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Agent-Based Modeling to Simulate Contamination Events and Evaluate Threat Management Strategies in Water Distribution Systems

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In the event of contamination of a water distribution system, decisions must be made to mitigate the impact of the contamination and to protect public health. Making threat management decisions while a contaminant spreads through the network is a dynamic and interactive process. Response actions taken by the utility managers and water consumption choices made by the consumers will affect the hydraulics, and thus the spread of the contaminant plume, in the network. A modeling framework that allows the simulation of a contamination event under the effects of actions taken by utility managers and consumers will be a useful tool for the analysis of alternative threat mitigation and management strategies. This article presents a multiagent modeling framework that combines agent-based, mechanistic, and dynamic methods. Agents select actions based on a set of rules that represent an individual's autonomy, goal-based desires, and reaction to the environment and the actions of other agents. Consumer behaviors including ingestion, mobility, reduction of water demands, and word-of-mouth communication are simulated. Management strategies are evaluated, including opening hydrants to flush the contaminant and broadcasts. As actions taken by consumer agents and utility operators affect demands and flows in the system, the mechanistic model is updated. Management strategies are evaluated based on the exposure of the population to the contaminant. The framework is designed to consider the typical issues involved in water distribution threat management and provides valuable analysis of threat containment strategies for water distribution system contamination events.

KEY WORDS: Contamination; sociotechnical model; threat management; water distribution

1. INTRODUCTION

Water distribution systems have been recognized as one of several critical infrastructure systems that are vulnerable to the threat of attack through the Public Health, Security, and Bioterrorism Preparedness and Response Act (PL 107-188).(1) A contaminant that is introduced to the water distribution system could cause acute health effects in a segment of a population.(2) For a threat that is deemed possible, the Response Protocol Toolbox published by the U.S. Environmental Protection Agency recommends the implementation of appropriate response actions, such as site characterization or hydraulic isolation of a tank.(3) Contaminants may propagate rapidly through a system, depending on hydraulic conditions and, therefore, actions should be selected and implemented in a timely manner to protect public health; conversely, false alarms and unnecessary interruption of water supply to fire departments and critical care facilities should be avoided. Given these difficulties in making real-time decisions during a

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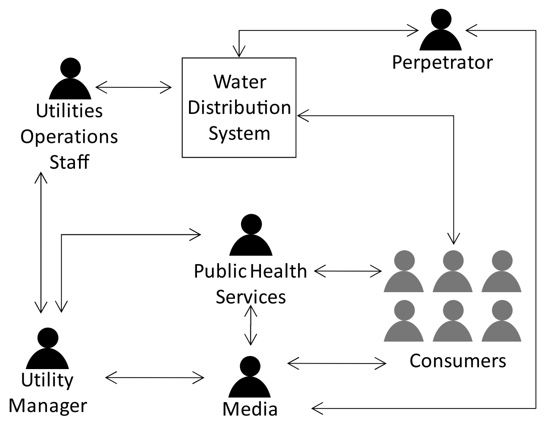

Fig. 1. During a contamination event, several actors interact with one another and the water distribution system.

contamination incident, it would be beneficial to identify effective strategies for managing contamination threats.

The *a priori* development of a set of response rules is complicated by the interactive and dynamic nature of contamination events.[3] Under an unfolding contamination event, interactions among many key actors in the system collectively influence the state of the contamination in the network, which recursively affects the reactions and responses of the actors. As the event progresses, consumers may reduce their water consumption based on word-of-mouth communication or alerts from public officials. Water utilities managers may contain the contamination or influence consumers' water usage through public health notices. These actions of consumers and managers could change the hydraulic conditions in the network, and further decisions should take into account the fluctuations of the contaminant plume. Fig. 1 depicts the interaction of individual actors, including the perpetrator, water utility operations staff, utility manager, media, public health services, and consumers associated with a water distribution network during a contamination event. Each actor receives information and stimuli from other individuals and the water distribution system, takes actions that directly or indirectly affect the hydraulics in the water distribution network, and passes on information to other actors. For example, utility managers may receive information of a threat from the utility operations staff, public health services, or the media, and make decisions toward the protection of consumers by contacting the media, instructing utility operators to isolate portions of the system or control flows in the network, or collecting more information before selecting any action. Water usage may fluctuate significantly from typical levels due to the reactions of consumers, such as household-level compliance with a boil water notice. Since the hydraulic conditions in the system are dictated by the demands of consumers, the spread of the contaminant plume will dynamically change with the varying demands. The shift in the contaminant plume may warrant reconsideration of management decisions about flow controls in the network, which may in turn affect the behavior of consumers.

To more realistically evaluate management strategies that must be inherently adaptive, dynamic simulation between the actions and reactions of the different actors and the propagation of the contaminant can be enabled through an integrated dynamic modeling framework. This article presents the use of agent-based modeling (ABM) as a framework for this problem. An agent-based model is a computational model for simulating the actions and interactions of autonomous actors in a network to determine their effects on the system as a whole. The agent-based simulation approach is coupled with a water distribution model to simulate the interaction and collective impact of consumer actions on the hydraulic conditions of the network and on the collective public health. ABM, as part of a complex adaptive system approach,[4] has been suggested as a potential framework to capture the dynamic interactions among water infrastructure and managers in the event of water distribution contamination.[5] This investigation extends and implements this paradigm to model the feedback mechanisms of the actions, reactions, and decisions of consumers and their impact on the water infrastructure. The modeling framework is applied to an illustrative water distribution system to evaluate the exposure of consumers under different management options.

The modeling framework described here will be useful for aiding in the management of water distribution contamination events. The framework is flexible and can be applied for municipalities to allow simulation of diverse types of contaminants, including conservative and nonconservative chemicals and microorganisms, and different locations and timing of the injection of contaminants. The value of the framework is in its capabilities to provide insight to the population characteristics and configurations of the water distribution system that may contribute to high levels of exposure. Analysis of simulation scenarios may identify the vulnerability of neighborhoods and facilities, infrastructure components, and communication connections among the public, the media, health care providers, and water utility managers. In addition, additional analysis such as optimization techniques may be applied to identify the most effective strategies for reducing public health consequences. The application of this framework for a virtual city, as presented here, demonstrates its development and potential use for assisting management and gaining insight to system characteristics and vulnerability. It is expected that future research will validate the simulation framework by testing it for historical contamination events and conduct vulnerability analysis and response planning for municipal water utilities.

2. AGENT-BASED MODELING FOR SIMULATING WATER DISTRIBUTION CONTAMINATION EVENTS

ABM is an approach for simulating the interaction of multiple actors within an environment.[4,6,7] Agents select individual actions based on rules of behavior in response to stimuli, such as environmental conditions and the actions of other agents. Rules may be specified as a set of if-then relationships or a decision tree, and may include probabilistic terms to provide variability and heterogeneity among the responses of agents. ABM allows the simulation of the emergence of complex phenomena in a system due to the aggregate behavior of all agents, though each agent's individual behavior may be simple and relatively easy to characterize.

Though ABM has been applied in a limited context for water supply management under normal operating conditions to simulate the interaction of water consumers and water utility managers,[8–11] the changes in the mechanics of the water distribution system due to consumer behaviors have not been considered. An ABM framework is developed here to simulate the interactions among consumers, utility managers, and the water distribution system (Fig. 2), as proposed by Zechman.[12,13] Each consumer in the water distribution system is simulated as an agent, who behaves according to a set of rules. These rules specify consumer behaviors, including the frequency with which a consumer drinks tap water and the response of a consumer to contaminant exposure, warnings from other consumers, and public health and safety announcements broadcasted by the water utility. Once the contaminant is introduced to the network, consumers who drink water at contaminated nodes are exposed. Afflicted consumers

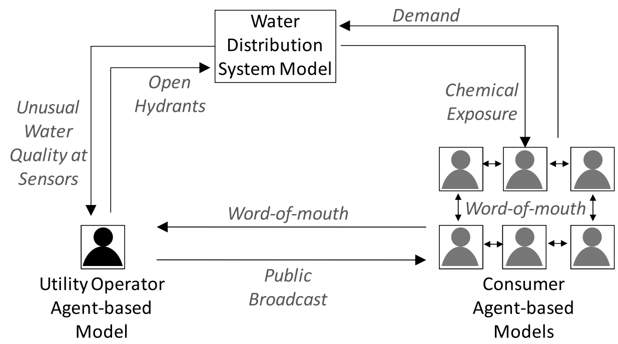

Fig. 2. Modeling framework couples agent-based models and a water distribution system model to enable the simulation of interactions among consumers, the water distribution system, and a utility operator.

may respond by ceasing to use water and alerting other consumers to the danger. Consumers who receive a warning from fellow consumers or from the utility may decrease water usage and alert other consumers to the danger. Rules for consumers' response to stimuli are specified probabilistically, so that the time of response may vary for each consumer.

A utility operator can also be modeled as an agent responding to an emergency caused by water contamination. The utility operator may select one of several response actions, such as opening fire hydrants or transmitting a "do not use" notice (Fig. 2). The stimuli that alerts a utility manager to an event, such as unusual water quality at sensors in the network and alerts from health care providers, are significantly uncertain. These triggers depend on the capabilities of water quality sensors to detect the contaminant, the acuity and experience of health care providers, and the protocol in place to receive and filter water utility consumer complaints. While the modeling framework may be used to simulate dynamic rules that capture these mechanisms, here it is demonstrated to test alternative rules or strategies that a water utility manager employs once he is aware of an event, regardless of the trigger that alerted him. This study tests a set of response strategies, including opening fire hydrants to flush the system and issuing broadcasts, to demonstrate the use of the framework for developing and understanding appropriate response actions for the water utility manager.

Actions of the consumers (e.g., changing water usage to affect demand) and actions of the utility operator (e.g., opening fire hydrants) change the hydraulics of the system. The agent-based models and water distribution model are coupled so that the dynamic hydraulic impact of the agents' decisions is

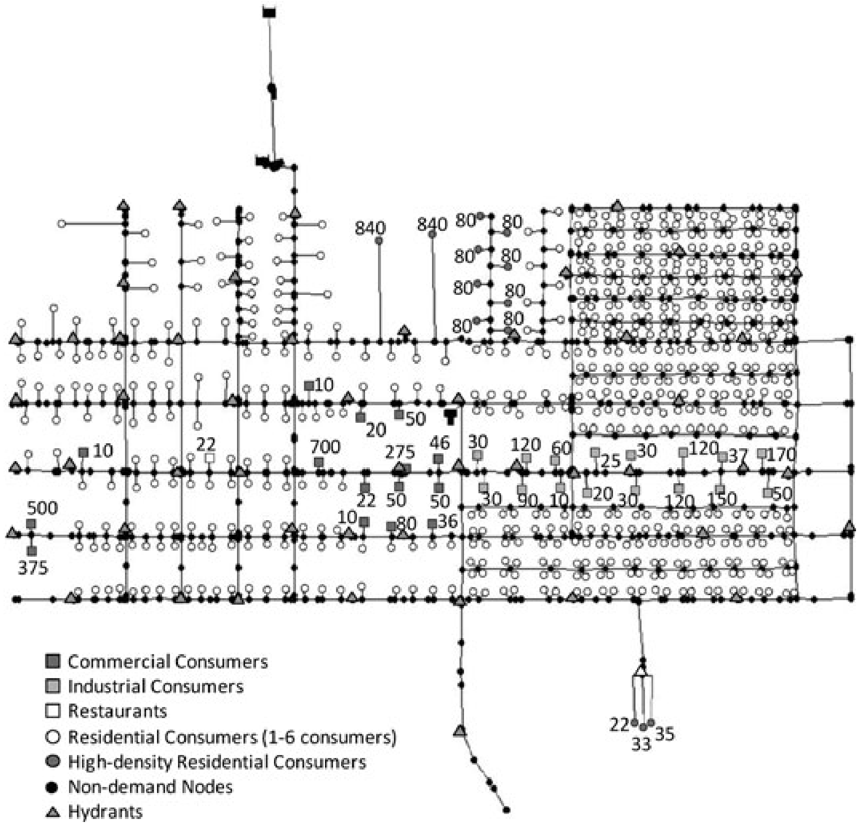

Fig. 3. Virtual city of Micropolis. Types of consumers and hydrants are shown at nodes. Numbers indicate the maximum number of consumers at a node at any time step.

simulated in a water distribution model. The commercially available ABM software AnyLogic[14] is coupled with the EPANET water distribution system model[15] for simulation of a contamination event. EPANET is a software program that simulates hydraulic and water quality conditions within pressurized pipe networks. A water distribution network is typically comprised of pipes, nodes (representing pipe junctions), pumps, valves, and storage tanks or reservoirs. EPANET computes the quantity of flow in pipes, the pressure at nodes, the height of water in tanks, and chemical concentrations in pipes and at nodes at discrete time steps.

3. EXAMPLE APPLICATION: A VIRTUAL CITY

Micropolis is a virtual city developed to provide a model of a realistic city for research in water distribution system planning and security.[16] The network characteristics mimic those of a municipal network based on the growth and development of a water distribution system over several decades. The water distribution system is modeled with 1,236 nodes, 575 mains, 486 service and hydrant connections, 197 valves, 28 hydrants, 8 pumps, 2 reservoirs, and 1 tank.

Demands are exerted at 458 nodes, characterized as residences, industries, restaurants, and commercial/institutional users (Fig. 3). Information characterizing the demand patterns for the four types of consumers is available as part of the Micropolis data. One to six inhabitants are located at each residential node, and the original Micropolis model was modified to represent the daily average demand at each residential node based on an average per capita domestic use of 100 gallons/person/day (379 L/person/day). Commercial nodes include businesses and establishments such as churches, schools, city hall, post offices, and grocery stores. Commercial and industrial average daily demands were estimated from reference tables,[17] and industries operate 24 hours a day with three shifts of workers. Diurnal demand patterns for all user types were defined based on hourly patterns[17] and are specified in EPANET through the use of demand factors, which vary at each time step and are multiplied by the base demand at a node (Fig. 4).

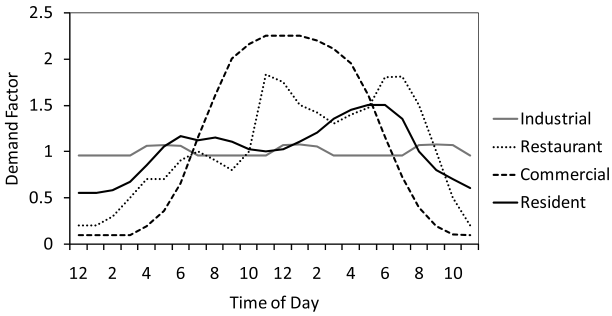

Fig. 4. Water demand factors for each type of consumer as modeled within Micropolis EPANET.

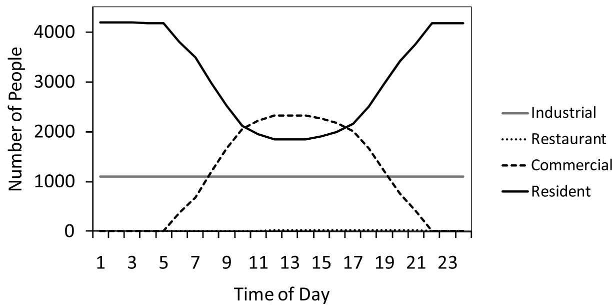

Fig. 5. Total number of consumers at each type of demand node.

3.1. Simulating Consumers with ABM

Since human activities impact the timing, location, and amount of tap water consumed, these activities may play a key role in influencing the variation in exposure. Each consumer in Micropolis is represented as an agent, and for each agent, a set of behaviors are simulated, including mobility, ingestion of tap water under normal conditions, changes in water usage, and communication with other agents.

3.1.1. Mobility

As the contaminant spreads through a network, individual consumers may move in and out of the contaminated area. An individual may live in a residence that is not within the contaminant plume, but work at a location that is within the spread of a contaminant plume. Micropolis population data tabulate the maximum number of individual consumers at each node. For this specific implementation, each agent represents one consumer in the population and is assigned a residential node as his home node. At each time step in the simulation, the number of agents at commercial and restaurant nodes is based on the normalized water demand factor (Fig. 4) multiplied by the maximum population at each node at that time step. The number of consumers at industrial nodes is assumed to remain constant, based on the 24-hour operation with three equal shifts, and at the beginning of each 8-hour shift, a random set of consumer agents arrive at each industrial node. Agents at commercial, industrial, and restaurant nodes are assigned randomly from residential nodes. Therefore, the number of consumers at a residential node is the initial number of individuals at that node less any agents that have been reallocated to another type of node, plus any agents that have been released from other nodes and return to their home node. In this way, the path of any single agent is not determined *a priori*, but is randomly assigned through the simulation. The total number of consumers at each type of node throughout a 24-hour period is shown in Fig. 5.

3.1.2. Ingestion

A set of studies have used various models for estimating consumer ingestion of a contaminant during water distribution contamination events. In calculating exposure, the rate of tap water ingested may be assumed to remain constant throughout an event[18] or to change proportionally to the demands exerted at a node at each time step.[19,20] More recently, Davis and Janke[21] proposed the combined use of an ingestion timing model to estimate the time a consumer ingests tap water, and an ingestion volume model to estimate the volume of tap water a consumer ingests. The total mass of contaminant consumed by an individual is then calculated as:

$$M = \sum_{i=1}^{n} V_i \times C_i, \tag{1}$$

where M = mass of contaminant consumed, n = number of ingestions, V_i = volume of water consumed at ingestion i, and C_i = concentration of contaminant in water at ingestion i.

Three ingestion timing models (*F5*, *R5*, and *P5*) were developed for specifying the times at which consumers ingest tap water.[21] Each timing model specifies that a consumer ingests tap water at three times per day, corresponding to meals. Every consumer also ingests tap water at two additional times, exactly halfway between meals for each model. The first model, *F5*, assumes a deterministic behavior, where each consumer ingests tap water at fixed

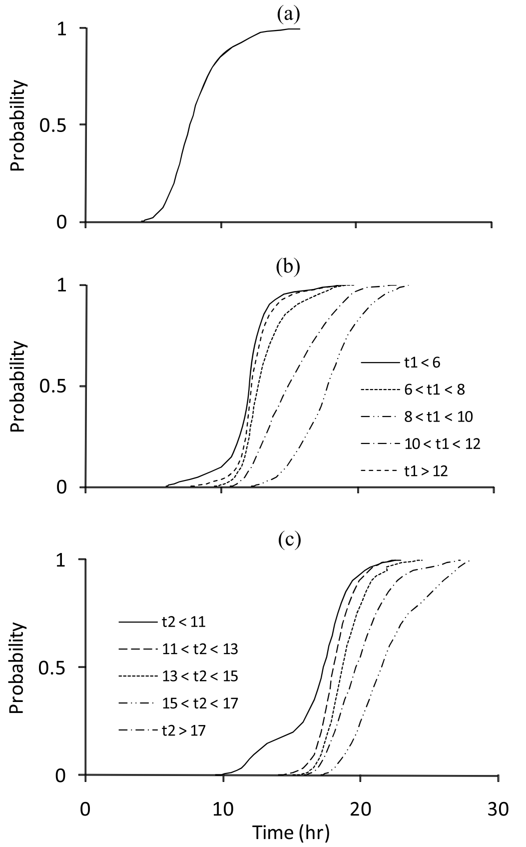

Fig. 6. Cumulative probability distributions for model *P5*. (a) Probability density for meal 1. (b) Probability for meal 2, where *t*1 is the time of meal 1. (c) Probability density for meal 3, where *t*2 is the time of meal 2.

mealtimes (7:00 a.m., 12:00 p.m., and 6:00 p.m.). The second model, *R5*, simulates a consumer who drinks tap water at three random times during the day. The third model, *P5,* is based on data available through the American Time-Use Survey.[22,23] For individuals who reported three daily ingestion events, the timing of the second and third meals depends on the timing of the previous meal. These relationships are formalized as probability distributions[24] (Fig. 6).

For consumers who work during the night shift (12:00 a.m.–8:00 a.m.) at the industry, drinking patterns are shifted eight hours to reflect alternative eating and sleeping habits. The final distribution of tap water ingestion for the residents of Micropolis is shown in Fig. 7 for each of the three ingestion models.

The total mass of contaminant consumed by an individual can be calculated using an estimation of the volume of water consumed together with the ingestion timing model. Davis and Janke used two different models to approximate the volume of water ingested.[21] The first model, M, assumes every individual ingests 1 L of tap water per day, and the second model, V, uses a probabilistic distribution developed by the U.S. Environmental Protection Agency[25] (Fig. 8). The volume of water ingested per person is divided uniformly among the five daily ingestions.

3.1.3. Word of Mouth and Changing Demand Patterns

An agent-based model of a consumer also includes rules governing a consumer's behavior to stop drinking water and warn other consumers. Consumers may stop using tap water if they are sickened and assume that tap water is the cause. For any contaminant introduced into the system, a consumer will experience symptoms once a threshold dose (for example, the lowest observable effect level, or LOEL), d_{th}, has been consumed. This model assumes that within a time period, t_e, after d_{th} has been consumed, the exposed consumer will change water usage patterns and warn other consumers. Consumers who are warned by other consumers that the water is contaminated will reduce their consumption of tap water within a time period, t_{wom}. This delay may represent time taken by a consumer to confirm a warning through media or other consumers. Consumers will most likely suspend ingestion and contact uses, such as kitchen and bathroom faucets, showers, dishwashing, and washing clothes, while other uses may continue to be exerted, such as toilets, leaks, and outdoor use. Based on data summarized by Vickers,[26] toilets, leaks, other uses, and outdoor use comprise on average 60% of the total demand for single-family residences. For apartment buildings, these uses represent 43% of the total demand for each household, where no water is used for outdoor purposes. For simulating the change in water usage, low-density and high-density residential consumers reduce demand patterns to 60% and 43%, respectively. Industrial users, restaurants, and commercial businesses maintain a baseline demand of 96%, 10%, and 20% use, respectively, even when all consumers at a node have stopped consuming water. These numbers are derived from the demand data in the original EPANET model and are based on the assumption that some uses will be continued even during a contamination event.

The following set of rules is implemented for the behavior of consumers.

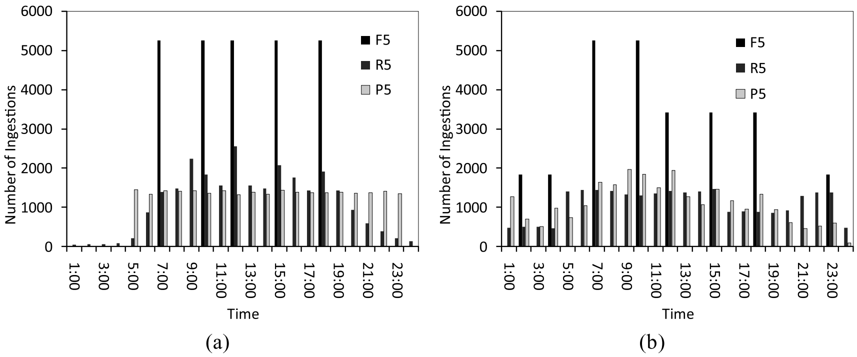

Fig. 7. (a) Distribution of ingestions using ingestion timing models, *F5*, *R5*, and *P5* for Micropolis residents. (b) Distribution of ingestions using ingestion timing models with an 8-hour shift in drinking patterns for consumers who work during the night shift. For each model, a consumer ingests tap water five times per day.

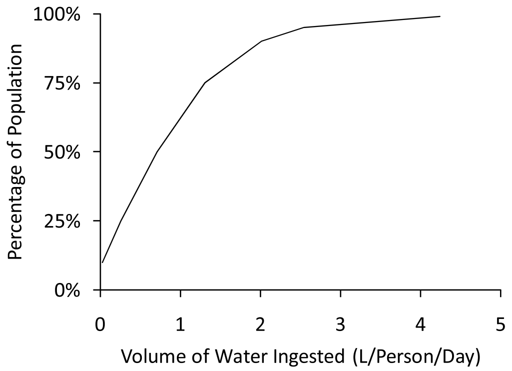

Fig. 8. Distribution of the volume of tap water ingested per capita per day.[25]

- If a consumer ingests a contaminant dose d_{th}, he will reduce his demand within t_e.
- If a consumer receives a warning from a family member (specified as a consumer at the same low-density residential node), he will heed the warning with a probability of p_f and reduce his demand within t_{wom}.
- If a consumer receives a warning from a colleague (specified as a consumer at the same nonresidential node) or a neighbor (a consumer at the same high-density residential node) he will heed the warning with a probability of p_c and reduce his demand within t_{wom}.
- If a consumer receives a warning through a public broadcast, he will heed the warning with a probability of p_b and reduce his demand immediately.
- If a consumer reduces his demand, he will alert all consumers at his node if he resides at a low-density residence or one neighbor if he resides at a high-density residential node, and one colleague if he is currently located at a nonresidential node.

Though there is a lack of data in the literature to describe the reaction times and choices of consumers in the event of water distribution contamination, a set of studies have documented the compliance of consumers with boil water notices. Angulo *et al.*[27] surveyed the behavior of citizens during a *Salmonellosis* epidemic and found a compliance rate to boil water orders of 69%. A study of an incident of possible sewage contamination of public water mains found that 64% of the population took some form of risk in response to a boil water notice, indicating a 36% compliance rate.[28] In another study, 42% of the population boiled water once they were made aware of an incident.[29] In response to an event that occurred in the Netherlands, 82% of the population complied with a boil water notice by buying bottled water or boiling water.[30] In a study of the 1993 Milwaukee *Cryptosporidium* incident, 84% of survey respondents took preventative actions once they were notified of the problem.[31] In a California incident, only 20% of the population complied with a notification,[32] and a study of the behavior of consumers in four towns in Oregon found that 76% of the population boiled water or bought bottled water in response to public alerts.[33]

The results reported in these studies indicate that the behavioral response of consumers may vary widely, and this response may be based on many influencing factors, including the type of media used to convey the message and any *a priori* community education concerning water contamination events. For the current simulation, a conservative value of 50% is used for p_b, which is the rate of compliance to boil water orders. The parameters necessary for modeling consumers in this framework are described in Table I.

3.2. Scenarios

A contamination event is simulated as a conservative contaminant introduced at the water tank at midnight (Fig. 9). The settings and characteristics of

Table I. Parameters for Characterizing Consumers

Parameter	Description	Value
t_e	Time to respond after exposed	U(1, 6) hours
t_{wom}	Time to respond to word-of-mouth communication	U(1, 6) hours
p_f	Probability of response to communication from family	100%
p_c	Probability of response to communication from neighbor/colleague	75%
p_b	Probability of response to broadcast	50%

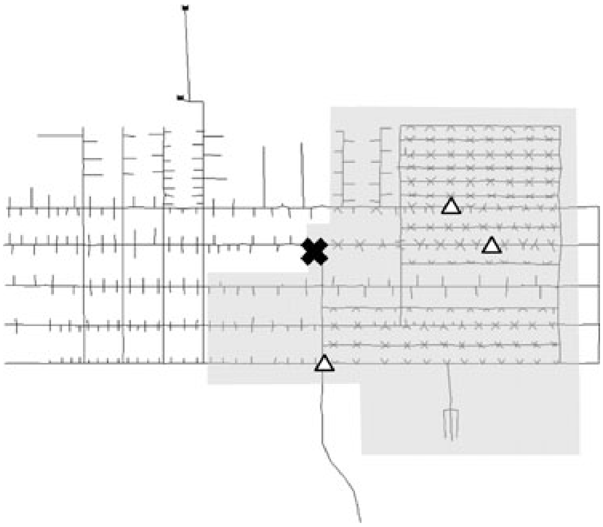

Fig. 9. Contamination event. **X** indicates the location of contamination. Triangles indicate hydrants opened under scenario 2. Shaded area represents the nodes within the plume boundary that receive a targeted broadcast under scenario 3.

Table II. Contaminant Source Characteristics

Source Characteristics	Value
Injection location and time	Tank, 12 a.m.
Injection mass	9,000 g
Injection duration	2 hour
d_{th}	{0.01, 0.1, 0.25, 0.5, 1.0, 2.0} mg

the event are shown in Table II. Using EPANET, hydraulic conditions are simulated in one-hour time steps, chemical transport is simulated in five-minute time steps, and results are reported in one-hour time steps.[34] The event in the network is simulated over a 48-hour period. The exposure of consumers is modeled and then management strategies are modeled and evaluated with respect to the reduction in the number of exposed consumers.

3.2.1. Exposure Scenarios

The exposure of the population to the contaminant injection is simulated, considering the behaviors of the consumers in three cases, where each case builds on the previous. *Case 1—ingestion* simulates the mobility and ingestion of consumers, without considering changes in consumer demands. Each ingestion timing model (*F5*, *R5*, and *P5*) is used in combination with the ingestion volume models (*M* and *V*). *Case 2—stop use* simulates ingestion, mobility, and consumers who decrease their demand in response to exposure to contaminated water. Exposed consumers change demand patterns, but do not warn other consumers. *Case 3—communication* simulates all behaviors, including ingestion, mobility, decreasing demands, and communication among consumers to warn others.

The threshold dose for a specific contaminant will significantly impact the consequences of a contamination event. The threshold dose can vary widely for different contaminants and individuals of different demographics. For example, Kroll[35] lists potential contaminants with median lethal doses for 70 kg persons ranging from 0.0001 mg to 300 mg. For the present study, six threshold doses are considered (0.01 mg, 0.1 mg, 0.25 m, 0.5 mg, 1 mg, and 2 mg). All consumers react to the same threshold dose, which represents that all residents of Micropolis have been modeled with the same body weight. The model can be updated to simulate a distribution of body weights for a community based on population demographics. Parameter settings for simulating exposure are listed in Table I. Further analysis is conducted to test the sensitivity of the model to different values for t_e and t_{wom}.

3.2.2. Management Scenarios

A water utility operator may become aware of an event through word of mouth, health care providers, or water quality sensors in the network, and if he is

Table III. Parameter Settings for Management Scenarios

Scenario Characteristics	Management Scenario 1. Opening Hydrants	2. Public Broadcasts	3. Hydrants and Public Broadcasts
Timing model	*P5*	*P5*	*P5*
Volume model	V	V	V
Consumer case	Case 3	Case 3	Case 3
Time hydrants opened	{1:00 a.m., 2:00 a.m., . . . , 12:00 p.m.}	NA	{1:00 a.m., 2:00 a.m., . . . , 12:00 p.m.}
Broadcast type	NA	Targeted, full	Full
Time broadcast received	NA	{1:00am, 2:00 a.m., . . . , 12:00 p.m.}	{1:00 a.m., 2:00 a.m., . . . , 12:00 p.m.}
Total number of simulations[a]	72	144	72

[a]Each simulation is executed for 30 random trials.

alerted early enough, may open fire hydrants to flush the contaminant or issue broadcasts. Three management scenarios are simulated. In the first scenario, three hydrants that are located close to the source of the contaminant are opened simultaneously for four hours (shown in Fig. 9). These hydrants were selected based on their proximity to the source and the general direction of contaminant propagation through the network. Preliminary simulations identified that flushing through these hydrants will not result in the loss of pressure in the system below standard operating conditions. Depending on how quickly the water utility operator is able to respond to the event, flushing at these hydrants will result in various degrees of public health protection. Twelve responses are simulated, which open hydrants up to 12 hours after the contaminant is first released.

A second management scenario simulates the use of a broadcast only, without opening fire hydrants. A public official may choose during a contamination event to issue a "do not drink" or "do not use" notice[3] through media including television, radio, door-to-door notifications, texts, and phone calls. Two broadcast types are considered in this simulation. A targeted broadcast is directed to nodes only within the boundary of the contaminant plume, which could be estimated by a water utility manager based on water quality sensors or knowledge of the system hydraulics (Fig. 9). A full broadcast is a more conservative protective measure and is directed to all residents in the network, without consideration of the location of the plume. Twelve scenarios are simulated for each type of broadcast, where broadcasts are received by consumers at different times after the contaminant is first released.

The third management scenario simulates the simultaneous use of opening hydrants and issuing a full broadcast. Characteristics of the three scenarios are summarized in Table III, and for all management scenarios, the timing model is *P5*, the volume model is V, and the consumer case is *case 3*.

4. RESULTS

4.1. Exposure Scenarios

The number of exposed consumers is simulated for the three cases, using the parameter settings given in Table I. For *case 1* (ingestion only), the cumulative distribution of the percent of the population who have ingested increasing levels of contaminant are shown in Fig. 10. Results are probabilistic due to the stochasticity present in the mobility of the agents; the ingestion timing models *R5* and *P5*; and the ingestion volume model V. Each model was executed for 30 trials to determine the range of results, where each trial was initiated with a different random seed. The trials were limited to 30 based on the computational limitations of executing a large number of model evaluations. The deterministic model *F5* estimates the most conservative impact on the population for both ingestion volume models M and V. The ingestion volume model V, which provides variability in the volume of water consumed, approximates more consumers exposed to higher doses than the volume model M. This comparison provides some insight to the sensitivity of the model to varying precision and types of data. The percentage of individuals shows only slight variation among the three timing models, as all three models simulate that each agent consumes water five times per day. At very high levels of exposure (above 10 mg), there is little difference among the models. For contaminants that cause health consequences at lower dosages, the type of

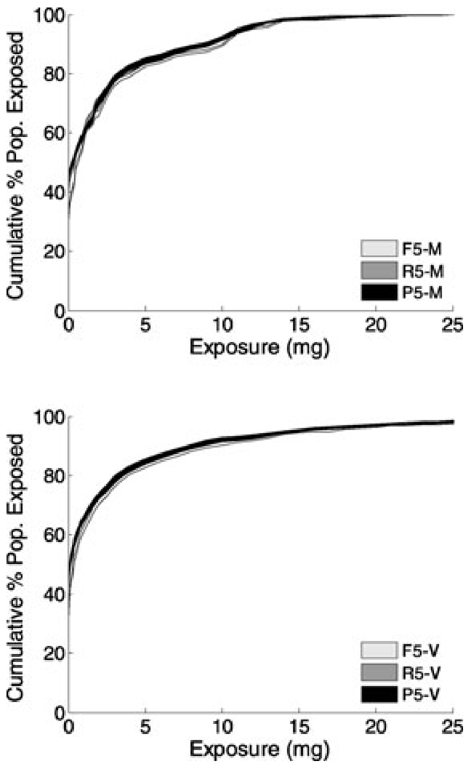

Fig. 10. Cumulative percent of the population exposed simulated for *case 1*. Results are shown for alternative ingestion timing and volume models. Volume models: *M*--every individual ingests 1 L of tap water per day; *V*—probabilistic distribution of the volume of water ingested. The band width represents the range of results for 30 trials executed using each model.

timing and volume information may become a significant factor in predicting the exposed number of consumers, and for doses less than 3 mg, the more precise volume model (*V*) results in smaller differences among the timing models. These results may help guide efforts for collecting additional information to refine the model. For the remaining investigations reported here, the *P5-V* ingestion model is used, as it is based on actual consumer data.

The contamination event is simulated for *case 1*, *case 2*, and *case 3* for six levels of threshold dose and 30 random trials for each level. These simulations demonstrate the public health impacts of consumer decisions to stop using water and warn other consumers. Fig. 11 shows the percentage of the population exposed, i.e., those who consume water with a contaminant concentration above the threshold dose, as the event progresses. For each of the threshold doses, the number of exposed consumers is approximately zero up to three hours (3:00 a.m. on the first day), and then there is a delay before *case 2* and *case 3* deviate from *case 1*, which occurs after about 14 hours (2:00 p.m. on the first day). This delay is due to the time taken for exposed consumers to change their water usage and communicate a warning (for *case 2* and *case 3*) and the time taken by warned consumers to change their water usages (for *case 3* only). For each threshold dose, the number of exposed consumers is greatest for *case 2*, and the number of exposed consumers for *cases 1* and *3* are similar.

For very potent chemicals with a threshold dose of 0.01 mg, there is a significant difference between the three cases. *Case 1* shows almost 70% of the population exposed at the end of a 48-hour period. The mechanisms modeled in *case 2* and *case 3* have a significant impact on the number of exposed consumers. For *case 2*, there is a higher mass of contaminant left in the system during the second day due to exposed consumers decreasing their water consumption. As a result, 85% of the population is exposed to the contaminant. *Case 3* demonstrates that though there is more contaminant left in the system during the second day, consumers who are not already exposed have been warned by other consumers, and do not consume the water, resulting in approximately 70% of the population exposed.

For an increasing threshold dose, the mechanisms of *case 2* and *case 3* have a decreasingly significant impact on the number of consumers exposed. As the threshold dose increases, the change in the number of exposed consumers among the three cases, in general, becomes almost negligible. This is due to several factors: fewer agents are exposed to the threshold dose; more time is required before agents accumulate a higher threshold dose and react; and the amount of contaminant available at the necessary locations in the network may limit the number of agents who can accumulate the threshold dose.

Sensitivity analysis was conducted to determine the impacts of the response times on the predicted number of exposed consumers. Three settings were simulated for t_e and t_{wom}, including one, six, and a uniform distribution of one to six hours, for a total of nine cases for each threshold dose. Each case was again simulated for 30 random trials (Fig. 12). For each threshold dose, the simulation shows only a slight variation among the nine cases, with the highest number of exposed consumers when t_e is one hour and t_{wom} is six hours. At these settings, exposed consumers respond quickly to the contaminant and reduce their consumption, which increases the amount of contaminant remaining in the system, and exposed

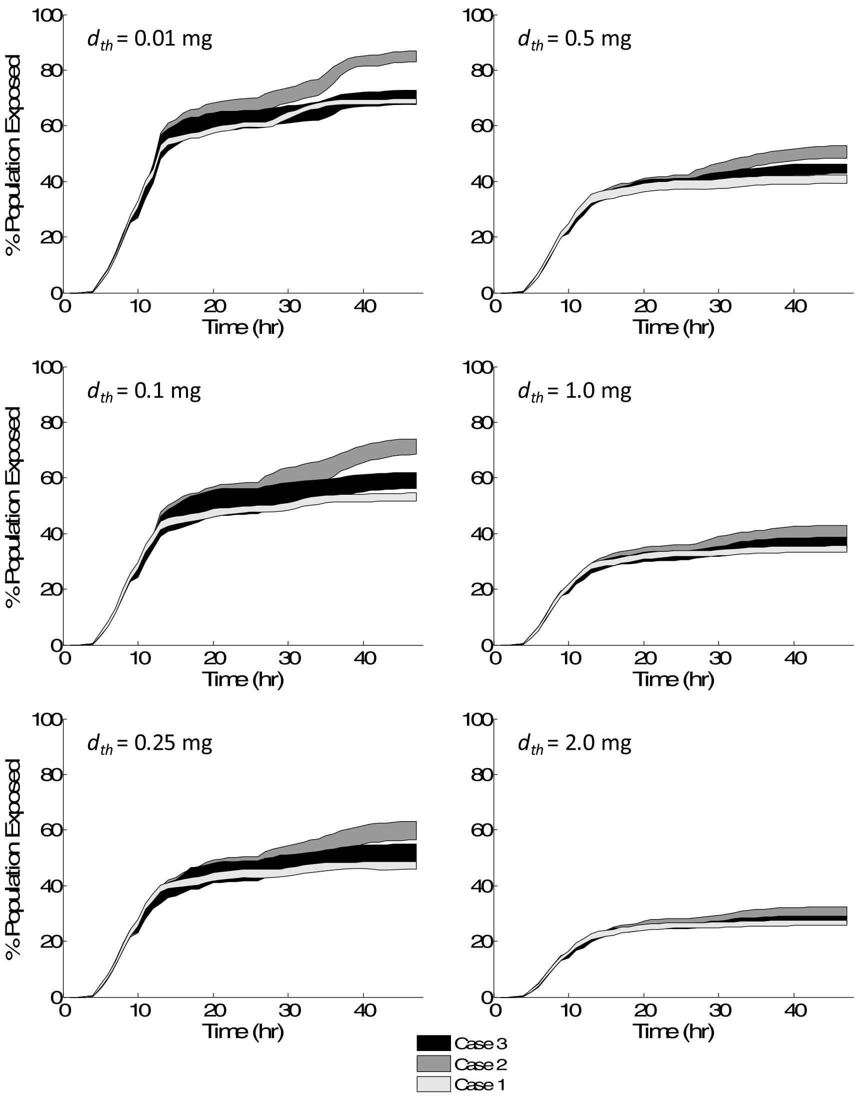

Fig. 11. Percent of population exposed to the threshold dose for varying levels of threshold dose throughout the simulated time period. Results are for 30 trials for each setting. Band width indicates the range of results.

consumers take more time to communicate a warning to other consumers. Modeling response times as random variables produces a slightly wider variation of predicted exposure among the 30 trials.

4.2. Management Scenarios

The parameter and scenario settings for three management scenarios, "opening hydrants," "broadcasts," and "opening hydrants and public broadcasts" are described in Table III, and the characteristics of consumers and the contamination scenario are described in Tables I and II, respectively. Twelve simulations were executed for hydrants opened from 1–12 hours after the contaminant was released at 12:00 a.m. Two types of broadcasts were simulated, a targeted broadcast to notify consumers within the contaminant plume boundary, and a full broadcast to the entire municipality. Twelve cases were again simulated, where broadcasts were sent to notify the public from 1–12 hours after the contaminant was released. Fig. 13 shows for the six levels of threshold dose the reduction in the number of exposed consumers for each management scenario, compared to the "do nothing" case, where no management action is taken.

Results demonstrate that the reduction in exposed consumers is similar for opening hydrants at different times up to 6:00 a.m. As the contaminant moves through the system, the majority of the contaminant mass is in the pipes nearest to the locations of the three hydrants at 6:00 a.m. After this

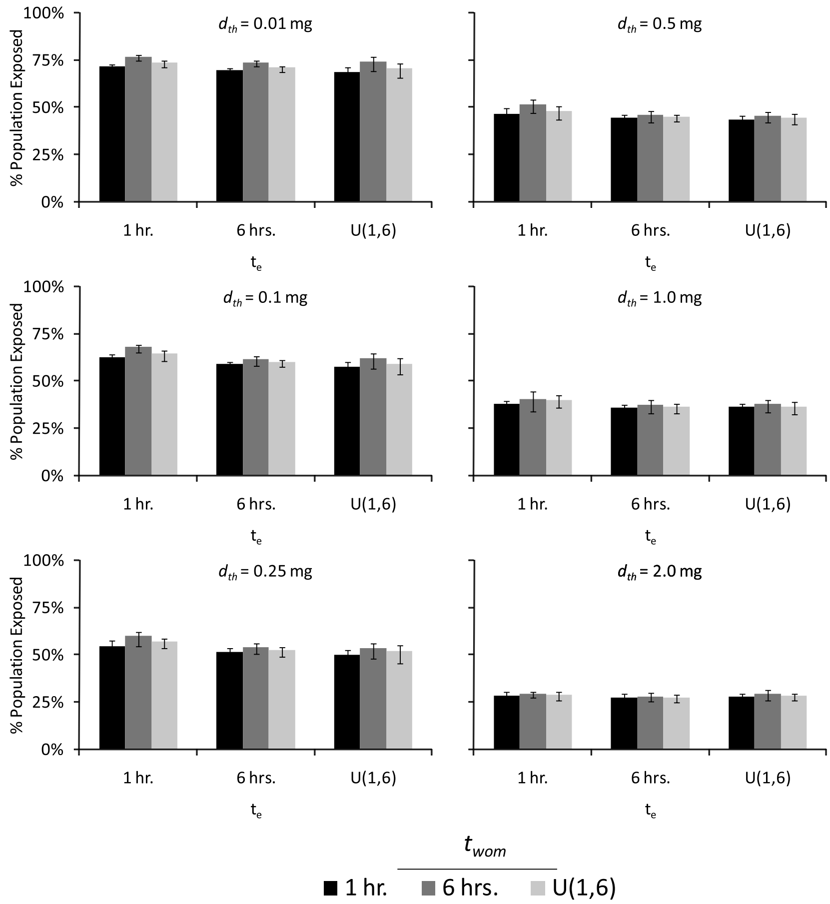

Fig. 12. Analysis of model sensitivity to changing parameters time of response to exposure, t_e, and time of response to word-of-mouth warnings, t_{wom}. Results show the average over 30 random trials. The setting "random" refers to a uniform distribution from 1 to 12. Error bars show the maximum and minimum of the 30 random trials.

time, the mass of the contaminant has moved past the hydrant locations, and the effectiveness of a flushing strategy decreases.

As expected, earlier broadcasts reduce the number of exposed consumers to a higher degree than later broadcasts, and there is a regular decrease in the reduction of exposed consumers as broadcasts occur later in the event (Fig. 13). The full broadcast protects more consumers as consumers located outside of the targeted area may later move to a contaminated node. Finally, the opening hydrants and full broadcast scenario results in the greatest protection of public health for almost all cases. The full broadcast alone results in slightly better protection than the combined approach, however, when the action is taken at 7:00 a.m. and 8:00 a.m. for threshold doses below 1.0 mg. This is because, for more potent chemicals, exposure occurs more quickly and, therefore, the timing of management decisions is more critical and can significantly impact the outcome. For these scenarios that involve more potent chemicals, opening hydrants later in the simulation results in changed hydraulic conditions that can actually expose more consumers to the contaminant, compared to using only a broadcast without opening hydrants.

Though a subset of the nodes are included in the targeted broadcast and consumers comply with the broadcast at a rate of 50%, the number of consumers that stop using water by the end of the 48-hour simulation varies between 75% and 100% for all 72 cases considered (six levels of threshold dose and 12 times of day). The ABM framework can be utilized to study and evaluate how social networks and communication behaviors impact the vulnerability of a community, as the number of consumers who stop using water above the expected value of 50% represent the impact of word-of-mouth communication. For the full broadcast, 85%–100% of consumers have stopped using water for all 72 cases considered, and for the hydrants and public broadcasts scenario, 80%–100%. These can be compared to the "do nothing" case, where the number of consumers who stop using water ranges from 55% to 95%. The higher percentage of consumers who stop using water

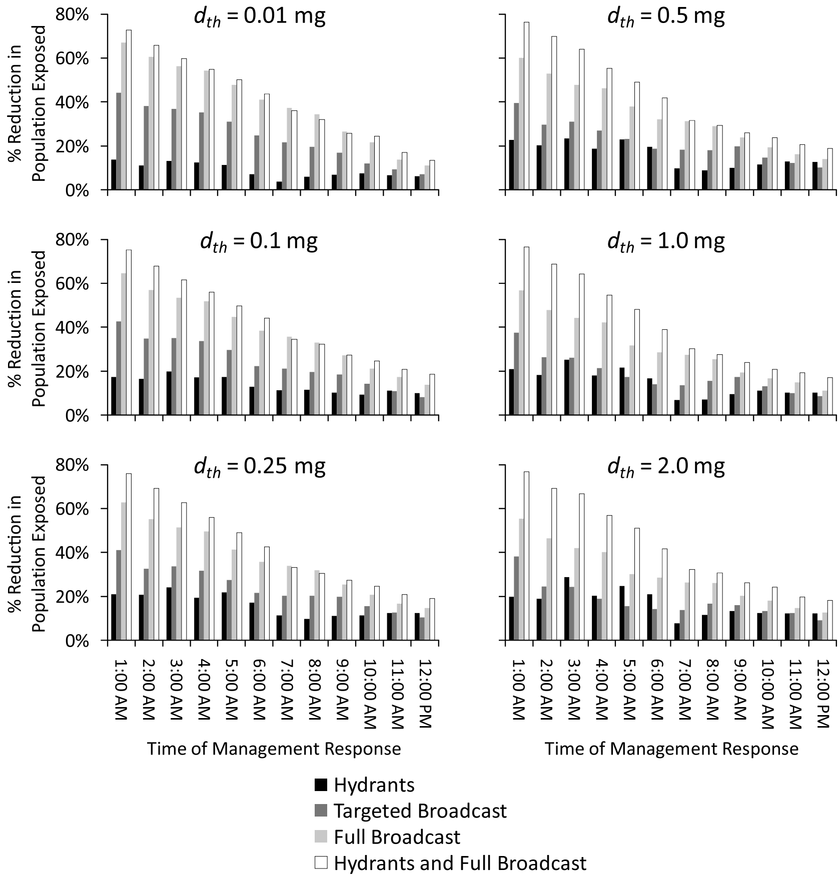

Fig. 13. Public health protection achieved by taking management actions at various times of day, including opening hydrants, targeted broadcast, full broadcast, and combined use of a full broadcast and opening hydrants, for different threshold dose levels. Results represent the average over 30 trials.

corresponds to more potent chemicals, where more consumers are exposed and alert their peers. These numbers are equally high for both scenarios that do and do not employ broadcasts, indicating the strength of the word-of-mouth communication in this model. For weaker chemicals that propagate through the network and population slowly, utilizing a broadcast increases the number of consumers who take protective actions. Though some conclusions may be are intuitive, the framework allows a quantitative approximation of the benefits of using different management strategies.

5. DISCUSSION

An ABM framework is demonstrated here for a realistic case study to facilitate the simulation of nonlinear interactions among consumers and water utility managers in the event of contamination of a water distribution system. This approach provides a framework that enables the integration of public health expertise and water distribution systems knowledge to comprehensively address water distribution threat management. A cross-disciplinary approach that combines the science and engineering of both fields of knowledge can provide more informed decision making. This work extends exposure modeling reported previously[18–21] by including simulation capabilities of consumer mobility and communication among consumers. It is demonstrated here that consumer behavior may impact overall public health through changing hydraulics in the system and alerting other consumers. Additionally, consumer behavior may impact the effectiveness of management strategies, due to variability in the location and to behavior of consumers.

While complete validation of an intentional water distribution contamination event will not be possible due to the lack of data in such an event, the modeling framework can be used to compare what-if scenarios. Miller and Page[4] suggest that an ABM framework may be used as a "computational petri dish" to simulate different events and responses and evaluate their expected consequences or benefits. For example, for the virtual city and the specific event studied here, broadcasts provide better public health protection than opening hydrants, and opening hydrants may adversely impact the number of exposed consumers, depending on the time that has elapsed after injection of the contaminant. The framework can be applied for water utilities in new locations by incorporating a simulation model of the water distribution system and information concerning population demographics, including weight, age, water consumption habits, and travel to and from places of business. Through studying and analyzing a set of contaminants and injections that vary in location and timing, utility managers will be better prepared to select appropriate management strategies in real-time response to an event. The modeling described here can be integrated within a vulnerability analysis framework for identification of the most vulnerable system components or likely locations of intrusion. This approach is being implemented in a simulation-optimization approach to extend the analysis and gain additional insights for threat management.(36)

Alternatively, the framework may be coupled with optimization methods to search for and identify optimal management strategies, as shown by water distribution threat management studies.(13,37–40) Optimization analysis can be conducted to identify the location, time of opening, and time of closure to best manage hydrant operations for flushing the system. Management strategies must ultimately be selected under a set of conflicting objectives, including cost-benefit information and the probability of success given the many uncertainties in the system. A comprehensive framework can be constructed using the ABM approach that combines vulnerability analysis for identification of potential threats and optimization analysis for identification of response planning strategies and their expected performance.

The scenarios modeled and analyzed here each carry a certain set of assumptions that should be evaluated carefully, and the limitations of these assumptions can be improved through additional research. For example, uncertainties in water distribution modeling include pipe frictional factors, storage of water in tanks, and the reaction and decay of contaminants. Simple simulation of the broadcast mechanisms has not included aspects such as the broadcast media or the time taken for decisionmakers to craft their response to the event. The impact of various mechanisms of broadcasts should be included in future modeling studies, along with the impact of educational programs meant to increase compliance to expected levels. ABM of the consumers can be improved through mental model studies and interviews. More realistic simulation of consumers would include heterogeneity in the population to represent a distribution of demographic characteristics. Simulating the variance in gender, age, and weight of consumers will capture the variability in the volume of ingested water and response to exposure. In addition, consumers can select from an array of protective actions, including using bottled water, boiling water, disinfecting by chlorine bleach, using water from a filter pitcher, and using hot water from the hot water heater; each will result in different values of demand reduction. Modeling improvements are being explored to include these considerations in extensions of the current ABM framework.(41,42) Future work can explore the dynamic interactions between utility operators and perpetrators as intelligent agents. Successive investigations will develop rules to characterize the interactions among utility operators, the media, public health providers, and perpetrators, and simulation of these interactions will enable the identification of increasingly sophisticated and efficient strategies for threat management.

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