A Combination of Simulated Annealing and Ant Colony System for the Capacitated Location-Routing Problem

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A Combination of Simulated Annealing and Ant Colony System for the Capacitated Location-Routing Problem

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Abstract. Location-Routing Problem (LRP) can model several life situations. In this paper we study The Capacitated Location Routing Problem (CLRP) which is defined as a combination of two problems: the Facility Location Problem (FLP) and the Vehicle Routing problem (VRP). We propose a two-phase approach to solve the CLRP. The approach is based on Simulated Annealing algorithm (SA) and Ant Colony System (ACS). The experimental results show the efficiency of our approach.

Keywords: Location-Routing, Ant Colony Optimization, Simulated annealing.

1 Introduction

In this paper, we consider the Capacitated Location Routing Problem (CLRP) defined as a combination of two difficult problems: the Facility Location Problem (FLP) and the Vehicle Routing Problem (VRP). The CLRP can be divided in two levels: a set of potential capacitated distribution centers (DC) and a set of customers. The problem is also constrained with capacities on the vehicles. Moreover, there is a homogeneous fleet of vehicles, where each customer is visited just once. The objective is to minimize the routing and the location costs.

Many different location-routing problems have been described in the literature, and they tend to be very difficult to solve since they merge two NP-hard problems: facility location and vehicle routing. In [7], a review of early works on location routing problems presents and summarizes the different types of formulations, solution algorithms and computational results of work published prior to 1988. More recently, Min et al. [8] developed a hierarchical taxonomy and classification scheme used to review the existing location routing literature. In [10], three heuristics for the LRP are proposed; they explore the effects of several environmental factors on the algorithm performance. Tuzun and Burke [11] introduced a novel two-phase architecture that integrates the location and routing decisions of the LRP. The two-phase approach coordinates two tabu search mechanisms - one seeking for a good facility configuration, and the other a good routing that corresponds to that configuration – in

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a computationally efficient algorithm. In [2], a cluster analysis based on sequential heuristic that uses simple procedures was presented. Moreover, four grouping techniques (hierarchical and non hierarchical) and six proximity measures were used to obtain several versions of the heuristic.

In this paper we present a Simulated Annealing (SA) and Ant Colony System (ACS) approach to the CLRP. The approach coordinates a SA and ACS where the first (SA) seeking the good facility configuration, and the second (ACS) a good routing that corresponds to this configuration. The remainder of this paper is organized as follows. In the section 2, the CLRP is formulated. Section 3 describes the approach proposed. Section 4 describes the computational results. Section 5 concludes the work.

2 Problem Formulation

The CLRP can be represented by a graph $Gr = (S, A)$, where $S = G \cup H$. G denotes the set of nodes of potential distribution centers and H the set of nodes for the customers. For each $i \in G$, let f_i be the cost for opening the distribution center i. A facility located at site r has a capacity p_r. For each $j \in H$, q_j denotes the demand of client j. Associated to each edge $(i, j) \in A$ there is a routing cost d_{ij} which represent the distance between nodes i and j. An example of the CLRP model is shown in Fig.1.

The objective is to find a set of distribution centers to be opened and a set of routes to service the clients from the opened distribution centers in such way that the opening costs plus the routing costs are minimize. We assume that 1) the capacity of each potential depot $i \in G$ is known, 2) the fleet of vehicles is homogeneous, 3) the routes start and end at the same facility, 4) each customer is serviced by one and only one vehicle, 5) the total load of the routes assigned to a depot must fit the capacity of that depot. The objective function minimizes the total cost of routing an locating the depots.

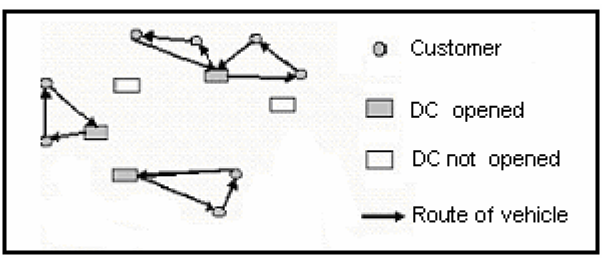

Fig. 1. Example of solution of CLRP (number of customers: 8, number of depots: 5)

3 A Simulated Annealing and Ant Colony System to the CLRP

In our approach, the CLRP is divided into two phases: facility location phase and routing phase. We propose a meta-heuristic approach based on the simulated annealing (SA) and ant colony system (ACS) to solve the combined location routing problem.

The SA is a search technique inspired by the physical process of annealing in metals, it is viewed as a probabilistic decision making process in which a control parameter called temperature is employed to evaluate the probability of accepting a move. The ACS is based on the behaviour of real ants searching for food. Real ants communicate with each other using an aromatic essence called pheromone, which they leave on the paths they traverse. If ants sense pheromone in their vicinity, they are likely to follow that pheromone, thus reinforcing this path. The pheromone trails reflect the 'memory' of the ant population. The quantity of the pheromone deposited on paths depends on both, the length of the paths as well as the quality of the food source found. The SA is used to find a good configuration of distribution centers (DC), and the ant colony system (ACS) is used to find the good routing corresponding to this configuration. The two phases will be tackled repeatedly until the total costs justify the algorithm termination. This two phase approach offers a simple and a natural representation of the CLRP. The two meta-heuristics are coordinated so that an efficient exploration of the solution space is performed.

3.1 Initialization

We represent a state of the facilities by a vector $D = \{D_1, D_2, ..., D_m\}$ where $D_i \in D$, $i \in \{1,...,m\}$ if the depot D_i is opened. Initially, a randomly selected distribution center is opened, and all of the other candidate depots closed. In this case, all the clients are affected to the facility opened; the initial solution is represented by S_0 . An estimation of the location and routing cost, $Cost(S_0)$, is computed by the sum of the distances of the client to the depot plus the capacity of that depot. If the constraint capacity of the facility selected is verified (the selected facility can serve all the clients) we use the ACS algorithm to obtain the initial routing for the open facility denoted Y_0 , The total cost of the objective function, $TCost$, is the sum of the cost of the facility opened $FixedCost(S)$ and the routing cost $Cost(Y_0)$ obtained by the ACS. We denote the courant best solution by $BestSol$ and the according best cost by $BestCost$.

3.2 Location Phase

The location phase tries to find a good configuration of distribution centers that allow reducing the cost of the last configuration. For the neighborhood system, in this phase, we apply two different types of moves: swap moves and add moves. For the affectation of customers to the depots, we take a simplistic approach, and assume that each customer is assigned to the closest open facility without violating the capacity constraint of facility. A solution S represents the opened depots and the set of customers assigned to each depot without considering the routes of vehicles.

We select randomly a solution $S' \in Neighborhood(S)$, this solution is accepted if: $\Delta S(=Cost(S') - Cost(S)) \prec 0$ O $\exp(-\Delta S / T) \succ \mu$ where $\mu \in [0,1]$ a random number uniformly distributed. $Cost(S)$ is the estimation of the routing cost corresponding to the courant configuration of depots, and $\exp(-\Delta S / T)$ is Metropolis criterion. When a configuration S' is accepted, the ACS algorithm is applied to find a routing solution Y', and then a total cost $TCost'$ is calculated. If the total cost $TCost'$ is improved (i.e. less than the courant cost $TCost$) then the best solution is modified ($BestSol \leftarrow Y'$, $BestCost \leftarrow TCost'$). The process is repeated with gradually lowering the temperature T for certain number of iteration until minimum is reached and stopping condition is verified. In the Following we detail the neighborhood system used in the location phase:

Swap moves. These types of moves open one facility currently closed and close one of the facilities simultaneously.

The swap moves explore the neighborhood to keep the number of open facilities in the solution constant, and search for a good configuration for a certain number of facilities, the location phase searches for the best swap move to perform. In order to select the best swap move, it is necessary to evaluate the cost of a swap move. The difference in the fixed cost when we open one facility and close another is straightforward (fixed cost of the facility to open - fixed cost of the facility to close). However, the difference in the routing cost is difficult to estimate. To do this, we take a simplistic approach, and assume that each customer is assigned to the closest open facility without violating the capacity constraint of facility. The difference in routing cost is then estimated using the difference in the direct distance between the customer and the facility according to the new and old assignments. The swap move evaluation is the sum of this routing cost estimate and the difference in the fixed cost. The swap move which yields the smallest evaluation is then performed, after the swap move is performed, the search resumes to the routing phase to update the routing according to the swap move.

Add moves. Having explored the configurations with the current number of facilities using the Swap moves, the search mechanism then increases the number of facilities by applying an add move.

An add move opens one of the currently closed facilities, and therefore increases the number of facilities by one. Here, the routing cost is again estimated using the difference in direct distances for the customer assignments before and after the add move. Since opening a facility can only improve the routing cost estimate, this cost is always negative. The fixed cost of the facility to be opened is then added to the routing estimate in order to calculate the overall cost estimate. As in the swap move, the search again returns to the routing phase in order to update the routing after the add move. After one add move, the search continues with a series of swap moves until the termination criterion is satisfied.

3.3 Routing Phase

After each swap or add move is performed, the routing phase is started from the best routing found for the previous facility configuration in order to modify the routing according to the current facility configuration. First, the customers are reassigned to the closest open facility with respecting the capacity constraint of the facilities. We obtain a certain number of clusters. A cluster is composed of one facility and a set of clients which are affected to this facility. We note that, the sum of customers' demand of each cluster doesn't exceed to the capacity of the facility. For each cluster, an ACS is executed to calculate the routing cost. The total cost is equal to the sum of routing cost of each cluster and the cost of opened facilities. If the total cost is smaller than the current best, we update the value of the best to the new value found and we go to the location phase. The algorithm is repeated for certain number of iterations.

In this section we describe the algorithm based on the Ant Colony System which is applied in each cluster to evaluate the routing cost:

Construction of vehicle routes. Initially, m ants are positioned on n customers randomly and initial pheromone trail levels are applied to arcs. In order to solve the capacitated vehicle routing problem (CVRP), artificial ants construct solutions by successively choosing a customer to visit, continuing until each customer has been visited. When constructing routes if all remaining choices would result in an infeasible solution due to vehicle capacity being exceeded then the depot is chosen and a new route is started. Ants choose the next city to visit using a combination of heuristic and pheromone information. During the construction of a route the ant modifies the amount of pheromone on the chosen arc by applying a local updating rule. Once all ants have constructed their tours then the amount of pheromone on arcs belonging to the best solution, as well as the global best solution, are updated according to the global updating rule**.**

The probabilistic rule used to construct routes is as follows. Ant k positioned on node i chooses the next customer j to visit with probability $p_k(i,j)$ given in Equation (1).

$$j = \begin{cases} \arg\max\{(\tau_{iu})^{\alpha}.(\eta_{iu})^{\beta}.(\gamma_{iu})^{\lambda}\} \; if \; q \le q_0 \\ J \; if \; q \succ q_0 \end{cases} \tag{1}$$

J is a random variable generated according to the probability distribution function given by:

$$p_{ij} = \begin{cases} \dfrac{(\tau_{ij})^{\alpha}.(\eta_{ij})^{\beta}.\ (\gamma_{ij})^{\lambda}}{\sum\limits_{u \ne F_k} (\tau_{iu})^{\alpha}.(\eta_{iu})^{\beta}.\ (\gamma_{iu})^{\lambda}} & \text{if } u \in F_k \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where q is a random number uniformly distributed in $[0,1]$ and q_0 is a parameter $(0 \le q_0 \le 1)$. τ_{ij} is the pheromone associated with arc (i,j) , η_{ij} is the heuristic desirability, known as visibility, and is the local heuristic function which is the inverse of the distance between customer i and j. The selection probability is then further extended by problem specific information. There, the inclusion of savings leads to better results. The saving function [9] is represented by $\gamma_{ij} = d_{i0} + d_{0j} - g.d_{ij} + f.\left|d_{i0} - d_{0j}\right|$ where f and g are two parameters. F_k is the set of feasible customers that remain to be visited by ant k and α , β and λ are a parameters which determine the relative importance of the trails, distance and the savings heuristic, respectively. The parameter q_0 determines the relative importance of exploitation against exploration. Before an ant selects the next customer to visit the random number q is generated. If $q \le q_0$ then exploitation is encouraged, whereas $q \succ q_0$ encourages biased exploration.

Update pheromone trail. While an ant is building its solution, the pheromone level on each arc (i, j) that is visited is updated according to the local updating rule given in Equation (3).

$$\tau_{ij} = (1-\rho) + \rho.\Delta\tau_{ij} \tag{3}$$

Where ρ is a parameter $(0 < \rho < 1)$ and $\Delta\tau_{ij} = \tau_0$ the initial pheromone trail.

Once all ants have built their tours then the global updating rule is applied. In the ACS method only the globally best ant is allowed to deposit pheromone in an attempt to guide the search. The global updating rule is given in the Equation (4).

$$\tau_{ij}^{\;new} = (1-\rho)\tau_{ij}^{\;old} + \rho\Delta\tau_{ij} \tag{4}$$

Where $0 < \rho < 0$ is the pheromone decay parameter, If arc (i,j) is used by the *best* ant then the pheromone trail is increased on that arc by $\Delta\tau_{ij}$ which is equal to $1/L^*$, where L^* is the length of the tour produced by the *best* ant.

After the ant system is initialised, the steps detailed above are repeated for a given number of iterations. Once each ant has produced a set of routes the local optimizer 2-opt is applied to improve the solutions if possible.

4 Computational Results

To evaluate our approach, computational tests were carried out on 11 CLRP instances (see Table 1) obtained from the literature. Data relative to the used instances are available in http://sweet.ua.pt/~iscf143/_private/SergioBarretoHomePage.htm.

Table 1 gives the computational results for the test problems obtained by our approach compared to the best solution published, where the CLRP instance column contains information about the author, the publication year and the author and the number of customers and potential Distribution centers. The best published cost column contains the best result obtained running a set of versions of a clustering heuristic in Barreto et al. [2], and Simul-Ant cost column contains the best result obtained running our approach.

The cost is the sum of distribution costs (Euclidean distances) with the fixed costs of depots installed.

Table 1. Computational results and comparisons

CLRP Instance	Best published cost	Simul-Ant cost
Gaskell67-21x5	435.9	**430.36**
Gaskell67-22x5	591.5	**586.69**
Gaskell67-29x5	**512.1**	**512.1**
Gaskell67-32x5	571.7	**569.3**
Gaskell67-32x5_2	511.4	**506.13**
Gaskell67-36x5	470.7	**470.42**
Min92-27x5	**3062**	**3062**
Min92-134x8	6238	**6208.78**
Perl83-12x2	**204**	**204**
Perl83-85x7	1656.9	**1651.30**
Perl83Cli55x15	1136.2	**1118.43**

From the table we observe that the preliminary results obtained by Simul-Ant improve, in the most of cases, the best results published obtained by clustering heuristic. Hence, our approach is efficient and competitive.

For the setting parameters we use 10 artificial ants, $\alpha = 1, \beta = 2, \lambda = 1$, $\rho = 0.1$, $q_0 = 0.75$ and $f = g = 2$ (to the savings function) for the ACS and $T = 100$ for the temperature parameter in SA.

5 Conclusion

This paper has focused on the development of a new algorithm for the CLRP. The algorithm combines two meta-heuristics, a simulated annealing and Ant colony system which cooperating together to optimize the cost of location and routing. Preliminary results show that our algorithm outperforms other algorithms by producing the best results for the set of tested instances. The paper shows the successful application of the SA search and the ACS system to the capacitated location routing problem.

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