Data-Driven Optimization Model for Automated External Defibrillator (AED) Placement for Singapore

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Abstract: Out-of-hospital cardiac arrest (OHCA) can happen anytime and a low survival rate is observed. The odds of survival decrease by 7-10% with every passing minute in the absence of life-saving measures. The problem of Automated External Defibrillators (AED) placement to deal with these OHCA cases will get increasingly more important as time passes on. To increase the chances of survival rate, this project has developed several AED deployment strategies to model the placement of AEDs in Singapore. The project was conducted in consultation with experts at SingHealth.

PROJECT OVERVIEW

Problem Objectives

1. To research existing AED deployment and OHCA locations around the world.
2. Developing AED placement strategies on a 2D representation of Singapore using Operation Research Techniques.

Key Skillsets

- Simulations to build models
- Operations Research
- Optimzation of resource allocation

Project Roadmap

Identifying Approaches for Model Building

- Clustering
- Mathematical Approaches
- Heuristical Approaches

Building Data-Driven Models for AED Deployment

- Computing using Python
- MCLP, PCM, Greedy Algorithm, Hierarchical Clustering

Testing and Analysis of Model Efficiency

- Identification of the best model using various metrics to measure performances
- Potential improvements for future modelling

METHODOLOGY

K-Means Clustering

The k-means clustering approach allows us to break down the large OHCA and AED dataset into smaller subsets by associating each observation with the closest centroid.

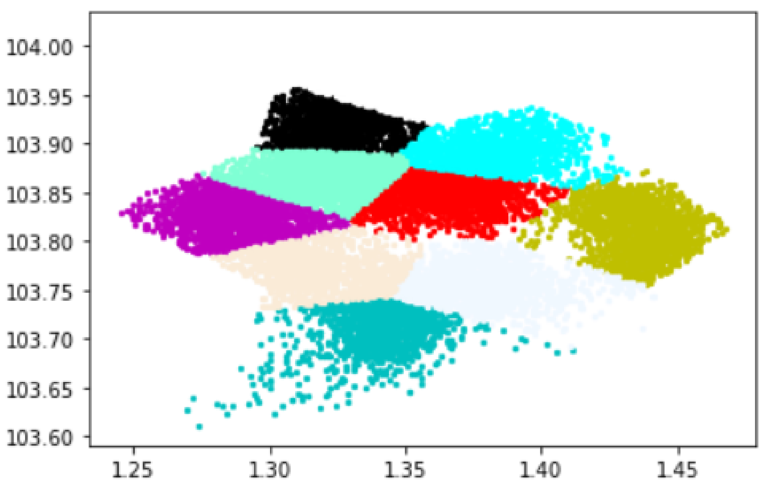


Figure 1: k-means plot of OHCA cases

The Elbow Silhouette Method was used to determine the optimal number of clusters to use in k-means clustering.

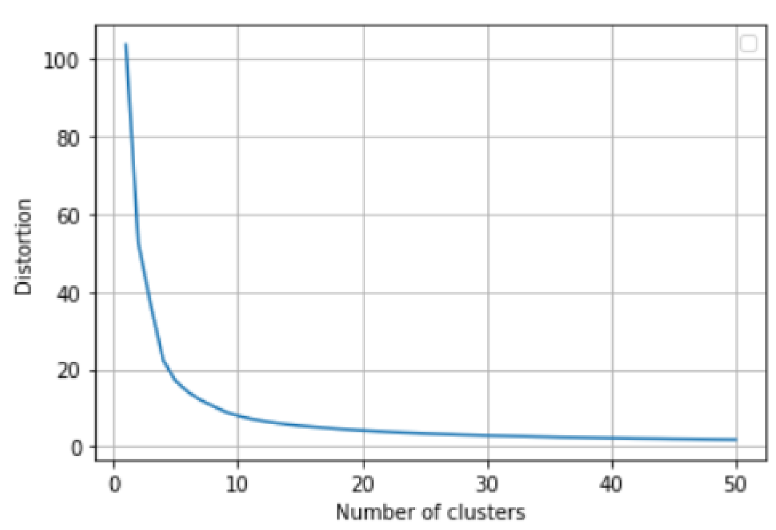


Figure 2: Elbow Method

Heuristic Approach

To determine the number of AEDs to assign to each OHCA cluster, 2 factors need to be considered.

1. Sparsity of the Cluster
2. Number of OHCAs in the cluster

To calculate (1), the average distance between each OHCA is calculated.

The number of AEDs to assign is then calculated via a density and population multiplier that is normalized among the clusters, which is also the average number of AEDs per cluster.

OHCA Generation Method-KDE

To estimate the spatial distribution of OHCAs in Singapore, we adopted Kernel Density Estimation (KDE). KDE uses the past OHCA coordinates, aggregates them and smoothens their contribution to give a density function.

Figure 3: Visualization of KDE generated dataset

Operations Research

Several algorithms have also been developed to tackle facility location problems like this. Algorithms explored include:

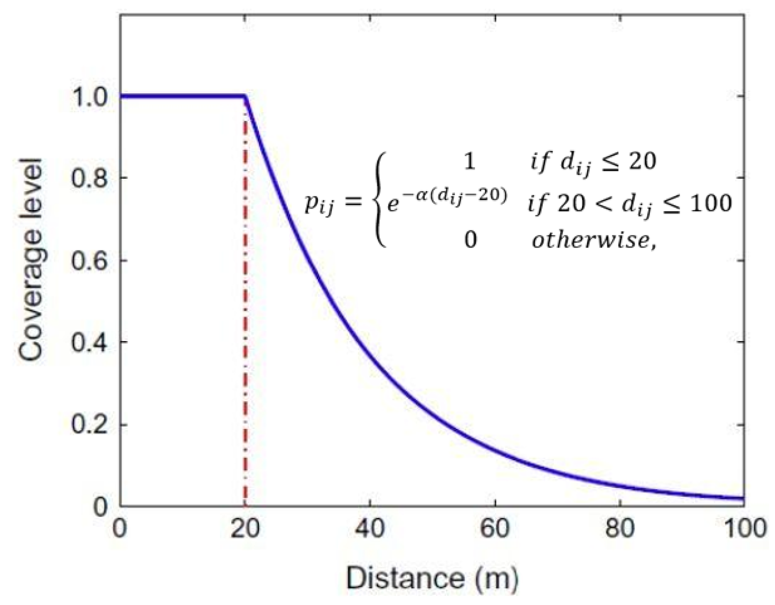
1. Maximal Coverage Location Problem (MCLP)
2. Probabilistic Coverage Model (PCM)
3. Greedy Algorithm
4. Hierarchical Clustering.

MCLP

Maximize	$z = \sum_{i \in I} a_i y_i$		
S.T.	$\sum_{j \in N_i} x_j \geq y_i$	for all $i \in I$	(1)
	$\sum_{j \in J} x_j = P$		(2)
	$x_j = (0,1)$	for all $j \in J$	(3)
	$y_i = (0,1)$	for all $i \in I$	(4)

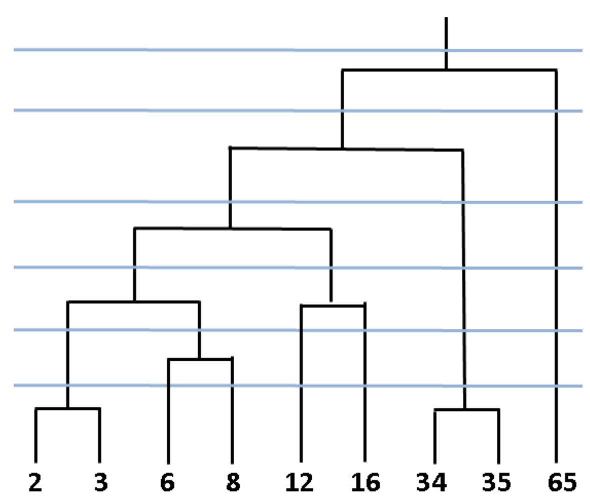
PCM

Maximize	$z = \sum_{j \in J} \sum_{i \in I_j} p_{ij} w_{ij}$		
S.T.	$w_{ij} \leq y_i$	$\forall\, i \in I, j \in J$	(1)
	$\sum_{i \in I_j} w_{ij} \leq 1$	$\forall\, j \in J$	(2)
	$w_{ij} \in \{0,1\}$	$\forall\, i \in I, j \in J$	(3)
	$\sum_{i \in I} y_i \leq N$	$\forall\, i \in I$	(4)
	$y_i \in \{0,1\}$	$\forall\, i \in I$	(5)



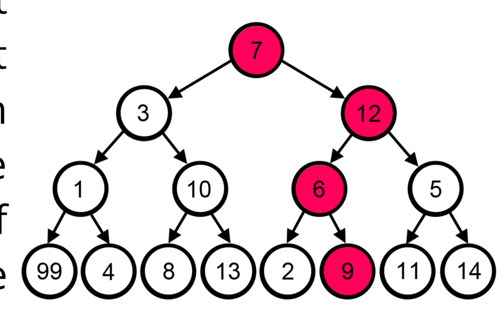
Hierarchical Clustering

Through agglomerative clustering, smaller clusters that are closest to each other are merged until the desired number of clusters are achieved. After clustering, the AED candidate locations closest to the cluster centroids are assigned.



Greedy Algorithm

GA chooses the best placement of AEDS at every step of the algorithm that ensures the placement within 100m of OHCAs. This increases the overall coverage of AEDs.



FINDINGS

Table 1: Results of AED solution on Training Sets

Algorithm	Total Coverage	Partial Coverage	Expected Survival	Average Distance
MCLP	0.702	0.162	0.498	172.802
PCM	0.702	0.377	0.655	158.579
Greedy	0.107	0.042	0.151	1757.386
Hierarchical Clustering	0.382	0.112	0.401	228.085

Table 2: Results of AED solution on Testing Sets

	Total Coverage	Partial Coverage	Expected Survival	Average Distance
MCLP	0.442	0.119	0.430	196.059
PCM	0.498	0.130	0.450	192.728
Greedy	0.090	0.031	0.141	1786.639
Hierarchical Clustering	0.374	0.108	0.396	229.732

Table 3: Performance Comparison of existing AED & PCM

	Total Coverage	Partial Coverage	Expected Survival	Average Distance
Existing AED (n=9182)	0.360	0.122	0.387	274
Multiple PCM (n=8658)	0.498	0.130	0.450	193

Figure 4: Training OHCA Coverage using PCM

Figure 5: Testing OHCA Coverage using PCM

Partial Coverage Function (PCF)

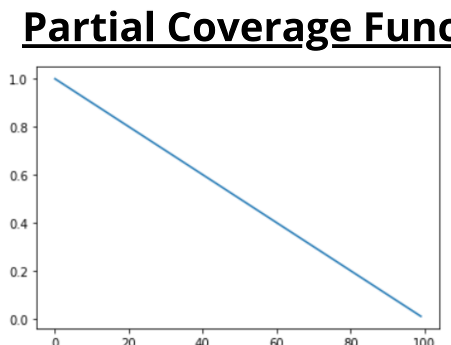


Figure 6: Linear PCF

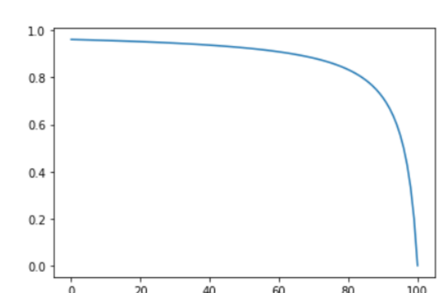


Figure 7: Concave PCF

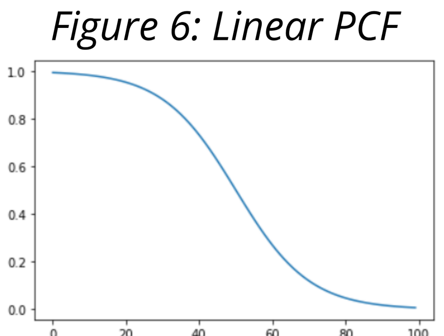


Figure 8: Logistic PCF

$$\begin{cases} P_{ij} = 1 - \dfrac{1}{100} D_{ij} \\ \dfrac{P_{ij}}{1 - P_{ij}} = 25 - \dfrac{1}{4} D_{ij} \\ P_{ij} = \dfrac{L}{1 + e^{-\alpha(D_0 - D_{ij})}} \text{, where } L = 1, \alpha = 0.1, D_0 = 50 \end{cases}$$

Recursive Improvement

Since the greedy algorithm does not fully hit the maximum amount of 12,000 AEDs in the PCM model yet, a possible improvement can be done by re-running the optimisation methodology for those uncovered OHCAs and unused AEDs. This greedy transfer step may be performed recursively until we hit the maximum amount of AEDs or until little improvement in the objective functions is found.

ASSUMPTIONS

1. AEDs are placed at every postal code location without any difficulties;
2. Placing the AED directly in the middle of the chosen AED candidate location;
3. Placing the AED only on the ground floor;
4. The average walking speed to the nearest AED is always 6km/h;
5. AED can only be placed at postal code locations;
6. The spatiotemporal model generated by KDE does not change.

FUTURE DIRECTION

1. Accurate modelling of the OHCA to AED distance through walking network mapping;
2. Logistic regression for the partial coverage function to make the model more realistic.
3. 3D model of AED placement in Singapore that caters to Singapore's high-rise environment;

Vertical Location Mathematical Model

1. We assume a high-rise building with n floors, has 2 elevators and 1 AED;
2. OHCA occurrence in each floor i follows a Poisson distribution λi;
3. The floor the elevator is on follows a discrete uniform random variable from 1 to n.

$$\frac{\lambda_1}{\lambda} \leq \frac{3n^2 - 2n + 1}{3n}$$

The decision criterion was shown by inequality in deciding if the AED should be elevator-based for high-rise buildings. Otherwise, lobby-based.

These approaches can help to improve the deployment of AEDs in Singapore and possibly improve the chances of survival from OHCAs.