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

Li Wanbing

National University of Singapore

Abstract

Out-of-hospital cardiac arrests (OHCAs) can occur anywhere and are becoming more common in Singapore. Passers-by can use Automated External Defibrillators (AEDs) to provide cardiopulmonary resuscitation on OHCA patients (CPR). The purpose of this study is to develop new data-driven models to improve the survival rate of OHCA patients in Singapore. Due to the computational complexity of large-scale test problems, previous attempts to solve the AED placement model were unsuccessful, thus a clustering approach is integrated to discover a computationally efficient solution for the entire country. The proposed method employs the KDE method to create artificial OHCA sets that can be utilized for model training and testing. The proposed models are trained on different levels of training data and their performance is evaluated on the testing set.

1. Introduction

1.1 Background

Out-of-hospital cardiac arrest (OHCA) is a life-threatening and time-critical disease that happens to more than 2,000 persons each year in Singapore, and during the period between 2016 and 2018 the number of OHCAs increased by 18.74%, approaching 3000 cases annually (White et al., 2020). Since there are more and more individuals suffering lifestyle diseases (e.g., diabetes, hypertension, obesity) which contribute to the risk of OHCA, and the aging population is getting serious, the Singapore OHCA incidence is anticipated to keep growing. However, the survival rate of the Utsein subgroup in Singapore is 11%, which is much lower than the average survival rate of 16.3% among other countries (Graham et al., 2008). Without aid measures, the chance of survival will decrease by 7-10% when a minute passes; nevertheless, laypersons can play a fetal role in the survival chain by identifying an OHCA, providing early cardiopulmonary resuscitation (CPR) and defibrillation capabilities.

The automated external defibrillator (AED) is a portable device used to defibrillate and diagnose patients with OHCA. The AED allows both ambulance paramedics and untrained bystanders to safely perform prehospital defibrillation. As a result, it increases the odds of survival for a patient with cardiac arrest. Through extensive studies of the nature of OHCAS and AEDs, it is concluded that enhanced cardiopulmonary resuscitation (CPR) programs by improving the number of AEDs and AED training can increase OHCA survivors (N Engl J Med, 2004). Therefore, placing AEDs at strategic locations is of great necessity to provide timely aid to OHCA patients.

Currently, the deployment of AED in Singapore is arranged by the Singapore Civil Defence Force (SCDF), which does not plan AEDs at a national level or take the historical OHCA data into account. When installing new AEDs, SCDF mainly considers two factors: the distance from other AEDs and the number of HDB flats covered by the AED. The distribution of current AEDs in Singapore is shown in Figure 1.1.1.

Figure 1.1.1: Current AED placement in Singapore

Assuming that an OHCA is considered fully covered if there is an AED within 100 meters, the total coverage rate is 38.91% with 100,000 OHCA points that are simulated in terms of the distribution of historical data, which shows a lot of room for improvement. The current coverage situation is shown in Figure 1.1.2.

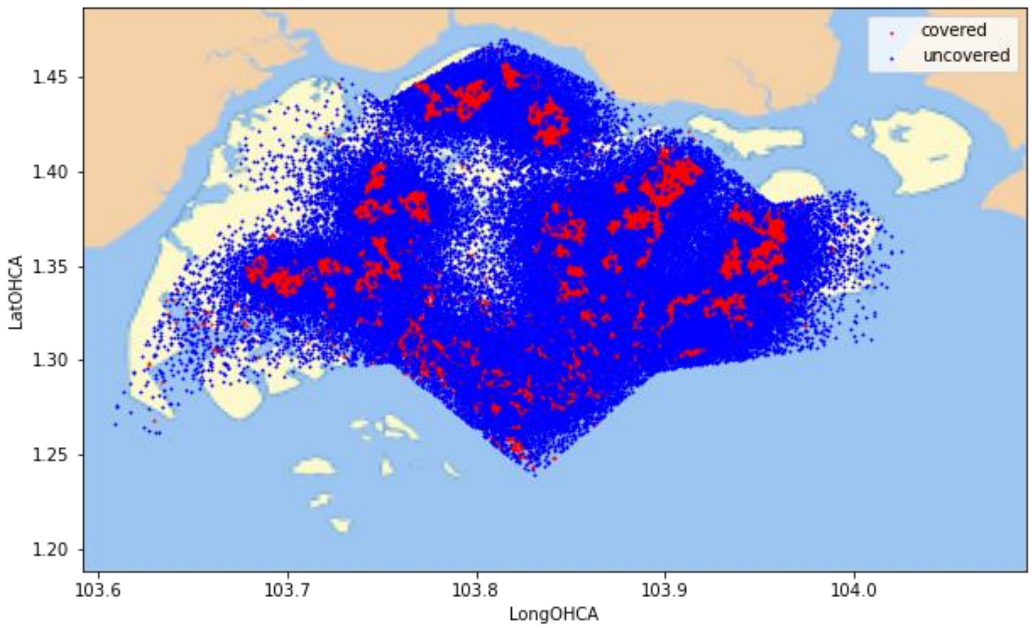


Figure 1.1.2: Coverage with current AED placement in Singapore

Performing Greedy Algorithm iteratively based on OHCA's density which means AEDs are first placed on the densest part of uncovered OHCA and then covered OHCAs are removed. Repeat this process iteratively until 21,353 AEDs were added, the total coverage of OHCAs increase to 75.10%. The limitation of total coverage improvement may be due to the absence of candidate AED around OHCA points in rare area. The AEDs addition and the coverage situation with newly added AEDs are demonstrated in Figure 1.1.3.

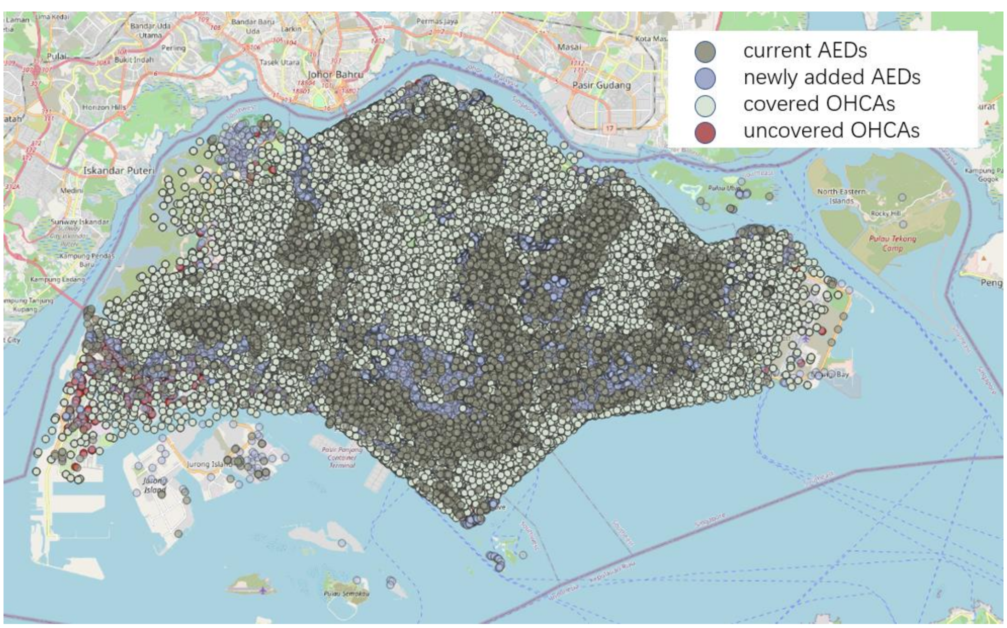


Figure 1.1.3: Coverage with newly added AED placement

1.2 Problem statement

The previous approach that was used to tackle AED deployment in Singapore was a mathematical model, namely maximum survival location problem. Metaheuristics, such as Genetic Algorithm and Greedy Algorithm, have been tried on to reduce the complexity of the model but they have failed to produce meaningful results for large dataset. The solutions of this approach experienced computation time and memory issues. Although Singapore is not a big country, the amount of data that has to be processed to find the optimal placements of AEDs for the OHCAs is huge. If the algorithm cannot be applied to the Singapore dataset, it is doubtful that other countries can use our methods in the first approach for themselves. Also, the approach does not factor in possible future cases of OHCAs due to the deterministic assumptions and thus, the train and test discrete OHCA demand were the same. This would most likely cause the model to overfit to the data and not be able to adapt to future OHCAs that are not within the original OHCA dataset.

Therefore, instead of finding out the best solution for distinct AEDs, new approach is proposed to break down the problem into smaller subsets of data to proceed with the analysis. The main purposes of this study are:

1) to find the AED placement strategy to achieve higher chances of survival of OHCA patients with limited candidate facilities
2) to compare and evaluate the optimal solution with the current AED placement
3) to provide efficient optimal AED solutions for large-scale test problem.

The four major assumptions are made to make the whole problem tractable:

1) AEDs can only be placed at postal code locations and can be placed in every postal code location without any difficulties.
2) The AED will be directly placed in the middle of the postal code if the AED candidate location is chosen.
3) The AED is placed only on the ground floor.
4) The walking speed to the nearest AED is always 6.15km/h.

2. Literature Review

2.1 Literature review of facility location problem

Two-dimensional facility placement planning and its applications to medical care, including emergency and humanitarian assistance facilities, have been covered in the majority of recent research on facility location challenges. The articles frame the location issues as optimization problems, which are usually handled by operations research.

An epsilon-constraint technique for a three-objective location–transportation issue for disaster response is suggested, and it is proven that the precise Pareto front is created (Rachida et al., 2013). This is the first problem with a Pareto dominance method, however all test cases in the case study are extremely tiny, and CPLEX spends a lot of time verifying for optimality, according to the article. A dynamic location model is presented for locating and relocating a fleet of ambulances in dynamic emergency medical service (EMS) systems, which can control the movements and locations of ambulances under various fluctuation styles that may happen over a given period of time, and the results of experiments carried out on real-world data sets show that the model provides better coverage of the EMS requirements (Mahdi et al., 2014). By briefly summarizing a few case studies, Chawis et al. (2017) provide an illustrated guide to the various emergency humanitarian facility deployment challenges. Minisum facility location problem, multi-objective location transportation model, set covering problem, maximum covering problem, and P-center problem are among included in the introduced models that may be selected and used to the AED situation, but more research needs to be done on the solution methods for large-sized problems. In the research of facility location decisions for a humanitarian relief chain responding to instant disasters, a model is proposed to determine the number and locations of distribution centers in a relief network as well as the amount of relief aid to be stocked at each distribution center to assist people encountered with the disasters, which is a modified form of the maximal covering location problem that is very relevant to the AED problem, particularly in terms of partial demand coverage (Burcu and Benita, 2008). Despite the fact that the data set is geophysical and global, it is still deemed a limited model since there are only 45 viable places for putting the centers in this research. To guide the public AED deployment, Chan et al (2016) generalize existing location models and incorporate differences in passerby behavior and it is showed that optimized AED deployment outperforms the existing approach by 40% in coverage and improvements in survival and cost-effectiveness are possible with optimization based on data from Toronto, Canada.

The articles are primarily dealing with areas that are small as in relation to the Singapore OHCA context and offer modest mathematical programs. Hence, innovative and different approaches must be created to suit the Singapore AED problem. Furthermore, the publications concentrate on the fundamental deterministic emergency demand, which would not be of much value to OHCA cases in Singapore.

2.2 Optimization Model

2.2.1 MCLP

The Maximal Covering Location Problem (MCLP) developed by Richard and Charles (2016) is one of optimization methods that has been widely utilized in covering the demand for a limited number of facilities, such as distribution centres (HADCs), ambulances and points of disbursements. The objective is to cover as many demand points as possible within the distance constraints. Figure 2.2.1 demonstrates the principle of MCLP.

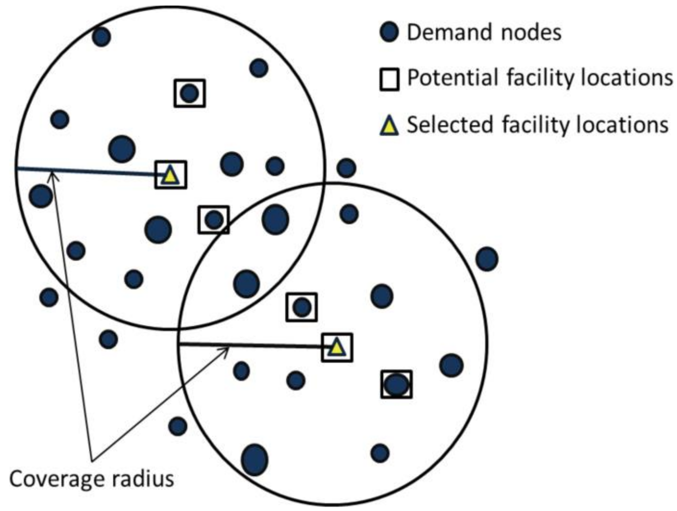


Figure 2.2.1: MCLP

The MCLP has the following mathematical formulation.

MCLP

$$Maximize\ z = \sum_{i \in I} a_i y_i \tag{1}$$

subject to

$$\sum_{j \in N_i} X_j \geq y_i \qquad \forall i \in I \tag{2}$$

$$\sum_{j \in J} X_j = P \tag{3}$$

$$X_j \,.\, y_i \in \{0.1\} \qquad \forall i \in I \;\; \forall j \in J \tag{4}$$

where

I denotes the set of demand nodes;

J denotes the set of facility sites;

S = the distance beyond which a demand point is considered "uncovered"
(the value of S can be chosen differently for each demand point if desired and S is set as 100 meters here);

d_{ij} = the shortest distance from node I to node j;

$X_i = \begin{cases} 1\ if\ a\ facility\ is\ allocared\ to\ site\ j \\ \qquad 0\ otherwise; \end{cases}$

$N_i = \{j \in J | d_{ij} \leq S\}$;

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

$P = the\ number\ of\ facilities\ to\ be\ located.$

In MCLP, the decision variable y_i takes the value of 1 if OHCA point i is covered by an AED within a 100m distance and takes the value of 0 otherwise. N_i is the set of AED sites within 100m distance and can serve OHCA i. In this case, a_i, the weight associated with each demand point, takes the value of 1 as the OHCAs are all equal and represent 1 patient. P is the number of AEDs to be installed. The constraint (2) ensures every OHCA i is covered (y_i can take the value of 1 in objective function (1)) if at least one AED within 100m distance is installed.

2.2.2 PCM

The reaction time is also a vital factor in the AED installation problem. Burcu and Benita (2008) integrated coverage-type objectives into their models to solve facility site planning challenges when response time is a valuable criterion. The probabilistic coverage model (PCM), developed by Chan et al. (2016), may be thought of as an extension of the MCLP. The binary coverage (which takes a value of 0 or 1) has been replaced with partial coverage, which implies that the occurrence of an OHCA is covered at a value between 0 and 1, which is calculated using the distance traveled from the OHCA to the AED. As illustrated in equation, it may be represented as an exponentially decaying coverage function (5). The coverage level, p_{ij}, by AED j reaches a maximum value of 1 when the distance between the bystander near OHCA i and AED j is less than 20m and then drops afterwards based on the bystander assumptions. Figure 2.2.2 depicts the relationship between distance and coverage level.

$$p_{ij} = \begin{cases} 1 & if\ d_{ij} \leq 20, \\ e^{-\alpha(d_{ij}-20)} & if\ 20 \leq d_{ij} \leq 100 \\ 0 & otherwise \end{cases} \tag{5}$$

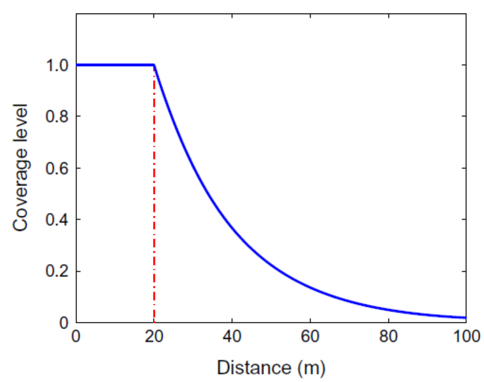


Figure 2.2.2: Graph of coverage level against distance

With the assumption that there is only one layperson being available to find and retrieve the nearest AED from the OHCA patient, the overall degree of coverage supplied to an OHCA becomes the best-case likelihood of covering OHCA. The following is how the probabilistic coverage model (PCM) is constructed.

PCM

$$Maximize\ Z = \sum_{i=1}^{m} \sum_{j \epsilon J_i} p_{ij} Y_{ij} \tag{6}$$

subject to

$$Y_{ij} \leq X_j \qquad \forall i \in I, j \in J_i \qquad (7)$$

$$\sum_{j \epsilon J_i} Y_{ij} \leq 1 \qquad \forall i \in I \qquad (8)$$

$$\sum_{j \epsilon J} X_j \leq n \qquad (9)$$

$$X_j . Y_{ij} \in \{0.1\} \qquad \forall i \in I \ \forall j \in J \qquad (10)$$

The symbols are defined in the same way as before, except that J_i is the set of AEDs with nonzero coverage from OHCA i, $J_i = \{j \in J | p_{ij} > 0\}$.

3. Solution: Description of Approach

3.1 Data Set and Study Area

3.1.1 OHCA Generation Method – KDE

Kernel Density Estimation (KDE) is a non-parametric method for estimating the probability density function of the original geographical dataset's probability density function (Stanisław, 2018). To estimate the geographical distribution of OHCAs in Singapore, KDE employed the historical OHCA coordinates, aggregated them and smoothed their contributions to produce a density function in both the x and y axes.

The Jordan Curve Theorem indicates that a point is inside a polygon if the number of crossings from an arbitrary direction is odd, and it is used by the KDE to truncate points on the x-y axes denoting longitude and latitude, respectively. Thus, the mainland Singapore polygon is constructed by adding 15 corner coordinates and counting the number of edges straight to the negative x-axis of a point. If the number of crossed edges is odd, as in Figure 3.1.1, the point is inside the polygon and therefore accepted; otherwise, it is rejected. This algorithm runs in $O(s)$ time, where s is the number of consecutive vertices of the polygon (Jeff,2009).

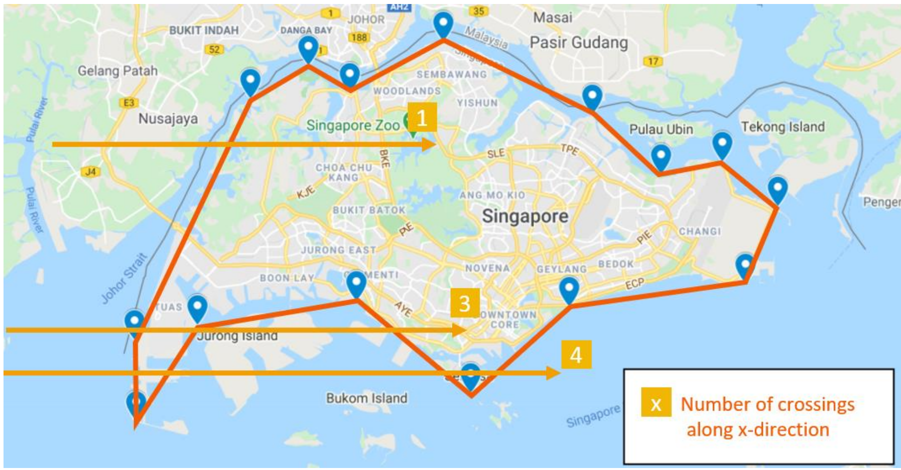


Figure 3.1.1: Illustration of accepting and rejecting coordinates

Following this, two sets of 100,000 OHCA synthetic samples are obtained respectively for model training and testing. Two of the KDE-generated datasets utilized in this experiment are shown in Figure 3.1.2.

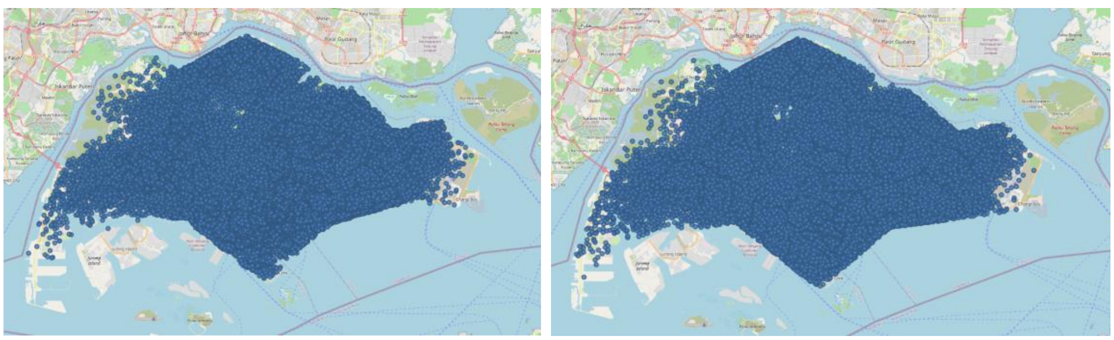


Figure 3.1.2: Visualization of two KDE-generated datasets

The link between the Utstain's survival rate and time to AED has been investigated in early studies. Researchers in the past used historical data to fit a power law model to the survival likelihood of an OHCA patient. In this section, the fitted model will be defined (12). As a result, the Haversine formula and the average travel speed of passersby may be used to calculate the travelling time in minutes, d_{ij}, for a return trip from OHCA i to the candidate AED site j for each OHCA position. The Haversine formula is used to determine the great-circle distance between two sphere coordinates. Equation (11) states how to calculate the geographic distance, d.

$$haversin\left(\frac{d}{r}\right) = haversin(\phi_2 - \phi_1) + \cos(\phi_2)\cos(\phi_1)\, haversin(\lambda_2 - \lambda_1) \qquad (11)$$

r is the radius of the earth. $\phi_1$and ϕ_2 are latitudes of the 2 points, and λ_1 and λ_2 are longitudes of the 2 points. Next, the survival probability p_{ij} follows the fitted power law function stated in equation (12).

$$p_{ij} = \begin{cases} 1 & \text{where } d_{ij} \leq 1 \\ 0.549\, d_{ij}^{-0.584} & \text{where } 1 \leq d_{ij} \leq 20 \\ 0 & \text{where } d_{ij} \geq 20 \end{cases} \qquad (12)$$

For each dataset, a probability of survival matrix P_{ij} was created from their respective OHCA and AED coordinates.

3.1.2 Subzone and Planning Area

The Urban Redevelopment Authority (URA) splits Singapore into regions, planning areas, and subzones to make urban planning easier. Smaller Planning Areas are created from the Planning Regions. Each Planning Area is subdivided further into smaller subzones, which are generally focused around a focal point such as a neighborhood center or activity node. Smaller Planning Areas are created from the Planning Regions. Each Planning Area has a population of around 150,000 people and is served by a town center as well as a number of local commercial/shopping areas.

To explore the model effectiveness and efficiency of addressing different scales of problem, the historical OHCA points, current AEDs and candidate AED locations are mapped into the belonging subzones or planning areas for the following analysis. There are 331 subzones and 55 planning areas in total. The subzones and planning area are shown in Figure 3.1.3 and Figure 3.1.4 respectively.

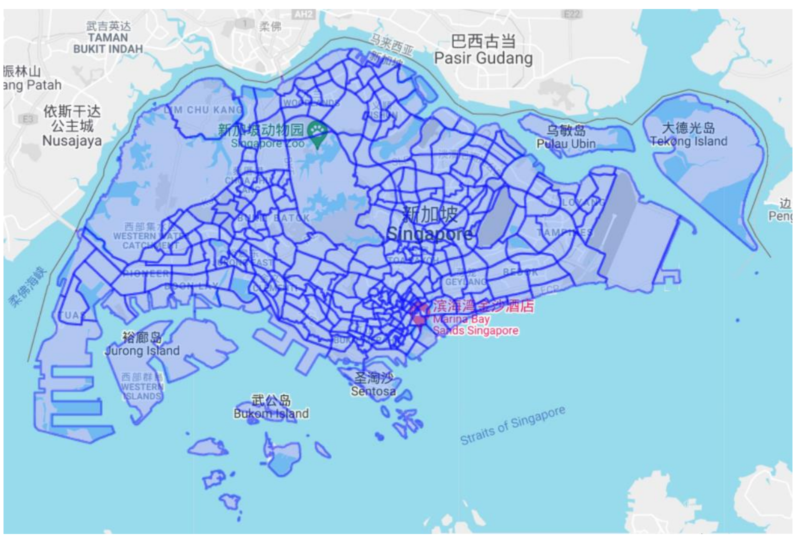


Figure 3.1.3: Subzone boundary

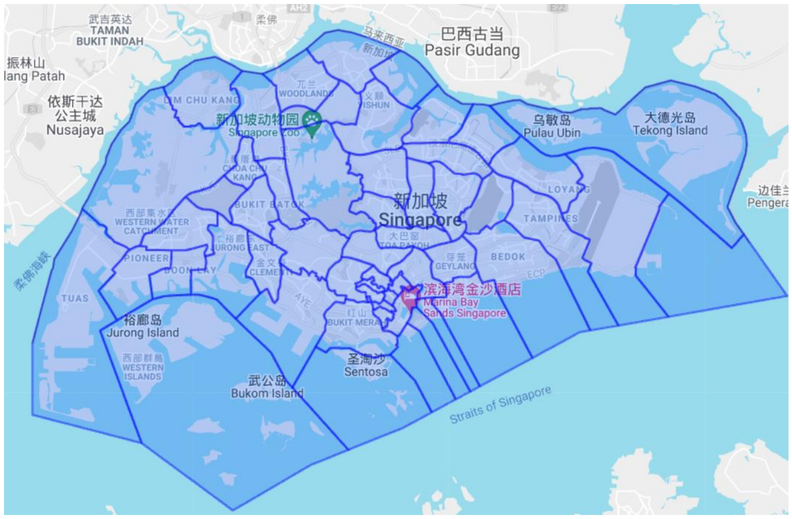


Figure 3.1.4: Planning area boundary

3.2 Clustering-based Approach

3.2.1 Clustering Approach

Clustering is used to find groups in the OHCA occurrences in Singapore as shown in Figure 3.2.1 and perform optimization individually on those clusters identified. The most basic and effective clustering method is k-means clustering. In k-means clustering, the algorithm determines the position of k centroids and proceeds to classify the existing data points under the k clusters based on the nearest mean. Here, the elbow method and silhouette method can be applied to gauge the optimal number of clusters, k.

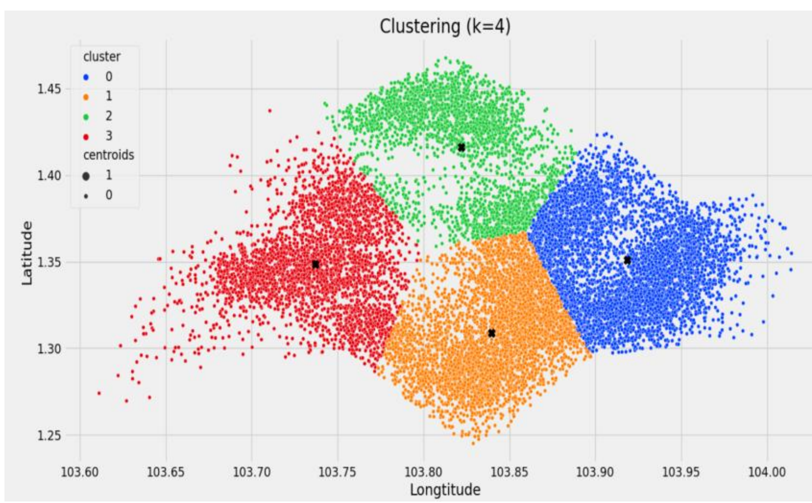


Figure 3.2.1: Example clustering of artificial OHCA points with their centroids

The elbow technique (Robert L.,1953) is a heuristic that allows humans to recognize a tapering of the total sum of squared errors as the k cut-off. For each k, the distortion, or the sum of squared distances between each point and its assigned center, is computed, and the elbow point is the best k value to pick. The elbow plot in Figure 3.2.2 does not provide the exact elbow point for the optimum k. As a result, additional factor should be taken into account when calculating the value of k.

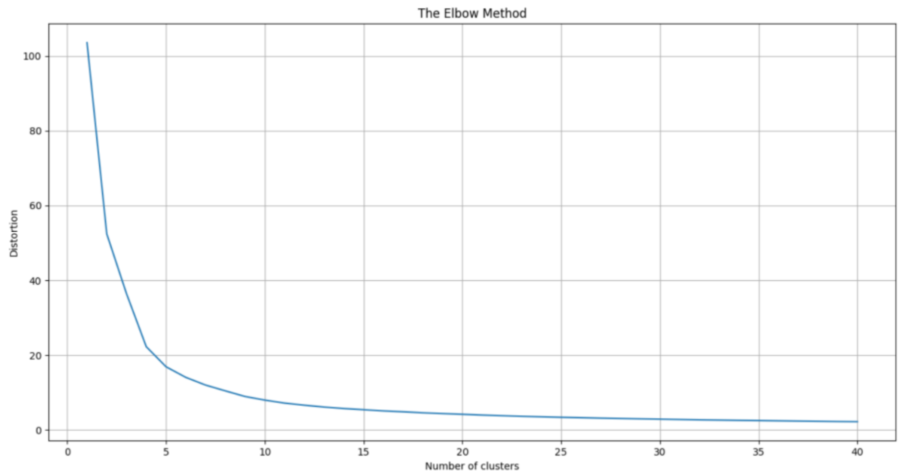


Figure 3.2.2: An elbow plot for an artificial OHCA dataset

The average silhouette technique, in which the ideal k has the maximum average silhouette among different values of k, is another way of finding the number of clusters (Leonard and Peter J., 1990). The silhouette width, for entity $i \in I$ is defined in equation (13). In equation (13), the silhouette width, $s(i)$, for entity $i \in I$ is defined. The ideal k can be better found from the plot of average silhouette against k because the maximum point is more obvious, as shown in Figure 3.2.3.

$$s(i) = \frac{b(i) - a(i)}{max(a(i), b(i))} \tag{13}$$

$a(i)$ is the dissimilarity measure between i and the rest entities in its cluster. $b(i)$ equals to the minimum of the average dissimilarity of i and all entities outside its cluster.

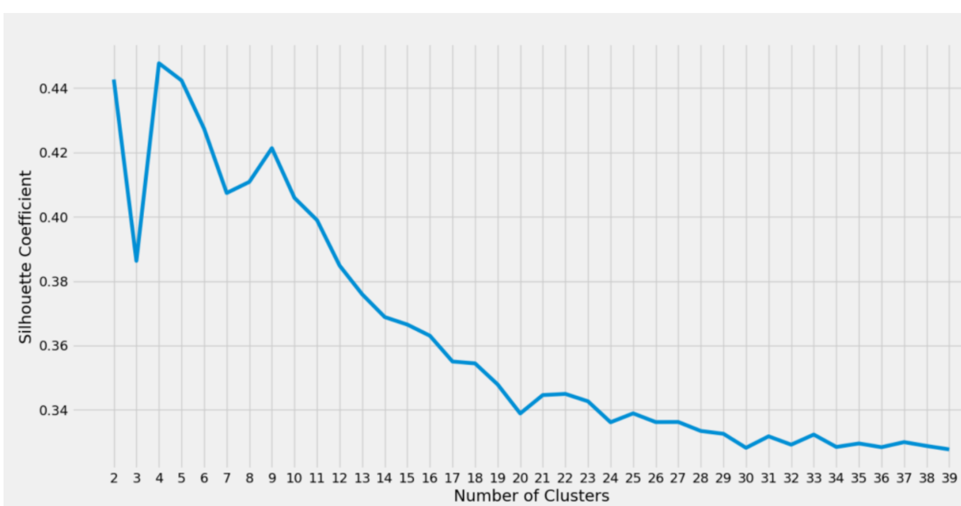


Figure 3.2.3: The silhouette method for an artificial OHCA dataset

The main steps in clustering the OHCA points are described in Algorithm 1.

Algorithm 1
1. Compute k-means clustering for a range of 1 to l clusters for all OHCA points. l is a pre-defined number for the maximum number of OHCA clusters. 2. For each k in step 1., calculate the total within-cluster sum of squares (wss) and average silhouette as described in equation (13). 3. Plot the curve of wss by k for the elbow plot, and the curve of average silhouette by k for the silhouette plot. 4. Determine the appropriate k from both plots in step 3. For the elbow plot, look for the location of the bend (knee). For the silhouette plot, look for the maximum point. 5. The final set of centroids are the clusters naturally formed around them.

This clustering method will be incorporated into the allocation algorithms.

3.2.2 Multiple MCLP

First OHCA samples are clustered and then MCLP is performed individually on each cluster. The steps in Multiple MCLP are described in Algorithm 2.

Algorithm 2
1. Perform k-means clustering on the OHCA occurrences and obtain k from the elbow method, as outlined in Algorithm 1. 2. Cluster the OHCA occurrences into the k clusters as determined in step 1. I_c is defined as the set of OHCA locations in cluster c. 3. Select the candidate AED locations for each of the k clusters. Use the k-means model fitted in step 1 to predict and label the belonged cluster of candidate AED. For each cluster c, let set J_c be the set of candidate AEDs suited for that cluster c. 4. Determine the number of AEDs to install, n_c, to allocate for cluster c. An example of the rationing for cluster c will be to take the ratio of $\|I_c\|$ to $\|I\|$. 5. Solve for the AED placement for each cluster c by solving MCLP characterised by (1), (2), (3) and (4), but with n_c replacing P, I_c replacing I and J_c replacing J. 6. The final set of AEDs to install will be the union of the AED solution sets found in step 5.

3.2.3 Multiple PCM

PCM is also performed on the divided cluster zones and then the solution AEDs are aggregated. The steps taken in Multiple PCM are described in

Algorithm 3.

Algorithm 3
1. Perform k-means clustering on the OHCA occurrences and obtain k from the elbow method, as outlined in Algorithm 1. 2. Cluster the OHCA occurrences into the k clusters as determined in step 1. I_c is defined as the set of OHCA locations in cluster c. 3. Select the candidate AED locations for each of the k clusters. Use the k-means model fitted in step 1 to predict and label the belonged cluster of candidate AED. For each cluster c, let set J_c be the set of candidate AEDs suited for that cluster c. 4. Determine the number of AEDs to install, n_c, to allocate for cluster c. An example of the rationing for cluster c will be to take the ratio of $\|I_c\|$ to $\|I\|$. 5. Solve for the AED placement for each cluster c by solving the probability coverage model characterised by (6), (7), (8), (9) and (10), but with n_c replacing n, I_c replacing I and J_c replacing J. 6. The final set of AEDs to install will be the union of the AED solution sets found in step 5.

3.3 Performance Metric

3.3.1 The Total Coverage Metric

To evaluate the effectiveness of a set of AEDs when confronted with a series of OHCA calls. The closest AED available is chosen for each artificial OHCA event. If the closest AED is within 100 meters, it successfully "covers" the OHCA, according to a common rule employed by many other studies (Ivan, et al., 2020). It is estimated what percentage of OHCAs are covered.

3.3.2 The Partial Coverage Metric

The partial coverage, as previously defined, treats coverage as a numeric rather than a binary feature. The criterion for locating the nearest AED remains the same, but the function in equation (5) that measures coverage has been expanded to a decimal between 1 and 0, as illustrated in Figure 2.2.

3.3.3 The Expected Survival Probability Metric

As an outcome, the expected survival is the average chance of surviving over all OHCA samples. The probability of survival for each OHCA is estimated using equation (12).

For an AED placement assessed on a group of OHCAs, the expected survival probability is the sum of the survival probabilities of the OHCAs divided by the number of OHCAs, with a value ranging from 0 to 1.

3.3.4 The Average Distance Metric

The straight-line distance to the nearest AED is determined using the haversine formula stated in (11) and the average distances among all OHCA are averaged instead of calculating the coverage level or declaring whether the OHCA is covered or not. The average distance for an AED placement tested on a group of OHCAs is the sum of the OHCAs' straight-line distances divided by the number of OHCAs, and its value is limited above 0. An AED installation in the best-case scenario would provide entire coverage, half coverage, and an estimated survival chance of 1, with an average distance of 0.

3.3.5 The Computational Time Metric

Running wall time on the same machine is used to measure the time complexity of an algorithm in this case, in order to judge whether the algorithm can work efficiently on large test problem.

3.4 Experiment Design

A data-driven solution system is created to approach the AED placement problem using the clustering-based approaches in the above section. The location of candidate and available AEDs, as well as historical OHCA data, are acquired and analyzed. To generate new synthetic OHCA data points that replicate future OHCA occurrences, statistical approaches are utilized. From the historic OHCA data, two distinct synthetic OHCA datasets are constructed. The training set is utilized to train the optimization models and arrive at the AED placement solution. The test set is used to assess the AED placement's performance and compare the models' results.

To gauge the computational efficiency for each of the test cases and find the model suitable for large-scale test problem, the models are experimented on three different scale of cases in Singapore: subzone-level cases, planning-area-level cases and the country-level case. The performance of models on subzone-level or planning-area-level cases are the aggregated results of models on each subzone or planning area.

To compare the performance of the proposed solutions with that of current AED placement, in the experiment, the maximum number of AEDs to install is set to be 9,880, which is the same with the current plan according to the information on the current AED updated as of early 2019

The design is represented by the schematic in Figure 3.4.1.

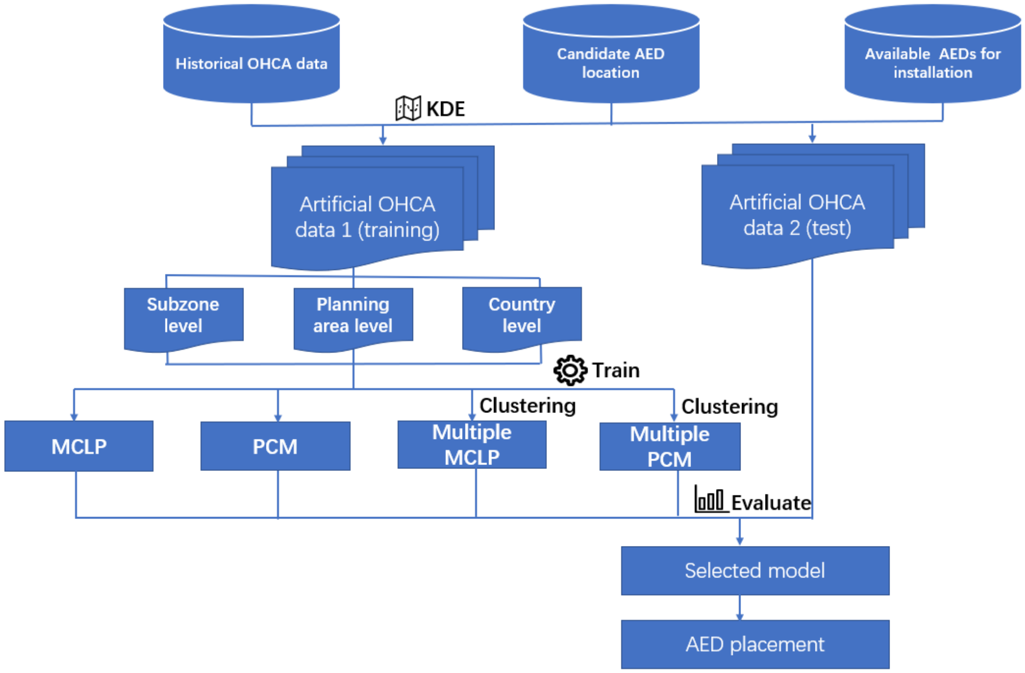


Figure 3.4.1: Schematic of experiment design

3.5 Result

MCLP, PCM, Multiple MCLP, and Multiple PCM are trained on the first artificial OHCA dataset at subzone level, planning area level and country level individually. In terms of elbow method, k is 2 when data is divided into multiple subzones and k is 3 when data is in planning areas.

From the results of subzone-level optimization and area-level optimization shown in Table 3.5.1 and Table 3.5.2, it can be seen that the performance of models on larger test problem is slightly better, but the computational time gets longer with as the size of data increases. PCM, the mathematical model without clustering, cannot work out on area-level problem due to the memory limit.

Table 3.5.1: Results of AED solution on subzone-level training set

	Total coverage	Partial coverage	Expected Survival	Average Distance to Closest AED (m)	Computational Time
MCLP	0.6770	0.1509	0.4917	162.32	2min 26s
PCM	0.5778	0.2307	0.5358	154.65	18min 9s
Multiple MCLP	0.6617	0.1476	0.4858	163.58	1min 30s
Multiple PCM	0.5683	0.2223	0.5283	153.93	8min 51s

Table 3.5.2: Results of AED solution on planning-area-level training set

	Total coverage	Partial coverage	Expected Survival	Average Distance to Closest AED (m)	Computational Time
MCLP	0.6913	0.1548	0.4954	161.51	8 min 23.7s
PCM	-	-	-	-	-
Multiple MCLP	0.6863	0.1515	0.4932	158.27	2min 42s
Multiple PCM	0.5717	0.2328	0.5328	164.48	13min 8s

Due to computational limitations, $k = 55$ is chosen as the models' input parameter instead of $k = 35$ determined by elbow method.
Table 3.5.3 summarizes training performance of the AED placement models on the entire dataset. Neither MCLP or PCM cannot apply to such large scale of dataset due to the out-of-memory issue. However, multiple MCLP and multiple PCM on the whole Singapore outperform the ones on small-size data based on the first four metrics. The length of computational time is between those of subzone-level and area-level, which implies a reasonable result. Both solutions deploy fewer AEDs than the current, but achieve much better metrics.

Table 3.5.3: Results of AED solution on country-level training set

	Total coverage	Partial coverage	Expected Survival	Average Distance to Closest AED (m)	Computational Time	AEDs to install
Current Plan	0.3891	0.1206	0.4054	246.79	-	9880
MCLP	-	-	-	-	-	-
PCM	-	-	-	-	-	-
Multiple MCLP	0.7003	0.1601	0.5058	146.39	5min 26s	9826
Multiple PCM	0.5930	0.2519	0.5487	176.56	22min 51s	9837

The visual representation of the OHCA coverage by multiple MCLP and multiple PCM on the training dataset is in Figure 3.5.1.

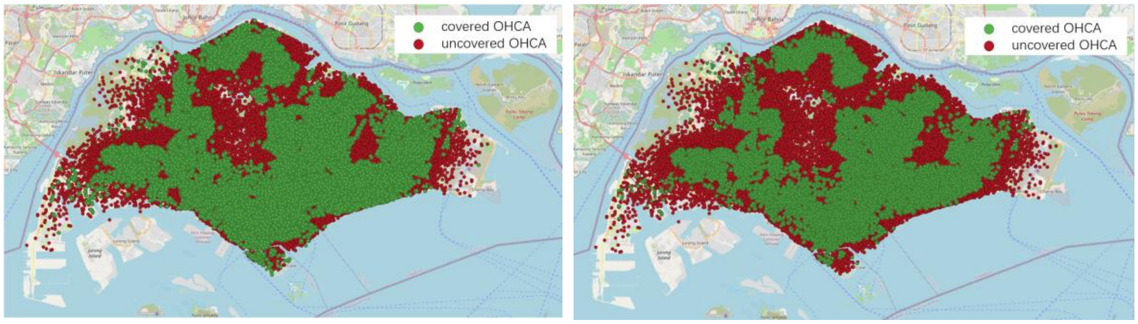


Figure 3.5.1: Training OHCA coverage using multiple MCLP and multiple PCM

After testing the AED placements on another artificial OHCA dataset, their performance was compared with one another to obtain the test performance. The performance of the suggested models on the test set is summarised in Table 3.5.4 and the visual representation of the test OHCA coverage from multiple MCLP and multiple PCM is shown in Figure 3.5.2.

Table 3.5.4: Results of AED Solution on Test set

	Total coverage	Partial coverage	Expected Survival	Average Distance to Closest AED (m)	AEDs to install
Current	0.3879	0.1196	0.4040	246.83	9880
Multiple MCLP	0.6239	0.1503	0.4919	150.76	9826
Multiple PCM	0.5480	0.1519	0.4765	186.60	9837

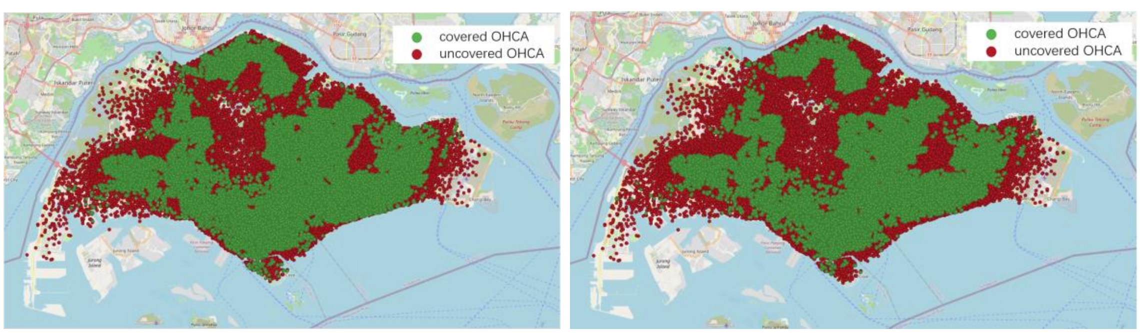


Figure 3.5.2: Test OHCA coverage using multiple MCLP and multiple PCM

4. Discussion

The two clustering-based models, multiple PCM and multiple MCLP, can produce feasible solutions within the reasonable time and memory limitation and allocate the AEDs better for the country wide problem in terms of the defined metrics. With the same or even a smaller number of AEDs, the optimized solutions derived from these two models dominated the current AED placement according to all the metrics measured. Thus, the new plan is much more cost-effective than the previous one.

The optimal solutions from the multiple MCLP model and multiple PCM, as well as the locations of the existing installed AEDs, are evaluated using Open Street Map, an open-source geographical information, to gain a better understanding of the optimization models and to better comprehend the differences between them. In Figure 4.1 100,000 OHCAs from the training set are plotted in a heat map. The dark-colored area near the map's bottom right indicates a higher concentration of OHCAs in and around the Bedok neighborhood in East Singapore.

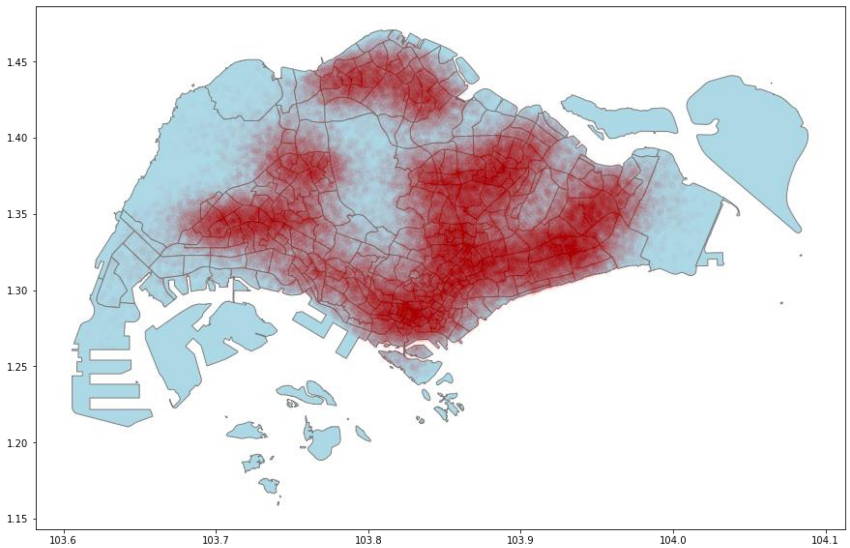
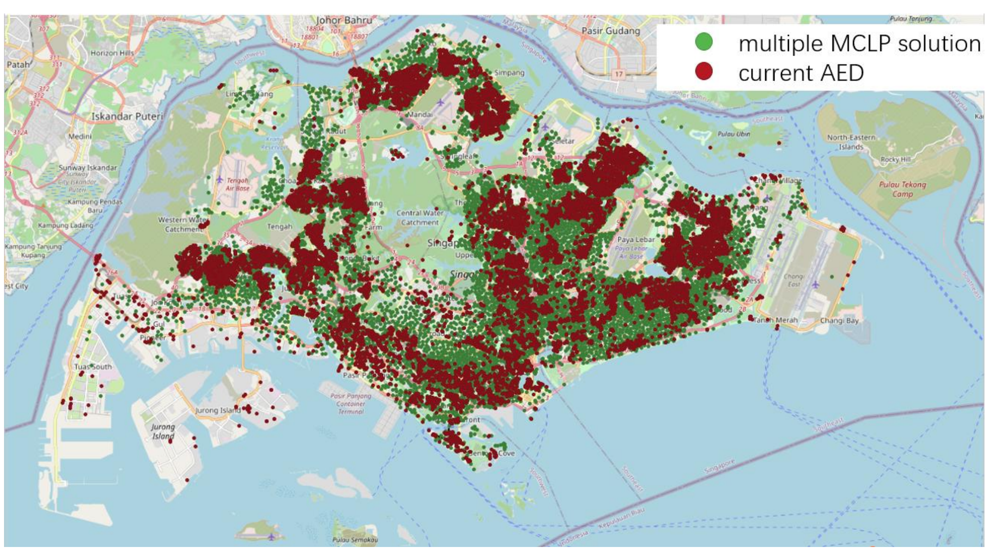


Figure 4.1: Heat Map of OHCAs from training set

The optimal solutions of the multiple MCLP model and multiple PCM, as well as the placement of the existing registered AEDs are shown in Figure 4.2. Compared current AED placement, both the two optimal solutions place more AEDs in areas densely populated with OHCAs and locate a large proportion of AEDs in the southeast.



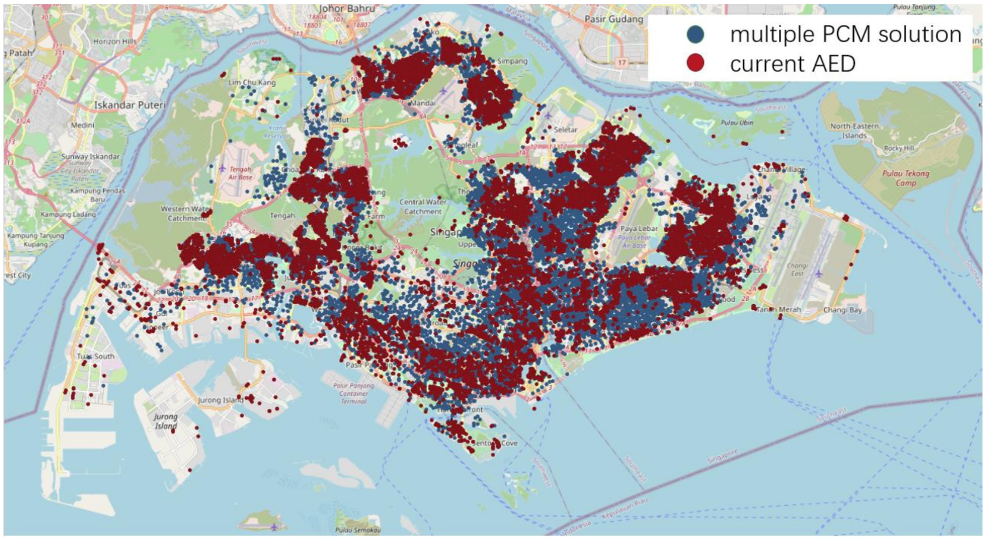


Figure 4.2: The distribution of optimal solutions and current AEDs

Taking Bedok Area as an example, Bedok is a built-up area in Singapore having 16,891 candidate sites for AED instalment. Only 475 of them are now occupied by AEDs, while both multiple MCLP and multiple PCM place 775 AEDs in this area. The great addition of AEDs determined by the two algorithms leads to a leap in coverage rate.

The difference between a non-binary coverage model (PCM) and a binary coverage model (MCLP) is illustrated by instance in Figure 4.3. When the true coverage function is decaying, the MCLP may result in suboptimal solutions. A residential area in Orchard Singapore with numerous historical OHCA points is depicted in the figure. The multiple MCLP model selects an AED location that covers nine OHCA points within 100 meters, but none within 20 meters, which results in adequate overall coverage but inadequate partial coverage. Multiple PCM, on the other hand, picks a location that covers nine cardiac arrests within 100-meter radius, ensuring full or nearly full coverage to two of them as well, resulting in a greater partial coverage than that of the multiple MCLP solution.

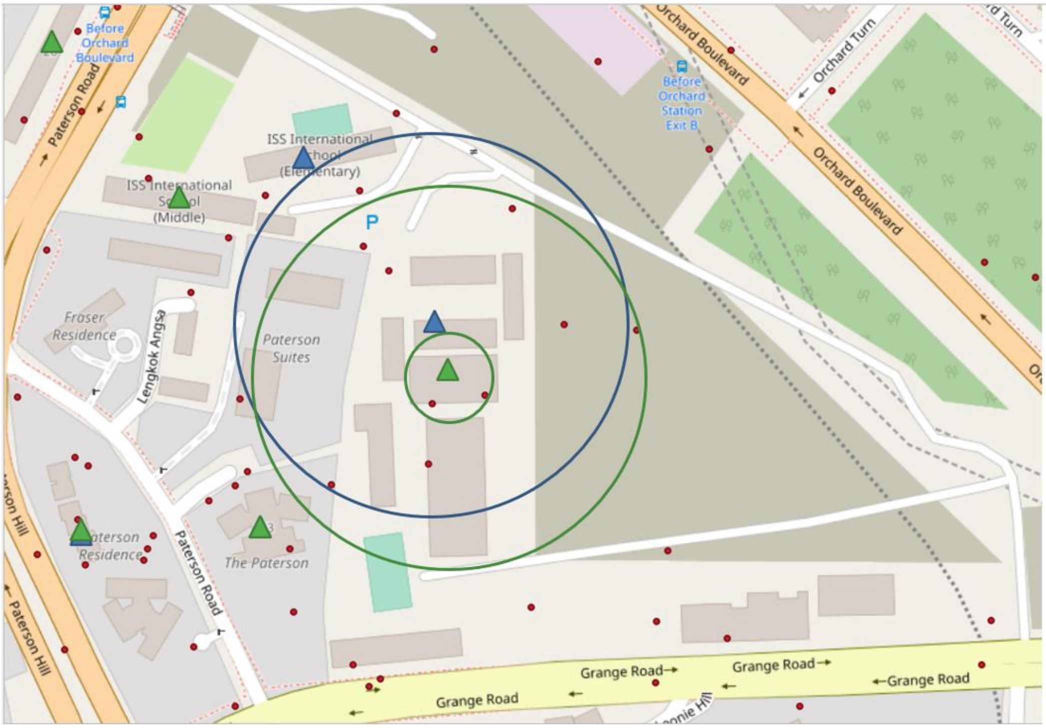


Figure 4.3 Optimal AED locations

Thus, for practical reasons, the multiple PCM is considered as the model for application since it provides greater partial coverage and an expected survival rate while maintaining a suitable overall coverage and average distance to the nearest AED. Despite taking up more memory and computing resources, the model can still figure out huge amounts of data in an acceptable amount of time.

5. Conclusions and Further Work

In comparison to the conventional placement of AEDs without island-wide assessment and ignoring historical data, data-driven ways to address the AED placement problem are a suitable stepping stone for emergency management. In Singapore, the clustering approach help to analyse and forecast OHCA instances, enabling for AED placement and optimization. Also, based on this, MCLP and PCM achieved considerably higher coverage and survival. This strategy is critical as the number and complexity of sites in Singapore grows, necessitating careful planning of AED resources. However, there are still certain assumptions made in the proposed technique that would take additional consideration to eliminate.

Research in the domain of urban challenges such as constrained pathing and spaces in buildings, as well as vertical travel, is needed to expand the ideas presented in this study.

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