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Sensor placement in water distribution systems using the S-PLACE Toolkit

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Abstract

This work presents a new software, the Sensor Placement (S-PLACE) Toolkit , for computing at which locations to install contaminant sensors in water distribution systems to reduce the impact risks. The S-PLACE Toolkit has been designed to be user-friendly, suitable for both the professional and the research community, programmed in Matlab utilizing the EPANET software library, with a modular software architecture to make it extensible. The use of the software is illustrated using benchmark networks which capture different types of real network topologies.

Keywords: Water distribution, Sensor placement, S-PLACE, Toolkit, EPANET, Matlab

1. Introduction

The problem of deciding where to install water quality and contamination sensors within water distribution networks, for enhancing monitoring and security capability, has been widely investigated within the last decade by the hydro-informatics and the water distribution systems research community (Hart and Murray, 2010). In most works, sensor placement is formulated as the optimization problem of selecting, out of all the feasible locations, a finite subset of nodes where sensors should be installed, in order to minimize one or more objectives (e.g. risk), with respect to certain impact metrics (e.g. number of people infected) (Ostfeld et al., 2008, Eliades and Polycarpou, 2010).

Various challenges have been identified in research, which affect the sensor placement solutions such as: the uncertainties in the system parameters, the stochastic demands, the solution methodology and its computational feasibility, the sensor inaccuracies, the impact metrics and the risk objectives selection, the contamination scenario selection and the use of mobile sensors (Comboul and Ghanem, 2013, Afshar and Mariño, 2012, Dorini et al., 2010, Weickgenannt et al., 2010, Krause et al., 2008, Preis and Ostfeld, 2008, Perelman and Ostfeld, 2013, 2010, Eliades et al., 2010).

Currently, the Threat Ensemble Vulnerability Assessment and Sensor Placement Optimization Tool (TEVA-SPOT v2.5) is the state-of-the-art in water distribution sensor placement software Murray et al. (2010) and is a powerful

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tool for the water distribution industry. The tool is based on the EPANET software engine, and utilizes the hydraulic and quality solver to simulate various contamination scenarios. The sensor placement problem is formulated as a mathematical program based on certain objective metrics and objective functions, taking into account response times and constraints. In addition, TEVA-SPOT utilizes a graphical user interface to depict the different sensor placement solutions.

Inspired by the usability of TEVA-SPOT, and motivated by the need of researchers in developing and comparing different methodologies and algorithms, a new programming platform has been developed, the "Sensor Placement Toolkit" (S-PLACE), which is implemented in Matlab's programming language. The software has been designed to be user-friendly, both for the academic as well as the professional community, making it easy to evaluate different algorithms under various scenarios. In addition, through its graphical interface, it provides an intuitive way of interfacing with the software and the network model. The software architecture is modular, and each module can be accessed independently through stand-alone functions. Furthermore, the S-PLACE is extendible, as it allows to add, modify or remove methods, as well as network elements, in accordance to the research objectives. For instance, the researcher can evaluate and compare different new risk functions, optimization algorithms and scenario selection algorithms.

The S-PLACE was developed using the "Matlab-EPANET Toolbox", an open development platform which incorporates methods to assist in the simulation, optimization and control of water distribution systems, utilizing Matlab's Class structures and the EPANET software library. The Toolbox is comprised of a set of functions which are based on the EPANET, along with other useful functions for visualization, simulation and data management. The S-PLACE Toolkit and the Matlab-EPANET Toolbox is reliased under an open-source license and is available at `https://github.com/KIOS-Research/splace-toolkit`.

The paper is organized as follows: Section 2 describes the sensor placement problem formulation. Section 3 presents the architecture of the S-PLACE Toolkit and Section 4 illustrates the use of the Toolkit through case studies using several benchmark networks which capture different types of real network topologies. Finally, Section 5 concludes the paper and future work is discussed.

2. Problem Formulation

In this section the problem of sensor placement is formulated. In general, the propagation and reaction dynamics in water distribution networks are described by a set of hyperbolic partial differential equations, which can be discretized using some numerical scheme in order to facilitate computational solutions (Rossman and Boulos, 1996). Following the formulation in (Eliades and Polycarpou, 2010), let $\mathbb{R}$ be the set of real numbers, k the discrete time with Δt time step, and let the state-space equations describing the contaminant propagation in a water distribution network segmented into N_x finite volume elements to be given by

$$x(k+1) = A(k; p_x)x(k) + \phi(p_x, p_\phi) \tag{1}$$

where $x(k) \in \mathbb{R}^{N_x}$ is the contaminant concentration vector at time k. The state matrix $A(k; p_x)$ is time-varying and depends on the distribution network topology as well as to the hydraulic parameter set p_x which affects water flows, such as consumer demands, node elevations, as well as pipe lengths/diameters and roughness coefficients. Function $\phi \in \mathbb{R}^{N_x}$ corresponds to the uncontrolled contaminant injection, which depends on the hydraulics parameter set p_x and the contaminant parameter set p_ϕ, such as the contaminant concentration profile, the contaminant injection location and the time the contamination begins. In (1) no chemical reactions of the contaminant substance are considered.

The parameters p_x, p_ϕ are in general partially or nominally known, and the uncertainty in the knowledge of these parameters may affect the final solutions. To alleviate this problem, we may consider constructing a number of contamination and hydraulic scenarios, with the aim of capturing the variability in the real water distribution network. Let $\mathcal{P}$ be the finite set of all the different hydraulic and contamination parameters considered, constructed through some suitable function, in which upper and lower bounds of each parameter along with grid or random sampling from within those bounds is considered. Each different hydraulic and contamination parameter set corresponds to a scenario, and $\mathcal{P}$ is comprised of N_p scenarios. The intuition behind using different scenarios, is to provide a more robust solution, which may be different from the solution computed if average parameter values were considered.

The impact damage caused to the consumers because of the consumption of contaminated water, can be estimated with respect to certain impact metrics, such that

$$z(k+1) = z(k) + f_z(x(k); p_z) \tag{2}$$

where $z(k) \in \mathbb{R}^{N_x}$ is the impact metric corresponding and f_z is a non-negative function which computes the increase of the contamination impact, which depends on the concentration state vector and the impact parameter set p_z (such as the average water consumption per person per day or the contaminant concentration threshold above which ingestion is harmful). In this work the Contaminated Water Consumption Volume (CWCV) is considered as the impact metric.

For each contamination scenario in $\mathcal{P}$ the impact in each location where water is consumed is calculated, by simulating the operation of the distribution system for a certain time (typically a few days). Specifically, for the i-th scenario, the quality dynamics are simulated and the impact dynamics are calculated for each consumption location; when the simulated contaminant concentration exceeds a certain detectable threshold at the j-th sensing node (i.e. a location where a quality sensor can be installed), the total impact is aggregated, thus computing the estimated overall impact $\Omega_{(i,j)}$. In this work, the (i, j)-th overall-impact corresponds to the estimated total volume of water consumed after simulating to the i-th scenario and after considering a quality sensor monitoring the j-th sensing node. The overall-impact matrix Ω is of size $N_p \times N_s$, where N_p is the number of scenarios considered and N_s the number of the possible sensing locations.

Finally, the optimization problem for contaminant sensor placement is formulated as a multi-objective risk-minimization problem, where the best solutions belong to a Pareto Front with respect to certain objectives. Specifically, the multi-objective optimization problem is formulated in this work as

$$\begin{aligned} Y = \underset{\chi \in \{1,0\}^{N_s}}{\operatorname{argmin}} & \{F_0(\chi), F_1(\chi; \Omega), F_2(\chi, \Omega)\}, \\ \text{subject to } & |\chi| \in \mathcal{X} \end{aligned} \tag{3}$$

where χ is the sensing node index, for which $\chi_l = 1$ when a sensor is installed and $\chi_l = 0$ when there is no sensor installed at the l-th sensing node, and $\mathcal{X}$ is the set of number-of-sensors considered in the optimization. Regarding the optimization functions: function F_0 is the number of sensors (or cost if available), F_1 is the estimated average impact-risk and F_2 is the estimated worst-case impact-risk. For computing the best Pareto Front solutions, the selection of the algorithm depends on the problem size. For small problems, an exhaustive search may be computationally feasible, whereas for larger problem other methods such as multi-objective evolutionary optimization algorithms can be applied.

After solving the optimization problem and the Pareto Solutions set has been constructed, decision makers may use higher-level reasoning to arrive at the final decision regarding at which nodes to install the sensors.

3. S-PLACE Toolkit Architecture

The S-PLACE Toolkit has been designed to have a modular architecture, so that it is possible to use, modify and remove modules and algorithms depending on the problem requirements, following a plug-in approach. The S-PLACE Tookit is based on the 'EPANET-Matlab Toolbox', a Matlab Class which wraps all the functionalities available by the EPANET dynamic libraries (Rossman, 2000), along with a number of custom-made functions which facilitate its programming.

The Toolkit extracts all the network parameters from the EPANET input file provided, which includes the network topology, pipe lengths and diameters, roughness coefficients, node elevations and demands, characteristics of tanks, valves, pumps, as well as quality parameters. The 'Data Module' communicates with EPANET and constructs an EPANET object which will be used by the other modules. In addition, the water distribution network is plotted in the Toolkit's GUI.

The 'Scenarios Construction Module' allows the user to select the parameter bounds and sampling method, for constructing the scenarios which will be used in the simulation module, $\mathcal{P}$ and these scenarios are stored in the Scenarios file (0-file). Next, all or some of the scenarios are simulated using the EPANET library to solve and store the different hydraulic scenarios (h-files), corresponding to the network flows, and then to solve and store the different

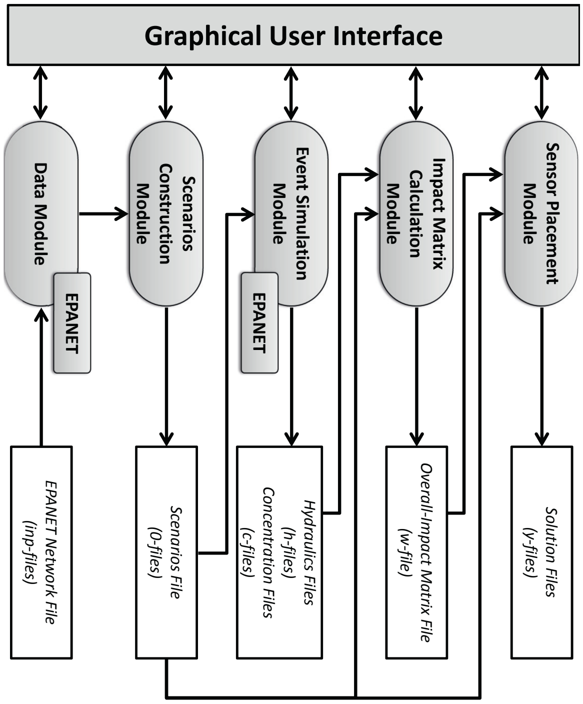

Fig. 1. The software architecture of the S-PLACE Toolkit.

quality scenarios with respect to some hydraulic scenario (c-files). As a result, the contaminant concentrations are calculated for each node which is either a consumption node or a possible sensing node. The 'Impact Matrix Calculation Module' utilizes the data from the scenarios and the simulation files, to calculate the damage caused by some contamination event. The overall-impact matrix Ω computed for all the N_p scenarios and the N_s sensing nodes, is stored in the Overall-Impact Matrix File (w-file). Finally, the "Sensor Placement Module" is used to compute the final solutions, based on the computed overall impact matrices and the scenarios. Through the GUI, the user specifies which method to use to solve the problem. For instance, exhaustive search methods would compute all the possible solution combinations, and calculate the Pareto Solutions. The node solutions are depicted graphically on the map, and are stored in the Solutions Files (y-files).

The main interface with the different modules and features is depicted in Fig. 2. The algorithms corresponding to each module appear automatically in the drop-down menus which are indicated with the labels '2' – '5'. To demonstrate the plug-in method in practice, consider the following example: Suppose that the user would like to create a new impact metric, for instance, to compute the Population Infected (PI) in the Impact Matrix Calculation Module ('4' in Fig. 2). A folder 'PopulationInfected' should be created in the './SPLACE/IMPACT/' path of the software, and within it create a Matlab method with the same name, 'PopulationInfected.m'. This method should utilize the concentration files and the scenario files in order to compute the corresponding overall impact matrix with respect to the Population Infected metric. The method would appear automatically in the SPLACE Toolkit.

4. Case Studies

The operation of the S-PLACE Toolkit is demonstrated using different benchmark networks: the 'Anytown' network (Walski et al., 1987) as well as networks from a research database of water distribution system models which was recently released by Jolly et al. (2013).

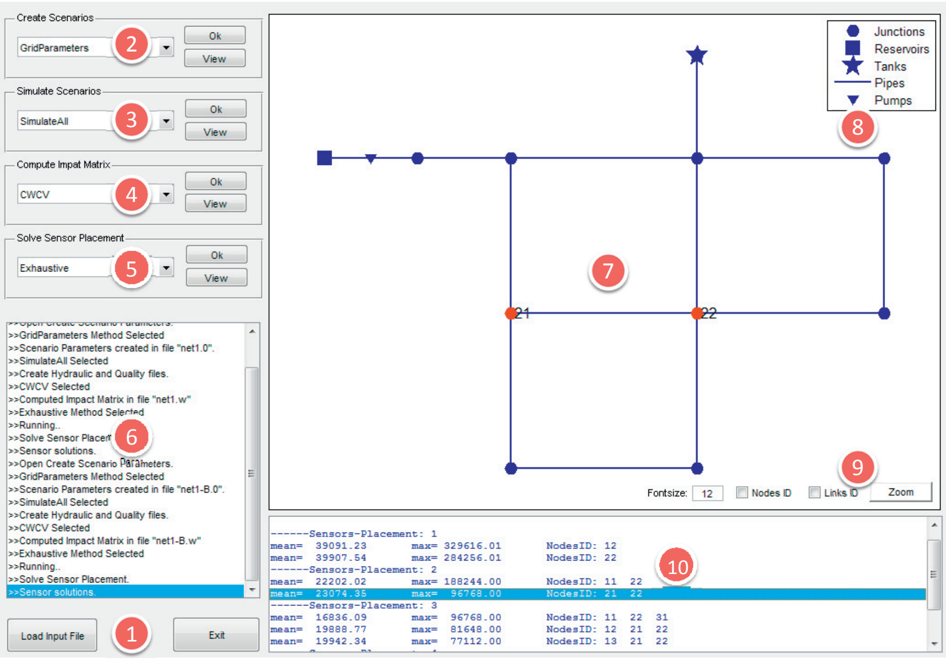

Fig. 2. The S-PLACE Toolkit Graphical User Interface is comprised of the following parts: 1) the network loading buttons, 2) the scenario construction method, 3) the scenario simulation method, 4) the impact-matrix calculation method, 5) the sensor placement solution method, 6) the message box, 7) the water distribution network, 8) the legend for the different network elements, 9) the graph options, 10) the results box where each solution is depicted automatically in the graph by highlighting the selected nodes.

4.1. Illustrative Example

The 'Anytown' network is comprised of 22 nodes, 1 reservoir, 2 tanks, 43 pipes and 3 pumps; further model details are available in (Walski et al., 1987). The selected parameters for the simulations are depicted in Fig. 3. A possible contamination can occur any time within the first simulation day, and the full simulation length is 48 hours. Single-source contamination events are considered in any node, and nodes with non-zero base-demands are considered to be suitable locations for installing water quality sensors. The contamination event corresponds to the injection of a contaminant at 10 mg/L for 2 hours. To capture the variability in the demands, we consider a 10% uncertainty in the base-demands of each node. In addition, we consider that 2 samples are taken with respect to the nominal values. For instance, for nodes 1–4, the nominal base demand is $[500, 200, 200, 600]$ gal/min, and for the simulation purposes, the following base-demand vectors are constructed $[450, 180, 180, 540]$ gal/min and $[550, 220, 220, 660]\}$ gal/min, corresponding to the lower and upper demands respectively. In addition, nodes with non-zero base demands are considered to be suitable locations for installing water quality sensors.

Eventually, 1250 scenarios are constructed and simulated to compute the contaminant concentrations. As impact metric, the contaminated water consumption volume is considered and the overall impact-response matrix Ω is computed. Because of the small problem size, the Pareto Front solutions for the $\{3, 4, 5\}$-sensor placement problem are computed through exhaustive search. One Pareto solution for the 4-sensor placement is depicted in Fig. 4, at nodes $\chi = \{$'5', '7', '10', '19'$\}$, for which the mean and worst-case contaminated water consumption volume is, with respect to the 1250 simulated scenarios, $F_1(\chi; \Omega) = 25\,062\ m^3$ and $F_2(\chi; \Omega) = 138\,808\ m^3$, respectively.

4.2. Application in Realistic Networks

Next, we demonstrate the how to S-PLACE Toolkit on three realistic benchmark networks models, 'KY3', 'KY5' and 'KY11', acquired from the research database released by Jolly et al. (2013).

Fig. 3. The parameters selected for the scenarios construction of the Anytown benchmark. Two base-demand vectors have been considered with 10% uncertainty with respect to the nominal values.

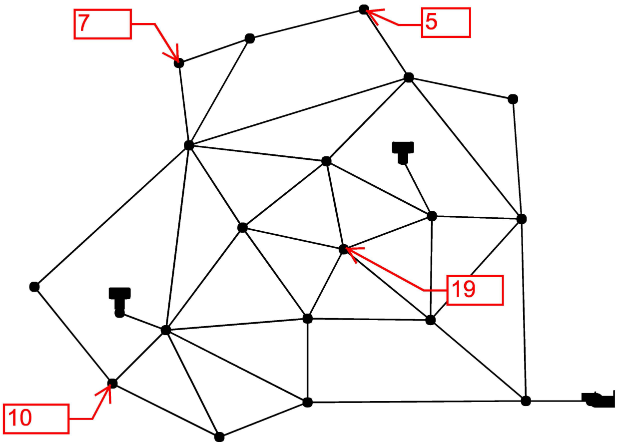

Fig. 4. A Pareto Solution selected for the 4-sensor placement problem. The corresponding nodes for installing sensors are indicated on the 'Anytown' network graph as red circles.

The KY3 benchmark has a 'Loop' topology, and is comprised of 263 junctions, 349 pipes, 3 tanks and 3 reservoirs. The {1,2}-sensor placement problem is solved when {1,2} contamination sources are considered. Intuitively, it is expected that some of the solutions in the 1-source problem will not be optimal with respect to the 2-source problem. This is shown in the results presented in Table 4.2, which indicate that certain solutions are more robust than others when more than one sources are considered. For instance, if one sensor is to be installed, a decision maker might prefer selecting node 'J-216', as it is an optimal location for both the 1-source and the 2-source problems. In addition, a decision maker might choose between the solutions {'J-140','J-174'} or {'J-174', 'J-178'}, which are Pareto solutions for both the 1-source and the 2-source problems.

The next case-study examines the benchmark network KY5, which has a 'Grid' topology and is comprised of 401 junctions, 496 pipes, 3 tanks and 4 reservoirs. A 20% uncertainty in the base-demands of each node is considered, and 3 samples are selected for each base-demand, thus constructing 32250 scenarios. In this case-study, when considering the scenarios without uncertainties and with 20% base-demand uncertainties, the the Pareto solutions for the {1,2}-sensor placement problem did not demonstrate significant differences, as seen in Table 2. The shared Pareto solutions for both problems, were: for the 1-sensor placement, 'J-135' and 'J-313', and for the 2-sensor placement, {'J-11', 'J-

Table 1. Pareto solutions for the {1,2}-sensor placement problem in benchmark KY3, as computed by the S-PLACE considering average model parameters and {1,2} contamination sources. The shared Pareto solutions for both cases are shown in bold typeface.

Contamination Sources	Number of Sensors $F_0(\chi)$	Average Impact-Risk $F_1(\chi)$	Maximum Impact-Risk $F_2(\chi)$	Sensor Nodes
1	1	23 394	219 749	J-140
1	1	21 800	278 912	**J-216**
1	2	17 999	133 268	J-111, J-178
1	2	15 776	151 078	**J-140, J-174**
1	2	16 912	141 392	**J-174, J-178**
2	1	43 568	327 311	J-167
2	1	38 898	361 571	**J-216**
2	2	27 412	199 724	J-121, J-174
2	2	27 083	201 267	**J-140, J-174**
2	2	26 701	338 346	J-159, J-174
2	2	28 971	181 042	**J-174, J-178**

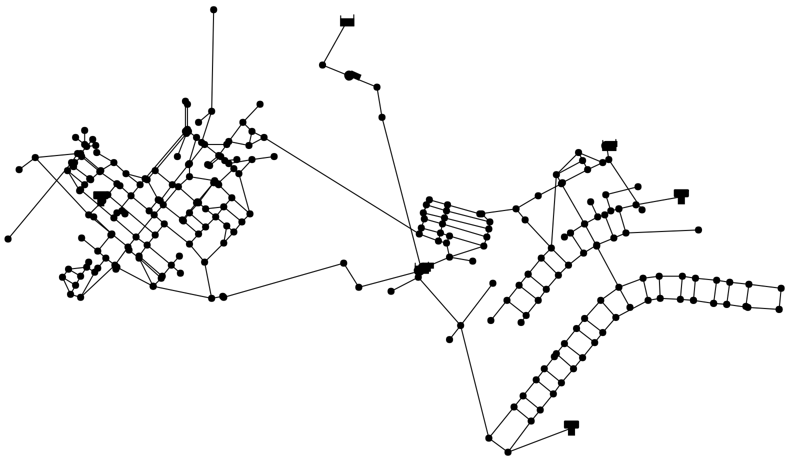

Fig. 5. The benchmark network KY3. The labels indicate the most significant nodes with respect to the Pareto solutions presented in Table 4.2.

217'}, {'J-12', 'J-217'} and {'J-208','J-217'}. Note that two Pareto solutions {'J-138', 'J-208'} and {'J-135', 'J-208'} which corresponded to the smallest worst-case impact-risks when 20% base-demand uncertainty is considered, do not appear in the case of 0% base-demand uncertainty.

The final case-study examines the benchmark network KY11, which has a 'Branch' topology, and is comprised of 728 junctions, 846 pipes, 28 tanks and 1 reservoir. In addition, there are 15 Pressure Reduction Valves (PRV) in the network. We consider that the contamination sensors should only be installed in locations where PRVs are currently installed; this is a realistic constraint since PRVs are usually located at some accessible location, typically connected to a power supply/grid and communicating through some wired, optical or wireless network. The possible sensing nodes (i.e. the PRV locations), are selected during the scenario parameters construction phase, and the system is simulated. As a result, the solution search-space is considerably smaller. The results are given in Table 3, for solving the {1,...,5}-sensor placement problem exhaustively.

5. Conclusions and Future Work

The problem of water quality monitoring for security has been widely investigated within the last decade, and a large volume of research work has been produced addressing various aspects of this problem. Software tools have been developed for the purpose, such as the TEVA-SPOT, which is considered the state-of-the-art in its field. In this work we demonstrate a new software tool, the Sensor Placement Toolkit (S-PLACE), whose goal is to provide an

Table 2. Pareto solutions for the {1,2}-sensor placement problem in benchmark KY5, as computed by the S-PLACE considering average model parameters and {0,20}% base demand uncertainty. The shared Pareto solutions for both cases are shown in bold typeface.

Base Demand Uncertainty (%)	Number of Sensors $F_0(\chi)$	Average Impact-Risk $F_1(\chi)$	Maximum Impact-Risk $F_2(\chi)$	Sensor Nodes
0	1	25 267	492 021	**J-135**
0	1	28 675	463 860	**J-313**
0	2	17 279	305 112	**J-11, J-217**
0	2	17 394	233 255	**J-12, J-217**
0	2	17 024	450 849	J-141, J-74
0	2	17 364	253 309	**J-208, J-217**
20	1	24 725	569 860	**J-135**
20	1	28 976	567 516	**J-313**
20	2	16 772	305 111	**J-11, J-217**
20	2	16 927	278 028	**J-12, J-217**
20	2	17 201	269 791	J-135, J-208
20	2	18 180	268 711	J-138, J-208
20	2	16 916	283 104	**J-208, J-217**

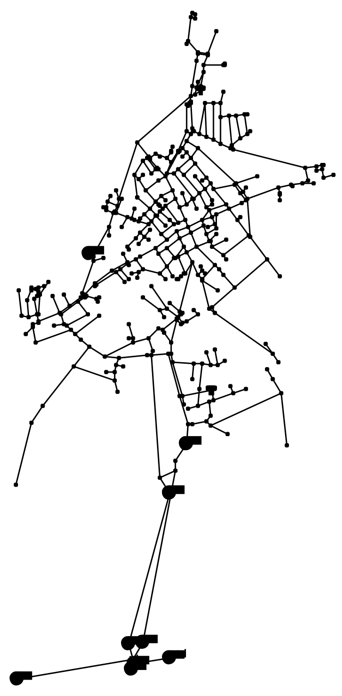

Fig. 6. The benchmark network KY5. The labels indicate the most significant nodes with respect to the Pareto solutions presented in Table 2.

easy-to-use and programmable framework for developing and benchmarking different algorithms, through a modular architecture, using the Matlab language and based on the EPANET libraries. A key feature of the new tool is the ability to add/modify functions in a plug-in approach.

The S-PLACE Toolkit is comprised of a set of methods for creating and simulating contamination and hydraulic scenarios, for calculating the impact damage due to a contamination event and for solving the sensor placement problem. In specific, it is possible to construct scenarios which capture the variance which may appear due to the parameter uncertainties. The different case-studies demonstrate the use of the S-PLACE Toolkit, specifically through the use of the 'Anytown' benchmark, as well as three realistic benchmark networks with loop, grid and branch topology. The

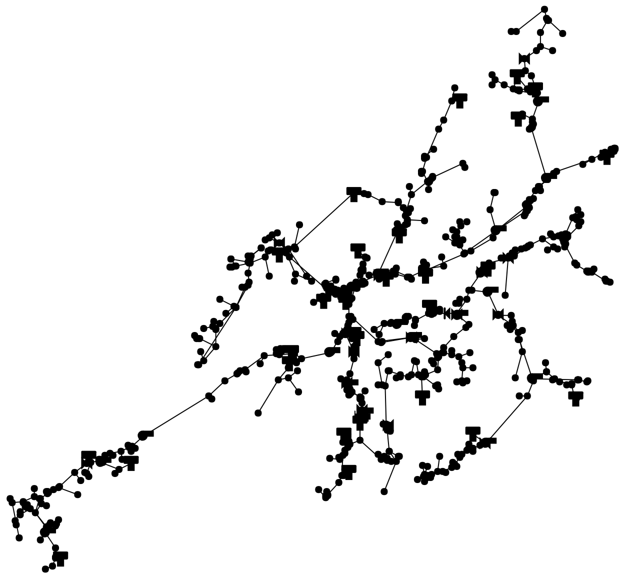

Fig. 7. The benchmark network KY11. The labels indicate the most significant nodes with respect to the Pareto solutions presented in Table 3.

Table 3. Pareto solutions for the {1,5}-sensor placement problem in benchmark KY11, as computed by the S-PLACE considering average model parameters.

Number of Sensors $F_0(\chi)$	Average Impact-Risk $F_1(\chi)$	Maximum Impact-Risk $F_2(\chi)$	Sensor Nodes
1	8 308	218 895	PRV-14
2	6 710	218 895	PRV-14, PRV-7
2	7 869	125 584	PRV-14, PRV-4
3	5 544	218 895	PRV-14, PRV-7, PRV-1
3	6 271	100 480	PRV-14, PRV-7, PRV-4
4	5 105	94 867	PRV-14, PRV-7, PRV-1, PRV-4
4	4 858	218 895	PRV-14, PRV-16, PRV-7, PRV-1
5	4 827	80 638	PRV-14, PRV-2, PRV-7, PRV-1, PRV-4
5	4 427	94 867	PRV-14, PRV-16, PRV-7, PRV-1, PRV-4

case studies demonstrate how the results may vary when the number of contamination source changes, when uncertainties are considered in the hydraulics, as well as when the solutions are constrained to a finite set of possible sensing locations at locations where pressure reduction valves are also installed.

The S-PLACE Toolkit software is released under an open-source licence and is available at `https://github.com/KIOS-Research/splace-toolkit`. Future expansions will allow the consideration of multiple impacts, include the EPANET-MSX libraries for simulating multiple chemical species within the network, and improve the tools for comparing and visualizing results from different methods.

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