Published in "Actes GISEH 2018", 2018, 27-29 August, Geneva, Switzerland, which should be cited to refer to this work.

Heterogeneous Vehicle Routing Problems with Synchronization: Application to Homecare Scheduling Routing Problem

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Abstract

Abstract: Home healthcare and home care depots are facing increasing demands and costs all over the world, because the increase of the number of dependent people that constitutes an important percentage of population and the growing necessity of some patients with special needs for support. Researchers are attracted by this issue that presents interesting customized scheduling and routing aspects. The objective is to optimize the assignment of visits to home caregivers and the sequence of visits execution. In reality, lunch break for caregivers is mandatory and heterogeneous fleet of vehicles are considered to services the patients. Thus, we introduce in this paper a new variant by taking into account breaks and heterogeneous fleet vehicles in addition to time windows and synchronization constraints. We call this specific problem as the Heterogeneous Vehicle Routing Problem with Synchronisation visit and Break (HVRPSB). We provided an Adaptive Large Neighboorhood search to solve this new variant. Numerical results on generated instances are provided to show the effectiveness of our developed algorithm to solve the HVRPSB.

Keywords: Vehicle routing problem, synchronization, Adaptive Large Neighboorhood search

1. Introduction

Home Care Services (HCS) are community health and nursing services that provide non clinical care to a dependent people at home. Home care services are provided by a visiting nurse, home health agencies, and organized community groups. It represents, particularly for elderly people, an alternative for placement in a residential care facility. Home Healthcare services (HHC) are medical and paramedical care services that provide clinical care at home by registered nurse, occupational/physical therapist or other skilled medical professionals. It is prescribed as part of a care plan following a hospitalization and represents an alternative for classical hospitalization at hospitals. The sector of HCS is growing because it is less costly (Lanzaronee et al., 2010) and it has a positive effect on a client's quality of life (Eveborn et al., 2009). The main problem is the daily scheduling task that determines which visit will be performed, on which day and time, and by which staff member. As mentioned by Bredström and Rönnqvist (2008), the daily assignment and scheduling task in Home (Health)care services can be modeled as a Vehicle Routing Problem with Synchronisation (VRPSyn). It consists of two components; Staff-to-visit assignment where each visit has to be assigned to a certain staff member, and route creation where for each care provider individual routes are constructed that determine at which day and what time each visit will be done. A wide set of constraints needs to be satisfied, like caregivers' working time window and synchronization requirements related to visits (Bredström and Rönnqvist, 2008, Afifi et al., 2016). Indeed, this kind of health care applications has been realized in many countries, such as Sweden (Eveborn et al., 2006), Italy (Fikar and Hirsch, 2015), Denmark (Rasmussen et al., 2012), Austria (Rest and Hirsch, 2016), and the United Kingdom (Akjiratikarl et al., 2007).

In reality, though, the VRPSyn is even more complex than what is described above, due to the presence of many requirements related to the requests of patients and to the fleet of vehicles. Consider the following examples of highly heterogeneous fleets: the organisation profit "Institution Genevoise de Maintien À Domicile (IMAD Geneva)" can offer to their staff several transportation moods such as the electric quadracycles, conventional and electric bike, hybrid and electric passenger cars and different Mobility Carsharing subscriptions (IMAD Genava, 2016). The major problem belonging to this category is the Heterogeneous fleet Vehicle Routing Problem (HVRP) introduced By Golden et al. (1984), this works with a limited heterogeneous fleet. Thus inspire us to incorporate a heterogeneous fleet similar to that found in IMAD Geneva to our problem. In, fact, using differents transportation moods in our cases such as the hybrid passengers' cars and bikes can be reduce the carbon dioxide-equivalent emissions (CO_2e) which is very encouraged by many governments (EEA, 2014). In other words, incorporating several transportation moods is used in order either to overcome their environmental effect readily or to fulfil new environmental regulations (US DOE, 2011).
In addition, we consider in our study that the caregivers are allowed to have lunch break during their working day that can tacked in the depot. Thus, this concept can be referred to the Multi-Trip VRP where the caregivers can perform up to two trips, e.g., one in the morning and one in the afternoon. The caregivers are then must have a lunch break at their depot between these two trips.

To sum up, based on these realistic observations, and to make our work more original, we consider the application of a heterogeneous fleet to services the patients by consideration a lunch break during the working day of a caregivers. We call this new variant as the Heterogeneous Vehicle Routing Problem with Synchronization visits and lunch Break (HVRPSB). Thus, our HVRPSB can be considered as combination of the traditional VRPSyn proposed by Bredström and Rönnqvist (2008), the HVRP introduced by Golden et al. (1984) and the MT-VRP studied firstly by Brandão and Mercer (1998). As far as we know this specific problem combination has not been examined so far and deserves to be studied, since these characteristics often occur together in practice.

The contributions of this work are as follows: i) The new variant of the Home Health Care routing and scheduling Problem called HVRPSB is introduced and a mathematical formulation of the problem is proposed; ii) an Adaptive Large Neighborhood Search (ALNS) are proposed to solve this problem; iii) A set of new instances is generated for the HVRPSB, based on the VRPSyn instances of Bredström and Rönnqvist (2008), iv) Numerical experiments are applied to demonstrate that our approaches provide high quality solutions for the new instances.

The rest of the paper is organized as follows. Section 2 contains the problem statement of the new variant of Home (Health)care Services scheduling and routing problem. Section 3 contains a state of the art of the VRPTW problem. Section 4 contains the provided Adaptive Large Neighboorhood Search (ALNS) method to solve the HVRPSB. Finally, Section 5 contains the computation and numerical results.

2. Literature Review

For a fairly recent survey on the VRP and its variants, see Gendreau et al. (2008) and Braekers et al. (2016). In what follows we review related literature on variants of Home (Health)care routing and scheduling problem, and the Vehicle Routing Problem with Synchronisation.

Extensions of the VRP include other features such as multiple trips, synchronization of vehicles and precedence between tasks are widely studied in the literature (Cappanera and Scutellà, 2014). In the VRP extension that covers Multiple Trips (MT-VRP) (Brandão and Mercer 1998), the employees could perform more than one trip on a day while a trip involves a series of tasks before going back to the depot to replenish resources or for break. Another extension of VRP is the synchronization of vehicles where two or more workers executing a task can be modeled in the same way as when two or more vehicles need to arrive simultaneously at the same customer location (Bredström and Rönnqvist 2008). There are many modelling ways and solution methods proposed in literature to tackle the VRP and its extensions. Salani and Vaca (2011) modeled the problem as multi-commodity network flow problem, and Bredström and Rönnqvist (2008) modeled it following a set partitioning/covering formulation. The VRPSyn models have been tackled using exact solving techniques such as constraint programming, branch and bound, and branch and price (Dohn et al., 2009; Bredström and Rönnqvist, 2008; Rasmussen et al., 2012), decomposition techniques (Laesanklang et al., 2015), and heuristics and meta-heuristics (Fikar and Hirsch, 2015; Hiermann et al., 2015; Rest and Hirsh, 2015; Afifi et al., 2016). For more details about the different variants and applications of the VRPSyn and home health care, the reader is referred to the surveys in Castillo-Salazar et al (2016).

The home care routing and scheduling problem is an application on the VRP. It deals with the routing design and assignment of visits to caregivers, with the main objective to minimize the total distance travelled by caregivers. Each patient specifies a time window when the visit should take place (Kallehauge 2008). Several variants of VRP in relation to home care routing and scheduling with time dependent constraints are provided in literature. Bredström and Rönnqvist (2008) are the first authors who dealt with home care routing and scheduling problem with time windows considering synchronization and precedence constraints. They showed the complexity of the problem and provided a mixed integer programming (MIP), two Branch & Price techniques and a heuristic, in addition to a benchmark instances that is the most considered in literature. They used a multi criteria objective function, minimizing preferences, travelling time, and maximal workload difference. They showed the Impact of synchronization constraints and time window size on the instance complexity. Kergosien et al, (2009) proposed an integer linear programming model and some technical improvements to deal with multiple traveling salesman problems with time windows and synchronization in Home Healthcare context. They considered a randomly generated instances to test the provided ILP and show the limitations for instances of real size. Afifi et al. (2016) provided a Simulated Annealing with Iterative Local Searches (SA-ILS) that highly improved the results found by Bredström and Rönnqvist (2008). Tests are made on the benchmark instances of Bredström and Rönnqvist (2008) by considering travel time and preferences as objective functions.

3. Problem Definition

The HVRPSB can be formally described as follows. Let G = (V, A) be an undirected graph with a node-set $V = N \, U \, C$, where N = $\{1, .., n\}$ corresponds to visits, and C = $\{0, n + 1\}$ correspond to the origin and destination depot, respectively. Let $A = \{(i, j): i, j \in V, i \neq j\}$ be the set of arcs connecting each pair of nodes. Each arc (i, j) in set A has associated non-negative travel time Tij. A limited heterogeneous fleet of K vehicles $(k = \{1, \ldots, K\})$ is assumed to be available at the initial depot to be used by the K caregivers to carry out all the daily visits to patients. We assume that travel speed is constant over a link The time window $[a_0, b_0]$ = $[a_{n+1}, b_{n+1}]$ is the available time for all the vehicles which means that all vehicles can only leave the initial depot after a_0 and must return to the final depot before b_0. Each visit i must start within the customer time window preference $[a_i, b_i]$ where a_i and $b_i$are respectively the earliest starting time of service and the latest starting time. A services time denoted D_i for each visit. Several visits are subject to synchronization constraints. We denote $P^{\,synch}$ the set of couples of visits that are synchronized. Since each caregiver has a vehicle, we use the terms (vehicles and caregivers) interchangeably. Each caregiver k, is allowed to work in the time window $[a_k, b_k]$. During this time, the caregiver must have a lunch break at the depot. The lunch break is taken within a given time window EL and LL, with a duration TL.

We now present the integer programming formulation for the HVRPS, which is inspired from the formulation of the VRPSyn of Bredström and Rönnqvist (2008). Binary variable x_{ijk} equal to 1 if and only if the vehicle k goes from i to j, 0 otherwise. Real variables t_{ik}that indicate the starting time of visit i if this latter is visited by vehicle k. Binary variable b_{ijk} is equal to 1 if the lunch break of vehicle k is held directly after carrying out the visit i and before traveling to visit j, 0 otherwise.

$$\text{Minimize} \quad \sum_{k \in K} \sum_{(i,j) \in A} T_{ij} x_{ijk} \tag{1}$$

Subject to

$$\sum_{k \in K} \sum_{j:(i,j) \in A} x_{ijk} = 1 \qquad \forall i \in V \setminus \{n+1\} \tag{2}$$

$$\sum_{j:(0,j) \in A} x_{0jk} = \sum_{j:(j,n+1) \in A} x_{j(n+1)k} = 1 \qquad \forall k \in K \tag{3}$$

$$\sum_{j:(i,j) \in A} x_{ijk} = \sum_{j:(j,i) \in A} x_{jik} \qquad \forall i \in V \setminus \{n+1\}; \forall k \in K \tag{4}$$

$$t_{ik} + (T_{ij} + D_i) x_{ijk} \le t_{jk} + b_i (1 - x_{ijk}) \qquad \forall (i,j) \in A; \forall k \in K \tag{5}$$

$$a_i \sum_{j \in V} x_{ijk} \le t_{ik} \le (b_i - D_i) \sum_{j \in V} x_{ijk} \qquad \forall i \in V; \forall k \in K \tag{6}$$

$$a_i \le t_{ik} \le b_i \qquad \forall i \in \{0, n+1\}; \forall k \in K \tag{7}$$

$$t_{jk} \ge t_{ik} + D_i + T_{i,n+1} + TL + T_{0j} + M(b_{ijk} - 1) \qquad \forall k \in K, \forall (i,j) \in A \tag{8}$$

$$EL + M(\sum_{j \in V} b_{ijk} - 1) \le t_{ik} + D_i + T_{i,n+1} \le LL - TL + M(1 - \sum_{j \in V} b_{ijk}) \qquad \forall k \in K, \forall i \in V \tag{9}$$

$$\sum_{(i,j) \in A} b_{ijk} = 1 \qquad \forall k \in K \tag{10}$$

$$b_{ijk} \le x_{ijk} \qquad \forall k \in K, (i,j) \in A \tag{11}$$

$$\sum_{k \in K} t_{ik} = \sum_{k \in K} t_{jk} \qquad \forall [i,j] \ in \ P^{synch} \tag{12}$$

$$x_{ijk}, b_{ijk} \in \{0,1\} \qquad \forall (i,j) \in A; \forall k \in K. \tag{13}$$

The objective function (1) consists in minimizing the total traveling time. Constraints (2) ensure each vehicle to leave from the depot, and return to the depot. Constraints (3) guarantee that vehicles enter and leave given nodes. Constraints (4) ensure the continuity of the routes. Constraints (5), (6) and (7) ensure that all customer demands are satisfied respecting time windows. Constraints (8) and (9) are about the starting of lunch breaks if taken in depot. Constraints (10) and (11) enforces that caregivers have lunch break, while M is a big value. Constraints (12) ensure the synchronization visits. Constraints (13) fix the nature of the decision variables.

4. Description of the ALNS metaheuristic

In this section, we present an enhanced Adaptive Large Neighborhood Search (ALNS) algorithm to solve the HVRPSB. The ALNS was used in solving a variety of VRPs (see, e.g., Ropke and Pisinger, 2006; Demir el al., 2012; and Li et al., 2016 and Masmoudi et al., 2016) but is not applied in VRPSyn. The structure of our ALNS algorithm is similar to that proposed by Demir et al. (2012). However, we consider here the required modifications of the algorithm pertaining to our HVRPSB. The algorithm executes n_{ALNS} iterations in order to find a global best solution x^* and its traveling time $f(x^*)$. Let x to be the initial solution and x_{best} the current best solution that generated randomly. The temperature T is initialized to its maximum value T_{max} and the weights and scores of the removal and insertion operators are also initialized. The weights and scores of the removal and insertion operators are updated during the search. At each n_{ALNS} iteration, in case when x_{best} is improved in the last iteration, one removal and one insertion operator are applied. Otherwise, two selected removal operators are performed in a random order to destroy the partial solution, followed by one insertion operator to repair the solution. Our insertion operators insert unserved requests, provided that there are feasible insertions positions respecting the synchronisation visits, time windows and maximum routes duration. Thus, a new solution x' is obtained. If the new solution x' is better than the

current solution, x' is accepted and becomes the current solution. Otherwise, x' is accepted only if it satisfies the SA acceptance criterion $e^{(f(x)-f(x')/T)}$. To improve the solution, an efficient local search strategy is applied at each best solution.
Each ALNS iteration selects a combination of operators (removal and insertion) according to their past performance and executes the corresponding move and improves the incumbent solution, or accepts it if the SA criterion is satisfied. In the formula, β is a random value between 0 and 1 and the temperature is reduced after each iteration by multiplying T by a cooling factor α as suggested by Ropke and Pisinger (2006). We note that, for the removal and insertions operators, we have followed the same operators described in Demir et al. (2012), namely the Random removal (RR, Worst-distance removal (WDR), Time-based removal (TR) and Shaw removal (SR), for the removal operators and Greedy insertion (GI), Regret insertion (RI) for the insertion operators.

Interest readers are referred to Demir et al. (2012) for more details about the ALNS framwork and the operators.

5. Computational Study

In this section, we detail the experimental results of our proposed algorithm. The algorithm is implemented in C language and performed on a configuration Intel inside 4 GHz and 2 GB of RAM operating Windows 7 with 32 bits.

5.1. Data set instances

A new data set instances is generated as we are not able aware of any benchmark data for the HVRPSB. Our new data set is adapted from the benchmark VRPSyn instances of Bredström and Rönnqvist (2008). The original data set contains contain three groups. The first group contains 25 instances named small instances; each instance is composed of 20 activities (particularly, 2 activities are synchronized) and 4 caregivers. The second group contains 15 instances named average instances; each instance is composed of 50 activities (particularly, 5 activities are synchronized) and 10 caregivers. The third group contains 10 instances named large instances; each instance is composed of 80 activities ((particularly, 8 activities are synchronized) and 16 caregivers. Caregivers are available throughout the entire planning horizon (9 hours). The customers' locations are uniformly distributed in a square area with the deposit located in central and duration are randomized to the normal distribution in order to have an average of 5 hours of workload for each caregiver. Traveling times and durations are rounded to whole numbers and measured in minutes.
In order to complete our data set, a time windows for lunch break is considered in this problem. The lunch time windows is set to EL=240 and LL=360 with a maximum duration TL=30min. In all instances, a 60 min period is added to the maximum working day in order to respect the number of vehicles in the original data.

5.2. Parameters setting

The parameter values of the ALNS algorithm affect their performance, so determination of the most suitable values of these parameters can contribute greatly to the improvement of final results. In this regards, we have chosen the parameters based on both recommendations from the literature. Following the findings in Demir et al. (2012), we have used the same parameters values that they used: for the initial removal operators P_d^0= 0.10 for the removal operators, and 0.125 for the insertion operators, r_p= 0.7, the score of a global better solution π_1=15, the score of a better solution, π_2=10, and the score of a worse solution, π_3=5. In addition, the temperature value T_{max}=100 is motivated by the experimental testing in Demir et al. (2012), and α =0.99975 as suggest by Ropke and Pisinger (2006).

5.3. Results on the HVRPSB new instances

This section details the results of our algorithm on the HVRPSB new instances. We have followed the same idea of Cordeau and Laporte (2003). The Table 1 report the total travel time of the best solution (Best) after using 10^3, 10^4 and 10^5 iterations, as denoted $ALNS_{10^3}$, $ALNS_{10^4}$ and $ALNS_{10^5}$, respectively. We executed our ALNS 10 runs for 10^4 iterations (denoted $ALNS_{10x10^4}$) with differents random initial solution at each time. The best solution is then retained. The column "BS" present the minimum best solution found by any of the best solution obtained from $ALNS_{10^3}$, $ALNS_{10^4}$, $ALNS_{10x10^4}$ and $ALNS_{10^5}$. The columns "Best%" presents the percentage of deviation from the best solution (BS).

Table 1

Results on our adapted HVRPSB instances

Inst	$ALNS_{10^3}$		$ALNS_{10^4}$		$ALNS_{10^5}$		$ALNS_{10x10^4}$		BS
	Best	Best%	Best	Best%	Best	Best%	Best	Best%	
a-4-20-s	93.60	1.11	93.34	0.83	92.57	0.00	92.57	0.00	92.57
a-4-20-s2	96.09	2.08	95.92	1.90	94.13	0.00	94.49	0.38	94.13
a-4-20-s3	136.79	15.54	121.91	2.97	118.39	0.00	121.26	2.42	118.39
a-4-20-m	119.61	25.81	110.24	15.96	99.16	4.30	95.07	0.00	95.07
a-4-20-m2	186.72	41.30	147.90	11.93	132.14	0.00	139.32	5.43	132.14
a-4-20-m3	161.83	74.82	119.62	29.22	92.57	0.00	94.37	1.94	92.57
a-4-20-l	116.16	0.95	116.16	0.95	115.22	0.13	115.07	0.00	115.07
a-10-50-s	240.93	5.12	231.93	1.19	230.05	0.37	229.20	0.00	229.20
a-10-50-s2	292.63	25.62	250.40	7.49	232.95	0.00	238.60	2.43	232.95
a-10-50-m1	281.49	23.99	243.00	7.03	227.03	0.00	228.52	0.66	227.03
a-10-50-m2	275.48	0.31	274.89	0.09	274.63	0.00	274.75	0.04	274.63
a-10-50-l1	261.46	3.43	258.01	2.06	252.79	0.00	256.28	1.38	252.79
a-10-50-l2	231.43	8.21	218.77	2.29	215.15	0.60	213.87	0.00	213.87
a-10-50-l3	241.41	12.77	227.06	6.07	218.65	2.14	214.07	0.00	214.07
a-16-80-s	265.94	10.66	243.23	1.21	240.32	0.00	242.18	0.77	240.32
a-16-80-s2	279.93	31.50	235.83	10.78	212.88	0.00	223.99	5.22	212.88
a-16-80-m1	239.29	2.06	234.71	0.11	234.46	0.00	234.72	0.11	234.46
a-16-80-m2	241.76	15.60	217.76	4.12	214.24	2.44	209.14	0.00	209.14
a-16-80-l1	314.15	21.69)	267.62	3.67	258.15	0.00	264.04	2.28	258.15
a-16-80-l2	333.42	49.87	244.02	9.69	222.47	0.00	244.00	9.68	222.47
Avg	***220.51***	***18.62***	***197.62***	***5.98***	***188.90***	***0.50***	***191.28***	***1.64***	***188.10***

The evaluation of the performance of our algorithm is difficult. For that, we use the best solution as a comparison reference, since the solutions of these instances are unknown. However, the results in Table 1 show that our ALNS it is able to obtain a high quality solution after 10^4 iterations. The average deviation from the best solutions was 18.62 % when using $ALNS_{10^3}$, 5.98% for the $ALNS_{10^4}$, 0.50% for the $ALNS_{10^5}$.and 1.64% when using $ALNS_{10x10^4}$.

As can be seems, using our ALNS with 10^5 iterations report the most best solutions with a low average deviation that equal to 0.50%.

6. Conclusions

This paper proposed the Heterogeneous Vehicle Routing Problem with Synchronization of visits and lunch Break (HVRPSB), where we considered realistic concepts related to the fleet of vehicles and for the caregivers. Specifically, we assume heterogeneous fleet vehicles composed by using electric quadracycles, conventional and electric bikes, hybrid and electric passenger cars instead of the heterogeneous conventional passengers' cars as studied in the majority studies of the VRP with Synchronization visits (VRPSyn). In addition, each caregiver must be take a lunch break during its working day is considered.

To solve this problem, an Adaptive Large Neighboorhood Search (ALNS) is developed. The results show that our algorithm is able to find a hight quality solutions in our new generated instances based on the benchmark VRP with Synchronization visits of Bredström and Rönnqvist (2008)

For future work, we plan to focus on another complex variant by considering unlimited heterogeneous fleet of vehicles and considering a multi-period planning horizon, with varying time windows of a user over these periods.

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