# Vehicle Routing with Multi-Modality: A Practical Application

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**Abstract** : *This work proposes multi-modal variants of the well-known Vehicle Routing Problem. It will be empirically shown that even a relatively simple metaheuristic (namely, the Large Neighborhood Search) is able to highlight the potential benefit of multi-modality.*

**Key-words** : *Vehicle Routing, Multi-Modality, Dial-A-Ride-Problem.*

## 1 Introduction

This paper proposes a generalization of the static day-ahead *Vehicle Routing Problem with Time Windows* (VRPTW), which consists in finding the set of routes of minimum cost that visit a set of jobs spread on a territory. Each job has a given duration and a given time window (TW). In the *Vehicle Routing Problem* (VRP) formulation, each worker moves from one job to another by driving her/his assigned car. In this work, multi-modality (MM) is possible as walking between jobs is allowed, and a car can transport multiple workers. These new features are expected to help reducing both the driving distance and the number of cars used, which are the two main objective functions minimized in the VRP literature [2], where usually, minimizing the number of vehicles has the largest priority. This generalization is called the *Multi-Modal Vehicle Routing Problem* (MMVRP).

This study is motivated by the network of a large energy provider (denoted here as *ABC* as it cannot be named because of a non-disclosure agreement) in which the workers have to visit clients in order to achieve different types of tasks (e.g., evaluate consumptions, upgrade consumer settings). *ABC* has observed that their workers often leave their vehicle and perform clustered jobs on foot even if their given planning would recommend to drive to their next jobs. This situation is obviously enhanced in an urban context, where distances between jobs can allow walking. Furthermore, when the parking spots are limited and when the traffic jam is dense, walking could help reducing the high uncertainty affecting the car travel times.

## 2 Literature Review

In the context of home-care staff scheduling, a formulation that shows some similarities with the introduced MMVRP is presented in [1], where nurses can walk between the patient's locations. The main discrepancy with our approach lies in the fact that nurses are not allowed to drive a car, and their transportation between jobs is ensured by an independent transportation system. Also, the main focus is put on the minimization of the number of vehicles without considering any trade-off with the overall driving distance. In the present approach, the trade-off between the reduction of vehicle and the total driving distance is analyzed.

Transporting the same worker along her/his schedule, with different vehicles, leads to a transportation problem of persons. This is tackled in the literature as the Dial-A-Ride-Problem (DARP) [4]. MM raises additional complexity to the DARP. First, all the routes that transport the same worker along her/his path of jobs are interdependent, meaning that a delay in a route can potentially be propagated to all other routes. This extends the DARP with a temporal precedence constraint between pick-up and delivery pairs. Second, the set of pick-up and delivery locations is not given as an input but is part of the optimization process. The only dependencies in the DARP context can be found in the DARP with transfers, where transportation requests can be split into multiple routes. Dependencies appear explicitly at transfer points, as the pick-up time at transfers depends on the previous associated deposit time.

# 3 Problem Formulation

Consider a set $J$ of $n$ jobs, a set $W$ of workers, and a set $K$ of homogeneous vehicles of capacity $Q$ (equal to the number of workers that can be transported in the same car). Both workers and vehicles start and end their working day at a central depot 0. Like the VRP, the MMVRP is defined on a complete graph $G = (V, A)$, where $V = J \cup \{0\}$ represents the set of nodes and $A = \{(i, j) \mid i, j \in V, i \neq j\}$ represents the set of arcs. With each arc $(i, j) \in A$ is associated a driving time $\tau^d_{i,j}$, a walking time $\tau^w_{i,j}$ and a distance $d_{i,j}$. With each job $j \in J$ is associated a processing time $p_j$ and a TW $[e_j, l_j]$. A worker is allowed to wait at a node in order to serve the associated job within its TW, and the daily walking distance of each worker is upper-bounded.

In a MM context, the number $|K|$ of cars can be lower than the number $|W|$ of workers. Therefore, the workers can be split into drivers and passengers. Drivers have to *(1)* perform their assigned jobs and *(2)* fulfill transportation requests of passengers. Both driver and passenger workers can walk to reach a job, but in the driver case, the return path to the car is mandatory. A walking path between consecutive jobs is called a *walking route* (WR). In a MM solution, the jobs can be partitioned into WRs, and the WRs must be partitioned in the workers planning. A WR is seen from the transportation point of view as a delivery (resp. pick-up) point where the WR starts (resp. ends). In the driver case, the pick-up and delivery points are the same. A WR can thus be agglomerated in two aggregated nodes (delivery and pick-up), the characteristics of which (aggregated TW and total duration) are computed according to the ordered set of jobs contained in the WR. The vehicles only visit these aggregated nodes, and the sequence of WRs in the workers' planning gives the set of all pick-ups and deliveries to be satisfied.

Three degrees of multi-modality are considered, ranging from (F1) to (F3). In each formulation, the objective is to first minimize the amount of used resource (i.e., workers and vehicles), and next the total routing cost, which is directly proportional to the driving distance. For each instance, anytime a feasible solution is found, a new instance is generated by reducing either $K$ or $W$ by one unit (i.e., removing a car or a worker).

- **(F1)** VRP: each worker is a driver, and a worker can only move using her/his assigned car.
- **(F2)** MMVRP with $|K| = |W|$: while each worker has her/his assigned car, a worker can visit a set of jobs by walking as long as her/his maximal walking distance is not reached.
- **(F3)** MMVRP with $|K| < |W|$: we allow for the possibility to have fewer cars than workers, and thus a vehicle can transport multiples workers. Each worker can walk to reach a job as long as her/his maximal walking distance is not reached.

The main goal of this work is to show that the potential benefit of multi-modality (when moving from (F1) to (F3)) can be already unveiled on rather small instances.

# 4 Solution Method

## 4.1 Large Neighborhood Search (LNS)

LNS [5] aims at improving the current solution $s$ by iteratively unbuild and rebuild it. At each step, $q$ (dynamic parameter) jobs are randomly removed from $s$ and are then sequentially reinserted (in a best-insertion fashion, as explained below) in order to get a new solution $s'$. LNS uses here the standard simulated annealing acceptation rule (SAAR) to decide with a certain probability whether to move (or not) the search from $s$ to $s'$. In our implementation, $W$ and $K$ are given for each instance. At each step of the LNS, $q$ is an integer randomly selected in $\{1, \ldots, 0.2 \cdot n\}$. The initial temperature of the SAAR allows for a deterioration of 20% with a probability 0.5, and the cooling is set such that the final temperature does not allow any deterioration. LNS was shown to deliver good results for (F1) in [5].

### 4.2 Job Best-Insertion Algorithm

To find the best position for inserting a job, all the eligible insertion positions are exhaustively tested. When a job is inserted, different cases must be considered depending on the type of insertion performed (i.e., either in a driver or in a passenger planning). Each insertion type leads to an associated method. In a MM context, we first check whether the insertion can be performed by extending an existing WR, or if a new WR must be created for the job to be inserted. The feasibility of an extension can be easily tested by updating the involved aggregated nodes at their specific positions in the route. But when a new WR is created, the number of potential insertion positions quickly increases. Indeed, the new WR must first be inserted in a worker planning (driver or passenger), and then this insertion must be evaluated within the chosen route.

In the driver case, the insertion is similar to the insertion in a VRP case (i.e., insert a node in a route). The number of tests to perform is in $O(n)$. In the passenger case, the insertion turns out to be more complicated. Assume that the new WR (denoted as $\omega_j$) is introduced between WRs $\omega_i$ and $\omega_{i+1}$ in a passenger planning. The transportation between the pick-up $P(\omega_i)$ at the end of $\omega_i$ and the delivery $D(\omega_{i+1})$ at the beginning of $\omega_{i+1}$ becomes obsolete and must thus be removed from the partial solution. Consequently, two new transportation requests must be satisfied: $(P(\omega_i) \rightarrow D(\omega_j))$ and $(P(\omega_j) \rightarrow D(\omega_{i+1}))$. In this case, the number of tests to be performed is in $O(n^4)$. To tackle this large complexity, we adapt the fast feasibility-check procedure introduced in [3], which allows verifying in constant time if inserting two pick-up and delivery pairs is feasible. To further reduce the number of feasible insertions to test, necessary conditions and filters are used to focus on the most promising insertions. For instance, we only test the five positions $i$ that minimize $d_{P(\omega_i),D(\omega_j)} + d_{P(\omega_j),D(\omega_{i+1})}$.

## 5 Computational Results

The instances are generated based on the real cases faced by *ABC*. The considered urban territory is modeled by a square grid of 10km $\times$ 10km, where the random location of the $n$ jobs is uniformly distributed. This situation obviously allows walking between some pairs of jobs. The duration of each job is randomly generated between 15 and 34 minutes, and the same TW [8am, 5:30pm] is considered for each job (in order to enrich the resulting solution space). In an urban context, the average vehicle speed is set to 30km/h, and the walking speed to 4km/h. The upper bound on the daily walking distance is set to 5km, and each vehicle can transport $Q = 2$ workers. The time limit $T$ of the LNS is set to $n$ minutes (i.e., it is proportional to the instance size), which turns out to give the method enough time to satisfyingly explore the solution space and provide reliable results. For each considered $n \in \{25, 45, 65, 85\}$, five instances are generated (with different job configurations on the grid), on which 10 LNS runs are performed. The used computer is a 3.4 GHz Intel Quad-core i7 with 8 GB DDR3 of RAM memory.

The results are presented in Table 1, where the above (resp. below) part represents formulation (F2) (resp. (F3)). First, the instance characteristics are given, namely $n, |W|$ and $|K|$. It means that for each instance, the available resource $W$ and $K$ is known. Therefore, only the transportation costs have to be minimized. The value of $|W|$ is the smallest obtained feasible value for (F1) with respect to $n$. Next, the average (over the five configurations associated with each triplet $(n, |W|, |K|)$, and over the ten runs) percentage gap is given with respect to the (F1) solution values. For instance, in the case $(n, |W|) = (25, 2)$: *(1)* no feasible solution was found for (F1) with $|K| = |W| = 1$; *(2)* formulation (F2) reduces the solution values by 6.5%; *(3)* formulation (F3) leads to a 2.6%-augmentation of the transportation costs but one vehicle is saved. Finally, in the last column, the same information (i.e., gaps) is provided, but for the most clustered configuration (as it allows better highlighting the MM potential benefit).

Consider first the fifth column involving all the configurations. On the one hand, for formulation (F2), the transportation cost improvement (versus the classical VRP formulation (F1)) increases with $n$, which confirms the benefit of allowing walking routes. On the other hand, considering formulation (F3) (again versus (F1)), one vehicle can be saved if additional transportation costs are encountered. The transportation costs degradation augments with $n$, which probably indicates the increasing complexity of larger problems. It however opens the door to interesting tradeoffs between the transportation costs and the total used resource. Indeed, company $ABC$ is likely to accept a reasonable augmentation of the transportation costs if a vehicle can be saved. When considering the sixth column, the same trend is osberved for formulation (F2) versus (F1). Interestingly, it appears that formulation (F3) can simultaneously reduce the number of vehicles as well as the transportation costs!

TAB. 1 – VRP versus MMVRP

| Formulation | $n$ | $\|W\|$ | $\|K\|$ | % gap (5 configurations) | % gap (most clustered configuration) |
|---|---|---|---|---|---|
| F2 | 25 | 2 | 2 | −6.5% | −7.4% |
| | 45 | 3 | 3 | −8.7% | −7.5% |
| | 65 | 4 | 4 | −13% | −12.5% |
| | 85 | 5 | 5 | −11.2% | −9.3% |
| F3 | 25 | 2 | 1 | 2.6% | −2.3% |
| | 45 | 3 | 2 | 14.9% | −4.7% |
| | 65 | 4 | 3 | 18.9% | −0.2% |
| | 85 | 5 | 4 | 42.9% | 22% |

# 6 Conclusions and Future Works

In this paper, a first step is performed in multi-modal vehicle routing, motivated by a real-case situation. It was numerically shown that using two travel modes (namely by car and on foot) instead of only one can be beneficial in terms of the total transportation costs and according to the employed resource (for instance, a reduced fleet of vehicles). A conservative case was however considered here, as congestion and parking spots limitation are not taken into account, and as the density of jobs is rather small (less than 1 job per km$^2$). Our observations might thus be amplified in such situations. Following these encouraging results, upcoming effort will be devoted to the development of a set of efficient metaheuristics to tackle several instances and of larger size. Another avenue of research consists in considering additional transportation modes for the involved workers, for example taxi service or an external transportation company, particularly if it allows reducing the fleet of vehicles at a reasonable additional cost.

# References

[1] C. Fikar and P. Hirsch. A matheuristic for routing real-world home service transport systems facilitating walking. *Journal of Cleaner Production*, 105:300–310, 2015.

[2] C. Koc, T. Bektas, O. Jabali, and G. Laporte. Thirty years of heterogeneous vehicle routing. *European Journal of Operational Research*, 249(1):1–21, 2016.

[3] R. Masson, F. Lehuédé, and O. Péton. Efficient feasibility testing for request insertion in the pickup and delivery problem with transfers. *Operations Research Letters*, 41(3):211–215, 2013.

[4] R. Masson, F. Lehuédé, and O. Péton. The dial-a-ride problem with transfers. *Computers and Operations Research*, 41(1):12–23, 2014.

[5] P. Shaw. Using constraint programming and local search methods to solve vehicle routing problems. *Lecture Notes in Computer Science*, 1520:417–431, 1998.