Metaheuristics for solving a Multimodal Home-Health Care Scheduling Problem

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1 Overview

Home Healthcare services (HHC) are of great interest, as patients prefer to be nursed at home and the average age is steadily increasing. The problem of scheduling the staff of a HHC provider is not simple, as many constraints have to be taken into account.

We consider a real-world setting, where, given a set of HHC service requests (missions) and a set of staff members (nurses), we want to find a roster, as well as associate tours, where every job is assigned to a nurse satisfying a set of hard constraints while minimizing the number of violations of a set of soft constraints and an objective value (e.g. travel time).

Nurses in the problem have the following properties that need to be considered:

- Each nurse has a skill level (qualification) assigned (e.g. Diplompflege,Reinigungsdienst).
- Nurses may not be available on some days due to contract issues (maximum number of working days per month), vacation, illness,...
- Nurses can work on different, non-overlapping shifts. These shifts have to be paid, no matter how many missions are performed.

There are two types of missions (requests)

- fixed missions (e.g. 'Mitarbeitergespräche') - these are defined before the roster is created and are assigned to specific nurses.
- unfixed missions (client requests) - can be (re)assigned to any nurse with the appropriate skill (qualification).

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The additional constraints can be split into hard constraints, these constraints have to be fulfilled for a feasible solution, and soft constraints, for which we try to minimize the violations. Hard constraints are:

- every request (client service) must be serviced
- time windows for starting times
- service durations (the length of a service cannot be changed)
- travel times
- higher skill levels dominate lower skill levels in the sense that a job can be done by any staff member having the required of a higher skill level
- client aspects (e.g. client prefers a non-smoking nurse)

Soft constraints are:

- preferred times (desired starting times)
- min/max shift lengths

Real-world HHC problems combine two classical NP-hard problems: vehicle routing with time windows and nurse rostering. As exact algorithms for these problems typically have very high computation times when applied to real-world instances containing e.g. around 500 nurses and 1000 missions to be scheduled, we focus here on heuristic approaches. Another challenge of HHC problems is the fact, that many real-world instances include many side constraints that vary between different service providers (e.g. nurse contracts). Therefore a flexible solving architecture is required, where constraints can be easily added and removed. As multimodality (i.e. use of different modes of transport) is considered, it is crucial for accurate schedules to use accurate travel time estimations. To meet this requirement, we use a large set of historical data from different transport modes (car, public transport,...).

2 Heuristic approaches

We implemented different (meta-)heuristics for tackling the HHC scheduling problem. A solution of the problem consists of mission to tour assignments, where every tour is assigned to one specific nurse. As fixed missions cannot be reassigned to other nurses, the problem can therefore be reduced to a problem of assigning unfixed missions to tours.

Based on the work of Rendl et.al. [7] this approach differs from others by the objective to provide a flexible framework to solve real-world HHC problems. According to [7], other meta-heuristic approaches use different setups and do not consider multimodality. The following heuristics use the same representation as described in [7] and also retrieve the initial solution from a CP Solver.

Simulated Annealing Hyper-Heuristic (SAHH)

We implemented a Simulated Annealing algorithm that works similarly to the Simulated Annealing Hyper-Heuristic described by Bai et al [2] but uses different neighbourhoods. The selection of a low-level heuristic (neighbourhood to be searched) is done using an adaptive learning approach, where the selection probability depends on an accept/tested ratio in a predefined learning period.

Similarly to the approach described in [7], the SAHH starts by identifying an initial solution with a constraint programming (CP) solver and then tries to improve the mission to tour assignment by utilizing a set of neighbourhoods such as 'swap-nurse'.

For each neighbourhood we use a random and two next-improvement step functions, where one tries to improve the penalty value without decreasing the objective value and vice versa, similarly to the approach in [1].

Memetic algorithm (MA)

Burke et al [2] showed in their work for the Nurse Rostering Problem (NRP) that good results can be obtained using an hybrid evolutionary algorithm (EA). Therefore this population based approach is also considered.

An EA [5] uses a pool of parent solutions which are pairwise recombined to create offsprings. These offsprings are then mutated and replace the pool of parent solutions following a specific a replacement strategy. A hybrid EA (or MA [6]) uses local search to improve the offsprings before the replacement is done.

As a solution is represented as a list, a special recombination operator is implemented: Given two parent solutions (P_1, P_2), the offspring is initially set to have the same tours as P_2. Then one nurse of P_1 is selected at random (n_i). Each unfixed mission of n_i assigned in P_1 is removed in the offspring solution. Then every remaining mission of n_i in the offspring solution is moved to the best nurse n_j, where $n_j \neq n_i$. In the final step, the missions of n_i in P_1 are assigned to n_i in the offspring solution.

To provide higher diversity during the search of the MA, the offspring is mutated by selecting a nurse n_i at random and reassigning all unfixed tours of this nurse to other nurses n_j, where $n_j \neq n_i$, maximizing the objective value.

For a given probability, an improvement heuristic will try to improve the offspring further. We use a Variable Neighbourhood Descent (VND) procedure, as described in [7]. To achieve a better balance between exploration and exploitation, the VND aborts after a certain time limit.

The population is replaced using a steady-state approach, where an offspring always replaces the worst solution in the current population.

Scatter Search

Another population based approach that we evaluate is scatter search. As described by Burke et. al. [3], this metaheuristic creates also good solutions for the NRP.

Scatter Search [4] uses a small population of diverse solutions and creates subsets of small size from this pool. These subsets are then combined using a solution combination method to create new solutions which are then improved using a local search algorithm.

We use the subset generation and combination operators as described in Burke et. al. [3]. The combination operators is a construction heuristic using candidates (mission to nurse assignments), which are ranked based on the votes of the guiding solutions, to create a new solution. To calculate the similarity of two solutions, we use a simple count of same mission to nurse assignments. For the improvement we use a VND [7] like for the MA described above.

3 Preliminary Results

First results, using 4 instances and a time limit of 10 minutes, show, that the MA performs best in terms of finding the best solutions. A Variable Neighbourhood Search (VNS), using a random shift-mission move as shaking procedure and the VND described in [7], performs 1-8% worse then the MA. The SAHH finds reasonably good solutions (around 17-35% worse) and was able to reduce the number of constraint violations in one instance. Scatter Search also seems promising (18-35%), but time expensive and therefore adjustments will be applied and tested in future work.

4 Discussion and Conclusion

In this abstract, we propose different approaches to solve real-world HHC instances in a flexible framework for different homecare service providers. The contribution of this work is to provide different algorithms for the HHC problem and evaluate their performance. As the flexibility is a particular goal of the framework, rather generally applicable solution techniques have to be considered where too specialized improvement and construction approaches must be avoided.

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