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Balancing the satisfaction of stakeholders in home health care coordination: a novel OptaPlanner CSP model

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Home Health Care Routing and Scheduling Problem (HHCRSP) has been widely investigated in operations research. In this paper, a model based on the Constraint Satisfaction Problem (CSP) is proposed, which is able to deal with daily HHCRSPs. Human factors are considered in our formulation of the problem and we seek a balance between the different stakeholders' satisfaction criteria. The considered temporal constraints are soft and controlled by the stakeholders' personalised tolerance and satisfaction rates. We will explain how this new Satisfaction-Oriented HHCRSP (SOH2CRSP) model is built and solved by using an open-source solver: the OptaPlanner. In order to examine the impact of human factors, a study will estimate the added value provided when satisfaction is considered in the problem formulation. The comparison is based on a use case derived from the dataset of an existing HHC organisation. The numerical results will show the benefits of our approach.

1. Scope of the study

In recent years, ageing populations and increasing life expectancies have led to growth in the number of elderly people suffering from frailty or a loss of autonomy. In parallel with this demographic change, an increase in chronic diseases such as diabetes or heart failure requires longer-term monitoring and care management. Faced with this challenge, hospitals have shown their limits in covering this care demand. In order to relieve the frequent saturation in their resource capacities, new strategic directions are appearing. One of these is related to a faster transfer of patients from hospitals to their homes, as well as a wider acceptance of home care as a mainstream segment of the healthcare system. This change is also justified by the desire of patients to be at home in a familiar environment with the people they like.

This is why we are currently witnessing the rapid growth of Home Health Care (HHC) organisations. They will be described in the following chapters as HHC systems, which are sub-components of general health systems. To clarify, HHC systems are locally implemented care units which are able to deliver services to patients at home. Most of the time, such organisations are legally independent and have their own structures and staffing. They are financially supported in many national healthcare systems and frequently have contracts with social insurance providers.

Despite this clear and global recognition, the tasks of HHC organisations at an operational level in the field are extremely complex. In short, an HHC system has to run collaborative processes that will guide caregivers through a network of operating environments which together give rise to a distributed system; i.e., a system where managing time and space are critical issues. These collaborative processes can be identified as a relevant modelling of part of the patient's pathway, but in this case, the patient does not have to travel to access resources. Each caregiver will go from one patient's home to the next according to their qualifications, the required care plan for each patient and the level of the patient's confidence for each caregiver regarding the expected care services. As the latter refers to human aspects, we will consider it with special attention.

Given the complexity of operational organisation in HHC systems, there are three primary aims of this research work: 1) To investigate the main concepts featuring the satisfaction of all stakeholders, starting from the relevant content in the literature, then establishing a knowledge bank to facilitate the mathematical formulation of planning problems in HHC systems considering this satisfaction of stakeholders. 2) To prepare Constraint Satisfaction Problem (CSP)-oriented optimisation in the search for solutions by the open-source OptaPlanner solver, which embeds modelling of the stakeholders' satisfaction requirements, and then to solve this CSP-based model by an efficient metaheuristic method. As far as we know, no studies have used an OptaPlanner-oriented model to address such a variant of the HHCRSP. 3) Finally, in an experimental part, we will show the computing performance of our approach by comparing the results obtained with those generated by an earlier Mixed Integer Linear Programming (MILP)-based exact method presented in (Zhang et al., 2021). We then perform an in-depth analysis of a large use case through a detailed comparison of the results with and without the satisfaction constraint, and analyse the impact of these satisfaction considerations.

The remainder of this paper is structured as follows: in Section 2, we will explain our systemic view of the HHC, regarding a service-based, business-oriented model. Then, we will present a literature review to assess the current status of satisfaction considerations in HHC system coordination. Section 3 is devoted to operations research and addresses a new formulation of an HHC operational coordination problem, called the Satisfaction-Oriented HHCRSP (SOH2CRSP), which is described as a variation of an HHCRSP formulation. Section 4 will explain how the implementation in the OptaPlanner solver (De Smet, 2006) was done. In Section 5, we deliver and comment on some computational results obtained through the performed experiments. These were conducted using an adequate case study showing the advantages and drawbacks of our approach when the satisfaction of stakeholders was modelled. Finally, prospective research paths are suggested in Section 6.

2. A health system perspective

2.1. HHC systems

The HHC system is a distributed socio-technical system in which human aspects play a vital role, as in other components of health systems. However, the spatio-temporal features are distinguished by their dominance in the HHC system.

Over the years, many HHC systems have searched for a kind of agility in trying to face the challenges of complexity by acting on these human factors. They have experimented with soft organisational rules. For example, the pool of caregivers will not be entirely made up of full-time employees. Some caregivers may have another part-time job in parallel, and they have to negotiate an individual contract to allow them to be actively involved in the HHC system. This situation allows HHC organisations to have a larger HHC team, although the availability of some caregivers can be limited.

In a holistic approach to our subject, we argue that care coordination is of prime interest in dealing with HHC systems. The principles of the coordination theory of (Malone & Crowston, 1994) state that "if there are no dependencies between activities, there is no coordination". An HHC system strives to manage care deliveries over a territory with the best of medical and paramedical practices. To do so, all the dependencies between activities (care services) for the same patient and among the set of resources (caregivers) must be carefully organised. At an operational level, and frequently on a daily basis, the HHC organisation must consistently choose the team of caregivers that will operate to fulfill the required care expectations. Basically, coordination relies on the intensive exchange of information among the different stakeholders involved in the HHC processes. Assuming there is a centralised vision of this coordination function, the requirement is to create and maintain a consistent set of daily scheduling and routing plans for caregivers, and daily care plans for the patients. Consequently, stakeholders refer to the following two classes of actors: (1) the set of patients and the people who support them; and (2) the set of caregivers who are service providers, along with the coordinator who manages the HHC organisation. It is presumed that the prerequisite for consistency in operational coordination outcomes is to have a collective awareness of the level of satisfaction of each class of stakeholders. This overall satisfaction (at the level of the whole HHC system) is the prime subject we will be concerned with. Therefore, the issue of care coordination in HHC systems is a concern, not only in designing plans and monitoring them, but also in reaching a high level of satisfaction for these two classes of stakeholders. It should be an important criterion for the quality of any HHC system.

2.2. HHC activity as a service

HHC services will represent the building blocks of the collaborative process introduced above. We have deliberately chosen to use this concept of service for the following reasons:

(1) There is a wide range of HHC services that can be performed, depending on the pathology and the condition of a patient. Therefore, it quickly becomes obvious for us to qualify demand at a generic level, while making an abstraction of unnecessary medical, social or individual details for coordination purposes. This choice is essential for solving the problem of coordination.

(2) The right level of granularity for each service helps to easily specify the allocation of resources, knowing the absolute necessity for assigning qualified caregivers. A service will act as a cornerstone between the two classes of stakeholders. A service is a set of care acts to be performed by a qualified provider (i.e., a caregiver in an HHC system) during a visit to a beneficiary (i.e.,

a patient in an HHC system). The duration of a service is presumed to be known.

(3) Planning will be described as sets of scheduled services whose feasibility is strongly affected by the observance of resource allocation rules.

(4) Finally, an HHC system will be defined as a two-part architecture, with one part being the service offer (the HHC organisation) and the other being the service demand (the patient in the HHC panel[1]). Therefore, the issue of coordination may be addressed as the challenge in matching these two parts, which can be a complex undertaking.

The goals associated with (4) are related to the systemic representation in Figure 1 at the coordination level. For (1), the purpose is to achieve the short-term (daily or weekly) assignment of caregivers for performing HHC services. For (2), the objective is to fulfill orders from patients on the service demand side. For (3), it is to generate caregiver work rounds to provide the services in the operational field. In this context, the usability of a Decision Support System (DSS) (Eom & Kim, 2006) for the purpose of HHC basic planning design is a primary concern. A DSS must be helpful for its main user, who has the HHC coordinator role, but due to the inherent complexity of the HHC system, the DSS must also deliver results that meet the expectations of all those engaged in care service offers and demands. Uncertainties (e.g., an uncertain duration in performing a care service by a different caregiver) and disturbances (e.g., a caregiver suddenly changes his/her available time slot) which naturally impact HHC organisations will not be included in this part of our research. We will focus only on a deterministic HHC coordination model.

2.3. Previous research on stakeholder satisfaction in HHC

The coordination problem we are addressing has been widely studied in the literature on Operations Research. The well-known Home Health Care Routing and Scheduling Problem (HHCRSP) (Cissé et al., 2017; Fikar & Hirsch, 2017) remains an active subject. Previous research has underscored a multiplicity of formulations relevant to the entire span of this complex HHC system. Several constraints that have to be considered for our two classes of stakeholders, and the specific features of the corresponding service ecosystem, have naturally paved the way for such extensive work.

For a broad overview of this subject, readers are invited to consider the most recent state-of-the-art review (DiMascolo et al., 2021). Over time, the HHCRSP has progressively evolved from a view that focused on the caregiver routing problem to a multi-stakeholder view. This progress is reflected in two main changes: (1) the necessary competence for providing high-quality care to the patient while considering his/her social environment, and (2) the level of stakeholder satisfaction (Lanzarone & Matta, 2014). In

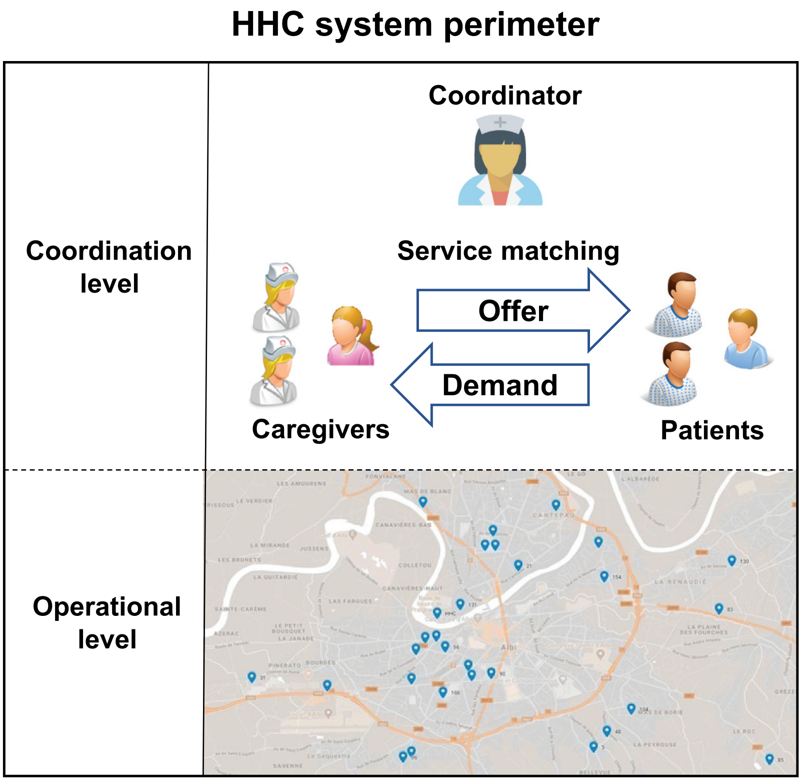

Figure 1. Schematic representation of an HHC system.

the following literature analysis, we will focus on studies where the second point has specifically been investigated.

2.3.1. Previous research related to the service demand side

Depending on the initial characteristics of care recipients, such as pathology, age, domestic context, and clinical/psychological/social details (Fathollahi-Fard et al., 2020), the delivery of care services can differ greatly from one person to the next. Some care services may be more demanding than others, and a portion of the panel may be categorised by patients with a high level of complexity in their care needs. Many medical scales are used to gauge a patient's level of complexity. For example, there are indexes that help to measure the level of autonomy of elderly people (Gayraud et al., 2013). We will assume that the HHC organisation is able to evaluate the level of difficulty in taking care of each patient in its panel.

Some patients may have preferences, and respect for these is a pledge of confidence. Among them, we will assume the existence of a list of preferred caregivers, due to acquaintanceship and the trust built up during previous positive experiences (Braekers et al., 2016). In (Méndez-Fernández et al., 2020), the authors highlight the importance of considering the opinions of patients when assigning caregivers. A list of affinity levels is used to express the level of satisfaction when assigning a specific caregiver to a specific patient. Normally, the duration of a care service is known, but the start time of a care service can be adjusted within a time window based on a patient's wish to receive care at a specific time during a day (Yuan & Fügenschuh, 2015). Each time window has a minimal and a maximal limit that will be interpreted as the earliest and latest arrival times of the required caregiver for the expected care delivery at the right location (Du et al., 2017).

2.3.2. Previous research related to the service offer side

The rapid development of HHC organisations has been aided by health demographics, but it has also been assisted by a greater integration of patient demand into the service offer. This includes a broad service offer with an effective diversity in terms of competencies. For example, some organisations tend to propose a wide range of potential aid for people, from medical to wellness purposes. The aim is to reduce as much as possible the burden on families, through an integration of services which requires a team of caregivers to perform. HHC organisations must thus engage qualified professionals in the field: nurses, therapists, social workers, doctors, housekeepers, etc. (Mankowska et al., 2014; Yuan & Fügenschuh, 2015). These caregivers are frequently employed on a contractual basis. In general, two types of work contracts are offered to them: "full-time" or "part-time" (Wirnitzer et al., 2016). Depending on specific availabilities, a wide variety of task capacities in terms of time can be respected. Additionally, HHC organisations can also adapt this flexibility to manage new requirements.

If the maximum daily workload is not limited, caregivers may be allowed to carry out a certain amount of overtime. However, such flexibility could be limited through the collective social agreements of the pool of professionals and/or by labour laws (Méndez-Fernández et al., 2020). A caregiver's maximum workload must conform not only to the work contract but also to regulations relating to the HHC system (C. -C. Lin et al., 2018). Furthermore, caregivers want to be compensated for the administrative work required to organise and document the care services they have provided (Shao et al., 2012), as well as for weekly meetings (Hiermann et al., 2015).

There is no doubt that respect for working time preferences, availabilities and a fair evaluation of expected incomes will all belong to the satisfaction criteria expressed by each professional.

2.3.3. Previous research related to mapping routes between the offer and demand sides

Organizing an HHC service is difficult because each service is associated with a geographical location and one or more time windows (patient availabilities) during which the service should be performed. The goal is to map out efficient routes along which all services will be delivered. These constraints can be divided into "hard constraints" and "soft constraints". The "hard constraints" refer to an obligation to be fulfilled (if not, the schedule will be rejected), whereas the "soft constraints" are attached to a preference which will not lead to an invalidation of the schedule if the constraints are not fully respected (Hiermann et al., 2015). Respect for temporal constraints (e.g., respect for the start time window of a care service) is important in the HHC system. Thus, two types of time windows are primarily discussed in the literature (Bazirha et al., 2019; Dekhici et al., 2019): the hard (or fixed) time window or the soft (or flexible) time window. A time slot can also be applied to indicate the earliest start and latest end time of the caregiver's work round (DiGaspero & Urli, 2014).

In regards to the quantity of required services, patients who have complex conditions may request several care services during the same day and will expect more than one visit and/or more than one caregiver per day (M. Lin et al., 2016; Marcon et al., 2017). According to (Mankowska et al., 2014), the temporal interdependence of care services can include two types: (1) simultaneous relationships that are considered in the literature to be "synchronisation constraints" (Bredström & Rönnqvist, 2008), and (2) precedence relationships that are frequently considered to be "precedence constraints" (Manavizadeh et al., 2020). In our study, we will consider "precedence constraints". In this case of multiple visits, avoiding any temporal overlap between a pair of successive service deliveries is recommended (M. Lin et al., 2016). In order to obtain the desired quality of service from a patient's perspective, we will insert an "inter-service time", a kind of relaxation time to be respected during service flows (Mankowska et al., 2014). "Synchronisation constraints" are mainly applied in the HHC system to handle specific cases such as bathing services, which require at least 2 caregivers to work in collaboration for overweight patients. (Parragh & Doerner, 2018) has performed an in-depth study on the application of this constraint in scheduling and routing problems.

A coordinator in the HHC organisation is a special stakeholder who assumes a decision-making role at a collective level and takes responsibility for the planning design. We could draw the hypothesis that this coordination function is in charge of managing the satisfaction criteria. These criteria are potentially conflicting, so creating a balance among the levels of individual satisfaction is a complicated task for the coordinator. In this case, the coordination effort will aim for consensus and in some sense, must mediate a solution that will be acceptable to a maximum of stakeholders. The least possible reduction in each personal satisfaction level is the goal. One possible way to carry out such mediation is to provide meaningful guidance for the management of care services in an HHC organisation. This guidance will be translated into Objective Functions (OFs) by operations research for processing by a decision support system. Globally speaking, satisfaction is frequently treated as minimising (1) time (e.g., total travel time), (2) costs (e.g., caregiver overtime costs), or (3) balance of round difficulties. For directive 1 in (Méndez-Fernández et al., 2020), the work schedule should minimise the wasted time between two consecutive services, including travel time. According to (Yalçındağ et al., 2016), the minimisation of total travel time also has an implication on travel costs. For directive 2, the cost of transportation is therefore one of the main economic levers for HHC organisations (Fathollahi-Fard et al., 2020). Thus, they seek to minimise this key criterion (En-Nahli et al., 2015). However, to ensure that all demands are satisfied, the cost of operations is another economic factor. This is a question of requesting the optimal number of caregivers for covering the required care services (Manavizadeh et al., 2020). In (Carello & Lanzarone, 2014), the goal is to reduce the costs associated with the daily overtime of caregivers. In addition, total caregiver overtime costs and travel costs are both minimised in (C. -C. Lin et al., 2018). For directive 3 in (Yalçındağ et al., 2016), the utilisation rates of each caregiver are used to perform personal workload balancing. These rates are defined as the ratio of the caregiver's actual workload to their theoretical maximum workload. In (Quintanilla et al., 2020), the authors seek to balance the number of visits performed by each caregiver. In (Gayraud et al., 2013), the objective is to distribute highly dependent (low autonomy) elderly patients among the different caregivers' rounds. In addition to these 3 main directives, we observe that in some works, the authors have chosen a multi-criteria objective function, such as in (Fathollahi-Fard et al., 2018, 2019; Liu et al., 2018). But the idea of working on the HHCRSP by balancing many satisfaction criteria (even though they may be contradictory) for all the stakeholders has not yet been intensively studied.

2.3.4. Lessons learned from previous research

Despite the fact that stakeholder satisfaction in HHC systems has been broadly considered, as discussed in our literature survey, this subject still remains an open challenge today with a huge margin for improvement. Since human aspects predominate in such socio-technical systems, we want to make a proposal capturing many facets of the related aspects in HHC systems. Many authors have included criteria on satisfaction, but to the best of our knowledge, there is no research work considering a model with a large collection of these human-centric needs, expressing many "customised" satisfaction criteria depending on the type of stakeholder involved in the HHC system.

Consequently, our work is an attempt to develop a planning system in accordance with this sensitivity, delimited by these five primary features:

(1) Patients will declare which caregivers they would like to be visited by, and symmetrically, caregivers will declare which patients they would not like to visit. Caregivers are divided into healthcare practitioners who have a direct contract with the HHC structure and those who are liberals. The declared "patient-caregiver" matching creates a link between the caregiver and the patient. Incompatibilities will be compiled to restrict the possible allocation of resources to services. The causes of incompatibility could be numerous, and we will not go into these details in this work. Notice that dealing with such preferences is difficult, so we will consider this relation to be a pure disjunction. We do not extend our proposal to a multi-scale evaluation of such compatibilities.
(2) We consider multiple time windows for the satisfaction of patients who want (a) to receive care

services at predefined times during a day, and (b) to maintain control of their personal schedule.
(3) An “inter-service time” is introduced in our model. Only (Mankowska et al., 2014) & (Rasmussen et al., 2012) consider relaxation times in their scheduling models, but this constraint is only applied between two services requested by a patient. However, in our approach, this constraint will apply to each successive pair of services on the schedule.
(4) The schedule of each caregiver must be carefully planned. One of their prime requirements is planning which fulfils their maximal workload and working hours.
(5) We quantify a per care service index which represents the difficulty the caregiver will have in delivering it. This indicator allows us to evaluate the total round difficulty for each caregiver, such as in (Gayraud et al., 2013), who consider the degree of dependence of each patient and minimise the dependence level of each caregiver’s round. In our approach, we want to go beyond a simple performance index and try to balance round difficulties over the set of all active caregivers. The purpose is to make an equitable distribution of complex patients inside the team.

Having in mind a participatory approach, the concepts at the foundation of satisfaction will be defined softly and be measured on an individual scale, using personal parameters to set up a profile for each stakeholder regarding each criterion. A generic representation will be defined in Section 4.3.2.

3. SOH2CRSP formulation

3.1. Description of coordination artefacts

We classify the daily HHCRSP in the category of the Vehicle Routing Problem (VRP) with Multiple Time Windows (VRPMTW). The multiple time windows specify the needs of patients depending on their availabilities. The expected care services will be distributed to patients at home via the rounds that caregivers are expected to perform. Our method is an extension of this HHCRSP model, which will be designated as Satisfaction-Oriented HHCRSP (SOH2CRSP).

Let us introduce here a set of assumptions for generating such consistent daily scheduling and routing inside a given HHC organisation. The following could be viewed as a set of business rules and good practices to apply:

- All care services must be performed. It is not allowed to have a requested care service which is not provided within a day.
- A care service must be carried out with exactly one caregiver, duly qualified. The same caregiver cannot be allocated to two different patients at the same time. The synchronisation constraints are not considered in our planning model.
- A caregiver should perform only feasible care services (for reasons of both qualification and compatibility), with respect to feature 1 of our planning system.
- A round is the series of trips stemming from an ordered set of care services that a caregiver should deliver. All rounds start from and end at the HHC organisation. For each round, we do not consider breaks or holidays, nor unexpected events like illness, travel accidents or any other form of uncertainty.
- If the caregiver arrives before the start of the time window at the expected location of the patient, the patient is presumed to be unavailable. This becomes idle time for this caregiver.
- No new caregiver can be included in the list of caregivers and no new care service can be added to the list of requests during the working day.

3.2. Tolerances in SOH2CRSP

Our SOH2CRSP formulation must be finalised in order to consider the satisfaction needs for the two main profiles of stakeholders (caregivers and patients). Firstly, considering the satisfaction of a patient:

- Regarding feature 2, the beginning of a service has to be scheduled as closely as possible within the time windows with respect to the preferences of the relevant patient. Each requested care service should normally be performed on time. Otherwise, if the patient has to wait, the waiting time must be within a range of tolerance that will be described formally in Section 4.3.2.
- Regarding feature 3, the time interval between two successive services for the same patient should be greater than his/her given inter-service time. We should respect these inter-service times as much as possible. In the case of violation of this constraint, a tolerance will be used to find an agreement between the stakeholders.

Symmetrically, considering caregivers, two sets of constraints are also added to the model:

- Regarding feature 4, the duration of a round for one caregiver should be respectful of his/her contractually committed maximum working hours. In the case of an overtime workload for this caregiver, the excess time worked should be as closely as possible within a tolerance that is acceptable to him/her.

- Regarding feature 5, the full set of planned rounds should provide a fair distribution. By this, we mean adjusting the level of difficulty of each round by smoothing to an average value over the whole set of active caregivers.

For cases of small-sized problems, an MILP-based formulation of our SOH2CRSP was presented in (Zhang et al., 2021). This approach successfully resolved basic use cases by exact method and helped us validate our model. However, due to the known NP-hard complexity of HHCRSP, the performance in terms of computation time was significantly reduced as the size of the problem increased. In an attempt to overcome these limits, we will present an alternative, which is a CSP-based approach. The advantages for tackling SOH2CRSP with such an alternative will be discussed. The application of problem-solving techniques based on metaheuristic methodologies will be the next step. This will provide insights for discussing the impacts of stakeholder satisfaction on HHC planning capabilities.

4. OptaPlanner-orientedmodel for solving SOH2CRSP

For many problems of a realistic size (e.g., more than 80 care services to schedule per day), an exact optimisation method may require very lengthy computation time to find an optimal solution. This may go far beyond what an HHC coordinator can tolerate (Bard et al., 2014). In facing this challenge of computation time, we propose investigating a new path. Our main idea is to upgrade our SOH2CRSP model by investing in a CSP formulation.

4.1. Constraint Satisfaction Problem-oriented modelling

The Constraint Satisfaction Problem (CSP) (Floudas & Pardalos, 1990) is a widely used approach in artificial intelligence for solving real-world problems expressed in terms of constraints (Floudas & Pardalos, 1990). According to (Russell & Norvig, 2002), a CSP is defined by the following triplet (X, D, C) where:

- $X = X_1, X_2, \ldots, X_N$ is the set of variables of the problem.
- D is a function that associates with each variable X_i and its domain $D(X_i)$ (possible values of X_i).
- $C = C_1, C_2, \ldots, C_M$ is the set of constraints of the problem. Each constraint is defined by a pair (t, R) where t is the set of variables related to the constraint and $t \in X$, R defines a relationship between these variables that will reduce solution space during a search.

Constraint programming is based on a relevant language that encodes and solves such problems for determining X values, using rules to take control over the search space D. The idea of constraint programming is to solve problems by stating constraints C on the domain of the problem, and consequently to find a solution that satisfies all of them (Barták, 1999). The ever-growing speed of processors makes them very powerful for solving combinatorial optimisation problems, not necessarily for ultimately obtaining an optimal solution, but in reaching a near-optimal level for the best solution (Rossi et al., 2006). Numerous well-known combinatorial problems have been solved efficiently using CSP-oriented approaches. We can refer to the graph colouring problem (Jensen & Toft, 2011) or the N-queens problem (Gutiérrez Naranjo et al., 2009).

Frequently, the operations research community suggests applying local search algorithms to compute an optimum when the problem complexity is NP-hard (Rossi et al., 2006). Considering real-world HHC coordination needs, we have to face the same problems of considerable size (exceeding hundreds of care services per day), along with the set of specific constraints mentioned above in SOH2CRSP. Our challenge is to meet this requirement for expected performance driven by minimal computation time.

Heuristics are the rules used to control the search for a solution in CSP solvers. Basic techniques such as constraints propagation, backtracking, or local searches are widely used for solving CSP in finite domains. They are effective for a wide range of constraints, including non-linear constraints. However, basic heuristics are too restricted for planning problems where the diversity of constraints is factual. To overcome this weakness, metaheuristics have been a candidate in conjunction with basic heuristics for gaining efficiency.

Many software libraries are available online for implementing CSP. Among them, we chose to select the OptaPlanner solver. A main reason for justifying this choice is the high level of expertise that Geoffrey De Smet (De Smet, 2006) (lead and founder of OptaPlanner) has on the Vehicle Routing Problem (VRP). In (Kosecka-Żurek, 2019), OptaPlanner solved a VRP involving what is known as the VRP waste collection mechanism in (Lozano Murciego et al., 2015), as well as a task assignment problem in (Macik, 2016). In (Rios de Souza & Martins, 2020), the work aims to explore different solutions for dealing with a garbage packaging problem, where the results obtained by different metaheuristics of a local search are compared using a benchmark module.

Consequently, through the use of OptaPlanner, we will primarily focus on a battery of metaheuristics which have shown their effectiveness for such NP-hard problems. Five metaheuristics are implemented in the resolution package of OptaPlanner: Hill Climbing (HC) (Goldfeld et al., 1966), Tabu Search (TS) (Glover & Laguna, 1998), the Great Deluge algorithm (GD) (Dueck, 1993), Variable Neighbor Descent (VND) (Gao et al., 2008) and Late Acceptance (LA) (Burke & Bykov, 2017). These should be used in combination with "construction" heuristics to compute a good initial value for the CSP variables, in a short computing time. First Fit, with its variation Weakest Fit and Strongest Fit (Bays, 1977), Allocate Entity From Queue (Semeria, 2001), Cheapest Insertion (Hassin & Keinan, 2008) and Regret Insertion (Diana & Dessouky, 2004), Allocate From Pool (Ke & Fang, 2004), and Scaling Construction Heuristics (Katayama et al., 2009) are construction heuristics supported in OptaPlanner. Starting from this initial state, the metaheuristics will perform the local search more efficiently and explore the search space while satisfying all constraints.

4.2. Overview of OptaPlanner architecture

OptaPlanner, released under the Apache Software licence, may also be seen as a lightweight and open planning engine, as it contains a specific approach for this kind of application. It allows Java programmers to process domain specific models by reusing existing models embedded in the software library. Thus, many variations of the VRP and the Traveling Salesman Problem (TSP) were made available to us that are close to the subject we are dealing with. The construction process of our optimisation model with OptaPlanner was performed in 3 steps: **CSP modelling**, **constraint declaration** and **resolution**. We will describe later how we implemented our SOH2CRSP by the reutilisation of OptaPlanner facilities.

4.2.1. OptaPlanner problem declaration

OptaPlanner follows an object-oriented approach using design patterns. An implementation needs to build a class diagram model of the planning problem under consideration. The semantics of each class is very expressive and is related to the real-world decision-making support system. This helps the modeller in thinking about the CSP formulation and in defining a well-structured formulation. Each class in the model must belong to only one of the following three categories (De Smet, 2006):

(1) *Problem Fact*: this category establishes the artefacts involved in the problem context whose data will not be altered by the solver during the solution search. But problem facts are also necessary for giving consistency during formal expression of the constraints.
(2) *Planning Entity*: this category explains what artefacts are to be planned. With a one-to-many association link between a given planning entity and a decision variable of the problem to be computed, the role of the "many" side is named as a *planning variable* and is annotated by the label *@PlanningVariable*. Therefore, an instantiation of a planning entity may be modified during the solution search process. A *Planning Entity* is annotated with the label *@PlanningEntity*.
(3) *Planning Solution*: this category refers to the problem assembly which is annotated by the label *@PlanningSolution*. It contains all the objects (annotated by *@ProblemFactCollectionProperty*) instantiated from the previous classes *Problem Fact* and *Planning Entity* and it will help specify the problem constraints that have to be satisfied.

For a type of planning problem such as a VRP or our SOH2CRSP, it is recommended to link the objects of a *Planning Entity* class in the OptaPlanner model in a **chain**. This chain concept is helpful for assigning time to planning variables. Time will be considered through events that will be computed by following the planning entities in a chain, whereas a chain specifies the order in which the planning entities will be chained. The size of the problem is decreased with this approach when compared to a predefined discretisation of the time axis that is frequently used in planning problem formulations. Consequently, the corresponding planning variables will also be chained in the solver. Notice that the order of the objects in a given chain could be modified by the solver during calculations. Each chain has an anchor that qualifies a common attribute of the chained objects. In a VRP problem, the anchor is the vehicle, whereas in our SOH2CRSP, it is the caregiver. Both are qualified by the route, which consists of chained planning entities that they will have to perform.

Three categories of secondary (non-genuine) decision variables are introduced in order to manage the dependencies between the elements in a chain in a very fluent manner. This dependency is always a specific relationship, systematically and continuously binding the calculation of secondary decision variables to the value of the primary (referred to as "genuine" in OptaPlanner) decision variables (refer to *planning variable @PlanningVariable*) (De Smet, 2006):

(1) *Custom Shadow Variable*: the value of this variable is deduced from the state of the decision variables (*@PlanningVariable*). It is annotated by *@CustomShadowVariable*. Typically, the start time and end time of a care service belong to this category.

(2) *Inverse Relation Shadow Variable*: this variable plays the role of an index that will interpret the result of a decision made. It is annotated by @*InverseRelationShadowVariable*. Typically, if a planning variable indicates the previous care service in a chain, then an inverse shadow variable can deliver the next care service of the same planning variable.
(3) *Anchor Shadow Variable*: a chain of planning entity classes has an anchor, which indicates the beginning of the chain. This anchor is annotated by @*AnchorShadowVariable*.

4.2.2. OptaPlanner constraint declaration

This phase consists in writing the rules representing the constraints of the problem to be respected. OptaPlanner provides four methods for achieving this purpose (De Smet, 2006):

(1) *Coding in Java*: all constraints are implemented in a Java method. This declaration method is not scalable.
(2) *Coding in incremental Java*: implementation of several low-level methods in Java to declare constraints. This declaration method is scalable, but very difficult to implement and maintain.
(3) *Constraint streams declaration*: each constraint is implemented as a separate stream in Java, which is easy to read, write and debug. This declaration method is scalable.
(4) *Drools-based declaration*: implementation of each constraint as a separate score rule using Drools.[2] This type of declaration is scalable. This is the choice we have made as it provides a high degree of freedom in specifying our problem.

4.2.3. OptaPlanner resolution parameters

OptaPlanner operates in two steps for solution generation: (1) the resolution of a problem by the solver, and (2) the evaluation of a solution by the score calculator.

The resolution of a problem by the solver is split into two parts. Firstly, to solve the problem, an initial solution is generated using construction heuristics, with limited processing time and the best possible quality. Secondly, the optimisation process consists in continuously searching by iteration for a better solution than the initial solution, through the use of one of the metaheuristic algorithms. In OptaPlanner, the configuration allows these optimisation algorithms to be chosen and their intrinsic parameters to be defined. The optimisation process ends when the stopping criteria have been reached. A stopping criterion is often defined as reaching either a maximum computation time limit or a certain number of iterations.

The evaluation of a solution is based on the "Score Director", which is an index of the penalties assigned by the modeller with regard to the satisfaction of constraints. The score of a given solution characterises the quality of this solution, and thus allows many solutions to be compared. OptaPlanner provides its own scoring system for each formulated constraint (De Smet, 2006). We use the scoring system composed of 2 levels (hard and soft). A hard score means that the "hard constraint" is respected. Conversely, if the hard score of a solution is less than 0 (the penalty value regarding the constraint violation is often a negative value), this solution is therefore considered an "infeasible" solution. A soft score is related to the respect of a "soft constraint". The higher a soft score is, the better a solution will be.

4.3. OptaPlanner-oriented SOH2CRSP model

The following subsections reuse the model construction tips introduced previously. We explain how to build the decision-making model of a daily SOH2CRSP in OptaPlanner.

4.3.1. CSP modeling

We firstly have to specify the model of our SOH2CRSP. Figure 2 shows the ten classes we have chosen to represent this HHC system and their relationships. We can easily observe the demand and offer archetypes. They are connected by the care services that act as a keystone class between them. The respective stakeholders are profiled by their own tolerances relative to the satisfaction criteria explained earlier.

OptaPlanner annotations are also included in Figure 2. We give further details about them in Tables 1 and 2. Table 1 is for the classes of the "problem fact" type (6 classes) which are considered to be data containers (cf.(1) in Section 4.2.1), while Table 2 is for those of the "planning entity" type (3 classes) with decision variables, whose values determine the optimised routing and scheduling solution (cf.(2) in Section 4.2.1). Finally, Table 3 defines the domains associated with decision variables.

Special attention must be paid to the "standstill" class in Table 2. We have the decision variable $prev_i$, which is the source of all the other secondary variables: $start_i$ (start time of the service), $next_i$ (next service in time), $next_k$ (next service of caregiver), and ass_i (assigned caregiver).

4.3.2. Constraint declaration

We have chosen the Drools Rule Language (DRL) to encode constraints. It facilitates the writing of constraints using a traditional formalisation of rules that is independent of the OptaPlanner model. Therefore, constraints can easily be added, modified or even deleted. DRL also provides primitives to compute the scores of constraints

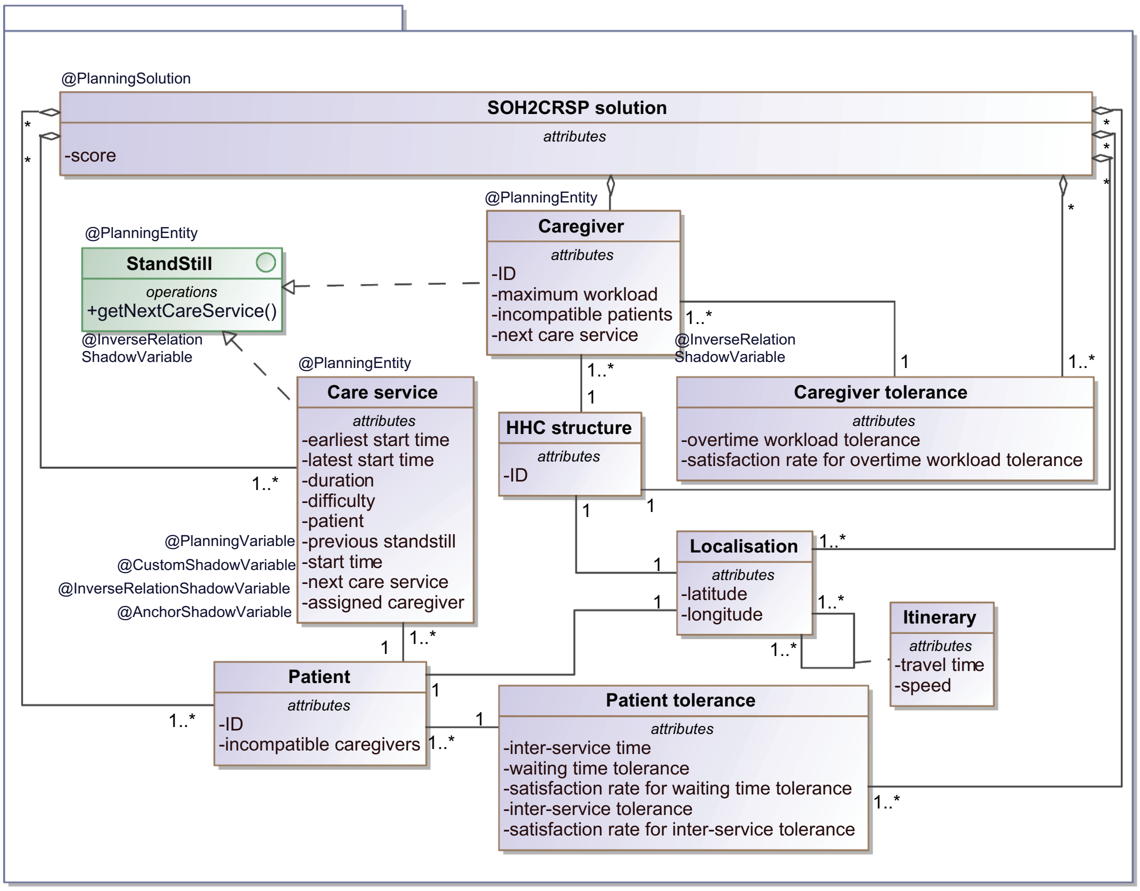

Figure 2. OptaPlanner-oriented SOH2CRSP model.

Table 1. Problem facts of the SOH2CRSP model.

	Attribute			
Class name	Name	Type	Notation	Description
HHC structure (H)	ID	String	id_h	-
Patient (P)	ID	String	id_p	-
	incompatible caregivers	List < >	inc_p	These caregivers cannot perform the care services requested by the patient p
Patient tolerance (PT)	inter-service time	Long	δ_p	Minimum time between 2 care services requested by the same patient p.
	waiting time tolerance	Long	α_p	Maximum tolerance time of patient p once the upper limit of the requested care service starting time window is exceeded.
	satisfaction rate for waiting time tolerance	Long	α_p^*	Satisfaction rate of patient p with respect to α_p where $\alpha_p^* \in [0, 100]$.
	inter-service tolerance	Long	β_p	Maximum tolerance time of patient p when the δ_p is not respected.
	satisfaction rate for inter-service tolerance	Long	β_p^*	Satisfaction rate of patient p with respect to β_p where $\beta_p^* \in [0, 100]$
Caregiver tolerance (KT)	overtime workload tolerance	Long	γ_k	Tolerance of caregiver k when the maximum workload is exceeded.
	satisfaction rate for overtime workload tolerance	Long	γ_k^*	Satisfaction rate of caregiver k with respect to γ_k where $\gamma_k^* \in [0, 100]$
Localization (L)	latitude	Double	al_{i^*}, al_{j^*}	The geographical information of two different locations
	longitude	Double	lo_{i^*}, lo_{j^*}	
Itinerary (I)	travel time	Long	$travel_{i^*j^*}$	The travel time between two locations $i^*, j^*.travel_{ij}$ is calculated as a bird's-eye view based on the 2 terrestrial coordinates, the calculation of travel time is based on Euclidean distance between two points i and j Danielsson (1980): $travel_{i^*j^*} = \frac{\sqrt{(al_{i^*} - al_{j^*})^2 + (lo_{i^*} - lo_{j^*})^2}}{sp}$
	speed	Long	sp	20 km/h as the estimated average downtown speed to calculate $travel_{i^*j^*}$.

for assessing the quality of a solution. A constraint statement in Drools consists of two parts based on first-order logic: the condition **When** and the consequence **Then**. For the **When** part, we specify the condition triggering the constraint and the parameters are identified by the "$ + name" syntax. In the **Then** part, we declare a formula for the score calculation. We have developed 7 constraints in the SOH2CRSP model, where 3 are hard constraints and 4 are soft constraints. OptaPlanner maximises the score in the "scoreHolder" class and makes a distinction between hard and soft penalties. Therefore, a negative value score is attached to each

Table 2. Planning entity of the SOH2CRSP model.

Class name	Attribute			
	Name	Type	Notation	Description
Standstill	-	-	-	**Interface** with the getNextCareService() method. This method is annotated by @InverseRelationShadowVariable. The "*Care service*" and "*Caregiver*" classes implement this interface for synchronization purposes. The specification of the method allows the "next care service" attribute to be shared by the two classes. This interface is the basis for the creation of a round for each caregiver, since each round is composed of a caregiver and the care services that she/he performs.
Caregiver (K)	ID	String	id_k	-
	maximum workload	Long	ξ_k	**Parameter**. Maximum workload of caregiver k per day.
	incompatible patients	List < >	inc_k	**Parameter**. Impossibility in assigning care services of incompatible patients to caregiver k.
	next care service	Object	$next_k$	**Inverse Relation Shadow Variable** based on the specification of the getNextCareService () method in Standstill interface.
Care service (C)	earliest start time	Long	e_i	**Parameter**. $[e_i, l_i]$defines the time windows requested by the patient p for the beginning of care service
	latest start time	Long	l_i	
	duration	Long	$duration_i$	**Parameter**. Processing time of care service i.
	difficulty	Long	dif_i	**Parameter**. Level of difficulty in performing care service i. The higher the value of this parameter, the more difficult it is for the care service to be executed.
	patient	Object	$benef_i$	**Parameter**. Beneficiary of a care service, a care service is requested by a patient p.
	previous standstill	Object	$prev_i$	**Planning Variable**.
	start time	Object	$start_i$	**Custom Shadow Variable** representing the start time of each care service.
	next care service	Object	$next_i$	**Inverse Relation Shadow Variable** based on the specification of the getNextCareService () method in Standstill interface.
	assigned caregiver	Object	ass_i	**Anchor Shadow Variable** representing the assigned caregiver to care service i.

Table 3. Domains of the decision variables in the SOH2CRSP model.

Class name	Variable name	Variable type	Domain
Caregiver (K)	next care service	Inverse Relation Shadow Variable	$next_k = \{C_1, C_2, \ldots, C_r\} \quad k \in K$, where r denotes the number of care services requested by patients.
Care service (C)	previous standstill	Planning Variable	$prev_i = \{C_1, C_2, \ldots, C_r\} \cup \{K_1, K_2, \ldots, K_n\} \quad i \in C$, where n denotes the number of registered caregivers per day.
	start time	Custom Shadow Variable	$start_i = [0, 1440] \quad i \in C$.
	next care service	Inverse Relation Shadow Variable	$next_i = \{C_1, C_2, \ldots C_r\} \quad i \in C$
	assigned caregiver	Anchor Shadow Variable	$ass_i = \{K_1, K_2, \ldots, K_n\} \quad i \in C$

unsatisfied constraint using the implementation of the following two methods:

- *scoreHolder.addHardConstraint Match(kcontext, -1)* for hard constraints; the penalty value is equal to −1 in the case of a hard constraint violation.
- *scoreHolder.addSoftConstraintMatch(kcontext, -scoreValue)* for soft constraints; the penalty value is representative of the relative weight of each soft constraint. It is a setting in which we have latitude for defining, which allows us to set a hierarchy in the spectrum of soft constraints. The harder the soft constraints are, the higher the *scoreValue*.

It is rational to specify constraints 1, 2, and 3 as hard constraints.

If a caregiver k arrives too early where a patient p is living, a waiting time is necessary before the expected availability of the patient begins (the earliest start time window of one requested care service), and a penalty is delivered in such a context. For each penalty, the hard global score of a solution will be subtracted by 1, which refers to (−1hard/0soft). Constraint 1 defines this time limitation.

Constraint 2 prevents the temporal overlap for two successive care services requested by the same patient p, while constraint 3 ensures that there is no incompatibility between patient p and caregiver k. If these constraints are not respected, the temporal overlap per occurrence or for each incompatible assignment will result in subtracting 1 from the global hard score.

Constraints 4, 5, 6, and 7 are soft constraints. They deal with the satisfaction of stakeholders in our SOH2CRSP.

Firstly, constraint 4 aims to create a fair distribution of care services with respect to the intrinsic difficulties regarding each round of any caregiver. To do so, we apply a scoring strategy which minimises the gap (i.e., maximises the negative gap) between the difficulty of each round ($Round_difficulty) and the average difficulty

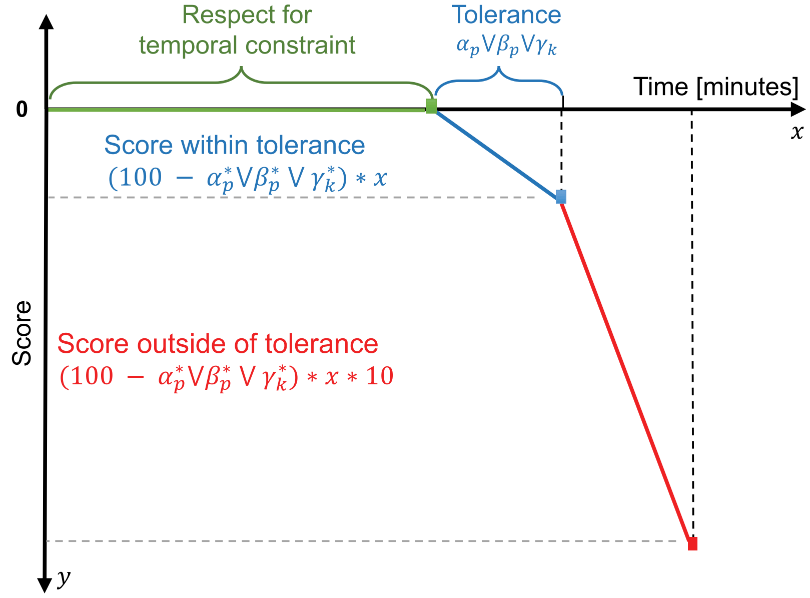

Figure 3. A linear function to model the relationship between the score and the exceeded time in a temporal constraint applied to constraints 5 to 7. The symbol $\alpha_p \vee \beta_p \vee \gamma_k$ depicts with an aggregated formulation the tolerance time for, respectively, the three different types of constraints (5,6, and 7) to be considered in the SOH2CRSP. The notation $\alpha_p^* \vee \beta_p^* \vee \gamma_k^*$ has the same meaning: it represents the satisfaction rate for the three types as a percentage unit.

of all rounds ($Total_difficulty/$Number_Caregiver). This strategy is very similar to a Standard Deviation (SD) variable. This example shows how to calculate the soft score of a caregiver : $services_a$, $services_b$, $services_c$ with, respectively, the performing difficulty 6,4 and 7 which are assigned to $caregiver_\beta$, while the average difficulty of all rounds is 15. Thus, the global soft score will be subtracted by $|(6+4+7)-15|$ for $caregiver_\beta$, which refers to (0hard/-2soft).

Next, constraints 5, 6, and 7 give consistency to the satisfaction of temporal constraints with tolerances related to the individual profiles of stakeholders (caregivers or patients). A generic translation of the satisfaction tolerance in a mathematical formulation has been defined. As shown in Figure 3, the proposal is a piecewise linear function of the score relative to the intensity of a temporal non-respect, according to the personalised tolerance exhibited by stakeholders. Note that if the violation value (overrun time) of these 3 constraints is less than the relevant tolerance (e.g., α_p in constraint 5), the slope of the linear function will be decreased from 100% (equals $100-\alpha_p^*$ in the same example): the more sensitive the stakeholder is to the excess of the upper tolerance time, the steeper the slope of the function. Considering a stakeholder's dissatisfaction at a high level of importance, the slope of the second part of this linear function has been chosen arbitrarily to be 10 times larger than the first part. The penalty becomes very harsh beyond this limit of confidence.

Therefore, constraints 5, 6, and 7 apply this model pattern to their scores with respect to the starting time window of a requested care service (constraint 5), to the inter-service time requested by a patient (constraint 6) and to the maximum daily workload of a caregiver (constraint 7). The example in Figure 4 demonstrates how to calculate the global soft score of a solution when constraints 5, 6, 7 are triggered.

5. A study of the added value of stakeholder satisfaction

5.1. *OptaPlanner solving strategy*

As explained earlier, the implementation of OptaPlanner implies a first choice of a construction algorithm among a set of many given heuristics for the definition of the initial solution. Then, it is necessary to select an optimisation algorithm from the set of proposed metaheuristics to search for the best solution within the decision variable space. In order to find the best choice of methods for a given problem, an embedded configuration tool called "benchmark" helps to make a comparative study. By this means, a particular problem can be submitted concurrently to many different pairs of available algorithms (one for the construction, one for the search of a solution), and the solutions are compared automatically through a report dashboard. The corresponding process is discussed extensively in (Macik, 2016). For these authors, who have primarily performed such a test on the task assignment problem, the result highlighted the fact that the most efficient construction heuristic was First Fit (Rios de Souza & Martins, 2020).

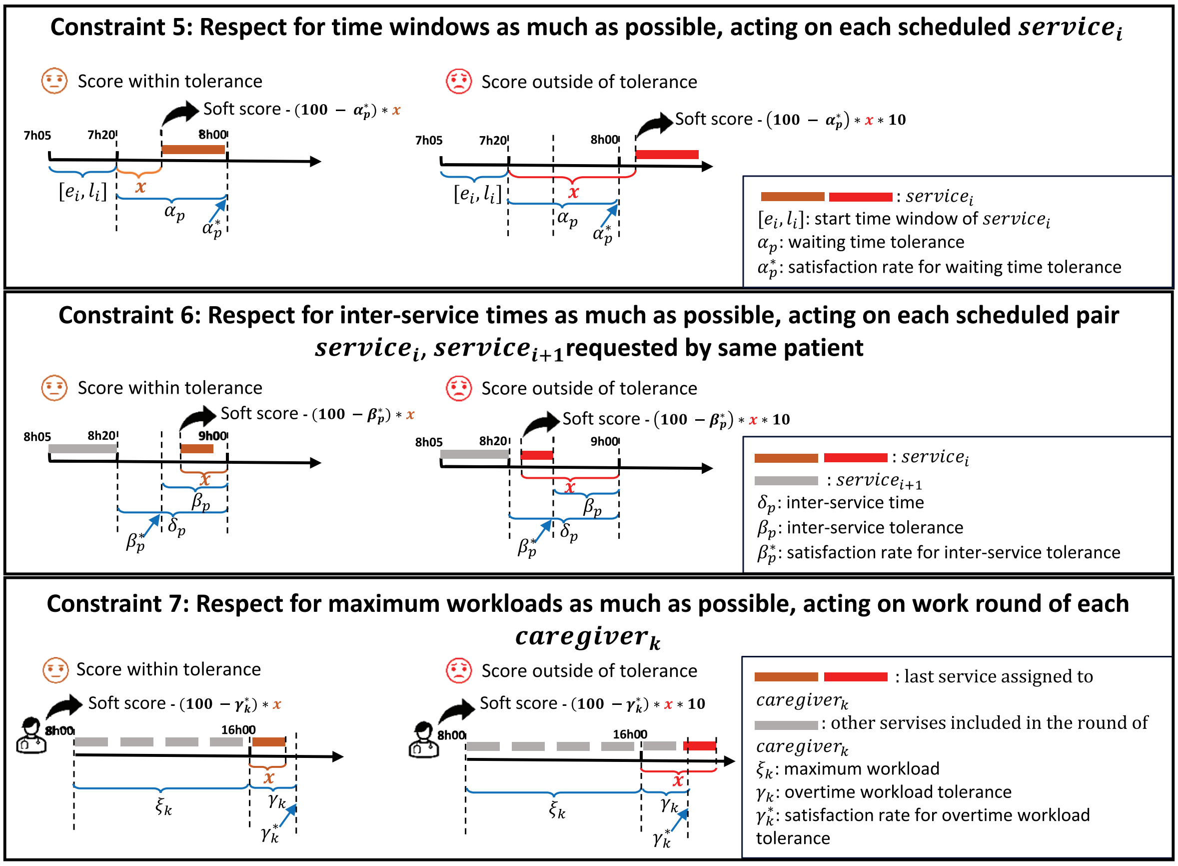

Figure 4. Soft score calculations for solutions when constraints 5, 6 and 7 are triggered.

Concerning the performance of the five available metaheuristics in OptaPlanner, the predefined default parameters for each metaheuristic algorithm were used without any change. The reason why lies in our wish to compare the obtained results starting from the same basic settings. Two criteria were used to check the end of calculation depending on whether: (1) the global score reached the upper bound of value 0 (the maximum score for both soft and hard parts), or (2) the computation time exceeded a delay of 8 minutes without making any new gain relative to the best current solution of the problem. Consequently, the benchmark test for the SOH2CRSP described in the next section demonstrated that the TS algorithm was the best method. All algorithms were able to find a feasible solution (the score for the "hard constraint" part = 0), but this was not the case for the "soft constraint" part. As illustrated in Figure 5, the soft score generated by a TS is the highest (−360) among all other results for the large-size problem "L_s130_p90_mp24_k16" (the description of this use case will be in Section 5.2.1). Thus, we decided to keep TS as the solving algorithm to perform our experimentation.

5.2. General experiment

In Zhang et al. (2021), a mathematical model based on MILP for the HHCRSP is proposed, with consideration of the same business constraints addressed in this paper. Furthermore, the considered objective is also identical for achieving a maximisation of total satisfaction regarding all stakeholders in the HHC system. This MILP-based model is able to address the problem in a medium-large dimension within a short computing time.

By investigating the field of comparisons between the OptaPlanner-based approximate method and the exact method, the main purpose of this comparative study is to examine the quality of solutions generated by our OptaPlanner-based approximate method.

To ensure this comparison, we firstly draw attention to the Objective Function formulated in Zhang et al. (2021):

$$maximize \frac{\sum_{p \in P} \mathbb{W}_p + \sum_{q \in Y} \mathbb{R}_q + \sum_{k \in K} \mathbb{O}_k + \sum_{k \in K} \mathbb{G}_k}{m + l + n \cdot 2} \quad (1)$$

The result of the objective function is in the range of [0,1] where:

- P: set of patients, with the index $p \in [0, m]$ and m denotes the number of patients.
- Υ: set of patients who request more than one care service, with the index $q \in [0, l]$ where l denotes the number of patients with multiple requests and $\Upsilon \subseteq$ P.

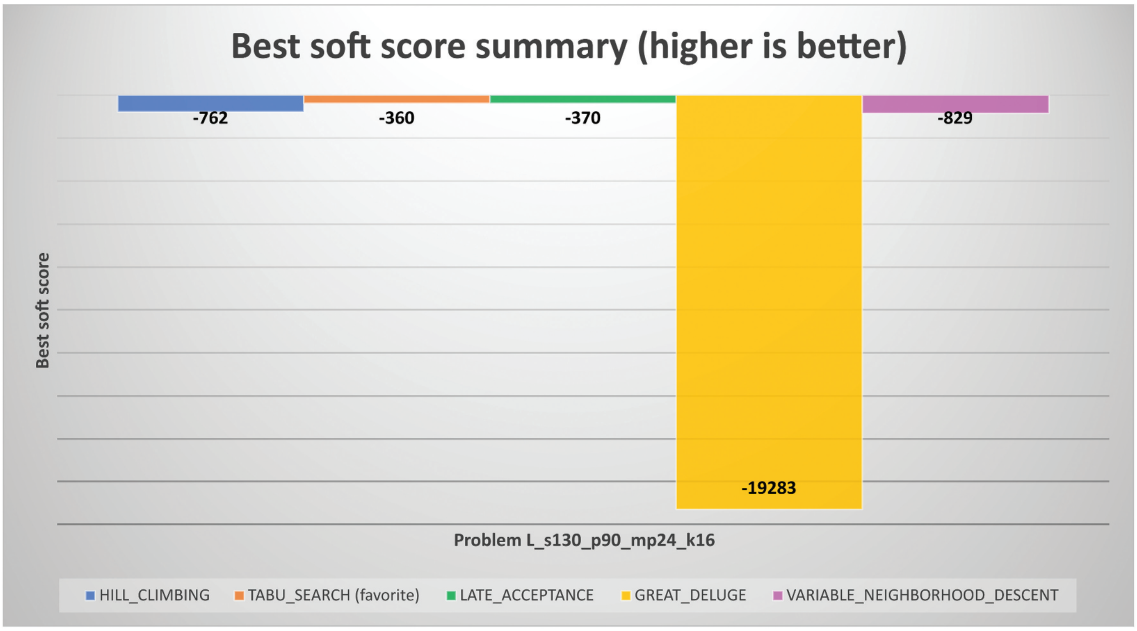

Figure 5. Benchmark results for "L_s130_p90_mp24_k16": a "soft constraint" score.

Table 4. Random generation of the bounds of stakeholder satisfaction and care service difficulty.

Viewpoint	Parameter	Upper bound	Lower bound	Comment
Caregiver	γ_k	50	100	In minutes
	γ_{k^*}	30	50	In %
	ξ_k	600	600	In minutes
Patient	α_p	30	60	In minutes
	α_{p^*}	30	50	In %
	β_p	1	20	In minutes
	β_{p^*}	30	50	In %
	dif_i	1	6	-

- K: set of caregivers, with the index $k \in [1, n]$ and n denotes the number of caregivers who are available to perform the daily care services.
- $\mathbb{W}_p$: satisfaction rate with respect to the set of waiting times for care services requested by patient p.
- $\mathbb{R}_q$: satisfaction rate with respect to the set of lacking inter-service times between the care services requested by patient q.
- $\mathbb{O}_k$: satisfaction rate with respect to the overtime workload of caregiver k.
- $\mathbb{G}_k$: round difficulty coefficient of caregiver k.

Then, we translate the representation of the results of the OptaPlanner-based approximate method in score format (e.g., 0hard/156soft), in such a way that the solution of the approximate method is represented by the objective function format illustrated in Equation 1. This translation process is realised by a feature of our test environment, as in Zhang et al. (2020).

5.2.1. State-of-the-art dataset presentation

Our experiment is based on the dataset presented in Zhang et al. (2021). The dataset is extracted from the database of an operational product belonging to a customer of the Berger-Levrault company. This customer is an HHC organisation providing services in a medium-sized town located in the west of France. Three instances of larger size are generated to bring our experiment closer to reality. The whole dataset is categorised into 4 groups: S (small size, with 10–30 care services), M (medium size, with 35–50 care services), ML (medium-large size, with 55–70 care services) and L (large size, with 110 and 130 care services). For each use case, a label is defined with the following structure: "**Group_s***XX***_p***YY***_mp***ZZ***_k***VV*", where the subscript s indicates the number of requested care services, the subscript p indicates the number of patients, the subscript mp indicates the number of patients who request more than 2 care services, and the subscript k represents the number of registered caregivers who are ready to perform their daily rounds.

As stakeholder satisfaction was not initially defined in the source of the data, we have randomly generated these parameters related to satisfaction within a given range. Table 4 illustrates the results for the caregivers and the patients, using the notations proposed in Table 1.

Table 5. Overall experimental results.

Use case	UB-CPLEX	OptaPlanner					
		OF-without satisfaction	OF-with satisfaction	CPU-without satisfaction	CPU-with satisfaction	Gap 1	Gap 2
S_s13_p6_mp6_k3	0.9694	0.5828	0.9193	0.1	73.5	5.17%	36.60%
M_s37_p21_mp11_k6	0.9991	0.4968	0.9974	0.2	11.6	0.17%	50.19%
M_s40_p25_mp10_k6	0.9992	0.5285	0.9984	0.2	10.8	0.08%	47.07%
M_s43_p23_mp12_k6	0.9989	0.4899	0.9978	0.2	13.9	0.11%	50.90%
M_s47_p26_mp13_k7	0.9988	0.5058	0.9976	0.2	12.8	0.12%	49.30%
M_s50_p26_mp13_k7	0.9993	0.4952	0.9990	0.3	12.3	0.03%	50.43%
ML_s55_p28_mp14_k8	1.0000	0.4832	1.0000	0.4	33.2	0.00%	51.68%
ML_s60_p31_mp18_k9	0.9994	0.6035	0.9971	0.4	11.8	0.23%	39.47%
ML_s61_p32_mp17_k8	1.0000	0.5805	1.0000	0.4	13.6	0.00%	41.95%
L_s81_p56_mp13_k11	0.9989	0.4631	0.9907	0.3	677.7	0.82%	53.26%
L_s110_p74_mp22_k15	0.9986	0.6045	0.9964	5.1	627.7	0.22%	39.33%
L_s130_p90_mp24_k16	0.9999	0.4761	0.9990	1.1	676.3	0.09%	52.34%

5.2.2. Numerical results

The experimental test was performed on a computer with Intel(R) Core (TM) i7-7500 U CPU 2.90 GHz and 16.0 GB RAM under the Windows 10 operating system. The results of our experiments are presented in Table 5. First, we show the overall performance in terms of computing time in seconds (CPU) for the OptaPlanner-oriented resolution approach. Secondly, to show the optimality of the solution generated by our solution approach, we show the gap between the Upper Bound (UB-CPLEX) and the Objective Function (OF) of the OptaPlanner-oriented solution with the consideration of satisfaction criteria (Gap 1). The UB-CPLEX is the bound given by the best node which is extracted from CPLEX when calculating the optimal solution for each use case by exact method. Finally, to evaluate the impacts that the satisfaction of stakeholders can have on HHC planning, for each instance, the second gap study (Gap 2) is carried out, which is based on a comparison of SOH2CRSP solutions with and without the satisfaction consideration (soft constraints).

As shown in Table 5, the results demonstrate the performance of our OptaPlanner-based SOH2CRSP model in reaching the approximate optimum solution ($Gap1 \approx 0$, except $Gap1_{S\_s13\_p6\_mp6\_k3} = 5.17\%$). The computing time is satisfactory even with a problem dimension up to the large size. Gap 2, however, shows the impact of considering satisfaction-related constraints on the optimisation result: if we do not consider these constraints in our model, the scheduling result becomes extremely unsatisfactory, with $\overline{Gap2} = 51.14\%$ for all experimental instances.

5.3. Experiment on L_s130_p90_mp24_k16

L_s130_p90_mp24_k16 is the biggest instance we tested; therefore, we would like to provide a more specific analysis of it and its corresponding scheduling results as generated by OptaPlanner. We will first explain some key features of this use case. To do so, we sought to create a form of identity card for instance L_s130_p90_mp24_k16 in which the input data format, starting with caregivers, then patients, and finally care services, is presented.

The coordination here concerns 16 caregivers. Table 6 summarises the acquaintanceships between caregivers and patients. On average, 3 patients are removed from the portfolio of a caregiver, and the standard deviation is about 3 patients. Such figures have to be considered relative to the total number of patients. As 90 patients have to be cared for, 3% of patients are declared to be non-compatible per caregiver.

The working time of caregivers is featured by the shift dates and the accepted workload. In our use case, all caregivers start at 8:00 a.m. and end at 9:40 p.m. For each caregiver in a working day, a workload of 10 hours is allowed between these two bounds. The mean overtime work tolerance is about 90 minutes with a Standard Deviation (SD) of $\approx$ 14 minutes.

All caregivers have to share a total of 130 care services to be delivered during their shifts. Table 7 gives the statistical distribution of 33 time windows over the 130 entities and the intensity of their use (count). For example, the first time window has been assigned 15 care services.

The waiting time accepted by patients in reference to the time windows has a mean of 44 minutes with a SD of 9 minutes. The minimal bound is 30 minutes and the maximal bound is 60. The pool of 90 patients leads to a wide travel matrix that was generated using geo-localisation facilities with a bird's-eye view, and the travel time between all the 2-tuples of patients was estimated by using Google Maps. To summarise this geographical distribution of service needs, we first

Table 6. Number of patients removed from the list of caregivers (CG).

CG#1	CG#2	CG#3	CG#4	CG#5	CG#6	CG#7	CG#8	CG#9	CG#10	CG#11	CG#12	CG#13	CG#14	CG#15	CG#16
4	2	0	1	2	5	8	0	10	4	6	5	2	0	0	0

Table 7. Summary of care service starting time windows ($[e_i, l_i]$, in minutes).

Earliest start time (e_i)	Latest start time (l_i)	Count
450	510	15
465	525	3
480	540	5
495	555	2
510	570	9
525	585	4
540	600	5
555	615	1
570	630	6
585	645	2
600	660	7
630	690	7
645	705	2
660	720	4
675	735	1
690	750	7
705	765	2
810	870	10
870	930	3
900	960	4
930	990	2
960	1020	2
990	1050	2
1005	1065	1
1020	1080	1
1035	1095	2
1050	1110	1
1065	1125	3
1080	1140	3
1095	1155	4
1110	1170	4
1125	1185	3
1140	1200	3

compute the statistical distribution for each service with respect to the others, and then we apply a new statistical abstract over the set of achieved distributions. The statistical analysis is detailed using mean, SD, maximal and minimal variables. For example, the mean average time for all the locations is about 10 minutes (9.96 minutes) and its SD = 0.69 minutes, while the mean of SDs = 4.90 minutes with an SD of SDs = 0.89 minutes. The minimum of shortest time is 0 and the maximum of longest time is 34 minutes. This is an expected result because the use case is drawn from a coordinating HHC system covering a territory that corresponds to a medium-sized town, which requires a reasonable travel time from one point to another in order for caregivers to perform the assigned care services.

Among 90 patients, 24 of them requested more than one care service. The range of demand went from one service to a maximum of four during a shift. 50% of the 24 patients asked for a second care service, while 66.7% (8 patients) of the remaining 12 patients asked for 3 services and 33.3% (4 patients) of the 12 patients asked for 4 services during the same shift.

Considering multiple service demands, the minimal inter-service time between two successive services (annotated by δ_p in Table 1) should be defined. The data are given for each patient and we have done a specific statistical analysis for them. The $\bar{\delta}_p = 43.6$ minutes with an SD = 9.2 minutes, in a spectrum ranging from 30 minutes to 58 minutes.

The difficulty of rounds performed by caregivers is included in the perimeter of our problem formulation. The input data used for this care service's dimension are delivered by an index providing a level of difficulty using a scale ranging from 0 to 6. The pool of patients is distributed around the level of 3.4 with an SD = 1.7, which means that the difficulty is sufficiently high so that this factor cannot be neglected with respect to the satisfaction of caregivers.

5.3.1. Methodological approach and results

Our purpose is to evaluate the impacts that the satisfaction of stakeholders can have on HHC planning. As shown in Gap 2 of Table 5, we have drawn an experimental strategy based on a comparison of SOH2CRSP with and without soft constraints (this refers to constraints 4, 5, 6, and 7, which represents the 4 satisfaction criteria considered for all stakeholders in our model). Planning without soft constraints is a basic and rough problem formulation. It tends to produce a baseline that is feasible planning. It will respect, as far as possible, acquaintanceships, time windows and inter-service time. We have not limited the working time of caregivers to 10 hours.

A total of 536 variables and 34,572 constraints has to be considered to solve this particular large-sized problem with the distributions described in Tables 8 and 9.

Two examples of planning regarding two SOH2CRSP models have been carefully studied, and the main characteristics of the solutions produced by the OptaPlanner have been summarised in Table 10. The upper part (down to the "Total" line) is relative to a caregiver analysis with output data, and the lower part is a statistical analysis of the data in each column.

For the first step in our analysis regarding the two solutions, the total number of care services (cf. line "Total" of the 2nd and 3rd columns in Table 10) are identical, which proves that all the services to

Table 8. Enumeration of decision variables.

Variable name	Notation	Related class	Variable type	Variable count
previous standstill	$prev_i$	Care service	@*PlanningVariable*	130
start time	$start_i$	Care service	@*CustomShadowVariable*	130
next care service	$next_i$	Care service	@*InverseRelationShadowVariable*	130
assigned caregiver	ass_i	Care service	@*AnchorShadowVariable*	130
next care service	$next_k$	Caregiver	@*InverseRelationShadowVariable*	16

Table 9. Enumeration of constraints.

Constraint name	Related variable					Constraint count
	$prev_i$	$start_i$	$next_i$	ass_i	$next_k$	
Constraint 1 (hard)		X				130
Constraint 2 (hard)		X				16900
Constraint 3 (hard)				X		16
Constraint 4 (Soft)				X	X	16
Constraint 5 (Soft)		X				130
Constraint 6 (Soft)		X				16900
Constraint 7 (Soft)	X		X	X		480

Table 10. SOH2CRSP solution without and with satisfaction criteria.

Caregiver #	Care service count		Total difficulty		Total service time		Total travel time	
	without satisfaction	with satisfaction	without satisfaction	with satisfaction	without satisfaction	with satisfaction	without satisfaction	with satisfaction
1	16	8	58	28	735	480	124	72
2	14	9	41	28	660	435	156	63
3	12	10	40	28	690	495	104	78
4	10	9	41	28	690	450	91	57
5	9	9	28	28	630	495	95	40
6	8	7	34	28	615	405	80	110
7	14	7	45	28	525	465	92	57
8	7	8	24	28	450	330	61	81
9	9	9	35	28	480	390	43	171
10	5	8	13	28	285	465	60	116
11	4	8	16	28	360	450	54	80
12	4	8	10	28	390	390	30	77
13	5	9	15	28	210	405	72	99
14	5	7	23	28	180	465	45	61
15	4	7	14	28	90	540	22	55
16	4	7	11	28	75	405	66	54
Total	130	130	448	448	7065	7065	1195	1271
Mean	8.13	8.13	28.00	28.00	441.56	441.56	74.69	79.44
SD	4.08	0.96	14.48	0.00	222.89	51.95	35.10	32.17
Min	4	7	10	28	75	330	22	40
Max	16	10	58	28	735	540	156	171

be planned have been allocated to a caregiver. On average, 8 services are performed by each of the caregivers. However, the distribution of services is not the same when the 2^{nd} and 3^{rd} columns are compared. This is illustrated by an SD that is drastically reduced when satisfaction criteria are considered. In the 2^{nd} column, each caregiver has a round that includes from 4 to 16 care services to perform, while the range is from 7 to 10 for the solution shown in the 3^{rd} column of Table 10. Secondly, the difficulty distribution is perfectly equitable with the satisfaction criteria since each caregiver has a total difficulty index of 28 (cf. the 5^{th} column in Table 10). This is not true for the solution without satisfaction criteria, shown in the 4^{th} column of Table 10, where the lowest limit is 10 and the upper limit is 58. The working time is split into two components, with, respectively, the time spent for performing the assigned care services and the necessary travel time from one patient to another. The comparison of SD for service time shows a reduction from 222.89 to 51.95 minutes: the workload seems to be more equitably distributed over the resources when considering the satisfaction criteria. While the mean travel time is logically the same in each solution, the travel times are different depending on the definition of the routes. The mean travel time is slightly higher for the solution with the satisfaction criteria ($\overline{Travel_{satis}} = 79.44 > \overline{Travel_{\neg satis}} = 74.69$). The SD and the range of values are quite similar.

From this first examination of the results, it appears that the consideration of satisfaction leads to planning that is very different. The soft constraints clearly play a role by reducing the differences among the rounds (round difficulties) and the routes of caregivers (distribution of workloads).

The analysis continues with the points of view that patients can have on the quality of the two examples of planning. We have developed our analysis in two parts:

- Columns 2 to 5 of Table 11 contain the statistics relative to the waiting time and the temporal value for non-respect of inter-service time.
- Columns 6 to 9 of Table 11 show the statistics for exceeding the time of caregivers' time windows and their idle times.

In Table 11, the effects of soft constraints are manifest. Both the total waiting time of patients and the excess

Table 11. Impact of satisfaction consideration.

	Waiting times		V. inter-service time*		Exceeding times**		Idle times	
	without satisfaction	with satisfaction	without satisfaction	with satisfaction	without satisfaction	with satisfaction	without satisfaction	with satisfaction
Patient's viewpoint	X	X	X	X				
Caregiver's viewpoint					X	X	X	X
Mean	321	0	13	0.25	1864	0	61	160
SD	302	0	19	1.22	1735	0	104	60
Min	0	0	0	0	15	0	0	40
Max	1279	0	71	6	5739	0	308	251
Range	1279	0	71	6	5724	0	308	211

* Temporal value of non-respect of inter-service time. ** Exceeding times regarding their time windows.

of time windows for caregivers are reduced. The reduction in non-respect of inter-service time is substantial, since the 13 minutes on average in the solution without considering satisfaction criteria becomes only 0.25 minutes on average in the solution considering satisfaction criteria.

The only comparative indicator that is worthwhile when considering satisfaction criteria is the total idle time of caregivers. The mean value of caregiver idle times is much higher in the solution considering satisfaction criteria, while the SD, as well as the range of values, are better. This is probably the price of having better planning with respect to other indicators. Notice that the upper bound of working time (10 hours) is respected for all caregivers in the solution with soft constraints (real working time/caregiver = total service times + total travel and idle times).

To conclude our experiments and offer some insight into the special features of our solution approach, after considering the constraints on satisfaction for all stakeholders, our SOH2CRSP model completely eliminates patient waiting times and the non-respect of inter-service times, while caregiver overtime work and caregiver round difficulties are balanced. We know that the patients' long waiting times for receiving care and the non-compliance with the interval between multiple services can lead to a significant decrease in patient satisfaction with respect to the delivered services and similarly, caregivers' overtime and unbalanced distribution of tasks in the medical team can result in a sharp decline in the quality of services. In addition, the considered temporal constraints are soft and controlled by the tolerance given by the stakeholder. This personalised tolerance explains the diversity of the stakeholders' personal characteristics; for example, some patients who are extremely sensitive to time will have 0 tolerance for waiting times. Knowing that the coordinator in an HHC organisation is especially concerned with the speed of problem solving, in terms of the computing performance of our model, the final two solutions were obtained within a reasonable computational time of approximately 10 minutes (676 seconds). The instance L_s130_p90_mp24_k16 and the two solutions (One that considers satisfaction criteria and the other that does not) can be found at https://www.researchgate.net/publication/365361723_Use_case_L_s130_p90_mp24_k16 and https://www.researchgate.net/publication/365361494_Two_solutions_L_s130_p90_mp24_k16.

6. Conclusions and perspectives

This research work addresses a model with a comparative study for solving the Home Health Care Routing and Scheduling Problem (HHCRSP) for a daily planning horizon. The originality of our work relates to the consideration of satisfaction for stakeholders, so the traditional HHCRSP is therefore transformed into a new Satisfaction-Oriented HHCRSP (SOH2CRSP). The satisfaction criteria was developed using specific constraints expressing the preferences of caregivers and patients on the one hand, and on the other hand, using tolerances for some of these preferences to an admissible extent in order to relax the problem-solving difficulty, if necessary. The tolerances are modelled according to the parameters that define the profile of a given stakeholder and his/her degree of tolerance for the criteria of satisfaction. A linear regression function is used as a pattern model to express each stakeholder's level of requirements. This kind of customisation is a way to truly consider the diversity of stakeholders related to the offer and demand of HHC services.

The search for a solution is operated by OptaPlanner. Our OptaPlanner-oriented SOH2CRSP model is explained extensively in this paper. By using an embedded benchmark module, we identified that the Tabu Search (TS) metaheuristic was the most efficient for SO2HCRSP solution generation.

To examine the quality of the solutions generated by OptaPlanner, we first performed an extensive experiment based on 12 real-life use cases, together with a critical analysis of the generated solutions between our method and a state-of-the-art exact method. Then, we focused on a comparative analysis using the largest-sized use case coming from the field of operations. The use case is introduced with a data structure that resembles an identity card, aiming to understand the main features of the HHC's underlying coordination. The planning obtained with and without considering four soft constraints has been synthetised. Many comparative indicators have been proposed. The advantages resulting from the SOH2CRSP model when considering satisfaction criteria are significantly demonstrated. At the end of this test, we gained confidence that the quality of the results of the solution generated when considering soft constraints are far better.

In future works, the results of our research will be disseminated by the Berger-Levrault company. We will improve our approach in two ways:

- Firstly, we want to capture the large amount of data in an easy way. To do this, we have begun to investigate the use of decision-making business models as a starting point for a model-driven engineering environment. The first steps have been successful and we are now trying to launch a specific project for completing this work.
- Secondly, to check that the generated schedules are consistent with the expectations of all stakeholders involved in coordination and operations management, we want to collaborate with a set of managers in an HHC organisation and obtain the benefit of their feedback as users of the planning tool. This will be a new area of investigation since the generated planning will be assessed by the end users, and in doing so, the overall utility of the satisfaction criteria will also be qualified. Finally, we will have to face a lot of the uncertainties that have been neglected up until now and manage these uncertain events through real-time data collected by mobile scheduling software during the delivery of care services by caregivers, which will help in the generation of dynamic solutions for SOH2CRSP.

Notes

1. A list of patients assigned to each care team in the practice.
2. Drools: https://www.drools.org/.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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