Drink. Water Eng. Sci., 5, 39–45, 2012
www.drink-water-eng-sci.net/5/39/2012/
doi:10.5194/dwes-5-39-2012

Drinking Water
Engineering and Science
Open Access

Modelling water quality in drinking water distribution networks from real-time direction data

S. Nazarovs, S. Dejus, and T. Juhna

Riga Technical University, Riga, Latvia

Correspondence to: S. Nazarovs (nazarow@yahoo.com)

Received: 14 February 2012 – Published in Drink. Water Eng. Sci. Discuss.: 2 March 2012
Revised: 9 August 2012 – Accepted: 9 August 2012 – Published: 17 August 2012

Abstract. Modelling of contamination spread and location of a contamination source in a water distribution network is an important task. There are several simulation tools developed, however the significant part of them is based on hydraulic models that need node demands as input data that sometimes may result in false negative results and put users at risk. The paper considers applicability of a real-time flow direction data based model for contaminant transport in a distribution network of a city and evaluates the optimal number of flow direction sensors. Simulation data suggest that the model is applicable for the distribution network of the city of Riga and that the optimal number of sensors in this case is around 200.

1 Introduction

Development of comprehensive tools for simulation of contamination transport and location of the contamination source in a water distribution network is a subject of scientific and engineering interest. In case of contamination outbreak contamination transport modelling tools enable more accurate determination of the area that is affected by the outbreak and requires cleaning. Modelling tools can also be used for locating the source of contamination for further elimination of the source and improvement of the network security that is particularly important in case of deliberate contamination of a water distribution network. Reports of deliberate contamination of networks in the past are summarized by Gleik (2006). Ostfeld (2005) presented a review of water quality modelling methods.

Contamination transport simulation tools research started in the early 80's (Ostfeld, 2005) and aims in three main directions:

- Development of governing equations for transport of contaminating agents, interactions with walls and reactions.
- Development of methods for solution of the equations.
- Development of practical network models capable of predicting which parts of network can be affected once the contamination is spotted at some point of the network.

The development of comprehensive mathematical models was focused on various types of contaminants; for modelling chlorine decay (Rossman et al., 1994; Clark et al., 1995; Ozdemir and Ger, 1999; Al-Omari and Chaudhry, 2001; Ozdemir and Ucak, 2002) and trihalomethanes formation (Clark, 1998; Elshorbagy et al., 2000; Li and Zhao, 2005) in water distribution networks. To model bacteria spread and regrowth in water distribution systems, Digiano and Zhang (2004) developed a mechanistic model. A mechanistic model with higher distinction between attached and bulk bacteria was proposed by Munavalli and Mohan Kumar (2005).

Mechanistic models for bacterial or chemical contamination have a significant drawback that impedes practical application of the models in the wake of a contamination incident. The models are based on equations of hydraulics, in other words a hydraulic model is used to calculate flows and pressure distribution in the system. Precise modelling of hydraulics requires accurate information about water demand in each node of a network. Therefore a water distribution network model is usually calibrated using flow and pressure data from the network as well as estimates of demand

Published by Copernicus Publications on behalf of the Delft University of Technology.

loads, based on population density and typical consumption patterns. Although a calibrated model describes network behavior well during normal operation, it may be inapplicable at small timescale like hours and minutes after contamination incident. Water demand in different parts of the network may fluctuate significantly at such a small timescale. In case contamination is detected in the system, fluctuations of demand patterns will be caused by issue of public health notices and directives in the first place. Changed colour and odour of contaminated water may prevent citizens from using water and contribute to demand reduction too.

The effect of above said demand fluctuations was demonstrated by Davidson et al. (2005) by simulating a contamination scenario close to one that occurred in Glasgow, Scotland in December 1997 where diesel fuel got into the water distribution network. Simulation results indicate that in the scenario involving issue of health notices and reduction of demand in a part of the network by 30 %, flow reversal in some pipes takes place that is not taken into account by the model with static demand.

Therefore flow patterns may change significantly due to reduction of demand after issue of public health notices. Public health notices, in particular an advice to boil water before drinking, are to be published in newspapers in case bacterial contamination is detected in the samples. If one of the water treatment plants gets contaminated, citizens in the area, the plant supplies water to, will be warned and advised not to drink tap water. If this happens, water consumption in the area may drop and flow direction in some pipes will be reversed allowing contaminated water to enter the areas normally supplied by other water treatment plants. Pipes where flow reversal is possible due to reduced consumption because of day-night cycle or health notices are the most sensitive parts of the network that may affect evaluation of contamination spread. Most of these pipes are located around the borders of segments supplied by different water treatment plants. Sensors may be installed on these pipes to monitor flow direction and see in which direction the contamination will spread.

Precise calculations of flow magnitude and direction in pipes after contamination incident may be virtually impossible. Errors in flow magnitude calculations will result in errors during simulation of contamination spread leading to false negative or false positive results at given segment of a water distribution network. The effect of false negative results involves some contaminated areas being declared clean thus putting general population at risk. False positive results may increase decontamination costs and cause unnecessary disruption in operation of water distribution network.

Therefore there is a need of more practical simulation tools based, to some extent, on real-time data rather than on estimated demands that would reduce probability of false negative and false positive results.

A practical approach to seeking a contamination source was offered by Besner at al. (2005). The idea is to gather statistical data on distribution system operation such as valve closures, repairs; consumer complains and water quality measurements. The statistical data can be used to track back the events that occurred in the system prior to a contamination incident, and, hopefully, indicate the contamination source. Nagib and Adel (2009) proposed to apply the predictive control algorithm to a water distribution system. The algorithm uses real-time data including parameters of active elements (e.g. pump speed, valve status) for modelling operation of the network. Kang and Lansey (2011) describe method of using real-time data (flow rates and pressure heads) for estimation of demands and pipe roughness coefficient.

An interesting approach to development of a practical tool for contamination tracking and source seeking has been presented by Davidson et al. (2005). The method eliminates need for demand estimations as real-time data on flow directions in pipes are used instead. The authors suggest that the size and location of the affected area in case of contamination incident depends primarily on flow directions in pipes rather than flow magnitudes.

The method proposed by Davidson et al. (2005) is based on the assumption that contamination can travel downstream only. Therefore, if flow direction sensors are installed in the network and real-time data on flow directions in pipes are available, it is possible to find all downstream pipes and junctions of the point where contamination has been detected. Given the contamination can travel downstream only, the downstream pipes are the only ones that may be contaminated. This does not necessarily mean that all downstream nodes and pipes will be contaminated, but the possibility of contamination cannot be ruled out for them. So real-time flow direction data makes it possible to tell how the contamination may be spreading from the node where it has been detected and also rule out parts of the water distribution network that are not located downstream of the contaminated node and therefore are not affected. In other words the proposed technique provides the worst-case scenario of possible contamination spread.

The flow direction data make it possible to find all upstream nodes and pipes too, so the data can provide suggestions where the contamination source may be located.

The data used for contamination spread simulation are the real-time data from several flow direction sensors as well as information on location of closed valves and check valves.

However the technique offered in the paper by Davidson et al. (2005) has a drawback. With too few sensors installed on the network the results may be inaccurate containing a large false positive error. By increasing the number of sensors one can improve accuracy of the model; however the costs of sensor installation and operation will also increase. Therefore a tradeoff should be found between installation costs of sensors and modelling accuracy.

The evaluation of the modelling error can be done with help of a hydraulic model of a water distribution network in

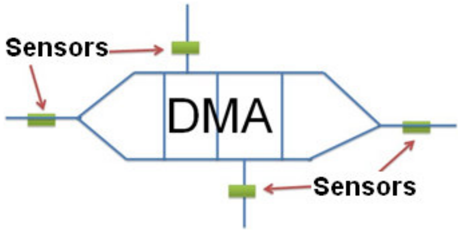

Figure 1. DMA concept.

the following way. Given the location of the contamination source is known, a water demand pattern can be fixed and simulations can be run on the network model so the affected part of the network is found for this pattern and the total contaminated pipe length is calculated. Once the affected area of the network has been determined, it is possible to select several pipes and assume that they have flow direction sensors. Then the simulations are run again taking into account that the flow direction in pipes without sensors is uncertain and if such a pipe is in contact with a contaminated node, the pipe is considered contaminated too. The total contaminated pipe length is calculated and the result is compared with the result of the simulation with the fixed demand pattern thus providing estimation of the error.

Choosing the optimal location of the sensors is crucial. One of the possible approaches is to install the sensors in such a way that the network is split into district metering areas (DMA) as shown in Fig. 1. The term "DMA" in this paper represents a part of water distribution system that is connected to the rest of the network through pipes with flow direction sensors. The more sensors are installed in the network, the smaller DMA areas may be. Each DMA has flow direction sensors on every pipe connecting it with other DMAs. There are no flow sensors inside the DMA.

Davidson et al. (2005) consider applicability of their proposed approach for a subdivision of a municipal water distribution network rather than for a whole city. The objective of this paper is to test applicability of this approach to a whole water distribution network of the city of Riga (Latvia) by running several contamination scenarios and find the optimal number of sensors for this network in order to obtain sufficient accuracy and reasonable installation and operation costs.

2 Methods

This paper considers several scenarios a bacterial contamination being introduced into the Riga distribution network. It is assumed that the bacterial contamination travels downstream with the flow and can also attach to pipe walls.

A model of the Riga water distribution network and demand pattern was used for simulations (Rubulis et al., 2012). The Riga network provides drinking water to approximately 700 000 inhabitants. The distribution network is supplied by three groundwater supply stations and by water treatment plant "Daugava" that takes water from the river Daugava. Water quality control and contamination detection is secured by a constant monitoring of water quality parameters in particular turbidity, pH and chlorine concentration at the exit of water treatment plants. Many contaminating agents are known to alter properties of water such as turbidity and pH (Inamori and Fujimoto, 2004).

Besides that bacterial contamination is monitored by taking water samples on a daily basis from various points of the network.

The Riga water distribution system model used in the paper includes 919 pipes and 574 junctions. The total length of the pipes in the model is 538 km. Pipes with diameter smaller than 200 mm are not included into the model. Three contamination scenarios with three different contamination sources were considered. Flow direction was found for each pipe in the model during the simulation, as if a flow direction sensor was installed on each of 919 pipes. All downstream pipes and nodes of the contamination source were found using the obtained flow direction data and total length of contaminated pipes was calculated by summing lengths of the downstream pipes. The result has been recorded and later used to normalize the data. Then some pipes were selected and marked as the ones having flow direction sensors. The pipes were selected in such a way that the network was split into DMAs. The placement of sensors was optimized. Several sites in the network where the sensors did not serve their purpose in an effective way because of very close location to each other were removed. To minimize the number of sensors installed, several optimization methods were used. First, for sites in the network where a link splits into 2 links with the same flow direction and sensors, the two sensors were removed and a new sensor was installed on the first link prior the splitting point (Fig. 2a). On sites where two consequent sensors were installed, the one that was closer to a treatment plant, was removed (Fig. 2b). It goes without saying that careful consideration should be made before each optimization step. After the sensor placement optimization step simulations were run again. Flow direction data from the first run were used for pipes marked with flow direction sensors. The pipes without sensors (the ones inside DMA) were considered contaminated if at least one pipe supplying the DMA was contaminated.

Flow direction sensors typically have a simple relay output. As soon as flow direction is changed or the flow is stopped, a signal may be sent to the data acquisition station via wireless communication device such as a GPRS modem. The time lapse between the moment when the flow direction is changed and the moment when the data are available to the user is mainly limited by data transfer rate through GPRS that may be relatively low (56 kilobit per second). However as amount of data sent from one sensor is just a few bytes (sensor address and status) time lapse between change in flow

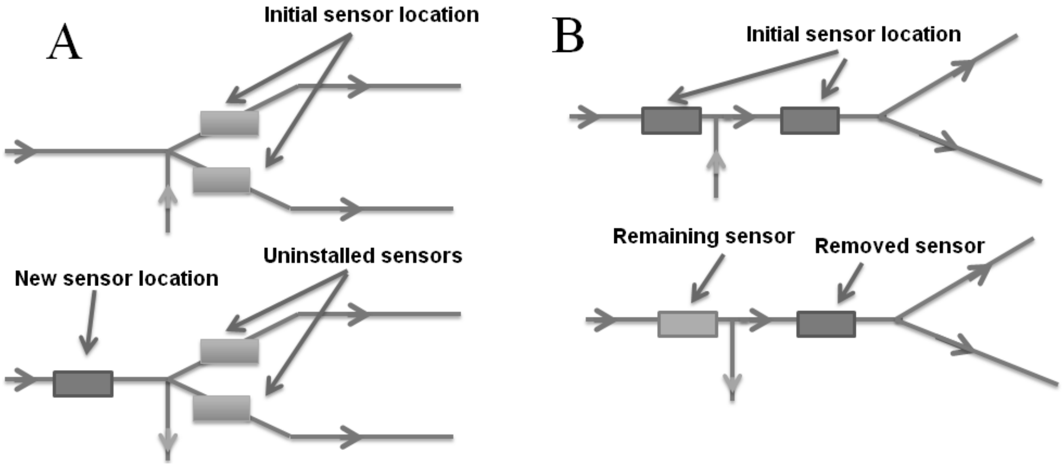

Figure 2. Methods of optimization of number of sensors.

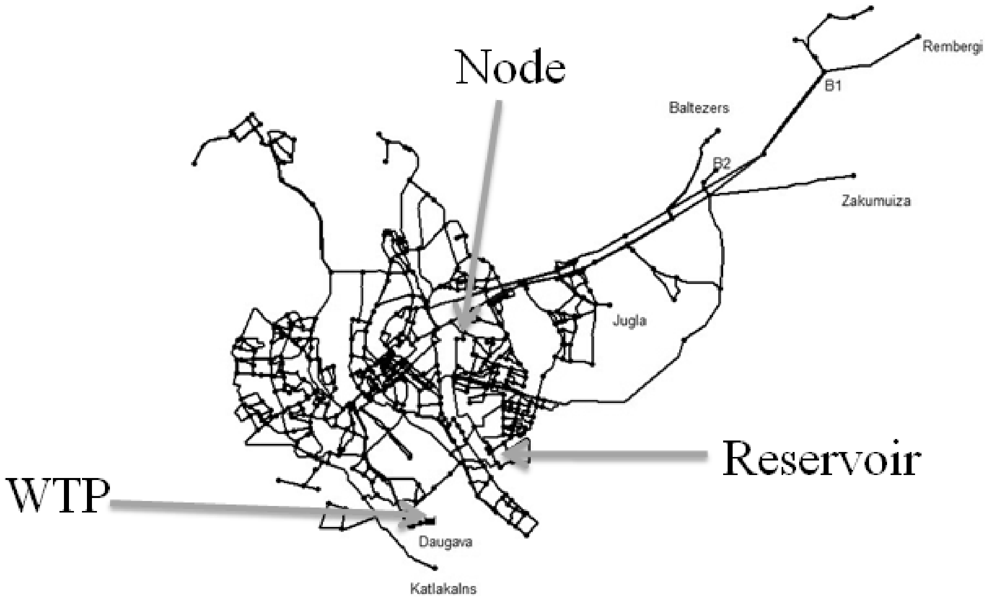

Figure 3. Contamination sources for different scenarios.

direction and data availability in the evaluation tool is in the range of several seconds.

Flow direction sensors are typically activated when flow is about 0.01 m s^{-1} or more. Pipes with smaller flows will be considered as "zero flow" pipes.

Effectiveness of several sensor installation patterns was evaluated by running simulations of 3 different contamination scenarios. Scenario 1: water treatment plant "Daugava" that produces about 50 % of drinking water in Riga city gets contaminated. Scenario 2: one of water reservoirs of Riga city water distribution network gets contaminated. Scenario 3: random node of the water distribution network gets contaminated. Locations of contamination sources in the hydraulic model are shown in Fig. 3.

Simulations were made for several number of sensors. Case studies with 57, 67, 160, 185 and 207 sensors were considered. Total contaminated pipe length was calculated for each number of sensors for every scenario.

3 Results and discussion

The data presented in this section represent total contaminated pipe length obtained from simulations of three different contamination scenarios for various numbers of flow direction sensors. The data are normalized for each scenario by taking the total contaminated pipe length for 919 sensors as unity. Averaged data points are obtained by calculating an average of total contaminated pipe lengths of three scenarios

Table 1. Simulation results.

	Scenario 1				Scenario 2				Scenario 3				
Number of sensors installed	Calculated contamination			Normalized Length	Calculated contamination			Normalized Length	Calculated contamination			Normalized Length	Average normalized contamination
	Pipes	Length (km)	Nodes		Pipes	Length (km)	Nodes		Pipes	Length (km)	Nodes		
919	558	256.09	348	1.0	66	30.50	48	1.0	234	99.38	157	1.0	1.0
207	609	284.70	378	1.1	66	30.50	48	1.0	354	172.76	238	1.7	1.3
185	621	305.64	387	1.2	66	30.50	48	1.0	401	198.67	260	2.0	1.4
160	648	317.04	401	1.2	82	35.76	57	1.2	420	209.10	271	2.1	1.5
67	618	305.43	384	1.2	128	54.89	91	1.8	587	340.75	374	3.4	2.1
57	630	309.88	391	1.2	140	60.70	97	2.0	592	342.35	377	3.4	2.2

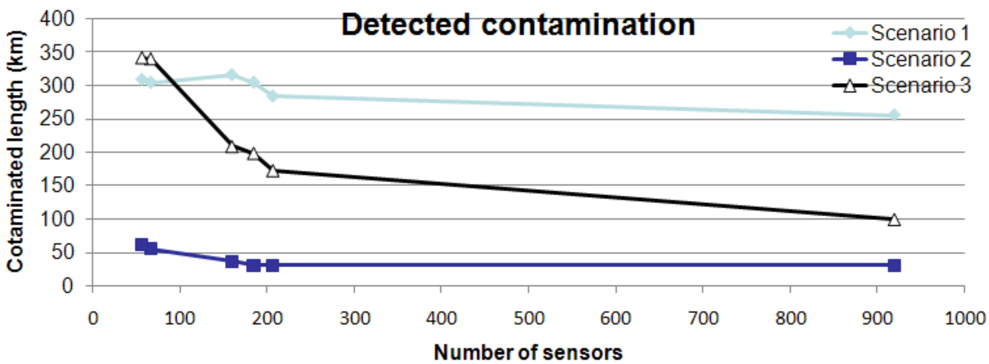

Figure 4. Simulated contamination length for various numbers of sensors.

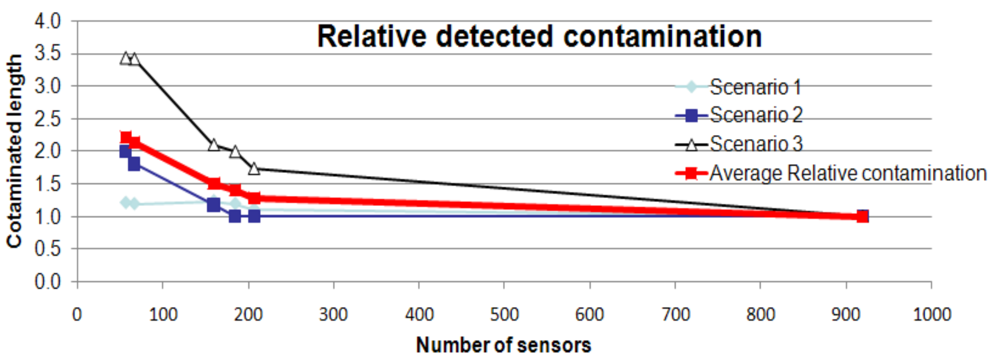

Figure 5. Normalized contamination length for various numbers of sensors.

for every number of sensors. The averaged curve is also normalized by taking average contaminated pipe length for 919 pipes.

The relationship between the number of sensors and total contaminated length for each scenario is presented in Fig. 4 and Table 1. Normalized data and average data for all three scenarios are presented in Fig. 5 and Table 1.

The simulation results suggest that optimal number of sensors for Riga network is around 200. Further increase in sensor number has little effect on simulated contamination length. For Riga model, installation of 207 sensors allows splitting the network into 25 DMAs. As mentioned before, sites where flows, supplied by different treatment plants, meet, are of special interest (Fig. 6). There are 67 such sites in Riga model.

The suggested flow direction sensor placement pattern for Riga network is shown in Fig. 7. Pipes with sensors installed are designated with triangles and marked in blue.

The obtained results demonstrate that number of sensors can be significantly reduced without major decrease of simulation results accuracy. According to Fig. 5, total simulated contaminated length on average increases only by about 20–30 % if number of sensors is reduced from 919 to 207 thus

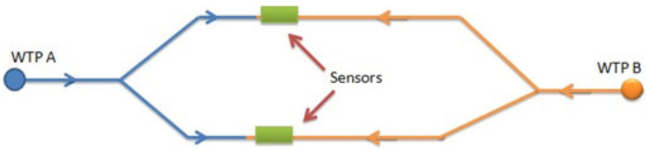

Figure 6. "Collision" sites for water from different treatment plants.

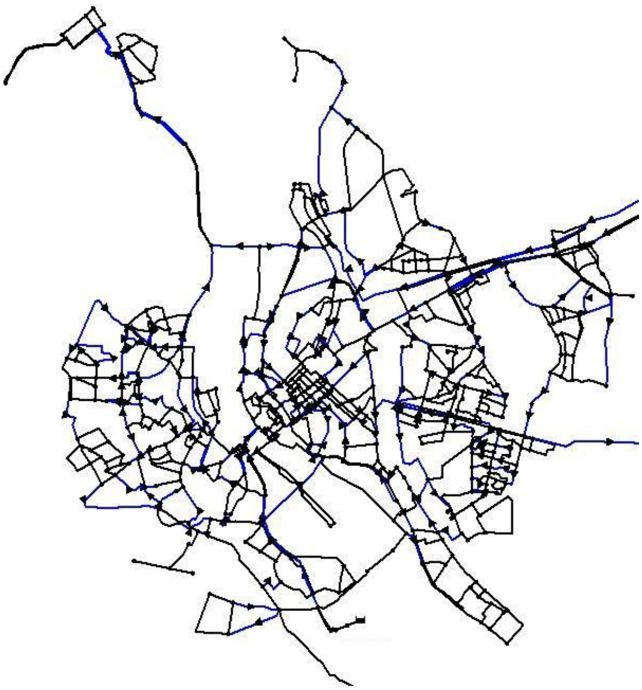

Figure 7. Suggested DMA distribution at Riga water distribution network. Sensor installation sites shown in blue.

more than four times cutting costs of installation and maintenance.

It should be also mentioned that flow direction sensors are relatively cheap and do not need sophisticated signal conditioning circuits. These properties of flow direction sensors allow reduction of costs compared to volumetric flow sensors.

4 Conclusions

Advances in communications technologies such as data transfer through GPRS stations and increasing calculation power of computers made it feasible to collect with practically meaningful frequency flow data from a water distribution network. Therefore it is possible to use real-time data from the network to track possible contamination spread as well as locate the source of contamination. Results presented in the paper suggest that flow direction-based method described by Davidson et al. (2005) may be applicable to the water distribution network of a city of a size of Riga (around 700 000 citizens). The network in this case can be split to about 25 DMA areas that require around 200 flow direction sensors. Splitting the network into distribution management areas allows reducing number of sensors. Usage of flow direction sensors instead of volumetric or velocity sensors helps to reduce installation and maintenance costs. Number of sensors can also be reduced by optimizing location of sensors.

Acknowledgements. This work has been undertaken as a part of the research project SECUREAU (Nr. 217976) which is supported by the European Union within the 7th Framework Programme. There hereby follows a disclaimer stating that the authors are solely responsible for the work. It does not represent the opinion of the Community and the Community is not responsible for any use that might be made of data appearing herein.

Edited by: I. Worm

References

Al-Omari, A. S. and Chaudhry, M. H.: Unsteady-state inverse chlorine modeling in pipe networks, J. Hydraul. Eng.-ASCE, 127, 669–677, 2001.

Besner, M. C., Gauthier, V., Trépanier, M., Leclair, M., and Prévost, M.: Interactive analyser for understanding water quality problems in distribution systems, Urban Water J., 2, 93–105, 2005.

Clark, R. M.: Chlorine demand and TTHM formation kinetics: a second-order model, J. Environ. Eng., 124, 16–24, 1998.

Clark, R. M., Rossman, L. A., and Wymer, L. J.: Modeling distribution system water quality: regulatory implications, J. Water Res. Pl.-ASCE, 121, 423–428, 1995.

Davidson, J., Bouchart, F., Cavill, S., and Jowitt, P.: Real-Time Connectivity Modeling of Water Distribution Networks to Predict Contamination Spread, J. Comput. Civil Eng., 19, 377–386, 2005.

Digiano, F. A. and Zhang, W.: Uncertainty analysis in a mechanistic model of bacterial regrowth in distribution systems, Environ. Sci. Technol., 38, 5925–5931, 2004.

Elshorbagy, W. E., Abu-Qdais, H., and Elsheamy, M. K.: Simulation of THM species in water distribution systems, Water Res., 34, 3431–3439, 2000.

Gleik, P. H.: Water and terrorism, Water Policy, 8, 481–503, 2006.

Inamori, Y. and Fujimoto N.: Physical/Mechanical Contamination of Water, Water Quality and Standards, Vol. 2, in: Encyclopedia of Life Support Systems (EOLSS), Developed under the Auspices of the UNESCO, Eolss Publishers, Oxford, UK, http://www.eolss.net, 2004.

Kang, D. and Lansey, K.: Demand and roughness estimation in water distribution systems, J. Water Res. Pl.-ASCE, 137, 20–30, 2011.

Li, X. and Zhao, H.: Development of a model for predicting trihalomethanes propagation in water distribution systems, Chemosphere, 62, 1028–1032, 2005.

Munavalli, G. R. and Mohan Kumar, M. S.: Water quality parameter estimation in a distribution system under dynamic state, Water Res., 39, 4287–4298, 2005.

Nagib, G. N. M. and Adel, A.: Water Supply Network System Control Based on Model Predictive Control, Proceedings of the

International MultiConference of Engineers and Computer Scientists (2), IMECS 2009, 18–20 March, Hong Kong, 2009.

Ostfeld, A.: A review of modeling water quality in distribution systems, Urban Water J., 2, 107–114, 2005.

Ozdemir, O. N. and Ger, A. M.: Unsteady 2-D chlorine transport in water supply pipes, Water Res., 33, 3637–3645, 1999.

Ozdemir, O. N. and Ucak, A.: Simulation of chlorine decay in drinking-water distribution systems, J. Environ. Eng., 128, 31–39, 2002.

Rossman, L. A., Clark, R. M., and Grayman, W. M.: Modeling chlorine residuals in drinking- water distribution systems, J. Environ. Eng., 120, 803–820, 1994.

Rubulis, J., Dejus, S., and Meksa, R.: Online measurement usage for predicting water age from tracer tests to validate a hydraulic model, Water Distribution Systems Analysis 2010 – Proceedings of the 12th International Conference, WSDA 2010, 1488–1497, 2012.