Complex Adaptive Systems Framework to Simulate the Performance of Hydrant Flushing Rules and Broadcasts during a Water Distribution System Contamination Event

M. Ehsan Shafiee, M.ASCE[1]; and Emily Zechman Berglund, M.ASCE[2]

Abstract: In the event that a contaminant is introduced to a water distribution system, utility managers must respond quickly to protect public health. Mitigation strategies specify response actions, such as warning consumers to reduce water activities using the news media and flushing contaminated water at hydrants. The performance of alternative response actions may be influenced by sociotechnical dynamics, as consumer reactions to contaminant exposure and information about the event can change water demands, hydraulics, propagation of a contaminant plume, and public health consequences. This research develops a modeling framework to test and evaluate mitigation decisions that a utility manager may take to protect public health over a wide range of contamination events. An agent-based modeling framework is developed to integrate social behaviors with technical artifacts in a sociotechnical model to evaluate the public health consequences of a water event. Social actors, including consumers and utility managers, are represented as agents and are coupled with a water distribution network model and a news media model to evaluate the performance of response strategies. Strategies for flushing hydrants are encoded as decision trees that specify the location and timing of hydrant flushing, based on the activation of water-quality sensors. The agent-based model is described using the Overview, Design, and Details protocol and is demonstrated for a virtual midsized municipality, Mesopolis. Results compare the effectiveness of flushing hydrants using cautious and adaptive response strategies and the use of the news media to disseminate warning messages. The framework can be applied for cities to evaluate alternative management strategies. **DOI:** 10.1061/(ASCE)WR.1943-5452.0000744. © *2017 American Society of Civil Engineers.*

Author keywords: Sociotechnical modeling; Agent-based modeling; Water quality; Contamination event; Mitigation strategies; News media.

Introduction

Water distribution networks that serve metropolitan areas are complex systems because they are large-scale, spatially extensive, and composed of multiple redundant pipe loops. Human actors affect the operations and hydraulics of water distribution, and their actions and interventions can increase the complexity of cause-and-effect relationships in a water network. Specifically, the relationship between the water distribution network and human decision making is tightly coupled in the case of a water-quality failure (Glouberman 2001; Woo and Kim 2003; Sadiq et al. 2008). In the event that a water supply is contaminated, public health consequences depend not only on characteristics of the contaminant release and hydraulics of the water network, but also on the behaviors of human actors as they interact with the water distribution network and one another. Water customers may reduce their water demands after becoming exposed, communicating with peers, or receiving messages from utility managers. Simultaneously, utility managers may alter hydraulics through a range of management options that may be implemented to isolate or move contaminated water. The adaptations in water demands and flows introduce dynamics in the contaminant movement and create challenges in predicting the propagation of the plume and public health impacts.

To analyze a water contamination event as a complex system, modeling and data about both the technical and social subsystems are required. Water distribution contamination events are described as sociotechnical systems (Glouberman 2001; Woo and Kim 2003), in which the interactions among technical systems and social actors influence the emergence of system-level properties, such as public health consequences. Complex adaptive system (CAS) simulation provides a framework to model complex sociotechnical systems and evaluate system-level responses based on the actions and interactions of decentralized actors and technical artifacts (Holland 1995). Agent-based modeling (ABM) can be used to simulate a CAS, through encoding a set of autonomous agents and simulating their behaviors using a set of mathematical and logical rules (Miller and Page 2007).

Previous work demonstrated the use of ABM to simulate the interactions of a set of consumer agents with the water distribution network (Zechman 2011; Shafiee and Zechman 2013). Other studies have been conducted to simulate technical responses that manage infrastructure operations (Poulin et al. 2006; Baranowski and LeBoeuf 2008; Alfonso et al. 2010; Gavanelli et al. 2012; Zechman 2013; Rasekh and Brumbelow 2014) and to model social responses that broadcast warnings using the news media (Shafiee 2013; Shafiee et al. 2016). These studies were conducted separately and do not provide the abilities to directly compare management strategies within a framework that captures the dynamics of complex decision making and behavioral responses. The research

[1]Data Scientist and Hydraulic Engineer, Sensus, Inc., 8601 Six Forks Rd. #700, Raleigh, NC 27615 (corresponding author). E-mail: mshafie@ncsu.edu

[2]Associate Professor, Dept. of Civil, Construction, and Environmental Engineering, North Carolina State Univ., 2501 Stinson Dr., 208 Mann Hall, Campus Box 7908, Raleigh, NC 27695.

Note. This manuscript was submitted on November 1, 2015; approved on September 27, 2016; published online on January 26, 2017. Discussion period open until June 26, 2017; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Water Resources Planning and Management***, © ASCE, ISSN 0733-9496.

presented here extends the ABM approach to evaluate the collective effect of diverse response actions to mitigate the public health consequences of a water event in a single model. Results compare the performance of social and technical management options to provide guidance about protecting a community, while accounting for the dynamics of consumer reactions and utility decision making. New behaviors are developed to represent the decision making of utility manager agents as they use optimized sensor-hydrant decision trees to flush contaminated water and to broadcast warnings. Utility manager agents may react to a water event immediately or may wait to collect more information, and results are compared for cautious (immediate) and adaptive decision-making strategies. The sociotechnical framework is formally presented using an overview, design, and details (ODD) protocol (Grimm et al. 2006). The ABM framework is demonstrated for Mesopolis, a virtual city of 150,000 residents.

Problem Definition and Background

Water distribution systems are vulnerable to contaminants, which may enter a pipe network through natural hazards (Hrudey and Hrudey 2004) or the actions of perpetrators (Greick 2006). A contaminant that is delivered to a population can severely impact public health (Kroll 2006). Utility mangers are encouraged to develop threat-management strategies to reduce consequences of water contamination events, such as hardening water networks using water-quality sensors and preparing management strategies to implement response actions (USEPA 2003).

The contamination of a water distribution network is a dynamic event due to feedback among a set of stakeholders, including consumers, the news media, and water utility managers. In a contamination event, the interactions among stakeholders influence the movement of contaminant in the network, which, in turn, affects the reactions and responses of stakeholders. Consumers may change water demands due to communication from peers or water advisories issued by utility managers. A water utility manager may open hydrants to flush the contaminant; managers and public officials may also influence consumer water use through water advisories. Hydraulic conditions may change due to actions and responses of consumers and managers, and subsequent decisions made by utility managers should consider fluctuations in the expected propagation of the contaminant plume and exposure of the population.

ABM is a computational model for simulating the actions and interactions of autonomous agents to evaluate the collective effect on system properties (Miller and Page 2007). Agents receive information about their environment, have goals, and select actions to change the environment and meet goals. Additionally, an agent can receive information from other agents and interact with them. Preliminary research explored simulation of water distribution contamination by coupling a water distribution system model with ABM, and this approach was applied to evaluate the public health consequences of contamination events for a small virtual city of 5,000 residents (Zechman 2010). Subsequent research applied the ABM framework for a community of 150,000 residents, extended the model to include more-realistic behaviors for consumer agents as they change their water activities, and demonstrated that consumer responses can substantially change flows in a network and the movement of the contaminant plume from expected regimes (Shafiee and Zechman 2013). The original modeling framework was further developed to simulate compliance of consumers with messages from peers and utility managers, based on surveys that were conducted in Boston, Massachusetts, and College Station, Texas (Shafiee 2013; Shafiee et al. 2016). The performance of alternative strategies for broadcasting water-use warnings were assessed using this framework. Optimization methods were coupled with the framework to route emergency vehicles to warn consumers (Shafiee and Berglund 2016) and characterize worst-case contamination scenarios (Rasekh et al. 2013).

Hydrant flushing is a response action that is easily implemented and inexpensive for maintaining high water quality in a distribution system (Friedman 2002). A hydrant strategy specifies the timing and location for opening hydrants to flush contaminated water from a distribution system to meet objectives of removing contaminant mass and avoiding any loss of pressure. Hydraulic simulation can be used to evaluate the performance of hydrant-flushing strategies, and research in water distribution threat management have developed simulation and optimization methodologies to identify hydrant strategies. A set of studies explored the use of optimization to identify strategies for operating hydrants and valves to minimize time of detection, the mass of contaminant at terminal nodes, public health impacts, cost of operations, and service interruptions (Poulin et al. 2006; Baranowski and LeBoeuf 2008; Alfonso et al. 2010; Gavanelli et al. 2012; Zechman 2013; Rasekh and Brumbelow 2014). These methods are limited by a shared characteristic: the optimization methods rely on the accurate identification of the location and source of the contamination event to identify an appropriate hydrant-flushing strategy, and each approach identifies an exact strategy for one event. However, during a contamination event, the exact location of the contaminant source may be unknown, and water-quality sensor information may be the only data available to indicate the movement of the contaminant plume. While source-identification methods have been developed that can be applied in real-time to locate the source and loading profile of the contaminant using streaming sensor information (e.g., Laird et al. 2005; Preis and Ostfeld 2006; Guan et al. 2006; Zechman and Ranjithan 2009; Liu et al. 2011, 2012), the use of computational methodologies for real-time source identification and hydrant-strategy optimization for realistic contamination events may be limited by sparsely located water-quality sensors and unresolvable uncertainty in source characteristics. Shafiee and Berglund (2015) developed the sensor-hydrant decision tree, which is new methodology to provide guidance for real-time decision-making in a contamination event through a protocol of response actions that is developed a priori. The sensor-hydrant decision tree is a library of rules to specify hydrant strategies and is created for an ensemble of sensors in a water distribution network to provide guidance in operating hydrants by sensor activation as an event unfolds, without knowledge of source characteristics. Though this methodology requires complex computational tools to build decision trees, the output is a library of responses that can be quickly accessed to provide guidance during an event. Real-time identification of contaminant source characteristics is not needed, and this method can readily be implemented in the field.

The sensor-hydrant decision tree approach is dynamic, and the performance of hydrant strategies may emerge as an event unfolds. Consumer decisions to stop using water can alter the movement of a contaminant plume, which may affect the timing of sensors and the implementation of hydrant strategies. The objective of the research conducted here is to couple together the simulation of consumer responses and simulation of utility responses by implementing sensor-hydrant decision trees within an ABM framework. The development of this framework provides capabilities to assess both sensor-hydrant decision trees and broadcasts, separately and in combination, for reducing the number of exposed consumers. The effect of consumer behaviors on the performance of mitigation strategies is also evaluated.

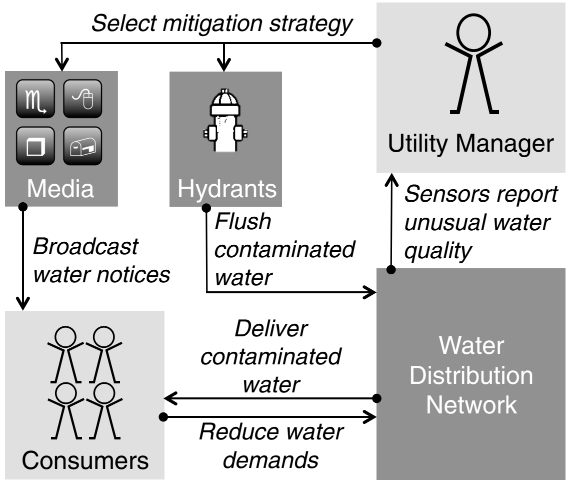

Fig. 1. ABM framework for simulating a sociotechnical water distribution contamination event; light gray boxes are social components; dark gray boxes are technical components; arrows indicate interactions among agents

Agent-Based Modeling Framework

Model Overview

An ABM framework is developed to simulate a water distribution contamination event and evaluate exposure and the effectiveness of mitigation strategies in protecting consumers (Fig. 1). The purpose of the ABM is to evaluate the number of exposed consumers and the dynamics of contaminant movement for a water contamination event. The number of exposed consumers is simulated based on the decisions of consumers and utility managers as they interact with one another and the water network. The study and modeling framework described here are developed to go beyond previously conducted studies about water-contamination events to simulate a realistic decision-making strategy for utility managers as they respond to water-quality information in real-time. The framework also extend previous research to study the impact of the interaction of multiple mitigation strategies, as they are implemented simultaneously, on public health.

The framework couples simulation of consumers, utility mangers, a water distribution network, and the news media. The ABM is simulated using *AnyLogic*, which is tightly coupled with a hydraulic simulation model, *EPANET*. The information about water quality and water demands are passed between *AnyLogic* and *EPANET* at each simulation time step. At the initialization of the simulation, consumer demands are aggregated at nodes, which are junctions at intersecting pipes. *EPANET* calculates the flow volumes, flow directions, and water quality in the pipe network. The simulation proceeds at discrete time steps for hydraulic calculations in *EPANET*, and at each time step, water-quality information is passed from the water distribution system model to the agents. As consumers reduce their water use, changes in demands are translated to the water distribution simulation. Similarly, as a utility manager agent opens hydrants, changes in demands at hydrants are translated as input to the hydraulic simulation. Hydraulic conditions for successive time steps are calculated by *EPANET*. This simulation establishes the feedback loop between the consumers, utility manager, and water distribution system.

The population of a municipality is used to determine the number of consumer agents that is initialized, and one utility manager agent is simulated. Data that are needed to initialize the ABM are an input file for the hydraulic simulation that describes the pipe network, size of the population, land-use information, and number of consumers at each node and time step.

Process Scheduling

The ABM proceeds in hourly time steps, and at each time step, the order of operations is as follows:

Step 1: The water distribution system model is executed to calculate the concentration of contaminant at each node;

Step 2: The volume of water that each agent drinks at the current time step is calculated, based on the probability that the agent drinks at that time. Agents are flagged as exposed if they consume a total amount of contaminant exceeding a critical threshold;

Step 3: The utility manager agent receives alerts from activated sensors. A sensor is activated when the concentration of contaminant is reported above a predefined threshold at the node where the sensor is located;

Step 4: If one or more sensors are activated and no sensors were previously activated in the event, the utility manager agent immediately disseminates a water advisory through radio and television;

Step 5: Consumers that are awake and using radio or television receive a warning from the utility manager;

Step 6: Consumers that become exposed or decide to comply with warnings send a warning message to consumer agents in their local networks;

Step 7: Consumers that are exposed or decide to comply with warnings reduce their demands and do not ingest water. Consumers maintain reduced demands and do not ingest water for the remainder of the simulation;

Step 8: If one or more sensors are activated and no sensors were previously activated in the event, the utility manager uses a sensor-hydrant tree to select a hydrant strategy to flush hydrants;

Step 9: Consumer agents move from a residential node to a nonresidential node, or from a nonresidential node to a residential node, if the time that the agent spends at a location has expired;

Step 10: The input file for the water distribution system is written to update the demands at nodes, based on the location of consumer agents that have reduced their demands and hydrants that are open; and

Step 11: If the maximum number of simulation time steps is reached, terminate the simulation. Otherwise, return to Step 1.

Water Distribution Network Model

EPANET is a hydraulic and water quality model that performs extended period simulation of water movement and of the fate and transport of water-quality constituents within pressurized pipe networks. The water distribution network is executed to simulate water distribution variables, including flow in pipes, pressure at nodes, and contaminant concentration at nodes.

Calculation of Contamination Concentration

The concentration of contaminant is calculated at each node for every time step. At each time step, the demands at nodes are updated based on the demand reductions that are specified by consumers [Eq. (4)]. The hydraulic file is updated, and *EPANET* is executed to calculate hydraulic conditions and water-quality constituent transport for one time step. Water-quality information is passed to agents for calculating the amount of contaminant that is ingested in "Ingestion and Exposure" section.

Sensor Activation

Sensors are simulated at a predefined set of nodes to represent water-quality sensors that are placed in a pipe network. At each

J. Water Resour. Plann. Manage., 2017, 143(4): 04017001

time step, the contaminant concentration is calculated at sensor nodes, and if the concentration exceeds a detection threshold, then the sensor is simulated as activated. A message is immediately passed to the utility manager agent to define which sensors have been activated at each time step.

Consumer Agent Model

Consumer agents represent individual residents of a community and are initialized with state variables to represent characteristics, as summarized in Table 1. Random values are generated for characteristics based on distributions given in Table 1 and the inverse of the exponential distribution

$$x = -x_m \ln(1 - p) \tag{1}$$

where x = value that is generated for the variable of interest and is assigned as a characteristic of a consumer agent; x_m = average of the variable of interest, which is obtained from Table 1; and p = probability that is randomly generated between 0.0 and 1.0. Behavioral rules are described next.

Ingestion and Exposure

A consumer agent ingests water five times each day. The timing for drinking water is assigned using a set of probability distributions that were developed based on time-use surveys (Davis and Janke 2009). At each ingestion event, an agent consumes one-fifth of the volume that is assigned as the daily water ingestion volume. The concentration of the contaminant is specified at each node using updated output from the water distribution network model, and as agents ingest contaminated water, the mass of contaminant accumulates in the body of an agent. Eq. (2) calculates the mass of contaminant that is ingested for every consumer at each time step

$$m_{tj} = c_{ti} \times v_{tij}: \quad \forall\ i = 1, \ldots, nb_t, \quad j = 1, \ldots, nb_c \tag{2}$$

where m_{tj} = mass of contaminant that is ingested by consumer j at time step t; c_{ti} = contaminant concentration at node i at time step t, which is the output from *EPANET*; v_{tij} = volume of water that is extracted by consumer j from node i at time step t; nb_t = total number of nodes in a water network; and nb_c = number of consumer agents in the ABM. The value, v_{tij}, is zero if no water ingestion event is specified at time step t or if the consumer is not at node i.

When agents ingest a dose of contaminant greater than 0.05 mg/kg of their body weight, they becomes exposed. This critical dose is chosen to simulate exposure to arsenic.

Using Media

Consumers can be warned that an event has occurred from broadcasts issued by utility managers. Time-use surveys are used to simulate agents as sleeping, using television, or using radio at each time step, and probability distributions for these actions are developed and described by Shafiee (2013) and Shafiee et al. (2016). Consumers receive a water notice when they use media that broadcasts a water advisory at the same time step.

Table 1. Parameters and State Variables for Consumer Agent

Parameter/state variable	Value/range of potential values
Number of age groups	11
Age range for each age group (years)	{≤0.5, 0.5–0.9, 1–3, 4–6, 7–10, 11–14, 15–19, 20–24, 25–54, 55–64, ≥65}
Percentage of females among consumers (%)	50.6%
Percentage of population, female by age group (%)	{0.8, 0.7, 4.9, 4.6, 6, 6, 7.4, 7.3, 44.6, 7.6, 10.1}
Percentage of population, male by age group (%)	{0.7, 0.7, 4.3, 4.5, 5.3, 5.9, 6.6, 7.1, 42.6, 8.6, 13.7}
Average weight, female by age group (kg)	{6, 9, 14, 20, 31, 50, 61, 64, 69, 71, 67}
Average weight, male by age group (kg)	{6, 9, 14, 21, 32, 52, 73, 80, 85, 84, 80}
Average volume of ingested water, female by age group (mL/day)	{301, 394, 316, 394, 430, 525, 653, 911, 1023, 1117, 1108}
Average volume of ingested water, male by age group (mL/day)	{291, 325, 306, 419, 474, 665, 861, 1039, 1182, 1172, 1153}
Peak time for ingestion of tap water, five events (Davis and Janke 2009)	{8 a.m., 10 a.m., 12 p.m., 3 p.m., 6 p.m.}
exposure threshold	0.05 mg/kg of consumer agents' body weight
Residential node	Generated using mobility algorithm
Non-residential node	Generated using mobility algorithm
Mode of working start time	8 a.m.
Average working duration (h)	8
Hourly probability of sleeping[a]	{0.85, 0.88, 0.93, 0.91, 0.90, 0.71, 0.52, 0.32, 0.11, 0.08, 0.03, 0.04, 0.04, 0.05, 0.06, 0.04, 0.03, 0.03, 0.03, 0.06, 0.10, 0.34, 0.50, 0.69}
Hourly probability of using radio[a]	{0.02, 0.00, 0.00, 0. 02, 0.02, 0.09, 0.30, 0.37, 0.23, 0.13, 0.04, 0.20, 0.08, 0.06, 0.06, 0.15, 0.28, 0.21, 0.11, 0.06, 0.02, 0.04, 0.02, 0.04}
Hourly probability of using television[a]	{0.03, 0.01, 0.00, 0.01, 0.05, 0.01, 0.14, 0.15, 0.05, 0.01, 0.00, 0.14, 0.01, 0.01, 0.01, 0.05, 0.26, 0.50, 0.18, 0.04, 0.06, 0.21, 0.27, 0.05}
Number of agents in communication network	15
Water demand reduction factor (%)	Uniform value [3.5, 41.7]
Location	Residential node or nonresidential node
Contaminant ingested (mg)	Real number
Warned	True/false
Exposed	True/false
Asleep	True/false
Using radio	True/false
Using television	True/false

[a]Time-based probabilities correspond to each hour, beginning at 12 a.m.

J. Water Resour. Plann. Manage., 2017, 143(4): 04017001

Compliance

A statistical model was developed to simulate the compliance of consumer agents with warning messages that are received from peers and utility managers. The model was developed using data collected through surveys conducted in College Station, Texas, and Boston, Massachusetts, to test perceptions and reactions in water events (Lindell et al. 2010). Participants in the surveys scored perceived characteristics—expertise, responsibility, and trustworthiness of stakeholders (peers and the utility manager)—a discrete number between 1 and 5. The results of the surveys demosntrate that consumers do not clearly perceive risks associated with drinking-water warnings and may not comply with a warning message.

A consumer agent perceives the expertise, responsibility, and trustworthiness of stakeholders (peers and the utility manager) and complies accordingly. Each consumer agent is assigned values to represent the expertise, protection responsibility, and trustworthiness that each stakeholder is perceived as having. A joint probability distribution was created to assign values for perceived characteristics using the survey data (Shafiee 2013; Shafiee et al. 2016). When agents receive a warning from a peer or the utility manager, they calculate a probability of compliance based on the values for their perceived characteristics of the stakeholder. The probability of compliance is compared with a random number to determine if the agent complies. Agents that comply with a warning contact other consumer agents and reduce water demand.

To calculate the compliance of a consumer with a water advisory, the compliance variable, C is derived using a conditional probability distribution:

$$P_C(c) = P_{C|E,R,T}(c|e,r,t) \tag{3}$$

where $P_C(c)$ = probability distribution of compliance; E = expertise; R = protection responsibility; T = trustworthiness; and e, r, and t = value of each variable, which takes an integer value from 1 to 5. The value of $P_{(C|E,R,T)}(c|e,r,t)$ is the conditional probability of compliance. Using the developed joint probability distribution, a value is given to E, R, and T for each consumer agent. Each agent randomly chooses the Uniform, Exponential, and Poisson probability functions as $P_{C|E,R,T}(c|e,r,t)$ to determine compliance probability.

Communication

Consumer agents are situated in a cluster of 15 agents to exchange information about a water event (Perry and Lindell 2007). The communication submodel is similar to a small world network (Watts 1999) and simulates a unidirectional flow of information. Each agent is assigned distinct communication attributes, where some consumers pass and receive information, some consumers only receive information, and some consumers are isolated from communication completely. Consumers pass information within the cluster at each time step, and only pass information if they select to comply with warnings or are exposed. Consumers that do not comply with warnings do not pass information.

Reducing Demands

A consumer agent that is exposed or complies with a warning reduces its water demands. The American Water Works Association reports that 70% of the total residential water demand for U.S. households is used for indoor activities (Mayer and DeOreo 1999). Consumer agents are encoded with a rule that reduces water use related to washing clothes (which is 15.4% of total water use) with a probability of 0.51; faucet (11.2%) with a probability of 0.43; shower (11.6%) with a probability of 0.38; and miscellaneous indoor uses (3.5%) with a probability of 1.0. This model gives a reduction in the range of 3.5–41.7% of total water use for each consumer agent. These probabilities and demands were developed based on survey data about the types of water activities that consumers would suspend in a water hazard (Lindell et al. 2010). In this survey, respondents were asked to indicate whether they believed that certain water activities would impact their health in the event that a water contamination warning was issued. The water activities included washing clothes, washing the kitchen, taking a shower, washing hands, rinsing the mouth, washing dishes, brewing coffee, cooking spaghetti, and rinsing fresh vegetables. New demands are calculated for the next time step using the following equation:

$$bd'_t = \frac{\sum_{i=1}^{i=K}(1 - RF_i)}{K} \times bd_t \tag{4}$$

where bd_t = original base demand at a node at time step t; K = number of consumers located at the node at time step t; RF_i = reduction factor decision made by consumer i at the node; and bd'_t = new base demand at the node. Demands are aggregated at nodes and written to the input file for the water distribution system model, which calculates hydraulic conditions at the next step (this model of calculating new demands is similar to results of the boil water advisory and other advisories that were issued during the historic water events).

Travel among Nodes

Consumer agents are simulated as traveling through a city, and their paths are generated using a mobility algorithm. The algorithm ensures that the time variation in the number of agents at a node matches diurnal variation in demands. The total number of consumers at nodes is calculated for each time step based on the demand volume and an assumed demand of 378.5 L (100 gal. per capita per day). Each agent is assigned values for a residential node, a nonresidential node, a departure time, and work duration. At the departure time, the agent leaves the residential node and arrives at the nonresidential node. After the amount of time specified by the work duration has expired in the simulation, the agent returns to its residential node. If the agent begins at the nonresidential node, it travels to its residential node after the work duration has expired. Each consumer agent is assigned a travel pattern to represent its activity during the day. For example, a consumer agent with a residential pattern stays at a residential node throughout the duration of the simulation, and a consumer agent with a commercial pattern leaves its residential node to visit a commercial node.

Utility Agent Model

The utility manager agent is modeled as a rule-based agent to represent utility managers who take response actions based on a predefined regional or national protocol (Hrudey and Hrudey 2004). The utility manager agent is initialized with parameters and state variables listed in Table 2 and modeled with a set of if-then condition statements to specify response actions based on the order of activated sensors. After a utility manager agent receives a message from a water quality sensor, the utility manager agent implements

Table 2. Parameters and State Variables for Water Utility Agent

Parameter/state variable	Value/range of potential values
Hydrant strategy (variable)	Cautious or adaptive
Number of water quality sensors (variable)	Input from water distribution system model
Alert received from sensor (state variable)	True/false

response actions to protect consumers, including opening hydrants and broadcasting water advisories through media.

Broadcasting Water Advisories

Utility manager agents issue broadcasts about water advisories using television and radio. As utility managers receive alerts from sensors, they issue broadcasts immediately. Delays in response time that may occur as utility managers verify a threat are not modeled.

Flushing Hydrants

Hydrant strategies specify the timing and location of opening hydrants to flush a contaminant. Because an extensive number of options may be available, strategies for opening hydrants are identified a priori, and the decision-making process for the utility manager agent is represented as a decision tree. Sensor-hydrant decision trees are encoded as if-then condition statements, and they specify the location and timing of flushing specific hydrants in response to the activation of sensors (Shafiee and Berglund 2015). Two types of decision trees are encoded to represent cautious and adaptive strategies for protecting public health. Cautious hydrant strategies are used to simulate that a utility manager takes action immediately after the activation of first sensor and does not spend additional time to receive the second warning or collect other information about the network. Adaptive hydrant strategies implement a stepwise approach to open hydrants, based on the progressive activation of sensors. Cautious decision trees may be preferred by a decision-maker who wishes to act quickly without waiting for additional information to enact management decisions, while adaptive strategies allow a decision-maker to update information and respond as additional data becomes available.

Decision trees are encoded as if-then condition statements, and they specify the location and timing of flushing specific hydrants in response to the activation of sensors. A utility manager agent is simulated as using either a cautious [risk-averse in Shafiee and Berglund (2015)] or adaptive approach to select hydrants. A utility manager who observes that a sensor is activated in the distribution system is acting under a significant amount of uncertainty. There are many contamination events (characterized by the location, injection mass, and start time) that may cause similar observations at water-quality sensors, and different events may cause a variety of readings at other sensors and a range of public health effects. For example, consider a sensor network composed of Sensor A and Sensor B placed in a water distribution system. A contamination event that occurs can be classified based on the activation of sensors, which is when a sensor detects the presence of a contaminant above a certain threshold. There are four contamination event classes, assuming that the sensor network provides complete coverage, and the events are classified by order of sensor activation as Event A, Event B, Event AB, and Event BA. Consider an event in which Sensor A is activated first. Using a cautious strategy [Fig. 2(a)], a utility manager agent flushes hydrants in response to the first sensor activation and does not attempt to predict the event class or wait to receive additional information. Cautious decision trees may be preferred by a decision maker who wishes to act quickly without waiting for additional information to enact management decisions. An adaptive management strategy can be used to implement a hydrant strategy in response to the activation of each sensor successively. Using an adaptive strategy [Fig. 2(b)], a utility manager agent opens a subset of hydrants and waits to receive information about activation of the second sensor to flush a second subset of hydrants. Shafiee and Berglund (2015) explored other types of decision trees. Here, the utility manager agent is simulated using cautious and adaptive trees in response to water-quality failures.

Design Concepts

The interconnections and behaviors of agents are described here as they connect to the principles of complex adaptive system science (Grimm et al. 2006).

Emergence

Public health effects and the movement of the contaminant plume emerge due to the interactions of consumers and the water distribution network. The performance of mitigation strategies is also an emergent property, based on the interaction among management strategies to protect consumers.

Interactions and Adaptations

Consumer agents interact through a social network model and with the water network by receiving contaminated water and reducing demands. The utility manager agent communicates with consumer agents by distributing warnings through the news media. The utility manager agent interacts with the water network by opening hydrants to flush contaminant and receiving water-quality data through sensor activation.

Adaptation are behaviors that directly or indirectly improve an individual's objective or fitness value through a set of if-then rules. Consumer agents and utility managers agents are not goal-seeking as defined in ABM literature (North and Macal 2007). Goal-seeking (goal-directed) agents attempt to improve their fitness using a set of rules to update their behaviors. Here, agents change their behaviors in response to the environment and other agents using predefined rules, without searching for an optimal response. Consumer agents reduce water demands in compliance with warnings or exposure; utility manager agents update hydrant strategies

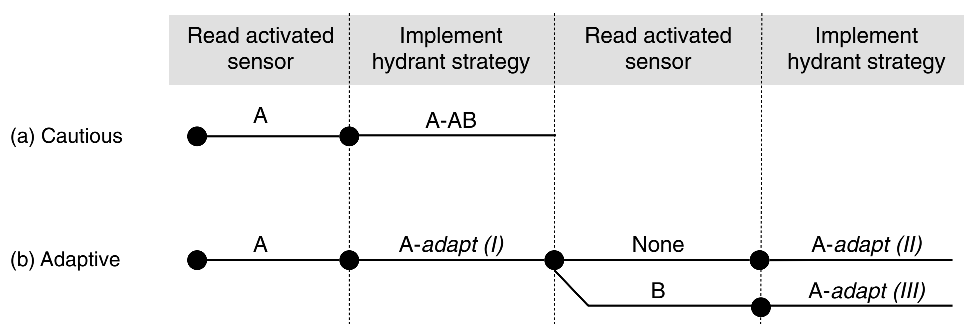

Fig. 2. Two sensor-hydrant decision trees for a hypothetical water network with two sensors (Sensors A and B); decision trees are shown for an event that activated Sensor A first; for each type of decision tree (cautious and adaptive), a second decision tree should be developed to respond to events that activate Sensor B first

using predetermined decision trees. For example, if a consumer agent is informed about the water event, this agent reduces water demand with some degree. This level of water demand reduction is not changed in subsequent time steps. Utility manager agents could be represented as goal-seeking agents by integrating optimization methodologies directly in their decision-making model to identify optimal hydrant strategies in real time as an event unfolds.

Stochasticity

Stochasticity is introduced to the model through demographic characteristics, such as weight, volume of ingested water, mobility of consumers, and demand reduction. These parameters are initialized randomly from a distribution of values for each simulation.

Observation

The user observes model output, which is calculated as the number of consumer agents that are exposed and number of consumer agents that do not drink water at each time step. A second observation from the model is the number of consumers that are warned by peers or the news media and are prevented from becoming exposed. The number of protected consumers is calculated as the difference between the number of consumers that are exposed without mitigation or warnings and the number of consumers that are exposed when those mechanisms are active.

Because the goal of this research is to explore the sociotechnical causes and consequences of a water distribution contamination event, a metric was introduced to measure sociotechnical changes by evaluating the interaction of consumer location and the contaminant plume (Shafiee and Zechman 2013). The coincidence population plume (CPP) index [Eq. (5)] is observed as the percentage of consumers who are located at nodes where the concentration of contaminant is greater than zero at each time step

$$\mathrm{CPP}(t) = \frac{\sum_{i=1}^{n} \frac{P_i(t)}{1-\delta[Q_i(t)]}}{P} \tag{5}$$

where $\mathrm{CPP}(t)$ = CPP index at time step t; $P_i(t)$ = population at node i and time step t; n = total number of terminal nodes in a water distribution system; $Q_i(t)$ = contaminant concentration at node i at time t; $\delta(x)$ = Dirac delta function; and P = total number of consumers. The terminal nodes extract water from the network as their base demand is greater than zero in the hydraulic file. The function $\delta(Qi)$ takes on a value of infinity when the contaminant concentration is zero, and a value of zero when the contaminant concentration is greater than zero. As hydraulic conditions change due to agent interactions, the contaminant plume moves in relationship to densely populated nodes and impacts the value of the CPP index.

Illustrative Case Study: Mesopolis

The ABM framework is demonstrated for Mesopolis, which is a virtual city. The Mesopolis dataset was developed as a case study for urban infrastructure research (Johnson and Brumbelow 2008). Mesopolis is simulated with diverse land uses, including residential, commercial, and industrial areas. In addition, a naval base, an airport, and a university are located within the city boundaries (Fig. 3). Water is withdrawn at an intake located south of the city from a river that runs north through the center of Mesopolis. A branched pipe delivers raw water to two water-treatment plants (WTP), located on opposite sides of the river. The West WTP supplies water to the older sections of Mesopolis, located on the western side of the river, and the East WTP distributes water to the

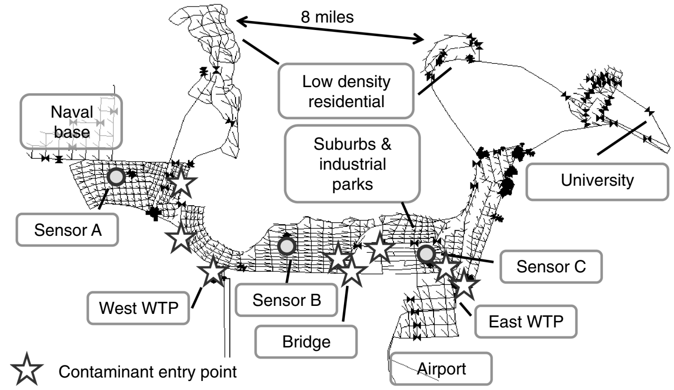

Fig. 3. Mesopolis water distribution network, land uses, sensor network, and points of contaminant entry

eastern section and, during peak demand periods, to a large portion of the central and western districts. The network is modeled as a skeletonized water network with one reservoir, 1,588 nodes (706 of these are terminal nodes), 2,058 pipes, 13 tanks, and 65 pumps. The population of Mesopolis is calculated at 150,000 consumers, based on an assumed demand of 378.5 L (100 gal. per capita) as a daily water demand. Four demand patterns are available to represent land uses: residential, commercial, industrial, and naval demand uses.

Three sensors are placed in the water distribution network to detect contaminant. Sensors A, B, and C (shown in Fig. 3) are located based on insight about flow directions and hydraulic zones that govern contaminant transport in Mesopolis. The sensors are simulated to detect 0.015 mg/L of arsenic and immediately send a warning alert to the utility manager.

Experimental Design

Contamination Events

A Monte Carlo simulation approach was applied to generate 300 contaminant events, and values for event characteristics were generated using probabilistic distributions of event characteristics (Table 3). Each contamination event is simulated at one of eight entry nodes, and 100 kg of arsenic are introduced to the pipe network for each contamination event. The set of entry nodes represents diverse patterns of contamination movement in the network through different hydraulic zones. The 100 kg of arsenic is used for simplicity and normalization of results. For the three-sensor network in Mesopolis, five classes of contamination events are generated when two activated sensors are used: Class A (118 events), Class AB (35 events), Class BA (18 events), Class BC (61 events), and Class CB (68 events).

Table 3. Contamination Events Are Generated Randomly Based on Probability Distributions that Describe Event Characteristics; Contaminant Load is 100 kg of Arsenic

Event characteristic	Probability distribution	Potential values
Event location	Discrete uniform	{West WTP, East WTP, IN0117, IN0255, IN0259, IN0350, IN0418, IN0977}
Demand multiplier	Continuous uniform	[0.9, 1.3]
Intrusion start time	Discrete uniform, hourly	{00:00, 01:00, 23:00}
Intrusion duration	Discrete uniform, hourly	{1, 2, 12}

J. Water Resour. Plann. Manage., 2017, 143(4): 04017001

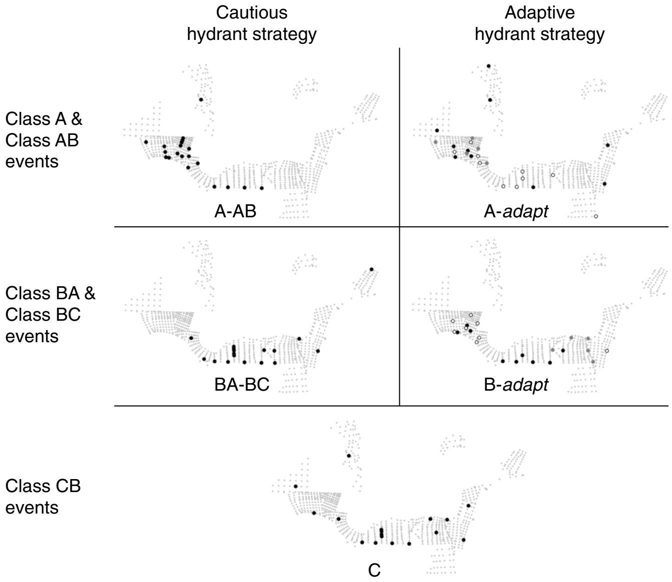

Fig. 4. Location of hydrants for the cautious and adaptive hydrant strategies; for adaptive hydrant strategies, the dark circles show the A-$adapt$ (I) and B-$adapt$ (I) hydrants, the open circles show the A-$adapt$ (II) and B-$adapt$ (II) hydrants, and the light gray circles show the A-$adapt$ (III) and B-$adapt$ (III) hydrants

Sensor-Hydrant Decision Trees

Decision trees were developed by Shafiee and Berglund (2015) for the ABC sensor network in Mesopolis using the set of 300 contamination events described in "Flushing Hydrant" section. Because a small number of pressure zones exist in Mesopolis, 300 contamination events are sufficient to represent the range of events and their effects that can occur in this network. A simulation-optimization methodology was developed by Shafiee and Berglund (2015) to identify hydrant strategies for each decision tree, as follows.

To identify a hydrant strategy for a class of water contamination events, the problem is formulated as an optimization model to maximize the average amount of contaminant that is removed using one hydrant strategy for three events. The set of events are drawn from one event class, and the average removal of contaminant is used as an approximation of the performance of one hydrant strategy (or solution) for events in that class. The optimization model is solved separately for each event class. The minimum pressure is defined at 14 m of head 137.9 kPa (20 psi) to provide the water pressure for firefighting activities, and the optimization model penalized solutions if the pressure fell below 137.9 kPa (20 psi) at any part of the network. The solution to the optimization model represents a hydrant strategy and includes the lists of 20 hydrants, with delays and durations. For each hydrant that is selected, a solution also specifies the time at which the hydrant should be opened and the duration over which the hydrant should remain open. The time at which each hydrant should be opened is measured as the delay after the sensor is activated, so that each hydrant can be opened at a unique time to improve the performance of flushing. The hydrant strategy is used as input for the simulation model, *EPANET*. The hydraulic simulator calculates both the amount of contaminant removed for each event and the water pressure at terminal nodes.

A noisy genetic algorithm (NGA) was applied to identify a solution that can perform well for all events in a class, by sampling a representative set of events for each solution evaluation. NGA (Smalley et al. 2000) follows the algorithmic steps of a genetic algorithm, including initialization of a random population, crossover, mutation, and selection of fit solutions. NGA, however, is designed to solve problems with noise or uncertainty in the evaluation of the objective function. The objective function is evaluated based on several realizations of the uncertain variables for each solution, and the fitness of a solution is assigned as the average of the set of sampled fitness values. For the hydrant strategy identification problem, the fitness of a solution is evaluated by randomly selecting three contamination events from the event class. For each selected event, the performance of a hydrant strategy is evaluated using an *EPANET* simulation, and the average across the three events is assigned as the fitness. The same amount of contaminant is introduced for each event, and each event is given equal weight in calculating the fitness function. The NGA was executed to identify hydrant strategies, using 200 individuals in a population, 75 generations, a crossover rate of 80%, and a mutation rate of 1%.

Cautious hydrant strategies are designed to be implemented after the activation of the first sensor (Fig. 4). The A-AB hydrant strategy is the cautious hydrant strategy for Class A and Class AB events, and the BA-BC hydrant strategy is the cautious hydrant strategy for Class BA and Class BC. Adaptive hydrant strategies, which require two strategies that are implemented successively, were also identified. In implementing the A-$adapt$ and B-$adapt$ strategies, the first portion of A-$adapt(I)$ and B-$adapt(I)$ are implemented after the activation of the first sensor (either Sensor A or Sensor B, respectively). When the second warning is received, either B-$adapt(II)$ or B-$adapt(III)$ is implemented for Class BA or BC, respectively, based on the activated sensor. For Class A and Class AB, A-$adapt(II)$ or A-$adapt(III)$ can be implemented, depending on whether or not Sensor B is activated. The C hydrant strategy is implemented for Class CB events, because any event that begins with a warning from Sensor C leads to a warning from Sensor B, due to the unique hydraulics in Mesopolis.

Mitigation Scenarios

Four scenarios are constructed to evaluate the effect of each response action or a combination of response actions on the number of exposed consumers for each event class. The No Mitigation Scenario provides a baseline and calculates the number of exposed consumers when no response strategy is enacted. The Hydrant Scenario uses a hydrant strategy as the only mitigation strategy to protect consumers from exposure; the Media Scenario simulates that the utility manager agent alerts consumers and does not open hydrants; and the Hydrant and Media Scenario enacts both mitigation strategies. For the Hydrant and the Hydrant and Media Scenarios, two sensor-hydrant decision trees are tested, namely cautious and adaptive sensor-hydrant decision trees, as described earlier.

Simulations

The ABM framework is executed for 15 contamination events from each event class (a total of 75 events) to evaluate alternative scenarios. The percentage of protected consumers is calculated as the number of consumers who are exposed when a mitigation strategy is used less the number of consumers who are exposed when no mitigation strategy is used, normalized by the number of consumers who are exposed when no mitigation strategy is used. The average performance is reported as the average percentage of protected consumers over 15 contamination events that are selected within a class. The ABM is simulated only once for each event and mitigation strategy, and as a result, the stochasticity inherent in the ABM is not reflected in this study. The stochasticity of the ABM was captured and reported in previous studies, in which the development of the sociotechnical model was studied in detail and the

J. Water Resour. Plann. Manage., 2017, 143(4): 04017001

effect of variability of the model parameters on the exposure was assessed (Shafiee and Zechman 2013). Each model execution requires 12 min to simulate a 10-day contamination event on a desktop computer with an i7 Intel core and 16 gigabytes of RAM.

Media Scenario Results

The Media Scenario is evaluated for each water event class and compared to the No Mitigation Scenario. The average number and standard deviation of consumers who are exposed is $8{,}205 \pm 2{,}580$, $6{,}663 \pm 2{,}133$, $6{,}540 \pm 2{,}165$, $7{,}292 \pm 1{,}730$, and $7{,}145 \pm 1{,}653$ consumers for Classes A, AB, BA, BC, and CB, respectively, when no response strategy is implemented. For the Media Scenario, there is a 9.8, 15.5, 19.8, 8.1, and 5.6% reduction in the number of exposed consumers for Class A, AB, BA, BC, and CB respectively. The news media informs on average, 39,328 consumers, which represent 25% of the population in Mesopolis.

Hydrant Scenario and Hydrant and Media Scenario Results

Cautious Sensor-Hydrant Decision Tree

The (1) Hydrant and (2) Hydrant and Media Scenarios are evaluated when a cautious decision tree is used for flushing hydrants [Fig. 5(a)]. Cautious hydrant strategies are implemented after the activation of the first sensor. Including the news media as a response action improves the public health protection by 4.4%, on average over all classes, in comparison to using hydrants alone. For these events in Class A, Class AB, and Class BA, the improvement when including the news media is 1.3%. For these events, hydrants are an effective approach because the contaminant plume is in a localized area. Hydrants remove a significant portion of the contaminant, and the effects of the media to further reduce public health impacts are limited. For events in Classes BC and CB, the contaminant spreads throughout Mesopolis, and hydrants do not change the movement of the plume significantly. The use of media is more effective for events in which contaminant spreads throughout the entire network. The use of media is more effective and increases the number of protected consumers by 7% for Class BC and CB events. For localized events, when the contaminant remains in one location or area of the network, response actions should be concentrated at the affected area for better protection.

The complexity and dynamics among actors that are simulated using the sociotechnical model affect the pattern of contamination movement and the predicted effectiveness of hydrant strategies. The performance of the cautious hydrant strategy is evaluated using *EPANET* alone and the sociotechnical model with the news media. The sociotechnical model predicts on average, that 4 kg less of the contaminant would be removed than the removal predicted by the *EPANET* simulation [Fig. 5(b)]. The difference is 9 kg for Class BA events and approximately 4 kg for Class A events.

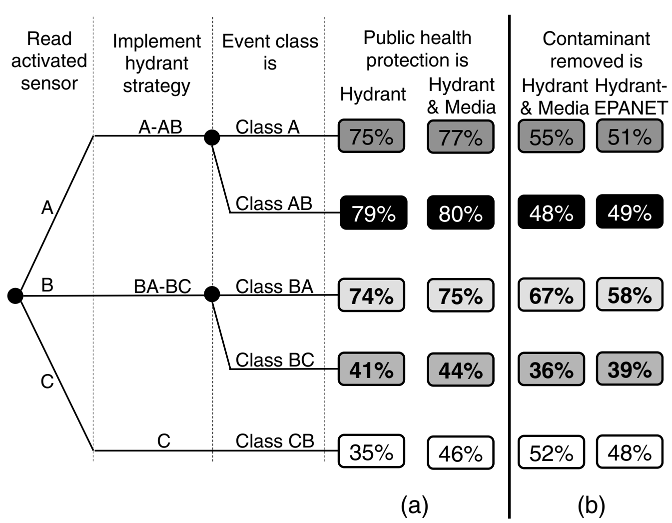

Fig. 5. Cautious sensor-hydrant decision tree; performance is represented as the percentage of (a) exposed consumers who are protected; (b) contaminant that is removed from the network using a mitigation strategy; boxes are shaded corresponding to the event class

Adaptive Sensor-Hydrant Decision Tree

The Hydrant and Hydrant and Media Scenarios are evaluated for an adaptive sensor-hydrant decision tree [Fig. 6(a)]. Including media as a response action improves the performance of hydrant strategies by 4.4%, on average over all event classes. As shown for the cautious strategy (in the previous section), for Class A and AB events, the media has a lower impact than expected because 20 hydrants are opened simultaneously, leading to hydraulic changes in the network. For the adaptive sensor-mitigation approach, however, the utility manager agent uses 10 hydrants after the first sensor is activated, and hydraulic conditions are not altered significantly. Therefore, the media can better protect consumers because hydrant strategies are not as effective.

The sociotechnical model with the news media predicts that an average of 9.2 kg less of the contaminant is removed across all contamination classes, compared to the *EPANET* simulations [Fig. 6(b)]. This difference is 20 kg for Class BA events and 0.5 kg for Class A events. Reductions in the drinking-water pattern of consumers in the west area of Mesopolis reduces the flow of contaminant to this area. The contamination remains close to hydrants that are opened for the Class BA events and is removed more effectively.

Comparison among strategies demonstrates that the effects of using the media with hydrant flushing is not additive. The improvement in the Hydrant and Media Scenario compared to the Hydrant Scenario is not equal to the value of the protection provided by the Media Scenario alone. The dynamics of a complex water contamination event creates difficulties in predicting the protection of a mitigation strategy, and response actions affect the expected performance when they are used in combination.

Emergent Dynamics in the Hydrant and Media Scenario

Two types of decision making (cautious and adaptive) are compared for the Hydrant and Media Strategy (Fig. 7). The cautious strategy performs better than the adaptive strategy. This observation is similar to results of the previous study that evaluated hydrant strategies using *EPANET* alone (Shafiee and Berglund 2015). The adaptive strategy can react as an event unfolds and may be advantageous in events where the contaminant plume diverges from its predicted path. In Class BA events, the adaptive hydrant strategy outperforms the cautious hydrant strategy by a small margin. The adaptive strategy gives decision makers an opportunity to identify the correct event class and take additional actions. Adaptive strategies can provide an advantage when human error or lack of confidence causes hesitation in implementing response actions.

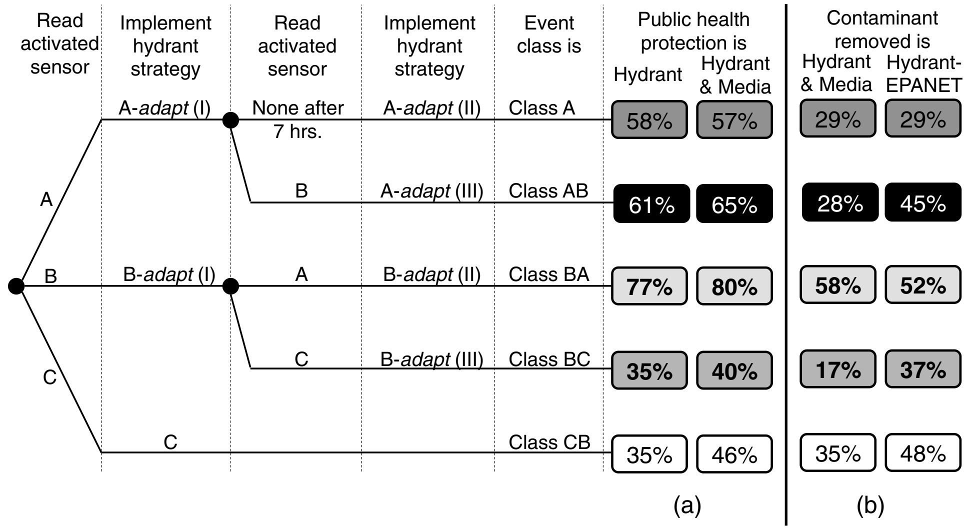

Fig. 6. Adaptive sensor-hydrant decision tree; performance is represented as the percentage of (a) exposed consumers who are protected; (b) contaminant that is removed from the network using a mitigation strategy; boxes are shaded corresponding to the event class

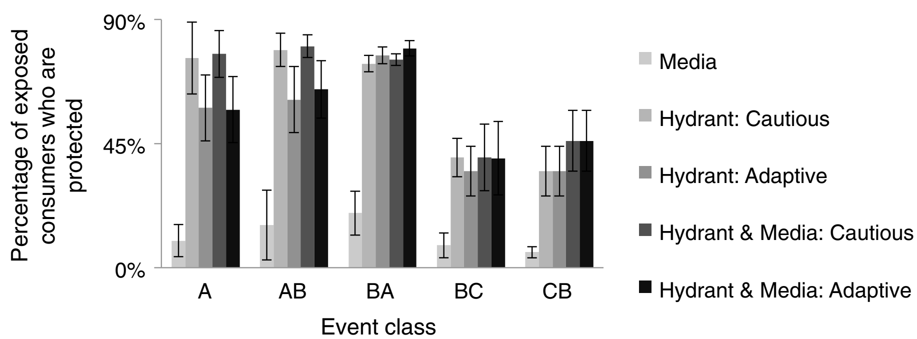

Fig. 7. Performance of the combined hydrant strategy and the news media for cautious and adaptive hydrant strategies; error bars show the range of the performance over all events in a class

Mass of Contaminant Removed from the Network

Cautious and adaptive hydrant strategies are evaluated based on the amount of contaminant that is removed from the network (Fig. 8). Hydrant strategies were identified by (Shafiee and Berglund 2015) to maximize the amount of contaminant that is removed over a randomly selected set of events from a class, and the performance of a hydrant strategy was evaluated in the optimization framework using hydraulic simulation alone (e.g., interactions of consumer agents were neglected). The amount of contaminant removed should be maximized as a surrogate for protecting public health. It is expected that a higher mass of contaminant that is removed will allow fewer consumers to have the opportunity to become exposed.

The performance of each hydrant strategy is evaluated using *EPANET* alone (labeled Hydrant-*EPANET* in Fig. 8) and compared to performance predicted by the ABM framework. Increasing complexity in the modeling has varying effects across event classes on the performance of hydrant strategies, because additional behaviors influence the contaminant plume movement. In general, sociotechnical interactions increase the efficiency of hydrants to remove contaminant for all events expect the Class AB events. For Class A events, exposure occurs in a more-localized area, and the adaptive reduction in drinking water demands by consumers reduces demands near the contaminant and allows contaminant to remain in the main pipe, where it is flushed by open hydrants. As a result, the hydrant strategies A-AB and A-*adapt* remove more contaminant when sociotechnical dynamics are included than when they are neglected.

Dynamics of Exposure

Fig. 9 shows the dynamics of consumer exposure for each class of contamination events for Hydrant and Media Scenarios. A large number of consumers are exposed within 48 h after the injection of the contaminant. Events show a second sharp increase in consumer exposure, which occurs during the second day. An effective hydrant strategy impacts the spread of the contaminant in the beginning of an event and reduces the exposure. For example, the A-AB hydrant strategy removes a large portion of the contaminant in the first day. The number of exposure does not increase during nighttime hours because the probability of consumers drinking water at these hours is relatively low.

For the No Mitigation Scenario, the contamination events produce a wide range of exposure, due to the variation in characteristics of the contamination events. The variation in exposure reduces when a hydrant strategy is implemented to flush contaminated water. Cautious hydrants strategies for Classes AB and BA (first and second rows in Fig. 9) reduce a large mass of contaminant and significantly reduce variation in exposure. Adaptive hydrant strategies remove a lower amount of contaminant and lead to a wider range of exposure. The amount of contaminant removed is shown in Fig. 8 for each scenario across all hydrant strategies.

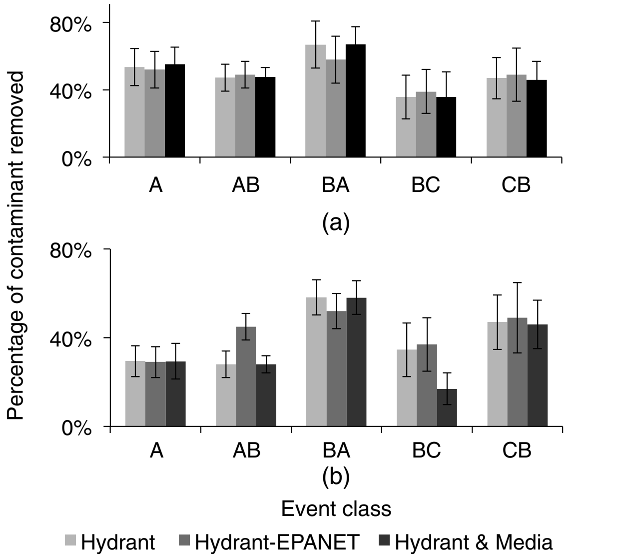

Fig. 8. Performance of hydrant strategies based on the amount of contaminant removed: (a) cautious hydrant strategies; (b) adaptive hydrant strategies; hydrant-*EPANET* is the hydrant scenario that is simulated using *EPANET* alone; Hydrant and Hydrant and Media Scenarios are evaluated using the ABM framework; error bars show the range of performance of each hydrant strategy over 15 contamination events in each class

Effect of Adaptive Behaviors on Hydraulics

Fig. 10 shows the effect of adaptive behavior of consumers on the hydraulics of Mesopolis using the CPP index. As described earlier, the CPP index represents the coincidence of the population and the contaminant, or the fraction of nodes at which consumers are present and the concentration of the contaminant is greater than zero. The CPP value remains less than 0.5 for the Class A, AB, and BA events. The value approaches 1.0 for events within Classes BC and CB. Class BC and CB include events which spread throughout the entire network and reach almost every node. In general, there is a wider variation in results for the CPP index and for the number of protected consumers for the Class BC and CB events. Generally, Class BC and CB events originate from three event locations on the east side of the Bridge node.

The CPP index represents a number at each time step, and demonstrates a periodic oscillation around 0.2 for the Class A, AB, and BA events. The oscillation appears in the data because consumers move between residential and nonresidential nodes. Opening hydrant strategies reduces the magnitude of the CPP index for all classes expect Class AB. All Class AB events introduce the contaminant to the water network from the Bridge node in one of two time windows: 1:00–3:00 a.m. or 2:00–3:00 p.m. For these events, the contaminant remains on the western side of the Bridge node for the entire simulation. Hydrant strategies reduce the contaminant concentration, but do not alter the location of the plume. The CPP counts the population at nodes without accounting for the magnitude of the contaminant concentration. As a result, the CPP index

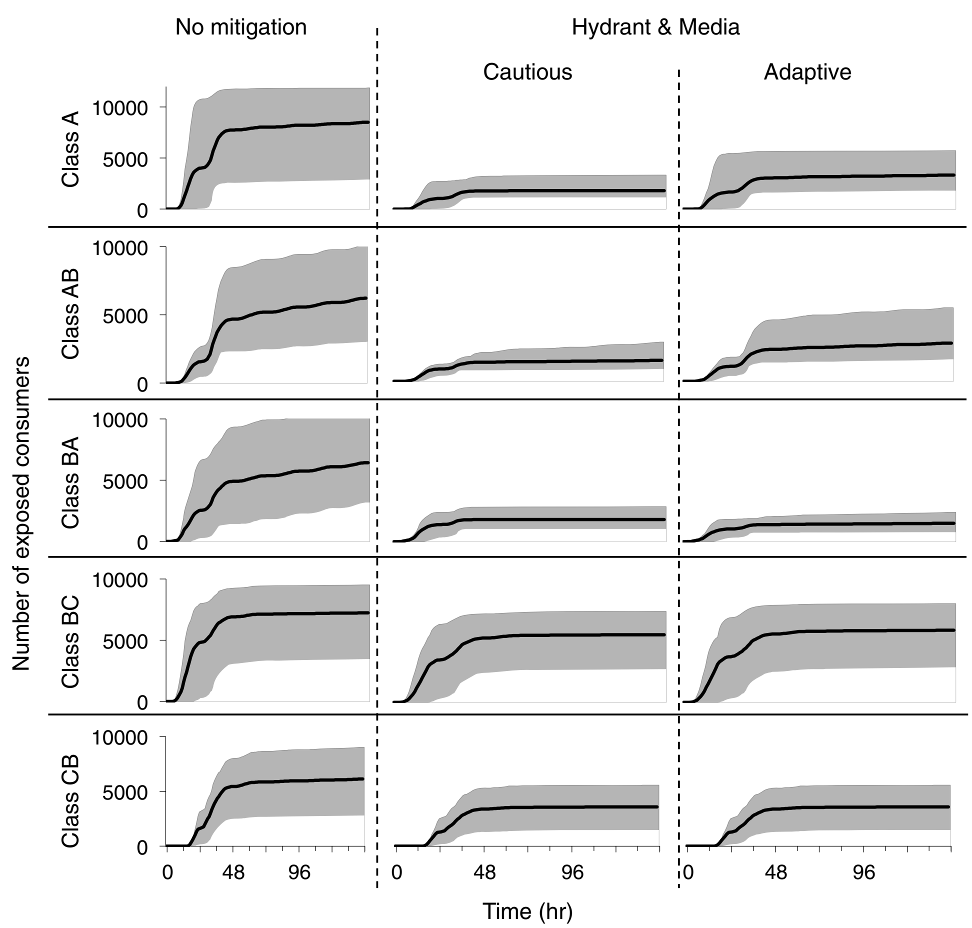

Fig. 9. Time series of the average number of exposed consumers for each class of contamination events; line is the average number of exposed consumers over 15 contamination events per class, and the shaded area is the range of exposure for these 15 events; upper and lower values for the range represent the maximum and minimum exposed consumers over 15 events at each time step

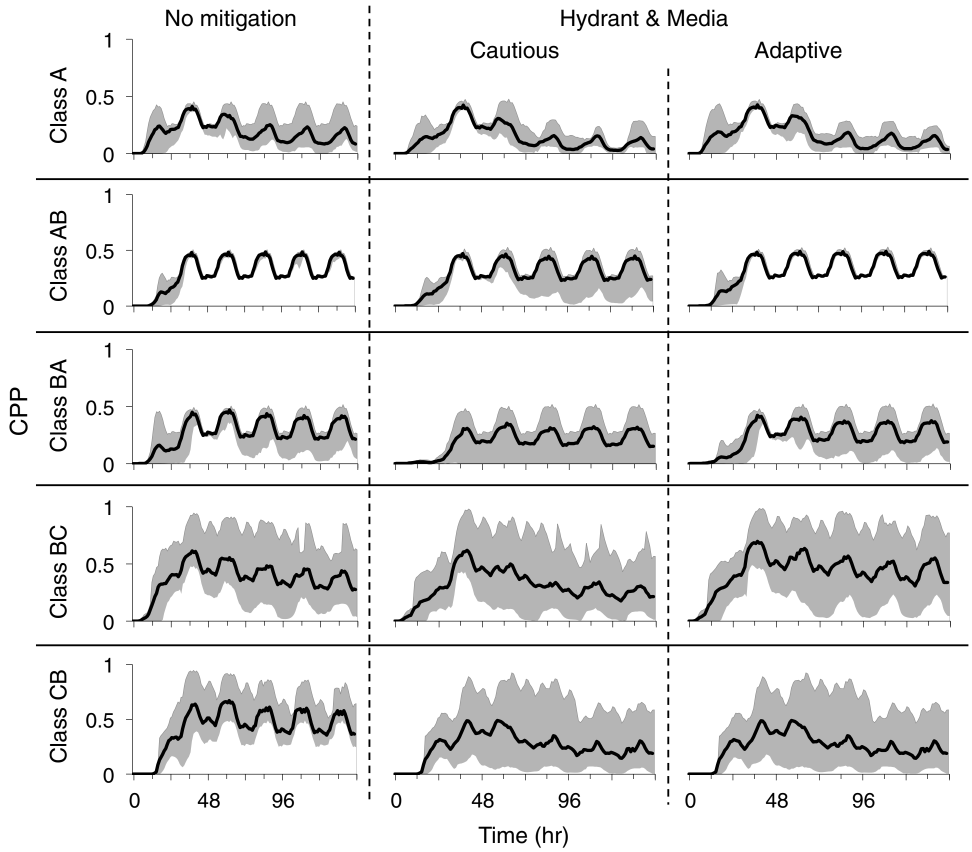

Fig. 10. Time series of the CPP index for each class of contamination events; the line is the average CPP index over 15 contamination events per class and the shaded area is the range of CPP index for these 15 events; the upper and lower values for the range represent the maximum and minimum CPP index over 15 events at each time step

for the No Mitigation Scenario is similar to that for the Hydrant and Media Scenario.

For the Class BA events, the contaminant enters the network from the Bridge, but at different injection times than the Class AB events. The contaminant plume moves through the network under altered hydraulic conditions, and hydrant strategies perform better for Class BA events than Class AB events (Fig. 8). As a result, the CPP index is reduced for all Hydrant and Media Strategies for Class BA events.

Each of the hydrant strategies was designed using *EPANET* alone to maximize contaminant removal and meet pressure requirements. When the strategies are simulated using *EPANET* alone, they do not allow pressures below 20 psi (137.9 kPa) for any of the scenarios. When the strategies are simulated using the ABM framework, changes in demands cause a variation in pressures beyond levels predicted by *EPANET* alone; however, the pressures remain above 20 psi (137.9 kPa) because the reduction of demands increases pressures. The minimum pressures across strategies is 21.45 psi (147.9 kPa) for Class A events, 22.69 psi (156.4 kPa) for Class AB, 25.21 psi (173.8 kPa) for Class BA, 27.47 psi (189.4 kPa) for Class BC, and 27.35 psi (188.4 kPa) for Class C events. The minimum pressure increases as the media response action is included. Hydrants were modeled here using demand-driven algorithms, while pressure-driven algorithms may provide a more-accurate simulation of pressures and flows due to hydrant operations.

Conclusions

A methodology is described and demonstrated for evaluating the effectiveness of mitigation strategies during water distribution contamination events using an ABM approach for modeling a sociotechnical water event. A water distribution network model is integrated with consumer and utility manager agents in a sociotechnical modeling approach. The utility manager agent manipulates hydrants to flush contaminated water and warn consumers by distributing water advisories using media. The ABM framework demonstrates the influence that the dynamic and adaptive interactions of social agents and technical components have on the prediction of water event consequences and performance of mitigation strategies. The contamination events are generated using a Monte Carlo Simulation approach, and contamination events are classified using the sensor information and the order of sensor activation. Mitigation strategies are developed by combining response actions and are evaluated for each event class by simulating the number of exposed consumers who are protected. Sensor-hydrant decision trees are constructed and can be used as guidance to protect consumers during a water event. Results demonstrate that the effectiveness of response actions change with spatial and temporal variation in consumer water demands. Adaptations in demands create changes in the predicted movement of a contaminant and, as a result, the exposure of consumers.

The framework that is developed here provides an approach to operationalize decision trees and test their performance in a dynamic environment. Hydrant-sensor decision trees were developed in a previous study using an optimization approach that does not account for sociotechnical dynamics. Results demonstrate that these strategies perform differently when sociotechnical dynamics are included in the simulation, compared to when an event is simulated using a water distribution system model alone. Hydrant strategies are developed as cautious or adaptive decision-making approaches. Cautious strategies are more effective at protecting public health, because a large amount of contaminant is removed immediately from the system. Adaptive strategies could be more competitive when sociotechnical dynamics are included because a decision-maker may adapt decisions based on changes in the contaminant plume. Results for the set of events that are simulated here, however, do not show that the adaptive strategy has an advantage. Results of this study are consistent with the results of the ABM-based simulation (Shafiee and Zechman 2013), in which it is shown that the movement of contaminant is changed if the behavior of consumers is included in the modeling of water contamination events. Therefore, using only a hydraulic model to develop adaptive hydrant strategies affects the performance quality of these strategies, which can be improved by identifying these strategies using a coupled ABM and optimization approach.

The ABM is parameterized with many variables, such as the exposure threshold and the number of consumers per cluster. The effect of variation of these variables on the number of exposed consumers was explored in previous studies (Shafiee and Zechman 2013); however, the sensitivity analysis of these variables is beyond the scope of the current study. Parameters that are used to characterize the utility manager agent may also affect the range of results. The utility manager agent responds immediately to an activation of a water-quality sensor, and a delay may reduce the effectiveness of predetermined hydrant strategies. The performance of hydrant strategies depend on the number of hydrants that can be opened, which is set at a total of 20 hydrants. In addition, the amount of entry contaminant is important factor. In this study, 100 kg of arsenic is modeled. A smaller load of arsenic may not reach hydrants that are located far from an entry point, because the contaminant may exit the network through service nodes or flushing hydrants. Results also depend on the sensor network, which was designed to provide coverage of all nodes in the network and detect an event within 10 h of its release. Sensors detect the contaminant at a low level, and the performance of hydrant strategies would be affected by less-sensitive sensors.

The effect of media broadcasts are simulated based on television and radio, and a word-of-mouth mechanism is included, which is based on small clusters of individuals. To more-realistically evaluate the effects of a media campaign to alert consumers, additional technologies, such as texting, social networking, and microblogging, can be simulated and evaluated. In addition, the spread of misinformation through these technologies can be simulated as it affects public health consequences. The increased compliance of consumers to water warnings may cause further unpredictability in the movement of the contaminant plume. Utilities may also consider a wider range of technical, or operational, response options. Utilities with diverse water supply sources may alter their mix to shut off a contaminated source or search for water import options. Utility managers may select from other operational decisions to isolate a section of the network and flush water to contain a contaminant. These decisions can be simulated in an ABM framework, though they are beyond the scope of the simulations presented here.

The ABM framework is based on the integration of social science and engineering management. Future research can include additional data, as it becomes available, to more-accurately represent consumer behaviors and utility management decision making during events. Each response action that is selected by a utility has a nonlinear effect on the system, and future research can optimize response actions simultaneously to identify solutions that perform well under all system dynamics. The performance quality of hydrant strategies may be improved by identifying strategies using a coupled ABM and optimization approach. The modeling framework can be applied using data for cities and municipalities to assess the resilience of a community during hazardous events by simulating the effects of social networks and management preparedness. The future studies may include the unidirectional hydrant strategies in combination of isolating the contaminated areas to explore the effect of contaminant isolation strategies in reducing the number of exposed consumers.

References

AnyLogic 6.7.1 [Computer software]. XJ-Technologies, Orlando, FL.

Alfonso, L., Jonoski, A., and Solomatine, D. (2010). "Multiobjective optimization of operational responses for contaminant flushing in water distribution networks." *J. Water Resour. Plann. Manage.*, 10.1061/(ASCE)0733-9496(2010)136:1(48), 48–58.

Baranowski, T. M., and LeBoeuf, E. J. (2008). "Consequence management utilizing optimization." *J. Water Resour. Plann. Manage.*, 10.1061/(ASCE)0733-9496(2008)134:4(386), 386–394.

Davis, M. J., and Janke, R. (2009). "Development of a probabilistic timing model for the ingestion of tap water." *J. Water Resour. Plann. Manage.*, 10.1061/(ASCE)0733-9496(2009)135:5(397), 397–405.

EPANET [Computer software]. U.S. Environmental Protection Agency, Washington, DC.

Friedman, M., Kirmeyer, G. J., and Antoun, E. (2002). "Developing and implementing a distribution system flushing program." *J. Am. Water Works Assoc.*, 94(7), 48–56.

Gavanelli, M., Nonato, M., Peano, A., Alvisi, S., and Franchini, M. (2012). "Genetic algorithms for scheduling devices operation in a water distribution system in response to contamination events." *Evolutionary computation in combinatorial optimization*, J. K. Hao and M. Middendorf, eds., Springer, Berlin, 124–135.

Glouberman, S. (2001). "Walkerton water and complex adaptive systems." *Healthcare Q.*, 4(4), 28–31.

Greick, P. (2006). "Water and terrorism." *Water Policy*, 8(6), 481–503.

Grimm, V., et al. (2006). "A standard protocol for describing individual-based and agent-based models." *Ecol. Modell.*, 198(1–2), 115–126.

Guan, J., Aral, M., Maslia, M., and Grayman, W. (2006). "Identification of contaminant sources in water distribution systems using simulation optimization method: Case study." *J. Water Resour. Plann. Manage.*, 10.1061/(ASCE)0733-9496(2006)132:4(252), 252–262.

Holland, J. (1995). *Hidden order: How adaptation builds complexity*, Helix Books, New York.

Hrudey, S., and Hrudey, E. (2004). *Safe drinking water: Lessons from recent outbreaks in affluent nations*, International Water Association, Oxford, U.K.

Johnson, G., and Brumbelow, K. (2008). "Developing Mesopolis-A virtual city for research in water distribution system and interdependent infrastructures." ⟨https://ceprofs.civil.tamu.edu/kbrumbelow/Mesopolis/index.htm⟩ (May 24, 2009).

Kroll, D. (2006). *Security our water supply protecting a vulnerable resources*, PennWell Publishers, Tulsa, OK.

Laird, C., Biegler, L., van Bloemen Waanders, B., and Bartlett, R. (2005). "Contamination source determination for water networks." *J. Water Resour. Plann. Manage.*, 10.1061/(ASCE)0733-9496(2005)131:2(125), 125–134.

Lindell, M., Mumpower, J., Wu, H. C., and Huang, S.-K. (2010). "Perceptions and expected responses to a water contamination emergency." Hazard Reduction and Recovery Center, Texas A&M Univ., College Station, TX.

Liu, L., Ranjithan, S., and Mahinthakumar, G. (2011). "Contamination source identification in water distribution systems using an adaptive dynamic optimization procedure." *J. Water Resour. Plann. Manage.*, 10.1061/(ASCE)WR.1943-5452.0000104, 183–192.

Liu, L., Zechman, E. M., Mahinthakumar, G., and Ranji Ranjithan, S. (2012). "Identifying contaminant sources for water distribution systems using a hybrid method." *Civ. Eng. Environ. Syst.*, 29(2), 123–136.

Mayer, P., and DeOreo, W. (1999). *Residential end uses of water*. American Water Works Association, Denver.

Miller, J., and Page, S. (2007). *Complex adaptive system*, Princeton University Press, Princeton, NJ.
North, M. J., and Macal, C. M. (2007). *Managing business complexity: Discovering strategic solutions with agent-based modeling and simulation*, Oxford University Press, New York.
Perry, R. W., and Lindell, M. K. (2007). *Emergency planning*, Wiley, Hoboken, NJ.
Poulin, A., Mailhot, A., Grondin, P., Delorme, L., and Villeneuve, J. P. (2006). "Optimization of operational response to contamination in water networks." *Water Distribution Systems Analysis Symp. Proc.*, ASCE, Reston, VA, 1–15.
Preis, A., and Ostfeld, A. (2006). "Contamination source identification in water systems: A hybrid model trees linear programming scheme." *J. Water Resour. Plann. Manage.*, 10.1061/(ASCE)0733-9496(2006)132:4(263), 263–273.
Rasekh, A., and Brumbelow, K. (2014). "Drinking water distribution systems contamination management to reduce public health impacts and system service interruptions." *Environ. Modell. Software*, 51(0), 12–25.
Rasekh, A., Shafiee, M. E., Zechman, E. M., and Brumbelow, K. (2013). "Sociotechnical risk assessment for water distribution system contamination threats." *J. Hydroinf.*, 16(3), 531–549.
Sadiq, R., Kleiner, Y., and Rajani, B. (2008). "Simulation-based localized sensitivity analyses (SALSA): An example of water quality failures in distribution networks." *World Environmental and Water Resources Congress*, ASCE, Reston, VA, 1–10.
Shafiee, M., and Berglund, E. (2015). "Real-time guidance for hydrant flushing using sensor-hydrant decision trees." *J. Water Resour. Plann. Manage.*, 10.1061/(ASCE)WR.1943-5452.0000475, 04014079.
Shafiee, M. E. (2013). "Modeling sociotechnical water distribution system contamination events to evaluate and identify mitigation strategies." North Carolina State Univ., Raleigh, NC.
Shafiee, M. E., and Berglund, E. Z. (2016). "Agent-based modeling and evolutionary computation for disseminating public advisories about hazardous material emergencies." *Comput. Environ. Urban Syst.*, 57, 12–25.
Shafiee, M. E., Berglund, E. Z., and Lindell, M. K. (2016). "An agent-based modeling framework for assessing the public health protection of water advisories." *Expert Syst. Appl.*, in press.
Shafiee, M. E., and Zechman, E. M. (2013). "An agent-based modeling framework for sociotechnical simulation of water distribution contamination events." *J. Hydroinf.*, 15(3), 862–880.
Smalley, B., Minsker, B., and Goldberg, D. (2000). "Risk-based in situ bioremediation design using a noisy genetic algorithm." *Water Resour. Res.*, 36(10), 3043–3052.
USEPA (United States Environmental Protection Agency). (2003). "Response protocol toolbox: Planning for and responding to drinking water contamination threats and incidents: Overview and application." *EPA Rep. 817–03–007*, Washington, DC.
Watts, D. J. (1999). *Small Worlds: The dynamics of networks between order and randomness*, Princeton University Press, Princeton, NJ.
Woo, D. M., and Kim, J. (2003). "Sociotechnical systems, risk management, and public health: comparing the North Battleford and Walkerton outbreaks." *Reliab. Eng. Syst. Saf.*, 80(3), 253–269.
Zechman, E. M. (2010). "Integrating complex adaptive system simulation and evolutionary computation to support water infrastructure threat management." *Proc., 12th Annual Conf. on Companion on Genetic and Evolutionary Computation*, Vol. 10, ACM, New York, 1809–1816.
Zechman, E. M. (2011). "Agent-based modeling to simulate contamination events and evaluate threat management strategies in water distribution systems." *Risk Anal.*, 31(5), 758–772.
Zechman, E. M. (2013). "Integrating evolution strategies and genetic algorithms with agent-based modeling for flushing a contaminated water distribution system." *J. Hydroinf.*, 15(3), 798–812.
Zechman, E. M., and Ranjithan, S. R. (2009). "Evolutionary computation-based methods for characterizing contaminant sources in a water distribution system." *J. Water Resour. Plann. Manage.*, 10.1061/(ASCE)0733-9496(2009)135:5(334), 334–343.