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Dynamic Sectorization - Conceptualization and Application

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Abstract. Sectorization is the division of a large area, territory or network into smaller parts considering one or more objectives. Dynamic sectorization deals with situations where it is convenient to discretize the time horizon in a certain number of periods. The decisions will not be isolated, and they will consider the past. The application areas are diverse and increasing due to uncertain times. This work proposes a conceptualization of dynamic sectorization and applies it to a distribution problem with variable demand. Furthermore, Genetic Algorithm is used to obtain solutions for the problem since it has several criteria; Analytical Hierarchy Process is used for the weighting procedure.

Keywords: Sectorization, Dynamic Sectorization, Genetic Algorithm, Analytical Hierarchy Process

1 Introduction

Sectorization is the division of a large area, territory or network into smaller parts considering one or more objectives, intending to optimize or simplify a problem. Sectorization problems have a vast field of applications, many of which arise due to real-world dilemmas. Such as designing sales territories, health care services and schools zones.

As uncertainty increases, distinct dynamic attributes emerge in sectorization problems, depending on the application at hand. In the case of a delivery company, their clients will not be the same every day, the demand of a client may differ each time s/he requires service or the number of trucks to make the distribution may change. Companies must make sectorization considering such fluctuations, to be better prepared without major changes. Then dynamic sectorization arises, although this concept may differ from author to author.

Dynamic sectorization deals with situations where it is convenient to discretize the time horizon in a certain number of periods ($t = 1, 2, ..., T$). A new sectorization is performed in each period, but the decisions will not be isolated since the information from previous periods is considered. Different strategies may be used to deal with the dynamic component, such as fitting a distribution or forecasting techniques.

This paper applies this concept of dynamic sectorization to a delivery company problem, where the demand changes over time. A Genetic Algorithm (GA) and Analytical Hierarchy Process (AHP) are used to solve the problem.

The remainder of the paper is organized as follows. Section 2 presents a review of the literature. Section 3 describes the dynamic sectorization problem. A solution method is proposed in Section 4 and, in Section 5, the corresponding results and a brief discussion are included.

2 Literature Review

This section briefly summarizes some of the literature relevant to the problem.

Sectorization problems have many real-world applications. Political districting is one of the oldest, aiming to divide the territory neutrally and avoid gerrymandering. Most of the time, political districting is subject to resectorization to adapt the current solution regarding the updates in the territory. Applications of this type of problem consider various criteria, such as equilibrium, compactness and contiguity [1,2]. Bação *et al.* [1] called it a zone design problem and presented a solution method based on a genetic algorithm for which they considered two objective functions and proposed two different types of gene encoding.

Another study field is the design of sales territories. It aims to divide a large commercial territory into certain zones and assign them to salespeople [3,4]. Salazar-Aguilar *et al.* [5] proposed a multi-objective scatter search procedure to a territory design problem, considering equilibrium and compactness as objectives. The results obtained with this metaheuristic are compared to the Scatter Tabu Search Procedure [6] and Non dominated Sorting Genetic Algorithm (NSGA-II)[7]. Lei *et al.* [8] solved a multi-objective dynamic stochastic districting and routing problem, in which the customers of a territory stochastically evolve over several periods of a planning horizon. They developed a preference-inspired co-evolutionary algorithm using mating restriction for the problem; results confirmed the superiority and effectiveness of the algorithm.

Moreover, health care districting is another application of sectorization problems. Home Health Care (HHC) represents an alternative to the traditional hospitalisation [9]; care services are provided to patients at their homes by a team composed of care providers, using a distribution network. Sectorization divides this network in a more optimized way. Gutierrez-Gutierrez *et al.* [10] studied this type of problem in a rapidly growing city and proposed a bi-objective mathematical model, identifying a trade-off that allows reaching better-compromised solutions. Their model is evaluated with real data instances from an HHC institution, which delivers services in the largest cities in Colombia. Lin *et al.* [11] formulated the care service districting as a multi-objective mixed-integer nonlinear programming model, with equilibrium and compactness as objective functions. NSGA-II was used to obtain results for this formulation.

Other attributes can be dynamic in sectorization problems. For instance, in [8,12,13], the clients are seen as the dynamic attribute, since they may leave or enter the territory from one period to another.

In the literature of dynamic sectorization, it is possible to see the usual criteria, compactness, equilibrium and contiguity, being used. However, from one period to another, the similarity of the sectors has a crucial role in dynamic sectorization problems. Yanık *et al.* [14] proposed a multi-period multi-criteria districting problem applied to a primary care scheme, a specific healthcare service in Turkey. Six criteria are considered: workload balance, capacity, accessibility, compactness, income equity, and similarity.

Airspace design appears to be the most studied field in the literature of dynamic sectorization. Airspace design consists of changing the airspace that the air traffic controllers manage to handle modifications in the airspace. The objective is to create sectors with a balanced workload but maintain a certain similarity from one period to another. Several approaches are considered in the literature. Wong *et al.* [15] used a rolling horizon optimization approach, where the shapes are changed based on a finite horizon of the traffic in future intervals, and evaluated the method's performance based on historical data from Singapore. On the other hand, Sergeev *et al.* [16] formulated the problem as a graph partitioning problem and solved it using a Genetic Algorithm, obtaining solutions that outperform the existing ones.

GA has been used to solve sectorization problems, as is the case of [17,18,19,20]. Some of these problems have more than one objective. In these cases, a composite weighted single objective function is used, whose weights have to be determined in some manner. Analytical Hierarchy Process (AHP), proposed by Saaty [21,22,23] is characterized for regarding the preferences of the decision-maker into consideration. For each pair of objectives, the decision-maker evaluates the importance of one objective over the other. This evaluation is expected to be coherent with the comparison scale, which takes integer values from 1 to 9, where 1 shows equal importance, while 9 shows extreme importance. Since unilateral comparisons are enough, $k(k-1)/2$ comparisons are required in AHP when k objectives are in question.

3 Problem Definition and Criteria

This section describes the dynamic sectorization problem of a delivery company and presents the criteria taken into account.

The time horizon is divided into periods, $t \in P = \{0, ..., T\}$ is the set of periods. Let $V = \{1, ..., n\}$ be the set of customers. The location of each customer does not change from one period to another and is known, given by its coordinates. The demands change over time and therefore constitute the dynamic component of the problem. l_i^t represents the demand of customer i in period t. Demands will follow a given probability distribution, as described later in Section 4.

Let $D = \{1, ..., k\}$ be the company's set of facilities whose locations o_j, $j \in D$, are known in advance. Moreover, each facility $j \in D$ has a limited capacity, a_j, which means that it can only supply up to this amount on total; the capacity is the same for all periods.

Finally, let us consider the binary decision variables x_{ij}^t, where

$$x_{ij}^t = \begin{cases} 1 & if\ customer\ i\ is\ assigned\ to\ facility\ j\ in\ period\ t \\ 0 & otherwise \end{cases} \tag{1}$$

The number of sectors must be equal to the number of facilities. Furthermore, each facility must have at least one customer, and each customer must be assigned to exactly one of the facilities.

The company's purpose is to design compact, contiguous and balanced sectors for each period, maintaining the sectors similar from one period to another. The details concerning the three considered objective functions and the measure to evaluate the similarity end this section.

Compactness The compactness of a sectorization improves by minimizing the dispersion within sectors. This way, the Euclidean distance $dist(o_j, p_j)$ between the location o_j of a facility j and the location p_j of the farthest customer assigned to j is considered. The compactness measure d, in Equation (2), sums up this distance for all facilities. Logically, the smaller the value, the higher the compactness of the sectors.

$$d = \sum_{j=1}^{k} dist(o_j, p_j) \tag{2}$$

Balance It is desirable to balance the sectors, which means that a facility has to supply more or less the same as the others. The balance measure proposed by Rodrigues and Ferreira (2015) [24] is used. The mean demand of the sectors, $\bar{q}$, is given by Equation (3).

$$\bar{q} = \frac{\sum_{j=1}^{k} q_j}{k},\ \text{where}\ q_j = \sum_{i=1}^{n} l_i^t x_{ij}^t \tag{3}$$

The Balance is given by the standard deviation of the demands of the sectors, $s_q^{'}$, which is calculated by Equation (4). The value of $s_q^{'}$ has to be minimized to obtain a better balance.

$$s_q^{'} = \sqrt{\frac{1}{k-1}\sum_{j=1}^{k}(q_j - \bar{q})^2} \tag{4}$$

Contiguity The third objective considered is contiguity; it evaluates the connectivity of the sectors. The contiguity measure proposed by Rodrigues and Ferreira (2015) [24] is used. Consider, for two customers w and i ($w \neq i$) of sector j:

$$m_{wi}^{j} = \begin{cases} 1 & if\ there\ is\ a\ path\ between\ customers\ w\ and\ i\ of\ sector\ j \\ 0 & otherwise \end{cases} \tag{5}$$

Equation (6) is used to calculate the contiguity of sector j, given by the total number of paths between its customers divided by the maximum number of possible links in sector j.

$$c_j = \frac{\sum_{i=1}^{n_j}(\sum_{w=1,w\neq i}^{n_j} m_{wi}^{j})}{n_j(n_j-1)} \tag{6}$$

where n_j represents the number of customers in sector j. Contiguity, $\bar{c}$, is given by the weighted average of the contiguities of the sectors, as shown in expression (7). In this case, the higher the value, the better the contiguity. Thus $(1 - \bar{c})$ is minimized, as it is for the other criteria.

$$\bar{c} = \frac{\sum_{j=1}^{k} c_j n_j}{n} \tag{7}$$

Similarity The similarity is a measure to evaluate the resemblance, or coincidence, between two solutions. In dynamic sectorization, it is relevant to measure how different is the sectorization of period $t+1$ from the one of the previous period t. In the delivery company problem, it is important that there are no major changes from a period to the following. The similarity measure used in this work is the percentage of customers that stay unchanged, which is given by:

$$\frac{\sum_{j\in D}\sum_{i\in V} x_{ij}^{t} x_{ij}^{t+1}}{\sum_{j\in D}\sum_{i\in V} x_{ij}^{t}}, \qquad t \in P. \tag{8}$$

This measure evaluates how much the similarity is being ensured by the solution method.

4 Solution Method

In the current work, GA, presented by Goldberg and Holland [25], and AHP are used in the solution method described in this section.

Some GA specific definitions, such as genetic encoding scheme, selection and crossover or mutation, should be decided carefully due to their effect on the final solution/s. This paper considers the matrix form binary grouping (MFBG) genetic encoding system due to its suitable scheme for sectorization, assignment, and related problems. MFBG is a matrix form genetic encoding scheme where rows represent basic units (customers, nodes, etc.) and columns represent sectors. Binary values show the assignment status of basic units to the sectors. More precisely, when a basic unit is assigned to a sector, the corresponding row takes the value of one in the cell where the column corresponds to that sector and takes the value of zero in every other cell of that row. MFBG has two restrictions: (i) each basic unit can be assigned to only one sector, and (ii) each sector must have at least one basic unit assigned. We assume that solutions that do not respect these restrictions are infeasible.

Tournament selection is used for the selection step where two randomly selected solutions are picked, and the superior one is selected as a parent for the crossover procedure. A multi-point crossover method proper for the chosen genetic encoding system is employed. In this method, several randomly selected rows are switched between two-parent solutions to generate two offspring solutions. The mutation is applied to offspring only every two generations. We use a very low mutation rate that randomly changes a basic unit's assignment to a sector if the mutation rate holds. Finally, the number of generations, G, is used as the stopping criteria.

As mentioned earlier, we consider a dynamic problem where changes in demand may occur from one period to the next. Over time, the sectorization is updated according to these changes, using the sectorization found in period t to create the initial population in period $t+1$ so that similarity between sectorizations is promoted. A whole GA procedure is completed independently from the previous or the next period. In other words, the two consecutive periods are only connected through the best solution found in the first of the two periods. This is evidenced in the pseudocode of Algorithm 1.

Algorithm 1 starts with a random initial population only in period $t=0$. In all subsequent periods, the best solution of the previous period is used to create the initial population of the current period. Moreover, the demands start to change only after the initial period, and according to a uniform or a normal distribution with the selected percentage. These changes in the demands are reflected in Expression (9).

$$L_i^{t+1} \sim U\left(l_i^t - \frac{\Delta\%}{100} l_i^t, \quad l_i^t + \frac{\Delta\%}{100} l_i^t\right) \quad or \quad L_i^{t+1} \sim N\left(l_i^t, \quad \frac{\frac{\Delta\%}{100} l_i^t}{3}\right) \tag{9}$$

Here l_i^t is the demand of the basic unit i at period t, and $\Delta\%$ is the deviation allowed to the demands, in percentage. Finally, L_i^{t+1} is the random variable representing the demand in period $t+1$, and U and N stand for the uniform and the normal probability distributions, respectively. The expressions in U are respectively the minimum and maximum parameters required in the uniform probability distribution. Regarding N, the expressions are respectively the mean and variance parameters needed in the normal probability distribution. If the demand decreases below zero, the basic unit is assumed to disappear from the instance.

Algorithm 1 GA for Dynamic Sectorization

Generate N random feasible solutions and insert into Population ($Pop_{size} = N$)
Evaluation of the solutions according to the fitness function
$Period := 0$
while $Period < T$ **do**
  if $Period > 0$ **then**
    Consider the demands of period $Period$
    Generate N feasible solutions based on the best solution found in the previous period and insert them into Population ($Pop_{size} = N$)
    Evaluation of the solutions according to the fitness function
  end if
  $Generation := 0$
  while $Generation < G$ **do**
    while $Pop_{size} < N \times 2$ **do**
      Select parents through tournament selection
      Create two offsprings using two-point crossover in each turn
      $Pop_{size} := Pop_{size} + 2$
    end while
    Mutate off-springs (for selected P_{mut})
    Merge offsprings into the population
    Evaluation of the solutions according to the fitness function
    while $Pop_{size} > N$ **do**
      Refinement: Delete the worst solution from the population
      $Pop_{size} := Pop_{size} - 1$
    end while
    $Generation := Generation + 1$
  end while
  Keep the best solution
  Calculate the similarity
  $Period := Period + 1$
end while

The evaluation step takes place by analysing the solutions regarding their performance according to the fitness function. Whether a solution is adequate for the problem depends on its fitness. Given h objectives, the composite weighted single objective function in Equation (10) is used to measure the fitness of the solutions.

$$F(x) = w_1 f_1(x) + w_2 f_2(x) + ... + w_h f_h(x), \ \ where \ \sum_{i=1}^{h} w_i = 1 \tag{10}$$

$F(x)$ shows the fitness value of a solution x, and $f_i(x)$ is the performance of solution x concerning objective i. Finally, w_i is the weight assigned to objective i using the AHP procedure.

When weighted composite single objective functions are used, there are two necessary operations: normalisation and weighting. Normalisation is necessary when the objective functions have different measurement units. In the current paper, min-max normalisation was used to standardise Balance and Compactness factors to set their values between 0 and 1, where zero is the best, and one is the worst. No normalisation was necessary for contiguity since its values already occur between 0 and 1.

5 Data and Results

This section describes the data and presents the main results. Additionally, results are briefly discussed.

The instance used in this paper was generated by us based on real data from a delivery company which included the coordinates of 350 customers and 10 facilities, the demand of each client, and the capacity of each facility. To simulate the dynamic demand, we considered the normal and uniform distributions, with the percentage of the demand to change equal to 10%. In the genetic algorithm, we used a population size of 50, a rate of mutation of 10% and the number of generations $G = 250$.

Table 1 presents the results obtained in each period for both distributions. The first thing to notice is how much the solutions worsen while moving in time. In the case of the normal distribution, the solution fitness gets worst by approximately 118%, and 98% in the uniform. Additionally, both compactness and contiguity also have increased in their values. The differences are not significant in terms of balance. The similarity values between solutions are above 85%, which is a high similarity value.

Table 1. GA Results

Distribution	Period	Compactness	Balance	Contiguity	Fitness	Similarity	Time (min)
Normal	0	0.703	0.054	0.023	0.260	-	38.65
	1	0.456	0.067	0.171	0.231	90.29%	
	2	0.798	0.068	0.315	0.394	85.88%	
	3	0.805	0.059	0.416	0.427	85.00%	
	4	0.860	0.101	0.579	0.513	87.35%	
	5	0.898	0.042	0.680	0.540	87.65%	
	6	0.951	0.084	0.667	0.567	86.76%	
Uniform	0	0.643	0.148	0.032	0.274	-	37.87
	1	0.411	0.059	0.114	0.195	84.71%	
	2	0.778	0.048	0.380	0.402	88.53%	
	3	0.891	0.084	0.450	0.475	85.88%	
	4	0.891	0.111	0.534	0.512	90.00%	
	5	0.916	0.070	0.592	0.526	86.76%	
	6	0.904	0.069	0.652	0.542	86.76%	

Table 2 presents the fitness values for totally random populations in period $t+1$. It shows much lower similarity values than the ones obtained when the population in period $t+1$ is generated from the best solution of the previous period (Table 1). However, fitness values tend to be smaller. These results emphasize the effectiveness of the proposed method in maintaining the similarity of the sectors for later periods.

Table 2. GA Results for totally random initial populations

Period	0	1	2	3	4	5	6
Fitness	0.260	0.201	0.352	0.362	0.293	0.302	0.322
Similarity	-	5%	19%	21%	32%	19%	17%

Fig. 1, Fig. 2 and Fig. 3 respectively show the visual representation of the sectors for periods $t = 0$, $t = 3$, and $t = 6$ when the normal distribution is used. Each colour is a sector associated with a facility, whose location is represented by a cross. The other geometric shapes are the clients.

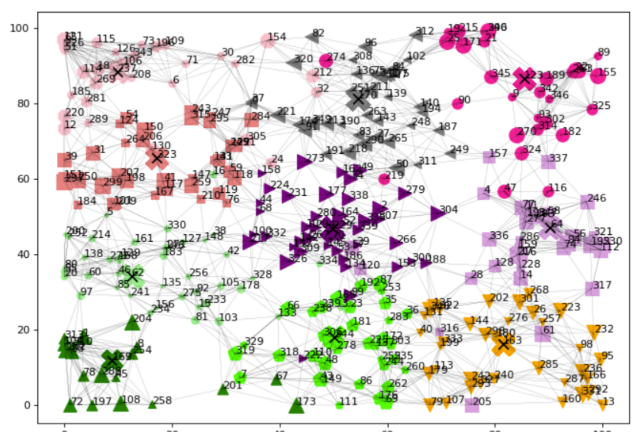

Fig. 1. Period=0

It is possible to see that the points are more scattered when the period increases; this happens because of the higher compactness values. Moreover, most of the points stay in the same sector, from one period to another, maintaining the sectors similar, as we intended.

Finally, we decided to see what happens when changing the percentage that the demand can deviate from. We observed that the fitness values remained within the same ranges.

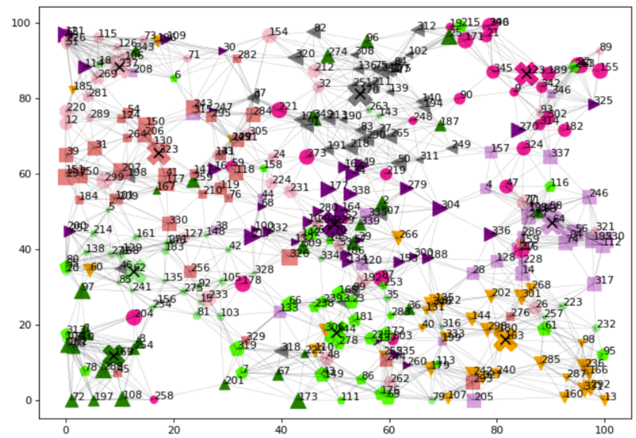

Fig. 2. Period=3

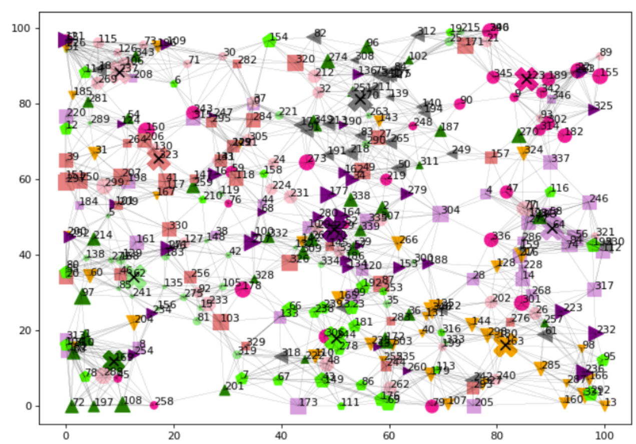

Fig. 3. Period=6

6 Conclusions and Future Work

Sectorization divides a set or region into smaller parts to help solve complex situations. Decision-making in sectorization problems can also be affected by growing uncertainty about the future. Thus, a dynamic perspective to handle such problems may be relevant. It is convenient to discretize the time horizon in a certain number of periods to deal with a dynamic situation, ensuring a sectorization with no major changes.

The main contributions of this work were the proposal of a conceptualization of dynamic sectorization and an application to a distribution problem, where the demand changes over time. The goal was to assign customers to a facility and create compact, contiguous, and balanced sectors. Moreover, we used a genetic algorithm to obtain a solution to the problem. Given that we considered three objectives, we used a composite weighted single objective function to calculate the solution's fitness. AHP was used to obtain the weights. The solution method was tested in two different demand cases, following a normal or uniform distribution. In both cases, the similarity values were above 85%, which means no major changes from one solution to another. The balance of the sectors stayed in the same range. However, compactness, contiguity and the solution's fitness were worse when the period increased. On the other hand, when similarity is not priority the solution's fitness are better.

In the future, the solution method should be tested with the real data from the company. In addition, we will address the case where the clients' locations change over time and integrate it with the dynamic demand. Another development will consist of proposing measures to evaluate the entire time horizon, particularly concerning the similarity of the solutions.

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