Interactive Visualization for Optimal Placement of Public-Access AEDs

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ABSTRACT

The purpose of this study is to provide a decision-making tool for visualizing various configurations of optimal placement of publicaccess Automated External Defibrillators (AEDs) deployed in an urban environment. Use of public-access AEDs has shown promising results in decreasing collapse-to-shock times among Sudden Cardiac Arrest (SCA) patients which is associated with improved patient outcomes [3] [4]. Prior studies have implemented mathematical optimization for placement of public-access AEDs [1]. The novelty of this study lies in the implementation of an interactive tool which allows a decision-maker to change parameters and observe effects on coverage and cost. The approach is deployed and tested for the city of Hoboken, NJ.

1 INTRODUCTION

In this paper we present an interactive decision-making tool for visualizing deployment configurations of public-access Automated External Defibrillators (AEDs) through the Maximal Covering Location Problem (MCLP). Geospatial demand and potential locations are visualized on a map along with output measures of evaluation. Interaction occurs using a web-based User Interface (UI) which enables decision-makers to change input parameters and evaluate configurations in real-time.

"Sudden cardiac arrest (SCA) is a condition in which the heart suddenly and unexpectedly stops beating. If this happens, blood stops flowing to the brain and other vital organs. SCA usually causes death if it's not treated within minutes." [5] Early defibrillation is critical for SCA patients as improved survival rates have been observed with bystander use of AEDs [3] [4]. For this reason, there has been support to deploy publicly-accessible AEDs in urban environments.

Prior studies have used mathematical optimization techniques to find optimal locations of a limited number of deployed AED devices [1]. Use of our interactive tool allows a decision-maker to change parameters and observe effects on coverage and cost. We implement the tool for a case study to present optimal placement of public-access AEDs deployed in the City of Hoboken, NJ.

The remainder of this paper is as follows: In Section 2, we review our modelling techniques, discuss input parameters, and output results. In Section 3, we discuss our visualization and UI. In Section 4, we introduce our case study. In Section 5, we conclude on our work and discuss future efforts.

2 MODELLING

The objective of MCLP is to locate a fixed number of devices, P, in a geographic area while seeking to cover the maximum population within a given service distance, S. MCLP was chosen to maximize the coverage of possible cardiac-related calls for a fixed number of

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IEEE Symposium on Visual Analytics Science and Technology 2014 November 9-14, Paris, France 978-1-4799-6227-3/14/\$31.00 ©2014 IEEE deployed devices. Output evaluators include cost of deploying P devices and the percentage of demand node coverage.

For the purposes of this study, MCLP was solved using the GNU GLPK software package. The model must be evaluated for ranges of maximum acceptable distance, *S*, and number of facilities, *P*. Optimal location of devices and covered demand nodes are recorded for each configuration. It is important to note the model can be expanded to include multiple objectives and be solved using a variety of methods.

The mathematical formulation of MCLP according to Church and Revelle is shown as follows [2]:

Maximize $z = \sum_{i \in I} a_i y_i$ S.T. $\sum_{j \in N_i} x_j \ge y_i \qquad \text{for all } i \in I$ $\sum_{j \in J} x_j = P$ $x_j = (0,1) \qquad \text{for all } j \in J$ $\bar{y}_i = (0,1) \qquad \text{for all } i \in I$

$x_j = \langle$	1 if a device is allocated to site j,	0 otherwise

 $y_i = \begin{cases} 1 \text{ if demand node i is covered by a device,} & 0 \text{ otherwise} \end{cases}$

 $a_i =$ population to be served at demand node i

 $N_i = \{ j \in J \mid d_{ij} \le S \}$

3 VISUALIZATION

An interactive visualization was created using a web-based User Interface (UI). The UI allows for decision-makers to evaluate and explore coverage and cost by changing maximum acceptable distance and number of devices. The interactive tool was implemented using Google Maps API, d3.js, and jQuery web technologies.

Markers on the map represent demand and device nodes. Red heart markers show placement of chosen device nodes. Right clicking on a red heart marker displays information about the device node such as name, latitude, and longitude, while left clicking displays a circle highlighting the area covered by that node. Blue markers show demand nodes which are within the service distance, *S*, of at least one device node. Gray markers show demand nodes that are not within the service distance of any device node.

A user can control the configuration of the tool using horizontal sliders located below the map. One slider controls the number of devices, P, and another slider controls the maximum allowed distance, S. The estimated monetary cost and demand node coverage percentage are shown for the current configuration. The bar graph shows the demand node coverage percentage for each number of devices given the current maximum allowed distance. A red bar highlights the currently selected configuration.

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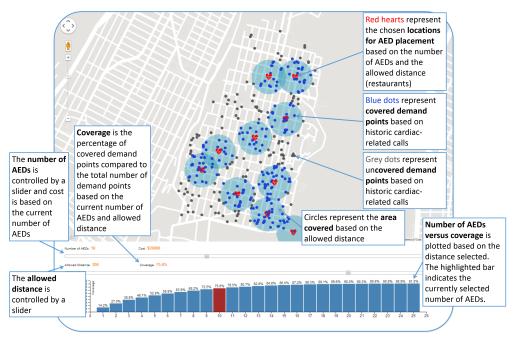


Figure 1: Implementation for AED Placement in Hoboken, NJ

4 CASE STUDY: AED PLACEMENT IN HOBOKEN, NJ

Call logs were obtained from the Hoboken Volunteer Ambulance Corps. The dataset contained date, time, location, and presenting problem for each call occurring between June 2008 and February 2013. A subset of the cardiac-related Hoboken EMS calls were used to build the geographic demand points. This subset was used due to limited number (48) of SCA incidents within the dataset. An assumption is made that cardiac-related calls show the potential for SCA-related calls and therefore give a similar geographic demand distribution.

A list of restaurants were collected as potential locations which can be sponsored to provide and secure public-access AEDs. This was used based on suggestions from prior research and deployment programs [1]. Figure 2 shows the demand nodes and location nodes as collected from the datasets.

The demand and location nodes were input into the MCLP model. P was set to range from 1 to 25 devices and S to range from 50m to 250m (50m increments). The model was run for each combination of P and S. Figure 1 shows the deployed tool.

5 CONCLUSION

We have developed an interactive tool for visualizing deployment configurations of public-access AEDs through the Maximal Covering Location Problem. The visualization allows decision-makers to compare various configurations of input parameters. The novelty lies in enabling users to change these input parameters and observe the effects on coverage and cost in real-time. The approach was deployed and tested for a proposed public-access AED program in the City of Hoboken, NJ.

Future work includes expanding the existing visualization tool into a simulation. This simulation will allow us to predict useful metrics such as future coverage, time-to-shock, survival rate, and cost of deployment. Additionally, we intend to expand the model to include a multi-objective optimization for coverage and device accessibility by time of day.

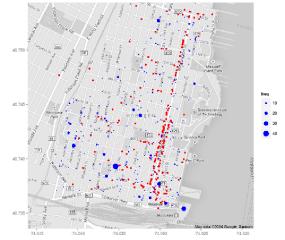


Figure 2: Demand Nodes (blue) and Location Nodes (red)

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