Integrating Evolutionary Computation and Sociotechnical Simulation for Flushing Contaminated Water Distribution Systems

M. Ehsan Shafiee
North Carolina State University
Department of Civil Engineering
Raleigh, NC
ehsanshafieem@gmail.com

Emily M. Zechman
North Carolina State University
Department of Civil Engineering
Raleigh, NC
emzechma@ncsu.edu

ABSTRACT

A water distribution contamination event occurs when a chemical or pathogen is introduced to a pipe network dedicated to the delivery of potable water. During an event, complex interactions among consumers, utility operators, decision makers, and the pipe network can influence the number of exposed consumers, as human actors adapt their water use activities in response to warnings or exposure. An agent-based model is developed to model the water contamination event and provides insight and understanding about the effect of interactions on public health, such as the number of exposed consumers. Utility operators can protect consumers using a wide range of mitigation responses, and opening a set of hydrants is typically an effective strategy for flushing contaminated water before it reaches consumers. The ABM framework is coupled with an Evolutionary Strategy (ES)-based search to identify an optimal strategy for manipulating hydrants to minimize the number of exposed consumers. The application of the simulation-optimization framework is demonstrated for a virtual mid-sized municipality, Mesopolis.

Categories and Subject Descriptors

I.2.11 [**Distributed Artificial Intelligence**]: Multiagent systems; J.2 [**Physical Science and Engineering**]: Engineering; G1.6 [**Optimization**]: Global optimization

General Terms

Algorithms

Keywords

Optimization, Evolutionary Strategy, Agent-Based Modeling, Water Distribution Contamination Event, Technical Response Action, Flushing, Opening Hydrants

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1. INTRODUCTION

Water utilities are responsible for developing plans for threat management when a contaminant is released in a water distribution network. Both intentional and accidental events can create public health emergencies. To prevent the exposure of a large population of consumers, water utility managers may develop a set of plans for protective actions, such as flushing the contaminant from the system by opening fire hydrants. A manager may become aware of a threat through water quality sensor information and a set of actions can be selected to warn consumers directly or remove contamination before it reaches consumers. In current practice, however, utility managers do not have a set of plans that are developed *a priori.* For example, manuals or libraries of appropriate responses should be developed specifically for a utiltiy, as response strategies will vary in their effectiveness based on the characteristics of a pipe network, the community who uses the water, and a specific contamination event. The research presented here develops a new methodology for creating a library of responses that a manager can use to respond to events in a water system.

Once a manager becomes aware of a contamination event, actions for protecting the public should be selected. One approach is to select hydrants located near the activated sensor to capture and flush the contaminant plume. A hydrant flushing strategy can be designed to minimize the number of exposed consumers for a contamination event through simulation of the event. A water contamination event, however, is a dynamic and complex event, and interactions among human actors in the system may cause unpredictable hydraulic patterns in the network and impact the performance of a hydrant flushing strategy. Both utility managers and consumers interact with the pipe network and one another and adapt their behaviors based on the information they receive. Adaptive responses to the event change the hydraulics in the system and the propagation of the contaminant plume. Utility managers can control the contaminant plume by opening a set of hydrants to flush contaminated water while manipulating a set of valves to confine the contaminant within an isolated section of the network. In addition, the manager may warn consumers about the event. As consumers receive information from the utility manager, media, and peers, they may reduce their consumption and use of tap water. Changes in water consumption feed back to the water network and impact hydraulics. The interactions among technical and social components creates a sociotechnical system, and prediction of the contaminant plume location emerges from the interactions among different actors and the engineering infrastructure. The presence and potential effects of decentralized interactions should be considered and taken into account in the process of designing effective hydrant strategies.

Due to the nonlinear and complex interactions of consumers, utility managers, and the water distribution infrastructure, the water contamination event can be studied and simulated as a Complex Adaptive System (CAS). A CAS is a system of autonomous actors which interact to generate system-level properties that could not be predicted through by individual consideration of components [8]. An agent-based model (ABM) can be used to simulate a CAS by representing individual actors that interact through a set of logical or mathematical rules [13]. An ABM approach was developed and is extended in this study to simulate a water network contamination event and assess the impact of interactions on the number of exposures [19]. The ABM is coupled with an evolutionary algorithm (EA) to identify strategies for manipulating hydrants to flush a contaminant while considering the complexity of interactions in the system. An Evolution Strategies (ES) approach is used to identify a set of hydrants that should be opened during an event that is detected using information from a water quality sensor network. The ES-based search utilizes operators that can search through a connected graph of nodes efficiently. The ABM-ES framework is demonstrated for a mid-sized virtual city of 150,000 consumers.

2. PROBLEM FORMULATION

Hydrants may be selected during a water contamination event to protect consumers by flushing out contaminated water. A hydrant strategy is defined here as the identification of a set of hydrants and the timing for opening and closing each hydrant. Previous studies explored objectives for identifying optimal hydrants strategies based on minimizing the amount of consumed contaminated water [1], the amount of contaminant in a network [3], and the number of exposed consumers [20]. These studies use optimization to identify one hydrant strategy for each contamination event. The limiting assumption of this approach is that to use a hydrant strategy, a utility manager must know exactly where and when the contaminant was released in the network. In many realistic cases, however, the utility manager would have information provided by a water quality sensor network and may not know the exact location of the contaminant intrusion. This study explores a new approach to solve the hydrant optimization problem. Instead of finding the best hydrant strategy for one contamination event, a hydrant strategy is identified for a set of contamination events. Each event that is included in the objective function is selected because it activates the same sensors over the duration of an event. Using this approach, the optimization framework identifies the most effective hydrant strategy for a specific sensor warning, rather than for a specific contamination event.

The performance of any hydrant strategy is its ability to protect consumers over a set of events that activate the same water quality sensor. The problem is formulated as followed to minimize the the average number of consumers who are exposed over these events (Eqn. 1).

$$\min Exposure = \frac{\sum_{k=1}^{k=M} f_k(\mathbf{L}, \mathbf{T}, \mathbf{D}) + V}{M} \tag{1}$$

$$\text{Subject to: } t_i \geq t_{manager} : t_i \in \mathbf{T} \tag{2}$$

$$V = \begin{cases} 0 & p_j \geq P_{min} : j = 1, \ldots, n_{nodes} \\ 150,000 & \text{otherwise} \end{cases} \tag{3}$$

where $Exposure$ is the average number of exposed consumers calculated over M water distribution contamination events. An event k is simulated by the function f_k, which is an ABM simulation of the water distribution contamination event (described in Section 4). $\mathbf{L} = \{l_1, \ldots, l_n\}$ is an array of the specific hydrants that should be opened; $\mathbf{T} = \{t_1, \ldots, t_n\}$ is the time step at which the corresponding hydrant is opened, and flushing is initialized; and $\mathbf{D} = \{d_1, \ldots, d_n\}$ is the duration that each hydrant remains open. $t_{manager}$ is the time that a utility manager becomes aware of a threat through activated water quality sensors, and hydrants can be opened only after this time. p_j is the pressure of water at node j and P_{min} is the minimum pressure predefined by a utility manager to maintain the serviceability of a water network, typically set at 20 psi. N_{nodes} is the number of nodes that are monitored for pressure violation (all terminal nodes) in a water network.

3. OVERVIEW OF INTEGRATED AGENT-BASED MODELING AND EVOLUTIONARY ALGORITHM FRAMEWORK

To solve the problem as formulated above, a computational framework couples an EA-based search with an ABM of the sociotechnical water distribution system. The EA-based search generates a population of individuals that represent solutions to the problem, and a hydrant strategy (represented as a set of decision variables) is passed to the ABM simulation, which calculates the quality of a strategy as the average number of exposed consumers over a set of contamination events. Based on the ABM simulation, the fitness of each solution is assigned, and the EA selects solutions to survive to the next iteration of search. The integration of the EA and ABM components is shown in Fig. 1, and the separate components are described below.

4. AGENT-BASED MODELING FRAMEWORK

ABM is an approach for simulating actors and interactions among actors to predict the collective effect of these interactions on system behavior. The agent is the underlying component of an ABM and is modeled to behave dynamically and adaptively. Agents have attributes, receive information from their environment or other agents, have goals, and achieve their goals by changing their behaviors.

The ABM approach has been used in water resources engineering problems to capture the dynamics and complexity of management and planning through simulating the interactions among infrastructure systems and social actors. A few studies use ABM to simulate the interaction of consumers and water utility managers under normal operating conditions [17, 2]. Shafiee and Zechman [15] developed a model

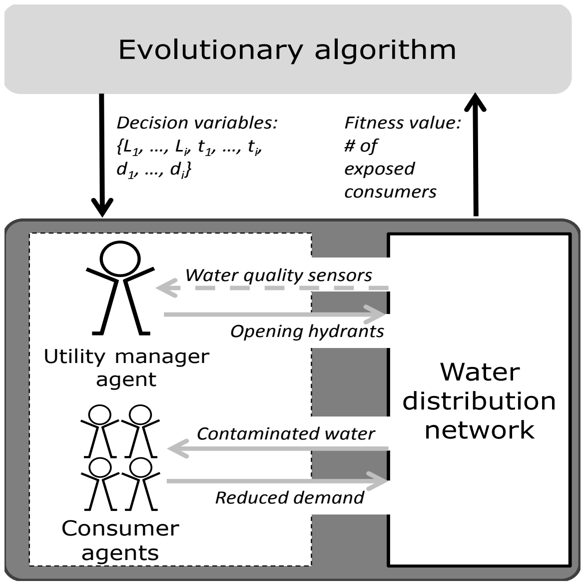

Figure 1: Simulation-optimization framework. An evolutionary algorithm (upper box) is coupled with a sociotechnical model (lower box) of a water distribution contamination event. A set of decision variables is passed to the simulation model and the fitness value is returned to the optimization algorithm.

of a water distribution contamination event using an ABM approach to connect a set of consumers with a water distribution network and predict the emergent number of exposed consumers; this framework and approach is extended here. The ABM framework of a water distribution contamination event (lower box of Fig. 1) couples agent models of human actors (on the left) and an engineering model of the technical water distribution network (on the right). The technical and social models are connected by a set of computational mechanisms that pass information among components. Water quality sensors are simulated at selected nodes to monitor for unusual water quality. If the contaminant levels exceed a predetermined threshold at a sensed node, a warning message is passed from a sensor to the utility manager agent. The utility manager agent is simulated with a hydrant strategy, which specifies the timing of opening hydrants. The selected hydrants are encoded in the water network simulation to represent new demands. Information is also passed between consumer agents and the water distribution system model. At each time step, each consumer receives a message from the water network of the concentration of contaminant in the water at the node where it is located. A consumer agent accumulates contaminant in its person, based on the concentration and volume of consumed water, until its exposure reaches a critical dose. Once the consumer is exposed, it passes warning messages to other consumers that it is exposed. Agents that are exposed to the contaminant or informed about the event reduce their water consumption demand. Demand reductions are translated to the distribution network by altering the input file to reflect new values at demand nodes. The hydraulic simulation is executed to calculate new flow directions and velocities as they are altered in the network due to opening and closing hydrants and demand reductions. This iterative process continues at each time step throughout the duration of the simulation. The ABM framework is implemented by connecting a water distribution simulation model, EPANET [14], with AnyLogic [18], which is a dynamic simulation software for discrete event modeling, system dynamics modeling, and ABM.

4.1 Water distribution system model

A water distribution system is composed of a network of pipes, pumps, and valves, and can be represented as a graph of links and nodes, where nodes represent junctions at the intersection of multiple pipes. EPANET is a model for simulating the hydraulics and transport of contaminants and chemical species within a water distribution pipe network. EPANET calculates flow, pressure, and contamination concentration at each network element using consumption demand exerted by consumers. Water quality sensors are simulated within the water distribution network to monitor the concentration of chemical and biological materials. The sensors are activated if the concentration of a contaminant exceeds a threshold based on regional or national water safety requirement [5]. This study simulates ideal sensors that accurately and precisely sense the contaminant of interest.

4.2 Water consumer agents

Consumer agents are modeled with mechanisms and characteristics, including demographic heterogeneity, water use behavior, communication among consumers, and adoption of protective strategies, as described originally by Shafiee and Zechman [16]. Brief descriptions of these behaviors are given below.

4.2.1 Demographic characteristics

A set of data (available on the U.S. Environmental Protection Agency website [6]) is used to generate consumer agents with demographic characteristics, including gender, age, and weight. The population of consumer agents represents national demographic statistics.

4.2.2 Water ingestion

A water use model is used for each consumer agent to characterize the volume of water ingested each day and the timing of water ingestion events. The water use model estimates the daily volume of water ingested by each consumer based on age and gender [6]. A timing model is adopted to predict the three major meals during which water is ingested based on a set of probabilistic distributions [4]. Two minor meals are taken at the mid-point between each major meal. The daily volume of water is divided uniformly among these five meals.

4.2.3 Adoption of protective actions

Each consumer is initialized with a set of water activities, which are categorized as indoor end-use water uses, including washing clothes (22% of total water demand), toilet (26%), shower (17%), faucet (16%), leakages (14%), and other miscellaneous indoor uses (5%) [12]. Consumers reduce their normal water demand as they become aware of a contamination event or are exposed through ingestion of the contaminant. An agent is assigned a probability for suspending each water activity in the event of a water contamination problem. The probability for suspending each water activity varies based on the perception of consumers that an activity would cause exposure, and these values are calculated based on a survey that was fielded for a group of water consumers [11]. The sum of suspended water activities is used to represent the reduction in the individual water demand, and the final reduction in demand for each consumer is between 5% and 41.7%. The demand at a node in a water distribution network is updated using Eqn. 4.

$$d_{new,j} = \frac{p_j - \sum_{i=1}^{p_j} r_{ji}}{p_j} d_{normal,j} \tag{4}$$

where $d_{normal,j}$ is the base demand for normal conditions at node j; p_j is the number of consumers at node j, r_{ji} is the reduction factor for consumer i at node j; and $d_{new,j}$ is the new demand at node j.

4.2.4 Mobility

Consumer agents exert water demands at different nodes during a simulation as they travel to and from businesses and residences. Each consumer agent is assigned a residential node, a non-residential node, a duration of time that the agent remains at the residential node, and the time at which the consumer leaves the residential node to visit the non-residential node. These parameters are decoded within the ABM simulation to derive the pattern of travel for each consumer and to simulate the nodes where consumers ingest contaminated water and change the typical demand pattern by reducing water use. The timing for traveling within the network was generated for the population to fit the the hourly distributions of demands (specified in the water distribution model input file) at non-residential nodes.

4.2.5 Word-of-mouth communication among consumers

Each consumer sends and receives messages with other agents through a word-of-mouth mechanism, using a cluster model [10], which is similar to the small world network model. In this model, a small number of agents are grouped as a cluster, and each agent has a specific role in sending and receiving information. Agents are assigned roles as an original source, intermediate receiver, ultimate receiver, or information isolate. The original source receives and passes information to the intermediate receiver. In addition to communicating with an original source, the intermediate receiver also passes information to the ultimate receiver. The ultimate receiver can receive information, but cannot pass it to other agents, and the information isolate never receives or passes information. The cluster size is predefined as 15 consumers with two original source agents, five intermediate receiver agents, seven ultimate receivers, and one information isolate agent.

4.3 Utility manager agent

The utility manager ensures the quality of water delivered to consumers by collecting information from sensor networks and implementing a hydrant strategy for opening hydrants. The hydrant strategy is passed to a utility manager agent from the ES algorithm as one solution. Each solution specifies a delay in opening hydrants as the amount of time (number of time steps) that passes after the the utility manager receives the first warning message from the sensor network. After the time delay, the utility manager opens a hydrant. The utility manager closes each hydrant separately after a specified period, which is encoded in each solution as the duration, or number of time steps the hydrant should remain open.

5. EVOLUTION STRATEGIES OPTIMIZATION

To solve the problem formation represented in Eqn. 1, an EA-based approach is developed using Evolutionary Strategies (ES), which is a population-based evolutionary search algorithm. As in other EAs, ES applies a set of operators to a population of individuals to evolve toward an optimal solution over generations. At each iteration, a reproduction operator creates a set of child individuals from parent individuals, and the combined array of parents (μ) and children (λ) compete to survive. ES uses mutation to create new individuals by taking small incremental steps through the decision space. An adaptive ES approach mutates the mutation rate itself. Adaptive ES represents each decision variable with an additional associated gene to specify the mutation rate that is applied to its decision variable, and the mutation rate become smaller for each decision variable as an individual converges to an optimal value. In this study, a specialized mutation operator is used for searching through a network of nodes [21]. The elitist graduated overselection operator is also used to avoid premature convergence. These mechanisms are described in the following sections.

5.1 Network-based mutation operator

The network-based mutation operator is designed to mutate nodes in a graph or network. Using an adaptive ES approach, an additional decision variable is created to represent a mutation rate that is associated with the decision variable representing the node, which is the location of a hydrant that should be opened. The mutation rate specifies a maximum distance for changing the current node. The distance is calculated as steps, where a node is within one step of the current node if it is connected to the current node by one link (e.g., pipe). An array of candidate nodes is created that lists all nodes within the maximum number of steps from the current node. A node is selected with uniform probability from the candidates to replace the current node in the array of decision variables.

5.2 Elitist graduated overselection operator

An ES-based search is often implemented with a deterministic selection approach. This approach may cause premature convergence, as a solution that is highly fit in early generations may be repeated in the population and drive out diverse solutions that would provide exploration capabilities in subsequent generations. The elitist graduated overselection operator is designed to allow lower quality solutions to survive [7]. In the elitist graduated overselection operator, an archive of the parent and children individuals is formed and ranked based on objective function values. An auxiliary subset of this archive is separated from the combined

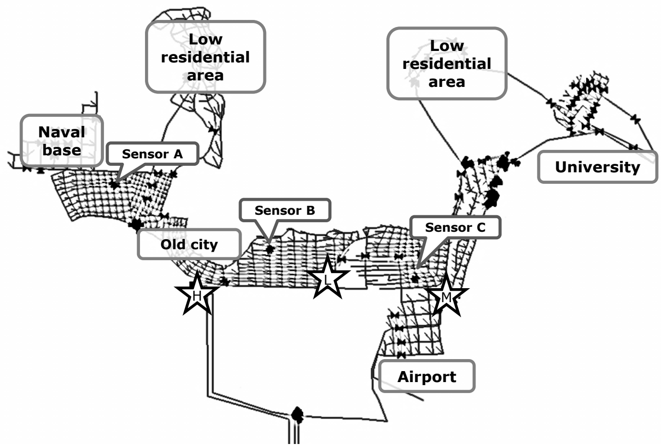

Figure 2: Mesopolis water distribution network; ensemble of water quality sensors, Sensors A, B, and C (filled circles); and nodes where contaminant is injected (stars). The level of contamination at each location is indicated as high (H), medium (M), or low (L).

individuals to participate in the selection operation. The initial size of the subset is predefined as an input parameter and described as a percentage of the population size. An individual is chosen with uniform probability from the subset with replacement. The subset size is increased by adding the highest-ranked individual left in the archive, and the next individual is selected from the subset. The subset continues to grow until the next population has been created. Through the use of the elitist graduate overselection operator, several copies of one solution may be created in the new population, and solutions that are not among the highest ranked solutions may survive in the new population.

6. ILLUSTRATIVE CASE STUDY: VIRTUAL CITY OF MESOPOLIS

The ABM-ES simulation-optimization framework is evaluated using a mid-sized virtual city, Mesopolis. Mesopolis was developed as a research tool for assessing algorithms and approaches for water distribution threat management (Fig. 2) [9]. The population of Mesopolis is approximately 150,000 people. The water distribution network is modeled with 1,588 nodes, 151 valves, 3,426 pipes, 69 pumps, one reservoir, and 13 storage tanks. Potable water is pumped from two water treatment plants that withdraw water from a surface water source. Consumers exert demands at a total of 704 terminal nodes. Node types, including residences, industries, airport, university, and commercial nodes, specify diurnal demand patterns. The water network is monitored with an ensemble of water quality sensors, which were placed at central nodes in the network on high-flow pipes. The diversity in land uses and the network topography provides a realistic case study for assessing the impact of hydrant strategies on the number of exposed consumers in Mesopolis.

7. CONTAMINATION EVENTS AND HYDRANT STRATEGIES

Three contamination events are simulated to represent the injection of high, medium, and low loads of arsenic at different locations in Mesopolis (Table 1). The occurrence probability of each event is not considered in this study, and a uniform probability is assigned for each event. Each event is simulated for ten random seeds, and the average and standard deviation (shown as $\pm$) are reported. When hydrants are not opened to flush out the contaminant, the number of exposed consumers is 4,439 $\pm$ 50, 3,851 $\pm$ 48, and 2,041 $\pm$ 66 for the high, medium, and low events, respectively. Each event activates only Sensor A.

The ABM-ES framework is applied to identify a hydrant strategy for the three events. Each hydrant strategy specifies three hydrants from 884 potential hydrants for flushing. Hydrants are modeled at nodes at which there are no demands exerted by consumers, and each hydrant is opened at a flow rate of 400 gpm from one to six hours after a sensor is activated and may remain open for up to six hours. The time of initialization indicates the delay after the Sensor A is activated before a hydrant is opened.To ensure the serviceability of the water network, a pressure of 20 psi should be met at all 704 demand nodes. In total, each solution has 18 decision variables: three decision variables for location, delay, and duration for each hydrant, and each decision variable is created with an additional associated gene to represent the mutation rate. The objective function value is calculated as the average performance of a strategy over the three events presented in Eqn. 1. The average performance of each hydrant strategy is determined by simulating three events and calculating the average over the number of exposed consumers for each simulation.

Table 1: Three contamination events are used to calculate the number of exposed consumers for each hydrant strategy. Each events has a duration of four hours.

Risk (Location)	Arsenic amount (kg)	Start time	Contamination detection time at sensor A
High	150	12:00AM	3:00AM
Medium	120	2:00AM	6:00AM
Low	80	4:00AM	11:00AM

8. RESULTS

The ABM-ES approach is executed to identify a hydrant strategy using the settings for the algorithmic parameters as shown in Table 2. Using these settings, a search generates 2,550 individuals, requiring a total of 7,650 function evaluations. Each function evaluation (execution of the ABM simulation) takes four minutes on a personal desktop computer to simulate a 24-hour event.

Five trials were executed using random seeds. The best solution from each trial is shown in Fig. 3, with the locations of the three hydrants that should be opened, the delay after the activation of Sensor A when each hydrant should be

Table 2: Algorithmic Settings for ES

Parameter	Setting
Trials	5
Population Size	50
Generations	50
λ	50
Overselection ratio	10%

opened, and the duration of flushing at each hydrant. The value of the objective function for each hydrant strategy is listed in Fig. 3, which is the average number of exposed consumers.

8.1 Best solution

The convergence plot for the best solution of the five trials, S1, is shown in Fig. 4. For any hydrant strategy, one time step (one hour in the simulation) passes after the sensor activation before a hydrant could be opened. For Solution S1, the first hydrant (H1) is identified with a delay of one hour, and as a result, the time at which the hydrant should be opened is 5:00AM, 8:00AM, and 1:00PM for the high, medium, and low events. To evaluate the effect of the stochasticity associated with the behavior of agents, each solution is simulated 10 times (Table 3). Solution S1 produces 1,813±53, 1,920±49, and 1,561±61 exposed consumers for the high, medium, and low events, respectively. S1 reduces the number of exposed consumers by 59%, 49%, and 23%, compared to the base case where no hydrants are opened. If the same hydrants are opened in the time step immediately after the contamination is released in the network, the number of exposed consumers is 1,645 ± 45 (reduction of 63% compared to no mitigation), 1,498 ± 40 (reduction of 69%), and 1,172 ± 51 (reduction of 43%). Further analysis can explore more strategic placement of sensors to detect events earlier and implement mitigation with a shorter response time to protect more consumers from exposure.

Table 3: Performance of the best solution from each trial.

Trial	Best solutions	Exposed consumers in high contamination scenario	Exposed consumers in medium contamination scenario	Exposed consumers in low contamination scenario
S1	1,695	1,813±53	1,920±49	1,561±61
S2	1,996	2,298±47	2,165±57	1,632±56
S3	2,019	2,368±59	2,271±48	1,530±64
S4	2,034.7	2,458±55	2,169±47	1,680±60
S5	2,128	2,341±51	2,385±57	1,776±68

8.2 Comparison of five solutions

The five solutions have similar performances, or objective function values. For each solution, the standard deviation (shown as ±) is relatively small, indicating that the effect of the randomness in the ABM simulation does not significantly impact the results. The solutions show a decreasing performance in the order S1, S2, S3, S4, and S5, with only some exception. Solution S3 ranks third with respect to the overall objective value, but it produces the most effective performance for the low event. This is because Hydrant H1 for Solution S3 flushes the eastern side of the network, which is significant in protecting consumers for the low event, though not as important for the medium and high events. Hydrant H1 is located on a main pipe and flushes a significant amount of contaminated water traveling through the system. In addition, there are several tanks located downstream of this hydrant that are filled during the night and drain during the day. Hydrant H1 flushes contaminant from the system that would be stored in the tank and released to the consumers later during the daytime.

The locations of open hydrants are diverse among the solutions. There is no hydrant that is included in each of the five solutions, and there is disparity among the solutions regarding the sections of the network where hydrants should be opened. Solutions S1, S2, and S3, are the highest performing solutions of the five solutions, and they show some similarity in the location of open hydrants; each solution flushes hydrants located in the upper northeast corner of the network, which is the location of a dense residential area where consumers actively exert demands throughout the simulation.

In general, the diversity among the decision characteristics of the solutions may indicate that many different hydrant strategies exist that solve the problem to the same degree (e.g., protect a similar number of consumers). More analysis is needed, however, to ensure that the solutions that have been identified are not local optima. The degree of non-uniqueness among hydrant strategies may also be due to disparity among the events that have been included in evaluation of the objective function. For the problem studied here, all events have only the activation of Sensor A in common; the events, however, have very different characteristics, such as contaminant load and location of injection. New information could be collected to more uniquely characterize events by installing additional sensors in the network or utilizing consumer complaint data. Using this new information, contamination events can be clustered into distinct groups, and the ABM-ES framework can be applied to identify more effective hydrant strategies.

8.3 Hydraulic conditions

Only a small number of solutions generated in the five trials violate the pressure constraint. This is because only three hydrants are opened throughout the network, which is a relatively large distribution system. In addition, the model of Mesopolis is skeletonized, where smaller pipes and household-level connections are not simulated. Instead, water consumption demands are clustered at a smaller set of nodes with aggregated demand values at levels that are similar to the hydrant flows. Twenty of the 704 demand nodes have a base demand greater than 100 gpm, and the university node exerts 3,000 gpm. An additional flow of 400 gpm, as simulated for the hydrant flow, does not significantly change the hydraulics of the network.

9. CONCLUSIONS

This study demonstrates a new approach for water distribution system threat management to minimize exposure to

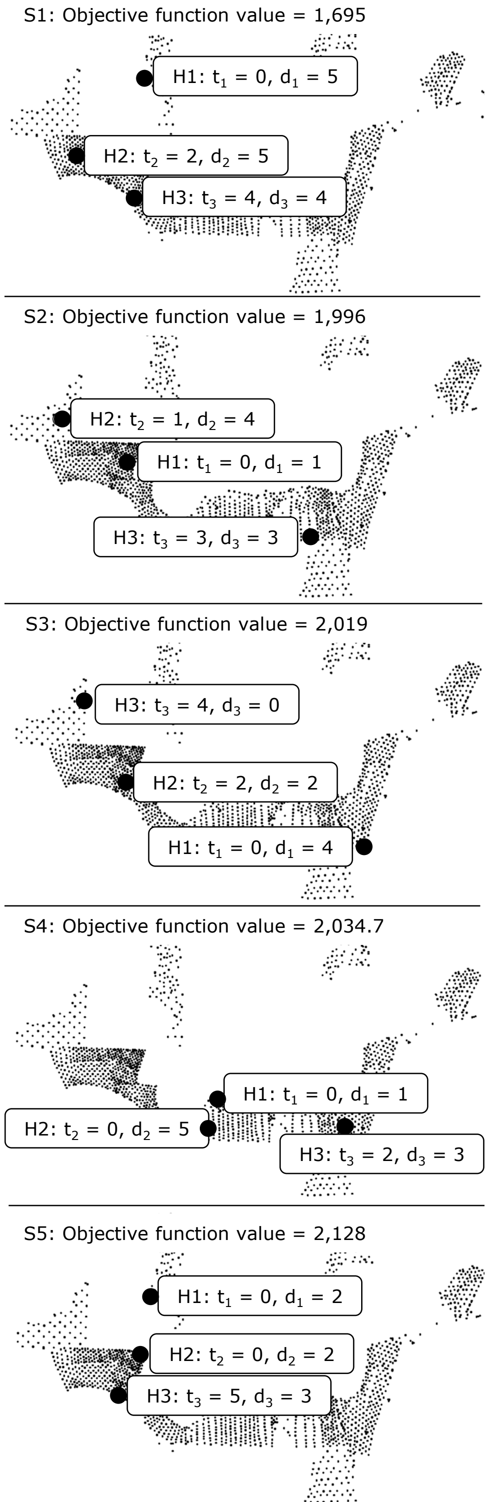

Figure 3: Location of hydrants for the best solution from each trial, along with the time (t) and duration (d) that each hydrant should be opened.

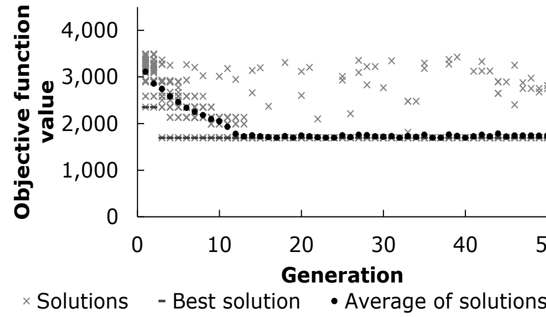

Figure 4: Convergence plot of Solution S1.

contamination through manipulating a set of hydrants for flushing the system. This research utilizes a ABM framework that simulates a sociotechnical water distribution contamination event, where the social and infrastructure systems interact to generate public health consequences. The ABM simulation is coupled with an ES-based search algorithm to identify the best hydrant strategy to protect consumers. For a case study, Mesopolis, the ES-based optimization is able to reduce the number of exposed consumers, compared to a base case without any protective actions. The framework that is developed here can be applied for managing real-world municipalities to determine the most effective hydrant strategies for removing a contaminant introduced to a water distribution network.

A significant contribution of this research is that a hydrant strategy is identified in association with the activation of a sensor, rather than identifying a hydrant strategy for a specific contamination event. For many contamination events, the location and time that a contaminant entered the system is not discovered until after the contaminant has exited the system, and the only real-time information available is sensor data. The approach developed here extends the research that has identified hydrant strategies to better assist managers in making real-time decisions by using the information that is available to them. The hydrant strategy does not rely on concentration or timing data for a sensor, which may be subject to significant error, but relies only on the activation of the sensor, or detection that a contaminant is present. The optimization framework can be applied in further research for a large set of contamination events to determine a library of rules for applying hydrant strategies based on the activation of different sensors in the network. A decision-maker can use the library to identify a hydrant strategy and will not need to rely on real-time execution of the simulation-optimization framework. If the likelihoods of individual events are known, these values can be used to weight the objective function to design hydrant strategies for more likely events. For example, exposed mains and treatment plants are more vulnerable to intentional contamination than buried connections.

The attributes and rules that determine the behavior of agents are simplified in this study and can be explored in future work for the real world application of this framework. For example, consumers have been simulated to immediately comply with warning messages from peers; a more realistic assumption may allow for a likelihood of compliance that would be involved in any human decision-making. In addition, the decision-maker responds immediately to the water quality sensors, and the sensitivity of the results to this assumption has not been explored in this study. Decision-makers typically take time to validate the presence of a threat before flushing the system or warning consumers. Further problem complexity may include the flow rate of hydrants as an additional set of decision variables, and the number of hydrants that are opened may be increased for more effective flushing. Finally, a decision-maker can select many different actions for reducing public health consequences, and combined strategies for both warning consumers and manipulating the hydraulic system should be optimized and identified simultaneously.

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