International journal of basic and applied research

www.pragatipublication.com

ISSN 2249-3352 (P) 2278-0505 (E)

Cosmos Impact Factor-5.86

Including a variety of riders and rides into the dial-a-ride concept and algorithm

Dr VV Sunil Kumar[1] , CH SRINIVASULU REDDY[2]
Assistant professor[1,2]
Department of CSE, Department of EEE
P.B.R.VISVODAYA INSTITUTE OF TECHNOLOGY & SCIENCE
S.P.S.R NELLORE DIST, A.P , INDIA , KAVALI-524201

abstract

Transportation between pickup and drop-off points is at the heart of dial-a-ride issues. Given that people require transportation, limitations on service quality, like time windows and maximum user ride time limits, are typically present. There are various categories of users in the real world's apps. It's possible to differentiate between four distinct kinds of transportation used for transporting patients and individuals with disabilities. Staff chairs, patient seats, stretcher spots, and wheelchair spots are all discussed. The majority of transportation businesses for the handicapped and sick also regularly dispose of various vehicle kinds. To solve the classic dial-a-ride issue, we include both mutations and branch-and-cut algorithms into the state of the art. A modern metaheuristic approach is also modified for use with this fresh issue. Vehicle waiting time with people on board is also studied, since it relates to service quality. Up to 40 request instances are optimally solved. The heuristic approach yields very good results.

Introduction

Dial-a-ride difficulties include arranging rides for customers between two distinct points on a map. Users typically schedule a pickup or drop-off location and a time slot for the service. For outgoing requests (from a house to a hospital, for instance), the destination is assigned a delivery window. An incoming request (say, from the hospital to home) will provide a window of time at the pickup point (the origin). In addition, there is a maximum allowable route length and riding time that must be adhered to. The goal is to find the most cost-effective way to fulfill all requests for patient transportation. In this article, we generalize the classic dial-a-ride issue (DARP), as specified, for instance, by Cordeau (2006), to include users and cars with varying characteristics. Heterogeneous DARP (HDARP) will be the term used to describe the ensuing issue. Patient transportation experiences at the Austrian Red Cross (ARC) inspired the incorporation of a diverse set of drivers and vehicles. There are three categories of ARC patients. A patient has the option of requesting a wheelchair, stretcher, or sitting transport. Additionally, a companion may join you. The ARC junks two distinct kinds of automobiles. There are four distinct transportation options available, depending on the type: staff seat, patient seat, stretcher place, and wheelchair place. In what follows, we'll call them "resources." The wheelchair spots (resource 3) are located in a separate room from the stretcher spots (resource 2) and the patient chairs (resource 1). Transporting passengers requires a vehicle with the necessary capacity for each individual. Guests often sit in the "staff" section, patients in wheelchairs in the "wheel chair" section, patients who want stretchers in the "patient" section, and so on. There are, however, so-called upgrading conditions: if there is no empty staff seat, a companion may sit in the patient's seat; if none of those options is available, the companion may sit on the stretcher. If there is no other accessible patient seat, the patient may sit on the stretcher instead, since this is permitted under Austrian legislation. Patients who need to be carried on a stretcher must be transported on a stretcher; wheelchair users must be transported in vehicles designed to accommodate their mobility device. User waiting time while in transit is another factor that has received less attention in the literature.

Users of dial-a-ride services are likely to tolerate some waiting time within the specified timeframe. However, in order to minimize user frustration, it's best to minimize the amount of time spent waiting once passengers are on board the vehicle. There is a psychological difference between waiting for a vehicle and waiting while traveling in one, with the exception of loading and unloading. The latter significantly lowers the overall impression of the service's quality. So, we'll modify the objective function to include a penalty for idling while people are waiting in a moving vehicle. In order to find a solution, metaheuristic approaches have been used extensively in previous papers that explore variants of the DARP. For instance, Toth and Vigo (1997) provide a tabu thresholding technique and a parallel insertion heuristic for a DARP that takes into account sitting and wheelchair travel as well as a variety of vehicle types. Metachronous et al. (2007) detail a heterogeneous adaptation of the DARP. Capacity-wise, there is a wide variety of vehicle types to choose from, but transport options are limited to driving. The created approach uses a tabu search algorithm to find a solution. The study of Rekiek et al. (2006) also takes into account the heterogeneity of vehicles in terms of varied capacity restrictions for a single mode of transportation within the framework of the DARP. A genetic algorithm that can form groups is used to resolve the suggested issue. Beaudry et al. (2009) modify the tabu search heuristic created by Cordeaux and Laporte (2003) for use in a dynamic setting, where it is used to the resolution of a heterogeneous DARP that occurs in major hospitals. A number of cars and three distinct transportation options (seated, on a bed, or in a wheelchair) are required to accommodate the needs. In order to solve a changing situation at a big German hospital, Hanne et al. (2009) create a computer-based planning system that takes into account hospital-specific restrictions such multi-dimensional capabilities.

Definition of the Issue

The HDARP may be seen of as an instance of the general directed graph G = (V,A), where V is the set of all vertices and A is the set of all arcs. Transport needs of n passengers must be met by a set K of m vehicles with varying characteristics. The quantity of a given resource r on board vehicle k is represented by the vector Cr,k, where k is any one of the vehicles in the set K. The ARC eliminates two categories of automobiles. Type 1 (T1) layouts include room for 1 caregiver, 6 patients, and 1 wheelchair. Type 2 (T2) has room for two caregivers, one individual in a wheelchair or stretcher, and one more person in a caregiver seat. Each vehicle k must leave from depot 0 and arrive at depot 2n + 1 while sticking to a time constraint of Tk. There is non-negativity in both the trip cost ck ij and the journey time t k ij for every arc (i,j) and every vehicle in the set K2. Pickup and drop-off vertices (i, n + i) are the building blocks of any transportation request. P = [1,...,n] denotes the set of pickup vertices, while D = [n + 1,...,2n] denotes the set of delivery vertices. One patient is waiting to be transferred at each pickup point. The patient may request any of the following three options for transportation. Each patient may be accompanied by a friend, family, or nurse (q0 i 14 1), and passengers may need to be conveyed sitting (q1 i 14 1), on a stretcher (q2 i 14 1), or in a wheelchair (q3 i 14 1). For any r 2 R = 0, 1, 2, 3, the demand at each delivery vertex is qr ni 14 qr i. Pickup (origin) and drop-off (destination) time windows [ei,li] are entered by each user.

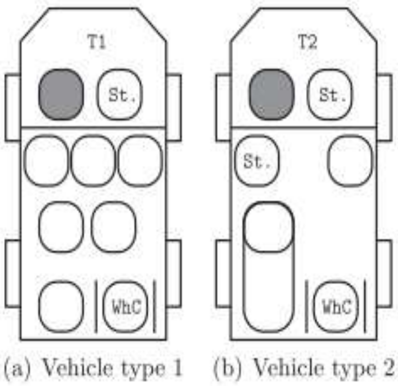

Fig. 1. Vehicle types at the ARC.

and beginning of service has to start within this time window. In case a vehicle arrives too early, it has to wait until service is possible. A maximum passenger ride time L is also considered, in order to keep quality of service at a reasonably high level. At each vertex loading or unloading operations last for a given service time di. Thus, the set of all vertices is given by

International journal of basic and applied research
www.pragatipublication.com
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

$V = P \cup D \cup \{0, 2n+1\}$, and the set of all arcs by $A = \{(i,j) | i \in V \setminus \{2n+1\}, j \in V \setminus \{0\}, i \neq j\}$.

Valid inequalities

Cordeau (2006) and Ropke et al. (2007) introduced new and adapted a number of existing valid inequalities for the DARP. In the following section we will review and adapt all these families of inequalities to the HDARP. Most valid inequalities can be used to strengthen both formulations, some are only valid for either of the two. If not stated otherwise, xij ¼ P k2K ðxk ijÞ in the 3-index formulation. Furthermore, for ease of exposition, let xðSÞ ¼ P i;j2SðxijÞ denote the number of arcs traversed in a set of vertices S

Strengthened bounds on time and load variables

In both the 3-index and the 2-index formulation, bounds on time variables, also denoted as time windows, can be strengthened as follows (Cordeau, 2006; Desrochers and Laporte, 1991):

$$B_i \geqslant e_i + \sum_{j \in V \setminus \{i\}} \max\{0, e_j - e_i + d_j + t_{ji}\} x_{ji},$$
$$B_i \leqslant l_i - \sum_{j \in V \setminus \{i\}} \max\{0, l_i - l_j + d_i + t_{ij}\} x_{ij}.$$

In the case of the 3-index formulation bounds on load variables can also be strengthened (based on Cordeau, 2006). In order to do so, let orig(i) be the set that contains the origin of i, if i is a destination, and otherwise the empty set. Thus, lower bounds can be strengthened as follows:

$$Q_i^{r,k} \geqslant \max\{0, q_i^r\} + \sum_{j \in V \setminus \{i, \mathrm{orig}(i)\}} \max\{0, q_j^r\} x_{ji}^k.$$

The intuition is that if arc (j,i) is used and qr j > 0, given that j is not the origin of i, the load at i hast to be greater or equal than qr j (plus qr i , if i is an origin). In case of upper bounds, we have to distinguish between origins and destinations. If i is an origin, i.e

i.e. $i \in P = \{1, \ldots, n\}$,

$$Q_i^{r,k} + \sum_{r'=r+1}^{2} Q_i^{r',k} \leqslant \hat{C}^{r,k} - \left(\hat{C}^{r,k} - \max_{j \in V \setminus \{i\}}\{\hat{q}_j^r\} - \hat{q}_i^r\right) x_{0i}^k - \sum_{j \in V \setminus \{i\}} \max\left\{0, \hat{q}_j^r\right\} x_{ij}^k,$$

Where

$$\hat{C}^{r,k} = C^{r,k} + \textstyle\sum_{r'=r+1}^{2} C^{r',k} \text{ and } \hat{q}_i^r = q_i^r + \textstyle\sum_{r'=r+1}^{2} q_i^{r'},$$

applies. The intuition behind this strengthening is that if i is visited directly after the depot 0, the load can be at most q^r i . In addition, if the vertex visited directly after i is an origin and q^r j > 0, then the load at i can be at most b Cr;k q^r j . If i is a destination.

i.e. $i \in D = \{n+1, \ldots, 2n\}$,

$$Q_i^{r,k} + \sum_{r'=r+1}^{2} Q_i^{r',k} \leqslant \min\left\{\hat{C}^{r,k}, \hat{C}^{r,k} + \hat{q}_i^r\right\} - \left(\hat{C}^{r,k} - \max_{j \in V \setminus \{i\}}\{\hat{q}_j^r\} - \hat{q}_i^r\right) x_{0i}^k,$$

Is used. The last term used in (68) cannot be used to strengthen (69). Consider

$\hat{C}^{r,k} = 1$, if $\hat{q}_i^r = -1$ and $\hat{q}_j^r = 1$ n Cosmos

International journal of basic and applied research

www.pragatipublication.com

ISSN 2249-3352 (P) 2278-0505 (E)

Cosmos Impact Factor-5.86

Then

$$(Q_i^{r,k} + \sum_{r'=r+1}^{r} Q_i^{r',k})$$

would have to be 61 which is clearly not valid, although visiting j after i is feasible with respect to capacity limits.

Algorithms that "branch and cut" We have built a branch-and-cut algorithm based on each of the new formulations we presented. We'll refer to the 3-index program-based algorithm as 3indexBC and the 2-index formulation-based method as 2indexBC. Combining the concepts of branching and cutting, branch-and-cut algorithms can more efficiently solve problems. When integrality requirements are removed from a MIP, the resulting program is a linear program (LP). These are (19) and (20) in the 3-index formulation and (57) and (58) in the 2-index formulation for our situation. In order to get a lower limit for the initial MIP, the optimum solution to the LP relaxation must be found. In contrast to the solution of the LP relaxation, branch-and-cut algorithms only take into account a minimal fraction of the original restrictions. In general, families of constraints that become exponentially large are left out. These are the constraints on pairs (44), (45), and infeasible paths (49), all of which apply to 2indexBC. Cutting-plane additions are made for all families of valid inequalities that serve simply to fortify the model. The present solution is analyzed using separation algorithms for violations of the missing constraints and the valid inequalities specified previously.

When there are missing constraints, we need the separation procedures to be accurate so that we know for sure if a violation occurs in any of the missing constraints. Heuristic separation procedures may be used if additional valid inequalities are found but are unnecessary for guaranteeing feasibility. If the separation procedures discover a violation of a constraint, a cut is added to the existing LP and the problem is re-solved. This approach is repeated until no more violations of restrictions can be found by the separation techniques. Here, the best possible answer to the LP relaxation of the original MIP has been found. If this number is an integer, then the original MIP's optimum solution has been found. If this is not the case, the original issue is split into two. Similarly to branch-and-bound, this approach involves branching on a variable whose current value is a fraction. The following principles for branching are used. Additional artificial variables are introduced in 3indexBC, similar to Cordeau (2006), to manage the allocation of requests to vehicles. These variables are prioritized while branching. Both 3indexBC and 2indexBC diverge on the variable that is the most non-integer. We'll call this number x1,3 (x1,3 = 0.4, for example) in 2indexBC. The creation of two offspring nodes is known as a branch. An LP is constructed at a child node with an extra constraint that puts a lower restriction on the target variable. This minimum value is equal to the variable's fractional value rounded up to the nearest integer, such as x1,3 P 1. A second LP is constructed at the second child node, this time with an extra constraint that places an upper restriction on the target variable. This maximum value is equal to the chosen variable's fractional value rounded up to the nearest integer, such as x1,360. Then, the two LPs are solved using the same method as the first LP relaxation: by adding cuts until no more inequalities are violated. If the best possible answer is not an integer, the child node becomes the parent of two additional nodes in the tree. The best answer to the original MIP is the one found by recursively solving the first two issues. We direct the reader interested in learning more about the branch-and-cut approach in general to Nader and Rinaldi (2002).

Experiments in computation

C++ is used for all of the code. CPLEX 11.0 and Concert Technology 2.5 are used in the branch-and-cut algorithms. A Pentium D machine running at 3.2 GHz with 4 GB of RAM is used for all tests. Three simulated datasets are used to evaluate each solution procedure. These are derived from a previously published data set that has been supplemented with additional real-world features. In the following, we will first examine the features of the automatically created test cases. The findings are addressed thereafter. Results from the two branch-and-cut algorithms are given first, followed by examples of solutions found using the modified VNS. Both methods are tried out with q = 0 (waiting is not penalized) and then with q = 100 (as recommended by the ARC) to eliminate the need for passengers to wait inside a moving vehicle.

Examples for testing

The 12 "A" examples with 2–4 cars and 16–48 requests are based on the conventional DARP as presented by Cordeau (2006). All users have a 3-minute service time, a maximum ride duration of 30 minutes, and a 15-minute time window length li ei = 15 minutes. Three randomly generated instances with varying degrees of heterogeneity are created for each input. Table 2 provides the odds for the introduction of heterogeneous users. Each request for patient transfer involves no more than one individual. In the "U" dataset, only seated passengers are counted; those who are standing are disregarded. In the "E" data set, 50% of the patients are believed to be sitting, 25% to be on a stretcher, and 25% to be in a wheelchair, while 10% are supposed to be accompanied by someone. At the end of the day, the real distribution of seated patients, stretcher patients, and wheelchair passengers across all static transports performed by the ARC in the city of Graz is reflected in the "I" data set. In addition, half of them is estimated to be traveling with a companion. Each dataset features a distinct fleet make and model. The "U" data set assumes a fleet environment where only T0 vehicles are in use. There may be up to three seated passengers in a vehicle of the T0 type. Data set "E" uses a fleet of T2 cars, each with room for 2 caregivers, 1 patient, 1 stretcher, and 1 wheelchair, whereas data set "I" generates a fleet that is more diverse. In this case, there will always be at least one of each kind of vehicle accessible thanks to a random distribution of the total number of vehicles between T1 and T2 vehicles. The ARC's fleet information is used to determine the T1 and T2 vehicle types.

Conclusions

In this work, we extend state-of-the-art models and algorithms for the classic dial-a-ride issue to account for a wider variety of cars and riders. There have been two suggested problem formulations: a simpler 3-index formulation and a more nuanced 2-index formulation that incorporates the supplied diverse fleet needs. The 2-index formulation in a branch-and-cut setting performs much better than the 3-index-based approach across all three datasets. Additionally, a variable neighbourhood search heuristic was modified from its original dial-a-ride problem form to better suit this variant of the problem. Incredibly accurate solutions are computed in a short amount of time. These findings imply the suggested strategy may be used to bigger (real world) examples as well. The results of studying the effects of fining drivers for waiting too long with passengers in the car have also been analysed. Results from heuristics have been compared for two extreme cases: one in which the cost component of the objective function is ignored, and another in which the penalization term is set to a large number. In the second case, the user doesn't have to wait to have their problems solved while in transit. When compared to the minimum cost setting, the latter produces average routing costs that are only 2.5% higher. The most you can pay is around a 6% premium. This suggests that, from a business's point of view, eliminating customer wait times when they are already in a vehicle does not significantly raise operating expenses.

References

[1] Ascheuer, N., Fischetti, M., Grötschel, M., 2000. A polyhedral study of the asymmetric traveling salesman problem with time windows. Networks 36, 69–79.

[2] Balas, E., Fischetti, M., Pulleyblank, W.R., 1995. The precedence-constraint asymmetric traveling salesman polytope. Math. Program. 68, 241–265.

[3] Baldacci, R., Battarra, M., Vigo, D., 2009. Valid inequalities for the fleet size and mix vehicle routing problem with fixed costs. Networks 54, 178–189.

[4] Beaudry, A., Laporte, G., Melo, T., Nickel, S., 2009. Dynamic transportation of patients to hospitals. OR Spectrum 32, 77–107.

[5] Berbeglia, G., Cordeau, J.-F., Gribkovskaia, I., Laporte, G., 2007. Static pickup and delivery problems: a classification scheme and survey. TOP 15, 1–31.

[6] Cordeau, J.-F., 2006. A branch-and-cut algorithm for the dial-a-ride problem. Oper. Res. 54, 573–586.

[7] Cordeau, J.-F., Laporte, G., 2003. A tabu search heuristic for the static multi-vehicle dial-a-ride problem. Transport. Res. Part B – Meth. 37, 579–594.

[8] Cordeau, J.-F., Laporte, G., 2007. The dial-a-ride problem: models and algorithms. Ann. Oper. Res. 153, 29–46.

[9] Desrochers, M., Laporte, G., 1991. Improvements and extensions to the Miller–Tucker–Zemlin subtour elimination constraints. Oper. Res. Lett. 10, 27–36.

[10] Desrosiers, J., Dumas, Y., Soumis, F., 1986. A dynamic programming solution of the large-scale single-vehicle dial-a-ride problem with time windows. Am. J. Math. Manage. Sci. 6, 301–325.

[11] Grötschel, M., Padberg, M.W., 1985. Polyhedral theory. In: The Traveling Salesman Problem. Wiley, New York, pp. 251–305.

[12] Hanne, T., Melo, T., Nickel, S., 2009. Bringing robustness to patient flow management through optimized patient transports in hospitals. Interfaces 39, 241– 255.

[13] Kirkpatrick, S., Gelatt Jr., C.D., Vecchi, M.P., 1983. Optimization by simulated annealing. Science 220, 671–680.

[14] Lysgaard, J., 2006. Reachability cuts for the vehicle routing problem with time windows. Eur. J. Oper. Res. 175, 210–223.

[15] Melachrinoudis, E., Ilhan, A.B., Min, H., 2007. A dial-a-ride problem for client transportation in a health-care organization. Comput. Oper. Res. 34, 742–759.

[16] Mladenovic, N., Hansen, P., 1997. Variable neighborhood search. Comput. Oper. Res. 24, 1097–1100.

[17] Naddef, D., Rinaldi, G., 2002. Branch-and-cut algorithms for the capacitated VRP. In: Toth, P., Vigo, D. (Eds.), The Vehicle Routing Problem, SIAM Monographs on Discrete Mathematics and Applications, vol. 9. SIAM, Philadelphia, pp. 53–84.

[18] Parragh, S.N., 2009. Ambulance Routing Problems with Rich Constraints and Multiple Objectives. Ph.D. Thesis, University of Vienna, Faculty of Business, Economics and Statistics.

[19] Parragh, S.N., Cordeau, J.-F., Doerner, K.F., Hartl, R.F., 2009a. Models and Algorithms for the Heterogeneous Dial-a-ride Problem with Driver Related Constraints. Technical Report, University of Vienna, Faculty of Business, Economics and Statistics.

[20] Parragh, S.N., Doerner, K.F., Gandibleux, X., Hartl, R.F., 2009b. A heuristic two-phase solution method for the multi-objective dial-a-ride problem. Networks 54, 227–242.