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A Simple Sensor Placement Approach for Regular Monitoring and Contamination Detection in Water Distribution Networks

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Abstract

Online sensors in water distribution networks primarily serves two purposes: (1) Assures quality of water delivered to consumers; (2) Early detection of contamination events so as to minimize its consequences. Most of the multi-objective techniques consider the second purpose and almost ignore the first purpose. In this study, a sensor placement problem is formulated to cover these two performance objectives simultaneously through maximization of: (1) Demand coverage; and (2) Time-constrained detection likelihood. These two objectives are combined into a single objective by using weights. Genetic Algorithm (GA) is used to obtain optimum sensor locations. The methodology is applied on a bench mark problem. Several solutions are obtained by varying the weights of two objectives. A simple method as an alternative to GA is suggested for sensor locations in large water distribution networks for reducing the computational efforts. Comparison of the two methods showed that the proposed simple method provided solutions close to that provided by GA.

Keywords: *contamination detection, sensor location, sensor placement, water distribution networks, water quality*

1. Introduction

The quality of water is regularly monitored at salient locations in the Water Distribution Networks (WDNs) to safeguard the consumers' health. Usually, one of the objectives in designing a monitoring system is to select least number of Monitoring Stations (MSs) to cover the entire network effectively. The past events of accidental and deliberate contamination and their possibility in future along with the likely impacts on consumers' health have attracted the attention of researchers on continuous online monitoring of water quality through online sensors. Several new objectives for design of a monitoring system have been proposed so as to detect contamination event as quickly as possible, after it occurs, and reduce potential public health and economic consequences. These objectives are: Time of Detection (TD), Volume of Contaminated water consumed by consumers (VC), Mass Consumed (MC), population exposed to contamination (PE), Extent of Contamination (EC), Detection Likelihood (DL), number or percentage of Failed Detections (NFD/ PFD), Sensor Response Time (SRT), risk and sensor detection redundancy (SDR). Since installation and maintenance of online sensors is costly, usually limited sensors are placed. Thus, the objective is to obtain optimal locations for the known number of sensors in the network.

In this paper, objective of regular monitoring and contamination detection is considered simultaneously and a new sensor location problem is formulated. The novel formulation consists of two simple performance objectives "Demand Coverage" and "Time-constrained Detection Likelihood". Demand Coverage (DC) is maximized to assure the quality of delivered water to maximum consumers during regular monitoring; and Time-Constrained Detection Likelihood (TCDL) is used for early detection of more number of contamination events. TCDL assures that all the detected events have time of detection within required Level of Service (LOS). In this study, LOS is defined in terms of time lapse between the entry of contaminant and its detection known as T-hour LOS (Rathi and Gupta, 2014b). This consideration however puts additional burden on designer of selecting proper LOS for time of detection. Further, the maximization of detection likelihood reduces negative consequences. Let us understand how? The negative consequences are usually considered through Volume Consumed (VC), Population Exposed (PE) and Extent of Contamination (EC) as discussed in Ostfeld *et al.* (2008). These consequences would reduce with reduction in time. Further, it is possible that some of the contamination events remain undetected while placing limited number of sensors. The negative consequences of such undetected events would be very high as compared to those events that are detected. Thus, maximization of TCDL minimizes the undetected events and their negative

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consequences indirectly and assuring early detection of contamination events.

Contaminant is assumed to travel along water and assumed to be detected as soon as it reaches any sensor location. The optimization problem for fixing desired number of sensor locations is solved using Genetic Algorithm (GA). As GA requires evaluation of objective function for several combinations of sensor locations, a simple methodology is used for evaluation of DC. The pertaining literature, assumption used in the proposed methodology, methodology for evaluation of DC and DL for known sensor locations, formulation of optimization problem and GA parameters, and its application to an example network are given in subsequent sections. GA requires number of simulations and therefore its application to large network problem is time-consuming. Herein, a simple methodology is suggested that selects sensor locations priority-wise as also suggested by many researchers such as Cozzolino *et al*. (2006), Krause *et al*. (2008) etc. The simple method is briefly described and applied to network 1 of BWSN to compare the results with GA. The application of simple method is also shown to a network from field.

2. Literature Review

Lee and Deininger (1992) were perhaps the first to develop a procedure for locating MSs based on the concept of "Demand Coverage" (DC). Since then several methodologies have been suggested. Watson *et al.* (2004) were the first to introduce multi-objective formulation to sensor placement by employing a mixed integer linear programming model over a wide range of design objectives. A brief review of multi-objective methodologies suggested by different researchers based on the type of objectives, methodology used for solution of problems, and special remarks on the cited work are given in Table 1. It can be observed that in most of the multi-objective based sensor network design, emphasis is given to an early detection of contamination and limiting or minimizing the consequences. Ostfeld *et al.* (2008) compared solutions provided by several algorithms based on four objectives: (1) TD; (2) PE; (3) VC; and (4) DL. The solutions provided by different algorithms provide distinctive set of sensor locations. The main emphasis was thus given to early detection of contaminant and minimizing the negative consequences. No importance was given to network coverage in terms of demand. Eliades and Polycarpou (2006) considered DC in addition to the four objectives as used in the Battle of Water Sensor Networks (BWSN) (Ostfeld and Salomons, 2006) and used a heuristic method in which Pareto optimal solutions were obtained for first location and all solution for first location were used to identify Pareto solutions for the first two locations. The process of

Table 1. Review of Multi-objective Methodologies

Citation	Objective	Methodology Used / Optimization Solver	Remarks
(1)	(2)	(3)	(4)
Propato (2006)	TD, VC, PE, EC and PFD	MIP and Heuristic	
Berry *et al.* (2006)		Branch and bound	
Berry *et al.* (2009)	PE, MC	IP, Local Search & NLP	Imperfect sensors
Dorini *et al.* (2006)	TD, PE, VC, DL	Modified cross-Entropy algorithm	
Propato and Piller (2006)	TD, PE, VC, DL	MIP	
Wu and Walski (2006)	TD, VC, DL	GA	
Huang *et al.* (2006)	TD, PE, DL	GA	
Eliades and Polycarpou (2006)	DC, TD, VC, PE, DL	Heuristic	
Preis and Ostfeld (2006)	TD, DL, SDR, CSIL	NSGA-II	
Preis and Ostfeld (2008)	TD, DL, SDR	NSGA-II	Heuristic method for CES
Austin *et al.* (2009)		NSGA-II	Imperfect mixing at nodes
Kim *et al.* (2010)	TD,DL	MOGA	Imperfect mixing at nodes
Aral *et al.* (2008)	TD, VC, DL	NSGA-II	
Aral *et al.* (2010)		PGA	
Krause *et al.* (2008)	TD, PE	Greedy and SA	
Comboul *et al.* (2013)		Greedy algorithm	Nodal demand uncertainty
Guidorzi *et al.* (2009)	VC, NFD	NSGA-II	Valves & hydrants operation to reduce VC
Weickgenannt *et al.* (2010)	Risk in terms of VC and NFD	NSGA-II	Heuristic method for CES
Dorini *et al.* (2010)	DL, PE	Heuristic method	SLOT Algorithm
Xu *et al.* (2010a)	DL, PE	Heuristic	Robust Model for accidental contamination
Shen and Mcbean (2011)	Time delay, SDR	NSGA-II	Select specific incident list event
Cozzolino et al. (2011)	TD, VC, PE, MC	GA	
Xu *et al.* (2010b)	DL or CSIL	MIP solver	Imperfect sensors
Ehsani *et al.* (2010)	TD,DL	NSGA-II and GA	

Notations – CES-Contamination event sampling, CSIL- Contamination source identification likelihood, PD-Population Density, SLOT-Sensor local optimal transformation.

obtaining Pareto solutions continued for the desired number of sensor locations and best solution is selected.

Majority of work as in Table 1 are related to sensor placement based on well-calibrated hydraulic and water quality models integrated with optimization techniques. Water quality analysis over a period of time for different contamination scenario is important for identifying accurate solution. In reality well-calibrated simulation models are rarely available from water utilities in developing country like India, and mostly partial information about the system is available (Xu *et al*., 2008; Perelman and Ostfeld, 2013). Thus, one school of thought is to combine various objectives, limit probable location of attacks, limit probable location of sensors, reduce size of network itself, consider sensor imperfectness, and suggest a method that is not computational intensive (may be heuristic) to obtain optimal solution and check robustness of solution (Watson *et al*., 2009; Krause *et al*., 2009; Xu *et al*., 2010a; Hart *et al*., 2010; Perelman *et al*., 2008, Perelman and Ostfeld, 2012, 2013; Davis *et al*., 2014; Eliades *et al.*, 2014; Schwartz *et al.*, 2014). Chang et al. (2011, 2012) suggested a sensor deployment strategy with less computational requirements. A new rule-based expert system, based on accessibility rule and complexity rule, was developed to tackle the complexity of the network and reduce the computer runtime while achieving the same level of robustness in planning and design. The accessibility rule ranks different nodes based on the number of downstream nodes that can be protected by a node; while complexity rule ranks different node based on number of inner nodes. Klise *et al.* (2013) suggested a two stage approach, in which sensors are placed at nodes of reduced network in first stage and transferred to nodes of original network in the second stage.

The other school of thought is to develop methodologies for real world problems to tackle the complexity of the network through simple parameters using graph theoretic and heuristic approaches. Xu *et al*. (2008) suggested procedure for identifying a set of key nodes for placing sensors based on “time-constrained receivability”. Receivability is defined by existence of one or more flow path. If flow from any node i could reach to node j, then node i is considered to be receivable at node j. When condition of time is imposed for flow to reach from node i to node j, the receivability becomes time-constrained. Chung et al. (2010) suggested a methodology based on “betweenness centrality” defined as centrality of a node in terms of degree to which the node falls on the shortest path between other pairs of nodes. Deuerlein *et al.* (2010) suggested capturing water hammer pressure condition in the network due to pumping of water for intrusion of contaminant to reduce long detection time. Perelman and Ostfeld (2012) suggested connectivity analysis for topological clustering of nodes. Besides Betweenness centrality, Perelman and Ostfeld (2013) considered various other measures of graph like “Eigenvector centrality”, “Closeness centrality”, “Page Rank”, “Edge Betweenness community”, “Kmeans” for location of sensors. Schal *et al.* (2013) studied optimally design sensor locations [obtained through TEVASPOT (Berry *et al*., 2008; Hart *et al*., 2008) for different types of network (Branch, Loop and Grid) for various graph parameters such as betweenness centrality, receivability, proximity to source or filling station with a view to develop a general guidelines for design of sensor networks for small utility in case calibrated network model is not available. Methods based on graph parameters that even do not take into account nodal demands or simple network hydraulics seems to be too crude to locate sensors.

3. Assumptions

The proposed methodology as suggested herein consists of following assumptions:

1. Individual contamination events are considered at all the nodes, i.e., single contamination event is considered at a time at any one of the nodes.
2. The time of detection is considered as sole measure of Level of Service (LOS). It is assumed that with the improvement (reduction) in time of detection, other measures of level of service such as PE, VC, Risk etc. will reduce.
3. Sensors are assumed to be perfect and capable of detecting how-so-ever small concentration of contaminant. Thus, the moment contaminant reaches the monitoring node, it is assumed to be detected without any delay.
4. Hydraulic simulation is carried out for dominating flow patterns. For pipes having reversal of flow, the flow direction is fixed as the one in which flow remains in that direction for major time period during period of simulation. However, dynamic simulation and multiple events at a node at different time can be considered (Eliades and Polycarpou, 2006).

4. Evaluation of Objective Parameters for Known Sensor Locations

Evaluation of Demand Coverage (DC) and time-constrained Detection Likelihood (TCDL) for a network with known sensor locations are given below.

4.1 Evaluating DC

Lee and Deininger (1992) defined DC as the total demand of all the nodes covered by a group of known MSs/sensors, which can be normalized and represented as fraction of total demand. To determine the upstream nodes covered by a monitoring station, the coverage criteria is used and defined as the minimum percentage of total water received at a monitoring node that should have passed through an upstream node to be able to consider it “covered”. In such a case, the lower the coverage criteria is fixed, the more will be the demand coverage of a monitoring node. Let us consider two coverage criteria of 60% and 30%. With coverage criteria as 60% (or 30%) only those upstream nodes will be included in covered nodes through which 60% (or 30%) of the total flow received at the monitoring node has passed. Naturally, the number of nodes covered with 30% coverage criteria will be more. Thus, demand coverage based on coverage criteria brings subjectivity in the design. Rathi and Gupta (2014a) considered the demands of all the nodes on the shortest path from the source to the monitoring node for determining DC with the assumption that major flows received at any node is through shortest path. The validity of the assumption actually depends on pipe diameters on different paths from source to sensor node. However, this assumption avoids the subjectivity that comes due to coverage criteria. It is observed that this simple method provides lesser value of the DC as some of the nodes not on the shortest path are excluded for which water quality can be predicted (Rathi and Gupta, 2014a). The determination of DC becomes easy by using simple method as no separate coverage matrix is required. The methodology consists of following steps:

1. Starting from the source/first node identify the shortest path for all nodes in the network using any algorithm [Floyd or Dikshtra's algorithm (Deo, 2004)].
2. With the known locations of sensors (randomly generated population), add demands of all the nodes on shortest paths from source to different nodes having sensor, without accounting demand of any node twice and normalize it with respect to total demand.

However, the use of simple methodology is optional. The DC can be evaluated by fixing the coverage criteria as suggested by Lee and Deininger (1992).

4.2 Evaluating TCDL

The T-hour LOS signifies that time required by contaminant from the point of contamination to reach one of the sensor node is less than T hours. With limited number of sensors, achieving a desired T-hour LOS may not be possible as some of the contamination events are either not detected, or may be detected after T hours and considered herein as events not detected. The methodology for evaluating TCDL consists of following steps:

1. Using the data available from hydraulic analysis, construct a shortest travel time matrix (Kansal *et al*., 2012).
2. Modify the travel time matrix for selected T-hour LOS where all elements in the matrix less than or equal to T-hour time of detection are retained and rest are ignored.
3. For randomly generated location of sensors, identify the number of contamination events that can be detected jointly by these sensors without considering any event twice.

Time Constrained Detection Likelihood (TCDL) is determined by dividing the number of events detected by the total number of contamination events.

4.3 Illustration

A small WDN (Zone II) of Manendragarh town in Koriya district of Chhattisgarh State in India from Kansal *et al.* (2012) is considered as an example network (shown in Fig. 1) to evaluate TCDL and DC for known sensor locations at nodes 4, 10, 15, 19 and 23. The network has 23 demand nodes and 25 pipe links. The flow direction and travel time at each node from the source are shown in Fig. 1. The nodal demands are given in Table 2.

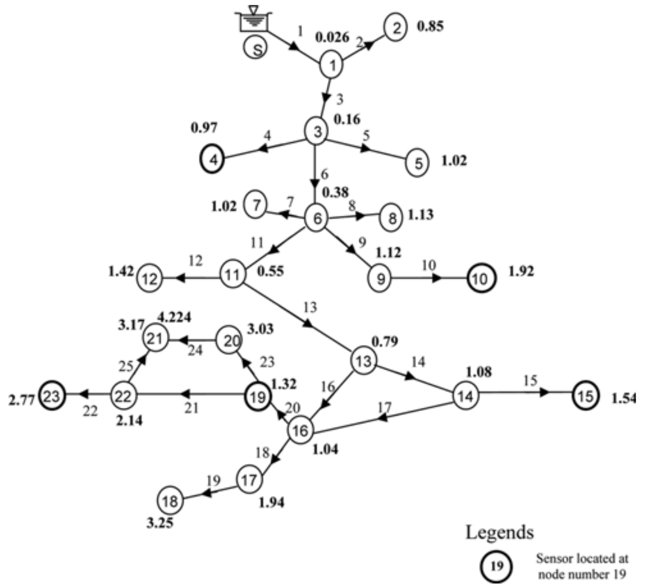

Fig. 1. A Small Network with Flow Direction and Travel Time from Source to Demand Nodes and Location of Sensors (Kansal *et al.*, 2012)

Table 2. Nodal Demands for a Network in Fig. 1.

Node no.	Nodal Demand	Node no.	Nodal Demand
S	0	12	58.75
1	287.71	13	354.24
2	184.9	14	317.09
3	597.89	15	103.68
4	147.74	16	412.13
5	184.9	17	221.18
6	583.2	18	102.82
7	88.99	19	280.8
8	88.13	20	198.72
9	243.65	21	184.03
10	103.68	22	252.29
11	287.71	23	58.75

Total demand of the network is 5342.98 m^3/day. Other details about the network can be obtained from Kansal *et al.* (2012).

4.3.1 Evaluating DC for Known Sensor Nodes 4, 10, 15, 19 and 23

Using simple method

1. Shortest paths are identified from the source S to each sensor nodes as shown in Table 3. For example, shortest path from source S to sensor at node 4 is S-1-3-4. This covers nodes S, 1, 3 and 4.
2. The nodes covered by sensors at five nodes 4, 10, 15, 19 and 23 can be identified as nodes S, 1, 3, 4, 6, 9, 10, 11, 13, 14, 15, 16, 19, 22 and 23.
3. Thus, combined coverage of these 5 sensor nodes is equal to addition of demands of all covered nodes which is 4030.56 m^3/day; and DC is 0.754 (= 4030.56/5342.98).

Table 3. Shortest Path to Assumed Sensor Locations for the Network of Fig. 1.

Location of sensor at node	Shortest path from source S
(1)	(2)
4	S-1-3-4
10	S-1-3-6-9-10
15	S-1-3-6-11-13-14-15
19	S-1-3-6-11-13-16-19
23	S-1-3-6-11-13-16-19-22-23

Using water fraction matrix with coverage criteria of 50%, a water fraction matrix is prepared which provides what fraction of water received at sensor node that has passed through upstream nodes. The water fraction matrix is converted to coverage matrix by eliminating all the values lower than the coverage criteria and making it 1 if it is above the coverage criteria. The DC is obtained by identifying the covered nodes by the sensors and adding their demands. For the example network, DC is obtained same as by the simple method.

4.3.2 Determination of TCDL for Known Sensor Locations at Nodes 4, 10, 15, 19 and 23

1. From the available data a shortest travel time matrix is constructed (Kansal *et al.*, 2012) which shows time taken by contaminant to reach from one node to other. This matrix is modified for 1-hour LOS wherein all elements in the matrix less than or equal to 1-hour time of detection are retained and rest are ignored as shown in Table 4.
2. Number of contamination events that can be covered by any sensor location is obtained by the number of entries in column pertaining to that sensor nodes. For example, sensor at node 4 covers 4 contamination events within 1 hour LOS as shown in rows 1, 2, 4 and 5. The number of events covered by a sensor at different locations is given in the last row of Table 4. For sensor locations at nodes 4, 10, 15, 19 and 23, total number of events covered would be addition of number of events covered by them minus the number of events covered twice and more. Total number of events covered by five stations is found to be 15 after subtracting the events covered twice or more. Thus, TCDL is 15/24 = 0.625.

5. Optimal Sensor Locations

5.1 Objective Function

The proposed objectives are: (1) Maximization of demand coverage; and (2) Maximization of time-constrained detection likelihood. Herein, these two objectives are combined by

Table 4. Modified travel time matrix for 1-hour LOS for Fig. 1.

Contaminant Node	Shortest travel time (in hours) to sensor node																							
	S	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
S	0	0.03	0.85	0.16	0.98		0.38					0.55		0.79										
1		0	0.82	0.14	0.95	0.99	0.36	0.99				0.52		0.77										
2			0																					
3				0	0.81	0.86	0.22	0.85	0.97	0.96		0.39		0.63	0.91		0.88							
4					0																			
5						0																		
6							0	0.64	0.75	0.74		0.17		0.41	0.69		0.66			0.94				
7								0																
8									0															
9										0	0.8													
10											0													
11												0	0.88	0.24	0.53	1	0.49			0.77				
12													0											
13														0	0.28	0.75	0.25			0.53				
14															0	0.47								
15																0								
16																	0	0.9		0.28				
17																		0						
18																			0					
19																				0			0.82	
20																					0			
21																						0		
22																							0	0.63
23																								0
No. of events covered	1	2	3	3	4	3	4	4	3	3	2	5	2	6	5	4	5	2	1	5	1	1	2	2

assigning weights based on the priority to these objectives as also done by Krause *et al.* (2008), and Xu *et al.* (2010a). If water supply authorities wish to design a monitoring system for regular monitoring (which may be mostly a case in developing countries), a weight of 100% can be assigned to DC. On the other hand, 100% weights can be assigned to TCDL, or a suitable combination of two can be selected. Thus, mathematically objective function Z can be expressed by selecting proper weights as:

$$\text{Max } Z = W \times DC + (1 - W) \times TCDL \tag{1}$$

Where W = The percentage weight in fraction associated with the objective DC.

The objective function is unconstrained as the weights are pre-selected and the maximum value of objective function could be 1.

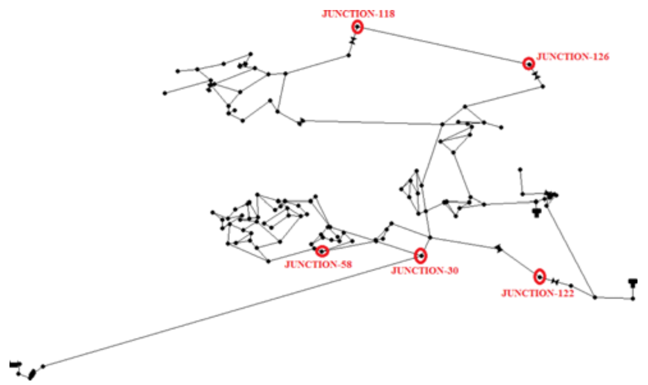

Fig. 2. Location of Best 5 Sensors for 3 Hour LOS for BWSN using GA

5.2 GA and Its Parameters

The unconstrained optimization problem Eq. (1) is solved using simple GA in which detected events are identified based on their time of detection. A contamination event is considered detected if its time of detection is found less than selected LOS. A simple GA method started with selection of random population of candidate solutions. Each member in the population is given a chance to improve in next generation based on its fitness. Three basic GA operators reproduction, cross-over and mutation are used. Elitism is also used to retain one or few good solutions in the next generation without change. The process of improvement continued for pre-selected number of generations and the best solution at the end is considered as optimal solution. GA parameters considered in this study are given in Table 5.

5.3 Illustrative Example - Network 1 of BWSN

An example network provided by the organizers of Battle of Water Sensor Networks (BWSN) (Ostfeld *et al*., 2008) is chosen to illustrate the solution methodology. The network has 126 nodes, one constant head source, two tanks and 168 pipe links as shown in Fig. 2. The BWSN organizer invited the participants to use their algorithm to place 5 and 20 number of sensors. The EPANET files for the network are available at the website http://www.exeter.ac.uk/cws/bwsn (Ostfeld *et al*., 2008). Four objective parameters TD, PE, VC and DL were considered to compare the solutions provided by different researchers. Network was simulated for 96 hour to acquire the information of dynamic flow pattern (Ostfeld *et al.,* 2008). A computer program named BWSN software utility program was prepared by Salomons (2006) that can be used to evaluate the four objective parameters for the known locations of sensors.

Table 5. GA Parameters Used

GA Parameters	Description
Selector	Tournament
Crossover type	Two point
Elitism	The best chromosome in each generation is included unchanged in the next generation
Crossover probability	0.95
Mutation probability	0.05
Number of generations	100
Population size	100
Running Time	Maximum of 10 min for network 1 of BWSN for selection of 5 sensors on PC Intel(R) Core(TM)2 Duo CPU E8500 @ 3.16GHz, 4.00 GB Memory

Herein, the sensor locations have been obtained with different consideration using the proposed GA based methodology. In this study, dominating flow patterns in pipelines (i.e., flow direction remains longer time in pipes during simulation hours) and averaged flow and velocities are considered for location of sensors. Initially, the weights were varied for both the objectives and 5 and 20 best sensor locations are obtained by considering LOS given by time of detection of 3 hrs. Thus, a contamination event is considered detected if is detected within 3 hrs by any of the sensor. GA program was run five times and solution with maximum objective function values in 5 runs are reported for each combination of weights. The results of best 5 and 20 locations are provided in Table 6. The following can be observed from Table 6.

1. The objective function values vary from 0.3821 to 0.7982 for 5 sensor locations. Both TCDL and DC have their maximum values when their weights are 100%.
2. Both DC and DL tries to locate the sensors far away from the sources to maximize their values. However, TCDL is bounded by TD and therefore sensor locations cannot go far away from the source and a compromised solution is obtained.
3. The same can be observed with 20 sensor locations.

The 5 and 20 best locations are also obtained for the equal weights of 50% for each objectives by considering different LOS (i.e time of detection as 3, 5, 10 and 20 hrs). The results are provided in Table 7. The following can be observed from Table 7.

1. The objective function value increases as LOS changes from 3 hrs to 20 hrs. This is due to the fact that TCDL improves as more number of events are accounted in detected category due to increased allowable time of detection. Thus, herein higher allowable time of detection itself shows poor level of service and the objective function value indicates best sensor

Table 6. Sensor Locations with Different Weights for Network 1 of BWSN

Weight to DC	Weight to DL	Sensor Location at Nodes	DC	TCDL	Objective Function Value
0	1	4, 21, 58, 90, 120	0.0962	0.3821	0.3821
0.3	0.7	30, 58, 118, 122,126	0.7163	0.2846	0.4141
0.5	0.5	30, 58, 118, 122, 126	0.7163	0.2846	0.5005
0.7	0.3	34, 74, 118, 122, 126	0.7909	0.1464	0.5976
1	0	34, 75, 118, 124, 126	0.7982	0.1138	0.7982
0	1	3, 4, 14, 21, 35, 58, 62, 64, 70, 74, 80, 83, 84, 88, 94, 98, 118, 120,122,126	0.7434	0.7154	0.7154
0.3	0.7	3, 4, 14, 21, 34, 35, 46, 58, 62, 74, 76, 83, 84, 88, 93, 98, 118, 122, 124,126	0.9350	0.7077	0.7757
0.5	0.5	4, 14, 21, 34, 35, 41, 45, 46, 52, 58, 62, 70, 74, 83, 84, 93, 98, 118, 122, 126	0.9437	0.6829	0.8133
0.7	0.3	4, 34, 35, 46, 50, 52, 58, 62, 74, 76, 83, 84, 90, 93, 100, 101, 118, 122, 124, 126	0.9572	0.6669	0.8701
1	0	2, 10, 34, 35, 43, 45, 46, 50, 52, 55, 75, 76, 77, 83, 84, 93, 100, 118, 123, 126	0.9934	0.4390	0.9934

Table 7. Sensor Locations with Different LOS for Network 1 of BWSN

Level of Service (LOS)	Sensor Location at Nodes	DC	TCDL	Objective Function Value
3	30, 58, 118, 124, 126	0.7163	0.2846	0.5005
5	34, 58, 118, 124, 126	0.7209	0.3171	0.5386
10	34, 58, 118, 124, 126,	0.7601	0.5122	0.6361
20	34, 83, 118, 124, 126	0.7709	0.6341	0.7025
3	4, 14, 21, 34, 35, 41, 45, 46, 52, 58, 62, 70, 74, 83, 84, 93, 98, 118, 122, 126	0.9437	0.6829	0.8133
5	4, 14, 21, 34, 35, 39, 46, 59, 64, 74, 76, 80, 83, 84, 89, 93, 101, 118, 124, 126	0.9312	0.8130	0.8721
10	11, 14, 34, 35, 43, 45, 52, 68, 72, 75, 76, 79, 82, 83, 93, 100, 101, 118, 124, 126	0.9665	0.9024	0.9345
20	3, 10, 11, 12, 34, 35, 45, 52, 53, 72, 75, 76, 83, 84, 93, 100, 111, 118, 124, 126	0.9726	0.9350	0.9538

locations.

2. To compare the consequences on PE and VC due to increased values of allowable time of detection, the BWSN software utility program is used. It is observed that the value of PE continuously increases for time of detection of 3, 5, 10 and 20 hrs are 322, 392, 398, and 413, respectively for 5 sensor locations. Similarly, the value VC also continuously increases and found to be 3577, 5354, 6518 and 11423 gallons, respectively for time of detection of 3, 5, 10 and 20 hrs.

GA requires number of simulations and therefore its application to large network problem is difficult. Therefore, a simple heuristic method is also proposed. The heuristic method is briefly described and applied to BWSN network to compare the result with GA. Its application is also shown to a network from field.

6. Proposed Simple Algorithm

The unconstrained optimization problem defined by Eq. (1) requires selection of required number of sensors to maximize the objective function value for pre-specified LOS. Herein, a methodology based on priority wise selection of sensor location as suggested by Krause *et a*l. (2008) is used. Initially, all nodes are considered as the candidate location of sensor placement and by considering sensor at each one of them separately, the objective function values are evaluated. The node at which sensor provides maximum value of objective function is selected

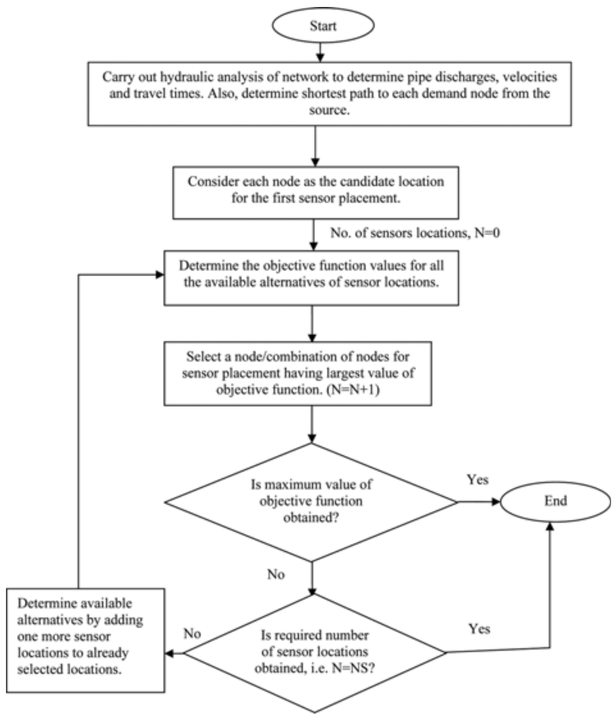

Fig. 3. Flow Chart of Proposed Methodology for Sensor Locations

as first sensor location. Then, for selection of subsequent sensor locations, various combinations of already selected sensor locations with one new location are considered. The combination that provides maximum value of objective function are selected. The entire procedure is also shown as Flow Chart in Fig. 3.

Detailed stepwise calculations are explained with small example network shown in Fig. 1. considering 1-hour LOS.

6.1 Application to Small Network

6.1.1 Fixing of First Sensor Location

1. Consider all nodes as a source of contamination, a shortest travel time matrix is generated and modified for "1-hour" LOS where all elements of shortest travel time matrix > 1 hour are removed as shown in Table 4. The detection coverage of every sensor location is the ratio number of nodes covered by them to total number of nodes (shown in column 4 of Table 8). For example, sensor at node 4 covers nodes S, 1, 3 and 4 out of 24 nodes, while sensor at node 5 covers only three nodes 1, 3 and 5 out of 24 nodes within 1 hour LOS. Therefore, DL is 0.1667 (=4/24) and 0.1250 (=3/24), respectively for sensors at nodes 4 and 5.
2. Starting from source S, shortest path for all 23 nodes in the networks are obtained using Dikshtra algorithm and demand coverage to all candidate sensor nodes are calculated by summing the demand of all the nodes on the shortest path. The demand coverage is normalized for each candidate sensor location node by dividing it with total demand of the network, i.e., 5342.98 m^3/day and shown in column 5 of Table 8. For example, for node 4, the nodes on the shortest path from source S are 1, 3 and 4 with respective demand of 287.71, 597.89 and 147.74 m^3/d. Thus, normalizes DC is 0.1934 (=1033.34/ 5342.98).
3. Evaluate the value of objective function considering equal weights to each objective. The objective function values are shown in column 6 of Table 8. For example, for sensor at node 4 objective function value is 0.1801 (= 0.5 × 0.1667 + 0.5 × 0.1934).
4. We observed that node 19 has highest objective function value shown in bold faces (column 6). Hence, first sensor is located at node 19.

Table 8. Evaluation of Objective Function Values for First Sensor Location for a Small Network

Node no.	Nodal Demand	Sensor location at node	Detection likelihood TCDL	Normalize value of DC	Objective function value
(1)	(2)	(3)	(4)	(5)	(6)
S	0	S	0.0417	0.0000	0.0209
1	287.71	1	0.0833	0.0538	0.0686
2	184.90	2	0.1250	0.0885	0.1068
3	597.89	3	0.1250	0.1658	0.1454
4	147.74	4	0.1667	0.1934	0.1801
5	184.90	5	0.1250	0.2004	0.1627
6	583.20	6	0.1667	0.2749	0.2208
7	88.99	7	0.1667	0.2916	0.2291
8	88.13	8	0.1250	0.2914	0.2082
9	243.65	9	0.1250	0.3205	0.2228
10	103.68	10	0.0833	0.3399	0.2116
11	287.71	11	0.2083	0.3288	0.2686
12	58.75	12	0.0833	0.3397	0.2116
13	354.24	13	**0.2500**	0.3951	0.3226
14	317.09	14	0.2083	0.4544	0.3314
15	103.68	15	0.1667	0.4738	0.3203
16	412.13	16	0.2083	0.4722	0.3403
17	221.18	17	0.0833	0.5136	0.2985
18	102.82	18	0.0417	0.5328	0.2873
19	280.80	19	0.2083	0.5247	**0.3665**
20	198.72	20	0.0417	0.5619	0.3018
21	184.03	21	0.0417	**0.6064**	0.3241
22	252.29	22	0.0833	0.5720	0.3277
23	58.75	23	0.0833	0.5830	0.3332

6.1.2 Fixing of Subsequent Sensor Locations

5. For selection of subsequent sensor location, a combination of sensor at 19 with a new location is considered. The increased objective function values due to addition of second sensor at new locations are obtained and a combination providing the maximum value of the objective function is selected. The details of iterative process is given in Table 9. The total number of nodes covered within 1 hour LOS by a combination of sensors are given in column 3. The TCDL, DC, normalized DC and objective function values are given in Columns (4) to (7), respectively. A total of 14 stations are required to achieve maximum value of objective function, i.e., 100% detection likelihood and 100% demand coverage.

6.2 Analysis of Results

1. Node 19 is the first to be selected as sensor location based on the highest combined value of demand coverage and detection likelihood. It can be seen from Table 8 that if the place-

Table 9. Iteration Details for Achieving Maximum Objective Function Value for 1-hour LOS for a Small Network

Iteration Number	Sensor located at node	Total Number of nodes covered	TCDL	DC (m^3/d)	Normalized DC	Objective function value
(1)	(2)	(3)	(4)	(5)	(6)	(7)
1st	19	5	0.208	2803.68	0.525	0.3665
2nd	4	9	0.375	2951.42	0.552	0.4635
3rd	15	11	0.458	3372.19	0.631	0.5445
4th	10	13	0.542	3719.52	0.696	0.6190
5th	23	15	0.625	4030.56	0.754	0.6895
6th	18	16	0.667	4354.56	0.815	0.7410
7th	20	17	0.708	4553.28	0.852	0.7800
8th	2	18	0.750	4738.18	0.887	0.8185
9th	5	19	0.792	4923.08	0.921	0.8565
10th	21	20	0.833	5107.11	0.956	0.8945
11th	7	21	0.875	5196.10	0.973	0.9240
12th	8	22	0.917	5284.23	0.989	0.9530
13th	12	23	0.958	5342.98	1.000	0.9790
14th	17	24	1.000	5342.98	1.000	1.0000

ment is done with the sole objective of DC (i.e., 100% weights to DC), the best location would have been node 21 (Max DC = 0.6064). In case of placement with sole objective of TCDL (i.e., 100% weights to TCDL), the best location would have been node 13 (Max TCDL = 0.25), Hence, node 19 is the best compromised location between nodes 13 and 21, where weighted addition of DC and TCDL is maximum.

2. From Table 9, it is observed that demand coverage became 100% in the 13^{th} iteration. However, TCDL was only 95.8% at this stage. One more station was required to increase the TCDL to 100%.
3. The DC and TCDL on addition of first five sensors are about 75.44% and 62.50%, respectively. The locations of first five stations are shown in Fig. 1. It can be seen that sensor locations are distributed in the entire network.

7. Application to BWSN and Comparison of Results with GA and Xu *et al.* (2008) Method

The 5 and 20 sensor locations for BWSN network are obtained using the heuristic method for different weights to objective functions and varying LOS. Xu *et al.* (2008) also proposed a heuristic method based on DL. Therefore, results for LOS of 10 hours are compared herein. Initially, a comparison is made for solutions for LOS of 10 hrs and weights in a ratio of 0.8:0.2 for TCDL:DC by GA and Proposed simple method as given in Table 10. Then, solution of proposed simple method is compared with Xu *et al.* (2008) solution under similar conditions, i.e. LOS 10 hrs and full weight to TCDL. Following can be observed from results:

1. It is observed that first 5 sensor locations given by both heuristic and GA are same in different cases. For example solutions S_1 and S_2 in Table 10.
2. As the number of sensor locations increase, the solution provided by simple method becomes slightly inferior as can be observed in case of most of the greedy algorithms. On comparing the solutions S_3 and S_4 (and also in some other cases not reported), the solution S_3 obtained by GA is better than S_4 obtained by simple method.
3. The comparison of sensor locations for both 5 and 20 sensors by proposed simple method and the heuristic method of Xu *et al*. (2008) showed that proposed method provided better objective function values (Compare solutions S_5 with S_6; and S_7 with S_8). Also the proposed method is more flexible, as it can incorporate two different objectives.

In the BWSN, the sensor locations provided by different researchers were compared on the basis of four objectives the expected time of detection (Z1), the expected population affected prior to detection (Z2), the expected consumption of contaminant water prior to detection (Z3), and the detection likelihood (Z4). A BWSN software utility is used to evaluate the four objectives. Utility 1 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 utility 2 is for “Calculate fitness” allows the user to calculate the fitness function for a given sensor layout design. These objectives are evaluated for the solution obtained for 10 hour LOS using proposed algorithm. Further, the demand coverage (Z5) is obtained for the proposed solution and compared with the other design solutions obtained using optimization and heuristic models. The optimal solution should be able to minimize Z1, Z2 and Z3 and maximize Z4 and Z5.

Solution S_1 provides sensor locations for the 10 hour LOS as 58, 83, 101, 118, and 124. The four performance objectives were evaluated by using the BWSN utility software and the result includes: (1) Z1 = 743 minutes, (2) Z2 = 293 persons, (3) Z3 = 5320 gallons, and (4) Z4 = 0.713 (i.e., 71.3%). The detection likelihood obtained through BWSN utility software are different than the values obtained earlier through proposed methodology due to the detailed analysis of water quality parameters. Hence, these values are more useful for comparison. The Demand Coverage (Z5) for the proposed solution is 0.439 (43.9%). These values are observed to be comparable with solutions provided by other researchers.

8. Application to Real Life Network

A WDN from Ground Service Reservoir (GSR) of Ramnagar

Table 10. Comparison of Solutions for 10 Hour LOS

Solution	Method	Sensor Location at Nodes	DC	TCDL	Z
		For 5 Sensor locations			
S_1	GA	58, 83, 101, 118, 124	0.4385	0.6341	0.5950
S_2	Proposed heuristics	58, 83, 101, 118, 124	0.4385	0.6341	0.5950
		For 20 Sensor locations			
S_3	GA	12, 14, 34, 35, 45, 64, 68, 71, 72, 75, 76, 83, 85, 88, 98, 100, 113, 118, 124, 126	0.9291	0.9268	0.9273
S_4	Proposed heuristics	7, 10, 11, 14, 34, 35, 45, 58, 72, 75, 76, 83, 87, 93, 100, 101, 114, 118, 124, 126	0.9486	0.9187	0.9247
		For 5 Sensor locations			
S_5	Proposed heuristics	45, 58, 79, 83, 118	0.3168	0.6423	0.6423
S_6	Xu *et al.*	68, 83, 101, 118, 122	0.4561	0.6098	0.6098
		For 20 Sensor locations			
S_7	Proposed heuristics	7, 10, 11, 12, 13, 14, 16, 35, 45, 58, 72, 75, 76, 79, 82, 83, 101, 118, 124, 126,	0.7546	0.9187	0.9187
S_8	Xu *et al.*	14, 46, 52, 68, 72, 75, 76, 83, 85, 89, 101, 114, 116, 117, 118, 122, 123, 124, 125, 126	0.7191	0.8618	0.8618

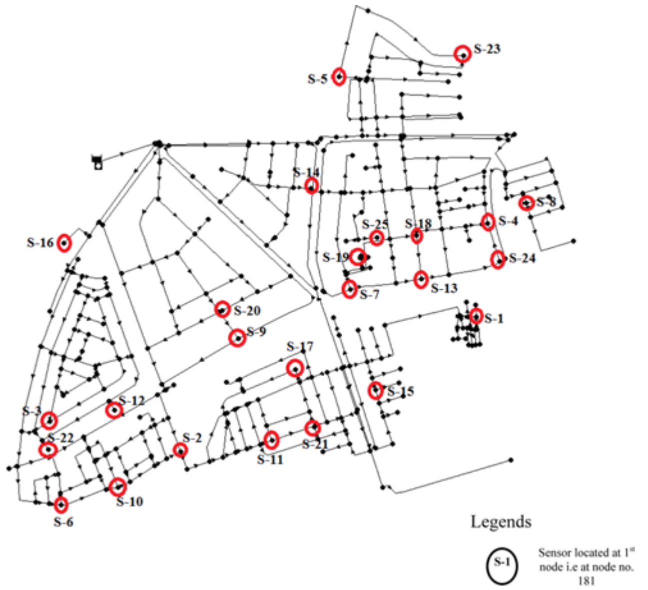

Fig. 4. Location of First Twenty-five Sensors for 1-hour LOS for Dharampeth Zone, Nagpur

(Dharampeth Zone of Nagpur city in Maharashtra, India) is considered for showing application of proposed heuristic methodology to real-time network. The layout of the Network is shown in Fig. 4. The network consists of 285 demand nodes and 367 pipes. The mode of water supply to this zone of Nagpur city is continuous. The present system is capable of supplying drinking water at 150 LPCD.

The network analysis is carried out for peak hour demand using pipe hydraulic analysis software WaterGem(V8i). The analysis provided pipe discharges and flow velocities. The obtained flow directions are shown in Fig. 4. Using the proposed heuristic methodology, location of the first 25 sensors are determined for the 1 hour LOS as shown in Fig. 4. The detection likelihood for the 25 sensors is observed to be 68.5% and the demand coverage is 75.4%. It can be observed from the Fig. 4 that the sensors locations (shown by symbol S) are distributed all over the network. The numbers of sensors are also obtained for LOS from 1 to 10 hrs as 117, 111, 103, 103, 102, 100, 99, 98, 98 and 98, respectively to achieve maximum value of objective function (i.e 100% TCDL and 100% DC). It can be seen that the network has 68 dead ends and all becomes sensor locations to provide maximum value of objective function.

9. Conclusions

Water authorities in developing countries like India are planning and installing online monitoring system for assuring water quality in distribution networks. The lack of network data is big hurdle in accurate water quality modelling and using its results for optimal location of monitoring systems. In this paper, a new multi-objective sensor placement problem is formulated to cover two types of objectives through maximization of (1) Demand coverage; and (2) Time-Constrained Detection likelihood, considering only the results of hydraulic analysis. These objectives are normalized and combined into a single objective by using weights. Any one of the objective can be given priority by increasing the weight over other depending upon the requirement of water authority. Genetic Algorithm is used to obtain sensor locations that maximize the weighted objective function. The suggested methodology is applied on the example network 1 of BWSN.

A simple method is also suggested considering above two objectives for priority-wise selection of sensor locations for application on large size network where optimization technique like GA becomes computationally exhaustive. Methodology is illustrated considering small example network. Sensor locations for 5 and 20 numbers are obtained using GA and heuristic algorithm for network 1 of BWSN considering different weights. Further, objective function value is also evaluated using both. For 5 sensor locations both simple and GA provided same results in terms of node number and objective function value. For 20 sensors, simple method provided little lower value of the objective function as compared to GA and some sensor locations were different. However, computational work required in simple method is less. It is concluded that proposed simple methodology gives comparable results to optimization technique and requires less computational efforts when applied on the large network.

The proposed method requires prior selection of LOS. No general guidelines can be suggested as it would depend on type of network. Several sensor placement options can be obtained by varying the LOS, and depending upon the budgetary and other constraints, a suitable sensor network design with acceptable LOS can be selected. This aspect can be further investigated in future work.

Notations

BWSN = The Battle of the Water Sensor Network
DC = Demand Coverage
DL = Detection likelihood
EC = Extent of contamination
GA = Genetic algorithm
GSR=Ground service reservoir
LPCD = Litre per capita per day
LOS = Level of service
MC = Mass consumed
MS = Monitoring station
NFD = Number of failed detection
PE = Population exposed to contamination
PFD = Percentage of failed detection
SDR = Sensor detection redundancy
SRT = Sensor response time
TCDL = Time Constraint detection likelihood
TD = Time to detection
TEVASPOT=Threat assemble vulnerability assessment sensor placement optimization tool
VC = Volume of water consumed

WDN = Water distribution networks
w = The percentage weight in fraction associated with the objective DC
Z = Objective function

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