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Optimal placement of public-access AEDs in urban environments

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ABSTRACT

Use of public-access Automated External Defibrillators (AEDs) is showing promising results in decreasing collapse-to-shock times among Sudden Cardiac Arrest (SCA) patients which is associated with improved patient outcomes. Bystander access to these medical devices ensure that the necessary care to victims of SCA is provided prior to arrival of emergency responders. Prior studies have suggested methods for deploying AEDs for public use by implementing mathematical optimization based on historic incidences of SCA. The purpose of this study is to improve upon these studies by developing a novel method for generating placement plans in urban environments. The novelty of this study is: (1) the use of route-based walking time instead of straight-line approximations; (2) introduction of temporal availability in deployed devices to account for location hours-of-operation; (3) use of a multi-objective optimization to balance decision-maker objectives; and (4) the implementation of an interactive decision-maker tool for observing effects on benefits and costs. The approach is deployed and evaluated for a case study in the city of Hoboken, New Jersey. This case study is simulated with a resulting average decrease of time-to-retrieve by 98.06 s indicating an estimated 11.44–16.30% survival probability improvement using our optimization technique compared to a baseline optimization.

1. Introduction

Seconds are critical to survivability of out-hospital Sudden Cardiac Arrest (SCA) patients because SCA typically causes death if proper care is not administered rapidly (NHLBI). Early defibrillation is key in the "Chain of Survival" for treating these patients (American Heart Association). This care can be provided by Automated External Defibrillators (AEDs); medical devices designed to provide cardiac defibrillation in out-of-hospital environments by bystanders with limited or no training (NHLBI; Soar et al., 2010). Improved response time, or decreased time-to-shock, using public-access AEDs has shown improved survival rates.

Increased survival rates have been shown with improved response time (or decreased time-to-shock) by bystanders (De Maio, Stiell, Wells, & Spaite, 2003; McNally et al., 2011; Vankipuram et al., 2014). Rapid response times are achieved by making AEDs publicly available for bystander use (Hazinski et al., 2005; Murakami et al., 2014). Public-access AED programs empower bystanders to provide early cardiac defibrillation by providing rapid and open access to AEDs. These programs have the potential to improve patient outcomes and save lives. However, achieving this goal requires optimization of these programs to balance benefits and cost constraints.

Previous studies suggest several methods for identifying effective placement of public-access defibrillators. Many of these studies focus on targeting placement based on building type or population demographics (Folke et al., 2009). Additionally, public buildings and spaces containing high foot-traffic are typically selected for AED placement (Folke et al., 2009). Recent studies have implemented mathematical optimization based on historical cardiac arrest calls to more accurately place the devices (Chan et al., 2013). These studies make several recommendations for future work and expansion.

In this paper, we propose a new approach to solving the public access AED location problem. The novelty of this study lies in: (1) the use of route-based walking time instead of straight-line approximations; (2) introduction of temporal availability in deployed devices to account for location hours-of-operation; (3) use of a multi-objective optimization to balance decision-maker objectives; and (4) the implementation of an interactive decision-maker tool for observing effects on benefits and costs.

The evolutionary optimization approach creates deployment configurations from potential locations and demand points which are identified throughout an urban environment. Each deployment

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configuration consists of potential locations selected to serve as actual locations of deployed devices. When a deployment configuration is generated, the following objective functions are evaluated: (I) coverage of geospatial demand within the maximum acceptable travel time; (II) temporal availability of deployed devices; and (III) the number of devices deployed. Functions I and II are maximized while Function III is minimized. Pareto optimal configurations are stored for further evaluation by simulation.

Discrete event simulation is used to test each deployment configuration from the optimization (Karnon et al., 2012). The simulation is evaluated in terms of time-to-retrieve the nearest available AED. Time-to-retrieve is used as an estimate for probability of survival. This allows the options to be narrowed based on the best potential configurations from the estimated performance.

Results of the optimization and simulation are visualized using a web-based user interface, which enables interaction by the decision-maker to change parameters and observe effects on key performance indicators. These indicators include estimated monetary cost, geospatial coverage, and temporal coverage for the current configuration. The city of Hoboken, NJ is used throughout the paper as a scenario to test the results of our approach in a real-world urban environment. Call logs were obtained from the Hoboken Volunteer Ambulance Corps (HVAC) (City of Hoboken, NJ,Hoboken Volunteer Ambulance Corps). Both a baseline optimization and the evolutionary optimization proposed in this paper are applied to the case study for comparison.

The remainder of this paper is organized as follows: In Section 2, we review prior publications related to AED placement. In Section 3, we introduce the data requirements and sample case study. In Section 4, we discuss our novel methodology. In Section 5, we conclude on our work and make suggestions for future work.

2. Literature review

The National Institutes of Health define Sudden Cardiac Arrest (SCA) as: "a condition in which the heart suddenly and unexpectedly stops beating. If this happens, blood stops flowing to the brain and other vital organs." (NHLBI) This means the probability of survival is related to the amount of time after the incident without treatment. Fig. B.1 illustrates how the probability of survival among SCA patients decreases from the ideal survival as time passes without proper care. A survival rate of 67% is considered a baseline for determining decay of SCA patient survivability (Larsen, Eisenberg, Cummins, & Hallstrom, 1993). This baseline implies theoretical ideal conditions where cardiopulmonary resucitation (CPR) and defibrillation are provided immediately following the incident. Studies show that the probability of survival decreases by approximately 7–10% per minute when CPR and defibrillation are not performed after SCA (Larsen et al., 1993; Valenzuela, Roe, Cretin, Spaite, & Larsen, 1997).

There is support to deploy publicly-accessible AEDs in urban environments by several non-profit organizations and government grant programs (Department of Health and Human Services). These funding programs aim to improve SCA survival by providing public-access to AEDs. However, these programs are limited by budget restrictions, which create the need to optimally place the devices such that they make the greatest impact. In recent years, there have been several studies published providing suggestions for ideal placement of AEDs for use by the public, which have given conflicting suggestions (see Chan et al., 2013; Liu et al., 2012; Folke et al., 2009; Portner, Pollack, Schirk, & Schlenker, 2004; Swor et al., 2003; Fedoruk, Currie, & Gobet, 2002). A brief summary of select prior studies is provided in Table A.1.

There are multiple studies suggesting the identification and deployment of AEDs in high foot-traffic areas. This has resulted in public buildings and spaces to be selected for AED placement by decision-makers. Fedoruk et al. (2002) studied ambulance call reports and identified that approximately 15% of cardiac arrest calls took place in high traffic, public places. Therefore it was proposed to implement devices in the public areas with high cardiac arrest frequency. Folke et al. (2009) identified public cardiac arrest incidents and proposed placement of AEDs in areas with high pedestrian traffic such as train stations and large public squares.

Portner et al. (2004) studied less urban areas for AED placement. The study identified out-of-hospital cardiac arrests in a sample area and found that approximately 48% of the arrests took place in healthcare facilities. The remaining incidents were found to be isolated events in different locations where first responders would be more effective than AED placement. Therefore, the study suggested to solely deploying AEDs in healthcare facilities, such as nursing homes, in rural areas.

Most recently, Chan et al. (2013) introduced a mathematical optimization technique to find optimal locations of a limited number of deployed AED devices throughout the city of Toronto. The optimization is based on the Maximal Coverage Location Problem (MCLP) used to identify a limited number of deployed devices where the maximum number of demand nodes are covered. Their results identified 30 locations to implement a new AED, which resulted in covering an additional 112 historical arrests. This improved the historic cardiac arrest call coverage from 23% to 32% and reduced the average distance to the closest AED from 281 m to 262 m.

Many of these studies make recommendations for future work and expansion. In this paper, we propose a new approach to solving the public access AED location problem and it includes many of the suggestions outlined in prior works.

3. Data

3.1. Requirements

The methods outlined throughout the remainder of this paper require the collection, processing, and analysis of several datasets. These available datasets include sets of demand points, **DP**, potential locations, **PL**, and a distance matrix, **DM**. Together, the data is used as inputs to the optimization, simulation, and visualization.

The set of demand points, **DP**, contains weighted geospatial points that indicate potential need for AED device usage. According to prior studies, the weighting function can be based on several different factors including geographic population density, historic emergency calls, and/or other factors (Daskin & Dean, 2004). In this study, call logs are obtained from Emergency Medical Service (EMS) providers containing historic emergency calls. The calls are clustered together according to a distance threshold. The demand point is located at the midpoint of calls and the corresponding weight is the sum of the number of calls falling within the threshold. It is recommended that the distance threshold be equal to the maximum acceptable distance (this concept will be discussed in later sections). A distance threshold of 250 m is used for this study.

The set of potential locations, **PL**, contains facilities which are identified as being able to host a new AED. Prior studies have used local businesses, restaurants, train stations, or public buildings as potential locations (Daskin & Dean, 2004). When selecting the set of potential locations, it is important to consider geographic diversity. For example, selecting locations densely clustered in a small area will result in poor optimization results because there will be no possibility to cover the demand points distant from the cluster. The hours of operation impact the temporal availability of the locations which, in turn, determine if the devices will be usable during an event.

The distance matrix, **DM**, contains the distance between each **DP** and **PL** and is size $|DP| \times |PL|$. Straight-line approximations using the Haversine distance formula have been used in prior studies (Siddiq, Brooks, & Chan, 2013). However, this estimation technique falls short when focusing on urban environments. Straight-line approximation would inaccurately measure the distances assuming people can move through buildings and other barriers common in dense cities. This inaccuracy is unacceptable for SCA survival where seconds matter. Therefore, the estimated walking distance is calculated using actual walking routes. The routes are obtained from a local instance of the OpenTripPlanner (OTP) (Byrd) navigation API which provides walking distances. The estimated human walking travel time is calculated from the distance matrix. However, assumptions are made that users know the location and best route to the device. This is fairly realistic since emergency dispatchers and smart phone apps can now be used to inform people of the location of AEDs.

3.2. Case study

We use a sample urban environment as case study for implementing our solution techniques to the public-access AED program. The city for testing the deployment program is selected by considering the following factors: (1) population size; (2) prior SCA occurrences; (3) status of current public-access AED program; and (4) data availability. Due to these reasons, Hoboken, New Jersey is an acceptable case study for testing methods of urban deployment of public access AEDs and serves as a model for future applications in other urban environments. The city of Hoboken, New Jersey lies on the coast of the Hudson River in the New York Metropolitan area. The city is densely populated with a population of approximately 50,000 residents living within 2 square miles (City of Hoboken, NJ). It serves as a major transit hub for commuters and is a significant tourist destination with an active social scene. Despite these factors, the city lacks a unified strategic plan for the registration, sponsorship, or deployment of public-access AEDs. The Hoboken Volunteer Ambulance Corps (HVAC) serves as the primary Emergency Medical Service (EMS) provider to the city of Hoboken (Hoboken Volunteer Ambulance Corps).

The HVAC keeps a record of each call dispatched to any of their units. This dataset is used to generate the **DP** set required for the methodology. The data is originally gathered from handwritten call reports which are entered into a database by the HVAC administrative staff. The database of call logs from June 2008 to February 2013 have been obtained for the purposes of this study. Each record contains date, time, location, and presenting medical problem of the emergency. It is important to note that all information was de-identified and no protected health information is collected or used in this study.

The **PL** set is created by collecting a list of 212 local restaurants and their corresponding hours of operation. Many the restaurants have long hours of operations and are geographically diverse in location which makes them sufficient to be used for the optimization. Fig. 1 shows the set **DP** and **PL** visualized on a map.

Typically, it is necessary to pre-process raw data collected about the urban environment in order to build the input datasets. Fig. 2 shows the process used for converting data into the required form. All of the input datasets are stored in databases after being generated. The **DP** dataset contains several missing fields and duplicate entries that require filtering. The presenting medical problem field contains a wide variety of entries that are manually standardized into 29 categories. The location field is standardized

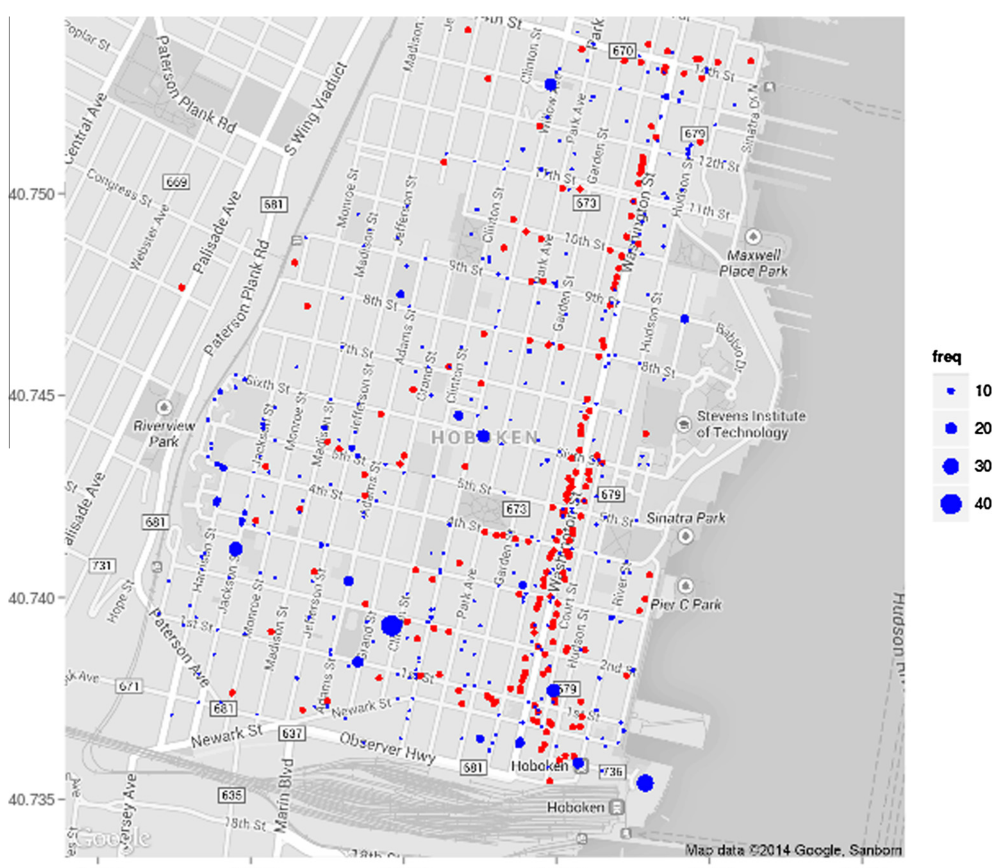

Fig. 1. A visualization of the geographic distribution of Demand Points and Potential Locations. Blue dots represent demand points and are sized according to potential demand, a_i. Red dots represent potential locations. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

in normal street address format. The Google Maps API is used to convert street addresses to geographic latitude and longitude coordinates (Google, 2014). The dataset contains several calls falling outside of the Hoboken city limits. These are removed as they are not pertinent to the study. Calls dispatched to other agencies operating in the area are not included in the dataset.

The **DP** dataset is divided into three subsets: `FULL` containing all calls, `CARDIAC` containing only cardiac-related calls, and `SCA` containing only SCA-related calls. These contained 18,042 calls, 812 calls, and 48 calls, respectively. The calls forming the `SCA` subset are considered calls where the patient most likely required the use of an AED. Figs. B.2 and B.3 show the temporal aggregations of the subsets. Figs. B.4 and B.5 show the geographic clustering of the subsets.

The `CARDIAC` subset is used to model the demand for AEDs in the case study. This subset of calls must be used because it contains the situations where an AED would possibly need to be deployed. These calls include any cardiac-related situations that place the patient in a risk category for Sudden Cardiac Arrest. Operationally, the decision to obtain an AED as a precaution would be at the discretion of the bystander and the emergency dispatcher.

4. Methodology

4.1. Optimization

The public-access AED location problem is solved to find optimal deployment configurations of AEDs in an urban environment. The optimization model requires several input variables and datasets prior to runtime as previously discussed. Output of the model consists of sets of optimal selections for AED placement and the objective function performance metric. Table A.2 provides a full list of optimization inputs and outputs.

The overall goal of the optimization is to reduce time-to-shock for a SCA patient in order to potentially increase the chance of survival (American Heart Association). The estimated time-to-shock is affected by several variables. Maximum acceptable distance, S, defines the distance at which a demand point is considered to be "covered" by a device and is set by the decision-maker. The geospatial coverage is the sum total of the weight of the demand points that are covered by at least one device. This variable is positively correlated to the number of devices deployed, which also increases deployment cost (New Hampshire Bureau of Emergency Medical Services). Temporal coverage behaves in the same manner as geospatial coverage.

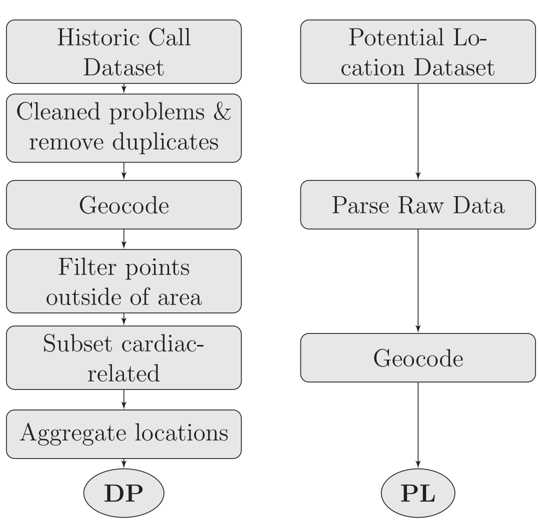

Fig. 2. The generalized process to convert the raw datasets into the proper data structure for the **DP** and **PL** sets.

The problem is therefore defined as: given the sets **PL** and **DP**, find a directed mapping between at most P nodes in **PL** to nodes in **DP** where the distance $DM_{ij} \leqslant S$ such that the objective function fitness, F, is optimal. Fig. 3 visualizes this definition.

4.1.1. Maximal Covering Location Problem

The Maximal Covering Location Problem (MCLP) has previously been used to determine optimal placement of public-access AEDs (Chan et al., 2013). We use MCLP as a baseline single-objective optimization model for determining AED locations. MCLP is used to find a Deployment Configuration (**DC**) of a limited number of devices, P, such that the maximal number of weighted demand points (**DP**) are covered by an AED device placed at a potential location (**PL**) within the maximum acceptable service distance or time, S (Church & Velle, 1974). It does not consider temporal availability of potential locations.

MCLP is mathematically formulated as follows:

$$\text{Maximize} \quad f = \sum_{i \in DP} a_i c_i \tag{1}$$

$$\begin{aligned} \text{S.T.} \quad & \sum_{j \in N_i} l_j \geqslant c_i && \text{for all } i \in DP \\ & \sum_{j \in PL} l_j = P \\ & a_i = [0, 1] && \text{for all } i \in DP \\ & c_i = \{0, 1\} && \text{for all } i \in DP \\ & l_j = \{0, 1\} && \text{for all } j \in PL \end{aligned}$$

where

a_i	Potential demand for service at DP_i, measured in number of prior calls
c_i	Binary variable indicating if demand node DP_i is covered by at least one AED
l_j	Binary decision variable that determines if a device is allocated to site PL_j

The optimization is solved using linear programming techniques (Church & Velle, 1974). We implement and solve the MCLP using the GNU Linear Programming Kit (GLPK) solver application (GNU). The solver is run for combinations of P and S so that several **DC** sets are generated.

4.1.2. Multi-objective optimization

The MCLP optimization for the AED problem generates solutions that best cover geospatial demand within the input

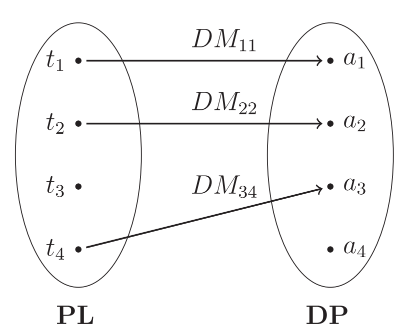

Fig. 3. The public-access AED location problem can be described as a directed mapping between nodes in **PL** and nodes in **DP**. Properties of the nodes and edges in the network are used to calculate objective functions.

constraints. However, MCLP is a single-objective optimization and cannot simultaneously consider both geospatial and temporal availability. Therefore, a multi-objective formulation of the problem is required in order to consider both types of coverage. An evolutionary algorithm is used to solve for multiple objectives (Zitzler & Thiele, 1999). Fig. B.6 outlines this technique.

Each of the required datasets are stored in a database so they are first loaded into a network data structure. This is accomplished using the Python NetworkX library (Hagberg Aric, Schult Dan, Swart Pieter, & NetworkX, 2014). This library is capable of rapidly implementing and performing computations on network-like data. It is the main tool used for calculating the objective functions.

Seed candidates are generated to initialize the evolutionary algorithm. The seeds are potential **DC**s where a random number of locations have been selected for AED placement. This ensures diversity in the initial generations of the algorithm (Zitzler & Thiele, 1999).

The following objective functions are evaluated: f_1, coverage of geospatial demand within the maximum acceptable travel time; f_2, temporal availability of deployed devices; f_3, the number of devices deployed. Function I and II are maximized while Function III is minimized.

(I) Maximize Geospatial Coverage

This objective aims to maximize the geospatial coverage of demand points covered by the **DC**. The function is the sum of the weighted demand nodes which are considered covered within the maximum acceptable distance or time, S, from at least one deployed device.

The objective function is formulated as:

$$\text{Maximize} \quad f_1 = \sum_{i \in DP} a_i c_i \tag{2}$$

where

$$a_i = [0, 1] \quad \text{for all } i \in DP$$
$$c_i = \{0, 1\} \quad \text{for all } i \in DP$$

(II) Maximize Temporal Availability

This objective aims to maximize the availability of the potential locations. This function is calculated as sum of the temporal availability of the devices in the **DC**.

The objective function is formulated as:

$$\text{Maximize} \quad f_2 = \sum_{j \in PL} t_j l_j \tag{3}$$

where

$$t_j = [0, 1] \quad \text{for all } j \in PL$$
$$l_j = \{0, 1\} \quad \text{for all } j \in PL$$

In this formulation, t_i represents the amount of time that location l_i has an AED available. The objective function f_2 maximizes the total amount of hours. But, since this function is calculated as the sum of the temporal availability of the devices in the **DC**, it already takes into account the hours of operation of the **PL**.

(III) Minimize Number of Deployed Devices

This objective aims to minimize the number of devices to be deployed. This function also is used to associate a financial cost to the potential **DC**. It is calculated as the sum of the devices in the **DC** and limited by a maximum number of devices.

The objective function is formulated as:

$$\text{Minimize} \quad f_3 = \sum_{j \in PL} l_j \tag{4}$$

where

$$\sum_{j \in PL} l_j \leqslant P$$
$$l_j = \{0, 1\} \quad \text{for all } j \in PL$$

The Pareto frontier consists of dominating solutions that are better or equal in terms of all objective functions and strictly better performing in at least one objective (Aaron Garrett; Zitzler & Thiele, 1999). The fitness function for each of the potential **DC** is tested for Pareto dominance after each of the objective functions is calculated (Deb, Pratap, Agarwal, & Meyarivan, 2002). Solutions in the Pareto frontier are stored for future evaluation. Table A.3 shows a sample of Pareto solution performances from the Hoboken optimization. Typically, several hundred solutions are expected to be stored in the Pareto frontier following this optimization process (Zitzler & Thiele, 1999).

Our use of the evolutionary algorithm is based on work and suggestions found in Hernandez, Ramirez-Marquez, Rainwater, Pohl, and Medal (2014). The algorithm NSGA-II is used on each generation of candidate solutions to produce the next generation and perform evaluation (Deb et al., 2002). The Python library Inspyred implements the necessary functions to the optimization using the NSGA-II algorithm (Aaron Garrett). The condition for termination is checked at the end of each generation. The optimization is typically terminated when a user-defined maximum number of generations is reached. The results are stored into a database after termination conditions are reached. These results are generated from the archive of potential solutions in the Pareto frontier. Each result contains the **DC** and the set of objective functions F for the potential solution.

4.2. Simulation

The amount of the optimization output limits the ability for a decision-maker to choose optimal solutions for implementation. Therefore, a simulation is used to reduce the number of viable solutions for further decision-maker evaluation. This is done by testing the performance of each potential **DC** from the optimization results. Performance is estimated in terms of time-to-retrieve the nearest public access AED by a bystander (Sakai et al., 2011). The time-to-retrieve is especially important as a metric of performance because it can be related to the probability of survival for the SCA patient as follows, and can be evaluated using the p-values found in that work:

$$P_L(survival|t) = \begin{cases} 0.67 - 0.07t & \text{if } 0 \leqslant t \leqslant 9.57 \text{ min} \\ 0 & \text{if } t > 9.57 \text{ min} \end{cases}$$

$$P_H(survival|t) = \begin{cases} 0.67 - 0.1t & \text{if } 0 \leqslant t \leqslant 6.7 \text{ min} \\ 0 & \text{if } t > 6.7 \text{ min} \end{cases}$$

This evaluation serves as a standard for evaluating all potential configurations against each other for superiority.

The simulation is implemented as a discrete event simulation (DES) where events indicate a cardiac-related emergency call determined to require an AED for use or as a precaution. These events occur in both the temporal and geospatial domain. Therefore, the following two distributions are used to generate events during the simulation: (1) the inter-arrival time distribution and (2) 2D geographic demand distribution. An event is first instantiated by the simulation subject to the inter-arrival time distribution. The size of the dataset being utilized, particularly calls related to cardiac arrest events, is not enough to utilize a non-homogenous Poisson process based on it. Therefore the simulation follows a Poisson process, so the inter-arrival time distribution is described by an exponential distribution taking the parameter of the mean inter-arrival time, $1/\lambda$, as the input (Karnon et al., 2012). Once an event is generated by this distribution, it must be placed in the geospatial environment. This is done by randomly selecting a location in the 2D continuous demand distribution based on prior calls. Therefore, areas that have had high demand for calls in the past are more likely to have calls in the simulation, however, all locations within the bounds of the simulation are valid event locations. Once the time and location of the simulated event is identified, the **DC** is queried to find the closest available device (considering hours-of-operation). A walking route is generated by the OpenTripPlanner API (Byrd) which provides the travel distance and estimated travel duration for the average human walking speed. This estimated travel duration is stored in a set for further evaluation to determine the performance of the configuration. Fig. B.7 shows a graphical representation of this simulation procedure. It is important to note that results of the simulation assume that the user knows where the device is and the best route to the device. This is justified by the fact that emergency dispatchers can route people to the nearest registered device.

Since SCA is a relatively rare event, several years of calls must be simulated in order to gain meaningful results. The following key statistics are recorded once the simulation is complete: shortest travel time, mean travel time, median travel time, and longest travel time. These statistics are used to narrow the selection of potential deployment configurations to ones that have the highest performance. Since travel time can serve as a partial estimate of time-to-shock it is also used to predict the probability of patient survival (Larsen et al., 1993; Valenzuela et al., 1997). This allows us to display results in terms of a cost-benefit trade-off.

The simulation is tested on the Hoboken case-study optimization results. A mean inter-arrival time of $1/\lambda = 783.8298$ h is used for the exponential inter-arrival distribution. This estimate is based on previous data collected from the `CARDIAC` data subset. The geographic distribution posed a challenge since the cluster demands points create a discrete distribution throughout the environment. This required a transformation into a continuous distribution in order to make all locations valid for a cardiac event while maintaining information regarding areas of known high demand. A 2-dimensional probability density function (PDF) is created using a kernel-density estimate using a Gaussian kernel as implemented in the Python NumPy package (Jones Eric, Oliphan Travis, & Peterson Pearu, 2014). This creates the appropriate continuous distribution within the bounds of geographic interest. Fig. 4 shows this geographic distribution PDF which was generated for Hoboken. Areas in the figure that are colored deeper red are considered "hot zones" and have a higher likelihood of new events being generated around these geographic areas. This distribution is sampled to generate events on the Cartesian plane (x, y).

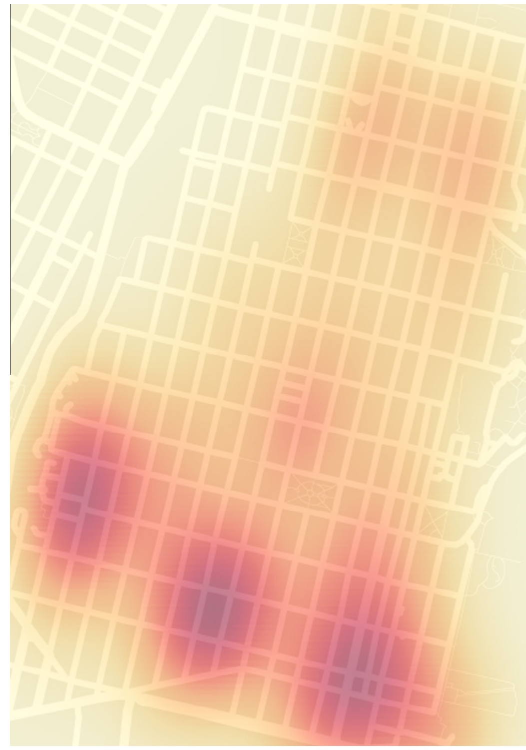

Fig. 4. 2D geographic PDF for generating randomly distributed SCA incidences. Red areas indicate "hotter" zones where incidences are more likely to occur. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4.3. Evaluation on case study

The optimization of AED placement is performed on the Hoboken dataset using both the MCLP and Multi-Objective optimization techniques presented. Each of these optimization runs generate a set of potential deployment configurations, **DC**s. Properties of these **DC**s include combinations of values of $P = [1\text{–}25]$ deployed AEDs and $S = [60, 120, 180, 240, 300]$ maximum acceptable service time. This set of combinations create 125 possible deployment configurations for the MCLP optimization. However, the Multi-Objective optimization creates several more results due to the consideration of temporal availability as an objective function. A Pareto frontier of 2279 potential solutions is created for the Hoboken optimization.

The simulation is run using all potential **DC**s generated from the results of both optimizations. As each event is generated in the simulation, the deployment configuration is evaluated based on the nearest available device in terms of estimated time-to-retrieve. Overall, the average MCLP time-to-retrieve is 337.79 s. The Multi-Objective Optimization technique improves this metric to 239.72 s. Therefore, it is found that the multi-objective optimization improves the average response time on average by 98.06 s.

The time-to-retrieve is translated into a patient survival probability using the methodology suggested in prior literature. A baseline for all patients is 67% with a 7–10% decrease in survival probability per minute without AED care. In our simulation results, this corresponds to an approximate 11.44–16.3% improvement in survival probability by using the Multi-Objective Optimization over the traditional MCLP optimization.

In order to reduce the Multi-objective Pareto set into options manageable for decision-making, the results of the simulation are used to evaluate and narrow the number of potential solutions. This yields a new Pareto frontier containing 122 potential **DC**s. Survival curves are created to visualize the probability distribution function resulting from each of these potential configurations. Figs. 5 and 6 show a comparison of two such options where one device and 25 devices are deployed, respectively. Mass towards the leftward area of the graph indicates a low patient survival probability, as shown in Fig. 5. Mass towards the rightward area of the graph indicates an improved patient survival probability, as shown in Fig. 6. Costs and benefits are weighed across all of these options by the decision maker. Fig. B.8 shows all options for a particular subset that can be used for this decision-making process.

4.4. Visualization

Interactive tools assist decision-makers in choosing the best configurations that meet their desired requirements (Batty et al., 2000). A web-based User Interface (UI) is created to visualize potential configurations. Multiple web technologies implement the UI including: Leaflet, OpenTripPlanner, Google Maps API, d3.js, and

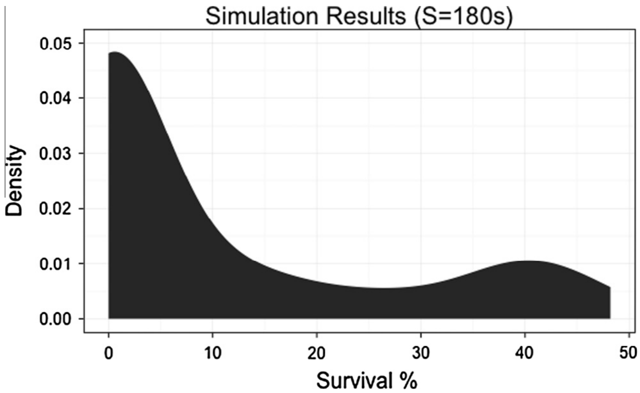

Fig. 5. Survival probability distribution function for $P = 1$ deployed AED and $S = 180$ s maximum acceptable walking time.

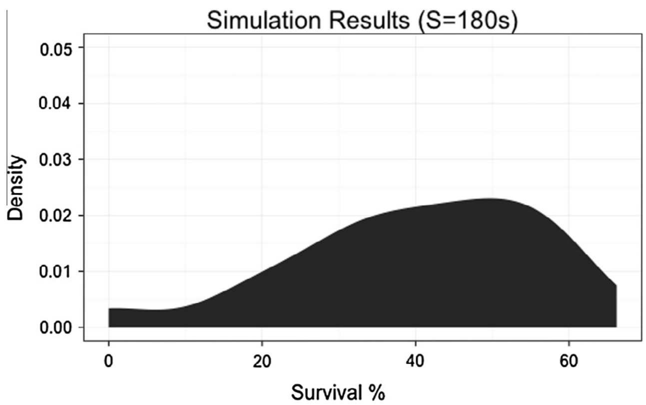

Fig. 6. Survival probability distribution function for $P = 25$ deployed AEDs and $S = 180$ s maximum acceptable walking time.

Table A.1
Prior studies.

Publication	Study location	Contribution
Chan et al. (2013) *Resuscitation*	Toronto, Ontario Dec 16, 2005 to July 15, 2010	Use of single objective mathematical optimization (MCLP) for locating AEDs in urban environment
Folke et al. (2009) *Circulation*	Copenhagen, Denmark Jan 1, 1994 to Dec 31, 2005	Focus on high-incidence areas of cardiac arrest for strategic placement of AEDs within a limited area of a city center and with acceptable costs
Portner et al. (2004) *Prehospital and Disaster Medicine*		Suggests placing AEDs in healthcare-related facilities for greatest impact on rural communities
Swor et al. (2003) *Resuscitation*	Michigan, USA Jan 1, 1997 to Dec 31, 2000	Focus on private locations for deployment strategies
Fedoruk et al. (2002) *Prehospital and Disaster Medicine*	Ontario, Canada Jan 1, 1994 to Dec 31, 2000	Identify site-specific incidence of arrest within communities in order to provide legitimacy for funding and planning of programs

jQuery. These technologies are used to enable decision-makers to manipulate constraints for real-time cost-benefit analysis. Fig. B.9 shows a screen shot of the implementation for Hoboken. The UI consists of several components discussed as follows:

Table A.2
Optimization inputs and outputs.

Input	Output
1. Demand Points (**DP**) 2. Potential Locations (**PL**) 3. Maximum Number of Deployed Devices (P) 4. Maximum Acceptable Distance or Travel Time (S)	1. Deployment Configuration (**DC**) 2. Objective Function Fitness $F = \{f_1, f_2, f_3, \ldots\}$

Table A.3
10 sample solutions from the Hoboken Pareto frontier where $S = 60$.

Geospatial coverage	Temporal coverage	# of devices
26	1	1
33	0.54	1
45	0.3	1
33	1.5	2
37	1.37	2
45	1.3	2
59	1.27	2
71	1.15	2
78	0.57	2
36	1.83	3

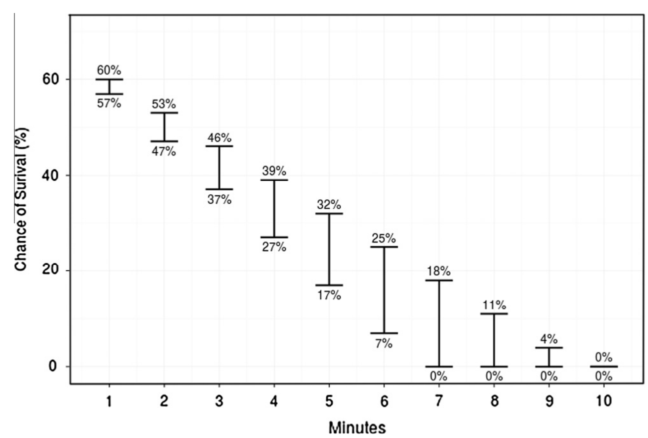

Fig. B.1. According the medical literature, the chance of survival for SCA patients decreases from 67% by approximately 7–10% each minute after arrest without defibrillation or CPR. (Larsen et al., 1993; Valenzuela et al., 1997) This graphic shows the range of survival for patients experiencing SCA as each minute passes without treatment.

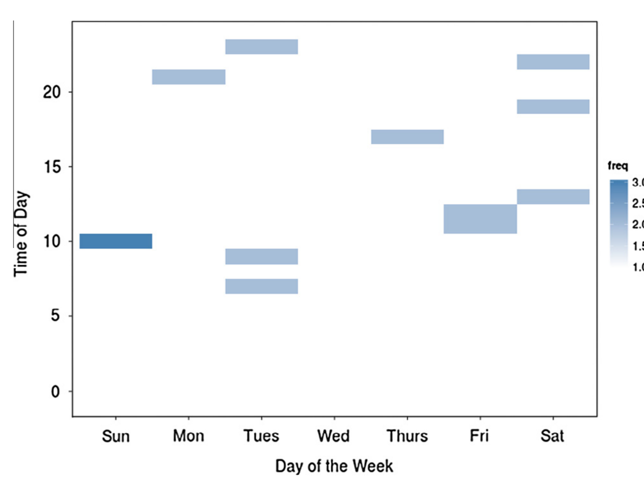

Fig. B.2. SCA subset aggregated temporally by day and time. Darker shading represents greater frequency.

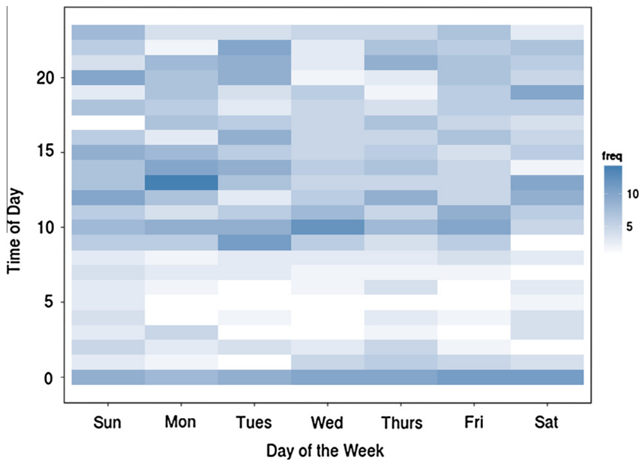

Fig. B.3. CARDIAC subset aggregated temporally by day and time. Darker shading represents greater frequency.

The UI allows the user to interact with the results that are being displayed. Horizontal sliders allow decision-makers to change the constraints of the deployment they wish to view. One slider controls the number of devices, *P*, and another slider controls the maximum allowed distance or time, *S*. The corresponding **DC** is loaded whenever the input constraints are changed.

The major portion of the UI consists of the map section. The currently loaded **DC** is displayed on the map. Each red heart represents a location that is selected for placement of an AED. Selecting a heart icon displays detailed information about the device node such as name, location, hours of operation, latitude, and longitude. Each heart is surrounded by a blue shaded polygon that indicates the geographic area within the maximum allowed travel time. Demand points that fall within this area are considered "covered" by the device.

Blue markers on the map represent demand nodes which are within the service time, *S*, of at least one device node. Grey markers represent demand nodes that are not within the service distance of any device node. Clicking on any of the markers triggers an animation showing the closest route to and from the nearest deployed device. Directions and trip statistics are also displayed in a window pane.

Statistics of the currently selected **DC** are displayed in the UI. Estimated monetary cost and demand point coverage are shown as text. A bar graph shows statistics for all possible configurations, and currently loaded **DC** is shaded in red. The bar graph can be configured to display statistics such as demand node coverage as a percentage, estimated time-to-shock, monetary cost, or estimated patient survival rate.

5. Conclusion

This paper presents a novel method for optimally placing public-access AEDs in urban environments. The method involves optimization, visualization and simulation so that decision-makers can make the best decisions given their cost-benefit constraints. The optimization is formulated using a multi-objective evolutionary algorithm that considers geospatial coverage, temporal coverage, and number of devices deployed. The simulation tests optimization output for performance in terms of time-to-retrieve a device. Finally, the results are displayed in an interactive decision-making user interface for selecting deployment configurations.

Solving the public-access AED problem poses many unique challenges. Our methodology addresses several fragile assumptions and other issues related to prior approaches to solve this

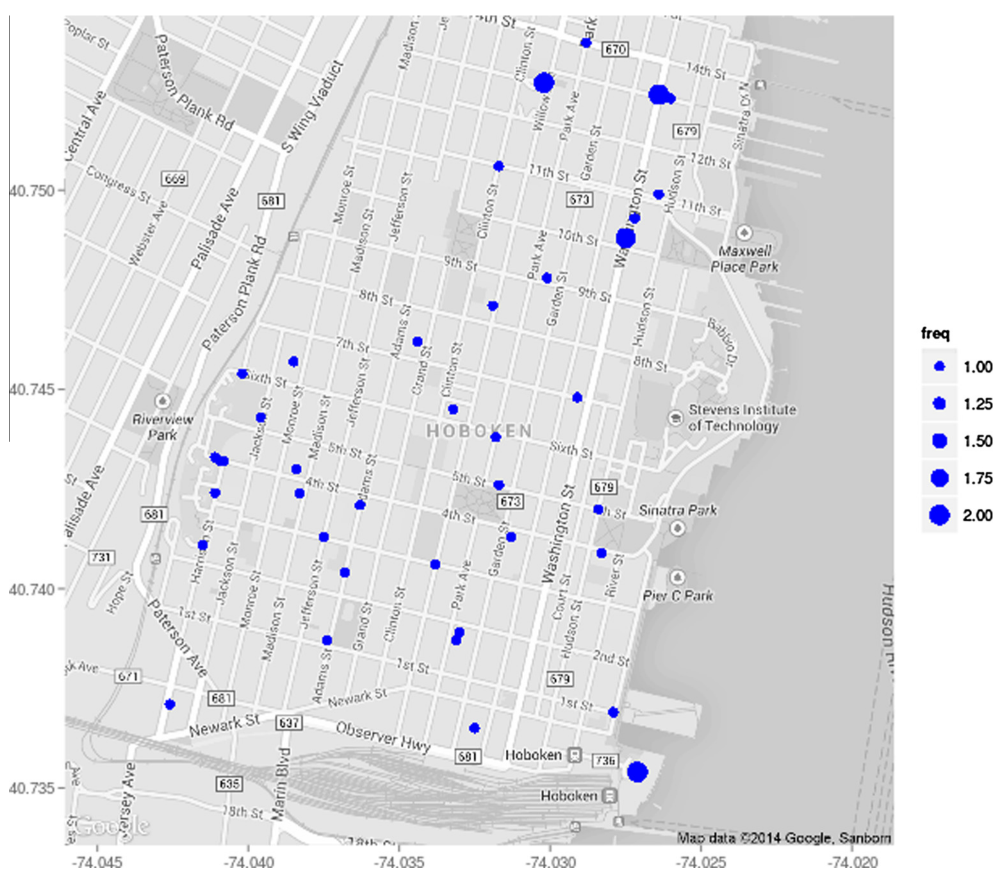

Fig. B.4. SCA subset aggregated geographically. Larger circles indicate higher frequency of occurrence.

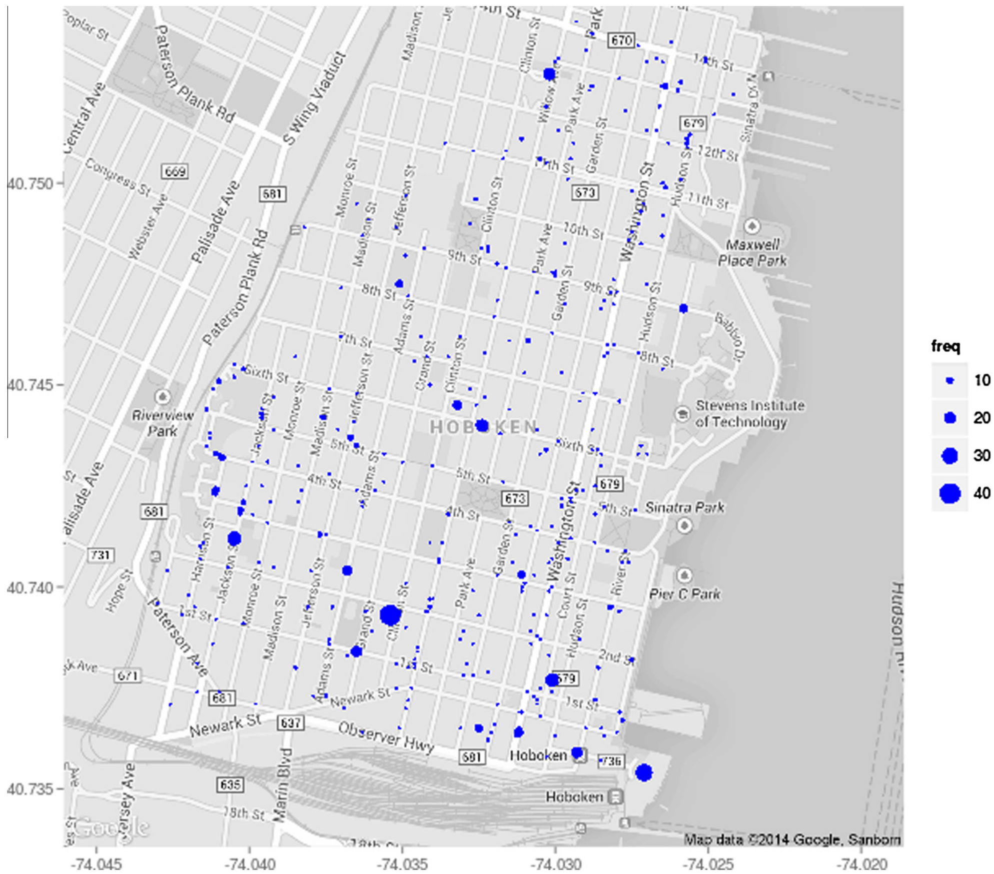

Fig. B.5. CARDIAC subset aggregated geographically. Larger circles indicate higher frequency of occurrence.

reality based facility location problem. The key contributions include: (1) the use of route-based walking time instead of straight-line approximations; (2) introduction of temporal availability in deployed devices to account for location hours-of-operation; (3) use of a multi-objective optimization to balance decision-maker objectives; and (4) the implementation of an interactive decision-maker tool for observing effects on benefits and costs.

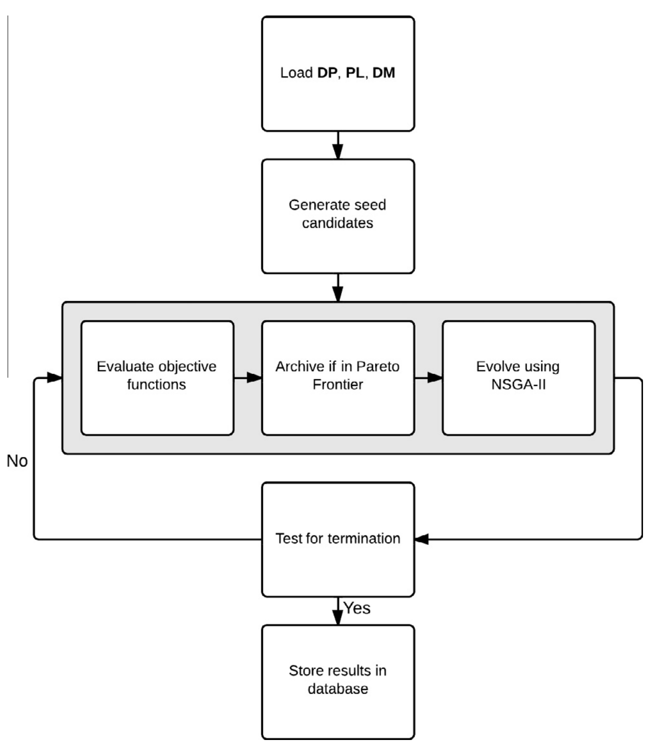

Fig. B.6. Multi-objective optimization flow.

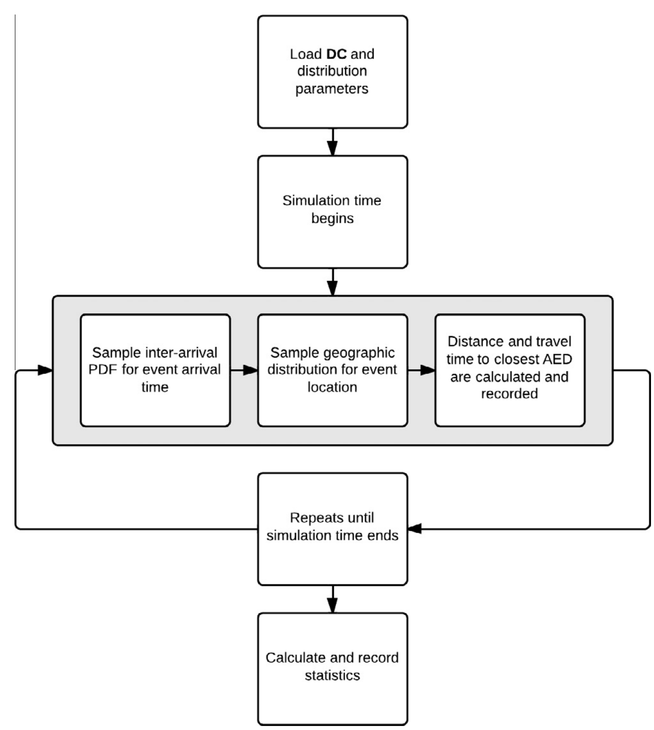

Fig. B.7. Discrete event optimization flow.

Consideration of walking distance and time is particularly important in this location problem because seconds matter when critical care is needed for SCA victims. Inclusion of this granular information is a major advance from prior studies' assumption of straight-line distance. Improvement on this prior assumption is particularly important in urban environments where obstacles can be challenging to navigate. It is important to note that inclusion of walking distance was particularly challenging due to the amount of time required to query OpenTripPlanner APIs.

Inclusion of temporal availability of deployed devices as an objective function ensures that hours of operation of potential locations are considered. This is important because devices that are not available for use during peak demand periods are useless to bystanders attempting to access the devices. Therefore, preference is given to locations that have more available hours during these high demand time periods.

The mathematical formulation and simulation maximize total temporal availability of the devices. As a consequence of this, solutions that have locations that open at the same times are equivalent to solutions that include locations that open at different times, as long as they are open the same amount of total time. Future research will address the current limitation that the availability of AED should be analyzed trying to maximize this temporal availability in a day. That is conjointly looking for the maximum covering with an added time dimension.

Use of a multi-objective optimization allows the introduction of several conflicting objectives that are necessary for describing the public-access AED location problem. Solving this optimization using the genetic algorithm NSGA-II generates many potential solutions. A simulation can be performed to filter out solutions for presentation to decision-makers. The approach allows for decision-makers to set their own priorities when determining which deployment solution is best for their urban environment.

Interactive visualizations allow for decision-makers to interact with the results of the applied methodology to gain insights into the important solutions based on their objective preferences. It enables the decision-makers to observe the effects of decisions in near real-time by interacting with the user interface. This helps bring meaning and validation to decisions made.

Overall, the methodology simulated a 98.06 s improvement in time-to-retrieve devices from the prior baseline model. This improvement corresponds to an estimated 11.44–16.30% improvement in patient survivability. These results show promising implications for deploying new and improving existing public AED programs in urban environments using the proposed methodology. We intend future work in this area to include: (1) considering currently deployed devices; (2) scaling for larger urban environments; and (3) accurately simulating human behavior in an emergency situations to improve time-to-retrieve estimations. Additionally, these contributions and unique approaches can be applied to other

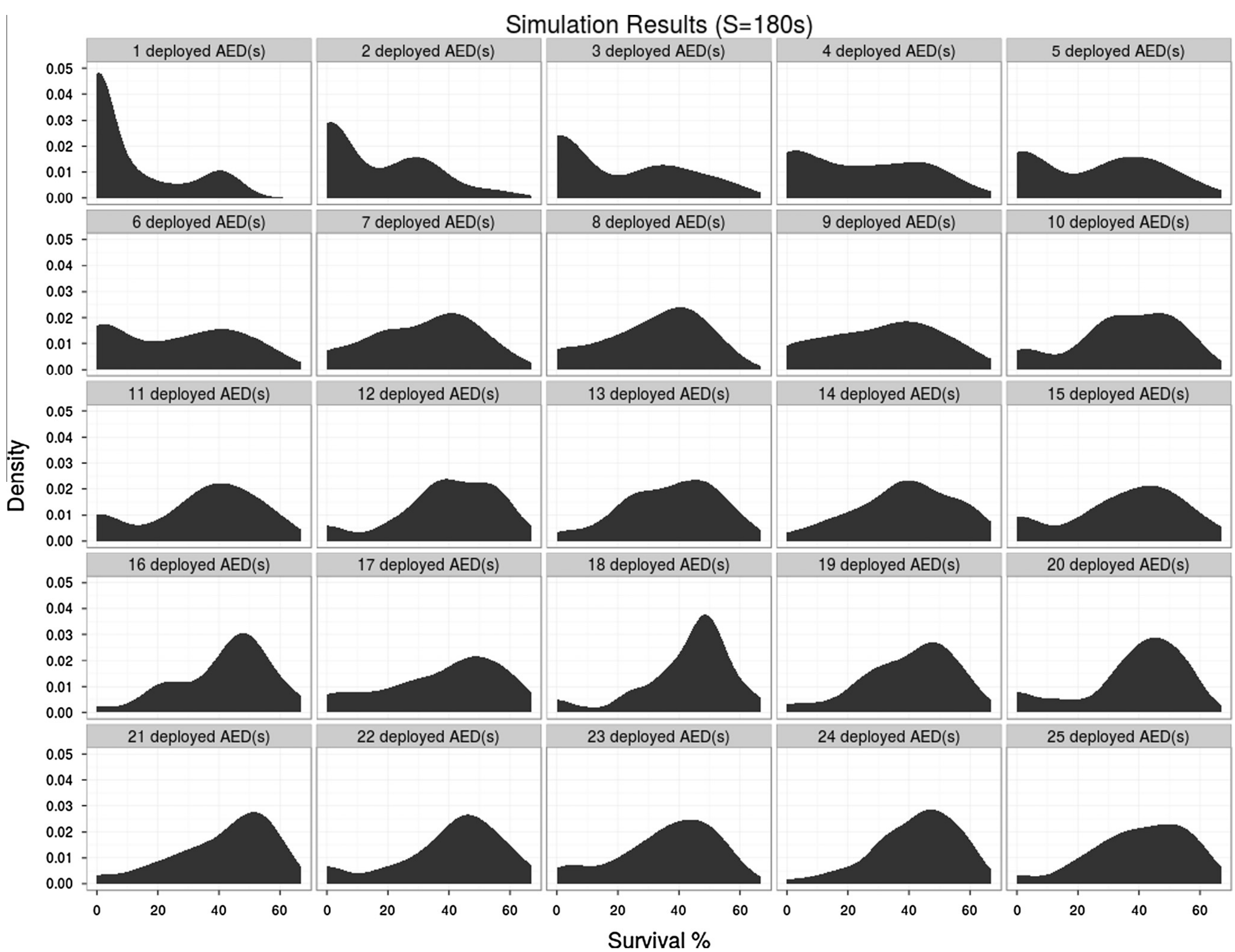

Fig. B.8. Survival PDFs of best **DC**s where $S = 180$ for 5-year DES. Probability of survival is determined by estimated time-to-retrieve the nearest available device.

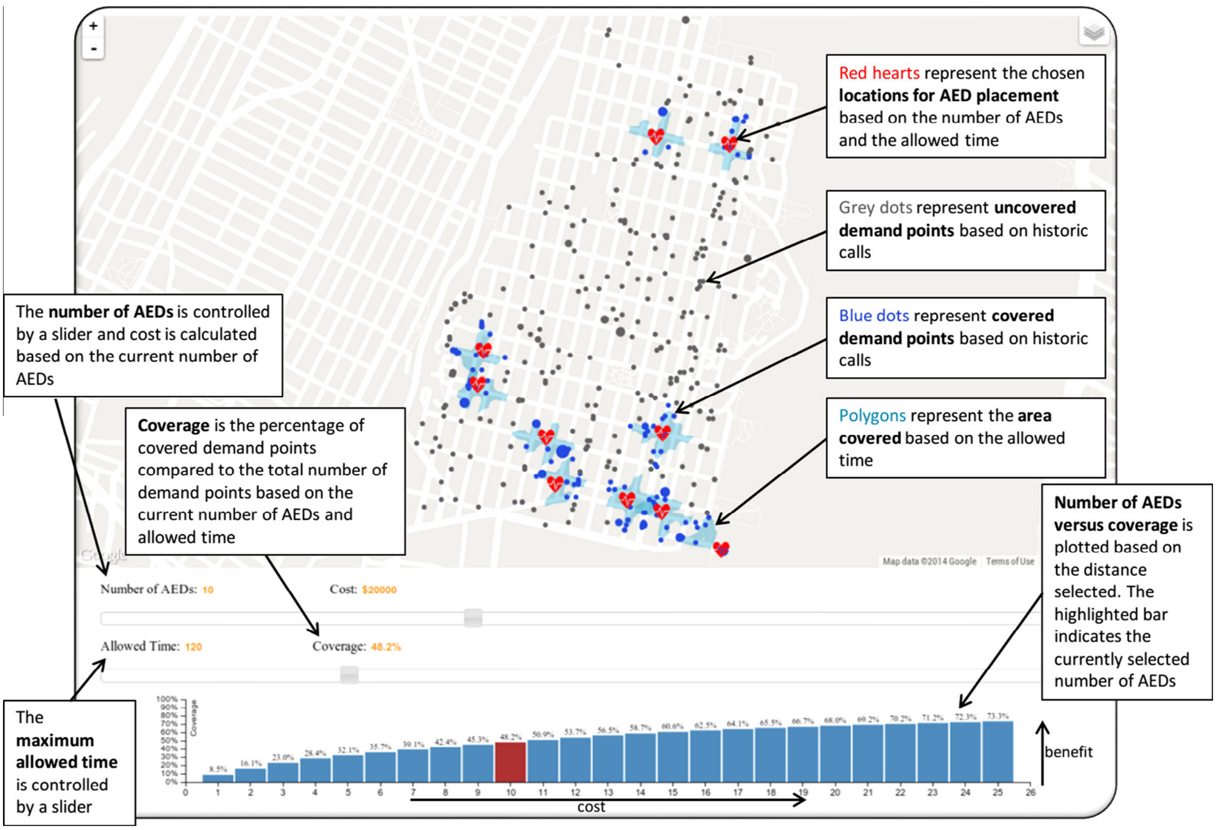

Fig. B.9. Implementation of the interactive visualization for choosing public-access AED location configurations in Hoboken, NJ.

facility location problems in similar or different areas with similar requirements.

Acknowledgements

The authors would like to thank the Hoboken Volunteer Ambulance Corps. for sharing their call logs for the purposes of this paper and for their dedicated service to the City of Hoboken.

Appendix A. Tables

See Tables A.1–A.3.

Appendix B. Figures

See Figs. B.1–B.9.

Appendix C. Acronyms

AED	Automated External Defibrillator
AHA	American Heart Association
CPR	Cardiopulmonary Resuscitation
DC	Deployment Configuration
DM	Distance Matrix
DP	Demand Point
EDA	Exploratory Data Analysis
EMS	Emergency Medical Services
HVAC	Hoboken Volunteer Ambulance Corps
MCLP	Maximal Covering Location Problem
NIH	National Institutes of Health
SCA	Sudden Cardiac Arrest
OTP	OpenTripPlanner
PDF	Probability Density Function
PHI	Protected Health Information
PL	Potential Location
UI	User Interface

Appendix D. Notation

D.1. Sets

DP	Set of demand points *where* $DP_i = [a_i, dx_i, dy_i, c_i]$
PL	Set of potential locations *where* $PL_j = [l_j, px_j, py_j, t_j]$
DM	Set of distances or travel time from each **DP** to each **PL** *where* DM_{ij} is the distance between DP_i and PL_j
DC	Set of locations chosen for the deployment configuration *where* $\mathbf{DC} = \{PL \mid PL_j(l_j = 1)\}$
N_i	Subset of **DP** within the maximum acceptable service distance of at least one **PL** *where* $\{i \in PL \mid DM_{ij} \leqslant S\}$
C_j	Subset of **DP** covered by at least one **PL** in the **DC**. *where* $\{DP \mid DP_i(c_i = 1)\}$
F	Set of objective functions *where* $F = \{f_1, f_2, f_3, \ldots\}$

D.2. Parameters

a_i	Potential demand for service at DP_i, measured in number of prior calls
dx_i, dy_i	Cartesian coordinates for DP_i
t_j	Temporal availability of PL_j, measured in percentage of the 24 h day
px_j, py_j	Cartesian coordinates for PL_j
S	Maximum acceptable service distance or time
P	Maximum number of devices to be deployed

D.3. Decision variables

l_j	Binary decision variable that determines if a device is allocated to site PL_j
c_i	Binary variable indicating if demand node DP_i is covered by at least one AED

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