Shift Planning Optimization in Regional Home Care Services in Switzerland

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Abstract

This paper presents a solution to optimize the scheduling of carer shifts in home care services in a regional setting in Switzerland. To achieve this, all necessary data is sent to a shift planning algorithm using constraint satisfaction, which is embedded within a module accessed via an API. This algorithm generates optimized daily schedules for each carer based on the received data, considering factors such as carer roles, absences, travel routes, and patient preferences. The generated schedules are then returned to and integrated within the home care software, where they can still be manually adjusted by the planner if needed. First tests show the feasibility of the approach.

Keywords

Home Care Services, Shift Planning, Constraint Satisfaction

1. Introduction

In the complex field of healthcare, particularly in home care services, the efficient scheduling of caregiver shifts is crucial for ensuring that patients receive timely and appropriate care[1]. The process of scheduling is not merely about assigning available caregivers to appointments; it involves a sophisticated balance of various constraints and preferences.

Constraint satisfaction [2], a subdomain of Artificial Intelligence (AI), a mathematical and computational approach used to find the best possible solution to a problem within a set of given constraints, has been used successfully in many application domains. It can be used in the context of caregiver scheduling, where the goal is to create an optimized schedule that meets the needs of both the patients and caregivers while adhering their numerous constraints. These constraints include caregiver availability, patient preferences, travel times, and the specific requirements of different types of appointments.

This paper describes a scheduling system that utilizes a constraint optimization algorithm to automatically generate daily schedules for caregivers within a rural region in Switzerland. It was conceived and implemented in close collaboration with a private home care service company and with the software company supporting their work. The developed software module presented in this paper is independent and can be integrated with an API call that sends anonymous data from the company software to the optimization module. The input to this system includes detailed information about the patients, caregivers, and appointments. For each patient, the system considers geographic location, preferences for specific caregivers, and any exclusions that prevent certain caregivers from being assigned. Caregivers are evaluated based on their roles, availability, and any absences that might conflict with potential appointments.

The algorithm works by analyzing this data to create a schedule that minimizes unassigned appointments and maximizes adherence to patient preferences and caregiver roles. The system also accounts for travel times between appointments to avoid overlaps and ensure that caregivers can move efficiently from one appointment to the next. The output is an optimized schedule that specifies the start and end times for each appointment and the assigned caregiver. This schedule is designed to be as close to optimal as possible, considering all the constraints and factors involved. The final schedule can still be

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manually adjusted by a planner, providing flexibility while ensuring that the most critical constraints have already been met. Using constraint optimization, this system ensures that the scheduling process is both efficient and adaptable, reducing the burden on planners and improving the overall quality of care.

The rest of this paper is organized as follows: Section 2 discusses the particularities of efficient scheduling of caregiver shifts and background. Section 3 discusses the methodology used. Section 4 describes the chosen software architecture. Section 5 presents the implementation, with a focus on the input/output and the applied constraints. Section 6 concludes with a description of the test run and the planned enhancements.

2. Background: Scheduling of Caregiver Shifts and Constraint Satisfaction

Homecare organizations ("Organisation de Soins à Domicile" or OSAD in French) care for patients in their own homes,. These organizations use software to digitize documentation by therapists and manual scheduling of their working hours. DEVECOM, for example, has developed and marketed a homecare management software package for administrative and medical aspects of its OSAD customers. In this software, care planning is carried out manually by schedulers. Such manual planning is tedious. Automating and, above all, optimizing them would bring enormous benefits for customers to align with the needs of healthcare professionals. Indeed, planning and distributing care to patients is an ongoing challenge, with many unpredictable events. This is central to quality of care, patient quality of life and cost efficiency. Many factors make this management complex and particular: the imperatives of scheduled treatments, distances between homes, the fragility of situations, emergency hospitalizations and falls[3].

The use of AI is being explored in various stages of the healthcare process, including clinical documentation and monitoring [4]. In the context of a shortage of healthcare professionals and an increase in the number of homecare patients due to an aging population, faster and more optimal contingency management will free up caregivers' time for patient care. However, in the regional market in which we find ourselves, we are not aware of any homecare networks that exploit AI for planning.

The use of AI for scheduling in home care services has been addressed in several research work. The inherent complexity of this task arises from the need to satisfy multiple conflicting constraints, including caregiver availability, patient preferences, legal requirements, and geographical considerations. AI-based solutions, particularly those leveraging constraint satisfaction and optimization techniques, have emerged as effective tools for addressing these challenges. In particular, constraint satisfaction problems (CSPs) provide a powerful framework for scheduling tasks where solutions must meet specific requirements. A CSP can be described by a set of variables. A solution consists of assigning a value to each variable. Each variable's value belongs to a domain, which may be either a finite set of discrete values (symbolic satisfaction) or a set of numerical intervals (continuous satisfaction). Consistency constraints apply to the variables, such as unary constraints, which determine the value of a single variable; binary constraints, which involve combinations of the values of two variables; and multiple constraints, which involve combinations of values across more than two variables. This formulation applies well to efficient scheduling of caregiver shifts.

In the domain of home care services, CSPs are utilized to generate schedules that align with the preferences and availability of both caregivers and patients. Studies such as those by Méndez-Fernández[5] highlight the use of constraint programming and bi-objective optimization to solve scheduling problems in home healthcare, emphasizing the flexibility of these methods to incorporate a wide range of constraints while balancing patient welfare and operational costs.

Several real-world implementations of AI-driven scheduling systems have demonstrated their impact on operational efficiency and care quality. For example, Pan and Mao[6] describe the development of a hybrid optimization algorithm in home healthcare that reduced operational costs and increased caregiver satisfaction by improving schedule adaptability. Similarly, Kummer[7] presents a biased random-key genetic algorithm tailored for the home health care problem, which efficiently addresses routing and scheduling challenges while ensuring compliance with operational constraints. These approaches demonstrate the practical advantages of AI-driven systems in enhancing service quality and minimizing manual scheduling efforts.

In this paper, we propose an approach to care planning that uses constraint satisfaction methods. This approach is based on the de-identified data acquired by DEVECOM for one of its OSAD customer, including on the one hand the numerous constraints of the caregivers, the needs of the patients and their medical evolution. It helps nurses to plan for the unexpected.

3. Methodology

The question this paper aims to answer in the context of collaboration with the homecare organization is the following: what automation is conceivable for planning homecare staff, and how could AI methods be used to design an optimized software for this planning? To do this, in this preliminary study, we want to collect existing platform data required for scheduling, identify and formalize the wide range of staff and patient constraints (such as patient preferences for time slots and limiting the number of caregivers involved in their care), quantify measures for improvement, propose a functional scheduling demonstrator, and define a scalable architecture. The data used for the optimization process includes anonymized records of approximately 60 patients and 25 caregivers from a regional homecare organization. On average, caregivers handle between 5-8 appointments per day, with scheduling updates occurring on a daily basis. The work is also focusing on optimizing travel times to improve working conditions, free up time for care and unforeseen events, and improve the efficiency of care provision.

We used an agile methodology with many iterations between DEVECOM, the OSAD customer and the applied research team, in which step by step a demonstrator was created and enriched with newcoming requirements. Tests were first quantitative tests, to achieve similar planning quality as with a human planning. Then there were integration tests, to make sure the optimization module was working well with the DEVECOM software and being used smoothly with its planning interface. In this paper however, we will only mention the quantitative tests, as the integration tests were not sufficiently done.

A strong requirement from the homecare organization with which the optimization module is developed is the necessity to separate the homecare management software of DEVECOM from a planning optimization module, to possibly allow a separate commercialization. Furthermore, data protection laws must be respected, which enforces not to externalize personal data. This is why the first step in the methodology was to define the software architecture setup, even before diving into the optimization question. This is explained in the next section.

4. Architecture

The homecare management software of DEVECOM is developed with WinDev[1] and deployed on the servers of their customer, a regional OSAD. The diagram below describes the architecture decided in discussion with the company in order to ensure potential separate commercialization. It shows step by step what happens during execution. Both Keycloak[2] (an open-source identity and access management IAM solution that provides a range of services to simplify the process of authentication and authorization across multiple systems) and the Constraint Optimization package are thought to be deployed on the servers of the customer, to ensure the data protection legal constraints.

The following steps are explained: 1. Ask for Token (WinDev to Keycloak): The WinDev application sends a request to Keycloak to obtain an authentication token. 2. Get Token (Keycloak to WinDev): Keycloak processes the request, verifies the credentials, and re-

[1] https://pcsoft.fr/
[2] https://www.keycloak.org/

turns an authentication token back to the WinDev application. This token will be used to authenticate subsequent API calls. 3. POST CALL (WinDev to API): With the token received, WinDev makes a POST request to the API that handles constraint optimization. 4. Verify Token (API to Keycloak): The API receives the request from WinDev and needs to verify the validity of the token. To do this, it sends the token back to Keycloak for verification. 5. Token Verified (Keycloak to API): Keycloak checks the token and returns a response to the API, confirming whether the token is valid or not. 6. Create Shift Plan (API - Constraint Optimization): Upon successful token verification, the API proceeds to the next step, which is running the constraint optimization algorithm. This process creates a shift plan based on the input data and predefined constraints. 7. Return Shift Plan (API to WinDev): Once the shift plan is created, the API returns the plan to the WinDev application in JSON format. This data can then be used by WinDev for further processing, display, or storage.

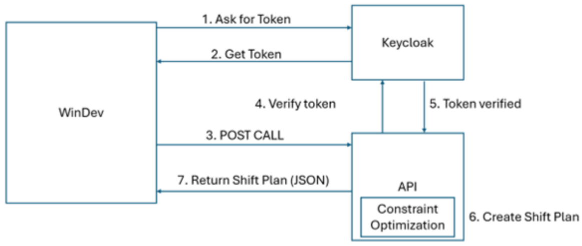

Figure 1: Architecture

5. Implementation

After the architecture was defined, an analysis of the available existing platform data required for scheduling has been identified. Furthermore, a wide range of staff and patient constraints has been formalized. Those will be sent in JSON format to the constraint module (in figure as Blackbox), with an answer back. The constraint module uses its own data model and the CP-SAT Solver[3]. The input JSON is structured to provide all the necessary data for generating a shift schedule for carers. It includes:

- **Metadata:** Such as the ID of the user that created the input.
- **List of patients:** Described only by a unique ID, their geographic coordinates, the list of carer IDs that are preferred by the patient, and the list of carer IDs that the patient does not want to be assigned.
- **List of carers:** Described only by a unique ID, and a role ID determining the types of appointments they can handle, and optionally a list of absence periods indicating when the carer is unavailable.
- **List of current appointments:** Described by a unique ID, starting and end time, type of appointment, and the patient ID to which the appointment is assigned.

The output JSON represents the optimized schedule generated by the system. It includes the following details:

- **Metadata:** General information about the scheduling process.
- **List of appointments:** Described by a unique identifier for the appointment, adjusted start and end time, and the ID of the carer assigned to this appointment.

To compute the optimal solution with the CP-SAT Solver, various factors are considered when creating the plan:

- **Role-Based Assignment:** Carers are assigned to appointments based on their role. Each role is eligible for specific types of appointments.
- **Absences:** The system checks if the carer is available during the appointment time, considering any scheduled absences. A carer cannot be assigned to an appointment that overlaps with their absence.

[3]https://developers.google.com/optimization/cp/cp_solver

- **Preferred Carer:** The system prioritizes assigning carers that are preferred by the patient. If a patient has specified preferred carers, the algorithm tries to assign one of them.
- **Exclusion Constraints:** If a patient has excluded certain carers, those carers are not assigned to the patient's appointments.
- **Fixed vs. Flexible Timing:** Appointments can have fixed times, where the start and end times must be strictly adhered to. If an appointment does not have a fixed time, the system can adjust the start and end times within a permissible range.
- **No Overlapping Appointments:** The system ensures that carers are not scheduled for overlapping appointments, considering the travel time required between consecutive appointments. The travel time is calculated based on the geographical locations of the patients.
- **Same Carer for All Appointments:** The system tries to assign the same carer to all appointments for a single patient on the same day, ensuring continuity of care.
- **Dual Carer Assignment:** The system identifies appointments that require more than one carer. It ensures that such appointments are scheduled for the required number of carers at the same time, coordinating their schedules to meet this need.
- **Minimize Unassigned Appointments:** The system aims to minimize the number of unassigned appointments.
- **Maximize Preferred Carer Assignments:** The algorithm also seeks to maximize the assignment of preferred carers to their respective patients.
- **Minimizing Travel Time:** Consecutive appointments are scheduled in a way that reduces travel distances for caregivers, thereby increasing the number of appointments they can be assigned.

These constraints and factors are designed to ensure that the shift scheduling process is efficient, meets the needs of both carers and patients, and adheres to all specified requirements and preferences.

6. Conclusion: Tests and Improvements

The optimization software and its integration were implemented and tested by human planners of the customer company. So far, a deployment in production was not yet done, as further improvements need to be achieved: refinements of the constraints descriptions still need to be done, with the goal to achieve an objective minimal time between visits of the carers.

Qualitative feedback from caregiving schedulers was collected through brief open interviews. This feedback helped identify shortcomings in the scheduling proposed by the software. Their input facilitated refinements in data entry and collection processes. A key benefit frequently cited was the ability to integrate the preferred carer to reduce the number of caregivers per care situation. Another added value perceived was related to the improved targeting of patient-requested time slots, eliminating the need for extensive manual recording. However, a notable challenge mentioned was accommodating the unique and diverse requests of individual caregivers within the scheduling framework.

Performance benchmarks are set in terms of the percentage of each day spent traveling and waiting. Optimal is below 16,6%, acceptable is between 16,6% and 22% and above 22% requires significant improvement. In comparison, professional human planners of the customer company achieve an average of 20%, whereas the current algorithm averages approximately 22% with ongoing enhancements. So, there are still improvements needed. To achieve this, future developments will focus on integrating stricter time constraints for appointments, such as setting the earliest start times, the latest end times, and the maximum allowed adjustments per appointment. These improvements are designed to better meet the needs of the patients by ensuring that their appointments are conducted within the preferred timeframe and with minimal disruptions. By enhancing the precision and reliability of schedules, the application aims to provide a higher level of comfort and satisfaction for patients, while maintaining operational efficiency. Other future improvements include real-time scheduling. An optimized adaptation of planning during unplanned events contributes to time savings in scheduling and better adaptability to unforeseen circumstances. Nevertheless, the tests have so far focused on native scheduling, which is the most time-consuming part of the planning process.

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