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A simple and effective evolutionary algorithm for the capacitated location–routing problem

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ABSTRACT

This paper proposes a hybrid genetic algorithm (GA) to solve the capacitated location–routing problem. The proposed algorithm follows the standard GA framework using local search procedures in the mutation phase. Computational evaluation was carried out on three sets of benchmark instances from the literature. Results show that, although relatively simple, the proposed algorithm is effective, providing competitive results for benchmark instances within reasonable computing time.

1. Introduction

Location–routing problems (LRP) deal with the combination of two types of decisions that often arise in logistics: the location of facilities and the design of the distribution routes. Several LRP variants have appeared in the literature [19,8], among which the capacitated location–routing problem (CLRP) has recently emerged as one of the most addressed.

The CLRP can be defined on a complete and undirected graph $G=(V,E)$ with a vertex set V and an edge set E. V consists of a subset J of m potential depots and a subset $I=V\setminus J$ of n clients. Each client $i\in I$ has a non-negative demand d_i, to be satisfied only once, and is to be assigned to a single depot $j\in J$ with capacity w_j. The shipment of clients' demand from the assigned depot is carried out by an unlimited fleet of homogeneous vehicles with capacity Q; each vehicle returning to the departure depot at the end of the route. The total demand of the clients assigned to each depot must not exceed its capacity and the total demand satisfied by any vehicle must not exceed Q. The following non-negative costs are incurred: fixed cost f_j when depot $j\in J$ has clients assigned and must be opened; fixed cost F for each vehicle used; and traveling cost c_{ij} each time edge $(i,j)\in E$ is in a vehicle route. The goal is to determine the set of depots to open and the tracing of the routes in order to minimize total costs.

The CLRP is NP-hard and only few instances with more than 100 clients have been solved to proven optimality [1,3,5,7] making heuristic approaches often more suitable for solving real-life instances. This paper proposes a simple but effective heuristic algorithm for solving the CLRP, namely, a hybrid genetic algorithm (GA) where local search procedures are used as mutation operators.

The remainder of this paper is organized as follows. Section 2 provides a brief review on the most recent heuristic algorithms for the CLRP. The proposed evolutionary algorithm is detailed in Section 3 and evaluated in Section 4. Finally, conclusions are drawn in Section 5.

2. Literature review

Recent surveys on the LRP are the works by Lopes et al. [19], Prodhon and Prins [26] and Drexl and Schneider [8]. In Lopes et al. [19] heuristic approaches are classified according to the adopted framework (how location and routing phases interact) and the used method(s), compiling results of several heuristics for the CLRP. Prodhon and Prins [26] and Drexl and Schneider [8] can be seen as complementary surveys: the former emphasizing the CLRP, detailing and comparing recent algorithms, and the latter focusing on other LRP variants. Although most methods in the literature follow a hierarchical framework and use tour construction and improvement typically within metaheuristics, no clear conclusions could be drawn on the best performing frameworks and methods. The most recent and relevant approaches are mentioned hereafter.

Barreto et al. [2] presents a clustering based heuristic for tackling the CLRP with no vehicle acquisition cost. Several clustering methods are used to obtain the routing data and then a facility location problem is solved with the collapsed routes.

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Marinakis and Marinaki [20] solved the same problem using a bilevel GA.

Addressing the CLRP strictly as defined previously are the following works.

Prins et al. [24] propose a constructive algorithm for the CLRP: extended savings heuristic. The heuristic is randomized and used in a greedy randomized adaptive search procedure (GRASP). The performance of this dedicated constructive algorithm is worth noting, which motivated further development, presented in Duhamel et al. [9], where a similar GRASP is hybridized with evolutionary local search.

In Prins et al. [25] facility location (through Lagrangean relaxation) and vehicle routing (using a granular tabu search) are performed iteratively. The time required to obtain good solutions is remarkable, mostly due to the effectiveness of granular tabu search (GTS) in the routing phase [30]. Also using GTS are the works by Escobar et al. [10] and Escobar et al. [11]: firstly in the improvement phase of its hybrid heuristic; then within a variable neighborhood search algorithm.

Other recent methods are by Yu et al. [32], with a simulated annealing (SA) based heuristic; Hemmelmayr et al. [14], using an adaptive large neighborhood search (ALNS) heuristic; Ting and Chen [29] with an ant colony optimization (ACO) algorithm; and Contardo et al. [6] slightly changing the GRASP by Prins et al. [24] and combining it with an integer-linear program.

Looking at the methods' performance, Escobar et al. [10] and Ting and Chen [29] show similar performance concerning both results and CPU times. These methods have been slightly improved by Escobar et al. [11], which provides a good trade-off of results and time to obtain them. The method by Contardo et al. [6] presents the best overall results for the benchmark instances from the literature at the expense of significantly higher computing times.

Concerning genetic algorithms for the CLRP two approaches can be found in the literature: a memetic algorithm with population management [23] and a bilevel GA [20].

The memetic algorithm by Prins et al. [23] uses a fixed length chromosome composed of a sequence of genes for the depots and another for the clients, requiring a dedicated procedure for fitness evaluation. As crossover may produce unfeasible offspring a repair procedure is used. Depot configuration is only changed by crossover and local search is used for improving routing. The method works on a small population of high quality solutions using a population management procedure for ensuring diversity.

The bilevel GA [20] solves the CLRP in two levels: in the first, solving the capacitated facility location problem; in the second, a vehicle routing problem (VRP) is solved for each of the individuals. Each individual in the population is a solution for the location problem and crossover and mutation only occurs at the first level. For obtaining the CLRP solution a VRP is solved in the second level using expanding neighborhood search (ENS). A large population and very few generations are used.

Both methods require efficient constructive algorithms for obtaining the initial population.

3. Evolutionary algorithm

The metaheuristic presented here follows the standard GA framework hybridized with local search procedures. The proposed algorithm shares some core principles with the hybrid GA by Prins [22], with good results for the VRP; the main being the use of local search as mutation operators. However, several new implementation aspects were developed or adapted to effectively address the CLRP. The most relevant are the chromosome representation and the crossover and mutation operators. The main components are detailed and the general structure of the algorithm is presented in the following sections. The similarities of this framework with memetic algorithms and scatter search are discussed in Prins [22].

16	1	3	4	7	10	16
18	2	6	18			
18	5	9	8	13	18	
16	11	12	15	14	16	

Fig. 1. Chromosome representation of a solution for the CLRP.

Compared with other genetic algorithms in the CLRP literature, the main advantages of the proposed approach are: an intuitive chromosome representation, also allowing an easy fitness evaluation; an efficient constructive algorithm is not necessary; feasible offspring provided by crossover; and a simple framework.

3.1. Chromosome representation

The chromosome in the proposed GA represents a complete solution, i.e., the collection of routes. Both the route (gene) length and the chromosome length are variable and depend on the number of clients serviced and the number of routes in the solution. For example, given a CLRP with 15 clients $I = \{1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15\}$ and 4 possible depot locations $J = \{16, 17, 18, 19\}$, the chromosome representation of a solution is provided in Fig. 1. The solution in the figure represents installing facilities 16 and 18, and servicing the clients in the given order by four routes (vehicles).

The adopted representation, assuming solution feasibility, together with the crossover operator (detailed in the following section), allows obtaining feasible children solutions. Thus, the use of repair methods to restore feasibility is avoided. Moreover, it allows a fast evaluation of its fitness value $Fitness(S)$: the total cost of solution S. Note that higher quality solutions have smaller fitness values.

3.2. Crossover operator

The proposed crossover operator (inspired by an operator proposed by Hosny and Mumford [15], for a VRP) tries to copy complete routes from the parent to the child, thus will be named route copy crossover (RCX). It operates by copying to the child a random number of routes (between 1/3 and 2/3) from one of the parents, and the remaining unvisited clients are placed in a relocation pool following the original order in the other parent. The clients in the relocation pool are then inserted in the child, in new routes, and using the currently open depots (as long as capacity is obeyed, randomly opening a new one otherwise). This preempts the use of repair methods as child solutions are always feasible. An example of the RCX is illustrated in Fig. 2.

In the example, assuming the first and third routes of Parent 1 are selected, both are copied to Child 1. The remaining clients not yet included in Child 1 (shown underlined in Parent 2) are copied, following their order of appearance, to the relocation pool.

The clients in the relocation pool are then used to form new routes in Child 1, using the currently open depots (opening more when depot capacity constraints are violated) and following the sequence as long as vehicle (route) capacity is obeyed.

The second child is created similarly, using the parents in reverse roles. The RCX allows inheriting some of the routes from one parent while at the same time randomizing the building of the child solution routes (yet still partially inheriting the structure of the route from the other parent). Moreover, the operator promotes solutions with few open depots and routes with little unused capacity, two features often found in good solutions.