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A matheuristic for routing real-world home service transport systems facilitating walking

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ABSTRACT

This paper provides a solution procedure for a state-dependent real-world routing and scheduling problem motivated by challenges faced in the urban home service industry. A transport service delivers staff members of different qualification levels to clients and picks them up after completion of their services. The possibility to walk to clients, interdependencies, time windows, assignment constraints as well as mandatory working time and break regulations are considered. The introduced matheuristic consists of two stages, identifying potential walking-routes and optimising the transport system. The presented numerical studies are performed with real-world based instances from the Austrian Red Cross, a major home health care provider in Austria. The results show that implementing walking and pooling of trips in solution procedures decreases the number of required vehicles substantially.

1. Introduction

Urbanisation causes various challenges like congestions and limited parking spaces for home service providers. This paper is motivated by a project performed with the Austrian Red Cross, a major home health care (HHC) provider in Austria; however, similar challenges occur in various home services such as appliance repair, routine maintenance and private tutoring. These services offer high social benefits for clients; nevertheless, they only contribute little to environmental sustainability (Halme et al., 2006). While public transport can be utilised in urban areas (e.g. Hiermann et al., 2013; Rest and Hirsch, 2013), it often lacks the flexibility of privately owned vehicle fleets due to infrequent service times and limited storage capacities for required equipment. As a result, most nurses operate separate vehicles, which leads to high fixed and operating costs as well as low vehicle utilisations, especially when facing long client service times. Additionally, a growing number of nurses are without driver's permits or reluctant to drive. Consequently, with HHC demand drastically increasing (Rest et al., 2012), novel sustainable concepts are required. This is further stimulated by stricter environmental regulations and the desire to decrease companies' ecological footprints. To achieve this, non-technology driven approaches are crucial (Moriarty and Honnery, 2013).

Motivated by these challenges, we introduce a solution procedure for the daily planning of HHC providers that operate multiple vehicles to deliver nurses to clients' homes and to pick them up after service is provided. Additionally, nurses can walk to clients. The presented work helps service providers to reduce their fleet and to lower fixed expenses while at the same time service quality is less impacted by the availability of parking spots. The pooling of trips as well as the option of walking can potentially decrease the environmental impact of the home service industry. The model is tested with instances based on real-world data. The contribution of this paper is twofold, namely describing this innovative real-world problem and providing a solution procedure to overcome current challenges. This supports decision-makers to investigate the impact of implementing transport systems, which facilitate both walking and trip pooling.

The remainder of this paper is organised as follows: Section 2 discusses related work. Section 3 defines the problem. Section 4 describes the two-stage solution procedure. Computational results are presented in Section 5 and concluding remarks in Section 6.

2. Related work

The introduced case has similarities with a broad range of problems such as the dial-a-ride problem (DARP), the truck and

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trailer routing problem (TTRP) and various real-world applications. DARPs, a special version of the pickup and delivery problem, occur in taxi and ambulance operations among others and deal with the transportation of customers from a pickup to a delivery location. Transport requests are predefined, which is a major difference to our problem where assignments are part of the optimisation. In most cases, the objective is to reduce the vehicles' drive times under maximum ride times, a user convenience constraint; however, a broad range of variants and extensions are found in the literature. For an overview of DARPs, refer to Cordeau and Laporte (2007), and Parragh et al. (2008).

Compared to the TTRP introduced by Chao (2002), where vehicles are uncoupled en-route as certain customers cannot be reached otherwise, sub-routes in our problem do not have to end at their start, but can end at any job. Furthermore, they can be continued on other vehicles and vehicles and nurses move individually at the same time. Lin (2011) introduces a two-stage heuristic for a real-world courier problem containing heavy resources, which carry lighter resources. These lighter resources, e.g. a courier, can pickup and deliver items independently after being unloaded by the heavier resource, which itself can serve clients. In contrast to our problem, the lighter resource can only re-join the heavier one at the last stop of the tour before returning to the depot. This also indicates that a lighter resource can only perform one sub-route. Compared to an independent strategy, lower average total costs and lower usages of heavy resources are achieved under certain conditions.

In the context of HHC, Trautsamwieser et al. (2011) consider different qualification levels, assignment constraints, working time regulations and mandatory breaks in daily planning, where each nurse operates a separate vehicle. An exact model and a variable neighbourhood search-based heuristic are proposed. Concerning working time regulations and mandatory breaks, related work is found in the context of various real-world applications. Nevertheless, despite their high importance in practice, only little attention is received in the literature. Goel (2009) proposes a large neighbourhood search to comply with European Community driving time regulations. Kok et al. (2010) show the significance of these regulations and the resulting increase in routes and durations. A restricted dynamic programming heuristic combined with a break scheduling heuristic is introduced.

Similarly, the impact of synchronisation and interdependencies on vehicle routing problems (VRP) is little analysed in the literature. Bredström and Rönnqvist (2008) describe real-world problems where including temporal synchronisation has a large impact on solution quality and feasibility. Solution approaches based on mixed integer programming are provided. To the best of our knowledge, Doerner et al. (2008) were the first to explicitly consider interdependent time windows in a real-world problem faced in blood transportation. As in our problem, a change in the sequence of one route can lead to infeasibility of all other routes. A mixed-integer programming model, three variants of heuristic solution approaches and a branch-and-bound algorithm are proposed. A survey by Drexl (2012) on synchronisation gives an extensive overview of its importance and the resulting challenges. Of special interest are VRPs with transfers or transshipments, where similar challenges are faced concerning feasibility testing and interdependencies as in our problem. Qu and Bard (2012) implement a propagation algorithm to check feasibility of insertions in an aircraft transport problem with transshipments. Masson et al. (2014) model the feasibility problem for a DARP with transfers as a simple temporal problem and use the Bellman-Ford-Cherkassky-Tarjan algorithm to solve it. None of these solution approaches consider mandatory break regulations or the additional option of walking to subsequent clients. Furthermore, both applications consider specific transfer locations and transfers are not mandatory. This is a major difference to our problem, where transfers occur at clients and have to be performed due to the time-lag between delivery and pickup.

In summary, a broad range of work has been done for related issues; however, published solution approaches are not directly applicable to our problem as various special characteristics are not considered.

3. Problem description

The problem is defined as an extended many-to-many multi-trip DARP. The following outlines the main differences to the classical DARP. (i) The objective is to minimise vehicles' drive times and working times over all nurses considering mandatory break and working time regulations. Service durations are constant and therefore excluded and breaks do not count towards working times. (ii) Transport requests are not predefined, but decided within the model. All jobs have to be served; however, individual requests depend on which nurse can be feasibly assigned at the lowest cost. Furthermore, this introduces interdependencies. The time at which a nurse has to be picked up from a job depends on when the nurse was delivered. (iii) Nurses can walk between jobs. Hence, not all jobs need to be visited by the transport service.

Input is a set J of n jobs ($i \in J$), each requiring a service with a certain qualification requirement q_i^J. To serve these jobs, the service provider has a set M of m nurses ($j \in M$), each associated with a qualification level q_j^M, and a set K of k vehicles ($h \in K$). Jobs can only be performed by a nurse of at least the same qualification level, i.e. $q_j^M \geq q_i^J$. To ensure employee satisfaction, the maximum deviation of qualification level and requirement is set to E, i.e. a nurse of level q_j^M can perform jobs of $[q_j^M - E, q_j^M]$. Additionally, the number of downgradings S, i.e. when an overqualified nurse performs a service, are limited. All jobs have to be started within a hard time window $[e_i, l_i]$, whereas e_i is the earliest and l_i the latest allowed start time. A service takes d_i time units; the service start time is denoted by B_i, while A_i^M and A_i^K denote the arrival time of the nurse and vehicle respectively.

The problem is defined on a complete graph $G = (V, A)$, where each job acts as a potential delivery and pickup location. As a consequence, the vertex set $V = \{v_0, v_1, \ldots, v_{2n+1}\}$ contains delivery vertices $D = \{v_1, \ldots, v_n\}$ and pickup vertices $P = \{v_{1+n}, \ldots, v_{2n}\}$ for all jobs. All tours start and end at a depot indicated by v_0 and v_{2n+1}. Each arc $(i,j) \in A$ is associated with a walking time $t_{i,j}^M$ and a driving time $t_{i,j}^K$. If utilised, the vehicle load Q_i is at least one, indicating the driver, who cannot serve any jobs. The maximum number of nurses on board is constrained by $C - 1$. Each vehicle can have multiple tours. Waiting of vehicles at any other place than the depot is not allowed and, as multiple drivers are available, the total time a vehicle can be utilised is not constrained.

The working time of a nurse is limited by H. If it exceeds R, a break of r time units has to be scheduled. This break starts before or after any job and ends at the same location. Furthermore, it has to be scheduled at a time so that between start or end of the working day and the break, no continuous working time longer than R exists. Maximum detours L of nurses due to other stops on the vehicles' tours must be observed to limit ride times. Therefore, the time spent between pickup and delivery on a vehicle's tour $t_{ij}^{K''}$ is compared to a direct transport ($t_{ij}^{K''} \leq t_{ij}^K + L$). Nurses can also walk to their next job; however, only if t_{ij}^M is below a predefined threshold F. Walking to any other places is not enabled. The cumulative walking time and cumulative wait time of a nurse between each delivery and pickup by the transport service are constrained by U and W respectively. Waiting at a job might result from arriving too early ($A_i^M < B_i$) or from waiting to be picked up ($B_i + d_i < A_{i+n}^K$).

Table 1 summarises the notation, Table 2 the objective and constraints of this problem.

3.1. Walking-routes

We define walking-routes as the job or sequence of jobs visited by a nurse between delivery and pickup by the transport service. If walking-routes consist of more than one job, delivery and pickup locations differ and nurses walk in between. Walking to and from the depot is not enabled as such routes do not have to be considered in the vehicle routing.

Example 1. *The left side of Fig. 1 gives a relaxed example with two nurses (M_1 with $q_1^M := 2$; M_2 with $q_2^M := 1$) and one vehicle. Eight jobs have to be visited*; $\{1, 4, 6, 7\}$ *with* $q_i^J := 1$ *and* $d_i := 45$ min *and* $\{2, 3, 5, 8\}$ *with* $q_i^J := 2$ *and* $d_i := 105$ min. *Starting from the depot, the vehicle visits J_1 and J_2 and delivers a nurse at each stop. M_1 arrives at J_1 after* 25 *minutes, M_2 at J_2 after* 28 *minutes. Note that M_2 needs an additional minute longer compared to a direct delivery from the depot due to the delivery of M_1. After finishing their jobs, both nurses walk to their next jobs, where M_1 downgrades at J_3. Both nurses have to take a break* ($r := 30$ min) *which is scheduled after a job. After completing the last job on their walking-routes, the vehicle picks them up and brings them back to the depot, as in the case of M_2, or to another job where M_1 starts a new walking-route.*

3.2. Interdependencies

Time-lags between deliveries and pickups introduce interdependencies between vehicles' and nurses' tours. To perform a pickup, the nurse and the vehicle have to be at the same vertex at the same time. To perform a delivery, the nurse has to be on board the vehicle. In the worst case, a change in one tour can lead to infeasibility of all other tours.

Table 1
Notation.

Notation	Definition
n	Number of jobs
m	Number of nurses
k	Number of vehicles
J	Set of jobs, $J = \{1, \ldots, n\}$, associated with a qualification requirement q_i^J
M	Set of nurses, $M = \{1, \ldots, m\}$, associated with a qualification level q_j^M
K	Set of vehicles, $K = \{1, \ldots, k\}$
D	Set of delivery vertices, $D = \{v_1, \ldots, v_n\}$
P	Set of pickup vertices, $P = \{v_{1+n}, \ldots, v_{2n}\}$
e_i, l_i	Earliest/latest start time of J_i
A_i^M	Nurse's arrival time at J_i
A_i^K	Vehicle's arrival time at J_i
B_i	Nurse's service start time at J_i
Q_i	Vehicle's load when leaving J_i
w_i	Nurse's wait time at J_i
d_i	Service duration of J_i
t_{ij}^K	Driving duration of (i, j)
t_{ij}^M	Walking duration of (i, j)
H	Maximum working time
R	Maximum working time without a break of r time units
F	Maximum walking duration between two jobs
C	Maximum vehicles' capacity including the driver
L	Maximum detour between pickup and delivery
U	Maximum nurse's cumulative walking between each delivery and pickup
W	Maximum nurse's cumulative waiting between each delivery and pickup
E	Maximum allowed qualification deviation between job and nurse
S	Maximum number of downgradings allowed per nurse

Table 2
Objective and constraints.

Objective	
Nurses' working times without service durations	Nurses' working times are the difference of when each nurse last returns to the depot and first leaves it, without times spent on breaks. From the objective value, constant service durations are deducted. Consequently, it includes times spent on vehicles, walked and waited.
Drivers' working times	Durations which the vehicles are not in the depot are added to the objective value to represent drivers' working times.
Constraints	
Number of nurses	Limits the number of available nurses per qualification level.
Maximum walking duration	Limits the walking duration between two jobs.
Cumulative maximum walking duration	Limits the sum of walking durations between each delivery and pickup.
Maximum working time	Limits the working time of a nurse.
Maximum working time without a break	Nurses who work longer than this threshold have to take a break.
Breaks	Breaks are scheduled before or after a job and end at their start location. Before and after this break, no continuous working duration longer than the maximum working time without a break is allowed.
Time windows	Each job has to be started within its hard time window.
Maximum ride time	Limits nurses' detours between each pickup and delivery.
Qualification requirements and deviations	Jobs are performed by nurses at or to a certain amount above the job's qualification requirement.
Downgradings	A nurse can perform a predefined maximum number of jobs requiring lower qualifications.
Maximum waiting of nurses	The sum of waiting times is limited between each delivery and pickup of a nurse.
Depot constraint	A nurse starts and ends the working day at the depot and trips from/to the depot are performed with the transport service.
Number of vehicles	Limits the number of available homogeneous vehicles.
Load constraint	At any given time, the vehicle capacity cannot be exceeded.
Vehicle waiting	Vehicles can only wait at the depot.

Example 2. *On the right side of Fig. 1, the visiting order of J_1 and J_2 is reversed. As a result, M_2 finishes the walking-route one minute earlier, while M_1 needs five minutes longer. Without interdependencies such a swap only requires an update and feasibility test in the corresponding tour. In our example, the vehicle has to pickup M_2 one minute earlier and M_1 five minutes later, which can lead to feasibility conflicts. Furthermore, at J_8, the nurse and the vehicle are no longer synchronised, which results in an additional, potentially infeasible, wait time of six minutes.*

As a result, time windows, working and break times have to be checked for feasibility and start times of each vehicle's tours have to be optimised. Note that the concept of forward slack time (Savelsbergh, 1992), which is often utilised to minimise waiting within one tour by postponing the start time to the optimal position, is not applicable in this setting as pickup times result from other tours' delivery times. Additionally, pickups and deliveries of one nurse might occur on different vehicles and postponing might be impossible due to later tours' start times. This might even require shifting earlier tours. Therefore, commonly used solution

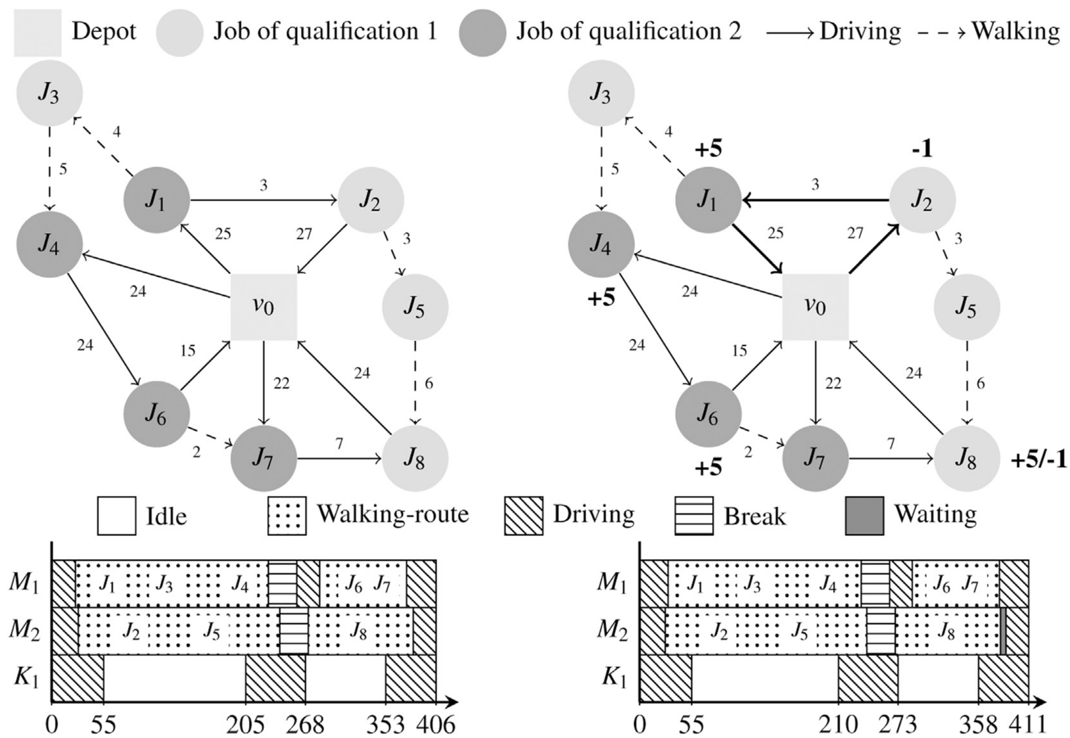


Fig. 1. A transport service with walking-routes (left); Interdependencies between tours (right).

approaches are not well-suited to deal with such problems as multiple vehicles' schedules are not considered.

4. Solution approach

We introduce a matheuristic consisting of two stages, creation of walking-routes and optimisation of the transport system. Fig. 2 gives an overview of the solution procedure. Stage 1 indicates where walking is possible and potentially beneficial. Therefore, a set of feasible walking-routes is created and promising ones are selected by set-partitioning. In Stage 2, starting from the initial set of walking-routes, multiple initial solutions to schedule and route nurses and vehicles are constructed by an extended biased-randomised savings heuristic. Starting from the best found, potentially infeasible, solution, a unified Tabu Search is implemented to restore feasibility and to optimise. This is combined with a walking-routes improvement operator to align the selected walking-routes with nurses' schedules and vehicles' tours.

4.1. Stage 1: selection of walking-routes

Stage 1 creates a set of feasible, non-dominated walking-routes *WR* and selects an initial set WR' containing each job exactly once. Walking takes in most cases longer than going with the transport service. Exceptions result from one-way streets or designated pedestrian areas. This gives driving a natural advantage over walking; however, if a vehicle is not available or costly to relocate, walking is beneficial. Additionally, driving may cause detours for other nurses on board and result in additional working times of drivers. Even deciding to drive where walking is faster might be necessary due to qualification constraints and working time regulations. Due to these trade-offs, *WR* has to provide flexibility to be able to select walking-routes, which fit the vehicle routing.

Algorithm 1 plots the creation of *WR*. For initialisation, *n* walking-routes, each containing a different single job, are added to *WR*. Afterwards, each walking-route in *WR* is tested for single jobs, which are not yet in this route and can be attached at the end. If adding is feasible, i.e. the extended walking-route complies to all

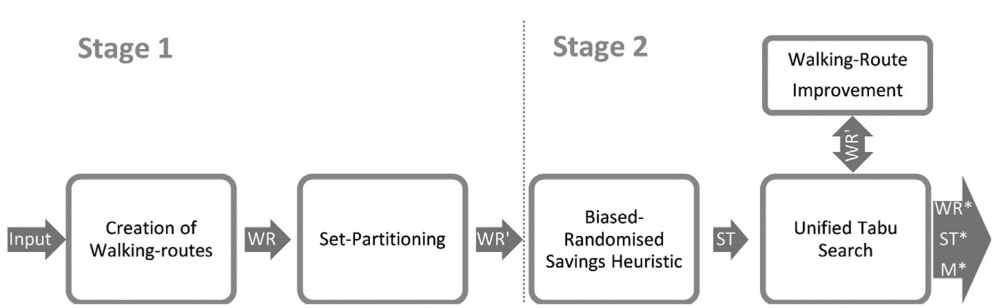


Fig. 2. Two-stage solution approach.

constraints, the walking-route is added to *WR*. The concept of forward slack time (Savelsbergh, 1992) is used to denote the resulting start time window of the walking-route. The procedure is repeated until no new walking-routes can be added.

Algorithm 1. *Construction of WR*

```
WR ← initialise(J);
i ← 1;
while i ≤ WR.size() do
    for j ∈ J do
        if J_j ∉ WR_i then
            WR'_i ← WR_i extended by J_j;
            if feasible(WR'_i) and !dominated(WR'_i) then
                add WR'_i to WR;
            end
        end
    end
    i++;
end
return WR
```

A dominance criterion is modelled to compare new walking-routes to all walking-routes in WR. If start and end jobs are the same and all other jobs are identical in any sequence, the one with a longer duration and tighter time window is removed. If equal, the new walking-route is deleted. However, walking-routes with longer durations, but wider time windows are kept as such walking-routes might enable additional jobs to be added later. Moreover, having wider time windows can be beneficial as more flexibility is given to the vehicle route optimisation.

Example 3. Fig. 3 *illustrates examples for stored and rejected walking-routes. Time windows of jobs and walking-routes are indicated in the squared brackets. To simplify,* d_i: $= 1$ min *at each job is assumed. Comparing* WR_1 *and* WR_2*, both walking-routes contain the same jobs and the same start and end location. Due to a higher duration compared to* WR_1*,* WR_2 *is removed. In contrast, when comparing* WR_3 *and* WR_4*,* WR_4 *is kept due to its wider time window.*

From *WR*, an initial set of walking-routes WR' containing each job exactly once is constructed. Optimising the duration of the selected walking-routes would result in each walking-route only consisting of one job. As a result, a set-partitioning model selects WR' minimising both walking-routes' durations d_{WR_i} and driving distances from the depot to delivery and pickup vertices (1). Constraints (2) guarantee that each job is selected exactly once and (3) enforce that the decision variables y_i are binary.

$$\text{Minimise}: \sum_{i \in WR} y_i \left(d_{WR_i} + t^K_{0,WR_{i_D}} + t^K_{WR_{i_P},0} \right) \tag{1}$$

$$\text{Subject to}: \sum_{i \in WR: j \in WR_i} y_i = 1 \quad \forall j \in J \tag{2}$$

$$\text{Subject to}: \; y_i \in \{0,1\} \quad \forall i \in WR \tag{3}$$

After the set-partitioning problem is solved, the problem size is reduced to the number of selected walking-routes n'. The first job of each selected walking-route is added to $D = \{v_1, \ldots, v_{n'}\}$ and the last job to $P = \{v_{1+n'}, \ldots, v_{2n'}\}$. Which WR' is best used for Stage 2 depends on the instance characteristics; however, the proposed set-partitioning model finds a WR' which is suited for different conditions as it explicitly deals with the trade-off between walking and driving.

4.2. Stage 2: optimizing the transport system

Stage 2 routes the vehicles and schedules each walking-route to a nurse. The latter is done by enforcing a first-in-first-out (FIFO) rule. If multiple nurses can be assigned to a job, the one who entered the vehicle first is assigned if qualifications, downgradings, wait times, breaks and maximum working time regulations are held in compliance. This requires checking all walking-routes before the delivery of the nurse as well as all subsequent walking-routes. Enforcing this FIFO rule is practical from a maximum ride time perspective, because delivering the nurse who entered the vehicle first results in the shortest maximum ride times.

Starting from WR', an initial solution is constructed. We tested three different constructive heuristics for our problem based on a time-oriented nearest neighbour heuristic (Solomon, 1987), a sequential savings heuristic (Clarke and Wright, 1964) and a parallel savings heuristic (Clarke and Wright, 1964), whereas the latter clearly outperforms the other approaches. From a myopic point of view, lowest total costs are reached if a picked up nurse is delivered to a nearby feasible walking-route. The parallel savings heuristic finds such pairs.

4.2.1. Parallel savings heuristic

The heuristic starts with a set of tours ST', where each tour contains only one walking-route with an individually assigned nurse. Two tours are merged if a total objective value reduction is achieved starting from the merger with the highest savings value. However, our approach differs substantially from the savings heuristic of Clarke and Wright (1964) due to the special problem characteristics. Savings values have to consider the total cost of a tour $c(ST'_i)$, which includes the time spent by all nurses on board the vehicle as well as by the driver. Therefore, the savings value is derived from the arcs travelled by the merged tour multiplied by the vehicle's load compared to the costs of the separate tours as shown in Equation (4).

$$\text{Savings}_{ST'_l,ST'_h} = \sum_{(i,j) \in ST'_l} \left(t^K_{i,j} Q_i \right) + \sum_{(i,j) \in ST'_h} \left(t^K_{i,j} Q_i \right) - \sum_{(i,j) \in ST'_{l,h}} \left(t^K_{i,j} Q'_i \right) \tag{4}$$

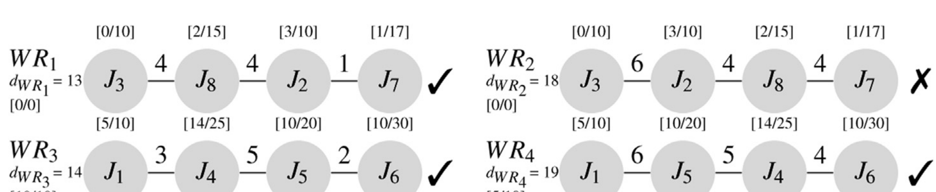


Fig. 3. Dominance criterion of walking-routes.

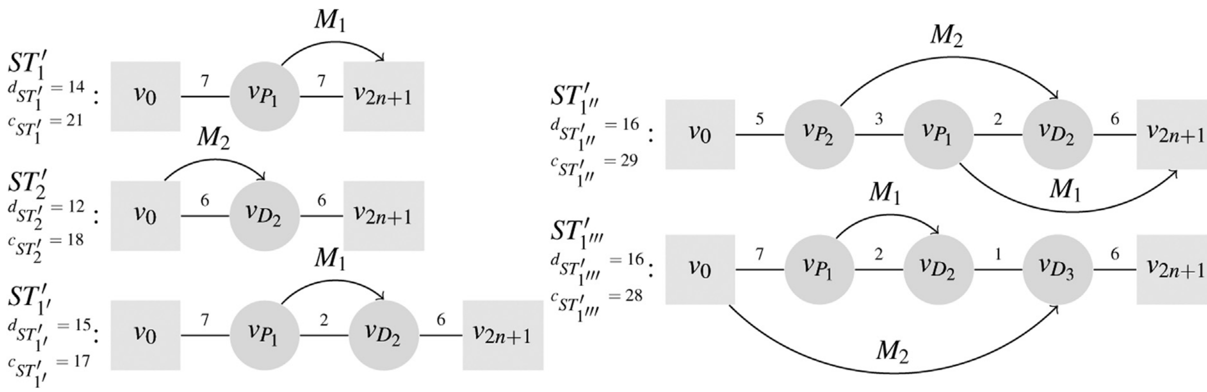


Fig. 4. Calculating and updating tour costs.

Example 4. Figure 4 *shows the savings values calculation where arrows indicate when nurses are on board. Merging* v_{P_1} *with* v_{D_2} *leads to a savings value of 22* ($c_{ST'_1} + c_{ST'_2} - c_{ST'_{1'}}$) *as* M_1 *is picked up and directly delivered to the next job. After performing this merger, savings values are updated. For instance, adding* v_{P_2} *in the front requires reassigning nurses, while attaching* v_{D_2} *at the end requires an additional nurse from the depot.*

A merger impacts all related savings values and can lead to a change in the nurses' schedules considering the FIFO rule. Moreover, merging tours require shifts in the start times of all related tours due to interdependencies between delivery and pickup times. In the best case scenario, this affects only two tours, i.e. the ones of the merged tours' pickups and deliveries. In most cases, however, if the related tours contain additional jobs that require updating their related pickups or deliveries, it propagates into multiple tours. As a consequence, the buffer by which the start time of a tour can be postponed always depends on the tightest constraint node in all related tours. This also leads to infeasible cycles where moves in start times are not possible.

Example 5. Fig. 5 *illustrates infeasible cycles on an example where* $d_{WR'_7} := 35\text{min}$ *and* $d_{WR'_3} := 30\text{min}$*. By checking the buffer of* ST'_2*, attaching* v_{P_7} *is possible. It requires postponing* ST'_1*; however, a move in its start time requires moving the start time of* ST'_2*. This again requires moving the start time of* ST'_1*, which results in an infinite loop.*

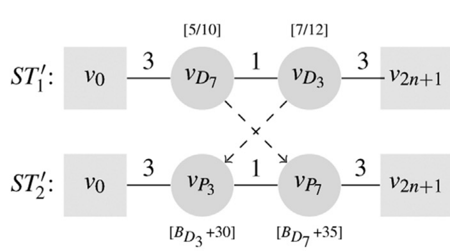
Working time, ride time and qualification compliance are checked at each calculation of savings values. In case of infeasibility, the merger is rejected. Required breaks, if feasible, are scheduled before pickups when evaluating mergers and require an update of all related start times and buffers as the time-lag between delivery and pickup is increased. Additionally, if walking-routes are served by different nurses after a merger, previously scheduled breaks have to be updated. Feasibility of breaks concerning the maximum continuous working time and waiting of nurses are not included in the calculation of savings values to speed-up construction; however, both factors are considered in the solution evaluation explained in Section 4.2.2.

The savings heuristic often returns solutions that require more vehicles and nurses than available. If an entire schedule of a surplus nurse can be performed by an overqualified vacant nurse, the nurses are exchanged. Two methods are introduced to further decrease the number of required nurses. Tours with negative savings values are merged if the number of surplus nurses can be reduced. Therefore, the savings values are divided by the number of reduced nurses. Additionally, schedules of two nurses can be combined into one if all constraints are fulfilled. In this case, an additional wait time at the depot might occur, which is limited by W. These two options are evaluated and the least costly one is executed. This is repeated until the number of given nurses of each qualification level is sufficient or no further options exist.

To schedule tours to vehicles, a simple insertion heuristic is used. Each constructed tour is indicated with a duration and time window. Starting with the tour having the tightest time window, all positions to insert the tour on each vehicle are checked until a feasible one is found. Shifting the start time is limited by the buffer and requires a shift in all related tours. If no feasible position exists, the tour is assigned to the vehicle with the least number of tours at the position where the smallest time conflict occurs. After all tours are assigned, ST' is evaluated.

4.2.2. Solution evaluation

Four penalty factors are added to the evaluation function $f(ST') = c(ST') + \alpha q(ST') + \gamma w(ST') + \tau t(ST') + \eta h(ST')$ to allow infeasible solutions during the search procedure. Costs $c(ST')$ include travel and wait times. Violations of capacity, time windows and ride times are denoted by $q(ST')$, $w(ST')$ and $t(ST')$ respectively. $h(ST')$ states how many nurses more than available are needed to serve ST'. Nurses' schedules have to comply with working time and break regulations. To test feasibility, nurses' schedules are first set ignoring start and wait times and only assignments between two



$ST'_1 : Start_1 = 3; A^K_{D_7} = 6; A^K_{D_3} = 7;$
$buffer_1 = min(l_{D_7} - A^K_{D_7}, l_{D_3} - A^K_{D_3}) = 4;$

$ST'_2 : buffer_2 = buffer_1;$
$A^K_{P_3} = 37 \rightarrow Start_2 = 34;$
$A^K_{P_7} = 41 \rightarrow Start_2 = 37;$
$\Rightarrow A^K_{P_3} = 40 \Rightarrow A^K_{D_3} = 10 \Rightarrow A^K_{D_7} = 9$
$\Rightarrow A^K_{P_7} = 44 \Rightarrow A^K_{P_3} = 43 \Rightarrow \ldots$

Fig. 5. Infeasible cycles.

nodes are checked, i.e. from depot or pickup to delivery. After all assignments, the complete schedule of each nurse is tested. If H or S is violated, nurses' schedules are split at the positions which lead to the least increases in $f(ST')$. Splitting indicates not delivering a previously picked up nurse, but instead delivering a new one from the depot. If a split is not possible, the penalty term $h(ST')$ is increased by one. This occurs if a walking-route's duration plus the time for delivery and pickup violates H.

Example 6. *Fig. 6 indicates splitting. The schedule of M_1 consists of three walking-routes leading to a working time violation, while M_2 is vacant. The split is performed at the cheapest position, assumingly at WR'_1. M_1 is not delivered to v_{D_1}, but instead returned to the depot. M_2 arrives from the depot at v_{D_1} and continues the further schedule previously assigned to M_1. Due to the nurses' additional time spent on the transport service, $c(ST'_1)$ increases.*

Breaks are placed within or after a walking-route and scheduled within $[\min(H, H'_i) - R, R]$ of the nurse's schedule, whereas H'_i indicates the working time in case of maximum waiting at each walking-route. This guarantees feasibility of the break position after optimisation of wait times as it considers the maximum potential working time under the current schedule. If no position complies with this rule, the nurse's schedule is split. If a split is not possible, i.e. breaks are required within walking-routes, but tight time windows do not allow, $h(ST')$ is increased by one.

Start times of ST' are optimised by solving a linear program. As wait times and time window violations contribute to $f(ST')$, the optimal start times of each vehicle's tour have to be calculated to fully evaluate a solution. Input is a solution ST' with a fixed order of tours per vehicle $ST'_{h,j}$. The objective function (5) sets each vehicle's tour's start time $A^K_{ST'_{h,j}}$ so that wait times w_i are minimised. If no feasible solution exists, the time window violation terms χ_i and φ_i are minimised to find the best infeasible solution. Therefore, the penalty terms are multiplied by the length of the planning horizon T (e.g. 1440 min). χ_i (φ_i) indicates that the vehicle arrives too early (too late). Constraints (6) limit the wait time per walking-route. (7) guarantee time window compliance of deliveries, whereas t'_i indicates the cumulative time it takes to reach i after starting from the depot based on the tour where i is included. (8) set the time-lag between delivery and pickup of the walking-route to its duration d_{WR_i}. By considering wait times after deliveries w_i and before pickups $w_{i+n'}$, these constraints ensure that vehicles and nurses are synchronised or that the relevant penalties are set accordingly. Additionally, if a break is scheduled at this walking-route, the pickup is further delayed by r_i. Otherwise, r_i equals zero. Note that breaks are not decision variables, but fixed prior to the run of the optimisation model. This is crucial to speed up computation time and to circumvent the need for binary variables. Furthermore, (9) enforce maximum working time compliance and ensure that no additional breaks are required after wait times are added to the nurses' schedules. Therefore, Z_j states the buffer between H (if a break is scheduled) or R (if no break is scheduled) and the current working time of the nurse including wait times within walking-routes $w_{WR'_i}$. Moreover, (10) ensure that multiple tours of one vehicle are not performed at the same time; (11) that vehicles' start times are within the planning horizon and (12) the non-negativity of the decision variables.

$$\text{Minimise}: \sum_{i=1}^{2n'} w_i + T \sum_{i=1}^{2n'} (\chi_i + \varphi_i) \tag{5}$$

$$\text{Subject to}: \quad w_i + w_{i+n'} + w_{WR'_i} \le W \quad \forall i \in D \tag{6}$$

$$e_i \le A^K_{ST'_{h,j}:i\in ST'_{h,j}} + t'_i + w_i + \chi_i + \varphi_i \le l_i \quad \forall i \in D \tag{7}$$

$$\begin{aligned} & A^K_{ST'_{h,j}:i\in ST'_{h,j}} + t'_i + w_i + \chi_i + \varphi_i + d_{WR'_i} + w_{i+n'} + r_i \\ & = A^K_{ST'_{h,j}:i+n'\in ST'_{h,j}} + t'_{i+n'} + \chi_{i+n'} + \varphi_{i+n'} \quad \forall i \in D \end{aligned} \tag{8}$$

$$\sum_{i\in M_j} (w_i + w_{i+n'}) \le Z_j \quad \forall j \in M \tag{9}$$

$$A^K_{ST'_{h,j-1}} + d_{ST'_{h,j-1}} \le A^K_{ST'_{h,j}} \quad \forall h \in K, \forall j \in ST'_h \setminus 0 \tag{10}$$

$$0 \le A^K_{ST'_{h,j}} \le T \quad \forall h \in K, \forall j \in ST'_h \tag{11}$$

$$w_i, \chi_i, \varphi_i \ge 0 \quad \forall i \in D \cup P \tag{12}$$

With the optimised tour start times and resulting wait times, schedules are finalised and wait times and time window violations are added to $f(ST')$. In case no solution is found by the linear program, ST' is rejected. Like in splitting, this occurs if a walking-route's duration plus the travel times for delivery and pickup violates H.

4.2.3. Biased-randomisation

In the savings heuristic, the first mergers have a strong impact. Time buffers are reduced after each merger, highly constraining feasible delivery and pickup times. Two mechanisms are introduced to deal with this problem characteristic. By implementing a biased-randomisation (Juan et al., 2013), multiple runs of the savings heuristic are performed in parallel. Hereby, savings values are ranked and a geometric distribution picks the next merger. The parameter β indicates the steepness of the distribution, whereas if β equals 0, the selection is randomly uniform. If β equals 1, the best ranked candidate is always picked. To further diversify, equally good candidates are sorted randomly as otherwise the same candidate is always ranked first and is selected with a higher

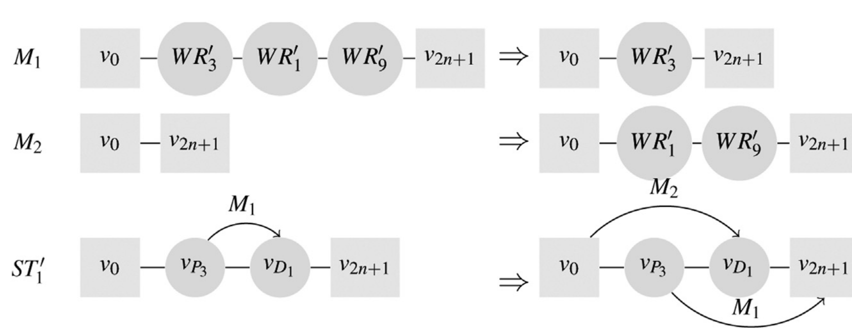


Fig. 6. Splitting nurses' schedules.

probability than equally good mergers. The heuristic stops after a specified number of runs and returns the best, potentially infeasible, solution *ST* as well as the best feasible solution, denoted by ST^*. Algorithm 2 plots the modified biased-randomised savings heuristic.

Algorithm 2. *Modified biased-randomised savings heuristic*

```
f(ST) ← ∞; f(ST*) ← ∞; WR′ ← SetPartitioning(WR);
while !terminate() do in parallel
    ST′, M ← initialise(WR′);
    while !savingslist.empty() do
        randomise() and sort();
        i, j ← biasedrandomise(β);
        merge(ST′_i, ST′_j) and updateaffectedST′(ST′_i, ST′_j);
        recalculatesavings(ST′_i, ST′_j);
    end
    mergeNurses(ST′, M) and assignTourstoVehicles(ST′);
    f(ST′) ← evaluate(ST′, M);
    if f(ST′) < f(ST) then
        f(ST) ← f(ST′) and ST ← ST′;
    end
    if f(ST′) < f(ST*) and feasible()
        f(ST*) ← f(ST′) and ST* ← ST′;
    end
end
return ST, ST*
```

4.2.4. Tabu search

Starting from *ST*, feasibility and optimisation are achieved based on a modified unified Tabu Search (Cordeau and Laporte, 2003) which shows good results for DARPs. Two neighbourhood operators, *PDmove* and *DPmove*, are used to modify a solution. *PDmove* places a delivery on a dummy vehicle only containing this job to find the best position for the corresponding pickup. This position is then fixed and the delivery is reinserted into the solution at its best position. In contrast, *DPmove* places a pickup on the dummy vehicle. The operators enable moving both interdependent nodes with respect to the time-lag and also perform intra-tour moves. To speed up computation times, *PDmove* (*DPmove*) is executed on even (uneven) iterations and several moves of the same type are evaluated in parallel. Additionally, after X_1 iterations without an improvement of ST^* or when ST^* is improved, all vehicles' tours are sequentially checked in random order if inserting or removing a return to the depot at any position improves the solution. If so, *ST* is updated.

Evaluating a solution, as explained in Section 4.2.2, is a time-intensive operation. As a result, $f(ST')$ is calculated in steps. After each step, $f(ST')$ is compared to the total evaluation function value of ST°, which denotes the best solution found so far at this iteration. As each step increases $f(ST')$, evaluation is aborted in case of a higher intermediary evaluation value to save run time. First, vehicle travel times, times spent by nurses walking and on board of vehicles as well as load and ride time violations are recalculated for the tours where a change occurred. Other tours do not change in this respect. Next, start and wait times are optimised. Last, surplus nurses are added to $f(ST')$.

To diversify, as proposed by Cordeau and Maischberger (2012), a penalty is added to all non-improving moves based on the relative number of times this move has been added to *ST* in respect to the total number of performed iterations λ. In our algorithm, this penalty depends on how often a delivery or pickup at a job has been added to a certain tour ρ_{i,ST'_j}. To account for single stop tours, which are frequently added and removed, the number of times a new single stop tour of a certain job is created is stored and new tours are initialised with these values. The penalty term is further multiplied by the weight ζ as shown in Equation (13).

$$g(ST') = f(ST')\left(1 + \zeta\frac{\rho_{i,ST'_j}}{\lambda}\right) \tag{13}$$

In each iteration, the best neighbourhood solution ST° is selected and acts as the current solution *ST* for the next iteration. The delivery or pickup, which was placed on the dummy vehicle, is added to the tabu list. As a result, moving this node to any position is forbidden for θ iterations; however, if moving improves ST^*, relocation is allowed. α, γ, τ and η are either divided by $1 + \delta$ if *ST* is feasible, or multiplied by the same value in case of violations to dynamically adjust the penalty weights.

Depending on the vehicle routing, the optimal set of walking-routes differs. To enable a modification of WR', after X_2 iterations without an improvement of ST^* or if ST^* is improved, a walking-route improvement operator is executed. All walking-routes in WR' are sequentially tested in random order for three modifications. First, if all jobs of two walking-routes can be merged in any sequence into one walking-route. Second, if a walking-route can be split in any sequence into two walking-routes and third, if the sequence of a selected walking-route can be exchanged. Due to the pre-processing in Stage 1, modification occurs with all potential candidates in *WR*, which are already evaluated and tested for feasibility. Note that a split adds a delivery and a pickup to the problem, while a merger removes them. Fig. 7 shows examples for walking-route modifications.

After walking-routes are changed, *PDmove* is run to optimise the tour positions of the modified pickups and deliveries. If an operator improves *ST*, the best modification of this walking-route is saved and acts as the new *ST* for the following operator or walking-route. This guides the search to fit WR' with the vehicle routing and instance characteristics. If only few vehicles are available, more walking is enforced; however, if the number of vehicles is sufficient, walking only occurs if beneficial.

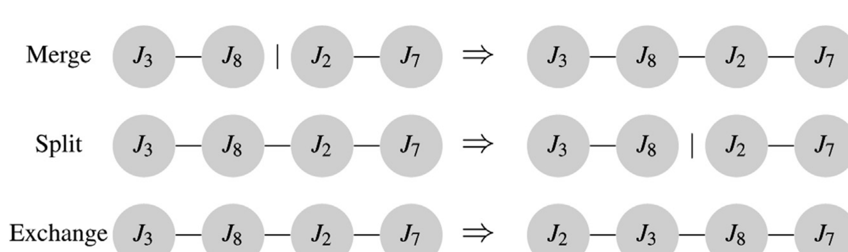


Fig. 7. Walking-route modifications.

The Tabu Search is stopped after a predefined time-limit or a maximum number of iterations and returns walking-routes, vehicles' tours and nurses' schedules of the best found feasible solution.

5. Computational experiments

The described matheuristic is coded in C++ with Microsoft Visual Studio 2012. FICO Xpress-BCL is used to solve the set-partitioning problem and the start time optimisation. Parallelisation is implemented with OpenMP. Computational results were gathered on an Intel Core i7-3930K, 32 GB RAM, with MS-Windows 7 as operating system and 6 threads operating in parallel. All instances and detailed solution files are available at https://www.wiso.boku.ac.at/en/production-and-logistics/research/instances/.

5.1. Instances

Due to the novelty of the concept in both academia and practice, no benchmark instances are available. Our solution procedure is tested with 30 instances based on real-world data provided by the Austrian Red Cross. Nurses have to visit clients to perform services of three qualification requirements varying from housekeeping assistance to medical treatments. Planning horizon is a day. Two geographic distributions of jobs are investigated, an urban and a sub-urban area, indicated in the instance names by “U” and “S” respectively. Duration matrices for walking and driving are calculated with ArcGIS Network Analyst and are based on OpenStreetMap data and a walking speed of 3.6 km/h. All durations are given in minutes and rounded to the next integer value. The mean walking duration between jobs is 29.51 (58.04) minutes for the urban (sub-urban) area. “n” indicates the number of jobs, “k” the given vehicles and “m” the given nurses separated by the different qualification levels starting with the lowest. Three different instance sizes are investigated, namely, 75,100 and 125 jobs. For the smaller instances, jobs where randomly removed from the full list of 125 until the target n was reached. Five different distributions of time windows, service times and qualification requirements were generated for each size and area. These were set based on the probabilities summarised in Table 3 originating from statistical analyses of approximately 2000 real-world visits.

Each vehicle has a C of 6, i.e. it can transport at maximum five nurses. Each nurse is allowed to perform one job at most one level below his/her qualification level ($S := 1; E := 1$). H is 600 min, R equals 360 min and breaks (r) last 30 min W is set to 15 min, F to 10 min, U to 20 min and L is limited by 15 min.

5.2. Parameter setting

To construct initial solutions, each thread executes 75 runs of the biased-randomised savings heuristic with $\beta := 0.45$, which showed the highest average improvement of all β in increments of 0.01 over all instances compared to a non-randomised run. The penalty factors α, γ, τ and η are initialised with 1. Based on Cordeau and Maischberger (2012), δ and ζ are independently set by a uniform distribution between [0, 1] to vary the aggressiveness of intensification and diversification. In accordance to Cordeau and Laporte (2003), θ is set randomly between $[0, 7.5\log_{10}n']$. After 25 iterations without an improvement of ST^*, these values are changed. Adding or removing depot trips (X_1) as well as walking-route improvements (X_2) are performed every $\lceil\sqrt{2n'}\rceil$ iterations without an improvement of ST^* or if ST^* is improved. Each instance is run 10 times to account for the random components in the solution procedures with a run time of 3600 s.

Table 4
Computational results. Bold values indicate the lowest (best) values.

Instance	TS-SPBS Min (min)	TS-SPBS Mean (min)	TS-GT Min (min)	TS-GT Mean (min)	Min ± (%)[a]
U1-n75-k2-m12-8-4	**521**	538.2	551	574.3	−5.44
U2-n75-k2-m12-8-4	**532**	543.3	560	571.9	−5.00
U3-n75-k2-m12-8-4	**526**	539.4	551	570.1	−4.54
U4-n75-k2-m12-8-4	**539**	546.0	552	568.4	−2.36
U5-n75-k2-m12-8-4	**571**	582.5	593	607.0	−3.71
U1-n100-k2-m16-10-6	**702**	708.8	732	770.5	−4.10
U2-n100-k2-m16-10-6	**707**	717.8	734	771.0	−3.68
U3-n100-k2-m16-10-6	**700**	710.6	743	768.1	−5.79
U4-n100-k2-m16-10-6	**690**	698.4	725	744.3	−4.83
U5-n100-k2-m16-10-6	**736**	742.8	755	794.1	−2.52
U1-n125-k2-m20-12-8	**817**	828.1	885	910.0	−7.68
U2-n125-k2-m20-12-8	**834**	846.8	897	920.1	−7.02
U3-n125-k2-m20-12-8	**838**	846.7	896	945.5	−6.47
U4-n125-k2-m20-12-8	**817**	830.1	857	913.1	−4.67
U5-n125-k2-m20-12-8	**791**	804.7	876	920.9	−9.70
S1-n75-k2-m12-8-4	826	832.4	**825**	854.8	0.12
S2-n75-k2-m12-8-4	**755**	771.0	767	791.1	−1.56
S3-n75-k2-m12-8-4	**793**	806.7	799	827.9	−0.75
S4-n75-k2-m12-8-4	**792**	804.7	822	854.8	−3.65
S5-n75-k2-m12-8-4	**821**	839.9	857	872.7	−4.20
S1-n100-k2-m16-10-6	**1027**	1038.4	1080	1102.3	−4.91
S2-n100-k2-m16-10-6	**998**	1011.7	1064	1089.1	−6.20
S3-n100-k2-m16-10-6	**1039**	1055.2	1109	1132.3	−6.31
S4-n100-k2-m16-10-6	**983**	998.1	1045	1067.7	−5.93
S5-n100-k2-m16-10-6	**1096**	1110.1	1171	1205.9	−6.40
S1-n125-k2-m20-12-8	**1224**	1233.3	1304	1346.3	−6.13
S2-n125-k2-m20-12-8	**1185**	1209.7	1253	1300.0	−5.43
S3-n125-k2-m20-12-8	**1201**	1243.5	1321	1362.4	−9.08
S4-n125-k2-m20-12-8	**1225**	1244.5	1274	1324.5	−3.85
S5-n125-k2-m20-12-8	**1213**	1231.7	1326	1358.0	−8.52

[a] TSSPBS_Min − TSGT_Min/TSGT_Min × 100.

5.3. Results

We compare two versions of the solution procedure. *TS-SPBS* uses set-partitioning and the modified biased-randomised savings heuristic as described in Section 4. In contrast, *TS-GT* starts solely with single stop walking-routes. The initial solution is constructed by adding all deliveries and pickups on one vehicle into one giant tour sorted by e_i. As a result, walking-route selection is completely given to the walking-route improvement operators within the Tabu Search allowing for a broader search procedure, while *TS-SPBS* starts more locally in a promising area of the solution space. The Tabu Search is identical in both versions. Table 4 summarises the

Table 3
Distribution of time windows, qualification requirements and service durations.

$[e_i, l_i]$	[360,630]	[630,900]	[900,1170]	[360,1170]									
Probability	0.25	0.35	0.25	0.15									
q_i^l	1						2					3	
Probability	0.70						0.20					0.10	
d_i	30	45	60	75	90	120	30	45	60	75	90	30	45	60
Probability	0.10	0.30	0.30	0.10	0.10	0.10	0.05	0.25	0.30	0.25	0.15	0.55	0.35	0.10

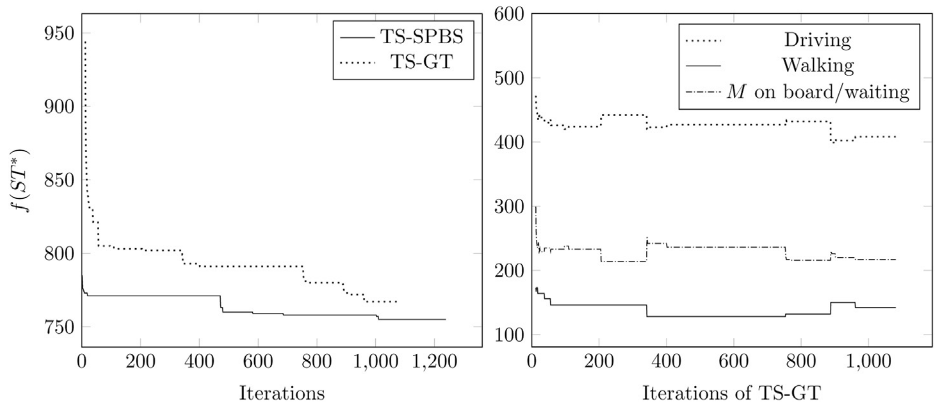


Fig. 8. Solution development for S2-n75-k2-m12-8-4.

computational results. The size of *WR* differs substantially per instance ranging from 225 to 70,500.

The results show the advantage of TS-SPBS. TS-GT performs worse on instances with a large size of *WR*, as the algorithm requires more walking-route improvements to find a suitable WR'. Fig. 8 plots the development of ST^* over run time for one sample instance and separates $f(ST^*)$ into the duration driven by the transport service, walked and spent by nurses on board vehicles plus wait times. Major improvements are achieved in the first iterations, providing feasible solutions after short run times. Note that even increasing the distance driven often results in improvements of ST^* if it reduces time spent on board by nurses. This is an interesting finding as improving the working time over all nurses and drivers does not necessarily lead to reductions in the distance driven. Nevertheless, our solution procedure can be modified easily by adjusting the evaluation function to consider various objectives of decision-makers.

Due to detours, additional wait times and as walking is often slower than driving, total working times of nurses increase compared to planning approaches where nurses operate separate vehicles and time spent looking for parking spaces is ignored. Our results, however, clearly indicate a huge advantage in facilitating walking, especially if jobs are clustered as in urban areas. Furthermore, the concept leads to major decreases in the number of required vehicles. Table 5 states the average number of nurses scheduled in ST^*, which further approximates required vehicles under current business practices, the resulting percentage reduction of vehicles by the proposed concept, the average number of pickups and the percentage of the objective value which is driven, walked and spent on board or waited by nurses.

Additionally, Fig. 9 plots the benefits of facilitating walking for one urban and one sub-urban instance. Substantial improvements are reached by allowing little walking, while enforcing long

Table 5
Average vehicle reduction, pickups, driving and walking in best found solutions.

	Avg.# of scheduled nurses	Avg. vehicle reduction of the concept (%)[a]	Avg.# of pickups	Avg. driving (%)[b]	Avg. walking (%)[c]	Avg. time nurses on board/waiting (%)[d]
U–N75–K2	15.20	−86.84	37.60	45.59	27.18	27.22
U–N100–K2	23.20	−91.38	45.00	44.13	28.49	27.38
U–N125–K2	26.40	−92.42	53.00	43.79	28.80	27.41
S–N75–K2	18.20	−89.01	50.60	55.24	14.33	30.43
S–N100–K2	24.80	−91.94	63.40	54.30	15.28	30.42
S–N125–K2	28.00	−92.86	74.80	53.14	17.34	29.51

[a] $(K/\text{Avg.\# of NursesinST}^* - 1) \times 100$.
[b] $\sum \text{Driving} / \sum f(ST^*) \times 100$.
[c] $\sum \text{Walking} / \sum f(ST^*) \times 100$.
[d] $\sum(\text{Ride Times of Nurses} + \text{Waiting}) / \sum f(ST^*) \times 100$.

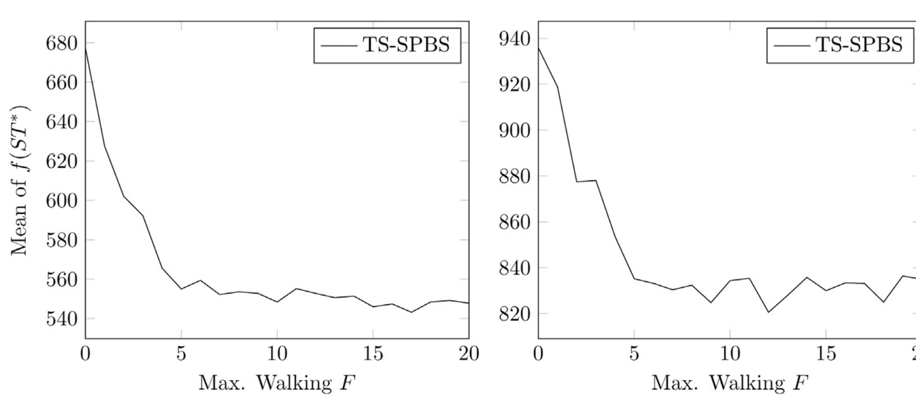


Fig. 9. Sensitivity of five runs with 500 iterations each to the maximum walking duration for U1-n75-k2-m12-8-4 (left) and S1-n75-k2-m12-8-4 (right).

walking durations do not lead to any further benefits. Increases in the objective value are due to the stochastic components of the algorithm.

For more sustainable concepts in practice, it is crucial that both pooling strategies as well as the option to walk are included in solution procedures. Our results indicate the huge potential benefit in doing so. By reducing the number of vehicles, fixed costs are decreased and service is less impacted by the availability of parking spaces. Particularly with increasing demand for home services, urbanisation and stricter environmental regulations, novel sustainable concepts have to be developed and analysed to guarantee future service quality of this crucial industry.

6. Conclusion

Recent challenges faced by home service providers require innovative transport concepts to provide high service levels, whilst being cost-effective and complying with environmental regulations. We developed a matheuristic for the daily planning of real-world home service transport systems, which deliver and pickup staff members to and from clients and facilitate walking. By considering various real-world requirements, the introduced solution procedure is capable of analysing this novel concept and therefore supports decision-makers in investigating the impact of its implementation. Results show that the number of required vehicles can be decreased substantially. Professional drivers relieve staff members of driving and parking pressures allowing them to relax aboard and prepare for their next jobs. Additionally, arrival times at clients are less impacted by failure to find parking spots.

Future work includes real-world case studies to evaluate the various trade-offs and environmental impacts of the concept under different objective functions. Execution times are certainly major limitations of the solution procedure as a linear program has to be solved at each solution evaluation due to interdependencies. Efficient neighbourhood reductions to limit the number of solution evaluations can improve this critical limitation. Additionally, real-world systems are prone to uncertainties and require robust solutions and efficient rescheduling algorithms. Therefore, results from the matheuristic can act as an input for solution procedures, which generate real-time solutions considering stochastic effects.

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