Chapter 5
A Biased-Randomized Heuristic for the Home Healthcare Routing Problem

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Abstract The home healthcare routing problem (HHRP) refers to the problem of allocating and routing caregivers to care-dependent people at their homes. It has been mostly tackled in the literature as a rich vehicle routing problem with time windows. This paper proposes a biased-randomized heuristic, based on the well-known savings heuristic, to solve the HHRP. The algorithm is tested in small but real-case instances where patients' visits may occur more than once a day and, in such cases, all the visits have to be performed by the same caregiver. The results show the algorithm provides good quality results in reasonably low computing times.

Keywords Home healthcare · Vehicle routing problem with time windows
Biased-randomized heuristic · Real case instances

5.1 Introduction

The increase in average life expectancy, as a result of new developments in medicine, along with the decrease of the birth rate in developed countries is making the so called "modern society" to grow older [12]. The decrease of informal care of the elderly is leading families to seek for institutionalization solutions, uprooting their relatives from the environment they are so deeply attached. These services may vary from social support, palliative care, personal care and/or food supply. The main benefits of home healthcare services include people's preference of remaining at home [5],

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preventing social isolation [15] and a better cost-efficiency ratio when compared to the provision of these services in institutions [16]. The Portuguese home healthcare services are mostly provided by private companies or charity organizations, with the latter considerably outnumbering the former. One of the major problems faced by home healthcare service providers is staff assignment and scheduling. Too often, these tasks are performed manually, thus requiring a huge amount of time and, given the complexity of such decisions, leading to poor quality scheduling and routing plans.

In this work we address the home healthcare routing problem (HHRP) faced by a non-profit organization operating in the Lisbon region. The service is managed by a social worker who is in charge of planning the tasks of 6 caregivers, who are working in teams of two. Given the nearness of the patients to be visited, the caregivers walk between patients' homes and the Parish Day Center. Every week, the social worker needs to provide each team with a list of patients and the visiting plan, so that all patients have their needs fulfilled. All the planning is done with pen and paper, and although she knows a more efficient planning can be done, she lacks the tools and the knowledge to develop them. This paper presents the first step to create a decision support tool for solving the HHRP. We propose an approach based on a biased-randomized version of a well-known routing heuristic, which can be easily embedded into a spreadsheet for facilitating managerial use.

This paper will develop as follows. In the next section a short literature review is presented focusing on the heuristic and meta-heuristic approaches that have been used to solve the HHRP problem so far. Next, an illustrative case will be introduced and compared with the traditional vehicle routing problem with time windows (VRPTW). In Sect. 5.4, details on the solving methodology are provided. Results will be presented and discussed in Sect. 5.5. Lastly, some conclusions and future work are given.

5.2 Literature Review

The HHRP fits within the resource planning and allocation problem [13]. Its operational level of decision has been mostly tackled in the literature as a rich VRPTW, as shown in the recent review of Fikar and Hirsch [8]. This is a very well known problem that has been deeply studied by the academia. However, the existing models do not cover some of the particularities one finds in the HHRP: continuity of care, nurses' skills that have to match patients' needs, and work regulations, among others.

The first works concerning the HHRP were published between 1998 and 2006. They addressed the problems in national context and proposed decision support systems (DSS) that integrated GIS technology. The first one was published in 1998 by Begur et al. [2]. These authors developed a DSS for the Visiting Nurse Association, in USA, to help them planning the allocation of nurses to patients and determine the daily visits sequence for each nurse. This DSS routing software is based on a well-known routing heuristic and provides simultaneously the assignment of patients and the routing for each nurse that minimizes the total travel time. Later in 2006, Bertels and Fahle [4] combined different meta-heuristics and exact approaches to address the nurse rostering problem and routing decisions taking into account patients' and nurses' preferences, legal aspects, nurses' qualifications, ergonomics, and other aspects. The developed algorithms were embedded into a DSS, which according to the authors can handle most real-life HHRPs. In the same year, Eveborn et al. [6] developed a different DSS, this time for a Swedish HHRP. In order to daily plan workers scheduling and patients' visits, they developed a heuristic based on the matching and set partitioning problems, where previously designed schedules were allocated to workers assuring that all patients were visit exactly once.

Since then, a very interesting amount of works have been published. Single- or multi-period problems, single- or multi-objective, and exact, heuristics, or combined solution approaches can already be found in the literature (see [8] for a very recent literature review). Although our problem is intrinsically a multi-period one, at this first step we addressed it as a single-period problem. Moreover, our problem is quite a small one and our main constraints are to assure that all visits to a patient are assigned to only one team ("loyalty" constraint), patients' time-windows are met, and that all teams have a mandatory lunch break at 1 P.M., which takes place at the day care center. Accordingly, we will focus on single-period problems with time-windows and mandatory breaks.

In 2007, Akjiratikari et al. [1] addressed the scheduling problem for home care workers in UK. These authors developed a particle swarm optimization meta-heuristic to design the visiting routes, so that the total distance traveled is minimized while capacity and time-windows constraints are satisfied. In 2011, Bachouch et al. [3] developed a mixed-integer linear model based on the VRPTW. Their model accounts for workers' skills, lunch breaks, working time regulations, and shared visits to patients. In their work, all patients are visit once, which means no loyalty constraints are needed.

In 2013, Hiermann et al. [9] studied the HHRP in a urban context considering that nurses could use different transportation modes for traveling between visits. They proposed and compared different meta-heuristic approaches and integrated them into a two-stage approach. This work was part of a larger project related with inter-modal transportation in Vienna. Also in Austria, Rest and Hirsh [14] tackle the HHRP as a time-dependent vehicle routing problem since workers travel by public transportations in an urban environment. These authors propose several methods, based on tabu search, to account for time-dependencies and multi-modality in transportation.

The above works have addressed problems with a considerable number of features that are not present in our particular problem at Lisbon. Therefore, a simpler but effective heuristic was needed to address our HHRP. The well-known savings heuristic has been applied in one of the first works to solve the HHRP [2], and it has recently been embedded in a meta-heuristic approach developed by Juan et al. [11]. Given the promising results published in the latter work and its relative simplicity, we decided to adapt it to our problem. Among the issues that appealed us are the existence of only one parameter to tune and the possibility to provide the decision maker with alternative good solutions.

5.3 Problem Description

This work is motivated by a real case study of a Portuguese catholic parish. This community offers several social services to population that lives nearby: meal delivery, activities of the daily living, adult day care, and transportation. The daily schedule of teams of two caregivers has to be planned so that all patients' requests are met. The request vary from twice a day to two days a week. Three teams of two caregivers perform activities of the daily living (such as bathing, dressing, medication assistance, home cleaning, etc.) in each visit. Each team should depart from the Parish Social Center and return there at the end of the day. At 1 P.M. they also go back to the Parish Social Center to have lunch (lunch-break). One of the teams has to arrive one hour earlier to help on preparing the meals. In short, the routing solution must fulfil the following constraints:

- Each patient must be visited by exactly one team.
- All teams depart from, and return to, the Parish Social Centre.
- Each visit must start within a given time window, previously defined.
- Each visit has a pre-defined duration which varies according to the activities performed.
- The working hours for caregivers vary from 08:00 to 16:00, or from 08:00 to 17:00, according to the day of the week.
- Lunch break: there is a mandatory break at the Parish Social Center of one hour duration, starting at 13:00.
- Among the three teams, one must return to the Parish Social Center at 12:00 to help on meals preparation and delivery.
- A patient with more than one visit scheduled for the day must be visited by the same team throughout all visits.

The first four constraints are the traditional ones for the VRPTW if we look into teams as "vehicles" and patients as "customers". The remaining four constraints are specific of the HHRP. Although in vehicle routing problems a customer might be visited more than once a day, the visits can be assigned to different vehicles. However, in the HHRP we are usually dealing with older people, which makes it convenient to assign the same team of nurses that have visited them earlier in the day.

The problem is defined on a graph $G = (N, A)$, the social centre corresponds to nodes 0 and $n + 1$, being the latter a replica of the former. As variables we defined a binary one, x_{ijk}, $(i, j) \in A$, $k \in K$ that has the value 1 if arc *(i, j)* is crossed by team k and 0 otherwise, as well as, a time variable w_{ik}, $i \in N$, $k \in K$ specifying service starting time at node i by team k. As objective function we considered the total walking distance, where c_{ij}, $(i, j) \in A$, represents the length of arc *(i, j)* (Eq. 5.1).

$$min \sum_{k \in K} \sum_{(i,j) \in A} c_{ij} x_{ijk} \tag{5.1}$$

5.4 Solving Approach

Our solving methodology is based on the MIRHA approach proposed by Juan et al. [11], which combines a classical greedy heuristic with a biased-randomization process and a local search.

The MIRHA Framework

The MIRHA framework is a two phase multi-start method: first, a biased-randomization of a classical heuristic generates an initial solution; then, this initial solution is iteratively improved by using a local search procedure. Being a generic framework, the choices concerning the classical heuristic and the local search strategy depend on the problem under study. In the case of the vehicle routing problem, authors propose the integration of the classical savings heuristic with Monte Carlo simulation as the approach to generate the initial solution [10]. For the local search phase, a divide-and-conquer strategy takes the solution apart allowing for smaller sub-solutions to be improved. One of the advantages of this approach, when compared with other meta-heuristics, is its simplicity and the few number of parameters that require a tuning process.

In many ways, MIRHA is similar to the GRASP meta-heuristic framework [7]. The construction of the solution is based on the evaluation of specific elements and their expected influence on the final solution. Both procedures make use of lists. However, while GRASP limits the number of candidates in the list to be considered and assumes all candidate elements to have the same probability of being selected (uniformly distributed), MIRHA does not limit the number of candidates in the list and it assigns a higher probability to those elements that are more promising (Fig. 5.1).

The savings heuristic starts by building an initial solution where each customer is visited in separated routes, thus having one vehicle for each customer. Then, routes are iteratively merged so that "nearby" customers can be included in the same route. The merging criteria is based on the savings concept: visiting two customers in the same route is "cheaper" than visiting each one directly from the depot (depot–customer–depot). One major disadvantage of the savings heuristic is its greediness, i.e., it always merges the routes connected by the edge at the top of the list of candidates.

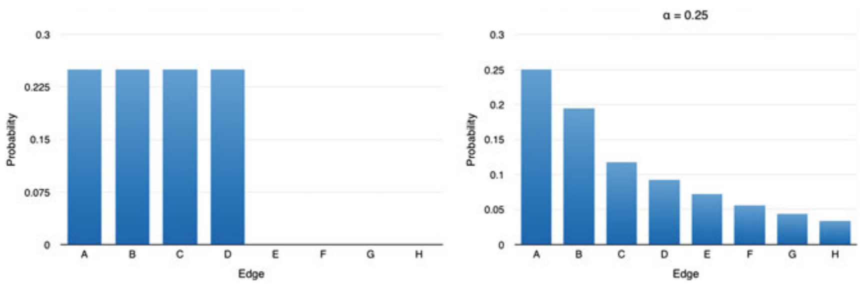

Fig. 5.1 Uniform (left) and Biased (right) randomized selection differences

Based on the savings concept, our algorithm assigns a probability to each item on the savings list, reflecting its quality. Therefore, as one goes down the list, the corresponding probability of being selected also decreases. Some experiments suggest the use of a Geometric probability distribution with parameter α, $0.05 \leq \alpha \leq 0.25$ (also randomly determined by the heuristic). The merging of routes is iteratively carried out until the savings list is empty. To further improve the solution, the heuristic is embedded into a multi-start procedure with a memory mechanism. This last feature stores "the best solution found"; this is to mean, it stores the order in which the nodes were visited in each route and the corresponding distance. When, in a new iteration, a solution contains a route with the same set of nodes as the ones stored in cache, the two solutions are compared (the new and cache one) and the best order will be the one used in the final solution. If the new order is the best one, the cache is updated. This approach is named as the cache procedure and has been successfully applied in [10, 11].

As mentioned above, the HHRP can be viewed as a VRPTW with some additional constraints. Therefore, we have adapted the previously described approach to fit our problem: no capacity constraints, time windows restrictions, and a fix number of routes.

The Adapted Procedure

When analysing patients' time windows, several cases show up: only morning visits, only afternoon visits, more than one visit (at least one in the morning and one in the afternoon), or no time window (for those patients that can be visited at any time during the day). So, taking advantage of these time windows, the MIHRA approach was adapted to fit the HHRP problem as shown in Fig. 5.2.

Firstly a morning solution is created by applying an efficient routing algorithm and assuring this time windows are met. At this first step, only the patients who have to be visited in the morning are considered. Then, the morning solution is used

```
Algorithm Heuristic for the HCP
while (elapsed time < time limit) do
morningsol <- build RandCWSsolution
     if morningsol.number_of_routes == number_of_teams
          afternoonsolTemplate = morningsol
          remove non shared from afternoonsolTemplate
          add afternoon patients
          adjust afternoon solution
          newSol = merge morning and afternoon solutions
          add  all day patients to newSol
     try improvement of newSol with cache memory
if newSol < bestSol
     newSol = bestSol
return bestSol
```

Fig. 5.2 Algorithm: pseudo-code for the proposed solving approach as a template for the afternoon solution, assuring that patients needing more than one visit will be assigned to the same team. The patients needing only one visit are removed from the route, since they have already been visited. The next step inserts patients needing only to be visited during the afternoon. They are added to the route with the minimum inserting time and assuring the time windows. To assure feasibility concerning these time windows, a node is only inserted into a route if the time difference between the two existing nodes is large enough to accommodate the new one. If nodes have very tight time windows and one node cannot be inserted in any of the existing routes, a new one is created. Lastly, those patients who have no constraints regarding the visiting period are inserted in one route again following a minimum insertion criteria and assuring the solution feasibility.

At this point, all patients have been assigned to a team. The final step performs a local improvement considering each route as a travelling salesman problem with time windows and taking advantage of a cache memory, which saves the best results from previous iterations to improve, whenever possible, the current solution.

The major differences between the original MIRHA approach and the one proposed for the HHRP are: *(i)* the morning solution is only accepted if the number of routes is the same as the number of teams; *(ii)* the α parameter of the Geometric distribution is not randomly determined; and *(iii)* time windows are imposed on nodes. Notice that, since teams have a mandatory lunch break, morning and afternoon routes could have been designed independently. However, in that case we could not guarantee that the loyalty constraints were satisfied.

Setting Running Times

In order to determine the running time, some tests were performed. The α value was set to a fixed value of 0.15 since, according to Juan et al. [10], good solutions were achieved for $\alpha \in [0.05, 0.2]$. This α value was then optimized (section below). Three instances were run for each time value. The average distance of each time limit is shown in Fig. 5.3. Given these results, the time limit was set to 500 s.

Setting the Value of α

As mentioned above, the Geometric distribution parameter, α, is fixed instead of being chosen randomly as in previous works. This parameter defines the Geometric

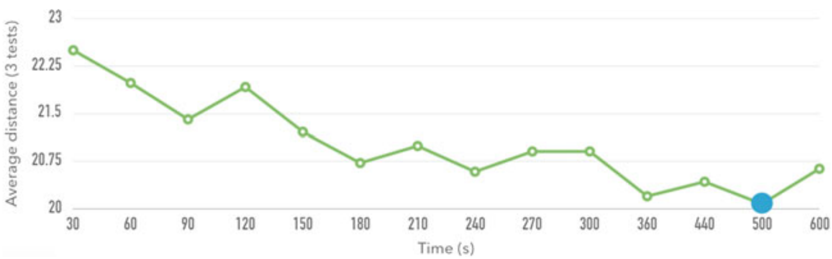

Fig. 5.3 Average distance for different iteration times

Fig. 5.4 Average distance for different α values

distribution that is used to calculate the probability of selection of each candidate in the savings list. Juan et al. [10] have found near-optimal results with values of α between 0.05 and 0.25. To assess the influence of the parameter α on the performance of our algorithm, we tested 10 different values and limited the runs to 500 s. The average results of three runs are shown in Fig. 5.4. These results allow us to conclude that the values referred in the work of Juan et al. [10] are the α values that provide better objective function values, therefore we set α to 0.05.

5.5 Results

The aforementioned algorithm was coded in Java and run on a personal computer with the OS X 10.11.6, an Intel Core i5 at 2.3 GHz, and 16 GB memory.

Table 5.1 shows the main characteristics of our HHRP instance together with some results. There are between 21–23 patients to visit each day of the week (# nodes) where some of them need to be visited more than once (# multiple visits). Thus, in total, 29–32 visits have to be scheduled and assigned to the three teams. It also presents the total walking and free time (both in minutes). The total walking time

Table 5.1 HHRP instance data by week day. Walking time (objective function) and free times are in minutes

Instance	# Nodes	# Multiple visits	Walking time	Free time total (on street/at centre)
Monday	21	11	195.9	315 (202/113)
Tuesday	22	8	228.9	469 (178/291)
Wednesday	21	9	224.7	306 (151/155)
Thursday	23	5	259.4	352 (125/227)
Friday	21	11	206.2	255 (70/185)

varies from 3 to 4.5 h, an average of 1–1.5 h per team. From meetings we had with the social worker in charge of this service, we know she thought they were working at their full capacity. However, the free time column shows that there is capacity to accommodate more visits. The total free time varies from 4 to about 8 h, representing the free time between visits about 42% of the total.

Figure 5.5 illustrates the routes the teams could perform on Monday morning and afternoon. The node colors indicate when the visits will take place: one morning or afternoon visit (black), visit any time of the day (orange) and multiple visits (green). The morning tours are larger than the afternoon tours since these two periods have different durations: mornings correspond to a 5-h period, while the afternoons have 3 or 4 h, depending on the day. Therefore, most patients with a full day time windows are mostly assigned to the morning visits.

When analysing routes among teams, one sees that team #2 (the red team) has the smallest area to cover and that its morning route has a "subtour". In fact, the "subtour" is caused by two morning visits that have to be made to patient 215, one early in the morning and a second before lunch time. Another aspect are the two "crossings" in team #3 morning route and team #1 afternoon route. This latter crossing can be avoided, as all patients have the same time window (not shown). Lastly, the routes are not balanced in terms of walking distance since, in the heuristic, no mechanism was considered to take this aspect into consideration.

Table 5.2 shows in detail the scheduling plan for team #1 (the yellow team). The first column shows the patient ID and the number of the visit (for instance, patient 267 has the first visit right after 8 a.m., and the second visit in the afternoon). This team has almost no free time since the difference between finishing the work at one patient and starting the work at the next one is spend on walking between both houses.

The HHCP has been also formulated as a MILP model. However, after 5 h, CPLEX was unable to provide solutions with a low gap with respect to the optimal solution. After those 5 h, the gap offered by Cplex was still over 10%.

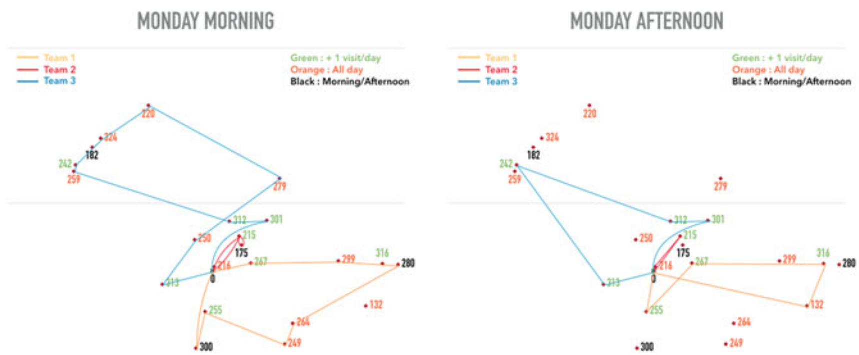

Fig. 5.5 Monday morning and afternoon visits per team

Table 5.2 Monday schedule for team #1. All values in minutes

Patient ID	Time window	Arrival time	Visit duration
Care Center			
267 (1)	[0, 240]	3	20
299	[0, 480]	28	20
316 (1)	[0, 180]	51	30
280	[0, 180]	82	45
264	[0, 480]	137	20
249	[0, 480]	159	20
255 (1)	[0, 240]	185	20
300	[0, 240]	210	20
Lunch	[300, 300]	300	60
255 (2)	[360, 480]	365	20
267 (2)	[360, 480]	391	20
316 (2)	[360, 480]	419	25
132	[0, 480]	449	20
Care Center		479	

5.6 Final Remarks and Future Work

This work presents a biased-randomized heuristic approach to solve a home health-care routing problem in the city of Lisbon. During the construction phase, our algorithm combines the classical savings heuristics with a biased-randomization procedure. In a second stage, routes are compared with the best route found at the time, which is stored in the cache, to try to improve the overall solution. These stages are embedded in a multi-start framework. Our algorithm accounts for time windows, mandatory lunch breaks, and loyalty between caregivers and patients, which are particular features of the studied problem.

The results show the applicability and adequacy of the approach in solving real-life problems. Finally, it is important to highlight that this algorithm is the first step to create a more sophisticated routing decision support tool for a home care center. The proposed procedure can easily provide more than one (good) schedule, allowing the planner to actively choose what she considers to be the best plan according to her utility function and other preferences that cannot be easily integrated into a mathematical model.

The next steps to take are: *(i)* the development of a local optimization procedure to improve the solution quality even further; and *(ii)* the design of medium and large size instances to test the heuristic in those scenarios. We also aim at extending the solution approach to a 5-day plan, since loyalty has to be assured during all the week.

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