Installing Fixed Sensors for Double Calibration and Early warning Detection Purposes

Olivier Piller, Jochen Deuerlein, Denis Gilbert, Jean-Marc Weber

Available online at www.sciencedirect.com

ScienceDirect

Procedia Engineering 119 (2015) 564 – 572

Procedia Engineering

www.elsevier.com/locate/procedia

13th Computer Control for Water Industry Conference, CCWI 2015

Installing Fixed Sensors for Double Calibration and Early-warning Detection Purposes

Olivier Piller[a,]*, Jochen Deuerlein[b], Denis Gilbert[a] and Jean-Marc Weber[c]

[a] *Irstea, Water Department, Bordeaux regional centre, Cestas F-33612, France*
[b] *3S Consult GmbH, Albtalstrasse 13, 76137 Karlsruhe, Germany*
[c] *Strasbourg Eurométropole, Service de l'Eau, 1 parc de l'Etoile, Strasbourg F- 67076, France*

Abstract

Water utilities have started to install water quality sensors to protect their network against intentional and accidental contamination events. In this context, for taking appropriate action, not only are early-warning detection systems important, but so is the identification of the contamination source, and knowledge of the present and future contamination extent. For the latter there is a need for reliable and updated network models. The main objective of this paper is to specify which performance criteria should be considered to place water quality and water quantity sensors for both early detection and model calibration. Firstly, a brief bibliographical review is given for optimal sensor location design. Next, formulations and objectives for early-warning detection are proposed. Problem formulations that aim to minimize the estimator variance for calibration are then specified. Finally, the method is applied on the real WDN system of the CUS water service (1,000 km, 25,000 nodes and 45,000 customers).

Peer-review under responsibility of the Scientific Committee of CCWI 2015

Keywords: Sensor placement; Computer-aided designs; Models; Early-warning detection system; Calibration; Multi-objective optimization.

1. Introduction

Drinking water distribution networks are exposed to malicious or accidental contamination. Several levels of response are conceivable. One of them consists of installing a sensor network to monitor the system in real time.

* Corresponding author. Tel.: +33 5 57 89 08 27; fax: +33 5 57 89 08 01.
E-mail address: Olivier.piller@irstea.fr

Peer-review under responsibility of the Scientific Committee of CCWI 2015
doi:10.1016/j.proeng.2015.08.909

Once a contamination has been detected, it is also important to take appropriate counter-measures. The *SMaRT-Online^{WDN}* [1] project relies on modeling to predict both hydraulics and water quality. An online model makes it possible to identify the contaminant source and perform a simulation of the contaminated area. The sensor system is intended for detection by an early-warning system and for online calibration of the transport model.

Firstly, a review of previously published research on sensor designs for water security and model calibration is presented. Then, the experiences of the *SMaRT-Online^{WDN}* partners in the two previous German National projects, *STATuS* and *IWaNet*, and in the FP7 European project, *SecurEau* [2], are reported.

1.1. Main previous published research in water quality sensor designs

One of the first formulations is the *demand coverage method* (DCM) by Lee and Deininger [3] for placing water quality monitoring stations (MS). A MS covers a node if a sufficient fraction of water flows from this node to the MS for a demand scenario. The design relies on the principle that the water quality decreases with time and distance from the source. One drawback of the method for its application to water security is that it is only based on water quantity under steady state.

Kessler *et al.* [4] have formulated a *set-covering problem* (SCP) to find the optimal layout for detecting a random pollution event. The optimal design satisfies a given level of service to the consumers that is defined by the maximum volume of consumed polluted water prior to detection. Ostfeld and Salomons [5] have generalized the previous problem formulation to calculate the domain of pollution with the complete transport model in order to better take into account the water dilution and the water quality changes. The SCP formulation searches for a safe cover for every pollution scenario. Uber *et al.* [6] have introduced a maximum coverage problem (MCP) with a weaker assumption for the cover. Solution of the set-covering problem is achieved by [4] using a graph heuristic algorithm suggested in the Christofides's book [7], by [5] using GAs and by [6] with a greedy algorithm.

Propato *et al.* [8] propose a MILP (Mixed Integer Linear Programming) formulation. Their generic objective function consists of costs that are impact factors for an EWDS, such as average time to detection, likelihood of detection, *etc.* Berry *et al.* [9] propose another variant with a formulation mathematically equivalent to the p-median facility location problem. They solve with a Greedy Randomized Adaptive Search Procedure (GRASP) and they quantify how close to optimality the solution is with the MIP Cplex solver or with LP bounds. Propato and Piller [10] solved the MILP problem in [8] with the MIP Cplex solver and observe near optimality for a greedy algorithm.

To discuss the convenience and the potential of each approach regarding designing an EWDS, the Battle of the Water Sensor Networks (BWSN) was held as part of the Eighth annual WDSA symposium in Cincinnati in 2006. Among diverse conclusions of the common paper by all the BWSN participants [11], it was concluded that there is not a single formulation/solving method solution that was superior to the others; better solutions were ones combining strength of the algorithm with engineering judgment and intuition. Interestingly, several future research directions were: definition of the pollution matrix and better contaminant event generation to better represent the network complexity; graph simplification or water quality model simplification without reducing the model prediction power; dual use of sensors (not only for security goals but for model calibration, *etc.*); inclusion of risks; sensor reliability and alarm generation with false positive and false negative classification; and finally incorporation of operational conditions. To a greater or lesser extent, all these research directions are explored in the *SMaRT-Online^{WDN}* project.

1.2. Main previously published research in model calibration for WDNs

Sensitivity analysis allows the determination of how "sensitive" our model is to change in the values of these parameters. They have been successfully applied to hydraulic sensitivity [12], hydraulic calibration [13-15] and hydraulic and water quality sampling design [16-20]. For the latter, it gives the most sensitive nodes where it would be most profitable to perform the necessary measures for calibration.

1.3. Experience of partners

Within the German collaborative research project *STATuS*, funded by the BMBF (13N10623, 2009 – 2013), a risk-based approach to water network security was taken. Some recommendations for the placement of sensors were derived from the results and graph forest/core decomposition of the network [21]:

- Sensors should be placed at so called path or crossroad nodes (in the core with degree > 2) only;
- Contamination event scenarios for sensor placement could focus on intrusion at path nodes;
- Graph theoretical bridge elements are well suited for sensor placement since a sensor on a bridge pipe separates the network into two parts without any ambiguity.

Within the collaborative research project *IWaNet* (funded by the BMBF, 01ISO9014B, 2009 – 2011) a hybrid sensor location method [22] was developed for placing water quality measurements (conductivity, temperature, pH) as well as hydraulic parameter ones (pressure, flow rate). For detection of contaminants, a mono-objective integer linear programming (ILP) algorithm was implemented. As objective function, the maximum coverage of pollution events was used. By fixing a maximum travel time, the competing objective of minimizing time to detection was also considered in a simplified way as a constraint. For solution of that problem a Greedy algorithm was implemented. The results were almost as good as those of the ILP but the running time could be reduced by a magnitude. Finally, the optimal locations for hydraulic measurements were calculated by a second Greedy-Algorithm that is based on pressure sensitivities with regards to the demands. This research is completed in the *SMaRT-Online*^{WDN} project.

The FP7 *SecurEau* project [2] (EC n° 217976) was aimed at the security and decontamination of drinking water distribution systems following a deliberate contamination. One project goal was the setup of an early-warning system, and a multi-objective problem was formulated. Several objectives were defined. Some of them are early-warning specific; others were introduced to mitigate the decontamination procedure; while the last ones decrease the population vulnerability and the financial cost. Two groups of constraints were considered in order to select sensor designs ready for use by water utilities. The first group is for the operational and capital costs. The second group encompasses all the location restrictions and limitations. A novel formulation was derived that reduces the problem size in term of unknowns and constraints, which leads to a Nonlinear Integer Programming problem formulation.

2. Materials and Methods

2.1. Early-warning sensor placement formulation

Half of the four conflicting objectives by Ostfeld *et al.* [11] that were part of The Battle of the Water Sensor Networks (BWSN) are retained. The average time to detection criterion is the simplest. It is defined as:

$$Z_1(\delta) = \sum_{j=1}^{Nsimu} p_j t_j(\delta) \tag{1}$$

Where, δ is a feasible sensor design (number and location); Nsimu is the number of contamination events to consider; p_j is the probability of a contamination event (p_j = 1/Nsimu for the equiprobable case); and t_j is the minimal detection time of the j^{th} contamination for the given sensor location δ.

The information of the population supplied at network nodes was not available from the water utility. A surrogate but robust objective design as proposed in the *SecurEau* project [2] is to consider the average fraction of population exposed prior to detection.

$$Z_2(\delta) = \sum_{j=1}^{Nsimu} p_j f_j(\delta) \tag{2}$$

Where f_j is the fraction population exposed to the j[th] contamination for the given sensor design δ. The likelihood of detection L_D is the average number of detections for a given sensor design. Its complement of one is the average number of failed detections that is:

$$L_D(\delta) = \sum_{j=1}^{Nsimu} p_j d_j(\delta) = 1 - Z_3(\delta) = 1 - \sum_{j=1}^{Nsimu} p_j (1 - d_j)(\delta) \tag{3}$$

Where d_j is the probability to raise an alarm given that the real contaminant event e_j has happened.

In order to protect a population that is at risk (*e.g.*, a hospital; a school; a vulnerable customer; and to a certain extent a normal consumer) the average fraction of population exposed at risk criterion is used. It is defined as:

$$Z_3(\delta) = \sum_{j=1}^{Nsimu} p_j r_j(\delta) \tag{4}$$

Where r_j is the fraction of population at risk that is exposed to the j[th] contamination before detection by the given sensor design δ. This criterion differs from the Z_2 fraction of population exposed (Eq. (2)) as the definition risk may differ from the connection number. An example of risk definition is 5, for presence of a hospital or a school; 3 for a safeguard consumer; and 1 for a normal consumer. More objective functions such as the installation cost were investigated but not reported here.

Two groups of constraints have to be considered in order to select sensor designs ready for use by water utilities.

The first group is for the operational and capital costs. To simplify, the operational cost was considered to be a linear function of the number of sensors. The installation cost for a monitoring station will greatly vary from one location to another. Nevertheless, an average installation cost may be given and used because of the amount of sensors to install. The capital cost may also be considered as a linear function of the sensor number. In this study, operational and capital costs are represented and valuated by the number of sensors.

The second group encompasses all the location restrictions and limitations. Some locations are selected by the water utility. This leads to defining a preselected sensor set P. Other locations should be avoided because they lead to technical and financial limitations: installation costs are too expensive and/or technical requirements such as minimum velocity (for optimization of chlorine sensor working) are not met. This defines the feasible sensor set F that is a superset of the preselected sensor set P.

The sensor design multi-objective problem may be formulated as:

$$\begin{aligned} &\min_{\delta} \left[Z_i(\delta) \right]_{i=1,.4}^{T} \\ &\text{subject to} : \mathrm{P} \subset \delta \subset \mathrm{F}, |\delta| = N_s \end{aligned} \tag{5}$$

Where P is the pre-selection set; F is the feasible set; Z_i is one of the four objective functions defined in Eqs. (1-4); and δ is the sensor design (decision) variable that is a subset of F and a superset of P. This problem consists of a Nonlinear Integer Programming problem that is multi-objective. The solution to this problem is a set of Pareto points. In this research work we solve with a customized greedy algorithm.

2.2. Calibration sensor placement formulation

As discussed in the background chapter, the nodal demands for short periods of time are rough estimates. Accordingly, they will constitute the unknowns that we seek to identify. Based on the nature of premise occupation and water use metering analysis, consumers may be grouped in few classes with the same demand multiplier time pattern. For example, one will distinguish domestic, residential and industrial consumer classes. Then, the consumers are aggregated at nodes. Few consumers of different classes can be aggregated at the same node. This reads:

$$\mathbf{d}(\mathrm{t}) = \mathbf{G}_d \mathbf{x}(t) \tag{6}$$

Where **d** is the nodal demand; $\mathbf{G}_\mathrm{d}$ is the nj by nd class matrix of nodal demand allocation; and $\mathbf{x}(t)$ is the demand class of size nd. The definition of such classes is a difficult task. A trade-off should be made between the model error resulting from simplification and the parameter uncertainty. Indeed, few parameters are easy to calibrate but errors in the model can be significant. Several authors have examined this question as well as the rational use of probability theory and automatic clustering [23, 24].

For a sensor design δ, the following reduced nonlinear regression equation to predict the observation may be defined:

$$\mathbf{y}^{mes}(\mathrm{t}) = \mathbf{S}_\delta \mathbf{y}(\mathbf{x}, t) + \varepsilon(t) \tag{7}$$

Where $\mathbf{y}^{\mathrm{mes}}$ is the vector of observation at time t; $\mathbf{S}_\delta$ is the selection matrix to select the state vector components that corresponds to the measurements δ; $\mathbf{y}(\mathbf{x},\mathrm{t})$ is the prediction vector calculated from the water quantity and the water quality models; and ε is the error or noise vector that we will assume distributed with mean zero and diagonal covariance matrix **C**. More specifically, we assume C of this form:

$$\mathbf{C} = \sigma^2 \mathrm{diag}\left(\Delta y_i^2\right) = \sigma^2 \mathbf{W}_\delta^{-1} \tag{8}$$

With $\Delta \mathrm{y}_\mathrm{i}$ the confidence we have for the i^{th} measurement at a given level; and sigma is a coefficient of proportionality. We assume these coefficients are proportional to the standard deviation of the model error.

We will call the *influence of the measurement error on the least-squares estimates*, the deviation from the solution with no measurement error. At first-order estimates, this estimation error fulfills the linear equation:

$$\delta \mathbf{x}_\varepsilon = \hat{\mathbf{x}}_\varepsilon - \hat{\mathbf{x}}_0 = \left(\mathbf{J}_\delta^T \mathbf{W}_\delta \mathbf{J}_\delta\right)^{-1} \mathbf{J}_\delta^T \mathbf{W}_\delta \varepsilon_\delta \tag{9}$$

With $\mathbf{J}_\delta$ is a Jacobian estimate that is assumed constant at the vicinity of the solution.

The main idea [14] is to choose a sensor design δ that minimizes the absolute value of the influence of measurement error Eq. (9) for measurement errors within the confidence limits defined with the $\Delta \mathrm{y}_\mathrm{i}$ values. For each design δ, we calculate:

$$\sup_{|(\varepsilon_\delta)_i| \le \Delta y_i} \left(\mathbf{J}_\delta^T \mathbf{W}_\delta \mathbf{J}_\delta\right)^{-1} \mathbf{J}_\delta^T \mathbf{W}_\delta \varepsilon_\delta = \left\| \left(\mathbf{W}_\delta^{0.5} \mathbf{J}_\delta\right)^+ \right\|_\infty \tag{10}$$

Where the infinity matrix norm is simply the maximum absolute value row sum of the matrix; $\mathbf{A}^+$ is the pseudo-inverse of matrix **A**; and $\mathbf{D}^{0.5}$ is such that $\mathbf{D} = \mathbf{D}^{0.5}\mathbf{D}^{0.5}$ with **D** a positive matrix.

The problem of optimal design for parameter calibration is formulated as:

$$\begin{aligned} &\min_\delta Z_\infty(\delta) \left\| \left(\mathbf{W}_\delta^{0.5} \mathbf{J}_\delta\right)^+ \right\|_\infty \\ &\text{subject to} : \mathrm{rank}\left(\mathbf{J}_\delta\right) = nd \end{aligned} \tag{11}$$

Where rank is the matrix rank operator. The full rank constraint the number of columns is to ensure the algebraic observability.

In the *SMaRT-Online*^{WDN} project, we solve the mono-objective problem Eq. (11) with a greedy algorithm and a sequential update of the pseudo-inverse by the incremental Greville's algorithm.

3. Application on the CUS network

3.1. Building the hydraulic model from GIS data

CUS (Strasbourg Eurométropole) water service (201 workers) supplies water to 400,000 inhabitants through a network composed of about 1,100 km cast iron pipes. The average daily production is about 105,000 m^3/day groundwater without any treatment. Distributed water is chlorinated at each of the 4 production sites and in the buffer tank.

The Porteau hydraulic model has been built by import of the pipe data sections from the CUS GIS. After substantial data cleansing, in particular to connect the graph, the complete network contains 52,651 pipes, pumping stations, and the main storage tank. The consumption is imported by projection of the subscriber positions on closest pipes. The operator chose a typical working day of consumption.

To calculate the various score criteria to compare sensor placements, it was necessary to allocate the number of connections and the notion of risk to the network junction nodes. The operator has positioned the subscribers at risk, while giving a weight according to the type of subscriber (5 the maximum for hospital, 1 a subscriber at risk, 0 for no sensitive subscribers); The level of risk was then allocated as for the consumption to pipes and split in the two end nodes for each pipe. All in all we have indicated the position of 49,612 connections; and the overall risk number is 9,680 for the CUS network.

The network was simplified by deletion of the antennas of small diameters and/or short lengths. Their consumptions, connections and levels of risk were summed and added at the root node of the antenna. The network graph obtained after simplification includes 16,001 links and 13,712 junction nodes. It is the basis of water quality multi-probe sensor for early-warning detection system.

3.2. Scenarios of contaminations for CUS network

5,000 contamination events were generated by random sampling of the node of intrusion, the starting time (between 0 to 24 hours), different injection mass, and the injection duration between 0 and 6 hours. The number of contaminations was calculated to represent approximately 1/3 of the number of nodes; this allows a relative uniform spatial and temporal distribution of the contaminations. Every simulation takes a few minutes.

3.3. Sensor placement for early-warning detection system

The optimal location of 200 sensors was sought for 8 different criteria of optimization. The total process time for all the optimization solving is 23 h CPU on a Xeon 3Ghz. The Figure 1 shows the criterion « average time to detection » versus the sensor cost (number of sensors) for seven different mono-objective optimizations (time to detection, likelihood of probability, population at risk, etc.). The line of dark blue points represents Pareto optimal choices of time to detection. With no sensors, 37h represents the average residence time in the network with no detection and normal demand. With 80 sensors at optimal location, detection is expected in less than 5 hours. With more than 120 sensors there is no significant improvement.

The Figure 2 compares the same different mono-objective solutions for the detection likelihood criterion (or detection probability) vs. the sensor costs. The detection probability curve (in brown) is a Pareto efficient frontier. We may notice that with 94 sensors the probability detection is 0.95 and for 200 sensors 0.99 is reached.

The position of the first 20 sensors following both criteria: time to detection and detection likelihood are totally different. So for the same sensor cost, it is necessary to arbitrate between the diverse possible criteria.

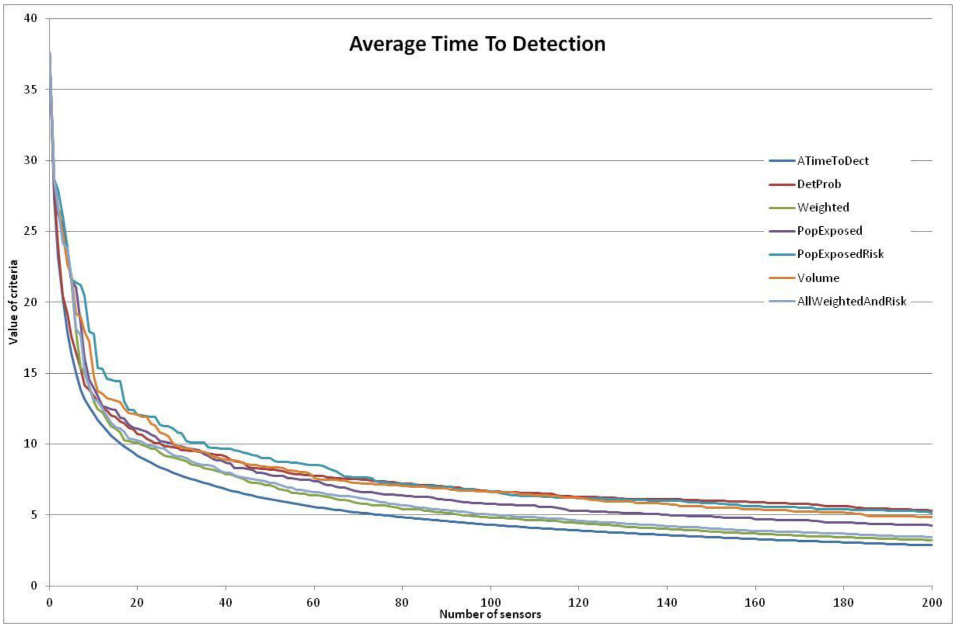

Fig. 1. Pareto front for average time to detection versus sensor cost with different criteria for CUS network.

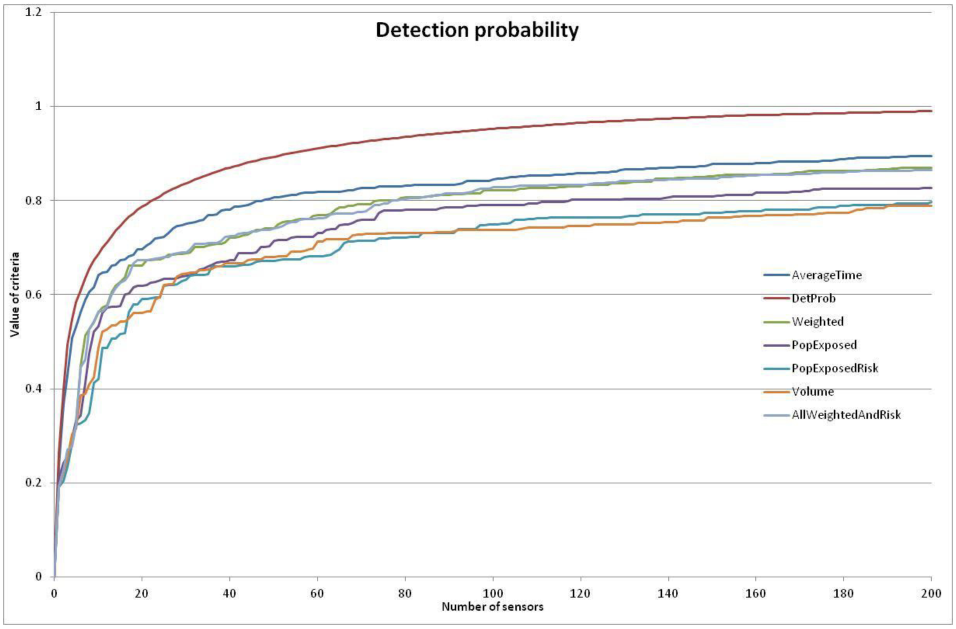

Fig. 2. Pareto front for detection likelihood versus sensor cost with different criteria for CUS network.

3.4. Sensor placement for online demand calibration

With a very looped network composed by mostly oversized pipes, velocity in pipes is very low and the calibration by measuring a head loss and identifying pipe roughness factors is very difficult to achieve in this situation. Flow rate metering was then preferred and 14 network sectors were instrumented for demand calibration of each sector. The algebraic sum of the inflows and outflows is measured by flow meters on the pumping stations outflows, by level on tank and new flow meters on sector limits.

During this project the initial 20 monitoring stations have been completed by 34 additional monitoring stations with flow rate in pipe, pressure, free chlorine, pH, temperature, more the conductivity for a cost of 40 k€/station.

4. Conclusions and perspective

This paper specifies which performance criteria should be considered to place water quality and water quantity sensors for both early-warning detection systems and model calibration. The optimal designs that are proposed come from a thorough analysis of the literature and from the *SMaRT-Online^{WDN}* consortium experience.

For early-warning detection systems, the following different objectives are defined to optimize the average time to detection, the fraction of population exposed, the likelihood of detection, the average fraction of population exposed at risk, and the installation cost. The solution is a two-step method. Firstly, several pollution events are simulated and several impact costs if no sensor for detection are worked out. Then, a multi-objective nonlinear integer-programming problem is solved to cover the pollution events under budget and limitation constraints. A trade-off may be found, using Pareto-efficient fronts on conflicting objectives.

Placing sensors for model calibration relies on selecting designs that reduce the influence of measurement errors on parameter estimation. The solution proposes to minimize the variance of the least-squares estimator. The objective function represents the sensitivity of the demand class parameter estimation to the measurement error. The full rank constraint restricts the design solution that leads to observability of parameters. The optimal sensor designs lead to a calibration problem with the best-condition numbers. The confidence interval for parameters will be reduced compared to another sensor design with higher score.

For the CUS network (Strasbourg Eurométropole), a network graph is obtained after simplification that includes 16,000 links and 14,000 junction nodes. It is the basis of water quality multi-probe sensor design for early-warning detection system. 5,000 uniformly distributed contamination events were generated by random sampling. Pareto optimal fronts were proposed to the water utility for average time to detection versus the sensor cost, and for detection likelihood versus the sensor cost. This makes possible the placement of additional 1 to 200 water quality multi-probe sensors. It was found that for more than 94 additional sensors there is no significant improvement for the detection likelihood, and 95% of the generated contamination events were detected in less than 5 hours. In the *SMaRT-Online^{WDN}* the early-warning optimal sensor placement was also achieved for the VEDIF [25] and the Berlin water utility.

This work will be completed in the *ResiWater* project [26] for design and management actions for improving resilience of water critical infrastructure systems.

Acknowledgements

The work presented in the paper is part of the French-German collaborative research project *SMaRT-Online^{WDN}* that is funded by the French National Research Agency (ANR; project: ANR-11-SECU-006) and the German Federal Ministry of Education and Research (BMBF; project: 13N12178).

References

[1] SMaRT-Online^{WDN} (2015), http://www.smart-onlinewdn.eu/, access on the 7th June 2015.
[2] Secureau (2015), http://www.secureau.eu/, access on the 7th of June 2015
[3] B. H. Lee, and R. A. Deininger, (1992). Optimal Locations of Monitoring Stations in Water Distribution System. Journal of Environmental Engineering, 118(1), 4-16.
[4] A. Kessler, A. Ostfeld, and G. Sinai (1998). Detecting Accidental Contaminations In Municipal Water Networks. Journal of Water Resources Planning and Management, 124(4), 192-198.
[5] A. Ostfeld, and E. Salomons (2004). Optimal Layout of Early-warning Detection Stations for Water Distribution Systems Security. Journal of Water Resources Planning and Management, 130(5), 377-385.

[6] J. G. Uber, R. Janke, R. Murray, and P. Meyer (2004). Greedy Heuristic Methods for Locating Water Quality Sensors in Distribution Systems. 2004 World Water and Environmental Resources Congress, Critical Transitions In Water And Environmental Resources Management, Salt Lake City, UT, printed by 2004, American Society of Civil Engineers, (CD-ROM).
[7] N. Christofides (1975). Graph theory: An algorithmic approach. Academic Press, Inc., San Diego, Calif.
[8] M. Propato, O. Piller, and J. G. Uber (2005). A sensor location model to detect contaminations in water distribution networks. World Water and Environmental Resources Congress (EWRI05), Anchorage, USA, May 15-19, 2005, 12.
[9] J. Berry, W. E. Hart, C. A. Phillips, J. G. Uber, and J.-P.Watson (2006). Sensor Placement in Municipal Water Networks with Temporal Integer Programming Models. Journal of Water Resources Planning and Management, 132(4), 218-224.
[10] M. Propato and O. Piller (2006). Battle of the Water Sensor Networks. 8th annual Water Distribution System Analysis Symposium, University of Cincinnati, Cincinnati, Ohio USA, August 27-30 2006, printed by ASCE, 8.
[11] A. Ostfeld *et al.* (2008). The Battle of the Water Sensor Networks (BWSN): A Design Challenge for Engineers and Algorithms. Journal of Water Resources Planning and Management, 134(6), 556-568.
[12] A. Bargiela, G. Hainsworth (1989). Pressure and flow uncertainty in water systems. Journal of Water Resources Planning and Management, Vol. 115, 2, March 1989, pp. 212-229.
[13] W. B. F. de Schaetzen (2000). Optimal Calibration and Sampling Design for Hydraulic Network Models. Engineering thesis from the University of Exeter, 277 pages, Exeter, UK.
[14] O. Piller (1995). Modeling the behavior of a network - Hydraulic analysis and sampling procedures for parameter estimation, Applied Mathematics thesis from the University of Bordeaux (PRES), 288 pages, Talence, France.
[15] Z. Kapelan (2002). Calibration of water distribution system hydraulic models, Engineering thesis from the Univ. of Exeter, 335 pages, Exeter, UK.
[16] G. Gancel (2006). Modélisation d'un problème inverse pour la qualité de l'eau dans les réseaux d'eau potable, Applied Mathematics thesis from the University of Bordeaux, 136 pages.
[17] C. A. Bush, and J. G. Uber (1998). Sampling Design Methods For Water Distribution Model Calibration. Journal of Water Resources Planning and Management, 124(6), 334-344.
[18] O. Piller, B. Brémond, and P. Morel (1999). A Spatial Sampling Procedure for Physical Diagnosis in a Drinking Water Supply Network. International Conference on Computing and Control for the Water Industry CCWI '99, Exeter, UK, printed by Research Studies Press ltd., Volume 1/2, 309-316.
[19] P. Cheung, O. Piller, and M. Propato (2005). Optimal Location of Water Quality Sensors in Supply Systems by Multiobjective Genetic Algorithms. Eight International Conference on Computing and Control in the Water Industry CCWI05 'Water Management for the 21st Century', University of Exeter, UK, printed by Centre for Water Systems, Volume 1/2, 203-208.
[20] D. Kang, and K. Lansey (2010). Optimal Meter Placement for Water Distribution System State Estimation. Journal of Water Resources Planning and Management, 136(3), 337-347.
[21] J. Deuerlein, A. Wolters, L. Meyer-Harries, and A. R. Simpson (2010). Graph decomposition in risk analysis and sensor placement for water distribution network security, 12th Annual Symposium on Water Distribution Systems Analysis, WDSA 2010, American Society of Civil Engineers, Tucson, Arizona, 12-15 September, 2010.
[22] R. Pinzinger, J. Deuerlein, A. Wolters, A. R. Simpson (2011). Alternative Approaches for Solving the Sensor Placement Problem in Large Networks. 13th Annual Symposium on Water Distribution Systems Analysis, WDSA 2011, ASCE, Palm Springs, USA, 22-26 May, 2011.
[23] Mallick, K. N., Ahmed, I., Tickle, K. S., and Lansey, K. E. (2002). "Determining Pipe Groupings for Water Distribution Networks." Journal of Water Resources Planning and Management, 128(2), 130-139.
[24] Moughton, L. J., Buchberger, S. G., Boccelli, D. L., Filion, Y. R., and Karney, B. W. (2006). "Effect of Time Step and Data Aggregation on Cross Correlation of Residential Demands." 8th Annual Symposium on Water Distribution Systems Analysis, Cincinnati, Ohio, USA, printed by ASCE, Volume 247/, 42-42.
[25] N. Cheifetz, A.C. Sandraz, C. Feliers, D. Gilbert, O. Piller, A. Lang (2015). An Incremental Sensor Placement Optimization in a Large Real-World Water System. 13th Computer Control for Water Industry (CCWI2015) international conference, Leicester, UK, 6 pages.
[26] ResiWater (2015), http://www.resiwater.eu/, being created.