# Sociotechnical Simulation and Evolutionary Algorithm Optimization for Routing Siren Vehicles in a Water Distribution Contamination Event

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## ABSTRACT

Water distribution contamination incidents occur when a poisonous chemical or pathogen is introduced intentionally or accidentally to the pipe network that delivers potable water to the residents of a municipality. These events pose a challenge to decision makers, who should quickly identify a threat and the most effective response actions for protection of public health. In these events, the dynamic interactions among consumers, utility managers, public health officials, and the water distribution pipe network affect the emergent exposure of consumers. An Agent-Based Modeling (ABM) approach is used to simulate the interactions among agents and flow conditions in the water distribution system to provide an understanding of effects of dynamic and adaptive behaviors on public health. While utility operators can protect consumers using a wide range of protective and mitigative responses, routing of siren vehicles can be effective as consumers are warned about a contaminant in the water system and respond by stopping different water activities, such as drinking water. Development of crisis management routing strategies, which are a set of routes to best warn and protect consumers from exposure, is enabled through a new simulation-optimization framework. A genetic algorithm and the ABM are coupled to find routes for siren vehicles that minimize the number of consumers who are exposed to contaminated tap water. The framework is demonstrated for an illustrative case study, a mid-sized virtual city, to identify efficient routes for protecting public health.

## Categories and Subject Descriptors

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

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## General Terms

Algorithms

## 1. INTRODUCTION

Water distribution infrastructure systems are vulnerable to intrusion of dangerous toxins, and management of these threats is of concern for public health officials and water utility managers. Contamination may occur intentionally or accidentally, and the resulting propagation of pathogens or chemicals through a pipe network can seriously threaten public health. The water distribution contamination event is a dynamic and interactive system, as mitigative and protective actions are taken by utility managers and consumers. Consumers may reduce their typical daily water consumption as they are informed about the threat or become exposed to a contaminant through drinking tap water. A utility manager may control the contaminant movement by flushing out water through hydrants or manipulating valves to isolate the pollution in a section of the network. The responses and actions taken by both the consumers and the utility managers can change system hydraulics, which is the state of the flow direction and volume in the pipes, and these hydraulic fluctuations that occur during the contamination event due to the interaction of humans can cause difficulties in predicting the location of the contaminant and the resulting public health consequences. To better simulate the emergent contaminant movement during a water distribution contamination event, a Complex Adaptive System (CAS) approach has been demonstrated for capturing the dynamic adaptive behaviors and feedback loops among actors and the water distribution system by coupling Agent-based Modeling (ABM) of consumers and utility managers with an engineering model of the pipe network [25, 16]. Using this sociotechnical simulation approach, the emergent state of public health can be predicted as the result of actions and interactions of autonomous consumers, utility managers, and public health agents.

In a contamination event, decision makers should select mitigative responses from a set of potential hydraulic and social management strategies. While hydraulic strategies are designed to directly manipulate components of the pipe network to control the contaminant propagation, social strategies attempt to alter the water use of consumers by alerting individuals about the emergency through the use of media, siren vehicles, tone-alert radio, telephones, text alerting, and face-to-face interaction [14, 13, 17]. Siren vehicles can be de-

ployed from fire stations to travel throughout a municipality and are an effective approach for distributing warning messages. The timing and routes selected for the vehicles can significantly impact the number of consumers who are protected, however, and the most effective route for each vehicle should be identified to maximize the protection of consumers.As the ABM framework provides understanding of how the dynamics in the system will impact the transport of the contaminant in the pipe network, it can be used to guide utility managers in the selection of vehicle routes. A new simulation-optimization approach is developed and demonstrate here to optimize the route for a siren vehicle to minimize exposed consumers during a water distribution contamination event by coupling the ABM with a genetic algorithm-based approach. While previous studies coupled the ABM framework with a scatter search-based algorithm to select hydraulic operations, including opening fire hydrants to flush the system [24], this study explores instead an approach for optimizing social management strategies. In addition, the framework is demonstrated for application to a mid-sized virtual city of 150,000 consumers to minimize exposure after contaminant is introduced to the pipe network.

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

ABM is a computational model for simulating the actions and interactions of autonomous agents to evaluate their collective effect on system properties. Enabled by an explosive growth in computational power over the past several decades, ABM has been employed as a powerful technique for exploring various Complex Adaptive Systems (CAS) in diverse disciplines of study. Agents receive information about their environment, have goals, and take action to change their environment and achieve their goals. Additionally, an agent can interact with other agents by receiving and conveying information.

An ABM approach can be used to characterize infrastructure systems and capture dynamic interactions among the state of the system, consumers, infrastructure conditions, and policy decisions, by simulating interacting agents that influence the emergent system properties through dynamic feedback loops. The interaction of water consumers and water utility managers has been simulated using ABM to study water supply management in normal operating conditions [21, 2]. These studies provide insight into the effect of interactions among consumer agents on the emerging demand pattern of a community and provide examples of rules for utility manager and consumer agents. Zechman [25] and Shafiee and Zechman [16] applied a CAS approach to simulate the water distribution system contamination event by coupling a water distribution model with an ABM and demonstrated the CAS approach for two example pipe networks serving diverse municipalities.

+ The modeling framework described here couples a water distribution simulator, EPANET [15], with an ABM framework, AnyLogic [20]. Consumers and utility managers are represented as agents and select active and reactive behaviors based on a set of rules. Consumer agents responds to a water contamination event using new information and signals that they receive from the infrastructure and the utility manager agent. The utility manager agent monitors the water distribution system and sends information about contamination of the system by deploying siren vehicles. The relevant characteristics and decisions of consumers, including water ingestion timings, volume of water ingestion, symptomatic responses to the ingested contaminant, word-of-mouth communications, and changes in water demand patterns are represented mathematically. The modeling framework is shown in Fig. 1, and consumer characteristics are described below. While the basis for this modeling system has been described in previous publications [24], additional mechanisms are described here beyond what was previously implemented. The new mechanisms are described below and include incorporation of demographic information to allow heterogeneity of consumer water use behaviors (Section 2.2); an improved clustering method for representing communication among consumers (Section 2.5); and a new modeling approach for simulating the likelihood of consumers to stop using water for different end uses (Section 2.6).

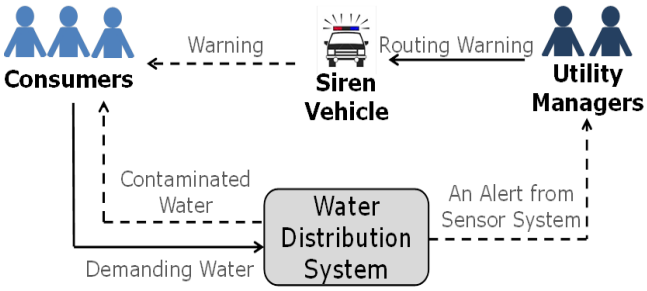


**Figure 1: Agent-Based Modeling Framework for water distribution contamination events. Information that is passed among agents is shown as a solid line, while actions exerted on components is shown as a dashed line.**

### 2.1 Water Distribution System Modeling

EPANET is a software for simulating water distribution pipe networks and performs extended-period simulation of hydraulic conditions and the transport and fate of contaminants and chemical species. Pipe networks consist of pipes, nodes (which are junctions of multiple pipes), pumps, valves, and storage tanks or reservoirs. EPANET calculates flows within each pipe, pressures at nodes, the height of water in storage tanks, and the concentration of chemical species within the network.

### 2.2 Demographic Characteristics

The weight, age, and gender of consumers impact how each consumer behaves and are represented based on widely available data [6]. This data is used to generate a population with characteristics that are statistically similar to national characteristics.

### 2.3 Water Ingestion

Both the amount of water that is ingested each day and the timing of ingestion events are required for the ABM calculations. Davis and Janke developed a model that combines the prediction of when a consumer ingests tap water with the predicted amount of tap water a consumer ingests per day

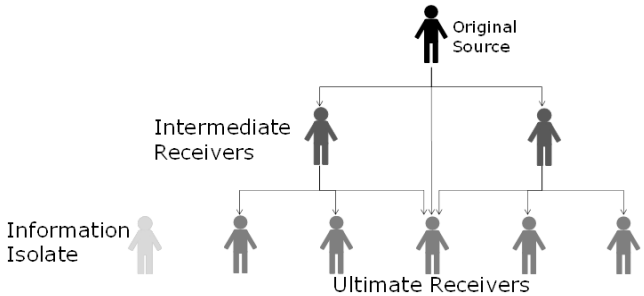


**Figure 2: Framework of social clusters for simulating word-of-mouth communication.**

[5, 4]. The daily volume of water ingested by each person is calculated using data published by the U.S. Environmental Protection Agency (EPA) that predicts the volume of water ingested based on age and gender [6]. Davis and Janke developed a timing model as a set of probabilistic distributions that estimate the times at which three meals are taken by each consumer [5]. Two minor meals are taken at the mid-point between each meal. The model assumes that consumers take five meals per day, which are the only times that consumers ingest tap water, and the total ingested volume of water is divided among these five meals.

## 2.4 Mobility

Mobility of consumers within a city also translates to poorly predicted changes in the hydraulic conditions in the water distribution system, as consumers travel to and from places of business and residences and exert demands for water at different nodes. To simulate mobility of the population, each consumer is assigned a residential and a non-residential node. The network provides the Cartesian coordinates of each node in the system, which is used to calculate the distance between nodes and represent travel time for any consumer. While traveling, consumers do not exert demands on the network and cannot be exposed to the contaminant. Consumers who have changed their water demands effect the expected diurnal pattern of water demands at both non-residential and residential nodes, based on their location at each time step.

## 2.5 Communication among Consumers

The ability of consumers to communicate actual or perceived risks to other consumers is included in the model as word-of-mouth communication. Each consumer is simulated within a social network and is connected to a number of other consumers. Any consumer who is exposed to the contaminant or is made aware of the event through warnings from siren vehicles or other consumers will alert individuals in his social network. Any consumer who receives an alert responds by reducing his water consumption. The social network for any one consumer is represented as a cluster [10], where different individuals are assigned the role of original source, intermediate receiver, ultimate receiver, or information isolate. Each cluster is composed of 15 individuals, with two intermediate sources. The structure of a cluster is shown in Fig. 2.

## 2.6 Adopting Protective Actions

As consumers become aware of the contamination event, they reduce their normal daily water demands and can reduce a set of many different water use activities. Lindell et al. [11] has listed water activities and evaluated the probability of suspending each water activity in a hypothetical water contamination event among residents in a college city. These water activities correspond to 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]. The final reduction in demand for each consumer is between 5% and 41.7%. The demand at any node is updated using Eqn. 1.

$$dnew_j = \frac{p_j - \sum_{i=1}^{p_j} r_{ji}}{p_j} dold_j \tag{1}$$

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

# 3. SIMULATION OF SIREN VEHICLES

Siren vehicles are simulated as traveling through the city using graph theory [22]. A set of points in the city are selected as part of a route, and the shortest path between each pair of nodes is calculated to form a loop. This model uses nodes from the water distribution system model to represent intersections of roads. As pipes typically lie beneath or along roads, this assumption is reasonable for this study. Siren vehicles begin at a fire station and return to the fire station once all nodes in a route have been visited.
A graph of $G(\bar{V},\bar{E})$ represents the road map of a city, where $\bar{V} = (v_1, v_2, ..., v_n)$ represent intersections, and $\bar{E} = (e_1, e_2, ..., e_m)$ represents road segments between pairs of intersections. To construct a route for one vehicle, a set of intersections are selected, and the shortest distance between each pair of sequential intersections is calculated using the back-tracking algorithm, which identifies the shortest path between two locations, or vertexes, in a graph of $G(\bar{V},\bar{E})$ by incrementally adding segments to build a path.
The travel time for an emergency vehicle over each road segment is calculated as [7]:

$$t = 0.765 + 1.11d \tag{2}$$

where $t$ is time in minutes and $d$ is length of the route in miles. The travel time for a vehicle is the sum of travel time over all segments. While a vehicle travels through the city, warning messages are transmitted to adjacent neighborhoods. The warning message is simulated as audible to consumers who are located within 0.5 miles from the route.

# 4. EVOLUTIONARY ALGORITHM-BASED APPROACH FOR ROUTE IDENTIFICATION

Many studies have coupled agent-based modeling simulation to an optimization technique to find the optimal decisions by considering the interactions between agents[8, 19].In the field of threat management for water distribution systems, and more specifically in event response planning, optimization methods have been applied to identify hydraulic management strategies for mitigating contamination events [3, 18, 1, 24]. These studies planned strategies for opening

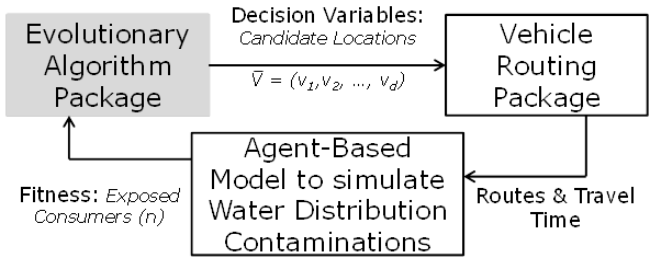


**Figure 3: Simulation-optimization framework.**

hydrants and closing valves within pipe networks to minimize consumer exposure. A simulation-optimization approach is taken here that couples a genetic algorithm (GA) [9] with the ABM framework to identify a route for a siren vehicle to minimize the number of exposed consumers. Individual solutions represent the route as a set of intersections, or nodes in the pipe network, $\bar{V} = (v_1, v_2, ..., v_d)$, where $d$ intersections are used to specify a route (Fig. 3). The specified route serves as an input to the ABM framework, which is used to calculate the number of exposed consumers as the fitness function for any solution. The GA-ABM framework minimizes exposure using the following optimization model:

$$\min n = f(\bar{V}) \tag{3}$$

where $n$ is the number of exposed consumers as a function of a set of nodes $\bar{V}$ to be routed. For the preliminary study presented here, only one siren vehicle is deployed to warn consumers. For a city the size of Mesopolis, typically there would be approximately nine fire stations. Future studies will simulate multiple vehicles, each of which would be deployed from a fire station.

## 5. ILLUSTRATIVE CASE STUDY: VIRTUAL CITY OF MESOPOLIS

The ABM-GA framework is applied here to Mesopolis, which is a mid-size virtual city that was developed to provide a model of a realistic city for research in water distribution system planning and security (Fig. 4). Mesopolis is a city of 150,000 inhabitants. The water distribution system is modeled with 1588 nodes, 151 valves, 3426 pipes, 69 pumps, one reservoir, and 13 tanks. Demands are exerted at 704 of the nodes, characterized as residences, industries, restaurants, airport, university, commercial, and industrial nodes. Two water treatment plants withdraw raw water from a source and distribute it throughout the city. The diversity in demand patterns and the topography of the system provides a realistic case study for examining a set of scenarios, assessing the impact of contamination on public health, and evaluating different management strategies.

## 6. ARSENIC CONTAMINATION EVENT

A contamination event is simulated in Mesopolis as an intentional hazard, where 300 kg of arsenic is injected to the system over a period of six hours, beginning at 12:00AM, at the West Treatment Plant (Fig. 4). A consumer is considered as exposed once he has ingested an amount of arsenic that exceeds 0.005% of his body weight in kilograms [23].

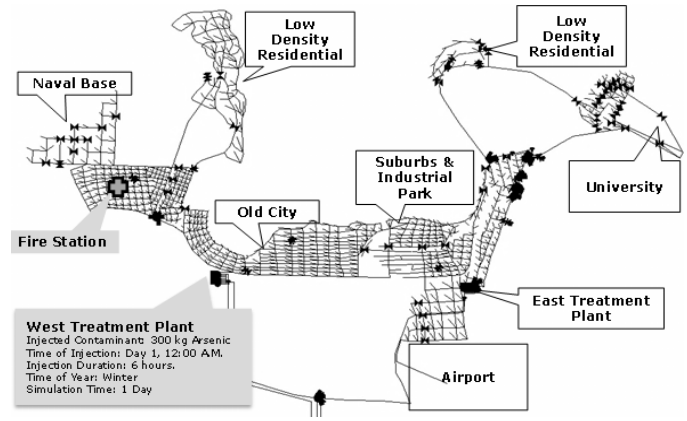


**Figure 4: Mesopolis water distribution network.**

**Table 1: Algorithm Settings for ABM-GA**

| Parameter | Setting |
|---|---|
| Trials | 5 |
| Population Size | 60 |
| Generations | 60 |
| Mutation Rate | 1% |
| Crossover Rate | 80% |

The arsenic event was simulated for 30 realizations, and the average number of exposed consumers is 10,577, with a standard deviation of 80. Stochasticity is present in the model due to the probabilistic nature of demographic information, ingestion timing and volumes, and mobility patterns, which are all assigned to consumers as random values at initialization of the simulation. For this simulation, the only protective action being taken that would prevent some consumers from being exposed is through the word-of-mouth. When the word-of-mouth mechanism is excluded, the average number of exposed consumers is 12,299 over 30 simulations, with a standard deviation of 96.

For this contamination event, the propagation of the contaminant plume is simulated over a 24-hour period. The polluted nodes of the pipe network are shown in Figure 5 at 6-hour time increments. A node is considered as polluted at a time step if the concentration of the contaminant exceeds 0.001 $\frac{mg}{L}$ at the node. The contaminant plume moves west from its location of injection, which is the West Treatment Plant, in the first 12 hours of simulation. The contaminant then travels into the northern most section of the network, which is a residential area, and then to the central section of the city.

## 7. RESULTS

For optimizing routes, it is assumed that the contamination is detected quickly, and one siren vehicle is deployed from a fire station one hour after the contaminant begins its release, or at 1:00AM. Each solution specifies 10 nodes in the network that are used for routing the vehicle. Parameter settings for the GA are shown in Table 1. The ABM-GA framework was executed for five random trials to optimize the modeled problem. Convergence of the GA is shown in Fig. 6. The convergence behavior for the five trials are sim-

**Table 2: Performance of five solutions.**

| Solution | Fitness | Exposed Consumers[1] (Routing) | Exposed Consumers[1] (Routing without word-of-mouth) | Travel Time (min.) |
|---|---|---|---|---|
| 1 | $4,977$ | $5,155 \pm 97$ | $9,469 \pm 78$ | 238 |
| 2 | $5,057$ | $5,194 \pm 73$ | $9,513 \pm 114$ | 236 |
| 3 | $5,074$ | $5,265 \pm 88$ | $9,676 \pm 81$ | 233 |
| 4 | $5,448$ | $5,602 \pm 97$ | $9,705.1 \pm 66$ | 228 |
| 5 | $5,678$ | $5,772 \pm 83$ | $10,170 \pm 90$ | 220 |

[1] Evaluation of solution over 30 trials, reported as average and standard deviation.

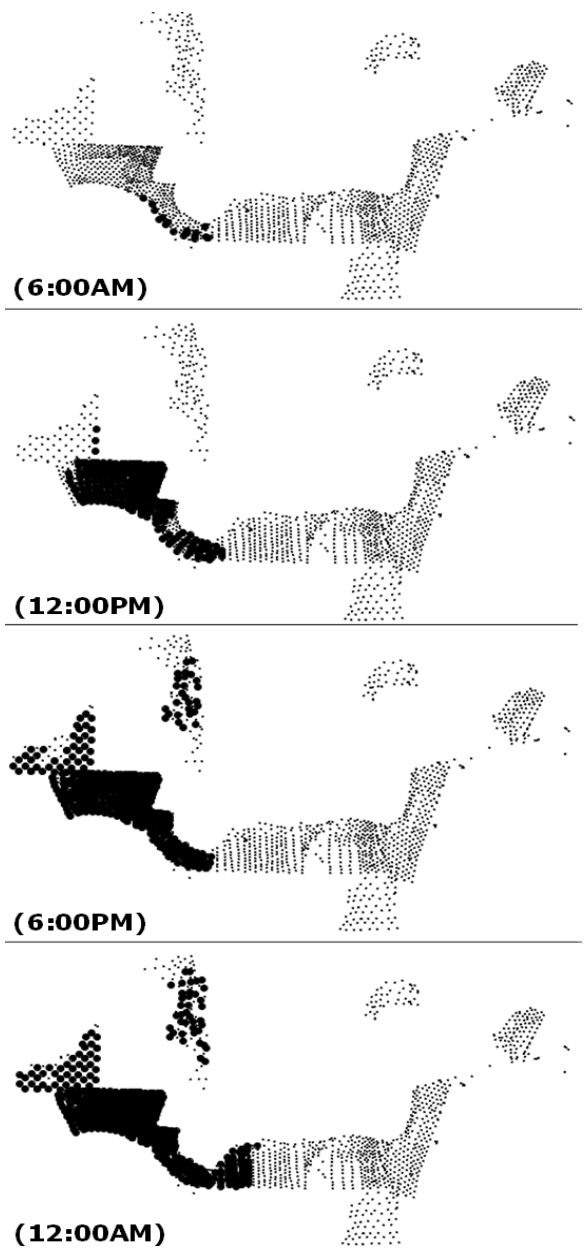


**Figure 5: Polluted nodes in Mesopolis during the contamination event. Dark circles indicate contaminated nodes**

ilar; for each trial, the average fitness of the population and the fitness of the best solution converge to similar values after 60 generations. The performance of the five solutions are shown in Table 2. Solutions 1, 2, and 3 represent routes with a low number of exposed consumers. Though the fitness function of a solution is a stochastic value due to the stochasticity in the ABM, each solution is evaluated only once to evaluate its fitness value, rather than as an average over a small set of trials, such as the approach taken by a noisy GAs. To better approximate the true performance of each optimized solution, each solution is post-processed and simulated for 30 simulation realizations using the ABM framework. These results (Table 2) reveal that the fitness value of each of the five solutions is close to the average number of exposed consumers, at 2-4% lower than the average. The standard deviation for the number of exposed consumers for each of the five solutions over 30 trials is 1-2% of the average, indicating that while there are several stochastic mechanisms included in the model, the overall performance of each solution does not vary considerably for different random trials. Each solution reduces the number of exposed consumers by approximately 50% when compared to the base case where no actions are taken to protect or warn consumers.

Each solution represents a route through the network, each of which is shown in Fig. 7. Solutions 1, 2, and 3 show similarity in the decision variables that specify how the vehicle should be routed. In these solutions, the vehicle travels first to the western part of the city, then visits the most northern residential section of the city, and finally makes a loop through the central area. For each solution, the route takes less than four hours to complete, while the plume spreads throughout the network over 24 hours. Solutions 1 and 2 route the vehicle to visit the locations where the plume will arrive in a pattern that is similar to the propagation of the plume (as shown in Fig. 5). The siren vehicle warns the consumers in the northern Low Density Residential Zone within the first few hours of the route, because they will be exposed to contaminated water early in the morning. The vehicle travels then to the Suburbs and Industrial Park in the central and eastern part of the city. Though these nodes do not receive any contaminated water during this event, 7000 consumers are located at industrial nodes, and they change shifts at 8:00AM. At that time, these consumers return to their residences, some of which are located in the western part of the city where the contaminated water is moving through the network. These consumers have been warned by the siren vehicle before returning home and have already reduced their water usage as a result. For example, Solution 4 takes only a short route through the industrial zone, and

the average number of exposed consumers increases by 9% compared to the best solution, Solution 1.

## 7.1 Sequence of Nodes in a Route

For each route, the sequence that the 10 nodes are visited is shown in Fig. 7. Solution 3 visits similar nodes as specified by Solutions 1 and 2, but visits the central part of the city first. The order of the visited nodes is not critical in this case because the total route is completed before the plume travels very far from the West Treatment Plant. The order of visiting different nodes may become more important if more delay is allowed between the time the contaminant is released in the system and the vehicle is deployed. In other cases, the speed of the emergency vehicles may vary from those assumed here, which would change the significance of the timing of the route. For this simulation, the length of a road segment is taken as the distance between two nodes, or pipe junctions, and 92% of the segments are between 500 and 3000 ft. in length, with corresponding speeds of 5-25 miles per hour.

## 7.2 Effects of Word-of-mouth and Siren Vehicles on Number of Exposed Consumers

The effectiveness of each route can be attributed to two mechanisms included in the model. When a vehicle passes through a route, consumers located at terminal nodes that are proximal to the route are warned, even if the nodes do not touch the route. As described above, consumers at terminal nodes within 0.5 miles of the route are also warned. Based on the density of nodes in Mesopolis, there are typically four nodes within 0.5 miles of any node. For Solutions 1-5, the number of terminal nodes that are contacted by the siren vehicle are 364, 361, 359, 341, and 330, respectively, out of 706 terminal nodes in the network. This indicates that a wide band of consumers along a route are able to receive information about the event. In addition, as the number of nodes reached by the siren vehicle decreases from Solution 1 to 5, the fitness also decreases (the number of exposed consumers increases) linearly.

The word-of-mouth mechanism is the second factor that can significantly increase the effectiveness of the siren vehicles. As shown in Table 2, when the word-of-mouth mechanism is not included in the simulation, and routing is the only channel for raising awareness of the event to allow consumers take protective actions, then the effects of routing are reduced, and the number of exposed consumers increases by 60-90% for the five solutions. For example, for Solution 1, the average number of exposed consumers is 5,155 when siren vehicles and the word-of-mouth are included; 9,469 when only siren vehicles are included; 10,577 when only the word-of-mouth mechanism is included; and 12,299 when neither mechanism is included (as shown above in Section 6). The siren vehicle as modeled here has a slightly stronger effect than just word-of-mouth alone in reducing the number of exposed consumers, but the word-of-mouth mechanism has a strong influence in enhancing the effects of siren vehicles. When a consumer receives a warning from a siren vehicle, he communicates with other consumers in his social network, which results in an overall increased reduction in the number of exposed consumers. Consumers are placed in clusters based on the node of their residence, however; when a consumer who is located at his residential node is warned by a siren vehicle and communicates with his peers, it is likely that these consumers have also been warned by the siren vehicle and the word-of-mouth communication has no effect to further protect consumers. The true effect of word-of-mouth can be seen for consumers that are located in the industrial zone when they are warned by a siren vehicle. These consumers are assigned to clusters with individuals who are located at their residences, which are nodes located throughout the city. These individuals have the potential to warn consumers who have not been alerted through the siren vehicle.

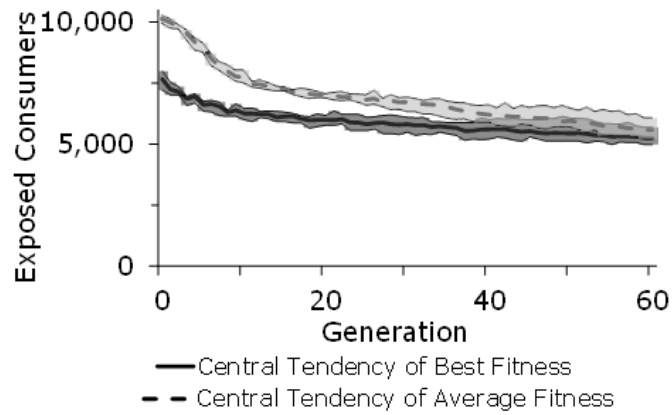


**Figure 6: Convergence of ABM-GA, shown as the range and central tendency of the best objective and average objective over the five trials.**

# 8. CONCLUSIONS

This study demonstrates a new approach for water distribution system threat management. The consequences of a contamination event for public health are minimized through the use of siren vehicles as a response plan. This research couples a new sociotechnical CAS model of a water distribution system with a GA to identify the best routing path for a siren vehicle to protect consumers in a virtual city, Mesopolis. The GA-based optimization is able to reduce the number of exposed consumers by approximately 50%, compared to a base case without any protective actions.

Some parameters used for simulating consumer behavior are simplified in this study and can be explored in future work. For example, all consumers react similarly to the same arsenic dose; consumers comply completely with warnings from both siren vehicles and peers; consumers pass information to peers and stop water activities within one hour (one time step of the water distribution system model) after being alerted or becoming exposed; and consumers are able to identify the source of exposure as the water system when they become sick. As some of these behaviors can significantly impact the quality of the results and the predicted health outcomes, they should be tested in further work through sensitivity analysis.

The framework that is developed here can be applied for municipalities to determine the most effective routes for deploying emergency vehicles. While only one vehicle was simulated here, many municipalities would be able to deploy a vehicle from each of several fire stations. Providing the best route for each vehicle will increase the complexity of the al-

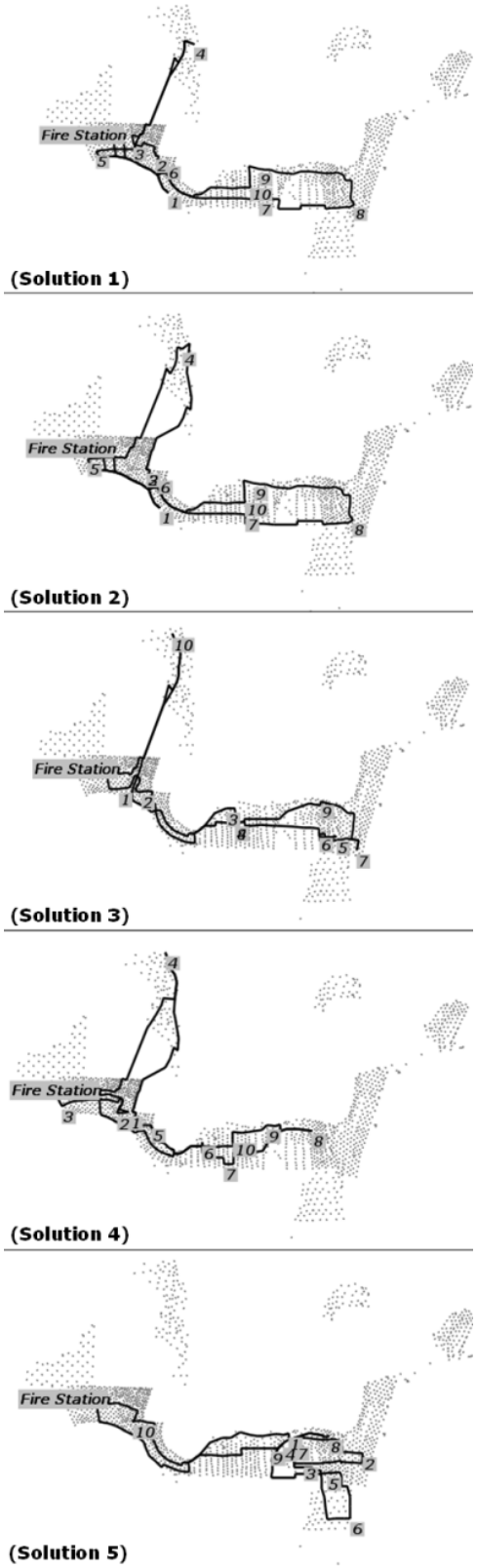


**Figure 7: Vehicle routes corresponding to Solutions 1-5. The sequence of nodes that the vehicle visits are ordered 1-10.**

gorithm. As consumers move among different zones in a city, routing a fleet of vehicles can be posed as a set of interconnected and inseparable problems. The set of routes should be identified simultaneously to maximize public health protection. In addition, 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 can be identified simultaneously.

## 9. ACKNOWLEDGMENTS

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