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.

I. 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 [1]. 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 [2], preventing social isolation [3] and a better cost-efficiency ratio when compared to the provision of these services in institutions [4]. 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

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manually, thus requiring a huge amount of time and, given the complexity of such decisions, leading to poor quality scheduling 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 work of 6 caregivers 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 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 section 4, details on the solving methodology are provided. Results will be presented and discussed in section 5. Lastly, some conclusions and future work are given.

II. Literature Review

The HHRP fits within the resource planning and allocation problem [5]. 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, [6]. 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 and addressed the problem in a national context and proposed decision support systems (DSS) that integrated GIS technology. The first one was published in 1998 by Begur *et al.*, [7]. They 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. The 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 [8] 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-world HHRPs. In the same year, Eveborn *et al.* [9] developed a different DSS, this time for a Swedish HHRP. In order to daily plan workers scheduling and patients visits, they developed an 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 [6] 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. at the day care center. Accordingly, we will focus on single-period problems with time-windows and mandatory breaks.

In 2007, Akjiratikari *et al.* [10] addressed the scheduling problem for home care workers in UK. Authors have 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.* [11] 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.* [12] studied the HHRP in a urban context considering that nurses could use different transportation models 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 [13] 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 ([7]), and it has recently been embedded in a meta-heuristic approach developed by Juan *et al.* [14]. 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.

III. 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 fulfill the following conditions:

- 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, defined by the user
- 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 one hour earlier than 13:00
- 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 old people, which makes it convenient to assign the same team of nurses that have visited them earlier in the day.

IV. Solving Approach

Our solving methodology is based on the MIRHA approach proposed by Juan *et al.* [14], 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; secondly, this initial solution is iteratively 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 - the SR-GCWS-CS, [15]. 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 setting process.

In many ways, MIRHA is similar to the GRASP metaheuristic framework [16]. 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, moreover, it assigns a higher probability to those elements that are more promising (Figure 1).

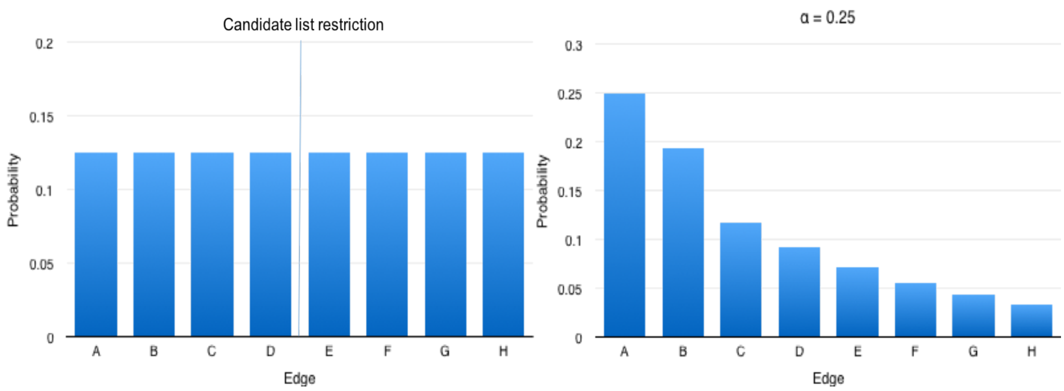

Figure 1: *Uniform (left) and Biased (right) randomized selection differences*

The savings heuristics 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 criteria to merge routes 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.

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 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 learning mechanism. This last feature stores the order the nodes were visited in each route and the corresponding objective value. If, in a new iteration, the same nodes are visited in the same route with a different order, the objective function values are compared so that the best order is employed. This approach is names as the cache procedure and has been successfully applied in [14]) and [15].

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 analyzing 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 Figure 2.

Firstly a morning solution is created by applying the SR-GCWS-CS routing algorithm and assuring that 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 as a template for the afternoon solution, assuring that patients needing more than one visit will be assigned to the same team. Those patients needing only one visit are removed from the route since they have already been visited. The next step inserts the patients who only need to be visited during the afternoon. They are added to the route with the minimum inserting time and assuring feasibility concerning the time windows. 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 traveling salesman problem with time windows and taking advantage of a cache procedure, 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)* the randomized version of the savings heuristic is extended so that a full-day solution is obtained. 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.

```
Algorithm Heuristic for the HCP
while (elapsed time < time limit) do
morningsol <- build RandCWSsolution
     if morningsol.number_of_routes == number_of_routespretended
          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
```

Figure 2: *Algorithm: Pseudo-code for the proposed solving approach.*

Setting Running Times

In order to determine the running time, some tests were performed. The α value was set to 0.15 since, according to Juan *et al.* [15], good solutions were achieved for $\alpha \in [0.05, 0.2]$. Figure 3 shows the average values obtained for each time limit. Given these results, we have set time limits to 500 seconds.

Setting the value of α

As mentioned above, the Geometric distribution parameter, α, is fixed instead of being chosen randomly as in the work of Juan *et al.* [15]. This parameter defines the Geometric distribution that is used to calculate the probability of selection of each candidate in the savings list. Juan *et al.* [15] 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 9 different values and limited the runs to 500 seconds. The average results of three runs are shown in Figure 4. These results allow us to conclude that lower α values provide better objective function values, therefore we set α to 0.05.

Figure 3: *Average distance for different iteration times.*

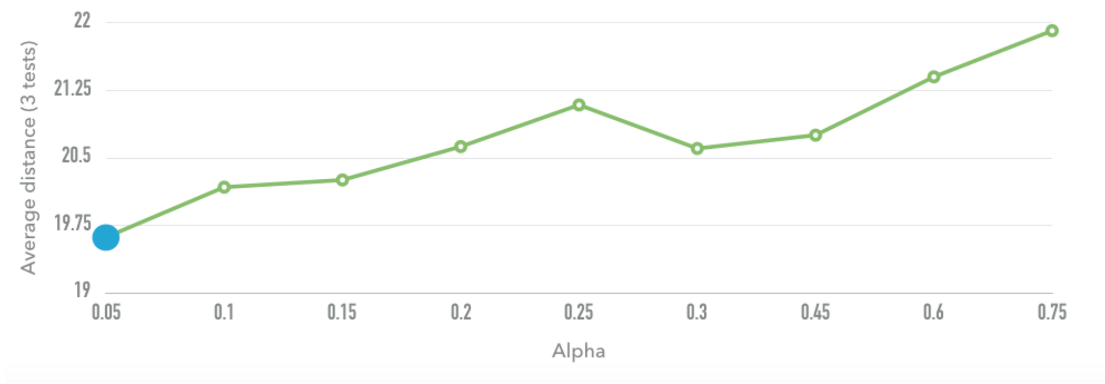

Figure 4: *Average distance for different α values.*

V. 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 1 shows the main characteristics of our HHRP instance together with some results. There are between 21 to 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 to 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 waking time varies from 3 to 4.5 hours, an average of 1 to 1.5 hours 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 hours, representing the free time between visits about 42% of the total.

Figure 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: Mondays mornings correspond to a 5-hour period, while the afternoons have 3 or 4 hours, depending on the day. Therefore, most patients with a full day time windows are mostly assigned to the morning visits.

When analyzing the 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 payed to patient 215, one early in the morning and a second one 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 balance in terms of walking distance, since no mechanism was considered in the heuristic to take this aspect into considerations.

Table 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 start the work at the next one is spend on walking between both houses.

The HHCP has been modelled as a MILP model. However, after 5 hours, CPLEX was unable to close the gap between bounds.

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)

Table 1: *HHRP instance data by week day. Walking time (objective function) and free times are in minutes.*

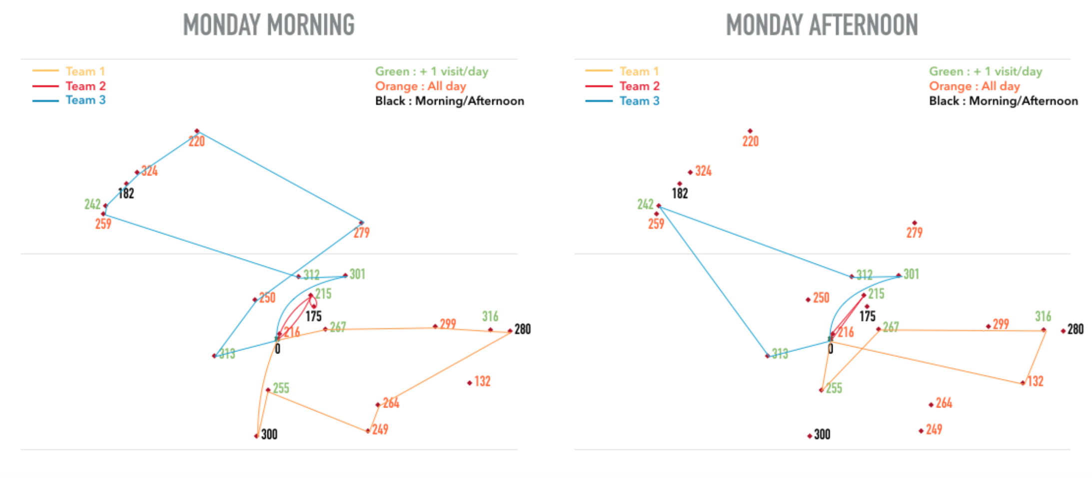

Figure 5: *Morning and afternoon visits on Monday per team.*

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	

Table 2: *Monday schedule for team #1. All values in minutes.*

VI. Final Remarks and Future Work

This work presents a biased-randomized heuristic approach to solve a home healthcare 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, it uses a local search optimization procedure. These stages are embedded in a multi-start framework. Our model considers the inclusion of time-windows, mandatory lunch breaks, and loyalty between caregivers and patients, which are particular features of the the studied problem.

The results show the applicability of the algorithm in solving real-life problems. Finally, it is important to highlight that this algorithm is the first step to create a more sophisticated and applicable routing support decision 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 the development of a local optimization procedure to improve the solution quality even further, and the designing of medium and large size instances to test the heuristic in those scenarios. We also aim to extent the solution approach to a 5-day plan, since loyalty has to be assured all week long.

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