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The Assignment-Dial-A-Ride-Problem

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Abstract

In this paper, we present the first Assignment-Dial-A-Ride problem motivated by a real-life problem faced by medico-social institutions in France. Every day, disabled people use ride-sharing services to go to an appropriate institution where they receive personal care. These institutions have to manage their staff to meet the demands of the people they receive. They have to solve three interconnected problems: the routing for the ride-sharing services; the assignment of disabled people to institutions; and the staff size in the institutions. We formulate a general Assignment-Dial-A-Ride problem to solve all three at the same time. We first present a matheuristic that iteratively generates routes using a large neighborhood search in which these routes are selected with a mixed integer linear program. After being validated on two special cases in the literature, the matheuristic is applied to real instances in three different areas in France. Several managerial results are derived. In particular, it is found that the amount of cost reduction induced by the people assignment is equivalent to the amount of cost reduction induced by the sharing of vehicles between institutions.

Keywords: health care operations management, allocation, sanitary transportation, dial-a-ride, matheuristic, large neighborhood search

Highlights

- This paper presents the first Assignment-Dial-A-Ride problem.
- We propose a solution method based on a metaheuristic combining a large neighborhood search and an exact method.
- 5 • A comparison with the literature and case studies on real instances in the healthcare context is provided.
- In terms of managerial insight, this new approach reduces the current cost up to 24% without degrading the service quality for users.

1 Introduction

10 In France, the medico-social sector is structured by a set of institutions and services that support people with disabilities and other vulnerabilities. Every day, each user is picked up at home and taken to their assigned medico-social institution (MSI) where they receive personal care throughout the day. At the end of the day, users are taken from their respective MSI to their homes. The assignment process is long and labor intensive. Indeed, each demand has particular needs and each MSI has particular services. As a consequence, satisfying
15 all the demands requires to test many different configurations of assignment.

The assignment process is carried out by the MDPH (*Maison Départementale des Personnes Handicapées*), the home for the disabled in each French *département*. A multidisciplinary team (EP) within this institution analyzes the applications of people with disabilities and, where relevant, refers them to a list of institutions and medical-social services (ESMS) adapted to their needs. More precisely, each user receives medical care throughout the week. Indeed, there is a care planning for each user that repeats weekly. As
25 a consequence, the EP must check if the MSIs' weekly planning can accommodate the candidate and try to build a valid planning for each weekday. An EP must process by hand over 200 referrals per month. Thus, it must change assignments and plannings accordingly every month. The referrals are processed one by one in order of arrival. As a consequence, the referrals' order
30 have a considerable impact on the overall performance of the system. Using a solver that processes all the demands simultaneously will facilitate this decision process. As a result, the quality of the assignment will be improved and the EP will spend less time on the applications' processing. Based on this analysis, the CDAPH, the commission for the rights and autonomy of the disabled
35 (*Commission des Droits et de l'Autonomie des Personnes Handicapées*) validates or refuses each application. If a candidate is accepted, the CDAPH also informs them about the reasons of acceptation and the care protocol. The person must apply for admission to one or more institutions listed by the CDAPH. This assignment process is more detailed in [1]. Because the resources of MSIs
40 are limited and the assignment process is so complex, previous decisions are not revised even if the context changes. Therefore, the impact of these decisions lasts several years. For example, if a space becomes available in a MSI closer to a patient's home, no steps are taken to review the current assignment.

Moreover, the transportation criterion is not explicitly taken into account in the assignment decision.

The daily transportation in the context of MSIs entails several problems. The first is related to the users' quality of life. Because they are in a vulnerable position due to their disabilities, their daily transportation should not take too long. However, a study presented by [2] shows the long duration of these users' ride times and the real need to reduce them. This study, carried out in the city of Lyon and surrounding areas, shows that trips are on average 48 kilometers long and last on average 74 minutes. The second issue is that the transportation also has an environmental impact of 1.42 million kg CO₂ eq and 4 million km per year for 245,000 trips. This environmental impact has to be limited. The final issue we address is the economic dimension. In the case of patients under the age of 18, who make up the majority here, the cost of this transportation system is funded directly by the MSIs. In 2017, medico-social transportation costs totaled 500 million euros, at national level, for all medico-social institutions put together [3]. This cost increased by 40% between 2006 and 2014 [4] and has had a significant impact on their global budget since this expense is the second largest after wages [5]. It follows that more money spent on transportation means less money spent on supporting people with disabilities and on the MSIs' services.

The assignment process also has an impact on the institutions' resources. Each institution has accreditation for a certain number of places and a predefined number of employees. Each employee has specific competencies. When a user is assigned to the facility, that individual uses one space allocated in the accreditation and also requires time from several appropriate caregivers. If this time is greater than the available resource, the excess will be counted as overtime. In practice, overtimes last until the next assignment at least or until additional staff is recruited. Additionally, temporary workers can be recruited for overtime.

This paper proposes a decision-making approach that integrates three aspects of the problem. The first aspect is the assignment of people with disabilities to a given MSI. The second aspect is the staff sizing at MSIs to be able to satisfy the needs of their users. The last aspect is the management of the shared door-to-door transportation service. This approach makes it possible to jointly optimize the proper use of resources and logistics costs. This is called Assignment-Dial-A-Ride-Problem (ADARP) in the rest of the paper. If used by the EP, some users might need to change MSI. However, this change would occur only once a month. Moreover, a monthly reassignment is also a chance for them to move to a closer MSI and thus, reduce their commuting time. For the sake of clarity, we focus our study only on the transportation from home to MSIs for one day. However, the results can easily be transposed to the reverse - transportation from MSIs to home - by reversing the routes in the solution. Combining the morning and afternoon problems would be ideal but is still challenging as the size of the problem would be multiplied by two. As a result, the computation duration would increase exponentially due to the

NP-hardness of the DARP. To build the weekly planning, the problem must be
90 solved for each weekday. Aspects related to route consistency are not considered in this study but constitute interesting research perspectives. We refer the reader to [6–8] for respectively, drivers, service times, and groups consistency.

The paper is structured as follows: Section 2 reviews the literature on related problems and presents our main contributions. Section 3 defines the
95 problem with its route-based formulation. The method developed to solve the ADARP is detailed in Section 4 and the case study is presented in Section 5. In Section 6, the parameters of the method are tuned, the components of the method are validated, and the method is challenged with results from the literature. Section 7 then presents managerial results derived from numerical
100 analyses of the case study. In Section 8, we finally summarize our main findings and indicate some interesting extensions of the model presented here.

2 Literature review

Despite having no added value to the care itself, transportation represents an
105 essential part of healthcare systems. Indeed, transportation is not a medical act. In that regard, this support activity must be as efficient as possible to improve the quality of service with a minimal cost. As described in [9], healthcare transportation is a complex problem due to its multiple aspects. As this domain has been extensively studied in the literature, we provide only a few references in order to be concise. The first aspect of medical transportation is
110 the nature of what is transported. It can be patients (e.g., [10], [11]), medical staff (e.g., [12], [13], [14]) or medical supplies (e.g., [15], [16]). In our study, we focus on the patient transportation. Second, it is possible to distinguish emergency transportation (e.g., [17], [18]), where the patient's life is directly in danger, from the non-emergency transportation (e.g., [19], [20], [21]). In
115 our case, we study non-emergency transportation. Finally, the transportation can be occasional (e.g., [10], [22]) or regular (e.g., [23], [24]). Our problem is about regular transportation. To summarize, the assignment dial a ride problem addresses the regular non-urgent patient transportation. As shown in [25], the regular non-urgent transportation is growing with the global increase
120 in life expectancy. As a consequence, long-term care has received increasing attention (e.g., [26]). In order to improve the efficiency of healthcare systems in the long run, we must be able to revise previous decisions that are no more relevant.

Motivated by a para-transit application, many variants of the Dial-A-Ride
125 Problem (DARP), as defined in [27], have emerged in the last two decades. The reader may refer to [28] and [29] for recent reviews. Because passengers are vulnerable, several specific constraints or objectives related to the quality of service are considered. For instance, the multi-criteria optimization of the total ride time and the routing cost is considered in [30], among others. The solution
130 consistency may also be considered during the week. Some passengers prefer to have the same driver every day [6], or to have the same pickup hours every day

[24]. These two papers study the impact of consistency on the total cost of the solution with a bi-objective analysis. Because some users are in wheelchairs, [31] introduces the impact of heterogeneous users and vehicles. In the same way, [10] study the possibility to configure the number of seats and wheelchairs in a vehicle before the departure, and [11] study the same possibility but during the route. Other extensions of the DARP consider the transfer of passengers from one vehicle to an other [32] or the multidepot-DARP [33, 34].

The possibility to choose between several destinations in vehicle routing problems (VRP) is introduced by [35]. In this paper, the authors present the Generalized-VRP (GVRP) which is a VRP where a client demand can be fulfilled by visiting one point in a list of alternatives. By adding time window constraints, [36] extend the previous model and introduce the GVRPTW. In the context of urban logistics, [37, 38] have extended the GVRPTW to the VRP-with Delivery Options (VRPDO). In the latter, a delivery can be made in certain lockers selected by the client, but the capacities of the lockers are finite and have to be taken into account for the delivery point selections.

In the context of dial-a-ride transportation, the Generalized-DARP presented by [39] was the first paper to consider the possibility of alternative pickup and delivery points. In that study, each passenger could be picked up at their initial position or could walk for a certain distance to reach an alternative pickup point. The same mechanism existed for alternative delivery points. The optimization model jointly optimizes the selection of the pickup and delivery points, and the selection of the routes.

The specificities of assignment problems in a medical context (i.e., long-term decisions, compatibility between needs and competencies, ...) make it difficult to transpose insights from other assignment studies with a different context. This is the reason why this paragraph focuses on other research works that also consider a medical context. The assignment of people with disabilities was studied by [40]. This study demonstrated the impact of alternative assignment policies on the performance of the healthcare system and on the quality of care. Transport was not taken into account. The study identified a number of points for improvement, including the long processing time due to the lack of computerization, and the failure to take logistical criteria into account in the choice of an assignment. In another work, [1] proposed a decision model for this assignment. In this model, a maximum distance between a patient's home and institutions was considered, but the management of the transportation service and the staff sizing were not.

Several contributions with respect to the literature are presented in this work. First, we introduce the first Assignment-Dial-A-Ride problem. This problem stems from a real-life issue faced by medico-social institutions which have to take three interconnected decisions pertaining to: 1) the routing for the ride-sharing services; 2) the assignment of users to geographical points; and 3) the staff sizing at the geographical points. Second, we present a matheuristic that iteratively generates and selects routes. Routes are generated with a large neighborhood search that includes an assignment problem, and are selected

using a mixed integer linear program. After being validated on instances from the literature for the Generalized-DARP and the VRPDO, the solution method is applied to real instances obtained from the sanitary transportation services in three different areas in France. Finally, we provide managerial insights derived from the numerical experiments. The cost reduction induced by the user (re)assignment is equivalent to the cost reduction induced by the sharing of the vehicles between institutions. Savings can thus be generated without increasing ride times, with less than a quarter of the users reassigned, and with small changes in institutions' staff.

3 Model

The model is presented with its route-based formulation. In this section, we introduce the notations used, the single route problem, and finally the route selection problem coupled with staff sizing.

3.1 Notations

Users

We consider a set of users \mathcal{U} . A user $u \in \mathcal{U}$ has to be served by the selection and execution of one of their itineraries \mathcal{I}_u . The pickup and delivery nodes of user $u \in \mathcal{U}$ and itinerary $i \in \mathcal{I}_u$ are denoted $P(u, i)$ and $D(u, i)$ respectively.

Nodes

Let $\mathcal{N} = \mathcal{P} \cup \mathcal{D} \cup \mathcal{O}^+ \cup \mathcal{O}^-$ be the set of all the nodes. From a user's perspective, $\mathcal{P} = \{P(u, i) \mid u \in \mathcal{U}, i \in \mathcal{I}_u\}$ is the set of pickup nodes, $\mathcal{D} = \{D(u, i) \mid u \in \mathcal{U}, i \in \mathcal{I}_u\}$ is the set of delivery nodes. From a driver's perspective, $\mathcal{O}^+ = \{o_k^+ \mid k \in \mathcal{K}\}$ is the set of starting depots for the beginning of the routes, and $\mathcal{O}^- = \{o_k^- \mid k \in \mathcal{K}\}$ is the set of ending depots for the end of the routes. Thus, any driver must start a route from a starting depot and finish it at an ending depot. In practice, the starting and ending depots are usually the same. However, we propose a formulation with differentiated starting and ending depots as it easily encompasses our case and others (e.g., drivers directly return home with the service vehicle).

Times

The time and the distance to go from node i to node j are denoted $\Gamma_{i,j}$ and $\Delta_{i,j}$ respectively. If a node $n \in \mathcal{N}$ is visited, the visit takes a service time S_n and the beginning of the service time has to be within a time window $[A_n, B_n]$. Then each user $u \in \mathcal{U}$ has a maximum ride time H_u .

Vehicles

Let \mathcal{K} be the set of heterogeneous vehicles. Each vehicle is assigned to a specific depot by the solution. The capacity of vehicle $k \in \mathcal{K}$ is denoted \bar{V}_k . The load variation corresponding to user $u \in \mathcal{U}$ in a vehicle is denoted V_u (it may be

215 more than one in case of obesity or an in-wheelchair user). By extension, we define the load variation for nodes such that $V_{P(u,i)} = -V_{D(u,i)} = V_u$ for all $i \in \mathcal{I}$. The load variation for nodes related to depots is zero. Then, when using vehicle k , the fixed cost, the distance cost, and the time cost are denoted C_k^f , C_k^d , and C^t respectively.

220 **Geography**

The set of geographical locations is denoted \mathcal{G} , and $G(n) \in \mathcal{G}$ is the geographical location of node $n \in \mathcal{N}$.

Resources

225 A user $u \in \mathcal{U}$ needs a quantity $E_{u,r}$ of resources $r \in \mathcal{R}$ with \mathcal{R} the set of resources. A resource corresponds to the amount of working time available for a particular care from caregivers with the corresponding competency. The availability of resource $r \in \mathcal{R}$ in geographical locality $g \in \mathcal{G}$ without paying for overtime is denoted $\bar{E}_{g,r}$ and the maximal quantity of resources with overtime (with paying) is denoted $\bar{E}_{g,r}^{ext}$. Then, C_r^{ext} is the resource extension cost per unit of resource $r \in \mathcal{R}$.

Route

235 For a given route ω , let $\mathcal{UI}(\omega)$ be the set of tuples (u, i) , where u is the user and $i \in \mathcal{I}_u$ the itinerary chosen for user $u \in \mathcal{U}$ in route ω . The ordered set of visited nodes is denoted $\mathcal{N}(\omega)$, and the first and last visited nodes of route $\omega \in \Omega$ are denoted $F(\omega) \in \mathcal{O}^+$ and $L(\omega) \in \mathcal{O}^-$ respectively. Then, the node visited just before node n in route ω is denoted $Q(\omega, n)$ with $n \in \mathcal{N}(\omega) \setminus \{F(\omega)\}$.

3.2 Single-route problem

The single route problem is formulated as follows. Each route needs to comply with these constraints while minimizing its costs.

240 The decision variables are: $t_{\omega,n}$, the beginning of service time for node n in route ω ; v_n , the load of the vehicle when leaving the node n ; and x_k that indicates whether or not the vehicle k is selected for the route ω .

$$\begin{aligned} \min f_\omega = & \sum_{k \in \mathcal{K}} C_k^f x_k + C^t (t_{\omega, L(\omega)} - t_{\omega, F(\omega)}) \\ & + \sum_{k \in \mathcal{K}} C_k^d x_k \sum_{n \in \mathcal{N}_\omega \setminus \{F(\omega)\}} \Delta_{Q(\omega, n), n} \end{aligned} \quad (1)$$

s.t.

$$t_{\omega, Q(\omega, n)} + \Gamma_{Q(\omega, n), n} + S_{Q(\omega, n)} \leq t_{\omega, n} \quad \forall n \in \mathcal{N}(\omega) \setminus \{F(\omega)\} \quad (2)$$

$$H_u \geq t_{\omega, D(ui)} - t_{\omega, P(ui)} - S_{P(ui)} \quad \forall ui \in \mathcal{UI}(\omega) \quad (3)$$

$$A_n \leq t_{\omega, n} \leq B_n \quad \forall n \in \mathcal{N}(\omega) \quad (4)$$

$$t_{\omega, P(ui)} \leq t_{\omega, D(ui)} \quad \forall ui \in \mathcal{UI}(\omega) \quad (5)$$

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$$v_{Q(\omega,n)} + V_n = v_n \quad \forall n \in \mathcal{N}(\omega) \setminus \{F(\omega)\} \quad (6)$$

$$v_n \leq \bar{V}_k x_k \quad \forall n \in \mathcal{N}(\omega), k \in \mathcal{K} \quad (7)$$

$$\sum_{k \in \mathcal{K}} x_k = 1 \quad (8)$$

$$t_{\omega,n}, v_n \in \mathbb{R}^+ \quad \forall n \in \mathcal{N}(\omega) \quad (9)$$

$$x_k \in \{0, 1\} \quad \forall k \in \mathcal{K} \quad (10)$$

The objective function (1) is a sum of the fixed cost related to the depreciation expense of the selected vehicle, the driver wage that is proportional to the duration of the route, and the distance cost. In practice, drivers' contracts truly relate to the duration of their routes and are not based on a fixed weekly salary.

Constraints (2) to (5) ensure respectively that the driving time and the service time are respected between the visits of the nodes, the ride times do not exceed the limit, the time windows are satisfied, and each pickup is before the associated delivery. Constraints (6) to (8) ensure respectively that the load increases when leaving pickup nodes and decreases for delivery nodes, the maximum capacity of the selected vehicle is not exceeded, and one vehicle is selected to serve the route.

3.3 Route selection problem and staff sizing

Even though the set of routes that satisfy the single-route problem (1)-(10) is huge, here we formulate the route selection problem by assuming that it is possible to list them all in a set Ω . Note that all combinations of itineraries have to be considered. A route $\omega \in \Omega$ is characterized by its cost f_ω and its set of tuples $\mathcal{UI}(\omega)$. The latter contains the list of users served by the route and the itineraries chosen for each user served. If two routes have the same set of users and itineraries, then only the cheapest can be kept in Ω and the other can be dropped.

The route selection model is now presented. The model consists in selecting some routes, taking into account the quantity of resources available in each geographical locality. The first decision variable y_ω (14) is a Boolean indicating whether or not the route ω is selected. The second decision variable $e_{g,r}$ (15) is the quantity of extra resources $r \in \mathcal{R}$ that must be spent to ensure that the needs of each user assigned to geographical locality $g \in \mathcal{G}$ will be satisfied.

$$\min f = \sum_{\omega \in \Omega} f_\omega y_\omega + \sum_{r \in \mathcal{R}} \sum_{g \in \mathcal{G}} C_r^{ext} e_{g,r} \quad (11)$$

s.t.

$$\bar{E}_{g,r} + e_{g,r} \geq \sum_{\omega \in \Omega} \sum_{\substack{u, i \in \mathcal{UI}(\omega) \\ g \in \{G(P(u, i)), \\ G(D(u, i))\}}} E_{u,r} y_\omega \quad \forall r \in \mathcal{R}, g \in \mathcal{G} \quad (12)$$

$$\sum_{\omega \in \Omega | u, i \in \mathcal{UI}(\omega)} y_{\omega} = 1 \quad \forall u \in \mathcal{U} \quad (13)$$

$$y_{\omega} \in \{0, 1\} \quad \forall \omega \in \Omega \quad (14)$$

$$0 \leq e_{g,r} \leq \bar{E}_{g,r}^{ext} \quad \forall g \in \mathcal{G}, r \in \mathcal{R} \quad (15)$$

270 The objective (11) is the sum of the cost of individually selected routes and the sum of all costs related to the payment of the extra resources in each geographical locality.

The model contains only two constraints. The first constraint (12) is related to the consumption of each resource r in each geographical locality g . The left-hand side of the inequality represents the amount of available resources r in locality g . This quantity is defined by the initial amount of available resource $\bar{E}_{g,r}$ and the quantity of extra resources $e_{g,r}$ that have to be paid. The right-hand side of the inequality represents the consumption related to the selected routes. With ω a selected route and $u, i \in \mathcal{UI}(\omega)$, if the itinerary i has its pickup or its delivery in geographical position g (i.e., $g \in \{G(P(u, i)), G(D(u, i))\}$), then user u consumes a quantity $E_{u,r}$ of resource r in locality g . The second constraint (13) is a classical set partitioning problem where all users have to be served once.

4 Solution method

285 The formulation presented in the previous section specifies our problem. However, the number of routes in Ω makes the problem intractable if formulated in that way. In this section, we will see how we can generate a subset of routes with a heuristic, and solve the route selection problem on this subset called “pool”, denoted by Ω' . Because the pool Ω' is a subset of Ω , the routes in Ω' have to be solutions to the single route problem. The heuristic used to fill the subset of routes is the Large Neighborhood Search (LNS). For each iteration of LNS, the routes of the solution found are added to Ω' . The route selection problem is then solved when the pool of routes contains ν routes. The rest of this section details this solution method.

295 4.1 General framework: Iterative Route Selection (IRS)

The general framework is presented in Algorithm 1 and is denoted by IRS (Iterative Route Selection). This is a hybrid column generation where the columns (i.e., the routes) are generated with a LNS and selected with a master problem formulated as a Mixed-Integer Linear Program (MILP).

300 The input parameters of IRS are: ν the initial number of routes used to solve the route selection problem; ε the constant positive multiplier for changing the pool size defined by ν ; τ the total time limit; and τ' the time limit for the MILP solver which solves the route selection problem.

305 First, the best solution is initialized empty (line 1). During a given execution time τ (line 2), the framework performs some iterations (lines 3 to 8). For

Algorithm 1 General framework: IRS

Parameters: $\nu, \varepsilon, \tau, \tau'$
Result: Best solution S^*
* Initialization * \
1: $S^* := \emptyset$
2: **while** execution time $< \tau$ **do**
 * Route generation with an LNS (see Section 4.2) * \
3: $\Omega', S^* := \text{LNS}(S^*, \nu)$
 \
 * Solve the route selection problem * \
4: Solve (11)-(15) with an MILP Solver, taking $\Omega = \Omega'$; warm start with S^* ; time limit τ'
 \
 * Update ν * \
5: **if** the route selection problem has been solved to optimality on two consecutive iterations **then**
6: $\nu := \lceil \nu \times (1 + \varepsilon) \rceil$
7: **else if** optimality was not proven on two consecutive iterations and S^* was not improved **then**
8: $\nu := \lfloor \max\{1, \nu/(1 + \varepsilon)\} \rfloor$
9: **end if**
10: **end while**

each iteration of the framework, the LNS creates a pool of routes Ω' (line 3). This pool is used to solve the route selection problem (line 4).

The parameter ν is dynamically adjusted according to the capacity of the MILP solver to solve the selection route problem (lines 5 to 8). As ν corresponds to the number of routes in Ω' , it correlates to the difficulty to solve the route selection problem. On the one hand, the optimal solution has a better potential when there are more routes in Ω' . But on the other hand, having more routes makes it more difficult to find this optimal solution. So, our goal is to have a pool of routes Ω' as large as possible but sufficiently small so the MILP solver finds the optimal solution. Hence, this dynamic adjustment of ν ensures that the MILP solver will reach proven optimality approximately half the time.

4.2 Large Neighborhood Search (LNS)

The Large Neighborhood Search (LNS) metaheuristic, introduced by [41], has been successfully used to solve several DARP variants (e.g., [32, 42]). It has also been combined to set covering/partitioning problems to create LNS-based matheuristics in several routing problems (e.g., [11, 38, 43]). The framework we used for the LNS is presented in Algorithm 2.

The LNS works with three solutions: best (S^*), current (S), and new (S'). At each beginning of the LNS, the current solution and the new solution are

Algorithm 2 Large Neighborhood Search algorithm

```

Parameters:  $S^*, \nu$ 
Result:  $\Omega', S^*$ 
  \* Initialization * \
1:  $S := S^*, S' := S^*$ 
2: reset  $\Omega'$  with the routes in  $S^*$ 
3: while  $|\Omega'| < \nu$  do
4:    $S' := S$ 

   \* Removal * \
5:   select a random percentage of users  $\mu$ 
6:   remove  $\mu$  percent of users from  $S'$  using a random removal operator

   \* Insertion * \
7:   solve the “assignment problem”
8:   insert half of the uninserted users in  $S'$  using a random insertion
   operator
9:   solve the “assignment problem”
10:  insert the remaining uninserted users in  $S'$  using a random insertion
   operator

   \* Update  $\Omega'$  * \
11:  add the routes in  $S'$  to  $\Omega'$ 

   \* Acceptation criteria * \
12:  if  $S' < S^*$  then
13:     $S^* := S', S := S'$ 
14:    reset  $\Omega'$  with the routes in  $S^*$ 
15:  else if  $S' < S * 1.05$  then
16:     $S := S'$ 
17:  end if
18: end while

```

initialized with the best solution (line 1). For each iteration, the current solution is copied into the new solution, after which the new solution is destroyed and repaired (lines 5 to 10). If the newly repaired solution outperforms the best, then it updates the best and the current ones (line 13). In our case, we use the simple “record-to-record” acceptance criterion [44] to manage the current solution. If the new solution under-performs the best solution with less than a 5% difference, then it updates the current solution (line 16). If the new solution under-performs the best solution with more than a 5% difference, the new solution is restored to be identical to the current one at the beginning of the new iteration (line 4).

During the LNS iterations, all the routes in the new solution are recorded in Ω' (line 11). The LNS stops when the number of routes in Ω' reaches ν

(line 3). At the beginning of an LNS, the pool is initialized with the routes of the best solution S^* only (line 2), and when the LNS improves the best solution S^* (mainly at the beginning of IRS), the pool Ω' is reinitialized (line 14).

At the beginning of each LNS iteration, a new solution identical to the current solution is partially destroyed. A percentage of the users, randomly chosen in $[\underline{\mu}, \bar{\mu}]$, is removed from the new solution (lines 5 to 6). The destroy operators used are the random removal and the historical node-pair removal introduced by [41]. To repair the solution, the non-inserted users are inserted one by one using a k -regret operator [41] with $k \in \{1, 2, 3, 4\}$. In a regular LNS, the users are inserted one by one just after the destroy step. However, the current procedure used here is: 1) choose one itinerary per non-inserted user by solving the “assignment problem” (detailed in Section 4.3); 2) insert 50% of non-inserted users; 3) solve the assignment problem again; and 4) insert the remaining non-inserted users (lines 7 to 10).

4.3 Assignment problem

The set of non-inserted users is denoted by $\mathcal{U}^{no} \subseteq \mathcal{U}$. To solve the assignment problem, we first compute an insertion cost estimation $F_{u,i}$ for all non-inserted users $u \in \mathcal{U}^{no}$ and for all itineraries $i \in \mathcal{I}_u$. The cost retained for $F_{u,i}$ is the minimum of the insertion costs over all positions of the inserted pickup and delivery in every route. The insertion cost is defined as the difference between the cost of the route after insertion and before insertion. We also compute the resulting availability $\bar{E}'_{g,r}$ of resources $r \in \mathcal{R}$ in geographical locality $g \in \mathcal{G}$, considering the users who are still inserted in the partially destroyed new solution.

$$\bar{E}'_{g,r} = \bar{E}_{g,r} - \sum_{u \in \left\{ \begin{array}{l} \text{users in the sol.} \\ \text{assigned to } g \end{array} \right\}} E_{u,r} \quad \forall u \in \mathcal{U}, g \in \mathcal{G}$$

Then, knowing $F_{u,i}$ and $\bar{E}'_{g,r}$, the following assignment problem is solved to choose the itineraries.

$$\min f^a = \sum_{u \in \mathcal{U}^{no}} \sum_{i \in \mathcal{I}_u} F_{u,i} z_{u,i} + \sum_{r \in \mathcal{R}} \sum_{g \in \mathcal{G}} C_r^{ext} e_{g,r} \quad (16)$$

s.t.

$$\sum_{i \in \mathcal{I}_u} z_{u,i} = 1 \quad \forall u \in \mathcal{U}^{no} \quad (17)$$

$$\bar{E}'_{g,r} + e_{g,r} \geq \sum_{u \in \mathcal{U}^{no}} \sum_{\substack{i \in \mathcal{I}_u \\ g \in \{G(P(u,i)), \\ G(D(u,i))\}}} E_{u,r} z_{u,i} \quad \forall r \in \mathcal{R}, g \in \mathcal{G} \quad (18)$$

$$z_{u,i} \in \{0, 1\} \quad \forall u \in \mathcal{U}^{no}, i \in \mathcal{I}_u \quad (19)$$

$$0 \leq e_{g,r} \leq \bar{E}_{g,r}^{ext} \quad \forall g \in \mathcal{G}, r \in \mathcal{R} \quad (20)$$

355 This problem looks like the route selection problem. However, these are not the routes that are selected, but one itinerary per user. The decision variable $z_{u,i}$ (19) indicates whether or not the itinerary i is selected for user u . As in the route selection problem, $e_{g,r}$ (20) represents the quantity of extra resource $r \in \mathcal{R}$ that has to be paid to ensure that each user assigned to geographical
 360 locality $g \in \mathcal{G}$ will be satisfied. The objective function (16) is the sum of the insertion cost estimation, that depends on selected itineraries, and the cost of the extra resources. Constraint (17) ensures the selection of one itinerary per user. Then, constraint (18) computes the extra resources needed, depending on the selected itineraries.

365 It is obvious that the assignment solution is not optimal. First, the insertion cost estimations $F_{u,i}$ are updated only twice per LNS iteration, once at the beginning and once after 50% of the insertions have been completed. Moreover, the insertion cost estimation is just the cheapest insertion at the moment of computation. However, Section 6.1 shows numerically that solving
 370 the assignment problem more or less frequently during the insertion procedure has little impact and does not significantly improve the overall performance of the method.

5 Case study

As presented in the introduction, ADARP is introduced in this paper to solve
 375 a real case of a Dial-A-Ride with user assignment and MSIs staff sizing.

Instances

We have 3 real instances for our problem. Table 1 presents their main characteristics. The first instance “Loire” is located in the Loire *département*, France. Despite being centered around a medium-sized city (Saint-Étienne), this area
 380 is mainly rural, so there is a low-density demand. The second instance “Rhône” is centered around the city of Lyon and the whole Rhône *département*. The area is urban and densely populated. The last instance “Savoie” covers the whole Savoie *département*. The study area is stretched out, the demand has a low density, and there are many mountains (French Alps) and valleys.

Table 1 Number of users, MSIs, and depots for the three instances

Inst.	Users	MSI	Depots
Loire	42	2	1
Rhône	125	4	2
Savoie	208	5	3

385 ***Current assignment***

For these three instances, we know the current user assignment to MSIs. We also know the average resources needed per user, i.e., we know $E_{u,r}$ for all users u and resources r .

Resource availability

For these experiments, it was not possible to obtain precisely the real availability of the resources of each MSI, i.e., current staff size. These were therefore estimated by adding all the average resources needed by users.

$$\bar{E}_{g,r} = \sum_{u \in \left\{ \begin{array}{l} \text{users currently} \\ \text{assigned to } g \end{array} \right\}} E_{u,r} \quad \forall r \in \mathcal{R}, g \in \mathcal{G}$$

390 ***Resources***

There are 6 resources. Resources C0 to C4 are different human resources needed by people with disabilities. It is possible to extend these resources up to a certain limit (i.e., $\bar{E}_{g,r}^{ext}$) using overtimes and temporary workers, but these extensions have costs (i.e., C_r^{ext}). The extensions related to C0 to C4 are tactical decisions. Resource C5 represents the MSI's accreditation, i.e., the number of users that can be assigned to an institution. In our basic instances, this resource cannot be changed because it seems to be a strategic decision to change the size of the building, the dining hall, the facilities, etc. However, a sensitivity analysis on these values is still presented in Section 7.1.

400 ***Time and distance***

The time and distance values from node i to j (i.e., $\Gamma_{i,j}$ and $\Delta_{i,j}$) have been computed using the API detailed in [45].

Maximal ride time

The theoretical maximal ride time of a user is equal to the duration of the direct itinerary of its current assignment, multiplied by a parameter called Direct Time Factor (DTF). MSIs would theoretically like to observe DTF = 1.5 but in practice, the max ride time is not really controlled by them. That is why the following experiments are done with DTF = 1.25, 1.5, and 1.75.

At the same time, any ride time up to 15 minutes is accepted by MSIs. Therefore, for each user, the maximal ride time used in the following experiments is the maximal value between 15 minutes and the current direct duration multiplied by DTF ($H_u = \max\{15; \max\{\Gamma_{P_{ui}, D_{ui}}\} \times DTF\}$), $\forall u \in \mathcal{U}, i \in \mathcal{I}_u$).

Time Windows

The reception time of MSIs are between 8:00 and 9:15. Therefore, all drop-offs happen within this time frame. For a DTF of 1.75, the width of the users' time windows follows the distribution presented in Table 2. Obviously, the

distribution is shifted towards the smaller time windows when the DTF is decreased.

Table 2 number of users relative to the width of the time windows for a DTF = 1.75

Inst.	width of the time window in minutes					
	[40, 44]	[45, 49]	[50, 54]	[55, 59]	[60, 64]	[65, 69]
Loire	0	10	7	6	17	2
Rhône	13	5	1	4	98	4
Savoie	9	46	39	47	66	1

Itineraries

420 For each user, all of its potential itineraries originate from his/her home. By default, all MSIs can receive all users. However, the maximum ride time precludes some itineraries from home to MSIs when the direct ride time for the itinerary is longer than the maximum ride time. Thus, the number of feasible itineraries increases with the DTF, as shown in Table 3. For the Savoie
425 instance with a DTF of 1.5, there are on average 1.97 feasible itineraries per user. If the DTF is reduced to 1.25, this number decreases to 1.57. On the opposite, if the DTF is increased to 1.75, then the average number of feasible itineraries increases to 2.33 per user. According to Table 4 whatever the chosen DTF, there is always at least one user with the maximum number of
430 feasible itineraries. In other words, at least one user can go to any of the MSIs.

Table 3 Average number of feasible itineraries (i.e., MSIs) per user depending on DTF

Inst.	DTF		
	1.25	1.50	1.75
Loire	1.60	1.71	1.79
Rhône	2.14	2.51	2.68
Savoie	1.57	1.97	2.33

Vehicles

There are 4 types of vehicles with different capacities and costs. The number of each type of vehicle available at each depot is not limited. In our case, buying a vehicle is actually a tactical decision by MSIs because it is easy for them to
435 sell, buy, exchange, or reconfigure vehicles to adapt their fleet as needed.

Depots

The depots are located at the car park of some MSIs. At the beginning of the day, the drivers travel to these MSIs with their own means of transport and

Table 4 Number of users with i feasible itineraries (i.e., MSIs) depending on DTF

Inst.	DTF	nb of feasible itineraries				
		1	2	3	4	5
Loire	1.25	17	25			
	1.50	12	30			
	1.75	9	33			
Rhône	1.25	54	26	19	26	
	1.50	44	19	16	46	
	1.75	36	24	9	56	
Savoie	1.25	128	53	16	10	1
	1.50	114	37	22	20	15
	1.75	97	34	18	29	30

take the MSI's vehicles. The drivers start and end their routes at the same
 440 MSI. As these MSIs have dedicated car parks, we can consider that there is
 no maximal number of vehicles at the depots.

6 Validation of the method

The solution method was coded in C++ and compiled with g++ 11. CPLEX
 22.1.0 was used for solving the route selection problem. The experiments were
 445 performed on an AMD EPYC 7702 2.1GHz processor. As in many articles in
 this research field, 5 runs are done per instance for numerical experiments.
 The values of the solution method parameters are the following. The initial
 number of routes ν in the pool Ω' that stops the LNS iterations is set to 100
 routes. The increasing or decreasing percentage ε of the number of routes ν
 450 is set to 25%. The MILP solver limit τ' for each IRS iteration is set to 10
 seconds. The proportion of users removed for each iteration of LNS is randomly
 chosen from a uniform distribution between $[\underline{\mu}, \overline{\mu}] = [10\%, 45\%]$. Lastly, the
 total time τ available to run IRS on instances Loire, Rhône, and Savoie are
 30, 60, and 120 minutes respectively. Each instance uses a different value for
 455 τ because the number of users significantly differs among them. This value
 ensures a sufficient number of iterations in order to reach good solutions.

6.1 Validation of the components and tuning of parameters

The route and the assignment components of the IRS are evaluated in Table 5.
 460 All values are the percentage deviation from the Best Known Solutions (BKS,
 presented in Appendix A). The first column presents the solutions obtained
 with the IRS framework presented in this paper. As we can see, the average
 gap obtained by the IRS is 0.32%. The results are pretty stable as the worst
 average gap over five runs is only 0.77% (for the Loire instance with DFT =
 465 1.75)

The noRSP (no route selection problem) column presents the case where the LNS is used to generate solutions and the route selection problem is never solved. For instance, in Algorithm 1 line 3 is used but line 4 is not. In this case, the average gap with the BKS increases to 2.06% and the results are not really stable. As an interpretation, the pool of routes acts as a memory that can be used to build better solutions. By using the LNS without the route selection problem, the solver is short-sighted as it just moves from one solution to another. Having a pool of saved routes allows the solver to simultaneously consider many routes that were generated at different moments.

In IRS, two assignment problems are solved at each iteration of LNS: at the beginning of the insertion procedures and after 50% of re-inserted users. The noAP (no Assignment Problem) column presents the case where an itinerary is assigned to a user by the k-regret insertion operator for each insertion during the LNS, and not by solving assignment problems with a MILP solver. In other words, instead of having only one candidate itinerary per user thanks to the assignment problem, all itineraries are candidates for insertion. Thus, the number of insertions that must be tested increases. As a consequence, the LNS takes more time for each insertion. In this case, the k-regret choice is based on the cheapest itinerary that maintains the capacity constraints. We can see the noAP method under-perform the IRS method by $1.70 - 0.32 = 1.38\%$.

Lastly, the LNS column corresponds to noRSP and noAP together. The method is a simple LNS with a record-to-record acceptance criterion and the k-regret insertion operator is used to select the best assignment of an itinerary to a user. With an average gap of 11.32%, this method is clearly not efficient.

Table 5 Evaluation of the components. Average gap with the BKS in % for 5 runs

Inst.	DTF	IRS	noRSP	noAP	LNS
Loire	1.25	0.00	0.00	0.00	1.70
	1.5	0.16	1.34	1.37	3.34
	1.75	0.77	1.30	1.57	1.57
Rhône	1.25	0.61	1.28	0.56	7.57
	1.5	0.26	1.43	1.29	13.96
	1.75	0.28	1.70	1.87	11.71
Savoie	1.25	0.24	1.93	1.08	11.63
	1.5	0.34	4.88	3.57	23.23
	1.75	0.22	4.71	3.99	27.19
mean		0.32	2.06	1.70	11.32

Table 6 shows how the number of times the assignment problem is solved, influences the overall performance of our matheuristic. Table 7 shows this influence on the number of iterations of the IRS and the LNS, and as well as on the size of the pool of routes ν . For ν , its initial value at the beginning of the resolution, its average value across the resolution, and its final value at the

end of the resolution are provided. In this table, the metrics are averaged over all the instances for all the DTF's values for the 5 runs. In both tables, column "1" represents the case where the assignment problem is solved only once after the destroy phase and at the beginning of the insertion phase; columns "2", "3", and "4" represent the cases where the assignment problem is solved 2, 3 or 4 times during one iteration, respectively, i.e after the destroy phase and every 50%, 33%, and 25% of inserted users. Then, column "all" is the case where the assignment problem is solved before each user insertion.

According to Table 6, the best result is obtained when the assignment problem is solved twice during an iteration of the LNS. Thus, this value is used in the rest of the experiments and serves as a basis for the following analysis. The main observation is that, irrespective of the number of assignment problems we solve from 1 to 4, the performance is fairly good and stable. Indeed on average, the gap difference is 0.2% ($= 0.52 - 0.32$) or less. The second observation is that solving the assignment problem each time a user is inserted gives poor results. In this case, the number of IRS iterations decreases by 71% ($= \frac{24.11-82.51}{82.51}$) and the number of LNS iterations decreases by 79%. This leads to a 0.84% ($= 1.16 - 0.32$) gap difference which is fairly larger than the one observed among columns 1, 2, 3, 4. While Table 6 shows the importance of the assignment problem, Table 7 shows that it is not required to solve the assignment problem often. Solving it too often will reduce the number of iterations of the IRS, but on the opposite, solving it too rarely will decrease the quality of the selected itineraries during the insertion phase of the LNS. The numerical results show that the balance is obtained when the assignment problem is solved twice during the LNS. However, these are the results for using the minimum insertion cost as a criterion for the route selection problem. Another criterion (e.g., average insertion cost) might result in different performances. As the results were good with minimum insertion cost, we decided to continue with it. Nevertheless, criterion selection is an interesting topic for future work. Our last observation is that the size of the pool of routes ν for the route selection problem increases during the resolution. It means that the MILP solver is able to handle a growing number of routes. This can be explained by the following. The MILP solver uses a warm start with the best solution. In addition, the proportion of bad routes relative to the best solution increases as the best solution improves. As a consequence, it becomes easier for the MILP solver to eliminate bad solutions during the route selection problem.

6.2 Comparison with the literature

Generalized-Dial-A-Ride Problem

The closest problem in the literature to ours is the GDARP presented by [39]. The authors use a Greedy Randomized Adaptive Search Procedure (GRASP) to solve their problems. In the GDARP, each user has one origin and one destination. The specificity is that a user can walk from his/her origin to one of the possible pickup locations and again walk from one of the possible drop-off locations to his/her destination. In this case, the ride happens only between

Table 6 Number of times the assignment problem is solved during an iteration of the LNS. Average gap with the BKS in % for 5 runs per line

Inst.	DTF	Number of solved assignment problems				
		1	2*	3	4	all
Loire	1.25	0.00	0.00	0.00	0.00	0.00
	1.5	0.16	0.16	0.16	0.00	0.65
	1.75	1.54	0.77	1.03	1.88	1.54
Rhône	1.25	0.79	0.61	0.38	0.49	0.74
	1.5	0.13	0.26	0.19	0.39	0.92
	1.75	0.19	0.28	0.29	0.29	1.03
Savoie	1.25	0.07	0.24	0.26	0.38	0.79
	1.5	0.60	0.34	0.61	0.65	2.81
	1.75	0.26	0.22	0.27	0.63	1.92
mean		0.42	0.32	0.36	0.52	1.16

*: chosen parameter

Table 7 Metrics relative to the number of times the assignment problem is solved during an iteration of the LNS.

Number of solved assignment problems	1	2*	3	4	0
Nb LNS iterations	113,416.31	76,173.96	68,450.20	57,601.27	15,932.73
Nb IRS iterations	98.38	82.51	68.33	60.24	24.11
initial ν	100	100	100	100	100
average ν	3,147.55	2,909.77	2,795.80	2,722.17	1,447.42
final ν	5,761.82	5,465.62	5,320.42	5,187.24	3,801.73

*: chosen parameter

the selected pickup and drop-off. Similarly to our problem, a user has multiple possible pickup and drop-off locations (i.e., multiple possible itineraries). However, there is no resource allocation similar to the staff sizing in our problem. In the model presented by [39], the objective is to minimize the itinerary duration of drivers and users from their respective origins to their respective destinations. To establish a proper comparison, our algorithm has been slightly adapted to use the same objective function.

Table 8 presents the results of the comparison between their results with a GRASP with 500 iterations and our IRS algorithm with 500 iterations on an instance with 50 users. To be fair, the LNS iterations are counted in the 500 iterations of the IRS. For each algorithm, results are given with one run. For each instance, IRS ameliorates the BKS slightly.

Vehicle Routing Problem with delivery options

Another problem close to ours is the VRPDO introduced by [37, 38]. Clients have several preferences for their delivery options, the total number of first and

Table 8 Comparison of costs for [39] instances with 500 iterations for GRASP and IRS

Inst.	GRASP	IRS
CM 51	16,232	16,202
CM 52	14,532	14,505
CM 53	13,912	13,896
CM 54	13,821	13,790
CM 55	13,824	13,814

second preferred options is constrained, some delivery options have capacities, and the objective is to minimize first the number of vehicles and then the cost, based on the distance only. Our algorithm has been adapted to these specific features. Table 9 presents the comparison between the best solution found with two methods (LNS-SPP and MathHeu) combining different LNSs and set partitioning problems with 5 runs in [37, 38] and the best solution found with 5 runs of the IRS algorithm. IRS's computation times are 30, 60, and 120 minutes for instance sizes 50, 100, and 200 respectively. The table presents for each best solution its number of routes ("Nb routes"), its cost ("Cost"), and the cost gap between the LNS-SPP & MathHeu and the IRS.

Instance types U and V have 2 and 1.5 delivery options per client on average respectively. We note that these instance types are fairly well solved with IRS. However, we find that the IRS algorithm performs poorly for the instance type UBC. The explanation is that the UBC instances are the U instances with large vehicle capacity. With large vehicle capacity, the length of the routes increases, so the time needed to perform an insertion with the K-regret procedure also increases. For this reason, the number of investigated routes during the IRS algorithm is reduced. This case, with large vehicle capacity and long routes, is rather far from our case study.

Table 9 Comparison with the best solutions in the literature [37, 38] and the best solutions for 5 runs of IRS

Type	Size	LNS-SPP & MathHeu		IRS		Gap
		Nb Routes	Cost (€)	Nb Routes	Cost (€)	Cost (%)
U	50	54	3,864	54	3,869	0.13
	100	105	6,499	105	6,511	0.19
	200	205	11,726	205	11,763	0.32
UBC	50	20	2,293	21*	2,272	-0.92*
	100	40	3,580	40	3,617	1.03
	200	80	6,048	80	6,181	2.19
V	50	54	3,742	54	3,720	-0.59
	100	104	7,001	104	6,964	-0.53
	200	203	13,669	203	13,471	-1.45

*: As the number of routes is not the same, the cost cannot be compared

7 Managerial results

At this point, it is reasonable to consider that the IRS algorithm is able to provide fairly good results on our instances. In this section, several analyses will be presented on our case study to derive managerial results from the MSIs' perspective and the users' perspective.

Four scenarios are considered. Scenario (A) refers to the current real case. Most of the time in the real case, a vehicle transports only those users who go to the same MSI, and the users are never reassigned from their current MSI to another one to improve transportation performance (including the user's ride time). Scenario (B) refers to an emerging practice where the transportation facilities of the MSIs are shared. Therefore, users from different MSIs can be in the same vehicle at the same time. In this scenario, users are not reassigned. Without being able to measure it precisely, we find that this sharing remains infrequent but is gradually being practiced more between the MSIs. Scenario (C) refers to the case where the vehicles are not shared but where users are assigned to the MSIs, taking into account the transportation cost. Scenario (D) refers to the case of ADARP, with users' assignments and vehicles sharing between MSIs.

7.1 From the MSIs' perspective

Cost and routes

Table 10 presents the cost and the number of routes for the 4 scenarios. As Scenario (A) is taken as a reference, the cost and the number of routes are presented as absolute values for this scenario and as relative values (gap in %) for the other scenarios. We note that the average saving from the vehicles sharing without assignment (B) is 8.12% of the cost of the current practice (A). By comparison, assignment without sharing (C) represents a 12.26% gain, and sharing and allocating (D) represents a 16.91% gain. We can easily conclude that the users' reassignment from one facility to another is a fine opportunity to reduce the expenses of socio-medical facilities. We also find that the evolution of the number of routes is strongly correlated to the cost savings in Scenarios (B) (C) and (D). Beyond the cost reduction, the reduction of the number of routes is an objective for the MSIs that would enable them to manage fewer vehicles and therefore also fewer drivers. We find a clear route number reduction tendency with the introduction of assignment flexibility. In some cases, this decrease can amount to more than 36% owing to the possibility of assignment only (Scenario (C), Inst. Sa, DTF=1.25). To conclude, the benefit related to a reassignment policy seems equivalent to the cost reduction related to vehicle sharing. Moreover, these two changes can be combined to further improve economic performance. However, from a managerial point of view, reassignment could be more advantageous than vehicle sharing which could potentially be difficult when the MSIs have to charge one another for the transport service. The reassignment option should then be considered a priority by MSIs wishing to collaborate with one another.

Table 10 Effect of user assignment and sharing of vehicles on the cost and the number of routes

Inst.	DTF	Scena. Assign. Shared Unit	Cost				Nb Routes			
			A	B	C	D	A	B	C	D
			No	No	Yes	Yes	No	No	Yes	Yes
			No	Yes	No	Yes	No	Yes	No	Yes
		€	%	%	%	#	%	%	%	
Loire	1.25		1,248	-7.16	-13.44	-19.66	13	-15.38	-15.38	-30.77
	1.5		1,023	-9.89	-17.04	-20.26	11	-18.18	-27.27	-36.36
	1.75		885	-8.73	-14.13	-16.03	9	-11.11	-22.22	-22.22
Rhône	1.25		1,931	-9.52	-9.49	-16.74	26	-15.38	-15.38	-26.92
	1.5		1,601	-9.52	-6.90	-14.22	20	-15.00	-15.00	-15.00
	1.75		1,408	-5.58	-3.57	-8.97	16	6.25	0.00	0.00
Savoie	1.25		4,225	-9.19	-19.95	-23.93	46	-15.22	-36.96	-34.78
	1.5		3,458	-7.34	-13.73	-18.01	34	-5.88	-26.47	-23.53
	1.75		3,137	-6.17	-12.11	-14.34	30	-10.00	-16.67	-20.00
mean			-8.12	-12.26	-16.91		-11.10	-19.48	-23.29	

Impact on the MSIs' payrolls

Table 11 presents the evolution of the two main expenses for MSIs: the cost related to the routes, and staff wages. These two costs are compared for Scenarios (A) and (D). Wages are the sum of the current wages of the staff (€1,931, €6,910, and €7,760 for respectively Loire, Rhône, and Savoie) and the overtime (cost for the extension of capacity). We can see that the sharing and the assignment decrease the routing cost significantly (up to 28.63%) but increase the cost of wages only slightly (no more than 2.56%). From a managerial point of view, it is interesting to note that the increase in salaries is relatively low, and therefore does not lead to a radical change in the payrolls of the MSIs. Thus, it could be considered that the allocation of human resources to institutions would be affected only slightly by the implementation of a reassignment policy.

Number of user places

Until now, the capacity of the MSIs (i.e., the number of users served) has been fixed as it is difficult to increase this value in real life. However, we studied the impact of such an increase on Scenario (D). Hence, Table 12 presents the cost of Scenario (A) compared with the different increase of C_5 in Scenario (D). As we can see, most of the assignment gain can be obtained without increasing their capacities. In addition, this gain does not seem significant above a 5% capacity increase.

Table 11 Evolution of the two main expenses for MSIs: routes and wages between Scenarios (A) and (D)

Inst.	DTF	Scena. Unit	Routes		Wages	
			A €	D %	A €	D %
Loire	1.25		1,247	-22.28	1,931	1.69
	1.5		1,023	-22.36	1,931	1.11
	1.75		884	-17.94	1,931	0.87
Rhône	1.25		1,931	-21.96	6,909	1.46
	1.5		1,600	-15.74	6,910	0.35
	1.75		1,408	-10.70	6,910	0.35
Savoie	1.25		4,225	-28.63	7,760	2.56
	1.5		3,457	-22.79	7,760	2.13
	1.75		3,137	-19.17	7,760	1.95
mean			-20.17		1.39	

Table 12 Impact of increasing the number of user places (Capacity C5)

Inst.	DTF	Scena. C5 Unit	A	D				
			0% €	+0% %	+5% %	+10% %	+20% %	+∞ %
Loire	1.25		1,247	-19.60	-22.40	-24.98	-26.65	-28.42
	1.5		1,023	-20.23	-22.29	-23.46	-24.05	-25.15
	1.75		884	-15.94	-17.45	-20.24	-21.27	-24.17
Rhône	1.25		1,931	-16.72	-18.08	-19.43	-19.50	-19.71
	1.5		1,600	-14.12	-14.86	-15.68	-15.66	-15.69
	1.75		1,408	-8.95	-11.15	-10.65	-10.57	-10.67
Savoie	1.25		4,225	-23.84	-26.32	-27.00	-27.72	-27.72
	1.5		3,457	-17.97	-20.70	-21.61	-23.19	-23.22
	1.75		3,137	-14.34	-17.38	-18.77	-19.29	-19.20
mean			-16.86	-18.96	-20.20	-20.88	-21.55	

7.2 From people with disabilities and other vulnerabilities perspective

Table 13 presents two indicators from a user's perspective. The first one is the ride time, which has to be as short as possible. The second one is the number of reassignments, which should also be as low as possible to avoid upsetting the previous habits of the user and the staff. Those indicators are important as they are directly linked to the quality of service. We find that sharing vehicles (B) does not have a significant impact on the ride time. However, the

645 reassignment does, with an average reduction of ride time of more than 5% (C, D). On the second indicator, we find that the cost saving for Scenario (D) can be obtained by reassigning less than a quarter of the users.

Table 13 Ride time evolution and proportion of users moved from their current assignment

Inst.	DTF	Scena. Assign. Shared Unit	Ride Time				Reassigned user	
			A No min.	B No %	C Yes %	D Yes %	C Yes %	D Yes %
Loire	1.25		36.44	-1.10	-1.77	-3.06	19.05	23.81
	1.5		41.06	5.76	-2.48	-1.01	23.81	19.05
	1.75		44.97	10.64	3.34	4.30	19.05	14.29
Rhône	1.25		25.14	0.60	-3.10	-3.27	12.80	12.80
	1.5		28.09	-0.67	-2.38	-3.96	9.60	8.00
	1.75		30.79	-3.87	-3.95	-8.42	8.00	8.00
Savoie	1.25		31.04	-1.12	-12.30	-11.03	24.04	21.63
	1.5		34.64	0.53	-11.26	-7.51	23.56	17.79
	1.75		40.09	-4.24	-16.29	-13.63	19.23	17.31
mean			34.69	0.73	-5.58	-5.29	17.68	15.85

8 Conclusion

650 In this paper, we addressed an important issue in the medico-social sector that impacts the quality of care, the cost of the system, and the system's environmental footprint. The goal is to integrate logistic aspects into users' assignment decisions by simultaneously solving three interrelated problems: the allocation of the users, the transportation of the users, and the assignment of the medical staff. We named this new problem the Assignment Dial-A-Ride Problem.
655 It can be seen as an extension of the GDARP and the VRPDO. This problem-solving approach jointly optimizes the routing for the shared transportation service, the assignment of users with disabilities and other vulnerabilities to geographical locations, and the extra resources needed at those locations.

To address this problem, we developed a matheuristic, the iteration route selection algorithm (IRS) which combines a LNS and a MILP solver. The LNS generates a pool of routes and the MILP solver chooses the best combination of these routes. For each iteration of the LNS, an assignment problem is solved twice during the insertion procedure. The method was validated on instances from the literature for the GDARP and the VRPDO. We then considered 3
665 real instances from the sanitary transportation of 3 *départements* in France.

The key finding is that a proper user assignment is paramount for improving the current transportation system. The saving induced by the assignment

is equivalent to that obtained by the transport sharing. Assignment and sharing can be combined to achieve a greater cost reduction. Compared with the current practice, this combination reduces costs by 17% on average and up to 24% without degrading the service quality. From the institutions' perspective, transportation costs can be reduced with very small changes in the staff size. From the perspective of users in vulnerable situations, the savings come with a slight decrease in transportation time and less than a quarter of users are reassigned.

For future research, we plan to develop a model to take human resources into account more precisely. For example, the ability to reallocate existing human resources between MSIs, considering the cost, the skills, and the distances, may be taken into account. A second line of research is related to the location of institutions themselves. From the public health policy point of view, it would be relevant to measure the impact of the opening or closing of an institution, or to modify its capacity in terms of access to care in a territory.

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Appendix A BKS Section 6.1

Table A1 Best known solution (BKS)

Inst.	DTF	Cost (€)
Loire	1.25	1,002.53
	1.50	816.02
	1.75	743.12
Rhône	1.25	1,608.01
	1.50	1,373.32
	1.75	1,281.98
Savoie	1.25	3,214.34
	1.50	2,834.83
	1.75	2,687.22

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