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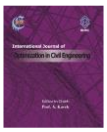

MULTIOBJECTIVE OPTIMIZATION OF SENSOR PLACEMENT IN WATER DISTRIBUTION NETWORKS; DUAL USE BENEFIT APPROACH

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ABSTRACT

Location and types of sensors may be integrated for simultaneous achievement of water security goals and other water utility objectives, such as regulatory monitoring requirements. Complying with the recent recommendations on dual benefits of sensors, this study addresses the optimal location of these types of sensors in a multipurpose approach.

The study presents two mathematical models for optimum location of sensors as static double use benefit model (SDUBM) and dynamic double use benefit model (DDUBM) which provides tradeoffs between maximum monitored volume of water known as "demand coverage" and minimum consumption of contaminated water. In the proposed modeling scheme, sensors are located to maximize dual use benefits of achieving water security goals and accomplishing regulatory monitoring requirements. The validity of the model is tested using two extensively tested example problems with multi-objective ant colony optimization (ACO) algorithm. The Pareto front for different number of sensors are presented and discussed.

CE Database subject headings: Water distribution systems; Drinking water; Water quality; Optimization; Security; Water pollution; Probe instruments; sensors.

Keywords: dual use sensor; sensor location; water distribution network; optimization; ant colony optimization; monitoring.

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1. INTRODUCTION

Distributed geography and multiple points of easy access make water distribution networks (WDN) inherently vulnerable to accidental and intentional contamination [1]. Looped characteristics and time varying flow patterns introduce additional challenges to detection of contaminations in water distribution systems. In addition to accidental and/or intentional contamination, the quality of water may deteriorate due to decay or growth of non-conservative constituents during the transport process .Previous studies have dealt with the water quality monitoring and optimal location of sensors in two different contexts. The first context considers gradual deterioration of water quality in the transport processes, whereas the second context emphasize on rapid quality changes due to intentional or accidental contamination of the network. In the first context, researchers mainly concentrate on the choice of the minimum set of sampling stations which maximizes the monitored volume of water known as "demand coverage". In other words, they look for optimal location of water quality stations to address any increase in coverage of the network and to create an ongoing management practice in water quality control [2, 3, 4, 5, 6, and 7]. In the second context, various measures of impacts on the public health are minimized over the accidental or intentional entry of contaminants [8]. Therefore, the main objective is to identify the best locations for monitoring stations which allows the contamination warning system to detect the intrusion in the most efficient way.

A contamination warning system (CWS) integrates data from online sensors with other detection strategies and routine sampling programs to enable rapid decision making and an effective response to contamination incidents [9]. In 2014, the U.S. Environmental protection Agency (EPA) presented a three-phase Water Security (WS) initiative emphasizing on (1) design of water quality surveillance and response system (2), performance evaluation of the surveillance and response system, and (3) release of Water Quality Surveillance and Response System Deployment. Important issues such as risk communication plans, detection system challenges, operational strategy, consequence management plans, and contamination warning system deployment have been addressed in a series of reports [10, 11, 12, 13, and 14]. In order to minimize the potential impact of any contamination threat to a water distribution network, the following three main steps (1) sensor placement for efficient detection of contamination in both spatial and temporal terms, (2) pollution source identification for determining the location of contamination event and (3) consequence management for minimizing the impacts and restoring the system to normal operation condition in a timely manner. This paper explores the optimum location of double purpose use of sensors for efficient detection of contamination while providing the highest quality coverage to the network. Most of the earlier researches have not utilized simulation of contaminants in their models [15, 16, 17, and 18].

The most recent articles deal with modeling schemes which explicitly simulates fate of the pollutants through the network [19, 20, 21, 22, 23, 24, and 25].

Very many of the earlier models deal with single objective scheme; however, there is a great tendency of considering multiple objectives in water distribution security and sensoring [26, 27, and 28]. Referring to practical application of sensor placement optimization, Skadsen et al. [29] described the sensor network design problem for the City of Ann Arbor. The latter simultaneously tackled the water quality and possible intentional

contamination issues. In an extensive survey, Hart and Murray [1] reviewed the array of optimization-based sensor placement strategies and critiqued these strategies. They categorized the existing literature of sensor placement optimization into nine groups by whether (1) Contaminant Transport Simulations Were Used to Compute Risk; (2) Sensor Failures Were Modeled; (3) Multiple Design Objectives Were Used during Optimization; (4) Data Uncertainties Were Modeled, and (5) Type of Optimization Objective They addressed the gaps in the existing drinking water sensor placement literature and identified several key issues for future works. They emphasized on possible dual use of sensors in water distribution networks and the way their placement may support other water utility needs is among the main concerns [1]:

"*Given the high costs of purchasing and maintaining sensor networks, most utilities will require other reasons for sustaining sensor programs, such as maintaining chlorine residuals, satisfying routine sampling regulations, managing disinfection by-products, monitoring pressure, or detecting leaks*".

Although extensive attention has been given to the optimal layout of early warning detection systems with respect to intentional biological or chemical attacks and assessment of the risk to population exposure, development of an efficient modeling scheme for optimum placement of monitoring stations with possible dual use benefits of sensors remains untouched. Recently, Afshar and Marino [6] employed a multi-objective version of ant colony optimization (NA-ACO) to develop a set of non-dominated solutions for optimal location of sensors considering two objectives. They emphasized that the proposed approach may help in developing an appropriate modeling scheme to account for dual use benefits of sensor in their location in water distribution networks.

Realizing the dual use benefits of sensor and complying with the recent recommendations this study intends to address the optimal design of sensor placement in water distribution networks with dual use benefits in a multi- purpose approach. In the proposed modeling scheme, sensor locations are integrated not only for achieving water security goals but also for accomplishing other water utility objectives, such as satisfying regulatory monitoring requirements. Therefore, the study intends to present two mathematical models for optimum location of sensors as static double use benefit model (SDUBM) and dynamic double use benefit model (DDUBM) to provide tradeoffs between maximum demand coverage and minimum consumption of contaminated water in static and dynamic visions. The study demonstrates the efficiency and performance of the proposed multi-objective ant colony optimization algorithm in solving the problem. The validity of the model is tested using two example bench mark problems. The set of non-dominated solutions forming the Pareto front for different number of sensors is presented.

2. PROBLEM FORMULATION

To formulate sensor location with dual use benefits in a water distribution network, two different versions are identified and mathematically presented. The first version is entitled as static dual use benefit model (SDUBM) and the second version is referred to as dynamic dual use benefit model (DDUBM) hereafter. Therefore, the sensors are located both for maximizing their coverage of the system for water quality monitoring and rapid

contamination detection.

2.1 Static dual use benefit model (SDUBM)

The static model benefits from hydraulic characteristics of the network, in which the transitions between time periods are ignored and each time period is treated independently. The rate and direction of flow for all pipelines and the demands for all nodes in the system are treated as the fixed hydraulic parameters of the network which will be provided by the hydraulic simulator. This paper employs EPANET [30] for hydraulic simulation of the network.

This modeling approach intends to locate the sensors with dual use benefit to maximize monitored volume of water known as "demand coverage" and minimize consumption of contaminated water before contamination detection in the network. To address these two objectives we integrate the two approaches proposed by Afshar and Marino [6] for maximizing demand coverage and Berry et al. [31] for minimizing total contaminated water consumption.

a. Maximize monitored volume of water (demand coverage)

For satisfying the regulatory monitoring requirements or collecting information to solve water quality problems, samples should be collected at representative locations. Here, demand coverage base method is used to quantify the term "representative". The terms covered or coverage refers to the monitored volume of water from which it is possible to infer the water quality at a node based on a measurement at some other node. For this purpose, the general structure of an optimization model for optimum location of monitoring stations in water network may be presented as [6]:

$$maximize \sum_{\beta=1}^{NL} \sum_{i=1}^{NN} d_{\beta i}.y_{\beta i} \tag{1}$$

Subject to:

$$P_{\beta in} = \frac{Q_{\beta in}}{S_{\beta n}} \forall i,n,\beta \tag{2}$$

$$w_{\beta kn} = 1 \qquad \forall \beta,k,n|k=n \tag{3}$$

$$w_{\beta kn} = \sum_{i=1}^{NN} P_{\beta in}.w_{\beta ki} \, \forall \beta,k,n|k \neq n \tag{4}$$

$$a_{\beta in} = 0 \quad if \;\; w_{\beta in} < \lambda \qquad \forall i,n,\beta \tag{5}$$

$$a_{\beta in} = 1 \quad if \;\; w_{\beta in} \geq \lambda \qquad \forall i,n,\beta \tag{6}$$

$$\sum_{i=1}^{NN} x_i \leq NS \tag{7}$$

$$\sum_{i=1}^{NN} \bar{a}_{\beta in}.x_i - y_{\beta n} \geq 0 \; \forall n, \beta \tag{8}$$

In which $P_{\beta in}$ and $Q_{\beta in}$ are the portion and quantity of water that node n directly receives from its surrounding node i in flow pattern (loading) β, respectively (input to the model). The binary variables, $x_i = 0,1$ forms the decision variables which shows whether a monitoring station is or is not located in node i. $w_{\beta kn}$ defines the fraction of demand at node n that has passed through upstream node k; $a_{\beta in}$ refers to the coverage matrix for flow pattern (loading) β; $S_{\beta n}$ is the total inflow of water to node n; NL refers to number of loadings; NS is the number of sampling stations (decision variable in multi-objective model); $d_{\beta i}$ is the demand at node i; $\bar{a}_{\beta in}$ = transpose of the coverage matrix; NN = number of nodes; $y_{\beta i} = 0,1$, which shows whether node i is covered or not; and λ = coverage criterion. The model considers NL different flow patterns (loadings) identified by β in the distribution network. For a given coverage criterion, this leads to NL different coverage matrices. Although this model uses linear combination of all objectives for identified flow patterns, one may easily replace it with a weighted one, in which different weights can be assigned to each loading (flow pattern). The term coverage criterion is a pre-defined criterion to evaluate whether the water quality at node i can represent the water quality at node n. If the fraction of water contributed to monitoring station i from node n $\{w_{in}\}$ is greater than the coverage criterion λ, it assumes node i is representative of node n.

In order to estimate the covered nodes a coverage matrix must be constructed. The coverage matrix is often obtained from water fractions that are summarized in a matrix form by changing all entries that can carry knowledge to upstream nodes to one and others to zero [2]. To eliminate the need for an off-line routine for identification of coverage matrices the approach proposed by Afshar and Marino [6] is employed and implemented in this study.

b. Minimize consumption of contaminated water

The basic mathematical formulation to minimize consumption of contaminated water is adapted from Berry et al. [31]. Disregarding the water velocity, the proposed approach relies on flow direction for identification of contaminated nodes. All nodes that lie in a positive path from contaminated node are assumed contaminated unless there is a sensor on that path. When a node is contaminated, with any concentration, populations at that node are assumed to be exposed to the pollution. The problem may be formulated as [31]:

$$minimize \sum_{i=1}^{n} \sum_{p=1}^{P} \sum_{j=1}^{n} \alpha_{ip} \mathrm{C}_{ipj} \delta_{jp} \tag{9}$$

$$\mathrm{C}_{ipi} = 1 \quad \forall \, i = 1 \ldots n, p = 1 \ldots P \tag{10}$$

$$\mathrm{C}_{ipj} \geq \mathrm{C}_{ipk} - s_k \quad \forall \, k \in V \;\; s.t. f_{kjp} = 1 \tag{11}$$

$$\sum_{i \in V} s_i \leq S_{max} \tag{12}$$

$$s_i \in \{0,1\} \quad \forall i \in V \tag{13}$$

Where S_{max} is the maximum number of sensors; α_{ip}, is the probability of an attack at node i during flow pattern p conditional on exactly one attack on a node during the same flow pattern; δ_{jp} is demand at node j while flow pattern p is active. Variable $C_{ipj} = 1$ if node j is contaminated by an attack at node i during flow pattern p, and 0 otherwise.

Therefore, the integrated model in static version (SDUBM) is defined by following two objectives:

$$\text{Minimize } \sum_{i=1}^{n} \sum_{p=1}^{P} \sum_{j=1}^{n} \alpha_{ip} C_{ipj} \delta_{jp} \tag{14}$$

$$\text{Maximize } \sum_{\beta=1}^{m} \sum_{i=1}^{n} d_{\beta i} y_{\beta i} \tag{15}$$

Which are subject to constraints numbers (2-8) and (10-13).

2.2. Dynamic dual purpose model (DDUBM)

SDUBM model does not precisely represent the temporal characteristics of contamination events and their impacts. To have a more representative method, the selection strategy should consider the changes in water quality as well as the quantity throughout the network. Water quality software like EPANET can compute time variation of contaminant concentration at each junction. With this information, it is possible to assess the impact of the contamination event over the simulation time and critical water quality conditions. The proposed DDUBM modeling scheme explicitly accounts for temporal and spatial changes of water quality throughout the network in a dynamic approach. It intends to find the optimal location of sensors for dual use benefit by maximizing quality-weighted demand coverage and minimizing consumption of contaminated water before contamination detection. To address these two objectives we integrated the general ideas proposed by Woo et al. [5] for maximizing quality-weighted demand coverage and Berry et al. [31] for minimizing total contaminated water consumption.

a. Maximize quality-weighted demand covered

Considering both water quality and quantity in optimal layout of monitoring networks may more effectively address the issue. Besides the largest demand coverage, location of the sampling stations is affected by the variation of nodal contaminant concentration. In this case, the severe negative conditions in water quality could also be captured [5]:

$$maximize \sum_{\beta=1}^{m} \sum_{i=1}^{n} c_{\beta i} d_{\beta i} y_{\beta i} \tag{16}$$

Subject to:

$$P_{\beta in} = \frac{Q_{\beta in}}{S_{\beta n}} \forall i, n, \beta \tag{17}$$

$$w_{\beta kn} = 1 \qquad \forall \beta, k, n | k = n \tag{18}$$

$$w_{\beta kn} = \sum_{i=1}^{NN} P_{\beta in} . w_{\beta ki} \, \forall \beta, k, n | k \neq n \tag{19}$$

$$a_{\beta in} = 0 \qquad if \;\; w_{\beta in} < \lambda \qquad \forall i, n, \beta \tag{20}$$

$$a_{\beta in} = 1 \qquad if \;\; w_{\beta in} \geq \lambda \qquad \forall i, n, \beta \tag{21}$$

$$\sum_{i=1}^{NN} x_i \leq NS \tag{22}$$

$$\sum_{i=1}^{NN} \bar{a}_{\beta in} . x_i - y_{\beta n} \geq 0 \, \forall n, \beta \tag{23}$$

Where, $c_{\beta i} = \frac{concentration\ of\ the\ constituent\ in\ the\ source}{concentration\ of\ the\ constituent\ in\ at\ node\ i}$

b. Minimization of contaminated water consumption

For considering water quality the results of simulation for each contamination event must be saved as concentration time series. If concentration of contaminant in a node exceeds the minimum predefined concentration, that node is considered *contaminated*. Using the output of the network simulator, the contaminated nodes are identified and stored in a matrix. With utilization of this matrix, a new matrix is constructed which addresses the volume of consumed contaminated water for a certain event (rows in the matrix) at a specific node (matrix columns). For a set of events $\forall \alpha \in A$ and equal probability of occurrence for each event, the general form of the model is adapted from Berry et al. [31]:

$$minimize \sum_{a \in A} \sum_{i=1}^{n} d_{ai} x_{ai} \tag{24}$$

$$\sum_{a \in A} x_{ai} = 1 \qquad \forall a \in A \tag{25}$$

$$x_{ai} \leq s_i \qquad \forall a \in A, i \in n \tag{26}$$

$$\sum_{i \in n} s_i \leq S_{max} \tag{27}$$

$$s_i \in \{0,1\} \quad \forall i \in V \tag{28}$$

Where d_{ai} is the volume of consumed contaminated water for event *a* if contaminant is detected in location *i* ; x_{ai} is an indicator which will be equal to 1 if contaminant is first detected in location *i* for scenario *a* and 0 otherwise. The binary decision variable s_i addresses the locations where sensors are placed. It will be equal to 1, if a sensor is placed in location i, and 0 otherwise. The maximum number of allowable sensors is designated by S_{max}. .s Therefore, the DDUBM may be defined by the following bi-objective optimization

problem:

$$\text{Maximize: } \sum_{\beta=1}^{m} \sum_{i=1}^{n} c_{\beta i} d_{\beta i} y_{\beta i} \quad (29)$$

$$\text{Minimize: } \sum_{a \in A} \sum_{i=1}^{n} d_{ai} x_{ai} \quad (30)$$

Objective functions 29 and 30 are subject to constraints (17-23) and (25-28).

3. MULTI-OBJECTIVE ACO; FORMULATION AND IMPLEMENTATION

The ant algorithm is an evolutionary optimization method first proposed by Dorigo et al. [32] for the solution of discrete combinatorial optimization problems such as the traveling salesman problem (TSP) and the quadratic assignment problem (QAP). Although considerable application of single objective ACO in different areas of water resources management have been reported [33, 34, 35], application of multi-objective ACO is limited.

In this study a multi-objective version of ACO algorithm, called Non-dominated Archiving ACO (NA-ACO) algorithm, is employed which benefits from different ant colonies in parallel [34]. The algorithm assigns a colony of agents for each objective. All the ants in one colony are assigned to locate a solution at the same time according to its own pre-assigned objective. Solutions found for one objective in one cycle in the first colony are not evaluated in the corresponding colony. Instead, the produced solutions are transferred to the next (second) colony to be evaluated according to the assigned objective of the new colony and the global trail of that colony is updated. The new solutions found based on the new pheromone trail in the second colony are transferred to the third colony (if any). The process of finding set of solutions in one colony and having the following colony to use these solutions for updating continues up to a predefined iteration called cycle iteration [34]. In this step, the values of the objectives are calculated according to the generated solutions of the last colony and the non-dominated ones are moved to the external set called "Archive". After the completion of a cycle, the global pheromone trails of all colonies are set to the initial value. In the next step, the second cycle is started and at the end of the cycle, derived non-dominated solutions are moved to the same archive. The dominated solutions of Archive are moved out and another pheromone updating is done for all colonies according to the existing solutions in archive. The whole process is repeated until all the non-dominated solutions (Pareto set) of archive satisfying all the constraints or a predetermined number of iterations is met. The solutions of the archive are the final Pareto answers of the multi-objective optimization problem.

The objective of the problem considered herein may be defined as maximizing the total covered demand in the network and minimizing the contaminated consumed water.

4. MODEL IMPLEMENTATION

4.1 Model verification

To check the validity of the developed models, they are first applied to a simple case

presented by Lee and Deininger [2].

The water distribution network consists of seven nodes with only one source of supply as shown in Fig. 1. For the static model (SDUBM), the problem with two potential monitoring stations is solved. The solution to the bi-objective problem, which intends to minimize the consumption of contaminant while maximizing the coverage of the system, resulted in 3 non-dominated solutions. Combination of sensor locations and associated values for the two objective functions are presented in Table 1. As illustrated in Table 1, none of these solutions are dominated with others and covered volume of water decreases as total consumed contaminated water decreases. The optimal locations of the sensors for highest coverage are nodes 5 and 6 that cover full demand. Exactly, the same result was reported by Lee and Deininger[2]. The optimal locations with the minimum consumption of contaminated water are nodes 4 and 6. With sensors located in nodes number 4 and 6, the expected volume of consumed contaminated water is approximated as 100 units for all events. There is another solution on the Pareto front which locates the sensors in nodes 5 and 7 which results in another non-dominated solution.

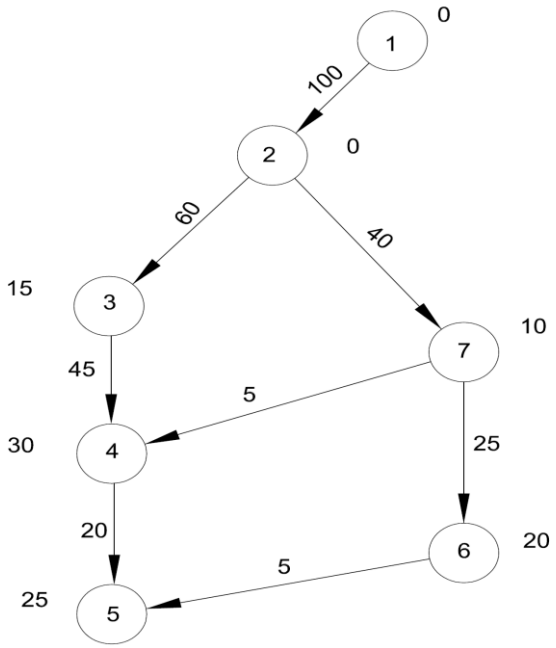


Figure 1. The structure of the Lee and Deininger's model

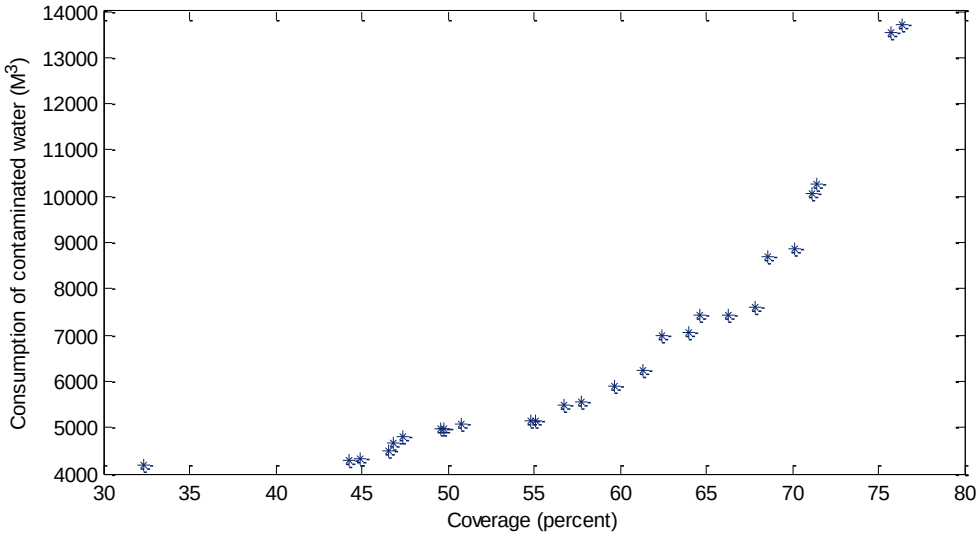
Table 1: The NA-ACO results for Lee and Deininger's network

NA-ACO	Node number	Coverage %	Consumption of contaminated water
Solution 1	5,6	100	225
Solution 2	5,7	80	185
Solution 3	4,6	75	100

4.2 Model application and results

To examine the full capabilities and performance of the proposed methodology and modeling scheme in locating the sensors in a multiple purpose dual use scheme, a real life large network (example network 2 from the EPANET) is considered. The network consists of 35 junctions, one tank and 40 pipes. In this example contamination event occurrence probability for all nodes is assumed to be equal and sensors may potentially be installed in all nodes.

Results for the SDUBM is presented in Fig. 2 which shows the Pareto front derived for the demand covered versus the consumption of contaminated water for two and four sensors in a dual sensor use scheme. Number of ants in each colony, number of cycle iteration, and number of total iteration are set to 25, 20, and 200, respectively. Since no priority is foreseen for sensor locations in specific nodes, the effect of heuristic value in the probability transition is disregarded.



(b)

Figure 2. The Pareto optimal front for the test example; (a) two and (b) four sensors

In Table 2, values of the initial and final solutions of optimal front (minimum demand covered versus minimum consumption of contaminated water and maximum demand covered versus maximum consumption of contaminated water) are presented. As presented in Table 2, by moving from solution 1 to solution 2 the demand coverage increased from 27.5 % to 50.8%; however, more than 7977 cubic meter of contaminated water will be consumed. Choosing a solution from the Pareto front which takes into consideration both objectives or gives priority to one of the objectives might be treated as a multi-criteria decision making process and is in the area of responsibility of decision maker. The solution is more sensitive for the case of 4 sensors, as presented in Table 3. In this case, moving from solution 1 to solution 2, increasing the demand coverage from 32.36% to 76.66% may triple the total contaminated water consumption by increasing it from 4207 to 13703 cubic meters.

Table 2: Values of the first and last solutions of the Pareto optimal front for two sensors (SDUBM)

NA-ACO	Node number	Coverage %	Consumption of contaminated water (m^3)
Solution 1	11-15	27.5	6566
Solution 2	31-14	50.8	14543

To make network more realistic for analyzing an extended period of operation, a time pattern is created that makes demands at nodes vary in a periodic way over the course of a day. For this example, a 1-hour pattern time step is used. To calculate the demand covered and consummation of contaminated water for each solution, 24 different flow scenarios may be considered for each one hour time step. With regard to pump station outflow pattern two scenarios can be considered for pump, OFF or ON. These two scenarios end up in two totally different flow patterns and directions in the network. Here extreme solutions of Pareto optimal front for two scenarios are analyzed and evaluated.

Solution 1 is the first extreme solution where sensors are located in nodes number 11 and 15. This solution provides the minimum consumption of contaminated water with only 27.5 percent of demand coverage. With the sensor in these nodes, the nodes that are covered by one station is a subsection of the nodes covered by other one then it is obvious that this solution can't exert high coverage on the network. For the second objective, however, the nodes 11, 16, 17, 18 with significantly high demands remain safe for most of the possible events. Solution 2 is the other extreme solution in which sensors are to be located in nodes number 31, 14. This solution provides the highest possible (maximum) coverage in the network. In another word, with 2 sensors there is no solution with its coverage exceeds 50.8 percent. For this solution the total expected consumed contaminated water will increase by more than 120 percent. This layout performs very weak against intentional attack, whereas its performance in flow coverage is quite satisfactory.

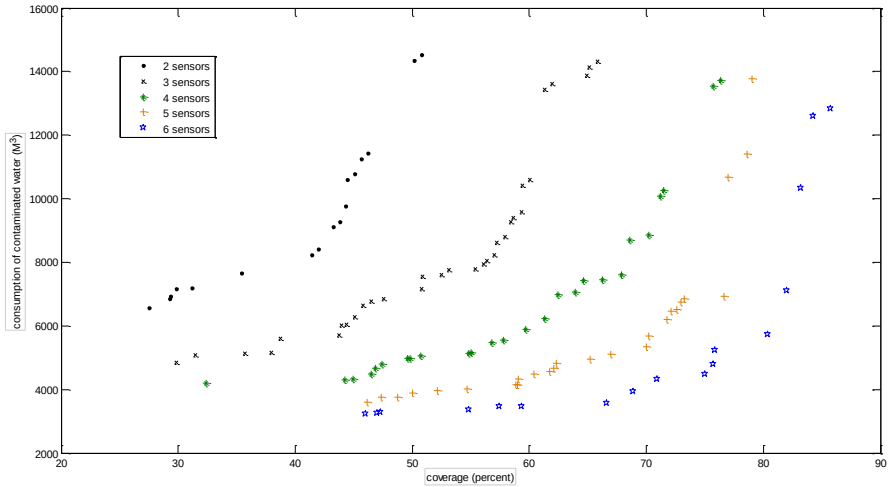


Figure 3. The set of Pareto optimal fronts for different sensor numbers (SDUBM)

To examine the effect of the number of sensors on Pareto optimal front, fronts for different number of sensors are derived and presented in Fig. 3. As expected, by increasing the number of available sensors, the front moves upward providing better coverage and reduction in consumed contaminated water. For instance, as illustrated in Fig. 3, it is impossible to cover 64 %of demand with two sensors. However, with 3 and 4 sensors one may cover 64 percent of demand with expected consumed contaminated water of 14035 and 6955 cubic meter, respectively. It means the expected consumed contaminated water may be reduced by %50 if the number of potential sensors increased from 3 to 4.

In order to explicitly account for water quality changes in the network when sensors are located in a dual use benefit vision, the DDUBM version of the model is applied to the same problem. In this approach, the scheme maximizes quality-weighted demand coverage and minimizing consumption of contaminated water before detection of contamination of the network.

To run the DDUBM model, for any possible event, the temporal and spatial variation of contaminant throughout the network must be determined and saved in an offline archive. Therefore, a set of possible scenarios (events) should be identified. Each contamination scenario is identified with the starting time, duration, and the rate of injection. This study assumes discrete events with two hours duration and 200 gram/minute injection rate. The system is simulated for 24 hours, assuming 12 possible contamination events at each node. Realizing the 35 junctions in the network, the total number of scenarios may be identified as 35*12=420 independent events. The EPANET 2.0 is used to simulate the system for all 420 contamination events. To determine the spatial and temporal variation of the contaminant in the network, the contaminant concentration for each event and each junction in 15-minute discrete time steps is extracted and saved in a 35*96 matrix. The rows in the matrix refer to the nodes in the network, and the columns show the contaminant concentration in 15 minutes time intervals for a 24-hour simulation period. A node is flagged as contaminated if the concentration of contaminant exceeds the pre-specified minimum level which is detectable by the sensors. For all 420 events, the initial time where a junction flagged as contaminated is identified and saved as detection time in a 420*35 matrix. If an event is not detected at all, the maximum simulation time (i.e., 1440 min) is considered as time of detection for that event. With utilization of the detection time matrix, the volume of consumed contaminated water at each node, prior to detection, will be determined and saved in a new matrix with 35 lines and 420 columns.

Results for the DDUBM are presented in Fig. 4 which shows the Pareto front derived for the demand covered versus the consumption of contaminated water for number of sensors ranging from 2 to 6 in a dual sensor use scheme. Number of ants in each colony, number of cycle iteration, and number of total iteration are set to 25, 20, and 200, respectively. Again, in the absence of any predefined priority for sensor locations in specific nodes, the effect of heuristic value in the probability transition is disregarded.

Table 3: Values of the first and last solutions on the Pareto optimal front for four sensors (SDUBM)

NA-ACO	Node number	Coverage %	Consumption of contaminated water (m^3)
Solution 1	17-11-14-5	32.36	4208
Solution 2	31-4-29-21	76.66	13703

Table 4: Values of the initial and terminal solutions of the Pareto optimal front for four sensors (DDUBM)

NA-ACO	Node number	Coverage	Consumption of contaminated water (m^3)
Solution 1	31-21-13-26	$1.93 * 10^5$	6185
Solution 2	33-10-29-18	$2.844 * 10^5$	29698

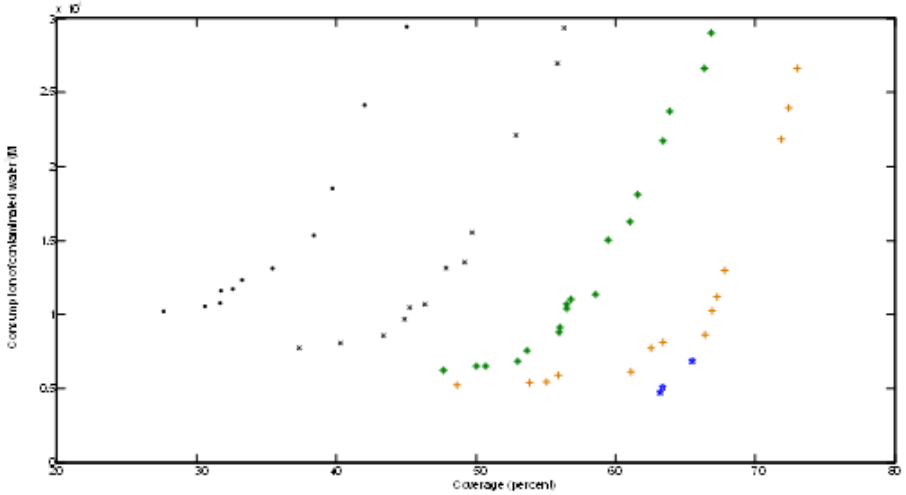
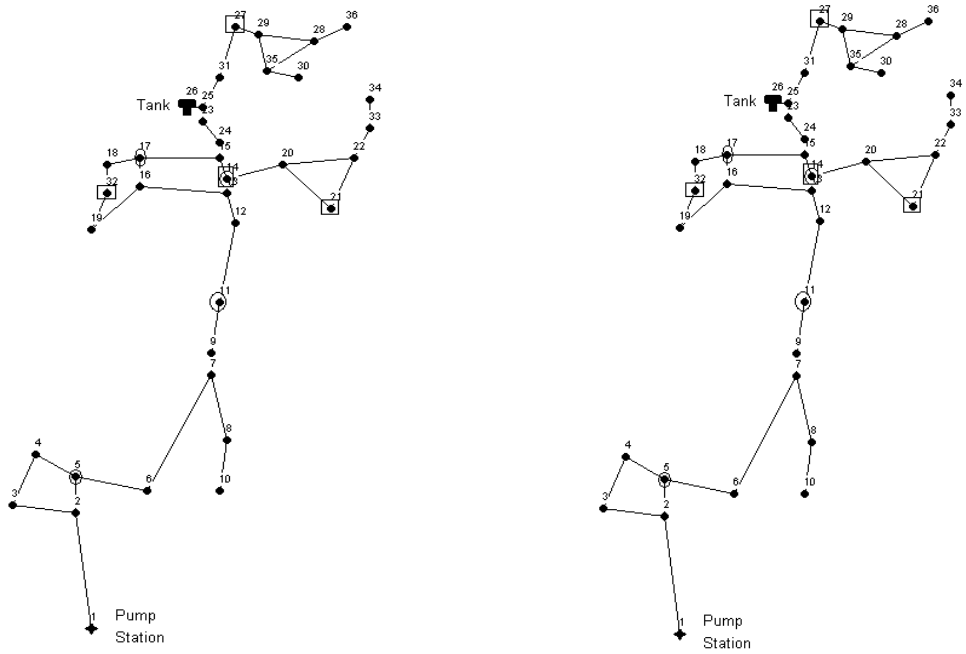


Figure 4. The set of Pareto optimal fronts for different sensor numbers (DDUBM)



(a) (b)

Figure 5. Location of sensors for the (a) first solution and (b) the last solution on the Pareto front for four potential sensors: SDUBM (○) , DDUBM (□)

The effects of number of sensors on the system performance may be addressed in Fig. 4. As illustrated, for a total weighted coverage of 1.6E5 the total consumed contaminated water may range from 7750 to almost 31000 of cubic meter for 3 and 2 sensors, respectively. In another word, the consumed contaminated water may increase by 300 percent if the total installed sensors be decreased from 3 to 2 sensors. The information provided in Fig. 5 illustrate the trade-off between numbers of sensors, total consumed contaminated water and weighted flow coverage.

Evaluation of the dynamic and static modes results show that various models with different assumptions may lead to multiple layouts for sensors. For comparison the results of two models some of the solutions for four sensors location are shown in Fig. 5. This figure shows that overlap between the solutions is inconsiderable.

At the end, it is worth to mention that comparison between the numeral values for placement of a predefined number of sensors isn't authentic because the model's assumptions and event simulation in two modes are completely different.

5. CONCLUSIONS

Besides accidental and intentional contamination, decay or growth of non-conservative constituents taking place during the transport process may cause deterioration of water quality. An online monitoring system may consist of sensors for identification of specific contaminants, or detection of significant changes in water quality that might indicate a contamination incident. This study developed and tested a multiobjective optimization model for locating the latter type of sensors for both water security purposes and regulatory monitoring.

Integration of water security goals and regularity monitoring requirement for dual use benefits of sensors made the model more constrained and highly expensive. The proposed modeling scheme, however, demonstrated the efficiency and performance of the proposed multi-objective ant colony optimization algorithm in solving the problem. The validity of the model was successfully tested using two well established example problems. It was illustrated that, for small number of sensors, the results may be very sensitive to the number of sensors in the system. Evaluation of the dynamic (DDUBM) and static (SDUBM) modes results show that various models with different assumptions may lead to multiple layouts for sensors. It was shown that overlap between the solutions is inconsiderable. It was concluded that comparison between the numeral values for placement of a predefined number of sensors isn't authentic because the model's assumptions and event simulation in two modes are completely different. For further study inclusion of full scale network simulation model in the scheme is recommended.

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