Short- and mid-term scheduling for home care personnel

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1 Introduction

It has become increasingly common to provide home care for groups with mobility issues, such as the elderly, rather than provide care at nursing homes or hospitals. In the past, this trend required new approaches for the efficient organization and management of staff within home care organizations in order to meet the requirements incurred by this new model of care. Solving the resulting optimization problem was, and remains, a challenging task, even for experienced human planners, given the many factors requiring consideration. Consequently, a significant amount of attention in operations research has been devoted to developing new algorithms for the automatic scheduling and routing of home care staff.

Examining the academic literature reveals that most state of the art studies focus almost exclusively on the problem's routing aspect. The personnel rostering and task scheduling characteristics considered within these publications very often oversimplify the practical requirements. For example, Rasmussen et al (2012) base their model on the vehicle routing problem with time windows, but integrate only a few side constraints representing the employees' contracts. Nickel et al (2012) acknowledge that rostering plays a vital role in home care scheduling. Their model assigns employees to shifts, which make up the scheduling period, while considering hard availabilities of employees.

Academic models typically focus on traditional vehicle routing objectives such as minimization of travel time. However, this somewhat contradicts practice, given that home care involves scheduling tasks which are often relatively long compared to the travel time between two locations. Furthermore, non-

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medical home care may be organized into geographical regions, resulting in intra-region travel rarely requiring much time. Focusing on employee- and patient-related objectives rather than routing objectives potentially yields significantly higher-quality solutions.

The present study proposes a rich model and optimization algorithm for home care scheduling problems with particular emphasis placed upon the complex nature of both patient and employee characteristics encountered in practice. The approach developed supports human planners in three Belgium home care organizations which provide care in both urban and rural regions. The model addresses both operational (short-term) and tactical levels (mid-term) simultaneously (Hulshof et al, 2012). Integrating both levels results in greater flexibility as regards the scheduling of available home care staff.

2 Problem description

Consider a set of patients P, each of which has a set of tasks T_p that must be scheduled, a set of employees E and a scheduling period D consisting of a number of consecutive days. The problem requires assigning each task $t \in \bigcup_{p \in P} T_p$, which must potentially be performed up to a certain frequency, by an employee $e \in E$ on a day $d \in D$, and to select a start time and duration for each scheduled task. The novelty of this particular problem lies in its rich personnel rostering constraints and the flexible scheduling of patients' tasks.

Each employee $e \in E$ is characterized by a depot location l_e, a set of qualifications Q_e and a set of availabilities A_d^e for each day $d \in D$. Each daily route begins and ends at the employee's depot, which is either the employee's home or a central office from which all employees leave. The set of availabilities A_d^e consists of a number of non-overlapping hard time windows defined as intervals $[s_i, f_i)$, which indicate when tasks may be performed by employee e on day d. Furthermore, each employee has a contract consisting of several time-related constraints restricting their working hours and days in various ways. Following the classification of Smet et al (2014), these time-related constraints may be categorized as either counter or series constraints. Table 1 shows an overview of the employees' time-related constraints considered in the proposed model.

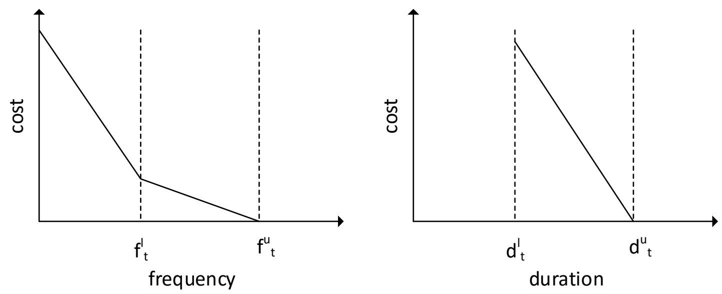
Counter constraints	Series constraints
Min/max hours worked	Min/max consecutive days worked
Min/max days worked	Min/max consecutive days idle
Min/max days idle	Min/max consecutive weekends worked
Min/max weekends worked	Min idle time between two consecutive days worked
Min/max weekends idle	

Table 1: Examples of time-related constraints

Each patient $p \in P$ is characterized by a location l_p, typically the patient's home, a cost c_{pe} for assigning this patient's tasks to employee e and a set of availabilities A_d^p for each day $d \in D$. The cost c_{pe} is calculated based on various patient preferences for particular employees. Patient availabilities are defined in the same way as those of employees. The days on which a patient's tasks are scheduled may be constrained similarly to how employee time-related constraints restrict their days worked. For example, the number of consecutive days a patient is visited may be constrained.

Each task $t \in T_p$ must be scheduled a number of times in a particular reference period $D_t \subseteq D$. A task's frequency is modeled as a range defined by a lower bound f_t^l and an upper bound f_t^u such that $0 \leq f_t^l \leq f_t^u$. Note that a task may be scheduled less than f_t^l, thereby incurring a proportional cost, but no more than f_t^u. In other words a task's frequency has a soft lower bound and a hard upper bound. A task's duration is similar to its frequency, insofar as both are considered flexible. Lower d_t^l and upper bounds d_t^u on duration are defined such that $0 \leq d_t^l \leq d_t^u$. Tasks can never be scheduled shorter than d_t^l or longer than d_t^u, meaning that a task's duration range is hard. Finally, each task t has a set of hard qualification requirements Q_t and priority levels reflecting the undesirability of scheduling a task less than f_t^l or f_t^u.

The objective function consists of three main parts: employee-related costs, patient-related costs and task-related costs. Employee costs are a weighted sum of contractual constraint violations, travel times and idle times. Patient costs are calculated as the sum of incurred assignment costs c_{pe}. Finally, task-related costs are a weighted sum of the deviation from both the frequency and duration range. Figures 1a and 1b illustrate how the cost varies in function of the scheduled frequency and duration, respectively. The slope of the functions is dependent on the weights associated with the relevant deviations.



(a) Frequency deviation (b) Duration deviation

Fig. 1: Cost calculation functions

A final term in the task-related costs reflects how evenly the scheduled tasks are distributed in D_t. This ensures that, for example, employees do not clean a patient's home on two consecutive days, but rather perform this task on other days of the week.

3 Proposed solution approach

A two-phase approach is employed for effectively generating solutions for the presented home care scheduling problem. First, a constructive heuristic generates an initial solution. Second, several local search neighborhoods are employed which modify an indirect solution representation to improve the initial solution. In both steps, a serial schedule generation scheme assigns start times to tasks in each daily route, enabling the correct calculation of objective values.

The constructive heuristic is a greedy algorithm which begins by sorting tasks based on various characteristics such as priority, duration and frequency. The algorithm then sequentially assigns these tasks f_t^u times to the best possible employee and day, setting the duration of each scheduled task to d_t^u.

Improving the initial solution is achieved by exploring different neighborhoods in a local search algorithm. These neighborhoods modify solutions by either (i) altering a task's assigned day, (ii) altering a task's assigned employee, (iii) changing the order a route's tasks, or, finally, (iv) modify a scheduled task's duration. For each new neighboring solution, if necessary, the schedule generation scheme updates the tasks' start and end times.

At present, data is being collected from a large home care organization located in Belgium which will be made publicly available at a later stage. Computational results of the algorithm and an analysis of this data will be presented at the conference.

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