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# Optimizing an integrated home care problem: A heuristic-based decision-support system

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ABSTRACT

With the continuous increase in longevity worldwide, the elderly population requiring home health and social care has been continuously growing over the years. Planning combined home health and social services has been shown to be a very difficult task for current decision-makers, not only due to the high number of working regulations and user-related necessities that need to be considered but also due to the need for synchronizing both types of services. Moreover, it is highly desirable that users are visited by the fewest number of different caregivers in the same kind of appointments (continuity of service). The complex and multi-objective nature of the synchronized home health and social care routing and scheduling problem has called for the development of automated planning systems that are able to obtain efficient solutions in reasonable computational times. In this work, we propose two heuristic methods to optimize routing and scheduling decisions for this problem with an extensive set of constraints and objectives. We use (real) data and information from current care providers in the Barcelona area to build and test our models and provide insights into parameter tuning and the trade-off between the associated operating costs, continuity of service and number of unscheduled services. The proposed tool is made available via a web-based decision support system that allows decision-makers to obtain efficient solutions in an intuitive, complete, and timely manner.

## 1. Introduction

According to the World Health Organization, life expectancy increased by more than 6 years between 2000 and 2019, from 66.8 years in 2000 to 73.4 years in 2019 (WHO, 2020). As a consequence of the continuous increase in longevity worldwide, elderly populations requiring home social and health care services have been growing over the years. As populations grow in age, more individuals tend to encounter reduced mobility over time, often needing long-term support for performing many of their basic daily activities. Moreover, it is known that most care-dependents prefer to live in their homes, as opposed to hospital or nursing homes, for as long as possible (Gillsjö et al., 2011), which has also been shown to be the most cost-effective alternative (OECD, 2017a).

In this context, home social care (HSC) services are often provided to (elderly) people with decreased autonomy but who are not necessarily ill (Gomes and Ramos, 2019). These services include tasks such as feeding, bathing, walking outdoors, or house cleaning. Human resources (caregivers) are not necessarily highly skilled, and therefore are often interchangeable, and they typically do not need to bring any materials or consumables as everything they need can be found at the user's home. Nevertheless, there are several constraints regarding working regulations, users' availability and the user–caregiver assignment decisions that need to be taken into account during the planning of HSC services.

Home health care (HHC) services have also been experiencing increased demand due to the continuous rise in the elderly population and a progressive shift from hospital to home care settings in more recent years (OECD, 2017b; Carpenter et al., 2017). As a result, the number of treatments delivered at the user's home has been rising over the last few decades, with a spike in home care treatments being observed during more recent years due to the COVID-19 pandemic (Sama et al., 2021). HHC refers to "medical and paramedical services delivered to patients at home" (Rais and Viana, 2011). Therefore, they are administered to patients who are ill (or have some kind of medical condition) and are receiving treatment at home. Contrary to HSC, caregivers in HHC are usually highly skilled (mainly medical doctors and nurses) and are permanently linked to the patient as the medical staff responsible for planning and monitoring the whole course of treatment of that patient. Thus, in HHC, caregivers are not interchangeable, and user–caregiver assignment decisions must be stable from week to week.

In some situations, users receive both types of care, thus raising the need for coordination between the different types of services. Planning

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combined home health and social care (HHSC) services has been shown to be a very difficult task for current decision-makers, not only due to the high number of working regulations and user-related restrictions that need to be considered but also due to the need for synchronizing both types of services. For instance, a (social) caregiver may be required to bathe a certain user before a doctor's visit. Alternatively, a hospital nurse may need to collect a blood sample from a user before a social caregiver gives him or her the first meal of the day. Moreover, it is highly desirable that users are visited by the same caregiver in the same kind of appointments, which is referred to as "continuity of service".

The multi-objective and highly constrained nature of the home health and social care routing and scheduling problem (HHSCRSP) makes obtaining efficient solutions an extremely complex and time-consuming task for actual planners. Currently, these tasks are most often done manually in practice, where planners typically split the pool of caregivers or users into smaller subsets and empirically assign services to caregivers accounting for all the regulations and logistic constraints. Social and health care providers are not only interested in a decision support system (DSS) that can (partially) automate and accelerate the laborious planning process, but they are also keen to find answers to some logistical questions such as the following. What is the impact of including synchronization requirements and dependencies between services? What happens if we increase the break length duration? Should we hire more caregivers on a part-time or full-time contract? These questions are addressed in a complementary analysis in this paper to provide insights into managerial questions faced by actual practitioners that can be answered by using the proposed methods.

Therefore, we propose two heuristic methods that are able to find high-quality solutions for the HHSCRSP problem while optimizing for different objectives, such as minimizing non-effective working time and maximizing the continuity of service. These methods optimize towards several other secondary objectives, such as minimizing the number of unscheduled jobs, minimizing the workload differences between caregivers, and minimizing the deviation between services for the same user. To the best of our knowledge, this is the first attempt to solve this problem, including all the necessary working regulations, one-week time horizons, continuity of service during the time horizon and between time horizons, synchronizations and dependencies between jobs, and the previously mentioned different objectives. The design of these heuristics was inspired by social and health care providers in the Barcelona area; nevertheless, both methods can be used (or easily adapted) to solve the HHSCRSP in any other context. Collaborating care providers have provided real data and information to test our models, in which we consider both generally applied constraints and particular restrictions from the Barcelona area and compare our solutions to those obtained by actual practitioners. Our results show that both methods are capable of obtaining efficient solutions regarding the comprehensive set of objectives considered, with low computational times. We also provide insights into parameter tuning, the trade-off between objectives, and the impact of some features of the problem in its solution. The proposed automated and holistic planning system has been made available via the development of a web-based DSS that planners can use to obtain an efficient solution in an intuitive manner.

The remainder of this paper is organized as follows: Section 2 describes the particular problem that we address and provides a literature review on similar approaches to solve similar problems. Section 3 is devoted to explaining the heuristic methods we propose. In Section 4, we outline our computational experiments analyzing the impact of the different parameters of the approaches and elements of the problem. Section 5 provides an overview of the DSS. Finally, the discussion and conclusions are summarized in Section 6.

## 2. Problem description and related literature

### 2.1. Problem description

Many different variants of the home care routing and scheduling problem have been proposed during the last 20 years, and for this reason, there is no unique and formal definition of it. Generally, the idea is to obtain assignment and routing decisions for a number of caregivers who provide home care services (hereafter 'jobs') to a number of users under certain conditions. Caregivers include doctors, nurses, cleaning staff, and other social workers. Users include both patients receiving any sort of health treatments at home and people with decreased autonomy and need for support who benefit from the assistance of social services. Therefore, the jobs that caregivers may provide range from cures and health treatments to bathing and feeding. These jobs are associated with the corresponding users and must be assigned to caregivers and sequenced to form routines for each period (e.g., a day) of a given planning horizon (e.g., a week).

To define the particular problem addressed in this work, we gathered information via interviews, conversations, and surveys performed with users and caregivers from both the social and health care organizations in the Barcelona area. All the requirements, restrictions and objectives considered in our models have been defined in accordance with the information collected during these collaboration activities with the Barcelona City Council and staff members from health care organizations (e.g., primary care centers). Notwithstanding the extensive list of features and constraints considered in this study, we have projected our models to be easily adaptive to a wide range of real applications by, for instance, removing or altering constraints or setting parameters according to the organizations' goals.

In the remainder of this section, we detail the different sets of constraints and objectives included in our problem.

#### 2.1.1. Working regulations

Most of the constraints considered in our study are defined, in practice, by the collective agreement obtained between the caregivers and administrative organizations that define the rights and duties for the contracted work. We refer to this set of rules as collective agreement (CA). In this regard, six main requirements must be considered and have been included in our proposal:

1. Working shifts: A job must start and finish within the daily working hours of the assigned caregiver. Caregivers have their own pre-defined working hours (e.g., 0800–1700), and each job must be started and finished within these labor time windows to comply with the contracted work hours.
2. Weekly working hours: The assignment of a job must respect the weekly working hours limit of the assigned caregiver. The CA sets weekly working time boundaries contracted with each caregiver, i.e., there is a limit on the maximum (and minimum) working hours that each staff member should work, in total, in a given week (e.g., 37 h). The increasing life expectancy and the continuously growing number of elderly people involve a demand of these home cares even higher than the one served currently and the consequent large waiting list to access them. Therefore, the minimum weekly working time is always achieved, and it is relaxed in our approach. In the highly unlikely event of falling into a situation where there are not enough jobs to fulfill the minimum weekly working time requirements, the pool of caregivers available and/or their daily available working time should be adjusted by the organization in the input data-set, i.e., resize the workforce accordingly before running the method.
3. Breaking time: There must be a break in the middle of each daily route. Each caregiver has the right to rest for a (short) time interval during their daily route. In our case study, for instance, part time workers usually have a break of 20 min, which should be planned after (at least) 2 h of consecutive work time has passed. For full-time (FT) workers, this break occurs as a meal break that divides the daily journey into two parts: the morning and afternoon shifts. Therefore, for FT workers, breaks are intended to be placed after 1300 and typically take 30 min, but they can vary up to 120 min at the discretion of each specific caregiver.

4. Consecutive daily working time: Each route must not exceed a predefined consecutive work time limit (without a break). According to the CA, under any circumstance, the consecutive work time may exceed a certain predefined threshold (e.g., 6 h, or 360 min). Although this threshold is seldom achieved due to the break insertion for routes that take longer than 2 h, it is needed to cover particular situations where the 6 h limit time could be exceeded without a break being inserted in between (e.g., scheduling one job of 1 h 30 min and then another job of 5 h would be possible without this constraint).
5. Rest time between two consecutive days: There is also a minimum rest time between two consecutive days to satisfy the rules of the CA. From one day to another, every caregiver must have a nonworking period of at least 12 h (720 min) for the Barcelona case study.
6. Working days: Caregivers are only assigned jobs on their contracted work days. Each caregiver is previously scheduled to work on specific days, e.g., Monday–Friday. This agenda already considers a mandatory minimum rest period of at least 2 days (48 h) during the whole week.

#### *2.1.2. Time constraints*

In addition to caregivers' time constraints stipulated by working regulations, there are other time requirements that our problem includes:

1. Time windows: Each job must start within its time window limits. There are specific time windows at which jobs must be performed, especially in social care. For instance, if the specific job is to cook and deliver lunch to a user, the job may have to be performed between 1300 and 1600. There are also evening jobs to, for instance, help a user get in bed before a night's sleep.
2. Travel times between locations: Each route of each caregiver on each day departs and arrives at a depot. In the HSC component, the depot is assumed to be the caregivers' home, and therefore, it is assumed that travel times between depots and users are equal to zero as the caregiver is assumed to start their journey at the first user's location and finish his or her labor journey at the last user. In the HHC component, caregivers typically depart and arrive from/to the primary health center to collect/drop materials, and therefore travel times from the depot and users are considered (usually between 5–30 min). Travel times can refer to any type of transportation mode, including walking, public transport or private car. In our case study in the high-density Barcelona area, transport between locations is performed by walking; however, the methods can accommodate any type of transportation method as long as the inputs are converted into travel times (in minutes).
3. Time horizon: Instead of developing an approach that provides one-day scheduling, we consider a one-week time horizon, as pointed out by stakeholders in both HSC and HHC. This allows us to model some other requirements about the jobs explained later.
4. Synchronization and dependencies: Synchronization refers to the need to provide two (or more) services at the same time for the same user. This requirement can involve only HSC jobs, HHC jobs or jobs that belong to both components. Health treatments that require the presence of both the doctor and the nurse are an example of services that must be provided jointly. Additionally, there are other kinds of temporal dependencies between jobs that we include in our approach, since they are especially relevant when planning HSC and HHC jobs and their coordination (e.g., one job before, or after, another job). For instance, a nurse may need to collect a blood sample while the user is fasting, so a social service involving feeding should only happen after the health service has been completed.

#### *2.1.3. Care requirements*

The way the jobs are provided and assigned is restricted by the following requirements:

(1) Skills or qualifications: In HSC, there are 2 types of qualifications for both jobs and caregivers: cleaning (C) or regular (R). Cleaning jobs refer to household cleaning and maintenance. They are typically scheduled once a week for a subset of users and do not require the involvement of the user in the activity. Regular jobs may include various types of jobs that usually include the user, such as cooking and feeding, bathing, walking outdoors, or preparing for bed. A caregiver qualified as R can provide any of these jobs. In HHC, the types of jobs to be performed belong to either a doctor (D) or a nurse (N). A doctor may perform any type of medical check-up or intervention on the user, while a nurse usually performs more standardized tasks, such as administering a medicine or blood collection. Each job must be assigned to a caregiver of the required qualification to perform it.
(2) Caregiver–user assignment: Unlike HSC users, HHC users must have their jobs always assigned to the same nurse and doctor. Therefore, an extra constraint must be respected when assigning a health job.
(3) Continuity of service: This concept refers to the assignment of the same caregiver or set of caregivers to the same user over time. As mentioned before, this is not relevant in HHC. However, in HSC, a caregiver with a certain qualification is desired to perform all jobs of a certain user for that qualification. This allows for a better monitoring of the individual needs and characteristics and the establishment of a relation of trust and acquaintanceship between the user and the caregiver, which is perceived as a higher quality of care. We take into account this performance indicator, keeping in mind that values above 2 caregivers per week for a given user is a non-desirable outcome.

#### *2.1.4. Objectives*

Finally, several objectives can be considered in this problem, taking into account the interest expressed by stakeholders:

(1) Minimizing non-effective working time, i.e., the sum of travel times and waiting times.
(2) Maximizing the continuity of service, i.e., the average number of caregivers assigned to a user. It includes the caregiver already preassigned to a user from previous planning horizons.
(3) Minimizing the number of unscheduled jobs, i.e., the total number of jobs that cannot be included in the scheduling considering all constraints. These jobs are scheduled manually after the planning process has been completed using, e.g., extra hours (at a higher cost) upon agreement with the caregivers from the corresponding area, or by assigning the unscheduled jobs to caregivers from neighbor areas.
(4) Minimizing the workload differences between caregivers, i.e., the average standard deviation of the total workload (travel times + waiting times + jobs' duration) assigned to caregivers (of the same qualification). Notice that the public home care system is overloaded and therefore this objective becomes relevant to ensure a quality of service and caregivers' satisfaction.
(5) Minimizing start time consistency of the same user's jobs, i.e., the average, amongst all users, of the standard deviation of the start time of all jobs (of the same qualification and time window) assigned to each user. Only users with 2 or more jobs on different days are included in this calculation.

As previously mentioned, our approaches are built focusing mainly on the first three objectives, although they also optimize towards the last two since concepts such as workload are included in their logic.

### 2.2. Related literature

The relevance of the home care routing and scheduling problem is evident simply by taking into account the number of proposals to solve its different variants in the literature. We refer readers to Fikar and Hirsch (2017) and Cissé et al. (2017) for surveys on the models and algorithms that have been reported and concentrate on some key papers. However, the vast majority of studies focus on HHC, and only a few of them explicitly consider HSC, which are commonly served by a different entity (Gomes and Ramos, 2019). To the best of our knowledge, there are no papers dealing with the integration of both health and social home care and considering all our objectives and constraints. Therefore, we provide references to the most similar approaches available emphasizing where this work differs. It is worth noting that due to the different countries' home care management approaches, authors usually include a diverse set of features, constraints and objectives, making the comparison between approaches quite complicated.

Focusing on working regulations, a few approaches in the literature consider some of them (e.g., maximum working time per day or rest between days) (Lasfargeas et al., 2019; Grenouilleau et al., 2019; Carello and Lanzarone, 2014), although only two works collect all the necessary aspects that we include in our proposal (Guericke and Suhl, 2017; Trautsamwieser and Hirsch, 2014).

Regarding time constraints, as previously stated, we consider job time windows, which are one of the most common features included in papers dealing with these problems, and a one-week time horizon. Although many of the initial approaches addressing this problem in the literature used to take into account a one-day time horizon (Begur et al., 1997; Rasmussen et al., 2012; Mankowska et al., 2014), longer time periods have been proposed during the last years (Wirnitzer et al., 2016; Yalçindag et al., 2016; Guericke and Suhl, 2017; Demirbilek et al., 2019; Fathollahi-Fard et al., 2019) due to the advantages that this involves when modeling other constraints. An example of these other constraints are those related to the continuity of service. We consider continuity of service during the time horizon as many other approaches (Borsani et al., 2006; Hertz and Lahrichi, 2009; Lanzarone et al., 2012; Carello and Lanzarone, 2014; Braekers et al., 2016; Guericke and Suhl, 2017; Decerle et al., 2018), but also between time horizons. Finally, synchronizations and dependencies between different jobs entail additional time constraints required in the home care environment. Synchronizations are included in some works (Maya Duque et al., 2015; Lasfargeas et al., 2019; Bredström and Rönnqvist, 2008; Redjem and Marcon, 2016; Frifita et al., 2017; Decerle et al., 2016; Mankowska et al., 2014). However, there are other types of temporal dependencies between jobs that we include in our approach, since they are especially relevant when planning health and social jobs and their coordination (e.g., one job just before another job or just after another job). To the best of our knowledge, only two previous approaches (Rasmussen et al., 2012; Lasfargeas et al., 2019) address it.

One of the main differences between our proposal and previous studies in the literature is related to the objective function. Most of the previous approaches deal with one objective function that usually corresponds to distance, travel time or costs (Begur et al., 1997; Akjiratikarl et al., 2007; Fikar and Hirsch, 2015; Bachouch et al., 2011; Cappanera and Scutellà, 2014; Frifita et al., 2017; Yalçindag et al., 2016; Trautsamwieser and Hirsch, 2014; Eveborn et al., 2006; Mankowska et al., 2014). Other approaches consider two objective functions. To cite some of them, Maya Duque et al. (2015) minimizes the total distance and maximizes the users' and caregivers' preferences; (Braekers et al., 2016) minimizes operating costs and the level of service offered according to customer preferences; (Fathollahi-Fard et al., 2019) minimizes total costs and the environmental impacts and green emissions; and Grenouilleau et al. (2019) minimizes costs and unplanned jobs. Three objective functions are included in only a few studies. Rasmussen et al. (2012) minimizes the total traveling costs, maximizes user–caregiver preferences and maximizes the number of served visits. Decerle et al. (2019) minimizes the total working time of caregivers while maximizing the quality of service and minimizing the maximum working time difference among nurses and auxiliary nurses. In this regard, our proposal includes two main objectives, namely, minimizing non-effective working time and maximizing the continuity of service, and optimizing other secondary objectives, such as minimizing the number of unscheduled jobs, minimizing the workload difference, and maximizing the time consistency. They are all important performance measures indicated by stakeholders and not included together in any previous work.

Regarding solution techniques, a few approaches applying exact methods to solve similar problems can be found (Rasmussen et al., 2012; Mankowska et al., 2014; Cappanera and Scutellà, 2014; Eveborn et al., 2006; Demirbilek et al., 2019). However, the great majority of home care planning problems that have been attempted to be solved using exact methods are not able to find the optimal solution for even small- to medium-sized instances. In Mankowska et al. (2014), for instance, the authors are not able to solve the problem to optimality within 10 h of CPU time for as few as 25 patients and 5 caregivers, which is considerably smaller than real-life instances such as the ones included in this paper. For these reasons, most of the studies in the literature apply (meta)heuristics due to their complexity (NP-Hard, as they are variants of the VRP): Akjiratikarl et al. (2007) used a particle swarm optimization methodology; Maya Duque et al. (2015) provided a randomized local search algorithm; Braekers et al. (2016) developed a local search; Frifita et al. (2017) proposed a general variable neighborhood search approach; Guericke and Suhl (2017) developed an adaptive large neighborhood search; Grenouilleau et al. (2019) provided a large neighborhood search; Lasfargeas et al. (2019) applied a variable neighborhood search; and Fathollahi-Fard et al. (2019) used simulated annealing. After our review of the literature, we decided to focus on the development of heuristics. In particular, we use a multistart framework based on constructive heuristics.

Finally, we point out that our research proposal has been implemented as a DSS that is currently used by the city council and some companies. Only a few approaches in the literature have reached this stage. Begur et al. (1997) provide a DSS for home health care. This integrates an optimizing model that minimizes the total travel time and includes very basic constraints about route construction, nurse time availability, and patient visitation requirements. The authors also integrated GIS software to visualize routes in maps. Later, Eveborn et al. (2006) developed Laps Care, a very basic DSS that seems to be deprecated. A more complete DSS was proposed by Maya Duque et al. (2015) to solve an HHSCRSP in Belgium. Nevertheless, it differs in many ways from our proposal, as mentioned in this literature review, such as the objective function, working regulations about break times, or the way the continuity of service is considered. Additionally, our DSS allows us to schedule health and social services separately or jointly, with the latter being a good point for coordination between both areas.

## 3. Greedy heuristic approach

We have developed two greedy heuristics to address the HHSCRSP considering all the constraints and objectives described in the previous section. Notice that both methods can be used (or adapted) to solve the problem in areas other than Barcelona by removing and/or adding new characteristics in an easy manner. The two methods are designed to construct routes in a particular way, leading to solutions optimized towards specific objectives. In the method *ConstructByCaregiver* (CxC), routes are constructed on a caregiver basis, leading primarily to the minimization of non-effective working time (travel time plus waiting time) associated with the caregivers' daily routes. The method *ConstructbyUser* (CxU), on the other hand, appends jobs to routes on a user basis, thus maximizing the level of continuity of service (i.e., minimizing the number of changes in caregiver for each given user). In this section, we describe the working principles of each of the proposed greedy constructive methods and explain how they are designed to obtain efficient solutions optimized towards the several objectives considered. These heuristics have been included in a multistart framework, which basically returns the best solution obtained among a predefined number of executions run sequentially.

In the following, we introduce some notation and formulas to better explain the operating principle of each heuristic. Let us describe the HHSCRSP as a set of caregivers $c \in \mathcal{C}$ available to perform a set of unscheduled jobs $j \in \mathcal{J}$, that belong to a set of users $p \in \mathcal{P}$, over a set of planning periods (days) $t \in \mathcal{T}$. The goal of each method is to construct the daily routes, i.e., the sequence of jobs to be performed by each caregiver on each given day of a planning horizon (a route may also be left empty). Routes are constructed by assigning jobs sequentially over the day, i.e., jobs are iteratively added to the tail of each route in construction. We use the notation shown in Table 1 to describe the parameters (inputs) and the notation in Table 2 to define the model variables. In both notations, only subscript letters refer to indices, while superscript letters are merely used to help identify the parameter or variable in use. Note that each element referring to time is expressed in minutes.

During the solution construction process of each method, when evaluating the feasibility of appending a certain job $j$, belonging to user $p$, to the tail of a route $\mathcal{R}_{ct}$ after job $i$ (or after the depot if the route is still empty), the following constraints must be satisfied:

- Job $j$ happens on day $t$:

$$day_j = t \tag{1}$$

- Job $j$ is not scheduled yet:

$$sched_j = 0 \tag{2}$$

- Caregiver has the required qualification to perform job $j$:

$$qual_j \in \mathcal{Q}_c \tag{3}$$

- There is enough daily work time available for, at least, caregiver $c$ to travel, wait, complete job $j$ and return to the depot:

$$wkl^d_{ct} + tt_{ij} + wt_j + dur_j + tt_{j0} \leq max^d_c \tag{4}$$

- There is enough weekly work time available for at least caregiver $c$ to travel, (wait), complete job $j$ and return to the depot:

$$wkl^w_c + tt_{ij} + wt_j + dur_j + tt_{j0} \leq max^w_c \tag{5}$$

- Job's time window can be satisfied:

$$TW^s_j \leq start_j \leq TW^e_j \tag{6}$$

- Caregiver's labor time window can be satisfied:

$$TW^s_{ct} \leq start_j - tt_{ij} \tag{7}$$

$$start_j + dur_j + tt_{j0} \leq TW^e_{ct} \tag{8}$$

- Rest time between consecutive days is respected:

$$(1440 - end_{c,t-1}) + start_j - tt_{ij} \geq R^d \tag{9}$$

- Daily maximum consecutive work time:

$$cons^d_{ct} + tt_{ij} + wt_j + dur_j + tt_{j0} \leq L \tag{10}$$

- If job $j$ refers to an HHC service, then the job must be scheduled on the route of the caregiver(s) previously assigned to the corresponding user $p$:

$$c \in C^0_p \tag{11}$$

- In method CxU, the waiting time before any job $j$ cannot surpass the predefined limit:

$$wt_j \leq \epsilon \tag{12}$$

**Table 1**
Notation used for the input parameters (static during the construction process).

| Model | Description |
|---|---|
| $\omega$ | penalization added to metric $crit_j$, in method CxC, if selecting job $j$ implies a change in caregiver(s) |
| $\epsilon$ | maximum time limit allowed for the travel + waiting time before a job $j$ is started in method CxU |
| $\alpha$ | probability of considering the job duration when evaluating the next job(s) to be selected |
| $\lambda$ | penalization added for each unscheduled job in the solution found by each method |
| $I$ | number of sequential executions (iterations) for which to run each method before selecting the best |
| **Jobs** | **Description** |
| $day_j$ | id of the day in which job $j$ must be performed |
| $dur_j$ | duration of job $j$ |
| $pat_j$ | id of user ($p$) corresponding to job $j$ |
| $qual_j$ | qualification required to perform job $j$ |
| $TW^s_j, TW^e_j$ | time of the day after/before which job $j$ must be started (job time window) |
| $tt_{ij}$ | travel time from location of job $i$ to location of job $j$ |
| $sync_j$ | id of job that must start simultaneously with job $j$, if any |
| $prec_j$ | id of job that must be completed before the start of job $j$, if any |
| $gap_j$ | minimum time span between the end of job $prec_j$ and the start of job $j$ |
| **Users** | **Description** |
| $C^0_p$ | set of caregivers previously assigned to user $p$, if any |
| **Caregivers** | **Description** |
| $max^d_c$ | maximum daily work time available for caregiver $c$ |
| $max^w_c$ | maximum weekly work time available for caregiver $c$ |
| $\mathcal{Q}_c$ | set of qualifications possessed by caregiver $c$ |
| $avail_{ct}$ | 1 if caregiver $c$ is available to work on day $t$, 0 otherwise |
| $TW^s_{ct}, TW^e_{ct}$ | time of the day at which caregiver $c$ is contracted to start/end working on day $t$ (caregiver time window) |
| $L$ | maximum uninterrupted daily work time allowed (without a break) |
| $R^d$ | minimum rest time between two consecutive days |
| $D_c$ | duration of a break for caregiver $c$ |
| $U_c$ | consecutive daily work time after which a break should be inserted for a part-time caregiver $c$ |
| $B_c$ | time of the day after which a break should be inserted for a full-time caregiver $c$ |

**Table 2**
Notation used for the model variables (dynamic during the construction process).

| Variables | Description |
|---|---|
| $\mathcal{R}_{ct}$ | sequence of job id's and breaks that define the route of caregiver $c$ in day $t$ |
| $wkl^w_c$ | total workload assigned to caregiver $c$ during the planning horizon |
| $wkl^d_{ct}$ | total workload assigned to caregiver $c$ in day $t$ |
| $wt_j$ | waiting time incurred by assigning job $j$ to the route in construction |
| $sched_j$ | 1 if job $j$ has been scheduled, 0 otherwise |
| $start_j$ | earliest time of the day at which job $j$ can be started if appended to the route in construction |
| $cons^d_{ct}$ | consecutive daily work time assigned to caregiver $c$ in day $t$ |
| $end_{ct}$ | time of the day at which route of caregiver $c$ ends on day $t$ |
| $time_{jct}$ | time of the day after job $j$ is completed in route of caregiver $c$ on day $t$ |
| $crit_j$ | value of the criterion (randomly) chosen to select the next job(s) in each method |
| $N^{uns}$ | number of unscheduled jobs |

Additionally, we include soft constraints that model synchronization and dependencies, as mentioned in Section 2. Let us refer to synchronizations as overlap dependencies and to the remaining dependencies as no-overlap dependencies. Overlap dependencies indicate that two jobs $i, j \in \mathcal{J}$ must start at the same time. In those cases, the dependency between jobs is bidirectional, as the assignment of either job depends on the other; thus, $sync_j = i$ and $sync_i = j$. Constraint (13) applies to

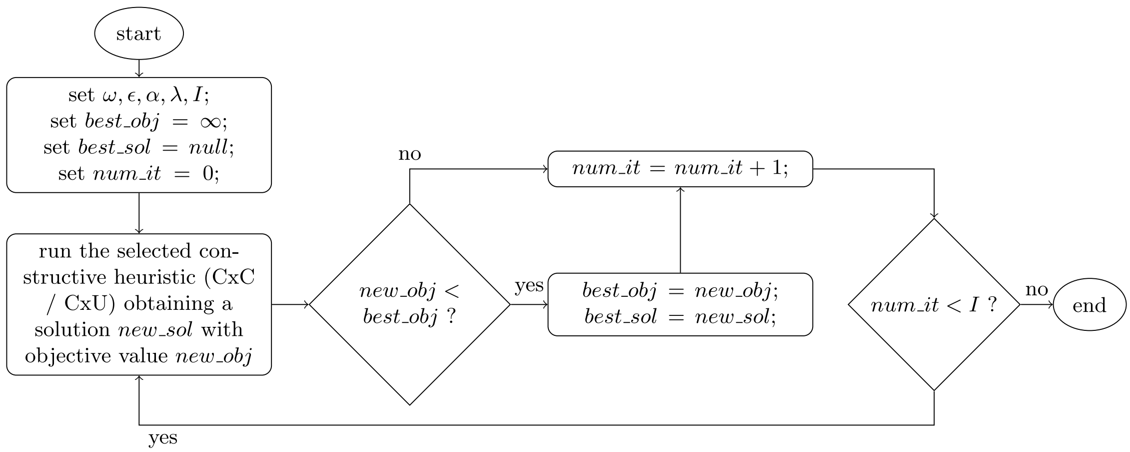


**Fig. 1.** Overview of the solution search and selection process.

any job $j$ for which $sync_j > 0$, and the related job $i = sync_j$ has already been scheduled, i.e., $sched_i = 1$:

$$start_j \geq start_i, \tag{13}$$

No-overlap dependencies indicate that two jobs $i, j \in \mathcal{J}$ must not coincide, but there is a precedence relation where job $i$ must be completed before job $j$ starts. A delay $gap_j \geq 0$ between the end of job $i$ and the start of job $j$ may apply. When a relation of this type exists, job $j$ will have indicated its predecessor as $prec_j = i$. Therefore, restriction (14) applies to any given job $j$ for which $prec_j > 0$ and job $i = prec_j$ has already been assigned to a route (i.e. $sched_i = 1$):

$$start_j \geq start_i + dur_i + gap_j \tag{14}$$

The function (15), used to evaluate a newly constructed solution, reflects the trade-off between non-effective working times and the number of unscheduled jobs according to parameter $\lambda$:

$$\min \sum_{i \in \mathcal{J}} \sum_{j \in \mathcal{J}} (tt_{ij} + wt_j) + \lambda N^{uns} \tag{15}$$

As shown in Fig. 1, the selected greedy heuristic is executed for a certain number of iterations $I$, i.e., the process is repeated until $I$ solutions have been constructed sequentially, from which the best is selected according to Eq. (15). Next, we describe the working principle of each method when constructing a solution in each iteration.

### 3.1. ConstructByCaregiver

This greedy heuristic method has been designed to primarily minimize the noneffective work time (travel + waiting time). The procedure operates for each day of the planning horizon sequentially. For each day $t$, the method primarily iterates over the caregivers' routes and then attempts to assign jobs that minimize the associated travel and waiting time, independent of the caregivers that have previously been assigned to that same user. The model parameter $\omega$ allows, to a limited extent, the user to minimize the changes in caregiver by considering a penalization in the metric if selecting that next job causes a change in the (habitual) caregiver for the corresponding user. The simplified flowchart of the CxC is presented in Fig. 2, and can be summarized in the following steps:

*Step 1:* Initialize. The method starts at the first day of the planning horizon ($t = 0$), and constructs routes of all caregivers for each $t \in \mathcal{T}$ sequentially. At this stage, for a given day $t$, all corresponding routes $\mathcal{R}_{ct}$ are empty, and daily tracking variables are reset.

*Step 2:* Sort available caregivers by increasing order of $wkl_c^w$. By iterating over caregivers sorted from the lowest to highest workload levels assigned so far, the method is able to minimize imbalances in workload over the planning horizon by prioritizing caregivers who have been assigned lower workloads in previous days.

*Step 3:* Select the next caregiver $c$ from the top to bottom of the list of *Step 2*, as long as $avail_{ct} = 1$.

*Step 4:* Define the set of all feasible jobs $\mathcal{J}_c^f$, i.e., all jobs that can be assigned to route $\mathcal{R}_{ct}$ satisfying constraints (1)–(11). If there are no feasible jobs available for scheduling in $\mathcal{R}_{ct}$, the method proceeds to the next caregiver on the list. In the case current unscheduled jobs in $t$ cannot be assigned to any caregiver, the method proceeds to the next day $t + 1$ and executes *Step 2*.

*Step 5:* Sort all jobs $j \in \mathcal{J}_c^f$ by ascending order of one of two criteria, chosen with the given probability $\alpha$. If a randomly generated real number $r \in [0, 1] > \alpha$, then the method computes $crit_j$ as the summation of the travel time plus the waiting time if job $j$ is chosen for route $r_{ct}$. In this way, the method selects the job that can be started the earliest. In case $r < \alpha$, the duration of each job $j$ is added to the previous $crit_j$; thus, the chosen job $j$ will be the one that can be finished the earliest from the set of all feasible and unscheduled jobs. This randomness in the selection of jobs allows the methods to, over many runs, potentially find combinations of job assignments that lead to solutions with a lower number of unscheduled jobs, which would otherwise not be achievable with a deterministic method.

*Step 6:* For each job $j \in \mathcal{J}_c^f$, if assigning the job implies a change in caregiver regarding the caregivers previously assigned to this user (including the caregiver(s) assigned to the user in the previous planning period), a penalization equal to $\omega$ minutes is added to $crit_j$. This penalization is intended to avoid excessive changes in caregivers for the sake of non-effective time minimization, which can be controlled by setting parameter $\omega$ according to the preferences of the user.

*Step 7:* Select the job with the minimum $crit_j$, append it to the tail of route $\mathcal{R}_{ct}$ and update all (daily) tracking variables. At this point, and in case caregiver $c$ works as part-time, the consecutive work time $cons_{ct}^d$ has surpassed the threshold defined for inserting a break ($U_c$) and no break has been inserted yet, a break of duration $D_c$ is added to route $\mathcal{R}_{ct}$. In the case of FT workers, if the time of the day after job $j$ surpasses the predefined threshold ($B_c$), a break of $D_c$ minutes is added to the route. All (daily) tracking variables are again updated.

*Step 8:* If there are still jobs that can be added to route $\mathcal{R}_{ct}$, go back to *Step 5*. Otherwise, close the route and proceed to *Step 9*.

*Step 9:* If there are unscheduled jobs in day $t$ that can be scheduled, i.e., they were not found infeasible in all caregivers, go to *Step 2*.

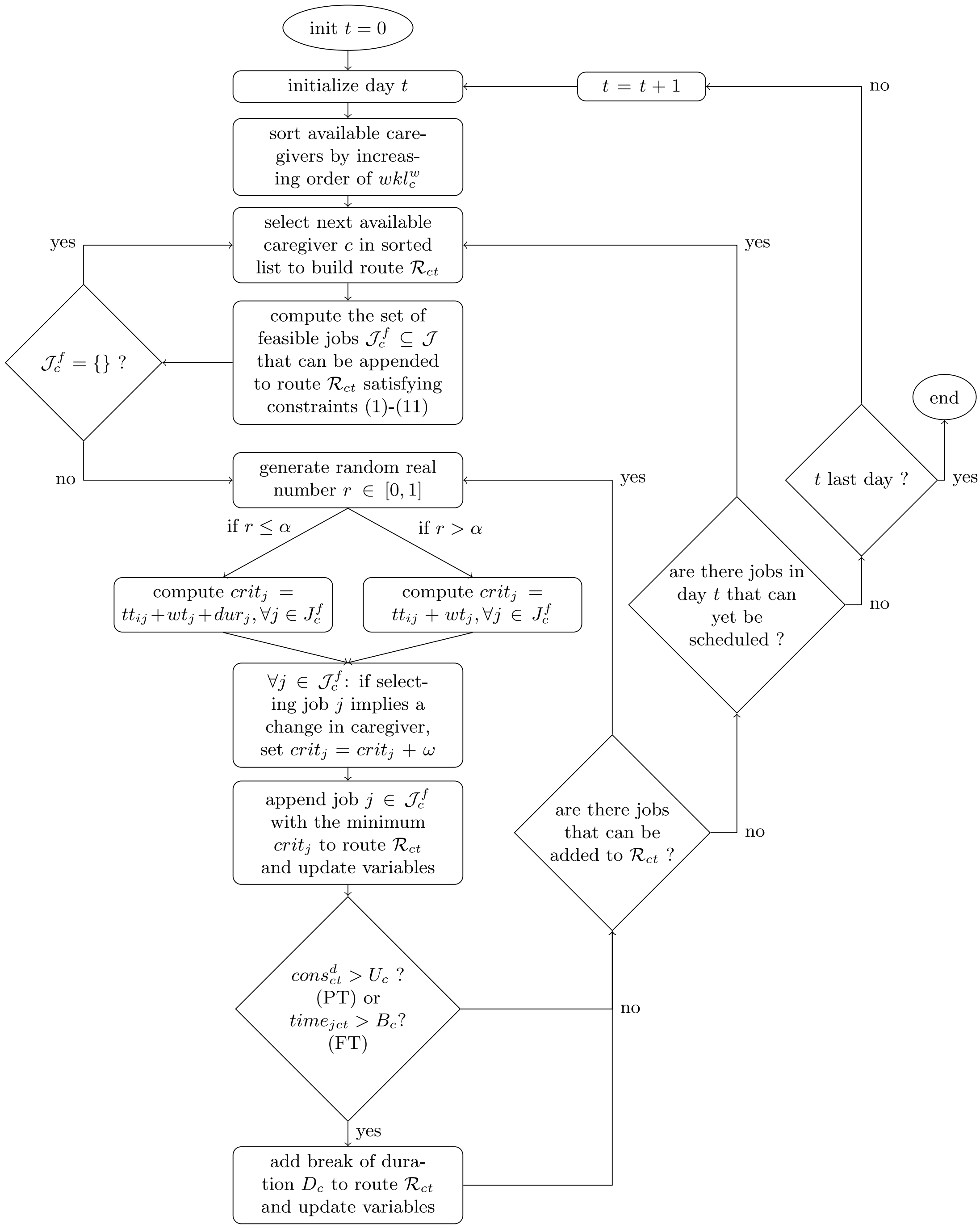


**Fig. 2.** Flowchart of the method *ConstructByCaregiver*.

Otherwise, increment day to $t + 1$ and proceed to *Step 1* unless $t$ is the last day of the planning horizon, in which case the method ends.

### 3.2. *ConstructbyUser*

This method has been designed to primarily maximize the continuity of service. In this method, a set of several jobs (called "block") of the same user ($\mathcal{B}_p$) can be assigned at once to the several routes (days) of a certain caregiver in multiple days of the week to maximize the level of continuity of service for periodic jobs. However, appending jobs $j \in \mathcal{B}_p$ to the tail of all routes of a chosen caregiver $c$ may lead to excessive waiting times in at least some of those routes. To control this trade-off, the model parameter $\epsilon$ allows the user to define a ceiling on the maximum waiting time permitted to maintain the continuity of service. The simplified flowchart of the CxU is shown in Fig. 3, and can be grouped into the following steps:

*Step 1:* Initialize. The method starts by sorting all unscheduled jobs $j \in \mathcal{J}$ by ascending order of one of two criteria, chosen with the given probability $\alpha$, as in the method CxC. If the randomly generated number $r \in [0, 1] > \alpha$, then the method computes $crit_j$ as the start of the time window of job $j$, i.e., the earliest the job(s) can be started, the most likely to be selected so that waiting times can be minimized. In case

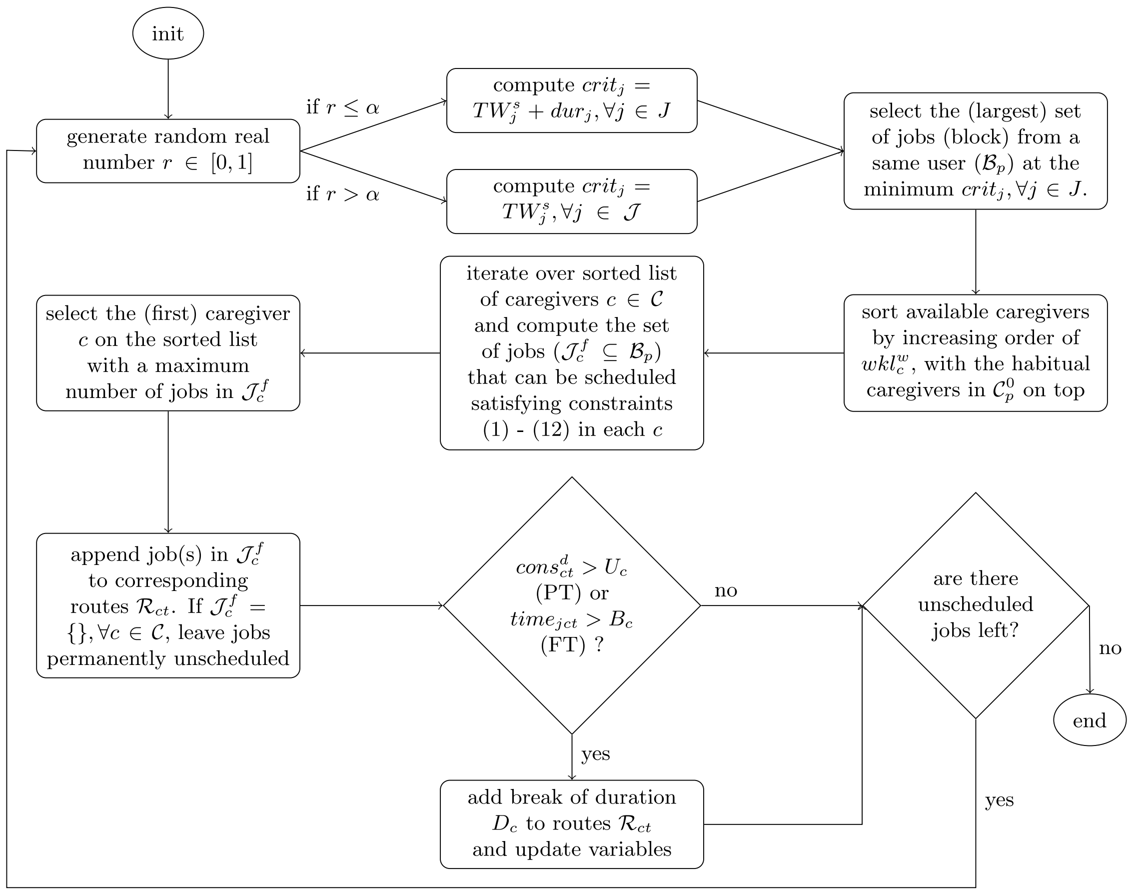


**Fig. 3.** Flowchart of the method *ConstructbyUser*.

$r < \alpha$, the duration of each job $j$ is added to $crit_j$, thus, the preferred job(s) will be the one(s) that can, theoretically, be finished the earliest. Once again, adding this randomness to the selection of jobs allows us to find solutions with a lower number of unscheduled jobs.

*Step 2:* Select the set of jobs $\mathcal{B}_p$, from the same user $p$, at the minimum value of $crit_j, \forall j \in J$ found in the previous step. In case there are jobs from multiple users at the lowest $crit_j$, select the largest block of jobs. If several exist, select the first on the list.

*Step 3:* Sort available caregivers by increasing order of $wkl_c^w$. Similar to CxC, by iterating over caregivers sorted from the lowest to highest workload levels assigned, the method is able to minimize imbalances in workload over the planning horizon. In this sorted list, the caregivers previously assigned to user $p$ (within the planning week or in the previous week) are given top priority.

*Step 4:* For each of the caregivers in the sorted list, compute the set of jobs ($\mathcal{J}_c^f \subseteq \mathcal{B}_p$) that can be scheduled satisfying constraints (1)–(12). Note that, unlike CxC, constraint (12) is now included to limit the maximum waiting time permitted to maintain the continuity of service when assigning multiple jobs at once.

*Step 5:* Select the first caregiver on the sorted list with a maximum number of jobs in $\mathcal{B}_p$ that can be scheduled on his or her daily routes. This criterion allows scheduling as many jobs from the same user as possible to the same caregiver, with the remaining jobs in $\mathcal{B}_p$ being left unscheduled to possibly be assigned to other caregiver(s).

*Step 6:* Append the feasible jobs in $\mathcal{J}_c^f$ to the corresponding routes of caregiver $c$ and update all (daily) tracking variables. If no caregivers were found where at least one job could be scheduled, i.e., $\mathcal{J}_c^f = \{\}$, it means that unscheduled jobs are no longer possible to be assigned and are therefore excluded from subsequent scheduling attempts by being left permanently unscheduled.

*Step 7:* As in the CxC method, for part-time caregivers, a break of duration $D_c$ is added to route $\mathcal{R}_{ct}$ if the consecutive work time $cons_{ct}^d$ has surpassed the threshold ($U_c$) and no break has been inserted yet. In the case of FT workers, a break is added to a route if the time of the day after job $j$ surpasses the predefined threshold ($B_c$) and no breaks have been assigned to it. All (daily) tracking variables are again updated.

*Step 8:* If there are unscheduled jobs that can be scheduled, i.e., they were not found infeasible in all caregivers' routes, the method proceeds to *Step 1*. Otherwise, the method ends.

## 4. Computations experiments

The methods have been programmed in C++, and experiments have been conducted on a desktop computer with an Intel Xeon 2.20 GHz and 8 GB of RAM running on a 64-bit version of Windows 10. The goal is to find a weekly schedule (e.g., Monday to Sunday), which means that the decision maker could hypothetically run the model during the last workday of the previous week (i.e., Friday) so that the maximum amount of data is known. Due to the influence of the stochasticity introduced by parameter $\alpha$ to randomly choose the criterion for the selection of a (next) job or user, all results presented in this section correspond to the average of 10 runs for each particular combination of parameters to fade out the effect of randomness (except if $\alpha = 0$ or $\alpha = 1$, in which case the methods are deterministic since the same criterion is applied for every selection).

In the following, we present the details about the input data, a parametric analysis, the results obtained for an HSC real case study in Barcelona, and finally, a study of the impact of features and model constraints on outcomes for the complete HHSCRSP.

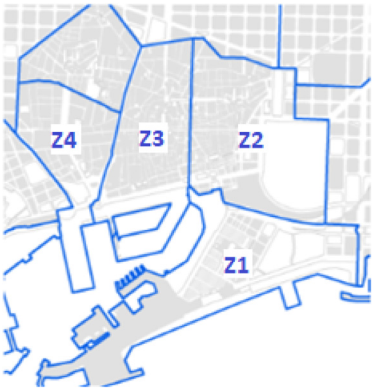


**Fig. 4.** Zones indicating the areas referring to our real test instances.

**Table 3**
Description of the real data obtained for the 4 zones of the Barcelona area included in the HSC analysis.

| Zone | #users | #jobs | #caregivers |
|---|---|---|---|
| Zone 1 | 231 | 790 | 44 |
| Zone 2 | 223 | 791 | 43 |
| Zone 3 | 189 | 684 | 40 |
| Zone 4 | 446 | 1677 | 86 |

### *4.1. Input data*

#### *4.1.1. Social care data*

For the HSC services, we used historical real data obtained from the social services division of the Barcelona City Council for the week between February 3, 2020 (Monday), and August 3, 2020 (Sunday). The planning of HSC services in the Barcelona area is performed separately per geographical area (zone). We obtained data from four zones Z1–Z4, as depicted in Fig. 4. Specific information about the size of the instance associated with each zone can be found in Table 3.

HSC services are delivered every day of the week. Using data from Z1, we verified that between 18% and 21% of the services are delivered daily from Monday to Friday, while only around 1% and 2% are performed on Saturday and Sunday, respectively. Jobs have five possible time windows assigned for their start time, with the early morning window (07:00–10:30) having by far the larger portion of the jobs (47%). The 10:30–13:00 time window corresponds to 29% of the jobs pool, followed by the 13;00–15;00 window at 16%, 15;00–19:00 at 5% and the night window (19:00–22:30) at only 3%. A total of 39% of the jobs last one hour, while a further 24% last one hour and a half, and 15% are predicted to last two hours. The remaining 23% of the jobs have a diverse range of durations from 30 to 330 min, with steps of 15 min. Furthermore, 13% of the social services were of the cleaning type ($qual_j = C$), while 87% were regular services ($qual_j = R$). Travel times between the locations of the users corresponding to those jobs range between 5–30 min, with travel times from and to the depot being zero after indication that the daily journey starts/ends at the first/last user's location.

Social caregivers have two possible shifts: part-time (PT) or full-time (FT). Of the 44 caregivers in Z1, 34 are part-time workers, of whom 32 work a morning shift (08:00–16:00) and 2 work an afternoon shift (16:00–22:00). The remaining 10 caregivers work on a full-time contract, meaning they can have jobs assigned between 08:00–22:00, subject to the remaining daily and weekly workload restrictions. Only 2 caregivers (one PT and one FT) were assigned to work exclusively on weekends, while the other 42 were contracted to work solely on labor days. From the caregivers' data-set, 7 perform cleaning activities ($Q_c = \{C\}$), and approximately 37 perform any sort of regular service ($Q_c = \{R\}$). The daily work time available per caregiver $max^d_c$ varies between 8 h and 12 h, while the weekly capacity $max^w_c$ ranges from 20 h and 37 h. A caregiver is allowed to work for a maximum consecutive time of only 6 h ($L = 360$). Moreover, all PT caregivers have a 20-minute break, which should be placed when their route length has surpassed 2 h of consecutive work time ($U^c = 120$). All FT caregivers are given a 30-minute break, which should be inserted if the time of the day has passed the predefined threshold ($B^c = 780$). The minimum rest time between two consecutive days is 12 h ($R^d = 720$).

#### *4.1.2. Health care data*

For the HHC services, and in the absence of real historical readily available data, we created all the necessary data according to the findings obtained from the several meetings with HHC managers and surveys taken within both users and caregivers. We estimated the characteristics, size, and specific input data parameters to build empirical distributions that (randomly) generated the values needed to conduct experiments.

In HHC services in the Barcelona area, each zone has a predefined number of care teams denominated "Unidades Basicas de Atención" (UBAs). Each UBA is composed of a nurse and a doctor and has its own predefined users (patients) who must always be visited by that same preassigned doctor and nurse. Therefore, when assigning health jobs, constraints (11) must apply. According to the information obtained from collaborating hospitals, each of the 7 UBAs included in Z1 has between 20 and 30 users undergoing treatment under their umbrella at any given time, and their team members work from Monday to Friday. Of the 14 caregivers (7 nurses and 7 doctors) included, 12 are PT workers, of whom 7 work a morning shift (08:00–15:00) and 5 work an afternoon shift (14:00–20:00). The remaining 2 caregivers work on an FT contract (08:00–20:00), so they can deliver services throughout the whole day given that all other restrictions are satisfied. The maximum daily work time $max^d_c$ varies between 6 h and 12 h, while the weekly capacity $max^w_c$ is limited at a maximum of 40 h. As with HSC, any caregiver is only allowed to work a maximum consecutive time of 6 h ($L = 360$). However, in this case, all caregivers have a 30-minute break, which should be placed when their route length has surpassed 2 h of consecutive work time ($U^c = 120$). The minimum rest time between two consecutive days is also 12 h ($R^d = 720$).

We used a uniform probability distribution (between 20 and 30) to generate the number of users per UBA, resulting in a total of 179 patients at an average of 25.6 users/UBA. From the 179 patients created for the 7 existing UBAs in Z1, some have one or more jobs performed at their home every week, while other users might have a visit every few weeks or months. The most appropriate way to represent this dynamic is to generate a number of weekly jobs per user according to a Poisson distribution. According to our findings, users had an average of one job per week, which means that in a given week, some users have no jobs at all, while others will have from one to five services assigned at a decreasing probability. In our generated data, 50 users have no jobs assigned at all, 71 users have one job, 38 users are given two jobs, 16 users with three services, 2 users have four jobs and there are 2 users that are visited daily . Amongst the 213 jobs, approx. 20% are performed by the doctor, and approximately 80% are performed by the nurse, with 18% to 22% of the jobs being delivered every weekday. Job durations vary mostly from 15 min (36%) to 30 min (53%), with a few jobs having 10 (4%) or 60 min (7%). Since job time windows were not a critical point for the health component, these were given the labor time windows of the corresponding UBA member according to the job qualification, which means that 46% have a morning window, 36% have an afternoon window, and the remaining 18% have a full day window. Travel times were randomly generated in the range of 5-30 min following a uniform distribution. Similar to HSC services, travel times from and to the depot are considered in the health component, since doctors and nurses must depart and return to the same health center to develop other tasks.

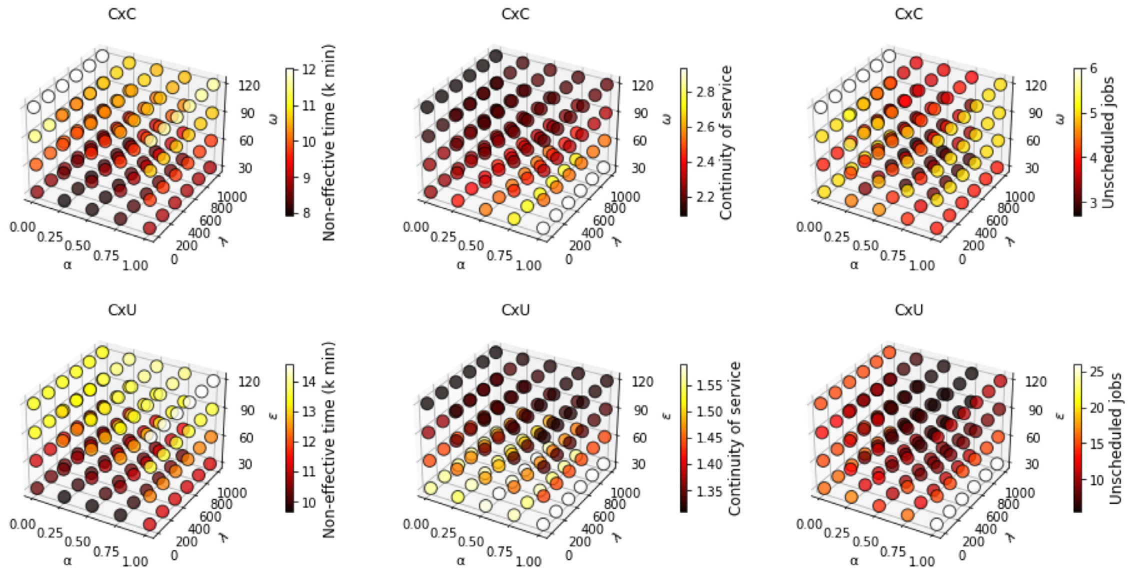


**Fig. 5.** Data points indicating the outcome of each combination of the parametric analysis for each of the three main KPIs (rows) for each method (columns).

**Table 4**
Parameters and corresponding values combined in the parametric analysis.

| Parameter | Values |
|---|---|
| $\omega/\epsilon$ | 30 - 60 - 90 - 120 |
| $\alpha$ | 0.00 - 0.25 - 0.50 - 0.75 - 1.00 |
| $\lambda$ | 0 - 200 - 400 - 600 - 800 - 1000 |
| $I$ | 100 |

### 4.2. Parametric analysis

The use of the proposed planning system requires a number of parameters to be set by the decision-maker before executing the program. This parameter setting should be done in accordance with the preferences and goals of the organization(s) using the tool, as the chosen combined values of these parameters will lead to specific performance levels regarding each of the considered KPIs. In this parametric analysis, we provide insights into the expected outcomes for each combination of a predefined set of reasonable values chosen for each parameter. The multivariate analysis helped set the values of the parameters for the remainder of our experiments. We perform this analysis using the data for Zone 1 described earlier, with both the social and health components being included but excluding dependencies.

#### 4.2.1. Model parameters

We defined a set of ranges and values for realistic model parameters that can be chosen by decision makers based on the information gathered with the meetings held with stakeholders and preliminary experiments. Table 4 presents the list of parameters and corresponding values tested in the multivariate analysis. Since the goal of this parametric analysis was to study the effect of internal model parameters (used in each run), the number of iterations $I$ was kept fixed at 100 in these preliminary experiments. We provide insights into the impact of the number of iterations later.

There are, in total, 120 combinations among the spectrum of discrete values defined for each parameter within each method. Fig. 5 shows six charts depicting the impact of each of the 120 combinations of parameter values in the results obtained by using the methods CxC (top row) and CxU (bottom row) for each of three main KPIs (columns) identified in our study: total noneffective time (left), number of unscheduled jobs (middle), and the continuity of service for regular social services (right). All three objectives considered are to be minimized; thus, darker balls represent the most desired combinations of parameters for each method/KPI, while lighter balls represent the less desirable outcomes.

As we can observe, there is a clear trade-off between the objectives considered in both methods. It is immediately clear that the CxC method is the preferred one for decision makers desiring short noneffective times, and $\omega$ should be set low (30). On the other hand, for decision makers more interested in achieving outstanding levels of continuity of service, the CxU method outperforms its counterpart, and the value of $\epsilon$ should be set high (120). In case the decision maker wants to achieve the most complete solution possible by minimizing the number of unscheduled jobs, then a certain randomness should be introduced in the system ($\alpha = 0.25 - 0.75$), and the value of $\lambda$ should be set high.

Note that parameters $\omega/\epsilon$ have the largest impact on the variation of outcomes. It is clear that lower values lead to increased continuity of service at the cost of higher non-effective times in both methods. Nevertheless, it is also evident how both methods optimize towards the different objectives they were designed for, with the CxC leading to overall lower values of noneffective time, and the CxU method outperforming CxC in continuity of service, as confirmed by the ranges of the corresponding hot scales. The parameter $\alpha$ appears to give overall satisfactory KPI levels in the range between 0.25 and 0.75, although there is some variation in the influence of this parameter depending on the levels of the parameter $\omega/\epsilon$. The CxC seems to work better with higher values of $\alpha$, except for the continuity of service. CxU seems to consistently perform better for smaller values of $\alpha$, except for the number of unscheduled jobs. As expected, the value of $\alpha$ has a special impact on the number of unscheduled jobs, since the introduction of variability in the way routes are built leads to higher probabilities of finding solutions that are able to accommodate more jobs. Note that when $\alpha$ is equal to 0 or 1, the methods become deterministic since the same criterion is used for every job/user selection throughout the whole method. In those cases, the number of iterations and the number of runs per combination becomes irrelevant as all solutions found are equal. Finally, the value of $\lambda$ provides the least impact on outcome variation, although it can have some influence on the trade-off between noneffective times and the number of unscheduled jobs. Lower values of this parameter favor the selection of a solution with lower non-effective times (among all 100 solutions generated in each run), while higher values avoid solutions with a high number of unscheduled jobs from being picked. In any case, a $\lambda$ value greater than 500 appears to have little to no influence on any of the KPIs.

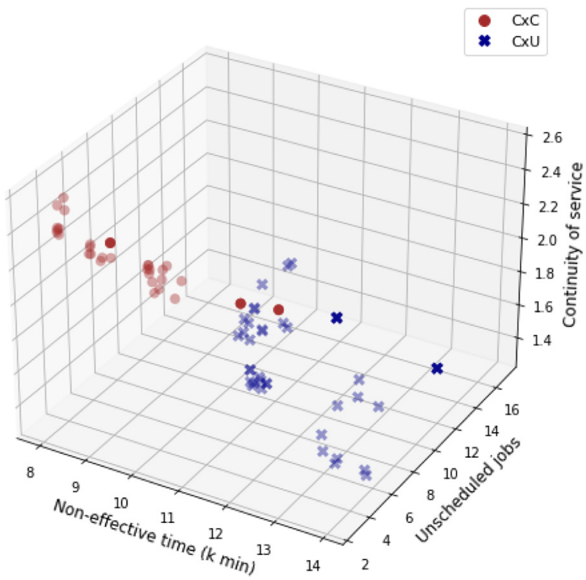


**Fig. 6.** Pareto front of all nondominated solutions of the parametric analysis for each method: CxC (red) and CxU (blue).

#### 4.2.2. Pareto front

From the set of all 240 solutions obtained in the parametric analysis, we have identified the set of nondominated solutions $S^n$. A solution is deemed dominated when there is at least one other solution with all objective values that are no worse than the original solution, and at least one of the objectives is better. We have identified a total of 160 nondominated solutions, 81 from the CxC method and 79 from the CxU method. Fig. 6 depicts the 3D visualization of the Pareto front for the same KPIs considered beforehand.

The dispersion of outcomes and the trade-off between the performance metrics are clear among the set of solutions in $S^n$ in both methods. The CxC method provides a more compact set of solutions, mostly resulting in lower values of non-effective time and high to moderate levels of continuity of service (2.19-2.48). Conversely, the CxU method provides solutions with very low levels of continuity of service (between 1.3 and 1.6) at the expense of increased non-effective times (between 9.6k and 14k) when compared with CxC (between 9k and 10k). In the blue dots, it is also possible to observe that solutions with fewer unscheduled jobs lead to overall higher non-effective times, thus reflecting the importance of an informed selection of parameters. In turn, the number of unscheduled jobs is consistently lower for the CxC, thus making it the best of the two when the aim is to obtain the most complete solution possible.

#### 4.2.3. Number of iterations

Last, we performed an analysis of the impact of the number of iterations ($I$) chosen when using each of the proposed methods. In these experiments, we fix the model parameters studied beforehand as follows: $\omega/\epsilon = 90$, $\alpha = 0.50$, and $\lambda = 500$ for both CxC and CxU. Fig. 7 shows the outcome for a possible number of iterations ranging from 1 to 1,000, with a step of 100, for those fixed model parameters. As it is expected that the number of iterations performed has a direct impact on the CPU time needed to conclude the running process, we added a fourth chart showing the impact of $I$ on CPU time. As we observe, there is no significant variation in the values of the KPIs with the variation in the number of iterations. Looking at the three main KPIs, we see that selecting a number of iterations that is higher than 500 has little to no effect on outcomes, with the largest gains being achieved by performing (at least) 100 iterations as opposed to a single one. Nevertheless, the computational effort needed to solve the problem increases linearly with the increase in the number of iterations. Therefore, we decided to keep the number of iterations equal to 500 for the remainder of our experiments. At the $I = 500$ level, the CPU time is still reasonably low (40 s for CxU and 25 for CxC). Surprisingly, there is a significant gap between the CPU times of both methods for the same iteration number, which tends to rise with the increase in the number of iterations chosen.

### 4.3. Improving HSC services in the barcelona area

In this section, we perform experiments limiting the scope to social services. Given that real data for the social services were available for testing and comparison, we ran both methods and compared outcomes with the performance obtained in practice under similar circumstances (excluding dependencies).

#### 4.3.1. Zone 1: trade-off analysis

We started by running more in-depth experiments for Zone 1 to study the trade-off between the three main objectives as a function of the variation in the model parameters $\omega/\epsilon$ by fixing the remaining parameters according to the insights obtained from the parametric analysis. In this trade-off analysis, the values of parameters $\omega/\epsilon$ vary between 30 and 120 min, with a step of 30 min, while the remaining

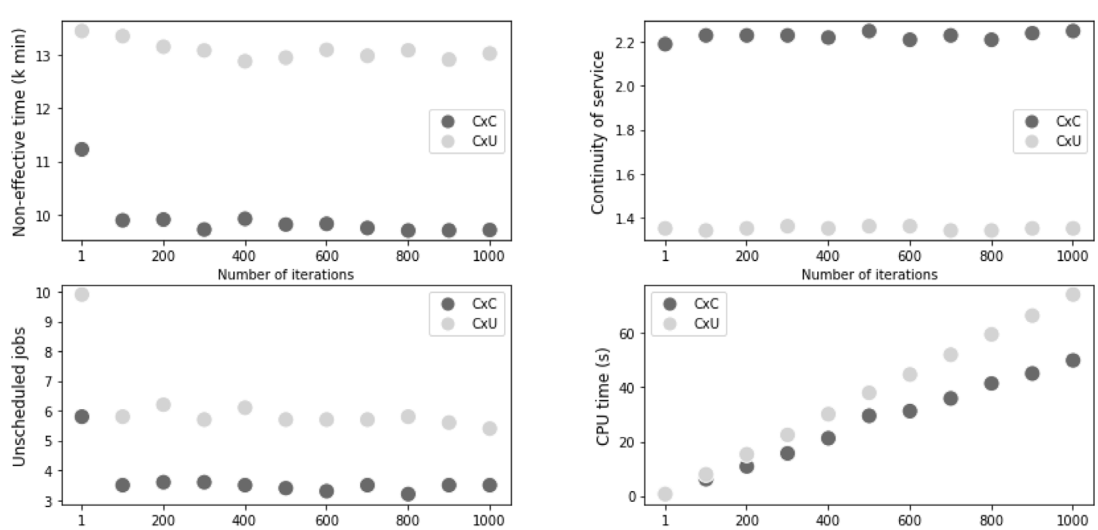


**Fig. 7.** Results of the iteration number analysis for a specific parameter configuration.

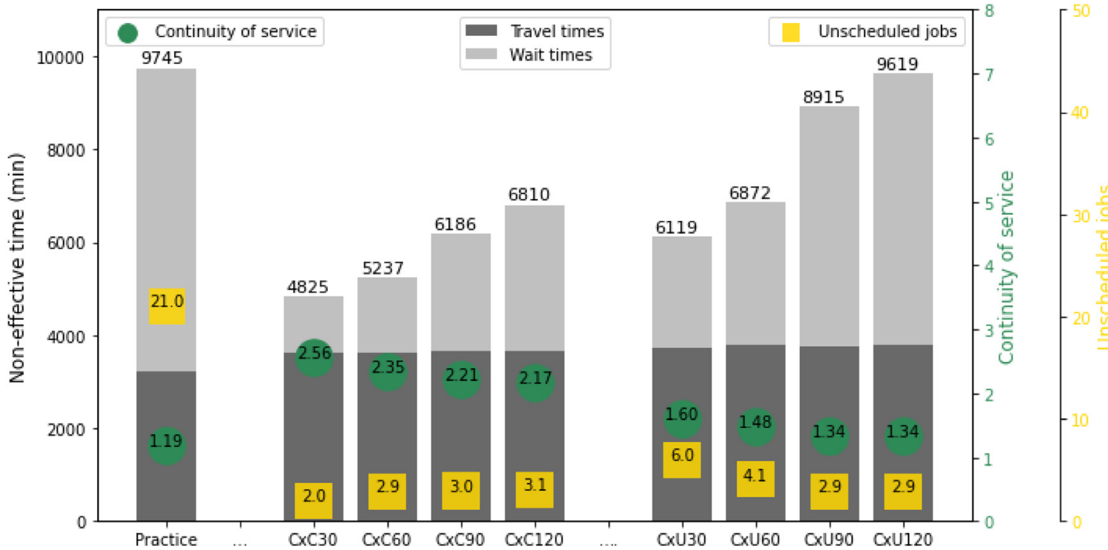


**Fig. 8.** Results for the HSC real instance and comparison with performance in practice for $\omega/\epsilon$ = {30;60;90;120} in both methods.

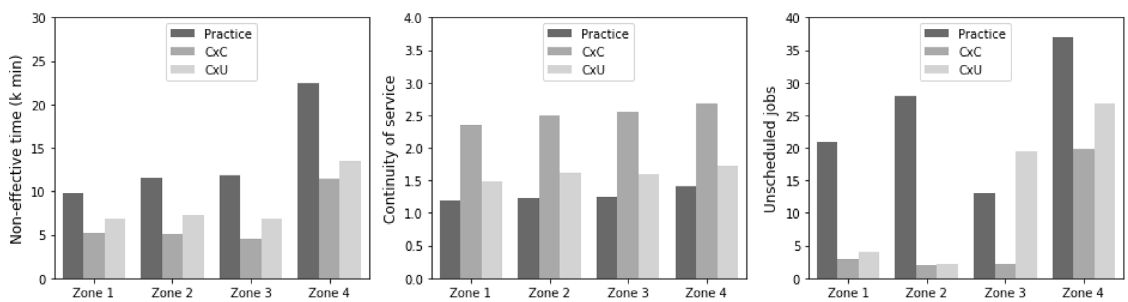


**Fig. 9.** Results for the four zone analysis and comparison with practice.

parameters are kept constant at $\alpha$ = 0.5, $\lambda$ = 500, and $I$ = 500. As in Section 4.2.1, each result represents the average of 10 runs for the respective configuration.

Fig. 8 compiles the outcomes of all three main KPIs and compares them to the outcomes obtained in practice during the same planning week (first bar to the left). Keep in mind that, for the solution manually built in practice, we have identified a number of constraints that were violated, such as the caregiver time windows (23 times) and daily work time (6 times) on the tested week alone, which allowed them to obtain lower values of continuity of service when compared to the outcomes obtained by our methods. Moreover, we considered the 21 unscheduled jobs in practice and those which had been assigned to caregivers assigned to a neighboring area. A stacked bar chart with travel times (dark gray) and waiting time (light gray) is used to represent non-effective times, the continuity of service (as the average number of caregivers per user) is represented by green dots, and the number of unscheduled jobs is represented by yellow squares. As we observe, both methods clearly optimize towards different primary goals. The heuristic CxC achieves greater levels of performance in avoiding non-effective times, with a minimum of less than 5,000 min, almost half of the time incurred by the social services organization on that same week. On the other hand, in terms of maximizing the continuity of service, the CxU method is clearly the most appropriate, with levels between 1.34 and 1.60 caregivers per user, on average. The number of unscheduled jobs is kept low in all parameter settings, varying between 2.0 and 6.0, on average, which corresponds to 0.3%–0.8% of the total number of jobs (790).

The values of $\omega/\epsilon$ should be set according to the service levels required by the organization, with low values leading to shorter times but higher service discontinuity for the CxC. Higher values of $\omega/\epsilon$ cause non-effective times to increase, but the continuity of service levels is rather low. The use of the CxU seems to lead to a slightly greater number of unscheduled jobs, especially for tighter $\omega/\epsilon$ values. Note that by choosing the appropriate method, the parameter $\omega/\epsilon$ alone allows us to go through a wide spectrum of solutions when compared with the comprehensive parameter analysis from Section 4.2.1. Although the performance of our algorithms outperformed the practical performance, we did not consider particular (and rare) constraints, such as mandatory assignments or nonassignments of caregivers to users, may have impacted the results in practice.

#### *4.3.2. Results for four different zones in the barcelona area*

Next, we performed experiments for all four zones of the Barcelona area for which data were available and compared the performance between the proposed methods and the current solution implemented by the HSC services of the area. Using the insights from the trade-off analysis, we set both parameters $\omega$ = 60 (CxC) and $\epsilon$ = 60 (CxU), as outcomes from Zone 1 (Fig. 8) provided moderate and acceptable values for all three KPIs. Fig. 9 contains three bar charts, each depicting the comparison between the solution implemented in practice and the solutions that could be delivered by the greedy methods in terms of the three main KPIs considered. As observed for Zone 1, our methods are able to clearly outperform the solutions manually constructed in practice for the minimization of noneffective times and number of unscheduled jobs while providing satisfactory levels of continuity of service, especially when applying the CxU method.

### *4.4. Complementary analyses for the HHSCRSP*

In this section, we study the impact of including additional features and model constraints on the performance of our models. We

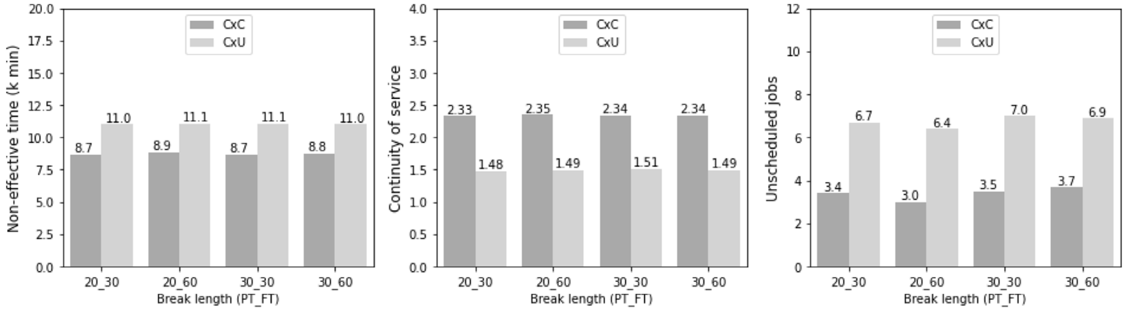


**Fig. 10.** Results for the break duration analysis.

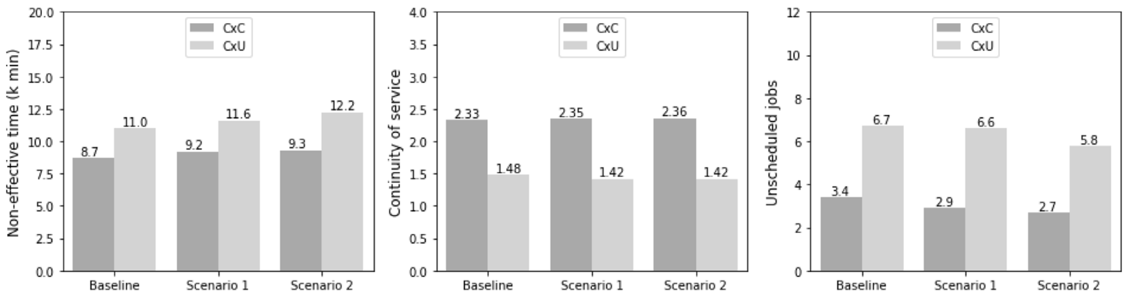


**Fig. 11.** Results for the caregivers' shift analysis.

**Table 5**
Baseline case and experimented scenarios for the shift type distribution in Zone 1.

| | Social | | | Health | Total |
|---|---|---|---|---|---|
| | Regular | | Cleaning | | |
| | #PT workers | #FT workers | # workers | # workers | |
| Baseline | 28 | 9 | | | |
| Scen. 1 (25% PT->FT) | 21 | 16 | 7 | 14 | 58 |
| Scen. 2 (50% PT->FT) | 14 | 23 | | | |

perform these analyses for the complete HHSCRSP, i.e., including both the social and health components, with and without synchronization/dependencies constraints. The scenarios tested in this section mainly involve changes in the social data, reflecting real-world queries obtained from the involved social partners. Information about possible scenarios of the interest of the involved health organizations has not been retrieved in time for this study; thus, we maintain the health data static throughout this section. Using real data from Zone 1 for the social component and generated data as described in Section 4.1 for the health component, we have assessed to what extent the introduction of alternative break duration and shift lengths, as well as the inclusion of synchronization (dependencies), can negatively affect performance. The model parameters were kept the same as in the previous section at $\omega = 60$, $\epsilon = 60$, $\alpha = 0.5$, $\lambda = 500$, and $I = 500$.

#### 4.4.1. Break times

In our baseline experiments, we set a break time $D_c = 20$ min for PT caregivers and $D_c = 30$ for FT caregivers as indicated by the collaborating organization. Nevertheless, they were interested in investigating whether extending the duration of these breaks would impact performance. For this reason, we have performed additional experiments in case PT workers would have 30-minute breaks, and FT caregivers would have an hour of resting time between services instead of 30 min. We ran experiments for the four combinations of those values. Fig. 10 shows the outcomes for the three main KPIs for each combination of break duration of PT and FT workers (PT_FT). As we can observe, there is little to no impact of longer break durations in noneffective times and continuity of service in both methods, with the values of those KPIs staying flat among all tested combinations. The number of unscheduled jobs, however, may be reduced by 12% (CxC) and 4% (CxU) if FT workers are given 60-minute breaks instead of 30 min.

#### 4.4.2. Caregivers' shifts

In the Barcelona area captured by our study, there was a predominance of PT workers over FT workers. Since the collaborating social care organization showed interest in studying the possibility of increasing the number of FT workers, we performed experiments increasing the percentage of FT workers by 25% and 50%, as shown in Table 5. The break duration (from 20 to 30 min) and daily time availability (from 6 h to 12 h) were adjusted accordingly.

The results (Fig. 11) show that the increase in the number of caregivers working in an FT shift in scenarios 1 and 2 may provide a reduction of 20% and 13% in the number of unscheduled jobs in the CxC and CxU methods, respectively, and an improvement in the level of continuity of service for the CxU method from 1.48 to 1.42 average caregivers per user. These improvements can be achieved at the expense of increased non-effective work time of 7% (CxC) and 11% (CxU), in addition to the associated workforce costs incurred by establishing FT contracts with the corresponding caregivers.

#### 4.4.3. Dependencies between services

In this analysis, we study the impact of including dependency relations between services. If dependencies between jobs exist, constraints (13) and (14) are included within the job selection process of each method. We include overlap and no-overlap dependencies, which can occur within each component (health and social) separately or between the two types of services. For the no-overlap case, a random number

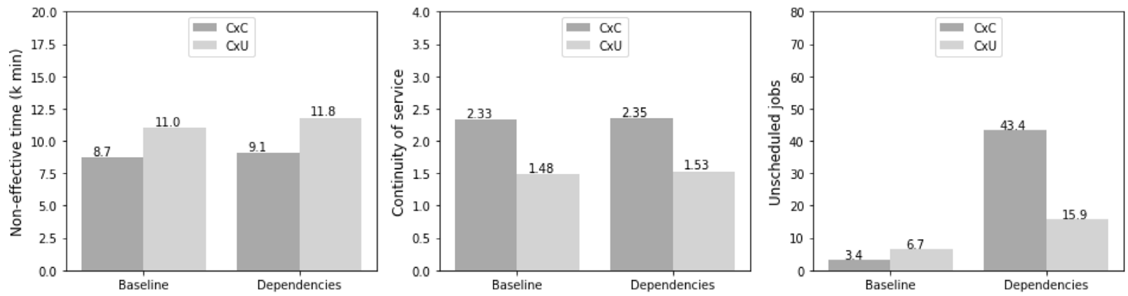


**Fig. 12.** Results for the dependencies analysis.

**Table 6**
Dependencies included in the experiments for Zone 1.

| Components | No overlap (type 1) | Overlap (type 2) | Total (% jobs) |
|---|---|---|---|
| Social-Social | 40 | 5 | 45 (5,7%) |
| Health-Health | 4 | 4 | 8 (3,7%) |
| Social-Health | 51 | 0 | 51 (5,1%) |

between 0 and 60 min, representing the delay between the end of the precedent job and the start of the predecessor, is generated. The number and type of the 104 dependencies randomly generated for this analysis are presented in Table 6, which were in line with the proportions verified in practice by the collaborating organizations. They were especially interested in assessing the impact of dependencies on the integrated planning and scheduling of both types of services by including realistic dependencies between jobs. The obtained results for Zone 1 are shown in Fig. 12. By including the additional constraints, we verified that overall noneffective times increased by 26% (CxC) and 30% (CxU). The number of unscheduled jobs has steeply increased from 3.7 to 43.4 in the CxC method and from 7.0 to 15.9 in the CxU method. The values of continuity of service experienced a moderate variation (1%–3%) when comparing with the baseline case without dependencies. Despite the added number of jobs to potentially be scheduled manually by including dependencies, the relative number is kept at acceptable levels of 4% and 1.5% of the total number of jobs planned for the target week. As in the previous analyses, with our methods, the decision-maker is able to evaluate the consequences of adding dependencies or not (and which type).

## 5. A decision support system for the HHSCRSP

The proposed heuristic methods for solving the HHSCRSP presented in this paper have been made available for use and testing via the development of a web-based DSS. The design, structure and functionalities of the application have been inspired by the necessities and operating procedures of the partner organizations in the Barcelona area. Nevertheless, similar to the greedy heuristic methods themselves, the developed platform can be easily adapted for use by any other organization in the world. The DSS is available worldwide at www.ephocas.com (login credentials may be granted upon reasonable request). A database (SQL Server) has been created to handle input and output data via the website front end, with the necessary calls and queries being made from within the C++ computer application, which is also executed from the front end. Both the database and the computer program are hosted in a virtual private server (VPS) running continuously and capable of processing requests around the clock. The online application is composed of four web pages: dashboard (default), setup (add new planning), results (KPIs), and planning (solution). After logging in with the private credentials, planners using the DSS are presented with a dashboard that depicts an overview of all (previous) plans, results, and model parameters used. At this stage, the decision maker is able to (re)visualize previous plans and corresponding results or to add a new plan as described next. In this way, the decision maker can use both methods (CxC and CxU) with little effort and quickly try out different combinations of parameters to obtain several solutions and evaluate the differences in KPIs before making a final decision on the solution to run in practice.

### 5.1. Setup page

On the setup page (Fig. 13), the decision maker can select the values for the model parameters and upload the input data necessary to generate a new plan. Input data containing all the information about caregivers, jobs and users (see Table 1) can be easily uploaded via an Excel file (.xlsx), with a template containing the required data fields and format being made available to fill in. Next, the decision maker indicates which components are involved in the intended planning: social, health, or both (to include constraints (12) or not), and if dependencies are included in the planning or not. After selecting the desired method to be used (CxC or CxU), it is necessary to define the corresponding model parameters $\omega$ and $\epsilon$ (0–400), as well as the number of iterations (1–1000) and the penalization $\lambda$ (1–1000). An informative balloon button is available for each parameter, displaying a brief explanation of the description and potential impact of the corresponding parameter. By hitting the "Planning" button (in green), a new plan is obtained, and the dashboard is updated with a newly added element containing the access to the results and the constructed schedule, as described next.

### 5.2. Results page

After a new plan has been generated, the decision maker can opt to visualize the "Results" page (Fig. 14), which depicts an overview of the most relevant performance indicators from the planners' perspective. On the left-hand side area, a box contains the main outcomes of the corresponding solution, per component, regarding noneffective working times, total break time and number of unscheduled jobs. Additionally, the DSS shows the level of continuity of service, the appointment consistency (average standard deviation of the jobs' start times for all users with two or more jobs), and the average and standard deviation of the caregivers' workload, per qualification. The total computational time spent to obtain the final solution, for most cases in a matter of seconds, is presented at the bottom of the left-hand side rectangle.

In the top-right area, a histogram of the continuity of service is shown. This chart includes only the familiar (regular) jobs of the social component, since cleaning jobs are performed (at most) once a week, and home health care services are mandatorily performed by the previous caregivers. With this chart, the decision maker has an overview of the percentage of the social users' population that is visited by 1, 2, 3, 4, or 5+ caregivers. In the example shown in Fig. 14, whose planning was obtained using the input data described in Section 4.1 for the CxU method, we can observe that approximately 62% of the users are visited by their habitual caregiver (the caregiver previously assigned to the user is considered on this calculation), and approximately 32% have their services performed by 2 caregivers, making a total of 94% of the

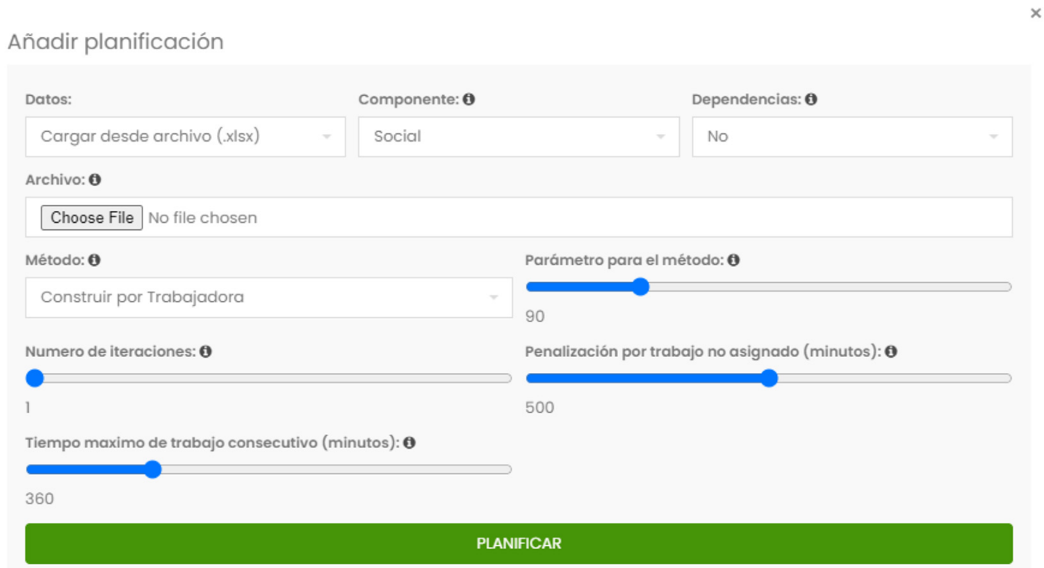


**Fig. 13.** Screenshot of the planning setup page of the web-based DSS.


**Fig. 14.** Screenshot of the results page of the DSS.

user population being visited by at most 2 caregivers with the same qualification, which was in line with the goals of the organization.

The bottom-right chart of Fig. 14 depicts the total weekly workload (noneffective and effective times included), in minutes, assigned to each caregiver individually. Colors representing the different qualifications are grouped together for an easy "intra-qualification" visualization and comparison. The example shows the workload assigned to the set of 58 caregivers, with a reasonably balanced workload amongst the majority of the caregivers within their qualification category (note that certain caregivers have lower contracted times and availability).

### 5.3. Planning overview (solution)

The schedule to be implemented can be visualized via the "Planning" page (Fig. 15). The daily routes (rows) of each caregiver are depicted in a Gantt-chart style, with colored boxes representing the sequence of jobs each caregiver should execute each day of the week from Monday–Sunday. Boxes of the same color represent jobs belonging to the same user, making it possible to observe the continuity of service provided by the same caregiver in an intuitive manner. The graphical user interface allows the user to scroll down to view the daily routes of all caregivers.

Several options and functions are available to adjust the schedule as needed. The DSS is provided with drop-down lists (top of the page) that allow filtering the routes shown by caregiver, by user, or by qualification with little effort. In the example, the first five rows represent the daily routes of caregiver #0 between Monday and Friday. This part-time caregiver is contracted to work during morning shifts on weekdays only. Caregiver #1, on the other hand, has a part-time contract but for the afternoon shift, as we can observe by the daily routes presented in the last five rows of the chart in Fig. 15. Changes to the schedule of any job can be made directly via the user interface, which executes the corresponding queries to alter the SQL database records. The start time or the duration planned for a specific job can be altered by moving or resizing, respectively, the corresponding box in a horizontal direction. By double-clicking on a box, the decision maker can also switch the caregiver assigned to the corresponding job via a drop-down list. Moreover, the full schedule, containing all the relevant information about the weekly plan (see Table 2), planned start and end times, and the assigned caregiver(s) are available to download in Excel format (.xlsx) by hitting the gray button at the top-right corner of the planning page.

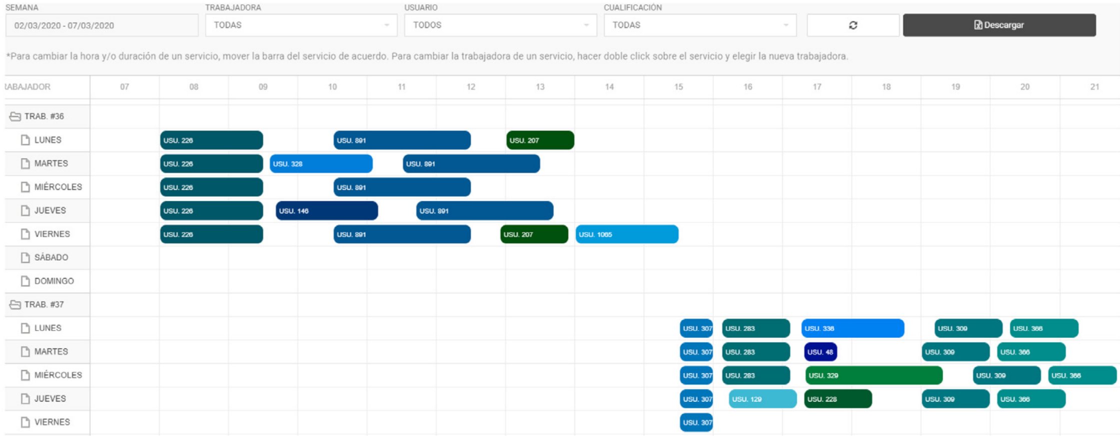


**Fig. 15.** Screenshot of the planning overview (solution) page of the DSS.

## 6. Discussion and conclusion

Considering the growth of the ageing population worldwide and the complexity of obtaining solutions to the HHSCRSP, we have proposed a tool that responds to this need. By means of a parametric analysis, we thoroughly checked the influence of the main parameters on the results obtained by our methods. One of the main conclusions extracted from this analysis is that $\omega$ and $\epsilon$ are the parameters that most impact the results, where lower values lead to increased continuity of service at the cost of higher non-effective times in both methods. It is also clear that, independent of the parameters, the CxC heuristic leads to overall lower values of noneffective time, and the heuristic CxU outperforms CxC in continuity of service, as expected due to the specific instructions included in each of these methods. Depending on the priorities and specific goals of the decision-maker, this analysis can serve as a guide for the selection of the right combination of parameters that leads to outcomes in accordance with their preferences. Moreover, the Pareto front can be a useful tool to show the trade-off between the different objectives or KPIs so that the decision-maker can evaluate his/her preferences and make the final decision.

Considering the insights obtained from the parametric analysis, we have validated our tool by means of computational experiments using real data from an HSC in Barcelona. We have obtained a range of solutions that outperformed the one obtained in practice in most of the KPIs and offered a potential continuity of service under the values required by stakeholders. Notice that the scheduling of a higher number of jobs and the reduction of noneffective working times can justify higher values of continuity of service. Although stakeholders initially manifested their desire to keep this value in the range of 1.00–2.00 caregivers per user, on average, solutions with a continuity of service above 2.00 aroused their interest due to the great values of the remaining KPIs. It is also noteworthy that the better outcomes of continuity of service recorded for the solution constructed manually in practice were obtained at the expense of several constraint violations that our methods avoid. In addition, we have demonstrated the benefits of offering more than one solution, with outcomes depicted as a Pareto front, to decision makers.

An important feature to highlight about the proposed methods is their robustness. We have applied them to different zones in the Barcelona area, reaching similar results among all areas. Once we have successfully tested the methods for the baseline data, decision-makers in the collaborating organizations have exposed their interests about evaluating the outcomes for certain "what-if" scenarios reflecting questions of their interest. Although break times have been reduced to the minimum required according to working regulations, some caregivers may prefer to have more time to have lunch at home (increasing their satisfaction at work). Therefore, we tested the impact of longer break times on the expected results. We found that there is little to no impact of longer break duration in noneffective times and continuity of service in both methods, with the values of those KPIs staying flat among all tested combinations. However, the number of unscheduled jobs may be reduced when FT worker breaks are 60 min instead of 30 min. This may be explained by the fact that by adding 30 min to the break time, the length of a route can be half an hour longer than in the baseline scenario. This may allow the methods to reach the completion of certain jobs (e.g., afternoon jobs for a morning shift route) that could not be achieved with 30-minute intervals due to the maximum consecutive work time constraint after a break.

Another what-if scenario that the collaborating social care organization has exposed is the transition of some PT workers into an FT contract, since this would increase their satisfaction and they would not have to complement their salary with additional jobs. In this regard, we have obtained a reduction in the number of unscheduled jobs and an improvement in the level of continuity of service at the expense of increased non-effective work times and workforce costs incurred by establishing those FT contracts. With this analysis, the decision-maker can trade off these additional costs against the performance gains to evaluate the cost-efficacy of the underlying decisions.

Finally, motivated by the idea of providing a highly necessary tool for integrated home care, we have checked the impact of including dependencies between jobs, which should lead to an increased quality of service for integrated health and social home care. We have observed that the overall non-effective times and unscheduled jobs increased, and the values of continuity of service experienced a moderate variation. Although the increase in noneffective times verified by including dependencies may be partially explained by the gap that a caregiver must ensure between no-overlap services, which forces them to incur extra waiting time to comply with the requirement, it is likely that the extra constraints have a direct impact on the (possible) assignment of nondependent jobs as well. This can be further corroborated by the number of unscheduled jobs, which has steeply increased.

To provide an easy-to-use tool that integrates our methods, we have developed a DSS with the potential to improve the quality of care. The heuristics designed to construct solutions have proven efficient in solving the problem without the need for any commercial solver or subscription-based service in a matter of seconds. This contrasts clearly with current practice where schedules are constructed manually, require the involvement of several planners and take several hours or days to be finalized. In our DSS, solutions are internally validated to confirm that all constraints and guidelines are integrated while keeping the number of unscheduled jobs to a minimum (1%–2%). Moreover, the web-based tool allows the decision maker to attempt, in a quick manner, several possible combinations of parameters and methods until a satisfactory solution (planning) is achieved. By being able to generate multiple schedules in a matter of minutes, the decision-maker can adjust parameters' values according to goals and preferences regarding noneffective work times and the continuity of service. Although optimality is not proven, our methods have proven capable of achieving highly satisfactory results for both of these main goals. In addition, the DSS provides insights into the (minimized) imbalances in the caregivers' assigned workload and the appointments' start time consistency for the same user. In case adjustments are needed to address specific particularities of certain caregivers and/or users, the tool also allows the obtained schedules to be manually adjusted according to the organization's preferences. Due to its objective and practical nature, the DSS has the potential to be highly scalable, i.e., be able to solve HHSCRSP problems of larger instance sizes (higher number of caregivers and jobs/users), as proven by solving for Zone 4 in Section 4.3.

Although the constructive heuristics proposed in this work are specifically designed for the home care services' routing and scheduling problem, we believe that they can serve as a reference for designing heuristics for problems with a similar structure in related areas such as the technician routing and scheduling problem (Pekel, 2020).

In general, our tool not only provides final, implementable solutions but can also be used as a system to test different options and evaluate the impact of some interventions and decisions through "what-if" scenarios. Although it has been conceived for home care in Barcelona, it can be easily adapted to other needs or peculiarities of other cities. Although it has been accepted and validated by collaborating organizations, we have encountered a barrier in its implementation for coordinated care between social and health components. This barrier is related to the absence of a responsible, centralized entity that makes the tool officially available to both types of services. Nevertheless, there are undergoing actions with all the involved entities to effectively establish such organizations in the near future. A possible extension to our proposal is related to adaptability. Since HHSC services are mainly composed of users and caregivers, the human component plays an important role in the development of a plan. Since this is an environment surrounded by uncertainty, it is common to find unexpected events during the planning horizon, e.g., users who are not at home due to a hospital admission that has not been communicated or users who do not open the door due to unforeseen circumstances, last-time sick leave of caregivers, etc. Although the "online" version of the problem is outside the scope of this work, the possibility of adapting the schedule to unforeseen events within the planning week or considering stochasticity in the data when generating the "offline" plan can further enhance the efficiency of our DSS.

## CRediT authorship contribution statement

**Bruno Vieira:** Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Visualization. **Jesica de Armas:** Conceptualization, Writing – original draft, Writing – review & editing, Resources, Visualization, Project administration, Funding acquisition. **Helena Ramalhinho:** Conceptualization, Writing – review & editing, Supervision, Funding acquisition.

## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Jesica de Armas reports financial support was provided by la Caixa Banking Foundation. Jesica de Armas reports a relationship with la Caixa Banking Foundation that includes: funding grants.

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## References

Akjiratikarl, C., Yenradee, P., Drake, P.R., 2007. PSO-based algorithm for home care worker scheduling in the UK. Comput. Ind. Eng. 53 (4), 559–583. http://dx.doi.org/10.1016/j.cie.2007.06.002.

Bachouch, R.B., Guinet, A., Hajri-Gabouj, S., 2011. A decision-making tool for home health care nurses' planning. Supply Chain Forum Int. J. 12 (1), 14–20. http://dx.doi.org/10.1080/16258312.2011.11517250.

Begur, S.V., Miller, D.M., Weaver, J.R., 1997. An integrated spatial DSS for scheduling and routing home-health-care nurses. INFORMS J. Appl. Anal. 27 (4), 35–48. http://dx.doi.org/10.1287/inte.27.4.35.

Borsani, V., Matta, A., Beschi, G., Sommaruga, F., 2006. A home care scheduling model for human resources. In: 2006 International Conference on Service Systems and Service Management, Vol. 1. pp. 449–454. http://dx.doi.org/10.1109/ICSSSM.2006.320504.

Braekers, K., Hartl, R.F., Parragh, S.N., Tricoire, F., 2016. A bi-objective home care scheduling problem: Analyzing the trade-off between costs and client inconvenience. European J. Oper. Res. 248, 428–443. http://dx.doi.org/10.1016/j.ejor.2015.07.028.

Bredström, D., Rönnqvist, M., 2008. Combined vehicle routing and scheduling with temporal precedence and synchronization constraints. European J. Oper. Res. 191 (1), 19–31. http://dx.doi.org/10.1016/j.ejor.2007.07.033.

Cappanera, P., Scutellà, M.G., 2014. Joint assignment, scheduling, and routing models to home care optimization: A pattern-based approach. Transp. Sci. 49, 830–852. http://dx.doi.org/10.1287/trsc.2014.0548.

Carello, G., Lanzarone, E., 2014. A cardinality-constrained robust model for the assignment problem in home care services. European J. Oper. Res. 236, 748–762. http://dx.doi.org/10.1016/j.ejor.2014.01.009.

Carpenter, D., Famolaro, T., Hassell, S., Kaeberle, B., Reefer, S., Robins, C., Siegel, S., 2017. Patient Safety in the Home: Assessment of Issues, Challenges, and Opportunities. Cambridge, Massachusetts: Institute for Healthcare Improvement.

Cissé, M., cindag, S.Y., Kergosien, Y., Şahin, E., Lenté, C., Matta, A., 2017. Or problems related to home health care: A review of relevant routing and scheduling problems. Oper. Res. Health Care 13–14, 1–22. http://dx.doi.org/10.1016/j.orhc.2017.06.001.

Decerle, J., Grunder, O., Hajjam El Hassani, A., Barakat, O., 2018. A matheuristic for a multi-depot home health care problem. IFAC-PapersOnLine 51 (11), 340–345. http://dx.doi.org/10.1016/j.ifacol.2018.08.306.

Decerle, J., Grunder, O., Hassani, A.H.E., Barakat, O., 2016. A two-phases matheuristic for the home care routing and scheduling problem. IFAC-PapersOnLine 49, 1484–1489. http://dx.doi.org/10.1016/j.ifacol.2016.07.781.

Decerle, J., Grunder, O., Hassani, A.H.E., Barakat, O., 2019. A memetic algorithm for multi-objective optimization of the home health care problem. Swarm Evol. Comput. 44, 712–727. http://dx.doi.org/10.1016/j.swevo.2018.08.014.

Demirbilek, M., Branke, J., Strauss, A., 2019. Dynamically accepting and scheduling patients for home healthcare. Health Care Manag. Sci. 22, 140–155. http://dx.doi.org/10.1007/s10729-017-9428-0.

Eveborn, P., Flisberg, P., Rönnqvist, M., 2006. Laps care–an operational system for staff planning of home care. European J. Oper. Res. 171 (3), 962–976. http://dx.doi.org/10.1016/j.ejor.2005.01.011.

Fathollahi-Fard, A.M., Govindan, K., Hajiaghaei-Keshteli, M., Ahmadi, A., 2019. A green home health care supply chain: New modified simulated annealing algorithms. J. Cleaner Prod. 240, 118200. http://dx.doi.org/10.1016/j.jclepro.2019.118200.

Fikar, C., Hirsch, P., 2015. A matheuristic for routing real-world home service transport systems facilitating walking. J. Cleaner Prod. 105, 300–310. http://dx.doi.org/10.1016/j.jclepro.2014.07.013.

Fikar, C., Hirsch, P., 2017. Home health care routing and scheduling: A review. Comput. Oper. Res. 77, 86–95. http://dx.doi.org/10.1016/j.cor.2016.07.019.

Frifita, S., Masmoudi, M., Euchi, J., 2017. General variable neighborhood search for home healthcare routing and scheduling problem with time windows and synchronized visits. Electron. Notes Discrete Math. 58, http://dx.doi.org/10.1016/j.endm.2017.03.009.

Gillsjö, C., Schwartz-Barcott, D., von Post, I., 2011. Home: The place the older adult can not imagine living without. BMC Geriatrics 11, 10.

Gomes, M.I., Ramos, T.R.P., 2019. Modelling and (re-)planning periodic home social care services with loyalty and non-loyalty features. European J. Oper. Res. 277 (1), 284–299. http://dx.doi.org/10.1016/j.ejor.2019.01.061.

Grenouilleau, F., Legrain, A., Lahrichi, N., Rousseau, L.-M., 2019. A set partitioning heuristic for the home health care routing and scheduling problem. European J. Oper. Res. 275 (1), 295–303. http://dx.doi.org/10.1016/j.ejor.2018.11.025.

Guericke, D., Suhl, L., 2017. The home health care problem with working regulations. OR Spectrum 39 (4), 977–1010. http://dx.doi.org/10.1007/s00291-017-0481-3.

Hertz, A., Lahrichi, N., 2009. A patient assignment algorithm for home care services. J. Oper. Res. Soc. 60 (4), 481–495. http://dx.doi.org/10.1057/palgrave.jors.2602574.

Lanzarone, E., Matta, A., Sahin, E., 2012. Operations management applied to home care services: The problem of assigning human resources to patients. IEEE Trans. Syst. Man Cybern. A Syst. Hum. 42 (6), 1346–1363. http://dx.doi.org/10.1109/TSMCA.2012.2210207.

Lasfargeas, S., Gagné, C., Sioud, A., 2019. Solving the home health care problem with temporal precedence and synchronization. In: Studies in Computational Intelligence, Vol. 774. Springer Verlag, pp. 251–267. http://dx.doi.org/10.1007/978-3-319-95104-1_16.

Mankowska, D.S., Meisel, F., Bierwirth, C., 2014. The home health care routing and scheduling problem with interdependent services. Health Care Manag. Sci. 17 (1), 15–30. http://dx.doi.org/10.1007/s10729-013-9243-1.

Maya Duque, P., Castro, M., Sörensen, K., Goos, P., 2015. Home care service planning. The case of landelijke thuiszorg. European J. Oper. Res. 243 (1), 292–301. http://dx.doi.org/10.1016/j.ejor.2014.11.008.

OECD, 2017a. Caring for Quality in Health. p. 84. http://dx.doi.org/10.1787/9789264267787-en, URL: https://www.oecd-ilibrary.org/content/publication/9789264267787-en.

OECD, 2017b. Health At a Glance 2017. p. 216. http://dx.doi.org/10.1787/health_glance-2017-en, URL: https://www.oecd-ilibrary.org/content/publication/health_glance-2017-en.

Pekel, E., 2020. Solving technician routing and scheduling problem using improved particle swarm optimization. Soft Comput. 24, 19007–19015.

Rais, A., Viana, A., 2011. Operations research in healthcare: A survey. Int. Trans. Oper. Res. 18 (1), 1–31.

Rasmussen, M.S., Justesen, T., Dohn, A., Larsen, J., 2012. The home care crew scheduling problem: Preference-based visit clustering and temporal dependencies. European J. Oper. Res. 219 (3), 598–610. http://dx.doi.org/10.1016/j.ejor.2011.10.048, Feature Clusters.

Redjem, R., Marcon, E., 2016. Operations management in the home care services: A heuristic for the caregivers' routing problem. Flex. Serv. Manuf. J. 28, 280–303. http://dx.doi.org/10.1007/s10696-015-9220-8.

Sama, S.R., Quinn, M.M., Galligan, C.J., Karlsson, N.D., Gore, R.J., Kriebel, D., Prentice, J.C., Osei-Poku, G., Carter, C.N., Markkanen, P.K., Lindberg, J.E., 2021. Impacts of the COVID-19 pandemic on home health and home care agency managers, clients, and aides: A cross-sectional survey, March to June, 2020. Home Health Care Manag. Pract. 33 (2), 125–129.

Trautsamwieser, A., Hirsch, P., 2014. A branch-price-and-cut approach for solving the medium-term home health care planning problem. Networks 64 (3), 143–159. http://dx.doi.org/10.1002/net.21566.

WHO, 2020. WHO Methods and Data Sources for Life Tables 1990–2019. Technical Report, World Health Organization.

Wirnitzer, J., Heckmann, I., Meyer, A., Nickel, S., 2016. Patient-based nurse rostering in home care. Oper. Res. Health Care 8, 91–102. http://dx.doi.org/10.1016/j.orhc.2015.08.005.

Yalçindag, S., Cappanera, P., Scutellà, M.G., Şahin, E., Matta, A., 2016. Pattern-based decompositions for human resource planning in home health care services. Comput. Oper. Res. 73, http://dx.doi.org/10.1016/j.cor.2016.02.011.