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Home health care scheduling activities

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Abstract. In this paper, we are interested in the Home health care (HHC) scheduling problem. The HHC office needs to minimize traveling costs and to optimize caregiver assignment to patients. Scheduling patient visits have to take into account unexpected situations based on the latest scheduling information. We first analyze the HHC scheduling problem as deterministic, then discuss the dynamic challenges and propose a rescheduling approach based on genetic algorithm. A platform is designed to evaluate the proposed approach. The obtained results showed that the scheduling system is able to compute high quality schedules and can deal with urgent unpredictable situations.

Keywords: home health care, scheduling, routing, genetic algorithm, rescheduling.

Introduction

Home Health Care (HHC) offers support and care such as medical, paramedical and social services for patients with clinical diseases at home. Several services are provided by HHC office depending on caregivers' constraints and patient's needs. The HHC scheduling problem could be regarded as a combination of the staff rostering problem and the Vehicle Routing Problem with Time Windows (VRPTW). The HHC structure need to assign visits to medical staff with respect to their working time, to the patient availability, etc.

In this paper, we focus on the scheduling and routing problem in the HHC context. Section 1 reviews the literature related to HHC scheduling problems. Section 2 presents the proposed approach. Section 3 shows experiments and results. Finally, perspectives for future research are presented.

1 Literature review

Considerable efforts have been devoted to scheduling in the HHC context. Most studies tend to focus on the HHC scheduling problem as a mathematical problem and consider it as a combination of two well-known problems: the staff rostering problem (SRP) and the vehicle routing problem with time windows (VRPTW) [Yuan and Fugenschuh, 2015]. From the rostering perspective, the problem is to assign practitioners to visits with a set of constrains [Di Mascolo et al., 2018] [Guy and Kunhee, 2018] [Nasir et al., 2018].

The problem is also viewed as an extension of the Traveling Salesman Problem (TSP) or the VRPTW e.g., [Mutingui and Mbohwa, 2013], [Cheng and Rich, 1998] and [Begur et al., 1997], etc. The literature is rich with HHC scheduling models that aim to achieve one or more objectives under constraints. Most of the objectives

focus on minimizing the costs, travel time, distance or balance workload among practitioners. A lot of works like [Bertels and Fahle, 2006] and [Parragh et al., 2016] consider the cost as one of the most important factors in this problem. A cost function includes service costs and travel costs and can include penalty in case of constraints violation. Patient and practitioner preferences are usually considered in the constraints and they are mostly linked to the service quality. The most common constraints included are practitioner qualification and visit types. Most models categorize the constraints as hard or soft. Constraints which cannot be violated are considered as hard, while others are treated as soft and the violation results in a violation penalty.

A very recent comprehensive overview of current work in the field of HHC routing and scheduling is provided by [Fikar and Hirsch, 2017]. They studied the problem from both the single-period and multiple-period perspective. Single period planning problems covered 25 journal publications while multiple-period studied 19. The review summarizes at first the studied literature taking into account solution methods, source of used data and the country of origin if exists. They also analyzed the different objectives involved in each study, each objective can be a maximization or a minimization function and can be a combination of various objectives eg. travel time, preferences, workload balance, etc. In contrast to the objectives, the constraints, categorized in the review as Time Windows, Skill Requirements, Working Time Regulations, Breaks, Precedence, Synchronization and Uncertainty, differ less between the reviewed articles. Some of the constraints eg. Time windows and skill requirements are common factors in most HHC scheduling and routing problems; however, the implementation of such constraints vary between the reviewed papers. The review showed that as for the single-period HHC problems, the majority of work develops metaheuristic solution procedures to solve it in addition to exact methods.

Many attempts have been made to implement GA in order to solve HHC scheduling and routing problem. In a major advance in 2017, [Du et al., 2017] focused on the HHC scheduling optimization problem with known demands and service capabilities. The aim is to minimize the total cost by creating an integer linear program, which took both the priorities of patients and constraints of time windows into consideration. The proposed model was solved using GA with local search and a case study was conducted for the empirical analysis which proved the effectiveness of the model. Another recent study on this topic used a Hybrid GA to solve the HHC scheduling problem with fuzzy demand [Shi et al., 2017]. In a first stage, the problem is reduced to the classical vehicle routing problem within a time window. In a second stage, the dispatcher preference index is introduced to express the dispatcher's attitude toward risk. The index is used to represent the dispatcher desire of using a vehicle using an interval from [0..1]. Another research work used Hybrid GA to solve the dynamic VRPTW. The particularities of this work are: the information can change after initial routes have been constructed or when not all informations are known when the routing process takes place. The authors used the modified Solomon benchmark to show the efficacy of their approach [Housroum et al., 2006]. Another work provides a valuable framework for HHC companies to make a robust schedule when arranging the caregivers [Shi et al., 2019].

Most of previous research works have been limited on the problem without considering many real life features such as distances and caregivers' unavailability. Time windows, qualifications, working time regulations and breaks are common in most HHC scheduling and routing problems. In our setting, the assignment of caregivers is done with respect to time window preferences (days for patients and caregivers, time frames for patients), skill level requirements, workload balance (4 patients at maximum for each caregiver), breaks (no visits assigned in breaks) and GIR which is a number obtained using a detailed grid called AGGIR to determine the level of dependency of patients. In addition to these constraints, we consider a penalty when the patient availability time window is violated.

In our first feature, we consider the scheduling and routing of caregivers in a real time manner. Daily plans are created along the period of care and the status of caregivers are tracked throughout the plans. Our second feature

considers the routing process on the basis of geographical patient positions which is our main contribution. The travel costs are one of the major cost factors for HHC organizations. The consideration of geographical location during the second decision (routing of caregivers to patients) can help to reduce the travel time and thus transportation costs as well. Finally, we treat another real-world problem which is the uncertainties due to multiple reasons. It is therefore important to find an optimal rescheduling for the planning in progress.

2 Proposed approach

2.1 HHC scheduling problem using Genetic Algorithm (GA)

The HHC scheduling problem can be seen as an extension of the TSP or the VRPTW where we have a set of points and a specific number of resources e.g. workers, equipment,... and the purpose is to figure out how to route multiple vehicles from a depot under a set of constraints at a minimum cost without violating the patient time window constraints. In order to solve this problem, we look at Genetic Algorithm (GA) originally developed by [Holland, 1975]. GA is an adaptive search heuristic that mimics the process of natural evolution. It maintains a population of candidate solutions for the problem at hand, and make it evolve by iteratively applying a set of stochastic operators.

In figure 1, we present the GA algorithm steps. The flowchart consists of the classic GA used to assign medical staff to visits and implemented to generate optimal routes. The three main GA operators - reproduction, crossover and mutation are applied on the random population consisting of a random route to create a new population. The route is evaluated and tested. Until the termination criterion is met, iteratively altered by the GA operators. The termination criterion examine whether an optimal solution is obtained, all the patients are visited within the adequate time window and the visits are assigned to caregivers [Vishnupriyan et al., 2008]. A useful GA approach in similar cases could be the Group GA (GGA) originally proposed by [Falkenauer, 1992]. The general structure of GGA is similar to the basic GA. However, the only difference is in the internal mechanisms of the coding scheme, and the implementation of the genetic operators. In what follows we present our implemented algorithm and the methods chosen for each different step in our example:

GGA Coding Scheme. The structure of the genetic coding applied in the algorithm can strongly influence the



performance of GGA [Mutingi and Mbohwa, 2012], [Filho and Tiberti, 2006]. Mutingi and Mbohwa developed a unique coding scheme which exploits the group structure of the scheduling problem. In the same vein, let C = [1, 2, 3, n]be a chromosome representing a set of n patients to be visited by m caregivers. The purpose of this representation is to simplify the partitioning of clients along C into m groups.

Population initialization. Create a population of N elements, each with randomly generated DNA. The DNA is randomly created by random assignments of patients to caregivers. A good technique could be to first arrange the activities in ascending order of their start times and in some cases of a tie arrange them according to their activity duration. This procedure increases the likelihood of the initialization process to generate initial feasible solutions.

Fitness evaluation. The fitness function tests how fit the solution is with respect to the problem in consideration. Let (i, j) represent a feasible trip, the medical

staff member departs from origin 0 which is usually the HHC structure and visits nodes i + 1, i + 2, ..., j - 1, and j. In our case, we need to produce a numeric score c_{ij} (1), calculating the sum of the distances between the cities from the source point 0 to the destination j passing through i patients and then, from the last patient residence j to the caregiver point of origin. However, time constraints need to be considered in the function, that is, the penalty costs incurred due to violation of time window preferences.

$$c_{ij} = v \left(d_{0,i+1} + \sum_{h=i+1}^{j-1} d_{h,h+1} + d_{j,0} \right) + k_e \sum_{i}^{j} \max(0, l_i - a_i) + k_l \sum_{i}^{j} \max(0, e_i - a_i) + Q_u$$
(1)

where, d_{ij} denotes the distances between successive clients *i* and *j*; *v* is the variable cost per traveled distance; k_e and k_l denote, respectively, the unit penalty costs when a caregiver reaches the patient home too early or too late; e_j and l_j , are the earliest start time and latest start times preferred by patient *j*; and a_j denotes the arriving time of caregiver at patient home *j*. Our add into this function is Q_u which is used to denote wether a caregiver is qualified to treat a patient or not by matching his skills level to the later GIR number. Q_u value can be equal to 1 or 0 indicating respectively, a qualified or a nonqualified caregiver.

Selection. Once the fitness has been calculated for all the members of the population, we can select the fittest members to become parents. There are different approaches of selection. In our case, we chose to apply a probabilistic method called roulette wheel.

Crossover. Crossover is a mechanism thorough which selected chromosomes mate to produce new offspring. This genetic operator will help us to explore unvisited regions in the solution space. Thus provide the algorithm with exploratory search abilities.

Mutation. Once the new chromosome is generated after crossover, we apply mutation before adding the child to the next generation.

Include the new population in the old list and repeat from step 2.

Termination. The process is repeated until a maximum number of generations is achieved. When searching for an optimal solution many conditions are considered. A workload of 4 patients at most is restricted for each caregiver and the patients are served within their time window preferences.

3 Experiments and results

To improve the patient health care treatment process, we design a platform to ensure that the coordinator makes decisions about staff assignment, patients' management, and optimal routes. Indeed, the coordinator and medical staff members can have information about the number of patients assigned, both being treated and waiting for treatment. It also allows better coordinator and communication between different actors. The system has several ergonomic interfaces that allow the coordinator to intervene and act on its functionalities. In the proposed platform, the coordinator uses the GUI to register and retrieve relevant data, assign staff to visits to be performed and route them to patients. The implemented GGA algorithm is the major component of the proposed platform. It is needed for the functioning of the system and it interacts with Google maps API to show the routing results. The implementation of the algorithm has 2 phases: first, the coordinator assigns the medical staff members everyday satisfying the patients time windows and matching the caregiver skills with the GIR number. Second, the coordinator routes the assigned staff to the patients in the map. The maps are built on Web mapping based services delivered by Geographic Information Systems (GIS) using navigation technologies which contain a

detailed description of the road network. Each customer is positioned automatically on the map through addressmatching. Before delivery, this data is also processed to make a logical connected network to use for travel-time calculations..

In this section, we present results of the scheduling and routing algorithm. In table 1, the scheduling algorithm performance is presented. The experiments consider small and larger size cases to assess the scalability of the proposed approach. The increasing of both caregivers and patients have a significant effect on the scheduling time. Depending on the number of caregivers, we tested the behavior of the system when we have 1, 2 or 4 patients assigned.

Number of caregivers	Number of patients	Scheduling Time (s)
	2	1.58
2	4	3.27
	8	5.09
4	4	7.43
	8	10.60
	16	12.44
8	8	13.80
	16	14.38
	32	16.73
16	16	18.62
	32	20.01
	64	22.69

Table 1. scheduling caregivers to patients

4 Conclusion and perspectives

We investigated in this paper the HHC scheduling and routing problem. We propose a decisionmaking paradigm approach to improve the quality of care services provided by HHC office. A dynamic approach based on GGA is proposed for the management of HHC, caregivers scheduling, founding routes and minimizing costs related to travel time. The uniqueness of the proposed approach is that it considers real time scheduling and routing, patient geolocations. One of our intended future research directions is to add the rescheduling approach to further overpass the staff unavailability. In some cases, the negotiation process can be terminated before its completion due to lack of available medical staff in the agency.

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