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Logistics Chain Optimization and Scheduling of Hospital Pharmacy Drugs Using Genetic Algorithms:
Morocco Case

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ABSTRACT

In recent years, the health sector has faced increasingly important challenges. Due to the economic crisis and competitions, hospitals are facing many issues affecting the supply chain, such as budget cuts or lack thereof as well as insufficient human resources. Although essential for an excellent service, logistics take up a considerable part of the budget as challenges need to be addressed such as delays in drugs delivery, transportation and storage conditions, routing and scheduling. As to governance, each hospital is assigned to a specific region, which cannot be defined due to political, demographic, or geographic issues. This paper focuses on multi-depot vehicle routing problem (MDVRP) in healthcare logistics to feed the hospital pharmacies. The idea is to apply MDVRP's approach to the health sector, specifically hospital pharmacies. In this projection, hospitals are considered to present clients, and central pharmacies present deposits. This problem (the MDVRP) is known by this nature NP-hard. For that, the heuristic method was used as genetic algorithm to solve the problem. The paper is organized as follows, the first section discusses, compares, and proposes clustering methods for healthcare facilities with applying them on Moroccan hospitals case; the second section proposes a genetic algorithm to resolve the MDVRP with a simulation.

KEYWORDS

Drugs Delivery, Genetic Algorithm, Hospital Clustering, Hospital Logistics, MDVRP, Pharmacy Clustering, Vehicle Routing

1. INTRODUCTION

Availability of medicines in hospital pharmacy is important as far as providing a good quality of service which led to the reduction of mortality and patient's satisfaction. Besides, a good pulling drugs system lead to reduced storage and logistics cost. Therefore, the authority control the drugs quantity and Medical equipment delivered.

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To solve the problems of late delivery and to ensure quality transport, hospital pharmacies are supplied by central or provincial pharmacies that must deliver drugs and equipments by vehicles. Furthermore, the availability of central pharmacies can solve other problems such as the reduce of overstocked and expired drugs, etc ...

Methods to clustering population and hospital, will be discussed in this paper on the first section based on bed demand, with comparison between K-means, weighted k means, and Density-based spatial clustering of applications with noise algorithms, with application in a Moroccan case. The second section, project the MDVRP to healthcare logistics making the hospitals as customers and centralized pharmacies as a depot, with an implementation of GA to resolve the NP-Hard nature of the problem.

Ministry of the health of Morocco has presented several recommendations in sector strategy (Stratégie Sectorielle 2012-2016, n.d.), including the creation of new pharmacies of storage as regional and provincial pharmacies, act N°147. In our work we propose a solution to improve the creation of new centralized pharmacies (CS) and determine the methodology of the delivery of drugs to hospitals, by clustering regions who will be served by a regional pharmacies as a first step, based on Performance indicators shared by the same ministry (Sante en Chiffres, 2015). the second step is to project the MDVRP problem to a logistic chain of healthcare by making the hospital as a customer and CS as a depot.

2. LITERATURE REVIEW

Clustering has been used to solve problems in diverse fields such as bioinformatics, and data mining. William Thomas has contributed in clustering hospital with clustering communities and hospitals simultaneously, which led to a geographically connected area of populations served by a common cluster of hospitals(Griffith, 1972; Thomas, 1979; Thomas et al., 1981), the approach has been applied by State of Michigan. Z.Obradovic(Albarakati & Obradovic, 2017) proposed an approach based on disease-specific hospital networks with considering similarity among symptoms. k-mean is among the most popular clustering algorithms (Jain, 2013), K-means is an unsupervised algorithm for non-hierarchical clustering, making it possible to group in K distinct clusters the observations of the data set. Thus, similar data will be in the same cluster. Paul L (Delamater et al., 2013) audited similarity in geographic location and patient utilization to create healthcare facilities clusters by using k-means clustering. Ruth Lavergne M (Lavergne, 2016) used cluster analysis to group healthcare facilities based on the distribution of healthcare spending across service categories with k-means as a clustering technique. On the other hand, Xiuguo Chen(Chen et al., 2009) used Weighted k-Means Algorithm to cluster Text, Driss and Abdellah(Serrou & Abouabdellah, 2016) showed that in the case of centralized pharmacies, the cost of transport is reduced, which makes the logistics chain less expensive. Many studies have been proposed to solve the routing and scheduling problem, in 1995 Sumarchrast and Markham (Nikbakhsh & Zegordi, 2010) introduced the MDVRP. William Ho (Ho et al., 2008) proposed two solutions for the MDVRP problem based on Genetic algorithm. Laporte, G (Laporte et al., 1988) and Lenstra, J.K(Lenstra & Rinnooy Kan, 1975) tried to solve the problem with exact methods, however Crevier B(Crevier et al., 2007) demonstrated that the both techniques are not effective. Necati Ara et.al (Aras et al., 2011) Solved for Priced MDVRP, they propose two methods: heuristic method to solve the MDVRP, and a mixed integer linear programming, and conclude that heuristics give better results. Damon Gulczynski(Gulczynski, 2010) solved the MDVRP with separate delivery by a heuristic based on integer programming.

3. REGIONAL CLUSTERING BASED ON PERFORMANCE INDICATORS

Many approaches have proposed to cluster hospitals (Thomas, 1979; Thomas et al., 1981). In our work, we propose clustering by Performance indicators linked to regions instead of hospitals, because the

Table 1. The HBC by region in morocco for 2015

Region	Central Location (lat,lng)	HBC
Oued Ed-Dahab-Lagouira	(22.733, -14,286)	53
Laâyoune-Boujdour-Sakia El Hamra	(25.443 -13,174)	313
Guelmim-Es Semara	(28.708 -9,545)	322
Souss-Massa-Draa	(31.120, -6,067	2199
Gharb-Chrarda-Beni Hssen	(34.543, -5,898)	757
Chaouia-Ouardigha	(33.047, -7,265)	1343
Marrakesh-Tensift-El Haouz	(31.562, -7,959)	2347
Grand Casablanca	(33.520, -7,568)	1826
Rabat-Sale-Zemmour-Zaer	(33.817, -6,237)	2884
Doukkala-Abda	(32.599, -8,660)	2872
Tadla-Azilal	(32.004, -6,578)	964
Meknes-Tafilalet	(31.905, -4,727)	663
Fes-Boulemane	(33.187, -4,233)	1474
Taza-Al Hoceima-Taounate	(34.258, -4,233)	1506
Tangier-Tetouan	(35.262, -5,561)	813
Oriental	(33.419, -2,145)	1739

creation of centralized pharmacies is for the purpose of serving a hospital pharmacy in determined regions and also the data is grouped by regions, the Performance indicators in our case are Hospital Bed Capacity (HBC) by region (Table 1).

3.1 Clustering Using K-Means

K-means is an unsupervised algorithm, making it possible to group in K distinct clusters the observations of the data set. Thus, similar data will be in the same cluster. Moreover, an observation can only be found in one cluster at a time (exclusivity of belonging). The same observation, therefore, cannot belong to two different clusters.

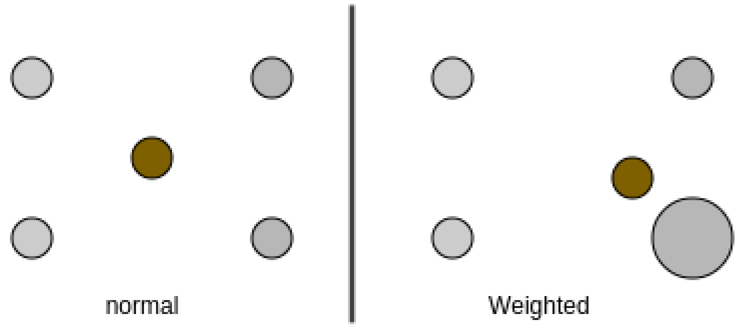
We present each center of region characterized by latitude and longitude as point.

As result for 3 clusters, a favoring result for cluster 1 with total of 15192 HBC and less than the half for cluster 2 with 6195 HBC, for cluster 3 the HBC is minim (Table 2).

Table 2. Distribution by clusters for each region using k-means with 3 clusters

Cluster	Region	HBC
Cluster 1	Souss-Massa-Draa / Gharb-Chrarda-Beni Hssen / Chaouia-Ouardigha / Marrakesh-Tensift-El Haouz / Grand Casablanca / Rabat-Sale-Zemmour-Zaer / Doukkala-Abda / Tadla-Azilal	15192
Cluster 2	Meknes-Tafilalet /Fes-Boulemane /Taza-Al Hoceima-Taounate /Tangier-Tetouan / Oriental	6195
Cluster 3	Oued Ed-Dahab-Lagouira / Laâyoune-Boujdour-Sakia El Hamra/ Guelmim…	688

Figure 1. Difference between centroid position in normal and weighted case



3.2 Clustering With Weighted k-Means

k-means algorithm groups data by assigning all points to the nearest clusters, and determining the cluster means. The algorithm repeats previous steps until points assemble. weighted k-means calculates automatically the feature weights in a cluster, adopting the idea that a feature can have different degrees of relevance from others (Figure 1).

The distance parameter can be as Euclidean distance. yet, as we are using geographic coordinate, the correct distance is Haversine distance or Haversine formula.

The Haversine formula makes it possible to determine the distance of a giving great-circle distances between two points of a sphere, from their longitudes and latitudes.

Weighted k-means present more suitable results in comparison with k-means The HBC in each cluster is equitable, except for the south regions because the points that represent the south regions are far from other points, which is acceptable, because the integration of these regions with other regions will increase the distance of the delivery, therefore, the costs of the transport will increase (Table 3).

4. VEHICLE ROUTING WITH SEVERAL CENTRALIZED PHARMACIES

One of today's most important challenges of logistics is the distribution of goods besides of routing path. The cost is associated to the distance, that is why we did not cluster north regions with other regions. Costs invested for transportation exceed 50% of the total cost of a supply chain(Santoso et al., 2014) the objective then is to minimize the distance traveled by a group of vehicles exposed to different requirements. So, the aim is to minimize the cost of combined routes on a Multi-depot vehicle routing problem (MDVRP), however, MDVRP is a non-deterministic polynomial time (NP-Hard) for deciding the courses of several vehicles of several depots to a group of customers simultaneously, and return to the same deposit without surpassing the capacity limit of each vehicle. We can group the approaches to solve the VRP into two doctrines: Exact and heuristics algorithms. obviously, the

Table 3. Results of weighted clustering with 3 clusters

Cluster	Region	HBC
Cluster 1	Souss-Massa-Draa / Chaouia-Ouardigha /Marrakesh-Tensift-El Haouz /Grand Casablanca / Doukkala-Abda /Tadla-Azilal	11551
Cluster 2	Rabat-Sale-Zemmour-Zaer / Gharb-Chrarda-Beni Hssen / Meknes-Tafilalet / Fes-Boulemane / Taza-Al Hoceima-Taounate / Tangier-Tetouan / Oriental	9836
Cluster 3	Oued Ed-Dahab-Lagouira /Laâyoune-Boujdour-Sakia El Hamra /Guelmim …	688

MDVRP is more complex than a simple VRP. Consequently, proposing an optimal solution for an NP-hard problem takes a long time, and maybe impossible with exact algorithm. Laporte, G(Laporte et al., 1988) and Lenstra, J.K(Lenstra & Rinnooy Kan, 1975) tried to solve the problem with exact methods. However Crevier, B(Crevier et al., 2007) demonstrated that both techniques are not effective. Necati Ara et.al(Aras et al., 2011) Solved for Priced MDVRP, which the vehicle visits a customer only if it is profitable, they propose two methods: heuristic method to solve the MDVRP, and a mixed integer linear programming, and conclude that heuristics give better results iIt is not realistic to use exact methods to solve large instances of the problem. Intelligent algorithm is more widely applied, so the proposition is GA as a heuristic algorithm and one of the most promising intelligent optimization method.

Distribution logistics incorporates all activities related to the supply of finished products and merchandise to a customer. The central point of distribution logistics is the transportation of goods from the manufacturer to the consumer. In our case, the manufacturer are a CS, and consumers are hospitals pharmacies. Raffaele I(Iannone et al., 2014) approved that adopting the centralized pharmacy model present considerable benefits especially cost saving. Driss and Abdellah (Serrou & Abouabdellah, 2016) showed that the costs of return of medications are reduced in the case of the centralized pharmacy structure by implementing the methodology on 10 Moroccan hospitals. Our contribution is to project the MDVRP into pharmacies logistics, with representing centralized pharmacy as a single depot and hospitals as a customer, some region needs more than single depot.

4.1 Mathematical Formulation

We can characterize our MDVRP mathematically as following:

- $G = \left(V, E\right)$ is a graph where V is the set of vertices partitioned into two collections.
- $V_h = \left\{V_1, V_2, ..., v_n\right\}$ represent the collection of hospital (or hospitals).
- $V_p = \left\{V_{N+1}, V_{N+2}, ..., v_{n+M}\right\}$ represent the collection of centralized pharmacies.

E set of edges connecting two points. A cost matrix $D = \left(D_{ij}\right)$ is length of arc $\left(v_i, v_j\right)$ corresponding to distance) expecting D symmetry, distance between set of three points satisfy triangle inequality. Each depot $V_{n+m} \in V_d$ has the same model, based k_m. The number of vehicles based at a depot) is identical vehicles and capacity Q. We consider the following: Each vehicle starts from a centralized pharmacy (CS), servicing a set of hospitals, and must return to the starting CS, every hospital is visited only once by a vehicle. Total demand for each route does not exceed the vehicle capacity Q. Vehicle cannot exceed the vehicle capacity Q, the number provided by CS is limited. While CS cannot serve another CS, the mean objective for MDVRP, in this case, is to link hospitals into the proper CS with minimization of a number of resources and distance traveled by vehicle across the network. n hospitals are grouped in m clusters. the number of vehicles based at a CS is km. Kj is a group of hospital linked to a vehicle. Based on Surekha P (Surekha & Sumathi, 2011), MDVRP formulation for finding x which is the minimizes can be described as: decision variables X and Y:

$$x_{ijkm} = \left\{hospitaljelse0\right\}$$

$$y_{ikm} = \left\{CSmelse0\right\}$$

$$MIN = \sum_{p=1}^{m} \sum_{q=1}^{k_p} \sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij} x_{ijqp} \quad (1)$$

subject to:

$$\sum_{i=1}^{n} q_i y_{iqp} \leq Q \tag{2}$$

$$0 \leq n_{jq} \leq n_j \tag{3}$$

$$\sum_{q=1}^{k_j} n_{jq} = n_j \forall j = 1 tom \tag{4}$$

$$\sum_{j=1}^{m} n_j = n \tag{5}$$

$$\sum_{p=1}^{m} \sum_{q=1}^{k_p} y_{iqp} = 1 \tag{6}$$

$$x_{ijqp} = 1 \vee 0 \tag{7}$$

$$y_{iqp} = 1 \vee 0 \tag{8}$$

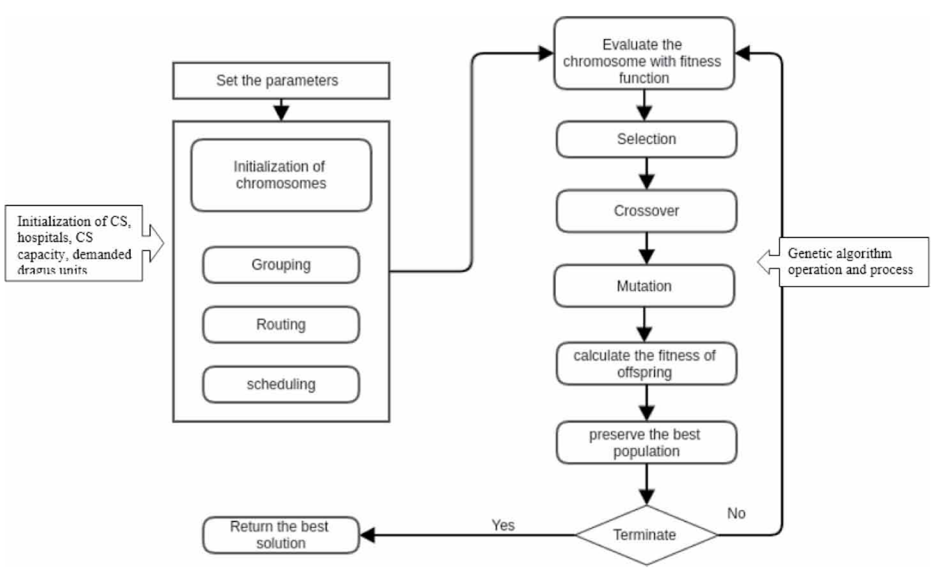
The objective function according to Equation (1) minimizes the total delivery distance and cost of each vehicle within a CS .(2) limits capacity Q of the vehicle, (3) indicate the hospitals served by every vehicle must not overtake the number of hospital a CS can deliver to .(4) shows the sum of the hospitals served by the whole route should be the sum of the hospitals served by CS m.(5) shows every hospital served by a CS .(6) guarantee that every hospital must be visited only once by a vehicle. (7)(8) is the values bound of the decision variables.

4.2 Genetic Algorithm

GA is an optimization technique based on a parallel search which makes it more efficient than other classical optimization techniques such as Tabu search method and simulated annealing. The idea of GA is to avoid getting trapped in a local optimum by genetic operators (crossover, mutation). GA maintain a population of possible random solution representing as a chromosome who can evolve as a generation. The chromosomes are evaluated to fitness. The best fitting chromosomes have a high probability to be selected for genetic operations such as crossover and mutation for the creation of the next generation. GA is the most widely class of heuristics methods used as an application to the MDVRP problem, that why GA has received great attention from many authors. Karakatic S (Karakatič & Podgorelec, 2015) present a comparative study of different GA types applied to MDVRP. William Ho (Ho et al., 2008) propose two solutions for the MDVRP, the first one consist on implementation of the GA as for solving the problem and the second one a hybrid method with Clarke and Wright saving method and nearest neighbor, and he proved that the last method performs better than the first one:

- **Initial Population:** First chromosomes is formed based on the routes CS and hospitals (first section). Consider an instance with 5 hospitals and 0 represent CS. If the path representation for this instance is (0 2 4 1 0 3 5 0), First route departs from the CS 0 and travels to (2 4 1) and return to CS. Second route leaves the CS 0, serves 3,5 and returns again.
- **Evaluation:** Evaluate each chromosome with measuring the fitness value, the operation starts in every CS simultaneously, that why it's normal that some vehicle in the network can achieve the objective (finish the delivery to all hospitals) while others can achieve the same objective later.
- **Selection:** For each generation, the best chromosome (based on fitness value) is selected and reproduction for the next generation, to generate new individuals in the population Willian Ho (Ho et al., 2008) use roulette wheel selection operation, while others use tournament selection (Surekha & Sumathi, 2011). selection strategy is based on fitness evaluation, chromosome will be selected with generated probability.
- **Genetic Operations:** The mutation and crossover used in GA as a genetic operation, both mutation and crossover affect the selected chromosomes with a genetic operations rate.
- **Crossover:** Ombuki-Berman (Ombuki-Berman & Hanshar, 2009) developed a technique for crossover based on BCRC - Best Cost Route Crossover - oriented to the vehicle routing problem with time windows (VRPTW). The classical order crossover is used by William Ho (Ho et al., 2008) to perform crossover into MDVRP. The aim is to combine the genetic information of exactly two parents to create new information.
- **Mutation:** Consists in swapping two distinct customers i and j randomly selected, there is much propositions of mutation methods, we can group them into two classes, heuristic mutation and inversion mutation. the effect is to flip a chromosome substring to create an offspring, mutation works on only one chromosome (Figure 2).

Figure 2. Flowchart of GA implementation



4.3 Simulation and Results

For the simulation, we used a list of a hospital by region from the Moroccan administration Open Data website, and we added a random demand of drugs to be served for the Casablanca region. In the purpose of this simulation we consider all of the facilities will be served by three CS (Tables 4-5).

Consider three CS with coordinate: CS1 {33.58212, -7.6594}, CS2 {33.57125, -7.5813}, CS3 {33.58200, -7.5289}, The capacity of each vehicle is 50 units, the population size is 10.

Table 4. List of healthcare facilities in Grand Casablanca region

Region	id	Hospital	Coordinate (lat,lng)	Drugs Unit
Grand Casablanca	1	Sekkat (Salam)	33.54631, -7.5884	30
Grand Casablanca	2	Centre de Léprologie	33.55384, -7.59255	40
Grand Casablanca	3	Mohamed V	33.58945, -7.55146	10
Grand Casablanca	4	Med Bouafi	33.55874, -7.60972	15
Grand Casablanca	5	Ben M’sick	33.55225, -7.5782	22
Grand Casablanca	6	Ibn Rochd	33.58125, -7.61976	41
Grand Casablanca	7	My Youssef	33.60274, -7.63226	13
Grand Casablanca	8	20 Aout 1953	33.57474, -7.6199	8
Grand Casablanca	9	Hôpital d’enfants	33.58088, -7.62111	21
Grand Casablanca	10	Al Hassani	33.55849, -7.68736	26
Grand Casablanca	11	Tit Mellil	33.54937, -7.48586	50
Grand Casablanca	12	My Abdellah	33.69778, -7.38551	14
Grand Casablanca	13	Sidi Othmane	33.55804, -7.57312	7
Grand Casablanca	14	Prince My Hassan	33.60457, -7.63394	13
Grand Casablanca	15	Al Mansour	33.6078, -7.50362	30

Table 5. Results of simulation for first and last generation

	CS 3	CS 2	CS 1
grouping	6, 7, 9, 14, 1, 2, 4	5, 8, 10, 11, 13	3, 12, 15
Initialization	14, 0, 6, 0, 7, 9, 0	1, 13, 0, 11, 0, 10, 5, 0, 8, 2, 0, 4, 0	3, 15, 0, 12, 0
1generation, fitness:55986	6, 0, 14, 7, 9, 0	1, 13, 0, 11, 0, 10, 5, 0, 8, 2, 0, 4, 0	3, 15, 0, 12, 0
Last generation fitness:49948	14, 7, 9, 0, 6, 0	4, 1, 0, 10, 5, 0, 11, 0, 2, 13, 0, 8, 0	12, 15, 0, 3, 0

First section of GA is to initialize inputs (CS, hospitals, capacity, dragus units). The result shows in grouping section a set of hospitals linked to a centralized pharmacy based on distance. Considering the initialization is scheduling operation, while the first end the lest (thousandth) generation is a set of chromosomes representing the MDVRP entity (first visited hospital to the last, with 0 representing the "back to centralized pharmacies"). Beside a well grouping, the result not only shows a combination of routing and scheduling for each centralized pharmacies, but also shows an optimization of one travel back to the centralized pharmacies at CS 3 wish lead to reduce the cost of transportation. The last generation (thousandth) the routing and scheduling have been mutated to a new generation to propose new scheduling.

5. CONCLUSION AND FUTURE WORK

For the first time to our knowledge, the MDVRP beside clustering for hospitals are proposed and studied. With a comparison of clustering methods, the weighted k-means algorithms show better results, yet, the simulation of clustering was applied for morocco case which means the clustering algorithm can be arguable for other cases or a region with unique geographic constraints.

This paper focuses on the healthcare sector, however, the approach can be applied in agricultural and food-processing logistics.

It should be noted that the model can be improved by considering nature of transportation (forward/reverse logistic model in case of medicament return) and conditions of transportation such as humidity, temperature, and ventilation. and also by providing a reliable tracking platform.

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