEM 7

2.1. Rule-Based Decision Support System for Case Study 1: Hardin No. 1 County Water District 7

2.1.1. Intensity Rule 7

2.1.2. Accessibility Rule 11

2.1.3. Complexity Rule 12

2.1.4. Experiment of Rule-Based Decision Support System Applications in Case Study 1 14

2.2. Rule-Based Decision Support System for Case Study 2: Network 1 in The Battle of the Water Sensor Network (BWSN) 20

2.2.1. Objective Indexes in the Battle of the Water Sensor Network 20

2.2.2. Experiment of Rule-Based Decision Support System Applications in Case Study 2 24

2.3. Rule-Based Decision Support System for Case Study 3: Network 2 in The Battle of the Water Sensor Network (BWSN) 27

2.3.1. Modified Complexity Rule 27

2.3.2. Weight Optimization.. 29

2.3.3. Experiment of Rule-Based Decision Support System Applications in Case Study 3 30

CHAPTER THREE: RESULTS AND DISCUSSIONS.. 35

3.1 Case Study 1: Hardin No. 1 County Water District 35

3.1.1 Results of Case Study 1 35

3.1.2. Discussion of Case Study 1.. 38

3.2 Case Study 2: Network 1 in The Battle of the Water Sensor Network (BWSN)............... 44

3.2.1. Results of Case Study 2 44

3.2.2. Discussions of Case Study 2 59

3.3. Case Study 3: Network 2 in The Battle of the Water Sensor Network (BWSN).............. 63

3.3.1. Results of Case Study 3 63

3.3.2. Discussions of Case Study 3 66

CHAPTER FOUR: CONCLUSION... 71

APPENDIX: INTERIM VOLUNTARY GUIDELINES FOR DESIGNING AND ONLINE CONTAMINANT MONITORING SYSTEM.. 73

LIST OF REFERENCES.. 80

LIST OF FIGURES

Figure 1.1 Hardin No.1 network 4

Figure 1.2. The layout of drinking water distribution network that is the testing bed of this case study. 5

Figure 1.3. Layout of Network 2. 6

Figure 2.1. Path reduction of a looped block. 13

Figure 2.2. Schematic of the RBDSS process... 15

Figure 2.3. Location of Kentucky in the United States... 16

Figure 2.4. Location of Hardin County in Kentucky. 16

Figure 2.5. Hardin No.1 network 17

Figure 2.6. Hardin No.1 network divided into 5 sections. WTP represents the water treatment plant... 18

Figure 2.7. The integrated procedure of the RBDSS 21

Figure 2.8. The evolution of sensor deployment strategies 23

Figure 2.9. The continuing evolution of sensor deployment strategies 23

Figure 2.10. The process schematic of this new rule-based decision Support system 25

Figure 2.11. The layout of the network partitioned by five subsystems.............................. 27

Figure 2.12. Modified Complexity Rule of RBDSS.. 29

Figure 2.13. The process schematic of this rule-based decision Support system for large water distribution 33

Figure 2.14. The sectorization of Network 2 into 10 sections. 34

Figure 3.1. Section 2 of the network. 37

Figure 3.2. Section 5 of the network. 37

Figure 3.3. Sensitivity analysis of sensor deployment for chlorine residual based on the size of the population protected. 39

Figure 3.4. Sensitivity analysis of sensor deployment for chlorine residual based on the exposure assessment. 39

Figure 3.5. Peak concentration of chlorine residual at the selected nodes. 40

Figure 3.6. Sensitivity analysis of sensor deployment for lead detection based on the size of the population protected. 42

Figure 3.7. Sensitivity analysis of sensor deployment for lead detection based on the exposure assessment. 42

Figure 3.8. Peak concentration of lead at the selected nodes. 43

Figure 3.9. Sensor deployment locations based on the RBDSS. 45

Figure 3.10a. The trade-off graph between the expected time of detection (Z1) and the detection likelihood (Z4). 61

Figure 3.10b. The trade-off graph of the expected population affected prior to detection (Z2) and the detection likelihood (Z4). 62

Figure 3.10c. The trade-off graph of the expected consumption of contaminated water prior to detection (Z3) and the detection likelihood (Z4). 63

Figure 3.11. The layout of the section 9 of network 2 with the selected sensor deployment locations 64

Figure 3.12a. The trade-off graph between the expected time of detection (Z1) and the detection likelihood (Z4) 68

Figure 3.12b. The trade-off graph of the expected population affected prior to detection (Z2) and the detection likelihood (Z4)... 69

Figure 3.12c. The trade-off graph of the expected consumption of contaminated water prior to detection (Z3) and the detection likelihood (Z4) 70

Figure 3.13. The ranks of models' performances based on three different correlations. 70

LIST OF TABLES

Table 3.1. Top 10 nodes selected for residual chlorine scenario by using the intensity, accessibility, and complexity rules in sequence. 35

Table 3.2. Top 10 nodes selected for lead scenario by using the intensity, accessibility, and complexity rules in sequence. 36

Table 3.3. Ranking of the selected sensors associated with two sensitivity analyses and peak concentration of chlorine residual at each node. 40

Table 3.4. Ranking of the selected sensors associated with two sensitivity analysis parameters and peak concentration of lead at each node. 43

Table 3.5. The comparisons of the results from NRBDSS with the other optimization and heuristic models in base case A (N1A5) 57

Table 3.6. The comparisons of the results from RBDSS with the other optimization and heuristic models in base case A (N2A20). 64

CHAPTER ONE: INTRODUCTION

1.1 Overview

Drinking water distribution systems are inherently vulnerable to accidental or intentional water contamination incidents. Because those networks are large, spatially distributed and complicated infrastructures, the possibility of human-related influences is significantly high (Buckel, 2000; Haestad et al., 2003; Karamouz et al, 2010). For example, in developing countries like Guatemala, inadequate clean water and waterborne bacterial infection among young children are the cause of disease and productivity losses equivalent to 2% of gross domestic product (Norstrom, 2007; Tune and Elmore, 2009); therefore, the total number of studies being conducted for vulnerability assessment, risk reduction, monitoring sensor network, and contamination warning system are excessive. In a recent case study of vulnerability assessment of water supply system components in a major city with five different criteria, including distribution, spread, visibility, exposure, and recovery, the failure of water distribution networks and water treatment plants was found to generate the highest human losses among other water supply failures (Karamouz et al., 2010). Because these incidents often have severe immediate and long-term human health consequences, drinking water distribution networks require intensive monitoring and security consideration using real-time early warning systems (EWS; Clark and Deininger, 2001; National Research Council, 2002). Hence, the vulnerability assessment of the drinking water distribution networks has been a focus of the United States Environmental Protection Agency (US EPA) since the attack of terrorist on September 11, 2001 (US EPA, 2010a). Since then, many rigorous research efforts were directed toward studying the water security issues and searching for optimal sensory deployment locations in order to warn populations from consuming contaminated water Developing robust models for achieving efficient and effective water monitoring performance in an early warning system (EWS) is one of the most important ways to protect the population from the exposure to water contaminations in these drinking water systems (US EPA, 2009).

To build a functional EWS, a sensor location system should be designed to satisfy multiple criteria with or without optimization schemes (Berry et al., 2003), yet sensor location optimization is often necessary because of the high cost of monitoring devices and to achieve the highest degree of protection for a finite number of sensors (Thompson et al., 2007, Thompson et al., 2009). Therefore, the methodologies for monitoring stations layout design have proposed in the past decade throughout the distribution system to detect the migration of any contaminations that can potentially risk consumer health (Kessler et al, 1998; Al-Zahrani and Moied, 2001; Woo et al, 2001; Haught et al., 2003; Ostfeld et al., 2004; Berry et al., 2003, 2005, 2006; Propato, 2006; Ghimire and Barkdoll, 2006; Preis et al, 2007; Berry and Barkdoll, 2008; Aral et al., 2010; Hart and Murray, 2010; Weickgenannt et al., 2010). Numerous technical approaches were developed for optimizing sensor placement, including mixed-integer programming (MIP) models (Lee et al., 1991; Lee and Deininger, 1992; Watson 2004; Berry et al. 2004, 2005; Propato 2005), combinatorial heuristics (Kessler et al., 1998; Kumar et al., 1999; Ostfeld and Salomons 2004), general-purpose metaheuristics (e.g., Ostfeld and Salomons, 2004), and lagrangian heuristics (Berry et al., 2008). In August 2006, the workshop conducted for "The Battle of the Water Sensor Network (BWSN): A Design Challenge for Engineers and Algorithms" was held as part of the Eight Annual Water Distribution Systems Analysis (WDSA) Symposium in Cincinnati, Ohio. The two actual water distribution networks, Network 1 and Network 2 representing a small and a large water distribution system, respectively were used for sensor deployment with respect to four objectives. They consist of the expected time of detection (Z1), the expected population affected prior to detection (Z2), the expected consumption of contaminant water prior to detection, and the detection likelihood (Z4). They were employed simultaneously to evaluate the performance of sensor deployment locations of 14 different suggested models/algorithms.

1.2 Objectives

In case study 1, this study developed a Rule-based Decision Support System (RBDSS) to generate near-optimal sensor deployment strategies with no computational burden in Hardin No.1 water distribution network in Kentucky shown in Figure 1.1. Three rules were derived to address the efficacy and efficiency characteristics: (1) intensity, (2) accessibility, and (3) complexity rules. Such an RBDSS is thus designed to minimize the total number of costly sensors and maximize the monitoring coverage to promote the cost-effectiveness of an EWS in any type of small communities. In this work we provide the formulation of the three rules for RBDSS, present a real-world application and results of an RBDSS, and apply these results to a rural community in Kentucky.

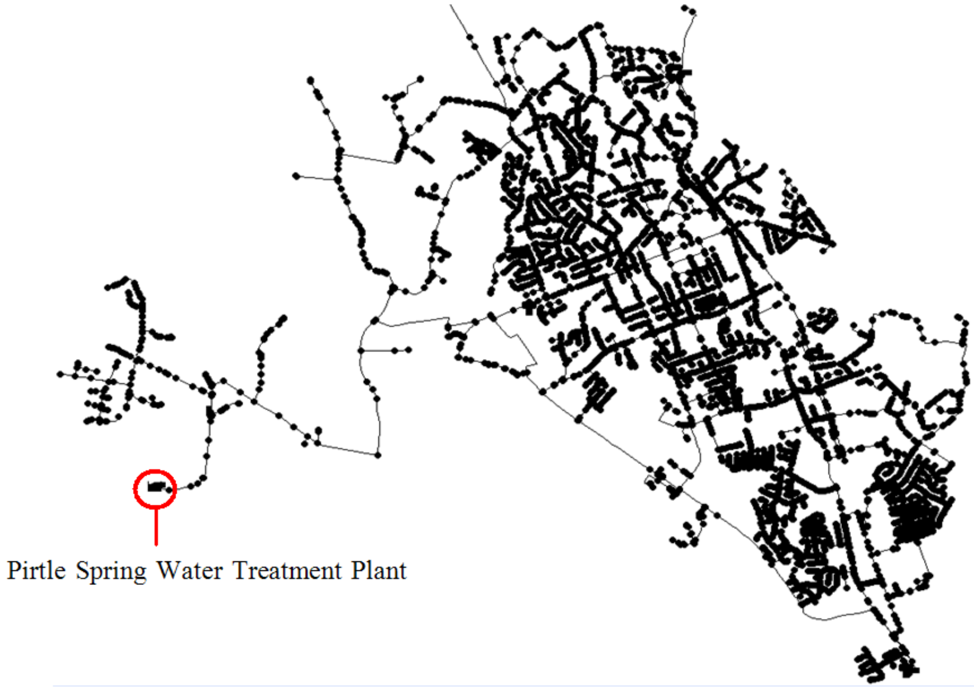

Figure 1.1 Hardin No.1 network

In case study 2, a rule-based decision Support system (RBDSS), constructed by using a combination of EPANET and EXCEL® , was developed in this case study to tackle the complexity of the network and reduce the computer runtime while achieving the same level of robustness in planning and design. Thus, the aim of this case study 2 is to present this ruled-based decision Support system (RBDSS), which consists of accessibility rule and complexity rule, and compare it against the 14 existing optimization and heuristic models used in BWSN. Based on the same drinking water network, Network 1, as shown in Figure 1.2 is the common test bed in this practice. Such a network, with 126 nodes, 1 source, 2 tanks, 168 pipes, 2 pumps, and 8 valves, provides a common ground to determine the effectiveness and efficiency of the sensor network design, with respect to four quantitative design objectives, for evaluating the robustness of the sensor locations.

2006).

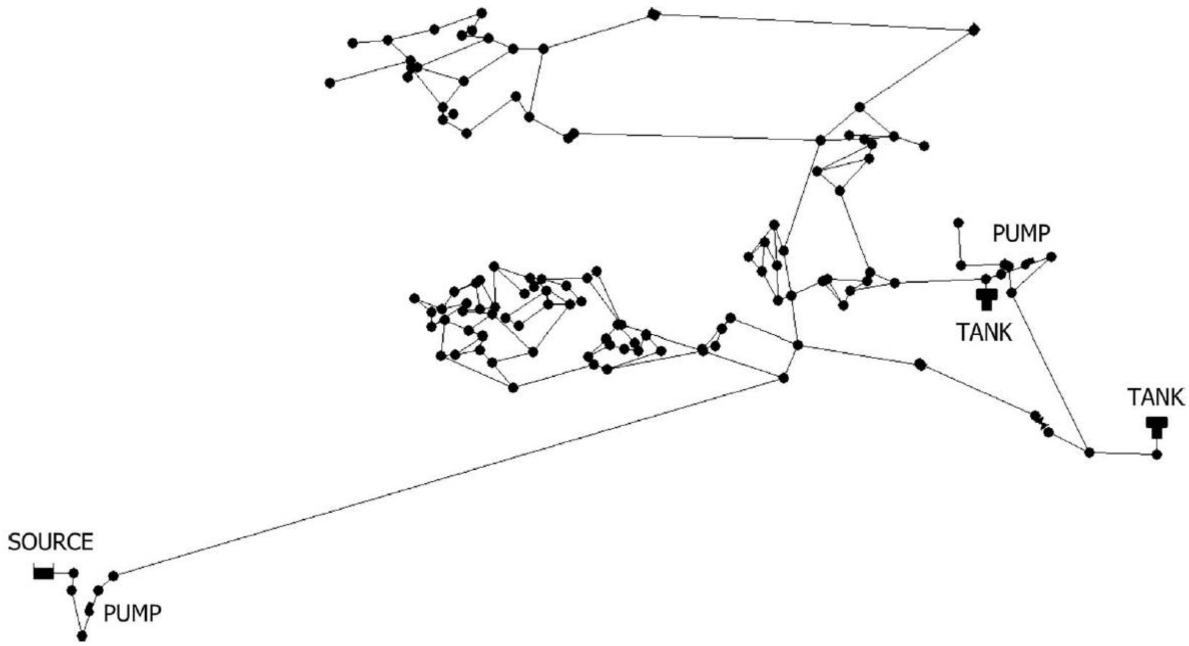

Figure 1.2. The layout of drinking water distribution network that is the testing bed of this case study (Ostfeld et al., 2008).

In contrast to Network 1, Network 2, which consists of 12,523 nodes, 2 sources, 2 tanks, 14,822 pipes, 4 pumps, and 5 valves and shown in Figure 1.3, had presented difficulties to some algorithms due to the significantly larger water distribution and higher complexity. Hence, only 11 models/algorithms were proposed for Network 2. For instance, the reason that mixed-integer programming (MILP) models cannot be applied for Network 2 is that it has higher uncertainty due to a larger runtime and is not applicable to handle larger water distribution networks due to the limitation of "NP complete" issues and computing power (Propato and Piller, 2006). In addition, the application of Network 2 was not well addressed by using multiobjective evaluation with a predator-prey model; the model has to be adapted to a new scenario because it may have some potential obstacle over specialization, disengagement or cycling, in coevolution (Gueli, 2006).

Given the difficulties founded by other proposed algorithms/models when focusing on Network 2 (e.g., a large-scale complex system), the objective of case study 3 is to illustrate the robustness, effectiveness, and efficacy of RBDSSs' algorithm in such a large-scale complex water distribution system for the purpose of demonstration. To achieve this goal, RBDSS was applied to analyze Network 2, Case N2A20, to generate a set of sensor deployment locations. These outcomes of RBDSS were then compared against the performance of sensor deployment locations via the BWSN-Software utilities in relation to other 10 models/algorithms based on the four objectives, from Z1 to Z4.

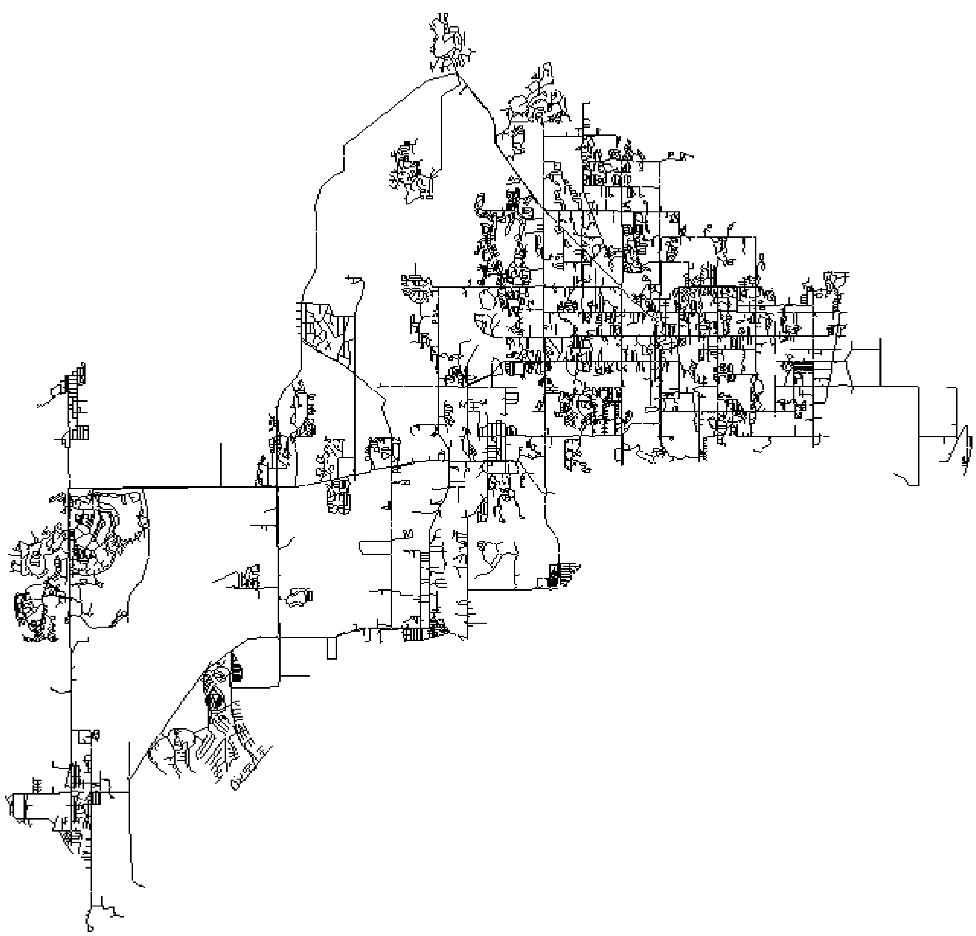

Figure 1.3. Layout of Network 2 (Ostfeld et al., 2008).

CHAPTER TWO: METHODOLOGY OF RULE-BASED DECISION SUPPORT SYSTEM

2.1. Rule-Based Decision Support System for Case Study 1: Hardin No. 1 County Water District

2.1.1. Intensity Rule

The intensity rule is designed with respect to population exposure to contamination incidents. The principle of this rule is to ensure that the concentration of targeted microorganisms, disinfection by-products, disinfectants, inorganic chemicals, organic chemicals, and/or radionuclides is under MCL, except for the residual chlorine concentration, which must meet the minimum concentration requirement of 0.2 mg/L but not exceed MCL of 4 mg/L, regulated by the US EPA (EPA, 2006; EPA, 2009). Thus, the intensity rule may be versatile in association with several chemical species of concern in the drinking water distribution networks to prevent fatalities in any incidental or accidental events. Regardless of the effect of diurnal variation, the node shall not exceed the MCL at any time during the day; on the contrary, nodes are ranked from highest to lowest exceedance, with nodes that exceed the MCL ranked highest, and the top “k” nodes are selected for deploying sensors. However, some chemicals must meet the minimum concentration standard (i.e., 0.2 mg/L of residual chlorine concentration; EPA, 2006). In this case, the objective is to minimize the summation of total concentrations at these nodes that violate (i.e., deceed) the minimum concentration standard.

For chlorine residual and trihalomethane scenarios, these two scenarios are the result of the first-order decay of chlorine concentration which is originally injected in water treatment plant, and since there is no rechlorination station existed in the distribution, the chlorine concentration will decrease as the water flow further away from the water treatment plant. Bubble sort is used in all three scenarios, chlorine residual, TTHMs, and lead. Since chlorine concentration is the parameter for chlorine residual and TTHMs scenario, bubble sort will rearrange the data by swapping them in the right order from the highest to the lowest chlorine concentration. After the sorting is completed, the set of the top nodes is for TTHMs sensor deployment, and the set of the bottom nodes is for chlorine residual sensor deployment. The objective of the intensity rule is to screen nodes which has chlorine concentration below the minimum chlorine concentration established by EPA as candidacy nodes for deploying sensors to detect chlorine residual concentration and to screen nodes which has chlorine concentration higher the maximum chlorine concentration established by WHO as candidacy nodes for deploying sensors to detect trihalomethane concentration. Nevertheless, if all of the nodes in the water distribution have chlorine concentration within the bounded range, which is from 0.2mg/L to 4.0 mg/L, sensor deployment will not be required.

To determine the near-optimal solution with a quick screening tool when the total number of nodes involved is high, LINGO®, an optimization solver, may be used to optimize the selection process of sensor locations. Because the intensity rule can be applicable to any chemicals or microorganisms regulated by the US EPA, the scenarios must specify the chemicals or microorganisms of interest. To detect exceedance–deceedance situations, simulation of the dynamic concentrations in a water distribution system using a well-developed simulation model, such as EPANET, may be performed. Using the outputs from EPANET, we can consider two objective functions concurrently in two separate small-scale optimization models. One objective function of this small-scale screening model is to maximize the detection limit of summation of exceedance concentrations of contaminant, such as total trihalomethanes (TTHM) and lead, in the network. Note that TTHM is a byproduct of chlorinating water that contains natural organics. The other objective function is to minimize the summation of deceedance concentrations of chlorine residual as regulated by the US EPA. These two small-scale optimization models can be formulated independently and applied collectively to finalize the implementation of the intensity rule. With this small-scale integrated simulation and optimization model, the sensor deployment can be carried out based on the assumptions that the budget is limited, the cost of the same type of sensor deployment is equal at every node location, and each monitoring event can generate the optimal solution independently with no mutually related effect.

Decision variables are a set of binary variables, x_i, defined as

$$x_i = \begin{cases} 1, if\ node\ i\ is\ selected \\ 0, otherwise \end{cases}.$$

Submodel 1: prevents the contaminant from exceeding the MCL:

$$\text{Maximize} \sum_{i=1}^{k} C_{i,max} x_i \tag{1}$$

Subject to:

$$S \geq ks \qquad \forall k \in N \tag{2}$$

$$\sum_{i=1}^{k} x_i \leq k \tag{3}$$

$$C_{i,max} \geq C_{MCL} \qquad \forall i \tag{4}$$

Submodel 2: performs the quality control of minimum concentration standard:

$$\text{Minimize} \sum_{i=1}^{k} C_{i,min} x_i \tag{5}$$

Subject to:

$$S \geq ks \qquad \forall k \in N \tag{6}$$

$$\sum_{i=1}^{k} x_i \leq k \quad ` \tag{7}$$

$$C_{i,min} \leq C_{MS} \qquad \forall i \tag{8}$$

where S is the total budget for sensor deployment ($); s is the cost of each deploying sensor per node ($); N is the number of junctions in the water distribution (dimensinless); k is the number of total sensor available to be deployed (dimensinless); i is the subscript representing the I sensor to be deployed up to k locations, 1 =1, 2,…, k; $C_{i,max}$ is the concentration of contaminant of interest at node that exceeds the MCL at i location (mg/L); $C_{i,min}$ is the concentration of chlorine residual at node that deceeds the minimum concentration standard at i location (mg/L); C_{MCL} is the MCL regulated by the US EPA (mg/L); and C_{MS} is the minimum concentration standard regulated by the US EPA (mg/L).

The objective function in equation 1 represents the maximum summation of concentration of contaminant that exceeded MCL in the drinking water distribution network, from which the candidate nodes for sensor deployment are determined. The objective function in equation 5 represents the minimum summation of concentration of residual chlorine concentration that violated the minimum standard of the US EPA in the drinking water network, from which the candidate nodes for sensor deployment are determined. Equations 3 and 7 represent cost constraint of sensors, which is determined by dividing the total budget (S) by the cost per sensor deployment (s) to ensure the number of sensors (k), not to exceed the upper bound as defined as the righ-hand-side values in the constraints. Equation 4 represents the constraint of maximum contamination level, MCL, associated with the objective function represented by equation 1. Equation 8 represents the constraint of minimum concentration standard associated with objective function represented by equation 5.

2.1.2. Accessibility Rule

Population exposure to potential contaminants is a specific concern related to the flow pattern in the network. The accessibility rule can be defined as the flow fraction from the main pipeline to subroutines in the remaining part of a network. Because the water flow in a particular pipeline at a given time step is driven by the downstream water demand within a spatiotemporal pattern, the fraction of water flow can be assumed as a surrogate index to indicate the percentage of population that could be affected when an unexpected contaminant intrusion occurs. This approach does not have to specify a certain node or pipeline at which the contaminant intrusion happens. Rather, the goal is to propose an optimal design to ensure maximum protection to the portion of the population residing in that part of the network. This implies that the higher the flow fraction at a certain node, the larger the population that could be affected by contaminant intrusion and could be protected by the sensor deployment strategies. From an economic perspective, placing sensors in a highly populated area may exhibit greater efficacy than deploying sensors in a low population area.

Because a higher flow fraction leads to greater population protection, the design objective of the accessibility rule is to maximize flow fractions associated with the predetermined number of sensors for deployment:

$$R = \sum_{j=1}^{k} \frac{q_j}{Q_j} \qquad \forall\, k \in N \qquad (7)$$

where Q_j is flow rate from the main pipe at j location; q_j is flow rate from the subroutine at j location; r_j is the flow fraction (= $q_j\ Q_{j\,/}$) at j location; R is the maximum summation of the flow fractions for k sensors; k is the predetermined total number of sensors for deployment; N is the number of junctions in the drinking water distribution networks.

The objective function can be achieved by calculating the flow fraction of every node with at least one or more secondary pipes connected to the main pipe. Then, the flow fractions are ranked from highest to lowest, and the top "k" nodes are selected based on the ranking system for possible sensor deployment. Such an analysis may be deemed as a supplemental step in addition to the intensity rule or may be performed independently for a small-community, should the community have no resources to carry out the essential calculation involved in the intensity rule.

2.1.3. Complexity Rule

The complexity rule originates from a branch of the graph theory of computation in computer science that focuses on classifying problems according to their inherent difficulties. In this case, the advantage of applying the complexity rule is its ability to solve sensor placement issues in a more explicit way for small-scale drinking water distribution networks that contain fewer intersections or loops among pipelines (Deuerlein et al., 2009). To translate the complexity rule into a programming algorithm, graph theory should be applied to develop the complexity formulas:

$$X = \sum_{i=1}^{k} x_i \qquad \forall\, k \in N \tag{8}$$

where X is the maximum summation of inner nodes within k path nodes; x_i is the number of inner nodes within impact zone, r_i, of the path node at i location; N is the number of junctions in the drinking water distribution network; k is the predetermined total number of sensors for deployment; and

$$r_i = \frac{\sum_{m=1}^{l} d_{i,m}}{l_i} \tag{9}$$

where r_i is the impact zone of the path node at i location; $d_{i,m}$ is the distance from the path node at i location to the inner node at m location; l_i is the number of inner nodes within the impact zone of the path node at i location.

For simplification of network analysis, the nodes of the block are first distinguished according to their nodal degree (number of connected links). All nodes can be categorized into two groups: a path node has one or more pipes connected to the main pipe; an inner node is located between two path nodes (Figure 2.1). The number of path nodes to receive deployed sensors is equal to the predetermined total number of sensors for deployment. The higher the number of nodes within a determined circular radius, the greater the population in this targeted area. Thus the objective of the complexity rule is to determine the number of path nodes with the maximum combined number of inner nodes based on path nodes' individual impact zones.

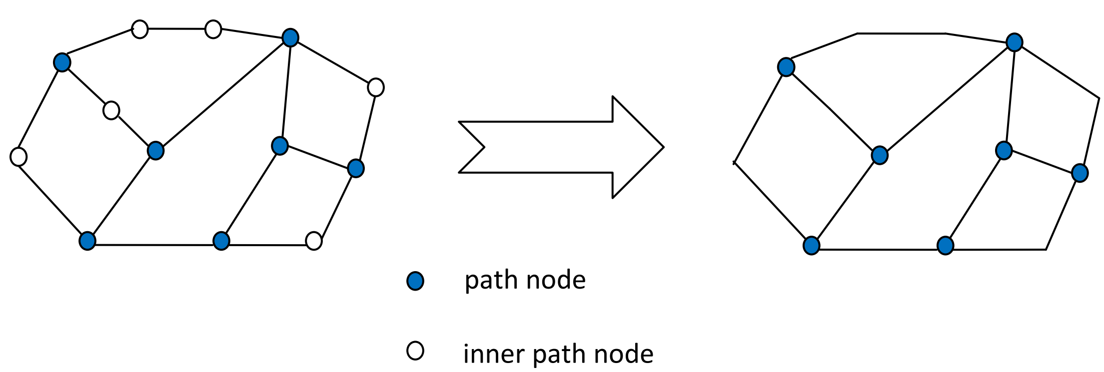

Figure 2.1. Path reduction of a looped block (Deuerlein et al., 2009).

The impact zone of a particular path node is determined by averaging the distance from all the inner nodes with a hydraulic connection to the path node. The number of inner nodes located within the determined circular radius of impact zone is then counted. Next, all the path nodes are ranked from highest to lowest based on the number of inner nodes. Finally, the top "k" path nodes are selected for sensor deployment. Again, such an analysis may be deemed as a supplemental step to the intensity and accessibility rules or may be performed independently for small-communities with no resources to carry out the essential calculation involved in the intensity rule.

2.1.4. Experiment of Rule-Based Decision Support System Applications in Case Study 1

The analytical process of constructing such an RBDSS consists of four phases, including data collection, dynamic simulation, development, and evaluation (Figure 2.2). The RBDSS is designed to ease the burden of large-scale sensor location optimization to minimize cost and maximize coverage of protection in drinking water networks with the aid of a predetermined number of sensors. Within this context, EPANET, EXCEL®, and LINGO were selected to Support essential dynamic simulations, data analysis, and selection of sensor locations, respectively in which EXCEL® was used to handle data streams in Support of EPANET simulation and LINGO optimization modules.

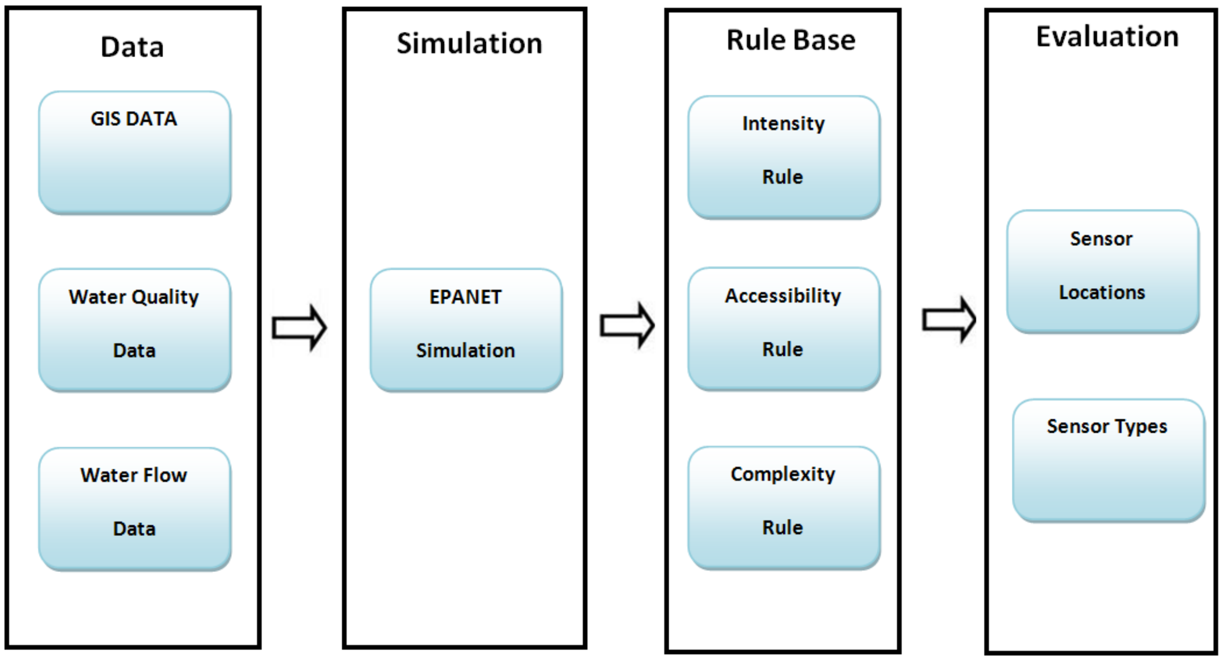

Figure 2.2. Schematic of the RBDSS process

Statistics compiled by the Kentucky Division of Water (DOW) from public water system data in 1995, and subsequently reported in the 1996, indicate that the greatest violators of federal drinking water regulations are those small systems serving 3300 people or fewer (CERS, 2007). Results from the analysis of these data reveal that 78% (942) of violations occurred in public water systems that serve fewer than 500 people (CERS, 2007). Of the 1207 total violations cited by Kentucky DOW, 93% were monitoring and reporting infractions (CERS, 2007). Yet small communities can rarely afford to integrate effective monitoring system into their networks; large cities typically have abundant resources to establish EWS to monitor water supplies and distribution network. Hence, cost-effective EWS for small-scale drinking water networks are desperately needed to monitor small drinking water networks and improve public safety.

To test the practicality of employing the rule-based decision Support system, the three rules were applied on the water distribution network in Hardin County Water District No. 1, a part of Elizabethtown in Kentucky (Figure 2.3–2.5). The population estimate in 2009 was 99,770 (U.S. Census Bureau, 2009). The county relies solely on the Pirtle Spring water treatment plant, located on the west side of the water distribution network (Figure 2.5), as its primary water source. The capacity of the plant is 2 MGD to supply residential areas. The chlorine dosage of the treatment plant is 1.70 mg/L, and no rechlorination stations are used to maintain the chlorine residual. The majority of the population is located at the Fort Knox army military base north of Elizabethtown.

Figure 2.3. Location of Kentucky in the United States (Benbennick, 2006).

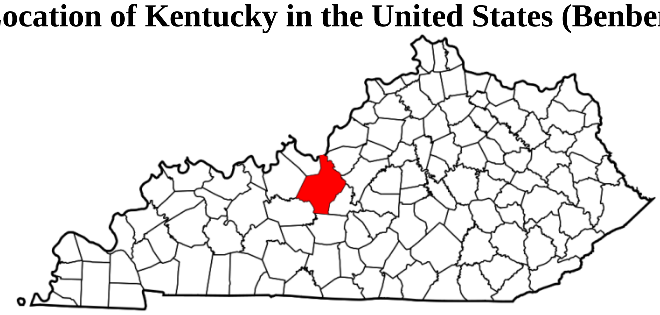

Figure 2.4. Location of Hardin County in Kentucky (Benbennick, 2006).

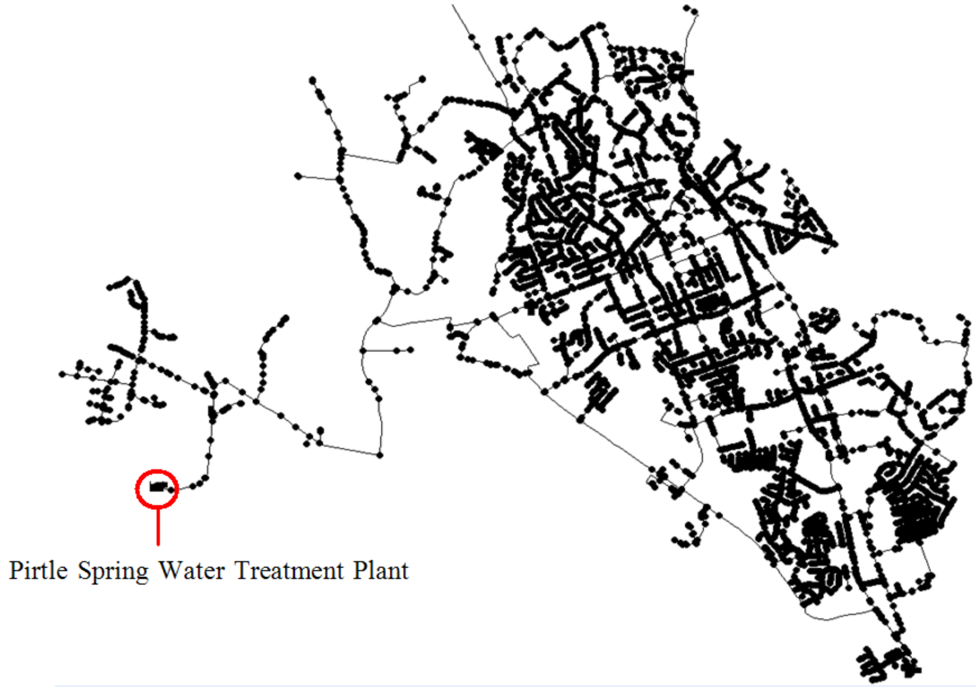

Figure 2.5. Hardin No.1 network

Although Hardin is not a big city, the assessment for optimal sensor deployment must be based on 5 different sections of the network (Figure 2.6) to ease the application. Three scenarios for EPANET simulation were prepared for residual chlorine, TTHM, and lead with the assumption that the available budget can be distributed to deploy 10 sensors in each scenario.

Figure 2.6. Hardin No.1 network divided into 5 sections. WTP represents the water treatment plant.

The RBDSS was applied to run the intensity, accessibility, and complexity rules in series to prioritize the location of the sensors. Although intensity, accessibility, and complexity rules are independent from one another, the three rules may be applied in series to discern the nodes' potential for sensor deployment. In other words, the collected data were analyzed first by the intensity rule to pinpoint more than 10 candidate nodes. The node contenders for sensor deployment obtained from the intensity rule are then evaluated by the accessibility rule to narrow down the candidate list. Finally, the final selected nodes are generated by the complexity rule based on the candidate nodes obtained from the accessibility rule to finalize the 10 nodes for sensor deployment.

To implement the intensity rule on the Hardin No.1 drinking water distribution network, the 720 hour simulation was performed using EPANET. Chlorine residual and TTHM scenarios were simulated to select the nodes that cannot meet the minimum standard or the MCL, respectively. In contrast, the lead scenario was simulated where the sensors should be deployed to provide optimal level of protection for these residents. At present, chlorine residual is regulated by EPA to meet the minimum standard of 0.2 mg/L (US EPA 2006). During the simulation, the actual chlorine dosage (1.70 mg/L) was injected at Pirtle Spring water treatment plant located at the lower west location of the network (Figure 2.5). After the scenario was simulated, the intensity rule was used to analyze the sensor deployment location by using equations 2, 3, 4, and 6 to select the nodes with simulated chlorine residual concentrations below the standard. The accessibility rule was then applied using equation 7, and the complexity rule was applied using equations 8 and 9 to determine the final sensor deployment nodes.

The second scenario evaluated TTHM. The MCL states that TTHM must remain below 0.08mg/L; however, because TTHM is a disinfection by-product of chlorine in the network, a chlorine concentration that remains below the MCL for chlorine (4.0 mg/L) indicates that TTHM would not form in the network. Thus, we combined this scenario testing with previous one.

Finally, lead, which is regulated by US EPA, has an MCL of 0.015 mg/L; however, this is a simulation intended to evaluate a possible accidental leakage or an intentional attack targeting the water tanks in Hardin No.1 network. As expected, all 10 sensors to be deployed are located in the pipe section 2 (Figure 2.6) because the concentrations of lead decreases as lead migrates farther away from the source location (i.e., Tank 26653). In the simulation, although the network consists of four water tanks, a lead concentration of 15 mg/L was released at the tank ID 26653 located at the area with the highest population density in the network (Figure 2.6). Then, equations 1, 3, 4, and 5 from the intensity rule, equation 7 from the accessibility rule, and equations 8 and 9 from the complexity rule were applied to indicate the nodes that could exceed the MCL.

To test robustness of the RBDSS, sensitivity analysis was performed. Because the simulation showed that the TTHM scenario did not require any sensor deployment, residual chlorine and lead scenarios are the only cases considered for sensitivity analysis. Two indexes, the size of the population protected and exposure level, are used for sensitivity analysis as the number of deployed sensor is increased. To determine the size of the population protected at the sensor location, the baseline demand at the selected node is divided by water consumption per capita to determine the size of the population protected at that node. In our case, the average water consumption rate is 100 gal/day/capita. Likewise, in the exposure assesment, which can be defined as the amount of substance consumed by a person at a given exporure level of a specified chemical or organism, can be calculated by multiplying the substance concentration at the selected node with the same water consumption rate per capita. These two indexes may be collectively used for final robustness assessment of the optimal sensor deployment strategies.

2.2. Rule-Based Decision Support System for Case Study 2: Network 1 in The Battle of the Water Sensor Network (BWSN)

2.2.1. Objective Indexes in the Battle of the Water Sensor Network

Since the RBDSS has two rules in the algorithm, the optimal solution for sensor deployment has to be contributed by both rules simultaneously. The integrated procedure for illustrating the concatenated algorithm of the RBDSS is listed in Figure 2.7. To make the two rules cohesively and coherently work together, a concurrent screening process is needed. Figure 2.8 describes such a screening process conceptually. Following the evolutionary pathway, an intermediate optimal solution can be improved as the RBDSS moves on from looking into the hydraulic response across these nodes to dropping minor and irrelevant nodes progressively throughout the algorithm. Figure 2.8a shows the intermediate optimal solutions at the beginning of the progressive pathway when none of the data is screened by the RBDSS. Those minor nodes being dropped are expressed by the dark red color in the circles. The intermediate optimal solution is solely based on the overlapped gray area with regard to the two rules as the evolution progresses. As the screening process progresses along the timeline, the intermediate optimal solutions being narrowed down by both rules makes the gray area become smaller gradually as shown from Figure 2.8b to Figure 2.8c. Finally, in Figure 2.8d, both rules have completed the screening and sequencing efforts, and the ranking process helps identify the ultimate optimal or near-optimal solution.

RBES

INPUT: Hydraulic simulated data

BEGIN

1) Calculate flow fraction at each node (Accessibility rule)
2) **If** (Subroutine flow (q_j) < Main pipe flow (Q_j) **and** (Subroutine flow (q_j) > 0) denotes the candidacy of node j
3) Rank flow fraction (q_j/Q_j) of each node from the highest to the lowest $(q_{j,max}\ to\ q_{j,min})$
4) **END If**
5) Calculate the number of inner node at each node (Complexity rule)
6) **If** (The number of inner node (x_j) > 0) denotes the candidacy of node j
7) Rank the number of inner node at each node from the highest to the lowest $(x_{j,max}\ to\ x_{j,min})$
8) **END If**
9) Compare the rankings
10) Select the sensor deployment nodes

END

Figure 2.7. The integrated procedure of the RBDSS

To compare the performance of the RBDSS against these existing 14 optimization and heuristic models, four designed objectives, denoted from Z1 to Z4, were used as the performance criteria as they were applied for the BWSN. This implies that the final optimal solution based on the RBDSS, as shown in Figure 2.8d, should become the constraint set associated with all four designed objectives simultaneously leading to a better trade-off in the decision making process. Figure 2.9 delineates the philosophy using a couple colored, intersected circles that are presented in different stages as the trade-offs in the decision making process move on. The final optimal solution, as shown by in gray color in Figure 2.8d, simply represents the last step of rule-based evolution. That initializes the evaluation process with respect to the four design objectives step by step as shown in Figure 2.9a. As the RBDSS is moving along toward picking up a new subset of nodes making the system better off, the four design objectives in the BWSN may be applied to demonstrate how the performance of the evolutionary pathway can improve the effectiveness of the water quality monitoring task in the network. When an additional objective is added progressively into the ongoing screening, the interactions between the constraint set and the objectives may be catalyzed by the imposed criterion stepwise toward the final illumination as shown in Figure 2.9e. As a result, the ultimate optimal sensor deployment strategy can literally be improved by the RBDSS and the four designed objectives toward a near compromised solution.

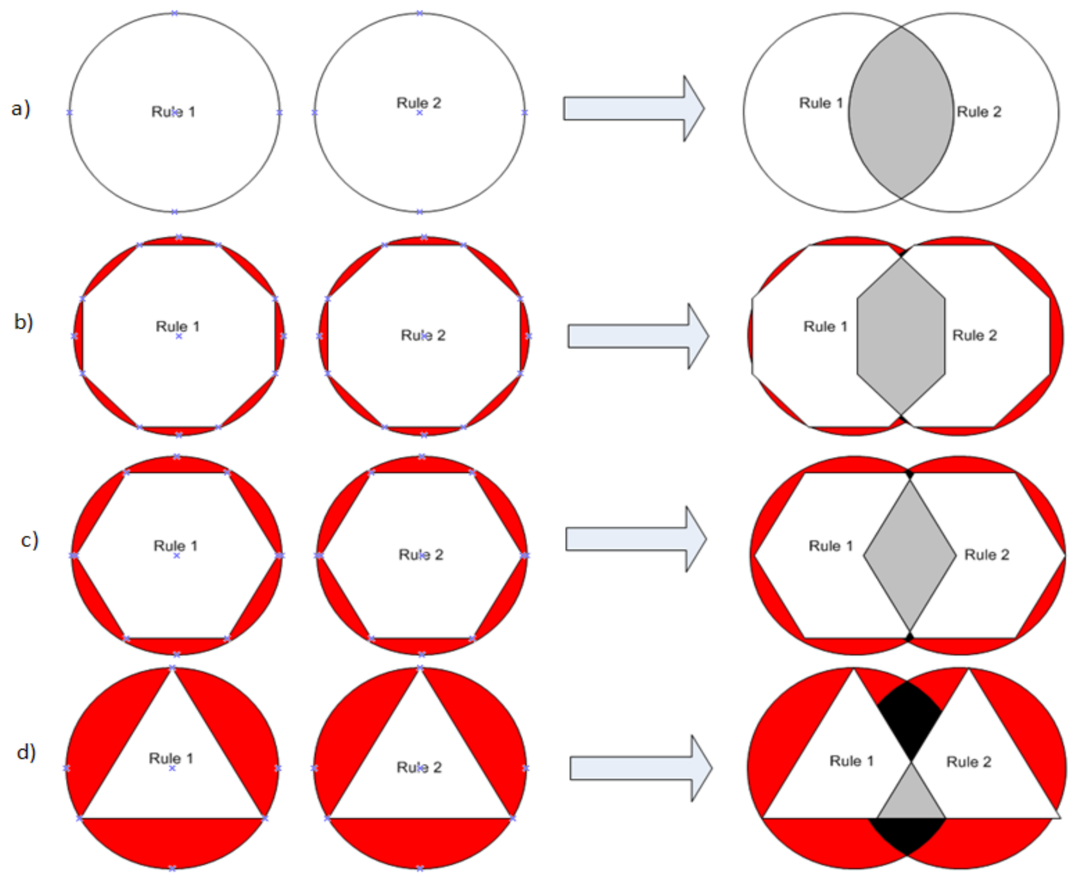

Figure 2.8. The evolution of sensor deployment strategies show how the solution can be improved by screening stepwise with respect to two rules. (i.e., Red area represents the eliminated nodes, gray area represents the optimal solution being narrowed down gradually after the integration of two rules, and black area represents an initial subset of the optimal solution.)

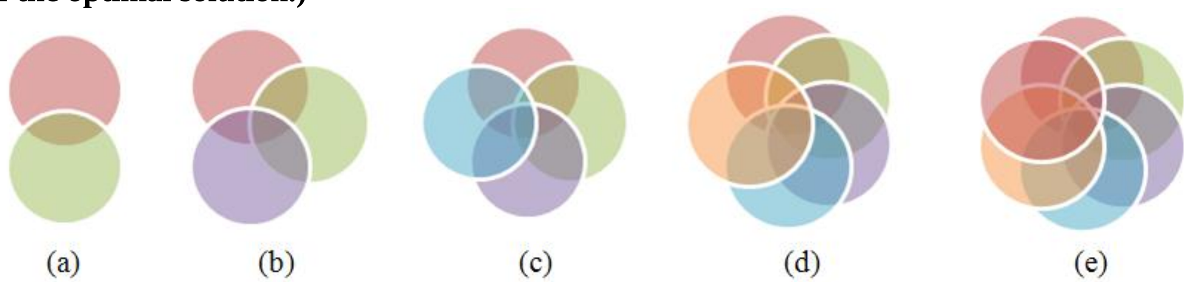

Figure 2.9. The continuing evolution of sensor deployment strategies show how the ultimate solution can be constrained by the RBDSS and improved by the four design objectives (i.e., pink circle represents accessibility rule, green circle represents complexity rule, violet circle represents the 1st objective (Z1), blue circle represents the 2nd objective (Z2), orange circle represents the 3rd objective (Z3), and purple circle represents the 4th objective (Z4)).

2.2.2. Experiment of Rule-Based Decision Support System Applications in Case Study 2

Figure 2.10 delineates five phases in the RBDSS experiment, including data collection, simulation analysis, rule base screening and node prioritization, design of sensor deployment locations, and evaluation of sensor locations with comparisons. In order to compare the results with previous optimization and heuristic models used in the BWSN, the same hydraulic data set was applied to the so-called Network 1 for the comparative analysis. During the first phase, as Figure 1.2 and Figure 2.11 shows, Network 1 that has four variable demand patterns consists of 126 nodes, one constant head source, two water tanks, and 168 pipes. During the second phase, the network was simulated for 96 hours to acquire the information of dynamic flow patterns (Ostfeld et al., 2008). The EPANET that is a well-calibrated dynamic simulation software available to download for free was used to perform the hydraulic simulation in the drinking water distribution system (EPA, 2010). The EPANET practice was conducted based on the 1-hour time step over the entire hydraulic simulation time period of 96 hours. Then, in the second phase, the RBDSS was applied to the simulated network, which was sectorized into 5 sections as shown in Figure 2.11, with respect to the accessibility rule and the complexity rule individually and collectively based on the same network environments. In the third phase, the EXCEL was used in the analysis to generate the prioritized nodes.

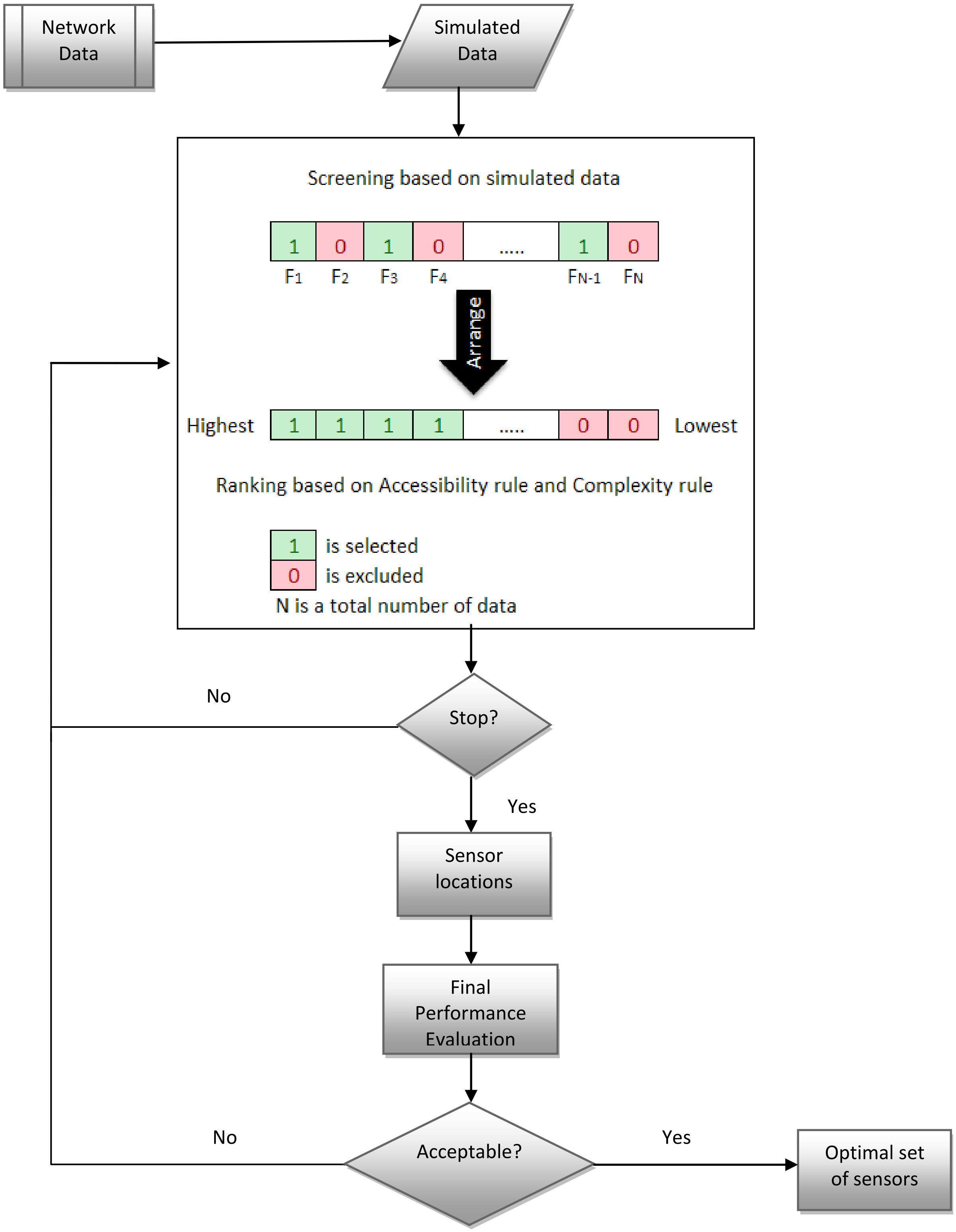

Figure 2.10. The process schematic of this new rule-based decision Support system in the experiment

In the fourth phase, the ranking was generated and the quantitative values of four design objectives may be produced to determine the ultimate optimal sensor placement locations with respect to the predetermined total number of sensor (i.e., we chose 5 in this practice). To illustrate robustness of the RBDSS, comparisons to the 14 optimization and heuristic models that is denoted as the base case A (N1A5) in BWSN in terms of these four objective function values can be made possible in the fifth phase (Salomons, 2006). The ultimate optimal solution should be able to minimize Z1, Z2, and Z3, while maximizing Z4. When using the BWSN-Software utilities to achieve the comparisons, The Utility 1 that is for "Build injection data" allows the user to create the data needed to evaluate the fitness function for a given sensor layout design, and the Utility 2 that is for "Calculate fitness" allows the user to calculate the fitness function for a given sensor layout design. After running both of the Utility 1 and Utility 2, respectively, the four design objectives from Z1 to Z4 can be generated based on the sensor deployment locations analyzed by the RBDSS. Iterations can be made possible if the trade-offs among these four objectives initialize such a process when taking the outputs of the RBDSS into account.

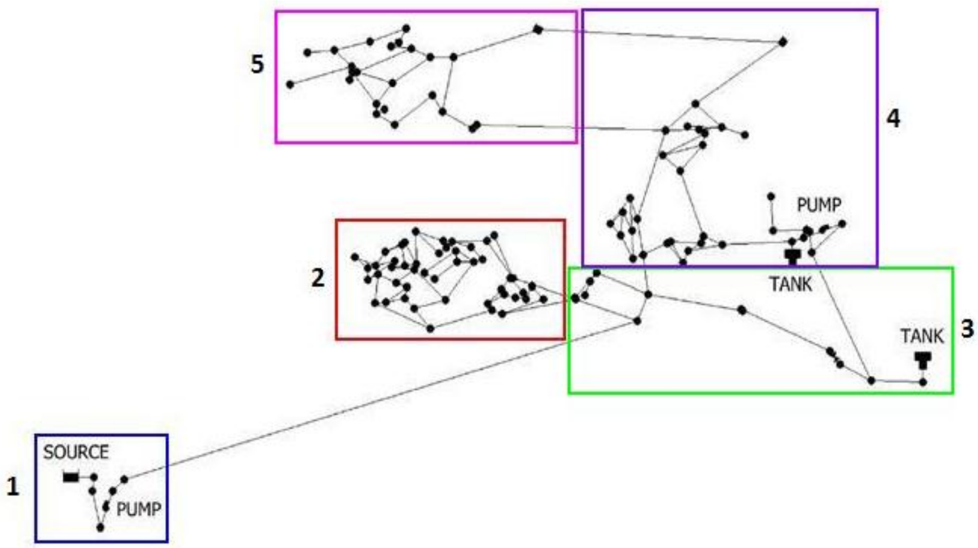

Figure 2.11. The layout of the network partitioned by five subsystems (Ostfeld et al., 2008)

2.3. Rule-Based Decision Support System for Case Study 3: Network 2 in The Battle of the Water Sensor Network (BWSN)

2.3.1. Modified Complexity Rule

Complexity rule is developed based on a branch of the graph theory in operation research, which focuses on classifying problems according to their inherent difficulties when solving a large network which contains significantly higher number of nodes and intersections than a small-scale network (Deuerlein et al., 2009). Since the population density of a large network, Network 2 in Figure 1.3, is not uniformly distributed throughout the water distribution like a small network which usually has a cluster of population density in a certain area of the network, the improved complexity rule is developed with the adjustment of algorithm for a large scale network. Instead of using only the number of inner nodes like the original complexity rule, the new complexity rule also includes the path nodes which surround the interested path nodes in the analysis. Even though the original complexity rule can effectively analyze small drinking water networks, when it is applied to a large network, which has high number of inner nodes due to the excessively high effective radius, is sometimes located in low population density because of the extensive length of pipeline which is designed to transfer water from one high population density to another in a large-scale network. As a result, the principle of new complexity rule is developed to count both the inner nodes and surrounded path nodes to redefine and shorter effective radius. With the improvement of complexity rule, the sensor deployment candidate locations are not only closer to highly populated area, but also better in holistic performances based on design objectives from Z1 to Z4.

For applications, the nodes in the drinking water distribution systems are categorized into inner nodes and path nodes as shown in Figure 2.1. A path node is defined as the node which has one or more pipes connected to the main pipe, and an inner node is defined as the node which locates between two path nodes. The methodology is to determine the number of combined inner nodes and path nodes within the determined impact zone which has hydraulic connection to the path node systematically. An effective radius for each path node can be calculated by dividing the summation of all pipe distance from an interested path node to the closest relevant inner node or surrounded path node in all direction by the number of combined inner node and surrounded path node stepwise for each path node throughout a network. Then, within the whole drinking water distribution network, the path nodes are ranked from the highest number of combined inner nodes and surrounded path nodes to the lowest number of combined inner nodes and surrounded path nodes. With the predetermined number of sensors to be deployed based on the budget, the sensor locations can be finally selected according to these rankings. The algorithm of complexity rule is listed below.

Complexity Rule of RBES

INPUT: Water distribution network layout data

BEGIN

1) Determine weight of complexity rule
2) Calculate the number of combined inner node and surrounded path node at each node
3) **If** (The number of combined node(x_j) > 0) denote the candidacy of node j
4) Rank the number of combined node of each node from the highest to the lowest ($x_{j,max}$ to $x_{j,min}$)
5) **END If**
6) Select the sensor deployment nodes based on the assigned weight
7) Combine the selected sensor locations with Accessibility rule

END

Figure 2.12. Modified Complexity Rule of RBDSS

2.3.2. Weight Optimization

For the analysis of using RBDSS in a large-scale water distribution network, using two rules with two different algorithms to generate two independent sets of sensor deployment locations and selecting half of the predetermined number of sensors from each rule can have a superior performance than using both rules in order to generate one set of sensor placement locations because the large skeleton of the network needed to be protected especially when the predetermined number of sensors to be deployed is low. For instance, if the predetermined number of sensor is 20 (e.g. case N2A20 of BWSN), when the performance of sensor locations is evaluated by using BWSN-software utility, using accessibility rule to generate 10 sensor placement locations and using complexity rule to generate another 10 sensor placement locations would have superior performance than using both rules simultaneously in order to generate 20 sensor deployment locations. As a result, weighted optimization is also embraced into the existing RBDSS. Even though RBDSS consists of two rules, accessibility rule and complexity rule, these two rules are assigned to have equal weight because each rule is as important as one another. Therefore, since the number of sensor, which can be based on financial incentive and a restricted budget, to be deployed is predetermined. Each rule shall produce half of the predetermined number of sensors because they carry the same weight. With this said, each rule may independently generate a set of sensor deployment locations based on its own algorithm. Then, the combination of two sets of sensor deployment locations would be the near optimal solution with the aid of RBDSS.

2.3.3. Experiment of Rule-Based Decision Support System Applications in Case Study 3

The methodology is divided into data collection, simulation analysis, weight assignment, rule base screening and node prioritization, design of sensor deployment locations, and evaluation of sensor locations with comparisons. The process schematic is shown in Figure 2.13. To compare the results with previous optimization and heuristic models/algorithms used in the BWSN, the same hydraulic data set was applied to Network 2. In the first phase, Network 2 that has four variable demand patterns consisting of 12,523 nodes, 2 sources, 2 tanks, 14,822 pipes, 4 pumps, and 5 valves, and subject to five variable demand patterns was organized for comparative analysis (Ostfeld et al., 2008). During the second phase, the network was simulated for a total extended period duration of 48 hours to acquire the information of dynamic flow patterns (Ostfeld et al., 2008). The EPANET, a well-calibrated dynamic simulation software available to download for free, was used to perform the hydraulic simulation in the large-scale drinking water distribution system (US EPA, 2010b).

In the third phase, weighted optimization method was applied based on both rules to determine the weight of each rule (i.e. 0.5 for both rules in this study). The weight can be used to prioritize one rule over the other rule, and the number of selected sensors from each rule is dependent on its assigned weight. The fourth phase is rule base screening and node prioritization. In this phase, the RBDSS was applied to the hydraulically simulated network, which was sectorized into 10 sections as shown in Figure 2.14, with respect to the accessibility rule and the complexity rule independently. Next, the EXCEL was used in the analysis to generate the prioritized nodes. The fifth phase is to design sensor deployment locations; the two independent lists of rankings across all candidate nodes were generated based on accessibility rule and complexity rule, respectively. Because the number of sensors is predetermined, and the weights were assigned to both rules, the sensor placement locations were determined by selecting top ranked nodes from ranking lists associated with both rules and their assigned weights. For instance, because the predetermined number of sensor for base case of N2A20 is 20, and the assigned weight for each rule in this study is 0.5, 10 sensor locations were selected from the highest ranks of each rule to generate a total of 20 locations.

Finally, the evaluation of proposed sensor locations was performed by using BWSN-software utility developed by Elad Salomons (Salomons, 2006). The software consists of two sections: “Build injection data” and “Calculate fitness”. “Build injection data” allows the user to create the data needed to evaluate the fitness function for a given sensor layout design, and “Calculate fitness” allows the user to calculate the fitness function for a given sensor layout design. Since the deployed sensors in Network 2 is being evaluated, a randomized matrix of 25,054 events (two injections at each node of the system, at two random times) was generated by “Build injection data” for the “Base Case A” to simulate the exact number of events which was produced by the other 11 models so that the evaluated sensor locations can be compared to the other models (Ostfeld, 2008). Then, the sensor locations were inputted into “Calculate fitness” to evaluate the four design objectives from Z1 to Z4 for RBDSS. Lastly, because the quantitative design objectives, from Z1 to Z4, were being used to evaluate the models' performances in BWSN, the evaluation of the same design objectives was necessary in order to draw upon a direct comparison between RBDSS and the other 10 models/algorithms by using the four design objectives as indexes. Even though there is trade-off among these four objectives, the ultimate solution shall minimize Z1, Z2, and Z3 while maximizing Z4 to provide the maximum security in water distribution networks. According to BWSN, these four design objectives can be defined in a greater detail as follows (Ostfeld, 2008):

- The expected time of detection (Z1) is defined as the elapsed time from the start of the contamination event, to the first identified presence of nonzero contaminant concentration;

- The expected population affected prior to detection (Z2) is defined as the number of population consumed contaminated water prior to detection,

- The expected consumption of contaminant water prior to detection (Z3) is defined as the volume of contaminated water prior to detection;

- The detection likelihood (Z4) is the probability of detection.

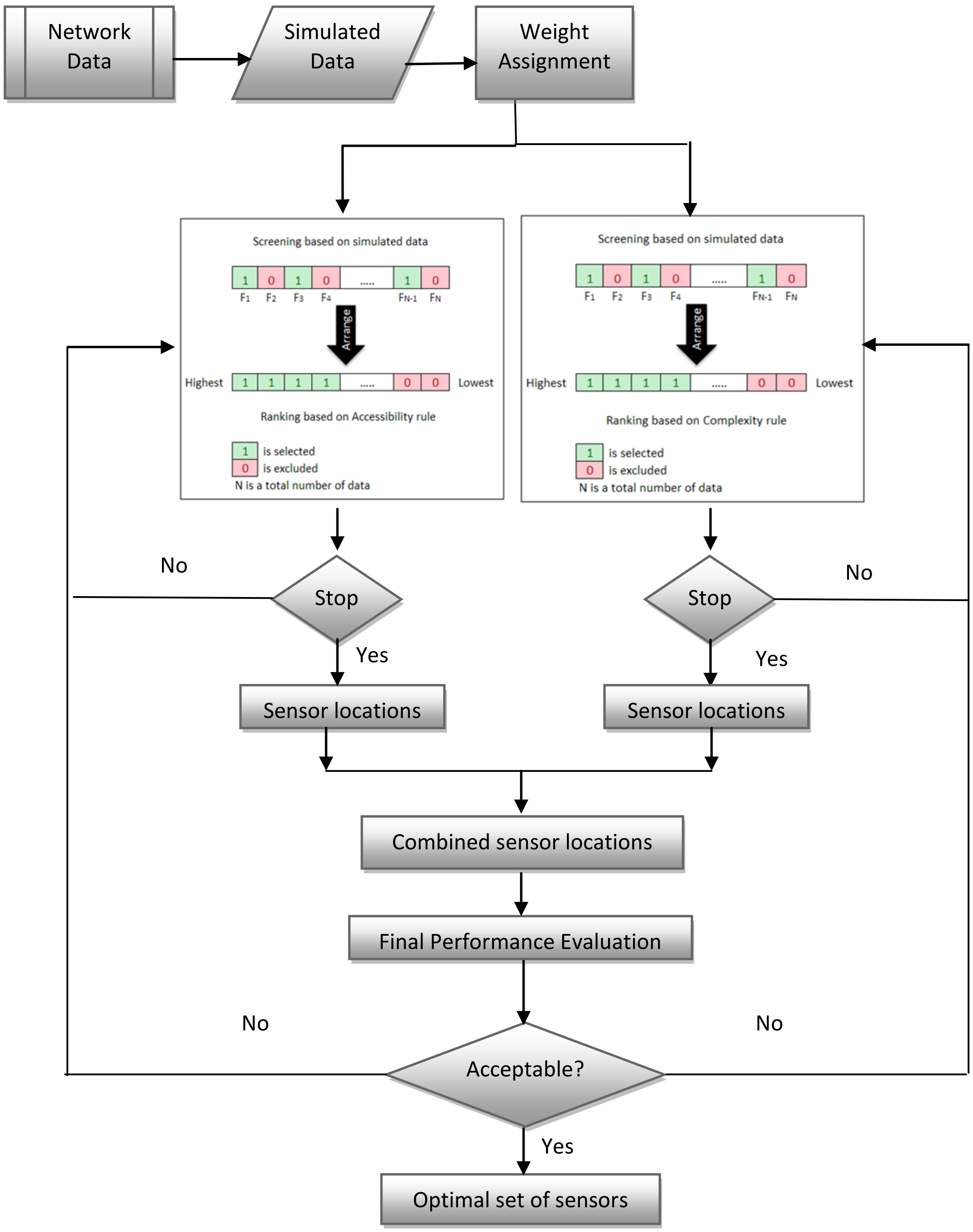

Figure 2.13. The process schematic of this rule-based decision Support system for large water distribution in the experiment

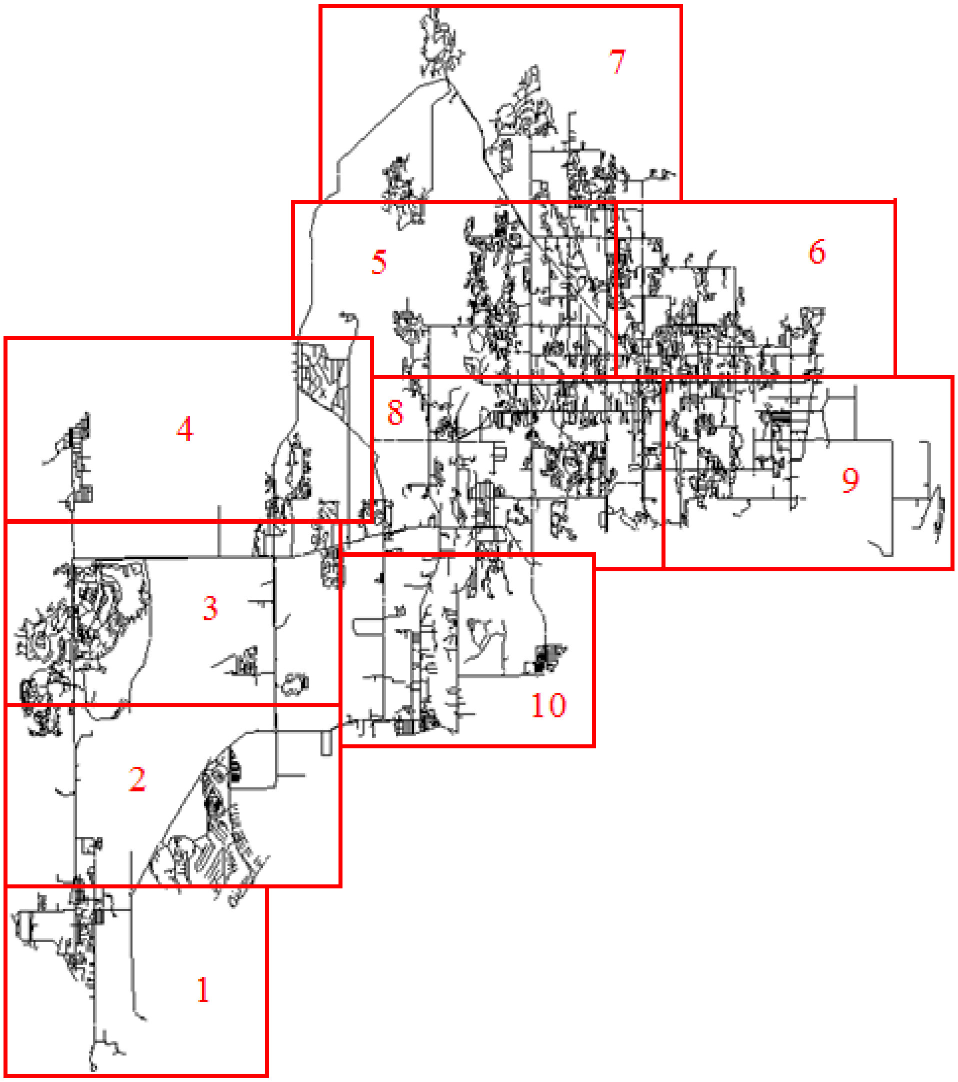

Figure 2.14. The sectorization of Network 2 into 10 sections (Ostfeld et al., 2008).

CHAPTER THREE: RESULTS AND DISCUSSIONS

3.1 Case Study 1: Hardin No. 1 County Water District

3.1.1 Results of Case Study 1

Ranking these selected nodes may further reveal the cost-effectiveness in sensor deployment should financial constraint be emphasized. In other words, the node with higher rank receives higher priority, implying a greater number of residents may be protected if the corresponding sensor can be deployed at that node. The rankings of sensor locations associated with different scenarios can be summarized for the residual chlorine scenario (Table 3.1) and the lead scenario (Table 3.2). For the TTHM scenario, none of the nodes in the network exceeds the MCL of, 4.0 mg/L; therefore, sensor deployment is not necessary. Because the network consists of 25,964 nodes and 15,600 pipes, only partial results were presented in Figure 3.1 and 3.2.

Table 3.1. Top 10 nodes selected for residual chlorine scenario by using the intensity, accessibility, and complexity rules in sequence.

No	Node ID		
	Intensity Rule	Accessibility Rule	Complexity Rule
1	1267	1267	1267
2	13779	6731	1573
3	6731	6643	5035
4	6643	1573	6794
5	1573	25358	3309
6	25358	5035	4363
7	5035	769	1986
8	769	6794	24519
9	251	3309	2008
10	6794	4363	2151
11	3309	1986	
12	4363	22285	
13	1986	24519	
14	1224	2008	
15	22285	2151	
16	1008		

No	Node ID		
	Intensity Rule	Accessibility Rule	Complexity Rule
17	24521		
18	24519		
19	2008		
20	2151		

Table 3.2. Top 10 nodes selected for lead scenario by using the intensity, accessibility, and complexity rules in sequence.

No	Node ID		
	Intensity Rule	Accessibility Rule	Complexity Rule
1	24813	24813	24837
2	212	209	25845
3	209	25837	1470
4	25837	25845	25880
5	25845	25869	25852
6	25869	1470	180
7	1470	25880	188
8	25880	171	196
9	171	25852	25898
10	25852	180	213
11	180	188	
12	178	196	
13	170	25898	
14	188	161	
15	196	213	
16	25910		
17	156		
18	25898		
19	161		
20	213		

Figure 3.1. Section 2 of the network. Green and blue circles represent the nodes selected for chlorine residual and lead scenarios, respectively. The red dot represents Tank 26653 in which lead is injected to simulate the third scenario. The nodes selected for chlorine residual and lead scenarios, are represented in green and blue circles respectively.

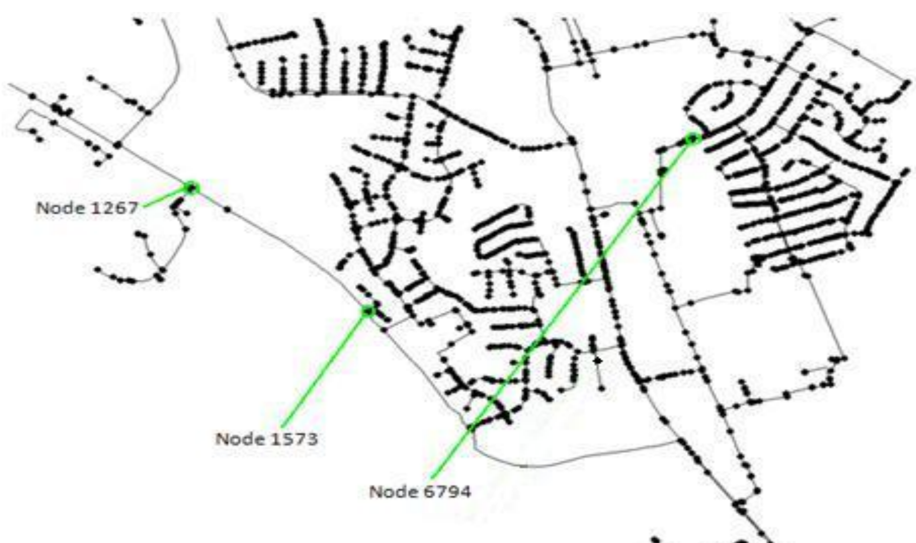

Figure 3.2. Section 5 of the network. Green and blue circles represent the nodes selected for chlorine residual and lead scenarios, respectively. The nodes selected for chlorine residual and lead scenarios, are represented in green and blue circles respectively.

3.1.2. Discussion of Case Study 1

The RBDSS outputs show that the selected nodes for sensor deployment to detect residual chlorine are located throughout the water network, except section 3 where the Pirtle Spring water treatment plant is located. This section should have the highest residual chlorine concentration, and there are no rechlorination stations in other sections of the drinking water distribution network. Residual chlorine simulation results indicate that the summation of the residual chlorine concentration of the selected nodes equals zero. In other words, these selected nodes are highly unlikely to be effectively disinfected by the chlorine dosed at the plant. Because none of these nodes are located along the main pipe lines, the lack of disinfection at the selected nodes would not cause a significant negative impact on the majority of the population.

The sensors for residual chlorine detection can be AccuChlor 2 Residual Chlorine Measurement System, CL17 Free Residual Chlorine Analyzer, or Series B20 Residual Chlorine Recorder with type B sensor (APPENDIX). For sensitivity analysis, the population protected is greater when a larger number of sensors can be deployed (Figure 3.3). The total number of protected residents is significantly small, however; only 12 people can be protected when 10 sensors are in place because the selected nodes with low residual chlorine are all located far from the water treatment plant and the population center of the county. In other words, these nodes are located at in low population density areas, and as a result, the deployed sensors can only protect a small number of people at those nodes. The lower exposure levels (Figure 3.4) indicate that the levels of residual chlorine that effectively disinfect at those nodes are below the minimum standard. Similarly, the selected nodes ranked 1 through 9 have peak residual chlorine concentrations of 0.0 mg/L (Figure 3.5; Table 3.3), indicating that the water flows at these selected nodes do not have any disinfection; therefore, they are selected to deploy sensors to detect such violations.

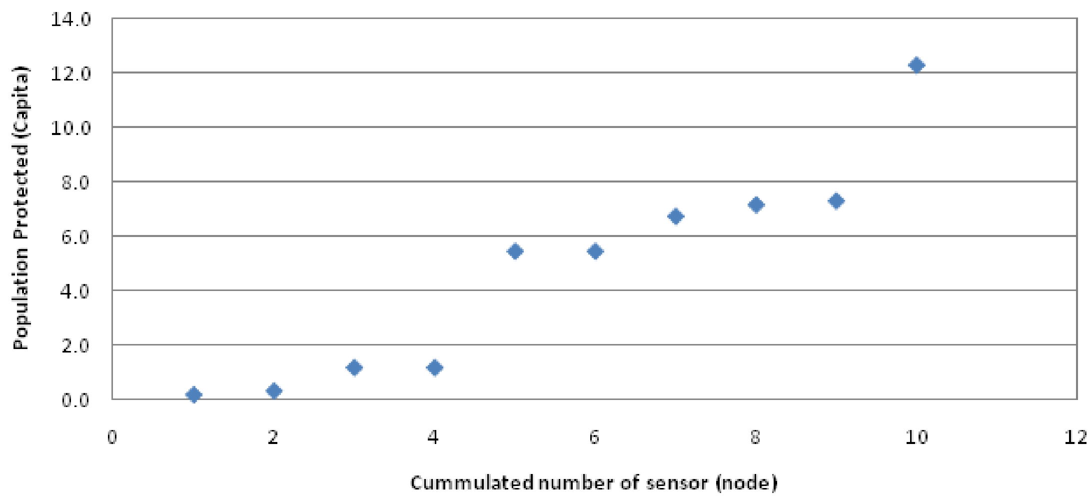

Figure 3.3. Sensitivity analysis of sensor deployment for chlorine residual based on the size of the population protected.

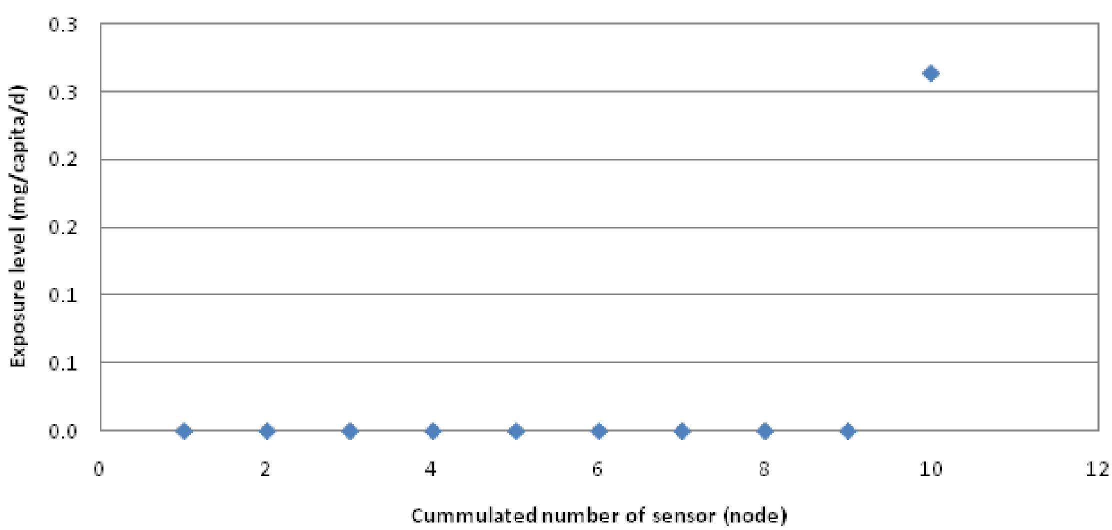

Figure 3.4. Sensitivity analysis of sensor deployment for chlorine residual based on the exposure assessment.

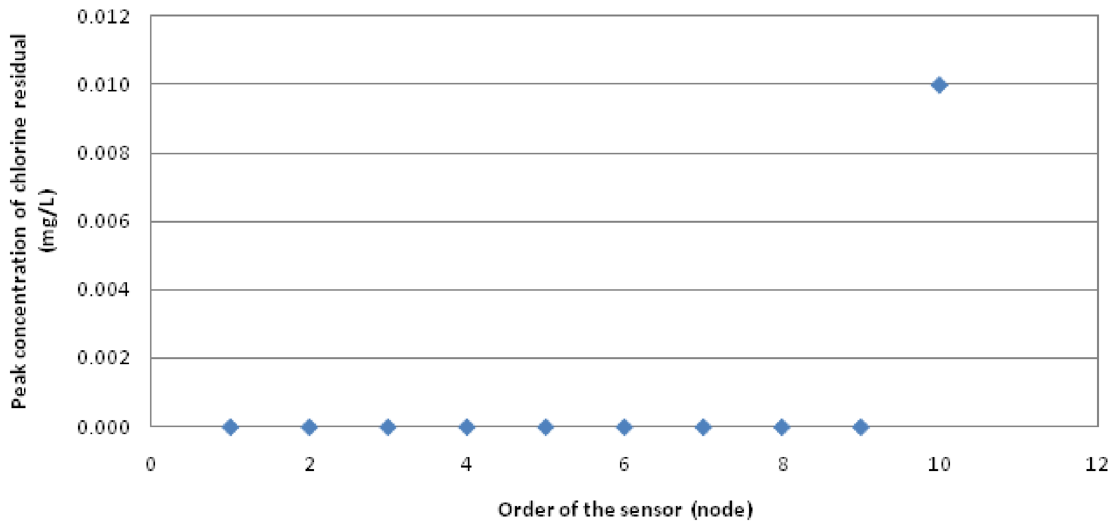

Figure 3.5. Peak concentration of chlorine residual at the selected nodes.

Table 3.3. Ranking of the selected sensors associated with two sensitivity analyses and peak concentration of chlorine residual at each node.

Sensor Rank	Sensor ID	Population Protected (capita)	Exposure Level (mg/capita/d)	Peak Concentration of Chlorine Residual (mg/L)
1	1267	0.1	0.0	0.00
2	1573	0.3	0.0	0.00
3	5035	1.1	0.0	0.00
4	6794	1.1	0.0	0.00
5	3309	5.4	0.0	0.00
6	4363	5.4	0.0	0.00
7	1986	6.7	0.0	0.00
8	24519	7.1	0.0	0.00
9	2008	7.3	0.0	0.00
10	2151	12.3	0.3	0.01

Finally, lead release due to either a terrorist attack or a pipe corrosion scenario can be explored. Based on the observations of the EPANET simulation outputs, as shown in Figure 3.1, these nodes are located along the first pipe section, which receives most of the outflow from the water tank and has a significantly higher lead concentrations than the other pipe sections.

Therefore, these selected nodes would require the installation of type A sensor of SMART 2 Colorimeter with the 3660-SC Reagent System Portable Cyanide Analyzer or Deltatox® instrument (see APPENDIX). In sensitivity analysis, the size of the population protected can be significantly increased as the total number of sensor to be deployed is increased (Figure 3.6). When 10 sensors are deployed in the lead scenario, 116,362 people are protected, much higher than the number in the residual chlorine scenario, because all the deployed sensors are located in the highly populated area of the county. Thus, more of the optimal locations for sensor deployment were in pipe section 2 to maximize the protection for largest population residing in this region. In addition, the sensitivity analysis for exposure assessment (Figure 3.7) indicates that the higher the number of sensor to be deployed, the lower the exposure level of the substance to the population. The level of exposure is decreased instantly as more sensors are deployed. For instance, when one sensor is deployed, the level of exposure is 31.42 mg/capita/day; but when 10 sensors are deployed, the level of exposure decreases dramatically to 13.20 mg/capita/day.

The marginal sensitivity of sensors for lead detection based on the exposure assessment (Figure 3.8) confirms the diminishing rate of return. The more sensors deployed, the smaller the marginal effect of sensor deployment. The cost effectiveness of the RBDSS (Table 3.4) is collectively based on three indexes, including population protected, exposure levels, and peak concentrations. When the node has the highest concentration of lead, it can be as high as 1.19 mg/L at the 1st selected node, yet the concentration becomes 0.5 mg/L at the 10th selected node because these selected nodes were ranked from the highest concentration to the lowest concentration.

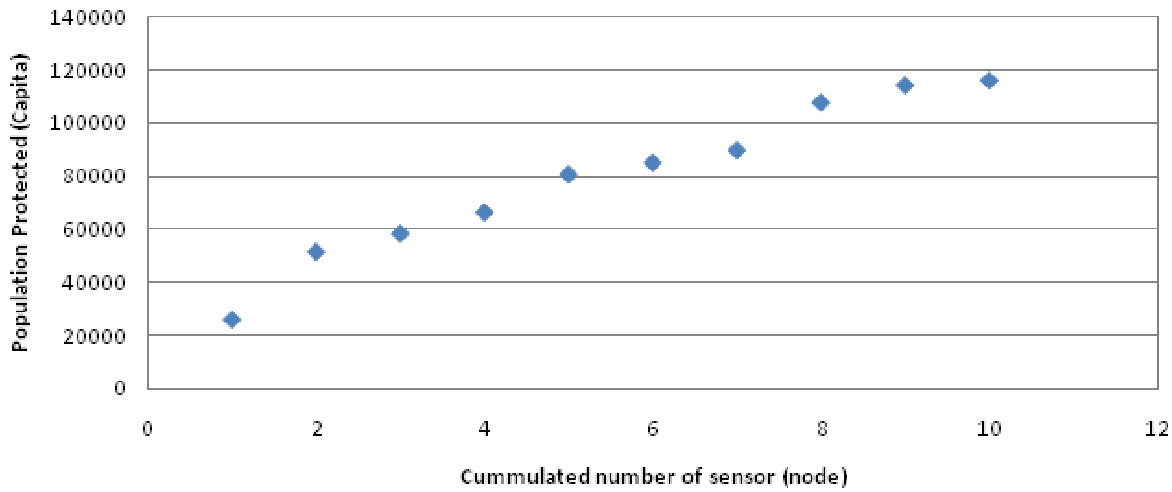

Figure 3.6. Sensitivity analysis of sensor deployment for lead detection based on the size of the population protected.

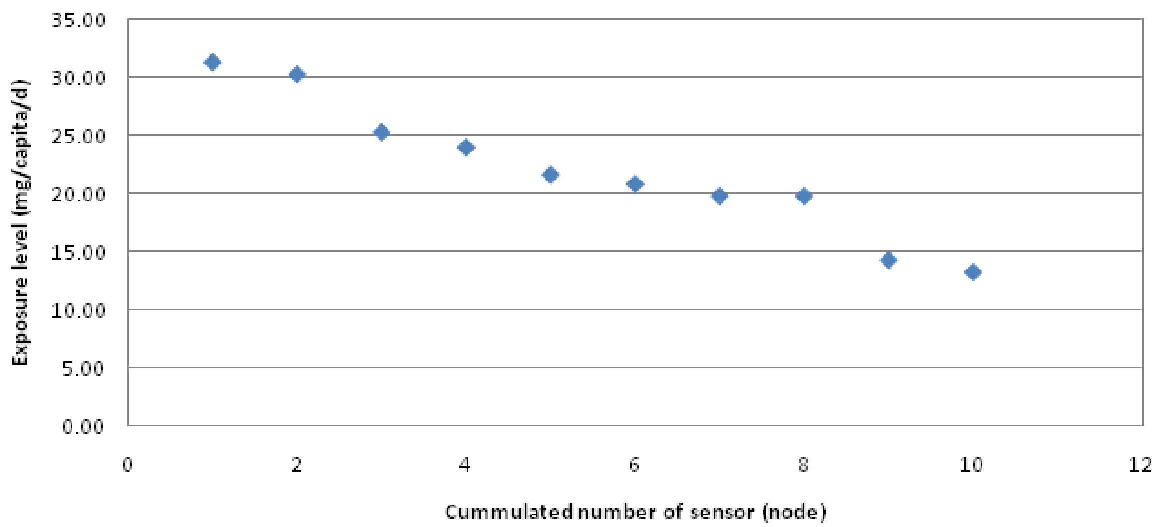

Figure 3.7. Sensitivity analysis of sensor deployment for lead detection based on the exposure assessment.

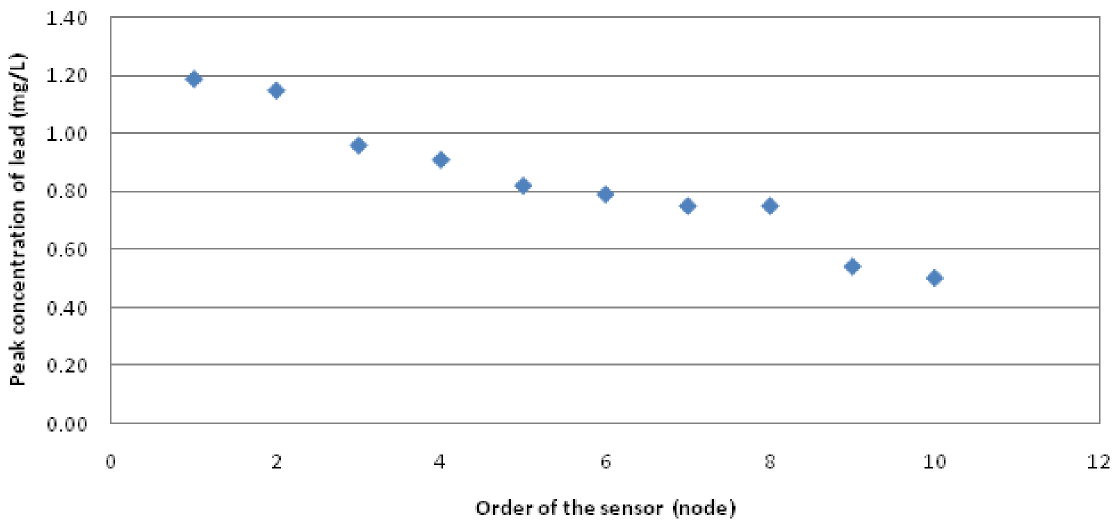

Figure 3.8. Peak concentration of lead at the selected nodes.

Table 3.4. Ranking of the selected sensors associated with two sensitivity analysis parameters and peak concentration of lead at each node.

Sensor Rank	Sensor ID	Population Protected (capita)	Exposure Level (mg/capita/d)	Peak Concentration of Lead (mg/L)
1	24837	25807	31.42	1.19
2	25845	51484	30.36	1.15
3	1470	58398	25.34	0.96
4	25880	66435	24.02	0.91
5	25852	80814	21.65	0.82
6	180	85238	20.86	0.79
7	188	89933	19.80	0.75
8	196	108021	19.80	0.75
9	25898	114537	14.26	0.54
10	213	116362	13.20	0.5

3.2 Case Study 2: Network 1 in The Battle of the Water Sensor Network (BWSN)

3.2.1. Results of Case Study 2

Based on the evaluation with the aid of the RBDSS, the selected five nodes that were prioritized and ranked are 47, 68, 76, 97, and 118, as shown in Figure 3.9. The computer runtime (i.e., CPU time) for running the RBDSS for tackling base case A (N1A1) via using the Dell PC 2.53 GHz 2.98 GB of RAM is approximately less than 1 second. The four objectives, as listed in Table 3.5, were evaluated by using the BWSN utility software and the outcome that our RBDSS algorithm achieved includes: 1) the expected time of detection (Z1) = 479 minutes, 2) the expected population affected prior to detection (Z2) is 479 persons, 3) the expected consumption of contaminant water prior to detection (Z3) = 2,824 gallons, and 4) the detection likelihood (Z4) = 0.575 (e.g., 57.5%). Table 3.5 summarizes the performance evaluation in terms of these four design objectives and the numbers marked in those parentheses within the last four columns are the ranks across the 15 methods associated with each objective. The whole arrangement follows the order of methods rather than the ranks though. The expected time of detection, Z1, is a critical index in real world application because the faster sensors detect the contamination in the water distribution process, the faster EWS can notify the public and shut down contaminated water delivery. On the other hands, the expected population affected prior to detection, Z2, and the expected consumption of contaminated water prior to detection, Z3 are not as effective as the first and last one (Z1 and Z4) when use them as criteria to determine sensor layout because Z2 and Z3 predict the possible affected population prior to detection, which are estimates under uncertainty.

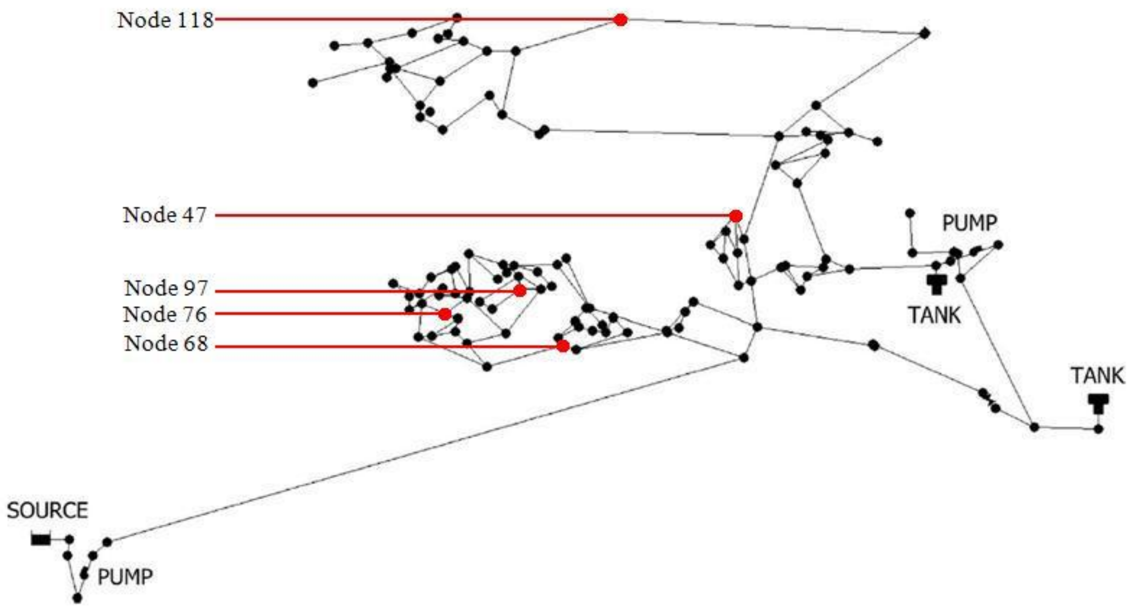

Figure 3.9. Sensor deployment locations based on the RBDSS (Ostfeld et al., 2008).

We found out that a model which has a significantly low Z2 and Z3 will not have a good performance because the EWS cannot alarm until sensor can detect the contamination. In addition, the model with significantly high Z1 and low Z4 will have other problems because it could take significantly long to detect contaminant and have high probability of missing detection due to low detection likelihood. As a result, the ideal model should have low Z1 and high Z4.

When the degree of these four design objectives achieved by the RBDSS were compared to the other 14 optimization and heuristic models by ranking Z1, Z2, and Z3 from the lowest to the highest and Z4 from the highest to the lowest, the performance associated with these four criteria namely Z1, Z2, Z3, and Z4 by using the RBDSS were ranked 6th, 7th, 4th, and 11th, respectively, among 15 candidates in total. At least, the RBDSS outperforms more than half of the optimization and heuristic models in terms of the first three important objectives including the expected time of detection (Z1), the expected population affected prior to detection (Z2), and the expected consumption of contaminant water prior to detection (Z3). As for the detection likelihood, it should be improved as the limitation of the total number of sensors allowable to deploy can be released to some extent.

Table 3.5. The comparisons of the results from NRBDSS with the other optimization and heuristic models in base case A (N1A5)

Model No.	Methodology	Sensor location (nodes)	Z1 (min)	Z2 (capita)	Z3 (gallons)	Z4 (detection likelihood, %)
1	a p-median formulation using a heuristic method (Berry, Hart, Phillips, & Watson, 2006)	17,21,68,79,122	542 (8)	140 (1)	2459 (1)	0.609 (10)
2	multiobjective optimization using noisy cross-entropy sensor locator (nCESL) (Dorini et al., 2006)	10,31,45,83,118	1068(15)	258 (10)	7983 (13)	0.801 (1)
3	multiobjective optimization using "iterative deepening of Pareto solutions" (Eliades & Polycarpou, 2006)	17,31,45,83,126	912 (14)	221 (8)	7862 (12)	0.763 (3)
4	a heuristic demand-based approach with the highest demand (Ghimire & Barkdoll, 2006a)	126,30,118,102,24	432 (3)	357 (14)	4287 (8)	0.367 (14)
5	a heuristic demand-based approach with the mass released (Ghimire & Barkdoll, 2006b)	126,30,102,118,58	424 (2)	331 (13)	3995 (7)	0.402 (13)
6	a generic algorithm simulation optimization based on a single objective function (Guan, Aral, Maslia, & Grayman, 2006)	17,31,81,98,102	642 (9)	159 (4)	2811 (3)	0.663 (8)
7	multiobjective optimization using a predator-prey model (Gueli, 2006)	112,118,109,100,84	794 (12)	403 (15)	10309 (15)	0.699 (6)
8	multiobjective genetic algorithm with data mining (Huang, McBean, & James, 2006)	68,81,82,97,118	541 (7)	280 (11)	4465 (9)	0.676 (7)

Model No.	Methodology	Sensor location (nodes)	Z1 (min)	Z2 (capita)	Z3 (gallons)	Z4 (detection likelihood, %)
9	a greedy algorithm (Krause et al., 2006)	17,83,122,31,45	842 (13)	181 (6)	3992 (6)	0.756 (4)
10	multiobjective optimization nondominated sorted genetic algorithm-II (NSGA II) (Ostfeld & Salomons, 2006)	117,71,98,68,82	461 (5)	250 (9)	4499 (10)	0.622 (9)
11	multiobjective optimization nondominated sorted genetic algorithm-II (NSGA II) (Preis & Ostfeld, 2006)	68,101,116,22,46	439 (4)	151 (3)	7109 (11)	0.477 (12)
12	a mixed-integer linear program (Propato & Piller, 2006)	17,22,68,83,123	711 (11)	164 (5)	3148 (5)	0.725 (5)
13	an engineering "strawman" approach (Trachtman, 2006)	1,29,102,30,20	391 (1)	142 (2)	2504 (2)	0.237 (15)
14	multiobjective optimization using a genetic algorithm (Wu & Walski, 2006)	45,68,83,100,108	704 (10)	303 (12)	8406 (14)	0.787 (2)
15	rule-based decision Support system (RBDSS)	47,68,76,97,118	479 (6)	209 (7)	2824 (4)	0.575 (11)

3.2.2. Discussions of Case Study 2

Based on Table 3.5, it is good to visualize the comparative advantages across the four design objective function values achieved by the 15 methods based on the paired approach. In Figure 3.10a, Z1 is compared against Z4. Four out of five optimization models which have the lower expected time of detection, Z1 and outperform the RBDSS also have lower probability of detection, Z4. As a consequence, there is no significant difference between these four models and the RBDSS in terms of Z1 since the difference is in a range between 88 and 18 minutes as the advantage of the RBDSS can be readily differentiated in terms of Z4. This finding makes the RBDSS stand out with higher priority. On the other hand, models that have higher detection likelihood (Z4) than the RBDSS normally have higher time of detection (Z1) ranging from 62 minutes to 589 minutes. Overall, in Figure 27a, the ideal solution in this regard is situated at the lower right corner. Based on the geometric distance from the ideal solution, the RBDSS can be ranked the 3rd or the 4th among 15 models approximately. Figure 3.10b shows the trade-off graph of the expected population affected prior to detection (Z2) and the detection likelihood (Z4)**.** The ideal solution is situated at the upper right corner reflecting the highest detection probability and the largest population to be protected. There are about half of the optimization and heuristic models, as listed in Table 3.5, that outweigh the RBDSS. Figure 3.10c shows trade-off graph of the expected consumption of contaminated water prior to detection (Z3) and the detection likelihood (Z4). The ideal solution is situated at the lower right corner reflecting the highest detection probability and the smallest amount of contaminated water that might be consumed before detection. The RBDSS can be ranked the 5th among 15 models approximately. Even though the comparision is being made based on the best solution from different models, the majority of the other models were proposing more than one set of solution. As a result, there are 18 nondominated solutions for case N1A5 from the other models. This is a significant advantage of RBDSS over the other models and algorithms because RBDSS generates only one set of solution which is an optimal solution for RBDSS's algorithms unlike the other models and algorithms which require objective indexes to determine whether the solution is a dominated solution or not.

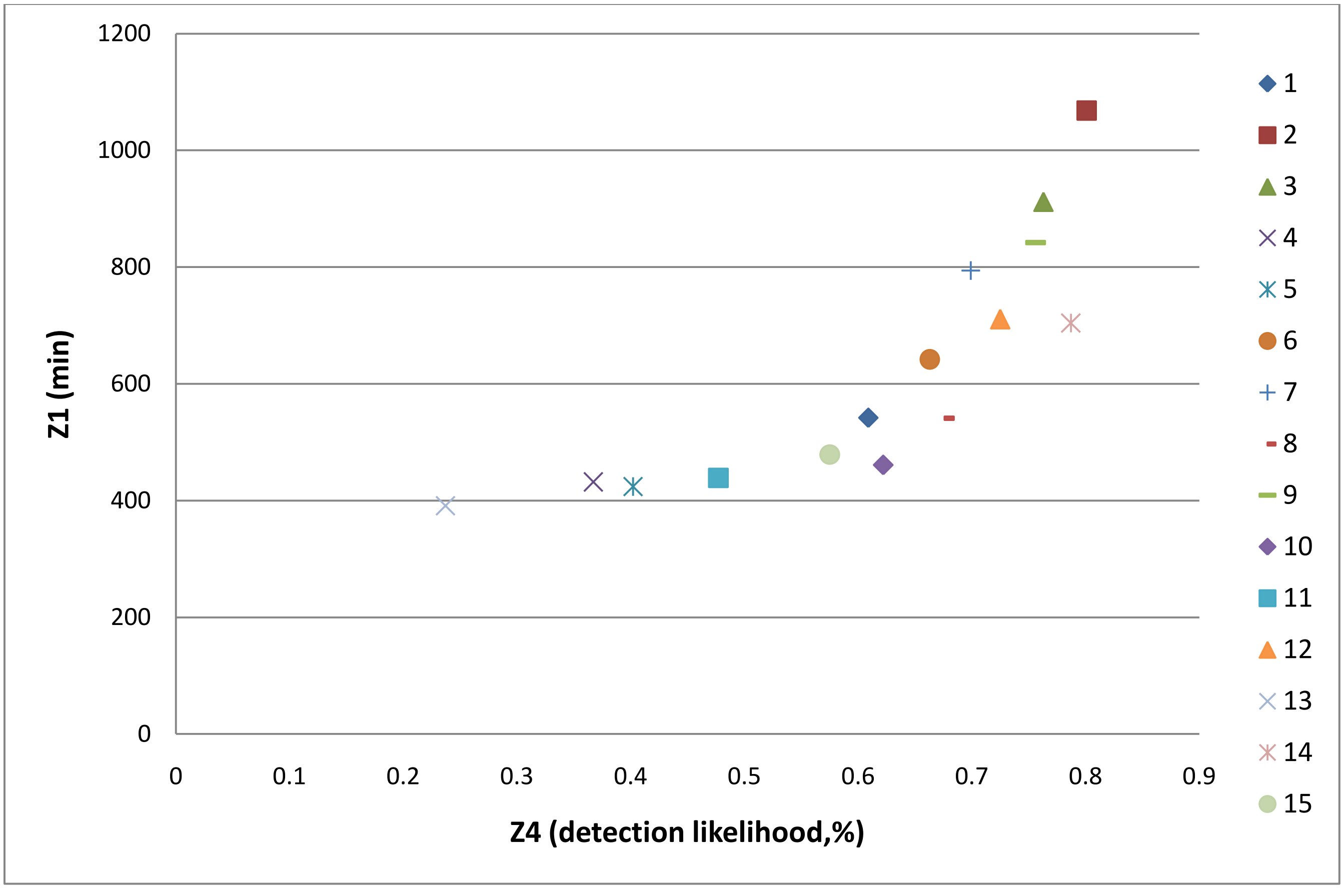

Figure 3.10a. The trade-off graph between the expected time of detection (Z1) and the detection likelihood (Z4).

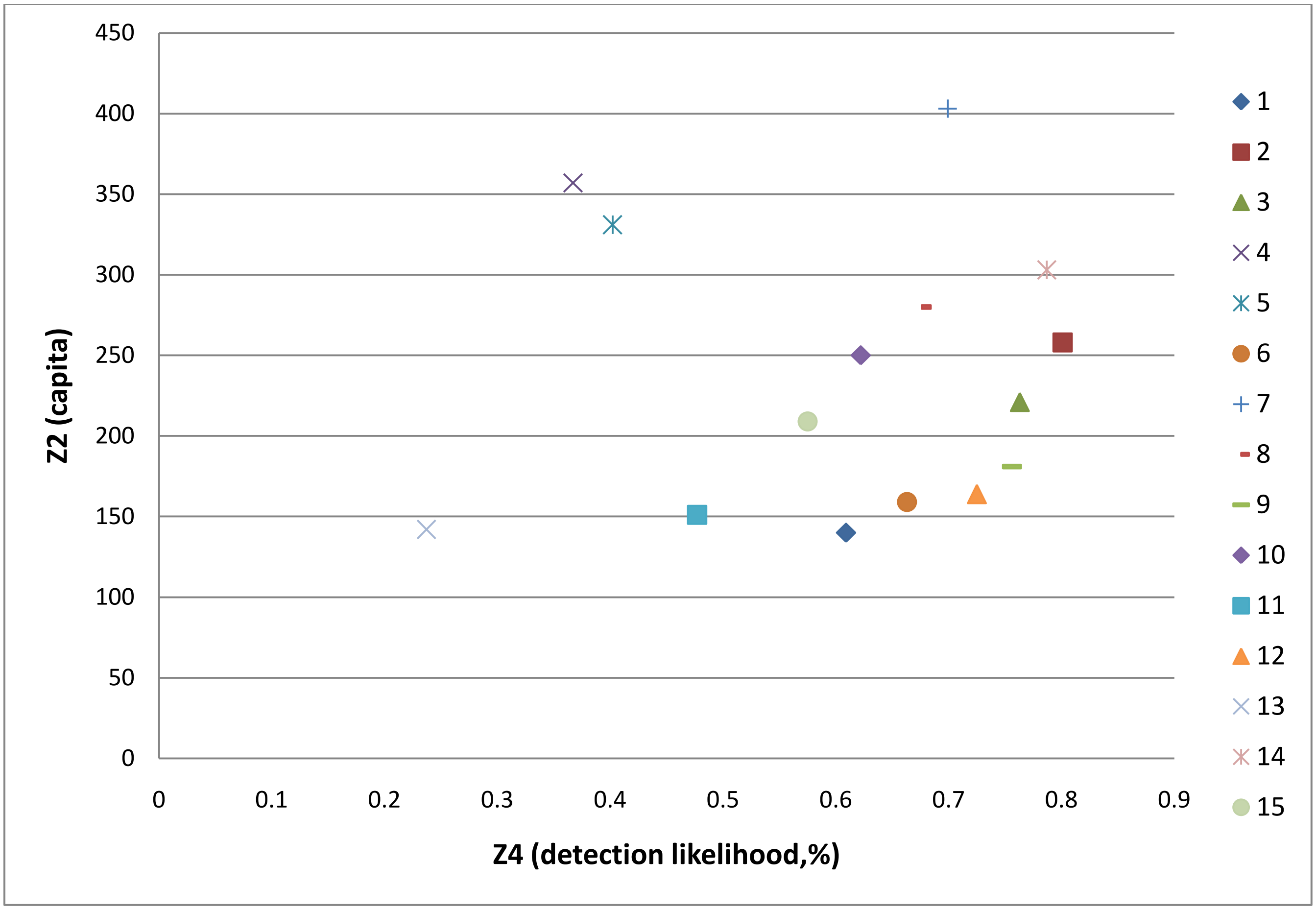

Figure 3.10b. The trade-off graph of the expected population affected prior to detection (Z2) and the detection likelihood (Z4).

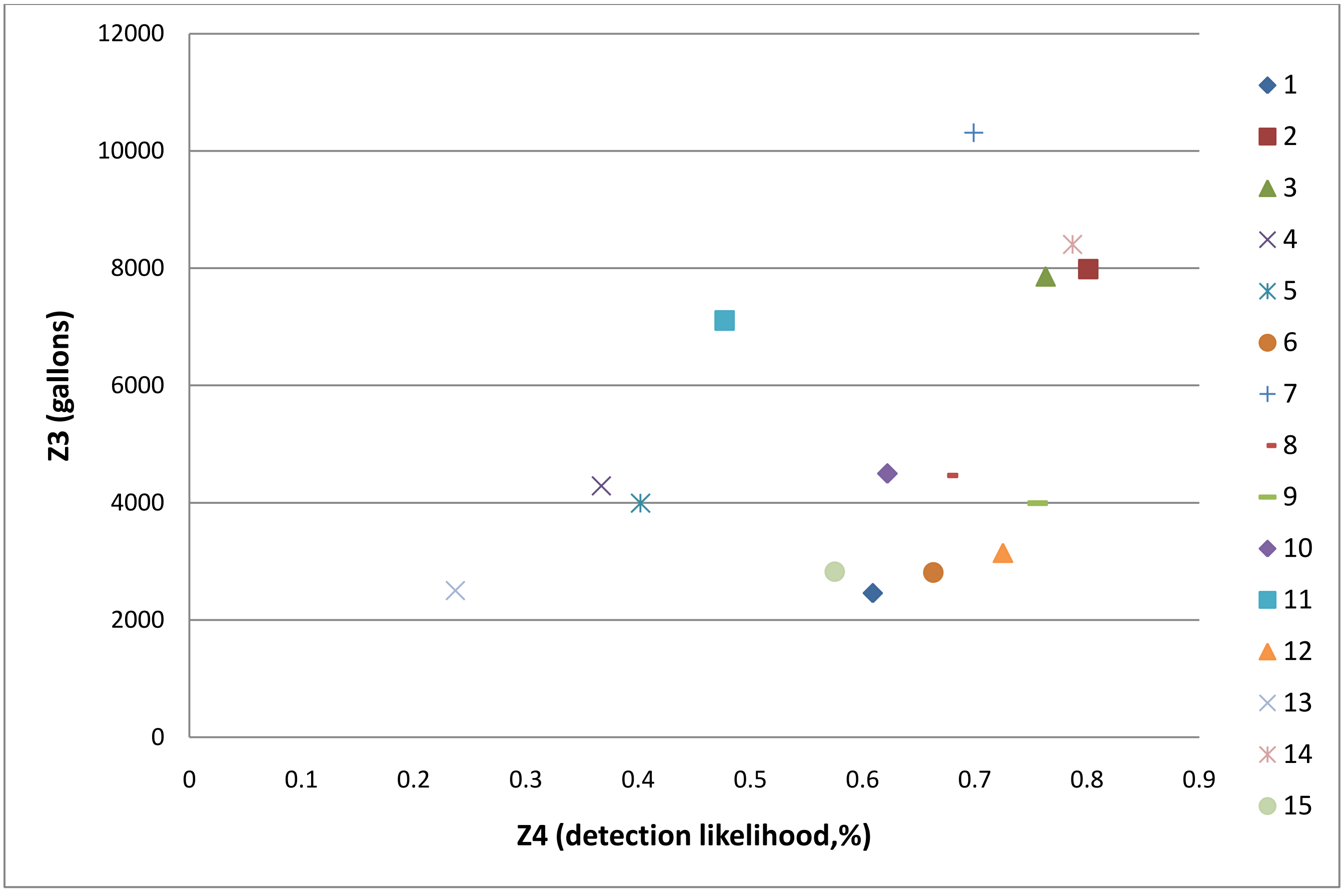

Figure 3.10c. The trade-off graph of the expected consumption of contaminated water prior to detection (Z3) and the detection likelihood (Z4).

<u>3.3. Case Study 3: Network 2 in The Battle of the Water Sensor Network (BWSN)</u>

3.3.1. Results of Case Study 3

Since Network 2 is too large to display the sensor locations in one figure, Network 2 was sectorized into 10 sections as shown in Figure 2.14. Based on the results of RBDSS, the proposed 20 sensor deployment locations by selecting top ten ranking of accessibility rule are 636, 1798, 1924, 3070, 3524, 3684, 4185, 4594, 5631, and 10502 and top ten ranking of complexity rule are 176, 1135, 3229, 4406, 4919, 5097, 6483, 7908, 8025, and 8900. Figure 3.11 is used for the purpose of demonstration of section 9 of the pipe Network 1. Table 3.6 presents an all-inclusive summary. . The four objectives, as listed in Table 3.6, were evaluated by using the BWSN-software utility and the outcome that our RBDSS algorithm achieved includes: 1) the expected time of detection (Z1) = 854 minutes, 2) the expected population affected prior to detection (Z2) is 1231 persons, 3) the expected consumption of contaminant water prior to detection (Z3) = 89,587 gallons, and 4) the detection likelihood (Z4) = 0.303 (e.g., 30.3%). Table 3.6 summarizes the performance evaluation in terms of these four design objectives and the numbers marked in those parentheses within the last four columns are the ranks across the 11 methods associated with each objective.

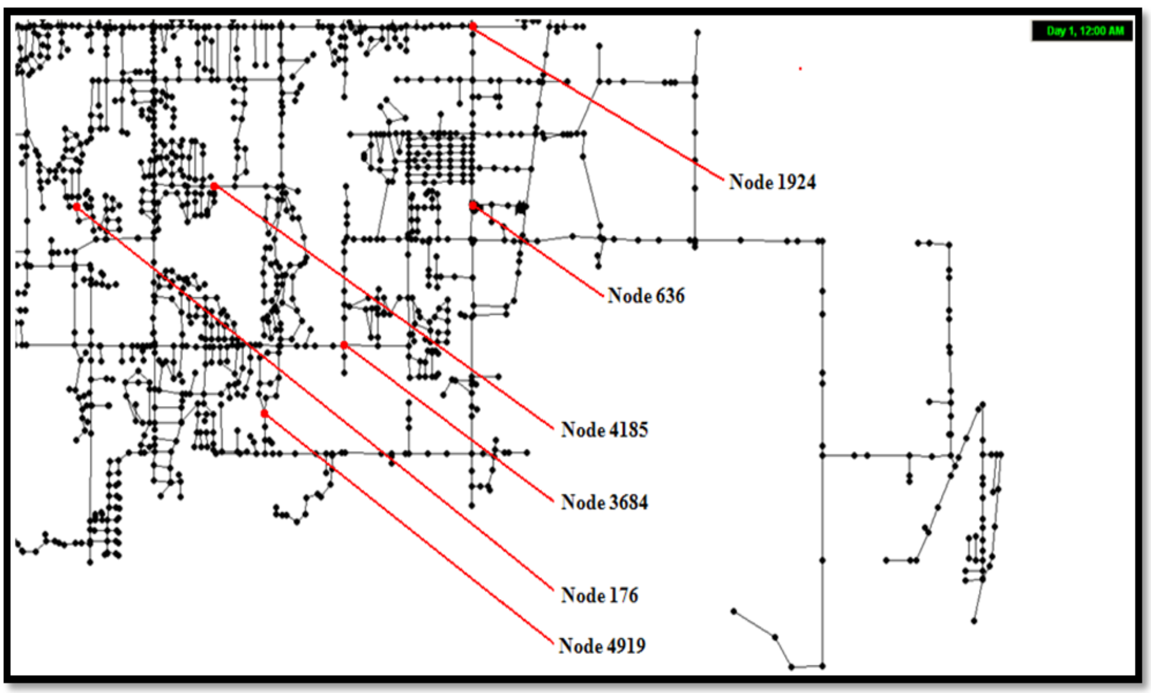

Figure 3.11. The layout of the section 9 of network 2 with the selected sensor deployment locations presented in red dot.

Table 3.6. The comparisons of the results from RBDSS with the other optimization and heuristic models in base case A (N2A20).

Model No.	Methodology	Sensor location (nodes)	Z1 (min)	Z2 (capita)	Z3 (gallons)	Z4 (detection likelihood, %)
1	a p-median formulation using a heuristic method (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	17456	0.366
2	multiobjective optimization using noisy cross-entropy sensor locator (nCESL) algorithm (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	1325	90255	0.401
3	multiobjective optimization using "iterative deepening of Pareto solutions" algorithm (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	1108	1600	121574	0.409
4	a heuristic demand-based approach with the highest demand and the mass released (Ghimire and Barkdoll, 2006b, Guan et al., 2006).	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	1090	1924	189281	0.300
5	a generic algorithm simulation optimization based on a single objective function (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	43585	0.308
6	multiobjective genetic algorithm with data mining (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	1264	78533	0.342

Model No.	Methodology	Sensor location (nodes)	Z1 (min)	Z2 (capita)	Z3 (gallons)	Z4 (detection likelihood, %)
7	a greedy algorithm (Krause et al., 2006).	10,874; 4,684; 11,304; 3,357; 1,184; 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	27458	0.397
8	multiobjective optimization nondominated sorted genetic algorithm-II (NSGA-II) (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	1093	1554	109931	0.384
9	an engineering "strawman" approach (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	1555	116922	0.217
10	multiobjective optimization using a genetic algorithm (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	1353	77312	0.420
11	rule-based decision support system (RBDSS)	176; 636; 1,135; 1,798; 1,924; 3,070; 3,229; 3,524; 3,684; 4,185; 4,406; 4,594; 4,919; 5,097; 5,631; 6,483; 7,908; 8,025; 8,900; 10,502	854	1231	89587	0.303

3.3.2. Discussions of Case Study 3

Based on the results in Table 3.6, the performance of RBDSS is comparable to the other 10 models/algorithms based on the values of four designed objectives, which were produced by using BWSN-software utility to evaluate sensor deployment locations proposed by RBDSS. The performance of RBDSS is actually within a leading position relative to another 10 models/algorithm. The four objectives generated by using RBDSS are ranked 6^{th}, 4^{th}, 6^{th}, and 9^{th} with respect to the expected time of detection (Z1), the expected population affected prior to detection (Z2), the expected consumption of contaminant water prior to detection, and the detection likelihood (Z4), respectively. Even though the rankings of four objectives based on RBDSS are not in the highest ranks over another 10 models/algorithms, they are not absolute disadvantages. Figure 3.12a shows the trade-off graph of the expected time of detection (Z1) and the detection likelihood (Z4)**.** RBDSS has a vertical distant very close to multiobjective genetic algorithm with data mining and multiobjective optimization using a genetic algorithm; this is due to the fact that the value Z1 for RBDSS is 854 minutes compared to 829 minutes and 850 minutes for multiobjective genetic algorithm with data mining and multiobjective optimization using a genetic algorithm, respectively. This indicates that the delay of the expected time of detection, Z1, for RBDSS is not significant number for a large water distribution network when comparing to the 5^{th} rank is only 4 minutes. Similar close-gap values among ranking can also be observed in the detection likelihood (Z4) category; a generic algorithm simulation optimization based on a single objective function can produce 30.8 % of detection likelihood while RBDSS's performance is 30.3%. Thus, the difference of the probability of sensor to detect contamination in the network between these two models is only 0.5%. In Figure 3.12b, the trade-off graph of the expected population affected prior to detection (Z2) and the detection likelihood (Z4) is shown. The optimal solution is located at the lower right corner which indicates the highest detection likelihood and the lowest expected population affected prior to detection. Figure 3.12c shows trade-off graph of the expected consumption of contaminated water prior to detection (Z3) and the detection likelihood (Z4). The ideal solution is situated at the lower right corner reflecting the highest detection probability and the lowest amount of contaminated water that might be consumed prior detection. In Figure 3.12b and Figure 3.12c, the distance from the optimal solution to the proposed solution can be used as a ranking which accounts for both objectives; the values based on RBDSS in Figure 3.12b and Figure 3.12c are approximately ranked 9th. Finally, since the lower right corners of Figure 3.12a to Figure 3.12c represent the optimal solution, the distance from the corner to the plotted data can be used as ranking performances based on the correlation stated in each figure. The closer the plotted data to the lower right corner is, the better solution is indicated. The ranks of models' performances based on three different correlations, which are Z1 and Z4 in Figure 3.12a, Z2 and Z4 in Figure 3.12b, and Z3 and Z4 in Figure 3.12c, can be displayed in bar graphs in Figure 3.13. According to Figure 3.13, it has shown that model number 1, 2, 6, 8, and 10 have unsteady ranking which may indicate the effects of trade-off among design objectives; on the other hand, model number 3, 4, 5, 7, 9, and 11 (RBDSS) display steady performances in every correlations. Even though RBDSS is ranked 9th in overall performances when it is ranked based on the correlations, the differences based on the distances toward the ultimate solution among model number 5, 6, 7, and 11 which are ranked from 6th to 9th in Figure 3.13 are minimal. Thereby, the differences based on the correlations among these four models are insignificant especially in the large-scale water distribution network. The computation time of using RBDSS is advantageous. Overall, the CPU runtime needed is less than 1 minute to fulfill all the tasks. Similarly with the case study 2, the majority of the other models were proposing more than one set of solution. As a result, there are 9 nondominated solutions for case N2A20 from the other models. This is a significant advantage of RBDSS over the other models and algorithms because RBDSS generates only one set of solution which is an optimal solution for RBDSS's algorithms unlike the other models and algorithms which require objective indexes to determine whether the solution is a dominated solution or not.

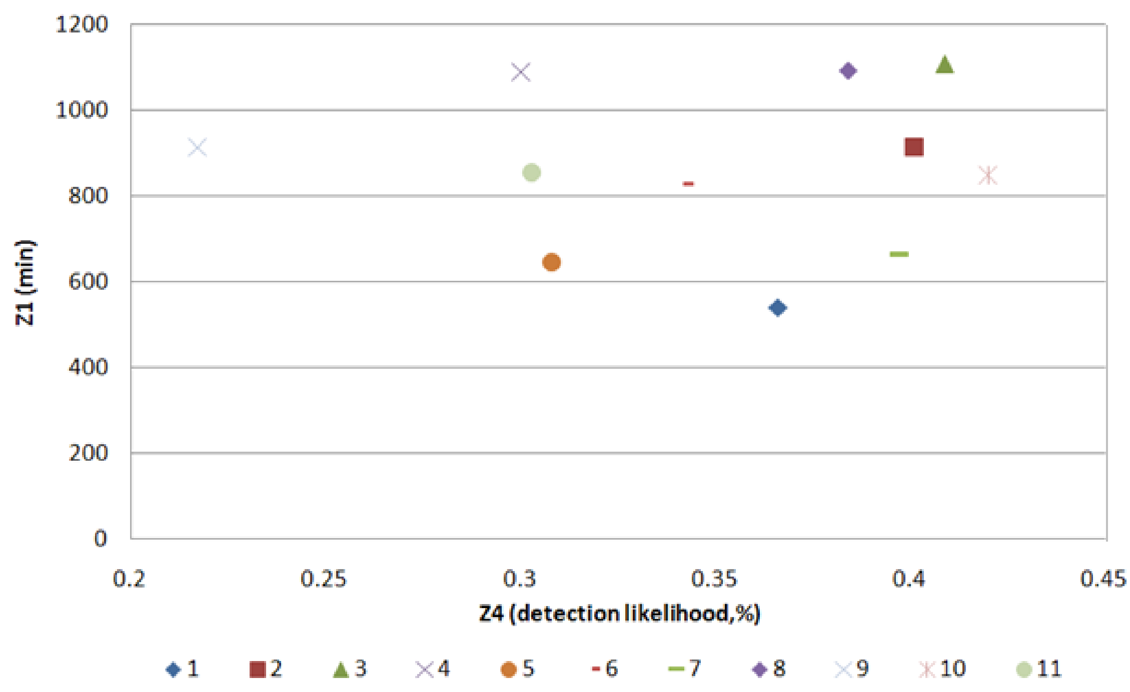

Figure 3.12a. The trade-off graph between the expected time of detection (Z1) and the detection likelihood (Z4). The legends on right are corresponding to the model numbers in Table 3.6.

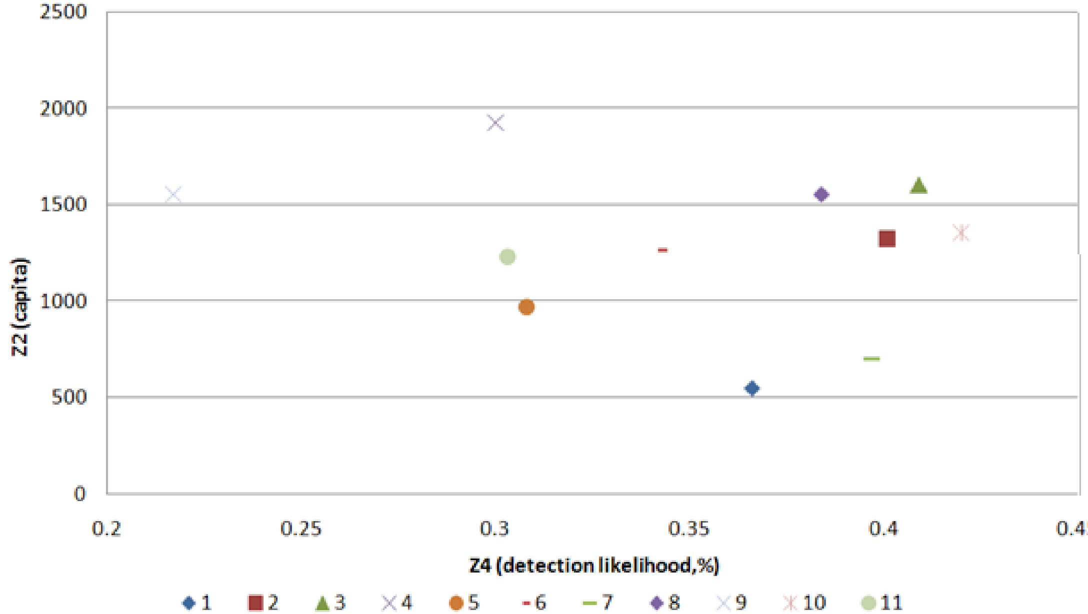

Figure 3.12b. The trade-off graph of the expected population affected prior to detection (Z2) and the detection likelihood (Z4). The legends on right are corresponding to the model numbers in Table 3.6.

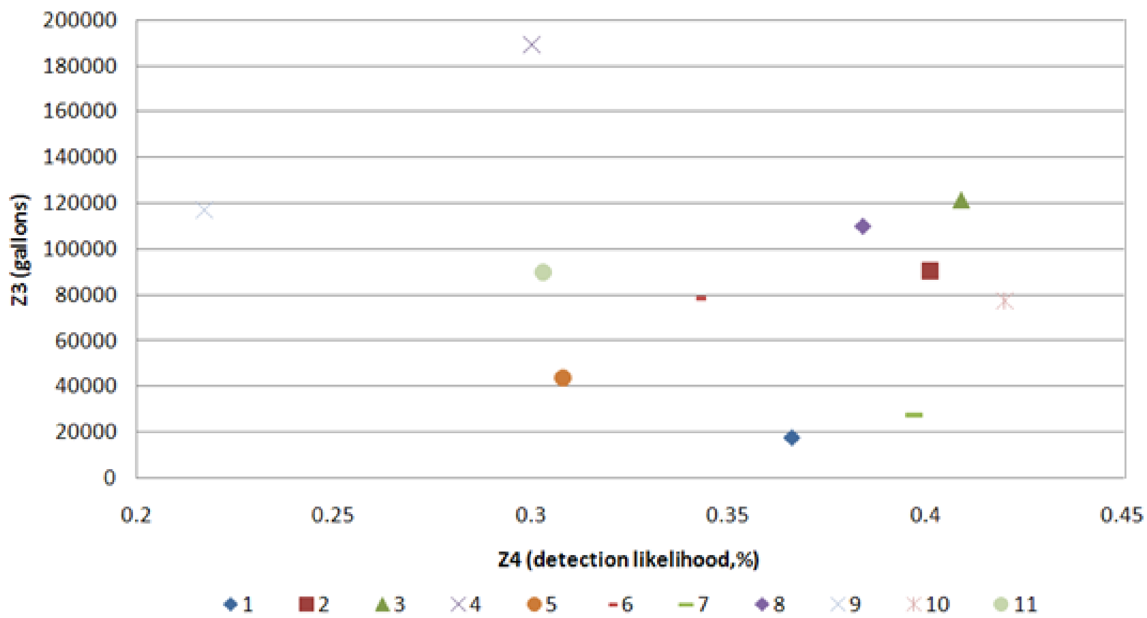

Figure 3.12c. The trade-off graph of the expected consumption of contaminated water prior to detection (Z3) and the detection likelihood (Z4). The legends on right are corresponding to the model numbers in Table 3.6.

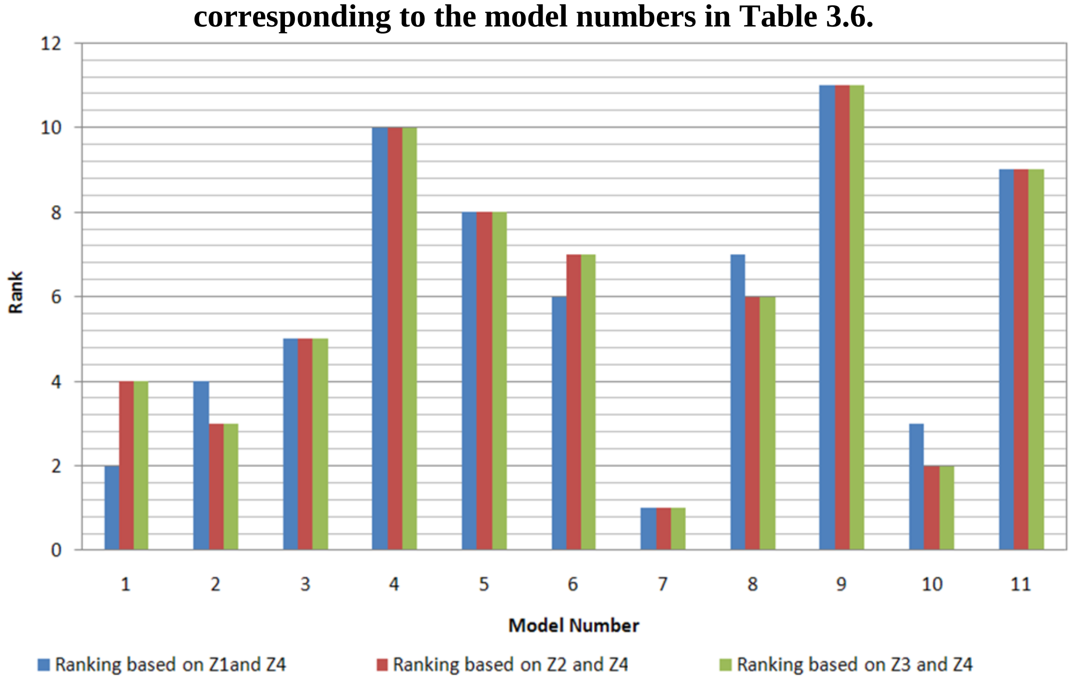

Figure 3.13. The ranks of models' performances based on three different correlations.

CHAPTER FOUR: CONCLUSION

In case study 1, The RBDSS associated with the three rules described in this study was proved effective to simplify and solve the sensor placement problem in a small-scale community, the Hardin County Water District No.1 in Kentucky. Overall, the correlation among the three rules can be drawn so that, based on the intensity rule, the location with the highest population density is proposed to deploy more sensors than others because higher exposure levels might occur along the main pipeline and water tanks. This vision is consistent with the fact that the flow factions of these areas picked up by the intensity rule should also be higher based on the accessibility rule, and the number of the inner nodes should be picked up more often based on the complexity rule. In case study 2, this rule-based decision support system (RBDSS) designed for sensor deployment in the drinking water network can perform well with only two rules. Two rules, including the accessibility and complexity rules, were derived to address the characteristics of effectiveness and efficiency required for sensor deployment in these networks. Comparisons between this new decision support system and 14 existing optimization and heuristic models confirm that the newly developed decision Support system in this study can always compete with most of the optimization models. In case study 3, even though the results based on RBDSS are not a dominated solution among other proposed models, there is no dominated solution for sensor deployment because the trade-off among four objectives cannot be achieved easily. Thereby, if the general guideline cannot be set, it would be difficult for engineers to justify whether the produced solution is the optimal solution or not. With the advancement of RBDSS, the final choice is literally dependent on engineering judgment to value one objective over the others and to select the best solution accordingly. As a result, the justification of priority of four design objectives can eventually be integrated to maximize the security for the civilians.

Lastly, there are advantages of RBDSS over the other models and algorithms. First, the complication and size of the water distributions do not limit the RBDSS from generating a set of sensors unlike some of the multiobjective programming models and mixed-integer programming (MILP) which can have long CPU runtime, NP-complete, and uncertainty due the large water distribution networks. Thereby, selecting RBDSS over the other models can guarantees that RBDSS can generate a set of sensor deployment locations. As already mentioned in the discussion sections in case study 2 and 3, the majority of the other models were proposing more than one set of solution. As a result, there are 18 nondominated solutions for case N1A5 and 9 nondominated solutions for case N2A20 from the other models. This is a significant advantage of RBDSS over the other models and algorithms because RBDSS generates only two set of solutions for Network 1 and Network 2 which are an optimal solutions for RBDSS's algorithms unlike the other models and algorithms which require objective indexes to determine which solution is the dominated solution for each network. Moreover, RBDSS can generate a set of sensor deployment locations with competitive results especially when financial constraint is being considered because RBDSS only rely on minimal computation and computerization can be performed by inexpensive software packages like EXCEL and EPANET under low computer specifications. Such an effective and efficient tools can not only generate the ultimate optimal sensor deployment locations for strengthen security in water distribution networks, but also make the water security design become more accessible to small drinking water networks in developing countries which may have a stringent budget constraint.

APPENDIX: INTERIM VOLUNTARY GUIDELINES FOR DESIGNING AND ONLINE CONTAMINANT MONITORING SYSTEM *(ASCE, AWWA, and WEF, 2004):*

Instrument/Testing Kit	Manufacturer	Parameters Observed	Sensor Type
4670 Series Turbidity System	ABB Instrumentation turbidity	turbidity	A
MiniTROLL	Electronic Data Solutions	collect real-time information for analysis of both short and long term water level trends	A
WTM500 On-line Turbidimeter	Sigrist	turbidity	A
Series B20 Residual Chlorine Recorder	Analytical Technology, Inc.	free chlorine, chloramines	B
Tox Screen	CheckLight, Ltd.	colchicines, cyanide, dicrotophos, thallium sulfate	B
VVR Water Anlysis System	Chemetrics	ammonia, bromine, chlorine, chlorine dioxide, chromate, copper, cyanide, DEHA, formaldehyde, glycol, hydrazine, hydrogen peroxide, iron, molybdate, nitrate, nitrite, oxygen (dissolved) ozone, peracetic acid, phenols, phosphate, silica, sulfide, zinc	B
Six-CENSETM	Dascore	chlorine (no reagents required), monochloramine or dissolved oxygen, pH, temperature, conductivity, ORP/REDOX	B
MP-TROLL 9000	Electronic Data Solutions	surface water quality monitoring, dissolved oxygen	B
Ocean Seven 316 Water Probe	General Oceanics, Inc.	pressure, temperature, conductivity, salinity, oxygen, pH, oxidationreduction potential.	A
WDM PipeSonde In-Pipe Probe	Hach	pH, ORP, conductivity, turbidity, dissolved oxygen, line pressure, temperature	A
Water Distribution Monitoring Panel (WDMP)	Hach	chlorine, conductivity, pH, turbidity, pressure, temperature	A/B
ToxTrak Toxicity Test Kit	Hach	toxicity of wastes and chemicals in wastewater treatment processes	B
AccuChlor 2 Residual Chlorine Measurement System	Hach	chlorine	B
CL17 Free Residual Chlorine Analyzer	Hach	chlorine	B

Instrument/Testing Kit	Manufacturer	Parameters Observed	Sensor Type
Series 4 Multiparameter Water Quality Monitoring Sondes	Hydrolab	ammonium, chloride, conductivity, dissolved oxygen, nitrate, pH/reference, pH/ORP/reference, temperature, TGD, turbidity, chlorophyll, PAR	A/B
Quanta – Display Multiparameter Water Quality Instrument	Hydrolab	temperature dissolved oxygen, conductivity, pH, ORP (redox), depth, turbidity	A
QuickTM II Test Kit and four other kits	Industrial Test Systems, Inc.	arsenic	B
PolyToxTM Rapid Toxicity Test	InterLab Supply, Ltd.	pH, dissolved oxygen (ppm), temperature (ºC), toxic metals (ppm)	A
BIOX 1010 BOD Analyzer	ISCO, Inc.	BOD measurement	B
SMART 2 Colorimeter with the 3660-SC Reagent System Portable Cyanide Analyzer	LaMotte Company	Alkalinity UDV, Aluminum, Ammonia, Nitrogen-LR (Fresh Water), Ammonia, Nitrogen-LR (Salt Water), Ammonia Nitrogen, Boron, Bromine LR, Bromine UDV, Cadmium, Carbohydrazide, Chloride, Chromium, Hexavalent, Chromium TesTab, Chromium (Total, Hex & Trivalent), Cobalt, COD COD SR 0-1500 without Mercury, COD HR 0-15,000 with Mercury, COD HR 0-15,000 without Mercury, Color, Copper BCA – LR, Copper Cuprizone, Copper DDC, Copper UDV, Cyanide, Cyanuric Acid, Cyanuric Acid UDV, DEHA, with Mercury, COD HR 0-15,000 without Mercury, Color, Copper BCA – LR, Copper Cuprizone, Copper DDC, Copper UDV, Cyanide, Cyanuric Acid, Cyanuric Acid UDV, DEHA, Dissolved Oxygen (DO), Erythorbic Acid, Fluoride, Hydrazine, Hydrogen Peroxide, Hydroquinone, Iodine, Iron, Iron UDV, Iron Phenanthroline, Lead, Manganese LR, Manganese HR, Mercury, Methylethylketoxime, Molybdenum HR, Nickel, Nitrate Nitrogen LR, Nitrate TesTab, Nitrite Nitrogen LR, Nitrite TesTab, Ozone LR, Ozone HR, pH CPR (Chlorphenol Red), pH PR (Phenol Red), pH TB	B

Instrument/Testing Kit	Manufacturer	Parameters Observed	Sensor Type
		(Thymol Blue), Phenol, Phosphate LR, Phosphate HR, Potassium, Silica LR, Silica HR, Sulfate HR, Sulfide LR, Surfactants, Tannin, Turbidity, Zinc LR	
PDV 6000 Heavy Metal	Monitoring Technologies	arsenic	C
Analyzer	International, Pty. Ltd.		C
Nano-BandTM Explorer Arsenic Test Kit	TraceDetect	arsenic	C
AF46 Dual Channel UV Absorption Sensor	Optek	acetone, aniline, benzene, halogens, HMF, hydrogen peroxide, ketones, trace mercury, nitric acid, ozone, phenols/phenates, sulfur dioxide, toluene, tracers, xylene	C
Mini-Analyst Model 942-032 Portable Cyanide Analyzer	Orbeco-Hellige	cyanide	C
AQUAfast® IV AQ4000 with AQ4006 Cyanide Reagents Portable Cyanide Analyzer	Thermo Orion (Thermo Electron Corporation)	cyanide	C
Model 96-06 Cyanide Electrode with Model 290 A+ Ion Selective Electrode Meter Portable Cyanide Analyzer	Thermo Orion (Thermo Electron Corporation)	cyanide	C
Cyanide Electrode	WTW Measurement	pH, DO, temperature or pH, cond., cyanide	
CN501 with Reference Electrode %503D, and Multi-parameter handheld 340i	Systems		A

Instrument/Testing Kit	Manufacturer	Parameters Observed	Sensor Type
Deltatox®	Strategic Diagnostics Inc. / Azur Environmental	phenol, lead, arsenic, mercury, sodium cyanide, selenium, potassium cyanide, chromium,PR-toxin, copper, aflatoxin, ochratoxin, rubratoxin, chloroform, ammonia, sodium lauryl sulfate, benzoyl cyanide, lindane, DDT, cresol, formaldehyde, malathion, carbaryl, flouroacetate, trinitrotoluene (TNT), parathion, 4-phehnyl toluene, carbofuran, pentachlorophenol, patulin, paraquat, diazinon, cyclohexamide, cadmium, quinine, dieldrin	B/C
F-NTK NECi Environmental Field Nitrate Test Kit	The Nitrate Elimination Co., Inc.	nitrate	B
NAS-2E In-situ Nutrient Analyzer	WS EnviroTech	nitrate (and/or nitrite) phosphate, silicate, and now ammonia.	B
YSI 600 R Multiparameter Probe	YSI Environmental	dissolved oxygen, temperature, conductivity, salinity, pH	A
YSI 600 XL Multiparameter Probe	YSI Environmental	dissolved oxygen, temperature, conductivity, ORP, salinity, vented level, depth, pH, TDS, specific conductance	A
YSI 6820 Multiparameter Probe	YSI Environmental	dissolved oxygen, temperature, conductivity, TDS, vented level, nitrate-nitrogen, chlorophyll, rhodamine, ammonium-nitrogen, specific conductance, ammonia, turbidity, chloride, salinity, depth, ORP, pH	A/B
bbe Algae Online Analyser	bbe	chlorophyll fluorescence	B
TD-700 Laboratory Fluorometer	Turner Designs	fluorescence, turbidity in one sample; available in three models: in vivo chlorophyll a/turbidity, rhodamine WT/turbidity,ammonium/extracted chlorophyll a	B
Aquafluor Fluorometer/Turbidimeter	Turner Designs	chlorophyll a, histamine, DO matter, ammonimum, cyanobacteria, DNA, RNA, LIVE/DEAD® BacLightTM Bacterial Viability Assay, alkaline phosphatase fluorescence	C
Self-contained	Turner Designs	chlorophyll a and rhodamine WT versions	

Instrument/Testing Kit	Manufacturer	Parameters Observed	Sensor Type
YSI 600 OMS Multiparameter Probe	YSI Environmental	chlorophyll, rhodamine, or turbidity in combination with temperature, conductivity, and depth in fresh, sea or polluted water	C
Colifast At-line Monitor (CALM)	Colifast	Provides water quality data for thermotolerant coliforms/E.coli and total coliforms.	C
Colifast Analyzer (CA)	Colifast	Tests for thermotolerant coliforms /*E.coli*, total coliforms, Total Viable Organisms and P. aeruginosa, are available.	C
Cyranose® 320	Cyrano Sciences	The unique polymer composite sensors have been shown to respond to a wide range of organic compounds, bacteria and natural products.	C
RiboPrinter® Microbial Characterization System	DuPont Qualicon	Up to eight bacterial isolates can be tested at one time, with results available eight hours from sample input.	C
MEL P/A Safe Drinking Water Laboratory	Hach	total coliforms and *E.coli*, chlorine, nitrate, TDS, pH	C
astroTOC HT (High Temperature)	Hach	TOC measurement	B
1950plus On-line TOC Analyzer	Hach	TOC measurement	B
EZ TOC Continuous Low-temperature Online TOC/TC Analyzer	ISCO, Inc.	TOC measurement	B
STIP-toc Continuous	ISCO, Inc.	TOC measurement	B
STIPTOX-adapt (W) On-line Toximeter	ISCO, Inc.	TOC measurement	B
Apollo 9000 HS Combustion TOC Analyzer	Teledyne Tekmar	TOC measurement	B
Phoenix 8000 UVPersulfate TOC Analyzer	Teledyne Tekmar	TOC measurement	B
TOC-4110 On-line Water Quality An	Shimadzu North America	NPOC(acidify/sparge removal of IC) and TC (standard). NPOC, TOC (TC-IC) (option). NPOC,TOC (TC-IC and POC + NPOC) (option)	B
Threat Detection KitTM	Kingwood Diagnostics, LLC	an early warning system.	B

Instrument/Testing Kit	Manufacturer	Parameters Observed	Sensor Type
Analyte 2000 Fiber Optic Fluorometer	Research International	performs evanescent-wave fluoroimmunoassays	B
Model 500 Microtox®	Strategic Diagnostics Inc. / Azur Environmental	Microtox Acute Toxicity, Microtox Chronic Toxicity, Mutatox, ATP	C

LIST OF REFERENCES

Al-Zahrani, M. and Moied K. (2001). Locating Optimum Water Quality Monitoring Stations in Water Distribution System. In *Bridging the Gap: Meeting the World's Water and Environmental Resources Challenges, Proceedings CD of the ASCE annual conference on Water Resources Planning and Management*, May 20-24, Orlando, Florida, USA.

Aral, M.M., Guan J. Marslia M.L. (2010) Optimal design of sensor placement in water distribution networks. Journal of Water Resources Planning and Management, 136(1), DOI: 10.1061/_ASCE_WR.1943-5452.0000001

Benbennick, D. (2006). (Wikipedia. A Map_of_Kentucky_highlighting_ Hardin_County .svg. PNG size 1000px.Accessed 18 April, 2010. <http://en.wikipedia.org/wiki/File:Map_of_ Kentucky_highlighting_Hardin_County.svg>

Berry, J. W., Boman, E., Phillips, C. A., and Riesen, L. A. (2008). Low-memory Lagrangian Relaxation Methods for Sensor Placement in Municipal Water Networks. *Proceedings CD of ASCE World Environmental and Water Resources Congress,* May 20-24, Orlando, Florida, USA.

Berry, J. W., Fleischer, L, Hart, W, and Phillips, C. (2003). Sensor Placement in Municipal Water Networks. In: *Proceedings CD of ASCE World Water and Environmental Resources Congress*, June 23 – 26, Philadelphia, PA, USA.

Berry, J.W., Fleischer, L., Hart, W.E., Phillips, C.A., and Watson, J.P. (2005). Sensor placement in municipal water networks. *Journal of Water Resources Planning and Management Division, ASCE*, 131(3), 237-243.

Berry, J., Hart, W. E., Phillips, C. A., and Uber, J. (2004). A general integer-programming based framework for sensor placement in municipal water networks. *Proceedings CD of ASCE World Water and Environment Resources Conference*, June 27-July 1, Salt Lake City, Utah, USA.

Berry, J.W., Hart, W.E., Phillips, C.A., Uber J.G., and Watson, J.P. (2006). Sensor placement in municipal water networks with temporal integer programming models. *Journal of Water Resources Planning and Management Division, ASCE,* 132(4), 218-224.

Buckle, P. (2000). "Assessing Resilience and Vulnerability in the Context of Emergencies: Guidelines, Victorian Government Publishing Service". Retrieved October 20, 2002 from www.anglia.ac.uk/geography/radix/ resources/buckle-guidelines.pdf.

Center for Water Resource Studies (CERS). (2007). Bowling Green, KY 270-745-8895 accessed in April, 2007.

Chang, N. P. Pongsanone, Natthaphon. and Ernest, Andrew (2011). “Comparisons between a Rule-based Decision Support System and Optimization Models for Sensor Deployment in a Small Drinking Water Network” *Decision Support System with Application*.

Clark, R. M., and Deininger, R. A. (2001). Minimizing the Vulnerability of Water Supplies to Natural and Terrorist Treats, *Proceedings of the American Water Works Association’s IMTech Conference*, Atlanta, GA, pp. 1-20, April 8-11, 2001.

Deuerlein, J., Wolters, A., and Roetsch, D. (2009). “Reliability Analysis of Water Distribution System Using Graph Decomposition”. *Proceedings CD of ASCE World Environmental and Water Resource Congress*, Kansas City, MO, May 17-21.

Dorini, G., Jonkergouw, P., Kapelan, Z., di Pierro, F., Khu, S. T., and Savic, D. (2006). "An Efficient Algorithm for Sensor Placement in Water Distribution Systems." *Proceedings CD of the 8th Annual Water Distribution System Analysis Symp.*, Cincinnati OH, USA.

Eliades, D., and Polycarpou, M. (2006). "Iterative deepening of Pareto solutions in water sensor Networks." *Proceedings CD of the 8th Annual Water Distribution System Analysis Symp.*, Cincinnati, OH, USA.

Ghimire, S. R., and Barkdoll, B. D. (2006a). "Heuristic method for the battle of the water network sensors: Demand-based approach." *Proceedings CD of the 8th Annual Water Distribution System Analysis Symp.*, Cincinnati, OH, USA.

Ghimire, S. R., and Barkdoll, B. D. (2006b). "A heuristic method for water quality sensor location in a municipal water distribution system: Mass related based approach." *Proceedings CD of the 8th Annual Water Distribution System Analysis Symp.*, Cincinnati, OH, USA.

Guan, J., Aral, M. M., Maslia, M. L., and Grayman, W. M. (2006). "Optimization Model and Algorithms for Design of Water Sensor Placement in Water Distribution Systems." *Proceedings CD of the 8th Annual Water Distribution System Analysis Symp.*, Cincinnati, OH, USA.

Gueli, R. (2006). "Predator-prey Model for Discrete Sensor Placement." *Proceedings CD of the 8th Annual Water Distribution System Analysis Symp.*, Cincinnati, OH, USA.

Haestad, M., Walski, T. M., Chase, D. V., Savic, D. A., Grayman, W., Backwith, S., Koelle, E., (2003). "Advanced Water Distribution Modeling and Management", Haestad Press, Waterbury, CT USA.

Hart W.E., Murray R. (2010). Review of sensor placement strategies for contamination warning system in drinking water distribution systems. Journal of Water Resources Planning and Management, 136(6), DOI: 10.1061/_ASCE_WR.1943-5452.0000081

Haught, R.C., Goodrich, J.A., and Herrmann J. (2003). "Evaluation of Water Monitoring Instrumentation at EPA's Water Awareness Technology Evaluation Research Security

Center." *Proceedings CD of Water Quality Technology Conference*, American WaterWorks Association, Philadelphia, Pennsylvania.

Huang, J. J., McBean, E. A., and James, W. (2006). "Multiobjective Optimization for Monitoring Sensor Placement in Water Distribution Systems." *Proceedings CD of the 8th Annual Water Distribution System Analysis Symp.,* Cincinnati, OH, USA.

Karamouz F. M., Saadati S., Ahmadi A., (2010). Vulnerability Assessment and Risk Reduction of Water Supply Systems. in *Proceedings CD of World Environmental and Water Resources Congress 2010: Challenges of Change. ASCE*.

Kessler, A., Ostfeld, A., and Sinai, G. (1998). Detecting accidental contaminations in municipal water networks. *Journal of Water Resources Planning and Management Division, ASCE*, 1998, 124(4), 192-198.

Krause, A., Leskovec, J., Isovitsch, S., Xu , J., Guestrin, C., VanBriesen , J., Small, M., and Fischbeck, P. (2006). "Optimizing Sensor Placements in Water Distribution Systems Using Submodular Function Maximization." *Proceedings CD of the 8th Annual Water Distribution System Analysis Symp.*, Cincinnati, OH, USA.

Kumar, A., Kansal, M. L., and Arora, G. (1999). Discussion of `detecting accidental contaminations in municipal water networks'. *Journal of Water Resources Planning and Management*, 125(4), 308310.

Lee, B. H. and Deininger, R. A. (1992). Optimal locations of monitoring stations in water distribution system. *Journal of Environmental Engineering*, 118(1), 416, 1992.

Lee, B. H. and Deininger, R. A. and Clark, R. M. (1991). Locating monitoring stations in waterdistribution systems. *Journal, Am. Water Works Assoc.*, p. 6066.

National Research Council (NRC) (2002). *Making the Nation Safer: The Role of Science and Technology in Countering Terrorism*, The National Academies Press, Washington, D.C.

Norstrom, A. (2007). Planning for drinking water and sanitation in peri-urban areas. *Swedish Water House Report 21*. SIWI, 2007.

Ostfeld, A., and Salomons, E. (2004). "Optimal Layout of Early Warning Detection Stations for Water Distribution Systems Security." *Journal of Water Resources Planning and Management*, 130, 377-385.

Ostfeld, A. and Salomons, E. (2006). "Sensor Network Design Proposal for the Battle of the Water Sensor Networks BWSN." *Proceedings CD of the 8th Annual Water Distribution System Analysis Symp.*, Cincinnati, OH, USA.

Ostfeld, A., Uber, J., and Salomons, E. (2006). "Battle of the water sensor networks BWSN : A design challenge for engineers and algorithms." *Proceedings CD of the 8th Annual Water Distribution System Analysis Symp.*, Cincinnati, OH, USA.

Ostfeld, A. Uber, J. G. Salomons, E. Berry, J. W. Hart, W. E. Phillips, C. A. Watson, J.-P. Dorini, G. Jonkergouw, P. Kapelan, Z. di Pierro, F. Khu, S.-T. Savic, D. Eliades, D. Polycarpou, M. Ghimire, S. R. Barkdoll, B. D. Gueli, R. Huang, J. J. McBean, E. A. James, W. Krause, A. Leskovec, J. Isovitsch, S. Jianhua, Guestrin, C. VanBriesen, J. Small, M. Fischbeck, P. Preis, A. Propato, M. Piller, O. Trachtman, G. B.Wu, Z. Y. and Walski, T. (2008). "The battle of the water sensor networks (BWSN): A design challenge for engineers and algorithms". *Journal of Water Resources Planning and Management, ASCE,* 134(6), pp. 556-568.

Preis, A., Mayochik, Y., and Ostfeld, A.(2007). Multiobjective Contaminant Detection Response Model. *Proceedings CD of ASCE World Environmental and Water Resources Congress,* May 15-19, Tampa, FL, USA.

Preis, A. and Ostfeld, A. (2006). "Multiobjective Sensor Design for Water Distribution Systems Security." *Proceedings CD of the 8th Annual Water Distribution System Analysis Symp*., Cincinnati, OH, USA.

Propato, M., Piller, O., and Uber, J. (2003). A Sensor *Location Model to Detect Contaminations in Water Distribution Networks. Proceedinbgs* CD of *World Water and Environmental Resources Congress, ASCE,* June 24- 26, Philadelphia, PA, USA.

Propato, M. (2006). Contamination warning in water networks: general mixed-integer linear models for sensor location design. *Journal of Water Resources Planning and Management Division, ASCE,* 132(4), 225-233.

Propato, M. and Piller, O. (2006). "Battle of the Water Sensor Networks." *Proceedings CD of the 8th Annual Water Distribution System Analysis Symp.,* Cincinnati, OH, USA.

Rossman, L.A., Clark, R.M., and Grayman, W.M. (1994). Modeling chlorine residuals in drinking-water distribution systems, *Jour. Env. Eng.*, 120(4), 803-820.

Salomons, E.(2006). "BWSN-Software utilities."http://www.watersimulation.com/wsp/bwsn accessed on July 19, 2010.

Thompson, K. A., Fann, S., Kadiyala, R., Hasit, Y.J., and Jacobson, G. (2009). Implementing a Contamination Warning System at a Department of Defense Facility: Case Study Port Hueneme, California. In Proceedings CD of *World Environmental and Water Resources Congress, ASCE.*

Thompson, S. L., Casman, E., Fischbeck, P., Small, M. J., and VanBriesen, J. M. (2007). Vulnerability Assessment of a Drinking Water Distribution System: Implications for Public Water Utilities. In Proceedings CD of *World Environmental and Water Resources Congress, ASCE.*

Trachtman, G. B. (2006). "A `Strawman' Common Sense Approach for Water Quality Sensor Site Selection." *Proceedings CD of the 8th Annual Water Distribution SystemAnalysis Symp.,* Cincinnati, OH, USA.

Tune J. and Elmore C. A., (2009). Drinking Water Field Analyses for the Detection and Enumeration of Coliform Bacteria in Rural Guatemalan Highlands. In Proceedings CD of *World Environmental and Water Resources Congress, ASCE*.

U.S. Census Bureau. (2009). Hardin county, Kentucky estimated population in 2009, April 15. United States of America Department of Commerce (2009). http://factfinder.census.gov/home/saff/main.html?_lang=en

US EPA. (2006). ICR Treatment Study Fact Sheet: The Simulated Distribution System Test. *US. Environmental Protection Agency.* EPA 814-B-96-002. Access May 3, 2010. http://www.epa.gov/ogwdw000/icr/icr_sds.html.

US EPA. (2009). National Primary Drinking Water Regulations. *US. EnvironmentalProtection Agency*. Washington DC, USA, EPA 816-F-09-004.

US EPA. (2010a). Distribution System Research and Information Collection Partnership Fact Sheet, Office of Water (4607M) EPA-815-F-10-001 May 2010. www.epa.gov/safewater and http://www.epa.gov/ogwdw000/disinfection/tcr/regulation_revisions_tcrdsac.html

US EPA. (2010b). EPANET http://www.epa.gov/nrmrl/wswrd/dw/epanet.html July. 19 2010.

Weickgenannt M., Kapelan Z., Blokker M., and Savic D.A. (2010) Risk-based sensor placement for contamination detection in water distribution systems. Journal of Water Resources Planning and Management, 136(6), DOI: 10.1061/_ASCE_WR.1943-5452.0000073.

Wikipedia (2010). Wikipedia. Map_of_USA_KY.svg. As PNG size 1000px. Accessed 18 April, 2010. <http://en.wikipedia.org/wiki/File:Map_of_USA_KY.svg>

Woo, H.M., Yoon, J.H., and Choi, D.Y. (2001). Optimal monitoring sites based on water quality and quantity in water distribution systems. In *Bridging the Gap: Meeting the World's Water and Environmental Resources Challenges, in Proceedings CD of the ASCE annual conference on Water Resources Planning and Management,* May 20-24, Orlando, Florida, USA.

Wu, Z. Y. and Walski, T. (2006). "Multiobjective Optimization of Sensor Placement in Water Distribution Systems." *Proceedings CD of the 8th Annual Water Distribution System Analysis Symp.,* Cincinnati, OH, USA.