2022 8th International Conference on Control, Decision and Information Technologies (CoDIT) | 978-1-6654-9607-0/22/$31.00 ©2022 IEEE | DOI: 10.1109/CODIT55151.2022.9804110

Geo-Clustering Model for Optimizing Locations of Public Health Emergency Operations and COVID-19 Vaccine Distribution Centers

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***Abstract*— Optimum location of vaccine distribution and Emergency Operation Centers (EOCs) is imperative to ensuring prompt and efficient vaccination of eligible population in any location of interest. The proximity of these vaccination centers is likely to positively affect the decision of the target population to present themselves for vaccination. In this paper, a computational model for optimizing the number and determining the location of depots or vaccine distribution centers, and amounts of vaccines to be stocked at each center, to satisfy the needs of the local population is proposed. A modified K-means++ is used to optimize the number of required centers and the approximate locations to ensure the usage of the least possible cost. The algorithm allows planners to enter two initial specific locations as depots, thereby avoiding the usual random selection of initial points. Using geospatial and population data, the resulting clusters are divided into two, on each iteration. Heap sort is used to select the next centroid. Optimization of these locations is iteratively done, until there are no more changes. An optimized number of vaccine distribution centers for any region of interest can be obtained. It ensures that least possible cost is used. Our algorithm avoids the usual random outcomes associated with K-means and provides a more efficient clustering output, with an improved time complexity. The application of the proposed algorithm to a real-world test instance indicates its effectiveness.**

Keywords: Facility Location-Allocation, Disaster Management, Optimization, Algorithms, COVID-19.

I. INTRODUCTION

In late 2019, coronavirus disease 2019 (COVID-19) emerged in Wuhan, Hubei province of China, causing a pandemic that has continued to wreak havoc, through unprecedented global spreading. As of September 1, 2021, over 218 million cases have been confirmed in over 219 countries and territories, with an average case fatality rate of 5.4% [1][2]. There are concerns that the burden and spread of COVID-19 in Low- and Middle-Income Countries (LMICs) of Africa and Southeast Asia might be substantially more significant than reported. Most countries in LMICs are characterized by inadequate health infrastructure and low resilience capabilities [3]. Efficient response plans, including optimization and pre-positioning of EOCs are required to effectively mitigate the impacts of COVID-19 and other public health outbreaks. Various vaccines have been approved for emergency prophylaxis use by the US Food and Drug Administration and similar regulatory agencies in other countries, in collaboration with the World Health Organization COVID-19 vaccine center. These include vaccines made by Pfizer-BioNTech, Moderna, Janssen, Novavax, Johnson and Johnson, AstraZeneca-Oxford and others. More than 60 additional vaccine candidates are also undergoing clinical development and testing. There are concerns about distribution strategies across the globe. This is one of the core factors necessitating the establishment of COVAX, the vaccines pillar of ACT Accelerator, co-led by Gavi, the Coalition for Epidemic Preparedness Innovations (CEPI) and WHO. It aims to guarantee fair and equitable access to COVID-19 vaccine for every country in the world. Most LMICs have received considerable doses of these vaccines, and are now faced with the issue of equitable distribution, amidst raging vaccine hesitancy.

Generally, comprehensive public health emergency response plans include an arrangement for the determination of physical locations of delivery centers or depots. This is necessary to avoid post-disaster ad-hoc approaches that are usually deployed whenever there is an outbreak of diseases, mostly in LMICs. Optimizing the number of required depots is particularly useful in low-resource countries, to ensure the least possible number of depots is used to cover the largest number of individuals or communities [4]. Many factors are taken into consideration when planning the location of these facilities. These include the topography of the location, accessibility to different types and capacities of vehicles, road network, and proximity to potential end-users. Providing a single facility, to cover a maximum number of individuals or demand points is a simple form of facility location problem, introduced by studies in [5]. However, finding the best locations from multiple candidate sites in a large geographical area is an NP-hard problem, as shown by Boonmee et al [6]. Existing solutions involve the use of linear or mixed integer programming, lagrangian decomposition and genetic algorithms, which can be broadly grouped into exact and approximation algorithms as shown in these studies by Sahraeian, Adeleke and others [7]–[10]. The depot location-allocation problem considers the best viable approach to deliver post-disaster interventions to the affected population. Time and cost are two main factors affect the decision to select a given location as a potential response facility. Time to deliver these interventions is a prime consideration, while cost is trade-off between expenditures for establishing new facility and maintaining an existing one, if it is within the allowed constraints. A concise integer programming model for determining the approximate locations of emergency response facilities is proposed in Boonmee et al [11]. It includes an objective function to maximize the total satisfiable demand within a predetermined distance parameter.

Mathematically, the emergency operation center location problem can be formulated, as a variant of the general facility location-allocation problem, by a set of integer programming, represented by equations (1) through (5). Let j represents an individual requiring vaccination or other medical counter measures and belonging to a set of nodes J, ($j \epsilon$ D). Let i represents a candidate facility site, ($i \epsilon F$). Consider the following notations and indices:

Decision Variables

$$y_i = \begin{cases} 1 & if\ facility\ i\ is\ open \\ 0 & otherwise \end{cases} \quad (1)$$

$$min \sum_{i \epsilon F} \sum_{j \epsilon D} c_{ij}\, x_{ij} + \sum_{i \epsilon F} f_j y_i \quad (2)$$

Subject to:

$$\sum_{j \epsilon D} d_j x_{ij} \leq S_i y_i \quad \forall\, i\ \varepsilon\ F, j\ \varepsilon\ D \quad (3)$$

$$\sum_{j \epsilon D} y_j x_{ij} = 1 \quad \forall\, i\ \varepsilon\ F \quad (4)$$

$$x_j, Y_{ij}\ \epsilon\ \{0,1\} \quad \forall\, i, j \quad (5)$$

The first part of the objective function (2) minimizes cost of transportation and total distance between demand locations and candidate facilities, while the second part optimizes the number of facilities and the cost of maintaining the facility. According to Constraint (3), the cumulative demands of all sites within a facility i will be, at most, equal to S_i, the total capacity of the facility. Constraint (4) ensures that each location j is assigned to at least one open facility. The binary conditions for the model variables are maintained by constraint (5).

Previous studies considered several factors when planning real-world emergency facility location, mostly in large-scale operations. These include service priorities, redundant facilities and the dynamics of candidate locations, according to studies by Arabani and Farahani in [7]. They suggested the consideration of trade-off between making location changes and cost of relief transportation to demand points. Some models are only concerned with allocation of facilities to ensure maximum coverage, while few of the suggested algorithms include consideration for routing. These include approaches suggested by Shen et al, Alenezy and Balcik et al in [12], [13] and [14] respectively. Maximal covering location models are formulated and suggested in Han et al [15] and [16], including some routing models for relief distribution. Hence, it can be seen that most available approaches for solving facility-location-allocation problem employs either GIS techniques or some form of mixed integer programming solutions. However, in this paper, the use of a data science clustering algorithm, in addition to GIS, is proposed.

The remaining part of the paper is structured as follows: the methodology adopted in this study and application of the algorithm to a real-life case study are presented in the next section. Section 3 presents the results while discussions of the results and limitations of the study are presented in section 4. The conclusion is presented in section 5.

Algorithm 1: Modified K-Means++ Geo-Clustering Algorithm

Input: *K = number of potential clusters;*
L = {l_1, l_2, …, l_n}: List of locations to be clustered;
D = {d_1, d_2,}: Two initial cluster centroids
Output: *C = {c_1, c_2, …c_k}:* Cluster centroids
Ei: { E(i)|i = 1, 2, … n} *: A list of clusters*

$N_k = 2$
foreach *d_1, d_2, do*
  calculate $argDist_1, argDist_2 \quad \forall\, d_1, d_2\ \varepsilon\ D$
  if $argDist_1$, < $argDist_2$, ***then***
    $d_1()\leftarrow l_i$ ► *assign l_i to cluster d_1*
  else $d_2()\leftarrow l_i$ ► *assign l_i to cluster d_1*
  end if
end for
foreach *$l_i \epsilon L$, do (i = 3, …n)*
  calculate $argDist_{i1}, argDist_{i2} \ \forall\, i, j\ \varepsilon\ C$
  ► *Haversine distances from centroids*
  c*all* ***heapSort***(d_i, n)
  N_k+= 2
  $(dist_{li})$ = largest ► *maximum distance from heapSort*
  $l_i \leftarrow$ new cluster centroid
  if $argDist_{i2}$, < $argDist_{j2}$, ***then***
  $d_{i1}()\leftarrow l_i$ ► *assign the location to cluster d_{i1}*
  else $d_{i2}()\leftarrow l_i$ ► *assign the location to cluster d_{i2}*
  end if
end for
until *K = N_k*

Fig. 1: Pseudocode of the clustering algorithm.

II. METHODOLOGY

A. Delineating the Demand Points

An adapted K-means ++ algorithm is proposed, with the aim of improving its output. Generally, K-means algorithm is a technique for partitioning n locations into k clusters in where each location belongs to the cluster with nearest mean, and the total distance between members of each group and their corresponding centroid is minimized. Unlike most traditional supervised machine learning algorithms, K-means classifies data without some previous training, with labeled classifiers or training set. The $\boldsymbol{n}$ entities are grouped into sets, S_i, $i = 1, 2, \dots k$, with the aim of minimizing the within-cluster sum of squares (WCSS) or the average squared Euclidean distance. The objective function is given in equation (6). The main objective is to minimize the sum of distances between the points and their respective cluster model.

$$j = \sum_{j=1}^{k}\sum_{i=1}^{n} || (x_i^j - \boldsymbol{c_j}||^2 \qquad 6$$

Procedure for Sorting Locations in a Cluster

```
procedure HeapSort (n[], i)
n = L = number of locations
size ← 0;
for i = n/2 downto 0
   swap n(1) with n(i)
   n.heapSize = n.heapSize − 1
end for
Max-Heapify (L, 1)
l: = 2i
r: = 2i+1
if l ≤ n.heapSize and (n[l] > n[i])
      largest = l
else largest = i
end if
if r ≤ n.heapSize and (n[r] > n[largest])
      largest = l
else largest = r
end if
if largest ≠ i
   swap n(i) with n(largest)
   Max-Heapify (n[],largest)
end if
```

Fig. 2: HeapSort procedure for finding the largest $argDist$

Where the term $|| (x_i^j - \boldsymbol{c_j}||^2$ estimates the distance between points of dispensing, x_i in cluster j, and the cluster's centroid, c_j. k is the number of clusters while n is the number of cases. A centroid is a mean or the central coordinator (depot) of the cluster. Usually, outputs from the standard K-means algorithm depend greatly on the choice of initial centroid values. The random selection of cluster centroid produces poor clustering and centroid locations. The modified algorithm involves selecting two locations, $d_1$and d_2 that are far apart from each other, from the list of demand points. Details of these two locations are received from the local public health officials and serve as initial depots. The coordinates are entered into the algorithm as initial centroid values. This avoids the usual random selection and ensures adequate coverage of the location of interest. The algorithm uses these inputs and initially divides the list of the demand points into two groups, with the given points as centroids. A demand point is a census tract or a collection of communities in rural areas, delineated using population data. This produces two initial clusters with each cluster containing about half of the demand points. For each of the two clusters, it calculates the distance from the centroid to all demand points and selects the demand point with the farthest distance(maxDist) as the centroid for the new cluster. It then calculates the distance from this centroid to each of the demand points $(\arg Dist_{j2})$ and compares this with distance to the initial centroid.

This procedure is similar to the space partitioning algorithm proposed by Jimenez et al in [17]. The possible value of k is obtained from local planners, and subsequently validated using Silhouette analysis. This is done iteratively for each of these new clusters until the desired number of clusters, k is reached (stopping criteria). The standard k-means is then applied to fit the clusters around the demand points and output fitted centroid values. This is done in Geoda application [18] to ensure the right population, corresponding to the number of vaccines required at each centroid, is obtained. The pseudocode of the modified algorithm is highlighted in Fig.1, while Fig. 2 presents the Heap sort procedure for the centroids. For the clustering, the coordinates of selected primary health centers (PHCs) in the 774 local government areas (LGAs) in Nigeria are obtained as demand points.

B. Study Area

Nigeria is a diverse tropical country in Central West Africa, with a population of 206.14million. It covers an area of 923,768 km2 square kilometers with population density of 218/km² [19]. Like many other countries, Nigeria experiences incessant emergencies. However, her emergencies are mostly man-made, including civil strife, ethnic crises, domestic terrorism, flooding and epidemic outbreaks, such as Lassa Fever, Onchocerciasis, Yellow Fever, Ebola Viral Hemorrhage, and fluctuating incidences or periodic rise in HIV-induced tuberculosis [20]–[22]. The current COVID -19 situation in Nigeria and the measures put in place by the government and health authorities to curtailed the spreading are summarized in this study [23]. Optimizing the location of these vaccination centers will assist in the equitable distribution of the vaccine among all states and local government areas, in accordance with the population of the locality. Using population and geographical data from all regions, the clustering of demand points is performed to obtain potential location of depots. A modified clustering approach, as described below, is applied. Nigeria has 774 local government areas (LGAs) which make up the 36 states and the Federal Capital Territory.

C. Evaluating Clustering Output Using Silhouette

To evaluate the outputs of the algorithm, a Silhouette Analysis (SA) is performed on the resulting number of clusters.

SA can be used to validate the consistency of a chosen similarity conditions for data points or distance between resulting clusters in a clustering algorithm. Aptly put, it is a means of measuring how close each node in a cluster is to all other nodes in that cluster or the cohesion amongst nodes in a cluster, and their separation from other clusters. Results from Silhouette Analysis are usually presented in a graphical plot, representing a succinct graphical view of how well each node has been classified. For a node $i \in L_i$, Silhouette value of i can be calculated thus:

$$s(i) = \frac{b(i) - a(i)}{max(i), b(i)}, \qquad if L_i > 1 \qquad (7)$$

Where $a(i)$ is the mean distance between $node\ i$ and all other nodes in the same cluster. $b(i)$ is the mean distance of node i to all points in any other cluster, of which i is not a member. Silhouette values lie in the range of [-1, 1]. A value of +1 indicates that the location is far away from its neighboring cluster and very close to the cluster it is assigned (good assignment!). Similarly, the value of -1 indicates that the point is close to its neighboring cluster than to the cluster it is assigned. A value of 0 indicates that is very close to the decision boundary of the distance between the two clusters. Hence, the higher the silhouette value, the better is the cluster configuration.

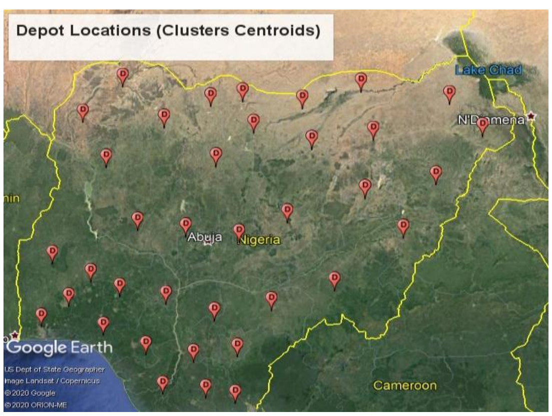

Fig. 3: The national map, showing the locations of the cluster depots

III. RESULTS

A. *Clustering Demand Points and Distribution Centers*

For the clustering, the coordinates of selected primary health centers (PHCs) in the 774 local government areas (LGAs) in Nigeria are obtained as demand points. The number of selected PHCs per LGA depends on the population of the area. Two tertiary federal medical centers, representing the northern and southern regions respectively, are used as initial centroids of the potential clusters. The algorithm considers the entire country as one geographical entity and attempts to divide it into 38 clusters. The two initial centroids: University of Maiduguri Teaching Hospital in Borno State (with longitude and latitude as 13.1809 and 11.826038 respectively) and EOC Ikorodu in Lagos state (with longitude and latitude as 3.5027 and 6.6232 respectively) serve as inputs into our approach. When 36 is used as initial value of k, the clustering output shown in the first part of Figure 4 is obtained. After 1000 iterations, the algorithm optimizes locations of these clusters and outputs the geographical coordinates of the centroids of these new clusters. The longitudes and latitudes of these new centroids (centers of the clusters) are plotted in a google earth as shown in Fig. 3. The nearest Primary Health Center or local government headquarters to the given coordinate is used as the depot. For example, the first centroid (Cluster 1) in table 3 (Longitude: 7.06088; Latitude: 5.8911) is Akokwa Medical Centre in Ideato South of Imo State (Eastern Nigeria), while the centroid for Cluster 38 is Gulani Local Government Headquarters in Yobe State (Northern Nigeria). A second level clustering of locations in a state and local government areas can also be done by applying the adapted algorithm to these resultant clusters.

B. *Silhouette Analysis of the Clustering Output*

Silhouette Analysis is used to evaluate the outputs of a clustering algorithms. The visualization of the silhouette analysis outcomes using k = 36, 38 and 40 are presented in Fig. 4. As seen on the plot, when k = 36, some of the clusters are not optimally filled. The equitable distribution of the clusters (assignment of demands points to specific groups) is prominent when k = 38. When k = 40, many of the clusters are superimposed on the other. This implies that too many clusters are being proposed for a comparatively smaller geographical area.

IV. DISCUSSION

This amended K-means ++ clustering procedure posts a higher quality result, with respect to the physical allocation of demand points. can be seen from the output of the Silhouette analysis of the clustering result. The time complexity of the standard K-means algorithm has been proven to be $O(nkt)$ and could get up to $O(n^2)$ in worst case scenario., where n, k and t are number of demand points, desired number of clusters and

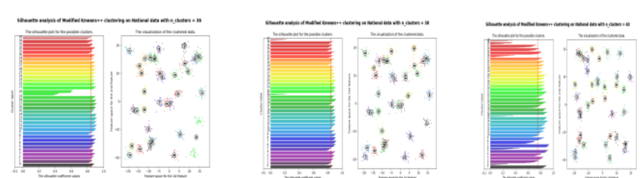

Fig. 4: Silhouette Analysis: Visual Representations and Comparison of k values

number of iterations respectively. For large datasets, it has been observed that t approximates n, $t \propto n$. Hence the effective time complexity becomes $O(n^2)$. However, the modified K-means ++ algorithm performs better, compared to the standard algorithm, in terms of memory and time complexity. The analysis yields a time complexity of $O\big(n\,log(n)\big)$, where n is the number of demand points. This can be shown by mathematically analyzing the cost of each operation in the pseudocode in algorithm 1. A heapsort approach is used for sorting the list of demand points and calculating distances, $\arg Dist_1$ and $\arg Dist_2$ using haversine metric. Each demand point is assigned to the cluster having the closest centroid. During the iteration process, some demand points remain in the original cluster while some are moved, in accordance with their relative distance to the new centroid. If the demand point stays in the same sub cluster, then the required complexity is $O(1)$, otherwise, it is $O(k)$. After each iteration, the number of relocation operations of demand points to other clusters decreases. Assuming half of the demand points move to the other clusters from their present clusters, until the convergence condition is met, time complexity of $O(nk/2)$ will be required. The total time complexity for assigning demand points to new clusters will be $O(nk)$.Therefore, the total time complexity of the proposed algorithm becomes $O(nlogn)$. However, one of the limitations of this approach is on the resulting number of clusters. The algorithm can only be applied to obtain an even number of clusters. The equitable distribution of clusters ensures adequate geographical coverage of demand points. A demand point is a census tract or a collection of communities in rural areas, delineated using population data. They are initially created with population data from the constituent communities. The algorithm is used to delineate these demand points. The population data of all LGAs in a cluster would be used to determine the quantity of vaccines needed at each center. The local public health planners can therefore make informed decision about where to locate the vaccination centers, to ensure accessibility to the population, within the limit of available resources. At a later stage of the vaccination campaign, if vaccine hesitancy persists, the health personnel may decide to deliver the vaccines to the end-users. This can be done using the routing optimization algorithm proposed by Akwafuo et al in [24]. Due to limited resources, application of emergency and vulnerability ranking can be applied.

V. CONCLUSION

In this paper, a modified version of the K-means ++ algorithm was applied to solving the public health facility location problem. In most LMICs, efficiently locating COVID-19 vaccine distribution centers is a challenging problem. Due to inadequate infrastructure and low resources, traditional health centers are always far away from the rural communities. Our algorithm takes the geo-spatial population data of the region of interest and optimizes the number of vaccination centers needed, such that least possible cost is used. It improves on the usual random outcome experienced when k-means is used in clustering, by requiring the planners to enter geo-spatial details of two initial locations. Mathematically, the amended algorithm delivers improved time complexity. However, the algorithm can be further improved to optimize any number of inputs, as opposed to the current status of optimizing even number of regions only.

Table 1: Coordinates of the optimized Centroids

Cluster ID	Longitude	Latitude
1	7.06088	5.8911
2	8.58057	11.8098
3	7.31664	4.95185
4	3.30636	6.76344
5	4.60718	7.97595
6	5.32225	7.60366
7	8.01393	4.81697
8	4.03482	7.32466
9	5.91788	6.08164
10	8.10633	6.04821
11	7.59326	6.98435
12	7.55635	12.5205
13	5.38403	13.0886
14	8.93438	7.2561
15	6.44533	7.41681
16	7.6864	10.9671
17	9.3459	9.5031
18	6.2856	5.02185
19	8.32077	12.6313
20	12.0047	9.06572
21	8.21482	9.00182
22	6.95394	9.16888
23	9.729	12.4147
24	4.3946	12.1687
25	9.9418	11.3704
26	12.7824	10.4035
27	5.00871	10.9724
28	3.63629	8.44436
29	11.1508	10.0936
30	5.78933	9.32433
31	13.1547	12.4513
32	6.43283	11.9928
33	4.88445	6.57173
34	10.4011	7.75009
35	11.3674	11.5742
36	13.8945	11.6114
37	11.1046	12.8198
38	7.083	8.88583

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