Capítulo 2

Metaheuristic-based optimization of treated water distribution in a Mexican City

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Abstract: Nowadays, urban areas are composed of logistic networks that form a compact and complex entity whose integration has a meaningful impact on the sustainability of the urban system. Currently, there are several models for the optimization of these networks mainly focused on the transport of products and people. One of these models is the Vehicle Routing Problem (VRP). The scientific literature provides evidence that Genetic Algorithms (GAs) find acceptable solutions to VRP. Besides, local searches optimize the GA solutions and hence reduce computing runtime. In this study, three algorithms for local search are compared: (1) Tabu search [11], (2) a threshold accepting approach, and (3) a multi-start local search based on cross exchanges [1]. Instances taken from a real-world case study of water distribution from the "Junta Municipal de Agua y Saneamiento de Ciudad Juárez" are considered for this analysis. Further results show that implemented local search algorithms reduce the traveled distance of the initial solutions.

Keywords: Local search; Drinking water distribution; Genetic Algorithm; Vehicle Routing Problem; Real-world Case Study

2.1. Introduction

Drinking water distribution is a major problem for every city, specially in cities with poor urban planification and increasing population. During summer, temperatures tend to rise extremely in desert cities. According to the UN, 9 % of the world's population does not have access to drinking water. It is expected that by 2050 at least 25 % of the world population will have a problem aggravated by the continuing shortage of fresh water [4]. Shortage of water in areas without access to

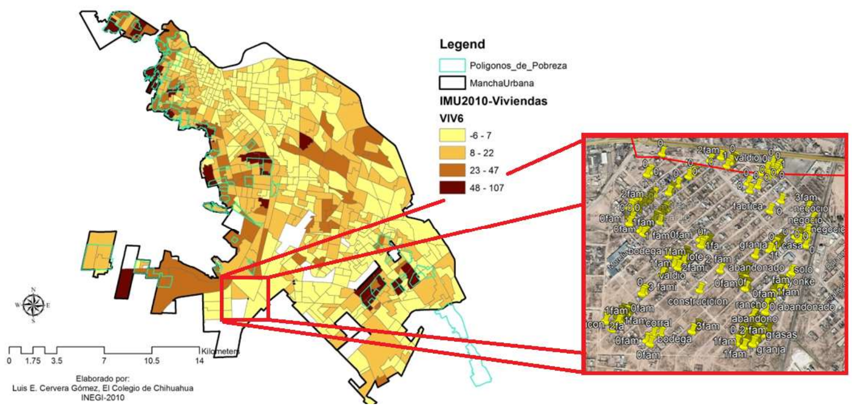


Figura 2.1: Largest poverty polygon study area in Ciudad Juárez according to El Colegio de Chihuahua

this resource may lead to severe cases of dehydration or even death from heat stroke, as occurrs in Ciudad Juárez. In this city there are poverty polygons where drinking water distribution is necessary for the quality of life of their population. The largest poverty polygon in Ciudad Juárez is shown in figure 2.1.

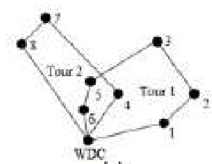
There are areas where companies cannot distribute the vital liquid via the water trucking system because long distances between delivery points. Having a good Water Distribution Systems (WDSs) is the main scope of any water agency. An algorithm that allows optimizing delivery times, load times and fuel savings for vehicles,is critical according to the variables previously involved [12]. The main objective of a route optimization algorithm is to improve the delivery efficiency from one point to another. This efficiency is delimited mainly by the distance, load time and capacity of the vehicles. These constraints are correlated to the geographical conditions and the deliveries that have to be made [6]. For this case study a genetic algorithm for VRP was implemented. However, the focus of the research is oriented to improve the delivery and distribution of water. The purpose is to decrease traveled distance and fuel costs. This research is organized as follows: Section 2 describes the GA for the VRP. Next, three methods for local search are examined: tabu search, threshold accepting and cross exchange. The results of the different algorithms are presented in Section 3. Section 4 discuss some conclusions and directions for future research.

2.2. Methodology

There are other bioinspired techniques that have been applied for VRP [9]. In this study, a Genetic Algorithm technique for the classic VRP is considered. The instances for this study were provided by the JMAS (Junta Municipal de Agua y Saneamiento), including the information on the demand of drinking water in Ciudad Juárez. These instances designate the capacity of the vehicles that will be used for the delivering service; the maximum distance a vehicle can travel, and contain the coordinates and the demand of the costumers (or the families) to be visited. In the proposed GA, every chromosome represents a solution that satisfies an instance with an allowed excess (unfitness). The chromosome contains the tours and the order in which the families or clients would be visited (see figure 2.2).

1	1	1	2	1	1	2	2
1	2	3	1	4	5	2	3

a)



b)

Figura 2.2: The chromosome model. a) A two-dimensional structure that holds the tour and the order in which every costumer or family will be visited. b) The tours stored in the chromosome shown in the structure, starting from the Water Distribution Center.

In the first step of the GA, an initial population of n size (number of deliveries) is created. The initial solutions are formed considering the polar coordinates of the points to be visited, with the depot (the water distribution center) placed at the origin. The first tour begins with the nearest client or family to the positive x-axis, and adds the next one considering this same condition. More families or clients will be added until an infraction in traveled distance occurs. When this happens, if the distance excess is smaller or equal to the allowed excess, the client or family will be added to the current tour and a new tour will be created. In order to explore solutions that would be expected to be more difficult to be generated via genetic operators, a local search is implemented. In the next section, different algorithms for local search are analyzed.

2.2.1. Three approaches for the local search procedure

Every time a solution is created during the execution of the GA (regardless if the solution was created in the initial population or during crossover), a local search procedure is applied to this new solution. The purpose of this process is to reduce the traveled distance for every tour in the solution by moving one or more deliveries to a near tour. There are several known algorithms for doing this. In this section, three algorithms for local search are analyzed and adapted to the VRP for drinking water distribution: (1) *Tabu Search*, (2) *Threshold Accepting* and (3) *Cross Exchange*. These methods were chosen for being heuristic and metaheuristic models. According to literature[2,5,12], the heuristic method (Cross-Exchange) and the meta-heuristics (Tabu Search and Threshold Accepting) are some of the most used models for VRP.

Tabu Search

The first implemented approach is based on the Tabu Search algorithm. It was introduced in 1989 by Fred Glover [7], in the same work he also introduced the notion of metaheuristic. This method was based on the resolution of real problems, through the application of concepts related to combinatorial optimization. Several algorithms implement local search techniques [3], our case study implements techniques based on tabu search to find a feasible solution, where there are three entities to consider: (1) depot, which is the water distribution center, where drinking water trucks fill their tanks for delivery. It is in the origin when de problem is modeled. (2) Routes: which represent the roads that vehicles transit for the distribution of water. (3) Customers: they are made up of households where water is distributed. The adaptation of the algorithm based on Tabu Search for this case study is shown in algorithm 1.

Algorithm 1: Tabu Search

```
BestSolution ← Solution;
MaxValueTabuList ← Value1;
TabuList ← [];
TabuTenure ← Value2;
while TabuTenure > 0 do
    for BestSolution.route[i] <BestSolution.route[maxLenght] do
        CandidateNode ← RadomNode;
        NewDistance ←
        CompareDistanceNodes(CandidateNode, ChosenNeighborhood);

        if NewDistance <OriginalDistance then
            BestSolution.route[I] ←
            SwaptNodes(CandidateNode, ChosenNeighborhood);
        end if
        if Lenght(LenghtTabuList) ≥ MaxValueTabuList then
            TabuList.RemoveLast(CandidateNode and
            ChosenNeighborhood);
        end if
        TabuList.Push(CandidateNode, ChosenNeighborhood);
        i++;
    end for
    TabuTernure–;
end while
return BestSolution;
```

Threshold Accepting

The second approach analyzed is based in the algorithm that was originally proposed by Dueck and Scheuer in 1990 [5], and it seeks for an unknown goal solution through the generation of pseudorandom solutions. The first step in this algorithm consists in setting a percentage that will dictate the maximum excess in cost allowed for the new solutions and a number of rounds or cycles. The percentage decreases after a cycle is completed, thus it is expected that new random solutions are more feasible and closer to the optimal over time. In order to generate solutions that move around the same domain, a neighborhood function is required. The adaptation of the algorithm for this study is shown in algorithm 2.

Algorithm 2: Threshold Accepting

```
BestSolution ← Solution;
for i = 1 to TotalRoutesInSolution do
    R ← GetRoute(BestSolution, i);
    CandidateNode ← RandomNode(R);
    NeighborRoute ← EvaluateNeighborhood(CandidateNode);
    I ← RandomIndex(1, Lenght(NeighborRoute)+1);
    NewRoute ← InsertNode(NeighborRoute, CandidateNode, I);
    DistanceExcess ← GetDistanceExcess(NewRoute);
    if DistanceExcess ≤ Ta then
        BestSolution ←
        ReplaceRoute(BestSolution, NeighborRoute, NewRoute);
    end if
    Ta ← ReduceExcess();
end for
return BestSolution;
```

Before calling the proposed method, the threshold-accepting variable *Ta* is set once. *Ta* is a proportion of the distance limit stated by the problem instances. Every solution that has an *unfitness* value bigger than zero would be sent to this procedure for local search. All the routes in the solution may be modified regardless if they exceed or do not the cost constraints. For every tour in the solution, a random client is chosen and, considering the location of this client and the adjacent tours, a neighborhood function returns the best adjacent tour in which the client would be moved. The neighborhood function finds which adjacent tour has the client with the nearest polar coordinate to the client to be moved. A new tour is generated by inserting the client in a random position in the adjacent tour determined in the previous step. If the difference between *Ta* and the excess in cost of the new rout is smaller or equal to zero, the new solution is kept and the original solution is discarded. After all the tours in the solution have been examined, the threshold-accepting variable is decreased. When *Ta* is equal to zero, no new solutions with excess would be considered.

Cross Exchange

The final algorithm analyzed in this research is a modification of the well-known Cross-exchange proposed by Bräysy [1]. Cross-exchange swaps segments of routes in a given solution. The routes must be adjacent from one another. In [10] the segment from the route 2 is inserted exactly where the segment of route 1 was removed. In addition, Bräysy proposed to swap segments that include customers closest to the customers on the other route. For this project, the maximum amount of customers in a segment was four (see algorithm 3).

Algorithm 3: Cross Exchange

```
foreach Node in Solution do
    foreach Node in CurrentRoute do
        foreach Node in NextRoute do
            if DistanceBetweenNodes ≤ DistanceToNeighbor
            then
                SwapCustomers
            end if
        end foreach
        foreach Node in PreviousRoute do
            if DistanceBetweenNodes ≤ DistanceToNeighbor
            then
                SwapCustomers
            end if
        end foreach
    end foreach
end foreach
return BestSolution;
```

For this algorithm, first we consider solutions that contain the minimum amount of routes. Then, each route is compared with its neighbor route. To do this, we calculate the distance between a customer from route 1 and a customer from route 2. If the distance is less than any distance between the customer from route 1 and its two neighbor customers, then the segment from route 2 is swapped. The process is repeated for each customer in both routes until all routes in the solution are compared.

2.3. Results

For validation purposes, the results of the three proposed approaches were obtained using the same instance to solve the GA. This instance corresponds to the Valle Dorado demand, a suburb located at south-west of Ciudad Juárez (see figure 2.1). The instance contains the demands of drinking water of houses, farms, churches and even schools. Seventy-one coordinates for deliveries are listed with their demands expressed in liters. The vehicle has a water storage capacity of 8000 liters. The results of this evaluation are presented next in table 2.1, in which the average distance of the seed solutions are compared against the distance obtained by the three approaches. The local search methods were applied to the same first ten solutions taken from the initial population, and each local search method was applied until complete fifteen cycles.

Solution	Initial	(1) Tabu S.	%	(2) Threshold A.	%	(3) Cross E.	%
1	43.56911	40.2365	3.33	40.4397	3.12	41.4656	2.10
2	43.63295	41.9456	1.68	43.2115	0.42	41.9548	1.67
3	43.73584	41.2943	2.44	41.2154	2.52	42.2364	1.49
4	43.57285	41.6544	1.91	42.5649	1.00	41.2141	2.35
5	43.5292	42.1365	1.39	42.3658	1.13	42.1648	1.36
6	43.43582	42.1365	1.44	43.4459	0.13	41.7648	1.74
7	43.57337	41.9324	1.64	41.5132	2.06	41.5483	2.02
8	43.5656	42.8646	0.70	42.2908.	1.27	41.9212	1.64
9	43.569	40.4806	3.08	40.4806	3.08	41.0318	2.18
10	43.62123	38.9454	4.67	37.3550	6.26	38.6987	4.92

Tabla 2.1: Comparison for the first ten solutions; the distance is expressed in kilometers.

2.4. Conclusions and future research

This research applies techniques that are based on genetic algorithms for the resolution of VRP problems to achieve an enhanced GA enriched by a local search. Our case study involved the water distribution department of JMAS. Techniques implemented were based on Tabu Search, Thershold Accepting and Cross Exchange which provided better optimization in the local search, in order to decrease the distance in each route. There are several directions for future work. We are going to solve the CVRP through Ant Colony Optimization (ACO) since it is expected that the parallelism achieves further improvements, as proposed by [8]. Determine the supply chain related with an emergence, or Humanitarian Logistics, will be a priority in our novel research as in [2]. Therefore, incorporating variants that represents not only the level of optimization in quantity terms by the new mathematical model, but also the conditions of quality of life in the objective function. Also is important define all dimensions on which, be improved using a novel model of Smart Cities based on Smart mobility.

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