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Skewed general variable neighborhood search for the location routing scheduling problem

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ABSTRACT

The integrated location routing scheduling problem is a variant of the well-known location routing problem. The location routing problem consists in selecting a set of depots to open and in building a set of routes from these depots, to serve a set of customers at minimum cost. In this variant, a vehicle can perform more than a single route in the planning period. As a consequence, the routes have to be scheduled within the workdays of each vehicle. The problem arises typically when routes are constrained to have a short duration. It happens for example within the boundaries of small geographic areas or in the transportation of perishable goods. In this paper, we propose a skewed general variable neighborhood search based heuristic to solve it. The algorithm is tested extensively and we show that it is efficient and provides the proven optimal solution in a significant number of cases. Moreover, it clearly outperforms a multi-start VND based heuristic that uses the same neighborhood structures.

1. Introduction

The optimization of integrated problems consists in addressing simultaneously different inter-related problems arising in the companies. This approach allows us to consider explicitly the strong inter-dependencies that arise in real world situations. The aim is to avoid finding solutions that are good or even optimal for an isolated problem, but are globally sub-optimal when considering the whole context where it occurs. The drawback of this integrated vision is that it typically results in the combination of problems that are, by themselves, already very complex.

The Location Routing Problem (LRP) is an example of such an integrated problem arising essentially in the supply chain. The problem consists in determining simultaneously the depots that should be opened or installed, together with the routes that a fleet of vehicles should perform from those depots so as to fulfill the demand of a set of customers and optimize a given objective function. Formally, the LRP combines two well-known NP-hard problems, namely the location problem and the vehicle routing problem. Hence, solving the LRP up to optimality is also NP-hard, but it may lead to significant savings compared to a separated resolution of the two problems, as in the LRP the operational costs are considered in a much broader way.

The LRP has been widely studied in the literature. Different surveys have been proposed by Laporte [25] and more recently by Nagy and Salhi [40], for example. A taxonomy was also proposed in [35], together with a classification scheme that applies to the solution approaches described in the literature. Most of the solution algorithms that are reported for the deterministic version of the problem rely on heuristic approaches. Nagy and Salhi [40] divide them into three groups: the clustering-based methods, the iterative methods and the hierarchical methods. Some examples can be found in [39,47,50,3,7,13]. In contrast, the number of exact methods is much smaller. Some contributions may be found in [26,27]. The number of contributions for variants of the LRP is also growing. The simplest variants assume, for example, constraints on the capacities of the depots [2,8,12,17,23], while others impose constraints on the total distances that each vehicle can perform [9].

In this paper, we address a variant of the LRP that has been considered recently in [28,29,1]. It combines the location problem and the Multi-trip Vehicle Routing Problem (MVRP), a variant of the

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classical vehicle routing problem where a vehicle can be assigned to more than one route per planning period. MVRP was first approached in [11]. Some exact [31,32,21,4,5] and heuristic solution methods [22,41,43,45,46] have been proposed in the literature for same variants of this problem, and surveys on this problem can be found in [15,10]. The problem can be seen as an integrated Location Routing Scheduling Problem (LRSP). It consists in choosing a set of depots to open, in building a set of routes from these depots to serve a set of customers and in assigning the routes to a fleet of capacitated vehicles. The difference between the standard LRP is that a vehicle can now perform more than a single route in the planning period, which implies scheduling the routes in the workdays of the vehicles. The problem was originally described in Lin et al. in [28] for the planning of a bill delivery service in a telecommunication company. The authors developed a metaheuristic approach based on simulated annealing to solve this variant, and compared it to the solutions provided by an exact branch-and-bound algorithm.

The work of [28] was later extended by Lin and Kwok in [29] for a multi-objective case with time and capacity constraints on the routes and capacitated depots. The authors consider an optimization criterion involving both the minimization of the total cost and the load and working time imbalance among vehicles. They propose a general tabu search algorithm with neighborhood structures consisting of insert and swap moves, a simple aspiration criterion based on the total cost of a solution, and the possibility of visiting infeasible solutions at the cost of a given penalty. Additionally, the authors develop and test a simulated annealing for this multi-objective version of the problem. They compare their different approaches on a set of real and simulated instances.

In [1], the authors propose two different formulations for the problem: a three-index commodity flow formulation and a set partitioning formulation. Based on the latter, the authors propose a branch-and-price algorithm. They define the concept of pairing, which is the schedule of one vehicle for the planning period, *i.e.* the set of routes one vehicle is scheduled to perform. The generation of pairings is done by solving a pricing problem that is an elementary shortest path problem with resource constraints. The authors propose two heuristic algorithms to solve it and only solve it exactly when no more attractive columns are identified by the heuristic methods. The approach is tested on instances with 5 potential depots and up to 40 customers. The total computing times reported in [1] go up to 6 h.

In [34], Macedo et al. explore a network flow formulation for the problem, strengthened with different families of valid inequalities. The authors compare their model with the three-index commodity flow formulation proposed in [1]. Based on this model, they develop an iterative rounding heuristic that relies on the continuous solutions provided by the linear relaxation of the model. The model is tested on benchmark instances with promising results using a commercial optimization solver.

In this paper, we propose a Variable Neighborhood Search (VNS) algorithm for the LRSP. The algorithm is based on different neighborhoods involving the routes, the workdays and the selection of depots. The algorithm is tested on a large set of benchmark instances and other randomly generated instances. To evaluate the quality of the solutions, we compare them with the lower and upper bounds provided by two integer programming formulations described in [34] and [1]. The computational results show that in many cases the VNS algorithm provides the proven optimal solution, while the optimality gap remains very small for all the remaining instances. In [33], some preliminary results are presented. Here, we provide a complete description of the algorithm with extended computational results showing the efficiency of the approach.

The paper is organized as follows. In Section 2, we formally define the problem, introduce all the related notation and review the two integer programming formulations that will be used to evaluate the quality of the solutions provided by our VNS algorithm. The algorithm is described in Section 3. In Section 4, we report an extensive set of computational experiments performed using benchmark and randomly generated instances. We further describe a multi-start VND based heuristic that uses some of the neighborhood structures used in our VNS. In order to asses the efficiency of the proposed VNS, we compare its solutions with lower bounds obtained by the two models described in Section 2 and with the results obtained by the multi-start VND algorithm. Some final conclusions are drawn in Section 5.

2. The integrated location routing scheduling problem

The integrated location routing scheduling problem is characterized by a set D of n_d depots that may be kept closed or opened, in which case a fixed cost of C_f^d units for each depot $d \in D$ is incurred. Each depot $d \in D$ has a capacity L_d, which may be different from depot to depot. The depots are used as a starting and ending point for the routes of the available vehicles. Each route must start and end at the same depot and each depot d has a set of allocated vehicles V_d, with $V = \cup_{d \in D} V_d$. All the vehicles have the same capacity Q. The workday of a vehicle consists of the set of routes performed during the same planning period. The time length of a workday cannot exceed W units. The set of n customers is denoted by N. Each customer $i \in N$ has an associated demand of b_i units, and it must be served by one and only one vehicle. The use of a vehicle v implies a fixed cost of C_v units. The cost and load of a route r are represented, respectively, by c_r and l_r.

The integrated location routing scheduling problem consists in determining the depots that should be opened, the routes that should be performed, and the way these routes are scheduled within the workdays of the vehicles so as to minimize the total cost involving the fixed costs for opening the depots and using the vehicles, plus the variable costs related to the distances traveled by the vehicles. The main difference between this problem and the standard LRP is that a vehicle can now perform more than a single route during its workday, which contrasts with the standard one-to-one correspondence between routes and vehicles assumed in the standard version.

2.1. A three-index commodity flow formulation

Let G be a digraph with a set of nodes representing the customers and the depots, and A be a set of arcs representing the links between these nodes, such that $G = (N \cup D, A)$. The time required to travel through the arc $(i,j) \in A$ is denoted by t_{ij}, while the corresponding unitary cost is represented by C^o.

For each vehicle $v \in V$, there is a binary variable x_{ijv} that determines whether vehicle v uses the arc $(i,j) \in A$ or not. The amount of flow that the vehicle $v \in V$ carries through arc $(i,j) \in A$ is represented by the integer variable y_{ijv}. The choice between opening or not a depot $d \in D$ is represented by the binary variable λ_d. The use of a vehicle $v \in V$ is determined by the binary variable h_v.

The three-index commodity flow model proposed in [1] states as follows:

$$\min \quad z_1(x,y,\lambda,h) = \sum_{d \in D} C_f^d \lambda_d + C_v \sum_{v \in V} h_v + \sum_{v \in V} \sum_{(i,j) \in A} t_{ij} x_{ijv} \qquad (1)$$

$$\text{s.t.} \quad \sum_{v \in V} \sum_{j \in (N \cup D)} x_{ijv} = 1, \quad \forall i \in N, \qquad (2)$$

$$\sum_{j \in (N \cup D)} x_{ijv} - \sum_{j \in (N \cup D)} x_{jiv} = 0, \quad \forall i \in N \cup D, \ \forall v \in V, \qquad (3)$$