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Agent-based modeling and evolutionary computation for disseminating public advisories about hazardous material emergencies

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ABSTRACT

In the event of a large-scale disaster, an important aspect of humanitarian logistics is the distribution of information or warnings to the affected population. This research develops the problem formulation and solution approach for a specific routing for relief problem, in which warnings should be disseminated to an affected community, using public announcement systems mounted on emergency vehicles. The problem statement is formulated to maximize the number of individuals of a community who are protected. An evolutionary algorithm framework is developed by coupling an agent-based model with a variable-length genetic algorithm to route emergency vehicles. The dynamics of interactions among consumers, emergency vehicles, and the spatiotemporal trajectory of the hazard are simulated using an agent-based modeling approach, and a variable-length genetic algorithm approach selects routes to warn a maximum number of consumers before they are affected by the emergency. The example that is explored in this research is contamination of a water distribution network. A fleet of emergency vehicles is equipped with public address systems and is deployed to warn consumers to stop using contaminated water. The framework is demonstrated for an illustrative virtual city, Mesopolis. The results of the evolutionary algorithm framework are compared with two conventional routing optimization approaches, including a covering tour problem approach and a manual routing approach, for four contamination scenarios. The evolutionary algorithm can be applied to route emergency service vehicles to broadcast information for other emergencies, such as flash flooding, hazardous materials incidents, and severe weather.
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1. Introduction

In the aftermath of large disasters, vehicles can be routed to carry critical resources, services, or information to the affected population. Logistical and transportation planning in relief efforts differ from routine decision-making, however, and new problem formulations and solution methods are needed. In planning relief efforts, lead times are low; stakes are high; supply and transportation data are typically unreliable, incomplete, or non-existent; and there are few performance measures that have been established to evaluate success (Beamon, 2004). Classic routing problems that are formulated to minimize cost, total travel time, or tour length do not properly reflect the relevant priorities in disaster relief. Deliveries should be fast and also fair to the affected population. For example, Campbell, Vandenbussche, and Hermann (2008) explored vehicle routing for relief efforts and formulated problem objectives to minimize suffering and the loss of life for a set of static demands. The traditional traveling salesman problem has been reformulated for application to relief effort planning by minimizing the cumulative waiting time of customers, rather than minimizing the tour length of a vehicle (Ngueveu, Prins, & Calvo, 2010; Ribeiro & Laporte, 2012). Relief operations may also be represented as maximal covering tour problems, in which stations and routes are selected to maximize the demand that is covered (Doerner, Focke, & Gutjahr, 2006; Naji-Azimi, Renaud, Ruiz, & Salari, 2012; Noltz, Doerner, Gutjahr, & Hartl, 2009; Tricoire, Graf, & Gutjahr, 2012).

The research presented here is motivated by the need for vehicle routing for a specific case of humanitarian efforts, in which information or warnings about a hazard should be disseminated to an affected community as a crisis progresses. To broadcast emergency information in disasters such as flash flooding, hazardous materials incidents, and severe weather, emergency service vehicles can be equipped with sirens and a built-in public announcement system (Golnaraghi, 2012). Alerts are disseminated by vehicles, which follow predetermined routes to warn citizens in designated neighborhoods. To distribute information most effectively, vehicle routing should be coordinated with the movement of the population and the concurrent spatiotemporal movement of the hazard. Individuals in the population may be mobile, adjust resource use, and exchange information about the emergency, which increases the dynamic and complex nature of the problem. For the problem of distributing information, the routing problem is formulated here to protect lives, rather than meet demands or minimize travel time.

An optimization approach is developed here to route vehicles for the dynamic problem described above. More broadly, this study explores

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the improvement in routes, based on the number of lives saved, that are identified using dynamic optimization with respect to static optimization. In the system defined in this research, the routing ecosystem is changing due to the interactions and movement of consumers and the hazardous material and is represented using an agent-based modeling approach. Routes are developed to distribute information or resources by anticipating the movement of hazardous material and the interactions of consumers. An agent-based modeling (ABM) approach is developed to simulate the dynamics of the transport of a hazardous material, the movement of emergency vehicles, and the exposure of individual members of a community based on their movement in a city and their communication about the event. While ABM has been used in many studies for vehicle routing (e.g. Baykasolu & Kaplanolu, 2015, Dia, 2002, Martinez, Correia, & Viegas, 2015), few studies have applied ABM for vehicle routing in emergency conditions. These studies simulate driver decisions in evacuation of urban areas (Chen, Meaker, & Zhan, 2006; Chen & Zhan, 2008; Naghawi & Wolshon, 2012). An optimization problem is formulated to maximize the number of consumers that are protected, or warned before they are affected by a hazard. An optimization approach is developed using a variable-length genetic algorithm (VGA), which uses a variable-length chromosome to represent routes of any length (e.g., number of nodes) for a fleet of vehicles. The VGA is coupled with the ABM to design tours for a fleet of vehicles to protect consumers. The simulation-optimization approach is demonstrated for a hazardous material emergency in which a water supply system is contaminated with arsenic. The framework is developed and demonstrated for routing emergency vehicles to warn consumers to change their use of contaminated water.

The remainder of the paper is organized as follows. Section 2 describes the characteristics of a water contamination event and the actors who are involved. Section 3 formulates the vehicle routing problem as a conventional Covering Tour Problem (CTP) and describes the application of an established approach, a coupled genetic algorithm (GA) and ant colony optimization (ACO), to solve it. Section 4 formulates the new routing problem to maximize the number of consumers who are protected, which introduces additional complexity to the problem definition. An evolutionary algorithm framework is developed in Section 5 for solving the vehicle routing problem by coupling a VGA and ABM. The evolutionary algorithm framework is applied for a mid-sized virtual city that is based on realistic pipe network characteristics and demographic data for a population of 150,000, as described in Section 6. A set of contamination scenarios are described in Section 7, and results are reported in Section 8. Results that are identified using the evolutionary algorithm framework are compared with a manual approach and the covering tour problem approach, which neglect the complexity of *sociotechnical* interactions among society, emergency services, and infrastructure, as the event progresses. Results demonstrate that the sociotechnical dynamics of a water event alter the effectiveness of routes for emergency vehicles, and the evolutionary algorithm framework identifies routes for a fleet of emergency vehicles that protect a larger number of consumers, compared to other routing approaches.

2. Water supply contamination event

Public health is threatened when chemical toxins or bacterial pathogens enter water distribution networks through deliberate actions or accidental incidents and are delivered to a large population dispersed over a wide geographical area (Hrudey & Hrudey, 2004). A water contamination event is a dynamic and complex event in which the interactions among the social and infrastructure systems create a sociotechnical system (Vicente & Christoffersen, 2006). The movement of the contaminant in the pipe network and public health consequences emerge from a set of complex adaptive interactions between consumer demands, utility operations, and the water distribution infrastructure (Rasekh, Shafiee, Zechman, & Brumbelow, 2014; Shafiee & Zechman, 2013; Zechman, 2011, 2013). A contaminant that enters a water network may be detected by water quality sensors, which alert managers about the threat of a contaminant. Once a contaminant is verified, a utility manger can select actions to protect consumers, including warning consumers to encourage a reduction in water contact uses. Consumers may become aware of a contaminant through symptoms of exposure, public advisories, and communication with peers and family members. As consumers reduce their use of water, they change their water demand patterns and the movement of contaminant plume from its expected coverage of the network.

Using public announcement systems mounted on emergency vehicles can be an effective approach to warn and protect consumers during an emergency (Perry & Lindell, 2003; Sorensen, Shumpert, & Vogt, 2004). Sorensen and Rogers (1988) report that 16% of communities with hazardous materials industries rely on route alert or door-to-door as a warning system, and 45% of these communities rely on a combination of media reports, emergency alert (siren) systems, and door-to-door or route alerts. Though recent technologies, such as microblogging and text messaging, may seem to make the use of route alerts obsolete, utility managers may continue to use route alerts for specific cases. In addition, recent surveys that were conducted to estimate the perception of consumers with warnings during a water contamination event show that only a portion of consumers complied with warnings after a water main break in Boston (Lindell, Mumpower, Wu, & Hwang, 2010). Similarly, surveys conducted in West Virginia after the Elk River Spill that occurred in January 2014 report that 37.0% of households surveyed under the Do Not Use order used West Virginia American Water (WVAW) water despite knowing about the restriction, 78.8% of these households reported showering in contaminated water, 46.8% reported using water to wash hands, and 27.7% reported drinking water or using it to prepare food (Disease Control et al., 2014). A mere 2.3% of households interviewed first learned about the Do Not Use Order from social media. It is evident that rigorous strategies are needed to warn an entire population and communicate real threats of danger, and while social media provides a promising strategy, it may not be the most effective approach in all communities at the current time. Cities such as San Francisco, CA, have developed plans to alert citizens about evacuation orders through several media outlets, including plans for officials to drive with bullhorns through an evacuation zone to make roving announcements. For emergencies in which citizens lose power, public-address vehicles may be the most effective broadcasting system. Route alerts may also be more effective in localized events in densely populated areas, such as college campuses and urban centers. Managers may select to use route alerts to communicate the severity of an event directly and reach segments of the population who may not use television, radio, or text messaging.

The effectiveness of routes chosen for emergency vehicles may be significantly impacted by sociotechnical interactions during an event. Public health consequences of emergencies emerge from complex dynamics, including interactions and feedbacks among consumers and the water distribution system. Consumers travel throughout a city during a day, and these patterns can impact their proximity to a vehicle route and their communication with other consumers about the presence of a contaminant threat. As consumers receive information about a water event, they may dynamically update their water demands by adopting personal protective actions to reduce their use of water and exposure to the contaminant. The exposure of any consumer depends on the route of the emergency vehicles, travel among nodes, consumption of contaminated water at diverse locations in a network, and changes in personal water use activities based on exposure symptoms and alerts about the event. As consumers change their water use, new demand patterns can change the flow directions and volumes in the pipe network and expose a different segment of the population than would be originally expected or predicted.

An agent-based modeling-water distribution (ABM-WD) approach is developed to address the complexity of a water contamination event. It is described below and is used to simulate consumers as agents who interact with other agents, the water infrastructure system, and siren vehicles.

3. Problem formulation and solution approach: routing to maximize coverage

The routing problem is formulated in this section using a conventional approach. Here, the original problem is decomposed into two sequential problems, which results in a problem that is more trivial to solve; however, the final solution is expected to be inferior to a solution found through solving the original problem. We use a decomposed approach to provide a benchmark for the new algorithm that is introduced here, the ABM-VGA (Section 5). Because we introduce in this work both a new problem (Section 4) and a new problem solution, the decomposed problem provides a realistic value for the expected performance of the ABM-VGA.

The conventional approach maximizes the coverage of demand nodes using a CTP formulation. The CTP is a classic vehicle routing problem that is solved to distribute a warning message uniformly among consumers, or nodes in a graph, and has been solved for humanitarian logistics applications to place distribution centers (Doerner et al., 2006; Naji-Azimi et al., 2012; Noltz et al., 2009; Tricoire et al., 2012). The CTP formulation identifies the least-cost tour to provide a service to a subset of nodes and cover the maximum number of nodes. Covered nodes may not be on the tour, but receive service if they are located within a pre-specified distance to a node that is included on the tour (John, 1989). The CTP can be solved by decomposing the problem into two sequential problems; a set covering problem and a traveling salesman problem (Gendreau, Laporte, & Semet, 1997). The set covering problem should minimize the number of nodes included in a tour to cover all nodes in a graph (Winston, 2004). The traveling salesman problem can then be solved to identify the shortest tour that would visit each node in the list of selected nodes exactly once and return to the starting node (Papadimitriou & Steiglitz, 1982). The CTP is defined as the placement of vertices to cover all nodes with a message and the selection of routes that minimize the time to reach all vertices with a warning message.

A few studies have explored algorithms for solving the CTP and reported, for example, the use of exact and metaheuristic searches (Ha, Bostel, Langevin, & Rousseau, 2013), branch-and-cut algorithms (Gendreau et al., 1997), and scatter search heuristics (Baldacci, Boschetti, Maniezzo, & Zamboni, 2005). A sequential GA-ACO approach was developed for placing distribution centers in disaster relief (Doerner et al., 2006), and the GA-ACO approach is implemented and used to solve the CTP in the research presented here, as a baseline to compare the new evolutionary algorithm framework (presented in subsequent sections). In solving the CTP, a GA (Goldberg, 1989) is applied to solve the set covering problem and identify a set of nodes in the water infrastructure network that should be visited to warn all consumers. Because pipelines typically follow road networks, nodes in a water network are used to represent nodes of a road network. Consumers are located at residential nodes in the network, and they are considered as warned if they are near a visited node, within a small distance that represents the distance over which a siren can be heard. Each solution is represented as a list of binary variables, where each variable represents a node in the network and takes a value of 1.0 if the node is included in the tour (after Beasley & Chu, 1996). Subsequently, ACO (Dorigo, Maniezzo, & Colorni, 1996) is applied to solve the traveling salesman problem and minimize the time it takes for a fleet of vehicles to visit the selected nodes. Ants select tours by evaluating the next link to travel upon arrival at a node. Links are selected probabilistically based on the amount of pheromone and the length of the link. Over many iterations, the shortest tour to visit all selected nodes emerges as ants leave pheromone on links that contribute to good solutions.

4. Problem formulation: routing to maximize protected consumers

The routing problem is formulated here to maximize the number of protected consumers in a contamination event, or the number of consumers that are warned before they are exposed to the contaminant. The contamination event is first simulated to generate the list of consumers who are exposed when no protection strategies are taken. The model maximizes the number of the consumers who are protected and are not exposed when warning tours are used as a protection strategy. The optimization model is formulated as:

$$\underset{\mathrm{x},\mathbf{t}}{\text{maximize}} \quad P = f_{ABM}(\mathrm{x}, \mathbf{t}) \tag{1}$$

subject to

$$\mathrm{x} = \left\{x_j^k\right\} : j \in 1, \dots, n_k; k \in 1, \dots, K \tag{2}$$

$$x_1^k = d^k : \forall k \in 1, \dots, K \tag{3}$$

$$\mathbf{t} = \left\{t^k\right\} : k \in 1, \dots, K \tag{4}$$

$$t_{detection} \le t^k \le t_{max} : t_{max} \le T, \forall k \in 1, \dots, K \tag{5}$$

where P is the number of consumers who are protected from becoming exposed. $\mathrm{x} = \{x^1, x^2, \dots, x^K\}$ and $\mathbf{t} = \{t^k\}$ are the decision variables. f_{ABM} represents the simulation model that is used to evaluate the performance of the decision variables and is described in the following section. Each array x^k is a list of nodes that are visited sequentially by vehicle k; there are K vehicles in the fleet. The numbers of nodes that vehicles can visit is not pre-specified or uniform; vehicle k visits n_k number of nodes and returns to its station after all nodes are met. Each vehicle k starts at its depot, d^k, and leaves at time t^k. The depot for each vehicle is located at a fire station. To ensure that vehicles return to their fire stations, a node d^k is added as the last node to a list of nodes x^K before the routes are simulated and evaluated.

5. Solution approach: evolutionary algorithm framework for maximizing protected consumers

Calculating the number of protected consumers (P) based on the specification of routes for a fleet of vehicles requires a dynamic simulation model. Consumers move within the network of nodes, drink water at nodes, receive warnings at nodes, and communicate with other consumers, creating a complex system of interactions. Once consumers are warned, they stop using water for some end uses and warn other consumers about the threat. An ABM-WD approach is described below that is used to calculate the number of exposed consumers for a water contamination event (Fig. 1a), and the ABM-VGA framework is developed to calculate the performance of a solution (x and **t**) and route vehicles to maximize P (Fig. 1b). The ABM-VGA framework neglects feedbacks among consumers and the water distribution system. Consumers change their water use after receiving a warning or after becoming sick, and the contaminant plume may move to unpredicted areas of the network due to changes in demands. These feedbacks are important to accurately calculate the number of exposed consumers; however, because the computation time is increased by these interactions, they are neglected in the ABM-VGA framework. The ABM-WD approach captures these interactions and is used, as described below, to post-process solutions (that is, sets of routes for a fleet of vehicles) that are identified by the ABM-VGA framework.

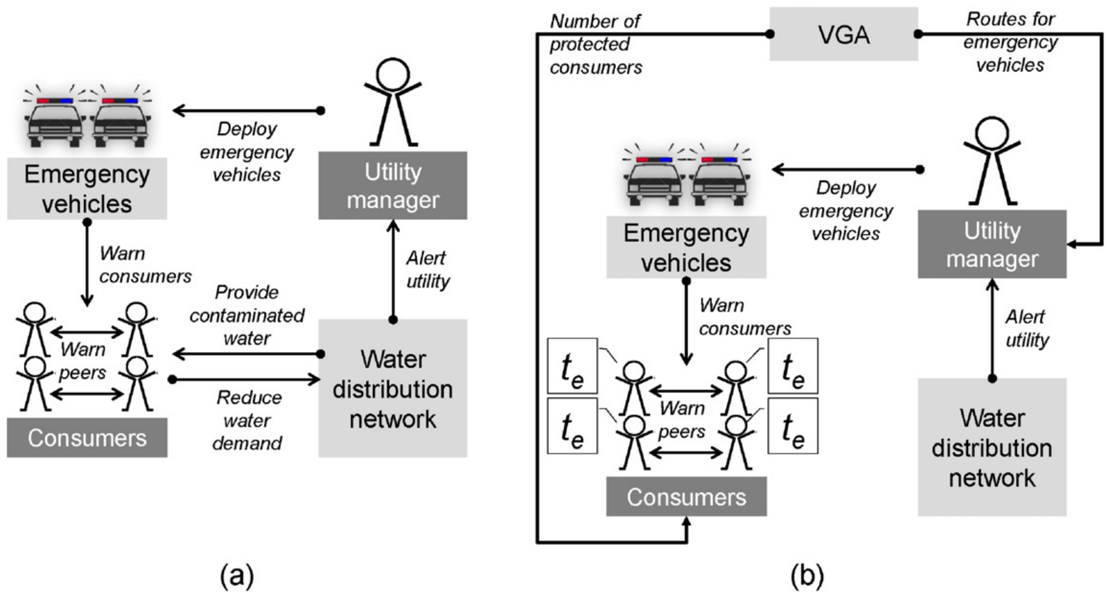

Fig. 1. Two frameworks are developed. (a) ABM-WD simulates interactions in a water contamination event to calculate the time of exposure, t_e, for each consumer. (b) ABM-VGA optimizes routes to maximize the number of protected consumers. Consumers that receive a warning before t_e are counted as protected.

5.1. ABM for a water distribution contamination event

5.1.1. ABM-WD framework

An ABM-WD approach simulates consumers, the utility operators, and siren-mounted emergency vehicles as agents. ABM uses microsimulation of agents within a system and assigns each agent a set of numeric properties, to represent attributes, and rules, to simulate behaviors (Axelrod, 1997; Miller & Page, 2007; Railsback & Grimm, 2012). The ABM-WD approach was developed and demonstrated to simulate water consumers as agents during contamination events for a small virtual city (Zechman, 2011) and for a mid-sized virtual city (Shafiee & Zechman, 2013) to evaluate public health consequences. In the ABM-WD framework described here (Fig. 1a), the emergent state of public health is measured as exposed consumers. Agents are modeled with a set of rules to represent water use, communication, and decision-making behaviors. The ABM-WD framework is implemented by coupling EPANET (Rossman, 2000), which is a hydraulic simulation model that calculates hydraulics and water quality in a pressurized pipe network, and AnyLogic (XJ-Technologies, 2012), which is an ABM software.

Each consumer agent is initialized with values for weight, age, and gender, based on U.S. census data. The probabilistic daily volume of ingested water is assigned to each consumer using demographic characteristics. Each agent is assigned five times during a day that it ingests water, based on water use studies (Davis & Janke, 2008). Agents are simulated as traveling through a city as follows: each agent is assigned a residential node, a non-residential node, a departure time, and work duration. At the departure time, the agent leaves the residential node and arrives at the non-residential node. After the amount of time specified by the work duration has expired in the simulation, the agent returns to its residential node. If the agent begins at the non-residential node, it travels to its residential node after the work duration has expired.

Consumer agents are assigned to clusters of 15 agents. Agents in the cluster have distinct communication attributes, where some consumers can receive information and pass information, some consumers only receive information, and some consumers are isolated from communication completely.

Consumers drink water following their assigned timing and volume values. The concentration of the contaminant is specified at each node using the water distribution system model. When an agent has ingested a mass of contaminant greater than 5% of its body weight, it is exposed. Once a consumer agent is exposed, it reduces its demands probabilistically. It also begins warning consumers in its clusters, based on its communication attributes. Consumers that are warned also reduce demands probabilistically. Demands are aggregated at nodes and written to the input file for the water distribution system model, which calculates hydraulic conditions at the next time step.

5.1.2. ABM framework

Evaluating one solution, which is composed of a set of tours for emergency vehicles, using the ABM-WD framework requires several minutes on a desktop computer, because at each time step of the simulation, the hydraulic model calculates water transport and quality at all nodes in the network, and the ABM-WD calculates the actions of all consumer agents. Optimizing routes will require execution of a large number of solutions using the ABM-WD framework, and the computational time for reaching convergence may become impractical. To reduce the computational time, a second ABM framework is developed for use in a simulation-optimization approach by decoupling the hydraulic model in the ABM-WD framework. This decoupling removes the feedback from the consumers to the water distribution system. The ABM-VGA ignores the mechanism in which the propagation of the contaminant plume is changed by consumers who reduce their demands earlier because of the warnings of vehicles.

To develop an ABM framework (Fig. 1b), the ABM-WD framework is executed to record when consumers become exposed from the water distribution network. For each consumer, the time that the consumer becomes exposed is recorded as a new attribute, *time of exposure* (or t_e in Fig. 2b). The time of exposure for those consumers who do not become exposed is *T*. Each consumer is simulated as traveling through the city, communicating with peers, adjusting water uses for some end uses, and receiving warnings from siren vehicles. If a consumer receives a warning from a siren vehicle before its time of exposure, the consumer is counted as a protected consumer. A set of attributes and rules that are used to model the consumers, utility manager, and emergency vehicles for the ABM framework is listed in Table 1. Patterns for movement by the agents are randomly assigned so that agents begin at residential (or non-residential) nodes, and visit non-residential (or residential) nodes after an assigned time has expired. Nodes and time of residence at a node have been assigned to each agent so that the aggregated pattern matches the patterns of water use at nodes within the city of Mesopolis. Many parameters are used to define the ABM, and these have been assigned based on available data describing the U.S.

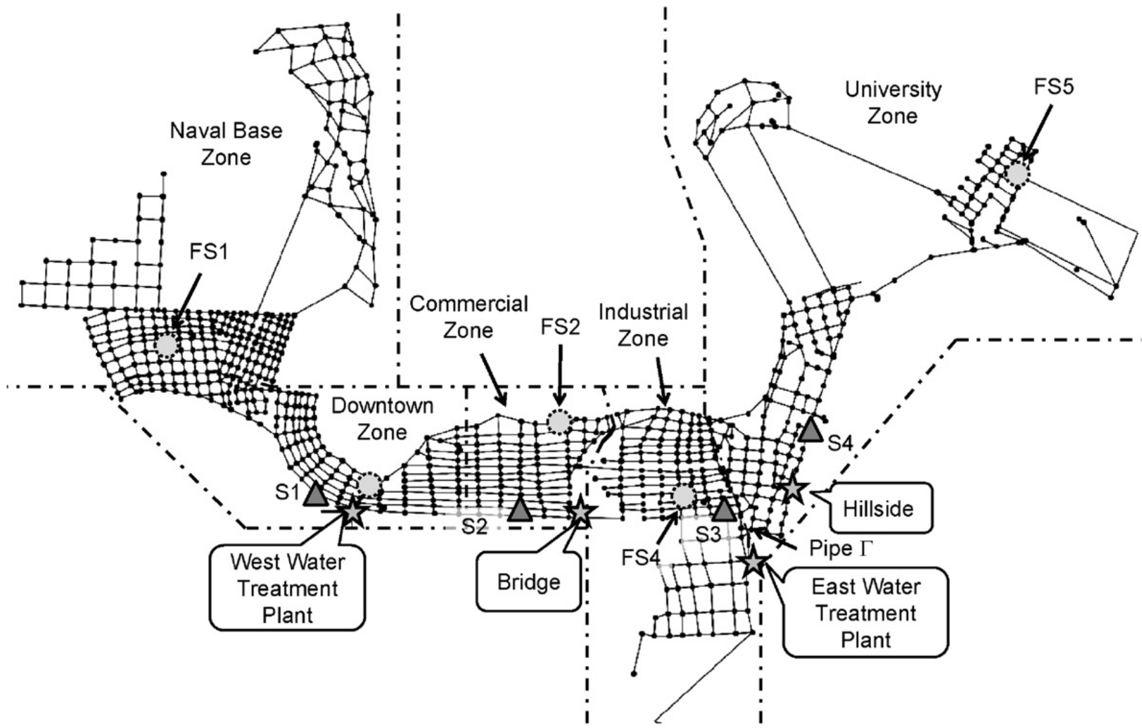

Fig. 2. Mesopolis road map, emergency zones, sensor network, and sites of four contamination events. Sensors are shown as S1, S2, S3, and S4. Fire stations are indicated as FS.

Table 1
Agent attributes and rules for the ABM framework (Fig. 1b).

Attributes	Value	Initialization
Consumer Agent		
At residential node	Boolean	True/false, randomly assigned
Departure time	Integer	Probability distribution
Work duration	Integer	Probability distribution
Time of exposure	Integer	ABM-WD simulation
Warned	Boolean	False
Protected	Boolean	False
Utility Manager Agent		
Alerted	Boolean	False
Emergency Vehicle Agent		
Velocity	Integer	16 km/h (10 mph)
Audible distance	Integer	400 m
Fleet size	Integer	5 vehicles

Behaviors	Rule	Outcome
Consumer Agent		
Travel among nodes	Agents assigned residential and non-residential nodes	Agents travel among nodes in one round trip per day
Communicate	Agents assigned to clusters of 15 members; exposed and warned agents warn other agents	"Warned" = true
Receive warning from emergency vehicle	Agents located within Audible distance of a node visited by emergency vehicle receive warning	"Warned" = true
Is protected	"Warned" = true, and Simulation time step < Time of exposure	"Protected" = true
Utility Manager Agent		
Detect contamination	Check if contamination concentration > 0.001 mg/L at a sensor	Deploy emergency vehicles
Emergency Vehicle Agent		
Leave depot	Agents follow routes	

population and sensitivity analysis, as described in previous research Shafiee and Zechman (2013). The reader is referred to previous work for detailed description of the ABM.

5.2. Variable-length genetic algorithm

The VGA (Smith, 1980) is similar to genetic programming, which uses a tree to represent a chromosome that grows and shrinks to build solutions (Koza, 1992). The VGA represents a chromosome (or set of decision variables for an individual solution) as a string of numbers or characters. The length of the string is not determined in advance and can increase and decrease while the search progresses. Specialized crossover and mutation operators are applied to create new solutions. The crossover operators swap two substrings of any size from randomly selected locations in two individual chromosomes. For mutation, a string of nodes is generated and inserted into an existing chromosome at a randomly selected location. A secondary mutation is used to randomly select a gene and change it to a new value. The VGA has been demonstrated for machine learning, clustering, classification (Srikanth et al., 1995), and engineering problems (Kajitani, Hoshino, Iwata, & Higuchi, 1996). Ahn and Ramakrishna (2002) developed a VGA for identifying a routing path in a multihop network.

Shafiee and Zechman (2011) developed a standard genetic algorithm approach with fixed-length chromosomes to solve the routing problem to maximize protected consumers. Results demonstrated that using a pre-determined size of the chromosome leads to a solution that is a local optima, and routes that protect a more consumers may be identified when a larger number of nodes are used to create the route. The VGA is applied here to route vehicles to maximize the number of protected consumers, and a variable-length chromosome is used to represent a tour. Each gene takes an integer value to represent a node that is visited by a vehicle, and the tour for each vehicle in a fleet is represented by one chromosome, or list of genes. An individual solution has a fixed number of chromosomes, corresponding to the number of vehicles in a fleet. A chromosome is decoded to represent a tour by connecting nodes sequentially using Dijkstra's algorithm (Dijkstra, 1959), which identifies the shortest path between a pair of nodes. Crossover and mutation are implemented as described above, and a tournament selection is used to select fit solutions for the next generation.

6. Illustrative case study

The ABM-VGA approach is applied to find emergency vehicle routes for contamination events that are modeled in a virtual city, Mesopolis, with a population of 150,000 (Johnson & Brumbelow, 2008). The city is modeled with residential, commercial, and industrial areas, in addition to a naval base, an airport, and a university (Fig. 2). The water supply source is a river that flows from south to north through the central downtown areas, and water is extracted 13 miles south of the city. Two water treatment plants supply water to the city through a water distribution system that is modeled as 2058 pipes, 1588 nodes, one reservoir, 13 tanks, and 65 pumps. Four different demand patterns are specified, which include residential, commercial, industrial, and naval demands. Demands are aggregated and exerted at terminal nodes. Roadways are assumed to follow the 869 intermediate nodes in the pipe network, and these nodes are used to construct tours. Mesopolis is divided into five emergency zones, and each zone houses a fire station, which serves as the depot for one emergency vehicle.

7. Contamination event scenarios

A set of contamination events is simulated to test routing algorithms for protecting consumers. Each contamination event introduces 50 kg/h of arsenic in the pipe network over a 6-hour duration, for a total of 300 kg injected into the system. Events occur at four locations: the West Water Treatment Plant (West WTP), the Bridge, the East Water Treatment Plant (East WTP), and the Hillside. The bridge crosses the river near the downtown area, and the Hillside event is located on a main line that delivers water to residents in the northeast section of the city, which is at a higher elevation than other areas in Mesopolis. All water events start at midnight. Events occur during the winter season, which influences the value for the global demand multiplier (set at 0.65), to simulate that flows are lower during the winter months when outdoor water use is not needed. Sensors are placed in the network (Fig. 2) so that for each event, the event is detected within a few minutes after 12 AM, and the utility manager is alerted immediately and deploys siren vehicles at 12 AM. Utility managers often take time to verify a threat before alerting the public, which can exacerbate public health effects (Kroll, 2006). Because verification time varies widely for reported incidents (Hrudey & Hrudey, 2004), the delay is neglected in the simulations. The optimization can be executed to include an assumed value for the delay by changing the lower limit for t^k in Eq. (5).

Each contamination event is simulated using the ABM-WD framework (Fig. 1a) to calculate the number of consumers who are exposed without any protection from siren vehicles. There is a stochasticity in the ABM-WD, due to the probability distributions that are used to initialize the consumer characteristics, and each contamination event is simulated using 30 random seeds. The numbers of exposed consumers are reported as average $\pm$ standard deviation of 30 trials, and are 31,098 $\pm$ 162; 29,497 $\pm$ 121; 27,065 $\pm$ 107; and 19,710 $\pm$ 88 for the East WTP, Bridge, West WTP, and Hillside events, respectively. Fig. 3 shows the contaminated area in Mesopolis for each contamination event at the last time step of the simulation, which is time step 48. The East WTP event propagates to the largest area, and the Hillside event covers the smallest area. The size of the contaminated area has a direct relationship to the severity of an event, but consumers who are located outside of the contaminated area may become exposed by traveling to contaminated nodes and may reduce their demands at nodes outside the contaminated area.

8. Results

For each contamination event, tours are developed using a manual routing approach; the GA-ACO approach to solve the CTP; and the ABM-VGA to route vehicles to maximize the number of protected consumers.

8.1. Manual route

A manual routing approach is implemented to mimic typical decision-making practices. If a utility manager identifies that siren vehicles can be used to disseminate warnings, the utility may develop tours a priori based on the experience of decision-makers. A set of tours was developed for Mesopolis. The route for each vehicle visits nodes in a regular pattern to ensure that all terminal nodes are within 400 m of a visited node. Nodes with high population are given a high priority to be included directly on the route. The manual route for Mesopolis consists of five distinct tours which cover all terminal nodes (Fig. 4a).

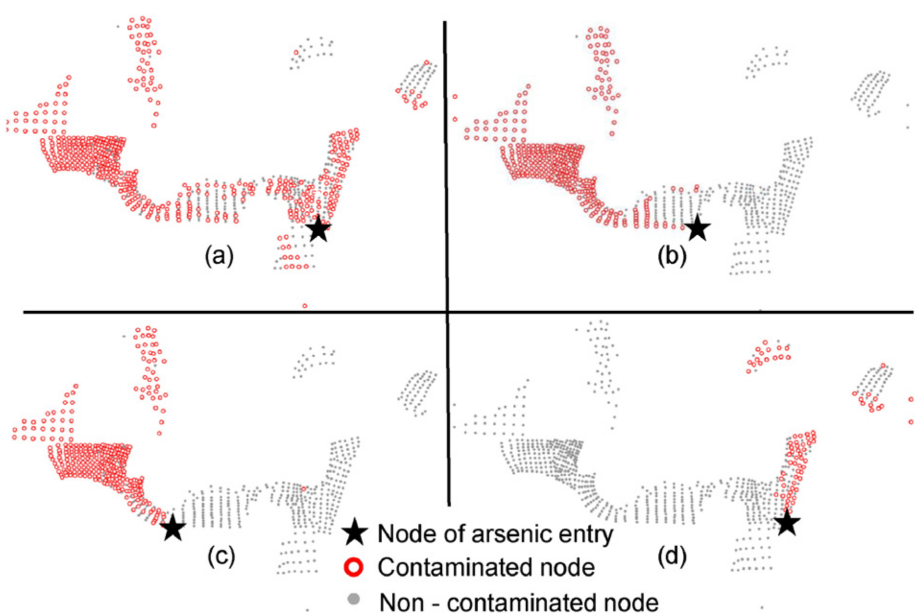

Fig. 3. The contaminated plume area at the last simulated time step for the (a) East WTP, (b) Bridge, (c) West WTP, and (d) Hillside contamination events.

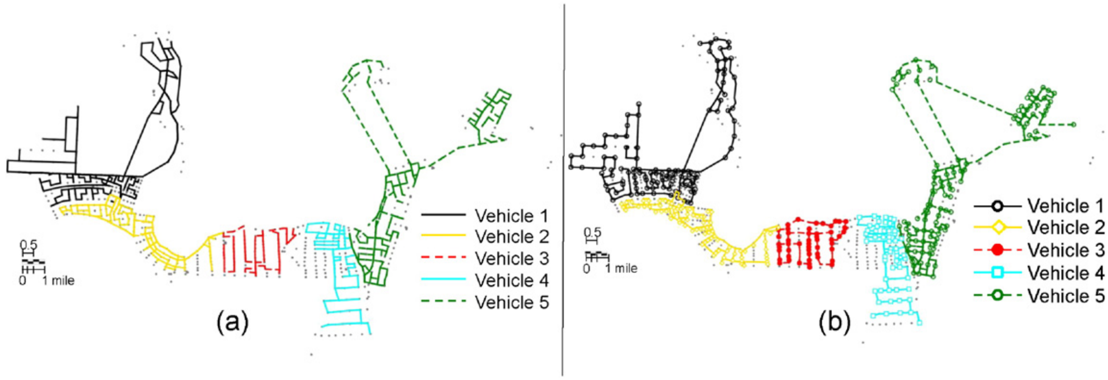

Fig. 4. Route for each vehicle identified using (a) manual route approach, and (b) GA-ACO approach.

8.2. Routes identified using the GA-ACO

The GA-ACO approach executes a GA to solve the set covering problem, followed by ACO to solve the traveling salesman problem. The GA is initialized with a population of 200 solutions; 200 generations; crossover rate of 80%; and mutation rate of 5%. The fitness of any solution, which should be minimized, is the set of nodes from the 869 intermediate nodes that should be included to cover 706 terminal nodes. The GA was executed for 30 random seeds. Convergence of the best solution is shown in Fig. 5a, with a fitness of 416 nodes.

The solution identified by the GA is used as input values for the ACO. Each node that is included in the tour is labeled based on its emergency zone (Fig. 2), and the ACO is applied to identify the shortest tour for the set of nodes in each zone separately. The ACO is initialized with a 100-ant clique, which searches over 50 iterations. The algorithmic parameters of the ACO include α, which is set at 2.0; β, at 1.0; Q, at 1000 m; the initial pheromone level, at 10; and the evaporation rate, at 0.1. Dijkstra's algorithm is applied to find the shortest route between each pair of nodes in the tour. Fig. 5b shows convergence of the ACO in identifying the shortest tour for the Commercial Zone. The five tours identified by the GA-ACO approach are shown in Fig. 4b. No vehicles are routed through the central portion of the city because there are no residential nodes in the area.

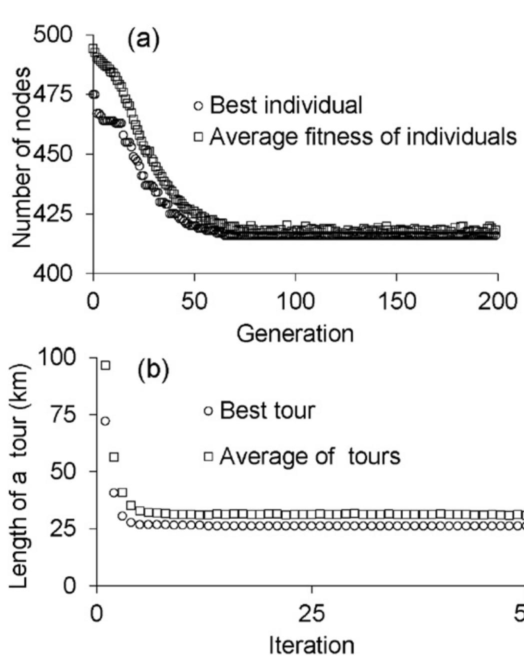

Fig. 5. Performance of GA-ACO. (a) Convergence plot for GA. (b) Convergence plot for ACO to identify a route in the Commercial Zone.

8.3. Routes identified using the ABM-VGA

The ABM-VGA is initialized with a population of 300; 200 generations; a crossover rate of 80%; and a mutation rate of 5%. A population size of 300 is large, when compared to problems in which numerical values are identified for a pre-determined number of decision variables. A large population size is needed to provide additional search power because this algorithm identifies both the number of decision variables (as a variable length chromosome) and the values for these decision variables. To avoid bloat, or the rapid generation of large chromosomes, the maximum length of each chromosome is limited to 120 nodes, and a solution with a chromosome longer than 120 nodes receives a penalty to reduce its fitness value. In Eq. (5), $t_{detection}$ and t_{max} are 12 AM and 12 PM respectively, and T, the simulation time is 48 h with time interval of 1 h.

The ABM-VGA is executed for five random seeds for each of the four contamination events. The number of random trials is less than the number used for the GA-ACO because of the time required for the simulation-optimization approach. For each event, the number of protected consumers for the five trials is similar. The percentage of the consumers who are protected with respect to the number of exposed consumers varies from 61 to 63%, 63–65%, 61–65%, and 79–84% for five trials at the East WTP, Bridge, West WTP, and Hillside events, respectively.

The convergence plot for the best solution within the population for each event is shown in Fig. 6, which shows that the ABM-VGA converges smoothly and that, for each event, the population has nearly completely converged to the best solution. The quality of individuals improves significantly in the first 75 generations, and subsequently, the quality increases gradually. The West WTP event and the Hillside event show a step-wise convergence, with little variation in the average fitness of the population as it converges, compared to the East WTP and Bridge events. For the West WTP and the Hillside contamination events, the contaminant plume is confined within a section of Mesopolis and does not contaminate as many nodes as the East WTP and Bridge events (shown in Fig. 3). Because the East WTP and Bridge events cover a larger portion of the network, the search is more sensitive, and small changes in the order of nodes in the tour can create larger variations in the objective space. For the West WTP and Hillside events, small changes to the routes do not affect the fitness of the solutions to the same extent, and a best solution remains the dominant solution for many generations.

The three sets of routes for each event as generated by the manual routing, GA-ACO, and ABM-VGA are compared (Fig. 7). Each set of tours is compared based on post-processing simulation using the ABM-WD framework (shown in Fig. 1a) to evaluate the solution for 30 random seeds. The ABM-VGA generates routes that result in the highest

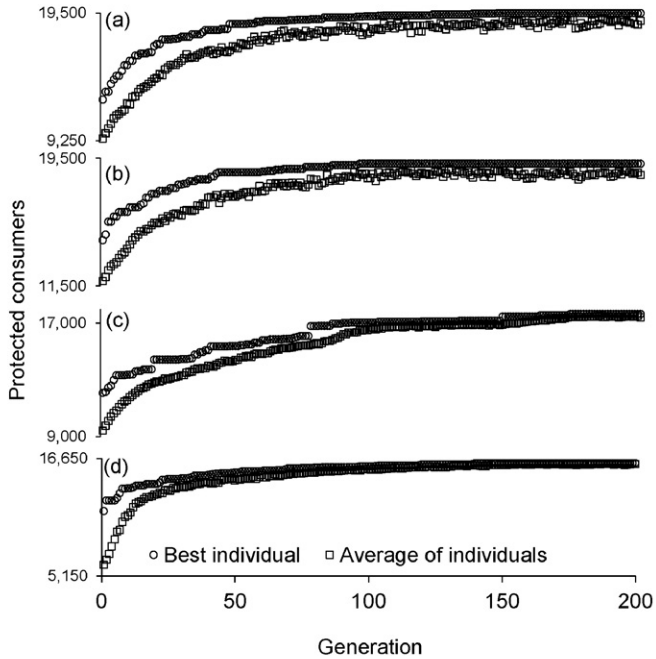

Fig 6. The convergence plot for the best solution identified using the ABM-VGA for the (a) East WTP, (b) Bridge, (c) West WTP, and (d) Hillside contamination event.

number of protected consumers for all contamination events, and the GA-ACO performs better than the manual routes. The difference between the GA-ACO and the VGA is negligible for the East WTP event. For the East WTP event, the contaminant is distributed to all nodes, and because the GA-ACO tours cover all nodes, the ABM-VGA protects only a few more consumers by controlling the time at which consumers receive warnings. For other events, the ABM-VGA improves consumer protection by scheduling the vehicle routes based on the movement of the contaminant.

The number of protected consumers when simulated using the ABM-WD framework are similar to the fitness values of the solutions that are identified using the ABM-VGA. The average of the 30 realizations for the East WTP, Bridge, and the West WTP shows 1.1%, −0.8%, and 0.7% deviation from the number of protected consumers predicted by the ABM-VGA. For the Hillside event, however, the ABM-WD framework predicts a 6.3% decrease in the number of protected consumers that is predicted by the VGA-ABM. The hydraulics of the Hillside event create unique conditions. Many consumers in the northeast area (the contaminated area in Fig. 6d) reduce their water demand within the first 24 h because emergency vehicles travel to the University Zone from the Industrial, Commercial, and Downtown Zones. As a result, there is a significant reduction (1470 gal per day over 48 h) in the flow of water in Pipe Γ (Fig. 2), which supplies water to the University Zone. These results highlight the importance of considering all feedback loops to predict the consequence of a complex system more accurately. Future research can couple the ABM-WD framework and VGA to identify more efficient routes for events in which hydraulics are significantly impacted by consumer interactions.

The tours generated by the ABM-VGA warn more consumers overall than the manual and GA-ACO tours. The total number of consumers who are warned, regardless of exposure, is an important management outcome to protect consumers from further exposure. The numbers of consumers that receive a warning from the siren vehicles are 72,241 ± 133 for the manual routes and 74,264 ± 82 for the GA-ACO routes. For these approaches, the number of warned consumers is the same for each event, though the total number of protected consumers varies based on the movement of the contaminant. For the ABM-VGA routes, the number of warned consumers is 87,828 ± 126; 87,283 ± 133; 84,069 ± 109; and 86,078 ± 221 for the East WTP, Bridge, West WTP, and Hillside events, respectively. The tours generated by the ABM-VGA warn 16% more consumers, on average over all events, than the GA-ACO tours, which results in 24% more protected consumers. Due to the word-of-mouth mechanism, all consumers, except for information isolates, become aware of the event, in each simulation, regardless of the tours that are used by the siren vehicles.

8.4. Tours

Tours identified using the ABM-VGA are shown in Fig. 8 and can be compared to tours for the manual route and GA-ACO, shown in Fig. 4. Nodes are selected in areas where the concentration of contaminant is higher for the West WTP, Bridge, and Hillside events. For the East WTP event, the nodes are selected uniformly across Mesopolis, due to the distribution of the contaminant across almost all nodes in the system. For the West WTP event, the contaminant stays isolated in the western

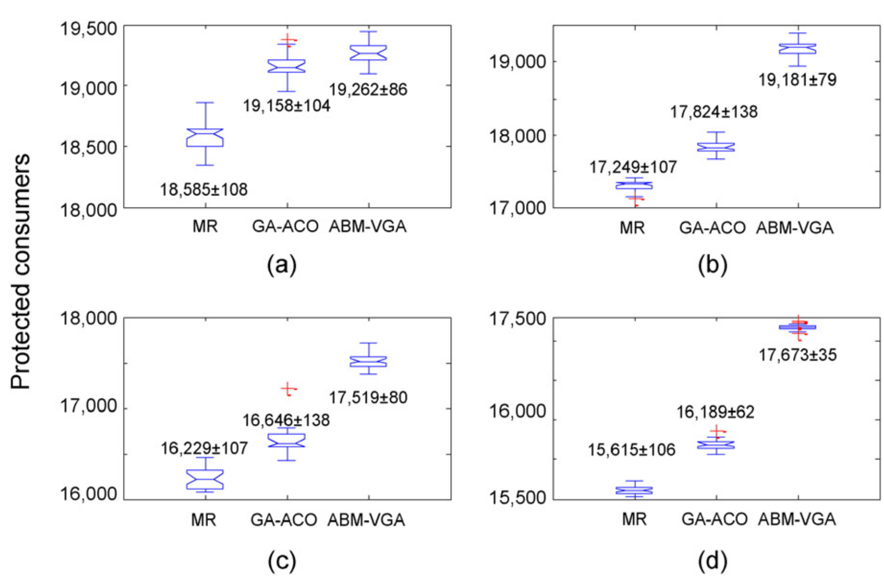

Fig. 7. Boxplot of protected consumers, simulated by 30 realizations of the ABM-WD framework for tours generated by the manual route, GA-ACO, and ABM-VGA for the (a) East WTP, (b) Bridge, (c) West WTP, and (d) Hillside contamination events. The value next to each boxplot shows the average and standard deviation of the protected consumers. MR indicates manual route.

part of Mesopolis. Some siren vehicles travel to the east part of Mesopolis, however, to warn consumers there that travel to contaminated areas as they visit non-residential nodes. Warning consumers in eastern Mesopolis also increases the diffusion of information to affected consumers via word-of-mouth.

8.5. Dynamics of exposure and protection

Fig. 9 shows the time series of protected consumers for the GA-ACO and ABM-VGA routes, in comparison with the number of consumers that would be exposed without the implementation of a protective strategy. For each event, consumers are exposed before midday of the first day, and the ABM-VGA and GA-ACO routes delay the first exposure by 1 h, compared to exposure without any protection strategy. The increasing trend in the number of protected consumers follows the shape of the number of exposed consumers; the hydraulics of the water network dominates the dynamics of exposure and performance of protective actions. The number of consumers for each time series remains constant from times step 21 to time step 32, because few consumers are likely to drink water during the night.

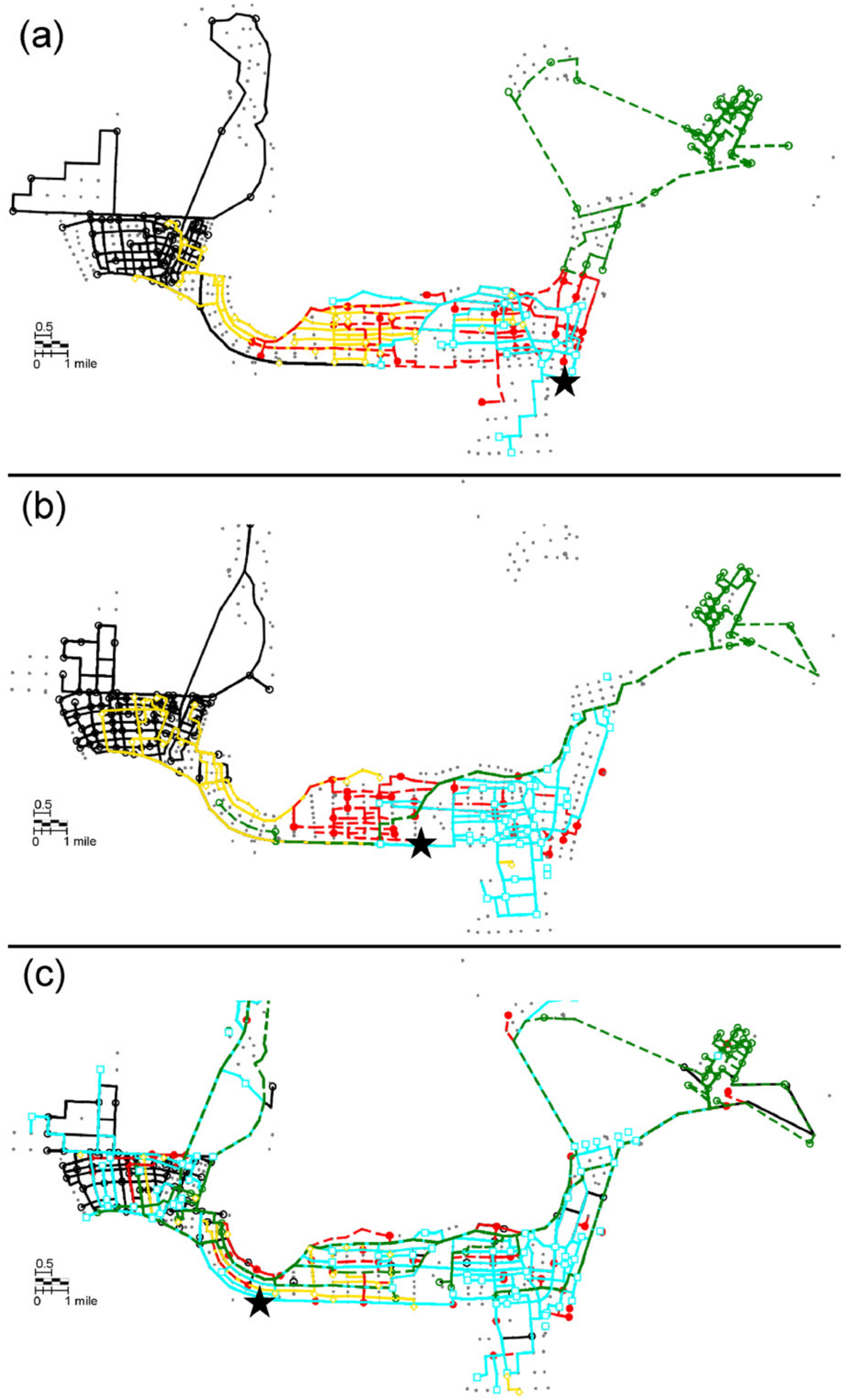

Fig. 8. Tours for each vehicle, identified using ABM-VGA, for the (a) East WTP, (b) Bridge, (c) West WTP, and (d) Hillside contamination events.

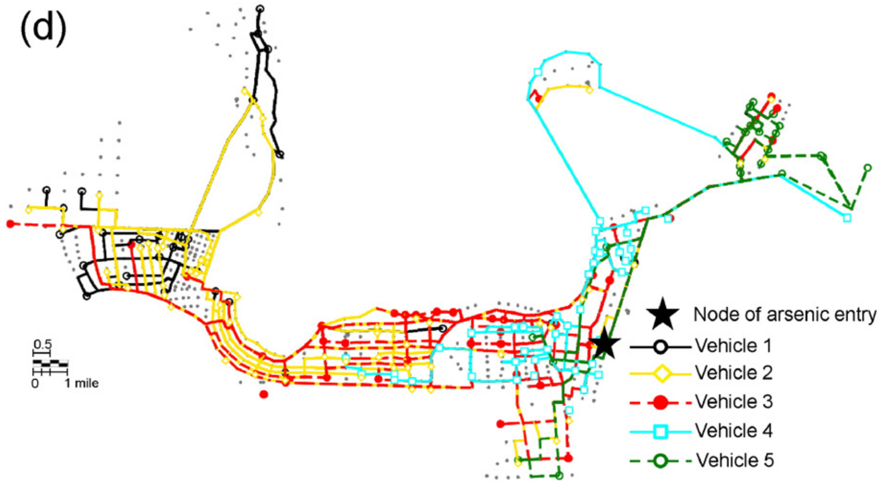

Fig. 8 (*continued*).

The number of nodes that are included in a solution is listed for each vehicle, followed by the number of nodes that are visited by the vehicle (Fig. 9). The number of nodes that are visited by the vehicle is a larger number, because when Dijkstra's algorithm is applied to connect pairs of nodes, the vehicle necessarily traverses additional nodes. For both the GA-ACO and the manual routes, tours are the same for each event. The manual routing approach results in tours that visit 118, 84, 49, 54, and 109 nodes, for the five vehicles. The ABM-VGA tours visit the highest number of nodes, compared to the other approaches. The average travel time for the vehicles following the manual routes is 9.4 h, and the average travel time for vehicles using the GA-ACO routes is 6.2 h. For example, Vehicle V5, which covers the University Zone, takes approximately 19 h to travel the manual route, and 12 h for the GA-ACO route. By comparison, the routes identified by the ABM-VGA have average travel times of 15.6, 17.4, 21.7, and 24.4 h for the East WTP, Bridge, West WTP, and Hillside events. For the ABM-VGA, the travel time and the length of tours are selected so that the vehicles are active for a longer period of time in a contaminated area. For the GA-ACO routes, vehicles return to fire stations before 6 AM, except vehicle V5. For all ABM-VGA routes, 12 out of 15 vehicles remain active in the system after 6 AM.

The start time for each vehicle for the manual route and GA-ACO is set to 12 AM, which is the time that the contaminant is confirmed. The ABM-VGA identifies routes for a few vehicles with a delay for their start times (Fig. 9). Specifically, Vehicles V1 and V2 start at 1 AM for the West WTP event, and Vehicles V2 and V4 start at 1 AM for the Hillside event. A decision-maker may be hesitant to create a delay in distributing warning messages, once she has determined to warn consumers and drafted a message. The effect of starting time on the performance of the routes is evaluated by simulating each event using a starting time of 12 AM for each vehicle as it follows the ABM-VGA tours. The difference in the number of protected consumers is less than a 1% reduction for all water events except for the East WTP, which showed a reduction of 6.4% in the number of protected consumers. The dynamics of consumer movement in the system are used to create efficient routes, and ignoring dynamics loses a small amount of the efficiency that is gained through the ABM-VGA approach.

Another important dynamic in the ABM-VGA framework is created through the word-of mouth mechanism. If a consumer agent is exposed or receives a warning, it passes a warning message to other consumer agents, which stop using water for a selected set of activities. To evaluate the importance of the word-of-mouth process, the best solution identified by the ABM-VGA was simulated again using the ABM-WD framework with the word-of-mouth mechanism deactivated. The number of protected consumers decreases by 44%, 40%, 38%, and 22%, for the East WTP, Bridge, West WTP, and Hillside events, respectively.

8.6. Sensitivity analysis

Initial investigations that developed the ABM approach for simulating a water contamination event explored the sensitivity of model results (e.g., number of exposed consumers) to the values that are used to characterize attributes of the consumer agents, including communication among peers and exposure to arsenic (Shafiee & Zechman, 2013). The performance of routes are also sensitive to model parameters that characterize the vehicles and sirens, including the velocity and the audible distance for vehicles. The effects of the velocity are tested by simulating the tours identified by each approach using a range of values for the velocity of vehicles (Fig. 10). The number of protected consumers increases as the velocity of vehicles increases for all routes, because more consumers are warned more quickly. The manual routes and GA-ACO routes are more sensitive to the vehicle velocity than the ABM-VGA routes. For the West WTP and Hillside events, the performance of the routes is more sensitive to the velocity. These events are confined within a limited portion of the network, and small changes affect the performance of routes.

Based on the time of day that a contamination event is initiated, congestion on roadways can affect the efficiency of routes. In addition, traffic accidents may occur and abnormal traffic patterns may arise due to the contamination event. Data does not exist to describe congestion patterns in Mesopolis, and this is not included in the present analysis. Application of the ABM-VGA framework for a real municipality can take into account diurnal patterns of congestion.

The routing algorithms identified tours using an audible distance of 400 m. The sensitivity of the routes is explored by reducing the audible distance to 300 and 200 m (Fig. 11). The performance of the manual route is reduced by 40% and 90%; the performance of the GA-ACO routes are reduced by 50% and 95%; and the performance of the ABM-VGA routes are reduced by 35% and 85%, for audible distances of 300 and 200 m, respectively. The GA-ACO routes are affected the most by changes in the audible distance, because nodes were selected by the GA for the set covering problem, using a covering distance of 400 m.

9. Conclusions

The routing of vehicles to provide critical resources during and after emergencies presents additional challenges beyond vehicle routing problems in routine conditions. New objectives should be considered in the planning process to explicitly address the need to expedite delivery of resources and provide fair treatment to segments of the population. The research presented here explores new problem formulations and solution approaches for humanitarian

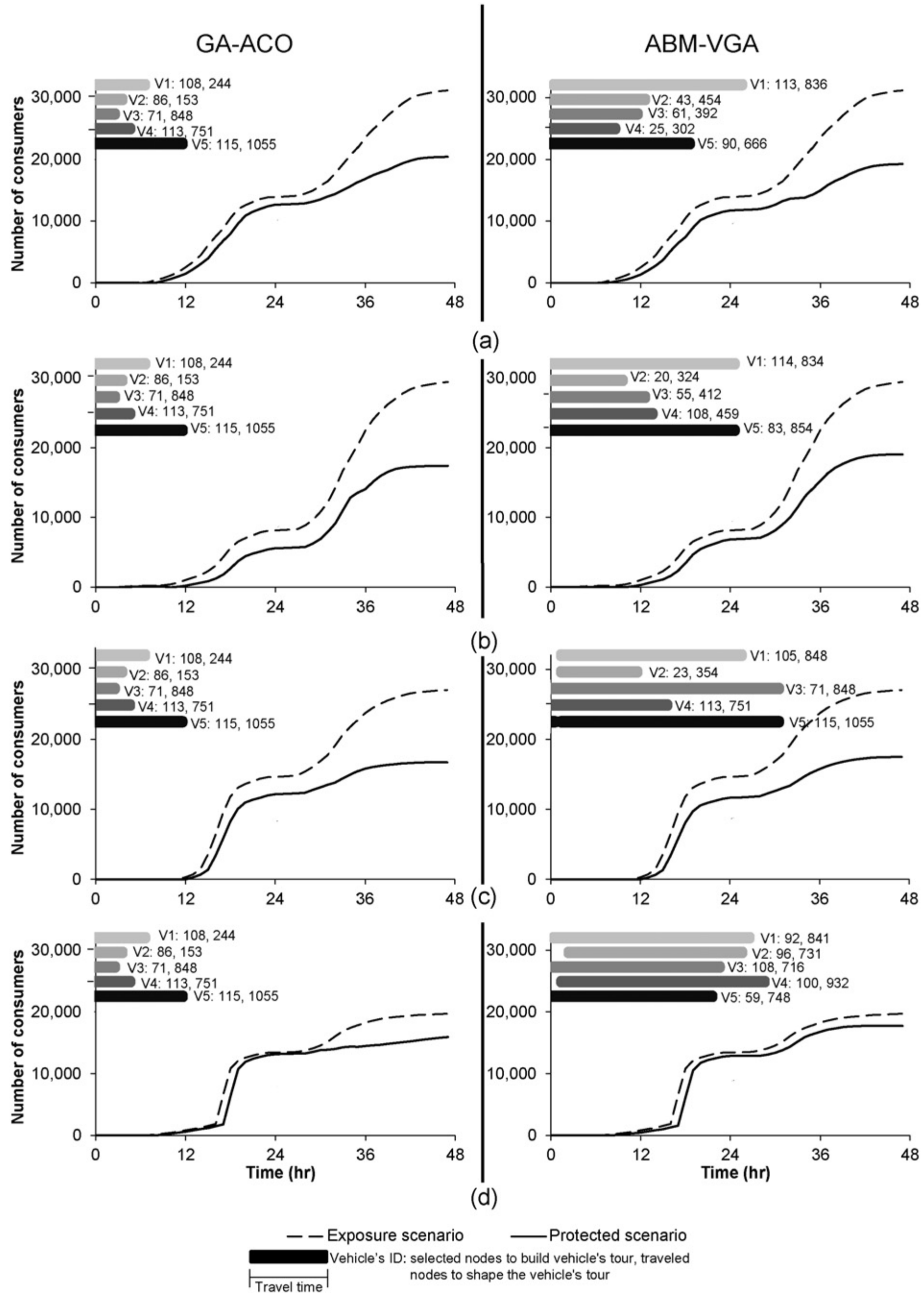

Fig. 9. Time series of exposed consumers, without routing, and protected consumers, warned by the GA-ACO (left column) and ABM-VGA (right column) approaches. The travel time, the number of selected nodes, and nodes that are traversed are shown for both approaches. Results shown for the (a) East WTP, (b) Bridge, (c) West WTP, and (d) Hillside events. Each time series represents an average of 30 random time series, simulated using the ABM-WD.

efforts. This research formulates an objective function to evaluate public health protection, simulates vehicle routing during an event as a dynamic problem, and develops VGA as a flexible and effective approach to route vehicles.

This research focuses on the contamination of a water supply as a large-scale emergency. The routing problem was formulated to maximize the number of protected consumers and was solved using an ABM-VGA approach, which builds routes for a fleet of vehicles to maximize the number of protected consumers. The ABM-VGA represents each route using a variable-length chromosome, which does not require a pre-specified set of nodes that should be included in the tour, or a pre-specified length for a tour. The variable-length chromosome can increase and decrease in length through genetic operators to increase the fitness of a solution. Each solution is evaluated based on the number of protected consumers, which is calculated through an ABM-WD approach that simulates the interactions of consumers, vehicles, utility managers, and water contamination. The ABM-VGA was applied to route vehicles for a set of contamination events, simulated in the virtual city of Mesopolis, and generated tours based on the dynamics of exposure that are distinctive for each event. The ABM-VGA was compared to routes that were developed by hand and to routes that were developed by using heuristic methods (GA-ACO) to solve the set covering and traveling salesman problems sequentially. The manual routing and GA-ACO approaches generated static solutions that are developed based only upon the characteristics of the graph of the road network, while neglecting dynamics of consumer and contaminant movement. The ABM-VGA tours protected 9–15% more consumers than the manual routing and GA-ACO routes. In general, the ABM-VGA tours protect 65% of those consumers who would be exposed without the use of a warning strategy.

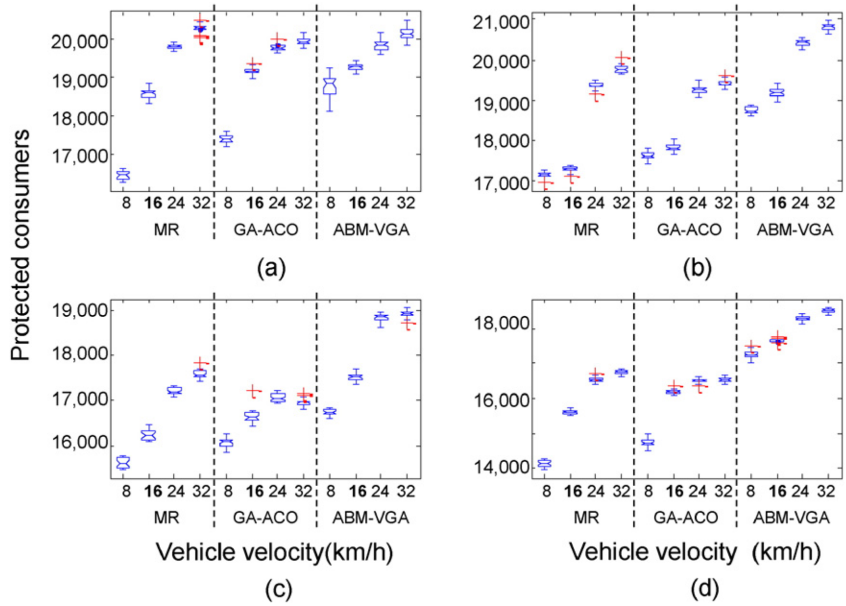

Fig. 10. Number of protected consumers for variations in the vehicle velocity for the (a) East WTP, (b) Bridge, (c) West WTP, and (d) Hillside events. Results shown for 30 simulations using the ABM-WD. The velocity used for optimization is shown in bold.

Tours generated by the ABM-VGA travel mainly within the contaminated area, but some nodes are visited that are not located in the contaminated area. By traveling to other regions of the networks, vehicles warn some consumers agents who travel to the contaminated area later in the simulated period and warn other consumers through word-of-mouth. A set of assumptions was used to parameterize the movement of vehicles, including the velocity and the audible distance. The sensitivity of these parameters was evaluated by simulating a range of values for each parameter separately. The model results may also be sensitive to the compliance of consumers, which was assumed to be 100% response.

To enable the simulation-optimization framework for a practical computing time, the water distribution system was not coupled with the ABM. A feedback loop between consumers and the water distribution pipe network does exist; consumers receive contaminated water from the water system and reduce their water demand after being warned and exposed. These changes in the demand influence the movement of a contaminant in the pipe network and can influence the performance of the routes, which are developed while neglecting this feedback. Specifically for the Hillside event, this feedback can create 6% loss in the number of protected consumers for the VGA tours. Future work can couple the VGA and ABM-WD to develop more efficient routes for events where the feedback between consumer demands and the water distribution can create new dynamics in the movement of the contaminant plume, and, consequently, in the number of exposed consumers.

This research explores vehicle routing as a dynamic problem. In crises, the actions of individual members of a community may create a complex system, as their behaviors create feedback and change the objective function landscape of the routing problem. These complexities

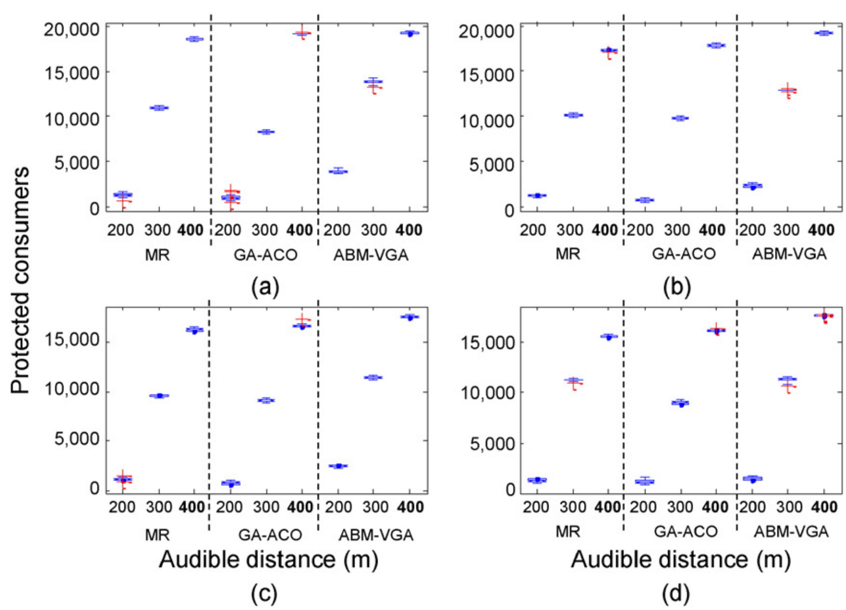

Fig. 11. Number of protected consumers for variations in the audible distance for the (a) East WTP, (b) Bridge, (c) West WTP, and (d) Hillside events. Results shown for 30 simulations using the ABM-WD. The audible distance used for optimization is shown in bold.

are explored here for a water supply contamination event. Other emergencies, such as flash flooding, severe weather, and hazardous materials emergencies, may warrant similar analysis, due to the effect of individual behaviors on disaster consequences. For example, ABM approaches have been developed to simulate evacuation in earthquakes (D'Orazio, Spalazzi, Quagliarini, & Bernardini, 2014), tsunamis (Sahal, Leone, & Peroche, 2013), hurricanes (Chen et al., 2006), and fire disasters (Shi, Ren, & Chen, 2009; Wagner & Agrawal, 2014). The approach developed here can be extended for these disaster scenarios to simulate crowd dynamics and identify routes to most effectively warn threatened individuals. The projected trajectory of hazardous materials in the environment or the effects of severe weather may be affected by the interactions of the population, and their behaviors may adversely or positively affect the delivery of services and information to other segments of the population. In addition, studies can explore the emergence of traffic congestion and accidents that may affect the progress of vehicles to deliver warnings to consumers effectively. Future research can explore the application of the evolutionary algorithm framework for other emergencies.

The model for vehicle routing can be extended by coupling the routing strategies with other communication means, such as media and SMS text messaging to warn consumers. Shafiee (2013) developed a model to simulate compliance with water advisories that are broadcast by media to encourage consumers to stop using water. The media model can be combined with the siren vehicle routing model to represent consumer exposure based on compliance with water advisories that are received via media and siren warnings. Advanced systems are being adopted in the water industry to provide the capabilities for more directed communication, and on-going research is exploring the use of targeted text messages that can be sent to consumers in affected pressure zones. Emerging research is developing the use of ABM for simulating the use of twitter and social media in emergencies (Herrmann, Rand, Schein, & Vodopivec, 2013; Takayasu et al., 2015), and additional work is needed to integrate new research and simulation of the use of social media for communicating about a water contamination incident within the ABM framework described here. The ABM framework can be extended to develop strategies for communicating most effectively by distributing messages in hazardous material emergencies.

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